<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3. Classification</td>
<td>51</td>
</tr>
<tr>
<td>8.1 Classifiers</td>
<td>51</td>
</tr>
<tr>
<td>8.2 Adapters</td>
<td>60</td>
</tr>
<tr>
<td>8.3 User-defined algorithms</td>
<td>61</td>
</tr>
<tr>
<td>8.4 Examples</td>
<td>63</td>
</tr>
<tr>
<td>8.5 Network</td>
<td>63</td>
</tr>
<tr>
<td>4. Evaluation</td>
<td>65</td>
</tr>
<tr>
<td>Datasets</td>
<td>69</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>73</td>
</tr>
<tr>
<td>12 Annotation</td>
<td>77</td>
</tr>
<tr>
<td>12.1 Generate annotation file</td>
<td>79</td>
</tr>
<tr>
<td>12.2 Manual labeling</td>
<td>80</td>
</tr>
<tr>
<td>12.3 Export/read annotation file</td>
<td>80</td>
</tr>
<tr>
<td>13 Classification algorithms</td>
<td>83</td>
</tr>
<tr>
<td>13.1 Supervised learning</td>
<td>84</td>
</tr>
<tr>
<td>13.2 Unsupervised learning</td>
<td>87</td>
</tr>
<tr>
<td>14 Performance</td>
<td>89</td>
</tr>
<tr>
<td>14.1 Indexing</td>
<td>89</td>
</tr>
<tr>
<td>14.2 Comparing</td>
<td>90</td>
</tr>
<tr>
<td>15 Contributing</td>
<td>93</td>
</tr>
<tr>
<td>15.1 Testing</td>
<td>93</td>
</tr>
<tr>
<td>15.2 Performance</td>
<td>93</td>
</tr>
<tr>
<td>16 Release notes</td>
<td>95</td>
</tr>
<tr>
<td>16.1 Version 0.15</td>
<td>95</td>
</tr>
<tr>
<td>16.2 Version 0.14</td>
<td>96</td>
</tr>
<tr>
<td>Bibliography</td>
<td>97</td>
</tr>
<tr>
<td>Index</td>
<td>99</td>
</tr>
</tbody>
</table>
All you need to start linking records.
CHAPTER 1

About

1.1 Introduction

The Python Record Linkage Toolkit is a library to link records in or between data sources. The toolkit provides most of the tools needed for record linkage and deduplication. The package contains indexing methods, functions to compare records and classifiers. The package is developed for research and the linking of small or medium sized files. The project is inspired by the Freely Extensible Biomedical Record Linkage (FEBRL) project, which is a great project. In contrast with FEBRL, the recordlinkage project makes extensive use of data manipulation tools like pandas and numpy. The use of pandas, a flexible and powerful data analysis and manipulation library for Python, makes the record linkage process much easier and faster. The extensive pandas library can be used to integrate your record linkage directly into existing data manipulation projects.

One of the aims of this project is to make an extensible record linkage framework. It is easy to include your own indexing algorithms, comparison/similarity measures and classifiers. The main features of the Python Record Linkage Toolkit are:

- Clean and standardise data with easy to use tools
- Make pairs of records with smart indexing methods such as blocking and sorted neighbourhood indexing
- Compare records with a large number of comparison and similarity measures for different types of variables such as strings, numbers and dates.
- Several classifications algorithms, both supervised and unsupervised algorithms.
- Common record linkage evaluation tools
- Several built-in datasets.

1.2 What is record linkage?

The term record linkage is used to indicate the procedure of bringing together information from two or more records that are believed to belong to the same entity. Record linkage is used to link data from multiple data sources or to find
duplicates in a single data source. In computer science, record linkage is also known as data matching or deduplication (in case of search duplicate records within a single file).

In record linkage, the attributes of the entity (stored in a record) are used to link two or more records. Attributes can be unique entity identifiers (SSN, license plate number), but also attributes like (sur)name, date of birth and car model/colour. The record linkage procedure can be represented as a workflow [Christen, 2012]. The steps are: cleaning, indexing, comparing, classifying and evaluation. If needed, the classified record pairs flow back to improve the previous step. The Python Record Linkage Toolkit follows this workflow.

See also:


1.3 How to link records?

Import the recordlinkage module with all important tools for record linkage and import the data manipulation framework pandas.

```python
import recordlinkage
import pandas
```

Consider that you try to link two datasets with personal information like name, sex and date of birth. Load these datasets into a pandas DataFrame.

```python
df_a = pandas.DataFrame(YOUR_FIRST_DATASET)
df_b = pandas.DataFrame(YOUR_SECOND_DATASET)
```

Comparing all record can be computationally intensive. Therefore, we make smart set of candidate links with one of the built-in indexing techniques like blocking. Only records pairs agreeing on the surname are included.

```python
indexer = recordlinkage.Index()
indexer.block('surname')
candidate_links = indexer.index(df_a, df_b)
```

Each candidate_link needs to be compared on the comparable attributes. This can be done easily with the Compare class and the available comparison and similarity measures.

```python
compare = recordlinkage.Compare()

compare.string('name', 'name', method='jarowinkler', threshold=0.85)
c ompare.exact('sex', 'gender')
c ompare.exact('dob', 'date_of_birth')
c ompare.string('streetname', 'streetname', method='damerau_levenshtein', threshold=0.7)
c ompare.exact('place', 'placename')
c ompare.exact('haircolor', 'haircolor', missing_value=9)
```

(continues on next page)
# The comparison vectors
`compare_vectors = compare.compute(candidate_links, df_a, df_b)`

This record linkage package contains several classification algorithms. Plenty of the algorithms need trainings data (supervised learning) while some others are unsupervised. An example of supervised learning:

```python
true_linkage = pandas.Series(YOUR_GOLDEN_DATA, index=pandas.MultiIndex(YOUR_MULTI_INDEX))
logrg = recordlinkage.LogisticRegressionClassifier()
logrg.fit(compare_vectors[true_linkage.index], true_linkage)
logrg.predict(compare_vectors)
```

and an example of unsupervised learning (the well known ECM-algorithm):

```python
ecm = recordlinkage.BernoulliEMClassifier()
ecm.fit_predict(compare_vectors)
```
2.1 Python version support

The Python Record Linkage Toolkit supports the versions of Python that Pandas supports as well. You can find the supported Python versions in the Pandas documentation.

2.2 Installation

The Python Record linkage Toolkit requires Python 3.6 or higher. Install the package easily with pip

```
pip install recordlinkage
```

You can also clone the project on Github.

To install all recommended and optional dependencies, run

```
pip install recordlinkage['all']
```

2.3 Dependencies

The Python Record Linkage Toolkit depends on the following packages:

- numpy
- pandas
- scipy
- sklearn
- jellyfish
- joblib
2.3.1 Recommended dependencies

- numexpr - accelerating certain numerical operations
- bottleneck - accelerating certain types of nan evaluations

2.3.2 Optional dependencies

- networkx - for network operations like connected components

Note: This page was generated from docs/guides/link_two_dataframes.ipynb. Run an online interactive version of this page with or .
3.1 Introduction

This example shows how two datasets with data about persons can be linked. We will try to link the data based on attributes like first name, surname, sex, date of birth, place and address. The data used in this example is part of Febrl and is fictitious.

First, start with importing the `recordlinkage` module. The submodule `recordlinkage.datasets` contains several datasets that can be used for testing. For this example, we use the Febrl datasets 4A and 4B. These datasets can be loaded with the function `load_febrl4`.

```
[1]: import recordlinkage
    from recordlinkage.datasets import load_febrl4
```

The datasets are loaded with the following code. The returned datasets are of type `pandas.DataFrame`. This makes it easy to manipulate the data if desired. For details about data manipulation with `pandas`, see their comprehensive documentation `http://pandas.pydata.org/`.

```
[2]: dfA, dfB = load_febrl4()
```

```
<table>
<thead>
<tr>
<th>rec_id</th>
<th>given_name</th>
<th>surname</th>
<th>street_number</th>
<th>address_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>rec-1070-org</td>
<td>michaela</td>
<td>neumann</td>
<td>8</td>
<td>stanley street</td>
</tr>
<tr>
<td>rec-1016-org</td>
<td>courtney</td>
<td>painter</td>
<td>12</td>
<td>pinkerton circuit</td>
</tr>
<tr>
<td>rec-4405-org</td>
<td>charles</td>
<td>green</td>
<td>38</td>
<td>salkauskas crescent</td>
</tr>
<tr>
<td>rec-1288-org</td>
<td>vanessa</td>
<td>parr</td>
<td>905</td>
<td>macquoid place</td>
</tr>
<tr>
<td>rec-3585-org</td>
<td>mikayla</td>
<td>malloney</td>
<td>37</td>
<td>randwick road</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>rec-2153-org</td>
<td>annabel</td>
<td>grierson</td>
<td>97</td>
<td>mclachlan crescent</td>
</tr>
<tr>
<td>rec-1604-org</td>
<td>sienna</td>
<td>musolino</td>
<td>22</td>
<td>smeanon circuit</td>
</tr>
<tr>
<td>rec-1003-org</td>
<td>bradley</td>
<td>matthews</td>
<td>2</td>
<td>jondol place</td>
</tr>
<tr>
<td>rec-4883-org</td>
<td>brodee</td>
<td>egan</td>
<td>88</td>
<td>axon street</td>
</tr>
<tr>
<td>rec-66-org</td>
<td>koula</td>
<td>houweling</td>
<td>3</td>
<td>mileham street</td>
</tr>
</tbody>
</table>
```

(continues on next page)
### 3.2 Make record pairs

It is very intuitive to compare each record in DataFrame \(dfA\) with all records of DataFrame \(dfB\). In fact, we want to make record pairs. Each record pair should contain one record of \(dfA\) and one record of \(dfB\). This process of making record pairs is also called “indexing”. With the \texttt{recordlinkage} module, indexing is easy. First, load the \texttt{Index} class and call the \texttt{.full} method. This object generates a full index on a \texttt{.index(...)} call. In case of deduplication of a single dataframe, one dataframe is sufficient as argument.

```python
[3]: indexer = recordlinkage.Index()
    indexer.full()
    pairs = indexer.index(dfA, dfB)
WARNING:recordlinkage:indexing - performance warning - A full index can result in a large number of record pairs.
```

With the method \texttt{index}, all possible (and unique) record pairs are made. The method returns a pandas.MultiIndex. The number of pairs is equal to the number of records in \(dfA\) times the number of records in \(dfB\).

```python
[4]: print (len(dfA), len(dfB), len(pairs))
5000 5000 25000000
```

Many of these record pairs do not belong to the same person. In case of one-to-one matching, the number of matches should be no more than the number of records in the smallest dataframe. In case of full indexing, \(\min(len(dfA), len(dfB))\),
len(N_dfB)) is much smaller than len(pairs). The recordlinkage module has some more advanced indexing methods to reduce the number of record pairs. Obvious non-matches are left out of the index. Note that if a matching record pair is not included in the index, it can not be matched anymore.

One of the most well known indexing methods is named blocking. This method includes only record pairs that are identical on one or more stored attributes of the person (or entity in general). The blocking method can be used in the recordlinkage module.

```python
[5]: indexer = recordlinkage.Index()
    indexer.block("given_name")
    candidate_links = indexer.index(dfA, dfB)
    len(candidate_links)
[5]: 77249
```

The argument “given_name” is the blocking variable. This variable has to be the name of a column in dfA and dfB. It is possible to parse a list of columns names to block on multiple variables. Blocking on multiple variables will reduce the number of record pairs even further.

Another implemented indexing method is Sorted Neighbourhood Indexing (recordlinkage.index.SortedNeighbourhood). This method is very useful when there are many misspellings in the string were used for indexing. In fact, sorted neighbourhood indexing is a generalisation of blocking. See the documentation for details about sorted neighbourhood indexing.

### 3.3 Compare records

Each record pair is a candidate match. To classify the candidate record pairs into matches and non-matches, compare the records on all attributes both records have in common. The recordlinkage module has a class named Compare. This class is used to compare the records. The following code shows how to compare attributes.

```python
[6]: compare_cl = recordlinkage.Compare()
    compare_cl.exact("given_name", "given_name", label="given_name")
    compare_cl.string("surname", "surname", method="jarowinkler", threshold=0.85, label="surname")
    compare_cl.exact("date_of_birth", "date_of_birth", label="date_of_birth")
    compare_cl.exact("suburb", "suburb", label="suburb")
    compare_cl.exact("state", "state", label="state")
    compare_cl.string("address_1", "address_1", threshold=0.85, label="address_1")
    features = compare_cl.compute(candidate_links, dfA, dfB)
```

The comparing of record pairs starts when the compute method is called. All attribute comparisons are stored in a DataFrame with horizontally the features and vertically the record pairs.

```sql
[7]: features
```

<table>
<thead>
<tr>
<th>rec_id_1</th>
<th>rec_id_2</th>
<th>given_name</th>
<th>surname</th>
<th>date_of_birth</th>
<th>suburb</th>
</tr>
</thead>
<tbody>
<tr>
<td>rec-1070-org</td>
<td>rec-3024-dup-0</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-2371-dup-0</td>
<td>rec-4652-dup-0</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-4795-du-0</td>
<td>rec-1314-du-0</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-4528-org</td>
<td>rec-4528-dup-0</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>rec-4887-org</td>
<td>rec-4887-dup-0</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>rec-4350-org</td>
<td>rec-4350-dup-0</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
```

(continues on next page)
The last step is to decide which records belong to the same person. In this example, we keep it simple:

```python
features.sum(axis=1).value_counts().sort_index(ascending=False)
```

```
6.0 1566
5.0 1332
4.0 343
3.0 146
2.0 16427
1.0 57435
dtype: int64
```

```
features[features.sum(axis=1) > 3]
```

```
rec_id_1  rec_id_2
given_name surname date_of_birth suburb \
... ...
```

(continues on next page)
3.4 Full code

[11]: import recordlinkage
from recordlinkage.datasets import load_febrl4

defA, dfB = load_febrl4()

# Indexation step
indexer = recordlinkage.Index()
indexer.block("given_name")
candidate_links = indexer.index(dfA, dfB)

# Comparison step

features = compare_cl.compute(candidate_links, dfA, dfB)

# Classification step
matches = features[features.sum(axis=1) > 3]
print(len(matches))

3241

Note: This page was generated from docs/guides/data_deduplication.ipynb. Run an online interactive version of this page with or .
4.1 Introduction

This example shows how to find records in datasets belonging to the same entity. In our case, we try to deduplicate a dataset with records of persons. We will try to link within the dataset based on attributes like first name, surname, sex, date of birth, place, and address. The data used in this example is part of Febrl and is fictitious.

First, start with importing the `recordlinkage` module. The submodule `recordlinkage.datasets` contains several datasets that can be used for testing. For this example, we use the Febrl dataset 1. This dataset contains 1000 records of which 500 original and 500 duplicates, with exactly one duplicate per original record. This dataset can be loaded with the function `load_febrl1`.

```
[1]: import recordlinkage
    from recordlinkage.datasets import load_febrl1

The dataset is loaded with the following code. The returned datasets are of type pandas.DataFrame. This makes it easy to manipulate the data if desired. For details about data manipulation with pandas, see their comprehensive documentation http://pandas.pydata.org/.

```
```
[2]: dfA = load_febrl1()
```

```
[2]:
    given_name     surname   street_number      address_1
rec_id
rec-223-org    NaN        waller         6   tullaroop street
rec-122-org    lachlan    berry          69  gliblin street
rec-373-org    deakin     sondergeld     48  goldfinch circuit
rec-10-dup-0   kayla      harrington    NaN  maltby circuit
rec-227-org    luke       purdon        23  ramsay place
...          ...        ...           ...        ...
rec-188-dup-0  stephanie  geu            28  bainton crescent
rec-334-dup-0  nicholas   NaN            289 britten-jonues drive
rec-469-dup-0  lachlan    katsiavos     29  paul coe crescent
rec-350-dup-0  monique    gergely       21  harwoos court
``` (continues on next page)
4.2 Make record pairs

It is very intuitive to start with comparing each record in DataFrame `dfA` with all other records in DataFrame `dfA`. In fact, we want to make record pairs. Each record pair should contain two different records of DataFrame `dfA`. This process of making record pairs is also called “indexing”. With the `recordlinkage` module, indexing is easy. First, load the `recordlinkage.Index` class and call the `.full` method. This object generates a full index on a `.index(...)` call. In case of deduplication of a single dataframe, one dataframe is sufficient as input argument.

```python
[3]: indexer = recordlinkage.Index()
    indexer.full()
    candidate_links = indexer.index(dfA)

WARNING:recordlinkage:indexing - performance warning - A full index can result in large number of record pairs.
```

With the method `index`, all possible (and unique) record pairs are made. The method returns a pandas. MultiIndex. The number of pairs is equal to the number of records in `dfA` choose 2.

```python
[4]: print (len(dfA), len(candidate_links))
    # (1000*1000-1000)/2 = 499500

1000 499500
```
Many of these record pairs do not belong to the same person. The recordlinkage toolkit has some more advanced indexing methods to reduce the number of record pairs. Obvious non-matches are left out of the index. Note that if a matching record pair is not included in the index, it can not be matched anymore.

One of the most well known indexing methods is named **blocking**. This method includes only record pairs that are identical on one or more stored attributes of the person (or entity in general). The blocking method can be used in the recordlinkage module.

```python
[5]: indexer = recordlinkage.Index()
    indexer.block("given_name")
    candidate_links = indexer.index(dfA)
    len(candidate_links)
[5]: 2082
```

The argument “given_name” is the blocking variable. This variable has to be the name of a column in dfA. It is possible to parse a list of columns names to block on multiple variables. Blocking on multiple variables will reduce the number of record pairs even further.

Another implemented indexing method is **Sorted Neighbourhood Indexing** (recordlinkage.index.sortedneighbourhood). This method is very useful when there are many misspellings in the string were used for indexing. In fact, sorted neighbourhood indexing is a generalisation of blocking. See the documentation for details about sorted neighbourhood indexing.

### 4.3 Compare records

Each record pair is a candidate match. To classify the candidate record pairs into matches and non-matches, compare the records on all attributes both records have in common. The recordlinkage module has a class named Compare. This class is used to compare the records. The following code shows how to compare attributes.

```python
[6]: compare_cl = recordlinkage.Compare()
    compare_cl.exact("given_name", "given_name", label="given_name")
    compare_cl.string("surname", "surname", method="jarowinkler", threshold=0.85, label="surname")
    compare_cl.exact("date_of_birth", "date_of_birth", label="date_of_birth")
    compare_cl.exact("suburb", "suburb", label="suburb")
    compare_cl.exact("state", "state", label="state")
    compare_cl.string("address_1", "address_1", threshold=0.85, label="address_1")
    features = compare_cl.compute(candidate_links, dfA)
```

The comparing of record pairs starts when the compute method is called. All attribute comparisons are stored in a DataFrame with horizontally the features and vertically the record pairs. The first 10 comparison vectors are:

```python
[7]: features.head(10)
```

<table>
<thead>
<tr>
<th>rec_id_1</th>
<th>rec_id_2</th>
<th>given_name</th>
<th>surname</th>
<th>date_of_birth</th>
<th>suburb</th>
</tr>
</thead>
<tbody>
<tr>
<td>rec-183-dup-0</td>
<td>rec-122-org</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-248-org</td>
<td>rec-122-org</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-122-dup-0</td>
<td>rec-183-dup-0</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-469-org</td>
<td>rec-122-org</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>rec-183-dup-0</td>
<td>rec-122-org</td>
<td>1</td>
<td>0.0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

(continues on next page)
The last step is to decide which records belong to the same person. In this example, we keep it simple:

```python
features.sum(axis=1).value_counts().sort_index(ascending=False)
```

<table>
<thead>
<tr>
<th>count</th>
<th>given_name</th>
<th>surname</th>
<th>date_of_birth</th>
<th>suburb</th>
<th>state</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.0</td>
<td>142</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.0</td>
<td>145</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.0</td>
<td>30</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>376</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>1380</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

dtype: int64

```python
matches = features[features.sum(axis=1) > 3]
matches
```

<table>
<thead>
<tr>
<th>rec_id_1</th>
<th>rec_id_2</th>
<th>given_name</th>
<th>surname</th>
<th>date_of_birth</th>
<th>suburb</th>
<th>state</th>
</tr>
</thead>
<tbody>
<tr>
<td>rec-122-dup-0</td>
<td>rec-122-org</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>rec-183-org</td>
<td>rec-183-dup-0</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>rec-248-org</td>
<td>rec-248-dup-0</td>
<td>1</td>
<td>1.0</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
### 4.4 Full code

```python
[11]:
import recordlinkage
from recordlinkage.datasets import load.febrl1

dfA = load.febrl1()

# Indexation step
indexer = recordlinkage.Index()
indexer.block(left_on="given_name")
candidate_links = indexer.index(dfA)

# Comparison step
compare_cl = recordlinkage.Compare()

compare_cl.exact("given_name", "given_name", label="given_name")
compare_cl.string("surname", "surname", method="jarowinkler", threshold=0.85, label="surname")
compare_cl.exact("date_of_birth", "date_of_birth", label="date_of_birth")
compare_cl.exact("suburb", "suburb", label="suburb")
compare_cl.exact("state", "state", label="state")
compare_cl.string("address_1", "address_1", threshold=0.85, label="address_1")

features = compare_cl.compute(candidate_links, dfA)

# Classification step
matches = features[features.sum(axis=1) > 3]
print(len(matches))
```
Preprocessing data, like cleaning and standardising, may increase your record linkage accuracy. The Python Record Linkage Toolkit contains several tools for data preprocessing. The preprocessing and standardising functions are available in the submodule `recordlinkage.preprocessing`. Import the algorithms in the following way:

```python
from recordlinkage.preprocessing import clean, phonetic
```

### 5.1 Cleaning

The Python Record Linkage Toolkit has some cleaning function from which `recordlinkage.preprocessing.clean()` is the most generic function. Pandas itself is also very useful for (string) data cleaning. See the pandas documentation on this topic: Working with Text Data.

```python
recordlinkage.preprocessing.clean(s, lowercase=True, replace_by_none='[^-\_A-Za-z0-9]+', replace_by_whitespace='[^\ _]', strip_accents=None, remove_brackets=True, encoding='utf-8', decode_error='strict')
```

Clean string variables.

Clean strings in the Series by removing unwanted tokens, whitespace and brackets.

**Parameters**

- `s (pandas.Series)` – A Series to clean.
- `lower (bool, optional)` – Convert strings in the Series to lowercase. Default True.
- `replace_by_none (str, optional)` – The matches of this regular expression are replaced by “”. Default None.
- `replace_by_whitespace (str, optional)` – The matches of this regular expression are replaced by a whitespace. Default None.
- `remove_brackets (bool, optional)` – Remove all content between brackets and the bracket themselves. Default True.
• **strip_accents**({'ascii', 'unicode', None}, optional) – Remove accents during the preprocessing step. ‘ascii’ is a fast method that only works on characters that have an direct ASCII mapping. ‘unicode’ is a slightly slower method that works on any characters. None (default) does nothing.

• **encoding**(str, optional) – If bytes are given, this encoding is used to decode. Default is ‘utf-8’.

• **decode_error**({'strict', 'ignore', 'replace'}, optional) – In-struction on what to do if a byte Series is given that contains characters not of the given encoding. By default, it is ‘strict’, meaning that a UnicodeDecodeError will be raised. Other values are ‘ignore’ and ‘replace’.

**Example**

```python
>>> import pandas
>>> from recordlinkage.preprocessing import clean
>>> names = ['Mary-ann',
          'Bob :)',
          'Angel',
          'Bob (alias Billy)',
          None]
>>> s = pandas.Series(names)
>>> print(clean(s))
0  mary ann
1     bob
2    angel
3     bob
4    NaN
dtype: object
```

**Returns** pandas.Series – A cleaned Series of strings.

recordlinkage.preprocessing.phonenumbers(s)
Clean phonenumber by removing all non-numbers (except +).

**Parameters** s (pandas.Series) – A Series to clean.

**Returns** pandas.Series – A Series with cleaned phonenumber.

recordlinkage.preprocessing.value_occurence(s)
Count the number of times each value occurs.

This function returns the counts for each row, in contrast with pandas.value_counts.

**Returns** pandas.Series – A Series with value counts.

### 5.2 Phonetic encoding

Phonetic algorithms are algorithms for indexing of words by their pronunciation. The most well-known algorithm is the Soundex algorithm. The Python Record Linkage Toolkit supports multiple algorithms through the recordlinkage.preprocessing.phonetic() function.
Note: Use phonetic algorithms in advance of the indexing and comparing step. This results in most situations in better performance.

```python
recordlinkage.preprocessing.phonetic(s, method, concat=True, encoding='utf-8', decode_error='strict')
```

Convert names or strings into phonetic codes.

The implemented algorithms are `soundex`, `nysiis`, `metaphone` or `match_rating`.

**Parameters**

- `s` (*pandas.Series*) – A pandas.Series with string values (often names) to encode.
- `method` (*str*) – The algorithm that is used to phonetically encode the values. The possible options are “soundex”, “nysiis”, “metaphone” or “match_rating”.
- `concat` (*bool, optional*) – Remove whitespace before phonetic encoding.
- `encoding` (*str, optional*) – If bytes are given, this encoding is used to decode. Default is ‘utf-8’.
- `decode_error` (*{'strict', 'ignore', 'replace'}, optional*) – Instruction on what to do if a byte Series is given that contains characters not of the given `encoding`. By default, it is ‘strict’, meaning that a UnicodeDecodeError will be raised. Other values are ‘ignore’ and ‘replace’.

**Returns** *pandas.Series* – A Series with phonetic encoded values.

```python
preprocessing.phonetic_algorithms = ['soundex', 'nysiis', 'metaphone', 'match_rating']
```

5.2. Phonetic encoding
The indexing module is used to make pairs of records. These pairs are called candidate links or candidate matches. There are several indexing algorithms available such as blocking and sorted neighborhood indexing. See [christen2012] and [christen2008] for background information about indexation.

The indexing module can be used for both linking and duplicate detection. In case of duplicate detection, only pairs in the upper triangular part of the matrix are returned. This means that the first record in each record pair is the largest identifier. For example, (“A2”, “A1”), (5, 2) and (“acb”, “abc”). The following image shows the record pairs for a complete set of record pairs.

6.1 recordlinkage.Index object

```python
class recordlinkage.Index(algorithms=[])  
Class to make an index of record pairs.

Parameters:
  algorithms (list) – A list of index algorithm classes. The classes are based on recordlinkage.base.BaseIndexAlgorithm

Example

Consider two historical datasets with census data to link. The datasets are named census_data_1980 and census_data_1990:
```

```python
indexer = recordlinkage.Index()
indexer.block(left_on='first_name', right_on='givenname')
indexer.index(census_data_1980, census_data_1990)
```

add(model)

Add a index method.

This method is used to add index algorithms. If multiple algorithms are added, the union of the record pairs from the algorithm is taken.
Parameters **model** *(list, class)* – A (list of) index algorithm(s) from `recordlinkage.index`.

**index** *(x, x_link=None)*

Make an index of record pairs.

Parameters

- **x** *(pandas.DataFrame)* – A pandas DataFrame. When `x_link` is None, the algorithm makes record pairs within the DataFrame. When `x_link` is not empty, the algorithm makes pairs between `x` and `x_link`.

- **x_link** *(pandas.DataFrame, optional)* – A second DataFrame to link with the DataFrame `x`.

Returns *pandas.MultiIndex* – A pandas.MultiIndex with record pairs. Each record pair contains the index labels of two records.

**full()**

Add a ‘full’ index.

Shortcut of `recordlinkage.index.Full`:

```python
from recordlinkage.index import Full

indexer = recordlinkage.Index()
indexer.add(Full())
```

**block(***args, **kwargs)**

Add a block index.

Shortcut of `recordlinkage.index.Block`:
from recordlinkage.index import Block
indexer = recordlinkage.Index()
indexer.add(Block())

sortedneighbourhood(*args, **kwargs)
Add a Sorted Neighbourhood Index.
Shortcut of recordlinkage.index.SortedNeighbourhood:

from recordlinkage.index import SortedNeighbourhood
indexer = recordlinkage.Index()
indexer.add(SortedNeighbourhood())

random(*args, **kwargs)
Add a random index.
Shortcut of recordlinkage.index.Random:

from recordlinkage.index import Random
indexer = recordlinkage.Index()
indexer.add(Random())

6.2 Algorithms

The Python Record Linkage Toolkit contains basic and advanced indexing (or blocking) algorithms to make record pairs. The algorithms are Python classes. Popular algorithms in the toolkit are:

• recordlinkage.index.Full,
• recordlinkage.index.Block,
• recordlinkage.index.SortedNeighbourhood

The algorithms are available in the submodule recordlinkage.index. Import the algorithms in the following way (use blocking algorithm as example):

from recordlinkage.index import Block

The full reference for the indexing algorithms in the toolkit is given below.

class recordlinkage.index.Full(**kwargs)
Class to generate a ‘full’ index.
A full index is an index with all possible combinations of record pairs. In case of linking, this indexation method generates the cartesian product of both DataFrame’s. In case of deduplicating DataFrame A, this indexation method are the pairs defined by the upper triangular matrix of the A x A.

Parameters **kwargs – Additional keyword arguments to pass to recordlinkage.base.BaseIndexAlgorithm.

Note: This indexation method can be slow for large DataFrame’s. The number of comparisons scales quadratic. Also, not all classifiers work well with large numbers of record pairs were most of the pairs are distinct.
index \((x, x_{\text{link}}=\text{None})\)

Make an index of record pairs.

Use a custom function to make record pairs of one or two dataframes. Each function should return a pandas.MultiIndex with record pairs.

**Parameters**

- \(x\) \((\text{pandas.DataFrame})\) – A pandas DataFrame. When \(x_{\text{link}}\) is None, the algorithm makes record pairs within the DataFrame. When \(x_{\text{link}}\) is not empty, the algorithm makes pairs between \(x\) and \(x_{\text{link}}\).

- \(x_{\text{link}}\) \((\text{pandas.DataFrame}, \text{optional})\) – A second DataFrame to link with the DataFrame \(x\).

**Returns** pandas.MultiIndex – A pandas.MultiIndex with record pairs. Each record pair contains the index labels of two records.

class recordlinkage.index.Block \((\text{left}_\text{on}=\text{None}, \text{right}_\text{on}=\text{None}, **\text{kwargs})\)

Make candidate record pairs that agree on one or more variables.

Returns all record pairs that agree on the given variable(s). This method is known as blocking. Blocking is an effective way to make a subset of the record space \((A \ast B)\).

**Parameters**

- \(\text{left}_\text{on}\) \((\text{label}, \text{optional})\) – A column name or a list of column names of dataframe \(A\). These columns are used to block on.

- \(\text{right}_\text{on}\) \((\text{label}, \text{optional})\) – A column name or a list of column names of dataframe \(B\). These columns are used to block on. If ‘right_on’ is None, the \(\text{left}_\text{on}\) value is used. Default None.

- **kwargs – Additional keyword arguments to pass to recordlinkage.base.BaseIndexAlgorithm.

**Examples**

In the following example, the record pairs are made for two historical datasets with census data. The datasets are named \text{census_data\_1980} and \text{census_data\_1990}.

```python
>>> indexer = recordlinkage.BlockIndex(on='first_name')
>>> indexer.index(census_data_1980, census_data_1990)
```
class recordlinkage.index.SortedNeighbourhood(left_on=None, right_on=None, window=3, sorting_key_values=None, block_on=[], block_left_on=[], block_right_on=[], **kwargs)

Make candidate record pairs with the SortedNeighbourhood algorithm.

This algorithm returns record pairs that agree on the sorting key, but also records pairs in their neighbourhood. A large window size results in more record pairs. A window size of 1 returns the blocking index.

The Sorted Neighbourhood Index method is a great method when there is relatively large amount of spelling mistakes. Blocking will fail in that situation because it excludes to many records on minor spelling mistakes.

Parameters

- **left_on** (*label, optional*) – The column name of the sorting key of the first/left dataframe.
- **right_on** (*label, optional*) – The column name of the sorting key of the second/right dataframe.
- **window** (*int, optional*) – The width of the window, default is 3
- **sorting_key_values** (*array, optional*) – A list of sorting key values (optional).
- **block_on** (*label*) – Additional columns to apply standard blocking on.
- **block_left_on** (*label*) – Additional columns in the left dataframe to apply standard blocking on.
- **block_right_on** (*label*) – Additional columns in the right dataframe to apply standard blocking on.
- ****kwargs – Additional keyword arguments to pass to recordlinkage.base.BaseIndexAlgorithm.

Examples

In the following example, the record pairs are made for two historical datasets with census data. The datasets are named census_data_1980 and census_data_1990.

```python
>>> indexer = recordlinkage.SortedNeighbourhoodIndex('first_name', window=9)
>>> indexer.index(census_data_1980, census_data_1990)
```

When the sorting key has different names in both dataframes:

```python
>>> indexer = recordlinkage.SortedNeighbourhoodIndex(
    left_on='first_name', right_on='given_name', window=9)
>>> indexer.index(census_data_1980, census_data_1990)
```

index
generate a record pairs.

Use a custom function to make record pairs of one or two dataframes. Each function should return a pandas.MultiIndex with record pairs.

Parameters
• **x** (**pandas.DataFrame**) – A pandas DataFrame. When x_link is None, the algorithm makes record pairs within the DataFrame. When x_link is not empty, the algorithm makes pairs between x and x_link.

• **x_link** (**pandas.DataFrame, optional**) – A second DataFrame to link with the DataFrame x.

**Returns**  
*pandas.MultiIndex* – A pandas.MultiIndex with record pairs. Each record pair contains the index labels of two records.

class recordlinkage.index.Random(n, replace=True, random_state=None, **kwargs)

Class to generate random pairs of records.

This class returns random pairs of records with or without replacement. Use the random_state parameter to seed the algorithm and reproduce results. This way to make record pairs is useful for the training of unsupervised learning models for record linkage.

**Parameters**

• **n** (**int**) – The number of record pairs to return. In case replace=False, the integer n should be bounded by 0 < n <= n_max where n_max is the maximum number of pairs possible.

• **replace** (**bool, optional**) – Whether the sample of record pairs is with or without replacement. Default: True

• **random_state** (**int or numpy.random.RandomState, optional**) – Seed for the random number generator (if int), or numpy.RandomState object.

• ****kwargs** – Additional keyword arguments to pass to *recordlinkage.base.BaseIndexAlgorithm*.

index(x, x_link=None)

Make an index of record pairs.

Use a custom function to make record pairs of one or two dataframes. Each function should return a pandas.MultiIndex with record pairs.

**Parameters**

• **x** (**pandas.DataFrame**) – A pandas DataFrame. When x_link is None, the algorithm makes record pairs within the DataFrame. When x_link is not empty, the algorithm makes pairs between x and x_link.

• **x_link** (**pandas.DataFrame, optional**) – A second DataFrame to link with the DataFrame x.

**Returns**  
*pandas.MultiIndex* – A pandas.MultiIndex with record pairs. Each record pair contains the index labels of two records.

### 6.3 User-defined algorithms

A user-defined algorithm can be defined based on *recordlinkage.base.BaseIndexAlgorithm*. The *recordlinkage.base.BaseIndexAlgorithm* class is an abstract base class that is used for indexing algorithms. The classes

• recordlinkage.index.Full

• recordlinkage.index.Block

• recordlinkage.index.SortedNeighbourhood

• recordlinkage.index.Random
are inherited from this abstract base class. You can use BaseIndexAlgorithm to create a user-defined/custom algorithm.

To create a custom algorithm, subclass the `recordlinkage.base.BaseIndexAlgorithm`. In the subclass, overwrite the `recordlinkage.base.BaseIndexAlgorithm._link_index()` method in case of linking two datasets. This method accepts two (tuples of) `pandas.Series` objects as arguments. Based on these Series objects, you create record pairs. The record pairs need to be returned in a 2-level `pandas.MultiIndex` object. The `pandas.MultiIndex.names` are the name of index of DataFrame A and name of the index of DataFrame B respectively. Overwrite the `recordlinkage.base.BaseIndexAlgorithm._dedup_index()` method in case of finding link within a single dataset (deduplication). This method accepts a single (tuples of) `pandas.Series` objects as arguments.

The algorithm for linking data frames can be used for finding duplicates as well. In this situation, DataFrame B is a copy of DataFrame A. The Pairs class removes pairs like (record_i, record_i) and one of the following (record_i, record_j) (record_j, record_i) under the hood. As result of this, only unique combinations are returned. If you do have a specific algorithm for finding duplicates, then you can overwrite the `_dedup_index` method. This method accepts only one argument (DataFrame A) and the internal base class does not look for combinations like explained above.

```python
class recordlinkage.base.BaseIndexAlgorithm(verify_integrity=True, suffixes=('1', '_2')):
    Base class for all index algorithms.

    BaseIndexAlgorithm is an abstract class for indexing algorithms. The method _link_index()

    Parameters
    • verify_integrity (bool) – Verify the integrity of the input dataframe(s). The index
      is checked for duplicate values.
    • suffixes (tuple) – If the names of the resulting MultiIndex are identical, the suffixes
      are used to distinguish the names.

Example

Make your own indexation class:

class CustomIndex(BaseIndexAlgorithm):
    def _link_index(self, df_a, df_b):
        # Custom index for linking.
        return ...

    def _dedup_index(self, df_a):
        # Custom index for duplicate detection, optional.
        return ...
```

Call the class in the same way:

```python
custom_index = CustomIndex():
custom_index.index()

_link_index(df_a, df_b)
Build an index for linking two datasets.

Parameters

6.3. User-defined algorithms
• **df_a** ((tuple of) `pandas.Series`) – The data of the left DataFrame to build the index with.

• **df_b** ((tuple of) `pandas.Series`) – The data of the right DataFrame to build the index with.

**Returns** `pandas.MultiIndex` – A pandas.MultiIndex with record pairs. Each record pair contains the index values of two records.

```python
_index(x, x_link=None)
```

Make an index of record pairs.

Use a custom function to make record pairs of one or two dataframes. Each function should return a pandas.MultiIndex with record pairs.

**Parameters**

- **x** (pandas.DataFrame) – A pandas DataFrame. When `x_link` is None, the algorithm makes record pairs within the DataFrame. When `x_link` is not empty, the algorithm makes pairs between `x` and `x_link`.

- **x_link** (pandas.DataFrame, optional) – A second DataFrame to link with the DataFrame `x`.

**Returns** `pandas.MultiIndex` – A pandas.MultiIndex with record pairs. Each record pair contains the index labels of two records.

### 6.4 Examples

```python
import recordlinkage as rl
from recordlinkage.datasets import load_febrl4
from recordlinkage.index import Block

df_a, df_b = load_febrl4()
indexer = rl.Index()
indexer.add(Block('given_name', 'given_name'))
indexer.add(Block('surname', 'surname'))
indexer.index(df_a, df_b)
```

Equivalent code:

```python
import recordlinkage as rl
from recordlinkage.datasets import load_febrl4

df_a, df_b = load_febrl4()
```
This example shows how to implement a custom indexing algorithm. The algorithm returns all record pairs of which the given names starts with the letter ‘W’.

```python
import recordlinkage
from recordlinkage.datasets import load_febrl4

df_a, df_b = load_febrl4()

from recordlinkage.base import BaseIndexAlgorithm

class FirstLetterWIndex(BaseIndexAlgorithm):
    """Custom class for indexing""

    def _link_index(self, df_a, df_b):
        """Make pairs with given names starting with the letter 'w'.""

        # Select records with names starting with a w.
        name_a_w = df_a[df_a['given_name'].str.startswith('w') == True]
        name_b_w = df_b[df_b['given_name'].str.startswith('w') == True]

        # Make a product of the two numpy arrays
        return pandas.MultiIndex.from_product(
            [name_a_w.index.values, name_b_w.index.values],
            names=[df_a.index.name, df_b.index.name]
        )

indexer = FirstLetterWIndex()
candidate_pairs = indexer.index(df_a, df_b)

print ('Returns a', type(candidate_pairs).__name__)
print ('Number of candidate record pairs starting with the letter w:', len(candidate_pairs))
```

The custom index class below does not restrict the first letter to ‘w’, but the first letter is an argument (named `letter`). This letter can is initialized during the setup of the class.

```python
class FirstLetterIndex(BaseIndexAlgorithm):
    """Custom class for indexing""

    def __init__(self, letter):
        super(FirstLetterIndex, self).__init__()

        # the letter to save
        self.letter = letter

    def _link_index(self, df_a, df_b):
        """Make record pairs that agree on the first letter of the given name.""

        # Select records with names starting with a 'letter'.
        a_startswith_w = df_a[df_a['given_name'].str.startswith(self.letter) == True]

        return pandas.MultiIndex.from_product(
            [a_startswith_w.index.values],
            names=[df_a.index.name]
        )

indexer = FirstLetterIndex()
candidate_pairs = indexer.index(df_a, df_b)

print ('Returns a', type(candidate_pairs).__name__)
print ('Number of candidate record pairs starting with the letter w:', len(candidate_pairs))
```
b_startswith_w = df_b[df_b['given_name'].str.startswith(self.letter) == True]

# Make a product of the two numpy arrays
return pandas.MultiIndex.from_product(
    [a_startswith_w.index.values, b_startswith_w.index.values],
    names=[df_a.index.name, df_b.index.name])
A set of informative, discriminating and independent features is important for a good classification of record pairs into matching and distinct pairs. The `recordlinkage.Compare` class and its methods can be used to compare records pairs. Several comparison methods are included such as string similarity measures, numerical measures and distance measures.

### 7.1 recordlinkage.Compare object

```python
class recordlinkage.Compare(features=[], n_jobs=1, indexing_type='label', **kwargs)
```

Class to compare record pairs with efficiently.

Class to compare the attributes of candidate record pairs. The `Compare` class has methods like `string`, `exact` and `numeric` to initialise the comparing of the records. The `compute` method is used to start the actual comparing.

#### Example

Consider two historical datasets with census data to link. The datasets are named `census_data_1980` and `census_data_1990`. The `MultiIndex candidates_pairs` contains the record pairs to compare. The record pairs are compared on the first name, last name, sex, date of birth, address, place, and income:

```python
# initialise class
comp = recordlinkage.Compare()

# initialise similarity measurement algorithms
comp.string('first_name', 'name', method='jarowinkler')
comp.string('lastname', 'lastname', method='jarowinkler')
comp.exact('dateofbirth', 'dob')
comp.exact('sex', 'sex')
comp.string('address', 'address', method='levenshtein')
comp.exact('place', 'place')
comp.numeric('income', 'income')
```

(continues on next page)
The method `.compute()` returns the DataFrame with the feature vectors.

```python
comp.compute(candidate_pairs, census_data_1980, census_data_1990)
```

**Parameters**

- **features** *(list)* – List of compare algorithms.
- **n_jobs** *(integer, optional (default=1))* – The number of jobs to run in parallel for comparing of record pairs. If -1, then the number of jobs is set to the number of cores.
- **indexing_type** *(string, optional (default='label'))* – The indexing type. The MultiIndex is used to index the DataFrame(s). This can be done with pandas `.loc` or with `.iloc`. Use the value ‘label’ to make use of `.loc` and ‘position’ to make use of `.iloc`. The value ‘position’ is only available when the MultiIndex consists of integers. The value ‘position’ is much faster.

**features**

A list of algorithms to create features.

**Type** *list*

**add** *(model)*

Add a compare method.

This method is used to add compare features.

Parameters

- **model** *(list, class)* – A (list of) compare feature(s) from `recordlinkage.compare`.

**compute** *(pairs, x, x_link=None)*

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

- **pairs** *(pandas.MultiIndex)* – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
- **x** *(pandas.DataFrame)* – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.
- **x_link** *(pandas.DataFrame, optional)* – The second DataFrame.

Returns *pandas.DataFrame* – A pandas DataFrame with feature vectors, i.e. the result of comparing each record pair.

**compare_vectorized** *(comp_func, labels_left, labels_right, *args, **kwargs)*

Compute the similarity between values with a callable.

This method initialises the comparing of values with a custom function/callable. The function/callable should accept numpy.ndarray’s.

**Example**
Record Linkage Toolkit Documentation, Release 0.15

```python
>>> comp = recordlinkage.Compare()
>>> comp.compare_vectorized(custom_callable, 'first_name', 'name')
>>> comp.compare(PAIRS, DATAFRAME1, DATAFRAME2)
```

Parameters

- `comp_func (function)` – A comparison function. This function can be a built-in function or a user defined comparison function. The function should accept numpy.ndarray's as first two arguments.
- `labels_left (label, pandas.Series, pandas.DataFrame)` – The labels, Series or DataFrame to compare.
- `labels_right (label, pandas.Series, pandas.DataFrame)` – The labels, Series or DataFrame to compare.
- `*args` – Additional arguments to pass to callable comp_func.
- `**kwargs` – Additional keyword arguments to pass to callable comp_func. (keyword 'label' is reserved.)
- `label ((list of) label(s))` – The name of the feature and the name of the column. IMPORTANT: This argument is a keyword argument and can not be part of the arguments of comp_func.

`exact (*args, **kwargs)`

Compare attributes of pairs exactly.

Shortcut of `recordlinkage.compare.Exact`:

```python
from recordlinkage.compare import Exact
indexer = recordlinkage.Compare()
indexer.add(Exact())
```

`string (*args, **kwargs)`

Compare attributes of pairs with string algorithm.

Shortcut of `recordlinkage.compare.String`:

```python
from recordlinkage.compare import String
indexer = recordlinkage.Compare()
indexer.add(String())
```

`numeric (*args, **kwargs)`

Compare attributes of pairs with numeric algorithm.

Shortcut of `recordlinkage.compare.Numeric`:

```python
from recordlinkage.compare import Numeric
indexer = recordlinkage.Compare()
indexer.add(Numeric())
```

`geo (*args, **kwargs)`

Compare attributes of pairs with geo algorithm.

Shortcut of `recordlinkage.compare.Geographic`:
from recordlinkage.compare import Geographic
indexer = recordlinkage.Compare()
indexer.add(Geographic())

def date(*args, **kwargs):
    Compare attributes of pairs with date algorithm.
    Shortcut of recordlinkage.compare.Date:
    from recordlinkage.compare import Date
    indexer = recordlinkage.Compare()
    indexer.add(Date())

7.2 Algorithms

class recordlinkage.compare.Exact (left_on, right_on, agree_value=1, disagree_value=0, missing_value=0, label=None)
    Compare the record pairs exactly.
    This class is used to compare records in an exact way. The similarity is 1 in case of agreement and 0 otherwise.

    Parameters
    • left_on (str or int) – Field name to compare in left DataFrame.
    • right_on (str or int) – Field name to compare in right DataFrame.
    • agree_value (float, str, numpy.dtype) – The value when two records are identical. Default 1. If ‘values’ is passed, then the value of the record pair is passed.
    • disagree_value (float, str, numpy.dtype) – The value when two records are not identical.
    • missing_value (float, str, numpy.dtype) – The value for a comparison with a missing value. Default 0.

    compute (pairs, x, x_link=None)
    Compare the records of each record pair.
    Calling this method starts the comparing of records.

    Parameters
    • pairs (pandas.MultiIndex) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
    • x (pandas.DataFrame) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.
    • x_link (pandas.DataFrame, optional) – The second DataFrame.


class recordlinkage.compare.String (left_on, right_on, method='levenshtein', threshold=None, missing_value=0.0, label=None)
    Compute the (partial) similarity between strings values.
This class is used to compare string values. The implemented algorithms are: ‘jaro’, ‘jarowinkler’, ‘levenshtein’, ‘damerau_levenshtein’, ‘qgram’ or ‘cosine’. In case of agreement, the similarity is 1 and in case of complete disagreement it is 0. The Python Record Linkage Toolkit uses the jellyfish package for the Jaro, Jaro-Winkler, Levenshtein and Damerau-Levenshtein algorithms.

**Parameters**

- **left_on** *(str or int)* – The name or position of the column in the left DataFrame.
- **right_on** *(str or int)* – The name or position of the column in the right DataFrame.
- **method** *(str, default 'levenshtein')* – An approximate string comparison method. Options are ['jaro', 'jarowinkler', 'levenshtein', 'damerau_levenshtein', 'qgram', 'cosine', 'smith_waterman', 'lcs']. Default: 'levenshtein'
- **threshold** *(float, tuple of floats)* – A threshold value. All approximate string comparisons higher or equal than this threshold are 1. Otherwise 0.
- **missing_value** *(numpy.dtype)* – The value for a comparison with a missing value. Default 0.

**compute** *(pairs, x, x_link=None)*

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

- **pairs** *(pandas.MultiIndex)* – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
- **x** *(pandas.DataFrame)* – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.
- **x_link** *(pandas.DataFrame, optional)* – The second DataFrame.


```
class recordlinkage.compare.Numeric(left_on, right_on, method='linear', offset=0.0, scale=1.0, origin=0.0, missing_value=0.0, label=None)
```

Compute the (partial) similarity between numeric values.

This class is used to compare numeric values. The implemented algorithms are: ‘step’, ‘linear’, ‘exp’, ‘gauss’ or ‘squared’. In case of agreement, the similarity is 1 and in case of complete disagreement it is 0. The implementation is similar with numeric comparing in ElasticSearch, a full-text search tool. The parameters are explained in the image below (source ElasticSearch, The Definitive Guide)
Parameters

- **left_on**(str or int) – The name or position of the column in the left DataFrame.
- **right_on**(str or int) – The name or position of the column in the right DataFrame.
- **offset**(float) – The offset. See image above.
- **scale**(float) – The scale of the numeric comparison method. See the image above. This argument is not available for the ‘step’ algorithm.
- **origin**(float) – The shift of bias between the values. See image above.
- **missing_value**(numpy.dtype) – The value if one or both records have a missing value on the compared field. Default 0.

**Note:** Numeric comparing can be an efficient way to compare date/time variables. This can be done by comparing the timestamps.

**compute**(pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

- **pairs**(pandas.MultiIndex) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
• `x (pandas.DataFrame)` – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.

• `x_link (pandas.DataFrame, optional)` – The second DataFrame.


class recordlinkage.compare.Geographic(left_on_lat, left_on_lng, right_on_lat, right_on_lng, method=None, offset=0.0, scale=1.0, origin=0.0, missing_value=0.0, label=None)

Compute the (partial) similarity between WGS84 coordinate values.

Compare the geometric (haversine) distance between two WGS- coordinates. The similarity algorithms are ‘step’, ‘linear’, ‘exp’, ‘gauss’ or ‘squared’. The similarity functions are the same as in recordlinkage.comparing.Compare.numeric()

Parameters

• `left_on_lat (tuple)` – The name or position of the latitude in the left DataFrame.

• `left_on_lng (tuple)` – The name or position of the longitude in the left DataFrame.

• `right_on_lat (tuple)` – The name or position of the latitude in the right DataFrame.

• `right_on_lng (tuple)` – The name or position of the longitude in the right DataFrame.


• `offset (float)` – The offset. See Compare.numeric.

• `scale (float)` – The scale of the numeric comparison method. See Compare.numeric. This argument is not available for the ‘step’ algorithm.

• `origin (float)` – The shift of bias between the values. See Compare.numeric.

• `missing_value (numpy.dtype)` – The value for a comparison with a missing value. Default 0.

compute (pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

• `pairs (pandas.MultiIndex)` – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.

• `x (pandas.DataFrame)` – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.

• `x_link (pandas.DataFrame, optional)` – The second DataFrame.


class recordlinkage.compare.Date(left_on, right_on, swap_month_day=0.5, swap_months='default', errors='coerce', missing_value=0.0, label=None)

Compute the (partial) similarity between date values.

Parameters
• **left_on** (*str or int*) – The name or position of the column in the left DataFrame.

• **right_on** (*str or int*) – The name or position of the column in the right DataFrame.

• **swap_month_day** (*float*) – The value if the month and day are swapped. Default 0.5.

• **swap_months** (*list of tuples*) – A list of tuples with common errors caused by the translating of months into numbers, i.e. October is month 10. The format of the tuples is `(month_good, month_bad, value)`. Default: `swap_months = [(6, 7, 0.5), (7, 6, 0.5), (9, 10, 0.5), (10, 9, 0.5)]`

• **missing_value** (*numpy.dtype*) – The value for a comparison with a missing value. Default 0.0.

**compute** (*pairs, x, x_link=None*)

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

• **pairs** (*pandas.MultiIndex*) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.

• **x** (*pandas.DataFrame*) – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.

• **x_link** (*pandas.DataFrame, optional*) – The second DataFrame.


**class recordlinkage.compare.Variable (left_on=None, right_on=None, missing_value=0.0, label=None)**

Add a variable of the dataframe as feature.

**Parameters**

• **left_on** (*str or int*) – The name or position of the column in the left DataFrame.

• **right_on** (*str or int*) – The name or position of the column in the right DataFrame.

• **missing_value** (*numpy.dtype*) – The value for a comparison with a missing value. Default 0.0.

**compute** (*pairs, x, x_link=None*)

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

• **pairs** (*pandas.MultiIndex*) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.

• **x** (*pandas.DataFrame*) – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.

• **x_link** (*pandas.DataFrame, optional*) – The second DataFrame.

class recordlinkage.compare.VariableA(on=None, missing_value=0.0, label=None)

Add a variable of the left dataframe as feature.

Parameters

• **on** (*str or int*) – The name or position of the column in the left DataFrame.

• **normalise** (*bool*) – Normalise the outcome. This is needed for good result in many classification models. Default True.

• **missing_value** (*numpy.dtype*) – The value for a comparison with a missing value. Default 0.0.

compute(pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

• **pairs** (*pandas.MultiIndex*) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.

• **x** (*pandas.DataFrame*) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.

• **x_link** (*pandas.DataFrame, optional*) – The second DataFrame.


class recordlinkage.compare.VariableB(on=None, missing_value=0.0, label=None)

Add a variable of the right dataframe as feature.

Parameters

• **on** (*str or int*) – The name or position of the column in the right DataFrame.

• **normalise** (*bool*) – Normalise the outcome. This is needed for good result in many classification models. Default True.

• **missing_value** (*numpy.dtype*) – The value for a comparison with a missing value. Default 0.0.

compute(pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

• **pairs** (*pandas.MultiIndex*) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.

• **x** (*pandas.DataFrame*) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.

• **x_link** (*pandas.DataFrame, optional*) – The second DataFrame.

class recordlinkage.compare.Frequency (left_on=None, right_on=None, normalise=True, missing_value=0.0, label=None)

Compute the (relative) frequency of each variable.

Parameters

• left_on (str or int) – The name or position of the column in the left DataFrame.
• right_on (str or int) – The name or position of the column in the right DataFrame.
• normalise (bool) – Normalise the outcome. This is needed for good result in many classification models. Default True.
• missing_value (numpy.dtype) – The value for a comparison with a missing value. Default 0.0.

compute (pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

• pairs (pandas.MultiIndex) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
• x (pandas.DataFrame) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.
• x_link (pandas.DataFrame, optional) – The second DataFrame.


class recordlinkage.compare.FrequencyA (on=None, normalise=True, missing_value=0.0, label=None)

Compute the frequency of a variable in the left dataframe.

Parameters

• on (str or int) – The name or position of the column in the left DataFrame.
• normalise (bool) – Normalise the outcome. This is needed for good result in many classification models. Default True.
• missing_value (numpy.dtype) – The value for a comparison with a missing value. Default 0.0.

compute (pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

Parameters

• pairs (pandas.MultiIndex) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
• x (pandas.DataFrame) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.
• x_link (pandas.DataFrame, optional) – The second DataFrame.

class recordlinkage.compare.FrequencyB(on=None, normalise=True, missing_value=0.0, label=None)

Compute the frequency of a variable in the right dataframe.

**Parameters**

- **on** (str or int) – The name or position of the column in the right DataFrame.
- **normalise** (bool) – Normalise the outcome. This is needed for good result in many classification models. Default True.
- **missing_value** (numpy.dtype) – The value for a comparison with a missing value. Default 0.0.

call compute(pairs, x, x_link=None)

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

- **pairs** (pandas.MultiIndex) – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
- **x** (pandas.DataFrame) – The DataFrame to link. If x_link is given, the comparing is a linking problem. If x_link is not given, the problem is one of duplicate detection.
- **x_link** (pandas.DataFrame, optional) – The second DataFrame.


### 7.3 User-defined algorithms

A user-defined algorithm can be defined based on `recordlinkage.base.BaseCompareFeature`. The `recordlinkage.base.BaseCompareFeature` class is an abstract base class that is used for compare algorithms. The classes

- recordlinkage.compare.Exact
- recordlinkage.compare.String
- recordlinkage.compare.Numeric
- recordlinkage.compare.Date

are inherited from this abstract base class. You can use BaseCompareFeature to create a user-defined/custom algorithm. Overwrite the abstract method `recordlinkage.base.BaseCompareFeature._compute_vectorized()` with the compare algorithm. A short example is given here:

```python
from recordlinkage.base import BaseCompareFeature

class CustomFeature(BaseCompareFeature):
    def _compute_vectorized(s1, s2):
        # algorithm that compares s1 and s2
```

(continues on next page)
A full description of the `recordlinkage.base.BaseCompareFeature` class:

```python
class recordlinkage.base.BaseCompareFeature(labels_left, labels_right, args=(), kwargs={}, label=None)
```

**Base abstract class for compare feature engineering.**

**Parameters**

- `labels_left (list, str, int)` – The labels to use for comparing record pairs in the left dataframe.
- `labels_right (list, str, int)` – The labels to use for comparing record pairs in the right dataframe (linking) or left dataframe (duplicate detection).
- `args (tuple)` – Additional arguments to pass to the `_compare_vectorized` method.
- `kwargs (tuple)` – Keyword additional arguments to pass to the `_compare_vectorized` method.
- `label (list, str, int)` – The identifying label(s) for the returned values.

**compute (pairs, x, x_link=None)**

Compare the records of each record pair.

Calling this method starts the comparing of records.

**Parameters**

- `pairs (pandas.MultiIndex)` – A pandas MultiIndex with the record pairs to compare. The indices in the MultiIndex are indices of the DataFrame(s) to link.
- `x (pandas.DataFrame)` – The DataFrame to link. If `x_link` is given, the comparing is a linking problem. If `x_link` is not given, the problem is one of duplicate detection.
- `x_link (pandas.DataFrame, optional)` – The second DataFrame.


**_compute (left_on, right_on)**

Compare the data on the left and right.

BaseCompareFeature._compute() and BaseCompareFeature.compute() differ on the accepted arguments. _compute accepts indexed data while compute accepts the record pairs and the DataFrame’s.

**Parameters**

- `left_on ((tuple of) pandas.Series)` – Data to compare with `right_on`
- `right_on ((tuple of) pandas.Series)` – Data to compare with `left_on`

_compute_vectorized(*args)
    Compare attributes (vectorized)

    Parameters

    Returns
        pandas.Series, pandas.DataFrame, numpy.ndarray – The result of comparing record
        pairs (the features). Can be a tuple with multiple pandas.Series, pandas.DataFrame,
        numpy.ndarray objects.

**Warning:** Do not change the order of the pairs in the MultiIndex.

### 7.4 Examples

#### 7.4.1 Example: High level usage

```python
import recordlinkage as rl
comparer = rl.Compare()
comparer.string('name_a', 'name_b', method='jarowinkler', threshold=0.85, label='name')
comparer.exact('sex', 'gender', label='gender')
comparer.date('dob', 'date_of_birth', label='date')
comparer.string('str_name', 'streetname', method='damerau_levenshtein', threshold=0.7, label='streetname')
comparer.exact('place', 'placename', label='placename')
comparer.numeric('income', 'income', method='gauss', offset=3, scale=3, missing_value=0.5, label='income')
comparer.compute(pairs, dfA, dfB)
```

#### 7.4.2 Example: Low level usage

```python
import recordlinkage as rl
from recordlinkage.compare import Exact, String, Numeric, Date
comparer = rl.Compare(
    String('name_a', 'name_b', method='jarowinkler', threshold=0.85, label='name'),
    Exact('sex', 'gender', label='gender'),
    Date('dob', 'date_of_birth', label='date'),
    String('str_name', 'streetname', method='damerau_levenshtein', threshold=0.7, label='streetname'),
    Exact('place', 'placename', label='placename'),
    Numeric('income', 'income', method='gauss', offset=3, scale=3, missing_value=0.5, label='income'))
comparer.compute(pairs, dfA, dfB)
```

The following examples give a feeling on the extensibility of the toolkit.
7.4.3 Example: User-defined algorithm 1

The following code defines a custom algorithm to compare zipcodes. The algorithm returns 1.0 for record pairs that agree on the zipcode and returns 0.0 for records that disagree on the zipcode. If the zipcodes disagree but the first two numbers are identical, then the algorithm returns 0.5.

```python
import recordlinkage as rl
from recordlinkage.base import BaseCompareFeature

class CompareZipCodes(BaseCompareFeature):
    def _compute_vectorized(self, s1, s2):
        """Compare zipcodes.
        If the zipcodes in both records are identical, the similarity
        is 1. If the first two values agree and the last two don’t, then
        the similarity is 0.5. Otherwise, the similarity is 0.
        """

        # check if the zipcode are identical (return 1 or 0)
        sim = (s1 == s2).astype(float)

        # check the first 2 numbers of the distinct comparisons
        sim[(sim == 0) & (s1.str[0:2] == s2.str[0:2])] = 0.5

        return sim

comparer = rl.Compare()
comparer.extract('given_name', 'given_name', 'y_name')
comparer.string('surname', 'surname', 'y_surname')
comparer.add(CompareZipCodes('postcode', 'postcode', label='y_postcode'))
comparer.compute(pairs, dfA, dfB)

0.0    71229
0.5    3166
1.0    2854
Name: sim_postcode, dtype: int64

Note: See recordlinkage.base.BaseCompareFeature for more details on how to subclass.

7.4.4 Example: User-defined algorithm 2

As you can see, one can pass the labels of the columns as arguments. The first argument is a column label, or a list of column labels, found in the first DataFrame (postcode in this example). The second argument is a column label, or a list of column labels, found in the second DataFrame (also postcode in this example). The recordlinkage.Compare class selects the columns with the given labels before passing them to the custom algorithm/function. The compare method in the recordlinkage.Compare class passes additional (keyword) arguments to the custom function.

Warning: Do not change the order of the pairs in the MultiIndex.

```python
import recordlinkage as rl
from recordlinkage.base import BaseCompareFeature
(continues on next page)```
class CompareZipCodes(BaseCompareFeature):
    
def __init__(self, left_on, right_on, partial_sim_value, *args, **kwargs):
        super(CompareZipCodes, self).__init__(left_on, right_on, *args, **kwargs)
        self.partial_sim_value = partial_sim_value

    
def _compute_vectorized(self, s1, s2):
        """Compare zipcodes.
        If the zipcodes in both records are identical, the similarity is 0. If the first two values agree and the last two don't, then the similarity is 0.5. Otherwise, the similarity is 0.
        """
        sim = (s1 == s2).astype(float)
        sim[(sim == 0) & (s1.str[0:2] == s2.str[0:2])] = self.partial_sim_value
        return sim

comparer = rl.Compare()
comparer.extract('given_name', 'given_name', 'y_name')
comparer.string('surname', 'surname', 'y_surname')
comparer.add(CompareZipCodes('postcode', 'postcode',
                             'partial_sim_value'=0.5, label='y_postcode'))
comparer.compute(pairs, dfA, dfB)

7.4.5 Example: User-defined algorithm 3

The Python Record Linkage Toolkit supports the comparison of more than two columns. This is especially useful in situations with multi-dimensional data (for example geographical coordinates) and situations where fields can be swapped.

The FEBRL4 dataset has two columns filled with address information (address_1 and address_2). In a naive approach, one compares address_1 of file A with address_1 of file B and address_2 of file A with address_2 of file B. If the values for address_1 and address_2 are swapped during the record generating process, the naive approach considers the addresses to be distinct. In a more advanced approach, address_1 of file A is compared with address_1 and address_2 of file B. Variable address_2 of file A is compared with address_1 and address_2 of file B. This is done with the single function given below.

import recordlinkage as rl
from recordlinkage.base import BaseCompareFeature

class CompareAddress(BaseCompareFeature):
    
def _compute_vectorized(self, s1_1, s1_2, s2_1, s2_2):
        """Compare addresses.
        Compare addresses. Compare address_1 of file A with address_1 and address_2 of file B. The same for address_2 of dataset 1.
        """
        pass

(continues on next page)
return \((s_1_1 == s_2_1) \lor (s_1_2 == s_2_2) \lor (s_1_1 == s_2_2) \lor (s_1_2 == s_2_1)\). astype(float)

comparer = rl.Compare()

# naive
comparer.add(CompareAddress('address_1', 'address_1', label='sim_address_1'))
comparer.add(CompareAddress('address_2', 'address_2', label='sim_address_2'))

# better
comparer.add(CompareAddress(('address_1', 'address_2'), ('address_1', 'address_2'), label='sim_address'))

features = comparer.compute(pairs, dfA, dfB)
features.mean()

The mean of the cross-over comparison is higher.

| sim_address_1 | 0.02488 |
| sim_address_2 | 0.02025 |
| sim_address  | 0.03566 |

dtype: float64
3. Classification

8.1 Classifiers

Classification is the step in the record linkage process were record pairs are classified into matches, non-matches and possible matches [Christen2012]. Classification algorithms can be supervised or unsupervised (with or without training data).

See also:

8.1.1 Supervised

```python
class recordlinkage.LogisticRegressionClassifier(coefficients=None, intercept=None, **kwargs)
```

Logistic Regression Classifier.

This classifier is an application of the logistic regression model (wikipedia). The classifier partitions candidate record pairs into matches and non-matches.

This algorithm is also known as Deterministic Record Linkage.

The LogisticRegressionClassifier classifier uses the `sklearn.linear_model.LogisticRegression` classification algorithm from SciKit-learn as kernel.

**Parameters**

- `coefficients (list, numpy.array)` – The coefficients of the logistic regression.
- `intercept (float)` – The interception value.
- `**kwargs` – Additional arguments to pass to `sklearn.linear_model.LogisticRegression`.

**kernel**

The kernel of the classifier. The kernel is `sklearn.linear_model.LogisticRegression` from SciKit-learn.

**Type** `sklearn.linear_model.LogisticRegression`
coefficients
   The coefficients of the logistic regression.
   Type list

intercept
   The interception value.
   Type float

fit (comparison_vectors, match_index=None)
   Train the classifier.

   Parameters
   • comparison_vectors (pandas.DataFrame) – The comparison vectors (or features) to train the model with.
   • match_index (pandas.MultiIndex) – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

   Returns None

Note: A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.

fit_predict (comparison_vectors, match_index=None)
   Train the classifier.

   Parameters
   • comparison_vectors (pandas.DataFrame) – The comparison vectors.
   • match_index (pandas.MultiIndex) – The true matches.
   • return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.

   Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

learn (*args, **kwargs)
   [DEPRECATED] Use ‘fit_predict’.

predict (comparison_vectors)
   Predict the class of the record pairs.

   Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.

   Parameters
   • comparison_vectors (pandas.DataFrame) – Dataframe with comparison vectors.
   • return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.

   Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

prob (comparison_vectors, return_type=None)
   Compute the probabilities for each record pair.
For each pair of records, estimate the probability of being a match.

**Parameters**

- `comparison_vectors (pandas.DataFrame)` – The dataframe with comparison vectors.
- `return_type (str)` – Deprecated. (default ‘series’)

**Returns** `pandas.Series` or `numpy.ndarray` – The probability of being a match for each record pair.

class recordlinkage.NaiveBayesClassifier(binarize=None, alpha=0.0001, use_col_names=True, **kwargs)

Naive Bayes Classifier.

The Naive Bayes classifier (wikipedia) partitions candidate record pairs into matches and non-matches. The classifier is based on probabilistic principles. The Naive Bayes classification method has a close mathematical connection with the Fellegi and Sunter model.

**Note:** The NaiveBayesClassifier classifier differs of the Naive Bayes models in SciKit-learn. With binary input vectors, the NaiveBayesClassifier behaves like `sklearn.naive_bayes.BernoulliNB`.

**Parameters**

- `binarize (float or None, optional (default=None))` – Threshold for binarizing (mapping to booleans) of sample features. If None, input is presumed to consist of multilevel vectors.
- `alpha (float)` – Additive (Laplace/Lidstone) smoothing parameter (0 for no smoothing). Default 1e-4.
- `use_col_names (bool)` – Use the column names of the pandas.DataFrame to identify the parameters. If False, the column index of the feature is used. Default True.

fit(X, *args, **kwargs)

Train the classifier.

**Parameters**

- `comparison_vectors (pandas.DataFrame)` – The comparison vectors (or features) to train the model with.
- `match_index (pandas.MultiIndex)` – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

**Note:** A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.

fit_predict(comparison_vectors, match_index= None)

Train the classifier.

**Parameters**

- `comparison_vectors (pandas.DataFrame)` – The comparison vectors.
- `match_index (pandas.MultiIndex)` – The true matches.
• **return_type** *(str)* – Deprecated. Use recordlinkage.options instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

**Returns** pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

**learn** (*args, **kwargs*)

[DEPRECATED] Use ‘fit_predict’.

**log_m_probs**

Log probability \(P(x_i=1|\text{Match})\) as described in the FS framework

**log_p**

Log match probability as described in the FS framework

**log_u_probs**

Log probability \(P(x_i=1|\text{Non-match})\) as described in the FS framework

**log_weights**

Log weights as described in the FS framework

**m_probs**

Probability \(P(x_i=1|\text{Match})\) as described in the FS framework

**P**

Match probability as described in the FS framework

**predict** *(comparison_vectors)*

Predict the class of the record pairs.

Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.

**Parameters**

• **comparison_vectors** *(pandas.DataFrame)* – Dataframe with comparison vectors.

• **return_type** *(str)* – Deprecated. Use recordlinkage.options instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

**Returns** pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

**prob** *(comparison_vectors, return_type=None)*

Compute the probabilities for each record pair.

For each pair of records, estimate the probability of being a match.

**Parameters**

• **comparison_vectors** *(pandas.DataFrame)* – The dataframe with comparison vectors.

• **return_type** *(str)* – Deprecated. (default ‘series’)

**Returns** pandas.Series or numpy.ndarray – The probability of being a match for each record pair.

**u_probs**

Probability \(P(x_i=1|\text{Non-match})\) as described in the FS framework

**weights**

Weights as described in the FS framework
class recordlinkage.SVMClassifier(*args, **kwargs)
    Support Vector Machines Classifier

    The Support Vector Machine classifier (wikipedia) partitions candidate record pairs into matches and non-matches. This implementation is a non-probabilistic binary linear classifier. Support vector machines are supervised learning models. Therefore, SVM classifiers need training data.

    The SVMClassifier classifier uses the sklearn.svm.LinearSVC classification algorithm from SciKit-learn as kernel.

    Parameters **kwargs – Arguments to pass to sklearn.svm.LinearSVC.

    kernel
    The kernel of the classifier. The kernel is sklearn.svm.LinearSVC from SciKit-learn.

        Type sklearn.svm.LinearSVC

    fit (comparison_vectors, match_index=None)
    Train the classifier.

        Parameters

            • comparison_vectors (pandas.DataFrame) – The comparison vectors (or features) to train the model with.

            • match_index (pandas.MultiIndex) – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

        Note: A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.

    fit_predict (comparison_vectors, match_index=None)
    Train the classifier.

        Parameters

            • comparison_vectors (pandas.DataFrame) – The comparison vectors.

            • match_index (pandas.MultiIndex) – The true matches.

            • return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.

        Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

    learn (*args, **kwargs)
    [DEPRECATED] Use ‘fit_predict’.

    predict (comparison_vectors)
    Predict the class of the record pairs.

    Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.

        Parameters

            • comparison_vectors (pandas.DataFrame) – Dataframe with comparison vectors.

            • return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.
Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

prob(*args, **kwargs)
Compute the probabilities for each record pair.
For each pair of records, estimate the probability of being a match.

Parameters
- comparison_vectors (pandas.DataFrame) – The dataframe with comparison vectors.
- return_type (str) – Deprecated. (default ‘series’)

Returns pandas.Series or numpy.ndarray – The probability of being a match for each record pair.

8.1.2 Unsupervised

class recordlinkage.ECMClassifier(init='jaro', binarize=None, max_iter=100, atol=0.0001, use_col_names=True, *args, **kwargs)
Expectation/Conditional Maximisation classifier (Unsupervised).
Expectation/Conditional Maximisation algorithm used to classify record pairs. This probabilistic record linkage algorithm is used in combination with Fellegi and Sunter model. This classifier doesn’t need training data (unsupervised).

Parameters
- max_iter (int) – The maximum number of iterations of the EM algorithm. Default 100.
- binarize (float or None, optional (default=None)) – Threshold for binarizing (mapping to booleans) of sample features. If None, input is presumed to already consist of binary vectors.
- atol (float) – The tolerance between parameters between each interation. If the difference between the parameters between the iterations is smaller than this value, the algorithm is considered to be converged. Default 10e-4.
- use_col_names (bool) – Use the column names of the pandas.DataFrame to identify the parameters. If False, the column index of the feature is used. Default True.

References

fit_predict(comparison_vectors, match_index=None)
Train the classifier.

Parameters
• **comparison_vectors** *(pandas.DataFrame)* – The comparison vectors.
• **match_index** *(pandas.MultiIndex)* – The true matches.
• **return_type** *(str)* – Deprecated. Use recordlinkage.options instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

    **Returns** pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

    **learn** (*args, **kwargs*)
       [DEPRECATED] Use `fit_predict`.

    **log_m_probs**
       Log probability P(x_i=1|Match) as described in the FS framework

    **log_p**
       Log match probability as described in the FS framework

    **log_u_probs**
       Log probability P(x_i=1|Non-match) as described in the FS framework

    **log_weights**
       Log weights as described in the FS framework

    **m_probs**
       Probability P(x_i=1|Match) as described in the FS framework

    **p**
       Match probability as described in the FS framework

    **predict** *(comparison_vectors)*
       Predict the class of the record pairs.
       Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.
       **Parameters**

       • **comparison_vectors** *(pandas.DataFrame)* – Dataframe with comparison vectors.

       • **return_type** *(str)* – Deprecated. Use recordlinkage.options instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

       **Returns** pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

    **prob** *(comparison_vectors, return_type=None)*
       Compute the probabilities for each record pair.
       For each pair of records, estimate the probability of being a match.
       **Parameters**

       • **comparison_vectors** *(pandas.DataFrame)* – The dataframe with comparison vectors.

       • **return_type** *(str)* – Deprecated. (default ‘series’)

       **Returns** pandas.Series or numpy.ndarray – The probability of being a match for each record pair.

    **u_probs**
       Probability P(x_i=1|Non-match) as described in the FS framework
weights
Weights as described in the FS framework

```
fit (X, *args, **kwargs)
```
Train the classifier.

Parameters

- **comparison_vectors** *(pandas.DataFrame)* – The comparison vectors (or features) to train the model with.
- **match_index** *(pandas.MultiIndex)* – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

**Note:** A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.

class recordlinkage.KMeansClassifier(match_cluster_center=None, non-match_cluster_center=None, **kwargs)

KMeans classifier.

The K-means clusterings algorithm (wikipedia) partitions candidate record pairs into matches and non-matches. Each comparison vector belongs to the cluster with the nearest mean.

The K-means algorithm is an unsupervised learning algorithm. The algorithm doesn’t need trainings data for fitting. The algorithm is calibrated for two clusters: a match cluster and a non-match cluster. The centers of these clusters can be given as arguments or set automatically.

The KMeansClassifier classifier uses the sklearn.cluster.KMeans clustering algorithm from SciKit-learn as kernel.

Parameters

- **match_cluster_center** *(list, numpy.array)* – The center of the match cluster.
  The length of the list/array must equal the number of comparison variables. If None, the match cluster center is set automatically. Default None.
- **nonmatch_cluster_center** *(list, numpy.array)* – The center of the non-match (distinct) cluster. The length of the list/array must equal the number of comparison variables. If None, the non-match cluster center is set automatically. Default None.
- ****kwargs** – Additional arguments to pass to sklearn.cluster.KMeans.

**kernel**
The kernel of the classifier. The kernel is sklearn.cluster.KMeans from SciKit-learn.

**Type** sklearn.cluster.KMeans

**match_cluster_center**
The center of the match cluster.

**Type** numpy.array

**nonmatch_cluster_center**
The center of the nonmatch (distinct) cluster.

**Type** numpy.array
Note: There are better methods for linking records than the k-means clustering algorithm. This algorithm can be useful for an (unsupervised) initial partition.

**prob** (*args, **kwargs)
Compute the probabilities for each record pair.

For each pair of records, estimate the probability of being a match.

**Parameters**
- **comparison_vectors** (*pandas.DataFrame*) – The dataframe with comparison vectors.
- **return_type** (*str*) – Deprecated. (default ‘series’)

**Returns** *pandas.Series or numpy.ndarray* – The probability of being a match for each record pair.

**fit** *(comparison_vectors, match_index=None)*
Train the classifier.

**Parameters**
- **comparison_vectors** (*pandas.DataFrame*) – The comparison vectors (or features) to train the model with.
- **match_index** (*pandas.MultiIndex*) – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

Note: A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.

**fit_predict** *(comparison_vectors, match_index=None)*
Train the classifier.

**Parameters**
- **comparison_vectors** (*pandas.DataFrame*) – The comparison vectors.
- **match_index** (*pandas.MultiIndex*) – The true matches.
- **return_type** (*str*) – Deprecated. Use recordlinkage.options instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

**Returns** *pandas.Series* – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

**learn** (*args, **kwargs*)
[DEPRECATED] Use ‘fit_predict’.

**predict** *(comparison_vectors)*
Predict the class of the record pairs.

Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.

**Parameters**
- **comparison_vectors** (*pandas.DataFrame*) – Dataframe with comparison vectors.
• `return_type (str)` – Deprecated. Use `recordlinkage.options` instead. Use the option `recordlinkage.set_option('classification.return_type', 'index')` instead.

Returns `pandas.Series` – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

### 8.2 Adapters

Adapters can be used to wrap a machine learning models from external packages like ScitKit-learn and Keras. For example, this makes it possible to classify record pairs with an neural network developed in Keras.

```python
class recordlinkage.adapters.SKLearnAdapter
    SciKit-learn adapter for record pair classification.

    SciKit-learn adapter for record pair classification with SciKit-learn models.

    # import ScitKit-Learn classifier
    from sklearn.ensemble import RandomForestClassifier

    # import BaseClassifier from recordlinkage.base
    from recordlinkage.base import BaseClassifier
    from recordlinkage.adapters import SKLearnClassifier
    from recordlinkage.datasets import binary_vectors

class RandomForest(SKLearnClassifier, BaseClassifier):
    def __init__(self, *args, **kwargs):
        super(self, RandomForest).__init__()

        # set the kernel
        kernel = RandomForestClassifier(*args, **kwargs)

        # make a sample dataset
        features, links = binary_vectors(10000, 2000, return_links=True)

        # initialise the random forest
        cl = RandomForest(n_estimators=20)
        cl.fit(features, links)

        # predict the matches
        cl.predict(...)
```

```python
class recordlinkage.adapters.KerasAdapter
    Keras adapter for record pair classification.

    Keras adapter for record pair classification with Keras models.

    Example of a Keras model used for classification.

    from tensorflow.keras import layers
    from recordlinkage.base import BaseClassifier
    from recordlinkage.adapters import KerasAdapter

    class NNClassifier(KerasAdapter, BaseClassifier):
        """Neural network classifier.""
        def __init__(self):
```

(continues on next page)
super(NNClassifier, self).__init__()

model = tf.keras.Sequential()
model.add(layers.Dense(16, input_dim=8, activation='relu'))
model.add(layers.Dense(8, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
model.compile(
    optimizer=tf.train.AdamOptimizer(0.001),
    loss='binary_crossentropy',
    metrics=['accuracy'])

self.kernel = model

# initialise the model
cl = NNClassifier()
# fit the model to the data
cl.fit(X_train, links_true)
# predict the class of the data
cl.predict(X_pred)

8.3 User-defined algorithms

Classifiers can make use of the recordlinkage.base.BaseClassifier for algorithms. ScitKit-learn based models may want recordlinkage.adapters.SKLearnAdapter as subclass as well.

class recordlinkage.base.BaseClassifier
    Base class for classification of records pairs.

    This class contains methods for training the classifier. Distinguish different types of training, such as supervised and unsupervised learning.

    learn(*args, **kwargs)
        [DEPRECATED] Use ‘fit_predict’.

    fit(comparison_vectors, match_index=None)
        Train the classifier.

        Parameters

        • comparison_vectors (pandas.DataFrame) – The comparison vectors (or features) to train the model with.

        • match_index (pandas.MultiIndex) – A pandas.MultiIndex object with the true matches. The MultiIndex contains only the true matches. Default None.

    fit_predict(comparison_vectors, match_index=None)
        Train the classifier.

        Parameters

        • comparison_vectors (pandas.DataFrame) – The comparison vectors.

Note: A note in case of finding links within a single dataset (for example duplicate detection). Ensure that the training record pairs are from the lower triangular part of the dataset/matrix. See detailed information here: link.
• match_index (pandas.MultiIndex) – The true matches.

• return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.

Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

predict (comparison_vectors)
Predict the class of the record pairs.

Classify a set of record pairs based on their comparison vectors into matches, non-matches and possible matches. The classifier has to be trained to call this method.

Parameters

• comparison_vectors (pandas.DataFrame) – Dataframe with comparison vectors.

• return_type (str) – Deprecated. Use recordlinkage.options instead. Use the option recordlinkage.set_option('classification.return_type', 'index') instead.

Returns pandas.Series – A pandas Series with the labels 1 (for the matches) and 0 (for the non-matches).

prob (comparison_vectors, return_type=None)
Compute the probabilities for each record pair.

For each pair of records, estimate the probability of being a match.

Parameters

• comparison_vectors (pandas.DataFrame) – The dataframe with comparison vectors.

• return_type (str) – Deprecated. (default ‘series’) 

Returns pandas.Series or numpy.ndarray – The probability of being a match for each record pair.

Probabilistic models can use the Fellegi and Sunter base class. This class is used for the recordlinkage.ECMClassifier and the recordlinkage.NaiveBayesClassifier.

class recordlinkage.classifiers.FellegiSunter (use_col_names=True, *args, **kwargs)
Fellegi and Sunter (1969) framework.

Meta class for probabilistic classification algorithms. The Fellegi and Sunter class is used for the recordlinkage.NaiveBayesClassifier and recordlinkage.ECMClassifier.

Parameters use_col_names (bool) – Use the column names of the pandas.DataFrame to identify the parameters. If False, the column index of the feature is used. Default True.

References

log_p
Log match probability as described in the FS framework

log_m_probs
Log probability P(x_i=1|Match) as described in the FS framework
log_u_probs
Log probability P(x_i=1|Non-match) as described in the FS framework

log_weights
Log weights as described in the FS framework

P
Match probability as described in the FS framework

m_probs
Probability P(x_i=1|Match) as described in the FS framework

u_probs
Probability P(x_i=1|Non-match) as described in the FS framework

weights
Weights as described in the FS framework

8.4 Examples

Unsupervised learning with the ECM algorithm. [See example on Github.](https://github.com/J535D165/recordlinkage/examples/unsupervised_learning.py)

8.5 Network

The Python Record Linkage Toolkit provides network/graph analysis tools for classification of record pairs into matches and distinct pairs. The toolkit provides the functionality for one-to-one linking and one-to-many linking. It is also possible to detect all connected components which is useful in data deduplication.

class recordlinkage.OneToOneLinking(method='greedy')

[EXPERIMENTAL] One-to-one linking

A record from dataset A can match at most one record from dataset B. For example, (a1, a2) are records from A and (b1, b2) are records from B. A linkage of (a1, b1), (a1, b2), (a2, b1), (a2, b2) is not one-to-one connected. One of the results of one-to-one linking can be (a1, b1), (a2, b2).

Parameters method (str) – The method to solve the problem. Only ‘greedy’ is supported at the moment.

Note: This class is experimental and might change in future versions.

compute (links)
Compute the one-to-one linking.

Parameters links (pandas.MultiIndex) – The pairs to apply linking to.

Returns pandas.MultiIndex – A one-to-one matched MultiIndex of record pairs.

class recordlinkage.OneToManyLinking(level=0, method='greedy')

[EXPERIMENTAL] One-to-many linking

A record from dataset A can link multiple records from dataset B, but a record from B can link to only one record of dataset A. Use the level argument to switch A and B.

Parameters
• **level** *(int)* – The level of the MultiIndex to have the one relations. The options are 0 or 1 (indication the level of the MultiIndex). Default 0.

• **method** *(str)* – The method to solve the problem. Only ‘greedy’ is supported at the moment.

**Example**

Consider a MultiIndex with record pairs constructed from datasets A and B. To link a record from B to at most one record of B, use the following syntax:

```python
> one_to_many = OneToManyLinking(0) > one_to_many.compute(links)
```

To link a record from B to at most one record of B, use:

```python
> one_to_many = OneToManyLinking(1) > one_to_many.compute(links)
```

**Note:** This class is experimental and might change in future versions.

**compute** *(links)*

Compute the one-to-many matching.

---

**class** recordlinkage.ConnectedComponents

[EXPERIMENTAL] Connected record pairs

This class identifies connected record pairs. Connected components are especially used in detecting duplicates in a single dataset.

**Note:** This class is experimental and might change in future versions.

**compute** *(links)*

Return the connected components.

---

**Parameters** links *(pandas.MultiIndex)* – The links to apply one-to-one matching on.

**Returns** list of pandas.MultiIndex – A list with pandas.MultiIndex objects. Each MultiIndex object represents a set of connected record pairs.
Evaluation of classifications plays an important role in record linkage. Express your classification quality in terms of accuracy, recall and F-score based on true positives, false positives, true negatives and false negatives.

\[ \text{reduction\_ratio} \left( \text{links\_pred}, \text{total} \right) \]

Compute the reduction ratio. The reduction ratio is 1 minus the ratio candidate matches and the maximum number of pairs possible.

**Parameters**

- \( \text{links\_pred} \) (int, pandas.MultiIndex) – The number of candidate record pairs or the pandas.MultiIndex with record pairs.
- \( \text{total} \) (pandas.DataFrame object(s)) – The DataFrames are used to compute the full index size with the full\_index\_size function.

**Returns** float – The reduction ratio.

\[ \text{true\_positives} \left( \text{links\_true}, \text{links\_pred} \right) \]

Count the number of True Positives.

Returns the number of correctly predicted links, also called the number of True Positives (TP).

**Parameters**

- \( \text{links\_true} \) (pandas.MultiIndex, pandas.DataFrame, pandas.Series) – The true (or actual) links.

**Returns** int – The number of correctly predicted links.

\[ \text{true\_negatives} \left( \text{links\_true}, \text{links\_pred}, \text{total} \right) \]

Count the number of True Negatives.

Returns the number of correctly predicted non-links, also called the number of True Negatives (TN).

**Parameters**
Record Linkage Toolkit Documentation, Release 0.15

- **links_true**: \((\text{pandas.MultiIndex, pandas.DataFrame, pandas.Series})\) – The true (or actual) links.
- **total**: \((\text{int, pandas.MultiIndex})\) – The count of all record pairs (both links and non-links). When the argument is a pandas.MultiIndex, the length of the index is used.

**Returns** \(\text{int}\) – The number of correctly predicted non-links.

**recordlinkage.false_positives**\((\text{links_true, links_pred})\)

Count the number of False Positives.

Returns the number of incorrect predictions of true non-links. (true non-links, but predicted as links). This value is known as the number of False Positives (FP).

**Parameters**
- **links_true**: \((\text{pandas.MultiIndex, pandas.DataFrame, pandas.Series})\) – The true (or actual) links.

**Returns** \(\text{int}\) – The number of false positives.

**recordlinkage.false_negatives**\((\text{links_true, links_pred})\)

Count the number of False Negatives.

Returns the number of incorrect predictions of true links. (true links, but predicted as non-links). This value is known as the number of False Negatives (FN).

**Parameters**
- **links_true**: \((\text{pandas.MultiIndex, pandas.DataFrame, pandas.Series})\) – The true (or actual) links.

**Returns** \(\text{int}\) – The number of false negatives.

**recordlinkage.confusion_matrix**\((\text{links_true, links_pred, total=None})\)

Compute the confusion matrix.

The confusion matrix is of the following form:

<table>
<thead>
<tr>
<th></th>
<th>Predicted Positives</th>
<th>Predicted Negatives</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>True Positives</strong></td>
<td>True Positives (TP)</td>
<td>False Negatives (FN)</td>
</tr>
<tr>
<td><strong>True Negatives</strong></td>
<td>False Positives (FP)</td>
<td>True Negatives (TN)</td>
</tr>
</tbody>
</table>

The confusion matrix is an informative way to analyse a prediction. The matrix can used to compute measures like precision and recall. The count of true prositivas is \([0,0]\), false negatives is \([0,1]\), true negatives is \([1,1]\) and false positives is \([1,0]\).

**Parameters**
- **links_true**: \((\text{pandas.MultiIndex, pandas.DataFrame, pandas.Series})\) – The true (or actual) links.
• \texttt{total (int, pandas.MultiIndex)} – The count of all record pairs (both links and non-links). When the argument is a pandas.MultiIndex, the length of the index is used. If the total is None, the number of True Negatives is not computed. Default None.

\textbf{Returns} \texttt{numpy.array} – The confusion matrix with TP, TN, FN, FP values.

\textbf{Note:} The number of True Negatives is computed based on the total argument. This argument is the number of record pairs of the entire matrix.

\texttt{recordlinkage.precision} (\texttt{links_true, links_pred})  
Compute the precision.  
The precision is given by TP/(TP+FP).

\textbf{Parameters}

• \texttt{links_true (pandas.MultiIndex, pandas.DataFrame, pandas.Series)} – The true (or actual) collection of links.


\textbf{Returns} \texttt{float} – The precision

\texttt{recordlinkage.recall} (\texttt{links_true, links_pred})  
Compute the recall/sensitivity.  
The recall is given by TP/(TP+FN).

\textbf{Parameters}

• \texttt{links_true (pandas.MultiIndex, pandas.DataFrame, pandas.Series)} – The true (or actual) collection of links.


\textbf{Returns} \texttt{float} – The recall

\texttt{recordlinkage.accuracy} (\texttt{links_true, links_pred, total})  
Compute the accuracy.  
The accuracy is given by (TP+TN)/(TP+FP+TN+FN).

\textbf{Parameters}

• \texttt{links_true (pandas.MultiIndex, pandas.DataFrame, pandas.Series)} – The true (or actual) collection of links.


• \texttt{total (int, pandas.MultiIndex)} – The count of all record pairs (both links and non-links). When the argument is a pandas.MultiIndex, the length of the index is used.

\textbf{Returns} \texttt{float} – The accuracy

\texttt{recordlinkage.specificity} (\texttt{links_true, links_pred, total})  
Compute the specificity.  
The specificity is given by TN/(FP+TN).

\textbf{Parameters}
• **links_true** (pandas.MultiIndex, pandas.DataFrame, pandas.Series) – The true (or actual) collection of links.


• **total** (int, pandas.MultiIndex) – The count of all record pairs (both links and non-links). When the argument is a pandas.MultiIndex, the length of the index is used.

**Returns** float – The specificity

```python
recordlinkage.fscore(links_true, links_pred)
```

Compute the F-score.

The F-score is given by \(2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall})\).

**Parameters**

• **links_true** (pandas.MultiIndex, pandas.DataFrame, pandas.Series) – The true (or actual) collection of links.


**Returns** float – The fscore

**Note:** If there are no pairs predicted as links, this measure will raise a ZeroDivisionError.

```python
recordlinkage.max_pairs(shape)
```

[DEPRECATED] Compute the maximum number of record pairs possible.

```python
recordlinkage.full_index_size(*args)
```

Compute the number of records in a full index.

Compute the number of records in a full index without building the index itself. The result is the maximum number of record pairs possible. This function is especially useful in measures like the reduction_ratio.

Deduplication: Given a DataFrame A with length N, the full index size is \(N(N-1)/2\). Linking: Given a DataFrame A with length N and a DataFrame B with length M, the full index size is \(N \times M\).

**Parameters**

• **args** (int, pandas.MultiIndex, pandas.Series, pandas.DataFrame) – A pandas object or a int representing the length of a dataset to link.

When there is one argument, it is assumed that the record linkage is a deduplication process.

**Examples**

Use integers: >>> full_index_size(10) # deduplication: 45 pairs >>> full_index_size(10, 10) # linking: 100 pairs

or pandas objects >>> full_index_size(DF) # deduplication: len(DF)*(len(DF)-1)/2 pairs >>> full_index_size(DF, DF) # linking: len(DF)*len(DF) pairs
Datasets

The Python Record Linkage Toolkit contains several open public datasets. Four datasets were generated by the developers of Febrl. In the future, we are developing tools to generate your own datasets.

```python
recordlinkage.datasets.load_krebsregister(block=[1, 2, 3, 4, 5, 6, 7, 8, 9, 10], missing_values=None, shuffle=True)
```

Load the Krebsregister dataset.

This dataset of comparison patterns was obtained in an epidemiological cancer study in Germany. The comparison patterns were created by the Institute for Medical Biostatistics, Epidemiology and Informatics (IMBEI) and the University Medical Center of Johannes Gutenberg University (Mainz, Germany). The dataset is available for research online.

“The records represent individual data including first and family name, sex, date of birth and postal code, which were collected through iterative insertions in the course of several years. The comparison patterns in this dataset are based on a sample of 100,000 records dating from 2005 to 2008. Data pairs were classified as “match” or “non-match” during an extensive manual review where several documentarists were involved. The resulting classification formed the basis for assessing the quality of the registry’s own record linkage procedure.

In order to limit the amount of patterns a blocking procedure was applied, which selects only record pairs that meet specific agreement conditions. The results of the following six blocking iterations were merged together:

- Phonetic equality of first name and family name, equality of date of birth.
- Phonetic equality of first name, equality of day of birth.
- Phonetic equality of first name, equality of month of birth.
- Phonetic equality of first name, equality of year of birth.
- Equality of complete date of birth.
- Phonetic equality of family name, equality of sex.

This procedure resulted in 5,749,132 record pairs, of which 20,931 are matches. The data set is split into 10 blocks of (approximately) equal size and ratio of matches to non-matches.”

Parameters
• **block** (*int, list*) – An integer or a list with integers between 1 and 10. The blocks are the blocks explained in the description.

• **missing_values** (*object, int, float*) – The value of the missing values. Default NaN.

• **shuffle** (*bool*) – Shuffle the record pairs. Default True.

**Returns** (*pandas.DataFrame, pandas.MultiIndex*) – A pandas.DataFrame with comparison vectors and a pandas.MultiIndex with the indices of the matches.

```python
def load_febrl1(return_links=False)
    Load the FEBRL 1 dataset.

    The Freely Extensible Biomedical Record Linkage (Febrl) package is distributed with a dataset generator and four datasets generated with the generator. This function returns the first Febrl dataset as a pandas.DataFrame.

    “This data set contains 1000 records (500 original and 500 duplicates, with exactly one duplicate per original record.”

    **Parameters** return_links (*bool*) – When True, the function returns also the true links.

    **Returns** pandas.DataFrame – A pandas.DataFrame with Febrl dataset1.csv. When return_links is True, the function returns also the true links. The true links are all links in the lower triangular part of the matrix.
```

```python
def load_febrl2(return_links=False)
    Load the FEBRL 2 dataset.

    The Freely Extensible Biomedical Record Linkage (Febrl) package is distributed with a dataset generator and four datasets generated with the generator. This function returns the second Febrl dataset as a pandas.DataFrame.

    “This data set contains 5000 records (4000 originals and 1000 duplicates), with a maximum of 5 duplicates based on one original record (and a poisson distribution of duplicate records). Distribution of duplicates: 19 originals records have 5 duplicate records 47 originals records have 4 duplicate records 107 originals records have 3 duplicate records 141 originals records have 2 duplicate records 114 originals records have 1 duplicate record 572 originals records have no duplicate record”

    **Parameters** return_links (*bool*) – When True, the function returns also the true links.

    **Returns** pandas.DataFrame – A pandas.DataFrame with Febrl dataset2.csv. When return_links is True, the function returns also the true links. The true links are all links in the lower triangular part of the matrix.
```

```python
def load_febrl3(return_links=False)
    Load the FEBRL 3 dataset.

    The Freely Extensible Biomedical Record Linkage (Febrl) package is distributed with a dataset generator and four datasets generated with the generator. This function returns the third Febrl dataset as a pandas.DataFrame.

    “This data set contains 5000 records (2000 originals and 3000 duplicates), with a maximum of 5 duplicates based on one original record (and a Zipf distribution of duplicate records). Distribution of duplicates: 168 originals records have 5 duplicate records 161 originals records have 4 duplicate records 212 originals records have 3 duplicate records 256 originals records have 2 duplicate records 368 originals records have 1 duplicate record 1835 originals records have no duplicate record”

    **Parameters** return_links (*bool*) – When True, the function returns also the true links.
Returns pandas.DataFrame – A pandas.DataFrame with FEBRL dataset3.csv. When return_links is True, the function returns also the true links. The true links are all links in the lower triangular part of the matrix.

recordlinkage.datasets.load_febrl4(return_links=False)
Load the FEBRL 4 datasets.

The Freely Extensible Biomedical Record Linkage (Febrl) package is distributed with a dataset generator and four datasets generated with the generator. This function returns the fourth Febrl dataset as a pandas.DataFrame.

"Generated as one data set with 10000 records (5000 originals and 5000 duplicates, with one duplicate per original), the originals have been split from the duplicates, into dataset4a.csv (containing the 5000 original records) and dataset4b.csv (containing the 5000 duplicate records) These two data sets can be used for testing linkage procedures."

Parameters return_links (bool) – When True, the function returns also the true links.

Returns (pandas.DataFrame, pandas.DataFrame) – A pandas.DataFrame with Febrl dataset4a.csv and a pandas dataframe with Febrl dataset4b.csv. When return_links is True, the function returns also the true links.

recordlinkage.datasets.binary_vectors(n, n_match, m=[0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 0.9], u=[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1], random_state=None, return_links=False, dtype=<class 'numpy.int8'>)
Generate random binary comparison vectors.

This function is used to generate random comparison vectors. The result of each comparison is a binary value (0 or 1).

Parameters

- **n** (int) – The total number of comparison vectors.
- **n_match** (int) – The number of matching record pairs.
- **m** (list, default [0.9] * 8, optional) – A list of m probabilities of each partially identifying variable. The m probability is the probability that an identifier in matching record pairs agrees.
- **u** (list, default [0.9] * 8, optional) – A list of u probabilities of each partially identifying variable. The u probability is the probability that an identifier in non-matching record pairs agrees.
- **random_state** (int or numpy.random.RandomState, optional) – Seed for the random number generator with an integer or numpy RandomState object.
- **return_links** (bool) – When True, the function returns also the true links.
- **dtype** (numpy.dtype) – The dtype of each column in the returned DataFrame.

Returns pandas.DataFrame – A dataframe with comparison vectors.
recordlinkage.index_split(index, chunks)
Function to split pandas.Index and pandas.MultiIndex objects.

Split pandas.Index and pandas.MultiIndex objects into chunks. This function is based on numpy.array_split().

Parameters
- **index** (pandas.Index, pandas.MultiIndex) – A pandas.Index or pandas.MultiIndex to split into chunks.
- **chunks** (int) – The number of parts to split the index into.

Returns
list – A list with chunked pandas.Index or pandas.MultiIndex objects.

recordlinkage.get_option(pat)
Retrieves the value of the specified option.

The available options with its descriptions:

classification.return_type [str] The format of the classification result. The value ‘index’ returns the classification result as a pandas.MultiIndex. The MultiIndex contains the predicted matching record pairs. The value ‘series’ returns a pandas.Series with zeros (distinct) and ones (matches). The argument value ‘array’ will return a numpy.ndarray with zeros and ones. [default: index] [currently: index]

indexing.pairs [str] Specify the format how record pairs are stored. By default, record pairs generated by the toolkit are returned in a pandas.MultiIndex object (‘multiindex’ option).

Valid values: ‘multiindex’ [default: multiindex] [currently: multiindex]

Parameters **pat** (str) – Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns **result** (the value of the option)

Raises OptionError : if no such option exists
recordlinkage.set_option(pat, value)
Sets the value of the specified option.

The available options with its descriptions:

classification.return_type [str] The format of the classification result. The value ‘index’ returns the classification result as a pandas.MultiIndex. The MultiIndex contains the predicted matching record pairs. The value ‘series’ returns a pandas.Series with zeros (distinct) and ones (matches). The argument value ‘array’ will return a numpy.ndarray with zeros and ones. [default: index] [currently: index]

indexing.pairs [str] Specify the format how record pairs are stored. By default, record pairs generated by the toolkit are returned in a pandas.MultiIndex object (‘multiindex’ option).

Valid values: ‘multiindex’ [default: multiindex] [currently: multiindex]

Parameters

• pat (str) – Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

• value – new value of option.

Returns None

Raises OptionError if no such option exists

recordlinkage.reset_option(pat)
Reset one or more options to their default value.

Pass “all” as argument to reset all options.

The available options with its descriptions:

classification.return_type [str] The format of the classification result. The value ‘index’ returns the classification result as a pandas.MultiIndex. The MultiIndex contains the predicted matching record pairs. The value ‘series’ returns a pandas.Series with zeros (distinct) and ones (matches). The argument value ‘array’ will return a numpy.ndarray with zeros and ones. [default: index] [currently: index]

indexing.pairs [str] Specify the format how record pairs are stored. By default, record pairs generated by the toolkit are returned in a pandas.MultiIndex object (‘multiindex’ option).

Valid values: ‘multiindex’ [default: multiindex] [currently: multiindex]

Parameters pat (str/regex) – If specified only options matching prefix* will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns None

recordlinkage.describe_option(pat, _print_desc=False)
Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

The available options with its descriptions:

classification.return_type [str] The format of the classification result. The value ‘index’ returns the classification result as a pandas.MultiIndex. The MultiIndex contains the predicted matching record pairs. The value ‘series’ returns a pandas.Series with zeros (distinct) and ones (matches). The argument value ‘array’ will return a numpy.ndarray with zeros and ones. [default: index] [currently: index]
**indexing.pairs**  [str] Specify the format how record pairs are stored. By default, record pairs generated by the toolkit are returned in a pandas.MultiIndex object (‘multiindex’ option).

Valid values: ‘multiindex’ [default: multiindex] [currently: multiindex]

**Parameters**

• **pat** *(str)* – Regexp pattern. All matching keys will have their description displayed.

• **_print_desc** *(bool, default True)* – If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

**Returns**

• *None by default, the description(s) as a unicode string if _print_desc

• *is False*
Manually labeled record pairs are useful in training and validation tasks. Training data is usually not available in record linkage applications because it is highly dataset and sample-specific. The Python Record Linkage Toolkit comes with a browser-based user interface for manually classifying record pairs. A hosted version of RecordLinkage ANNOTATOR can be found on Github.
<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Phone</th>
<th>City</th>
</tr>
</thead>
<tbody>
<tr>
<td>Michaela</td>
<td>8 Stanley Street</td>
<td>4232</td>
<td>Miami</td>
</tr>
<tr>
<td>Neumann</td>
<td></td>
<td></td>
<td>Winston Hills</td>
</tr>
</tbody>
</table>
12.1. Generate annotation file

The RecordLinkage ANNOTATOR software requires a structured annotation file. The required schema of the annotation file is open. The function `recordlinkage.write_annotation_file()` can be used to render and save an annotation file. The function can be used for both linking and deduplication purposes.

\[
\text{recordlinkage.write_annotation_file}(fp, \ \text{pairs}, \ \text{df}_a, \ \text{df}_b=None, \ \text{dataset}_a\_name=None, \ \text{dataset}_b\_name=None, *\text{args}, **\text{kwargs})
\]

Render and export annotation file.

This function renders and annotation object and stores it in a json file. The function is a wrapper around the `AnnotationWrapper` class.

**Parameters**

- `fp` *(str)* – The path to the annotation file.
- `pairs` *(pandas.MultiIndex)* – The record pairs to annotate.
- `df_a` *(pandas.DataFrame)* – The data frame with full record information for the pairs.
- `df_b` *(pandas.DataFrame)* – In case of data linkage, this is the second data frame. Default None.
- `dataset_a_name` *(str)* – The name of the first data frame.
- `dataset_b_name` *(str)* – In case of data linkage, the name of the second data frame. Default None.

12.1.1 Linking

This is a simple example of the code to render an annotation file for linking records:

```python
import recordlinkage as rl
from recordlinkage.index import Block
from recordlinkage.datasets import load_febrl4

df_a, df_b = load_febrl4()

blocker = Block("surname", "surname")
pairs = blocker.index(df_a, df_b)

rl.write_annotation_file(
    "annotation_demo_linking.json",
    pairs[0:50],
    df_a,
    df_b,
    dataset_a_name="Febrl4 A",
    dataset_b_name="Febrl4 B"
)
```

12.1.2 Deduplication

This is a simple example of the code to render an annotation file for duplicate detection:
import recordlinkage as rl
from recordlinkage.index import Block
from recordlinkage.datasets import load_febrl1

df_a = load_febrl1()

blocker = Block("surname", "surname")

pairs = blocker.index(df_a)

rl.write_annotation_file(
    "annotation_demo_dedup.json",
    pairs[0:50],
    df_a,
    dataset_a_name="Febrl1 A"
)

12.2 Manual labeling

Go to RecordLinkage ANNOTATOR or start the server yourself.

Choose the annotation file on the landing screen or use the drag and drop functionality. A new screen shows the first record pair to label. Start labeling data the manually. Use the button Match for record pairs belonging to the same entity. Use Distinct for record pairs belonging to different entities. After all records are labeled by hand, the result can be saved to a file.

12.3 Export/read annotation file

After labeling all record pairs, you can export the annotation file to a JSON file. Use the function recordlinkage. read_annotation_file() to read the results.

import recordlinkage as rl

result = rl.read_annotation_file('my_annotation.json')
print(result.links)

The function recordlinkage. read_annotation_file() reads the file and returns an recordlinkage. annotation.AnnotationResult object. This object contains links and distinct attributes that return a pandas.MultiIndex object.

recordlinkage. read_annotation_file(fp)
Read annotation file.

Parameters fp (str) – The path to the annotation file.

Returns AnnotationResult – An AnnotationResult object.

Example

Read the links from an annotation file:
```python
> annotation = read_annotation_file("result.json")
> print(annotation.links)
```

class recordlinkage.annotation.AnnotationResult(pairs=[], version=1)

Result of (manual) annotation.

**Parameters**
- **pairs** *(list)* – Raw data of each record pair in the annotation file.
- **version** *(str)* – The version number corresponding to the file structure.

**links**

Return the links.

Returns `pandas.MultiIndex` – The links stored in a pandas MultiIndex.

**distinct**

Return the distinct pairs.

Returns `pandas.MultiIndex` – The distinct pairs stored in a pandas MultiIndex.

**unknown**

Return the unknown or unlaballed pairs.

Returns `pandas.MultiIndex` – The unknown or unlaballed pairs stored in a pandas MultiIndex.

```python
classmethod from_dict(d)

Create AnnotationResult from dict

Parameters d *(dict)* – The annotation file as a dict.

Returns AnnotationResult – An AnnotationResult object.
```

```python
classmethod from_file(fp)

Create AnnotationResult from file

Parameters fp *(str)* – The path to the annotation file.

Returns AnnotationResult – An AnnotationResult object.
```
CHAPTER 13

Classification algorithms

In the context of record linkage, classification refers to the process of dividing record pairs into matches and non-matches (distinct pairs). There are dozens of classification algorithms for record linkage. Roughly speaking, classification algorithms fall into two groups:

- **supervised learning algorithms** - These algorithms make use of trainings data. If you do have trainings data, then you can use supervised learning algorithms. Most supervised learning algorithms offer good accuracy and reliability. Examples of supervised learning algorithms in the Python Record Linkage Toolkit are Logistic Regression, Naive Bayes and Support Vector Machines.

- **unsupervised learning algorithms** - These algorithms do not need training data. The Python Record Linkage Toolkit supports K-means clustering and an Expectation/Conditional Maximisation classifier.

First things first

The examples below make use of the Krebs register (German for cancer registry) dataset. The Krebs register dataset contains comparison vectors of a large set of record pairs. For each record pair, it is known if the records represent the same person (match) or not (non-match). This was done with a massive clerical review. First, import the recordlinkage module and load the Krebs register data. The dataset contains 5749132 compared record pairs and has the following variables: first name, last name, sex, birthday, birth month, birth year and zip code. The Krebs register contains len(krebs_true_links) == 20931 matching record pairs.

```
In [1]: import pandas
   ...: import recordlinkage as rl
   ...: from recordlinkage.datasets import load_krebsregister
   ...:
In [2]: krebs_X, krebs_true_links = load_krebsregister(missing_values=0)
   ...: krebs_X
   ...:
Out[2]:
   cmp_firstname1  cmp_firstname2  ...  cmp_birthyear  cmp_zipcode
id1  id2                              ...
22161 38467 1.000000 0.0 ... 0.0 0.0
38713 75352 0.000000 0.0 ... 0.0 0.0
```

(continues on next page)
Most classifiers can not handle comparison vectors with missing values. To prevent issues with the classification algorithms, we convert the missing values into disagreeing comparisons (using argument missing_values=0). This approach for handling missing values is widely used in record linkage applications.

```
In [3]: krebs_X.describe()
Out[3]:

<table>
<thead>
<tr>
<th>cmp_firstname1</th>
<th>cmp_firstname2</th>
<th>...</th>
<th>cmp_birthyear</th>
<th>cmp_zipcode</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>5.749132e+06</td>
<td></td>
<td>5.749132e+06</td>
<td>5.749132e+06</td>
</tr>
<tr>
<td>mean</td>
<td>7.127776e-01</td>
<td></td>
<td>1.623376e-02</td>
<td>2.227178e-01</td>
</tr>
<tr>
<td>std</td>
<td>3.888388e-01</td>
<td></td>
<td>1.251994e-01</td>
<td>1.410704e-01</td>
</tr>
<tr>
<td>min</td>
<td>0.000000e+00</td>
<td></td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
</tr>
<tr>
<td>25%</td>
<td>2.857143e-01</td>
<td></td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
</tr>
<tr>
<td>50%</td>
<td>1.000000e+00</td>
<td></td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
</tr>
<tr>
<td>75%</td>
<td>1.000000e+00</td>
<td></td>
<td>0.000000e+00</td>
<td>0.000000e+00</td>
</tr>
<tr>
<td>max</td>
<td>1.000000e+00</td>
<td></td>
<td>1.000000e+00</td>
<td>1.000000e+00</td>
</tr>
</tbody>
</table>

[8 rows x 9 columns]
```

### 13.1 Supervised learning

As described before, supervised learning algorithms do need training data. Training data is data for which the true match status is known for each comparison vector. In the example in this section, we consider that the true match status of the first 5000 record pairs of the Krebs register data is known.

```
In [4]: golden_pairs = krebs_X[0:5000]
    ...
    # 2093 matching pairs
    ...
    golden_matches_index = golden_pairs.index.intersection(krebs_true_links)
    ...
Out[4]:
MultiIndex([(89874, 89876), (79126, 84983), (40350, 83715), (75394, 92002), (23323, 27823), (31059, 72216), (28464, 69899), (33613, 64971), (23546, 27978), (29922, 46075), (22436, 23281), (34064, 43424), ...
```

(continues on next page)
(14811, 14882),
(34287, 81544),
(28539, 34715),
(17937, 63083),
(49588, 71543),
(88108, 94380),
(34171, 46602),
(35967, 71229),
(69924, 74737),
(46933, 47037),
(32487, 61025),
(20713, 48727),
names=['id1', 'id2'])

13.1.1 Logistic regression

The recordlinkage.LogisticRegressionClassifier classifier is an application of the logistic regression model. This supervised learning method is one of the oldest classification algorithms used in record linkage. In situations with enough training data, the algorithm gives relatively good results.

```
in [5]: # Initialize the classifier
...: logreg = rl.LogisticRegressionClassifier()
...

in [6]: # Train the classifier
...: logreg.fit(golden_pairs, golden_matches_index)
...: print ("Intercept: ", logreg.intercept)
...: print ("Coefficients: ", logreg.coefficients)
...
Intercept: -11.75993701313958
Coefficients: [ 1.62052151e+00 7.85074832e-02 2.93697610e+00 -5.22801106e-04
4.29397318e-01 1.96144730e+00 1.43218255e+00 1.98293940e+00
3.17172106e+00]
```

Predict the match status for all record pairs.

```
in [7]: result_logreg = logreg.predict(krebs_X)
...: len(result_logreg)
...
Out[7]: 19871
```

```
in [8]: rl.confusion_matrix(krebs_true_links, result_logreg, len(krebs_X))
Out[8]:
array([[ 19867, 1064],
       [ 4, 5728197]])
```

The F-score for this prediction is

```
in [9]: rl.fscore(krebs_true_links, result_logreg)
Out[9]: 0.9738248125091908
```

The predicted number of matches is not much more than the 20931 true matches. The result was achieved with a small training dataset of 5000 record pairs.
In (older) literature, record linkage procedures are often divided in deterministic record linkage and probabilistic record linkage. The Logistic Regression Classifier belongs to deterministic record linkage methods. Each feature/variable has a certain importance (named weight). The weight is multiplied with the comparison/similarity vector. If the total sum exceeds a certain threshold, it is considered to be a match.

```python
In [10]: intercept = -9
   ....: coefficients = [2.0, 1.0, 3.0, 1.0, 1.0, 1.0, 1.0, 2.0, 3.0]
   ....:

In [11]: logreg = rl.LogisticRegressionClassifier(coefficients, intercept)
   ....: result_logreg_pretrained = logreg.predict(krebs_X)
   ....:
Out[11]: 21303

In [12]: rl.confusion_matrix(krebs_true_links, result_logreg_pretrained, len(krebs_X))
Out[12]: array([[ 20857,  74],
               [  446, 572755]])
```

The F-score for this classification is

```python
In [13]: rl.fscore(krebs_true_links, result_logreg_pretrained)
Out[13]: 0.987687645025335
```

For the given coefficients, the F-score is better than the situation without training data. Surprising? No (use more training data and the result will improve).

### 13.1.2 Naive Bayes

In contrast to the logistic regression classifier, the Naive Bayes classifier is a probabilistic classifier. The probabilistic record linkage framework by Fellegi and Sunter (1969) is the most well-known probabilistic classification method for record linkage. Later, it was proved that the Fellegi and Sunter method is mathematically equivalent to the Naive Bayes method in case of assuming independence between comparison variables.

```python
In [14]: # Train the classifier
   ....: nb = rl.NaiveBayesClassifier(binarize=0.3)
   ....: nb.fit(golden_pairs, golden_matches_index)
   ....:

In [15]: # Predict the match status for all record pairs
   ....: result_nb = nb.predict(krebs_X)
   ....: len(result_nb)
   ....:
Out[15]: 19837

In [16]: rl.confusion_matrix(krebs_true_links, result_nb, len(krebs_X))
Out[16]: array([[ 19825, 1106],
               [  12, 5728189]])
```

The F-score for this classification is

```python
In [17]: rl.fscore(krebs_true_links, result_nb)
Out[17]: 0.9725765306122448
```
13.1.3 Support Vector Machines

Support Vector Machines (SVM) have become increasingly popular in record linkage. The algorithm performs well there is only a small amount of training data available. The implementation of SVM in the Python Record Linkage Toolkit is a linear SVM algorithm.

```python
In [18]: # Train the classifier
......: svm = rl.SVMClassifier()
......: svm.fit(golden_pairs, golden_matches_index)
......:

In [19]: # Predict the match status for all record pairs
......: result_svm = svm.predict(krebs_X)
......: len(result_svm)
......:
Out[19]: 20839

In [20]: rl.confusion_matrix(krebs_true_links, result_svm, len(krebs_X))
Out[20]: array([[ 20797, 134],
[ 350728, 5377473]])
```

The F-score for this classification is

```python
In [21]: rl.fscore(krebs_true_links, result_svm)
Out[21]: 0.997127124730668
```

13.2 Unsupervised learning

In situations without training data, unsupervised learning can be a solution for record linkage problems. In this section, we discuss two unsupervised learning methods. One algorithm is K-means clustering, and the other algorithm is an implementation of the Expectation-Maximisation algorithm. Most of the time, unsupervised learning algorithms take more computational time because of the iterative structure in these algorithms.

13.2.1 K-means clustering

The K-means clustering algorithm is well-known and widely used in big data analysis. The K-means classifier in the Python Record Linkage Toolkit package is configured in such a way that it can be used for linking records. For more info about the K-means clustering see Wikipedia.

```python
In [22]: kmeans = rl.KMeansClassifier()
......: result_kmeans = kmeans.fit_predict(krebs_X)
......: len(result_kmeans)
......:
Out[22]: 371525

In [23]: rl.confusion_matrix(krebs_true_links, result_kmeans, len(krebs_X))
Out[23]: array([[ 20797, 134],
[ 350728, 5377473]])
```
### 13.2.2 Expectation/Conditional Maximization Algorithm

The ECM-algorithm is an Expectation-Maximisation algorithm with some additional constraints. This algorithm is closely related to the Naive Bayes algorithm. The ECM algorithm is also closely related to estimating the parameters in the Fellegi and Sunter (1969) framework. The algorithms assume that the attributes are independent of each other. The Naive Bayes algorithm uses the same principles.

```python
In [25]: # Train the classifier
    ....: ecm = rl.ECMClassifier(binarize=0.8)
    ....: result_ecm = ecm.fit_predict(krebs_X)
    ....: len(result_ecm)
    ....:
Out [25]: 19834
```

```python
In [26]: rl.confusion_matrix(krebs_true_links, result_ecm, len(krebs_X))
Out [26]: array([[ 19830,  1101],
               [   4, 5728197]])
```

The F-score for this classification is

```python
In [27]: rl.fscore(krebs_true_links, result_ecm)
Out [27]: 0.9728934134674353
```
Performance plays an important role in record linkage. Record linkage problems scale quadratically with the size of the dataset(s). The number of record pairs can be enormous and so are the number of comparisons. The Python Record Linkage Toolkit can be used for large scale record linkage applications. Nevertheless, the toolkit is developed with experimenting in first place and performance on the second place. This page provides tips and tricks to improve the performance.

Do you know more tricks? Let us know!

### 14.1 Indexing

#### 14.1.1 Block on multiple columns

Blocking is an effective way to increase the performance of your record linkage. If the performance of your implementation is still poor, decrease the number of pairs by blocking on multiple variables. This implies that the record pair is agrees on two or more variables. In the following example, the record pairs agree on the given name and surname.

```python
from recordlinkage.index import Block
indexer = Block(left_on=['first_name', 'surname'],
                 right_on=['name', 'surname'])
pairs = indexer.index(dfA, dfB)
```

You might exclude more links then desired. This can be solved by repeating the process with different blocking variables.

```python
indexer = recordlinkage.Index()
indexer.block(left_on=['first_name', 'surname'],
              right_on=['name', 'surname'])
indexer.block(left_on=['first_name', 'age'],
              right_on=['name', 'age'])
pairs = indexer.index(dfA, dfB)
```
Note: Sorted Neighbourhood indexing supports, besides the sorted neighbourhood, additional blocking on variables.

14.1.2 Make record pairs

The structure of the Python Record Linkage Toolkit has a drawback for the performance. In the indexation step (the step in which record pairs are selected), only the index of both records is stored. The entire records are not stored. This results in less memory usage. The drawback is that the records need to be queried from the data.

14.2 Comparing

14.2.1 Compare only discriminating variables

Not all variables may be worth comparing in a record linkage. Some variables do not discriminate the links of the non-links or do have only minor effects. These variables can be excluded. Only discriminating and informative should be included.

14.2.2 Prevent string comparisons

String similarity measures and phonetic encodings are computationally expensive. Phonetic encoding takes place on the original data, while string simililitary measures are applied on the record pairs. After phonetic encoding of the string variables, exact comparing can be used instead of computing the string similarity of all record pairs. If the number of candidate pairs is much larger than the number of records in both datasets together, then consider using phonetic encoding of string variables instead of string comparison.

14.2.3 String comparing

Comparing strings is computationally expensive. The Python Record Linkage Toolkit uses the package jellyfish for string comparisons. The package has two implementations, a C and a Python implementation. Ensure yourself of having the C-version installed (import jellyfish.cjellyfish should not raise an exception).

There can be a large difference in the performance of different string comparison algorithms. The Jaro and Jaro-Winkler methods are faster than the Levenshtein distance and much faster than the Damerau-Levenshtein distance.

14.2.4 Indexing with large files

Sometimes, the input files are very large. In that case, it can be hard to make an index without running out of memory in the indexing step or in the comparing step. recordlinkage has a method to deal with large files. It is fast, although is not primary developed to be fast. SQL databases may outperform this method. It is especially developed for the useability. The idea was to split the input files into small blocks. For each block the record pairs are computed. Then iterate over the blocks. Consider full indexing:

```python
import recordlinkage
import numpy

cl = recordlinkage.index.Full()

for dfB_subset in numpy.split(dfB):
    (continues on next page)```
# a subset of record pairs
pairs_subset = cl.index(dfA, dfB_subset)

# Your analysis on pairs_subset here
Thanks for your interest in contributing to the Python Record Linkage Toolkit. There is a lot of work to do. See Github for the contributors to this package.

The workflow for contributing is as follows:

- clone https://github.com/J535D165/recordlinkage.git
- Make a branch with your modifications/contributions
- Write tests
- Run all tests
- Do a pull request

### 15.1 Testing

Install pytest:

```
pip install pytest
```

Run the following command to test the package

```
python -m pytest tests/
```

### 15.2 Performance

Performance is very important in record linkage. The performance is monitored for all serious modifications of the core API. The performance monitoring is performed with Airspeed Velocity (asv).

Install Airspeed Velocity:
Run the following command from the root of the repository to test the performance of the current version of the package:

```
asv run
```

Run the following command to test all versions since tag v0.6.0

```
asv run --skip-existing-commits v0.6.0..master
```
16.1 Version 0.15

- Remove deprecated recordlinkage classes (#173)
- Bump min Python version to 3.6, ideally 3.8+ (#171)
- Bump min pandas version to >=1
- Resolve deprecation warnings for numpy and pandas
- Happy lint, sort imports, format code with yapf
- Remove unnecessary np.sort in SNI algorithm (#141)
- Fix bug for cosine and qgram string comparisons with threshold (#135)
- Fix several typos in docs (#151)(#152)(#153)(#154)(#163)(#164)
- Fix random indexer (#158)
- Fix various deprecation warnings and broken docs build (#170)
- Fix broken docs build due to pandas depr warnings (#169)
- Fix broken build and removed warning messages (#168)
- Update narrative
- Replace Travis by Github Actions (#132)
- Fix broken test NotFittedError
- Fix bug in low memory random sampling and add more tests (#130)
- Add extras_require to setup.py for deps management
- Add banner to README and update title
- Add Binder and Colab buttons at tutorials (#174)

Special thanks to Tomasz Waleń @twalen and other contributors for their work on this release.
16.2 Version 0.14

- Drop Python 2.7 and Python 3.4 support. (#91)
- Upgrade minimal pandas version to 0.23.
- Simplify the use of all cpus in parallel mode. (#102)
- Store large example datasets in user home folder or use environment variable. Before, example datasets were stored in the package. (see issue #42) (#92)
- Add support to write and read annotation files for recordlinkage ANNOTATOR. See the docs and https://github.com/J535D165/recordlinkage-annotator for more information.
- Replace `.labels` by `.codes` for pandas.MultiIndex objects for newer versions of pandas (>0.24). (#103)
- Fix totals for pandas.MultiIndex input on confusion matrix and accuracy metrics. (see issue #84) (#109)
- Initialize Compare with (a list of) features (Bug). (#124)
- Various updates in relation to deprecation warnings in third-party libraries such as sklearn, pandas and networkx.
Bibliography


Symbols

_index() (recordlinkage.base.BaseIndexAlgorithm method), 32
_link_index() (recordlinkage.base.BaseIndexAlgorithm method), 31

A
accuracy() (in module recordlinkage), 67
add() (recordlinkage.Compare method), 36
add() (recordlinkage.Index method), 25
AnnotationResult (class in recordlinkage.annotation), 81

B
BaseClassifier (class in recordlinkage.base), 61
BaseCompareFeature (class in recordlinkage.base), 46
BaseIndexAlgorithm (class in recordlinkage.base), 46
binary_vectors() (in module recordlinkage.datasets), 71
Block (class in recordlinkage.index), 28
block() (recordlinkage.Index method), 26

C
clean() (in module recordlinkage.preprocessing), 21
coefficients (recordlinkage.LogisticRegressionClassifier attribute), 52
Compare (class in recordlinkage), 35
compare_vectorized() (recordlinkage.Compare method), 36
compute() (recordlinkage.base.BaseCompareFeature method), 46
compute() (recordlinkage.Compare method), 36
compute() (recordlinkage.compare.Date method), 42
compute() (recordlinkage.compare.Exact method), 38
compute() (recordlinkage.compare.Frequency method), 44
compute() (recordlinkage.compare.FrequencyA method), 44
compute() (recordlinkage.compare.FrequencyB method), 45
compute() (recordlinkage.compare.Geographic method), 41
compute() (recordlinkage.compare.Numeric method), 40
compute() (recordlinkage.compare.String method), 39
compute() (recordlinkage.compare.Variable method), 42
compute() (recordlinkage.compare.VariableA method), 43
compute() (recordlinkage.compare.VariableB method), 43
compute() (recordlinkage.ConnectedComponents method), 64
compute() (recordlinkage.OneToOneLinking method), 63
confusion_matrix() (in module recordlinkage), 66
DisconnectedComponents (class in recordlinkage), 64

D
Date (class in recordlinkage.compare), 41
date() (recordlinkage.Compare method), 38
describe_option() (in module recordlinkage.annotation), 74
distinct (recordlinkage.annotation.AnnotationResult attribute), 81

E
ECMClassifier (class in recordlinkage), 56
<table>
<thead>
<tr>
<th>Index (class in recordlinkage)</th>
<th>25</th>
</tr>
</thead>
<tbody>
<tr>
<td>index() (recordlinkage.base.BaseIndexAlgorithm method)</td>
<td>32</td>
</tr>
<tr>
<td>index() (recordlinkage.Index method)</td>
<td>26</td>
</tr>
<tr>
<td>index() (recordlinkage.index.Block method)</td>
<td>28</td>
</tr>
<tr>
<td>index() (recordlinkage.index.Full method)</td>
<td>27</td>
</tr>
<tr>
<td>index() (recordlinkage.index.Random method)</td>
<td>30</td>
</tr>
<tr>
<td>index() (recordlinkage.index.SortedNeighbourhood method)</td>
<td>29</td>
</tr>
<tr>
<td>index_split() (in module recordlinkage)</td>
<td>73</td>
</tr>
<tr>
<td>intercept (recordlinkage.LogisticRegressionClassifier attribute)</td>
<td>52</td>
</tr>
<tr>
<td>KerasAdapter (class in recordlinkage.adapters)</td>
<td>60</td>
</tr>
<tr>
<td>kernel (recordlinkage.KMeansClassifier attribute)</td>
<td>58</td>
</tr>
<tr>
<td>kernel (recordlinkage.LogisticRegressionClassifier attribute)</td>
<td>51</td>
</tr>
<tr>
<td>kernel (recordlinkage.SVMClassifier attribute)</td>
<td>55</td>
</tr>
<tr>
<td>KMeansClassifier (class in recordlinkage)</td>
<td>58</td>
</tr>
<tr>
<td>learn() (recordlinkage.base.BaseClassifier method)</td>
<td>61</td>
</tr>
<tr>
<td>learn() (recordlinkage.ECMClassifier method)</td>
<td>57</td>
</tr>
<tr>
<td>learn() (recordlinkage.KMeansClassifier method)</td>
<td>59</td>
</tr>
<tr>
<td>learn() (recordlinkage.LogisticRegressionClassifier method)</td>
<td>52</td>
</tr>
<tr>
<td>learn() (recordlinkage.NaiveBayesClassifier method)</td>
<td>54</td>
</tr>
<tr>
<td>learn() (recordlinkage.SVMClassifier method)</td>
<td>55</td>
</tr>
<tr>
<td>links (recordlinkage.annotation.AnnotationResult attribute)</td>
<td>81</td>
</tr>
<tr>
<td>load_febr11() (in module recordlinkage.datasets)</td>
<td>70</td>
</tr>
<tr>
<td>load_febr12() (in module recordlinkage.datasets)</td>
<td>70</td>
</tr>
<tr>
<td>load_febr13() (in module recordlinkage.datasets)</td>
<td>70</td>
</tr>
<tr>
<td>load_febr14() (in module recordlinkage.datasets)</td>
<td>71</td>
</tr>
<tr>
<td>load_krebsregister() (in module recordlinkage.datasets)</td>
<td>69</td>
</tr>
<tr>
<td>log_m_probs (recordlinkage.classifiers.FellegiSunter attribute)</td>
<td>62</td>
</tr>
<tr>
<td>log_m_probs (recordlinkage.ECMClassifier attribute)</td>
<td>57</td>
</tr>
<tr>
<td>log_m_probs (recordlinkage.NaiveBayesClassifier attribute)</td>
<td>54</td>
</tr>
<tr>
<td>log_p (recordlinkage.classifiers.FellegiSunter attribute)</td>
<td>62</td>
</tr>
<tr>
<td>log_p (recordlinkage.ECMClassifier attribute)</td>
<td>57</td>
</tr>
<tr>
<td>log_p (recordlinkage.NaiveBayesClassifier attribute)</td>
<td>54</td>
</tr>
<tr>
<td>log_u_probs (recordlinkage.classifiers.FellegiSunter attribute)</td>
<td>62</td>
</tr>
<tr>
<td>log_u_probs (recordlinkage.ECMClassifier attribute)</td>
<td>57</td>
</tr>
</tbody>
</table>

---

**Exact** (class in recordlinkage.compare), 38

**false_negatives** (in module recordlinkage), 66

**false_positives** (in module recordlinkage), 66

**features** (recordlinkage.Compare attribute), 36

**F**

**fit() (recordlinkage.base.BaseClassifier method)**, 61

**fit() (recordlinkage.ECMClassifier method)**, 58

**fit() (recordlinkage.KMeansClassifier method)**, 59

**fit() (recordlinkage.LogisticRegressionClassifier method)**, 52

**fit() (recordlinkage.NaiveBayesClassifier method)**, 53

**fit() (recordlinkage.SVMClassifier method)**, 55

**fit_predict() (recordlinkage.base.BaseClassifier method)**, 61

**fit_predict() (recordlinkage.ECMClassifier method)**, 56

**fit_predict() (recordlinkage.KMeansClassifier method)**, 59

**fit_predict() (recordlinkage.LogisticRegressionClassifier method)**, 52

**fit_predict() (recordlinkage.NaiveBayesClassifier method)**, 53

**fit_predict() (recordlinkage.SVMClassifier method)**, 55

**Frequency** (class in recordlinkage.compare), 43

**FrequencyA** (class in recordlinkage.compare), 44

**FrequencyB** (class in recordlinkage.compare), 45

**from_dict()** (recordlinkage.annotation.AnnotationResult attribute), 81

**from_file()** (recordlinkage.annotation.AnnotationResult attribute), 81

**fscore()** (in module recordlinkage), 68

**Full** (class in recordlinkage.index), 27

**full()** (recordlinkage.Index method), 26

**full_index_size()** (in module recordlinkage), 68

**G**

**geo()** (recordlinkage.Compare method), 37

**Geographic** (class in recordlinkage.compare), 41

**get_option()** (in module recordlinkage), 73

**I**

**Index** (class in recordlinkage), 25

**index()** (recordlinkage.base.BaseIndexAlgorithm method), 32

**index()** (recordlinkage.Index method), 26

**index()** (recordlinkage.index.Block method), 28

**index()** (recordlinkage.index.Full method), 27

**index()** (recordlinkage.index.Random method), 30

**index()** (recordlinkage.index.SortedNeighbourhood method), 29

**index_split()** (in module recordlinkage), 73

**intercept** (recordlinkage.LogisticRegressionClassifier attribute), 52

**K**

**KerasAdapter** (class in recordlinkage.adapters), 60

**kernel** (recordlinkage.KMeansClassifier attribute), 58

**kernel** (recordlinkage.LogisticRegressionClassifier attribute), 51

**KMeansClassifier** (class in recordlinkage), 58

**L**

**learn()** (recordlinkage.base.BaseClassifier method), 61

**learn()** (recordlinkage.ECMClassifier method), 57

**learn()** (recordlinkage.KMeansClassifier method), 59

**learn()** (recordlinkage.LogisticRegressionClassifier method), 52

**learn()** (recordlinkage.NaiveBayesClassifier method), 54

**learn()** (recordlinkage.SVMClassifier method), 55

**links** (recordlinkage.annotation.AnnotationResult attribute), 81

**load_febr11()** (in module recordlinkage.datasets), 70

**load_febr12()** (in module recordlinkage.datasets), 70

**load_febr13()** (in module recordlinkage.datasets), 70

**load_febr14()** (in module recordlinkage.datasets), 71

**load_krebsregister()** (in module recordlinkage.datasets), 69

**log_m_probs** (recordlinkage.classifiers.FellegiSunter attribute), 62

**log_m_probs** (recordlinkage.ECMClassifier attribute), 57

**log_m_probs** (recordlinkage.NaiveBayesClassifier attribute), 54

**log_p** (recordlinkage.classifiers.FellegiSunter attribute), 62

**log_p** (recordlinkage.ECMClassifier attribute), 57

**log_p** (recordlinkage.NaiveBayesClassifier attribute), 54

**log_u_probs** (recordlinkage.classifiers.FellegiSunter attribute), 62

**log_u_probs** (recordlinkage.ECMClassifier attribute), 57
Index 101

log_u_probs (recordlinkage.NaiveBayesClassifier.attribute), 54
log_weights (recordlinkage.classifiers.FellegiSunter.attribute), 63
log_weights (recordlinkage.ECMClassifier.attribute), 57
log_weights (recordlinkage.NaiveBayesClassifier.attribute), 54
LogisticRegressionClassifier (class in recordlinkage), 51

M
m_probs (recordlinkage.classifiers.FellegiSunter.attribute), 63
m_probs (recordlinkage.ECMClassifier.attribute), 57
m_probs (recordlinkage.NaiveBayesClassifier.attribute), 54
match_cluster_center (recordlinkage.KMeansClassifier.attribute), 58
max_pairs() (in module recordlinkage), 68

N
NaiveBayesClassifier (class in recordlinkage), 53
nonmatch_cluster_center (recordlinkage.KMeansClassifier.attribute), 58
Numeric (class in recordlinkage.compare), 39
numeric() (recordlinkage.Compare.method), 37

O
OneToManyLinking (class in recordlinkage), 63
OneToOneLinking (class in recordlinkage), 63

P
p (recordlinkage.classifiers.FellegiSunter.attribute), 63
p (recordlinkage.ECMClassifier.attribute), 57
p (recordlinkage.NaiveBayesClassifier.attribute), 54
phonenumbers() (in module recordlinkage.preprocessing), 22
phonetic() (in module recordlinkage.preprocessing), 23
phonetic_algorithms (recordlinkage.preprocessing.attribute), 23
precision() (in module recordlinkage), 67
predict() (recordlinkage.base.BaseClassifier.method), 62
predict() (recordlinkage.ECMClassifier.method), 57
predict() (recordlinkage.KMeansClassifier.method), 59
predict() (recordlinkage.LogisticRegressionClassifier.method), 52
predict() (recordlinkage.NaiveBayesClassifier.method), 54
predict() (recordlinkage.SVMClassifier.method), 55
prob() (recordlinkage.base.BaseClassifier.method), 62
prob() (recordlinkage.ECMClassifier.method), 57
prob() (recordlinkage.KMeansClassifier.method), 59
prob() (recordlinkage.LogisticRegressionClassifier.method), 52
prob() (recordlinkage.NaiveBayesClassifier.method), 54
prob() (recordlinkage.SVMClassifier.method), 56

R
Random (class in recordlinkage.index), 30
random() (recordlinkage.Index.method), 27
read_annotation_file() (in module recordlinkage), 80
recall() (in module recordlinkage), 67
recordlinkage.compare (module), 38
recordlinkage.index (module), 27
reduction_ratio() (in module recordlinkage), 65
reset_option() (in module recordlinkage), 74

S
set_option() (in module recordlinkage), 73
SKLearnAdapter (class in recordlinkage.adapters), 60
SortedNeighbourhood (class in recordlinkage.index), 28
sortedneighbourhood() (recordlinkage.Index.method), 27
specificity() (in module recordlinkage), 67
String (class in recordlinkage.compare), 38
string() (recordlinkage.Compare.method), 37
SVMClassifier (class in recordlinkage), 54

T
ture_negatives() (in module recordlinkage), 65
ture_positives() (in module recordlinkage), 65

U
u_probs (recordlinkage.classifiers.FellegiSunter.attribute), 63
u_probs (recordlinkage.ECMClassifier.attribute), 57
u_probs (recordlinkage.NaiveBayesClassifier.attribute), 54
unknown (recordlinkage.annotation.AnnotationResult.attribute), 81

V
value_occurrence() (in module recordlinkage.preprocessing), 22
Variable (class in recordlinkage.compare), 42
VariableA (class in recordlinkage.compare), 42
VariableB (class in recordlinkage.compare), 43

Index
weights (recordlinkage.classifiers.FellegiSunter attribute), 63
weights (recordlinkage.ECMClassifier attribute), 57
weights (recordlinkage.NaiveBayesClassifier attribute), 54
write_annotation_file() (in module recordlinkage), 79