In this chapter

Chapter 4 - Record linkage

Minimum edit distance

I	N	T	E	N	T	I	O	N

E	X	E	C	U	T	I	O	N

Least possible amount of steps needed to transition from one string to another

Minimum edit distance

I	N	T	E	N	T	I	O	N

E	X	E	C	U	T	I	O	N

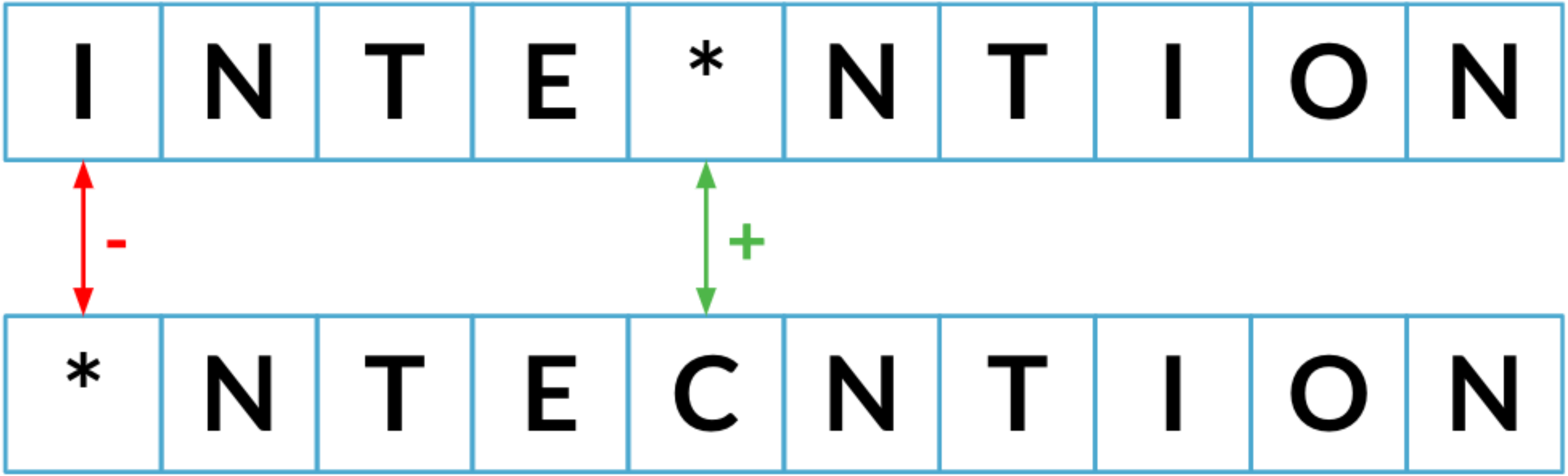
+ Insertion
- Deletion
Substitution
Transposition

Least possible amount of steps needed to transition from one string to another

Minimum edit distance

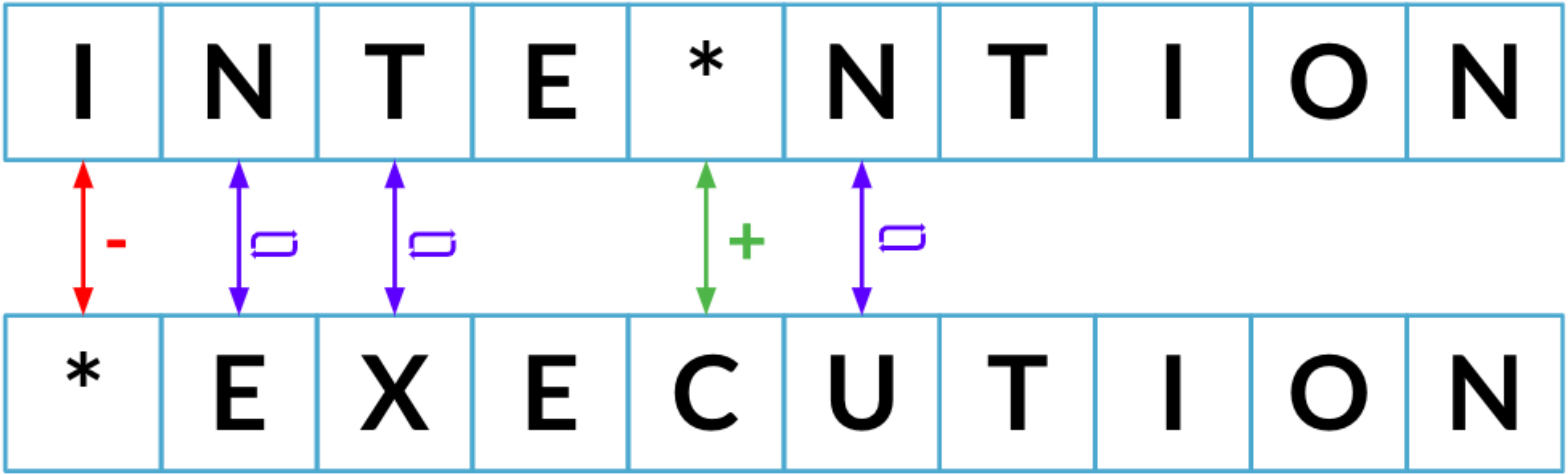
I	N	T	E	N	T	I	O	N

Minimum edit distance



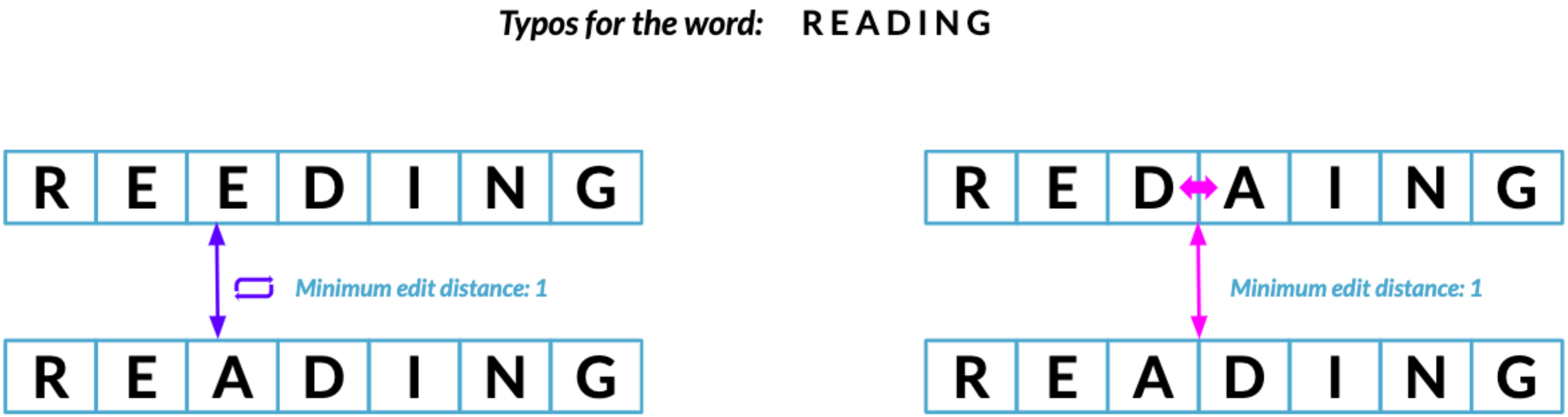
Minimum edit distance so far: 2

Minimum edit distance



Minimum edit distance: 5

Minimum edit distance



Minimum edit distance algorithms

Algorithm	Operations
Damerau-Levenshtein	insertion, substitution, deletion, transposition
Levenshtein	insertion, substitution, deletion
Hamming	substitution only
Jaro distance	transposition only
...	...

Possible packages: `nltk` , `fuzzywuzzy` , `textdistance` ..

Minimum edit distance algorithms

Algorithm	Operations
Damerau-Levenshtein	insertion, substitution, deletion, transposition
Levenshtein	***insertion, substitution, deletion***
Hamming	substitution only
Jaro distance	transposition only
...	...

Possible packages: `fuzzywuzzy`

FuzzyBuzzy library is developed to compare to strings. We have other modules like regex, difflib to compare strings. But, FuzzyBuzzy is unique in its way. The methods from this library returns score out of 100 of how much the strings matched instead of true, false or string.

Simple string comparison

```
# Lets us compare between two strings
from fuzzywuzzy import fuzz

# Compare reeding vs reading
fuzz.WRatio('Reeding', 'Reading')
```

```
86
```

There are many methods of comparing string in python. Some of the main methods are:
- Using regex
- Simple compare
- Using difflib

But one of the very easy method is by using fuzzywuzzy library where we can have a score out of 100, that denotes two string are equal by giving similarity index. Fuzzy string matching is the process of finding strings that match a given pattern. Basically it uses Levenshtein Distance to calculate the differences between sequences.

Partial strings and different orderings

```
# Partial string comparison
fuzz.WRatio('Houston Rockets', 'Rockets')
```

```
90
```

```
# Partial string comparison with different order
fuzz.WRatio('Houston Rockets vs Los Angeles Lakers', 'Lakers vs Rockets')
```

```
86
```

Comparison with arrays

```python
# Import process
from fuzzywuzzy import process

# Define string and array of possible matches
string = "Houston Rockets vs Los Angeles Lakers"
choices = pd.Series(['Rockets vs Lakers', 'Lakers vs Rockets',
                     'Houson vs Los Angeles', 'Heat vs Bulls'])

process.extract(string, choices, limit = 2)
```

```
[('Rockets vs Lakers', 86, 0), ('Lakers vs Rockets', 86, 1)]
```

Collapsing categories with string similarity

Chapter 2

Use `.replace()` to collapse `"eur"` into `"Europe"`

What if there are too many variations?

`"EU"` , `"eur"` , `"Europ"` , `"Europa"` , `"Erope"` , `"Evropa"` ...

String similarity!

Collapsing categories with string matching

```
print(survey)
```

```
id          state  move_scores
0      California            1
1            Cali            1
2      Calefornia            1
3      Calefornie            3
4      Californie            0
5       Calfornia            2
6      Calefernia            0
7        New York            2
8   New York City            2
...
```

```
categories
```

```
   state
0  California
1  New York
```

Collapsing all of the state

```
from fuzzywuzzy import process
# For each correct category
for state in categories['state']:
  # Find potential matches in states with typoes
    matches = process.extract(state, survey['state'], limit = survey.shape[0])
    # For each potential match match
    for potential_match in matches:
       # If high similarity score
        if potential_match[1] >= 80:
          # Replace typo with correct category
          survey.loc[survey['state'] == potential_match[0], 'state'] = state
```

Record linkage

Event	Time
Houston Rockets vs Chicago Bulls	19:00
Miami Heat vs Los Angeles Lakers	19:00
Brooklyn Nets vs Orlando Magic	20:00
Denver Nuggets vs Miami Heat	21:00
San Antonio Spurs vs Atlanta Hawks	21:00

Event	Time
NBA: Nets vs Magic	8pm
NBA: Bulls vs Rockets	9pm
NBA: Heat vs Lakers	7pm
NBA: Grizzlies vs Heat	10pm
NBA: Heat vs Cavaliers	9pm

Let's practice!

CLEANING DATA IN PYTHON

Motivation

Event	Time
Houston Rockets vs Chicago Bulls	19:00
Miami Heat vs Los Angeles Lakers	19:00
Brooklyn Nets vs Orlando Magic	20:00
Denver Nuggets vs Miami Heat	21:00
San Antonio Spurs vs Atlanta Hawks	21:00

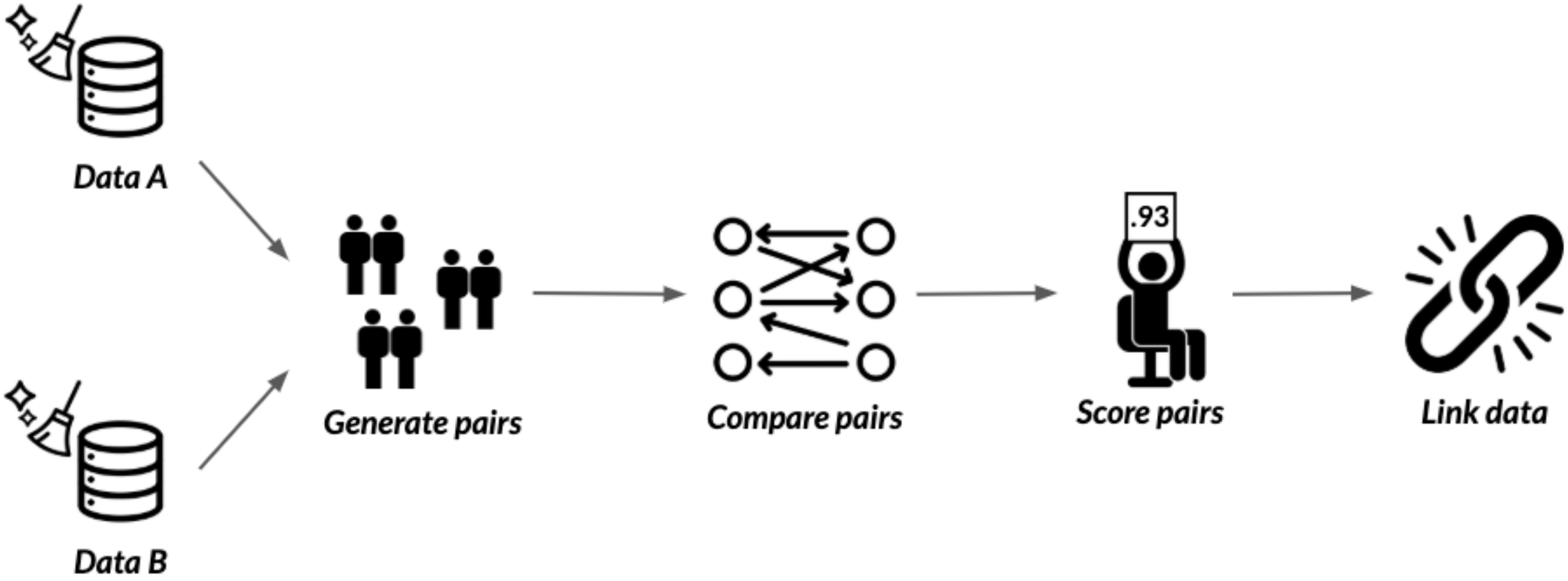
Event	Time
NBA: Nets vs Magic	8pm
NBA: Bulls vs Rockets	9pm
NBA: Heat vs Lakers	7pm
NBA: Grizzlies vs Heat	10pm
NBA: Heat vs Cavaliers	9pm

When joins won't work

Event	Time
Houston Rockets vs Chicago Bulls	19:00
Miami Heat vs Los Angeles Lakers	19:00
Brooklyn Nets vs Orlando Magic	20:00
Denver Nuggets vs Miami Heat	21:00
San Antonio Spurs vs Atlanta Hawks	21:00

Event	Time
NBA: Nets vs Magic	8pm
NBA: Bulls vs Rockets	9pm
NBA: Heat vs Lakers	7pm
NBA: Grizzlies vs Heat	10pm
NBA: Heat vs Cavaliers	9pm

Record linkage



The `recordlinkage` package

Our DataFrames

`census_A`

```
               given_name  surname date_of_birth         suburb state  address_1
rec_id
rec-1070-org     michaela  neumann      19151111  winston hills   cal  stanley street
rec-1016-org     courtney  painter      19161214      richlands   txs  pinkerton circuit
...
```

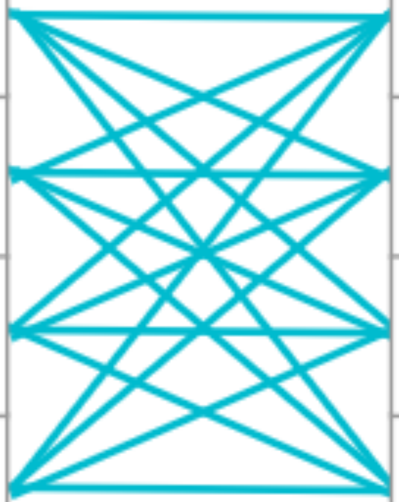
`census_B`

```
                given_name  surname date_of_birth             suburb state  address_1
rec_id
rec-561-dup-0        elton      NaN      19651013         windermere   ny   light setreet
rec-2642-dup-0   mitchell     maxon      19390212         north ryde   cal  edkins street
...
```

Generating pairs

census_A

rec_id	given_name	...	state
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...



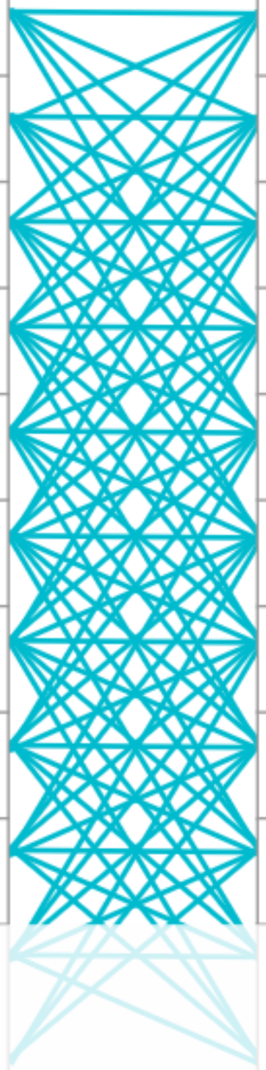
census_B

rec_id	given_name	...	state
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...

Generating pairs

census_A

rec_id	given_name	...	state
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...



census_B

rec_id	given_name	...	state
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...
...	...	...	...

Blocking

`census_A`

rec_id	given_name	...	state
...	...	...	cal
...	...	...	ny
...	...	...	txs
...	...	...	txs

`census_A`

rec_id	given_name	...	state
...	...	...	cal
...	...	...	txs
...	...	...	ny
...	...	...	cal

Generating pairs

```
# Import recordlinkage
import recordlinkage

# Create indexing object
indexer = recordlinkage.Index()

# Generate pairs blocked on state
indexer.block('state')
pairs = indexer.index(census_A, census_B)
```

Generating pairs

```
print(pairs)
```

```
MultiIndex(levels=[['rec-1007-org', 'rec-1016-org', 'rec-1054-org', 'rec-1066-org',
'rec-1070-org', 'rec-1075-org', 'rec-1080-org', 'rec-110-org', 'rec-1146-org',
'rec-1157-org', 'rec-1165-org', 'rec-1185-org', 'rec-1234-org', 'rec-1271-org',
'rec-1280-org',..........
66, 14, 13, 18, 34, 39, 0, 16, 80, 50, 20, 69, 28, 25, 49, 77, 51, 85, 52, 63, 74, 61,
83, 91, 22, 26, 55, 84, 11, 81, 97, 56, 27, 48, 2, 64, 5, 17, 29, 60, 72, 47, 92, 12,
95, 15, 19, 57, 37, 70, 94]], names=['rec_id_1', 'rec_id_2'])
```

Comparing the DataFrames

```
# Generate the pairs
pairs = indexer.index(census_A, census_B)
# Create a Compare object
compare_cl = recordlinkage.Compare()

# Find exact matches for pairs of date_of_birth and state
compare_cl.exact('date_of_birth', 'date_of_birth', label='date_of_birth')
compare_cl.exact('state', 'state', label='state')
# Find similar matches for pairs of surname and address_1 using string similarity
compare_cl.string('surname', 'surname', threshold=0.85, label='surname')
compare_cl.string('address_1', 'address_1', threshold=0.85, label='address_1')

# Find matches
potential_matches = compare_cl.compute(pairs, census_A, census_B)
```

Finding matching pairs

```
print(potential_matches)
```

```
                              date_of_birth  state  surname  address_1
rec_id_1     rec_id_2
rec-1070-org rec-561-dup-0                0      1      0.0        0.0
             rec-2642-dup-0               0      1      0.0        0.0
             rec-608-dup-0                0      1      0.0        0.0
...
rec-1631-org rec-4070-dup-0               0      1      0.0        0.0
             rec-4862-dup-0               0      1      0.0        0.0
             rec-629-dup-0                0      1      0.0        0.0
...
```

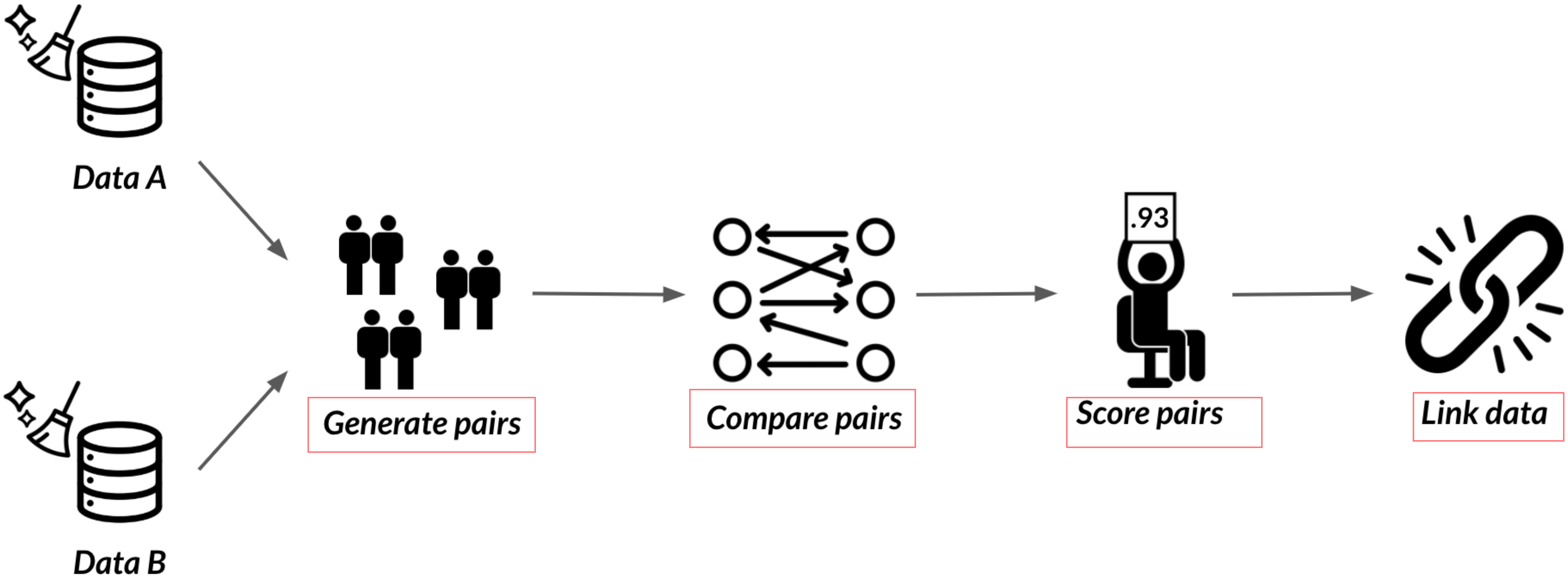
Finding the only pairs we want

```
potential_matches[potential_matches.sum(axis = 1) => 2]
```

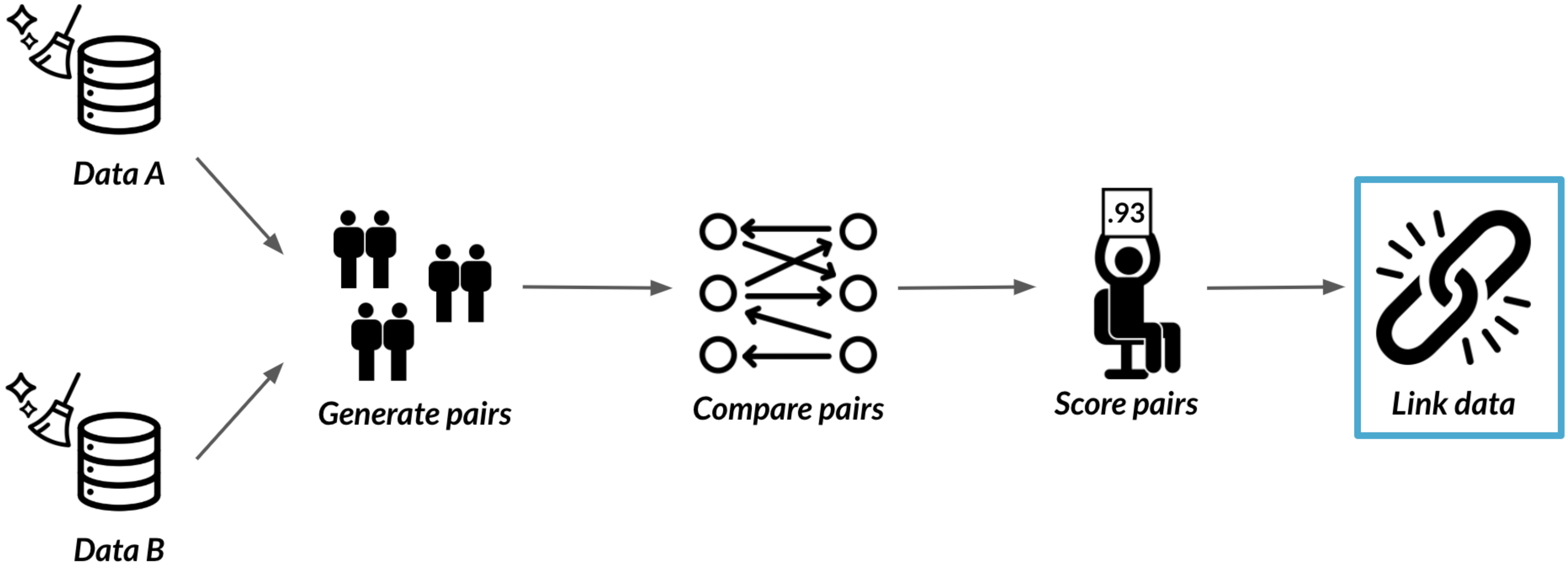
```
                               date_of_birth  state  surname  address_1
rec_id_1      rec_id_2
rec-4878-org rec-4878-dup-0              1      1      1.0        0.0
rec-417-org  rec-2867-dup-0              0      1      0.0        1.0
rec-3964-org rec-394-dup-0               0      1      1.0        0.0
rec-1373-org rec-4051-dup-0              0      1      1.0        0.0
             rec-802-dup-0               0      1      1.0        0.0
rec-3540-org rec-470-dup-0               0      1      1.0        0.0
```

Let's practice!

Record linkage



Record linkage



Our DataFrames

`census_A`

```
              given_name  surname date_of_birth        suburb state  address_1
rec_id
rec-1070-org    michaela  neumann      19151111 winston hills   nsw  stanley street
rec-1016-org    courtney  painter      19161214    richlands   vic  pinkerton circuit
...
```

`census_B`

```
              given_name  surname date_of_birth             suburb state  address_1
rec_id
rec-561-dup-0      elton      NaN      19651013         windermere   vic  light setreet
rec-2642-dup-0  mitchell    maxon      19390212         north ryde   nsw  edkins street
...
```

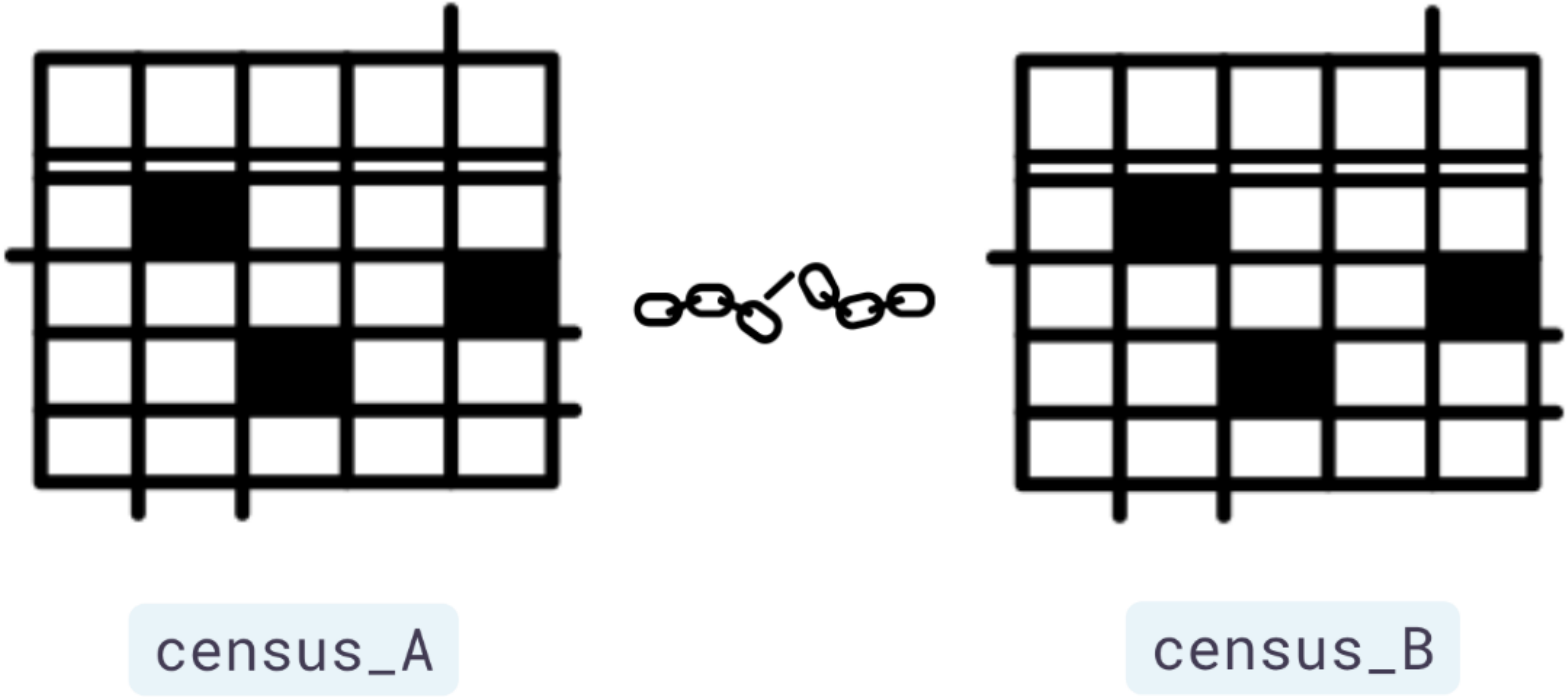
What we've already done

```
# Import recordlinkage and generate full pairs
import recordlinkage
indexer = recordlinkage.Index()
indexer.block('state')
full_pairs = indexer.index(census_A, census_B)

# Comparison step
compare_cl = recordlinkage.Compare()
compare_cl.exact('date_of_birth', 'date_of_birth', label='date_of_birth')
compare_cl.exact('state', 'state', label='state')
compare_cl.string('surname', 'surname', threshold=0.85, label='surname')
compare_cl.string('address_1', 'address_1', threshold=0.85, label='address_1')

potential_matches = compare_cl.compute(full_pairs, census_A, census_B)
```

What we're doing now



Our potential matches

```
potential_matches
```

```
                                    date_of_birth  state  surname  address_1
rec_id_1     rec_id_2
rec-1070-org rec-561-dup-0                      0      1      0.0        0.0
             rec-2642-dup-0                     0      1      0.0        0.0
             rec-608-dup-0                      0      1      0.0        0.0
...                                           ...    ...      ...        ...
rec-1631-org rec-1697-dup-0                     0      1      0.0        0.0
             rec-4404-dup-0                     0      1      0.0        0.0
             rec-3780-dup-0                     0      1      0.0        0.0
...                                           ...    ...      ...        ...
```

Our potential matches

```
potential_matches
```

```
census_A                   date_of_birth  state  surname  address_1
rec_id_1     rec_id_2
rec-1070-org rec-561-dup-0             0      1      0.0        0.0
             rec-2642-dup-0            0      1      0.0        0.0
             rec-608-dup-0             0      1      0.0        0.0
...                                  ...    ...      ...        ...
rec-1631-org rec-1697-dup-0            0      1      0.0        0.0
             rec-4404-dup-0            0      1      0.0        0.0
             rec-3780-dup-0            0      1      0.0        0.0
...                                  ...    ...      ...        ...
```

Our potential matches

```
potential_matches
```

```
census_A     census_B        date_of_birth  state  surname  address_1
rec_id_1     rec_id_2
rec-1070-org rec-561-dup-0               0      1      0.0        0.0
             rec-2642-dup-0              0      1      0.0        0.0
             rec-608-dup-0               0      1      0.0        0.0
...                                    ...    ...      ...        ...
rec-1631-org rec-1697-dup-0              0      1      0.0        0.0
             rec-4404-dup-0              0      1      0.0        0.0
             rec-3780-dup-0              0      1      0.0        0.0
...                                    ...    ...      ...        ...
```

Our potential matches

```
potential_matches
```

```
census_A      census_B         date_of_birth  state  surname  address_1
rec_id_1      rec_id_2
rec-1070-org  rec-561-dup-0                0      1      0.0        0.0
              rec-2642-dup-0               0      1      0.0        0.0
              rec-608-dup-0                0      1      0.0        0.0
...                                      ...    ...      ...        ...
rec-1631-org  rec-1697-dup-0               0      1      0.0        0.0
              rec-4404-dup-0               0      1      0.0        0.0
              rec-3780-dup-0               0      1      0.0        0.0
...                                      ...    ...      ...        ...
```

Probable matches

```
matches = potential_matches[potential_matches.sum(axis = 1) >= 3]
print(matches)
```

```
                              date_of_birth  state  surname  address_1
rec_id_1      rec_id_2
rec-2404-org  rec-2404-dup-0              1      1      1.0        1.0
rec-4178-org  rec-4178-dup-0              1      1      1.0        1.0
rec-1054-org  rec-1054-dup-0              1      1      1.0        1.0
...           ...                       ...    ...      ...        ...
rec-1234-org  rec-1234-dup-0              1      1      1.0        1.0
rec-1271-org  rec-1271-dup-0              1      1      1.0        1.0
```

Probable matches

```
matches = potential_matches[potential_matches.sum(axis = 1) >= 3]
print(matches)
```

	census_B	date_of_birth	state	surname	address_1
rec_id_1	rec_id_2				
rec-2404-org	rec-2404-dup-0	1	1	1.0	1.0
rec-4178-org	rec-4178-dup-0	1	1	1.0	1.0
rec-1054-org	rec-1054-dup-0	1	1	1.0	1.0
...	...	...	...	...	...
rec-1234-org	rec-1234-dup-0	1	1	1.0	1.0
rec-1271-org	rec-1271-dup-0	1	1	1.0	1.0

Get the indices

```
matches.index
```

```
MultiIndex(levels=[['rec-1007-org', 'rec-1016-org', 'rec-1054-org', 'rec-1066-org',
'rec-1070-org', 'rec-1075-org', 'rec-1080-org', 'rec-110-org', ...
```

```
# Get indices from census_B only
duplicate_rows = matches.index.get_level_values(1)
print(census_B_index)
```

```
Index(['rec-2404-dup-0', 'rec-4178-dup-0', 'rec-1054-dup-0', 'rec-4663-dup-0',
       'rec-485-dup-0', 'rec-2950-dup-0', 'rec-1234-dup-0', ... , 'rec-299-dup-0'])
```

Linking DataFrames

```
# Finding duplicates in census_B
census_B_duplicates = census_B[census_B.index.isin(duplicate_rows)]

# Finding new rows in census_B
census_B_new = census_B[~census_B.index.isin(duplicate_rows)]
```

```
# Link the DataFrames!
full_census = census_A.append(census_B_new)
```

```python
# Import recordlinkage and generate pairs and compare across columns
...
# Generate potential matches
potential_matches = compare_cl.compute(full_pairs, census_A, census_B)

# Isolate matches with matching values for 3 or more columns
matches = potential_matches[potential_matches.sum(axis = 1) >= 3]

# Get index for matching census_B rows only
duplicate_rows = matches.index.get_level_values(1)

# Finding new rows in census_B
census_B_new = census_B[~census_B.index.isin(duplicate_rows)]

# Link the DataFrames!
full_census = census_A.append(census_B_new)
```

Let's practice!

CLEANING DATA IN PYTHON

What we've learned

Diagnose dirty data

Side effects of dirty data

Clean data

What we've learned

Data Type Constraints

Strings
Numeric data
...

Data Range Constraints

Out of range data
Out of range dates
...

Uniqueness Constraints

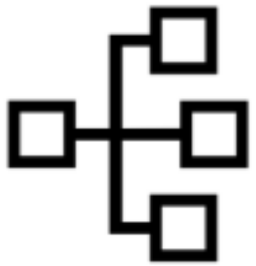
Finding duplicates
Treating them
...

Chapter 1 - Common data problems

What we've learned

Membership Constraints

Finding inconsistent categories
Treating them with joins
...



Categorical Variables

Finding inconsistent categories
Collapsing them into less
...

Cleaning Text Data

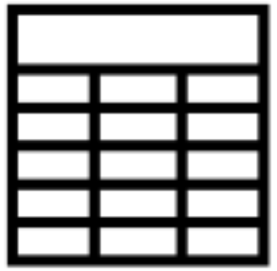
Unifying formats
Finding lengths
...

Chapter 2 - Text and categorical data problems

What we've learned

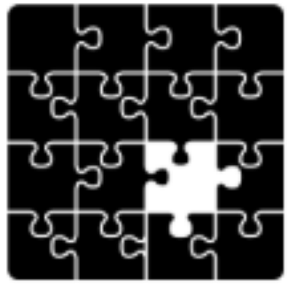
Uniformity

Unifying currency formats
Unifying date formats
...



Cross field validation

Summing across rows
Building assert functions
...

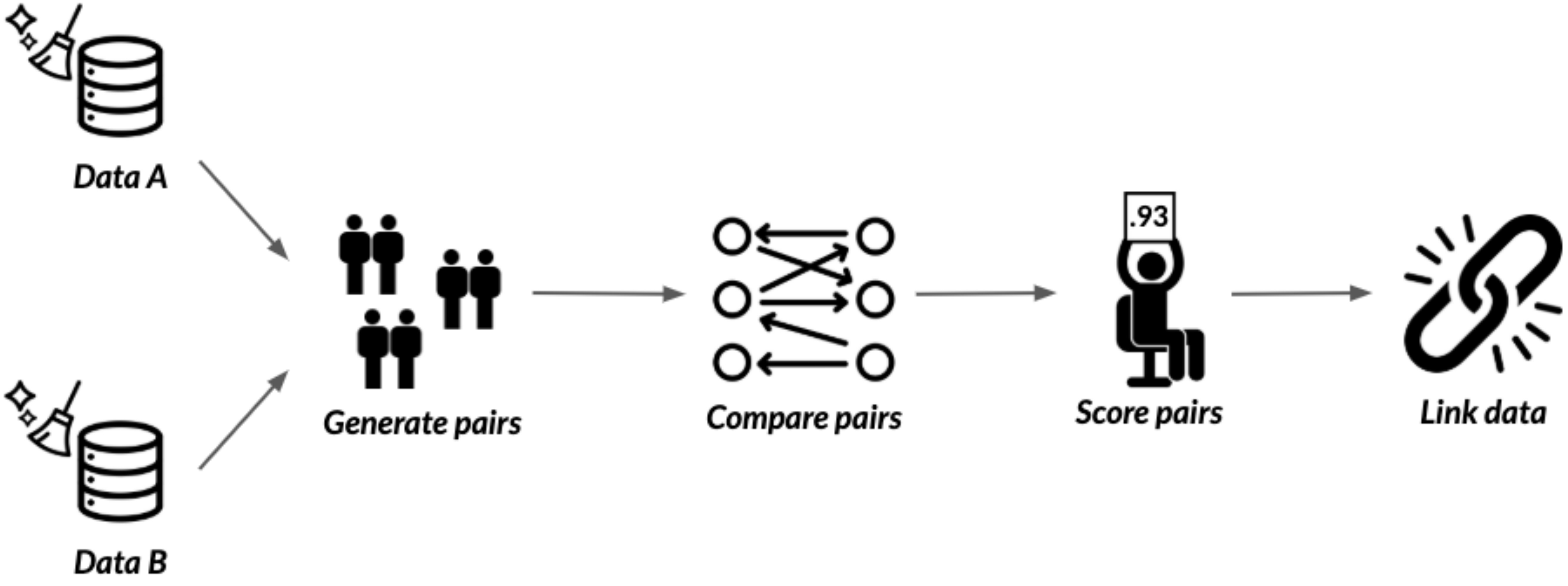


Completeness

Finding missing data
Treating them
...

Chapter 3 - Advanced data problems

What we've learned

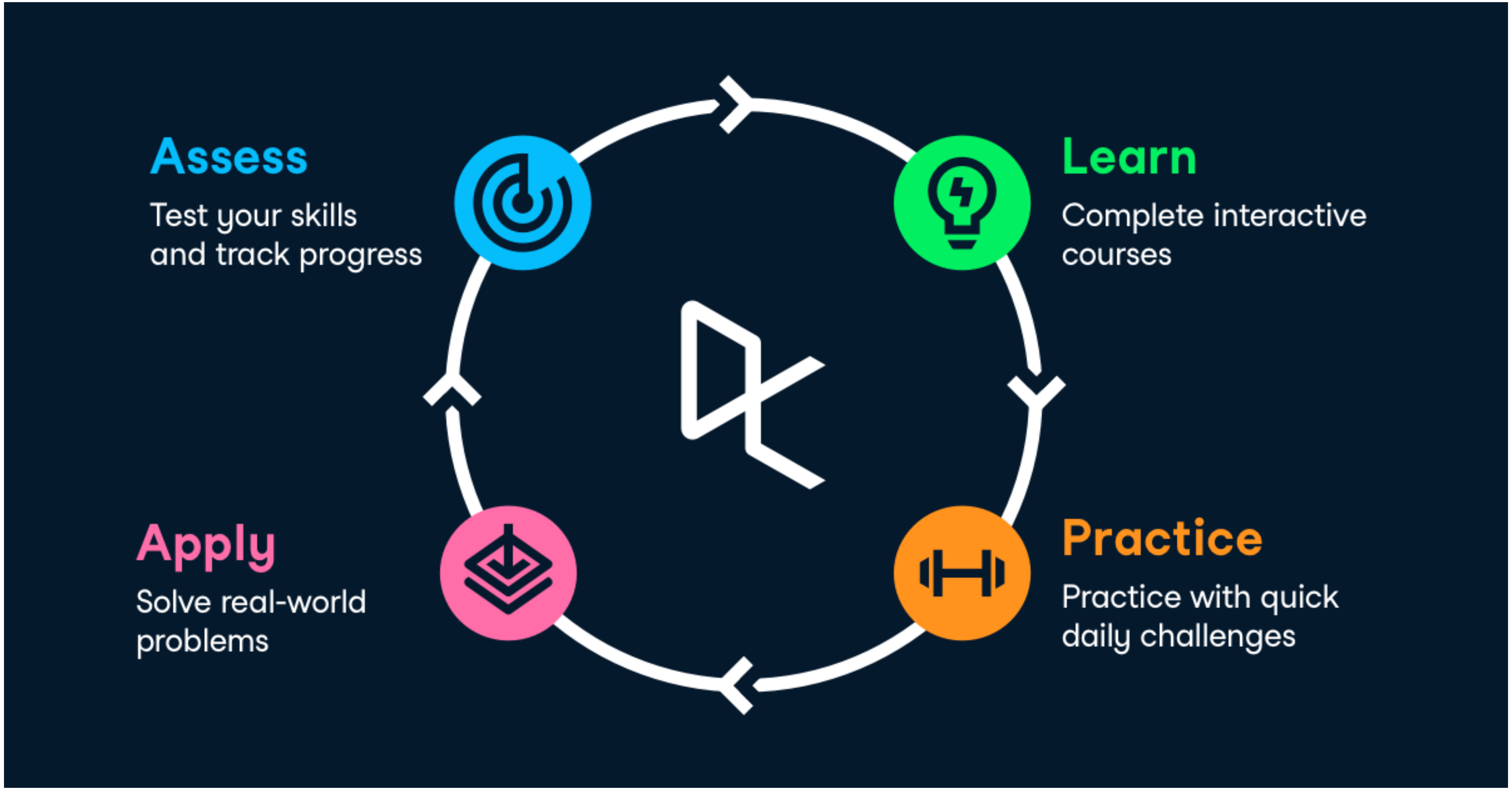


Chapter 4 - Record linkage

More to learn on DataCamp!

- Working with Dates and Times in Python
- Regular Expressions in Python
- Dealing with Missing Data in Python
- And more!

More to learn!



More to learn!

Thank you!

CLEANING DATA IN PYTHON