

Paul Bradshaw

## What do you need to know?

- Common info problems: wrong format, inconsistent case, HTML, spaces, etc.
- Python: Converting, combining, import-and-clean
- Python: Use algorithms to correct variant spelling

### Problems to watch out for:

- Numbers/dates treated as strings
- Vice-versa: e.g. company 'numbers'
- Combined data (addresses)
- Different data in one column (country, region, city)
- Variant spellings
- Mistypings missing decimals etc.

## Help us. Oh god no. (Part 1)

Merged cells
Empty rows
Headings across multiple rows
Different information in same
column
Different terms for same thing

sheet\_name= name (string) or index
skip\_rows= how many rows before
header row?

## Help us. Oh god no.

# Multiple files? The os library Multiple sheets? Pandas's .ExcelFile() and .sheet\_names

```
xls = pd.ExcelFile('excel_file_path.xls')

# Now you can list all sheets in the file
xls.sheet_names
# ['house', 'house_extra', ...]

# to read just one sheet to dataframe:
df = pd.read_excel(file_name, sheetname="house")
```

#### ▼ Fill down using ffill

The ffill function will fill down when given axis=0 (to fill across use axis=1).

Note that this fills row index 1 with the values from row 0, too. So it's a good thing we removed that row first.

#fill down into empty cells (axis 0 means columns)
overview21mardf = overview21mardf.ffill(axis=0)
#show the results
overview21mardf

df.ffill(axis=0) fill down empty cells with whatever is above

```
#https://pandas.pydata.org/docs/reference/api/pandas.melt.html
longdf = pd.melt(df,id_vars='lad21cd', value_name='value', var_name="original_col")
print(longdf)
```

```
lad21cd original_col value
Ľ÷
           E06000001
                                      20
           E06000002
                                     NaN
           E06000003
                                     NaN
           E06000004
                                      12
           E06000005
                                     NaN
                                     . . .
   28792
          W06000020
                             G. 10
                                     93
                             G. 10
   28793
          W06000021
                                     416
   28794
          W06000022
                             G. 10
                                     177
                             G.10 1623
   28795
          W06000023
   28796 W06000024
                             G. 10
                                     109
```

[28797 rows x 3 columns]

## pd.melt() wide to long (columns become values)

```
[ ] #use the parse function to interpret a string as a datetime object parse('September 18, 2020 at 11:05AM')
```

```
datetime.datetime(2020, 9, 18, 11, 5)
```

from dateutil.parser import parse parse ('September 18, 2020 at 11:05AM') convert strings to datetime objects



#### **Navigation**

Release history

Download files

#### **Project links**

**\*** Homepage

#### **Statistics**

GitHub statistics:

\* Stars: 10

Forks: 0

Open issues/PRs: 0

View statistics for this project via <u>Libraries.io</u> ∠, or by using <u>our public</u> <u>dataset on Google BigQuery</u> ∠

#### **Project description**

#### Fuzz Up [W.I.P.]

build passing codecov 89% pypi v0.0.15 downloads 46/month license MIT fuzzup offers a simple approach for clustering strings based on Levenshtein

Distance using Fuzzy Matching in conjunction with Hierarchical Clustering.



#### Installation guide

fuzzup can be installed from the Python Package Index (PyPI) by:

pip install fuzzup

If you want the development version then install directly from Github.

#### Workflow

fuzzup organizes strings by forming clusters from them. It does so in 3 steps:

1. Compute all of the mutual string distances (Levensteihn Distances/fuzzy ratios) between the strings

#### https://pypi.org/project/fuzzup/

```
# strings we want to cluster
    person_names = ['Donald Trump', 'Donald Trump',
                        'J. biden', 'joe biden', 'Biden',
                        'Bide', 'mark esper', 'Christopher c . miller',
                        'jim mattis', 'Nancy Pelosi', 'trumps',
                        'Trump', 'Donald', 'miller']
    from fuzzup.gear import form_clusters_and_rank
    form clusters_and_rank(person_names)

/usr/local/lib/python3.7/dist-packages/fuzzywuzzy/fuzz.py:11: UserWarning
     warnings.warn('Using slow pure-python SequenceMatcher. Install python-L
    [{'COUNT': 4,
      'PROMOTED_STRING': 'joe biden',
      'RANK': 2.
      'STRINGS': ['Bide', 'Biden', 'J. biden', 'joe biden']},
    {'COUNT': 2,
      'PROMOTED_STRING': 'Christopher c . miller',
     'RANK': 3,
      'STRINGS': ['Christopher c . miller', 'miller']},
    {'COUNT': 5,
      'PROMOTED_STRING': 'Donald Trump',
      'RANK': 1,
      'STRINGS': ['Donald', 'Donald Trump', 'Trump', 'trumps']},
    {'COUNT': 1,
      'PROMOTED STRING': 'Nancy Pelosi',
      'RANK': 6,
      'STRINGS': ['Nancy Pelosi']},
    {'COUNT': 1.
```

'PROMOTED STRING': 'iim mattic'

```
#create empty list
prefstrings = []

#loop through original names
for i in person_names:
    #loop through dicts of clusters of names
for d in rankdict:
    #if the original name is in the list of strings
    if i in d['STRINGS']:
        #print that and the 'promoted' (preferred) one
        print(i, "=", d['PROMOTED_STRING'])
        #add promoted one to list
        prefstrings.append(d['PROMOTED_STRING'])
```

```
Donald Trump = Donald Trump

Donald Trump = Donald Trump

J. biden = joe biden

joe biden = joe biden

Biden = joe biden

Bide = joe biden

mark esper = mark esper

Christopher c . miller = Christopher c . miller

jim mattis = jim mattis

Nancy Pelosi = Nancy Pelosi

trumps = Donald Trump

Trump = Donald Trump
```

## Algorithms (from Open Refine)

Fingerprint: looks for items with identical characters, e.g. "John Smith," and "Smith, John"

metaphone3: looks for similar sounds, e.g. "Horowitz" and "Horowicz"

**PPM**: partial matches - try increasing radius to increase

Nearest neighbor: looks for shared clusters of characters, e.g. "Johnson" and "Johnsons"

**Levenshtein**: looks for number of edits needed to change one to another, e.g. "New York" -> "newyork" = 3 edits



#### LOCALIZATION

Add more accuracy to your request by localizing your query:

Example Italy Request GET https://gender-api.com/get?name=Andrea&country=IT&key=<your private server key> **Example Germany** Request GET https://gender-api.com/get?name=Andrea&country=DE&key=<your private server key> Field Description Type Name to query String name ISO 3166 ALPHA-2 Country Code String country Your private server key key String Response **Example Italy** 

```
//In Italy, Andrea is male.
{"name": "andrea", "name_sanitized": "Andrea", "country": "IT", "gender": "male", "samples": 1068, "accuracy": 95, "c
```

## **Hooray!**



more

## Parse ♥ addresses, ♣ names or ≁ any unstructured text into useful components

23 Main St. Suite 100 Chicago, IL	Address part	Tag
	123	AddressNumber
	Main	StreetName
	St.	StreetNamePostType
	Suite	OccupancyType
	100	Occupancyldentifier
	Chicago	PlaceName
	IL	StateName

## **Hooray!**

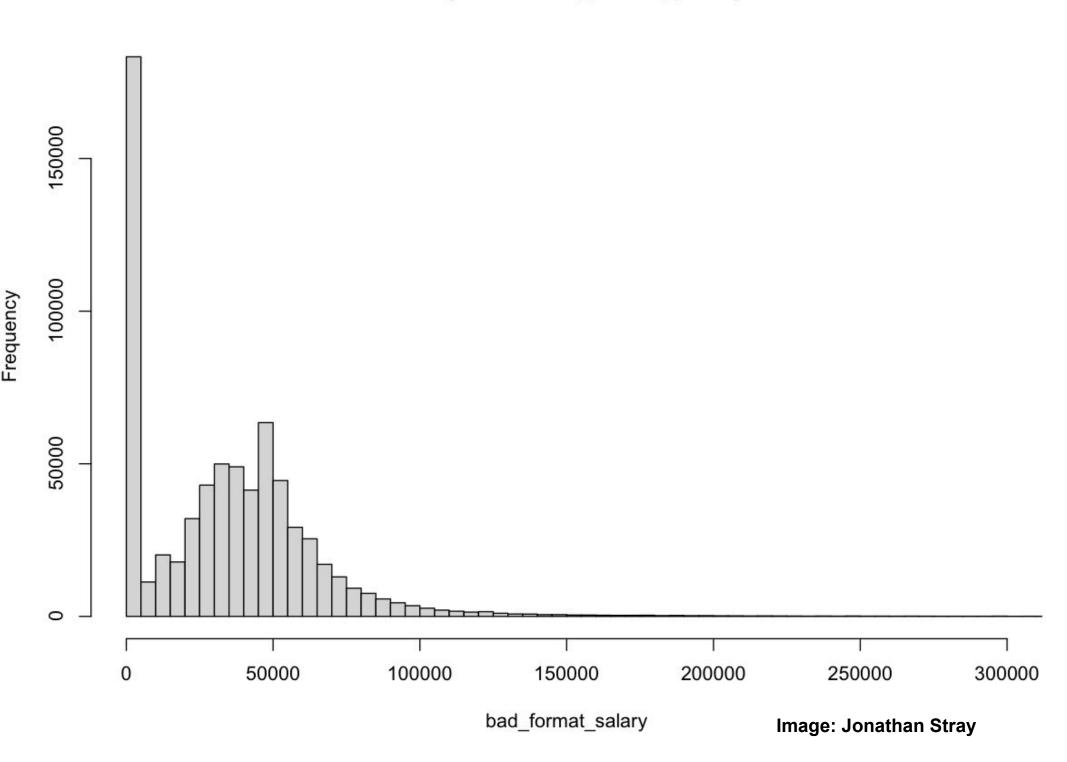




- row counts (e.g. correct number of provinces?)
- histograms
- do the numbers add up?

- alternate data sources
- expert knowledge
- previous versions
- common sense!

#### Histogram of bad\_format\_salary



#### HIGH TURNOUT FAVORED PUTIN ...

Vladimir Putin's United Russia party did best in precincts with reported turnout far above the national level of 60.2%. Opposition parties followed a more usual curve. Such extra 'turnout' could be accounted for by fraud such as ballot-box stuffing, election experts say.

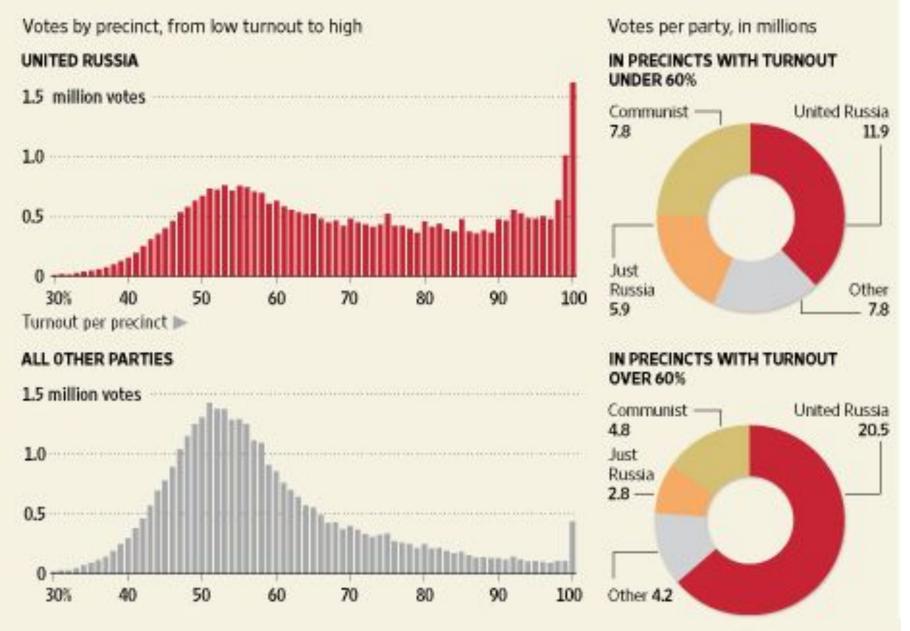


Image: Jonathan Stray

## What to remember

- If you have a problem, someone has probably already solved it before (APIs and libraries)
- Look out for outliers
- Break down the problem, and solve each part separately