Topic 3 - Further Python (3 hours)

July 5, 2022

#

Computational Statistics with Python

##

Topic 3: Further Python

##

Expected lecture time: 2-3 hours

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0.1 The Pandas series object

Series is a one-dimensional labeled array from the library Pandas capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.).

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
# Using Numpy's pseudo random number generator
import numpy as np
data = np.random.randn(20)
index = range(1990, 2010)
```

[3]:
```
print (data)
print (list(index))
```

```
[ 1.07412852  0.03522929 -0.00307068 -0.7969454   0.08838703 -0.09938906
 -0.56601135  0.98303324 -1.46928736  1.53688249  0.18417489  0.61477394
 -0.12605095  1.60410251  0.74209285  0.74957552 -0.312181   -0.46701963
  1.1470691  -1.22639548]
[1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002,
2003, 2004, 2005, 2006, 2007, 2008, 2009]
```

[4]:
```
y = pd.Series(data, index=index)
```

[5]:
```
print (y)
```

```
1990    1.074129
1991    0.035229
1992   -0.003071
1993   -0.796945
1994    0.088387
1995   -0.099389
1996   -0.566011
1997    0.983033
1998   -1.469287
1999    1.536882
2000    0.184175
2001    0.614774
2002   -0.126051
2003    1.604103
2004    0.742093
2005    0.749576
2006   -0.312181
2007   -0.467020
2008    1.147069
2009   -1.226395
dtype: float64
```

[6]:
```
salaries = {
    'juan': 1500, 'maria': 2560.34, 'cesc': None, 'juan carlos': 2451
}
```

[7]:
```
s = pd.Series(salaries)
```

[7]:
```
print (s)
```

```
juan           1500.00
maria          2560.34
cesc               NaN
juan carlos    2451.00
dtype: float64
```

0.1.1 Access series as arrays

[9]:
```
print (s[:2])
print (s[s > s.median()], '\n')
print (np.log(s), '\n')
print (s + s, '\n')
print (s * 3, '\n')
print (y[4:8] + y[4:10])
```

```
juan     1500.00
```

```
maria    2560.34
dtype: float64
maria    2560.34
dtype: float64

juan           7.313220
maria          7.847895
cesc                NaN
juan carlos    7.804251
dtype: float64

juan           3000.00
maria          5120.68
cesc               NaN
juan carlos    4902.00
dtype: float64

juan           4500.00
maria          7681.02
cesc               NaN
juan carlos    7353.00
dtype: float64

1994    0.176774
1995   -0.198778
1996   -1.132023
1997    1.966066
1998         NaN
1999         NaN
dtype: float64
```

0.1.2 Difference between Python list and Pandas series

[10]:
```
my_list = ['a', 'b', 'c', 'd']
print(my_list)
```

```
['a', 'b', 'c', 'd']
```

[11]:
```
my_series = pd.Series(my_list, index = [2,1,3,0])
print(my_series)
```

```
2    a
1    b
3    c
0    d
dtype: object
```

[14]:
```
print(my_series[3])
```

```
c
```

[15]:
```python
print(my_list[3])
```

```
d
```

1 Data Frames

From http://pandas.pydata.org/pandas-docs/stable/dsintro.html#dataframe

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A series
- Another data frame

Along with the data, you can optionally pass index (row labels) and columns (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

[16]:
```python
y = 2020
s = 2000
k = {'Smith': y, 'McDonald': s}
k
```

[16]:
```
{'Smith': 2020, 'McDonald': 2000}
```

[18]:
```python
df = pd.DataFrame(k.items())
df
```

[18]:

	0	1
0	Smith	2020
1	McDonald	2000

[19]:
```python
print (df)
```

```
          0     1
0     Smith  2020
1  McDonald  2000
```

[20]:
```python
pd.DataFrame(k.items(), columns=['Name', 'Salary'])
```

[20]:
```
       Name  Salary
0     Smith    2020
1  McDonald    2000
```

[21]:
```
s = pd.Series(k, name='DateValue')
```

[22]:
```
s.index.name = 'Name'
s
```

[22]:
```
Name
Smith       2020
McDonald    2000
Name: DateValue, dtype: int64
```

1.1 Loading and manipulating data

Retrieve the complete local dataset from Kaggle website.

[27]:
```
accidents = 'accidents_2012_to_2014.csv'
A = pd.read_csv(accidents, low_memory=False, index_col=0)
A
```

[27]:
```
                Location_Easting_OSGR  Location_Northing_OSGR  Longitude  \
Accident_Index
201201BS70001                  527200                  178760  -0.169101
201201BS70002                  524930                  181430  -0.200838
201201BS70003                  525860                  178080  -0.188636
201201BS70004                  524980                  181030  -0.200259
201201BS70005                  526170                  179200  -0.183773
…                                …                       …         …
2.01E+12                       310037                  597647  -3.417278
2.01E+12                       321509                  574063  -3.230255
2.01E+12                       321337                  566365  -3.230826
2.01E+12                       323869                  566853  -3.191397
2.01E+12                       314072                  579971  -3.348426

                 Latitude  Police_Force  Accident_Severity  \
Accident_Index
201201BS70001   51.493429             1                  3
201201BS70002   51.517931             1                  3
201201BS70003   51.487618             1                  3
201201BS70004   51.514325             1                  3
201201BS70005   51.497614             1                  3
…                   …            …                 …
2.01E+12        55.264773            98                  2
2.01E+12        55.054855            98                  3
2.01E+12        54.985668            98                  3
```

```
2.01E+12       54.990446           98                  2
2.01E+12       55.106700           98                  3

               Number_of_Vehicles  Number_of_Casualties        Date  \
Accident_Index
201201BS70001                   2                     1  19/01/2012
201201BS70002                   2                     1  04/01/2012
201201BS70003                   2                     1  10/01/2012
201201BS70004                   1                     1  18/01/2012
201201BS70005                   1                     1  17/01/2012
…                             …                   …           …
2.01E+12                        2                     1  07/12/2014
2.01E+12                        2                     2  11/12/2014
2.01E+12                        1                     1  09/12/2014
2.01E+12                        3                     2  17/12/2014
2.01E+12                        2                     2  24/12/2014

               Day_of_Week  …      Pedestrian_Crossing-Physical_Facilities  \
Accident_Index              …
201201BS70001            5  …  Pedestrian phase at traffic signal junction
201201BS70002            4  …        No physical crossing within 50 meters
201201BS70003            3  …             non-junction pedestrian crossing
201201BS70004            4  …        No physical crossing within 50 meters
201201BS70005            3  …        No physical crossing within 50 meters
…                     …  …                                            …
2.01E+12                 1  …        No physical crossing within 50 meters
2.01E+12                 5  …        No physical crossing within 50 meters
2.01E+12                 3  …        No physical crossing within 50 meters
2.01E+12                 4  …        No physical crossing within 50 meters
2.01E+12                 4  …        No physical crossing within 50 meters

                                   Light_Conditions  \
Accident_Index
201201BS70001  Darkness: Street lights present and lit
201201BS70002  Darkness: Street lights present and lit
201201BS70003           Daylight: Street light present
201201BS70004           Daylight: Street light present
201201BS70005  Darkness: Street lights present and lit
…                                               …
2.01E+12                 Darkeness: No street lighting
2.01E+12                 Darkeness: No street lighting
2.01E+12       Darkness: Street lights present and lit
2.01E+12                 Darkeness: No street lighting
2.01E+12                Daylight: Street light present

                        Weather_Conditions  Road_Surface_Conditions  \
Accident_Index
```

```
201201BS70001      Fine without high winds                     Dry
201201BS70002      Fine without high winds                     Dry
201201BS70003      Fine without high winds                     Dry
201201BS70004      Fine without high winds                     Dry
201201BS70005      Fine without high winds                     Dry
…                                     …                     …
2.01E+12        Snowing without high winds                    Snow
2.01E+12           Fine without high winds                    Snow
2.01E+12           Fine without high winds               Frost/Ice
2.01E+12        Raining without high winds                Wet/Damp
2.01E+12           Fine without high winds                Wet/Damp

                Special_Conditions_at_Site Carriageway_Hazards  \
Accident_Index
201201BS70001                         None                None
201201BS70002                         None                None
201201BS70003                         None                None
201201BS70004                         None                None
201201BS70005                         None                None
…                                     …                 …
2.01E+12                              None                None
2.01E+12                              None                None
2.01E+12                              None                None
2.01E+12                              None                None
2.01E+12                              None                None

                Urban_or_Rural_Area  \
Accident_Index
201201BS70001                     1
201201BS70002                     1
201201BS70003                     1
201201BS70004                     1
201201BS70005                     1
…                               …
2.01E+12                          2
2.01E+12                          2
2.01E+12                          2
2.01E+12                          2
2.01E+12                          2

                Did_Police_Officer_Attend_Scene_of_Accident  \
Accident_Index
201201BS70001                                           Yes
201201BS70002                                           Yes
201201BS70003                                           Yes
201201BS70004                                           Yes
201201BS70005                                           Yes
```

```
…                                                      …
2.01E+12                                                 Yes
2.01E+12                                                 Yes
2.01E+12                                                 Yes
2.01E+12                                                 Yes
2.01E+12                                                 Yes

               LSOA_of_Accident_Location  Year
Accident_Index
201201BS70001                  E01002821  2012
201201BS70002                  E01004760  2012
201201BS70003                  E01002893  2012
201201BS70004                  E01002886  2012
201201BS70005                  E01002890  2012
…                                    …    …
2.01E+12                             NaN  2014
2.01E+12                             NaN  2014
2.01E+12                             NaN  2014
2.01E+12                             NaN  2014
2.01E+12                             NaN  2014

[464697 rows x 32 columns]
```

[28]:
```
A.head()
```

[28]:
```
                Location_Easting_OSGR  Location_Northing_OSGR  Longitude  \
Accident_Index
201201BS70001                  527200                  178760  -0.169101
201201BS70002                  524930                  181430  -0.200838
201201BS70003                  525860                  178080  -0.188636
201201BS70004                  524980                  181030  -0.200259
201201BS70005                  526170                  179200  -0.183773

                 Latitude  Police_Force  Accident_Severity  \
Accident_Index
201201BS70001   51.493429             1                  3
201201BS70002   51.517931             1                  3
201201BS70003   51.487618             1                  3
201201BS70004   51.514325             1                  3
201201BS70005   51.497614             1                  3

                Number_of_Vehicles  Number_of_Casualties        Date  \
Accident_Index
201201BS70001                    2                     1  19/01/2012
201201BS70002                    2                     1  04/01/2012
201201BS70003                    2                     1  10/01/2012
201201BS70004                    1                     1  18/01/2012
```

```
201201BS70005                  1                     1  17/01/2012

                Day_of_Week  …      Pedestrian_Crossing-Physical_Facilities  \
Accident_Index               …
201201BS70001             5  …  Pedestrian phase at traffic signal junction
201201BS70002             4  …        No physical crossing within 50 meters
201201BS70003             3  …             non-junction pedestrian crossing
201201BS70004             4  …        No physical crossing within 50 meters
201201BS70005             3  …        No physical crossing within 50 meters

                                       Light_Conditions  \
Accident_Index
201201BS70001   Darkness: Street lights present and lit
201201BS70002   Darkness: Street lights present and lit
201201BS70003            Daylight: Street light present
201201BS70004            Daylight: Street light present
201201BS70005   Darkness: Street lights present and lit

                     Weather_Conditions  Road_Surface_Conditions  \
Accident_Index
201201BS70001   Fine without high winds                      Dry
201201BS70002   Fine without high winds                      Dry
201201BS70003   Fine without high winds                      Dry
201201BS70004   Fine without high winds                      Dry
201201BS70005   Fine without high winds                      Dry

                Special_Conditions_at_Site Carriageway_Hazards  \
Accident_Index
201201BS70001                         None                None
201201BS70002                         None                None
201201BS70003                         None                None
201201BS70004                         None                None
201201BS70005                         None                None

                Urban_or_Rural_Area  \
Accident_Index
201201BS70001                     1
201201BS70002                     1
201201BS70003                     1
201201BS70004                     1
201201BS70005                     1

                Did_Police_Officer_Attend_Scene_of_Accident  \
Accident_Index
201201BS70001                                           Yes
201201BS70002                                           Yes
201201BS70003                                           Yes
```

```
201201BS70004                                          Yes
201201BS70005                                          Yes

               LSOA_of_Accident_Location  Year
Accident_Index
201201BS70001                  E01002821  2012
201201BS70002                  E01004760  2012
201201BS70003                  E01002893  2012
201201BS70004                  E01002886  2012
201201BS70005                  E01002890  2012

[5 rows x 32 columns]
```

[29]:
```
A[['Date', 'Time']].head()
```

[29]:
```
                      Date   Time
Accident_Index
201201BS70001   19/01/2012  20:35
201201BS70002   04/01/2012  17:00
201201BS70003   10/01/2012  10:07
201201BS70004   18/01/2012  12:20
201201BS70005   17/01/2012  20:24
```

[23]:
```
A.dtypes
```

[23]:
```
Location_Easting_OSGR                           int64
Location_Northing_OSGR                          int64
Longitude                                     float64
Latitude                                      float64
Police_Force                                    int64
Accident_Severity                               int64
Number_of_Vehicles                              int64
Number_of_Casualties                            int64
Date                                           object
Day_of_Week                                     int64
Time                                           object
Local_Authority_(District)                      int64
Local_Authority_(Highway)                      object
1st_Road_Class                                  int64
1st_Road_Number                                 int64
Road_Type                                      object
Speed_limit                                     int64
Junction_Detail                               float64
Junction_Control                               object
2nd_Road_Class                                  int64
2nd_Road_Number                                 int64
Pedestrian_Crossing-Human_Control              object
```

```
Pedestrian_Crossing-Physical_Facilities          object
Light_Conditions                                 object
Weather_Conditions                               object
Road_Surface_Conditions                          object
Special_Conditions_at_Site                       object
Carriageway_Hazards                              object
Urban_or_Rural_Area                               int64
Did_Police_Officer_Attend_Scene_of_Accident      object
LSOA_of_Accident_Location                        object
Year                                              int64
dtype: object
```

[30]:
```
from datetime import datetime

def todate(d, t):
    try:
        dt = datetime.strptime(" ".join([d, t]), '%d/%m/%Y %H:%M')
    except TypeError:
        dt = np.nan
    return dt
```

[31]:
```
A['Datetime'] = [todate(x.Date, x.Time) for i, x in A.iterrows()]
```

[32]:
```
A[['Datetime', 'Police_Force']].head()
```

[32]:
```
                          Datetime  Police_Force
Accident_Index
201201BS70001  2012-01-19 20:35:00             1
201201BS70002  2012-01-04 17:00:00             1
201201BS70003  2012-01-10 10:07:00             1
201201BS70004  2012-01-18 12:20:00             1
201201BS70005  2012-01-17 20:24:00             1
```

[33]:
```
A.shape
```

[33]:
```
(464697, 33)
```

[34]:
```
A.dtypes
```

[34]:
```
Location_Easting_OSGR                                   int64
Location_Northing_OSGR                                  int64
Longitude                                             float64
Latitude                                              float64
Police_Force                                            int64
Accident_Severity                                       int64
Number_of_Vehicles                                      int64
Number_of_Casualties                                    int64
```

```
Date                                                  object
Day_of_Week                                            int64
Time                                                  object
Local_Authority_(District)                             int64
Local_Authority_(Highway)                             object
1st_Road_Class                                         int64
1st_Road_Number                                        int64
Road_Type                                             object
Speed_limit                                            int64
Junction_Detail                                      float64
Junction_Control                                      object
2nd_Road_Class                                         int64
2nd_Road_Number                                        int64
Pedestrian_Crossing-Human_Control                     object
Pedestrian_Crossing-Physical_Facilities               object
Light_Conditions                                      object
Weather_Conditions                                    object
Road_Surface_Conditions                               object
Special_Conditions_at_Site                            object
Carriageway_Hazards                                   object
Urban_or_Rural_Area                                    int64
Did_Police_Officer_Attend_Scene_of_Accident           object
LSOA_of_Accident_Location                             object
Year                                                   int64
Datetime                                      datetime64[ns]
dtype: object
```

1.2 Access dataframe by index and col

[35]:
```
my_df = A.iloc[2:6] # gets rows (or columns) at particular positions in the␣
↪index (so it only takes integers).
my_df
```

[35]:
```
                Location_Easting_OSGR  Location_Northing_OSGR  Longitude  \
Accident_Index
201201BS70003                  525860                  178080  -0.188636
201201BS70004                  524980                  181030  -0.200259
201201BS70005                  526170                  179200  -0.183773
201201BS70006                  526090                  177600  -0.185496

                 Latitude  Police_Force  Accident_Severity  \
Accident_Index
201201BS70003   51.487618             1                  3
201201BS70004   51.514325             1                  3
201201BS70005   51.497614             1                  3
201201BS70006   51.483253             1                  3
```

```
               Number_of_Vehicles  Number_of_Casualties        Date  \
Accident_Index
201201BS70003                   2                     1  10/01/2012
201201BS70004                   1                     1  18/01/2012
201201BS70005                   1                     1  17/01/2012
201201BS70006                   2                     1  19/01/2012

               Day_of_Week  …                       Light_Conditions  \
Accident_Index              …
201201BS70003            3  …            Daylight: Street light present
201201BS70004            4  …            Daylight: Street light present
201201BS70005            3  …  Darkness: Street lights present and lit
201201BS70006            5  …  Darkness: Street lights present and lit

                       Weather_Conditions Road_Surface_Conditions  \
Accident_Index
201201BS70003     Fine without high winds                     Dry
201201BS70004     Fine without high winds                     Dry
201201BS70005     Fine without high winds                     Dry
201201BS70006  Raining without high winds                 Wet/Damp

               Special_Conditions_at_Site  Carriageway_Hazards  \
Accident_Index
201201BS70003                        None                 None
201201BS70004                        None                 None
201201BS70005                        None                 None
201201BS70006                        None                 None

              Urban_or_Rural_Area  \
Accident_Index
201201BS70003                   1
201201BS70004                   1
201201BS70005                   1
201201BS70006                   1

               Did_Police_Officer_Attend_Scene_of_Accident  \
Accident_Index
201201BS70003                                          Yes
201201BS70004                                          Yes
201201BS70005                                          Yes
201201BS70006                                          Yes

               LSOA_of_Accident_Location  Year            Datetime
Accident_Index
201201BS70003                  E01002893  2012 2012-01-10 10:07:00
201201BS70004                  E01002886  2012 2012-01-18 12:20:00
201201BS70005                  E01002890  2012 2012-01-17 20:24:00
```

```
201201BS70006                      E01002912  2012 2012-01-19 07:30:00

[4 rows x 33 columns]
```

[36]:

```
#SUBSETTING a data frame
selection = A[A['Road_Surface_Conditions'] == 'Dry'].sort_values(
    'Number_of_Casualties', ascending=False)
selection
#selection[['Weather_Conditions', 'Police_Force',
#            'Accident_Severity', 'Number_of_Vehicles', 'Number_of_Casualties']].
 ↪head()
```

[36]:

```
                Location_Easting_OSGR  Location_Northing_OSGR  Longitude  \
Accident_Index
20144100J0489                  523000                  199780  -0.222211
201411NH11644                  418196                  552132  -1.718034
2.01E+12                       591380                  169440   0.749417
2.01E+12                       375840                  203065  -2.351207
201422E404170                  355950                  235980  -2.643371
…                                …                       …          …
201297QC00409                  304120                  637780  -3.524192
201297QC00510                  281810                  652360  -3.884585
201297QC00605                  294640                  612550  -3.665077
201297QC00606                  302140                  641540  -3.556962
2.01E+12                       311812                  580747  -3.384080

                 Latitude  Police_Force  Accident_Severity  \
Accident_Index
20144100J0489   51.683269            41                  2
201411NH11644   54.863663            11                  2
2.01E+12        51.391660            46                  2
2.01E+12        51.725734            53                  2
201422E404170   52.020443            22                  2
…                  …           …                …
201297QC00409   55.624152            97                  3
201297QC00510   55.750175            97                  3
201297QC00605   55.395579            97                  3
201297QC00606   55.657530            97                  1
2.01E+12        55.113274            98                  3

                Number_of_Vehicles  Number_of_Casualties        Date  \
Accident_Index
20144100J0489                    2                    93  20/10/2014
201411NH11644                    2                    87  03/06/2014
2.01E+12                        67                    70  05/09/2013
2.01E+12                         1                    54  19/08/2014
201422E404170                    2                    41  10/11/2014
```

```
…                                …                     …         …
201297QC00409                        5                          1  07/09/2012
201297QC00510                        2                          1  02/10/2012
201297QC00605                        1                          1  05/05/2012
201297QC00606                        2                          1  05/06/2012
2.01E+12                             1                          1  17/11/2014

                Day_of_Week  …              Light_Conditions  \
Accident_Index               …
20144100J0489             2  …  Daylight: Street light present
201411NH11644             3  …  Daylight: Street light present
2.01E+12                  5  …  Daylight: Street light present
2.01E+12                  3  …  Daylight: Street light present
201422E404170             2  …  Daylight: Street light present
…                       …  …                             …
201297QC00409             6  …  Daylight: Street light present
201297QC00510             3  …  Daylight: Street light present
201297QC00605             7  …  Daylight: Street light present
201297QC00606             3  …  Daylight: Street light present
2.01E+12                  2  …  Daylight: Street light present

                     Weather_Conditions Road_Surface_Conditions  \
Accident_Index
20144100J0489   Fine without high winds                     Dry
201411NH11644   Fine without high winds                     Dry
2.01E+12                    Fog or mist                     Dry
2.01E+12        Fine without high winds                     Dry
201422E404170   Fine without high winds                     Dry
…                                     …                     …
201297QC00409   Fine without high winds                     Dry
201297QC00510   Fine without high winds                     Dry
201297QC00605   Fine without high winds                     Dry
201297QC00606   Fine without high winds                     Dry
2.01E+12        Fine without high winds                     Dry

                Special_Conditions_at_Site  Carriageway_Hazards  \
Accident_Index
20144100J0489                         None                 None
201411NH11644                         None                 None
2.01E+12                              None                 None
2.01E+12                              None                 None
201422E404170                         None                 None
…                                      …                    …
201297QC00409                         None                 None
201297QC00510                         None                 None
201297QC00605       Road surface defective                 None
201297QC00606                         None                 None
```

```
2.01E+12                              None                 None

               Urban_or_Rural_Area  \
Accident_Index
20144100J0489                    2
201411NH11644                    2
2.01E+12                         2
2.01E+12                         2
201422E404170                    2
…                              …
201297QC00409                    2
201297QC00510                    2
201297QC00605                    2
201297QC00606                    2
2.01E+12                         2

                Did_Police_Officer_Attend_Scene_of_Accident  \
Accident_Index
20144100J0489                                         Yes
201411NH11644                                         Yes
2.01E+12                                              Yes
2.01E+12                                              Yes
201422E404170                                         Yes
…                                                   …
201297QC00409                                         Yes
201297QC00510                                         Yes
201297QC00605                                          No
201297QC00606                                         Yes
2.01E+12                                              Yes

                LSOA_of_Accident_Location  Year            Datetime
Accident_Index
20144100J0489                   E01023584  2014 2014-10-20 08:22:00
201411NH11644                   E01020624  2014 2014-06-03 08:22:00
2.01E+12                        E01024597  2013 2013-09-05 07:15:00
2.01E+12                        E01022371  2014 2014-08-19 09:57:00
201422E404170                   E01014026  2014 2014-11-10 08:20:00
…                                     …    …                   …
201297QC00409                         NaN  2012 2012-09-07 15:45:00
201297QC00510                         NaN  2012 2012-10-02 17:45:00
201297QC00605                         NaN  2012 2012-05-05 16:00:00
201297QC00606                         NaN  2012 2012-06-05 15:39:00
2.01E+12                              NaN  2014 2014-11-17 13:10:00

[319370 rows x 33 columns]
```

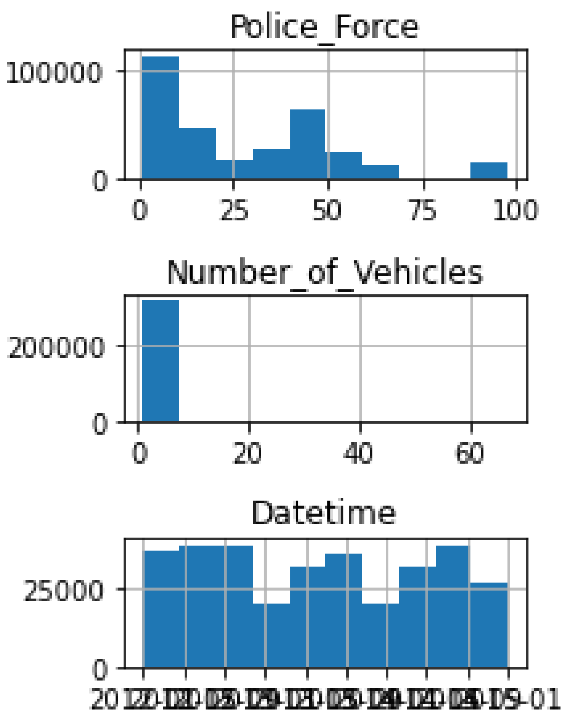
[37]:
```python
selection[['Weather_Conditions', 'Police_Force', 'Accident_Severity',
           'Number_of_Vehicles', 'Number_of_Casualties']].
 ↪groupby('Weather_Conditions').mean()
```

[37]:
```
                             Police_Force  Accident_Severity  \
Weather_Conditions
Fine with high winds            32.652875           2.811360
Fine without high winds         27.051892           2.830949
Fog or mist                     39.051163           2.797674
Other                           29.449333           2.868000
Raining with high winds         32.687500           2.833333
Raining without high winds      38.734211           2.873684
Snowing with high winds         45.666667           2.666667
Snowing without high winds      31.560976           2.902439
Unknown                         27.058422           2.872004

                             Number_of_Vehicles  Number_of_Casualties
Weather_Conditions
Fine with high winds                   1.796283              1.352384
Fine without high winds                1.846165              1.321455
Fog or mist                            1.997674              1.520930
Other                                  1.788000              1.269333
Raining with high winds                1.895833              1.458333
Raining without high winds             1.792105              1.297368
Snowing with high winds                1.777778              1.777778
Snowing without high winds             1.780488              1.195122
Unknown                                1.766977              1.217710
```

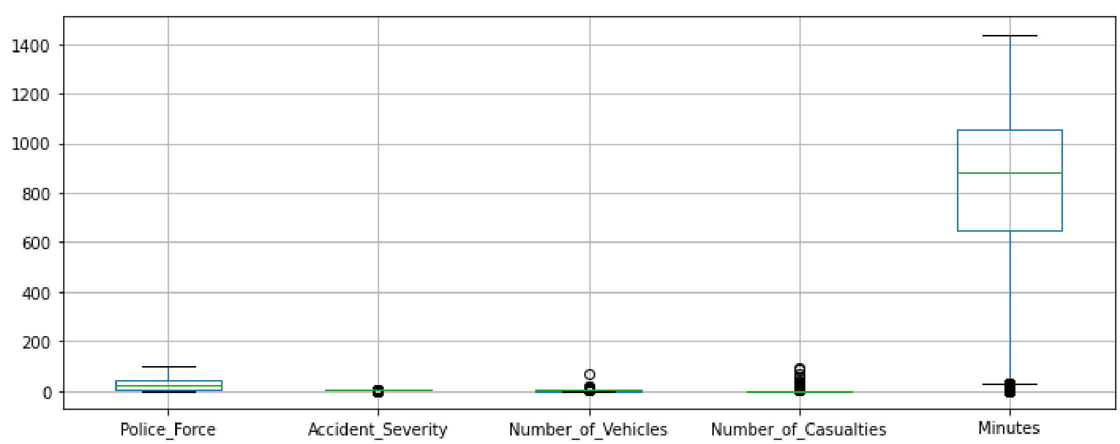
[38]:
```python
sel = selection[['Weather_Conditions', 'Police_Force', 'Accident_Severity',
           'Number_of_Vehicles', 'Number_of_Casualties', 'Datetime']]
```

[34]:
```python
sel.hist()
plt.tight_layout()
plt.show()
```

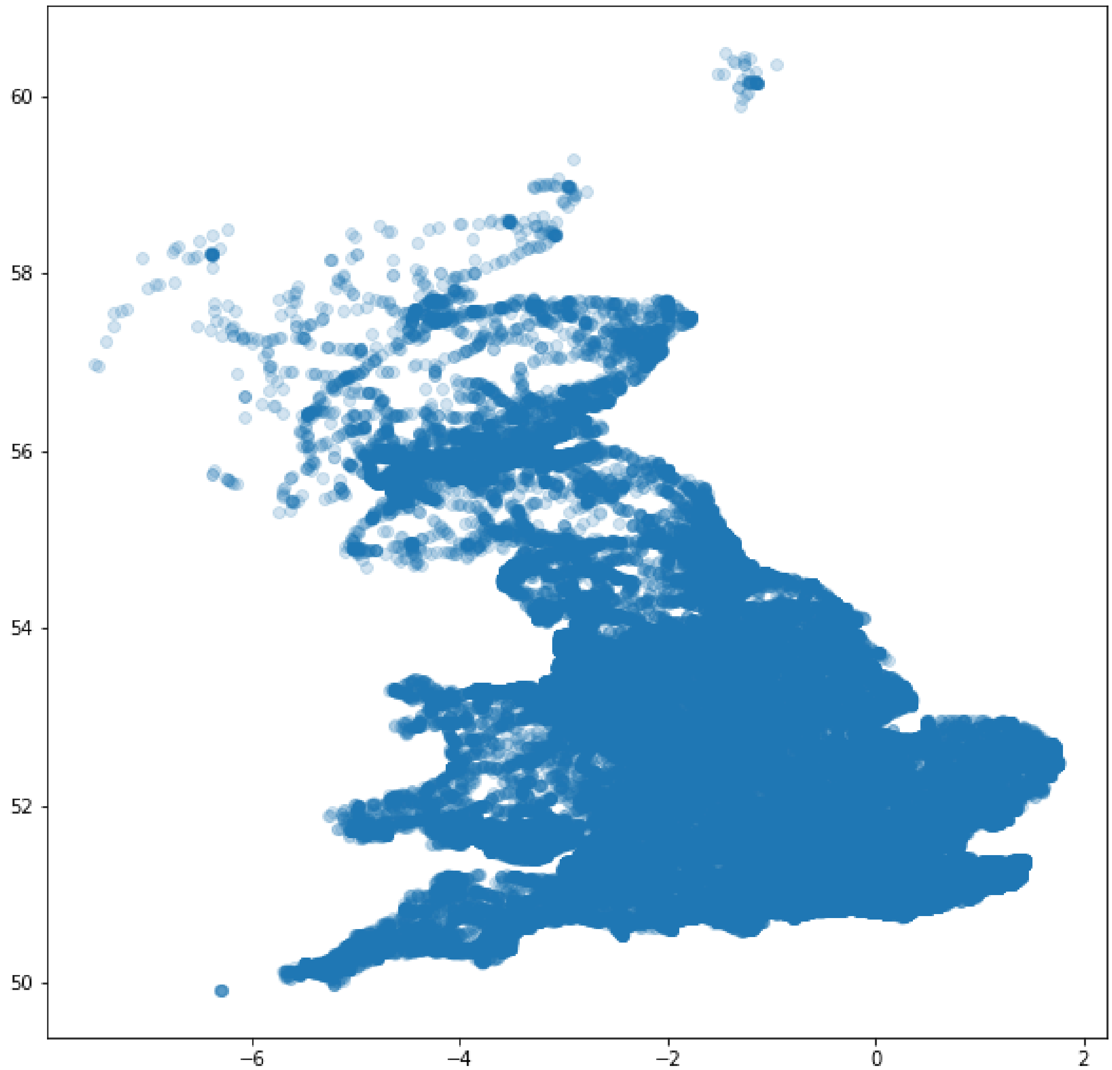



```
[40]: minutes = []
      for i, row in sel.iterrows():
          h, m = row['Datetime'].hour, row['Datetime'].minute
          minutes.append(h*60 + m)
      sel = sel.copy()
      sel['Minutes'] = minutes
```

```
[42]: fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(10, 4), sharey=True)
      sel.boxplot(ax=axes)
      plt.tight_layout()
      plt.show()
```



[38]:
```
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(10, 10), sharey=True)
axes.scatter(selection.Longitude.values, selection.Latitude.values, alpha=0.2)
plt.show()
```



[43]:
```
pip install geopandas
```

```
Requirement already satisfied: geopandas in /opt/anaconda3/lib/python3.8/site-
packages (0.9.0)
Requirement already satisfied: fiona>=1.8 in /opt/anaconda3/lib/python3.8/site-
packages (from geopandas) (1.8.19)
Requirement already satisfied: shapely>=1.6 in
/opt/anaconda3/lib/python3.8/site-packages (from geopandas) (1.7.1)
```

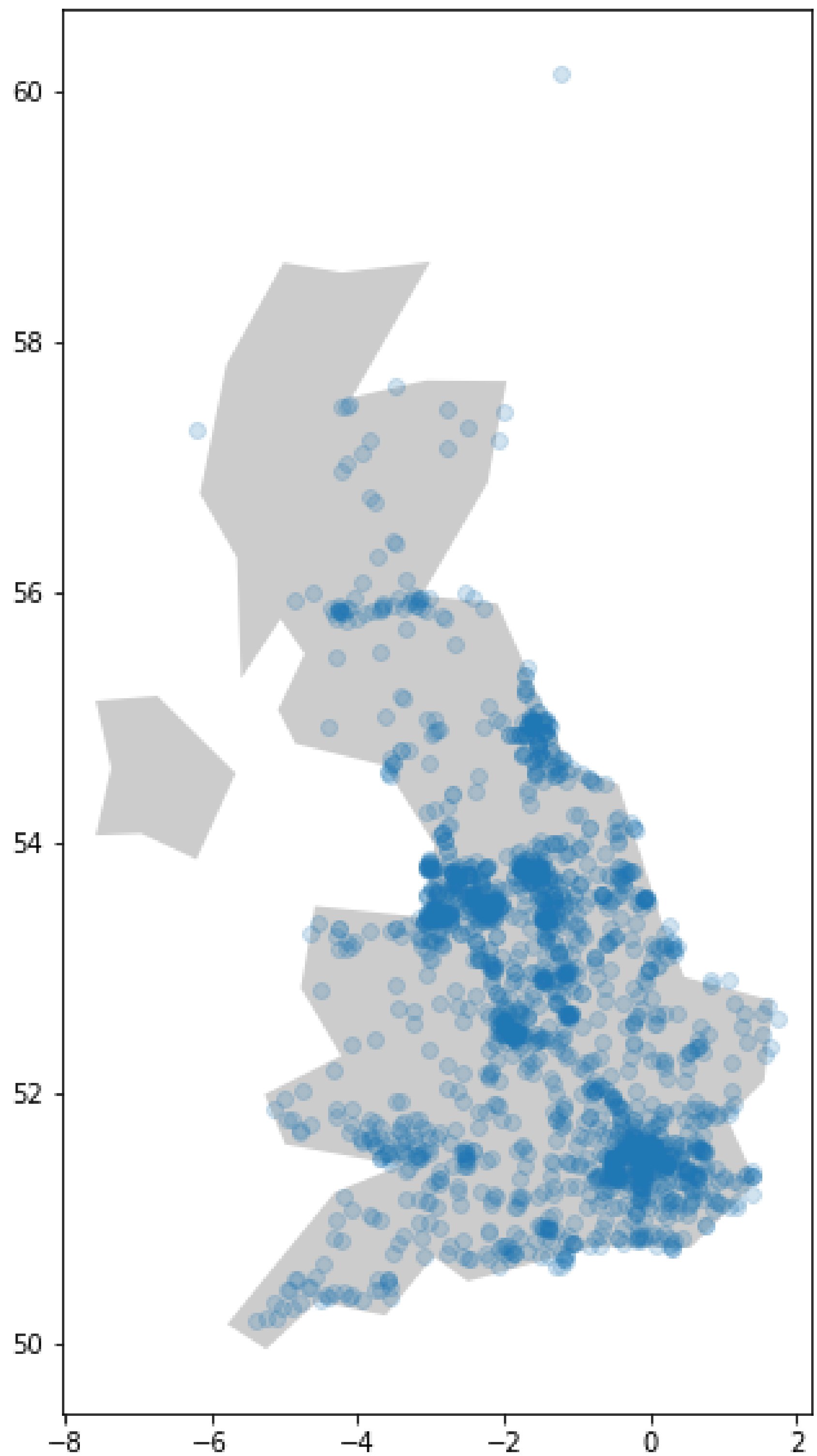
```
Requirement already satisfied: pandas>=0.24.0 in
/opt/anaconda3/lib/python3.8/site-packages (from geopandas) (1.3.4)
Requirement already satisfied: pyproj>=2.2.0 in
/opt/anaconda3/lib/python3.8/site-packages (from geopandas) (3.0.1)
Requirement already satisfied: attrs>=17 in /opt/anaconda3/lib/python3.8/site-
packages (from fiona>=1.8->geopandas) (20.3.0)
Requirement already satisfied: cligj>=0.5 in /opt/anaconda3/lib/python3.8/site-
packages (from fiona>=1.8->geopandas) (0.7.1)
Requirement already satisfied: six>=1.7 in /opt/anaconda3/lib/python3.8/site-
packages (from fiona>=1.8->geopandas) (1.15.0)
Requirement already satisfied: certifi in /opt/anaconda3/lib/python3.8/site-
packages (from fiona>=1.8->geopandas) (2020.12.5)
Requirement already satisfied: click-plugins>=1.0 in
/opt/anaconda3/lib/python3.8/site-packages (from fiona>=1.8->geopandas) (1.1.1)
Requirement already satisfied: click<8,>=4.0 in
/opt/anaconda3/lib/python3.8/site-packages (from fiona>=1.8->geopandas) (7.1.2)
Requirement already satisfied: munch in /opt/anaconda3/lib/python3.8/site-
packages (from fiona>=1.8->geopandas) (2.5.0)
Requirement already satisfied: python-dateutil>=2.7.3 in
/opt/anaconda3/lib/python3.8/site-packages (from pandas>=0.24.0->geopandas)
(2.8.1)
Requirement already satisfied: pytz>=2017.3 in
/opt/anaconda3/lib/python3.8/site-packages (from pandas>=0.24.0->geopandas)
(2021.1)
Requirement already satisfied: numpy>=1.17.3 in
/opt/anaconda3/lib/python3.8/site-packages (from pandas>=0.24.0->geopandas)
(1.22.1)
WARNING: You are using pip version 21.2.2; however, version 22.1.2 is
available.
You should consider upgrading via the '/opt/anaconda3/bin/python -m pip install
--upgrade pip' command.
Note: you may need to restart the kernel to use updated packages.
```

[44]:
```
import geopandas as gpd
```

[45]:
```
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
```

[46]:
```
UK = world[world['iso_a3']=='GBR']
```

[47]:
```
limit = 2000
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(10, 10), sharey=True)
UK.plot(ax=axes, color='#CCCCCC')
axes.scatter(selection.Longitude.values[:limit], selection.Latitude.values[:
 ↪limit], alpha=0.2)
plt.show()
```


60
58
56
54
52
50
−8
−6
−4
−2
0
2

2 Standard tools for machine learning

[51]:
```
# Standard import for ML
import numpy as np
import os
import tarfile
import requests
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
%matplotlib inline

# Matplotlib defaul setting
# When using the 'inline' backend, your matplotlib graphs will be included in␣
↪your notebook, next to the code
%matplotlib inline

mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
#np1. + any method or function you want to use
```

3 Get the data

Get the housing data (https://www.kaggle.com/harrywang/housing) from the Web through requests and load into a DataFrame from file

[ ]:
```

```

[53]:
```
url_data = "https://raw.githubusercontent.com/ageron/handson-ml/master/datasets/
↪housing/housing.tgz"
data_path = os.path.join("datasets", "housing")
if not os.path.isdir(data_path):
    os.makedirs(data_path)
with open(os.path.join(data_path,'housing.tgz'),'wb') as f:
    f.write(requests.get(url_data).content)
housing_tgz = tarfile.open(os.path.join(data_path,'housing.tgz'))
housing_tgz.extractall(path=data_path)
housing_tgz.close()
```

[54]:
```
housing = pd.read_csv('datasets/housing/housing.csv')
```

3.1 Data exploration

[8]:
```
housing.head()
```

[8]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
1    -122.22     37.86                21.0       7099.0          1106.0
2    -122.24     37.85                52.0       1467.0           190.0
3    -122.25     37.85                52.0       1274.0           235.0
4    -122.25     37.85                52.0       1627.0           280.0

   population  households  median_income  median_house_value ocean_proximity
0       322.0       126.0         8.3252            452600.0        NEAR BAY
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY
2       496.0       177.0         7.2574            352100.0        NEAR BAY
3       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

Get information about all the columns

[55]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

Count the unique values in column (e.g. *ocean_proximity*)

[56]:
```
housing['ocean_proximity'].value_counts()
```

[56]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

Summary statistics of the columns

[57]:
```
housing.describe()
```

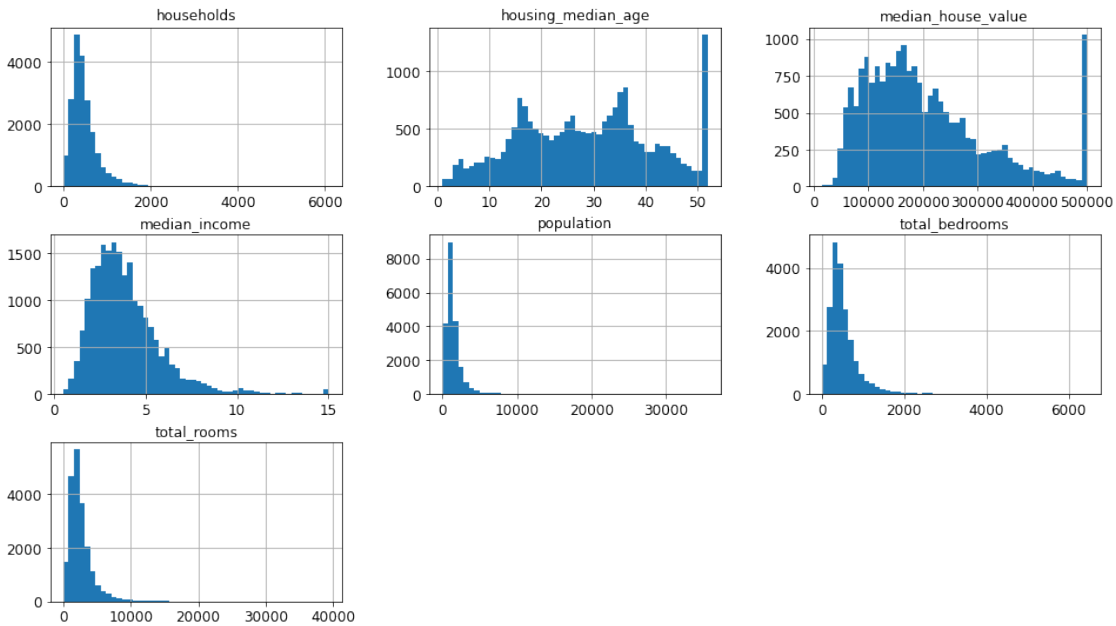
[57]:
```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

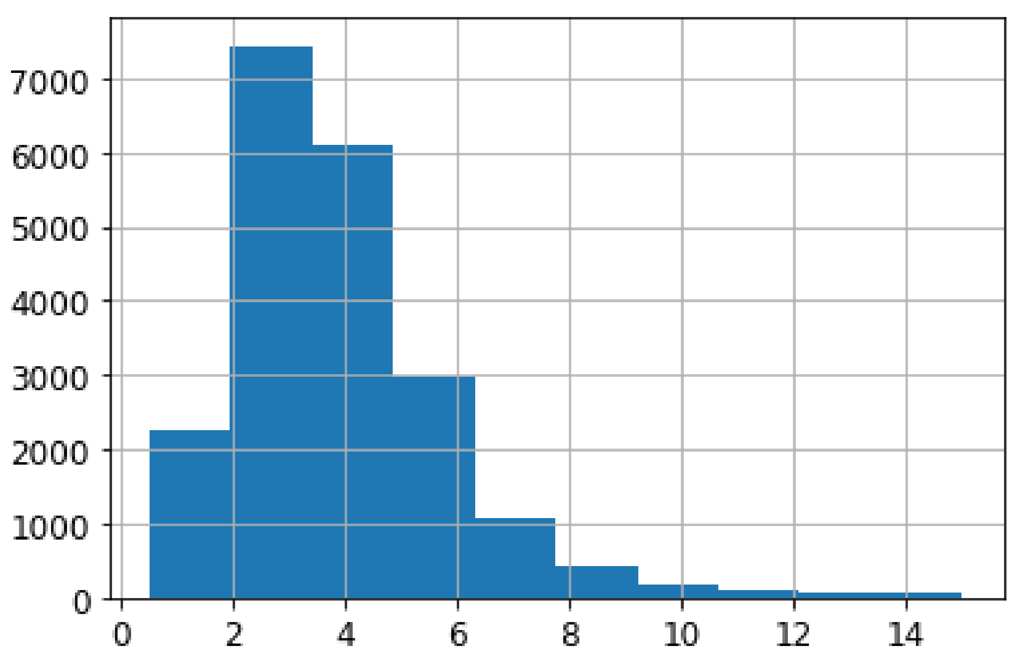
Simple visualization of the distribution of a subset of features: 'households','housing_median_age', 'median_house_value','median_income','population','total_bedrooms','total_rooms'

[58]:
```
housing.hist(column=['households','housing_median_age',␣
↪'median_house_value','median_income','population','total_bedrooms','total_rooms'],
            bins=50,
            figsize=(16,9))
plt.show()
```




```
[59]: housing['median_income'].hist()
```

```
[59]: <AxesSubplot:>
```



[60]:
```
housing['income_cat'] = pd.cut(housing['median_income'],
                               bins=[0,1.5,3,4.5,6, np.inf],
                               labels = ['Very Low', 'Low', 'Medium', 'High',␣
 ↪'Very High'])
housing
```

[60]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0        -122.23     37.88                41.0        880.0           129.0
1        -122.22     37.86                21.0       7099.0          1106.0
2        -122.24     37.85                52.0       1467.0           190.0
3        -122.25     37.85                52.0       1274.0           235.0
4        -122.25     37.85                52.0       1627.0           280.0
…            …         …                    …           …             …
20635    -121.09     39.48                25.0       1665.0           374.0
20636    -121.21     39.49                18.0        697.0           150.0
20637    -121.22     39.43                17.0       2254.0           485.0
20638    -121.32     39.43                18.0       1860.0           409.0
20639    -121.24     39.37                16.0       2785.0           616.0

       population  households  median_income  median_house_value  \
0           322.0       126.0         8.3252            452600.0
1          2401.0      1138.0         8.3014            358500.0
2           496.0       177.0         7.2574            352100.0
3           558.0       219.0         5.6431            341300.0
4           565.0       259.0         3.8462            342200.0
…             …          …              …                  …
20635       845.0       330.0         1.5603             78100.0
20636       356.0       114.0         2.5568             77100.0
20637      1007.0       433.0         1.7000             92300.0
20638       741.0       349.0         1.8672             84700.0
20639      1387.0       530.0         2.3886             89400.0

      ocean_proximity income_cat
0            NEAR BAY  Very High
1            NEAR BAY  Very High
2            NEAR BAY  Very High
3            NEAR BAY       High
4            NEAR BAY     Medium
…                 …          …
20635          INLAND        Low
20636          INLAND        Low
20637          INLAND        Low
20638          INLAND        Low
20639          INLAND        Low

[20640 rows x 11 columns]
```

4 Partitioning the dataset into separate training and test sets

4.1 1) Random partition

[61]:
```python
from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(housing, test_size = 0.2, random_state =␣
↪42)
```

[62]:
```python
train_set.head()
```

[62]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
14196    -117.03     32.71                33.0       3126.0           627.0
8267     -118.16     33.77                49.0       3382.0           787.0
17445    -120.48     34.66                 4.0       1897.0           331.0
14265    -117.11     32.69                36.0       1421.0           367.0
2271     -119.80     36.78                43.0       2382.0           431.0

       population  households  median_income  median_house_value  \
14196      2300.0       623.0         3.2596            103000.0
8267       1314.0       756.0         3.8125            382100.0
17445       915.0       336.0         4.1563            172600.0
14265      1418.0       355.0         1.9425             93400.0
2271        874.0       380.0         3.5542             96500.0

      ocean_proximity income_cat
14196      NEAR OCEAN     Medium
8267       NEAR OCEAN     Medium
17445      NEAR OCEAN     Medium
14265      NEAR OCEAN        Low
2271           INLAND     Medium
```

We assign 20% of the sample to the test and the remaining 80% to the training, BUT no guarantee both training and test sets have the same label/outcome distribution, especially when the dataset is small. Let's see…

[63]:
```python
def income_cat_proportions(data):
    return data['income_cat'].value_counts() / len(data)
```

[64]:
```python
compare_props = pd.DataFrame({
    'Overall': income_cat_proportions(housing),
    'Random' : income_cat_proportions(test_set)
}).sort_index()
```

[65]:
```python
compare_props['Rand %error'] = 100 * compare_props['Random'] /␣
↪compare_props['Overall'] - 100
```

[67]:
```python
compare_props
```

[67]:

	Overall	Random	Rand %error
Very Low	0.039826	0.040213	0.973236
Low	0.318847	0.324370	1.732260
Medium	0.350581	0.358527	2.266446
High	0.176308	0.167393	-5.056334
Very High	0.114438	0.109496	-4.318374

4.2 2) Stratified Sampling

[68]:

```
# StratifiedShuffleSplit creates splits by preserving the same percentage
# for each target class as in the complete set.
from sklearn.model_selection import StratifiedShuffleSplit

splitObject = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)

train_index, test_index = next(splitObject.split(housing,␣
 ↪housing['income_cat']))

stratified_train_set = housing.loc[train_index]
stratified_test_set = housing.loc[test_index]

stratified_train_set.shape, stratified_test_set.shape, housing.shape
```

[68]: ((16512, 11), (4128, 11), (20640, 11))

[69]:

```
compare_props['Stratified'] = stratified_test_set['income_cat'].value_counts() /
 ↪ len(stratified_test_set)
```

[70]:

```
compare_props['Stratified %error'] = 100 * compare_props['Stratified'] /␣
 ↪compare_props['Overall'] - 100
```

[71]:

```
compare_props
```

[71]:

	Overall	Random	Rand %error	Stratified	Stratified %error
Very Low	0.039826	0.040213	0.973236	0.039729	-0.243309
Low	0.318847	0.324370	1.732260	0.318798	-0.015195
Medium	0.350581	0.358527	2.266446	0.350533	-0.013820
High	0.176308	0.167393	-5.056334	0.176357	0.027480
Very High	0.114438	0.109496	-4.318374	0.114583	0.127011

5 Prepare the data for Machine Learning algorithms

[72]:

```
stratified_train_set
```

[72]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
16126    -122.47     37.79                52.0        437.0           105.0
17709    -121.82     37.33                23.0       3279.0           647.0
2501     -120.38     36.76                25.0        991.0           272.0
2123     -119.71     36.76                28.0       2675.0           527.0
2144     -119.76     36.77                36.0       2507.0           466.0
…            …        …                   …           …              …
3382     -118.27     34.25                35.0        779.0           143.0
841      -122.08     37.59                16.0       1816.0           365.0
11749    -121.15     38.80                20.0       2104.0           370.0
3940     -118.59     34.21                34.0       1943.0           320.0
18827    -122.26     41.66                17.0       1885.0           350.0

       population  households  median_income  median_house_value  \
16126       194.0        87.0         2.8125            500001.0
17709      2582.0       630.0         4.3782            175800.0
2501        941.0       262.0         1.8125             58000.0
2123       1392.0       521.0         2.3108             72000.0
2144       1227.0       474.0         2.7850             72300.0
…             …           …            …                  …
3382        371.0       150.0         4.6635            230100.0
841        1367.0       355.0         4.2350            156300.0
11749       745.0       314.0         4.1685            217500.0
3940        895.0       305.0         5.0462            227700.0
18827       953.0       328.0         2.1607             61400.0

      ocean_proximity income_cat
16126        NEAR BAY        Low
17709       <1H OCEAN     Medium
2501           INLAND        Low
2123           INLAND        Low
2144           INLAND        Low
…                 …          …
3382        <1H OCEAN       High
841          NEAR BAY     Medium
11749          INLAND     Medium
3940        <1H OCEAN       High
18827          INLAND        Low

[16512 rows x 11 columns]
```

[73]:
```python
housing = stratified_train_set.drop('median_house_value',axis=1)
housing_label = stratified_train_set['median_house_value'].copy()
housing.columns
```

[73]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
```

```
        'ocean_proximity', 'income_cat'],
       dtype='object')
```

[74]:
```
housing_label
```

[74]:
```
16126    500001.0
17709    175800.0
2501      58000.0
2123      72000.0
2144      72300.0
           …
3382     230100.0
841      156300.0
11749    217500.0
3940     227700.0
18827     61400.0
Name: median_house_value, Length: 16512, dtype: float64
```

5.1 Identifying missing values

[76]:
```
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

[76]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
8383     -118.36     33.96                26.0       3543.0             NaN
10915    -117.87     33.73                45.0       2264.0             NaN
11311    -117.96     33.78                33.0       1520.0             NaN
696      -122.10     37.69                41.0        746.0             NaN
15137    -116.91     32.83                16.0       5203.0             NaN

       population  households  median_income ocean_proximity income_cat
8383       2742.0       951.0         2.5504       <1H OCEAN        Low
10915      1970.0       499.0         3.4193       <1H OCEAN     Medium
11311       658.0       242.0         4.8750       <1H OCEAN       High
696         387.0       161.0         3.9063        NEAR BAY     Medium
15137      2515.0       862.0         4.1050       <1H OCEAN     Medium
```

5.2 Eliminating rows with missing values

[78]:
```
sample_incomplete_rows.dropna(subset=['total_bedrooms'], axis=0)
```

[78]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, ocean_proximity, income_cat]
Index: []
```

5.3 Eliminating variables with missing values

[79]:
```
sample_incomplete_rows.dropna(axis=1)
```

[79]:
```
       longitude  latitude  housing_median_age  total_rooms  population  \
8383     -118.36     33.96                26.0       3543.0      2742.0
10915    -117.87     33.73                45.0       2264.0      1970.0
11311    -117.96     33.78                33.0       1520.0       658.0
696      -122.10     37.69                41.0        746.0       387.0
15137    -116.91     32.83                16.0       5203.0      2515.0

       households  median_income ocean_proximity income_cat
8383        951.0         2.5504       <1H OCEAN        Low
10915       499.0         3.4193       <1H OCEAN     Medium
11311       242.0         4.8750       <1H OCEAN       High
696         161.0         3.9063        NEAR BAY     Medium
15137       862.0         4.1050       <1H OCEAN     Medium
```

5.4 Imputing missing values

5.4.1 1) Pandas

[80]:
```
median = housing['total_bedrooms'].median()
sample_incomplete_rows['total_bedrooms'].fillna(median, inplace=True)
sample_incomplete_rows
```

[80]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
8383     -118.36     33.96                26.0       3543.0           437.0
10915    -117.87     33.73                45.0       2264.0           437.0
11311    -117.96     33.78                33.0       1520.0           437.0
696      -122.10     37.69                41.0        746.0           437.0
15137    -116.91     32.83                16.0       5203.0           437.0

       population  households  median_income ocean_proximity income_cat
8383       2742.0       951.0         2.5504       <1H OCEAN        Low
10915      1970.0       499.0         3.4193       <1H OCEAN     Medium
11311       658.0       242.0         4.8750       <1H OCEAN       High
696         387.0       161.0         3.9063        NEAR BAY     Medium
15137      2515.0       862.0         4.1050       <1H OCEAN     Medium
```

5.4.2 2) Scikit-Learn

The **SimpleImputer** class.

The SimpleImputer class provides basic strategies for imputing missing values. Missing values can be imputed with a provided constant value, or using the statistics (mean, median or most frequent) of each column in which the missing values are located.

[81]:
```python
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values = np.nan, strategy = 'median')
```

Remove the text attribute because median can only be calculated on numerical attributes:

[36]:
```python
housing_num = housing.select_dtypes(include=[np.number])
```

[37]:
```python
imputer.fit(housing_num)
```

[37]:
```
SimpleImputer(strategy='median')
```

[38]:
```python
imputer.statistics_
```

[38]:
```
array([-118.5   ,   34.26  ,   29.    , 2137.    ,  437.    , 1170.    ,
        411.    ,    3.5375])
```

Transform the training set:

[39]:
```python
X = imputer.transform(housing_num)
X
```

[39]:
```
array([[-1.2247e+02,  3.7790e+01,  5.2000e+01, …,  1.9400e+02,
         8.7000e+01,  2.8125e+00],
       [-1.2182e+02,  3.7330e+01,  2.3000e+01, …,  2.5820e+03,
         6.3000e+02,  4.3782e+00],
       [-1.2038e+02,  3.6760e+01,  2.5000e+01, …,  9.4100e+02,
         2.6200e+02,  1.8125e+00],
       …,
       [-1.2115e+02,  3.8800e+01,  2.0000e+01, …,  7.4500e+02,
         3.1400e+02,  4.1685e+00],
       [-1.1859e+02,  3.4210e+01,  3.4000e+01, …,  8.9500e+02,
         3.0500e+02,  5.0462e+00],
       [-1.2226e+02,  4.1660e+01,  1.7000e+01, …,  9.5300e+02,
         3.2800e+02,  2.1607e+00]])
```

Scikit-Learn API is organized around a bunch of design principles:

Consistency: all object share a consistent and simple interface

Estimator: object that can estimate some parameters. Estimation performed by the method fit which takes only a dataset as parameter, any other parameter is an hyperparameter

Transformers: some estimators transform a dataset. The transformation is performed by the method transform with the dataset to transform as a parameter. It returns the transformed dataset. There is a convenient fit_transform method, which is optimized and runs much faster

Predictors: some estimator are able to make predictions. A predictor has a method predict that takes a dataset of new samples and returns the corresponding predictions

```
</li>
<li><b>Inspection</b>: all hyperparameter are accessible via instance variable as well as the l
```

```
<li><b>Nonproliferation of classes</b>: datasets are Numpy arrays or Scipy sparse matrices. No
<li><b>Composition</b>: existing building block are reusable</li>
<li><b>Sensible defaults</b>: reasonable default values.</li>
```

[82]:
```python
imputer.strategy
```

[82]:
```
'median'
```

[41]:
```python
housing_trasformed = pd.DataFrame(X, columns= housing_num.columns, index =␣
↪list(housing.index.values))
```

5.5 Encoding nominal features

[87]:
```python
housing_cat = housing[['ocean_proximity']]
housing_cat
```

[87]:
```
      ocean_proximity
16126        NEAR BAY
17709       <1H OCEAN
2501           INLAND
2123           INLAND
2144           INLAND
…                 …
3382        <1H OCEAN
841          NEAR BAY
11749          INLAND
3940        <1H OCEAN
18827          INLAND

[16512 rows x 1 columns]
```

To convert categorical features to such integer codes, we can use the **OrdinalEncoder**. This estimator transforms each categorical feature to one new feature of integers (0 to n_categories - 1)

[88]:
```python
from sklearn.preprocessing import OrdinalEncoder
```

[89]:
```python
ordinal_encoder = OrdinalEncoder()
housing_cat_encoded = ordinal_encoder.fit_transform(housing_cat)
housing_cat_encoded[:10]
```

[89]:
```
array([[3.],
       [0.],
       [1.],
       [1.],
       [1.],
       [0.],
       [4.],
```

```
       [1.],
       [0.],
       [1.]])
```

Such integer representation can, however, not be used directly with all scikit-learn estimators, as these expect continuous input, and would interpret the categories as being ordered, which is often not desired. A common workaround to this issue is to use a technique called **one-hot encoding**

[90]:
```
from sklearn.preprocessing import OneHotEncoder

cat_encoder = OneHotEncoder()
housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
```

By default, the `OneHotEncoder` class returns a sparse array, but we can convert it to a dense array if needed by calling the `toarray()` method:

[91]:
```
housing_cat_1hot.toarray()[0:6]
```

[91]:
```
array([[0., 0., 0., 1., 0.],
       [1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.]])
```

Alternatively, you can set `sparse=False` when creating the `OneHotEncoder`:

[56]:
```
cat_encoder = OneHotEncoder(sparse = False)
housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
type(housing_cat_1hot)
```

[56]:
```
numpy.ndarray
```

[57]:
```
cat_encoder.categories_
```

[57]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

5.6 Attributes creation

Let's create a new transformer to add extra attributes. All you need is to convert an existing Python function into a transformer to assist in data cleaning or processing. You can implement a transformer from an arbitrary function with the class **FunctionTransformer**

[92]:
```
housing.columns
```

[92]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
```

```
       'ocean_proximity', 'income_cat'],
      dtype='object')
```

[100]:
```
rooms_ix, bed_rooms_ix, population_ix, household_ix = [
    list(housing.columns).index(col) for col in␣
↪['total_rooms','total_bedrooms','population','households']
]

def add_extra_features(X):
    roomsXhouse = X[:, rooms_ix] / X[:, household_ix]
    popXhouse = X[:,population_ix] / X[:,household_ix]
    return np.c_[X,roomsXhouse, popXhouse]

from sklearn.preprocessing import FunctionTransformer
attr_adder = FunctionTransformer(add_extra_features, validate = False)

housinhg_extra = attr_adder.fit_transform(housing.values)
```

[101]:
```
housinhg_extra_df = pd.DataFrame(housinhg_extra,
                                 columns = list(housing.columns)+['a','b'])
housinhg_extra_df.head()
```

[101]:
```
  longitude latitude housing_median_age total_rooms total_bedrooms population  \
0   -122.47    37.79               52.0       437.0          105.0      194.0
1   -121.82    37.33               23.0      3279.0          647.0     2582.0
2   -120.38    36.76               25.0       991.0          272.0      941.0
3   -119.71    36.76               28.0      2675.0          527.0     1392.0
4   -119.76    36.77               36.0      2507.0          466.0     1227.0

  households median_income ocean_proximity income_cat         a         b
0       87.0        2.8125        NEAR BAY        Low  5.022989  2.229885
1      630.0        4.3782       <1H OCEAN     Medium  5.204762  4.098413
2      262.0        1.8125          INLAND        Low  3.782443  3.591603
3      521.0        2.3108          INLAND        Low  5.134357  2.671785
4      474.0         2.785          INLAND        Low   5.28903  2.588608
```

5.7 Attribute or feature scaling

ML algorithms don't perform well when the numerical attributes have very different scales. Two classes to report all the attributes to the same scale:

- **Mix-max scaling**: SkLearn provides the transformer **MinMaxScaler**
- **Standardization**: SkLearn provides the transformer **StandardScaler**

5.8 Transformation Pipeline

Since there are many transformation steps that need to be executed in the right order, need a way to automatically create this sequence of transformation. SkLearn provides the **Pipeline** class. This class takes an arbitrary number of SkLearn transformers, as a list of name/estimator pairs. When you call the method *fit()*, it runs the method *fit_transform()* of each element in list, sequentially

Now let's build a pipeline for preprocessing the numerical attributes:

[103]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy = 'median')),
    ('attribs_adder', FunctionTransformer(add_extra_features, validate=False)),
    ('std_scaler', StandardScaler())
])

housing_num_tr = num_pipeline.fit_transform(housinhg_extra_df)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-103-b29347a14477> in <module>
      8 ])
      9
---> 10 housing_num_tr = num_pipeline.fit_transform(housinhg_extra_df)

/opt/anaconda3/lib/python3.8/site-packages/sklearn/pipeline.py in␣
 ↪fit_transform(self, X, y, **fit_params)
    376         """
    377         fit_params_steps = self._check_fit_params(**fit_params)
--> 378         Xt = self._fit(X, y, **fit_params_steps)
    379
    380         last_step = self._final_estimator

/opt/anaconda3/lib/python3.8/site-packages/sklearn/pipeline.py in _fit(self, X,␣
 ↪y, **fit_params_steps)
    301                 cloned_transformer = clone(transformer)
    302             # Fit or load from cache the current transformer
--> 303             X, fitted_transformer = fit_transform_one_cached(

    304                 cloned_transformer, X, y, None,
    305                 message_clsname='Pipeline',

/opt/anaconda3/lib/python3.8/site-packages/joblib/memory.py in __call__(self,␣
 ↪*args, **kwargs)
    350
    351     def __call__(self, *args, **kwargs):
--> 352         return self.func(*args, **kwargs)
    353
    354     def call_and_shelve(self, *args, **kwargs):
```

```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/pipeline.py in␣
↪_fit_transform_one(transformer, X, y, weight, message_clsname, message,␣
↪**fit_params)
    752     with _print_elapsed_time(message_clsname, message):
    753         if hasattr(transformer, 'fit_transform'):
--> 754             res = transformer.fit_transform(X, y, **fit_params)
    755         else:
    756             res = transformer.fit(X, y, **fit_params).transform(X)

/opt/anaconda3/lib/python3.8/site-packages/sklearn/base.py in␣
↪fit_transform(self, X, y, **fit_params)
    697         if y is None:
    698             # fit method of arity 1 (unsupervised transformation)
--> 699             return self.fit(X, **fit_params).transform(X)
    700         else:
    701             # fit method of arity 2 (supervised transformation)

/opt/anaconda3/lib/python3.8/site-packages/sklearn/impute/_base.py in fit(self,␣
↪X, y)
    286         self : SimpleImputer
    287         """
--> 288         X = self._validate_input(X, in_fit=True)
    289 
    290         # default fill_value is 0 for numerical input and "missing_valu"

/opt/anaconda3/lib/python3.8/site-packages/sklearn/impute/_base.py in␣
↪_validate_input(self, X, in_fit)
    258                 new_ve = ValueError("Cannot use {} strategy with␣
↪non-numeric "
    259                                     "data:\n{}".format(self.strategy,␣
↪ve))
--> 260                 raise new_ve from None
    261             else:
    262                 raise ve

ValueError: Cannot use median strategy with non-numeric data:
could not convert string to float: 'NEAR BAY'
```

[62]:
```
housing_num_tr.shape
```

[62]:
```
(16512, 10)
```

If you have a Pandas DataFrame it is now preferable to use the **ColumnTransformer** class that was introduced in SkLearn 0.20.

[104]:
```
from sklearn.compose import ColumnTransformer
```

[106]:
```
num_attribs = list(housing_num)
cat_attribs = ['ocean_proximity']

full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_attribs),
    ('cat', OneHotEncoder(), cat_attribs)
])

housing_final = full_pipeline.fit_transform(housing)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-106-1a782cbf41f5> in <module>
----> 1 num_attribs = list(housing_num)
      2 cat_attribs = ['ocean_proximity']
      3
      4 full_pipeline = ColumnTransformer([
      5     ('num', num_pipeline, num_attribs),

NameError: name 'housing_num' is not defined
```

[65]:
```
housing_final.shape, housing.values.shape
```

[65]:
```
((16512, 15), (16512, 10))
```

[68]:
```
housing_final[0:6]
```

[68]:
```
array([[-1.44853942,  1.00749903,  1.85042332, -1.00225667, -1.02608971,
        -1.09987832, -1.0732447 , -0.55467031, -0.17413103, -0.07471997,
         0.        ,  0.        ,  0.        ,  1.        ,  0.        ],
       [-1.12372271,  0.79233009, -0.44832649,  0.28300714,  0.2522925 ,
         1.0191734 ,  0.32798234,  0.26444129, -0.09511204,  0.08667068,
         1.        ,  0.        ,  0.        ,  0.        ,  0.        ],
       [-0.40412878,  0.52570771, -0.28979202, -0.75171615, -0.63219704,
        -0.43700912, -0.62165219, -1.0778303 , -0.71341051,  0.04289592,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ],
       [-0.06931772,  0.52570771, -0.05199032,  0.00985466, -0.03074415,
        -0.03680296,  0.04670472, -0.81713968, -0.12571786, -0.03655167,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ],
       [-0.09430362,  0.5303853 ,  0.58214756, -0.06612152, -0.17462112,
        -0.18321985, -0.07458012, -0.56905721, -0.05847994, -0.04373597,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ],
       [ 0.72023674, -0.84950247,  1.21628544, -0.46770993, -0.61332793,
        -0.54881839, -0.56488056,  0.87481206,  0.12047978, -0.01945555,
         1.        ,  0.        ,  0.        ,  0.        ,  0.        ]])
```

6 Extra material

6.1 Model persistence using joblib

[105]:
```
my_model = full_pipeline
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-105-c829ee97a232> in <module>
----> 1 my_model = full_pipeline

NameError: name 'full_pipeline' is not defined
```

[71]:
```
#from sklearn.externals import joblib
import joblib
joblib.dump(my_model, "full_pipeline.pkl") # DIFF
my_model_loaded = joblib.load("full_pipeline.pkl") # DIFF
```

[72]:
```
my_model_loaded
```

[72]:
```
ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('imputer',
SimpleImputer(strategy='median')),
                                                 ('attribs_adder',
FunctionTransformer(func=<function add_extra_features at 0x7fe58e0aaa60>)),
                                                 ('std_scaler',
                                                  StandardScaler())]),
                                 ['longitude', 'latitude', 'housing_median_age',
                                  'total_rooms', 'total_bedrooms', 'population',
                                  'households', 'median_income']),
                                ('cat', OneHotEncoder(), ['ocean_proximity'])])
```

6.2 Some further examples of using pickle

[107]:
```
import pandas as pd
import pickle
```

[109]:
```
print ('convert: csv -> pkl')
datimaggio18 = pd.read_csv('01_2018.csv', delimiter=';', header=0,␣
 ↪encoding='mac_roman')
datimaggio18
```

```
convert: csv -> pkl
```

[109]:
```
        Bicicletta Tipo_bici  Cliente Data_riferimento_prelievo  \
0             7486      Bike   141116                  01/01/18
```

```
1            8279      Bike   265468                  01/01/18
2            1284      Bike   232605                  01/01/18
3            7411      Bike    21489                  01/01/18
4            1730      Bike   220370                  01/01/18
…               …         …        …                      …
250156       7780      Bike   308325                  31/01/18
250157       3562      Bike   163545                  31/01/18
250158      11108     eBike    81098                  31/01/18
250159       7828      Bike    17302                  31/01/18
250160       6992      Bike   234044                  31/01/18

         Data_prelievo  Ora_prelievo  Giorno_prelievo  Mese_prelievo  \
0       01/01/18 07:18             7                1              1
1       01/01/18 07:35             7                1              1
2       01/01/18 07:49             7                1              1
3       01/01/18 07:56             7                1              1
4       01/01/18 07:58             7                1              1
…                    …           …                …              …
250156  01/02/18 00:37             0                1              2
250157  01/02/18 00:42             0                1              2
250158  01/02/18 00:52             0                1              2
250159  01/02/18 00:58             0                1              2
250160  01/02/18 00:59             0                1              2

        Anno_prelievo  GMA_prelievo  …  Precipitazioni_GA  Press_atm_GA  \
0                2018        112018  …                Yes          1012
1                2018        112018  …                Yes          1012
2                2018        112018  …                Yes          1012
3                2018        112018  …                Yes          1012
4                2018        112018  …                Yes          1012
…                 …            …  …                  …             …
250156           2018        122018  …                Yes          1005
250157           2018        122018  …                Yes          1005
250158           2018        122018  …                Yes          1005
250159           2018        122018  …                Yes          1005
250160           2018        122018  …                Yes          1005

        Pm10_GP  Pm25_GP No2_mean_GP  Co_mean_GP Pm10_GA Pm25_GA  No2_mean_GA  \
0            39       38        40.1         0.9      39      38         40.1
1            39       38        40.1         0.9      39      38         40.1
2            39       38        40.1         0.9      39      38         40.1
3            39       38        40.1         0.9      39      38         40.1
4            39       38        40.1         0.9      39      38         40.1
…           …       …          …           …      …     …           …
250156       35       29        44.0         0.7      35      29         44.0
250157       35       29        44.0         0.7      35      29         44.0
250158       35       29        44.0         0.7      35      29         44.0
```

```
250159      35      29      44.0      0.7      35      29      44.0
250160      35      29      44.0      0.7      35      29      44.0

        Co_mean_GA
0              0.9
1              0.9
2              0.9
3              0.9
4              0.9
…            …
250156         0.7
250157         0.7
250158         0.7
250159         0.7
250160         0.7

[250161 rows x 52 columns]
```

[110]:
```
pickle.dump(datimaggio18, open("datimaggio18.pkl", "wb"))
```

[111]:
```
bikemi = pd.read_pickle('datimaggio18.pkl'.format(5,2018))
```

[78]:
```
print('Number of rents')
len(bikemi)
```

```
Number of rents
```

[78]:
```
250161
```

[79]:
```
bikemi['Cliente'].nunique()
```

[79]:
```
24944
```

7 Let's see a bit of statistical visualization tools

[113]:
```
from IPython.core.pylabtools import figsize
import numpy as np
from matplotlib import pyplot as plt
figsize(12.5, 4)

import scipy.stats as stats
a = np.arange(16)
poi = stats.poisson
lambda_ = [1.5, 4.25]
colours = ["red", "blue"]
```

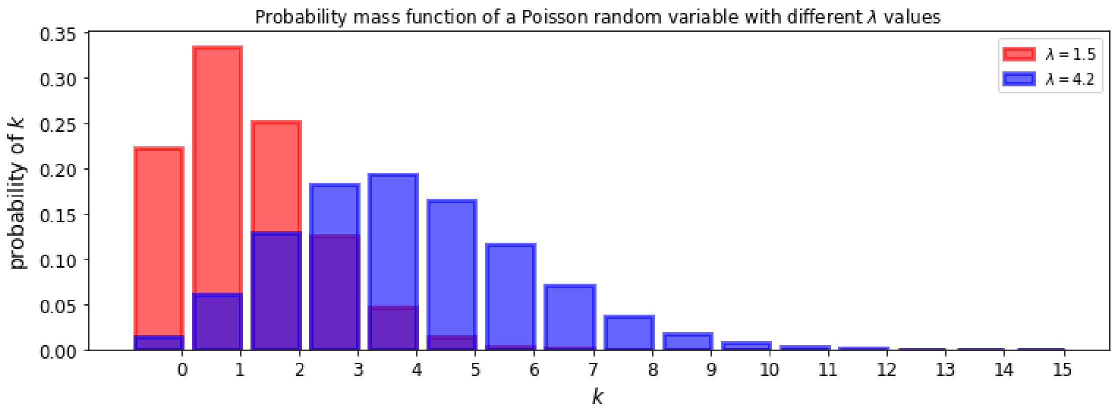
```
plt.bar(a, poi.pmf(a, lambda_[0]), color=colours[0],
        label="$\lambda = %.1f$" % lambda_[0], alpha=0.60,
        edgecolor=colours[0], lw="3")

plt.bar(a, poi.pmf(a, lambda_[1]), color=colours[1],
        label="$\lambda = %.1f$" % lambda_[1], alpha=0.60,
        edgecolor=colours[1], lw="3")

plt.xticks(a + 0.4, a)
plt.legend()
plt.ylabel("probability of $k$")
plt.xlabel("$k$")
plt.title("Probability mass function of a Poisson random variable with␣
 ↪different \
$\lambda$ values")
```

[113]:

```
Text(0.5, 1.0, 'Probability mass function of a Poisson random variable with
different $\\lambda$ values')
```



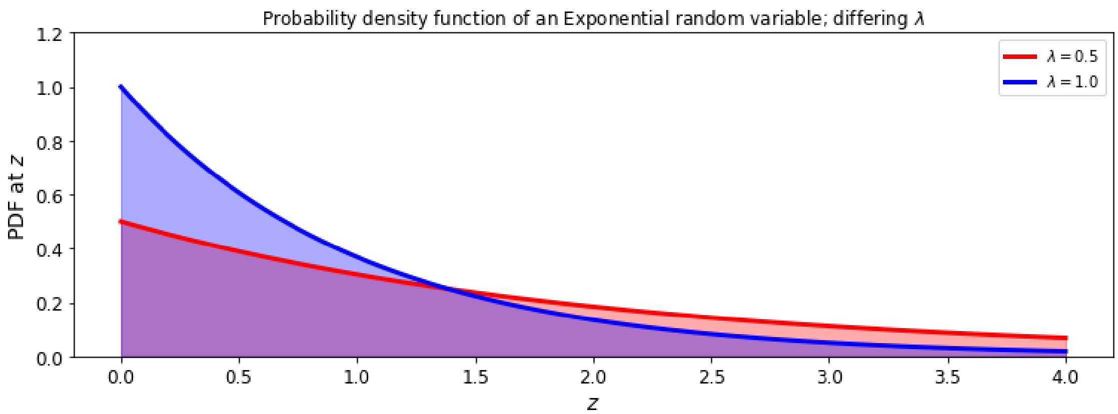
[114]:

```
a = np.linspace(0, 4, 100)
expo = stats.expon
lambda_ = [0.5, 1]

for l, c in zip(lambda_, colours):
    plt.plot(a, expo.pdf(a, scale=1. / l), lw=3,
             color=c, label="$\lambda = %.1f$" % l)
    plt.fill_between(a, expo.pdf(a, scale=1. / l), color=c, alpha=.33)

plt.legend()
plt.ylabel("PDF at $z$")
plt.xlabel("$z$")
plt.ylim(0, 1.2)
```

```
plt.title("Probability density function of an Exponential random variable;\
 differing $\lambda$");
```




```
[82]: figsize(12.5, 3.5)
count_data = np.loadtxt("/Users/giancarlomanzi/Documents/Box Sync BackUp PC␣
 ↪Lavoro 24062015/documenti/Ricerca/ALTERNATIVE ERASMUS PROJECT/NUOVO PROGETTO␣
 ↪DI VISITING/Lectures/Topic 2 - Introduction to Python and the␣
 ↪Anaconda-Jupyter environment - 3 hours/txtdata.csv")
n_count_data = len(count_data)
plt.bar(np.arange(n_count_data), count_data, color="#348ABD")
plt.xlabel("Time (days)")
plt.ylabel("count of text-msgs received")
plt.title("Did the user's texting habits change over time?")
plt.xlim(0, n_count_data);
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-82-a439bff65e7e> in <module>
      1 figsize(12.5, 3.5)
----> 2 count_data = np.loadtxt("/Users/giancarlomanzi/Documents/Box Sync BackUp␣
 ↪PC Lavoro 24062015/documenti/Ricerca/ALTERNATIVE ERASMUS PROJECT/NUOVO␣
 ↪PROGETTO DI VISITING/Lectures/Topic 2 - Introduction to Python and the␣
 ↪Anaconda-Jupyter environment - 3 hours/txtdata.csv")
      3 n_count_data = len(count_data)
      4 plt.bar(np.arange(n_count_data), count_data, color="#348ABD")
      5 plt.xlabel("Time (days)")

/opt/anaconda3/lib/python3.8/site-packages/numpy/lib/npyio.py in loadtxt(fname,␣
 ↪dtype, comments, delimiter, converters, skiprows, usecols, unpack, ndmin,␣
 ↪encoding, max_rows, like)
   1040             fname = os_fspath(fname)
   1041         if _is_string_like(fname):
-> 1042             fh = np.lib._datasource.open(fname, 'rt', encoding=encoding
```

```
   1043             fencoding = getattr(fh, 'encoding', 'latin1')
   1044             line_iter = iter(fh)

/opt/anaconda3/lib/python3.8/site-packages/numpy/lib/_datasource.py in␣
 ↪open(path, mode, destpath, encoding, newline)
    191
    192     ds = DataSource(destpath)
--> 193     return ds.open(path, mode, encoding=encoding, newline=newline)
    194
    195

/opt/anaconda3/lib/python3.8/site-packages/numpy/lib/_datasource.py in␣
 ↪open(self, path, mode, encoding, newline)
    530                                       encoding=encoding, newline=newline)
    531         else:
--> 532             raise FileNotFoundError(f"{path} not found.")
    533
    534

FileNotFoundError: /Users/giancarlomanzi/Documents/Box Sync BackUp PC Lavoro␣
 ↪24062015/documenti/Ricerca/ALTERNATIVE ERASMUS PROJECT/NUOVO PROGETTO DI␣
 ↪VISITING/Lectures/Topic 2 - Introduction to Python and the Anaconda-Jupyter␣
 ↪environment - 3 hours/txtdata.csv not found.
```

7.1 Pipelines in text mining/natural language processing

- We spend a lot of time in pre-processing and cleaning data
- Therefore we need to create multipurpose software objects to be used in different situations.
- For this we can use the Pipeline tool in scikit-learn.
- It is composed by *transformers* (tools for transforming data, for example to normalize a variable) and *estimators* (for example a fitting or predicting tool).
- All transformers and estimators in scikit-learn are implemented as Python *classes*, each with their own attributes and methods.
- We use *inherited* classes from scikit-learn to implement our own class.

[115]:
```
# Example of inheritance
from sklearn.preprocessing import OneHotEncoder
#Some data:
X = [[0, 0, 3], [1, 1, 0], [0, 2, 1], [1, 0, 2]]
#Initializing an object of class OneHotEncoder
# Here we are "inheriting" classes from OneHotEncoder into the variable␣
 ↪'one_hot_enc'
one_hot_enc = OneHotEncoder( sparse = True )

#Calling methods on our OneHotEncoder object
one_hot_enc.fit( X ) #returns nothing
transformed_data = one_hot_enc.transform(X).toarray() #returns something
```

```
#fit_transformed_data = one_hot_enc.transform( X ) #returns something
```

[116]:
```
print(pd.DataFrame(X))
#Comments: The first column takes on 2 values, the second 3 and the fourth 4
```

```
   0  1  2
0  0  0  3
1  1  1  0
2  0  2  1
3  1  0  2
```

[117]:
```
print(transformed_data)
#Comments: the first two columns express the binary coding of the first␣
↪"feature";
# the next three columns express the binary coding of the second "feature";
# The next four columns express the binary coding of the third "feature";
```

```
[[1. 0. 1. 0. 0. 0. 0. 0. 1.]
 [0. 1. 0. 1. 0. 1. 0. 0. 0.]
 [1. 0. 0. 0. 1. 0. 1. 0. 0.]
 [0. 1. 1. 0. 0. 0. 0. 1. 0.]]
```

7.2 Pipelines in text mining/natural language processing (2)

- Our own trasformer will be formed by inheriting from some other scikit-learn class.
- See a tutorial here https://www.programiz.com/python-programming/class about classes and objects in python and a tutorial here https://www.programiz.com/python-programming/inheritance about inheritance.
- The base classes inherited from scikit-learn are TransformerMixin (https://scikit-learn.org/stable/modules/generated/sklearn.base.TransformerMixin.html) and BaseEstimator (https://scikit-learn.org/stable/modules/generated/sklearn.base.BaseEstimator.html).

[118]:
```
import numpy as np
import pandas as pd
```

[121]:
```
# Load Data
pd.set_option('display.max_colwidth', None)
BikeSent = pd.read_csv("BikeMiSentiment2019_UTF-8.csv", sep=';')
BikeSent
```

[121]:
```
           v1  \
0    positive
1    positive
2    negative
3    positive
4    positive
..        …
995  negative
```

```
996   positive
997   positive
998   positive
999   positive

                                                                 v2
0    When I had problems with the return of the bike, the assistance was very
kind, but could not solve the problem quickly nor prevent me from being charged
for the rental because I had exceeded half an hour (not because of the route I
took carried out, but due to the impossibility of hanging up the bike in 2
different stations). It would be desirable to be able to solve problems more
efficiently or at least not to charge the user in the event of a reported
malfunction. For the rest, when the service works, it's really practical and
useful.\t
1
more electric bikes. often even if present they are not available when there are
few, why?\t
2
pay more attention to stations that very often are without bicycles or full and
do not allow their repositioning\t
3
essential to insert bikes with child seats\t
4
extension completed at train and metro stations not yet served\t
..
…
995
Main problem I think is the maintenance of traditional bikes, often you are
forced to change bikes several times before finding a functioning one\t
996
I feel good but without a credit card you can't even buy a day card, it doesn't
seem right because students like me often only have a prepaid card\t
997
I don't have any suggestions at the moment. the comment, thank you for the
excellent service provided.\t
998
I would like it if the number of red ebikes increased considerably\t
999
need more maintenance, stations in the center with too many bikes\t

[1000 rows x 2 columns]
```

[122]:
```python
# Rename columns
BikeSent.columns = ["target", "text"]
BikeSent.head()
```

[122]:
```
      target  \
0  positive
1  positive
2  negative
3  positive
4  positive

                                                                text
0  When I had problems with the return of the bike, the assistance was very
kind, but could not solve the problem quickly nor prevent me from being charged
for the rental because I had exceeded half an hour (not because of the route I
took carried out, but due to the impossibility of hanging up the bike in 2
different stations). It would be desirable to be able to solve problems more
efficiently or at least not to charge the user in the event of a reported
malfunction. For the rest, when the service works, it's really practical and
useful.\t
1
more electric bikes. often even if present they are not available when there are
few, why?\t
2
pay more attention to stations that very often are without bicycles or full and
do not allow their repositioning\t
3
essential to insert bikes with child seats\t
4
extension completed at train and metro stations not yet served\t
```

[123]:
```python
# Encode categories
BikeSent['target'] = np.where(BikeSent['target']=='positive',1,0)
BikeSent.head()
```

[123]:
```
   target  \
0       1
1       1
2       0
3       1
4       1

                                                                text
0  When I had problems with the return of the bike, the assistance was very
kind, but could not solve the problem quickly nor prevent me from being charged
for the rental because I had exceeded half an hour (not because of the route I
took carried out, but due to the impossibility of hanging up the bike in 2
different stations). It would be desirable to be able to solve problems more
efficiently or at least not to charge the user in the event of a reported
malfunction. For the rest, when the service works, it's really practical and
useful.\t
```

```
1
more electric bikes. often even if present they are not available when there are
few, why?\t
2
pay more attention to stations that very often are without bicycles or full and
do not allow their repositioning\t
3
essential to insert bikes with child seats\t
4
extension completed at train and metro stations not yet served\t
```

[124]:
```
# split the sample in train (used also for cross-validation) + test
from sklearn.model_selection import train_test_split
X = BikeSent[['text']]
y = BikeSent['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.10,␣
↪random_state=42)
```

[125]:
```
X_train
```

[125]:
```
                              text
716  Luckily I have tried the new bicycle models a few times and they are
definitely uncomfortable. I think there is a design error because the saddle is
too far forward and you have difficulty pedaling. I hope you realize this before
increasing the number of bikes you buy\t
351
Improve the bike pickup and storage system. For older people they are too heavy
to lift\t
936                           I kindly ask you to make the stall n. 151 Balilla
- Tibaldi. Sometimes it is uninhabitable and there are few bicycles available or
they are generally few or poorly functioning (eg deflated wheels, poorly
functioning brakes, gearshift changes).\t
256
bikes should be maintained much, much better, often with badly maintained
bicycles and without brakes or even for the electrics that the battery does not
work\t
635
Increase maintenance\t
..
…
106                                                                  A really
useful service, I hope in the possibility of using 24 hours a day, especially
for us young people it can be very useful at night when the vehicles are almost
zero and you are forced to use taxis.\t
270
only problem to report too often the stalls do not record the correct
establishment of the bike and you risk icorrerere nela penalty\t
```

```
860                                                                     Some
discounts for the renewal of the subscription. The offers seem to me always and
only for the new subscribers. In addition, a few more conventions for Bikemi
subscribers who give discounts elsewhere.\t
435
the service is smart but is very limited by the location of the stations. They
are all a center. There isn't one in Stazione Lambrate or the eastern suburbs.\t
102
good\t

[900 rows x 1 columns]
```

7.3 Custom Transformers

7.3.1 Cleaning Text

- We create here our own transformer (which will be a class) inheriting the TransformerMixin and the BaseEstimator classes from scikit-learn

[126]:
```python
from sklearn.base import BaseEstimator
from sklearn.base import TransformerMixin
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import SnowballStemmer

# Custom Transformer (Inheriting from classes)
class CleanText( BaseEstimator, TransformerMixin ):

    # Class Constructor
    # The class constructor is formed by a function with double underscore __ :
    # these are called 'special functions' as they have special meaning.
    # In particular the '__init__' gets called whenever
    # a new object of that class is instantiated,
    # and are used to initialize all the necessary variables.
    # In this example we initialize the language variable 'lang' with 'English'
    # and pick the SnowballStemmer as the default stemmer.
    def __init__( self, lang = "english"):
        self.lang = lang
        self.stemmer = SnowballStemmer(self.lang)

    # The 'fit' method here is used to instantiate the class on the 'self'␣
↪variable
    # and return the object itself
    def fit( self, X, y = None ):
        return self

    # Custom function: this applies the stemmer just created in the '__init__'
    # part to the 'self' variable
```

```
    def clean( self, x ):
        words   = [self.stemmer.stem(word) for word in word_tokenize(x.lower())␣
↪if word.isalpha() and word not in stopwords.words("english")]
        return " ".join(words)

    # Method that describes what we need this transformer to do i.e. cleaning␣
↪the text
    # in the 'text' column in the data frame.
    # This will be used later on in the usage of the custom transformer
    # within the pipeline.
    def transform( self, X, y = None ):
        return X["text"].apply(self.clean)
```

7.3.2 Feature extraction

[127]:
```
# Custom Transformer: same parts as the previous custom transformer
# This one will be used for feature extraction

class CustomFeatures( BaseEstimator, TransformerMixin ):

    # Class Constructor
    def __init__( self ):
        return

    # Return self nothing else to do here
    def fit( self, X, y = None ):
        return self

    # Method that describes what we need this transformer to do i.e.
    # returning length, digits and punctuations in the 'text' column in data␣
↪frame
    def transform( self, X, y = None ):
        f            = pd.DataFrame()
        f['len']     = X['text'].str.len()
        f['digits'] = X['text'].str.findall(r'\d').str.len()
        f['punct']  = X['text'].str.findall(r'[^a-zA-Z\d\s:]').str.len()
        return f[['len','digits','punct']]
```

7.4 Pipeline usage

7.4.1 Pipeline for data pre processing

[129]:
```
from sklearn.pipeline import Pipeline
from sklearn.pipeline import FeatureUnion
# FeatureUnion combines two or more pipelines or transformers
# and is very fast!
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.preprocessing import StandardScaler
# Our first pipeline called 'pipe' will be formed by three 'steps' or parts:
# 1)"extract" which in turns is formed through FeatureUnion which
# put together two parts:
# "terms" (formed by a pipeline with the CleanText() transformer we created␣
↪above
# and the TfidVectorize text vectorizing transformer from scikit-learn) and␣
↪"custom"
# (formed by the CustomFeatures transformer we created above);
# 2) "select", formed by the scikit-learn transformer method "SelectKBest" for␣
↪feature
# selection with a chi squared score function;
# 3) "scale", same as 2) using the StandardScaler method from scikit-learn.
# The whole pipeline will be used as pre-processing task in classifying␣
↪pipelines.
pipe = Pipeline([("extract", FeatureUnion([("terms", Pipeline([('clean',␣
↪CleanText()),
                                                              ('tfidf',␣
↪TfidfVectorizer())])),
                                          ("custom", CustomFeatures())])),
                 ("select", SelectKBest(score_func = chi2)),
                 ("scale", StandardScaler(with_mean = False))])
```

7.4.2 Classifier implemented through pipelines: Logistic Model

[131]:
```
# Logistic Model
from sklearn.linear_model import LogisticRegression
pipe_logistic = Pipeline([('pre_process', pipe),
                          ('classify', LogisticRegression(max_iter=10000, tol=0.
↪1, solver='lbfgs'))])
```

[132]:
```
# Fit on training
pipe_logistic.fit(X_train, y_train)
```

[132]:
```
Pipeline(steps=[('pre_process',
                 Pipeline(steps=[('extract',
                                  FeatureUnion(transformer_list=[('terms',
Pipeline(steps=[('clean',
   CleanText()),
  ('tfidf',
   TfidfVectorizer())])),
                                                                 ('custom',
CustomFeatures())])),
                                 ('select',
                                  SelectKBest(score_func=<function chi2 at
```

```
0x7f83b3de78b0>)),
                                     ('scale', StandardScaler(with_mean=False))])),
                  ('classify', LogisticRegression(max_iter=10000, tol=0.1))])
```

[133]:
```
# Evaluate on test
# The F1 score can be interpreted as a weighted average of the precision and␣
↪recall,
# where an F1 score reaches its best value at 1 and worst score at 0.
#The relative contribution of precision
# and recall to the F1 score are equal. The formula for the F1 score is:
# F1 = 2 * (precision * recall) / (precision + recall)
from sklearn.metrics import f1_score
y_pred = pipe_logistic.predict(X_test)
f1_score(y_test, y_pred)
```

[133]:
```
0.7972972972972973
```

[98]:
```
# we can classify new messages!
msg = pd.DataFrame(columns = ["text"],
                   data    = ["The bikes are heavy and unwieldy. The collection␣
↪and return of the bicycle is super-comfortable because the bikes are heavy"])

pipe_logistic.predict(msg)
```

[98]:
```
array([1])
```

[99]:
```
# we can classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                   #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
↪credit and details of great offers pls reply 2 this text with your valid␣
↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["Satisfied"])


pipe_logistic.predict(msg)
```

[99]:
```
array([1])
```

7.5 Using bi-grams

[100]:
```
# extract features
pipe_extract = FeatureUnion([("terms", Pipeline([('clean', CleanText()),
                                                 ('tfidf',␣
↪TfidfVectorizer())])),
```

```
                                ("custom", CustomFeatures())])

# select and scale features
pipe_select_scale = Pipeline([("select", SelectKBest(score_func = chi2)),
                              ("scale", StandardScaler(with_mean = False))])
```

[101]:
```
# extract features
# you can also use bi-grams:
X_extract = pipe_extract.set_params(terms__tfidf__ngram_range = (1,2)).
 ↪fit_transform(X_train, y_train)
```

[102]:
```
print(X_extract)
```

```
  (0, 697)	0.07090144070985319
  (0, 745)	0.17483279959508186
  (0, 785)	0.043180618930796104
  (0, 814)	0.17483279959508186
  (0, 1163)	0.1648630344692586
  (0, 1895)	0.14402927962636455
  (0, 1900)	0.17483279959508186
  (0, 1940)	0.1648630344692586
  (0, 1942)	0.17483279959508186
  (0, 2001)	0.1523026158602164
  (0, 2004)	0.17483279959508186
  (0, 2318)	0.1648630344692586
  (0, 2320)	0.17483279959508186
  (0, 2605)	0.1307761823598249
  (0, 2609)	0.17483279959508186
  (0, 2799)	0.157789373540365
  (0, 2800)	0.17483279959508186
  (0, 3315)	0.13525918980549953
  (0, 3323)	0.17483279959508186
  (0, 3509)	0.09334204887662222
  (0, 3529)	0.12370252143093134
  (0, 4020)	0.17483279959508186
  (0, 4021)	0.17483279959508186
  (0, 4343)	0.1523026158602164
  (0, 4346)	0.17483279959508186
  :	:
  (898, 1293)	0.14945135091427067
  (898, 1311)	0.25345986443799984
  (898, 2151)	0.23900642479096382
  (898, 2153)	0.25345986443799984
  (898, 3706)	0.20880316378705438
  (898, 3708)	0.25345986443799984
  (898, 3882)	0.20880316378705438
  (898, 3884)	0.25345986443799984
```

```
  (898, 3923)	0.1771738498926844
  (898, 3935)	0.23900642479096382
  (898, 4862)	0.1334273238341794
  (898, 4894)	0.25345986443799984
  (898, 6233)	0.09131789001952145
  (898, 6325)	0.25345986443799984
  (898, 6480)	0.23900642479096382
  (898, 6481)	0.25345986443799984
  (898, 6700)	0.0829510509697508
  (898, 6721)	0.20404322788705004
  (898, 6857)	0.25345986443799984
  (898, 6858)	0.25345986443799984
  (898, 6955)	0.18673654039843596
  (898, 8149)	158.0
  (898, 8151)	4.0
  (899, 3095)	1.0
  (899, 8149)	5.0
```

[103]:
```python
# extract all features
X_select_scale = pipe_select_scale.set_params(select__k = 500).
 ↪fit_transform(X_extract, y_train)
print(X_select_scale)
```

```
  (0, 222)	1.7463975570695727
  (0, 224)	4.868401476553422
  (0, 332)	3.3310922794931095
  (0, 391)	3.8799422337719514
  (0, 457)	4.664456373753558
  (0, 498)	2.431404727966195
  (0, 499)	0.6518039044082895
  (1, 215)	1.955545214342361
  (1, 216)	4.391664155129969
  (1, 498)	0.7954037771785323
  (1, 499)	0.32590195220414475
  (2, 190)	3.9374599587618193
  (2, 415)	2.9160268437218404
  (2, 498)	2.205437745813203
  (2, 499)	2.607215617633158
  (3, 30)	3.467617207975343
  (3, 35)	19.81764758098014
  (3, 44)	4.029061322449084
  (3, 254)	17.490606015887288
  (3, 283)	21.01627223472825
  (3, 294)	1.5146934286923344
  (3, 295)	9.407246305477612
  (3, 487)	4.614820388219279
  (3, 498)	1.4371500064930298
  (3, 499)	0.6518039044082895
```

```
  :	:
  (893, 494)	2.240618278439294
  (893, 498)	1.6992717057905007
  (893, 499)	0.6518039044082895
  (894, 347)	2.7889851989069125
  (894, 498)	0.831558494323011
  (895, 211)	2.8248704708645893
  (895, 397)	1.0910163308028165
  (895, 498)	1.8529292536545352
  (895, 499)	0.9777058566124343
  (896, 72)	24.41599739893815
  (896, 294)	1.6522845847666836
  (896, 309)	16.430593476368912
  (896, 352)	2.675593080916396
  (896, 380)	4.5285814862791804
  (896, 386)	13.6708637361617
  (896, 498)	1.202144345053918
  (897, 13)	2.5695129210768552
  (897, 191)	6.145400961179911
  (897, 498)	1.8438905743684155
  (897, 499)	1.303607808816579
  (898, 397)	1.4938347656108477
  (898, 498)	1.4281113272069101
  (898, 499)	1.303607808816579
  (899, 193)	11.497860975131363
  (899, 498)	0.04519339643059842
```

7.5.1 Using cross-validation with parameters (grid)

[104]:
```python
# Select best hyperparameters by cross validation
from sklearn.model_selection import GridSearchCV

# Model
logistic = LogisticRegression(max_iter=10000, tol=0.1, solver='lbfgs')

# Parameters: (np.logspace returns numbers spaced evenly on a log scale.)
param_logistic = {
    'C': np.logspace(-4, 4, 4)
}

# For an explanation of the 'C' parameter in scikit-learn logistic regression␣
 ↪see:
# https://stackoverflow.com/questions/22851316/
 ↪what-is-the-inverse-of-regularization-strength-in-logistic-regression-how-shoul
# C= 1/\lambda where \lambda can be assimilated to the regulatization parameter
# you probably have seen in the lasso regression
# Grid Search
```

```python
cv_logistic = GridSearchCV(logistic, param_logistic, cv=10, scoring='f1')
cv_logistic.fit(X_select_scale, y_train)
```

[104]:
```
GridSearchCV(cv=10, estimator=LogisticRegression(max_iter=10000, tol=0.1),
             param_grid={'C': array([1.00000000e-04, 4.64158883e-02,
2.15443469e+01, 1.00000000e+04])},
             scoring='f1')
```

[105]:
```python
# See https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.
 ↪GridSearchCV.html
print(cv_logistic.best_estimator_)
```

```
LogisticRegression(C=0.046415888336127774, max_iter=10000, tol=0.1)
```

[106]:
```python
print(cv_logistic.best_score_)
```

```
0.9020406477845386
```

7.5.2 Similar with pipeline

[107]:
```python
# Pipe Logistic
pipe_logistic = Pipeline([('select_scale', pipe_select_scale),
                          ('classify', LogisticRegression(max_iter=10000, tol=0.
 ↪1, solver='lbfgs'))])

# Parameters of pipelines can be set using '__' separated parameter names:
param_logistic = {
    'classify__C': np.logspace(-4, 4, 3),
    'select_scale__select__k': [600, 1000, 5000]
}

cv_logistic = GridSearchCV(pipe_logistic, param_logistic, cv=10, scoring='f1')
cv_logistic.fit(X_extract, y_train)
```

[107]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('select_scale',
                                        Pipeline(steps=[('select',
                                                         SelectKBest(k=500,
score_func=<function chi2 at 0x7fe565f9b1f0>)),
                                                        ('scale',
StandardScaler(with_mean=False))])),
                                       ('classify',
                                        LogisticRegression(max_iter=10000,
                                                           tol=0.1))]),
             param_grid={'classify__C': array([1.e-04, 1.e+00, 1.e+04]),
                         'select_scale__select__k': [600, 1000, 5000]},
             scoring='f1')
```

[108]:
```
print(cv_logistic.best_estimator_)
```

```
Pipeline(steps=[('select_scale',
                 Pipeline(steps=[('select',
                                  SelectKBest(k=5000,
                                              score_func=<function chi2 at
0x7fe565f9b1f0>)),
                                 ('scale', StandardScaler(with_mean=False))])),
                ('classify',
                 LogisticRegression(C=10000.0, max_iter=10000, tol=0.1))])
```

[109]:
```
print(cv_logistic.best_score_)
```

```
0.8457155973785053
```

7.6 Other Models

7.6.1 Naive Bayes

[110]:
```
from sklearn.naive_bayes import MultinomialNB

# Pipe NB
pipe_nb = Pipeline([('select_scale', pipe_select_scale),
                    ('classify', MultinomialNB())])

# Parameters of pipelines can be set using '__' separated parameter names:
param_nb = {
    'classify__alpha': [0.5, 1, 10],
    'select_scale__select__k': [600, 1000, 5000]
}

cv_nb = GridSearchCV(pipe_nb, param_nb, cv=10, scoring='f1')
cv_nb.fit(X_extract, y_train)
print(cv_nb.best_score_)
```

```
0.8301298848126655
```

[111]:
```
# full pipeline
model = Pipeline([("extract", FeatureUnion([("terms", Pipeline([('clean',␣
 ↪CleanText()),
                                                                ('tfidf',␣
 ↪TfidfVectorizer(ngram_range = (1,2)))])),
                                            ("custom", CustomFeatures())])),
                  ("select", SelectKBest(score_func = chi2, k = 1000)),
                  ("scale", StandardScaler(with_mean = False)),
                  ("classify", MultinomialNB())])

# fitting
```

```
model.fit(X_train, y_train)

# final evaluation
y_pred = model.predict(X_test)
f1_score(y_test, y_pred)
```

[111]: 0.782608695652174

```
[112]: # we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                   #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
↪credit and details of great offers pls reply 2 this text with your valid␣
↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["The bikes are heavy and unwieldy. The collection␣
↪and return of the bicycle is super-comfortable because the bikes are heavy"])

model.predict(msg)
```

[112]: array([0])

```
[113]: # we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                   #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
↪credit and details of great offers pls reply 2 this text with your valid␣
↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["Satisfied"])


model.predict(msg)
```

[113]: array([1])

7.6.2 Support Vector Machine

```
[114]: from sklearn.svm import LinearSVC

# Pipe SVC
pipe_svc = Pipeline([('select_scale', pipe_select_scale),
                     ('classify', LinearSVC(max_iter=10000, tol=0.1))])

# Parameters of pipelines can be set using ‘__’ separated parameter names:
param_svc = {
    'classify__C': [0.01, 0.1, 1],
```

```
    'select_scale__select__k': [600, 1000, 5000]
}

cv_svc = GridSearchCV(pipe_svc, param_svc, cv=10, scoring='f1')
cv_svc.fit(X_extract, y_train)
print(cv_svc.best_score_)
```

0.8463498495228174

[115]:
```
# full pipeline
model = Pipeline([("extract", FeatureUnion([("terms", Pipeline([('clean',␣
↪CleanText()),
                                                                 ('tfidf',␣
↪TfidfVectorizer(ngram_range = (1,2)))])),
                                             ("custom", CustomFeatures())])),
                 ("select", SelectKBest(score_func = chi2, k = 1000)),
                 ("scale", StandardScaler(with_mean = False)),
                 ("classify", LinearSVC(C = 1, max_iter=10000, tol=0.1))])

# fitting
model.fit(X_train, y_train)

# final evaluation
y_pred = model.predict(X_test)
f1_score(y_test, y_pred)
```

[115]: 0.7972972972972973

[116]:
```
# we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                   #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
↪credit and details of great offers pls reply 2 this text with your valid␣
↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["The bikes are heavy and unwieldy. The collection␣
↪and return of the bicycle is super-comfortable because the bikes are heavy"])

model.predict(msg)
```

[116]: array([0])

[117]:
```
# we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                   #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
↪credit and details of great offers pls reply 2 this text with your valid␣
↪name, house no and postcode"])
```

```
msg = pd.DataFrame(columns = ["text"],
                   data    = ["Satisfied"])


model.predict(msg)
```

[117]: array([1])

7.6.3 Random Forest

[118]:
```
from sklearn.ensemble import RandomForestClassifier

# Pipe RF
pipe_rf = Pipeline([('select_scale', pipe_select_scale),
                    ('classify', RandomForestClassifier())])

# Parameters of pipelines can be set using '__' separated parameter names:
param_rf = {
    'classify__n_estimators': [100, 200],
    'select_scale__select__k': [600, 1000]
}

cv_rf = GridSearchCV(pipe_rf, param_rf, cv=10, scoring='f1')
cv_rf.fit(X_extract, y_train)
print(cv_rf.best_score_)
```

0.850498859773985

[119]:
```
# full pipeline
model = Pipeline([("extract", FeatureUnion([("terms", Pipeline([('clean',␣
 ↪CleanText()),
                                                                  ('tfidf',␣
 ↪TfidfVectorizer(ngram_range = (1,2))))])),
                                            ("custom", CustomFeatures())])),
                  ("select", SelectKBest(score_func = chi2, k = 1000)),
                  ("scale", StandardScaler(with_mean = False)),
                  ("classify", RandomForestClassifier())])

# fitting
model.fit(X_train, y_train)

# final evaluation
y_pred = model.predict(X_test)
f1_score(y_test, y_pred)
```

[119]: 0.8079470198675497

[120]:
```
# we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                    #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
 ↪credit and details of great offers pls reply 2 this text with your valid␣
 ↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["The bikes are heavy and unwieldy. The collection␣
 ↪and return of the bicycle is super-comfortable because the bikes are heavy"])

model.predict(msg)
```

[120]:
```
array([1])
```

[121]:
```
# we are now able to classify new messages!
#msg = pd.DataFrame(columns = ["text"],
                    #data    = ["REMINDER FROM O2: To get 2.50 pounds free call␣
 ↪credit and details of great offers pls reply 2 this text with your valid␣
 ↪name, house no and postcode"])

msg = pd.DataFrame(columns = ["text"],
                   data    = ["Satisfied"])


model.predict(msg)
```

[121]:
```
array([1])
```

7.7 Long Example 1: Text clustering

[122]:
```
import re
import string
import pandas as pd
```

[123]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
```

7.8 Full text for clustering

This corpus contain some strings about Google and some strings about TF-IDF from Wikipedia. Just for example

[124]:
```
all_text = """
Google and Facebook are strangling the free press to death. Democracy is the␣
 ↪loser
Your 60-second guide to security stuff Google touted today at Next '18
```

```
A Guide to Using Android Without Selling Your Soul to Google
Review: Lenovo’s Google Smart Display is pretty and intelligent
Google Maps user spots mysterious object submerged off the coast of Greece -␣
↪and no-one knows what it is
Android is better than IOS
In information retrieval, tf-idf or TFIDF, short for term frequency-inverse␣
↪document frequency
is a numerical statistic that is intended to reflect how important
a word is to a document in a collection or corpus.
It is often used as a weighting factor in searches of information retrieval
text mining, and user modeling. The tf-idf value increases proportionally
to the number of times a word appears in the document
and is offset by the frequency of the word in the corpus
""".split("\n")[1:-1]
```

[125]:
```
all_text
```

[125]:
```
['Google and Facebook are strangling the free press to death. Democracy is the
loser',
 "Your 60-second guide to security stuff Google touted today at Next '18",
 'A Guide to Using Android Without Selling Your Soul to Google',
 'Review: Lenovo’s Google Smart Display is pretty and intelligent',
 'Google Maps user spots mysterious object submerged off the coast of Greece -
and no-one knows what it is',
 'Android is better than IOS',
 'In information retrieval, tf-idf or TFIDF, short for term frequency-inverse
document frequency',
 'is a numerical statistic that is intended to reflect how important ',
 'a word is to a document in a collection or corpus.',
 'It is often used as a weighting factor in searches of information retrieval',
 'text mining, and user modeling. The tf-idf value increases proportionally',
 'to the number of times a word appears in the document',
 'and is offset by the frequency of the word in the corpus']
```

7.9 Preprocessing and tokenizing

Firstly, we must bring every chars to lowercase and remove all punctuation, because it’s not important for our task, but is very harmful for clustering algorithm. After that, we’ll split strings to array of words.

[126]:
```
def preprocessing(line):
    line = line.lower()
    line = re.sub(r"[{}]".format(string.punctuation), " ", line)
    return line
```

Now, let’s calculate tf-idf for this corpus

[127]:
```
tfidf_vectorizer = TfidfVectorizer(preprocessor=preprocessing)
tfidf = tfidf_vectorizer.fit_transform(all_text)
```

7.10 K-means

[128]:
```
kmeans = KMeans(n_clusters=2)
```

[129]:
```
list(zip(kmeans.fit_predict(tfidf), all_text))
```

[129]:
```
[(1,
  'Google and Facebook are strangling the free press to death. Democracy is the
loser'),
 (1, "Your 60-second guide to security stuff Google touted today at Next '18"),
 (1, 'A Guide to Using Android Without Selling Your Soul to Google'),
 (1, 'Review: Lenovo’s Google Smart Display is pretty and intelligent'),
 (1,
  'Google Maps user spots mysterious object submerged off the coast of Greece -
and no-one knows what it is'),
 (1, 'Android is better than IOS'),
 (0,
  'In information retrieval, tf-idf or TFIDF, short for term frequency-inverse
document frequency'),
 (1, 'is a numerical statistic that is intended to reflect how important '),
 (0, 'a word is to a document in a collection or corpus.'),
 (0,
  'It is often used as a weighting factor in searches of information
retrieval'),
 (0,
  'text mining, and user modeling. The tf-idf value increases proportionally'),
 (0, 'to the number of times a word appears in the document'),
 (0, 'and is offset by the frequency of the word in the corpus')]
```

7.11 Agglomerative Clustering

[130]:
```
hac = AgglomerativeClustering(n_clusters=2, affinity='cosine',␣
 ↪linkage='average')
```

[131]:
```
list(zip(hac.fit_predict(tfidf.toarray()), all_text))
```

[131]:
```
[(0,
  'Google and Facebook are strangling the free press to death. Democracy is the
loser'),
 (1, "Your 60-second guide to security stuff Google touted today at Next '18"),
 (1, 'A Guide to Using Android Without Selling Your Soul to Google'),
 (0, 'Review: Lenovo’s Google Smart Display is pretty and intelligent'),
 (0,
```

```
  'Google Maps user spots mysterious object submerged off the coast of Greece -
and no-one knows what it is'),
 (1, 'Android is better than IOS'),
 (0,
  'In information retrieval, tf-idf or TFIDF, short for term frequency-inverse
document frequency'),
 (1, 'is a numerical statistic that is intended to reflect how important '),
 (0, 'a word is to a document in a collection or corpus.'),
 (0,
  'It is often used as a weighting factor in searches of information
retrieval'),
 (0,
  'text mining, and user modeling. The tf-idf value increases proportionally'),
 (0, 'to the number of times a word appears in the document'),
 (0, 'and is offset by the frequency of the word in the corpus')]
```

7.12 Example 2: Topic model (1): BikeMi survey

[134]:
```
import nltk
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/giancarlomanzi/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[134]: True

7.12.1 Cleaning and pre-processing

[135]:
```
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
import string
stop=set(stopwords.words('english'))
exclude=set(string.punctuation)
lemma=WordNetLemmatizer()
def clean(doc):
    stop_free=" ".join([i for i in doc.lower().split() if i not in stop])
    punc_free=''.join(ch for ch in stop_free if ch not in exclude)
    normalized=" ".join(lemma.lemmatize(word) for word in punc_free.split())
    return normalized
```

[136]:
```
import pandas as pd
df = pd.read_csv('Polarity2014Reduced.csv', sep = ";", header = 0)
df.columns=['review','sentiment']
df2=df[df['sentiment']==-1]
df2.shape
```

[136]: (354, 2)

[137]:
```
doc_complete=df2.iloc[0:2065,0].values.tolist()
doc_clean=[clean(doc).split() for doc in doc_complete]
```

8 Getting the document-term matrix

[138]:
```
from sklearn.feature_extraction.text import CountVectorizer
import numpy as np
SOME_FIXED_SEED = 42
np.random.seed(SOME_FIXED_SEED)
```

[139]:
```
cv=CountVectorizer(min_df=2,max_df=50,ngram_range=(1,2), token_pattern=None,␣
 ↪tokenizer=lambda doc:doc,preprocessor=lambda doc:doc)
```

[140]:
```
cv_features=cv.fit_transform(doc_clean)
print(cv_features.shape)
vocabulary=np.array(cv.get_feature_names())
```

```
(354, 1392)
```

[141]:
```
vocabulary
```

[141]:
```
array(['1', '1 volta', '10', …, '√® stato', '√® troppo', '√® un'],
      dtype='<U24')
```

[142]:
```
vocabulary
```

[142]:
```
array(['1', '1 volta', '10', …, '√® stato', '√® troppo', '√® un'],
      dtype='<U24')
```

9 LDA ANALYSIS

[143]:
```
# Using sklearn.decomposition LDA with 11 topics
from sklearn.decomposition import LatentDirichletAllocation
TOTAL_TOPICS=11
```

[144]:
```
lda_model=LatentDirichletAllocation(n_components=TOTAL_TOPICS,max_iter=500,max_doc_update_iter
 ↪,random_state=42,n_jobs=16)
```

[145]:
```
# Using the transformer 'fit_transform'
document_topics=lda_model.fit_transform(cv_features)
```

[146]:
```
document_topics.shape
```

[146]: (354, 11)

[145]:
```
# Extraqcting the most important 10 terms for each topic
topic_terms=lda_model.components_
top_terms=10 # number of 'top terms'
topic_key_terms_idxs=np.argsort(-np.absolute(topic_terms), axis=1)[:,:top_terms]
topic_keyterms=vocabulary[topic_key_terms_idxs]
topics=[', '.join(topic) for topic in topic_keyterms]
pd.set_option('display.max_colwidth',-1)
topics_df=pd.DataFrame(topics,columns=['Term per Topic'], index=['Topic'+str(t)␣
 ↪for t in range(1,TOTAL_TOPICS+1)])
topics_df
```

```
<ipython-input-145-515db2202b96>:7: FutureWarning: Passing a negative integer is
deprecated in version 1.0 and will not be supported in future version. Instead,
use None to not limit the column width.
  pd.set_option('display.max_colwidth',-1)
```

[145]:

```
                                 Term per Topic
Topic1   della, completamente, servizio, la bici, possibilit√†, possibilit√† di,
tramite, segnalare, app, troppo
Topic2   servizio, bicicletta, lasciare, la bicicletta, cambio, stalli, se, le
stazioni, lasciare la, la bici
Topic3   piene, con, sempre, al, vuote, molto, tutte, alcune, le colonnine,
colonnine
Topic4   mi, da, mi √®, servizio, stazione, la bici, se, √® capitato, capitato,
bikemi
Topic5   con, tempo, migliorare, al, ecc, cambio, sistema, delle bici,
migliorare il, anche
Topic6   essere, con, le bici, frequenza, essere pi√ , manutenzione, bike, bici
con, bici sono, troppo
Topic7   pi√  spesso, al, gomme, spesso le, della, cambio, le bici, del,
gonfiare, controllare
Topic8   possibilit√† di, possibilit√†, segnalare, della, di segnalare, che non,
dei, controllare pi√ , delle biciclette, al
Topic9   troppo, piste, piste ciclabili, ciclabili, cambio, con, problemi,
ruote, manutenzione, sgonfie
Topic10  anche, le stazioni, stazione, molto, piene, servizio, tempo, del, da,
cambio
Topic11  stalli, gli, centro, gli stalli, ci, nelle, di punta, punta, aumentare,
le bici
```

[146]:
```
dt_df=pd.DataFrame(document_topics,columns=['T'+str(i) for i in␣
 ↪range(1,TOTAL_TOPICS+1)])
dt_df
```

[146]:
```
           T1        T2        T3        T4        T5        T6        T7  \
0    0.005348  0.005348  0.005348  0.005348  0.005348  0.005348  0.005348
1    0.009091  0.909084  0.009091  0.009091  0.009091  0.009091  0.009092
2    0.002841  0.971589  0.002841  0.002841  0.002841  0.002841  0.002841
3    0.015152  0.015153  0.015154  0.848456  0.015152  0.015160  0.015157
4    0.001567  0.001567  0.984325  0.001567  0.001567  0.001567  0.001567
..        …         …         …         …         …         …         …
349  0.003637  0.003637  0.003636  0.003637  0.003636  0.003637  0.003637
350  0.010101  0.010102  0.010102  0.898987  0.010101  0.010101  0.010102
351  0.018183  0.018182  0.018182  0.018182  0.018183  0.018182  0.018183
352  0.002392  0.002393  0.002393  0.002392  0.002392  0.002392  0.002392
353  0.011365  0.011364  0.011364  0.011364  0.886355  0.011365  0.011365

           T8        T9       T10       T11
0    0.005348  0.946523  0.005348  0.005348
1    0.009092  0.009093  0.009091  0.009091
2    0.002841  0.002841  0.002841  0.002841
3    0.015152  0.015156  0.015152  0.015157
4    0.001567  0.001568  0.001567  0.001568
..        …         …         …         …
349  0.003637  0.433846  0.003637  0.533425
350  0.010101  0.010101  0.010101  0.010101
351  0.818175  0.018182  0.018182  0.018182
352  0.002392  0.002393  0.976075  0.002392
353  0.011365  0.011364  0.011364  0.011364

[354 rows x 11 columns]
```

[147]:
```python
# Column 'Contribution%' gives the max probability among the 354
# features (terms) for each topic
dt_df=pd.DataFrame(document_topics,columns=['T'+str(i) for i in␣
↪range(1,TOTAL_TOPICS+1)])
pd.options.display.float_format='{:,.5f}'.format
pd.set_option('display.max_colwidth',200)
max_contrib_topics=dt_df.max(axis=0)
dominant_topics=max_contrib_topics.index
contrib_perc=max_contrib_topics.values
document_numbers=[dt_df[dt_df[t]==max_contrib_topics.loc[t]].index[0] for t in␣
↪dominant_topics]
results_df=pd.DataFrame({'Dominant Topic':dominant_topics,'Contribution%':
↪contrib_perc, 'Answer Num': document_numbers,'Topic':topics_df['Term per␣
↪Topic']})
results_df
```

[147]:
```
       Dominant Topic  Contribution%  Answer Num  \
Topic1             T1        0.97159         193
Topic2             T2        0.99209         179
```

```
Topic3              T3        0.98510        52
Topic4              T4        0.98978       328
Topic5              T5        0.99072        28
Topic6              T6        0.96503       126
Topic7              T7        0.98557       342
Topic8              T8        0.96503       174
Topic9              T9        0.98943       294
Topic10            T10        0.98864       198
Topic11            T11        0.99126       114

                                       Topic
Topic1               della, completamente, servizio, la bici, possibilit√†,
possibilit√† di, tramite, segnalare, app, troppo
Topic2                  servizio, bicicletta, lasciare, la bicicletta, cambio,
stalli, se, le stazioni, lasciare la, la bici
Topic3                                          piene, con, sempre, al, vuote,
molto, tutte, alcune, le colonnine, colonnine
Topic4                                         mi, da, mi √®, servizio,
stazione, la bici, se, √® capitato, capitato, bikemi
Topic5                                   con, tempo, migliorare, al, ecc,
cambio, sistema, delle bici, migliorare il, anche
Topic6                          essere, con, le bici, frequenza, essere pi√ ,
manutenzione, bike, bici con, bici sono, troppo
Topic7                                pi√  spesso, al, gomme, spesso le, della,
cambio, le bici, del, gonfiare, controllare
Topic8   possibilit√† di, possibilit√†, segnalare, della, di segnalare, che non,
dei, controllare pi√ , delle biciclette, al
Topic9                         troppo, piste, piste ciclabili, ciclabili, cambio,
con, problemi, ruote, manutenzione, sgonfie
Topic10                                         anche, le stazioni, stazione,
molto, piene, servizio, tempo, del, da, cambio
Topic11                                      stalli, gli, centro, gli stalli,
ci, nelle, di punta, punta, aumentare, le bici
```

[148]:

```python
# This gives, for each topic, the % of features having prob >0.9
numT1=np.count_nonzero(dt_df['T1']>0.9)
FrT1=numT1/2133
numT2=np.count_nonzero(dt_df['T2']>0.9)
FrT2=numT2/2133
numT3=np.count_nonzero(dt_df['T3']>0.9)
FrT3=numT3/2133
numT4=np.count_nonzero(dt_df['T4']>0.9)
FrT4=numT4/2133
numT5=np.count_nonzero(dt_df['T5']>0.9)
FrT5=numT5/2133
numT6=np.count_nonzero(dt_df['T6']>0.9)
FrT6=numT6/2133
```

```
numT7=np.count_nonzero(dt_df['T7']>0.9)
FrT7=numT7/2133
numT8=np.count_nonzero(dt_df['T8']>0.9)
FrT8=numT8/2133
numT9=np.count_nonzero(dt_df['T9']>0.9)
FrT9=numT9/2133
numT10=np.count_nonzero(dt_df['T10']>0.9)
FrT10=numT10/2133
numT11=np.count_nonzero(dt_df['T11']>0.9)
FrT11=numT11/2133
d=(FrT1,FrT2,FrT3,FrT4,FrT5,FrT6,FrT7,FrT8,FrT9,FrT10,FrT11)
df_Fr=pd.DataFrame(data=d)
results_df.insert(4,'Freq 0.9-1',df_Fr.values)
results_df
```

[148]:

```
        Dominant Topic  Contribution%  Answer Num  \
Topic1              T1        0.97159         193
Topic2              T2        0.99209         179
Topic3              T3        0.98510          52
Topic4              T4        0.98978         328
Topic5              T5        0.99072          28
Topic6              T6        0.96503         126
Topic7              T7        0.98557         342
Topic8              T8        0.96503         174
Topic9              T9        0.98943         294
Topic10            T10        0.98864         198
Topic11            T11        0.99126         114

                                               Topic  \
Topic1               della, completamente, servizio, la bici, possibilit√†,
possibilit√† di, tramite, segnalare, app, troppo
Topic2                  servizio, bicicletta, lasciare, la bicicletta, cambio,
stalli, se, le stazioni, lasciare la, la bici
Topic3                                          piene, con, sempre, al, vuote,
molto, tutte, alcune, le colonnine, colonnine
Topic4                                         mi, da, mi √®, servizio,
stazione, la bici, se, √® capitato, capitato, bikemi
Topic5                                    con, tempo, migliorare, al, ecc,
cambio, sistema, delle bici, migliorare il, anche
Topic6                        essere, con, le bici, frequenza, essere pi√ ,
manutenzione, bike, bici con, bici sono, troppo
Topic7                                 pi√  spesso, al, gomme, spesso le, della,
cambio, le bici, del, gonfiare, controllare
Topic8   possibilit√† di, possibilit√†, segnalare, della, di segnalare, che non,
dei, controllare pi√ , delle biciclette, al
Topic9                        troppo, piste, piste ciclabili, ciclabili, cambio,
con, problemi, ruote, manutenzione, sgonfie
```

```
Topic10                                         anche, le stazioni, stazione,
molto, piene, servizio, tempo, del, da, cambio
Topic11                                      stalli, gli, centro, gli stalli,
ci, nelle, di punta, punta, aumentare, le bici

         Freq 0.9-1
Topic1      0.00516
Topic2      0.01547
Topic3      0.01172
Topic4      0.00891
Topic5      0.00609
Topic6      0.00469
Topic7      0.00797
Topic8      0.00797
Topic9      0.02391
Topic10     0.00656
Topic11     0.01828
```

[1]:

```
#This is to let you have larger fonts...
from IPython.core.display import HTML
HTML("""
<style>

div.cell { /* Tunes the space between cells */
margin-top:1em;
margin-bottom:1em;
}

div.text_cell_render h1 { /* Main titles bigger, centered */
font-size: 2.2em;
line-height:1.4em;
text-align:center;
}

div.text_cell_render h2 { /*  Parts names nearer from text */
margin-bottom: -0.4em;
}


div.text_cell_render { /* Customize text cells */
font-family: 'Times New Roman';
font-size:1.5em;
line-height:1.4em;
padding-left:3em;
padding-right:3em;
}
</style>
```

```
""")
```

[1]: <IPython.core.display.HTML object>

```
[ ]:
```