pandas puzzles

short puzzles for testing your knowledge of pandas' power.

Since pandas is a large library with many different specialist features and functions, these excercises focus mainly on the fundamentals of manipulating data (indexing, grouping, aggregating, cleaning), making use of the core DataFrame and Series objects.

Many of the excerises here are stright-forward in that the solutions require no more than a few lines of code (in pandas or NumPy... don't go using pure Python or Cython!). Choosing the right methods and following best practices is the underlying goal.

The exercises are loosely divided in sections. Each section has a difficulty rating; these ratings are subjective, of course, but should be a seen as a rough guide as to how inventive the required solution is.

If you're just starting out with pandas and you are looking for some other resources, the official documentation is very extensive. In particular, some good places get a broader overview of pandas are...

- 10 minutes to pandas
- pandas basics
- tutorials
- cookbook and idioms

Enjoy the puzzles!

New Section

Importing pandas

Getting started and checking your pandas setup

Difficulty: easy

1. Import pandas under the alias pd.

```
import pandas as pd #1min
```

2. Print the version of pandas that has been imported.

```
print (pd.__version__) #3min
1.3.5
```

3. Print out all the *version* information of the libraries that are required by the pandas library.

INSTALLED VERSIONS

python-bits : 64 0S : Linux 0S-release : 5.4.188+ Version : #1 SMP Sun Apr 24 10:03:06 PDT 2022 machine : *26.64

machine : x86_64
processor : x86_64
byteorder : little
LC_ALL : None
LANG

: en_US.UTF-8 : en_US.UTF-8 LOCALE

: 1.3.5 : 1.21.6 pandas numpy : 2022.1 pytz dateutil : 2.8.2 pip : 21.1.3 setuptools : 57.4.0 Cython : 0.29.30 Cython : 3.6.4 pytest hypothesis : None sphinx : 1.8.6 : None blosc feather feather : 0.4.1 xlsxwriter : None lxml.etree : 4.2.6 html5lib : 1.0.1

pymysql

psycopg2

: None : 2.7.6.1 (dt dec pq3 ext lo64) : 2.11.3 jinja2 : 5.5.0 IPython pandas datareader: 0.9.0 bs4 : 4.6.3 bottleneck : 1.3.4 : None fsspec fastparquet : None : None gcsfs matplotlib : 3.2.2 numexpr : 2.8.1 odfpy : None : 3.0.10 : 0.13.3 openpyxl pandas_gbq : 6.0.1 pyarrow

: None

pyxlsb

```
s3fs
                : None
scipy
                : 1.4.1
sqlalchemy
               : 1.4.36
tables
                : 3.7.0
tabulate
                : 0.8.9
xarray
                : 0.20.2
                : 1.1.0
xlrd
xlwt
                : 1.3.0
numba
                : 0.51.2
```

DataFrame basics

A few of the fundamental routines for selecting, sorting, adding and aggregating data in DataFrames

Difficulty: easy

Note: remember to import numpy using:

```
import numpy as np
```

Consider the following Python dictionary data and Python list labels:

(This is just some meaningless data I made up with the theme of animals and trips to a vet.)

4. Create a DataFrame df from this dictionary data which has the index labels.

```
import numpy as np
```

5. Display a summary of the basic information about this DataFrame and its data (*hint:* there is a single method that can be called on the DataFrame).

```
df.info() # 3min
<class 'pandas.core.frame.DataFrame'>
Index: 10 entries, a to j
Data columns (total 4 columns):
     Column
                Non-Null Count
                                 Dtype
- - -
     _ _ _ _ _
                _____
                                 _ _ _ _
 0
     animal
                10 non-null
                                 object
                8 non-null
 1
     age
                                 float64
 2
     visits
                10 non-null
                                 int64
 3
     priority 10 non-null
                                 object
dtypes: float64(1), int64(1), object(2)
memory usage: 400.0+ bytes
6. Return the first 3 rows of the DataFrame df.
df.head(3) #1min
  animal
               visits priority
         age
          2.5
     cat
                     1
а
                             ves
b
     cat
         3.0
                     3
                             yes
                     2
   snake
         0.5
                              no
7. Select just the 'animal' and 'age' columns from the DataFrame df.
df sel cols=df[['animal', 'age']]
print (df_sel_cols) #2min
  animal
          age
          2.5
а
     cat
     cat
          3.0
b
         0.5
С
   snake
d
     dog
          NaN
     dog
          5.0
е
f
          2.0
     cat
   snake
         4.5
g
h
     cat
         NaN
i
     dog 7.0
j
     dog 3.0
8. Select the data in rows [3, 4, 8] and in columns ['animal', 'age'].
df sel rows1 = df sel cols.iloc[[3, 4, 8]]
print (df_sel_rows1) #3min
  animal
          age
          NaN
     dog
d
     dog
          5.0
е
     dog
          7.0
```

9. Select only the rows where the number of visits is greater than 3.

```
crit1=df['visits']>=3
df sel rows2 = df[crit1]
print (df_sel_rows2) #20min
  animal
           age visits priority
b
     cat
           3.0
                      3
                              yes
                      3
d
     dog
           NaN
                              yes
                      3
f
     cat
           2.0
                               no
10. Select the rows where the age is missing, i.e. it is NaN.
crit2 = df['age'].isnull()
df sel rows3 = df[crit2]
print (df sel rows3) #10min
  animal
           age visits priority
d
     dog
           NaN
                      3
                              yes
                      1
h
     cat
           NaN
                              yes
11. Select the rows where the animal is a cat and the age is less than 3.
crit4 = (df['animal']=='cat') & (df['age']<3)</pre>
df sel rows4 = df[crit4]
print (df_sel_rows4) #5min
  animal
           age visits priority
           2.5
     cat
                      1
а
                              yes
f
     cat
           2.0
                      3
                               no
12. Select the rows the age is between 2 and 4 (inclusive).
crit5 = (df['age'] >=2) & (df['age'] <=4)</pre>
df sel rows5 = df[crit5]
print (df sel rows5)
                        #5min
           age visits priority
  animal
           2.5
                      1
а
     cat
                              yes
                      3
b
     cat
           3.0
                              yes
f
                      3
     cat
           2.0
                               no
           3.0
                      1
i
     dog
                               no
13. Change the age in row 'f' to 1.5.
df['age'].loc['f'] = 1.5
print (df) #10min
  animal
           age
               visits priority
а
     cat
           2.5
                      1
                              yes
                      3
           3.0
b
     cat
                              yes
                      2
   snake
           0.5
C
                               no
d
           NaN
                      3
     dog
                              ves
                      2
     dog
           5.0
е
                               no
f
     cat
           1.5
                      3
                               no
```

```
snake 4.5
                     1
                              no
g
h
                     1
     cat NaN
                             yes
i
     dog 7.0
                     2
                              no
     dog 3.0
                     1
i
                              no
/usr/local/lib/python3.7/dist-packages/pandas/core/indexing.py:1732:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  self. setitem single block(indexer, value, name)
14. Calculate the sum of all visits in df (i.e. find the total number of visits).
sum visits = df['visits'].sum()
print (sum visits) #2min
19
15. Calculate the mean age for each different animal in df.
df grouped=df.groupby(['animal'])['age'].agg('mean')
print (df grouped) #10min
animal
cat
         2.333333
dog
         5.000000
         2,500000
snake
Name: age, dtype: float64
16. Append a new row 'k' to df with your choice of values for each column. Then delete
that row to return the original DataFrame.
new_row = ['goat', 1.5, 2, 'yes']
df.loc['k'] = new row
#print(df)
df=df.drop(['k'])
print(df) #20min
  animal
         age visits priority
          2.5
                     1
а
     cat
                             yes
b
     cat
         3.0
                     3
                             ves
   snake 0.5
                     2
С
                              no
                     3
d
     dog
          NaN
                             yes
                     2
e
     dog
          5.0
                              no
                     3
f
     cat 1.5
                              no
                     1
   snake 4.5
g
                              no
                     1
h
     cat
         NaN
                             yes
```

2

1

no

no

i

i

dog 7.0

dog 3.0

17. Count the number of each type of animal in df.

```
df_grouped1 = df.groupby(['animal'])['animal'].agg('count')
print (df_grouped1) #5min

animal
cat    4
dog    4
snake    2
Name: animal, dtype: int64
```

18. Sort df first by the values in the 'age' in *decending* order, then by the value in the 'visits' column in *ascending* order (so row i should be first, and row d should be last).

```
df_sorted = df.sort_values(['age', 'visits'], ascending=[False, True])
print (df_sorted) #5min
```

```
animal
          age visits priority
i
     dog
          7.0
                      2
                               no
                      2
     dog
           5.0
е
                               no
   snake 4.5
                      1
                               no
g
     dog
          3.0
                      1
j
                               no
b
           3.0
                      3
     cat
                              yes
                      1
     cat 2.5
а
                              yes
f
          1.5
                      3
     cat
                               no
                      2
С
   snake 0.5
                               no
                      1
h
     cat
          NaN
                              yes
                      3
d
     dog
          NaN
                              yes
```

19. The 'priority' column contains the values 'yes' and 'no'. Replace this column with a column of boolean values: 'yes' should be True and 'no' should be False.

```
df['priority'] = df['priority'].replace(['yes', 'no'], ['True',
'False'])
print (df) #20min
          age visits priority
  animal
     cat
          2.5
                     1
                           True
а
     cat
                     3
          3.0
                           True
b
                     2
С
   snake 0.5
                          False
d
     dog
          NaN
                     3
                           True
                     2
          5.0
                          False
е
     doa
                     3
f
     cat
          1.5
                          False
                     1
                          False
g
   snake
         4.5
h
     cat
          NaN
                     1
                           True
                     2
                          False
i
     dog
          7.0
                     1
                          False
i
     dog 3.0
```

20. In the 'animal' column, change the 'snake' entries to 'python'.

```
df['animal'] = df['animal'].replace('snake', 'python')
print(df) #10min
```

```
visits priority
   animal
            age
            2.5
                              True
      cat
                       1
а
                       3
b
      cat
            3.0
                              True
                       2
            0.5
                             False
С
   python
                       3
d
      dog
            NaN
                              True
                       2
е
      dog
            5.0
                             False
                       3
f
            1.5
                            False
      cat
            4.5
                       1
                             False
g
   python
h
            NaN
                       1
                             True
      cat
i
            7.0
                       2
                             False
      dog
            3.0
                       1
                             False
j
      dog
```

21. For each animal type and each number of visits, find the mean age. In other words, each row is an animal, each column is a number of visits and the values are the mean ages (*hint: use a pivot table*).

DataFrames: beyond the basics

Slightly trickier: you may need to combine two or more methods to get the right answer

Difficulty: medium

The previous section was tour through some basic but essential DataFrame operations. Below are some ways that you might need to cut your data, but for which there is no single "out of the box" method.

22. You have a DataFrame df with a column 'A' of integers. For example:

```
df = pd.DataFrame(\{'A': [1, 2, 2, 3, 4, 5, 5, 5, 6, 7, 7]\})
```

How do you filter out rows which contain the same integer as the row immediately above?

You should be left with a column containing the following values:

```
3
4
  4
5
  5
8
  6
9
  7
23. Given a DataFrame of numeric values, say
df = pd.DataFrame(np.random.random(size=(5, 3))) # a 5x3 frame of
float values
how do you subtract the row mean from each element in the row?
df = pd.DataFrame(np.random.random(size=(5, 3)))
df sub = df.sub(df.mean(axis=1), axis=0)
print (df sub) #20min
                                2
0 -0.025186 -0.000606 0.025792
```

24. Suppose you have DataFrame with 10 columns of real numbers, for example:

```
df = pd.DataFrame(np.random.random(size=(5, 10)),
columns=list('abcdefghij'))
```

Which column of numbers has the smallest sum? Return that column's label.

```
df = pd.DataFrame(np.random.random(size=(5, 10)),
columns=list('abcdefghij'))
col_label = df.sum().idxmin()
print (col_label) #2min
d
```

25. How do you count how many unique rows a DataFrame has (i.e. ignore all rows that are duplicates)? As input, use a DataFrame of zeros and ones with 10 rows and 3 columns.

```
df = pd.DataFrame(np.random.randint(0, 2, size=(10, 3)))
df = pd.DataFrame(np.random.randint(0, 2, size=(10, 3)))
unique_rows = len(df) - df.duplicated(keep = False).sum()
print(unique_rows) #10min
```

The next three puzzles are slightly harder.

1 0.399801 -0.043536 -0.356265 2 0.204901 -0.020128 -0.184774 3 -0.204229 0.192870 0.011359 4 -0.569243 0.339169 0.230074

26. In the cell below, you have a DataFrame df that consists of 10 columns of floating-point numbers. Exactly 5 entries in each row are NaN values.

For each row of the DataFrame, find the column which contains the third NaN value.

You should return a Series of column labels: e, c, d, h, d

```
nan = np.nan
data = [[0.04,
                nan,
                       nan, 0.25, nan, 0.43, 0.71, 0.51,
                nan, nan, 0.04, 0.76, nan,
                                                nan, 0.67, 0.76, 0.16],
        [ nan,
        [ nan,
                nan, 0.5, nan, 0.31, 0.4, nan, nan, 0.24, 0.01],
                nan, nan, 0.62, 0.73, 0.26, 0.85, nan,
        [0.49.
                                                             nan,
                                                                   nanl.
        [ nan,
                nan, 0.41, nan, 0.05, nan, 0.61, nan, 0.48, 0.68]]
columns = list('abcdefghij')
df = pd.DataFrame(data, columns=columns)
# write a solution to the question here
df thirdNaN=(df.isnull().cumsum(axis=1) == 3).idxmax(axis=1)
print (df thirdNaN) #15min
     е
1
     C
2
     d
3
     h
4
     d
dtype: object
27. A DataFrame has a column of groups 'grps' and and column of integer values 'vals':
df = pd.DataFrame({'grps': list('aaabbcaabcccbbc'),
                    'vals':
[12,345,3,1,45,14,4,52,54,23,235,21,57,3,87]})
For each group, find the sum of the three greatest values. You should end up with the
answer as follows:
grps
     409
     156
     345
```

```
b 156 c 345 Name: vals, dtype: int64 /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: FutureWarning: Using the level keyword in DataFrame and Series aggregations is deprecated and will be removed in a future version. Use groupby instead. df.sum(level=1) should use df.groupby(level=1).sum().
```

28. The DataFrame df constructed below has two integer columns 'A' and 'B'. The values in 'A' are between 1 and 100 (inclusive).

For each group of 10 consecutive integers in 'A' (i.e. (0, 10], (10, 20], ...), calculate the sum of the corresponding values in column 'B'.

The answer should be a Series as follows:

```
(0, 10]
              635
(10, 201)
              360
(20, 30]
              315
(30, 40]
              306
(40, 50]
              750
(50, 60]
              284
(60, 70]
              424
(70, 80]
              526
(80, 90]
              835
(90, 100]
              852
df = pd.DataFrame(np.random.RandomState(8765).randint(1, 101,
size=(100, 2)), columns = ["A", "B"])
# write a solution to the question here
df = df.groupby(pd.cut(df['A'], np.arange(0, 101, 10)))['B'].sum()
print(df) #20min
Α
(0, 10]
              635
(10, 20]
              360
(20, 30]
             315
(30, 401)
              306
(40, 50]
              750
(50, 60]
              284
(60, 70]
              424
(70, 80]
              526
(80, 90]
             835
(90, 100]
              852
Name: B, dtype: int64
```

DataFrames: harder problems

These might require a bit of thinking outside the box...

...but all are solvable using just the usual pandas/NumPy methods (and so avoid using explicit for loops).

Difficulty: *hard*

29. Consider a DataFrame df where there is an integer column 'X':

```
df = pd.DataFrame(\{'X': [7, 2, 0, 3, 4, 2, 5, 0, 3, 4]\})
```

For each value, count the difference back to the previous zero (or the start of the Series, whichever is closer). These values should therefore be

```
[1, 2, 0, 1, 2, 3, 4, 0, 1, 2]
```

Make this a new column 'Y'.

 $\frac{7}{7}$

1 2 2 2 0 0

3 3 1

4 4 2

5 2 3 6 5 4

7 0 0

8 3 1

0 1 2

30. Consider the DataFrame constructed below which contains rows and columns of numerical data.

Create a list of the column-row index locations of the 3 largest values in this DataFrame. In this case, the answer should be:

31. You are given the DataFrame below with a column of group IDs, 'grps', and a column of corresponding integer values, 'vals'.

Create a new column 'patched_values' which contains the same values as the 'vals' any negative values in 'vals' with the group mean:

| | vals | grps | <pre>patched_vals</pre> |
|----|------|------|-------------------------|
| 0 | - 12 | Α | 13.6 |
| 1 | -7 | В | 28.0 |
| 2 | - 14 | Α | 13.6 |
| 3 | 4 | Α | 4.0 |
| 4 | -7 | Α | 13.6 |
| 5 | 28 | В | 28.0 |
| 6 | -2 | Α | 13.6 |
| 7 | -1 | Α | 13.6 |
| 8 | 8 | Α | 8.0 |
| 9 | -2 | В | 28.0 |
| 10 | 28 | Α | 28.0 |
| 11 | 12 | Α | 12.0 |
| 12 | 16 | Α | 16.0 |
| 13 | - 24 | Α | 13.6 |
| 14 | -12 | Α | 13.6 |

32. Implement a rolling mean over groups with window size 3, which ignores NaN value. For example consider the following DataFrame:

```
>>> df = pd.DataFrame({'group': list('aabbabbbabab'),
                         'value': [1, 2, 3, np.nan, 2, 3, np.nan, 1, 7,
3, np.nan, 8]})
>>> df
   group value
0
             1.0
       а
1
       а
            2.0
2
            3.0
       b
3
       b
            NaN
4
            2.0
       a
5
            3.0
       b
6
            NaN
       b
7
            1.0
       b
8
       a
            7.0
9
       b
            3.0
10
       а
            NaN
11
       b
            8.0
```

The goal is to compute the Series:

```
1.000000
0
1
      1.500000
2
      3.000000
3
      3.000000
4
      1.666667
5
      3.000000
6
      3.000000
7
      2.000000
8
      3.666667
9
      2,000000
10
      4.500000
11
      4.000000
```

E.g. the first window of size three for group 'b' has values 3.0, NaN and 3.0 and occurs at row index 5. Instead of being NaN the value in the new column at this row index should be 3.0 (just the two non-NaN values are used to compute the mean (3+3)/2)

Series and DatetimeIndex

Exercises for creating and manipulating Series with datetime data

Difficulty: easy/medium

pandas is fantastic for working with dates and times. These puzzles explore some of this functionality.

33. Create a DatetimeIndex that contains each business day of 2015 and use it to index a Series of random numbers. Let's call this Series s.

```
dti = pd.date range(start='2015-01-01', end='2015-12-31', freq='B')
s = pd.Series(np.random.rand(len(dti)), index=dti)
print(s) #15min
2015-01-01
              0.409074
2015-01-02
              0.978121
2015-01-05
              0.566613
2015-01-06
              0.058111
2015-01-07
              0.512211
              0.576461
2015 - 12 - 25
2015-12-28
              0.224682
2015-12-29
              0.430470
2015-12-30
              0.946864
2015-12-31
              0.457968
Freq: B, Length: 261, dtype: float64
```

34. Find the sum of the values in **s** for every Wednesday.

```
sum = s[s.index.weekday == 2].sum()
print(sum) #5min
```

35. For each calendar month in **s**, find the mean of values.

```
mean vals = s.resample('M').mean()
print(mean vals) #5min
              0.559769
2015-01-31
2015-02-28
              0.472341
2015-03-31
              0.538845
2015-04-30
              0.506323
2015-05-31
              0.489136
2015-06-30
              0.414893
2015-07-31
              0.473189
2015-08-31
              0.511495
2015-09-30
              0.507998
2015-10-31
              0.562078
2015-11-30
              0.531517
2015-12-31
              0.547604
Freq: M, dtype: float64
```

36. For each group of four consecutive calendar months in s, find the date on which the highest value occurred.

```
mean val = s.resample('M').mean()
print(mean val) #5min
2015-01-31
              0.559769
2015-02-28
              0.472341
2015-03-31
              0.538845
2015-04-30
              0.506323
2015-05-31
              0.489136
2015-06-30
              0.414893
2015-07-31
              0.473189
2015-08-31
              0.511495
2015-09-30
              0.507998
2015-10-31
              0.562078
2015 - 11 - 30
              0.531517
2015-12-31
              0.547604
Freq: M, dtype: float64
```

37. Create a DateTimeIndex consisting of the third Thursday in each month for the years 2015 and 2016.

```
idx = pd.date_range('2015-01-01', '2016-12-31', freq='WOM-3THU')
print(idx) #10min
DatetimeIndex(['2015-01-15',
                              '2015-02-19',
                                             '2015-03-19',
                                                            '2015-04-16',
                2015-05-21',
                                             '2015-07-16',
                              '2015-06-18',
                                                            '2015-08-20'
                                             '2015-11-19',
                              '2015-10-15',
                '2015-09-17',
                                                            '2015-12-17'
                              '2016-02-18',
                                             '2016-03-17',
                '2016-01-21',
                                                            '2016-04-21'
                '2016-05-19', '2016-06-16', '2016-07-21', '2016-08-18',
```

```
\label{eq:condition} $$ $ '2016-09-15', '2016-10-20', '2016-11-17', '2016-12-15'], $$ $ $ dtype='datetime64[ns]', freq='WOM-3THU') $$
```

Cleaning Data

Making a DataFrame easier to work with

Difficulty: easy/medium

It happens all the time: someone gives you data containing malformed strings, Python, lists and missing data. How do you tidy it up so you can get on with the analysis?

Take this monstrosity as the DataFrame to use in the following puzzles:

Formatted, it looks like this:

```
From To
                      FlightNumber
                                    RecentDelays
                                                                Airline
       LoNDon_paris
0
                           10045.0
                                         [23, 47]
                                                                 KLM(!)
1
       MAdrid miLAN
                                                     <Air France> (12)
                               NaN
                                               []
2
   londON StockhOlm
                           10065.0
                                     [24, 43, 87]
                                                   (British Airways. )
3
     Budapest PaRis
                                             [13]
                                                        12. Air France
                               NaN
4
    Brussels_londOn
                           10085.0
                                         [67, 32]
                                                            "Swiss Air"
```

(It's some flight data I made up; it's not meant to be accurate in any way.)

38. Some values in the **FlightNumber** column are missing (they are NaN). These numbers are meant to increase by 10 with each row so 10055 and 10075 need to be put in place. Modify df to fill in these missing numbers and make the column an integer column (instead of a float column).

```
df['FlightNumber'] = df['FlightNumber'].interpolate().astype(int)
print(df['FlightNumber']) #15min

0    10045
1    10055
2    10065
3    10075
4    10085
Name: FlightNumber, dtype: int64
```

39. The **From_To** column would be better as two separate columns! Split each string on the underscore delimiter _ to give a new temporary DataFrame called 'temp' with the correct values. Assign the correct column names 'From' and 'To' to this temporary DataFrame.

```
temp = df.From To.str.split('_', expand=True)
temp.columns = ['From', 'To']
print(temp)
              #5min
       From
                    To
0
     LoNDon
                 paris
1
     MAdrid
                 miLAN
2
     londON StockhOlm
3
  Budapest
                 PaRis
  Brussels
                lond0n
```

40. Notice how the capitalisation of the city names is all mixed up in this temporary DataFrame 'temp'. Standardise the strings so that only the first letter is uppercase (e.g. "londON" should become "London".)

```
temp['From'] = temp['From'].str.capitalize()
temp['To'] = temp['To'].str.capitalize()
print(temp)
              #5min
       From
                    Tο
     London
                 Paris
0
1
     Madrid
                 Milan
2
     London Stockholm
3
  Budapest
                 Paris
  Brussels
                London
```

41. Delete the **From_To** column from df and attach the temporary DataFrame 'temp' from the previous questions.

```
df = df.drop('From To', axis=1)
df = df.join(temp)
print(df)
             #5min
   FlightNumber
                 RecentDelays
                                           Airline
                                                         From
To
          10045
                     [23, 47]
                                                       London
                                            KLM(!)
Paris
          10055
                           []
                                 <Air France> (12)
                                                       Madrid
```

```
Milan
          10065
                 [24, 43, 87]
                               (British Airways.)
                                                       London
2
Stockholm
          10075
                         [13]
                                    12. Air France Budapest
Paris
                                        "Swiss Air"
          10085
                     [67, 32]
                                                     Brussels
London
```

42. In the **Airline** column, you can see some extra puctuation and symbols have appeared around the airline names. Pull out just the airline name. E.g. '(British Airways.)' should become 'British Airways'.

43. In the RecentDelays column, the values have been entered into the DataFrame as a list. We would like each first value in its own column, each second value in its own column, and so on. If there isn't an Nth value, the value should be NaN.

Expand the Series of lists into a DataFrame named delays, rename the columns delay_1, delay_2, etc. and replace the unwanted RecentDelays column in df with delays.

```
delays = df['RecentDelays'].apply(pd.Series)
delays.columns = ['delay_{}'.format(n) for n in range(1,
len(delays.columns)+1)]
df = df.drop('RecentDelays', axis=1).join(delays)
print(df) #30min
```

| Fligh | tNumber | Airline | From | To | delay_1 | |
|----------------------|---------|-----------------|----------|-----------|---------|--|
| delay_2 0 47.0 | 10045 | KLM | London | Paris | 23.0 | |
| 1 | 10055 | Air France | Madrid | Milan | NaN | |
| NaN 2 43.0 | 10065 | British Airways | London | Stockholm | 24.0 | |
| 3 | 10075 | Air France | Budapest | Paris | 13.0 | |
| NaN 4 32.0 | 10085 | Swiss Air | Brussels | London | 67.0 | |

```
delay_3
0 NaN
```

```
1 NaN
2 87.0
3 NaN
4 NaN
```

The DataFrame should look much better now.

| FlightNumber | | Airline | From | To | delay_1 | |
|--------------|------------------|-----------------|----------|-----------|---------|--|
| delay_2 0 | delay_3 10045 | KLM | London | Paris | 23.0 | |
| 47.0 | NaN | KLIT | London | F 01 13 | 23.0 | |
| 1 | 10055 | Air France | Madrid | Milan | NaN | |
| NaN | NaN | | | | | |
| 2 | 10065 | British Airways | London | Stockholm | 24.0 | |
| 43.0 | 87.0 | | | | | |
| 3 | 10075 | Air France | Budapest | Paris | 13.0 | |
| NaN | NaN | | | | | |
| 4 | 10085 | Swiss Air | Brussels | London | 67.0 | |
| 32.0 | NaN | | | | | |

Using MultiIndexes

Go beyond flat DataFrames with additional index levels

Difficulty: medium

Previous exercises have seen us analysing data from DataFrames equipped with a single index level. However, pandas also gives you the possibilty of indexing your data using *multiple* levels. This is very much like adding new dimensions to a Series or a DataFrame. For example, a Series is 1D, but by using a MultiIndex with 2 levels we gain of much the same functionality as a 2D DataFrame.

The set of puzzles below explores how you might use multiple index levels to enhance data analysis.

To warm up, we'll look make a Series with two index levels.

44. Given the lists letters = ['A', 'B', 'C'] and numbers = list(range(10)), construct a MultiIndex object from the product of the two lists. Use it to index a Series of random numbers. Call this Series s.

```
import pandas as pd

letters = ['A', 'B', 'C']
numbers = list(range(10))

multi_idx = pd.MultiIndex.from_product([letters, numbers])
s = pd.Series(np.random.rand(30), index=multi_idx)
print(s) #20min
```

```
1
        0.687915
        0.111853
   2
   3
        0.636129
   4
        0.588547
   5
        0.189700
   6
        0.888148
   7
        0.068398
   8
        0.056247
   9
        0.771034
   0
        0.067540
   1
        0.932084
   2
        0.619941
   3
        0.803332
   4
        0.610752
   5
        0.276955
   6
        0.467640
   7
        0.148595
   8
        0.813688
   9
        0.967769
C
   0
        0.205735
   1
        0.726326
   2
        0.230221
   3
        0.055780
   4
        0.440057
   5
        0.626687
   6
        0.230927
   7
        0.747400
   8
        0.092317
        0.120675
dtype: float64
45. Check the index of s is lexicographically sorted (this is a necessary proprty for indexing
to work correctly with a MultiIndex).
statement = s.index.is_lexsorted()
print(statement)
True
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
FutureWarning: MultiIndex.is_lexsorted is deprecated as a public
function, users should use MultiIndex.is monotonic increasing instead.
  """Entry point for launching an IPython kernel.
```

46. Select the labels 1, 3 and 6 from the second level of the MultiIndexed Series.

sel_indices = s.loc[:, [1, 3, 6]]

print (sel indices) #10min

0.687915

0.636129

1

3

Α

0.140618

A 0

```
0.888148
В
  1
        0.932084
        0.803332
   6
        0.467640
  1
\mathbf{C}
        0.726326
   3
        0.055780
   6
        0.230927
dtype: float64
47. Slice the Series s; slice up to label 'B' for the first level and from label 5 onwards for the
second level.
sliced indices = s.loc[pd.IndexSlice[:'B', 5:]]
print (sliced indices) #15min
  5
        0.189700
   6
        0.888148
   7
        0.068398
   8
        0.056247
   9
        0.771034
  5
В
        0.276955
   6
        0.467640
   7
        0.148595
   8
        0.813688
        0.967769
dtype: float64
48. Sum the values in s for each label in the first level (you should have Series giving you a
total for labels A, B and C).
sum indices lev0 = s.sum(level=0)
print(sum_indices_lev0) #15min
Α
     4.138590
     5.708295
R
C
     3.476123
dtype: float64
/usr/local/lib/python3.7/dist-packages/ipykernel launcher.py:1:
FutureWarning: Using the level keyword in DataFrame and Series
aggregations is deprecated and will be removed in a future version.
Use groupby instead. df.sum(level=1) should use
df.groupby(level=1).sum().
  """Entry point for launching an IPython kernel.
49. Suppose that sum() (and other methods) did not accept a level keyword argument.
How else could you perform the equivalent of s.sum(level=1)?
sum indices lev1 = s.unstack().sum(axis=0)
```

print(sum indices lev1) #15min

```
0
     0.413893
1
     2.346325
2
     0.962015
3
     1.495240
4
     1.639356
5
     1.093342
6
     1.586714
7
     0.964393
8
     0.962252
9
     1.859477
dtype: float64
```

50. Exchange the levels of the MultiIndex so we have an index of the form (letters, numbers). Is this new Series properly lexsorted? If not, sort it.

```
new s = s.swaplevel(0, 1)
#is lexsorted?
is lexsorted = new s.index.is lexsorted()
print(is_lexsorted)
#sort it
new_s = new_s.sort_index()
print(new s) #15min
False
  Α
        0.140618
   В
        0.067540
   C
        0.205735
1
  Α
        0.687915
   В
        0.932084
   C
        0.726326
2
   Α
        0.111853
   В
        0.619941
   C
        0.230221
3
        0.636129
   Α
   В
        0.803332
   C
        0.055780
4
  Α
        0.588547
   В
        0.610752
   C
        0.440057
5
        0.189700
   Α
   В
        0.276955
   C
        0.626687
6
   Α
        0.888148
   В
        0.467640
   C
        0.230927
   Α
7
        0.068398
   В
        0.148595
   C
        0.747400
8
        0.056247
   Α
        0.813688
```

```
C 0.092317
9 A 0.771034
B 0.967769
C 0.120675
dtype: float64
```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
FutureWarning: MultiIndex.is_lexsorted is deprecated as a public function, users should use MultiIndex.is_monotonic_increasing instead.
This is separate from the ipykernel package so we can avoid doing imports until

Minesweeper

Generate the numbers for safe squares in a Minesweeper grid

Difficulty: *medium* to *hard*

If you've ever used an older version of Windows, there's a good chance you've played with Minesweeper:

https://en.wikipedia.org/wiki/Minesweeper_(video_game)

If you're not familiar with the game, imagine a grid of squares: some of these squares conceal a mine. If you click on a mine, you lose instantly. If you click on a safe square, you reveal a number telling you how many mines are found in the squares that are immediately adjacent. The aim of the game is to uncover all squares in the grid that do not contain a mine.

In this section, we'll make a DataFrame that contains the necessary data for a game of Minesweeper: coordinates of the squares, whether the square contains a mine and the number of mines found on adjacent squares.

51. Let's suppose we're playing Minesweeper on a 5 by 4 grid, i.e.

```
X = 5Y = 4
```

To begin, generate a DataFrame df with two columns, 'x' and 'y' containing every coordinate for this grid. That is, the DataFrame should start:

```
this:
```

```
coord_lst = [(0,0), (1,0), (2,0), (3,0), (4,0), (0,1), (1,1),
(2, 1), (3, 1), (4, 1), (0, 2), (1, 2), (2, 2), (3, 2), (4, 2), (0, 2)
3), (1, 3), (2, 3), (3, 3), (4, 3)]
X = [0, 1, 2, 3, 4, 0, 1, 2, 3, 4, 0, 1, 2, 3, 4, 0, 1, 2, 3, 4]
Y = [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3]
df = pd.DataFrame(\{'X': X, 'Y':Y\}) #df.size = 5*4 = 20
print (df) #30min
(3, 2)
    Χ
       Υ
    0
       0
    1
1
       0
2
    2
       0
3
    3
       0
4
    4
       0
5
    0
       1
6
    1
       1
7
    2
       1
8
    3
       1
9
    4
       1
10
       2
    0
11
    1
       2
    2
       2
12
       2
13
    3
       2
14
    4
15
       3
    0
       3
16
    1
17
    2
       3
    3
       3
18
19
       3
```

. For this DataFrame df, create a new column of zeros (safe) and ones (mine). The probability of a mine occurring at each location should be 0.4.

```
#initially all points are safe (we don't know where mines are) and prob_mine = 0.4 for all safe points. Additionally, we create a list 'mine' were 1 means there is a mine, 0 = no mine df_state_0 = df.assign(safe = [0]*20, mine = [0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1], prob_mine = [0.4]*20) #initial state of the grid print(df_state_0) #30min
```

```
Υ
    Χ
            safe
                   mine
                           prob mine
        0
0
    0
                                  0.4
                0
                       0
1
    1
        0
                0
                       0
                                  0.4
2
    2
        0
                0
                       1
                                  0.4
3
    3
        0
                0
                       0
                                  0.4
4
    4
        0
                0
                       1
                                  0.4
5
    0
        1
                0
                                  0.4
                       0
```

```
0.4
6
    1
      1
             0
                    0
7
    2
      1
             0
                    0
                              0.4
                              0.4
8
    3
      1
             0
                    1
9
    4
      1
             0
                    1
                              0.4
      2
10
   0
             0
                    0
                              0.4
       2
11
    1
             0
                    0
                              0.4
   2
      2
             0
12
                    1
                              0.4
      2
13
   3
             0
                    0
                              0.4
14
   4
      2
             0
                    1
                              0.4
      3
15
   0
             0
                    0
                              0.4
16
    1
      3
             0
                    0
                              0.4
      3
17
   2
             0
                    1
                              0.4
18
   3
      3
             0
                    0
                              0.4
   4
      3
19
             0
                    1
                              0.4
```

. Now create a new column for this DataFrame called 'adjacent'. This column should contain the number of mines found on adjacent squares in the grid.

(E.g. for the first row, which is the entry for the coordinate (0, 0), count how many mines are found on the coordinates (0, 1), (1, 0) and (1, 1).)

```
#Initial game model
#column 'adjacent' is dynamic, it holds the transformation of the grid
as we progressivelly reveal more mines(mine =1 for the respective
coordinate,
#safe=1(no longer safe) and prob mine =1-definitely there is a mine
there) or when we enter the final catastrophic state
#when we step on a mine, case in which entire column 'safe' becomes 1,
mine' becomes 1, 'prob mine' becomes 1 and for which game is over with
a LOSS
#(final state with LOSS, FSL)
#Game also enters the final state with WIN (FSW) when we manage to
reveal all dangerous places in the grid, using the mechanisms of the
game and the succesive
#changes/transitions described above, without entering the FSL, that
is transitioning successfully to either one of the following states
described below:
\#MP(safe => (0->1), mine => (0->1), prob mine => (0.4->1)) (mine => (0.4->1))
presence MP) or MA(safe \Rightarrow (0->0), mine \Rightarrow (0->0), prob mine \Rightarrow (0.4-
>0)) (mine absence MA)
#So FSW is our DataFrame with rows of types (0, 0, 0) or (1, 1, 1) for
the columns [safe, mine, prob mine] and
#FWL is our DataFrame with all rows of types (1, 1, 1) for the columns
[safe, mine, prob mine]
#Counting the mines in each row on 'adjacent' column, means to
calculate sum() over all the adjacent coordinates for which we have a
modified state
```

#Marginal coordinates (of type (0, y) or (x, 0), a formation of $| \ | \)$

#inner coordinates have 4 neighbours of type (x, y) with x != 0, y != 0, making a cross like formation, have 4 neighbours for which we need to calculate the sum # We create 2 criteria for filtering the pairs of coordinates of df,

accordingly:
Initially, we'll populate this column with zeros.

df_state_0 = df_state_0.assign(adjacent = [0]*20)
print(df state 0) #120min

| | Χ | Υ | safe | mine | prob_mine | adjacent |
|----|---|---|------|------|-----------|----------|
| 0 | 0 | 0 | 0 | 0 | 0.4 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0.4 | 0 |
| 2 | 2 | 0 | 0 | 1 | 0.4 | 0 |
| 3 | 3 | 0 | 0 | 0 | 0.4 | 0 |
| 4 | 4 | 0 | 0 | 1 | 0.4 | 0 |
| 5 | 0 | 1 | 0 | 0 | 0.4 | 0 |
| 6 | 1 | 1 | 0 | 0 | 0.4 | 0 |
| 7 | 2 | 1 | 0 | 0 | 0.4 | 0 |
| 8 | 3 | 1 | 0 | 1 | 0.4 | 0 |
| 9 | 4 | 1 | 0 | 1 | 0.4 | 0 |
| 10 | 0 | 2 | 0 | 0 | 0.4 | 0 |
| 11 | 1 | 2 | 0 | 0 | 0.4 | 0 |
| 12 | 2 | 2 | 0 | 1 | 0.4 | 0 |
| 13 | 3 | 2 | 0 | 0 | 0.4 | 0 |
| 14 | 4 | 2 | 0 | 1 | 0.4 | 0 |
| 15 | 0 | 3 | 0 | 0 | 0.4 | 0 |
| 16 | 1 | 3 | 0 | 0 | 0.4 | 0 |
| 17 | 2 | 3 | 0 | 1 | 0.4 | 0 |
| 18 | 3 | 3 | 0 | 0 | 0.4 | 0 |
| 19 | 4 | 3 | 0 | 1 | 0.4 | 0 |

54. For rows of the DataFrame that contain a mine, set the value in the 'adjacent' column to NaN.

```
df_state_0.loc[df_state_0['mine']==1, 'adjacent'] = np.nan
```

print(df_state_0) #30min

| | Χ | Υ | safe | mine | prob_mine | adjacent |
|---|---|---|------|------|-----------|----------|
| 0 | 0 | 0 | 0 | 0 | 0.4 | 0.0 |
| 1 | 1 | 0 | 0 | 0 | 0.4 | 0.0 |
| 2 | 2 | 0 | 0 | 1 | 0.4 | NaN |
| 3 | 3 | 0 | 0 | 0 | 0.4 | 0.0 |
| 4 | 4 | 0 | 0 | 1 | 0.4 | NaN |
| 5 | 0 | 1 | 0 | 0 | 0.4 | 0.0 |
| 6 | 1 | 1 | 0 | 0 | 0.4 | 0.0 |
| 7 | 2 | 1 | 0 | 0 | 0.4 | 0.0 |
| 8 | 3 | 1 | 0 | 1 | 0.4 | NaN |
| 9 | 4 | 1 | 0 | 1 | 0.4 | NaN |

| 10 | 0 | 2 | 0 | 0 | 0.4 | 0.0 |
|----|---|---|---|---|-----|-----|
| 11 | 1 | 2 | Θ | 0 | 0.4 | 0.0 |
| 12 | 2 | 2 | Θ | 1 | 0.4 | NaN |
| 13 | 3 | 2 | Θ | 0 | 0.4 | 0.0 |
| 14 | 4 | 2 | Θ | 1 | 0.4 | NaN |
| 15 | 0 | 3 | Θ | 0 | 0.4 | 0.0 |
| 16 | 1 | 3 | Θ | 0 | 0.4 | 0.0 |
| 17 | 2 | 3 | Θ | 1 | 0.4 | NaN |
| 18 | 3 | 3 | Θ | 0 | 0.4 | 0.0 |
| 19 | 4 | 3 | 0 | 1 | 0.4 | NaN |

55. Finally, convert the DataFrame to grid of the adjacent mine counts: columns are the x coordinate, rows are the y coordinate.

```
df_state_0 = df_state_0.set_index(['Y', 'X']).unstack()
print(df state 0) #20min
```

| | fe | | | | | mine | | | | | prob_mine | | | | |
|-----------|----------|--------|---|---|---|------|---|---|---|---|-----------|-----|-----|-----|-----|
| adja X | cen 0 | t 1 | 2 | 3 | 4 | 0 | 1 | 2 | 2 | 4 | 0 | 1 | 2 | 3 | 4 |
| 0 Y | U | 1 | ۷ | J | 4 | U | 1 | ۷ | J | 4 | 0 | 1 | 2 | 3 | 4 |
| 0 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 1 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 2 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |

| Х | 1 | 2 | 3 | 4 |
|---|-----|-----|-----|-----|
| Υ | | | | |
| 0 | 0.0 | NaN | 0.0 | NaN |
| 1 | 0.0 | 0.0 | NaN | NaN |
| 2 | 0.0 | NaN | 0.0 | NaN |
| 3 | 0.0 | NaN | 0.0 | NaN |

Plotting

Visualize trends and patterns in data

Difficulty: medium

To really get a good understanding of the data contained in your DataFrame, it is often essential to create plots: if you're lucky, trends and anomalies will jump right out at you. This functionality is baked into pandas and the puzzles below explore some of what's possible with the library.

56. Pandas is highly integrated with the plotting library matplotlib, and makes plotting DataFrames very user-friendly! Plotting in a notebook environment usually makes use of the following boilerplate:

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
```

matplotlib is the plotting library which pandas' plotting functionality is built upon, and it is usually aliased to plt.

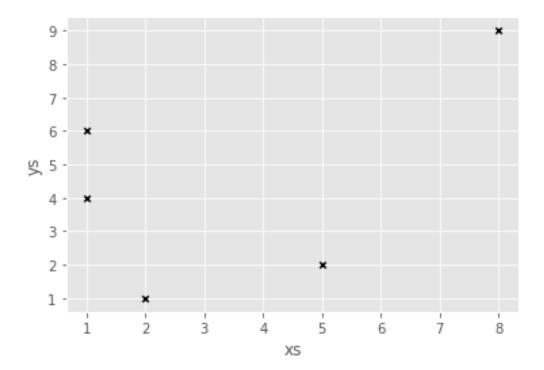
%matplotlib inline tells the notebook to show plots inline, instead of creating them in a separate window.

plt.style.use('ggplot') is a style theme that most people find agreeable, based upon the styling of R's ggplot package.

For starters, make a scatter plot of this random data, but use black X's instead of the default markers.

```
df = pd.DataFrame({"xs":[1,5,2,8,1], "ys":[4,2,1,9,6]})
Consult the documentation if you get stuck!
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

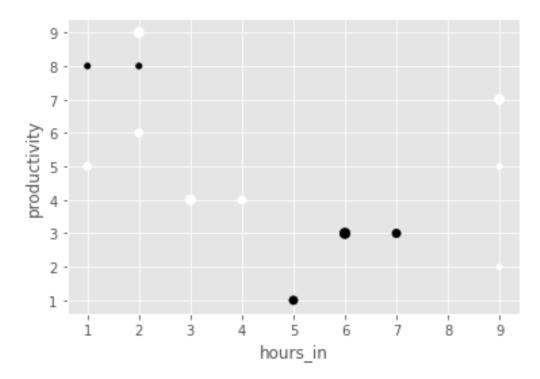
df = pd.DataFrame({'xs':[1, 5, 2, 8, 1], 'ys':[4, 2, 1, 9, 6]})
df.plot.scatter('xs', "ys", color = 'black', marker = "x" ) #10min
<matplotlib.axes. subplots.AxesSubplot at 0x7fb97b04c790>
```



57. Columns in your DataFrame can also be used to modify colors and sizes. Bill has been keeping track of his performance at work over time, as well as how good he was feeling that day, and whether he had a cup of coffee in the morning. Make a plot which incorporates all four features of this DataFrame.

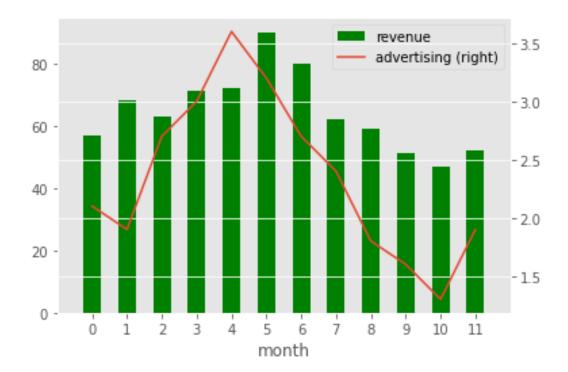
(Hint: If you're having trouble seeing the plot, try multiplying the Series which you choose to represent size by 10 or more)

The chart doesn't have to be pretty: this isn't a course in data viz!



58. What if we want to plot multiple things? Pandas allows you to pass in a matplotlib *Axis* object for plots, and plots will also return an Axis object.

Make a bar plot of monthly revenue with a line plot of monthly advertising spending (numbers in millions)



Now we're finally ready to create a candlestick chart, which is a very common tool used to analyze stock price data. A candlestick chart shows the opening, closing, highest, and lowest price for a stock during a time window. The color of the "candle" (the thick part of the bar) is green if the stock closed above its opening price, or red if below.

Candlestick Example

This was initially designed to be a pandas plotting challenge, but it just so happens that this type of plot is just not feasible using pandas' methods. If you are unfamiliar with matplotlib, we have provided a function that will plot the chart for you so long as you can use pandas to get the data into the correct format.

Your first step should be to get the data in the correct format using pandas' time-series grouping function. We would like each candle to represent an hour's worth of data. You can write your own aggregation function which returns the open/high/low/close, but pandas has a built-in which also does this.

The below cell contains helper functions. Call day_stock_data() to generate a DataFrame containing the prices a hypothetical stock sold for, and the time the sale occurred. Call plot_candlestick(df) on your properly aggregated and formatted stock data to print the candlestick chart.

```
import numpy as np
def float_to_time(x):
    return str(int(x)) + ":" + str(int(x%1 * 60)).zfill(2) + ":" +
str(int(x*60 % 1 * 60)).zfill(2)

def day_stock_data():
```

```
#NYSE is open from 9:30 to 4:00
    time = 9.5
    price = 100
    results = [(float to time(time), price)]
    while time < 16:
        elapsed = np.random.exponential(.001)
        time += elapsed
        if time > 16:
            break
        price diff = np.random.uniform(.999, 1.001)
        price *= price diff
        results.append((float to time(time), price))
    df = pd.DataFrame(results, columns = ['time', 'price'])
    df.time = pd.to datetime(df.time)
    return df
#Don't read me unless you get stuck!
def plot_candlestick(agg):
    agg is a DataFrame which has a DatetimeIndex and five columns:
["open", "high", "low", "close", "color"]
    fig, ax = plt.subplots()
    for time in agg.index:
        ax.plot([time.hour] * 2, agg.loc[time, ["high","low"]].values,
color = "black")
        ax.plot([time.hour] * 2, agg.loc[time,
["open", "close"]].values, color = agg.loc[time, "color"], linewidth =
10)
    ax.set xlim((8,16))
    ax.set ylabel("Price")
    ax.set xlabel("Hour")
    ax.set title("OHLC of Stock Value During Trading Day")
    plt.show()
59. Generate a day's worth of random stock data, and aggregate / reformat it so that it has
hourly summaries of the opening, highest, lowest, and closing prices
df = day_stock_data()
df.head()
df.set index("time", inplace = True)
agg = df.resample("H").ohlc()
agg.columns = agg.columns.droplevel()
agg["color"] = (agg.close > agg.open).map({True:"green",False:"red"})
agg.head() #30min
```

| color | | open | high | low | close |
|----------------------------|----------|------------|------------|-----------|------------|
| time | | | | | |
| 2022-05-30 | 09:00:00 | 100.000000 | 101.152079 | 99.399094 | 100.679088 |
| green 2022-05-30 red | 10:00:00 | 100.590830 | 101.082190 | 97.545361 | 97.956964 |
| 2022-05-30 red | 11:00:00 | 97.948237 | 98.348030 | 96.099787 | 97.100671 |
| 2022-05-30 green | 12:00:00 | 97.044675 | 98.393450 | 95.493610 | 97.510688 |
| 2022-05-30 green | 13:00:00 | 97.477409 | 100.029392 | 97.089258 | 99.648462 |

60. Now that you have your properly-formatted data, try to plot it yourself as a candlestick chart. Use the plot_candlestick(df) function above, or matplotlib's plot documentation if you get stuck.

plot_candlestick(agg) #10min

