Elements Of Data Science - F2020

Week 12: Time Series, Data Processing, Delivery and Databases

12/7/2020

TODOs

- Readings:
    - Final Review Sheet

- Quiz 12, **Due Sunday Dec 13th, 11:59pm ET**
- HW4, **Due Friday Dec 18th 11:59pm ET**
- Final
    - Release Monday night 12/14
    - Due **Saturday Dec 19th, 11:59pm ET**
    - Have 24hrs after starting exam to finish
    - 30-40 questions (fill in the blank/multiple choice/short answer)
    - Online via Gradescope
    - Questions asked/answered **privately** via Piazza
    - Open-book, open-note, open-python

Today

- Imbalanced Classes
- Finish Time Series
- Data processing and delivery
- Connecting to databases with sqlalchemy and pandas

Questions?

Dealing With Imbalanced Classes

- See imbalanced_classes.ipynb or .pdf

Timeseries in Python so far:

- `datetime .date .time .datetime .timedelta`
- format with `.strftime()`
- parse time with `pd.to_datetime()`
- `pandas Timestamp Timedelta DatetimeIndex`
- Indexing with `DatetimeIndex`
- Frequencies
- Timezones

Additional pandas functionality we won't discuss:

- `Period` and `PeriodIndex`
- `Panels`

Next: Operations on Time Series data

Shifting

- Moving data backward or forward in time (lagging/leading)
- Ex: calculate percent change

In [2]:
```
ts = pd.Series([1,2,8],
               index=pd.date_range('1/1/2019',periods=3,freq='M'))
ts
```

Out[2]:
```
2019-01-31    1
2019-02-28    2
2019-03-31    8
Freq: M, dtype: int64
```

In [3]:
```
ts.shift(1) # yesterday's value
```

Out[3]:
```
2019-01-31    NaN
2019-02-28    1.0
2019-03-31    2.0
Freq: M, dtype: float64
```

Shifting

- **percent change :**
  - (new_value - old_value) / old_value
  - (new_value / old_value) - 1

In [4]:
```python
#  multiply by 100 to turn into a percent
((ts / ts.shift(1)) - 1) * 100
```

Out[4]:
```
2019-01-31      NaN
2019-02-28    100.0
2019-03-31    300.0
Freq: M, dtype: float64
```

Example Dataset: Twitter Stock

In [5]:

```
# first run: conda install pandas-datareader
#from pandas_datareader import data
#df_twtr = data.DataReader('TWTR', start='2015', end='2021', data_source='yahoo')
df_twtr = pd.read_csv('../data/twtr_2015-2020.csv',parse_dates=['Date'],index_col='Date')
df_twtr.head(3)
```

Out[5]:

Date	High	Low	Open	Close	Volume	Adj Close
2015-01-02	36.740002	35.540001	36.230000	36.560001	12062500	36.560001
2015-01-05	37.110001	35.639999	36.259998	36.380001	15062700	36.380001
2015-01-06	39.450001	36.040001	36.270000	38.759998	33050800	38.759998

In [6]:

```
fig,ax = plt.subplots(1,1,figsize=(12,6))
df_twtr[['Close']].plot(ax=ax);
ax.set_ylabel('stock price');
```

Shifting Example: Twitter Close

- Calculate Percent Change

In [7]:
```
# (today / yesterday) - 1
((df_twtr.Close / df_twtr.Close.shift(1)) - 1).tail(5)
```

Out[7]:
```
Date
2020-11-23    0.005819
2020-11-24    0.006453
2020-11-25    0.026531
2020-11-27    0.003446
2020-11-30   -0.001717
Name: Close, dtype: float64
```

In [8]:
```
# plot percent change of close in 2020
fig,ax = plt.subplots(1,1,figsize=(12,6))
close_2020 = df_twtr.loc['2020','Close']
((close_2020 / close_2020.shift(1)) - 1 ).plot(marker='x',ax=ax);
ax.set_ylabel('percent change');
```

Resampling

- Convert from one frequency to another
- **Downsampling**
  - from higher to lower (day to month)
  - need to aggregate
- **Upsampling**
  - from lower to higher (month to day)
  - need to fill missing
- Can also be used to set frequency from None

Resampling: Initialize Frequency

In [9]:
```
df_twtr.index
```

Out[9]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2020-11-16', '2020-11-17', '2020-11-18', '2020-11-19',
               '2020-11-20', '2020-11-23', '2020-11-24', '2020-11-25',
               '2020-11-27', '2020-11-30'],
              dtype='datetime64[ns]', name='Date', length=1489, freq=None)
```

In [10]:
```
df_twtr_B = df_twtr.resample('B').asfreq() # set frequency to business day
df_twtr_B.index
```

Out[10]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06', '2015-01-07',
               '2015-01-08', '2015-01-09', '2015-01-12', '2015-01-13',
               '2015-01-14', '2015-01-15',
               ...
               '2020-11-17', '2020-11-18', '2020-11-19', '2020-11-20',
               '2020-11-23', '2020-11-24', '2020-11-25', '2020-11-26',
               '2020-11-27', '2020-11-30'],
              dtype='datetime64[ns]', name='Date', length=1542, freq='B')
```

Resampling: Downsampling

- Go from higher/shorter to lower/longer
- Need to aggregate (like groupby)
- Example: Downsampling from business day to business quarter

In [11]:
```
df_twtr_BQ = df_twtr.resample('BQ')
df_twtr_BQ
```

Out[11]:
```
<pandas.core.resample.DatetimeIndexResampler object at 0x7f61faf1cd30>
```

In [12]:
```
str(df_twtr_BQ)
```

Out[12]:
```
'DatetimeIndexResampler [freq=<BusinessQuarterEnd: startingMonth=12>, axis=0, closed=right, label=right, convention=start, orig
in=start_day]'
```

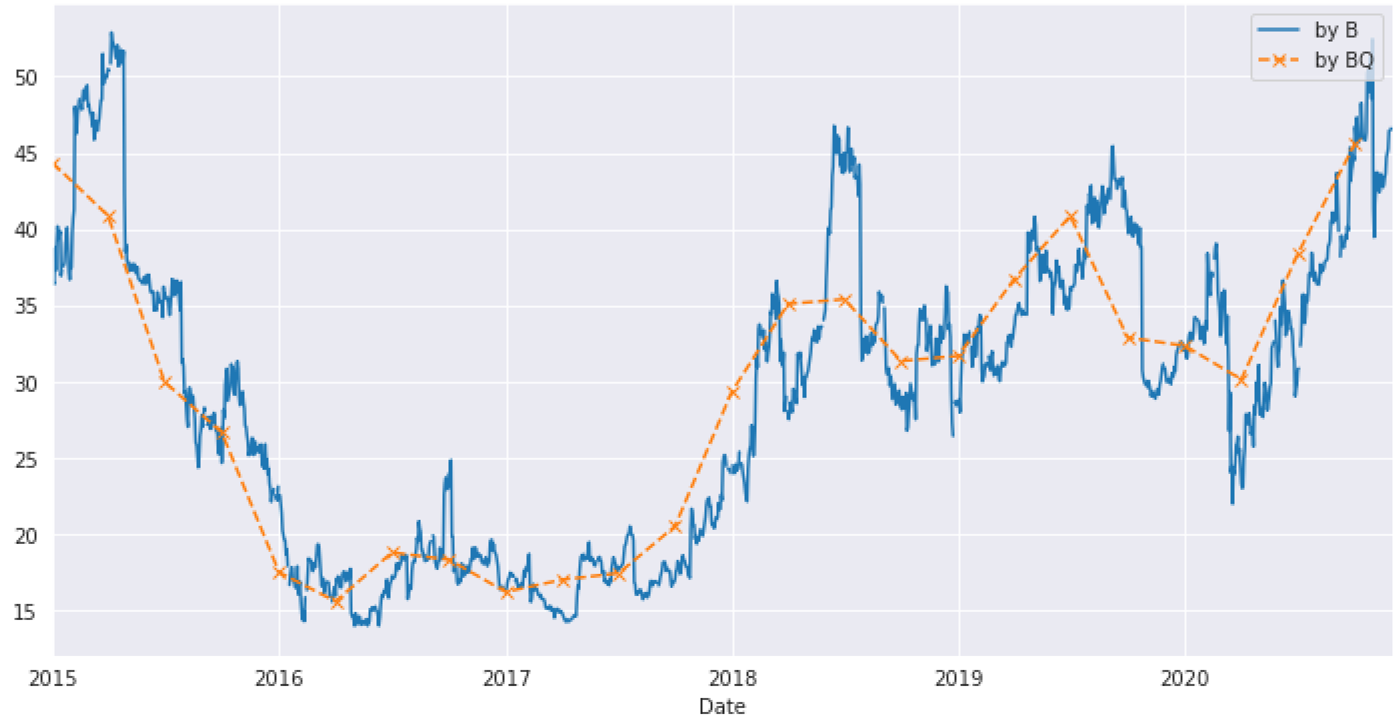
In [13]:
```
df_twtr_BQ.mean().head(3)
```

Out[13]:

	High	Low	Open	Close	Volume	Adj Close
Date						
2015-03-31	45.080328	43.552459	44.228688	44.335574	2.084619e+07	44.335574
2015-06-30	41.634921	40.385079	41.173492	40.874603	2.232030e+07	40.874603
2015-09-30	30.638281	29.420625	30.047812	30.000625	2.031210e+07	30.000625

Resampling: Downsampling

In [14]:
```
fig,ax = plt.subplots(1,1,figsize=(12,6))
df_twtr_B.Close.plot(style='-', label='by B',ax=ax)
df_twtr_BQ.Close.mean().plot(style='--',marker='x',label='by BQ',ax=ax)
plt.legend(loc='upper right');
```



Resampling: Upsampling

- Go from lower/longer to higher/shorter
- Need to decide how to handle missing values
- Example: Upsample from business day to hour

In [15]:
```
df_twtr_B.index[:3]
```

Out[15]:
```
DatetimeIndex(['2015-01-02', '2015-01-05', '2015-01-06'], dtype='datetime64[ns]', name='Date', freq='B')
```

In [16]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[0:3]
```

Out[16]:
```
Date
2015-01-02 00:00:00    36.560001
2015-01-02 01:00:00          NaN
2015-01-02 02:00:00          NaN
Freq: H, Name: Close, dtype: float64
```

In [17]:
```
df_twtr_B.Close.resample('H').asfreq().iloc[70:73]
```

Out[17]:
```
Date
2015-01-04 22:00:00          NaN
2015-01-04 23:00:00          NaN
2015-01-05 00:00:00    36.380001
Freq: H, Name: Close, dtype: float64
```

Resampling: Upsampling

- `ffill()` : Forward Fill

```
In [18]: df_twtr_B.Close.resample('H').ffill().head(3)

Out[18]: Date
         2015-01-02 00:00:00    36.560001
         2015-01-02 01:00:00    36.560001
         2015-01-02 02:00:00    36.560001
         Freq: H, Name: Close, dtype: float64
```

- `bfill()` : Backward Fill

```
In [19]: df_twtr_B.Close.resample('H').bfill().head(3)

Out[19]: Date
         2015-01-02 00:00:00    36.560001
         2015-01-02 01:00:00    36.380001
         2015-01-02 02:00:00    36.380001
         Freq: H, Name: Close, dtype: float64
```

Moving Windows

- Apply function on a fixed window moving accross time
- Method of smoothing out the data
- **center** : place values at center of window

In [20]:
```
df_twtr_B.Close['2020-11-02':'2020-11-06']
```

Out[20]:
```
Date
2020-11-02    39.470001
2020-11-03    41.730000
2020-11-04    42.759998
2020-11-05    43.709999
2020-11-06    43.119999
Freq: B, Name: Close, dtype: float64
```

In [21]:
```
rolling = df_twtr_B.Close.rolling(5, center=True)
rolling
```

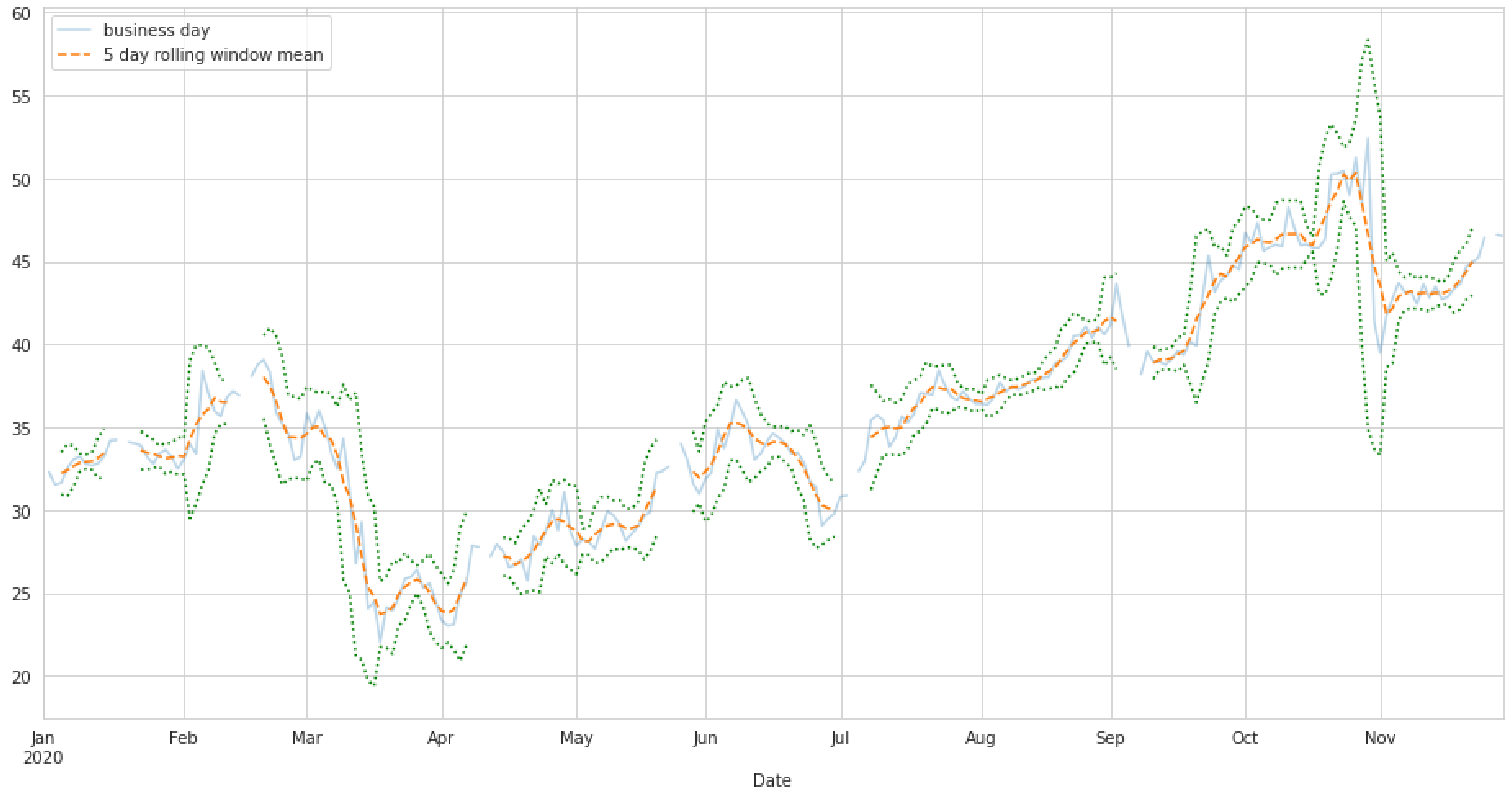
Out[21]:
```
Rolling [window=5,center=True,axis=0]
```

In [22]:
```
rolling.mean()['2020-11-02':'2020-11-06']
```

Out[22]:
```
Date
2020-11-02    43.550000
2020-11-03    41.806000
2020-11-04    42.157999
2020-11-05    42.901999
2020-11-06    43.037999
Freq: B, Name: Close, dtype: float64
```

Moving Windows

In [23]:
```
sns.set_style("whitegrid")
fig,ax = plt.subplots(1,1,figsize=(16,8));
df_twtr_B['2020'].Close.plot(style='-',alpha=0.3,label='business day');
rolling.mean()['2020'].plot(style='--',label='5 day rolling window mean');
(rolling.mean()['2020'] + 2*rolling.std()['2020']).plot(style=':',c='g',label='_nolegend_');
(rolling.mean()['2020'] - 2*rolling.std()['2020']).plot(style=':',c='g',label='_nolegend_');
ax.legend();
```



Demo

- bike_travel_example.ipynb

Timeseries Operations Review

- Shifting
- Resampling
    - Downsampling
    - Upsampling
- Moving/Rolling Windows

Questions?

Data Processing and Delivery: ETL

- **E**xtract **T**ransform **L**oad

- Extract: Reading in data
- Transform: Transforming data
- Load: Delivering data

Extract: Various Data Sources

- flatfiles (csv, excel)
- semi-structured documents (json, html)
- unstructured documents
- data + schema (dataframe, parquet)
- APIs (wikipedia, twitter, spotify, etc.)
- databases

- Pandas to the rescue!
- Plus other specialized libraries

Extracting Data with Pandas

- read_csv
- read_excel
- read_parquet

- read_json
- read_html

- read_sql
- read_clipboard
- ...

Extract Data: CSV

Comma Separated Values

In [24]:
```
%cat ../data/example.csv
```

```
Year,Make,Model,Description,Price
1997,Ford,E350,"ac, abs, moon",3000.00
1999,Chevy,"Venture Extended Edition","",4900.00
1999,Chevy,"Venture Extended Edition, Very Large",,5000.00
1996,Jeep,Grand Cherokee,"MUST SELL! air, moon roof, loaded",4799.00
```

In [25]:
```
df = pd.read_csv('../data/example.csv',header=0,sep=',')
df
```

Out[25]:

	Year	Make	Model	Description	Price
0	1997	Ford	E350	ac, abs, moon	3000.0
1	1999	Chevy	Venture Extended Edition	NaN	4900.0
2	1999	Chevy	Venture Extended Edition, Very Large	NaN	5000.0
3	1996	Jeep	Grand Cherokee	MUST SELL! air, moon roof, loaded	4799.0

Extract Data: Excel

	A	B	C	D	E
1	Year	Make	Model	Description	Price
2	1997	Ford	E350	ac, abs, moon	3000
3	1999	Chevy	Venture Extended Edition		4900
4	1999	Chevy	Venture Extended Edition, Very Large		5000
5	1996	Jeep	Grand Cherokee	MUST SELL! air, moon roof, loaded	4799

In [26]:

```
# first run: conda install -n eods-f20 xlrd
pd.read_excel('../data/example.xlsx',sheet_name='Sheet1')
```

Out[26]:

	Year	Make	Model	Description	Price
0	1997	Ford	E350	ac, abs, moon	3000
1	1999	Chevy	Venture Extended Edition	NaN	4900
2	1999	Chevy	Venture Extended Edition, Very Large	NaN	5000
3	1996	Jeep	Grand Cherokee	MUST SELL! air, moon roof, loaded	4799

Extract Data: Parquet

- open source column-oriented data storage
- part of the Apache Hadoop ecosystem
- often used when working with Spark
- requires additional parsing engine eg `pyarrow`
- includes both data and **schema**
- **Schema** : metadata about the dataset (column names, datatypes, etc.)

Extract Data: JSON

- **J**ava**S**cript **O**bject **N**otation
- often seen as return from api call
- looks like a dictionary or list of dictionaries
- pretty print using json.loads(json_string)

```
{
  "firstName": "John",
  "lastName": "Smith",
  "isAlive": true,
  "age": 27,
  "phoneNumbers": [
    {
      "type": "home",
      "number": "212 555-1234"
    },
    {
```

Extract Data: JSON

In [27]:

```
json = """
{"0": {"Year": 1997,
  "Make": "Ford",
  "Model": "E350",
  "Description": "ac, abs, moon",
  "Price": 3000.0},
 "1": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition",
  "Description": null,
  "Price": 4900.0},
 "2": {"Year": 1999,
  "Make": "Chevy",
  "Model": "Venture Extended Edition, Very Large",
  "Description": null,
  "Price": 5000.0},
 "3": {"Year": 1996,
  "Make": "Jeep",
  "Model": "Grand Cherokee",
  "Description": "MUST SELL! air, moon roof, loaded",
  "Price": 4799.0}}
"""
```

In [28]:

```
pd.read_json(json,orient='index')
```

Out[28]:

	Year	Make	Model	Description	Price
0	1997	Ford	E350	ac, abs, moon	3000
1	1999	Chevy	Venture Extended Edition	None	4900
2	1999	Chevy	Venture Extended Edition, Very Large	None	5000
3	1996	Jeep	Grand Cherokee	MUST SELL! air, moon roof, loaded	4799

Extract Data: HTML

- **H**yper**T**ext **M**arkup **L**anguage
- Parse with BeautifulSoup

In [29]:

```
html = """
<html>
    <head>
        <title>Example</title>
    </head>
    <body>
        <p id="first" class="example"><strong>Example text!</strong></p>
        <p id="second" class="example">And More!</p>
    </body>
</html>
"""

from bs4 import BeautifulSoup

soup = BeautifulSoup(html)
[p.text for p in soup('p')]
```

Out[29]:

```
['Example text!', 'And More!']
```

Extract Data: APIs

- **A**pplication **P**rogramming **I**nterface
- defines interactions between software components and resourses
- most datasources have an API
- some require authentication
- python libraries exist for most common APIs

- **requests**: library for making web requests and accessing the results

API Example: Wikipedia

In [30]:
```python
import requests
url = 'http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles='
title = 'Data Science'
title = title.replace(' ','%20')
print(url+title)
```

```
http://en.wikipedia.org/w/api.php?action=query&prop=info&format=json&titles=Data%20Science
```

In [31]:
```python
resp = requests.get(url+title)
resp.json()
```

Out[31]:

```
{'batchcomplete': '',
 'query': {'pages': {'49495124': {'pageid': 49495124,
    'ns': 0,
    'title': 'Data Science',
    'contentmodel': 'wikitext',
    'pagelanguage': 'en',
    'pagelanguagehtmlcode': 'en',
    'pagelanguagedir': 'ltr',
    'touched': '2020-12-01T22:30:17Z',
    'lastrevid': 706007296,
    'length': 26,
    'redirect': '',
    'new': ''}}}}
```

API Example: Twitter

1. Apply for Twitter developer account
2. Create a Twitter application to generate tokens and secrets

In [32]:
```python
with open('/home/bgibson/proj/twitter/twitter_consumer_key.txt') as f:
    consumer_key = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_consumer_secret.txt') as f:
    consumer_secret = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token.txt') as f:
    access_token = f.read().strip()
with open('/home/bgibson/proj/twitter/twitter_access_token_secret.txt') as f:
    access_token_secret = f.read().strip()

# need to run: conda install -n eods-f20 twython
from twython import Twython
twitter = Twython(consumer_key,consumer_secret,access_token,access_token_secret)
```

In [33]:
```python
public_tweets = twitter.search(q='columbia')['statuses']
for status in public_tweets[:3]:
    print('-------')
    print(status["text"])
```

```
-------
RT @columbiaydsa: "While this is a conversation currently centered in Morningside Heights, we hope that it will spread and star
t a national…
-------
When it comes to building trust and managing your team's workload, transparency is key. Learn how the Media &amp; Creat… http
s://t.co/qYshlsNBt5
-------
All indoor and outdoor adult team sports are now prohibited in B.C. and children's programs have returned to earlie… https://t.
co/q8xt9DvFht
```

Transforming Data

- Standardization
- Creating dummy variables
- Filling missing data
- One-Hot-Encoding
- Binning
- Parsing natural language
- Dimensionality reduction
- etc...

Transform: Pipeline Example 1

In [34]:
```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split

# generate some data to play with
X, y = make_classification(n_samples=500,
                           n_features=5,
                           n_informative=2, # number of informative features
                           random_state=42)
X.shape
```

Out[34]:
```
(500, 5)
```

In [35]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,stratify=y,test_size=.1)

X_train[:2].round(2)
```

Out[35]:
```
array([[-2.28,  0.73,  0.02, -1.99, -2.11],
       [ 2.08,  2.06, -0.22,  0.48, -0.18]])
```

In [36]:
```
pd.Series(y_train).value_counts()
```

Out[36]:
```
1    226
0    224
dtype: int64
```

Transform: Pipeline Example 1 Cont.

In [37]:
```
from sklearn.feature_selection import SelectKBest,f_classif
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline

feature_filter = SelectKBest(f_classif, k=2)
clf = SVC(kernel='linear')

pipeline = Pipeline([('select', feature_filter), ('svc', clf)])

pipeline.set_params(svc__C=.1).fit(X_train, y_train)
```

Out[37]:
```
Pipeline(steps=[('select', SelectKBest(k=2)),
                ('svc', SVC(C=0.1, kernel='linear'))])
```

In [38]:
```
pipeline.score(X_test,y_test)
```

Out[38]:
```
0.86
```

In [39]:
```
np.where(pipeline['select'].get_support())[0]
```

Out[39]:
```
array([0, 2])
```

Transform: Pipeline Example 2

In [40]:
```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression

# from https://scikit-learn.org/stable/auto_examples/compose/plot_column_transformer_mixed_types.html#sphx-glr-auto-examples-com
# Read data from Titanic dataset.
titanic_url = ('https://raw.githubusercontent.com/amueller/'
               'scipy-2017-sklearn/091d371/notebooks/datasets/titanic3.csv')
df_titanic = pd.read_csv(titanic_url)[['age','fare','embarked','sex','pclass','survived']]

# Numeric Features:
# - age: float.
# - fare: float.
# Categorical Features:
# - embarked: categories encoded as strings {'C', 'S', 'Q'}.
# - sex: categories encoded as strings {'female', 'male'}.
# - pclass: ordinal integers {1, 2, 3}.
```

In [41]:
```
df_titanic.head(3)
```

Out[41]:

	age	fare	embarked	sex	pclass	survived
0	29.0000	211.3375	S	female	1	1
1	0.9167	151.5500	S	male	1	1
2	2.0000	151.5500	S	female	1	0

ColumnTransformer

- Transform sets of columns differently as part of a pipeline

In [42]:
```python
from sklearn.compose import ColumnTransformer

numeric_features = ['age', 'fare']
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')), # fill missing values with median
    ('scaler', StandardScaler())])                 # scale features
```

In [43]:
```python
categorical_features = ['embarked', 'sex', 'pclass']
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')), # fill missing value with 'missing'
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])                   # one hot encode
```

In [44]:
```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)])
```

In [45]:
```python
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', LogisticRegression(solver='lbfgs', random_state=42))])
```

Transform: Pipeline Example 2 Cont.

In [46]:
```
X = df_titanic.drop('survived', axis=1)
y = df_titanic['survived']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf.fit(X_train, y_train)
print(f"train set score: {clf.score(X_train, y_train):.3f}")
print(f"test set score : {clf.score(X_test, y_test):.3f}")
```

```
train set score: 0.784
test set score : 0.771
```

In [47]:
```
from sklearn.model_selection import GridSearchCV

# grid search deep inside the pipeline
param_grid = {
    'preprocessor__num__imputer__strategy': ['mean', 'median'],
    'classifier__C': [0.1, 1.0, 10, 100],
}

gs_pipeline = GridSearchCV(clf, param_grid, cv=3)
gs_pipeline.fit(X_train, y_train)
print("best test set score from grid search: {:.3f}".format(gs_pipeline.score(X_test, y_test)))
print("best parameter settings: {}".format(gs_pipeline.best_params_))
```

```
best test set score from grid search: 0.771
best parameter settings: {'classifier__C': 100, 'preprocessor__num__imputer__strategy': 'median'}
```

Loading Data with pandas

- to_csv
- to excel
- to_json
- to_html
- to_parquet

- to_sql
- to_clipboard

- to_pickle

Delivering Data With Flask

- Flask : lightweight web server
- can be used to create a small API to:
    - return transformed data
    - return predictions
    - return datasets
    - ...

Aside: Running python scripts from the command line

In [48]:
```
!cat ../src/sample_script.py
```

```
# import necessary libraries and function
from datetime import datetime

# python as usual
# will run as script or on import
run_or_imported_at = datetime.now()
print(f"this was run or imported at {run_or_imported_at}")
print(f"{__name__ = :s}")

if __name__ == "__main__":
    # will only run if this is a script
    # won't be run if imported
    print("running as a script")
```

In [49]:
```
import sys
sys.path.append('../src/')

import sample_script
```

```
this was run or imported at 2020-12-07 17:30:32.674361
__name__ = sample_script
```

In [50]:
```
print(sample_script.run_or_imported_at)
```

```
2020-12-07 17:30:32.674361
```

Aside: Function Decorators

- act like wrappers around functions
- decorators are prefixed by the "@" symbol
- placed above the function to be wrapped

In [51]:
```python
def my_decorator(func):
    def wrapper():
        print("Happens before the function is called.")
        func()
        print("Happens after the function is called.")
    return wrapper

@my_decorator
def say_hello():
    print("Hello")

say_hello()
```

```
Happens before the function is called.
Hello
Happens after the function is called.
```

Creating APIs: Flask

Need to run: `conda install -n  eods-f20 flask`

```
In [52]: !cat ../src/hello_flask.py
```

```
from flask import Flask, escape, request

app = Flask(__name__)

@app.route('/')
def hello():
    name = request.args.get("name", "World")
    return f'Hello, {escape(name)}!\n'

if __name__ == '__main__':
    app.run()
```

1. at command line, run: `$ python hello_flask.py`

2. in ipython (or notebook)

```
import requests
r = requests.get('http://127.0.0.1:5000/?name=Bryan')
print(r.text)
```

Creating APIs: Flask with Multiple Routes

In [53]:
```
!cat ../src/die_flask.py
```

```
import numpy as np
from flask import Flask, request, jsonify

app = Flask(__name__)

@app.route("/")
def help():
    return "Give the number of sides the die should have.\n"

@app.route("/<int:sides>")
def roll_die(sides):
    return str(np.random.randint(1,sides+1))

@app.route("/json/<int:sides>")
def roll_die_json(sides):
    return jsonify({'sides': sides,'roll': np.random.randint(1,sides+1)})

if __name__ == '__main__':
    app.run()
```

GET vs POST

- **GET** : pass information in the url

    ```
    127.0.0.1:5000/?firstname=Bryan&lastname=Gibson
    ```

- **POST** : pass information as additional http request (often JSON)

```
127.0.0.1:5000/
{'firstname':'Bryan','lastname':'Gibson'}
```

Creating APIs: Flask

- Export trained models (and other data structures) using `pickle`

In [54]:
```
import pickle as pkl
with open('../data/titanic_pipeline_clf.pkl','wb') as f:
    pkl.dump(gs_pipeline,f)
```

Creating APIs: Deliver Predictions Using Flask

In [55]:
```
!cat ../src/titanic_clf.py
```

```
from flask import Flask, escape, request, jsonify
import pickle as pkl
import pandas as pd

# need to train and pickle classifier first
with open('../data/titanic_pipeline_clf.pkl','rb') as f:
    clf = pkl.load(f)

app = Flask(__name__)

@app.route('/',methods=['POST'])
def predict():
    prediction = None
    query = pd.DataFrame(request.form,index=[0])
    print(query,flush=True)
    if query is not None:
        prediction = clf.predict(query)
    if prediction:
        return jsonify([str(x) for x in prediction])
    else:
        return 'no predictions made'

if __name__ == '__main__':
    app.run()
```

Creating APIs: Deliver Predictions Using Flask Cont.

In [56]:
```
query_label = df_titanic.iloc[0].loc['survived']
```

In [57]:
```
query = df_titanic.iloc[0,:-1].to_dict()
query
```

Out[57]:
```
{'age': 29.0, 'fare': 211.3375, 'embarked': 'S', 'sex': 'female', 'pclass': 1}
```

In [58]:
```
query_label
```

Out[58]:
```
1
```

In [59]:
```
# first start script from command line: python titanic_clf.py
# then uncomment the line below
#requests.post('http://127.0.0.1:5000/', data=query).text
```

Data Processing Summary

- ETL
- reading datafiles using pandas
- website scraping (requests,BeautifulSoup)
- accessing data via API
- Tranforming data with Pipelines
- Exposing data via API (Flask)

Questions?

Accessing Databases with Python

- databases vs flat-files
- Relational Databases and SQL
- NoSQL databases

Flat Files

Company Details

E_ID	Name	Department	Dept_ID	Manager_Name
101	Anoop	Accounts	AC-10	Mr Gagan Thakral
201	Anurag	Accounts	AC-10	Mr Gagan Thakral
301	Rakesh	Accounts	AC-10	Mr Gagan Thakral
401	Saurav	Accounts	AC-10	Mr Gagan Thakral

- eg: csv, json, etc
- Pros
    - Ease of access
    - Simple to transport
- Cons
    - May include redundant information
    - Slow to search
    - No integity checks

Relational Databases

- Data stored in **tables** (rows/columns)
- Table columns have well defined datatype requirements
- Complex **indexes** can be set up over often used data/searches
- Row level security, separate from the operating system
- Related data is stored in separate tables, referenced by **keys**

- Many commonly used Relational Databases
  - sqlite (small footprint db, might already have it installed)
  - Mysql
  - PostgreSQL
  - Microsoft SQL Server
  - Oracle

Database Normalization

- Organize data in accordance with **normal forms**

- Rules designed to:
    - reduce data redundancy
    - improve data integrity

- Rules like:
    - Has Primary Key
    - No repeating groups
    - Cells have single values
    - No partial dependencies on keys (use whole key)
    - ...

Database Normalization

Company Details

E_ID	Name	Department	Dept_ID	Manager_Name
101	**Anoop**	**Accounts**	**AC-10**	**Mr Gagan Thakral**
201	**Anurag**	**Accounts**	**AC-10**	**Mr Gagan Thakral**
301	**Rakesh**	**Accounts**	**AC-10**	**Mr Gagan Thakral**
401	**Saurav**	**Accounts**	**AC-10**	**Mr Gagan Thakral**

E_ID	Name	Dept_ID
101	**Anoop**	**AC-10**
201	**Anurag**	**AC-10**
301	**Rakesh**	**AC-10**
401	**Saurav**	**AC-10**

Employee_Details

Dept_ID	Department	Manager_Name
A-10	**Accounts**	**Mr Gagan Thakral**

Department_Details

From https://www.minigranth.com/dbms-tutorial/database-normalization-dbms/

De-Normalization

- But we want a single table/dataframe!
- Very often need to **denormalize**
- .. using joins! (see more later)

Structured Query Language (SQL)

- (Semi) standard language for querying, transforming and returning data
- Notable characteristics:
  - generally case independent
  - white-space is ignored
  - strings denoted with single quotes
  - comments start with double-dash "--"

```sql
SELECT
    client_id
    ,lastname
FROM
    company_db.bi.clients --usually database.schema.table
WHERE
    lastname LIKE 'Gi%'   --only include rows with lastname starting with Gi
LIMIT 10
```

Small but Powerful DB: SQLite3

- likely already have it installed
- many programs use it to store configurations, history, etc
- good place to play around with sql

```
bgibson@civet:~$ sqlite3
SQLite version 3.22.0 2018-01-22 18:45:57
Enter ".help" for usage hints.
Connected to a transient in-memory database.
Use ".open FILENAME" to reopen on a persistent database.
sqlite>
```

Accessing Relational DBs: `sqlalchemy`

- flexible library for accessing a variety of sql dbs
- can use to query through pandas itself to retrieve a dataframe

In [60]:

```python
import sqlalchemy

# sqlite sqlalchemy relative path syntax: 'sqlite:///[path to database file]'
engine = sqlalchemy.create_engine('sqlite:///../data/example_business.sqlite')

# read all records from the table sales
sql = """
SELECT
    *
FROM
    clients
"""

pd.read_sql(sql,engine)
```

Out[60]:

	client_id	firstname	lastname	home_address_id
0	102	Mikel	Rouse	1002
1	103	Laura	Gibson	1003
2	104	None	Reeves	1003
3	105	Scott	Payseur	1004

SQL: SELECT

In [61]:

```
sql="""
SELECT
    client_id
    ,lastname
FROM
    clients
"""

pd.read_sql(sql,engine)
```

Out[61]:

	client_id	lastname
0	102	Rouse
1	103	Gibson
2	104	Reeves
3	105	Payseur

SQL: AS alias

In [62]:

```
sql="""
SELECT
    client_id AS Cid
    ,lastname AS Lastname
FROM
    clients ca
"""

pd.read_sql(sql,engine)
```

Out[62]:

	Cid	Lastname
0	102	Rouse
1	103	Gibson
2	104	Reeves
3	105	Payseur

SQL: * (wildcard)

In [63]:

```
sql="""
SELECT
    *
FROM
    clients
"""
clients = pd.read_sql(sql,engine)
clients
```

Out[63]:

	client_id	firstname	lastname	home_address_id
0	102	Mikel	Rouse	1002
1	103	Laura	Gibson	1003
2	104	None	Reeves	1003
3	105	Scott	Payseur	1004

In [64]:

```
sql="""
SELECT
    *
FROM
    addresses
"""
addresses = pd.read_sql(sql,engine)
addresses
```

Out[64]:

	address_id	address
0	1002	1 First Ave.
1	1003	2 Second Ave.
2	1005	3 Third Ave.

SQL: WHERE

In [65]:

```
sql = """
SELECT
    *
FROM
    clients
WHERE home_address_id = 1003
"""

pd.read_sql(sql,engine)
```

Out[65]:

	client_id	firstname	lastname	home_address_id
0	103	Laura	Gibson	1003
1	104	None	Reeves	1003

In [66]:

```
sql = """
SELECT
    *
FROM
    clients
WHERE home_address_id = 1003 AND lastname LIKE 'Gi%'
"""

pd.read_sql(sql,engine)
```

Out[66]:

	client_id	firstname	lastname	home_address_id
0	103	Laura	Gibson	1003

SQL: (INNER) JOIN

In [67]:
```
sql="""
SELECT
    c.firstname
    ,a.address
FROM clients AS c
JOIN addresses AS a ON c.home_address_id = a.address_id
WHERE c.firstname IS NOT NULL
"""

pd.read_sql(sql,engine)
```

Out[67]:

	firstname	address
0	Mikel	1 First Ave.
1	Laura	2 Second Ave.

SQL: LEFT JOIN

In [68]:

```
sql="""
SELECT
    c.firstname,a.address
FROM clients AS c
LEFT JOIN addresses AS a ON c.home_address_id = a.address_id
WHERE c.firstname IS NOT NULL
"""

pd.read_sql(sql,engine)
```

Out[68]:

	firstname	address
0	Mikel	1 First Ave.
1	Laura	2 Second Ave.
2	Scott	None

SQL: RIGHT JOIN

In [69]:
```
# this will cause an error in pandas, right join not supported in sqlalchemy + sqlite3
sql="""
SELECT
    c.firstname,a.address
FROM clients AS c
RIGHT JOIN addresses AS a ON c.home_address_id = a.address_id
"""
#pd.read_sql(sql,engine)
```

In [70]:
```
sql="""
SELECT
    c.firstname,a.address
from addresses a
LEFT JOIN clients AS c ON c.home_address_id = a.address_id
"""
pd.read_sql(sql,engine)
```

Out[70]:

	firstname	address
0	Mikel	1 First Ave.
1	None	2 Second Ave.
2	Laura	2 Second Ave.
3	None	3 Third Ave.

In [71]:
```
pd.merge(clients,addresses,left_on='home_address_id',right_on='address_id',how='right')[['firstname','address']]
```

Out[71]:

	firstname	address
0	Mikel	1 First Ave.
1	Laura	2 Second Ave.
2	None	2 Second Ave.
3	NaN	3 Third Ave.

SQL: FULL OUTER JOIN

In [72]:

```
# this will cause an error in pandas, outer join not supported in sqlalchemy + sqlite3
sql="""
SELECT
    c.firstname,a.address
FROM clients AS c
OUTER JOIN addresses AS a ON c.home_address_id = a.address_id
"""
#pd.read_sql(sql,engine)
```

In [73]:

```
pd.merge(clients,addresses,left_on='home_address_id',right_on='address_id',how='outer')[['firstname','address']]
```

Out[73]:

	firstname	address
0	Mikel	1 First Ave.
1	Laura	2 Second Ave.
2	None	2 Second Ave.
3	Scott	NaN
4	NaN	3 Third Ave.

SQL: And Much More!

- Multiple Joins
- DISTINCT
- COUNT
- ORDER BY
- GROUP BY
- LIMIT
- Operators (string concatenate operator is '||' in sqlite)
- Subqueries
- HAVING
- see Data Science From Scratch Ch. 23

NoSQL

- Anything that isn't traditional SQL/RDBMS
    - key-value (Redis,Berkely DB)
    - document store (MongoDB, DocumentDB)
    - wide column (Cassandra, HBase, DynamoDB)
    - graph (Neo4j)

- Rapidly growing field to fit needs
- Probably more as we speak

Example: Mongo

- records represented as documents (think json)
- very flexible structure
- great way to store semi-structure data
- a lot of processing needed to turn into feature vectors

- contains databases (db)
  - which contain collections (like tables)
  - which you then do finds on

Example: Mongo

- Need to have Mongo running on your local machine with a 'twitter_db' database

In [74]:
```
# conda install -n eods-f20 pymongo
import pymongo

# start up our client, defaults to the local machine
mdb = pymongo.MongoClient()

# get a connection to a database
db = mdb.twitter_db

# get a connection to a collection in that database
coll = db.twitter_collection
```

Example: Mongo

In [75]:

```python
# get one record
coll.find_one()

example_output = """
{'_id': ObjectId('59c95e2c2471847a9783c400'),
 'created_at': 'Mon Sep 25 19:51:08 +0000 2017',
 'id': 912404120484511749,
 'id_str': '912404120484511749',
 'text': 'RT @YarmolukDan: Waste Management Just Got Cleaner and More Efficient https://t.co/HtaXzfxbrA #DataScience #DataScient
 'source': '<a href="http://twitter.com/download/android" rel="nofollow">Twitter for Android</a>',
 'truncated': False,
 'in_reply_to_status_id': None,
 'in_reply_to_status_id_str': None,
 'in_reply_to_user_id': None,
 'in_reply_to_user_id_str': None,
 'in_reply_to_screen_name': None,
 'user': {'id': 912391257430794241,
  'id_str': '912391257430794241',
  'name': 'Roxane Wattenbarger',
  'screen_name': 'roxanewattenba6',
  'location': None,
  'url': None,
  'description': 'l',
  'translator_type': 'none',
  ...'
}
"""
```

Questions?