project_2_starter

October 24, 2018

1 Project 2: Breakout Strategy

1.1 Instructions

Each problem consists of a function to implement and instructions on how to implement the function. The parts of the function that need to be implemented are marked with a `# TODO` comment. After implementing the function, run the cell to test it against the unit tests we've provided. For each problem, we provide one or more unit tests from our `project_tests` package. These unit tests won't tell you if your answer is correct, but will warn you of any major errors. Your code will be checked for the correct solution when you submit it to Udacity.

1.2 Packages

When you implement the functions, you'll only need to you use the packages you've used in the classroom, like Pandas and Numpy. These packages will be imported for you. We recommend you don't add any import statements, otherwise the grader might not be able to run your code.

The other packages that we're importing are `helper`, `project_helper`, and `project_tests`. These are custom packages built to help you solve the problems. The `helper` and `project_helper` module contains utility functions and graph functions. The `project_tests` contains the unit tests for all the problems.

1.2.1 Install Packages

```
In [1]: import sys
        !{sys.executable} -m pip install -r requirements.txt
```

```
Requirement already satisfied: colour==0.1.5 in /opt/conda/lib/python3.6/site-packages (from -r
Collecting cvxpy==1.0.3 (from -r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/a1/59/2613468ffbbe3a818934d06b81b9f4877fe0
    100% || 880kB 655kB/s ta 0:00:011
Requirement already satisfied: cycler==0.10.0 in /opt/conda/lib/python3.6/site-packages/cycler-0
Collecting numpy==1.13.3 (from -r requirements.txt (line 4))
  Downloading https://files.pythonhosted.org/packages/57/a7/e3e6bd9d595125e1abbe162e323fd2d06f6f
    100% || 17.0MB 37kB/s  eta 0:00:01   22% |                         | 3.8MB 22.9MB/s eta 0:00:
Collecting pandas==0.21.1 (from -r requirements.txt (line 5))
  Downloading https://files.pythonhosted.org/packages/3a/e1/6c514df670b887c77838ab856f57783c07e8
    100% || 26.2MB 23kB/s  eta 0:00:01   12% |                             | 3.2MB 17.7MB/s eta 0
Collecting plotly==2.2.3 (from -r requirements.txt (line 6))
```

```
  Downloading https://files.pythonhosted.org/packages/99/a6/8214b6564bf4ace9bec8a26e7f89832792be
    100% || 1.1MB 557kB/s eta 0:00:01
Requirement already satisfied: pyparsing==2.2.0 in /opt/conda/lib/python3.6/site-packages (from
Requirement already satisfied: python-dateutil==2.6.1 in /opt/conda/lib/python3.6/site-packages
Requirement already satisfied: pytz==2017.3 in /opt/conda/lib/python3.6/site-packages (from -r r
Requirement already satisfied: requests==2.18.4 in /opt/conda/lib/python3.6/site-packages (from
Collecting scipy==1.0.0 (from -r requirements.txt (line 11))
  Downloading https://files.pythonhosted.org/packages/d8/5e/caa01ba7be11600b6a9d39265440d7b3be3d
    100% || 50.0MB 12kB/s  eta 0:00:01   12% |                            | 6.4MB 14.5MB/s eta 0
Requirement already satisfied: scikit-learn==0.19.1 in /opt/conda/lib/python3.6/site-packages (f
Requirement already satisfied: six==1.11.0 in /opt/conda/lib/python3.6/site-packages (from -r re
Collecting tqdm==4.19.5 (from -r requirements.txt (line 14))
  Downloading https://files.pythonhosted.org/packages/71/3c/341b4fa23cb3abc335207dba057c790f3bb3
    100% || 61kB 4.3MB/s eta 0:00:01
Collecting zipline==1.2.0 (from -r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/15/d3/689f2a940478b82ac57c751a40460598221f
    100% || 665kB 859kB/s eta 0:00:01    37% |                    | 245kB 27.4MB/s eta 0:00:01
Collecting osqp (from cvxpy==1.0.3->-r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/43/f2/bbeb83c0da6fd89a6d835b98d85ec76c04f3
    100% || 153kB 3.6MB/s eta 0:00:01
Collecting ecos>=2 (from cvxpy==1.0.3->-r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/b6/b4/988b15513b13e8ea2eac65e97d84221ac515
    100% || 122kB 3.6MB/s eta 0:00:01
Collecting scs>=1.1.3 (from cvxpy==1.0.3->-r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/b3/fd/6e01c4f4a69fcc6c3db130ba55572089e78e
    100% || 143kB 3.2MB/s eta 0:00:01
Collecting multiprocess (from cvxpy==1.0.3->-r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/7a/ee/b9bf3e171f936743758ef924622d8dd00516
    100% || 1.4MB 443kB/s eta 0:00:01
Requirement already satisfied: fastcache in /opt/conda/lib/python3.6/site-packages (from cvxpy==
Requirement already satisfied: toolz in /opt/conda/lib/python3.6/site-packages (from cvxpy==1.0.
Requirement already satisfied: decorator>=4.0.6 in /opt/conda/lib/python3.6/site-packages (from
Requirement already satisfied: nbformat>=4.2 in /opt/conda/lib/python3.6/site-packages (from plo
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /opt/conda/lib/python3.6/site-packages (
Requirement already satisfied: idna<2.7,>=2.5 in /opt/conda/lib/python3.6/site-packages (from re
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /opt/conda/lib/python3.6/site-packages (
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.6/site-packages (fro
Requirement already satisfied: pip>=7.1.0 in /opt/conda/lib/python3.6/site-packages (from ziplin
Requirement already satisfied: setuptools>18.0 in /opt/conda/lib/python3.6/site-packages (from z
Collecting Logbook>=0.12.5 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/74/fc/3e7557ed1ef1bd4e3ee189fc670416abfc71
    100% || 92kB 4.3MB/s eta 0:00:01
Collecting requests-file>=1.4.1 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/23/9c/6e63c23c39e53d3df41c77a3d05a49a42c4e
Collecting pandas-datareader<0.6,>=0.2.1 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/40/c5/cc720f531bbde0efeab940de400d0fcc95e8
    100% || 81kB 3.4MB/s ta 0:00:01:01
Requirement already satisfied: patsy>=0.4.0 in /opt/conda/lib/python3.6/site-packages (from zipl
```

```
Requirement already satisfied: statsmodels>=0.6.1 in /opt/conda/lib/python3.6/site-packages (fro
Requirement already satisfied: Cython>=0.25.2 in /opt/conda/lib/python3.6/site-packages (from zi
Collecting cyordereddict>=0.2.2 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/d1/1a/364cbfd927be1b743c7f0a985a7f1f7e8a51
    100% || 143kB 3.4MB/s eta 0:00:01
Collecting bottleneck>=1.0.0 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/05/ae/cedf5323f398ab4e4ff92d6c431a3e1c6a18
    100% || 112kB 3.8MB/s eta 0:00:01
Collecting contextlib2>=0.4.0 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/a2/71/8273a7eeed0aff6a854237ab5453bc9aa67d
Requirement already satisfied: networkx<2.0,>=1.9.1 in /opt/conda/lib/python3.6/site-packages (f
Requirement already satisfied: numexpr>=2.6.1 in /opt/conda/lib/python3.6/site-packages (from zi
Collecting bcolz<1,>=0.12.1 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/6c/8b/1ffa01f872cac36173c5eb95b58c01040d8d
    100% || 624kB 969kB/s eta 0:00:01   14% |                              | 92kB 11.4MB/s eta 0:00
Requirement already satisfied: click>=4.0.0 in /opt/conda/lib/python3.6/site-packages (from zipl
Collecting multipledispatch>=0.4.8 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/89/79/429ecef45fd5e4504f7474d4c3c3c4668c26
Requirement already satisfied: MarkupSafe>=0.23 in /opt/conda/lib/python3.6/site-packages (from
Requirement already satisfied: Mako>=1.0.1 in /opt/conda/lib/python3.6/site-packages/Mako-1.0.7-
Requirement already satisfied: sqlalchemy>=1.0.8 in /opt/conda/lib/python3.6/site-packages (from
Collecting alembic>=0.7.7 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/1a/37/8df0e37d730f096f5a41514823eaec3c5e16
    100% || 1.0MB 587kB/s eta 0:00:01
Collecting sortedcontainers>=1.4.4 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/be/e3/a065de5fdd5849450a8a16a52a96c8db5f49
Collecting intervaltree>=2.1.0 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/ca/c1/450d109b70fa58ca9d77972b02f69222412f
Collecting lru-dict>=1.1.4 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/00/a5/32ed6e10246cd341ca8cc205acea5d208e40
Collecting empyrical>=0.4.2 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/7b/55/a01b05162b764830dbbac868462f44cd847a
    100% || 51kB 2.9MB/s ta 0:00:01
Collecting tables>=3.3.0 (from zipline==1.2.0->-r requirements.txt (line 15))
  Downloading https://files.pythonhosted.org/packages/d7/1b/21f4c7f296b718575c17ef25e61c05742a28
    100% || 3.8MB 170kB/s eta 0:00:01    82% |     | 3.1MB 17.6MB/s eta 0:00:01
Requirement already satisfied: future in /opt/conda/lib/python3.6/site-packages (from osqp->cvxp
Collecting dill>=0.2.8.1 (from multiprocess->cvxpy==1.0.3->-r requirements.txt (line 2))
  Downloading https://files.pythonhosted.org/packages/6f/78/8b96476f4ae426db71c6e86a8e6a81407f01
    100% || 153kB 3.1MB/s eta 0:00:01
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /opt/conda/lib/python3.6/site-packages
Requirement already satisfied: ipython-genutils in /opt/conda/lib/python3.6/site-packages (from
Requirement already satisfied: jupyter-core in /opt/conda/lib/python3.6/site-packages (from nbfo
Requirement already satisfied: traitlets>=4.1 in /opt/conda/lib/python3.6/site-packages (from nb
Collecting requests-ftp (from pandas-datareader<0.6,>=0.2.1->zipline==1.2.0->-r requirements.txt
  Downloading https://files.pythonhosted.org/packages/3d/ca/14b2ad1e93b5195eeaf56b86b7ecfd5ea2d5
Collecting python-editor>=0.3 (from alembic>=0.7.7->zipline==1.2.0->-r requirements.txt (line 15
  Downloading https://files.pythonhosted.org/packages/65/1e/adf6e000ea5dc909aa420352d6ba37f16434
```

```
Building wheels for collected packages: cvxpy, plotly, zipline, ecos, scs, multiprocess, Logbook
  Running setup.py bdist_wheel for cvxpy ... done
  Stored in directory: /root/.cache/pip/wheels/2b/60/0b/0c2596528665e21d698d6f84a3406c52044c7b4c
  Running setup.py bdist_wheel for plotly ... done
  Stored in directory: /root/.cache/pip/wheels/98/54/81/dd92d5b0858fac680cd7bdb8800eb26c001dd9f5
  Running setup.py bdist_wheel for zipline ... done
  Stored in directory: /root/.cache/pip/wheels/5d/20/7d/b48368c8634b1cb6cc7232833b2780a265d4217c
  Running setup.py bdist_wheel for ecos ... done
  Stored in directory: /root/.cache/pip/wheels/50/91/1b/568de3c087b3399b03d130e71b1fd048ec072c45
  Running setup.py bdist_wheel for scs ... done
  Stored in directory: /root/.cache/pip/wheels/ff/f0/aa/530ccd478d7d9900b4e9ef5bc5a39e895ce110be
  Running setup.py bdist_wheel for multiprocess ... done
  Stored in directory: /root/.cache/pip/wheels/8b/36/e5/96614ab62baf927e9bc06889ea794a8e87552b84
  Running setup.py bdist_wheel for Logbook ... done
  Stored in directory: /root/.cache/pip/wheels/06/13/e9/88e9e8184d89671ffc754dc80f5eb01dabd72071
  Running setup.py bdist_wheel for cyordereddict ... done
  Stored in directory: /root/.cache/pip/wheels/0b/9d/8b/5bf3e22c1edd59b50f11bb19dec9dfcfe5a479fc
  Running setup.py bdist_wheel for bottleneck ... done
  Stored in directory: /root/.cache/pip/wheels/f2/bf/ec/e0f39aa27001525ad455139ee57ec7d0776fe074
  Running setup.py bdist_wheel for bcolz ... done
  Stored in directory: /root/.cache/pip/wheels/c5/cc/1b/2cf1f88959af5d7f4d449b7fc6c9452d0ecbd86f
  Running setup.py bdist_wheel for alembic ... done
  Stored in directory: /root/.cache/pip/wheels/67/59/2e/bbf7e5d1ac878f9735223846512f71782bd7889e
  Running setup.py bdist_wheel for intervaltree ... done
  Stored in directory: /root/.cache/pip/wheels/6b/cf/b0/f7ef2d0f504d26f3e9e70c2369e5725591ccfaf6
  Running setup.py bdist_wheel for lru-dict ... done
  Stored in directory: /root/.cache/pip/wheels/b7/ef/06/fbdd555907a7d438fb33e4c8675f771ff1cf4191
  Running setup.py bdist_wheel for empyrical ... done
  Stored in directory: /root/.cache/pip/wheels/83/14/73/34fb27552601518d28bd0813d75124be76d94ab2
  Running setup.py bdist_wheel for dill ... done
  Stored in directory: /root/.cache/pip/wheels/e2/5d/17/f87cb7751896ac629b435a8696f83ee75b11029f
  Running setup.py bdist_wheel for requests-ftp ... done
  Stored in directory: /root/.cache/pip/wheels/2a/98/32/37195e45a3392a73d9f65c488cbea30fe5bad76a
  Running setup.py bdist_wheel for python-editor ... done
  Stored in directory: /root/.cache/pip/wheels/36/e0/98/ba386b125a00ea9dd52e2c16aa2ec0adbbd639b8
Successfully built cvxpy plotly zipline ecos scs multiprocess Logbook cyordereddict bottleneck b
Installing collected packages: numpy, scipy, osqp, ecos, scs, dill, multiprocess, cvxpy, pandas,
  Found existing installation: numpy 1.12.1
    Uninstalling numpy-1.12.1:
      Successfully uninstalled numpy-1.12.1
  Found existing installation: scipy 0.19.1
    Uninstalling scipy-0.19.1:
      Successfully uninstalled scipy-0.19.1
  Found existing installation: dill 0.2.7.1
    Uninstalling dill-0.2.7.1:
      Successfully uninstalled dill-0.2.7.1
  Found existing installation: pandas 0.20.3
    Uninstalling pandas-0.20.3:
```

```
      Successfully uninstalled pandas-0.20.3
  Found existing installation: plotly 2.0.15
    Uninstalling plotly-2.0.15:
      Successfully uninstalled plotly-2.0.15
  Found existing installation: tqdm 4.11.2
    Uninstalling tqdm-4.11.2:
      Successfully uninstalled tqdm-4.11.2
Successfully installed Logbook-1.4.1 alembic-1.0.1 bcolz-0.12.1 bottleneck-1.2.1 contextlib2-0.5
You are using pip version 9.0.1, however version 18.1 is available.You should consider upgrading
```

1.2.2 Load Packages

```
In [2]: import pandas as pd
        import numpy as np
        import helper
        import project_helper
        import project_tests
```

1.3 Market Data

1.3.1 Load Data

While using real data will give you hands on experience, it's doesn't cover all the topics we try to condense in one project. We'll solve this by creating new stocks. We've create a scenario where companies mining Terbium are making huge profits. All the companies in this sector of the market are made up. They represent a sector with large growth that will be used for demonstration latter in this project.

```
In [3]: df_original = pd.read_csv('../../data/project_2/eod-quotemedia.csv', parse_dates=['date'

        # Add TB sector to the market
        df = df_original
        df = pd.concat([df] + project_helper.generate_tb_sector(df[df['ticker'] == 'AAPL']['date

        close = df.reset_index().pivot(index='date', columns='ticker', values='adj_close')
        high = df.reset_index().pivot(index='date', columns='ticker', values='adj_high')
        low = df.reset_index().pivot(index='date', columns='ticker', values='adj_low')

        print('Loaded Data')
```

```
Loaded Data
```

1.3.2 View Data

To see what one of these 2-d matrices looks like, let's take a look at the closing prices matrix.

```
In [4]: close
```

Out[4]:
```
ticker                A         AAL          AAP         AAPL        ABBV  \
date
2013-07-01 29.99418563 16.17609308  81.13821681  53.10917319 34.92447839
2013-07-02 29.65013670 15.81983388  80.72207258  54.31224742 35.42807578
2013-07-03 29.70518453 16.12794994  81.23729877  54.61204262 35.44486235
2013-07-05 30.43456826 16.21460758  81.82188233  54.17338125 35.85613355
2013-07-08 30.52402098 16.31089385  82.95141667  53.86579916 36.66188936
2013-07-09 30.68916447 16.71529618  82.43619048  54.81320389 36.35973093
2013-07-10 31.17771395 16.53235227  81.99032166  54.60295791 36.85493502
2013-07-11 31.45983407 16.72492481  82.00022986  55.45406479 37.08155384
2013-07-12 31.48047700 16.90786872  81.91105609  55.35309481 38.15724076
2013-07-15 31.72819223 17.10044125  82.61453801  55.47379158 37.79303181
2013-07-16 31.59057266 17.28338516  81.62371841  55.83133953 37.10696377
2013-07-17 31.38414330 17.76481650  80.74188897  55.84626440 37.23401341
2013-07-18 31.58369168 17.73593062  81.74261676  56.03418797 37.53893253
2013-07-19 31.79012104 17.55298671  81.45527908  55.15063572 37.70833205
2013-07-22 32.20297975 17.47595770  81.99032166  55.32713852 38.08948096
2013-07-23 31.97590746 17.37967143  81.94078068  54.37713815 37.53046256
2013-07-24 32.17545584 17.81295964  80.78152175  57.17003539 36.96297418
2013-07-25 32.10664605 18.13070432  81.46518728  56.90917464 37.47117273
2013-07-26 31.37726233 18.38104862  81.88133151  57.23233050 37.93702140
2013-07-29 31.19835688 18.51584940  81.57417743  58.11484449 38.16571074
2013-07-30 30.86118893 18.48696352  81.43546269  58.83253602 37.86079161
2013-07-31 30.77861719 18.63139292  81.73270857  58.73000866 38.52144972
2013-08-01 31.68002538 18.66027880  82.66407899  59.26808264 38.32664028
2013-08-02 31.91397865 18.21736196  82.70371177  60.02912118 38.38593011
2013-08-05 31.61121560 18.45807764  82.64426260  60.92591114 37.86926159
2013-08-06 31.70754930 18.21736196  82.41637409  60.38082896 38.01325118
2013-08-07 31.84516887 18.16921883  81.53454465  60.34578796 37.75068193
2013-08-08 31.54928679 18.27513373  80.90042011  60.22638901 38.16571074
2013-08-09 31.80388300 17.90924591  82.40646589  59.36939001 37.86926159
2013-08-12 31.96214550 18.12107570  81.69307578  61.05595360 38.14877079
...                ...         ...          ...          ...         ...
2017-05-19 55.50327007 44.83282860 151.06072036 150.70113045 63.42995100
2017-05-22 55.45382835 45.81435227 146.97179877 151.61679784 63.29454092
2017-05-23 58.00502088 46.26049939 140.27992953 151.42972601 63.68142686
2017-05-24 58.56865644 46.36955757 132.66057320 150.97681525 63.76847620
2017-05-25 58.63787484 47.60885514 131.61341035 151.49864721 64.14569000
2017-05-26 58.84553005 48.32269053 133.79749286 151.24265417 63.89421413
2017-05-30 59.69592756 47.54936885 132.63065426 151.30172949 63.85552554
2017-05-31 59.66626253 47.99551598 133.26892494 150.40575387 63.85552554
2017-06-01 60.05190791 48.63003633 136.72954883 150.81928108 64.52290380
2017-06-02 60.13101466 49.09601221 137.42765739 153.05429719 65.04519983
2017-06-05 59.72559259 49.31412858 135.20368297 151.55772252 65.29667569
2017-06-06 59.42894229 49.31412858 130.94522072 152.06970859 65.64487304
2017-06-07 59.95302448 50.42453920 130.26705812 152.97553010 66.49602213
2017-06-08 59.47838401 50.98965889 125.57975776 152.60138644 66.50569428
2017-06-09 58.54887976 49.83959075 128.01316475 146.68400898 67.38585980
```

```
2017-06-12 58.33133621 49.05635469 130.59616644 143.17887358 67.25044972
2017-06-13 58.61809816 49.02661155 131.27432905 144.33084223 67.38585980
2017-06-14 58.71698159 48.96712526 130.23713918 142.92288054 68.20799244
2017-06-15 58.54887976 48.68952261 130.79562603 142.06628846 68.28536963
2017-06-16 58.84553005 48.37226243 129.80830106 140.07741950 68.72061632
2017-06-19 59.87391774 49.23481354 129.24981421 144.08469508 69.00110863
2017-06-20 59.65637419 47.61876952 123.24608056 142.77519225 68.88504285
2017-06-21 59.12240366 48.01534474 119.84529455 143.62193844 69.00110863
2017-06-22 59.93324780 48.55072128 120.43399427 143.38563718 70.78078399
2017-06-23 59.10262697 48.21363235 119.47610998 144.02561977 70.25848796
2017-06-26 58.57854478 48.36234805 121.52159207 143.57270901 70.35520945
2017-06-27 58.22256443 48.08474540 121.69121741 141.51491885 70.01668424
2017-06-28 58.73675827 48.82832394 116.45278767 143.58255490 70.52930812
2017-06-29 58.27398382 49.19515602 115.79424221 141.46568942 70.10373358
2017-06-30 58.77942143 49.88916265 116.33305213 141.80044954 70.13275003

ticker             ABC         ABT          ACN         ADBE         ADI  \
date
2013-07-01 50.86319750 31.42538772  64.69409505  46.23500000 39.91336014
2013-07-02 50.69676639 31.27288084  64.71204071  46.03000000 39.86057632
2013-07-03 50.93716689 30.72565028  65.21451912  46.42000000 40.18607651
2013-07-05 51.37173702 31.32670680  66.07591068  47.00000000 40.65233352
2013-07-08 52.03746147 31.76628544  66.82065546  46.62500000 40.25645492
2013-07-09 51.69535307 31.16522893  66.48866080  47.26000000 40.69632003
2013-07-10 52.28710814 31.16522893  66.71298151  47.25000000 41.10979324
2013-07-11 53.72026495 31.85599537  67.47567196  47.99000000 42.22705062
2013-07-12 53.98840397 31.81096287  67.76280247  48.39000000 42.53495620
2013-07-15 53.84971137 31.95506689  68.41781897  48.12000000 42.57894271
2013-07-16 53.88669607 32.15320992  67.55642741  47.48500000 42.68451033
2013-07-17 54.06237335 32.26128793  67.43978064  48.04000000 42.80767257
2013-07-18 53.91443458 32.15320992  67.69101984  48.19000000 42.52615889
2013-07-19 54.37674323 32.30632044  67.49361761  48.07000000 42.20945601
2013-07-22 54.54317435 32.24327493  67.29621538  48.28000000 42.17426681
2013-07-23 53.28569482 33.03584705  66.62325323  48.07000000 42.56134810
2013-07-24 52.49052395 32.82869752  66.14769330  47.80000000 42.42938857
2013-07-25 53.26720248 32.94578204  65.62726924  47.79000000 42.88684829
2013-07-26 54.06237335 33.12591207  65.60932358  47.64000000 42.71969954
2013-07-29 53.98840397 33.08988606  64.93636143  47.17000000 42.66691573
2013-07-30 53.84046520 33.21597708  66.16563896  47.36000000 43.04519972
2013-07-31 53.87744989 32.99081455  66.22844876  47.28000000 43.44107832
2013-08-01 54.36749706 33.17995107  67.16162295  47.70000000 43.93372725
2013-08-02 54.07161953 33.09889256  66.92832940  47.45000000 43.87214613
2013-08-05 54.58015904 32.82869752  66.60530757  47.63000000 43.61702437
2013-08-06 54.23805064 32.51346997  65.72597036  47.39000000 43.47626753
2013-08-07 54.31202002 32.36035945  65.50164964  47.10000000 43.23874037
2013-08-08 55.11643707 32.35135295  65.48370398  47.51000000 43.19475386
2013-08-09 55.00548300 32.32433344  65.97720956  47.18000000 43.10678084
2013-08-12 54.24729681 32.33333995  65.31322023  47.20000000 43.46747023
```

```
...                ...         ...          ...          ...         ...
2017-05-19 87.59994036 42.31486674 118.75601310 136.43000000 79.14250576
2017-05-22 87.91434122 42.87370534 120.45421034 138.86000000 79.97056004
2017-05-23 87.62941544 42.82468441 119.90450488 139.52000000 79.84391644
2017-05-24 88.39576754 42.67762162 119.70818149 141.12000000 79.99978549
2017-05-25 89.51582062 43.08939743 120.83704093 142.85000000 80.21410542
2017-05-26 89.40774532 43.83451556 120.63090138 141.89000000 80.67197073
2017-05-30 89.43722040 44.11883696 121.49472426 142.41000000 82.61059193
2017-05-31 90.16427240 44.76591323 122.18185609 141.86000000 83.54580618
2017-06-01 91.51030109 45.19729742 122.98678196 141.38000000 80.08746182
2017-06-02 91.94260228 45.58946486 123.42850956 143.48000000 78.82102586
2017-06-05 91.68715157 45.70711509 124.25306776 143.59000000 76.71679380
2017-06-06 90.08567218 45.45220625 124.00766354 143.03000000 78.03193884
2017-06-07 90.32147283 45.64828997 124.22361925 143.62000000 79.18147302
2017-06-08 89.96777186 45.80515695 123.85060483 142.63000000 80.75863709
2017-06-09 90.48849829 46.36399555 123.50703891 138.05000000 76.99695384
2017-06-12 90.74394899 46.24634532 123.97821503 137.25000000 78.11370356
2017-06-13 91.37275071 46.53066671 124.73406004 139.09000000 79.57331502
2017-06-14 92.25700314 46.70714206 124.91075109 138.25000000 79.28922957
2017-06-15 92.77772957 47.17774299 124.69479537 137.52000000 78.12349961
2017-06-16 90.91097444 47.26598066 125.21505233 137.84000000 78.40758506
2017-06-19 92.10962773 47.93266531 125.42119188 140.35000000 78.73085471
2017-06-20 91.61837639 47.81501508 124.20398692 140.91000000 77.58471685
2017-06-21 93.94690777 47.61893136 124.77332472 144.24000000 78.34880876
2017-06-22 94.68378480 48.30522438 119.83579169 143.69000000 79.66147947
2017-06-23 94.14340831 48.11894484 120.48365885 145.41000000 79.88678863
2017-06-26 94.31043377 47.95227368 120.09101209 144.96000000 78.92677572
2017-06-27 93.85848253 47.71697322 119.94376955 142.54000000 76.54633554
2017-06-28 94.69360982 47.53069368 121.46527575 143.81000000 77.58471685
2017-06-29 94.08445815 47.77579833 120.72906307 141.24000000 76.15449354
2017-06-30 92.87597984 47.65814810 121.40637874 141.44000000 76.21326984

ticker            ...          XL        XLNX         XOM        XRAY  \
date              ...
2013-07-01        ...  27.66879066 35.28892781 76.32080247 40.02387348
2013-07-02        ...  27.54228410 35.05903252 76.60816761 39.96552964
2013-07-03        ...  27.33445191 35.28008569 76.65042719 40.00442554
2013-07-05        ...  27.69589920 35.80177117 77.39419581 40.67537968
2013-07-08        ...  27.98505704 35.20050655 77.96892611 40.64620776
2013-07-09        ...  28.31939579 35.50113886 78.89018496 40.80179133
2013-07-10        ...  27.95794850 36.39419366 78.45068533 40.71427558
2013-07-11        ...  28.50011944 37.00430040 78.83102155 41.01571874
2013-07-12        ...  28.92482002 38.00346072 78.94089646 40.83096325
2013-07-15        ...  29.27723113 38.17146113 78.81411772 40.84068723
2013-07-16        ...  29.04229039 38.27314559 78.85637730 40.86013517
2013-07-17        ...  29.18686931 38.48977769 78.99160796 40.93792696
2013-07-18        ...  29.55735279 40.52346684 79.76918424 41.22964615
2013-07-19        ...  29.71096789 40.54999322 80.43688561 41.24909410
```

2013-07-22	...	29.84651063	40.59420386	80.14952046	41.49219343
2013-07-23	...	29.13265221	40.52346684	80.46224136	41.32688588
2013-07-24	...	28.73506019	40.24051879	80.28475112	41.15185437
2013-07-25	...	29.02421802	41.05399445	80.26784729	40.91847901
2013-07-26	...	29.11457985	40.83294128	80.11571280	40.98654682
2013-07-29	...	28.92482002	40.38199282	79.47336717	40.93792696
2013-07-30	...	28.38264907	40.88599404	79.28742502	41.08378656
2013-07-31	...	28.32843198	41.28388974	79.23671352	41.69639686
2013-08-01	...	28.97000093	41.69062757	78.37461808	41.71584481
2013-08-02	...	28.87060292	41.12473146	77.71536862	41.78391262
2013-08-05	...	28.60855363	41.00978381	77.41109964	41.52136535
2013-08-06	...	28.34650434	40.50305117	77.30967665	41.40467767
2013-08-07	...	28.19288924	40.52972131	77.19980174	41.22964615
2013-08-08	...	28.02120177	40.52083127	77.57168605	41.57970919
2013-08-09	...	27.86758667	40.27190997	77.20825366	41.39495370
2013-08-12	...	27.76818866	40.35192038	76.50187303	41.53108932
...	...	...	...	...	...
2017-05-19	...	40.43133035	65.31985198	78.78898294	61.13598414
2017-05-22	...	40.86051697	66.15263846	79.13518133	62.09836493
2017-05-23	...	41.31896631	62.67453024	79.41406336	62.65396622
2017-05-24	...	41.61159355	63.13501218	79.13518133	62.23726525
2017-05-25	...	42.29439045	64.10496348	78.61588375	62.57459460
2017-05-26	...	42.23586500	64.51645797	78.42355131	62.22734380
2017-05-30	...	42.33340741	64.38909063	77.99080333	62.12812929
2017-05-31	...	42.61628041	65.35904193	77.41380602	63.02105992
2017-06-01	...	42.54800072	65.30025701	77.60613845	63.55681830
2017-06-02	...	42.21635651	65.52559923	76.45214383	63.94375491
2017-06-05	...	41.72864445	65.79013140	77.04837438	63.39807508
2017-06-06	...	41.48478841	66.24081585	78.09658617	63.05082428
2017-06-07	...	41.45552569	66.49555053	77.80808751	63.10043153
2017-06-08	...	41.18240693	66.69150029	77.52920548	62.95160976
2017-06-09	...	41.52380538	64.07557102	78.98131538	62.84247379
2017-06-12	...	41.13363573	62.92926493	79.75064513	62.25710816
2017-06-13	...	41.54331386	63.46812677	79.77949499	62.78294509
2017-06-14	...	41.97472897	63.56610164	78.92361565	63.22941040
2017-06-15	...	42.63165652	63.54650667	79.10633146	62.81270944
2017-06-16	...	43.18073029	63.42893681	80.28917595	63.19964605
2017-06-19	...	43.23955963	64.56544541	79.58716256	63.47744669
2017-06-20	...	43.33760851	63.93840619	79.15441457	62.85239525
2017-06-21	...	43.15131563	64.78099015	78.31776847	63.26909621
2017-06-22	...	42.42575385	65.23167459	77.97157008	63.32862492
2017-06-23	...	42.56302230	66.16243594	78.48125104	63.33854637
2017-06-26	...	42.76892496	65.99587865	78.12543603	63.56673975
2017-06-27	...	43.14151074	63.78164638	78.00041995	63.92391201
2017-06-28	...	43.30819385	64.67321778	78.40431807	64.82428373
2017-06-29	...	43.27877918	62.88027749	77.60613845	64.10898129
2017-06-30	...	42.94541296	63.01744232	77.63498832	64.41695873

ticker	XRX	XYL	YUM	ZBH	ZION	\
date						
2013-07-01	22.10666494	25.75338607	45.48038323	71.89882693	27.85858718	
2013-07-02	22.08273998	25.61367511	45.40266113	72.93417195	28.03893238	
2013-07-03	22.20236479	25.73475794	46.06329899	72.30145844	28.18131017	
2013-07-05	22.58516418	26.06075017	46.41304845	73.16424628	29.39626730	
2013-07-08	22.48946433	26.22840332	46.95062632	73.89282298	29.57661249	
2013-07-09	22.48946433	26.58233774	47.28094525	73.70108798	28.91218282	
2013-07-10	22.96796358	26.98284247	47.08340158	74.00785631	28.32368796	
2013-07-11	23.23113816	27.03872686	46.54333492	74.93774876	27.84909533	
2013-07-12	23.49431274	27.08529718	45.96422730	75.68549560	28.44708204	
2013-07-15	23.54216266	27.06666905	46.69299195	76.27027369	28.77929688	
2013-07-16	23.27898808	26.61959399	46.56936223	76.81670381	28.06740794	
2013-07-17	23.18328823	26.66616431	46.45874617	78.30261578	28.06740794	
2013-07-18	23.49431274	26.94558622	46.97929234	78.81069986	28.77929688	
2013-07-19	23.20721320	26.81518933	46.90121042	81.16898043	28.99760949	
2013-07-22	23.47038778	26.88970184	46.50429396	81.02518181	29.27287321	
2013-07-23	23.42253785	26.74067682	45.82758393	81.00601167	28.38063907	
2013-07-24	23.51823770	26.62890805	46.49128030	80.56503316	28.53250871	
2013-07-25	23.44646282	26.85244558	46.91422407	79.47217195	28.19080202	
2013-07-26	23.18328823	26.70342056	48.15052124	80.98684153	28.04842424	
2013-07-29	23.08758839	26.50782523	47.83819353	80.16240164	27.71620940	
2013-07-30	23.06366342	23.78811863	47.53237266	79.55844670	27.77316051	
2013-07-31	23.20721320	23.21996075	47.44778390	80.02819050	28.13385091	
2013-08-01	23.70963740	23.46212640	48.08545297	80.97725310	28.61793539	
2013-08-02	23.92496206	23.53663891	48.40428750	80.52668616	28.61793539	
2013-08-05	24.09243679	23.54595298	48.68408107	80.46916901	28.39962278	
2013-08-06	23.85318717	23.68566393	48.15052124	79.56803513	27.88706274	
2013-08-07	23.61393755	23.19201856	48.07243931	79.17498438	27.57383161	
2013-08-08	23.87711213	23.26653107	48.21558951	79.84604489	28.01994868	
2013-08-09	23.99673694	23.26653107	48.41079433	79.15581519	27.99147312	
2013-08-12	24.28383649	23.12682011	48.45634212	78.90656401	28.10537535	
...	...	...	...	...	...	
2017-05-19	26.81497802	51.24320268	68.90686651	116.46112494	39.54646594	
2017-05-22	26.73836380	51.49936943	69.83126290	116.57989212	39.65494752	
2017-05-23	26.62344247	52.19890171	69.74275686	116.59968666	40.76934918	
2017-05-24	26.89159225	52.01106475	70.75565928	117.87643393	40.13818363	
2017-05-25	26.77667091	51.53652928	70.93267135	118.07437924	40.31569894	
2017-05-26	26.81497802	50.82472608	70.89333534	118.00509838	39.89163460	
2017-05-30	27.12143491	51.20039999	71.20802347	117.21331713	39.31964082	
2017-05-31	27.08312780	51.54641544	71.43420556	117.98530385	39.51688006	
2017-06-01	27.19804914	51.84300011	72.60445204	121.40975776	39.99025421	
2017-06-02	27.12143491	52.39662482	72.76179611	122.66671050	39.54646594	
2017-06-05	26.73836380	52.59434793	72.96831019	122.65681324	39.90149656	
2017-06-06	26.81497802	52.09015400	73.08631824	122.89434761	39.70425733	
2017-06-07	26.96820647	52.85138798	73.02731422	123.07249839	39.90149656	
2017-06-08	26.81497802	52.97002185	72.74212810	123.88407418	40.81865898	
2017-06-09	26.58513535	53.35558192	71.88656975	123.72571793	41.75554533	

```
2017-06-12 27.04482069 53.40501269 70.71632326 123.71582066 42.33740107
2017-06-13 26.85328513 53.17763111 71.46370757 124.18099215 42.53464030
2017-06-14 26.54682824 53.04911109 71.82756572 124.30965660 42.63325991
2017-06-15 26.61386569 53.34569576 71.40470355 124.54719098 42.27822930
2017-06-16 27.29381692 53.43467116 71.57188162 124.62636910 42.49519245
2017-06-19 27.57154347 53.55330503 72.70279208 125.78434918 42.76146542
2017-06-20 27.13101169 53.26660652 72.68312408 125.91301364 42.36698695
2017-06-21 26.70005669 52.93047722 73.16499028 127.43719255 41.74568337
2017-06-22 26.78624769 53.23694805 73.30266633 128.29986262 41.71609749
2017-06-23 27.23635625 53.71148352 73.57801845 128.00239018 41.35120491
2017-06-26 27.95461459 54.05749897 73.49934641 127.97264293 41.75554533
2017-06-27 27.75350225 53.87954816 72.74212810 127.16946735 41.95278457
2017-06-28 28.28980181 54.34419748 72.91914017 127.42727680 42.37684891
2017-06-29 28.12560699 54.27499439 72.23075989 126.81250043 43.38276899
2017-06-30 27.74892476 54.79896064 72.53561401 127.31820357 43.30387330

ticker             ZTS
date
2013-07-01 29.44789315
2013-07-02 28.57244125
2013-07-03 28.16838652
2013-07-05 29.02459772
2013-07-08 29.76536472
2013-07-09 29.80384612
2013-07-10 29.86156823
2013-07-11 29.74612402
2013-07-12 30.15979909
2013-07-15 30.38106716
2013-07-16 29.97701243
2013-07-17 29.81346647
2013-07-18 29.64992051
2013-07-19 29.09194018
2013-07-22 29.12080123
2013-07-23 28.91877387
2013-07-24 28.76484826
2013-07-25 29.36130999
2013-07-26 29.27472684
2013-07-29 28.94763492
2013-07-30 28.96206545
2013-07-31 28.74031861
2013-08-01 29.07775945
2013-08-02 29.82977047
2013-08-05 30.12864664
2013-08-06 30.01295264
2013-08-07 30.11900548
2013-08-08 30.11900548
2013-08-09 29.80084697
2013-08-12 29.24165929
```

```
...                ...
2017-05-19 59.92967369
2017-05-22 59.92967369
2017-05-23 61.04261076
2017-05-24 61.90712437
2017-05-25 62.18535864
2017-05-26 62.21516946
2017-05-30 61.86737662
2017-05-31 61.88725050
2017-06-01 62.24498027
2017-06-02 62.10586314
2017-06-05 62.27479108
2017-06-06 62.58283617
2017-06-07 62.86107043
2017-06-08 62.18535864
2017-06-09 62.19529558
2017-06-12 61.45996216
2017-06-13 61.67360633
2017-06-14 61.94235833
2017-06-15 62.10161877
2017-06-16 62.26087921
2017-06-19 62.73866054
2017-06-20 62.70879921
2017-06-21 62.70879921
2017-06-22 63.21644187
2017-06-23 62.48981610
2017-06-26 62.43009343
2017-06-27 62.46990854
2017-06-28 62.65903032
2017-06-29 62.21111032
2017-06-30 62.09166499

[1009 rows x 519 columns]
```

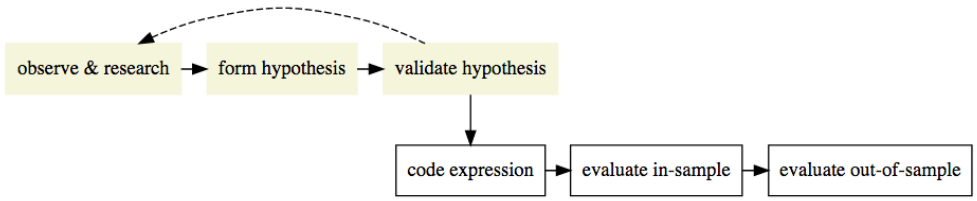
1.3.3 Stock Example

Let's see what a single stock looks like from the closing prices. For this example and future display examples in this project, we'll use Apple's stock (AAPL). If we tried to graph all the stocks, it would be too much information.

```
In [5]: apple_ticker = 'AAPL'
        project_helper.plot_stock(close[apple_ticker], '{} Stock'.format(apple_ticker))
```

1.4 The Alpha Research Process

In this project you will code and evaluate a "breakout" signal. It is important to understand where these steps fit in the alpha research workflow. The signal-to-noise ratio in trading signals is very low and, as such, it is very easy to fall into the trap of *overfitting* to noise. It is therefore inadvisable



image

to jump right into signal coding. To help mitigate overfitting, it is best to start with a general observation and hypothesis; i.e., you should be able to answer the following question *before* you touch any data:

> What feature of markets or investor behaviour would lead to a persistent anomaly that my signal will try to use?

Ideally the assumptions behind the hypothesis will be testable *before* you actually code and evaluate the signal itself. The workflow therefore is as follows:

In this project, we assume that the first three steps area done ("observe & research", "form hypothesis", "validate hypothesis"). The hypothesis you'll be using for this project is the following: - In the absence of news or significant investor trading interest, stocks oscillate in a range. - Traders seek to capitalize on this range-bound behaviour periodically by selling/shorting at the top of the range and buying/covering at the bottom of the range. This behaviour reinforces the existence of the range. - When stocks break out of the range, due to, e.g., a significant news release or from market pressure from a large investor: - the liquidity traders who have been providing liquidity at the bounds of the range seek to cover their positions to mitigate losses, thus magnifying the move out of the range, *and* - the move out of the range attracts other investor interest; these investors, due to the behavioural bias of *herding* (e.g., Herd Behavior) build positions which favor continuation of the trend.

Using this hypothesis, let start coding.. ## Compute the Highs and Lows in a Window You'll use the price highs and lows as an indicator for the breakout strategy. In this section, implement `get_high_lows_lookback` to get the maximum high price and minimum low price over a window of days. The variable `lookback_days` contains the number of days to look in the past. Make sure this doesn't include the current day.

```
In [6]: def get_high_lows_lookback(high, low, lookback_days):
            """
            Get the highs and lows in a lookback window.

            Parameters
            ----------
            high : DataFrame
                High price for each ticker and date
            low : DataFrame
                Low price for each ticker and date
            lookback_days : int
                The number of days to look back
```

```
Returns
-------
lookback_high : DataFrame
    Lookback high price for each ticker and date
lookback_low : DataFrame
    Lookback low price for each ticker and date
"""
#TODO: Implement function
#

# NOTE: Wasn't sure what this was asking for until I read 'Juanma G' explanation.
#       https://knowledge.udacity.com/questions/10954
#
# Juanma G Explanation:
# Index and columns are those from the original DataFrame. The project is asking to
# is the maximum value for that ticker given a window (for the high) and the minimum
# For example, imagine your high (the parameter) is somethin like this:
# -----------------| JOPR |OQA | ........
# 2008-03-25 | 3 | 6 | ........
# 2008-03-26 | 1 | 2 | ........
# 2008-03-27 | 7 | 9 | ........
# 2008-03-28 | 8 | 7 | ........
# 2008-03-29 | 3 | 5 | ........
# And you are using a window of size 2 excluding the current value. The output shoul
# -----------------| JOPR | OQA | ........
# 2008-03-25 | NaN | NaN | ........
# 2008-03-26 | NaN | NaN | ........
# 2008-03-27 | 3 | 6 | ........
# 2008-03-28 | 7 | 9 | ........
# 2008-03-29 | 8 | 9 | ........
#
# Why? Well, for the 'JOPR' column the first 2 values are NaN cause they do not have
# information for the window to compute the maximum. For 2008-03-27 the window is [3
# For the low parameter the operations are the same, but you need to find the minimu
#
#-----------------------------------------------------------------
# My implementation
#
# What this is doing:
# -We have a pandas dataframe dedicated for just the high prices for each ticker and
# -We do not include today, so we use .shift(1) to go back 1 day
# -We use .rolling() to provide rolling window calculations, we provide the number o
#  https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.rolling.h
# -Find the max and the min of the high and low respectively.
# -Return the resulting dataframes.
lookback_high = high.shift(1).rolling(lookback_days).max()
lookback_low = low.shift(1).rolling(lookback_days).min()
```

```
        return lookback_high, lookback_low

    project_tests.test_get_high_lows_lookback(get_high_lows_lookback)
```

```
Tests Passed
```

1.4.1 View Data

Let's use your implementation of `get_high_lows_lookback` to get the highs and lows for the past 50 days and compare it to it their respective stock. Just like last time, we'll use Apple's stock as the example to look at.

```
In [7]: lookback_days = 50
        lookback_high, lookback_low = get_high_lows_lookback(high, low, lookback_days)
        project_helper.plot_high_low(
            close[apple_ticker],
            lookback_high[apple_ticker],
            lookback_low[apple_ticker],
            'High and Low of {} Stock'.format(apple_ticker))
```

1.5 Compute Long and Short Signals

Using the generated indicator of highs and lows, create long and short signals using a breakout strategy. Implement `get_long_short` to generate the following signals:

Signal	Condition
-1	Low > Close Price
1	High < Close Price
0	Otherwise

In this chart, **Close Price** is the `close` parameter. **Low** and **High** are the values generated from `get_high_lows_lookback`, the `lookback_high` and `lookback_low` parameters.

```
In [8]: def get_long_short(close, lookback_high, lookback_low):
            """
            Generate the signals long, short, and do nothing.

            Parameters
            ----------
            close : DataFrame
                Close price for each ticker and date
            lookback_high : DataFrame
                Lookback high price for each ticker and date
            lookback_low : DataFrame
                Lookback low price for each ticker and date

            Returns
```

```
        -------
        long_short : DataFrame
            The long, short, and do nothing signals for each ticker and date
        """
        #TODO: Implement function

        # -Create a DataFrame for the return with the same size by copying the close DataFra
        # -Make all values 0 by default.
        long_short = close.copy()
        long_short[:] = 0

        # Create masks (booleans of True and False) for signal generation
        mask_plus_one_signal = lookback_high < close
        mask_minus_one_signal = lookback_low > close

        # Change values accordingly for the return DataFrame based on masks
        long_short[mask_plus_one_signal] = 1
        long_short[mask_minus_one_signal] = -1

        # Cast to int64
        # NOTE: Return a copy when copy=True
        #       https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.asty
        long_short = long_short.astype( np.int64,
                                        copy=True )
        return long_short

    project_tests.test_get_long_short(get_long_short)
```

```
Tests Passed
```

1.5.1 View Data

Let's compare the signals you generated against the close prices. This chart will show a lot of signals. Too many in fact. We'll talk about filtering the redundant signals in the next problem.

```
In [9]: signal = get_long_short(close, lookback_high, lookback_low)
        project_helper.plot_signal(
            close[apple_ticker],
            signal[apple_ticker],
            'Long and Short of {} Stock'.format(apple_ticker))
```

1.6 Filter Signals

That was a lot of repeated signals! If we're already shorting a stock, having an additional signal to short a stock isn't helpful for this strategy. This also applies to additional long signals when the last signal was long.

Implement `filter_signals` to filter out repeated long or short signals within the `lookahead_days`. If the previous signal was the same, change the signal to `0` (do nothing signal). For example, say you have a single stock time series that is

`[1, 0, 1, 0, 1, 0, -1, -1]`

Running `filter_signals` with a lookahead of 3 days should turn those signals into

`[1, 0, 0, 0, 1, 0, -1, 0]`

To help you implement the function, we have provided you with the `clear_signals` function. This will remove all signals within a window after the last signal. For example, say you're using a windows size of 3 with `clear_signals`. It would turn the Series of long signals

`[0, 1, 0, 0, 1, 1, 0, 1, 0]`

into

`[0, 1, 0, 0, 0, 1, 0, 0, 0]`

`clear_signals` only takes a Series of the same type of signals, where `1` is the signal and `0` is no signal. It can't take a mix of long and short signals. Using this function, implement `filter_signals`.

For implementing `filter_signals`, we don't reccommend you try to find a vectorized solution. Instead, you should use the `iterrows` over each column.

```
In [10]: def clear_signals(signals, window_size):
             """
             Clear out signals in a Series of just long or short signals.

             Remove the number of signals down to 1 within the window size time period.

             Parameters
             ----------
             signals : Pandas Series
                 The long, short, or do nothing signals
             window_size : int
                 The number of days to have a single signal

             Returns
             -------
             signals : Pandas Series
                 Signals with the signals removed from the window size
             """
             # Start with buffer of window size
             # This handles the edge case of calculating past_signal in the beginning
             clean_signals = [0]*window_size

             for signal_i, current_signal in enumerate(signals):
                 # Check if there was a signal in the past window_size of days
                 has_past_signal = bool(sum(clean_signals[signal_i:signal_i+window_size]))
                 # Use the current signal if there's no past signal, else 0/False
                 clean_signals.append(not has_past_signal and current_signal)

             # Remove buffer
             clean_signals = clean_signals[window_size:]
```

```python
    # Return the signals as a Series of Ints
    return pd.Series(np.array(clean_signals).astype(np.int), signals.index)


def filter_signals(signal, lookahead_days):
    """
    Filter out signals in a DataFrame.

    Parameters
    ----------
    signal : DataFrame
        The long, short, and do nothing signals for each ticker and date
    lookahead_days : int
        The number of days to look ahead

    Returns
    -------
    filtered_signal : DataFrame
        The filtered long, short, and do nothing signals for each ticker and date
    """
    #TODO: Implement function

    # Copy to the final result
    filtered_signal = signal.copy()

    # Zero-out by default
    filtered_signal[:] = 0

    # DEBUG
    #
    #print(signal)

    # Because clear_signals only takes a Series of the same type of signals,
    # where 1 is the signal and 0 is no signal. It can't take a mix of long and short s
    # we are going to make two DataFrames, one for long signals and one for short signa
    #
    # NOTE: clear_signals can take all 1 and 0 OR -1 and 0. It just can't take 1, -1, a
    df_long =  signal.copy()
    df_short = signal.copy()

    # Make masks to know what to remove.
    # For the long DataFrame, remove short signals
    # For the short DataFrame, remove the long signals
    mask_remove_short = df_long == -1
    mask_remove_long = df_short == 1

    # Remove unwanted signals by making it equal to zero.
```

```python
    df_long[mask_remove_short] = 0
    df_short[mask_remove_long] = 0

    # Copy the long and short DataFrames to versions that will be filtered
    df_long_filtered = df_long.copy()
    df_short_filtered = df_short.copy()

    # DEBUG
    #
    #print(df_long)
    #print(df_short)

    # Cycle through the columns.
    # NOTE: A column of a pandas DataFrame is a pandas Series
    # NOTE: df_long and df_short will have the same columns since they were split from
    #       the same original source. This means we only have to iterate once for both
    #       DataFrames.
    for column in df_long:

        # DEBUG
        #
        #print(df_long[column])

        # Filter the pandas Series using the custom function
        df_long_filtered[column] = clear_signals( df_long[column],
                                                  lookahead_days )
        #
        # # NOTE: clear_signals can take all 1 and 0 OR -1 and 0. It just can't take 1,
        df_short_filtered[column] = clear_signals( df_short[column],
                                                   lookahead_days )

        # Combine the final result
        # NOTE: Adding the filtered long and short DataFrames work because the when we
        #       signal (-1, 0, 1), we know that it will be mutually exclusive. Meaning
        #       if there is a 1 in the long DataFrame, there cannot be a -1 in the shor
        #       be zero. Basically, if a DataFrame as a value that is not 0 the other D
        #       value of 0. So when you add the two DataFrames, the end results will no
        filtered_signal[column] = df_long_filtered[column] + df_short_filtered[column]

    ###########################
    # NOTE: The suggestion was to use iterrows over each column. However iterrows itera
    #       and returns a Series. Unless you flip the columns as index and index as col
    #       DataFrame, the row is not what you want to filter. You could possibly use i
    #       but I found the method I use works. I am not sure the speed comparison.
    ###########################

    return filtered_signal
```

```
project_tests.test_filter_signals(filter_signals)
```

```
Tests Passed
```

1.6.1 View Data

Let's view the same chart as before, but with the redundant signals removed.

```
In [11]: signal_5 = filter_signals(signal, 5)
         signal_10 = filter_signals(signal, 10)
         signal_20 = filter_signals(signal, 20)
         for signal_data, signal_days in [(signal_5, 5), (signal_10, 10), (signal_20, 20)]:
             project_helper.plot_signal(
                 close[apple_ticker],
                 signal_data[apple_ticker],
                 'Long and Short of {} Stock with {} day signal window'.format(apple_ticker, sig
```

1.7 Lookahead Close Prices

With the trading signal done, we can start working on evaluating how many days to short or long the stocks. In this problem, implement `get_lookahead_prices` to get the close price days ahead in time. You can get the number of days from the variable `lookahead_days`. We'll use the lookahead prices to calculate future returns in another problem.

```
In [12]: def get_lookahead_prices(close, lookahead_days):
             """
             Get the lookahead prices for `lookahead_days` number of days.

             Parameters
             ----------
             close : DataFrame
                 Close price for each ticker and date
             lookahead_days : int
                 The number of days to look ahead

             Returns
             -------
             lookahead_prices : DataFrame
                 The lookahead prices for each ticker and date
             """
             #TODO: Implement function

             # NOTE: This was kind of weird because the problem asked to get future prices
             #       which we almost never do due to look-ahead bias. I wasn't sure if that was
             #       what they were asking to do.
             #
             #       Anyway, the .shift() method usually takes positive int to get previous valu
             #       I am assuming positive numbers go back and not negative numbers because you
```

```
    #       are more likely to look back in time instead of forward in time. To look ah
    #       (into the future,) you have to use positive numbers.
    lookahead_prices = close.shift(-lookahead_days)

    return lookahead_prices

project_tests.test_get_lookahead_prices(get_lookahead_prices)
```

```
Tests Passed
```

1.7.1 View Data

Using the `get_lookahead_prices` function, let's generate lookahead closing prices for 5, 10, and 20 days.

Let's also chart a subsection of a few months of the Apple stock instead of years. This will allow you to view the differences between the 5, 10, and 20 day lookaheads. Otherwise, they will mesh together when looking at a chart that is zoomed out.

```
In [13]: lookahead_5 = get_lookahead_prices(close, 5)
         lookahead_10 = get_lookahead_prices(close, 10)
         lookahead_20 = get_lookahead_prices(close, 20)
         project_helper.plot_lookahead_prices(
             close[apple_ticker].iloc[150:250],
             [
                 (lookahead_5[apple_ticker].iloc[150:250], 5),
                 (lookahead_10[apple_ticker].iloc[150:250], 10),
                 (lookahead_20[apple_ticker].iloc[150:250], 20)],
             '5, 10, and 20 day Lookahead Prices for Slice of {} Stock'.format(apple_ticker))
```

1.8 Lookahead Price Returns

Implement `get_return_lookahead` to generate the log price return between the closing price and the lookahead price.

```
In [14]: def get_return_lookahead(close, lookahead_prices):
             """
             Calculate the log returns from the lookahead days to the signal day.

             Parameters
             ----------
             close : DataFrame
                 Close price for each ticker and date
             lookahead_prices : DataFrame
                 The lookahead prices for each ticker and date

             Returns
             -------
             lookahead_returns : DataFrame
```

```
        The lookahead log returns for each ticker and date
    """
    #TODO: Implement function
    lookahead_returns = np.log(lookahead_prices) - np.log(close)

    return lookahead_returns

project_tests.test_get_return_lookahead(get_return_lookahead)
```

```
Tests Passed
```

1.8.1 View Data

Using the same lookahead prices and same subsection of the Apple stock from the previous problem, we'll view the lookahead returns.

In order to view price returns on the same chart as the stock, a second y-axis will be added. When viewing this chart, the axis for the price of the stock will be on the left side, like previous charts. The axis for price returns will be located on the right side.

```
In [15]: price_return_5 = get_return_lookahead(close, lookahead_5)
         price_return_10 = get_return_lookahead(close, lookahead_10)
         price_return_20 = get_return_lookahead(close, lookahead_20)
         project_helper.plot_price_returns(
             close[apple_ticker].iloc[150:250],
             [
                 (price_return_5[apple_ticker].iloc[150:250], 5),
                 (price_return_10[apple_ticker].iloc[150:250], 10),
                 (price_return_20[apple_ticker].iloc[150:250], 20)],
             '5, 10, and 20 day Lookahead Returns for Slice {} Stock'.format(apple_ticker))
```

1.9 Compute the Signal Return

Using the price returns generate the signal returns.

```
In [16]: def get_signal_return(signal, lookahead_returns):
             """
             Compute the signal returns.

             Parameters
             ----------
             signal : DataFrame
                 The long, short, and do nothing signals for each ticker and date
             lookahead_returns : DataFrame
                 The lookahead log returns for each ticker and date

             Returns
             -------
             signal_return : DataFrame
```

```
        Signal returns for each ticker and date
    """
    #TODO: Implement function

    # Copy returns to final output to get the same size.
    # Default all values to 0.
    signal_return = lookahead_returns.copy()
    signal_return[:] = 0

    # DEBUG
    #
    #print(lookahead_returns.isnull().values)

    # Leave nan (not a number) values intact
    mask_nan = lookahead_returns.isnull().values
    signal_return[mask_nan] = np.nan

    # Get masks for long and short
    mask_signals_long = signal == 1
    mask_signals_short = signal == -1

    # Use the values for long position if the mask said it is a long position.
    # NOTE: for short position, negate it.
    signal_return[mask_signals_long] = lookahead_returns[mask_signals_long]
    signal_return[mask_signals_short] = -lookahead_returns[mask_signals_short]

    return signal_return

project_tests.test_get_signal_return(get_signal_return)
```

```
Tests Passed
```

1.9.1 View Data

Let's continue using the previous lookahead prices to view the signal returns. Just like before, the axis for the signal returns is on the right side of the chart.

```
In [17]: title_string = '{} day LookaheadSignal Returns for {} Stock'
         signal_return_5 = get_signal_return(signal_5, price_return_5)
         signal_return_10 = get_signal_return(signal_10, price_return_10)
         signal_return_20 = get_signal_return(signal_20, price_return_20)
         project_helper.plot_signal_returns(
             close[apple_ticker],
             [
                 (signal_return_5[apple_ticker], signal_5[apple_ticker], 5),
                 (signal_return_10[apple_ticker], signal_10[apple_ticker], 10),
                 (signal_return_20[apple_ticker], signal_20[apple_ticker], 20)],
             [title_string.format(5, apple_ticker), title_string.format(10, apple_ticker), title
```

1.10 Test for Significance

1.10.1 Histogram

Let's plot a histogram of the signal return values.

```
In [18]: project_helper.plot_signal_histograms(
             [signal_return_5, signal_return_10, signal_return_20],
             'Signal Return',
             ('5 Days', '10 Days', '20 Days'))
```

1.10.2 Question: What do the histograms tell you about the signal returns?

#TODO: Put Answer In this Cell

All three histograms visually seem to be normally distributed and not skewed to one side. To test mathematically, we could see if the total area under the curve is equal to 1 (https://www.pqsystems.com/qualityadvisor/DataAnalysisTools/interpretation/histogram_compare_to_norm However, there seems to be outliers in 10 and 20 day histograms on the right side.

1.11 Outliers

You might have noticed the outliers in the 10 and 20 day histograms. To better visualize the outliers, let's compare the 5, 10, and 20 day signals returns to normal distributions with the same mean and deviation for each signal return distributions.

```
In [24]: project_helper.plot_signal_to_normal_histograms(
             [signal_return_5, signal_return_10, signal_return_20],
             'Signal Return',
             ('5 Days', '10 Days', '20 Days'))
```

1.12 Kolmogorov-Smirnov Test

While you can see the outliers in the histogram, we need to find the stocks that are causing these outlying returns. We'll use the Kolmogorov-Smirnov Test or KS-Test. This test will be applied to teach ticker's signal returns where a long or short signal exits.

```
In [25]: # Filter out returns that don't have a long or short signal.
         long_short_signal_returns_5 = signal_return_5[signal_5 != 0].stack()
         long_short_signal_returns_10 = signal_return_10[signal_10 != 0].stack()
         long_short_signal_returns_20 = signal_return_20[signal_20 != 0].stack()

         # Get just ticker and signal return
         long_short_signal_returns_5 = long_short_signal_returns_5.reset_index().iloc[:, [1,2]]
         long_short_signal_returns_5.columns = ['ticker', 'signal_return']
         long_short_signal_returns_10 = long_short_signal_returns_10.reset_index().iloc[:, [1,2]
         long_short_signal_returns_10.columns = ['ticker', 'signal_return']
         long_short_signal_returns_20 = long_short_signal_returns_20.reset_index().iloc[:, [1,2]
         long_short_signal_returns_20.columns = ['ticker', 'signal_return']

         # View some of the data
         long_short_signal_returns_5.head(10)
```

```
Out[25]:    ticker  signal_return
         0       A     0.00732604
         1     ABC     0.01639650
         2     ADP     0.00981520
         3  AGENEN     0.02698490
         4    AKAM     0.04400495
         5    ALGN     0.01545561
         6     APC     0.00305859
         7      BA     0.08061297
         8  BAKERI     0.02298007
         9     BCR     0.00933418
```

This gives you the data to use in the KS-Test.

Now it's time to implement the function `calculate_kstest` to use Kolmogorov-Smirnov test (KS test) between a normal distribution and each stock's signal returns. Run KS test on a normal distribution against each stock's signal returns. Use `scipy.stats.kstest` perform the KS test.

For this function, we don't reccommend you try to find a vectorized solution. Instead, you should iterate over the `groupby` function.

```
In [26]: from scipy.stats import kstest


         def calculate_kstest(long_short_signal_returns):
             """
             Calculate the KS-Test against the signal returns with a long or short signal.

             Parameters
             ----------
             long_short_signal_returns : DataFrame
                 The signal returns which have a signal.
                 This DataFrame contains two columns, "ticker" and "signal_return"

             Returns
             -------
             ks_values : Pandas Series
                 KS static for all the tickers
             p_values : Pandas Series
                 P value for all the tickers
             """
             #TODO: Implement function

             # Create pandas series for return
             ks_values = pd.Series()
             p_values = pd.Series()

             # Arguments for scipy.stats.kstest
             # https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.stats.kstest.ht
             #
```

```
    # Distribution parameters, used if rvs or cdf are strings.
    normal_args = ( np.mean(long_short_signal_returns),
                    np.std(long_short_signal_returns) )

    grouped = long_short_signal_returns.groupby('ticker')
    for name, group in grouped:
            sample = group['signal_return'].values

            # https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.stats.k
            # https://docs.scipy.org/doc/scipy-0.14.0/reference/stats.html#module-scipy
            # https://stackoverflow.com/questions/17901112/using-scipys-stats-kstest-mo
            test_stat, p_value = kstest(sample, 'norm', normal_args)

            # Put in pandas Series.
            ks_values[name] = test_stat
            p_values[name] = p_value

    return ks_values, p_values


project_tests.test_calculate_kstest(calculate_kstest)
```

```
Tests Passed
```

1.12.1 View Data

Using the signal returns we created above, let's calculate the ks and p values.

```
In [27]: ks_values_5, p_values_5 = calculate_kstest(long_short_signal_returns_5)
         ks_values_10, p_values_10 = calculate_kstest(long_short_signal_returns_10)
         ks_values_20, p_values_20 = calculate_kstest(long_short_signal_returns_20)

         print('ks_values_5')
         print(ks_values_5.head(10))
         print('p_values_5')
         print(p_values_5.head(10))
```

```
ks_values_5
A       0.17217972
AAL     0.10740675
AAP     0.19700650
AAPL    0.15568721
ABBV    0.16821204
ABC     0.21418277
ABT     0.21377786
ACN     0.28226878
ADBE    0.24273341
ADI     0.19434552
```

```
dtype: float64
p_values_5
A       0.18690894
AAL     0.72486962
AAP     0.04494729
AAPL    0.24693576
ABBV    0.24655673
ABC     0.02726227
ABT     0.04822146
ACN     0.00584267
ADBE    0.00910251
ADI     0.09871237
dtype: float64
```

1.13 Find Outliers

With the ks and p values calculate, let's find which symbols are the outliers. Implement the `find_outliers` function to find the following outliers: - Symbols that pass the null hypothesis with a p-value less than `pvalue_threshold`. - Symbols that with a KS value above `ks_threshold`.

```
In [35]: def find_outliers(ks_values, p_values, ks_threshold, pvalue_threshold=0.05):
             """
             Find outlying symbols using KS values and P-values

             Parameters
             ----------
             ks_values : Pandas Series
                 KS static for all the tickers
             p_values : Pandas Series
                 P value for all the tickers
             ks_threshold : float
                 The threshold for the KS statistic
             pvalue_threshold : float
                 The threshold for the p-value

             Returns
             -------
             outliers : set of str
                 Symbols that are outliers
             """
             #TODO: Implement function

             # List of tickers that are outliers.
             # Will convert into a set later.
             list_outliers_p_values = []
             list_outliers_ks_values = []
```

```
    # DEBUG
    #
    #print(ks_values)
    #print(p_values)
    #print(ks_threshold)
    #print(pvalue_threshold)

    # Mask the creteria
    mask_p_values = p_values < pvalue_threshold
    mask_ks_values = ks_values > ks_threshold

    # Get the index that meet the creteria
    # NOTE: .index is a parameter that returns the corresponding index which is a type
    #       .values converts the pandas index to python list.
    list_outliers_p_values = p_values[mask_p_values].index.values
    #
    # Same idea
    list_outliers_ks_values = ks_values[mask_ks_values].index.values

    # DEBUG
    #
    #print( p_values[mask_p_values].index.values )

    # Convert list into sets and find intersection, meaning
    # symbols that are outliers in both.
    set_outliers_p_values = set(list_outliers_p_values)
    set_outliers_ks_values = set(list_outliers_ks_values)

    # Find intersection, meaning symbols that are outliers in both.
    outliers = set_outliers_p_values.intersection(set_outliers_ks_values)

    return outliers


project_tests.test_find_outliers(find_outliers)
```

```
Tests Passed
```

1.13.1 View Data

Using the `find_outliers` function you implemented, let's see what we found.

```
In [36]: ks_threshold = 0.8
         outliers_5 = find_outliers(ks_values_5, p_values_5, ks_threshold)
         outliers_10 = find_outliers(ks_values_10, p_values_10, ks_threshold)
         outliers_20 = find_outliers(ks_values_20, p_values_20, ks_threshold)
```

```
outlier_tickers = outliers_5.union(outliers_10).union(outliers_20)
print('{} Outliers Found:\n{}'.format(len(outlier_tickers), ', '.join(list(outlier_tick
```

```
24 Outliers Found:
ORPHAN, BAKERI, CLUSIA, GESNER, HUMILI, ALTAIC, AGENEN, BIFLOR, SPRENG, URUMIE, KAUFMA, TURKES,
```

1.13.2 Show Significance without Outliers

Let's compare the 5, 10, and 20 day signals returns without outliers to normal distributions. Also, let's see how the P-Value has changed with the outliers removed.

```
In [37]: good_tickers = list(set(close.columns) - outlier_tickers)

         project_helper.plot_signal_to_normal_histograms(
             [signal_return_5[good_tickers], signal_return_10[good_tickers], signal_return_20[go
             'Signal Return Without Outliers',
             ('5 Days', '10 Days', '20 Days'))
```

That's more like it! The returns are closer to a normal distribution. You have finished the research phase of a Breakout Strategy. You can now submit your project. ## Submission Now that you're done with the project, it's time to submit it. Click the submit button in the bottom right. One of our reviewers will give you feedback on your project with a pass or not passed grade. You can continue to the next section while you wait for feedback.