w3

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[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from pytrends.request import TrendReq

# Imputer
from sklearn.impute import KNNImputer
from sklearn.model_selection import train_test_split

# Turn off warnings
import warnings
warnings.filterwarnings('ignore')
```

1 0.) Clean the Apple Data to get a quarterly series of EPS.

[ ]:
```
data = pd.read_csv('AAPL_quarterly_financials.csv')
```

[ ]:
```
# Transposing the data and setting the first row as the column names
data = data.T
data.columns = ['dates'] +  data.iloc[0,:]
data = data.drop(data.index[0:2,])
```

[ ]:
```
# Converting data.index to datetime
data.index = pd.to_datetime(data.index)
```

[ ]:
```
# Ordering the data from oldest to newest
data = data.sort_index()
```

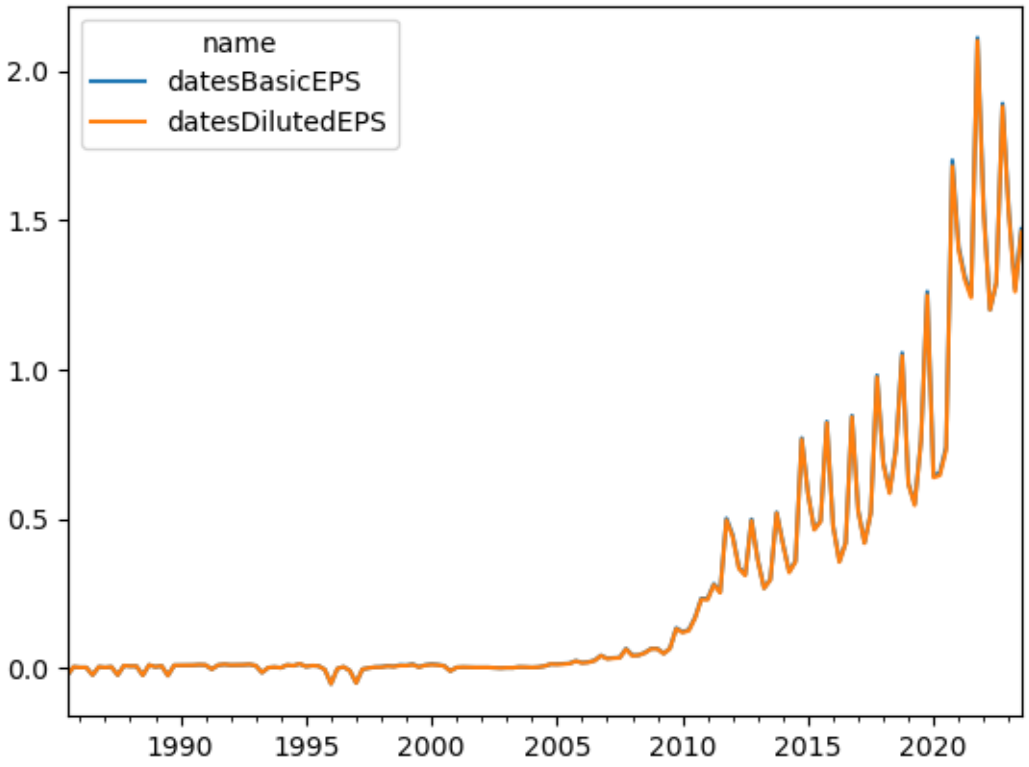
[ ]:
```
# Converting to numeric, but the numbers are strings with commas.
data = data.apply(lambda x: x.str.replace(',',''))
data = data.apply(pd.to_numeric)
```

[ ]:
```
# Using an nearest neighbor imputer to fill in missing values.
# The 5 nearest neighbors are used to fill in the missing values.
imputer = KNNImputer(n_neighbors=5)
data = pd.DataFrame(
    imputer.fit_transform(data),
    columns=data.columns,
    index=data.index
)
```

[ ]:
```
# Getting a DataFrame containing the columns that contain the word 'EPS'
eps_name = data.columns.str.contains('EPS')
eps = data.iloc[:,eps_name]
```

[ ]:
```
eps.plot()
```

[ ]: <Axes: >



2 1.) Come up with 6 search terms you think could nowcast earnings. (Different than the ones I used) Add in 3 terms that that you think will not Nowcast earnings. Pull in the gtrends data. Clean it to have a quarterly average.

[ ]:
```
# Create pytrends object
pytrends = TrendReq(hl='en-US', tz=360)

# Set up the keywords and the timeframe
keywords = [
    'Apple',
    'Macintosh',
    'Apple Stocks',
    'Apple Financial',
    'Apple Earnings',
    'NASDAQ',
    'SP500',
    'GDP',
    'Technology',
    'Linear Regression',
    'Bayes Theorem',
    'UCLA'
]  # Add your keywords here
start_date = '2004-01-01'
end_date = '2024-01-01'

# Create an empty DataFrame to store the results
df = pd.DataFrame()

# Iterate through keywords and fetch data
for keyword in keywords:
    pytrends.build_payload([keyword], cat=0, timeframe=f'{start_date}␣
 ↪{end_date}', geo='', gprop='')
    interest_over_time_df = pytrends.interest_over_time()
    df[keyword] = interest_over_time_df[keyword]
```

[ ]:
```
df = df.resample('Q').sum()
```

[ ]:
```
y = eps.iloc[:,0]
```

[ ]:
```
# Subset y into the same time period as X
first_date = max(df.index[0], y.index[0])
last_date = min(df.index[-1], y.index[-1]) + pd.DateOffset(months=3)
```

[ ]:
```
df = df.loc[first_date:last_date]
y = y.loc[first_date:last_date]
```

3 2.) Normalize all the X data

[ ]:
```
from sklearn.preprocessing import StandardScaler
```

[ ]:
```
scaler = StandardScaler()
```

[ ]:
```
X_scaled = scaler.fit_transform(df)
```

4 3.) Import data. Train, Test, Holdout (80%,15%,5%)

5 4.) Run a Lasso with lambda of .5. Plot a bar chart.

[ ]:
```
from sklearn.linear_model import Lasso
```

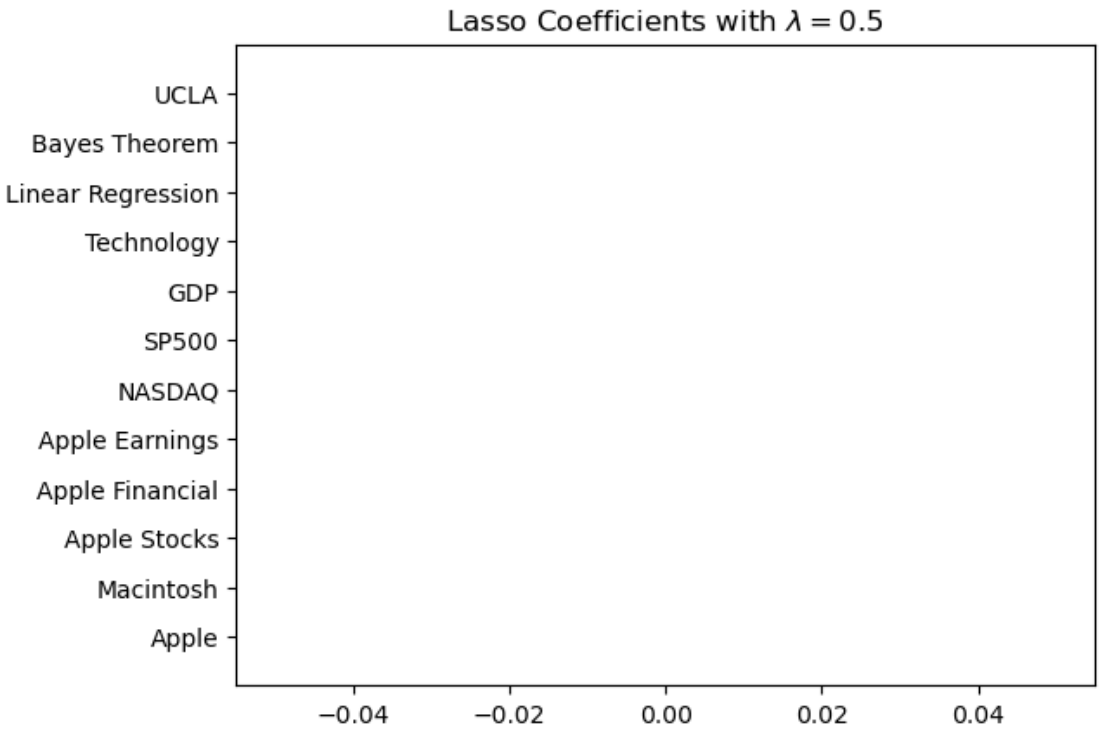
[ ]:
```
lasso = Lasso(alpha=0.5)
```

[ ]:
```
lasso_result = lasso.fit(X_scaled,y)
```

6 5.) Do these coefficient magnitudes make sense?

[ ]:
```
plt.barh(df.columns, lasso_result.coef_)
plt.title('Lasso Coefficients with $\lambda = 0.5$')
plt.plot()
```

[ ]: []



7 6.) Run a for loop looking at 10 different Lambdas and plot the coefficient magnitude for each.

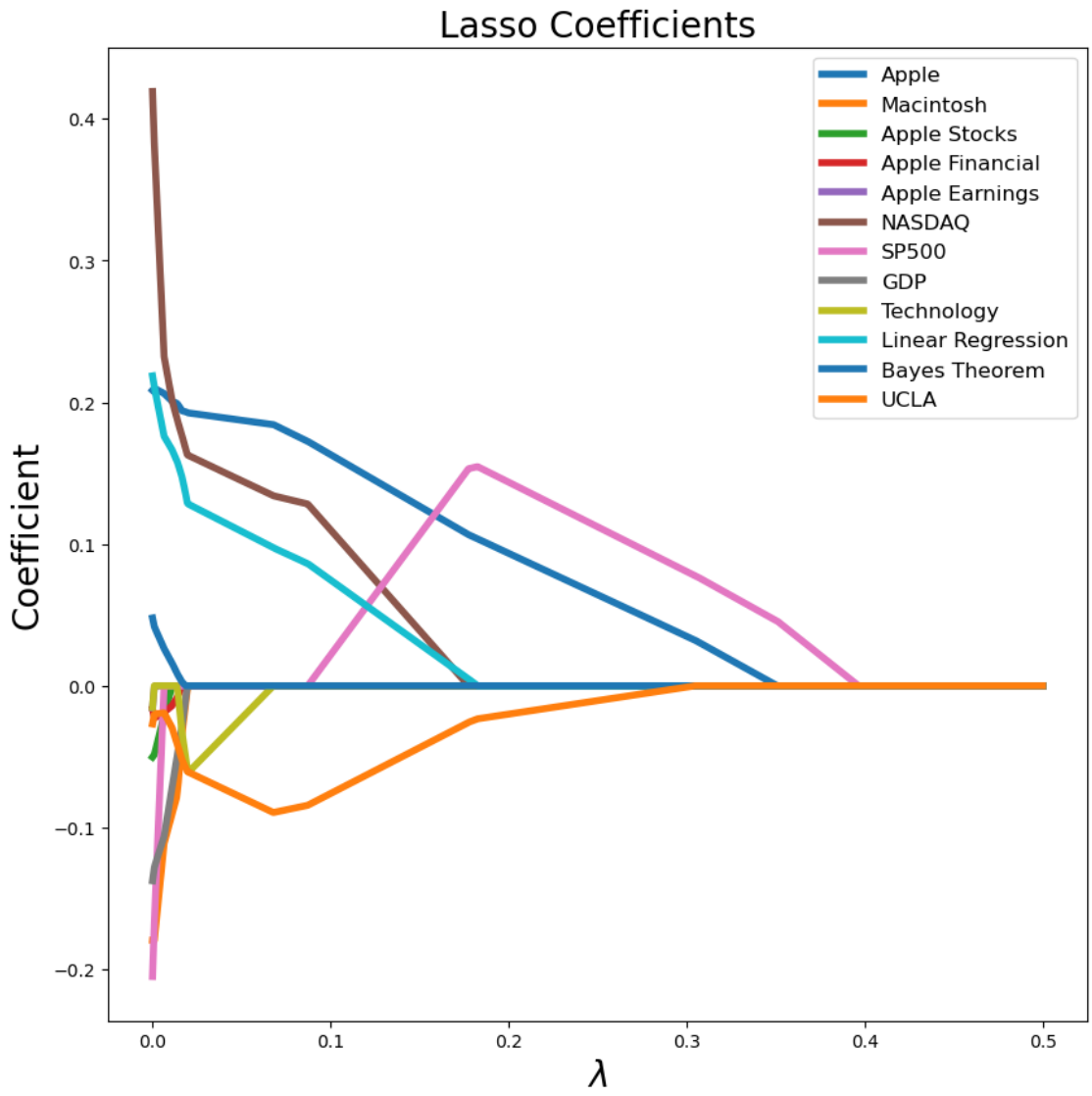
[ ]:
```
l_sim = np.linspace(0, 0.5, 1_000)
coef = np.nan * np.ones((len(l_sim), X_scaled.shape[1]))
for i, l in enumerate(l_sim):
    lasso = Lasso(alpha=l)
    lasso_result = lasso.fit(X_scaled,y)
    coef[i,:] = lasso_result.coef_
```

```
/tmp/ipykernel_43335/285329737.py:5: UserWarning: With alpha=0, this algorithm
does not converge well. You are advised to use the LinearRegression estimator
  lasso_result = lasso.fit(X_scaled,y)
/home/m4wnn/anaconda3/lib/python3.11/site-
packages/sklearn/linear_model/_coordinate_descent.py:631: UserWarning:
Coordinate descent with no regularization may lead to unexpected results and is
discouraged.
  model = cd_fast.enet_coordinate_descent(
/home/m4wnn/anaconda3/lib/python3.11/site-
packages/sklearn/linear_model/_coordinate_descent.py:631: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
```

```
gap: 9.334e-01, tolerance: 2.057e-03 Linear regression models with null weight
for the l1 regularization term are more efficiently fitted using one of the
solvers implemented in sklearn.linear_model.Ridge/RidgeCV instead.
  model = cd_fast.enet_coordinate_descent(
```

[ ]:
```
plt.figure(figsize=(10,10))
for i in range(coef.shape[1]):
    plt.plot(
        l_sim, coef[:,i],
        label=df.columns[i],
        linewidth=4
    )
plt.legend(
    df.columns,
    fontsize=12,
)
plt.title('Lasso Coefficients', fontsize=20)
plt.xlabel('$\lambda$', fontsize=20)
plt.ylabel('Coefficient', fontsize=20)
```

[ ]:
```
Text(0, 0.5, 'Coefficient')
```



8 7.) Run a cross validation. What is your ideal lambda?

[ ]:
```
from sklearn.linear_model import LassoCV
```

[ ]:
```
modCV = LassoCV(cv=5).fit(X_scaled,y)
```

[ ]:
```
opt_l = modCV.alpha_
opt_coef = modCV.coef_
print(f'Optimal lambda: {np.round(opt_l, 5)}')
```

```
Optimal lambda: 0.0037
```

[ ]:
```
plt.barh(df.columns, opt_coef)
plt.title(f'Lasso Coefficients with optimal $\lambda = {np.round(opt_l, 5)}$')
plt.plot()
```

[ ]: []