SEC1 3 - Homework

January 24, 2024

[209]:
```
import pandas as pd
from pytrends.request import TrendReq
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

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

[44]:
```
data = pd.read_csv('AAPL_quarterly_financials.csv', index_col=0, header=None).T
y = data.reindex(index=data.index[::-1])
y.set_index('name', inplace=True)
y.drop(y.tail(1).index,inplace=True)
y.index = pd.to_datetime(y.index)
Y = y['BasicEPS']
Y = Y.fillna(0.)
Y
```

[44]:
```
name
1985-09-30      0.0
1985-12-31    0.004
1986-03-31    0.002
1986-06-30    0.002
1986-09-30      0.0
              …
2022-09-30     1.29
2022-12-31     1.89
2023-03-31     1.53
2023-06-30     1.27
2023-09-30     1.47
Name: BasicEPS, Length: 153, dtype: object
```

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.

[176]:
```
# Create pytrends object
pytrends = TrendReq(hl='en-US', tz=360)

# Set up the keywords and the timeframe
keywords = ["Credit card","Debt","Job","Extra income","Cellphone","Apple␣
 ↪Store","Ucla","Hospital","Tickets","Bank"]  # 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]
```

[177]:
```
dfq = df.resample('Q').mean()
dfq = dfq[dfq.index <= '2023-09-30']
dfq
```

[177]:

date	Credit card	Debt	Job	Extra income	Cellphone	Apple Store	Ucla	Hospital	Tickets	Bank
2004-03-31	51.000000	62.000000	71.666667	70.666667	86.333333	6.333333	87.000000	79.333333	88.666667	63.666667
2004-06-30	47.000000	57.000000	69.666667	68.333333	82.666667	6.333333	83.000000	76.000000	90.666667	65.000000
2004-09-30	52.333333	56.000000	68.000000	86.666667	90.333333					
2004-12-31	50.000000	60.333333	60.000000	61.333333	89.333333					
2005-03-31	46.666667	59.000000	67.333333	77.666667	92.666667					
…	…	…	…	…	…					
2022-09-30	93.333333	50.333333	51.333333	79.333333	30.666667					
2022-12-31	85.333333	48.333333	44.000000	76.666667	29.333333					
2023-03-31	86.666667	54.333333	47.333333	77.333333	30.333333					
2023-06-30	83.333333	65.666667	47.666667	69.000000	27.666667					
2023-09-30	89.333333	47.333333	47.000000	70.333333	30.666667					

```
2004-09-30     8.333333  74.333333  78.666667  91.666667  67.666667
2004-12-31    10.333333  87.000000  74.333333  90.333333  65.333333
2005-03-31    11.000000  81.666667  79.333333  97.666667  66.333333
…                   …          …          …          …          …
2022-09-30    24.666667  33.000000  89.000000  70.666667  82.333333
2022-12-31    24.666667  41.000000  75.000000  67.333333  73.000000
2023-03-31    19.000000  41.333333  82.666667  65.333333  80.000000
2023-06-30    17.666667  29.000000  79.666667  66.666667  79.666667
2023-09-30    21.333333  29.000000  81.333333  74.333333  78.666667

[79 rows x 10 columns]
```

3 2.) Normalize all the X data

[178]:
```
from sklearn.preprocessing import StandardScaler
```

[179]:
```
scaler = StandardScaler()
```

[180]:
```
X_scaled = scaler.fit_transform(dfq)
```

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

[181]:
```
from sklearn.linear_model import Lasso
```

[212]:
```
Y_04 = Y[Y.index >= '2004-03-31']
```

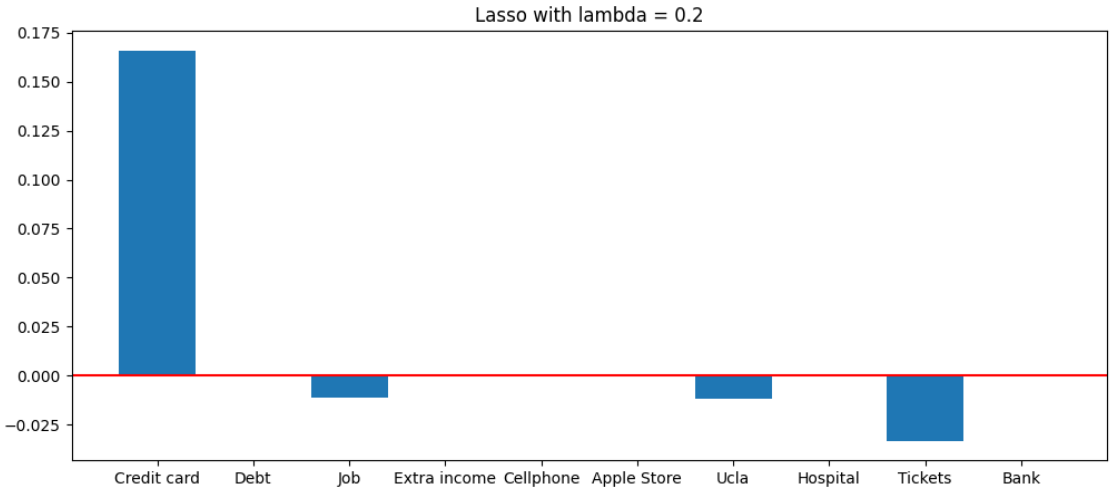
[213]:
```
lasso = Lasso(alpha = 0.2)
```

[214]:
```
lasso.fit(X_scaled,Y_04)
```

[214]:
```
Lasso(alpha=0.2)
```

[215]:
```
coefficients = lasso.coef_
```

[216]:
```
names = ['Credit card', 'Debt', 'Job', 'Extra income', 'Cellphone',
       'Apple Store', 'Ucla', 'Hospital', 'Tickets', 'Bank']

plt.figure(figsize=(12,5))
plt.title('Lasso with lambda = 0.2')
plt.bar(range(len(coefficients)), coefficients, tick_label=names)
plt.axhline(0, color = 'red')
plt.show()
```



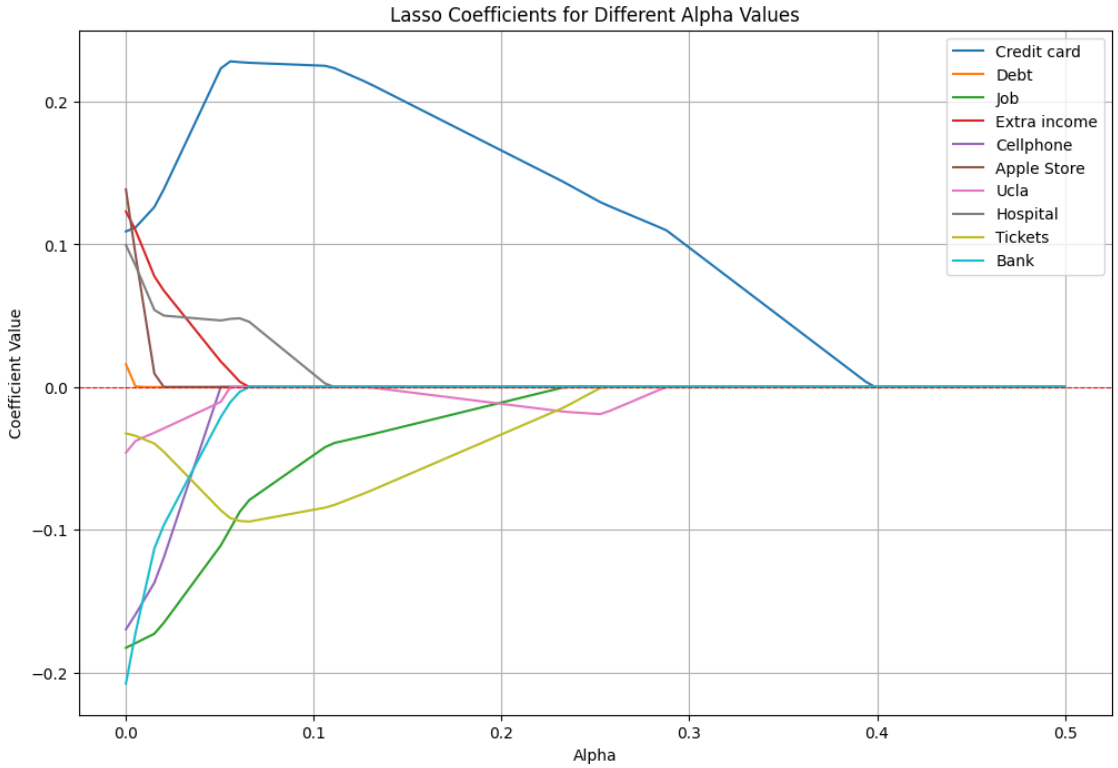
5 5.) Do these coefficient magnitudes make sense?

The direction of the coefficients do not always make sense. Credit card appears to impact positively to apple revenues probably because when the economic situation is well, people are more willing to acquire more debt. Job searches have a negative coefficient because people are in a worse situation and probably looking for new job opportunities. However, Ucla and tickets have no immediate intuition.

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

[228]:
```
alphas = np.linspace(0, 0.5, 100)

# List to store coefficients for each alpha
coefficients_list = []

# Loop through different alpha values
for alpha in alphas:
    lasso = Lasso(alpha=alpha)
    lasso.fit(X_scaled, Y_04)
    coefficients = lasso.coef_
    coefficients_list.append(coefficients)

# Transpose the coefficients list for easier plotting
coefficients_array = np.array(coefficients_list).T

# Plotting
plt.figure(figsize=(12, 8))
```

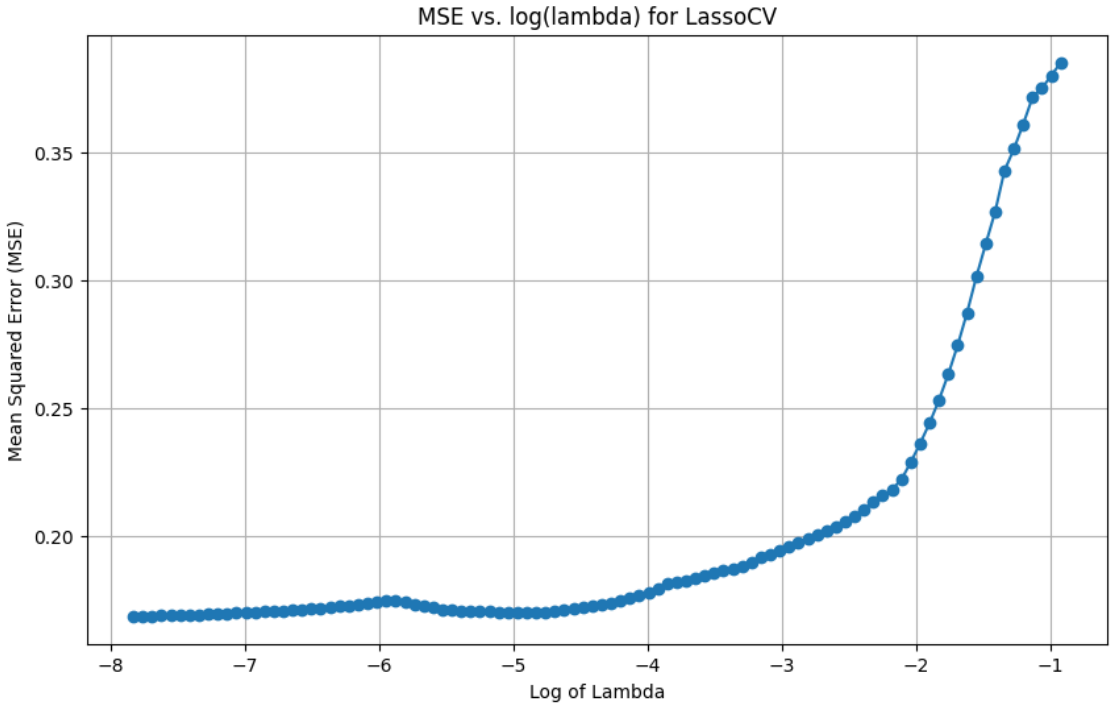
```
for i in range(len(names)):
    plt.plot(alphas, coefficients_array[i], label=names[i])

plt.xlabel('Alpha')
plt.ylabel('Coefficient Value')
plt.title('Lasso Coefficients for Different Alpha Values')
plt.axhline(0, color='red', linestyle='--', linewidth=0.8)
plt.legend()
plt.grid(True)
plt.show()
```



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

[226]:
```
from sklearn.linear_model import LassoCV
modCV = LassoCV().fit(X_scaled,Y_04)

alphas = modCV.alphas_
mse_values = modCV.mse_path_.mean(axis=1)

# Plotting
plt.figure(figsize=(10, 6))
```

```
plt.plot(np.log(alphas), mse_values, marker='o')
plt.xlabel('Log of Lambda')
plt.ylabel('Mean Squared Error (MSE)')
plt.title('MSE vs. log(lambda) for LassoCV')
plt.grid(True)
plt.show()
```



[225]:
```
# Minimum lambda
a=modCV.alpha_
a
```

[225]: 0.000397672271760685

Seems that the optimal lambda is very close to zero: 0.0003976