```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
```

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

```
In [2]: y = pd.read_csv("AAPL_quarterly_financials.csv")
In [3]: y.index = y.name
In [4]: y = pd.DataFrame(y.loc["BasicEPS", :]).iloc[2:,:]
In [5]: y.index = pd.to_datetime(y.index)
In [6]: # CHECK IF NAS ARE NO DIVIDEND PERIOD
         y = y.sort_index().fillna(0.)
        y.isnull().sum()
In [7]:
         BasicEPS
Out[7]:
         dtype: int64
In [8]:
         y.head()
Out[8]:
                    BasicEPS
         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
In [9]:
         y.tail()
                    BasicEPS
Out[9]:
         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
```

2.) 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

```
In [10]: from pytrends.request import TrendReq
In [56]: # Create pytrends object
         pytrends = TrendReq(hl='en-US', tz=360)
         # Set up the keywords and the timeframe
         keywords = ['Microsoft', "inflation", 'Apple Watch', 'layoffs', 'ebt', 'apple tv', 'wa
         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}', ged
             interest_over_time_df = pytrends.interest_over_time()
             df[keyword] = interest_over_time_df[keyword]
         df.resample("Q").mean()
In [57]:
```

Out[57]:		Microsoft	inflation	Apple Watch	layoffs	ebt	apple tv	waffle fries	valentines day	cemet
	date									
	2004- 03-31	93.000000	47.000000	0.000000	11.333333	5.333333	2.000000	4.333333	35.333333	71.333
	2004- 06-30	91.666667	43.333333	0.000000	9.333333	5.333333	1.333333	0.000000	1.000000	97.000
	2004- 09-30	86.333333	36.000000	0.000000	9.333333	5.666667	2.000000	12.000000	0.666667	81.000
	2004- 12-31	81.000000	39.000000	0.000000	10.000000	5.666667	2.000000	7.333333	1.666667	74.666
	2005- 03-31	83.000000	39.000000	0.000000	9.666667	5.000000	2.000000	3.000000	35.000000	70.333
	•••									
	2023- 03-31	27.333333	73.666667	65.333333	68.666667	67.000000	59.000000	75.666667	20.333333	11.666
	2023- 06-30	25.333333	61.000000	63.000000	38.333333	57.333333	62.000000	65.666667	1.000000	14.333
	2023- 09-30	25.333333	59.333333	71.333333	27.333333	70.666667	71.666667	66.000000	1.000000	13.000
	2023- 12-31	26.000000	60.333333	81.000000	29.666667	54.000000	66.333333	62.000000	1.333333	13.333
	2024- 03-31	28.000000	62.000000	72.000000	44.000000	59.000000	74.000000	67.000000	10.000000	12.000
	81 row	s x 9 colum	nns							

81 rows × 9 columns

```
In [58]: df = df.resample("Q").mean()

In []:

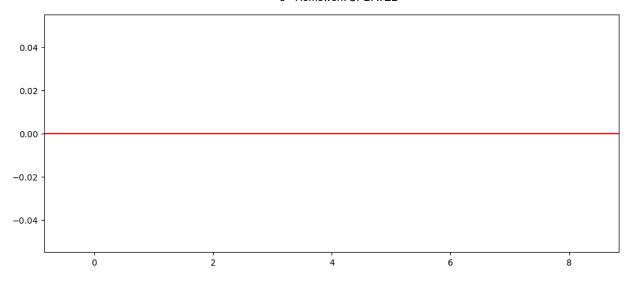
In [59]: # ALIGN DATA
    temp = pd.concat([y, df],axis = 1).dropna()
    y = temp[["BasicEPS"]].copy()
    df = temp.iloc[:,1:].copy()
```

3.) Normalize all the X data

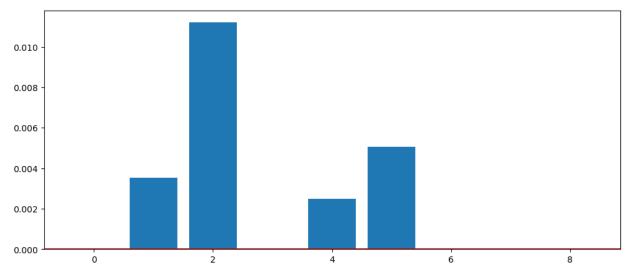
```
In [60]: from sklearn.preprocessing import StandardScaler
In [61]: scaler = StandardScaler()
In [62]: X_scaler = scaler.fit_transform(df)
```

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

```
from sklearn.linear_model import Lasso
  In [83]:
            lasso = Lasso(alpha = .5)
  In [84]:
            lasso.fit(X_scaler,y)
  In [90]:
 Out[90]:
                    Lasso
            Lasso(alpha=0.5)
            coefficients = lasso.coef_
  In [91]:
  In [92]:
            df.head()
 Out[92]:
                                                                                waffle
                                         Apple
                                                                                       valentines
                   Microsoft
                               inflation
                                                   layoffs
                                                               ebt apple tv
                                                                                                   cemetary
                                        Watch
                                                                                  fries
            2004-
                   93.000000 47.000000
                                            0.0
                                                11.333333 5.333333 2.000000
                                                                              4.333333
                                                                                        35.333333 71.333333
            03-31
            2004-
                    91.666667 43.333333
                                            0.0
                                                 9.333333 5.333333 1.333333
                                                                              0.000000
                                                                                         1.000000
                                                                                                   97.000000
            06-30
            2004-
                   86.333333 36.000000
                                            0.0
                                                 9.333333
                                                          5.666667
                                                                    2.000000
                                                                             12.000000
                                                                                         0.666667
                                                                                                   81.000000
            09-30
            2004-
                   81.000000
                             39.000000
                                                10.000000
                                                          5.666667
                                                                    2.000000
                                                                              7.333333
                                                                                         1.666667
                                                                                                   74.666667
            12-31
            2005-
                   83.000000 39.000000
                                           0.0
                                                 9.666667 5.000000 2.000000
                                                                              3.000000
                                                                                        35.000000 70.333333
            03-31
4
            plt.figure(figsize = (12,5))
  In [93]:
            plt.bar(range(len(coefficients)), coefficients)
            plt.axhline(0, color = "red")
            plt.show()
            #model under scaler transformations shows no models
```



```
In [89]: plt.figure(figsize = (12,5))
  plt.bar(range(len(coefficients)), coefficients)
  plt.axhline(0, color = "red")
  plt.show()
#this is the model under non scaler X
```



In []:

5.) Do these coefficient magnitudes make sense?

magnitudes seem to make sense as the two of the strongest coefficients remaining are the apple watch and apple to which we would expect to be most strongly related, and the unrelated terms are dropped