

```
#import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

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

```
#read data APPL_quarterly_financials.csv
#extract the EPS data of it and preprocess it
df = pd.read_csv('AAPL_quarterly_financials.csv', sep=",",
                 ,index_col= 0 )
df = df.T
df.drop(['ttm'],inplace=True)
df_mt = df[['BasicEPS']]
df_mt.fillna(method="backfill",inplace=True)
df_mt.fillna(0,inplace=True)
df_mt.index = pd.to_datetime(df_mt.index)
df_mt.sort_index(inplace=True,ascending=1)
eps_data = df_mt
```

```
/var/folders/_b/4lj1bh0s4473m5xx061k14lc0000gn/T/
ipykernel_17862/2059250550.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation:

https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
df_mt.fillna(method="backfill",inplace=True)
/var/folders/_b/4lj1bh0s4473m5xx061k14lc0000gn/T/ipykernel_17862/20592
50550.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation:

https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
df_mt.fillna(0,inplace=True)
/var/folders/_b/4lj1bh0s4473m5xx061k14lc0000gn/T/ipykernel_17862/20592
50550.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation:

https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
df_mt.sort_index(inplace=True,ascending=1)
```

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

DELETE

```
#split the data into train and test  
#leave 5% holdout  
train_eps,test_eps =  
train_test_split(eps_data,train_size=0.80,test_size=0.10)
```

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

```
# Create pytrends object  
from pytrends.request import TrendReq  
pytrends = TrendReq(hl='en-US', tz=360)  
  
# Set up the keywords and the timeframe  
  
#CHANGE THE KEYWORDS LIST FOR BEST NOWCASTING    <-----  
#-----  
#-----  
#-----  
#keywords =  
['Lakers','Warriors','Celtics','Bulls','Knicks','Heat','Spurs','Rocket  
s']  
relevant_keywords =  
['iphone','iwatch','mac','Siri','Android','Samsung']  
irrelevant_keywords = ['turbocharger','otologist','peanut worms']  
#combine the relevant and irrelevant keywords  
keywords = relevant_keywords + irrelevant_keywords  
#the start date and end date of the data could remain the same  
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.fillna(method="backfill", inplace=True)
#change df into quaterly data
df = df.resample("Q").mean()[:"20231230"]

```

2.) Normalize all the X data

```

#Normalize the data using StandardScaler
from sklearn.preprocessing import MinMaxScaler, StandardScaler
eps_data = eps_data.resample("Q").mean()[ "2004-01-01":]
display("data scale: ",df.shape,eps_data.shape)
scalar = StandardScaler()

X_std = scalar.fit_transform(df)
display(pd.DataFrame(X_std,index=df.index,columns=df.columns).head())
#y = scalar.fit_transform(eps_data)
y = eps_data.values

```

'data scale: '

(79, 9)

(79, 1)

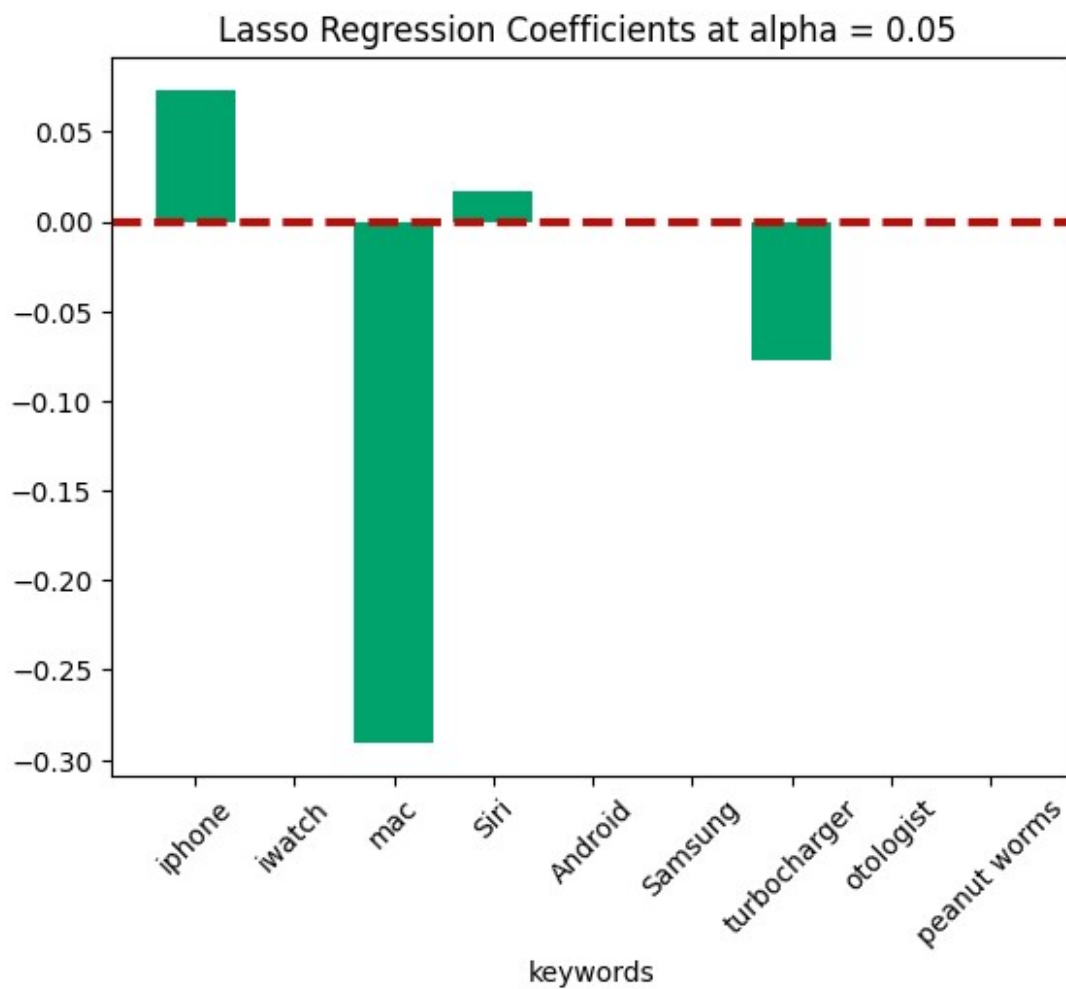
| | iphone | iwatch | mac | Siri | Android | Samsung |
|------------|-----------|-----------|----------|-----------|-----------|-----------|
| \ | | | | | | |
| date | | | | | | |
| 2004-03-31 | -1.821981 | -1.047574 | 0.422144 | -1.181210 | -1.233305 | -1.737747 |
| 2004-06-30 | -1.821981 | -1.047574 | 0.159072 | -1.181210 | -1.233305 | -1.789578 |
| 2004-09-30 | -1.821981 | -1.047574 | 0.098364 | -1.181210 | -1.233305 | -1.616809 |
| 2004-12-31 | -1.821981 | -1.047574 | 0.482852 | -0.949530 | -1.233305 | -1.478594 |
| 2005-03-31 | -1.821981 | -1.085140 | 0.826869 | -1.052499 | -1.233305 | -1.530425 |

| | turbocharger | otologist | peanut worms |
|------|--------------|-----------|--------------|
| date | | | |

| | | | |
|------------|----------|-----------|----------|
| 2004-03-31 | 3.230881 | -2.072235 | 2.644384 |
| 2004-06-30 | 3.167989 | 6.932580 | 2.112139 |
| 2004-09-30 | 3.042203 | -1.214634 | 2.484710 |
| 2004-12-31 | 2.497133 | 2.168128 | 3.495977 |
| 2005-03-31 | 2.790632 | -0.499966 | 2.484710 |

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

```
from sklearn.linear_model import Lasso
#write a function to run the Lasso regression of multivariate
def run_lasso_regression(X, y, alpha):
    lasso = Lasso(alpha=alpha)
    lasso.fit(X, y)
    return lasso
alpha = 0.05
reg = run_lasso_regression(X_std,y,alpha)
plt.bar(range(len(reg.coef_)),
        reg.coef_,tick_label=df.columns,color= "#00A36C")
plt.axhline(0, color='#B90E0A', linestyle="--",linewidth=3)
plt.title("Lasso Regression Coefficients at alpha = {}".format(alpha))
plt.xlabel("keywords")
plt.xticks(rotation=45)
plt.show()
reg.fit(X_std,y)
print("Lasso regression score: {}".format(alpha),reg.score(X_std,y))
print(pd.DataFrame(reg.coef_,index=df.columns,columns=["coef"]))
```



Lasso regression score: 0.05 0.7220954110695137

| | coef |
|--------------|-----------|
| iphone | 0.073392 |
| iwatch | 0.000000 |
| mac | -0.290366 |
| Siri | 0.017055 |
| Android | -0.000000 |
| Samsung | 0.000000 |
| turbocharger | -0.077801 |
| otologist | -0.000000 |
| peanut worms | -0.000000 |

5.) Do these coefficient magnitudes make sense?

```
#yes the coefficients magnitudes make sense  
#the coefficients of the irrelevant keywords are close to zero  
#the coefficients of the relevant keywords are not close to zero,  
#with siri and iphone having the highest coefficients  
#strongest positive correlation with the EPS  
  
#however, the coefficients of mac is unexpectedly negative
```

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

```
#create a list of alpha values  
alphas = [0,0.01,0.05,0.1,0.2,0.5,0.8,1,5,10]  
#run the lasso regression for all the alpha values  
#and store the scores in a dataframe  
scores = pd.DataFrame(columns=["score"],index=alphas)  
for alpha in alphas:  
    reg = run_lasso_regression(X_std,y,alpha)  
    scores.loc[alpha] = reg.score(X_std,y)  
plt.plot(scores.index,scores["score"],color="#32612d")  
plt.title("Lasso Regression Score vs Alpha")  
plt.xlabel("alpha")  
plt.ylabel("Lasso regression score")  
display(scores)  
print("best alpha: ",scores[scores["score"] ==  
scores["score"].max()].index.values[0])  
#the best alpha is 0, which means no regularization, with OLS being  
the best result
```

```
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/  
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this  
algorithm does not converge well. You are advised to use the  
LinearRegression estimator
```

```
    return fit_method(estimator, *args, **kwargs)  
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/  
site-packages/sklearn/linear_model/_coordinate_descent.py:628:  
UserWarning: Coordinate descent with no regularization may lead to  
unexpected results and is discouraged.
```

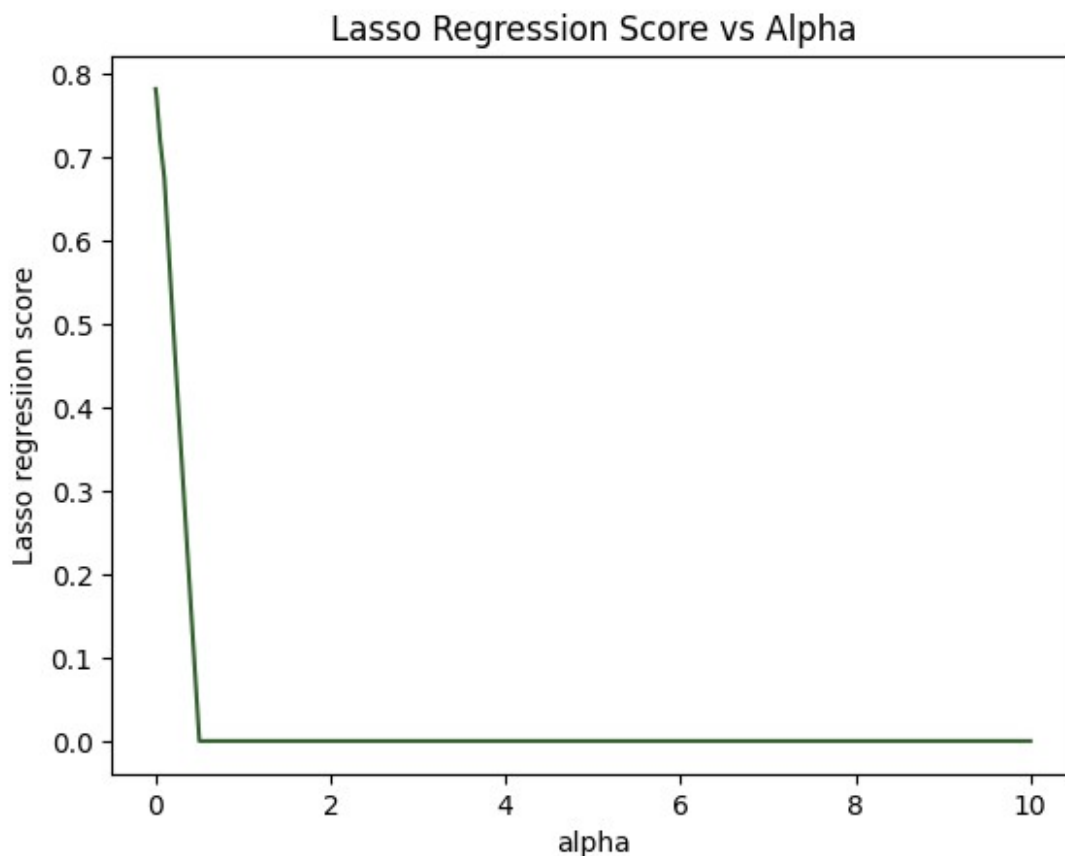
```
    model = cd_fast.enet_coordinate_descent(  
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/  
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
```

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: 2.241e+00, tolerance: 2.062e-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(
```

| | score |
|-------|----------|
| 0.00 | 0.782675 |
| 0.01 | 0.774425 |
| 0.05 | 0.722095 |
| 0.10 | 0.675648 |
| 0.20 | 0.499942 |
| 0.50 | 0.0 |
| 0.80 | 0.0 |
| 1.00 | 0.0 |
| 5.00 | 0.0 |
| 10.00 | 0.0 |

best alpha: 0.0



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

```
#using cross validation to find the best alpha
from sklearn.model_selection import cross_val_score

n = 5
#run the lasso regression for all the alpha values
#and store the scores in a dataframe
scores_cross_validation = pd.DataFrame(columns=['score{}'.format(i)
for i in range(1,n+1)])

for alpha in alphas:
    lasso = Lasso(alpha=alpha)
    fit = cross_val_score(lasso, X_std, y, cv=n)
    scores_cross_validation.loc[str(alpha)] = fit
scores_cross_validation["mean"] = scores_cross_validation.mean(axis=1)
scores_cross_validation['std'] = scores_cross_validation.std(axis=1)
display(scores_cross_validation)
#the higher cross validation score, the better
#the lower std, the better

#return the alpha with the highest cross validation score
best_alpha = scores_cross_validation["mean"].idxmax()
print("best alpha: ",best_alpha," with cross validation score:
",scores_cross_validation.loc[best_alpha,"mean"])
scores_cross_validation.drop(["mean","std"],axis=1,inplace=True)
scores_cross_validation.T.boxplot().set_title("Lasso Regression Cross
Validation Scores")
#the ideal alpha is 0.01, with comparatively high cross validation
score
#and low std

/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this
algorithm does not converge well. You are advised to use the
LinearRegression estimator
    return fit_method(estimator, *args, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
UserWarning: Coordinate descent with no regularization may lead to
unexpected results and is discouraged.
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
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: 1.418e+00, tolerance:
```



```

1.570e-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(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this
algorithm does not converge well. You are advised to use the
LinearRegression estimator
    return fit_method(estimator, *args, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
UserWarning: Coordinate descent with no regularization may lead to
unexpected results and is discouraged.
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
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: 1.916e+00, tolerance:
1.768e-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(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this
algorithm does not converge well. You are advised to use the
LinearRegression estimator
    return fit_method(estimator, *args, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
UserWarning: Coordinate descent with no regularization may lead to
unexpected results and is discouraged.
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
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: 1.715e+00, tolerance:
2.015e-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(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this
algorithm does not converge well. You are advised to use the
LinearRegression estimator
    return fit_method(estimator, *args, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:

```

```

UserWarning: Coordinate descent with no regularization may lead to
unexpected results and is discouraged.
  model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
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: 1.437e+00, tolerance:
1.916e-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(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/base.py:1152: UserWarning: With alpha=0, this
algorithm does not converge well. You are advised to use the
LinearRegression estimator
    return fit_method(estimator, *args, **kwargs)
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
UserWarning: Coordinate descent with no regularization may lead to
unexpected results and is discouraged.
  model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/sklearn/linear_model/_coordinate_descent.py:628:
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: 6.105e-01, tolerance:
5.790e-04 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(

```

| | score1 | score2 | score3 | score4 | score5 |
|-------------|---------------|------------|-----------|-----------|-----------|
| mean \ | | | | | |
| 0 | -26315.872364 | -5.519213 | -8.268378 | -1.387026 | -1.895554 |
| 5266.588507 | | | | | |
| 0.01 | -9132.655165 | -2.687613 | -2.410305 | -1.361706 | -2.471721 |
| 1828.317302 | | | | | |
| 0.05 | -595.029472 | -0.826945 | -0.483071 | -1.087152 | -3.771273 |
| 120.239583 | | | | | |
| 0.1 | -816.775443 | -1.350524 | -0.294203 | -0.588779 | -4.774161 |
| 164.756622 | | | | | |
| 0.2 | -999.921665 | -4.174646 | -0.032768 | -0.010107 | -5.731659 |
| 201.974169 | | | | | |
| 0.5 | -1511.669868 | -14.569639 | -0.246827 | -0.658656 | -6.167944 |
| 306.662587 | | | | | |
| 0.8 | -1511.669868 | -14.569639 | -0.246827 | -0.658656 | -6.167944 |
| 306.662587 | | | | | |
| 1 | -1511.669868 | -14.569639 | -0.246827 | -0.658656 | -6.167944 |
| 306.662587 | | | | | |

```

5      -1511.669868 -14.569639 -0.246827 -0.658656 -6.167944 -
306.662587
10     -1511.669868 -14.569639 -0.246827 -0.658656 -6.167944 -
306.662587

```

```

          std
0      10524.642228
0.01   3652.168960
0.05    237.397813
0.1     326.013328
0.2     398.980148
0.5     602.525832
0.8     602.525832
1       602.525832
5       602.525832
10      602.525832

```

```
best alpha:  0.05  with cross validation score:  -120.23958262019039
```

```
Text(0.5, 1.0, 'Lasso Regression Cross Validation Scores')
```

