S&P_500_Dataset

By Hatem Elgenedy

November 7, 2025

[141]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from datetime import datetime
from dateutil.relativedelta import relativedelta
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
```

[142]:
```
import os

file_path = "/Users/hatemelgenedy/Desktop/AI and Data Science Microsoft course/
 ↪Projects/S& P 500 dataset/sp500_index.csv"

if not os.path.exists(file_path):
        raise FileNotFoundError(f"CSV file not found at {file_path}")

# read the CSV; skip malformed lines if any
df = pd.read_csv(file_path, on_bad_lines='skip')
df.head(6)
```

[142]:

	Date	S&P500
0	2014-12-22	2078.54
1	2014-12-23	2082.17
2	2014-12-24	2081.88
3	2014-12-26	2088.77
4	2014-12-29	2090.57
5	2014-12-30	2080.35

[143]:
```
!pip install ydata-profiling
from ydata_profiling import ProfileReport
profile = ProfileReport(df, title="S&P 500 Dataset Profiling Report",␣
 ↪explorative=True)
profile.to_notebook_iframe()
```

```
Requirement already satisfied: ydata-profiling in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (4.17.0)
Requirement already satisfied: scipy<1.16,>=1.4.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (1.13.1)
Requirement already satisfied: pandas!=1.4.0,<3.0,>1.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (2.3.1)
Requirement already satisfied: matplotlib<=3.10,>=3.5 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (3.10.0)
Requirement already satisfied: pydantic>=2 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (2.11.7)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (6.0.2)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (3.1.6)
Requirement already satisfied: visions<0.8.2,>=0.7.5 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
visions[type_image_path]<0.8.2,>=0.7.5->ydata-profiling) (0.8.1)
Requirement already satisfied: numpy<2.2,>=1.16.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (1.26.4)
Requirement already satisfied: minify-html>=0.15.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (0.18.1)
Requirement already satisfied: filetype>=1.0.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (1.2.0)
Requirement already satisfied: phik<0.13,>=0.11.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (0.12.5)
Requirement already satisfied: requests<3,>=2.24.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (2.32.4)
Requirement already satisfied: tqdm<5,>=4.48.2 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (4.67.1)
Requirement already satisfied: seaborn<0.14,>=0.10.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (0.13.2)
Requirement already satisfied: multimethod<2,>=1.4 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (1.12)
Requirement already satisfied: statsmodels<1,>=0.13.2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (0.14.5)
Requirement already satisfied: typeguard<5,>=3 in /opt/anaconda3/envs/anaconda-
```

```
nlp/lib/python3.11/site-packages (from ydata-profiling) (4.4.4)
Requirement already satisfied: imagehash==4.3.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (4.3.1)
Requirement already satisfied: wordcloud>=1.9.3 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (1.9.4)
Requirement already satisfied: dacite>=1.8 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata-profiling) (1.9.2)
Requirement already satisfied: numba<=0.61,>=0.56.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from ydata-
profiling) (0.61.0)
Requirement already satisfied: PyWavelets in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from imagehash==4.3.1->ydata-profiling)
(1.9.0)
Requirement already satisfied: pillow in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from imagehash==4.3.1->ydata-profiling)
(11.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from jinja2<3.2,>=2.11.1->ydata-profiling)
(3.0.2)
Requirement already satisfied: contourpy>=1.0.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata-profiling)
(1.3.1)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata-profiling)
(0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata-profiling) (4.55.3)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata-profiling) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata-profiling)
(24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata-profiling)
(3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata-profiling) (2.9.0.post0)
Requirement already satisfied: llvmlite<0.45,>=0.44.0dev0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
numba<=0.61,>=0.56.0->ydata-profiling) (0.44.0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from pandas!=1.4.0,<3.0,>1.1->ydata-profiling)
(2025.2)
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from pandas!=1.4.0,<3.0,>1.1->ydata-profiling)
```

```
(2025.2)
Requirement already satisfied: joblib>=0.14.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from phik<0.13,>=0.11.1->ydata-profiling)
(1.5.1)
Requirement already satisfied: charset_normalizer<4,>=2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata-profiling) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from requests<3,>=2.24.0->ydata-profiling)
(3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata-profiling) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata-profiling) (2025.8.3)
Requirement already satisfied: patsy>=0.5.6 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from statsmodels<1,>=0.13.2->ydata-profiling)
(1.0.2)
Requirement already satisfied: typing_extensions>=4.14.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
typeguard<5,>=3->ydata-profiling) (4.15.0)
Requirement already satisfied: attrs>=19.3.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata-profiling)
(24.3.0)
Requirement already satisfied: networkx>=2.4 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata-profiling)
(3.4.2)
Requirement already satisfied: puremagic in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata-profiling)
(1.30)
Requirement already satisfied: annotated-types>=0.6.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata-profiling) (0.6.0)
Requirement already satisfied: pydantic-core==2.33.2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata-profiling) (2.33.2)
Requirement already satisfied: typing-inspection>=0.4.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata-profiling) (0.4.0)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from python-
dateutil>=2.7->matplotlib<=3.10,>=3.5->ydata-profiling) (1.17.0)

Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

```
100%|      | 2/2 [00:00<00:00, 12.46it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
<IPython.core.display.HTML object>
```

[144]:
```
profile.to_file("S&P_500_report.html")
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[145]:
```
df.isnull().sum()
```

[145]:
```
Date      0
S&P500    0
dtype: int64
```

[146]:
```
duplicates = df . duplicated().sum()
print(duplicates)
```

```
0
```

[147]:
```
df.shape
```

[147]:
```
(2517, 2)
```

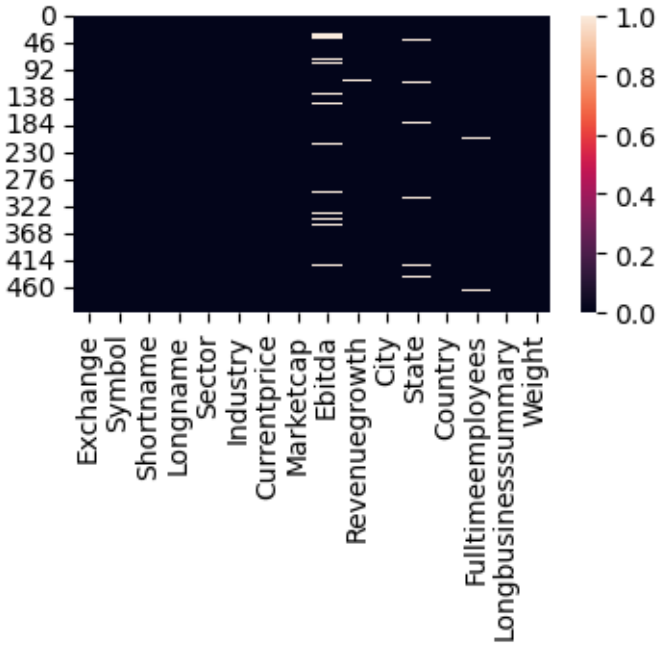
[148]:
```
print(df.columns)
```

```
Index(['Date', 'S&P500'], dtype='object')
```

[149]:
```
companies_file_path = "/Users/hatemelgenedy/Desktop/AI and Data Science␣
 ↪Microsoft course/Projects/S& P 500 dataset/sp500_companies.csv"

df = pd.read_csv(companies_file_path, on_bad_lines='skip')


df["Weight"] = pd.to_numeric(df["Weight"], errors="coerce")
df["Marketcap"] = pd.to_numeric(df["Marketcap"], errors="coerce")
df = df.dropna(subset=["Weight", "Marketcap"]).reset_index(drop=True)
```

[150]:
```
plt.figure(figsize = (4,2))
sns.heatmap(df.isnull())
```

[150]:
```
<Axes: >
```



[151]:
```
null_percentage = df.isnull()/df.shape[0]*100
null_percentage
```

[151]:

	Exchange	Symbol	Shortname	Longname	Sector	Industry	Currentprice	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
..	…	…	…	…	…	…	…	
497	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
498	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
499	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
500	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
501	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

	Marketcap	Ebitda	Revenuegrowth	City	State	Country	\
0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	
..	…	…	…	…	…	…	
497	0.0	0.0	0.0	0.0	0.0	0.0	
498	0.0	0.0	0.0	0.0	0.0	0.0	

```
499        0.0     0.0            0.0   0.0    0.0      0.0
500        0.0     0.0            0.0   0.0    0.0      0.0
501        0.0     0.0            0.0   0.0    0.0      0.0

     Fulltimeemployees  Longbusinesssummary  Weight
0             0.000000                  0.0     0.0
1             0.000000                  0.0     0.0
2             0.000000                  0.0     0.0
3             0.000000                  0.0     0.0
4             0.000000                  0.0     0.0
..                 …                    …       …
497           0.000000                  0.0     0.0
498           0.000000                  0.0     0.0
499           0.000000                  0.0     0.0
500           0.000000                  0.0     0.0
501           0.199203                  0.0     0.0

[502 rows x 16 columns]
```

[152]:
```
df.shape
```

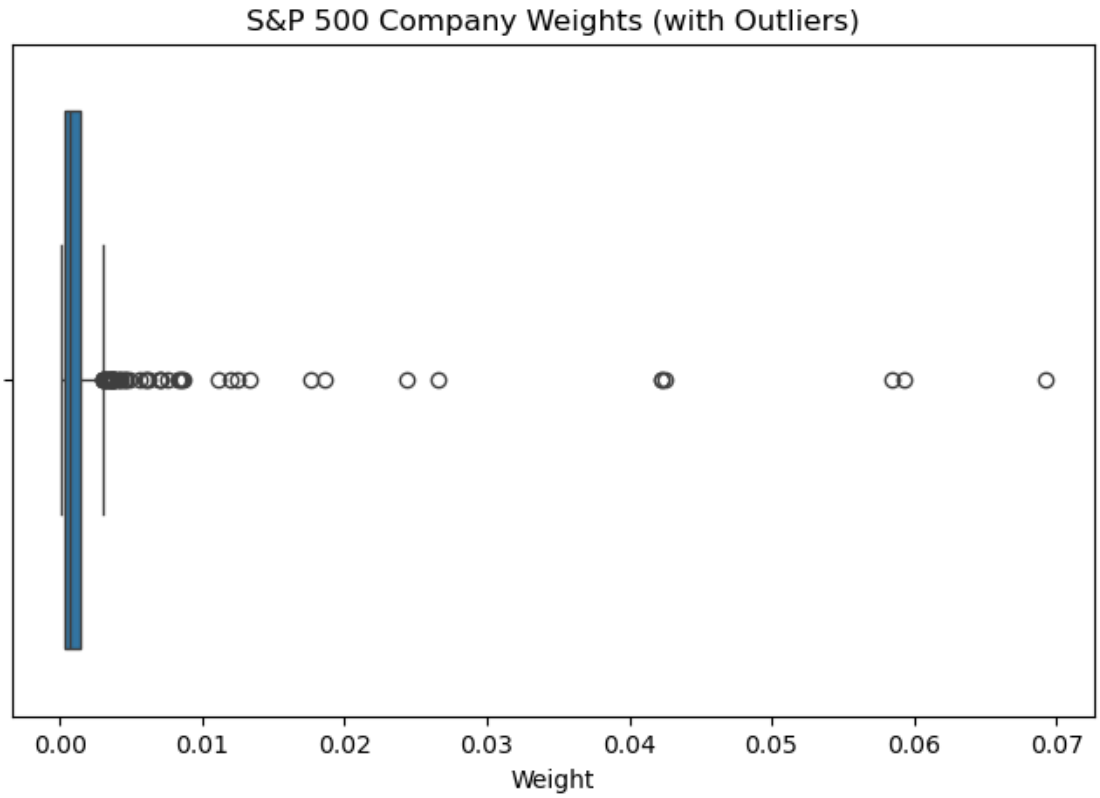
[152]:
```
(502, 16)
```

[153]:
```
def iqr_bounds(s, k=1.5):
  q1,q3 = s.quantile(0.25) , s.quantile(0.75)
  iqr = q3 - q1
  return q1 - k*iqr , q3 +k*iqr


df["log10_mcap"] = np.log10(df["Marketcap"].astype(float))


w_low, w_high = iqr_bounds(df["Weight"])
m_low , m_high = iqr_bounds(df["log10_mcap"])

mask_w = (df["Weight"] <w_low) | (df ["Weight"] > w_high)
mask_m = (df["log10_mcap"] < m_low) | (df["log10_mcap"] > m_high)
mask_any =  mask_w | mask_m

df["Outlier_Weight"] = mask_w
df["Outlier_Mcaplog"] = mask_m
df["Outlier_Any"] = mask_any

label_col = "Shortname" if "Shortname" in df.columns else ("Longname" if␣
 ↪"Longname" in df.columns else "Symbol")
outliers = df.loc[mask_any , ["Symbol" , label_col , "Weight" , "Marketcap"]]
```

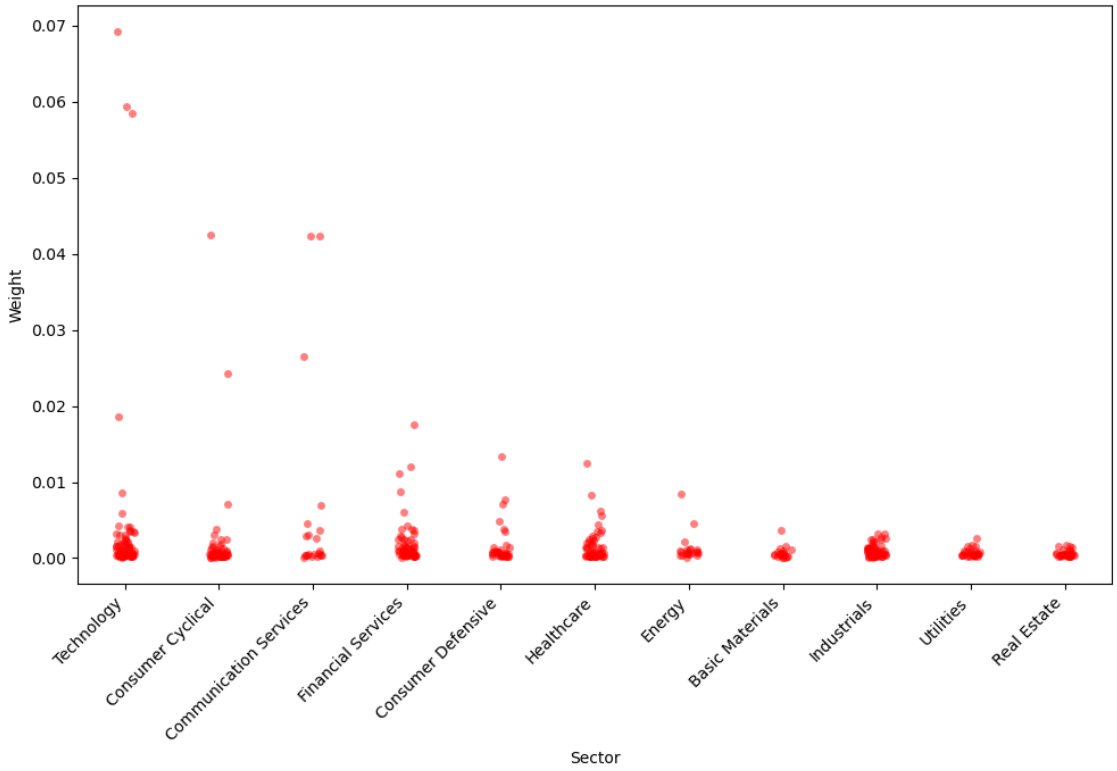
```
print("IQR thresholds :")
print(f" Weight :  low = {w_low : .3f} , high = {w_high :.3f}")
print("\nOutier countd : \n" , df[["Outlier_Weight" , "Outlier_Mcaplog" ,␣
 ↪"Outlier_Any"]] )
```

```
IQR thresholds :
 Weight :  low = -0.001 , high = 0.003

Outier countd :
      Outlier_Weight  Outlier_Mcaplog  Outlier_Any
0               True             True         True
1               True             True         True
2               True             True         True
3               True             True         True
4               True             True         True
..               …                …            …
497            False            False        False
498            False            False        False
499            False            False        False
500            False            False        False
501            False            False        False

[502 rows x 3 columns]
```

[154]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
sns.boxplot(x=df["Weight"])
plt.title("S&P 500 Company Weights (with Outliers)")
plt.xlabel("Weight")
plt.show()
```



[185]:
```
plt.figure(figsize = (10,7))
sns.stripplot(data = df , x = 'Sector' , y = 'Weight' , color = 'r' , jitter =␣
 ↪True , alpha = 0.5)

plt.xticks(rotation = 45 , ha = 'right')
plt.tight_layout()
```



[156]:
```
model = LinearRegression()
```

[157]:
```
x = df[['Sector']]
y = df[['Weight']]
```

[158]:
```
X = df.drop(columns = ['Sector'])
y = df[['Weight']]
```

[159]:
```
df_clean = df.dropna(subset = ["Weight", "Sector"]).reset_index(drop = True)
X = df_clean[["Sector"]].to_numpy()
y = df_clean[["Weight"]].to_numpy()
```

[160]:
```
X = pd.get_dummies(df[['Sector']], drop_first=True)
y = df[['Weight']].apply(pd.to_numeric, errors='coerce')
mask = y['Weight'].notna()
X, y = X.loc[mask], y.loc[mask]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

model = LinearRegression().fit(X_train, y_train)
```

[161]:
```
X = pd.get_dummies(df[['Sector']], drop_first = True)
y = pd.to_numeric(df['Weight'], errors = 'coerce')
```

[162]:
```
X_train , X_test , y_train , y_test = train_test_split(X, y , test_size = 0.2 ,␣
↪random_state = 42)
```

[163]:
```
print('80% input traning data :' , X_train.shape)
print('20% input testing data :' , X_test.shape)
```

```
80% input traning data : (401, 10)
20% input testing data : (101, 10)
```

[164]:
```
print("X_train shape :" , X_train.shape)
print("X_test shape :" , X_test.shape)
print("y_train shape :" , y_train.shape)
print("y_test shape" , y_test.shape)
```

```
X_train shape : (401, 10)
X_test shape : (101, 10)
y_train shape : (401,)
y_test shape (101,)
```

[165]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder ,StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

[166]:
```
model = LinearRegression()
```

[167]:
```
model.fit(X_train , y_train)
```

[167]:
```
LinearRegression()
```

[168]:
```
y_pred = model.predict(X_test)
```

[186]:
```
features = ['Marketcap', 'RevenueGrowth', 'Employees', 'PEratio',␣
↪'DividendYield']
target = 'Weight'
```

[187]:
```
y_pred[:5]
```

[187]:
```
array([0.0023986 , 0.0017719 , 0.00237563, 0.00067109, 0.00237563])
```

[170]:
```
y_test[:5]
```

[170]:
```
268    0.000577
73     0.002450
289    0.000532
```

```
155    0.001159
104    0.001605
Name: Weight, dtype: float64
```

[189]:
```
y_pred_1d = np.asarray(y_pred).ravel()
y_test_1d = np.asarray(y_test).ravel()
```

[190]:
```
compare = pd.DataFrame({
    "Predicted" : np.ravel(y_pred),
    "Actual":     np.ravel(y_test) if not hasattr(y_test , "to_numpy") else␣
 ↪y_test.to_numpy().ravel()})
print(compare.head())
```

```
   Predicted    Actual
0   0.002399  0.000577
1   0.001772  0.002450
2   0.002376  0.000532
3   0.000671  0.001159
4   0.002376  0.001605
```

[195]:
```
from sklearn.metrics import mean_squared_error
```

[196]:
```
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("R²:", r2)
print("MAE:", mae)
print("RMSE:", rmse)
```

```
R²: -0.016411245199545066
MAE: 0.0027731236401882017
RMSE: 0.009123135476645521
```

[191]:
```
compare = pd.DataFrame({"Predicted" :np.ravel(y_pred),
                        "Actual": np.ravel(y_test)}, index = X_test.index)
```

[192]:
```
from sklearn.metrics import r2_score
```

[193]:
```
print(r2_score(y_pred,y_test))
```

```
-36.41707159049202
```

[176]:
```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import numpy as np

y_true = np.ravel(y_test)
y_hat  = np.ravel(y_pred)
```

```
r2  = r2_score(y_true, y_hat)
mae = mean_absolute_error(y_true, y_hat)
rmse = np.sqrt(mean_squared_error(y_true, y_hat))
print(f"R²:   {r2:.4f}")
print(f"MAE:  {mae:.4f}")
print(f"RMSE: {rmse:.4f}")
```

```
R²:   -0.0164
MAE:  0.0028
RMSE: 0.0091
```

[177]:
```
y_true = np.ravel(y_test)
y_hat  = np.ravel(y_pred)

# Baseline: always predict mean(y_train)
y_base = np.full_like(y_true, fill_value=np.mean(y_train))

print("Model vs Baseline")
print("R2  (model):", r2_score(y_true, y_hat))
print("R2 (base)  :", r2_score(y_true, y_base))        # should be ~0 by␣
 ↪definition
print("MAE (model):", mean_absolute_error(y_true, y_hat))
print("MAE (base) :", mean_absolute_error(y_true, y_base))
print("RMSE(model):", np.sqrt(mean_squared_error(y_true, y_hat)))
print("RMSE(base) :", np.sqrt(mean_squared_error(y_true, y_base)))
```

```
Model vs Baseline
R2  (model): -0.016411245199545066
R2 (base)  : -0.010383930477205539
MAE (model): 0.0027731236401882017
MAE (base) : 0.0027448834996816134
RMSE(model): 0.009123135476645521
RMSE(base) : 0.009096045176677364
```

[178]:
```
y_range = y_true.max() - y_true.min()
y_std   = y_true.std()

nrmse_range = np.sqrt(mean_squared_error(y_true, y_hat)) / (y_range if y_range!
 ↪=0 else 1)
nrmse_std   = np.sqrt(mean_squared_error(y_true, y_hat)) / (y_std   if y_std!=0␣
 ↪  else 1)
print("NRMSE (fraction of range):", nrmse_range)
print("NRMSE (fraction of std)  :", nrmse_std)
```

```
NRMSE (fraction of range): 0.13204967848105265
NRMSE (fraction of std)  : 1.0081722299287683
```

[198]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
rf = RandomForestRegressor(n_estimators=300, max_depth=10, random_state=42)
rf.fit(X_scaled, y)
y_pred = rf.predict(X_scaled)
```

[199]:
```
r2 = r2_score(y, y_pred)
mae = mean_absolute_error(y, y_pred)
rmse = np.sqrt(mean_squared_error(y, y_pred))

print(f"R²: {r2:.3f}")
print(f"MAE: {mae:.4f}")
print(f"RMSE: {rmse:.4f}")
```

```
R²: 0.049
MAE: 0.0022
RMSE: 0.0060
```

[202]:
```
print(df.columns)
```

```
Index(['Exchange', 'Symbol', 'Shortname', 'Longname', 'Sector', 'Industry',
       'Currentprice', 'Marketcap', 'Ebitda', 'Revenuegrowth', 'City', 'State',
       'Country', 'Fulltimeemployees', 'Longbusinesssummary', 'Weight',
       'log10_mcap', 'Outlier_Weight', 'Outlier_Mcaplog', 'Outlier_Any'],
      dtype='object')
```

[204]:
```
features = ['Marketcap', 'Currentprice', 'Ebitda', 'Revenuegrowth',␣
 ↪'Fulltimeemployees', 'log10_mcap']
target = 'Weight'

# Drop missing values
df_clean = df[features + [target]].dropna()

X = df_clean[features]
y = df_clean[target]

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Gradient Boosting Model
```

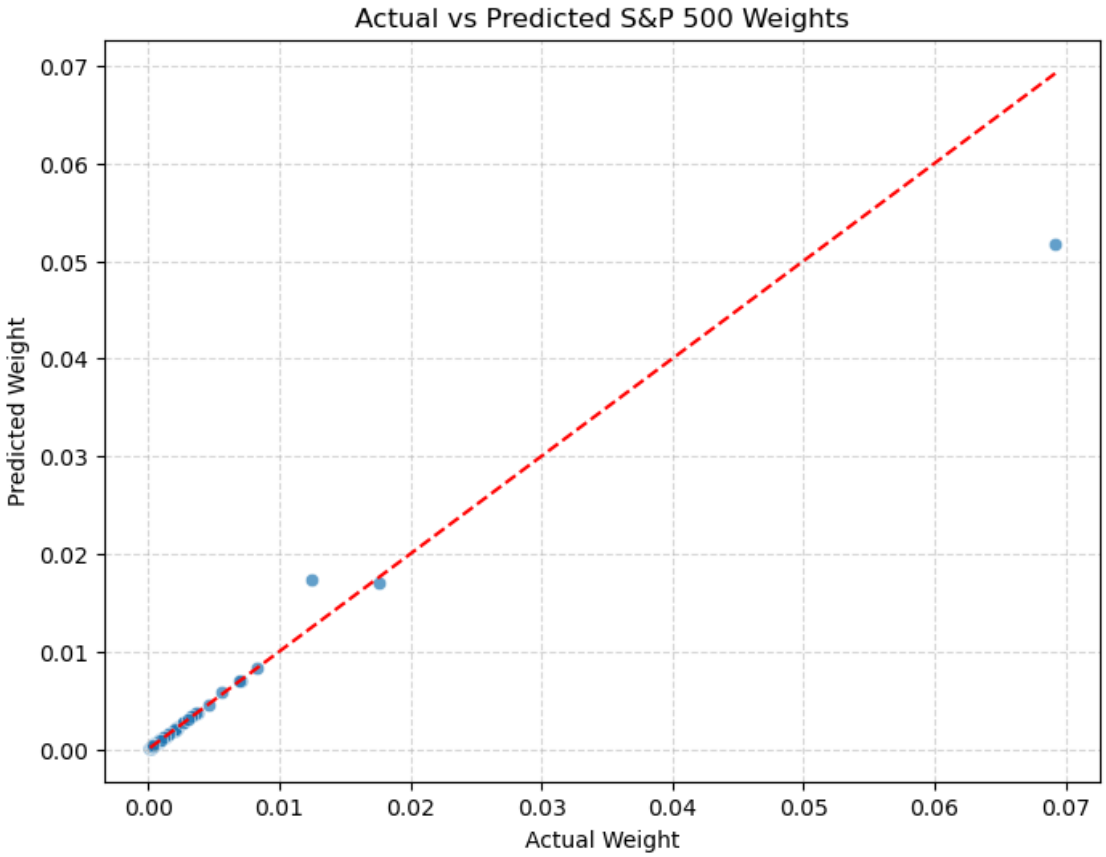
```
gb = GradientBoostingRegressor(n_estimators=500, learning_rate=0.05,␣
 ↪max_depth=5, random_state=42)
gb.fit(X_train_scaled, y_train)
y_pred = gb.predict(X_test_scaled)

# Evaluate performance
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f"R²: {r2:.3f}")
print(f"MAE: {mae:.6f}")
print(f"RMSE: {rmse:.6f}")
```

```
R²: 0.936
MAE: 0.000256
RMSE: 0.001877
```

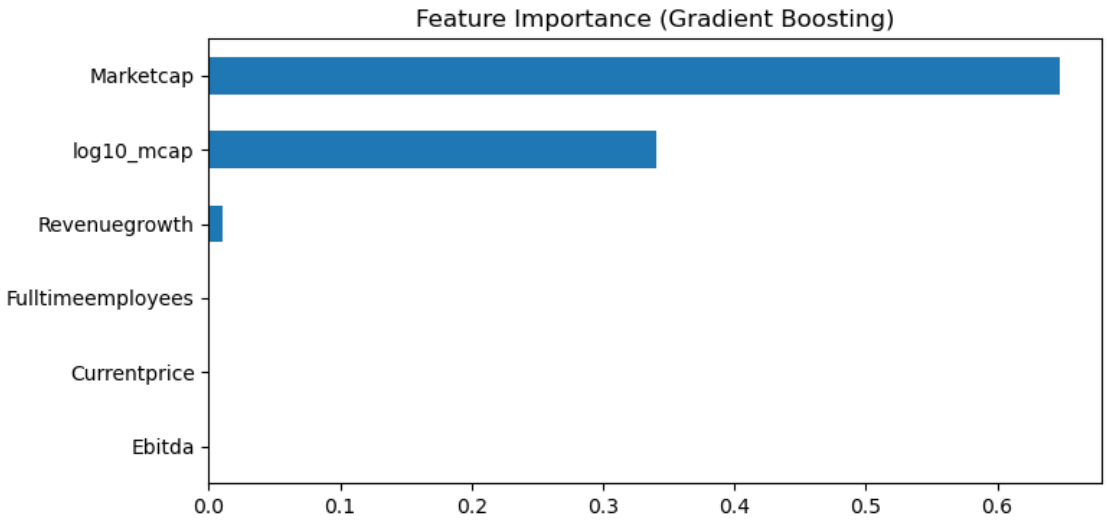
[205]:
```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(gb, X_train_scaled, y_train, cv=5, scoring='r2')
print("Cross-validated R²:", np.mean(cv_scores))
```

```
Cross-validated R²: 0.956206476977691
```

[206]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.7)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.title("Actual vs Predicted S&P 500 Weights")
plt.xlabel("Actual Weight")
plt.ylabel("Predicted Weight")
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```



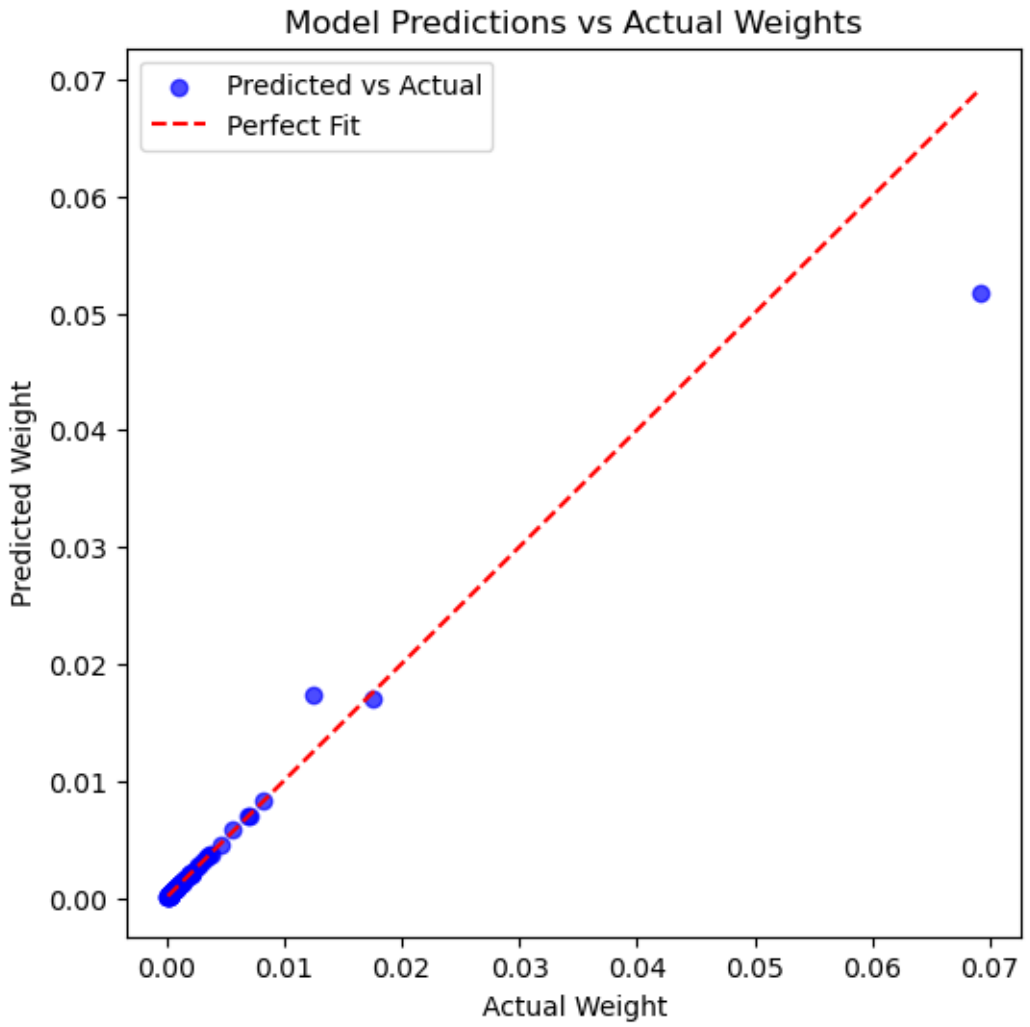
[217]:
```
importance = pd.Series(gb.feature_importances_, index=features).
  ↪sort_values(ascending=True)
importance.plot(kind='barh', figsize=(8,4), title='Feature Importance (Gradient␣
  ↪Boosting)')
plt.show()
```



[209]:
```
features = [
    'Marketcap',
    'Currentprice',
    'Ebitda',
    'Revenuegrowth',
    'Fulltimeemployees',
    'log10_mcap'      # this is already a great feature
]
target = 'Weight'
```

[210]:
```
from sklearn.ensemble import GradientBoostingRegressor

gb = GradientBoostingRegressor(n_estimators=500, learning_rate=0.05,␣
 ↪max_depth=5, random_state=42)
gb.fit(X_train, y_train)
y_pred_gb = gb.predict(X_test)
```

[211]:
```
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred, alpha=0.7, color='blue', label='Predicted vs␣
 ↪Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
 ↪label='Perfect Fit')

plt.title("Model Predictions vs Actual Weights")
plt.xlabel("Actual Weight")
plt.ylabel("Predicted Weight")
plt.legend()
plt.show()
```



[212]:
```
df.head()
```

[212]:

	Exchange	Symbol	Shortname	Longname	Sector	Industry	Currentprice
0	NMS	AAPL	Apple Inc.	Apple Inc.	Technology	Consumer Electronics	254.49
1	NMS	NVDA	NVIDIA Corporation	NVIDIA Corporation	Technology	Semiconductors	134.70
2	NMS	MSFT	Microsoft Corporation	Microsoft Corporation	Technology	Software - Infrastructure	436.60
3	NMS	AMZN	Amazon.com, Inc.	Amazon.com, Inc.	Consumer Cyclical	Internet Retail	224.92
4	NMS	GOOGL	Alphabet Inc.	Alphabet Inc.	Communication Services	Internet Content & Information	191.41

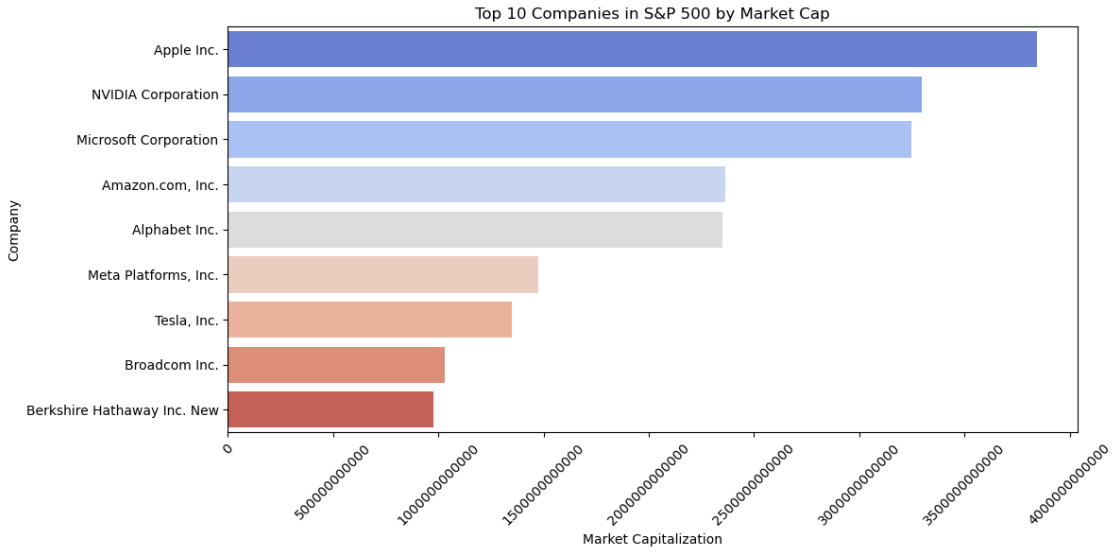
```
       Marketcap        Ebitda  Revenuegrowth           City State  \
0  3846819807232  1.346610e+11          0.061      Cupertino    CA
1  3298803056640  6.118400e+10          1.224    Santa Clara    CA
2  3246068596736  1.365520e+11          0.160        Redmond    WA
3  2365033807872  1.115830e+11          0.110        Seattle    WA
4  2351625142272  1.234700e+11          0.151  Mountain View    CA

         Country  Fulltimeemployees  \
0  United States           164000.0
1  United States            29600.0
2  United States           228000.0
3  United States          1551000.0
4  United States           181269.0

                                Longbusinesssummary    Weight  log10_mcap  \
0  Apple Inc. designs, manufactures, and markets …  0.069209   12.585102
1  NVIDIA Corporation provides graphics and compu…  0.059350   12.518356
2  Microsoft Corporation develops and supports so…  0.058401   12.511358
3  Amazon.com, Inc. engages in the retail sale of…  0.042550   12.373837
4  Alphabet Inc. offers various products and plat…  0.042309   12.371368

   Outlier_Weight  Outlier_Mcaplog  Outlier_Any
0            True             True         True
1            True             True         True
2            True             True         True
3            True             True         True
4            True             True         True
```

[213]:
```
top_marketcap = df.sort_values(by="Marketcap", ascending=False).head(10)

print(top_marketcap[['Sector', 'Industry', 'Marketcap']])
```

```
                 Sector                        Industry      Marketcap
0            Technology            Consumer Electronics  3846819807232
1            Technology                 Semiconductors  3298803056640
2            Technology       Software - Infrastructure  3246068596736
3      Consumer Cyclical                 Internet Retail  2365033807872
4  Communication Services  Internet Content & Information  2351625142272
5  Communication Services  Internet Content & Information  2351623045120
6  Communication Services  Internet Content & Information  1477457739776
7      Consumer Cyclical              Auto Manufacturers  1351627833344
8            Technology                 Semiconductors  1031217348608
9     Financial Services         Insurance - Diversified   978776031232
```

[214]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='Marketcap', y='Shortname', data=top_marketcap.head(10),␣
 ↪palette='coolwarm')
```

```
plt.title("Top 10 Companies in S&P 500 by Market Cap")
plt.xlabel("Market Capitalization")
plt.ylabel("Company")
plt.ticklabel_format(style='plain', axis='x')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[215]:
```
top_price = df.sort_values(by="Weight", ascending=False).head(10)
print(top_price[['Sector', 'Industry', 'Weight']])
```

```
                  Sector                       Industry    Weight
0             Technology           Consumer Electronics  0.069209
1             Technology                 Semiconductors  0.059350
2             Technology      Software - Infrastructure  0.058401
3      Consumer Cyclical                Internet Retail  0.042550
4  Communication Services  Internet Content & Information  0.042309
5  Communication Services  Internet Content & Information  0.042309
6  Communication Services  Internet Content & Information  0.026581
7      Consumer Cyclical             Auto Manufacturers  0.024317
8             Technology                 Semiconductors  0.018553
9     Financial Services         Insurance - Diversified  0.017609
```

[216]:
```
plt.figure(figsize = (10,6))
sns.barplot(x='Weight', y='Industry', data=top_price, palette='bright')
plt.title("Top 10 Companies in S&P 500 by Weight")
plt.xlabel("Weight")
plt.ylabel("Industry")
plt.ticklabel_format(style='plain', axis='x')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```