STOCK MARKET PREDICTION USING LSTM

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
plt.style.use("fivethirtyeight")
%matplotlib inline
```

Getting the Data:

The first step is to get the data and load it to memory. We will get our stock data from the Yahoo Finance website. Yahoo Finance is a rich resource of financial market data and tools to find compelling investments. To get the data from Yahoo Finance, we will be using yfinance library which offers a threaded and Pythonic way to download market data from Yahoo

```
from pandas_datareader.data import DataReader
import yfinance as yf
from pandas_datareader import data as pdr
from datetime import datetime
yf.pdr_override()


tech_list = ['AAPL', 'GOOG', 'MSFT', 'AMZN'] # The tech stocks we'll use for this analysis

tech_list = ['AAPL', 'GOOG', 'MSFT', 'AMZN'] # Set up End and Start times for data gr

end = datetime.now()
start = datetime(end.year - 1, end.month, end.day)

for stock in tech_list:
    globals()[stock] = yf.download(stock, start, end)

company_list = [AAPL, GOOG, MSFT, AMZN]
company_name = ["APPLE", "GOOGLE", "MICROSOFT", "AMAZON"]

for company, com_name in zip(company_list, company_name):
    company["company_name"] = com_name

df = pd.concat(company_list, axis=0)
df.head(10)
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
```

	Open	High	Low	Close	Adj Close	Volume	company_nai
Date							
2023-07-14	190.229996	191.179993	189.630005	190.690002	189.682663	41573900	APPL
2023-07-17	191.899994	194.320007	191.809998	193.990005	192.965195	50520200	APPL
2023-07-18	193.350006	194.330002	192.419998	193.729996	192.706573	48353800	APPL
2023-07-19	193.100006	198.229996	192.649994	195.100006	194.069351	80507300	APPL
2023-07-20	195.089996	196.470001	192.500000	193.130005	192.109772	59581200	APPL
2023-07-21	194.100006	194.970001	191.229996	191.940002	190.926056	71917800	APPL

Next steps: Generate code with df View recommended plots

Descriptive Statistics about the Data :

.describe() generates descriptive statistics. Descriptive statistics include those that summarize the central tendency, dispersion, and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

```
AAPL.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	253.000000	253.000000	253.000000	253.000000	253.000000	2.530000e+02
mean	185.155620	186.779012	183.675178	185.262214	184.815166	6.033181e+07
std	12.803750	13.015109	12.645465	12.909299	12.989302	2.473572e+07
min	165.350006	166.399994	164.080002	165.000000	164.776505	2.404830e+07
25%	175.309998	177.080002	173.740005	175.460007	174.802902	4.696490e+07
50%	183.919998	185.149994	182.110001	184.119995	183.610962	5.376350e+07
75%	191.899994	193.000000	190.830002	192.250000	191.562653	6.613340e+07
max	231.311996	233.080002	229.250000	232.979996	232.979996	2.464214e+08

Information About the Data :

.info() method prints information about a DataFrame including the index dtype and columns, non-null values, and memory usage.

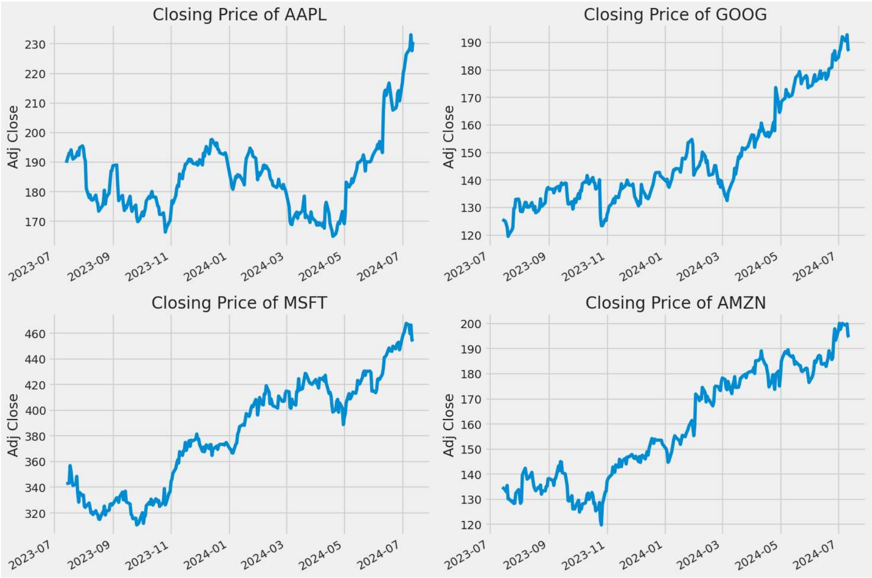
```
AAPL.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 251 entries, 2023-07-14 to 2024-07-12
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Open          251 non-null    float64
 1   High          251 non-null    float64
 2   Low           251 non-null    float64
 3   Close         251 non-null    float64
 4   Adj Close     251 non-null    float64
 5   Volume        251 non-null    int64  
 6   company_name  251 non-null    object 
dtypes: float64(5), int64(1), object(1)
memory usage: 15.7+ KB
```

Closing Price :

The closing price is the last price at which the stock is traded during the regular trading day. A stock's closing price is the standard benchmark used by investors to track its performance over time.

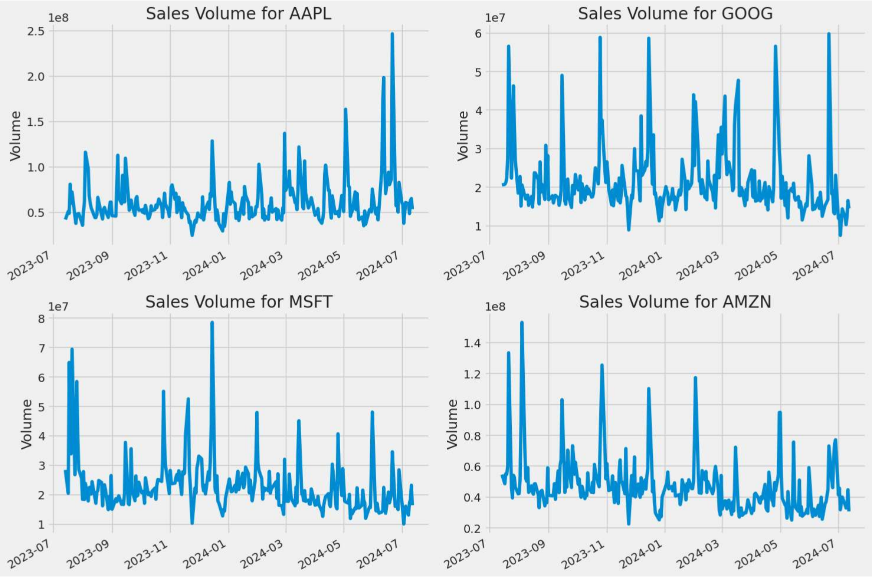
```
# Let's see a historical view of the closing price
plt.figure(figsize=(15, 10))
plt.subplots_adjust(top=1.25, bottom=1.2)

for i, company in enumerate(company_list, 1):
    plt.subplot(2, 2, i)
    company['Adj Close'].plot()
    plt.ylabel('Adj Close')
    plt.xlabel(None)
    plt.title(f"Closing Price of {tech_list[i - 1]}")

plt.tight_layout()
```



Volume of Sales :

Volume is the amount of an asset or security that changes hands over some period of time, often over the course of a day. For instance, the stock trading volume would refer to the number of shares of security traded between its daily open and close. Trading volume, and changes to volume over the course of time, are important inputs for technical traders.

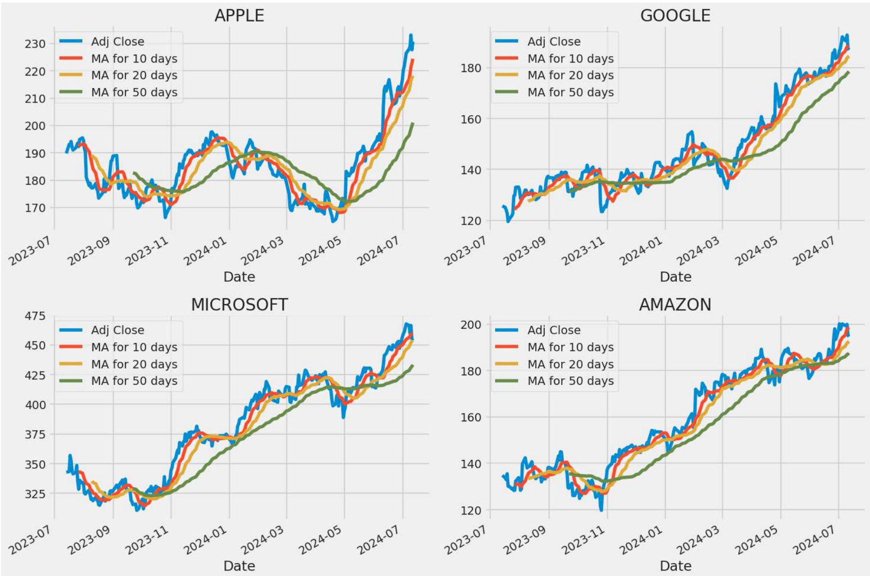
```
# Now let's plot the total volume of stock being traded each day
plt.figure(figsize=(15, 10))
plt.subplots_adjust(top=1.25, bottom=1.2)

for i, company in enumerate(company_list, 1):
    plt.subplot(2, 2, i)
    company['Volume'].plot()
    plt.ylabel('Volume')
    plt.xlabel(None)
    plt.title(f"Sales Volume for {tech_list[i - 1]}")

plt.tight_layout()
```



What was the moving average of the various stocks?

The moving average (MA) is a simple technical analysis tool that smooths out price data by creating a constantly updated average price. The average is taken over a specific period of time, like 10 days, 20 minutes, 30 weeks, or any time period the trader chooses.

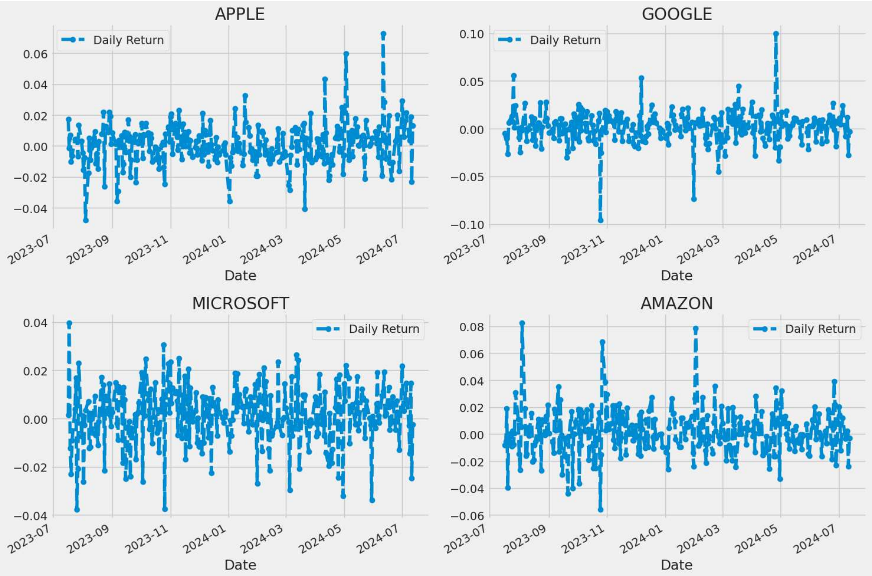
```
mov_avg_day = [10, 20, 50]

for ma in mov_avg_day:
    for company in company_list:
        column_name = f"MA for {ma} days"
        company[column_name] = company['Adj Close'].rolling(ma).mean()


fig, axes = plt.subplots(nrows=2, ncols=2)
fig.set_figheight(10)
fig.set_figwidth(15)

AAPL[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50 days']].plot(ax=axes[0,0])
axes[0,0].set_title('APPLE')

GOOG[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50 days']].plot(ax=axes[0,1])
axes[0,1].set_title('GOOGLE')

MSFT[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50 days']].plot(ax=axes[1,0])
axes[1,0].set_title('MICROSOFT')

AMZN[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50 days']].plot(ax=axes[1,1])
axes[1,1].set_title('AMAZON')

fig.tight_layout()
```



What was the daily return of the stock on average?

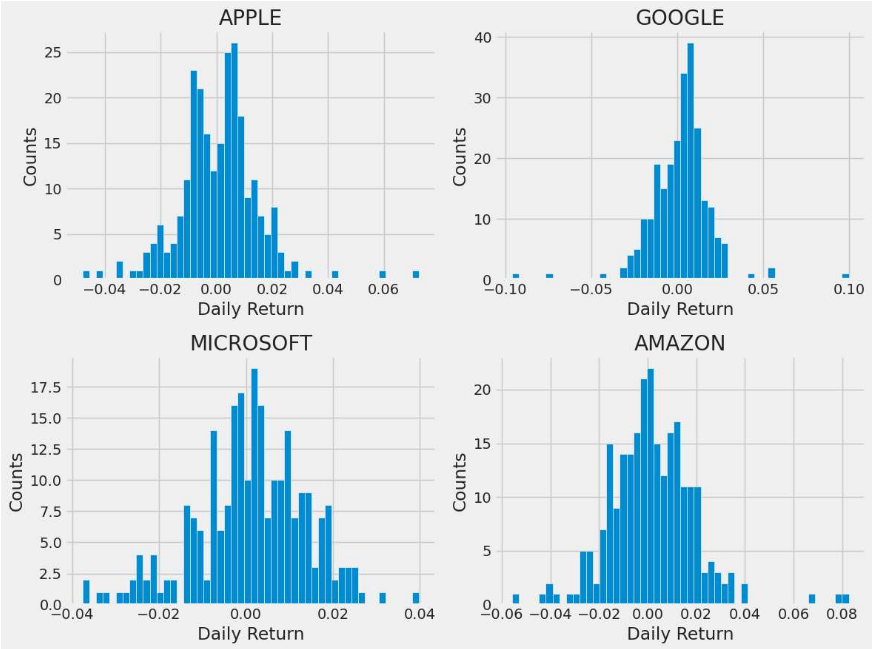
Now that we've done some baseline analysis, let's go ahead and dive a little deeper. We're now going to analyze the risk of the stock. In order to do so we'll need to take a closer look at the daily changes of the stock, and not just its absolute value. Let's go ahead and use pandas to retrieve teh daily returns for the Apple stock.

```
# We'll use pct_change to find the percent change for each day
for company in company_list:
    company['Daily Return'] = company['Adj Close'].pct_change()

# Then we'll plot the daily return percentage
fig, axes = plt.subplots(nrows=2, ncols=2)
fig.set_figheight(10)
fig.set_figwidth(15)

AAPL['Daily Return'].plot(ax=axes[0,0], legend=True, linestyle='--', marker='o')
axes[0,0].set_title('APPLE')

GOOG['Daily Return'].plot(ax=axes[0,1], legend=True, linestyle='--', marker='o')
axes[0,1].set_title('GOOGLE')

MSFT['Daily Return'].plot(ax=axes[1,0], legend=True, linestyle='--', marker='o')
axes[1,0].set_title('MICROSOFT')

AMZN['Daily Return'].plot(ax=axes[1,1], legend=True, linestyle='--', marker='o')
axes[1,1].set_title('AMAZON')

fig.tight_layout()
```




```
plt.figure(figsize=(12, 9))

for i, company in enumerate(company_list, 1):
    plt.subplot(2, 2, i)
    company['Daily Return'].hist(bins=50)
    plt.xlabel('Daily Return')
```

```
    plt.ylabel('Counts')
    plt.title(f'{company_name[i - 1]}')

plt.tight_layout()
```



What was the correlation between different stocks closing prices?

Correlation is a statistic that measures the degree to which two variables move in relation to each other which has a value that must fall between -1.0 and +1.0. Correlation measures association, but doesn't show if x causes y or vice versa — or if the association is caused by a third factor[1].

Now what if we wanted to analyze the returns of all the stocks in our list? Let's go ahead and build a DataFrame with all the ['Close'] columns for each of the stocks dataframes.

```
# Grab all the closing prices for the tech stock list into one DataFrame

closing_df = pdr.get_data_yahoo(tech_list, start=start, end=end)['Adj Close']

tech_rets = closing_df.pct_change()
tech_rets.head()
```

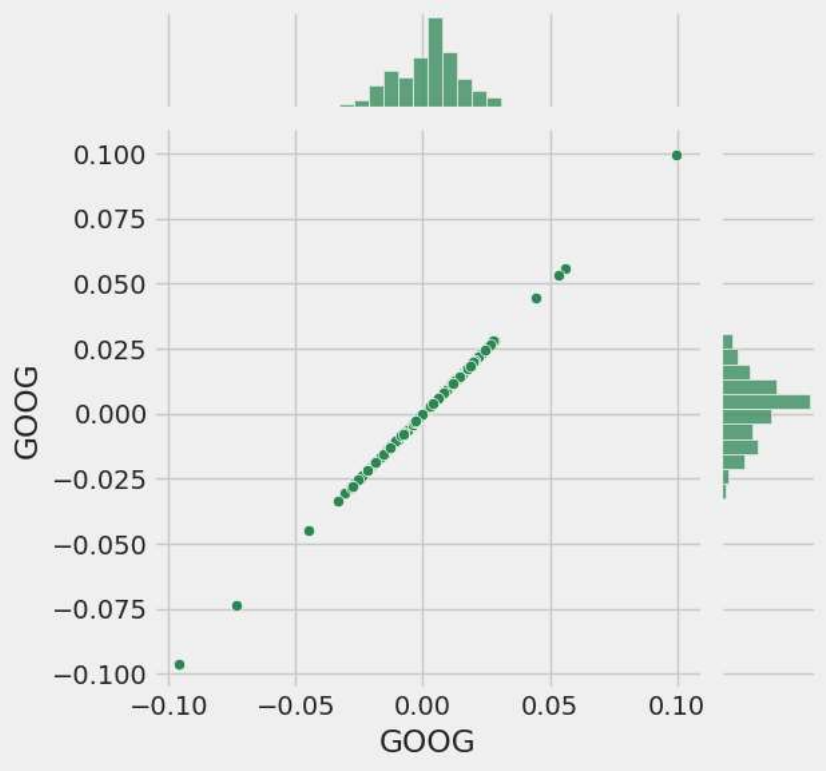
```
[*********************100%%**********************]  4 of 4 completed
```

Ticker	AAPL	AMZN	GOOG	MSFT
Date				
2023-07-14	NaN	NaN	NaN	NaN
2023-07-17	0.017305	-0.008316	-0.005092	0.001419
2023-07-18	-0.001340	-0.005466	-0.007836	0.039800
2023-07-19	0.007072	0.019047	-0.010477	-0.012267
2023-07-20	-0.010097	-0.039894	-0.026470	-0.023121

Next steps: Generate code with tech_rets View recommended plots

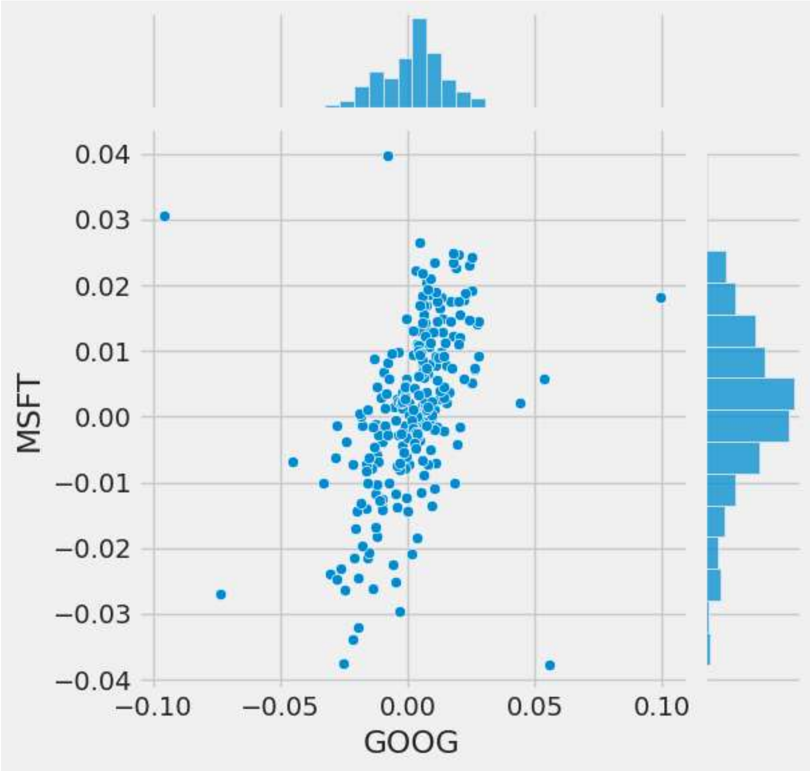
```
# Comparing Google to itself should show a perfectly linear relationship
sns.jointplot(x='GOOG', y='GOOG', data=tech_rets, kind='scatter', color='seagreen')
```

```
<seaborn.axisgrid.JointGrid at 0x7af7a53bbac0>
```



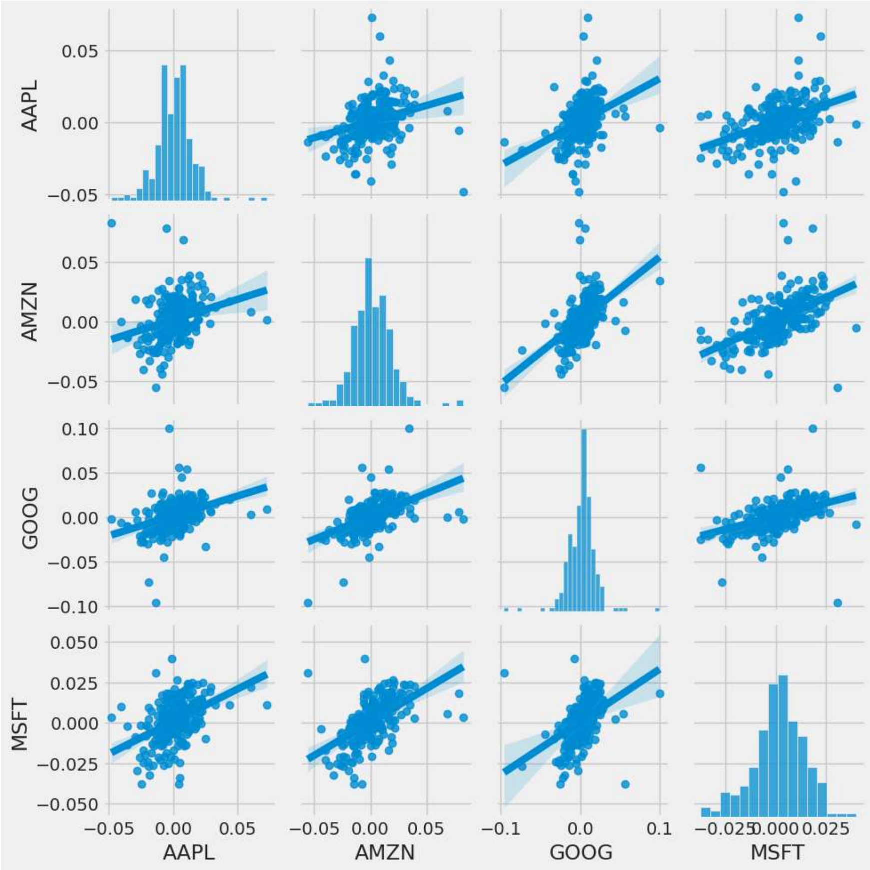

```
# We'll use joinplot to compare the daily returns of Google and Microsoft
sns.jointplot(x='GOOG', y='MSFT', data=tech_rets, kind='scatter')
```

```
<seaborn.axisgrid.JointGrid at 0x7af7a5a02b90>
```



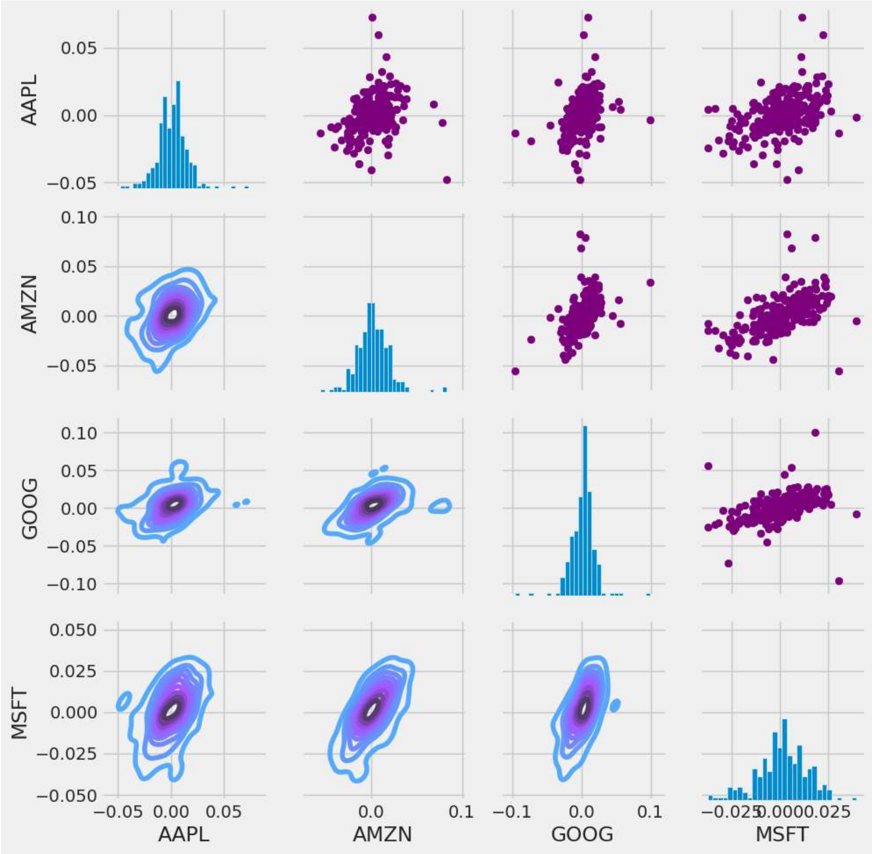

```
# We can simply call pairplot on our DataFrame for an automatic visual analysis
# of all the comparisons

sns.pairplot(tech_rets, kind='reg')
```

<seaborn.axisgrid.PairGrid at 0x7af7a5b4cdc0>



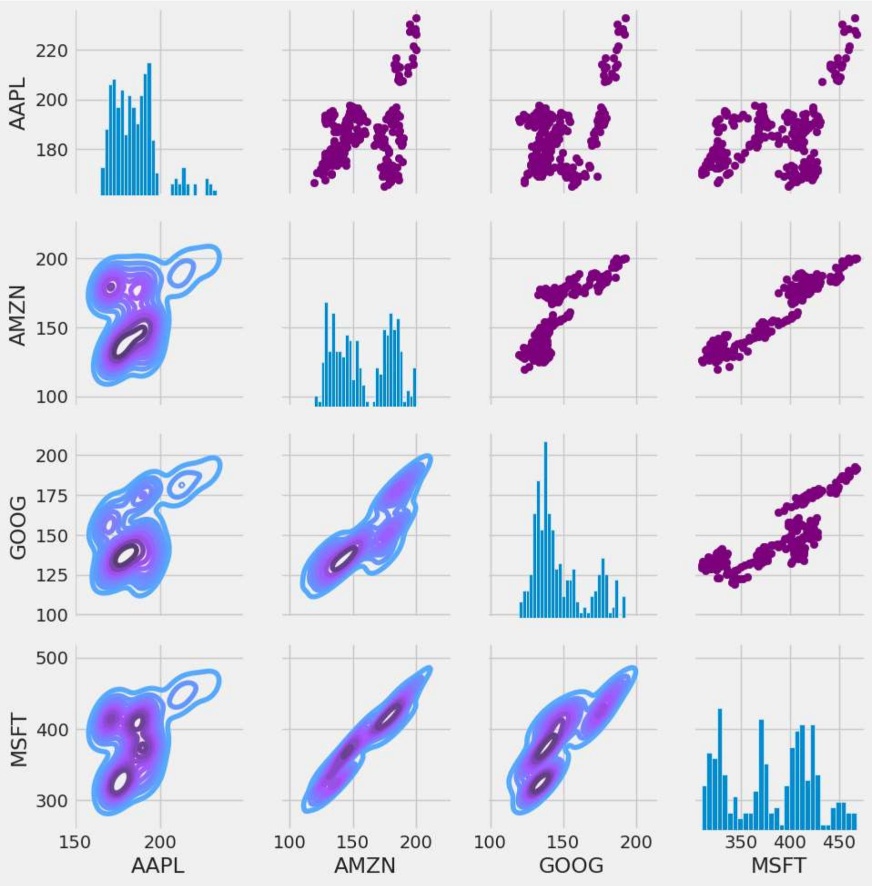

```
# Set up our figure by naming it returns_fig, call PairPLot on the DataFrame
return_fig = sns.PairGrid(tech_rets.dropna())

return_fig.map_upper(plt.scatter, color='purple')
return_fig.map_lower(sns.kdeplot, cmap='cool_d')

return_fig.map_diag(plt.hist, bins=30)
```

<seaborn.axisgrid.PairGrid at 0x7af79c62a260>



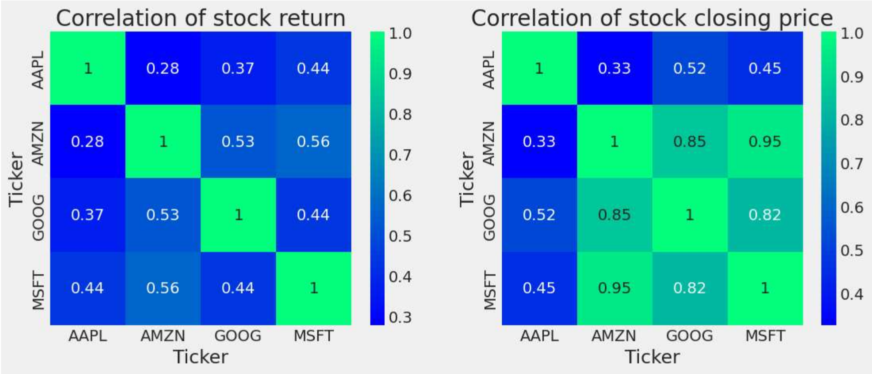

```
# Set up our figure by naming it returns_fig, call PairPLot on the DataFrame
returns_fig = sns.PairGrid(closing_df)

returns_fig.map_upper(plt.scatter,color='purple')
returns_fig.map_lower(sns.kdeplot,cmap='cool_d')

# Finally we'll define the diagonal as a series of histogram plots of the daily return
returns_fig.map_diag(plt.hist,bins=30)
```

```
<seaborn.axisgrid.PairGrid at 0x7af795c1bb20>
```




```
plt.figure(figsize=(12, 10))

plt.subplot(2, 2, 1)
sns.heatmap(tech_rets.corr(), annot=True, cmap='winter')
plt.title('Correlation of stock return')

plt.subplot(2, 2, 2)
sns.heatmap(closing_df.corr(), annot=True, cmap='winter')
plt.title('Correlation of stock closing price')
```

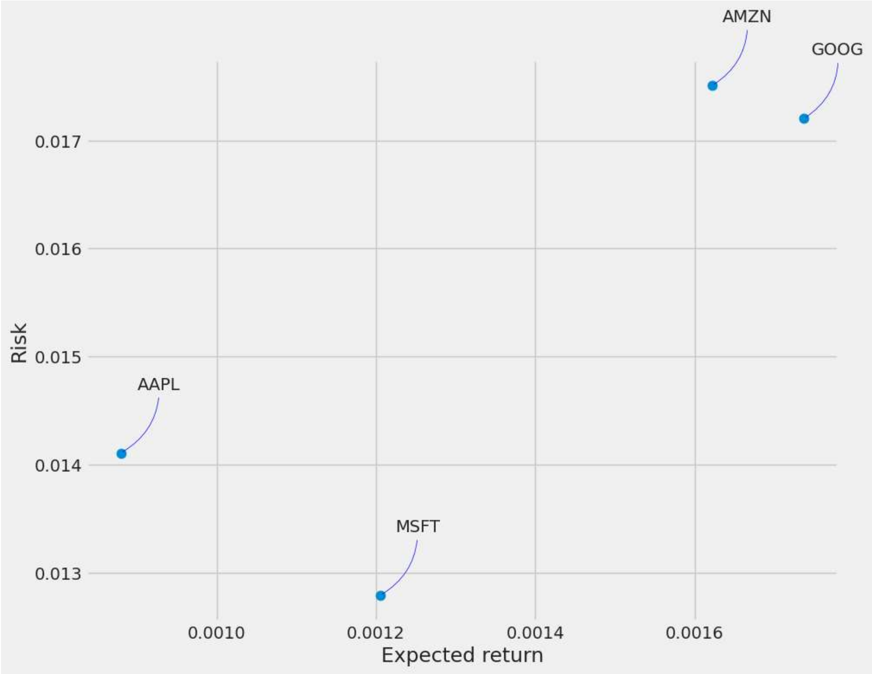
```
Text(0.5, 1.0, 'Correlation of stock closing price')
```



How much value do we put at risk by investing in a particular stock?

There are many ways we can quantify risk, one of the most basic ways using the information we've gathered on daily percentage returns is by comparing the expected return with the standard deviation of the daily returns.

```
rets = tech_rets.dropna()

area = np.pi * 20

plt.figure(figsize=(10, 8))
plt.scatter(rets.mean(), rets.std(), s=area)
plt.xlabel('Expected return')
plt.ylabel('Risk')

for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(label, xy=(x, y), xytext=(50, 50), textcoords='offset points', ha='right', va='bottom',
                 arrowprops=dict(arrowstyle='-', color='blue', connectionstyle='arc3,rad=-0.3'))
```




```
# Get the stock quote
df = pdr.get_data_yahoo('AAPL', start='2012-01-01', end=datetime.now())
df
```

```
[*********************100%%**********************]  1 of 1 completed
```

Date	Open	High	Low	Close	Adj Close	Volume
2012-01-03	14.621429	14.732143	14.607143	14.686786	12.416985	302220800
2012-01-04	14.642857	14.810000	14.617143	14.765714	12.483714	260022000
2012-01-05	14.819643	14.948214	14.738214	14.929643	12.622308	271269600
2012-01-06	14.991786	15.098214	14.972143	15.085714	12.754256	318292800
2012-01-09	15.196429	15.276786	15.048214	15.061786	12.734028	394024400
...	...	...	...	...	...	...
2024-07-08	227.089996	227.850006	223.250000	227.820007	227.820007	59085900
2024-07-09	227.929993	229.399994	226.369995	228.679993	228.679993	48076100

Next steps: Generate code with df View recommended plots

```
plt.figure(figsize=(16,6))
plt.title('Close Price History')
plt.plot(df['Close'])
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.show()
```


```
# Create a new dataframe with only the 'Close column
data = df.filter(['Close'])
# Convert the dataframe to a numpy array
dataset = data.values
# Get the number of rows to train the model on
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len
```

```
2994
```

```
# Scale the data
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```

```
array([[0.00337523],
       [0.00373558],
       [0.004484  ]
```