Navigating the Nasdaq: A Data-Driven Exploration of Tech Sector Dynamics and Investment Opportunities

1. Contribution Checkpoints:

A: Project idea - 5%

B: Dataset Curation and Preprocessing - 10%

C: Data Exploration and Summary Statistics - 10%

D: ML Algorithm Design/Development - 25%

E: ML Algorithm Training and Test Data Analysis - 20%

F: Visualization, Result Analysis, Conclusion - 15%

G: Final Tutorial Report Creation - 10%

H: Additional (not listed above, if any) - 5%

Member 1: Jay Patel, Contribution: 100%

"We, all team members, agree together that the above information is true, and we are confident about our contributions to this submitted project/final tutorial."

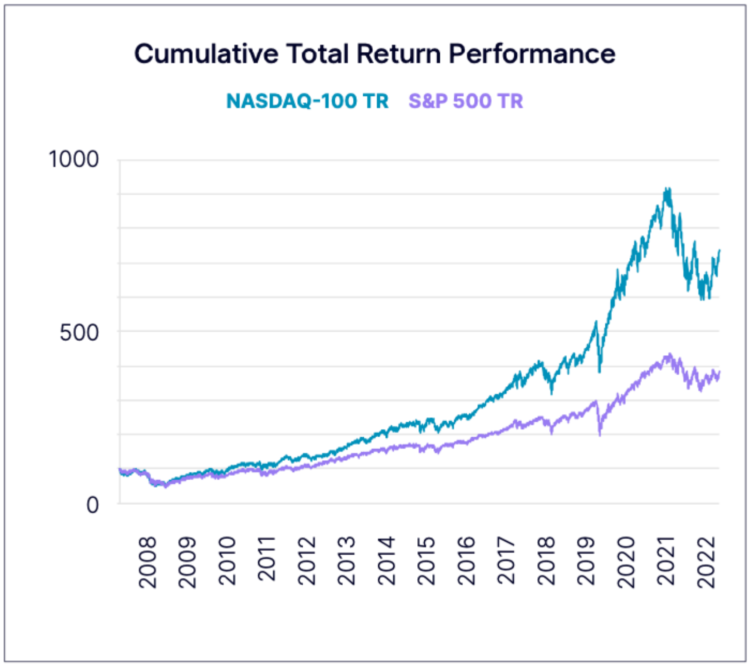
Jay Patel, 05/07/2024

1. Member 1: Jay Patel - I did everything by myself(solo).

Introduction

In an era where technology profoundly influences every aspect of society, understanding the dynamics of tech companies within the stock market is more crucial than ever. This project focuses on the Nasdaq, a stock ETF renowned for its emphasis on technology-oriented stocks, contrasting it with broader market indices like the S&P 500. More information about the difference between the S&P 500 and Nasdaq-100 can be found here: The Dow vs. Nasdaq vs. S&P 500: What's the difference?Bankratehttps://www.bankrate.com › investing › the-dow-nasdaq-...

As technology's role and impact expand exponentially, its significance in terms of utility and investment potential also grows. This phenomenon is reflected in the performance comparisons between major stock indices. Specifically, the Nasdaq-100, which predominantly features technology-oriented companies, has consistently outperformed the broader-market S&P 500 ETF, which includes the top 500 companies across all industries. This divergence underscores the pivotal role of technology in contemporary economic growth. The increasing integration of technology into our daily lives and its rapid advancement further solidify the argument for the Nasdaq's superior investment prospects, both short-term and long-term. Supporting this, a study conducted by the Nasdaq over a 15-year period from 2008 to 2023 highlighted a stark contrast in returns: the tech-focused Nasdaq-100 achieved a cumulative total return of 637%, significantly surpassing the 281% return of the S&P 500. These figures not only demonstrate the impressive growth of the tech sector but also position the Nasdaq as a more advantageous investment choice in an increasingly tech-driven world. Here is a visual:



Further information and sourcing can be found here: https://www.nasdaq.com/nasdaq100-vs-sp500-performance

We will conduct an analysis of a dataset encompassing the top 50 tech companies listed on the Nasdaq, detailing attributes such as sub-sector, headquarters state, founding year, annual revenue for 2022-2023, market cap, stock name, annual income tax, and employee size. The next step will be to identify patterns and trends within these leading tech companies. These insights will then be leveraged to assess the broader Nasdaq stock exchange, which hosts over 3,000 tech-related companies, aiming to pinpoint similar, yet lesser-known firms with strong growth potential. This analysis is particularly crucial as we move towards a tech-centric global economy, driven by rapid advancements and widespread adoption in areas such as Artificial Intelligence (AI), Virtual Reality (VR), Blockchain technology, quantum computing, and cybersecurity. Identifying these trends will enable us to discover promising investment opportunities in the burgeoning tech sector.

Research Questions:

1. Historical Revenue Trends: Are companies founded before the year 2000 more financially successful than those founded afterward? This question will be explored through a T-test comparing the average revenues of these two groups, providing insights into the impact of establishment era on financial performance.
2. Sector Performance: Does the sub-sector classification (e.g., semiconductors, consumer electronics) influence a company's financial success? An ANOVA test will be employed to investigate if there are statistically significant differences in average annual revenues across various tech sub-sectors.
3. Revenue and Market Cap Correlation: Is there a strong correlation between a company's revenue and its market capitalization? This analysis seeks to establish whether higher revenues are indicative of higher market caps, which could suggest a company's status as a growth stock. A Chi-Squared test will be employed to determine if there's a significant association between annual revenue and market cap, potentially guiding investors in identifying high-growth

opportunities within the tech sector.

Goal & Significance:

In a world increasingly driven by technological innovation, this study seeks to deepen the understanding of the dynamics within the tech sector, specifically through the lens of financial performance on the Nasdaq. By examining detailed characteristics of the top 50 tech companies—ranging from their founding era and sub-sector classification to their financial metrics like annual revenue and market capitalization—this analysis aims to unearth patterns and insights that reveal the critical factors influencing their success. These insights will not only serve as a valuable resource for investors and analysts looking to pinpoint high-potential investment opportunities but will also offer a strategic perspective on how different variables such as company age, industry sub-sector, and size impact economic viability and growth potential. Furthermore, leveraging the insights derived from our initial analysis, we plan to develop a machine learning model that can effectively distinguish between high-growth and low-growth companies. This model will identify firms with the potential to yield substantial returns, categorizing them based on predictive indicators of growth such as revenue trends, market capitalization, and sector-specific dynamics. By deploying this model, we aim to provide investors and financial analysts with a powerful tool that not only forecasts future growth prospects but also aids in making more informed and strategic investment decisions in the rapidly evolving tech sector.

```python
# Imports
import pandas as pd
import numpy as np
from scipy.stats import ttest_ind
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import zscore
from scipy.stats import chi2_contingency
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.pipeline import make_pipeline
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from sklearn.metrics import classification_report, confusion_matrix,
        ConfusionMatrixDisplay
```

Data Curation

The primary dataset for this project comprises information on the top 50 technology companies listed on the Nasdaq. This dataset includes vital metrics such as sub-sector classification, headquarters state, founding year, annual revenue for 2022-2023, market capitalization, stock name, annual income tax, and employee size. The purpose of using this dataset is to develop a predictive model that can analyze the dynamics of the tech sector, focusing on various factors that influence financial performance such as company age, sector, and financial metrics.

The source of this dataset is https://www.kaggle.com/datasets/lamiatabassum/top-50-us-tech-companies-2022-2023-dataset, which provides comprehensive and updated financial data essential for conducting high-quality market analysis.

In addition to the top 50 tech companies' dataset, the analysis will extend to the broader Nasdaq, which includes over 3000 companies. This comprehensive dataset will serve as the application ground for the predictive model developed from the top 50 companies' data. By applying the model to a wider array of companies, the project aims to identify similar companies that might not be as prominent but show potential for growth, thereby assisting investors and analysts in discovering lucrative investment opportunities within the rapidly evolving tech market.

This dataset, encompassing the broader Nasdaq listings, is sourced from https://stockanalysis.com/stocks/screener/. This dataset will enable a comparative analysis, enhancing the effectiveness of the findings and extending the model's applicability beyond the top 50 tech firms.

Below is the Top 50 Tech Companies' Dataframe:

```
top_50_Tech_df = pd.read_csv("Top50Tech.csv")
top_50_Tech_df
```

	Company Name	Industry	Sector	HQ State	Founding Year	Annual Revenue 2022-2023 (USD in Billions)	Market Cap (USD in Trillions)	Stock Name
0	Apple Inc.	Technology	Consumer Electronics	California	1976	387.53	2.520	AAPL
1	Microsoft Corporation	Technology	Software Infrastructure	Washington	1975	204.09	2.037	MSFT
2	Alphabet (Google)	Technology	Software Infrastructure	California	1998	282.83	1.350	GOOG
3	Amazon	Technology	Software Application	Washington	1994	513.98	1.030	AMZN
4	NVIDIA Corporation	Technology	Semiconductors	California	1993	26.97	0.653	NVDA
5	Tesla	Technology	Software Infrastructure	Texas	2003	81.46	0.625	TSLA
6	Meta Platforms	Technology	Software Infrastructure	California	2004	116.60	0.524	META
7	Broadcom Inc.	Technology	Semiconductors	California	1961	34.41	0.266	AVGO
8	Oracle Corporation	Technology	Software Infrastructure	Texas	1977	46.07	0.236	ORCL
9	Cisco Systems Inc.	Technology	Communication Equipments	California	1984	53.16	0.208	CSCO
10	Salesforce Inc.	Technology	Software Application	California	1999	31.35	0.189	CRM
11	Adobe Inc.	Technology	Software Infrastructure	California	1982	17.60	0.172	ADBE
12	Texas Instruments Inc.	Technology	Semiconductors	Texas	1930	20.02	0.162	TXN
13	Advanced Micro Devices (AMD)	Technology	Semiconductors	California	1969	23.60	0.155	AMD

	Inc.							
14	Qualcomm Inc.	Technology	Semiconductors	California	1985	42.95	0.138	QCOM
15	Netflix	Technology	Software Application	California	1997	31.61	0.136	NFLX
16	Intel Corporation	Technology	Semiconductors	California	1968	63.05	0.118	INTC
17	Intuit Inc.	Technology	Software Application	California	1983	13.68	0.118	INTU
18	IBM Corporation	Technology	IT Services	New York	1911	60.52	0.113	IBM
19	Applied Materials Inc.	Technology	Semiconductors	California	1967	26.25	0.102	AMAT
20	Booking Holdings	Technology	Software Application	Connecticut	1996	17.09	0.097	BKNG
21	Analog Devices Inc.	Technology	Semiconductors	Massachusetts	1965	12.57	0.095	ADI
22	ServiceNow Inc.	Technology	Software Application	California	2004	7.24	0.090	NOW
23	Automatic Data Processing	Technology	Software Application	New Jersey	1949	16.67	0.090	ADP
24	PayPal Holdings Inc.	Technology	Software Infrastructure	California	1998	27.51	0.087	PYPL
25	Airbnb	Technology	Software Application	California	2008	8.39	0.078	ABNB
26	Fiserv Inc.	Technology	IT Services	Wisconsin	1984	17.73	0.071	FISV
27	Lam Research Corporation	Technology	Semiconductors	California	1980	19.04	0.069	LRCX
28	Uber Technologies Inc.	Technology	Software Application	California	2009	31.87	0.066	UBER
29	Micron Technology	Technology	Semiconductors	Idaho	1978	27.15	0.064	MU
30	Equinix	Technology	IT Services	California	1998	7.26	0.064	EQIX
31	Activision Blizzard	Technology	Software Application	California	2008	7.52	0.063	ATVI
32	Palo Alto Networks Inc.	Technology	Software Infrastructure	California	2005	6.15	0.059	PANW
33	Synopsys Inc.	Technology	Software Infrastructure	California	1986	5.17	0.057	SNPS
34	Cadence Design Systems Inc.	Technology	Software Application	California	1988	3.56	0.057	CDNS
35	KLA Corporation	Technology	Semiconductors	California	1997	10.48	0.053	KLAC
36	Arista Networks Inc.	Technology	Computer Hardware	California	2004	4.38	0.052	ANET
37	VMware Inc.	Technology	Software Infrastructure	California	1998	13.34	0.051	VMW
38	Workday Inc.	Technology	Software Application	California	2005	6.21	0.049	WDAY
			Software In-					

39	Fortinet Inc.	Technology	frastructure	California	2000	4.41	0.049	FTNT
40	Block Inc.	Technology	Software Infrastructure	California	2009	17.53	0.047	SQ
41	Snowflake Inc.	Technology	Software Application	Montana	2012	2.06	0.046	SNOW
42	Roper Technologies	Technology	Electronic Components	Florida	1890	5.61	0.046	ROP
43	Microchip Technology Inc.	Technology	Semiconductors	Arizona	1989	8.05	0.045	MCHP
44	Autodesk Inc.	Technology	Software Application	California	1982	5.00	0.045	ADSK
45	GlobalFoundries	Technology	Semiconductors	New York	2009	8.10	0.038	GFS
46	IQVIA Holdings	Technology	Software Application	North Carolina	1982	14.41	0.037	IQV
47	Marvell Technology Inc.	Technology	Semiconductors	California	1995	5.91	0.035	MRVL
48	Dell Technologies Inc.	Technology	Computer Hardware	Texas	1984	102.30	0.028	DELL
49	HP Inc.	Technology	Computer Hardware	California	1939	59.78	0.028	HPQ

Below is the Nasdaq Stock Excahnge DataFrame:

```
nasdaq_stocks_df = pd.read_csv("screener-stocks.csv")
nasdaq_stocks_df
```

	Symbol	Company Name	Market Cap	Stock Price	Industry	Volume	Revenue	Emp
0	MSFT	Microsoft Corporation	3073557477400	413.54	Software - Infrastructure	16346811	2.365840e+11	2210
1	AAPL	Apple Inc	2805947649000	181.71	Consumer Electronics	76249821	3.816230e+11	1610
2	NVDA	NVIDIA Corporation	2303500000000	921.40	Semiconductors	36942636	6.092200e+10	2960
3	GOOGL	Alphabet Inc.	2089125712023	168.10	Internet Content & Information	21268591	3.181460e+11	1825
4	GOOG	Alphabet Inc.	2088769047682	169.83	Internet Content & Information	15057181	3.181460e+11	1823
...	...	...	...	...	...	...	...	...
3380	APVO	Aptevo Therapeutics Inc.	747507	1.11	Biotechnology	807301	NaN	40.0
3381	CETX	Cemtrex, Inc.	285128	0.27	Software - Infrastructure	1365144	6.427649e+07	328.
3382	BDRX	Biodexa Pharmaceuticals Plc	279208	1.11	Biotechnology	308645	4.822780e+05	21.0
3383	JFBR	Jeffs' Brands Ltd	263915	0.22	Internet Retail	1657025	1.000800e+07	10.0
3384	AIMAU	Aimfinity Investment Corp. I	99769	11.40	Shell Companies	55	NaN	NaN

3385 rows × 9 columns

Below, the sectors/industries are listed of both dataframes

```
top_50_sectors = top_50_Tech_df["Sector"].unique()
print("Top 50 Sectors:", top_50_sectors)

print()
print()

unique_nasdaq = nasdaq_stocks_df['Industry'].unique()
print("Nasdaq Sectors:", unique_nasdaq)
```

```
Top 50 Sectors: ['Consumer Electronics' 'Software Infrastructure'
'Software Application'
 'Semiconductors' 'Communication Equipments' 'IT Services'
 'Computer Hardware' 'Electronic Components']


Nasdaq Sectors: ['Software - Infrastructure' 'Consumer Electronics'
'Semiconductors'
 'Internet Content & Information' 'Internet Retail' 'Auto Manufactur-
ers'
 'Semiconductor Equipment & Materials' 'Discount Stores' 'Entertain-
ment'
 'Beverages - Non-Alcoholic' 'Drug Manufacturers - General'
```

```
 'Specialty Chemicals' 'Communication Equipment' 'Telecom Services'
 'Software - Application' 'Medical Instruments & Supplies' 'Conglomer-
ates'
 'Travel Services' 'Biotechnology' 'Staffing & Employment Services'
 'Confectioners' 'Restaurants' 'Financial Data & Stock Exchanges'
 'Specialty Business Services' 'Credit Services' 'Lodging' 'Railroads'
 'REIT - Specialty' 'Electronic Gaming & Multimedia'
 'Utilities - Renewable' 'Specialty Retail'
 'Farm & Heavy Construction Machinery' 'Medical Devices' 'Capital Mar-
kets'
 'Computer Hardware' 'Utilities - Regulated Electric' 'Apparel Retail'
 'Packaged Foods' 'Diagnostics & Research' 'Trucking'
 'Industrial Distribution' 'Real Estate Services'
 'Insurance - Diversified' 'Health Information Services'
 'Oil & Gas Exploration & Production' 'Consulting Services'
 'Information Technology Services' 'Oil & Gas Equipment & Services'
 'Banks - Regional' 'Insurance Brokers' 'Airlines' 'Asset Management'
 'Aerospace & Defense' 'Auto Parts' 'Steel' 'Gambling' 'Solar'
 'Insurance - Property & Casualty' 'Integrated Freight & Logistics'
 'Specialty Industrial Machinery' 'Pharmaceutical Retailers'
 'Drug Manufacturers - Specialty & Generic'
 'Scientific & Technical Instruments' 'REIT - Hotel & Motel'
 'Tools & Accessories' 'Oil & Gas Midstream' 'Electronic Components'
 'Engineering & Construction' 'Resorts & Casinos' 'REIT - Retail'
 'Medical Distribution' 'Leisure' 'Broadcasting' 'Gold'
 'Rental & Leasing Services' 'Footwear & Accessories' 'Grocery Stores'
 'Oil & Gas Refining & Marketing' 'Lumber & Wood Production'
 'REIT - Mortgage' 'Medical Care Facilities'
 'Electronics & Computer Distribution' 'Building Products & Equipment'
 'Packaging & Containers' 'Waste Management' 'Utilities - Regulated
Gas'
 'Mortgage Finance' 'Recreational Vehicles' 'Insurance - Specialty'
 'Apparel Manufacturing' 'Oil & Gas Drilling'
 'Electrical Equipment & Parts' 'Infrastructure Operations'
 'Airports & Air Services' 'Education & Training Services'
 'Household & Personal Products' 'Utilities - Diversified'
 'Auto & Truck Dealerships' 'REIT - Healthcare Facilities' 'Chemicals'
 'Insurance - Life' 'Residential Construction' 'Thermal Coal'
 'Marine Shipping' 'Personal Services' 'Farm Products'
 'Furnishings, Fixtures & Appliances' 'Advertising Agencies'
 'Building Materials' 'Food Distribution' 'Home Improvement Retail'
 'Other Industrial Metals & Mining' 'Beverages - Wineries & Distil-
leries'
 'Security & Protection Services' 'Aluminum' 'Healthcare Plans'
 'Shell Companies' 'Publishing' 'Utilities - Regulated Water'
 'Financial Conglomerates' 'Uranium' 'Pollution & Treatment Controls'
 'Coking Coal' 'Agricultural Inputs' 'Metal Fabrication'
 'Paper & Paper Products' 'REIT - Diversified'
 'Business Equipment & Supplies' 'Insurance - Reinsurance' 'Luxury
Goods'
 'Real Estate - Development' 'Tobacco' 'Other Precious Metals & Min-
ing'
 'REIT - Industrial' 'Real Estate - Diversified' 'REIT - Office'
 'Oil & Gas Integrated' nan 'Industrials' 'Sanitary Services' 'Other'
 'Textile Manufacturing']
```

We ran into a issue!! One dataframe includes information on the top 50 tech companies, while the second dataset encompasses a broader list of 3,000 companies from various fields with a focus on technology. However, we face a challenge: the second dataset categorizes companies by broad sectors, whereas the first is more specific, detailing sub-sectors within the technology field. To address this, we need to refine the second dataset to identify and extract those sectors that are relevant to technology.

We got the sectors/industries but we see that there are many non-tech related industries and also we want the tech industries to fall under categories that is similar to the top 50 tech companies' dataset, so we will create a new dataset of only the tech companies from the nasdaq as there are over 3000 companies but not all are in the tech sector.

```
industry_mapping = {
    'Computer Software: Programming, Data Processing': 'Software Infrastructure',
    'Computer Software: Prepackaged Software': 'Software Application',
    'EDP Services': 'Software Infrastructure',
    'Semiconductors': 'Semiconductors',
    'Industrial Machinery/Components': 'Semiconductors',
    'Computer Manufacturing': 'Consumer Electronics',
    'Computer peripheral equipment': 'Computer Hardware',
    'Retail: Computer Software & Peripheral Equipment': 'Consumer Electronics',
    'Communication Equipment': 'Communication Equipments',
    'Telecommunications Equipment': 'Communication Equipments',
    'Electronic Components': 'Electronic Components',
    'Internet Content & Information': 'Software Application',
    'Software - Infrastructure': 'Software Infrastructure',
    'Software - Application': 'Software Application',
}

# Create a new column called Sector
nasdaq_stocks_df['Sector'] = nasdaq_stocks_df['Industry'].map(industry_mapping)


tech_companies_df = nasdaq_stocks_df[nasdaq_stocks_df['Sector'].notna()]
tech_companies_df['Sector'].fillna('Software Application',
        inplace=True)


tech_companies_df
```

```
<ipython-input-5-82a3f5579be0>:22: 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
  tech_companies_df['Sector'].fillna('Software Application', inplace=True)
```

	Symbol	Company Name	Market Cap	Stock Price	Industry	Volume	Revenue	Emplo
0	MSFT	Microsoft Corporation	3073557477400	413.54	Software - Infrastructure	16346811	2.365840e+11	22100c
2	NVDA	NVIDIA Corporation	2303500000000	921.40	Semiconductors	36942636	6.092200e+10	29600.
3	GOOGL	Alphabet Inc.	2089125712023	168.10	Internet Content & Information	21268591	3.181460e+11	182502
4	GOOG	Alphabet Inc.	2088769047682	169.83	Internet Content & Information	15057181	3.181460e+11	182381
6	META	Meta Platforms, Inc.	1181213245790	465.68	Internet Content & Information	15039623	1.427110e+11	67317.c
...	...	...	...	...	...	...	...	...
3354	ASNS	Actelis Networks, Inc.	1848706	0.61	Communication Equipment	210101	5.606000e+06	43.0
3358	FRGT	Freight Technologies, Inc.	1734473	0.71	Software - Application	233388	1.967969e+07	88.0
3360	SYTA	Siyata Mobile Inc.	1683827	2.75	Communication Equipment	399173	8.233301e+06	23.0
3364	TAOP	Taoping Inc.	1575681	0.97	Software - Infrastructure	36222	3.863564e+07	63.0
3381	CETX	Cemtrex, Inc.	285128	0.27	Software - Infrastructure	1365144	6.427649e+07	328.0

464 rows × 10 columns

Next problem is that the Revenue categories are not the same in both data sets as the Top 50 tech companies are measured in billions and in the Tech Nasdaq Companies the Revenue is a large number so I need to figure a way to so both are displayed on the same level. Since most small companies will not be earning in the billions, it would be easier if I convert the Revenue categories of both dataframes to Revenue in millions. Converting the billions into millions will help the model be more accurate later on as most of the small Nasdaq companies don't earn a billion plus so the numbers will toss the model and the statistical test off.

```
# Renaming and converting revenue in top_50_Tech_df
top_50_Tech_df.rename(columns={'Annual Revenue 2022-2023 (USD in Billions)': 'Annual Revenue 2022-2023 (USD in Millions)'}, inplace=True)
top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'] = top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'].apply(lambda x: x * 1000).round(3)


tech_companies_df.rename(columns={'Revenue': 'Annual Revenue 2022-2023 (USD in Millions)'}, inplace=True)
tech_companies_df['Annual Revenue 2022-2023 (USD in Millions)'] = tech_companies_df['Annual Revenue 2022-2023 (USD in Millions)'].apply(lambda x: x / 1e6 if x > 1e6 else x).round(3)


print(top_50_Tech_df[['Company Name', 'Annual Revenue 2022-2023 (USD in Millions)']].tail())
print(tech_companies_df[['Company Name', 'Annual Revenue 2022-2023 (USD in Millions)']].tail())
```

```
               Company Name  Annual Revenue 2022-2023 (USD in Mil-
lions)
45          GlobalFoundries
8100.0
46           IQVIA Holdings
14410.0
47  Marvell Technology Inc.
5910.0
48   Dell Technologies Inc.
102300.0
49                  HP Inc.
59780.0
                    Company Name  Annual Revenue 2022-2023 (USD in
Millions)
3354      Actelis Networks, Inc.
5.606
3358  Freight Technologies, Inc.
19.680
3360          Siyata Mobile Inc.
8.233
3364                Taoping Inc.
38.636
3381               Cemtrex, Inc.
64.276

<ipython-input-6-8271f0744b4d>:5: 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/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df.rename(columns={'Revenue': 'Annual Revenue 2022-
2023 (USD in Millions)'}, inplace=True)
<ipython-input-6-8271f0744b4d>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Annual Revenue 2022-2023 (USD in Millions)'] =
tech_companies_df['Annual Revenue 2022-2023 (USD in Millions)'].ap-
ply(lambda x: x / 1e6 if x > 1e6 else x).round(3)
```

Now our revenues are in line so we can compare on them on the same field now.

Next in the tech_companies_df, teh Employees and Founded columns need to be integers not decimals. Also rename those columns to match the Top 50 tech stock df.

```
tech_companies_df['Employees'] = tech_companies_df['Employees'].fill-
        na(0).astype(int)
tech_companies_df.rename(columns={'Employees': 'Employee Size'}, in-
        place=True)


tech_companies_df['Founded'] =
        tech_companies_df['Founded'].fillna(0).astype(int)
tech_companies_df.rename(columns={'Founded': 'Founding Year'},
        inplace=True)
```

```
top_50_Tech_df.rename(columns={'Annual Revenue 2022-2023 (USD in Bil-
        lions)': 'Annual Revenue 2022-2023 (USD in Millions)'}, in-
        place=True)

tech_companies_df
```

```
<ipython-input-7-782185e66960>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Employees'] = tech_companies_df['Employ-
ees'].fillna(0).astype(int)
<ipython-input-7-782185e66960>:2: 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/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df.rename(columns={'Employees': 'Employee Size'}, in-
place=True)
<ipython-input-7-782185e66960>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Founded'] = tech_companies_df['Founded'].fill-
na(0).astype(int)
<ipython-input-7-782185e66960>:5: 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/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df.rename(columns={'Founded': 'Founding Year'}, in-
place=True)
```

	Symbol	Company Name	Market Cap	Stock Price	Industry	Volume	Annual Revenue 2022-2023 (USD in Millions)	Employe Siz
0	MSFT	Microsoft Corporation	3073557477400	413.54	Software - Infrastructure	16346811	236584.000	221000
2	NVDA	NVIDIA Corporation	2303500000000	921.40	Semiconductors	36942636	60922.000	29600
3	GOOGL	Alphabet Inc.	2089125712023	168.10	Internet Content & Information	21268591	318146.000	182502
4	GOOG	Alphabet Inc.	2088769047682	169.83	Internet Content & Information	15057181	318146.000	182381
6	META	Meta Platforms, Inc.	1181213245790	465.68	Internet Content & Information	15039623	142711.000	67317
...	...	...	...	...	...	...	...	...
3354	ASNS	Actelis Networks, Inc.	1848706	0.61	Communication Equipment	210101	5.606	43
3358	FRGT	Freight Technologies, Inc.	1734473	0.71	Software - Application	233388	19.680	88
3360	SYTA	Siyata Mobile Inc.	1683827	2.75	Communication Equipment	399173	8.233	23
3364	TAOP	Taoping Inc.	1575681	0.97	Software - Infrastructure	36222	38.636	63
3381	CETX	Cemtrex, Inc.	285128	0.27	Software - Infrastructure	1365144	64.276	328

464 rows × 10 columns

We also need to match the market cap in both data sets so the model can use it properly as one is in trillions and one is the whole number. To make it easier for the model, we changed it to Market Cap in Billions.

```
# Convert and rename Market Cap in top_50_Tech_df from trillions to billions
top_50_Tech_df['Market Cap (USD in Billions)'] = top_50_Tech_df['Market Cap (USD in Trillions)'] * 1000
top_50_Tech_df.drop(columns=['Market Cap (USD in Trillions)'], inplace=True)  # Remove old column

# Convert and rename Market Cap in tech_companies_df from large numbers to billions
tech_companies_df['Market Cap (USD in Billions)'] = tech_companies_df['Market Cap'] / 1e9
tech_companies_df.drop(columns=['Market Cap'], inplace=True)  # Remove old column

print(top_50_Tech_df[['Company Name', 'Market Cap (USD in Billions)']].tail())
print(tech_companies_df[['Company Name', 'Market Cap (USD in Billions)']].tail())
```

```
                   Company Name  Market Cap (USD in Billions)
```

```
45         GlobalFoundries                         38.0
46           IQVIA Holdings                         37.0
47  Marvell Technology Inc.                         35.0
48   Dell Technologies Inc.                         28.0
49                  HP Inc.                         28.0
                   Company Name  Market Cap (USD in Billions)
3354      Actelis Networks, Inc.                      0.001849
3358  Freight Technologies, Inc.                      0.001734
3360          Siyata Mobile Inc.                      0.001684
3364                Taoping Inc.                      0.001576
3381               Cemtrex, Inc.                      0.000285

<ipython-input-8-9dfede839383>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Market Cap (USD in Billions)'] = tech_compa-
nies_df['Market Cap'] / 1e9
<ipython-input-8-9dfede839383>:7: 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/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df.drop(columns=['Market Cap'], inplace=True)  # Re-
move old column
```

Now all our data is cleaned and ready to be used for our Exploratory Data Analysis(EAD).

Exploratory Data Analysis(EAD)

Goal is to do our exploratory data analysis on the Top 50 tech companies then build a ML model and test it on the Nasdaq where hopefully we can find future winners! This is because we know the top 50 are winners so using patterns and trends from the top 50 we can make a model that help find other winners.

Also we hope to address our research questions with our EDA!!

Research Question 1-Historical Revenue Trends: Are companies founded before the year 2000 more financially successful than those founded afterward?

This question will be explored through a T-test comparing the average revenues of these two groups, providing insights into the impact of establishment era on financial performance.

T-test for Annual Revenue of companies founded before 2000 vs after 2000. Let's invetigate our first observation which is doing a t-test.

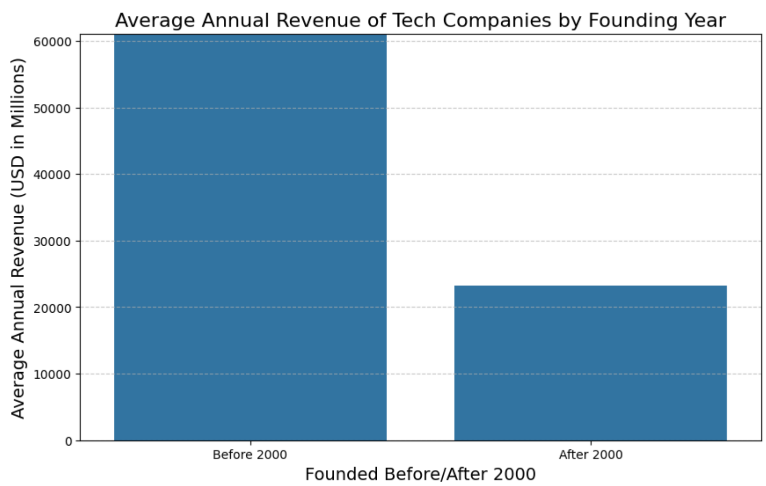
Null hypothesis: The average "Annual Revenue" of companies founded after 2000 are the same as the companies founded before 2000.

Alternative hypothesis: The average "Annual Revenue" of companies founded after 2000 is not the same as the companies founded before 2000.

T-test on Top 50 Tech Companies:

```python
before_2000 = top_50_Tech_df[top_50_Tech_df['Founding Year'] <= 1999]
after_2000 = top_50_Tech_df[top_50_Tech_df['Founding Year'] >= 2000]

t_stat, p_value = ttest_ind(before_2000['Annual Revenue 2022-2023 (USD in Millions)'], after_2000['Annual Revenue 2022-2023 (USD in Millions)'], equal_var=False)

print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < 0.05:
    print("We reject the null hypothesis, indicating no significant differences in average annual revenue between companies founded before and after 2000.")
else:
    print("We fail to reject the null hypothesis, suggesting significant differences in average annual revenue between these groups.")


top_50_Tech_df['Founded After 2000'] = top_50_Tech_df['Founding Year'] >= 2000
average_revenue = top_50_Tech_df.groupby('Founded After 2000')['Annual Revenue 2022-2023 (USD in Millions)'].mean().reset_index()
plt.figure(figsize=(10, 6))
sns.barplot(x='Founded After 2000', y='Annual Revenue 2022-2023 (USD in Millions)', data=average_revenue)
plt.title('Average Annual Revenue of Tech Companies by Founding Year', fontsize=16)
plt.xlabel('Founded Before/After 2000', fontsize=14)
plt.ylabel('Average Annual Revenue (USD in Millions)', fontsize=14)
plt.xticks([0, 1], ['Before 2000', 'After 2000'])
plt.ylim(0, max(average_revenue['Annual Revenue 2022-2023 (USD in Millions)']) + 50)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
T-statistic: 1.8381534451918802
P-value: 0.07225167312605085
We fail to reject the null hypothesis, suggesting significant differences in average annual revenue between these groups.
```



For the top 50 Tech stocks we reject the null hypothesis and accept the alternative which tells us the average "Annual Revenue" of companies founded after 2000 is significantly different than that of companies founded before 2000. This helps show that older companies has significantly higher revenue than those founded after 2000.

Research Question 2-Sector Performance: Does the sub-sector classification (e.g., semiconductors, consumer electronics) influence a company's financial success?

An ANOVA test will be employed to investigate if there are statistically significant differences in average annual revenues across various tech sub-sectors.

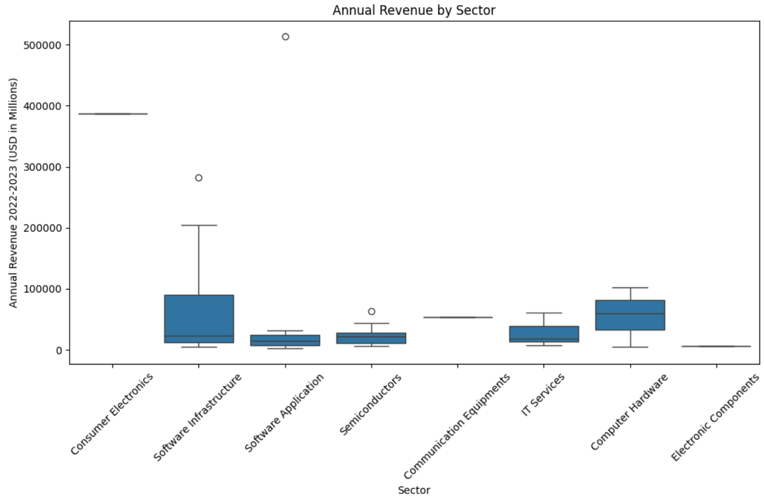
We want to investigate if the sector is correlated to revenue. To do this we will use an ANOVA test to determine if there's a statistically significant difference in average annual revenue among different sectors. This can possibly tell us that maybe certain sectors have better profit margins.

Null hypothesis: The mean annual revenue is the same across all sectors.

Alternative hypothesis: At least one sector's mean annual revenue is significantly different from the others.

```
fvalue, pvalue = stats.f_oneway(
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Consumer Electronics']
        ['Annual Revenue 2022-2023 (USD in Millions)'],
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Software In-
        frastructure']['Annual Revenue 2022-2023 (USD in Millions)'],
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Software Application']
        ['Annual Revenue 2022-2023 (USD in Millions)'],

    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Semiconductors']['An-
        nual Revenue 2022-2023 (USD in Millions)'],
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Communication Equip-
        ments']['Annual Revenue 2022-2023 (USD in Millions)'],
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'IT Services']['Annual
        Revenue 2022-2023 (USD in Millions)'],

    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Computer Hardware']
        ['Annual Revenue 2022-2023 (USD in Millions)'],
    top_50_Tech_df[top_50_Tech_df['Sector'] == 'Electronic
        Components']['Annual Revenue 2022-2023 (USD in Millions)']

)
print(f"F-Statistic: {fvalue}, P-value: {pvalue}")

if pvalue < 0.05:
    print("We reject the null hypothesis. There is a statistically
        significant difference in the mean annual revenue between sec-
        tors.")
else:
    print("We fail to reject the null hypothesis. There is no statis-
        tically significant difference in the mean annual revenue
        across sectors.")


plt.figure(figsize=(12, 6))
sns.boxplot(x='Sector', y='Annual Revenue 2022-2023 (USD in
        Millions)', data=top_50_Tech_df)
plt.xticks(rotation=45)
plt.title('Annual Revenue by Sector')
plt.show()
```

```
F-Statistic: 2.3636143972891883, P-value: 0.039440146740987135
We reject the null hypothesis. There is a statistically significant
difference in the mean annual revenue between sectors.
```



Now, we reject the null hypothesis so we can conclude that there are sectors that have higher revenue then others. Lets conduct a post hoc test since we reject our null hypothesis to find what groups are significantly different than others.

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

results = pairwise_tukeyhsd(endog=top_50_Tech_df['Annual Revenue 2022-
        2023 (USD in Millions)'],
                                groups=top_50_Tech_df['Sector'],
                                alpha=0.05)
print(results)
```

```
                       Multiple Comparison of Means - Tukey HSD,
FWER=0.05
======================================================================
         group1                  group2          meandiff   p-adj
lower        upper    reject
----------------------------------------------------------------------
------------------------------
Communication Equipments       Computer Hardware    2326.6667    1.0
-325778.0458 330431.3792  False
Communication Equipments    Consumer Electronics     334370.0 0.1662
-67474.5639 736214.5639  False
Communication Equipments   Electronic Components     -47550.0 0.9999
-449394.5639 354294.5639  False
Communication Equipments             IT Services  -24656.6667    1.0
-352761.3792 303448.0458  False
Communication Equipments          Semiconductors  -29692.1429    1.0
-323812.2473 264427.9616  False
Communication Equipments    Software Application      -5784.0    1.0
-299249.7763 287681.7763  False
Communication Equipments Software Infrastructure   15403.3333    1.0
-280346.2578 311152.9245  False
       Computer Hardware    Consumer Electronics  332043.3333 0.0455
3938.6208 660148.0458   True
       Computer Hardware   Electronic Components  -49876.6667 0.9997
-377981.3792 278228.0458  False
       Computer Hardware             IT Services  -26983.3333 0.9999
-258988.4005 205021.7338  False
```

```
       Computer Hardware         Semiconductors  -32018.8095 0.9991
-212795.7014 148758.0824  False
       Computer Hardware    Software Application   -8110.6667    1.0
-187821.0189 171599.6856  False
       Computer Hardware Software Infrastructure   13076.6667    1.0
-170339.4435 196492.7769  False
    Consumer Electronics   Electronic Components    -381920.0  0.073
-783764.5639  19924.5639  False
    Consumer Electronics            IT Services -359026.6667 0.0232
-687131.3792 -30921.9542   True
    Consumer Electronics         Semiconductors -364062.1429 0.0066
-658182.2473 -69942.0384   True
    Consumer Electronics    Software Application    -340154.0 0.0133
-633619.7763 -46688.2237   True
    Consumer Electronics Software Infrastructure -318966.6667 0.0265
-614716.2578 -23217.0755   True
   Electronic Components            IT Services   22893.3333    1.0
-305211.3792 350998.0458  False
   Electronic Components         Semiconductors   17857.8571    1.0
-276262.2473 311977.9616  False
   Electronic Components    Software Application      41766.0 0.9998
-251699.7763 335231.7763  False
   Electronic Components Software Infrastructure   62953.3333 0.9972
-232796.2578 358702.9245  False
             IT Services         Semiconductors   -5035.4762    1.0
-185812.3681 175741.4157  False
             IT Services    Software Application   18872.6667    1.0
-160837.6856 198583.0189  False
             IT Services Software Infrastructure      40060.0 0.9967
-143356.1102 223476.1102  False
          Semiconductors    Software Application   23908.1429 0.9958
-81684.2062 129500.4919  False
          Semiconductors Software Infrastructure   45095.4762 0.8989
-66687.3622 156878.3146  False
    Software Application Software Infrastructure   21187.3333 0.9985
-88862.3328 131236.9995  False
----------------------------------------------------------------------
------------------------------
```

This tells us that the sector has a impact on Revenue which is a sign of a high growth company. We can conclude that high growth stocks are usually in Consumer Electronics, Software Infrastructure, and Software Application. This shows us that the top category is Consumer Electronics and Electronic Components is the last.

Research Question 3-Revenue and Market Cap Correlation: Is there a strong correlation between a company's revenue and its market capitalization?

This analysis seeks to establish whether higher revenues are indicative of higher market caps, which could suggest a company's status as a growth stock. A Chi-Squared test will be employed to determine if there's a significant association between annual revenue and market cap, potentially guiding investors in identifying high-growth opportunities within the tech sector.

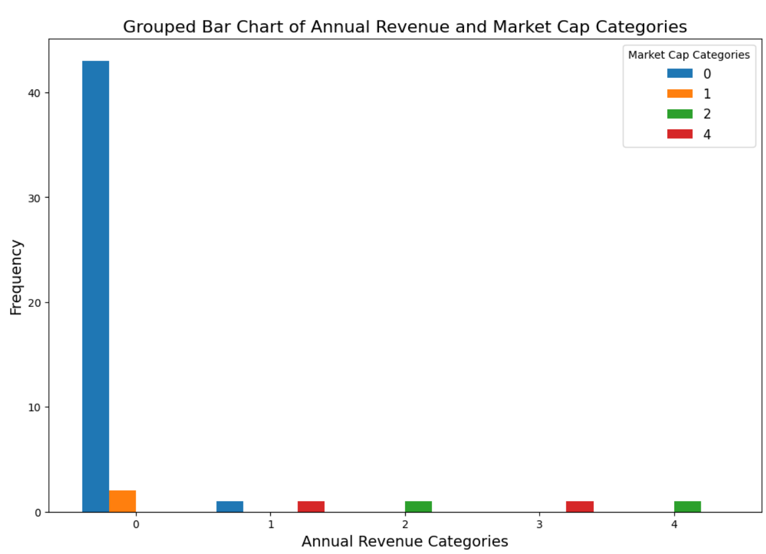
Chi-Squared Test to test if there is a relationship between Annual Revenue and Market Cap.

Null hypothesis: There is no association between annual revenue and market cap.

Alternate hypothesis: There is an association between annual revenue and market cap.

```
revenue_bins = pd.cut(top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'], bins=5, labels=False)
market_cap_bins = pd.cut(top_50_Tech_df['Market Cap (USD in Billions)'], bins=5, labels=False)


contingency_table = pd.crosstab(revenue_bins, market_cap_bins)
chi2, p, dof, expected = chi2_contingency(contingency_table)


print(f"Chi-squared statistic: {chi2}")
print(f"P-value: {p}")


if p < 0.05:
    print("We reject the null hypothesis. There is an association between annual revenue and market cap categories.")
else:
    print("We fail to reject the null hypothesis. There is no association between annual revenue and market cap categories.")


contingency_table.plot(kind='bar', figsize=(12, 8), width=0.8)
plt.title('Grouped Bar Chart of Annual Revenue and Market Cap Categories', fontsize=16)
plt.xlabel('Annual Revenue Categories', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.legend(title='Market Cap Categories', fontsize=12)
plt.xticks(rotation=0)
plt.show()
```

```
Chi-squared statistic: 86.98232323232322
P-value: 1.8901995025699208e-13
We reject the null hypothesis. There is an association between annual revenue and market cap categories.
```



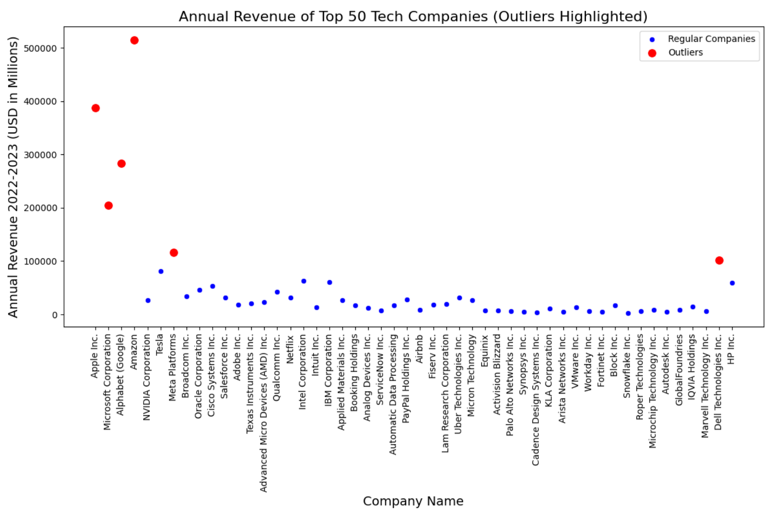
The bars represent the frequency of companies within each combination of annual revenue and market cap category. We can see that majority of the companies fall in the 0 group of annual revenue, with very few in the remaining categories. This indicates a skewed distribution where most companies have a similar level of annual revenue that falls into the first category, and only a few companies have revenue in the higher market cap categories. This shows that the data may be very concentrated which can create a reason to investigate further.

Lets investigate our data to find if there are any outliers that might mess up our analysis later on. To do this we can conduct an Interquartile Range (IQR) Method to find any outliers.

```
Q1 = top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'].quantile(0.25)
Q3 = top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'].quantile(0.75)
IQR = Q3 - Q1
outliers = top_50_Tech_df[(top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'] < (Q1 - 1.5 * IQR)) | (top_50_Tech_df['Annual Revenue 2022-2023 (USD in Millions)'] > (Q3 + 1.5 * IQR))]
print(outliers)


plt.figure(figsize=(12, 8))
sns.scatterplot(x='Company Name', y='Annual Revenue 2022-2023 (USD in Millions)', data=top_50_Tech_df, color='blue', label='Regular Companies')
sns.scatterplot(x='Company Name', y='Annual Revenue 2022-2023 (USD in Millions)', data=outliers, color='red', label='Outliers', s=100)
plt.xticks(rotation=90)
plt.title('Annual Revenue of Top 50 Tech Companies (Outliers Highlighted)', fontsize=16)
plt.xlabel('Company Name', fontsize=14)
plt.ylabel('Annual Revenue 2022-2023 (USD in Millions)', fontsize=14)
plt.legend()
plt.tight_layout()
plt.show()
```

```
              Company Name    Industry                  Sector    HQ
State  \
0               Apple Inc.  Technology     Consumer Electronics  Cali-
fornia
1     Microsoft Corporation  Technology  Software Infrastructure  Wash-
ington
2         Alphabet (Google)  Technology  Software Infrastructure  Cali-
fornia
3                   Amazon  Technology     Software Application  Wash-
ington
6            Meta Platforms  Technology  Software Infrastructure  Cali-
fornia
48  Dell Technologies Inc.  Technology        Computer Hardware
Texas

    Founding Year  Annual Revenue 2022-2023 (USD in Millions) Stock
Name  \
0            1976                                        387530.0
AAPL
1            1975                                        204090.0
MSFT
2            1998                                        282830.0
GOOG
3            1994                                        513980.0
AMZN
6            2004                                        116600.0
META
```

```
48          1984                                     102300.0
DELL

    Annual Income Tax in 2022-2023 (USD in Billions)  Employee Size  \
0                                             18.314         164000
1                                             15.139         221000
2                                             11.356         190234
3                                             -3.217        1541000
6                                              5.619          86482
48                                             0.981         133000

    Market Cap (USD in Billions)  Founded After 2000
0                         2520.0               False
1                         2037.0               False
2                         1350.0               False
3                         1030.0               False
6                          524.0                True
48                          28.0               False
```



We can see that Apple Inc., Microsoft Corporation, Alphabet (Google), Amazon, Meta Platforms, and Dell Technologies Inc. have been identified as outliers in terms of annual revenue. This indicates that these companies are industry leaders, significantly outperforming their peers in the tech sector. The outliers in the dataset can have a significant impact on statistical analyses, such as calculations of mean and standard deviation. These outliers out perform their peers meaning they may have patterns that can be used to find high growth stocks. We found that the outliers fall under Consumer Electronics, Software Infrastructure, and Software Application which indicates that these sectors are high performing as they have higher revenue, we can use this as a sign for high growth.

Exploratory Data Analysis Conclusion: We conducted various test only on the top 50 as they are the most successful out of the 3000+ stocks in the Nasdaq. The reason we did not run tests on the Nasdaq tech stock is because they would not have provided any trends or patterns as they are vey small companies with very little performance. Remember our goal is to use the top 50 to find the best patterns and trends which we can use to find the next high growth stocks.

Primary Analysis & Visualization

For my machine learning model, I intend to integrate both Classification and Regression techniques to effectively analyze and predict the growth trajectories of teh Nasdaq companies. Initially I will split companies into two categories: high-growth and low-growth, this classification will be based on certain financial metrics such as historical revenue trends and market capitalization.

Then, I will employ Linear Regression to model the future financial performance of these groups. The regression analysis will aim to forecast key financial outcomes, enabling us to distinguish which group, high-growth or low-growth, presents a better investment profile over the long term. This mix of an approach allows for a refined understanding of potential growth trajectories within the tech sectors.

The methodology will first be applied to the top 50 tech companies to develop and refine the predictive models. Subsequently, the refined models will be tested against a broader dataset of Nasdaq-listed tech stocks to validate their effectiveness and to identify promising investment opportunities among a larger pool of companies. This step will ensure that our findings are more effective and applicable across a diverse set of tech sectors.

```
median_growth = top_50_Tech_df['Annual Revenue 2022-2023 (USD in Mil-
        lions)'].median()
top_50_Tech_df['Growth Label'] = (top_50_Tech_df['Annual Revenue 2022-
        2023 (USD in Millions)'] > median_growth).astype(int)


X = top_50_Tech_df[['Market Cap (USD in Billions)', 'Founding Year']]
y = top_50_Tech_df['Growth Label']


X_train, X_test, y_train, y_test = train_test_split(X, y,
        test_size=0.3, random_state=42)


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


classifier = LogisticRegression()
classifier.fit(X_train_scaled, y_train)


predictions = classifier.predict(X_test_scaled)


print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.64      1.00      0.78         7
           1       1.00      0.50      0.67         8

    accuracy                           0.73        15
   macro avg       0.82      0.75      0.72        15
weighted avg       0.83      0.73      0.72        15
```

Analysis of our results: 0 = Low-growth 1 = High-growth

Precision:

Class 0 (0.64): This indicates that when the model predicts a company is in the low-growth group, it is correct 64% of the time.

Class 1 (1.00): This indicates that when the model predicts high-growth, it is correct every time.

Recall:

Class 0 (1.00): This indicates that the model successfully identifies all actual low-growth cases.

Class 1 (0.50): This indicates that the model correctly identifies only 50% of the actual high-growth cases.

F1-score:

Class 0 (0.78): This is the harmonic mean of precision and recall for the low-growth class. A score of 0.78 indicates a good balance between precision and recall.

Class 1 (0.67): This score for the high-growth class indicates a smaller balance compared to the low-growth class, due to the lower recall rate.

Overall: The ratio of correctly predicted instances to the total instances in the dataset is 73%. Basically, the accuracy is 73%.

```
high_growth_companies = top_50_Tech_df[top_50_Tech_df['Growth Label'] == 1]

X_reg = high_growth_companies[['Market Cap (USD in Billions)', 'Founding Year']]
y_reg = high_growth_companies['Annual Revenue 2022-2023 (USD in Millions)']

X_reg_train, X_reg_test, y_reg_train, y_reg_test = train_test_split(X_reg, y_reg, test_size=0.3, random_state=42)

X_reg_train_scaled = scaler.fit_transform(X_reg_train)
X_reg_test_scaled = scaler.transform(X_reg_test)

regressor = LinearRegression()
regressor.fit(X_reg_train_scaled, y_reg_train)

reg_predictions = regressor.predict(X_reg_test_scaled)

mse = mean_squared_error(y_reg_test, reg_predictions)
print(f"Mean Squared Error: {mse}")
```

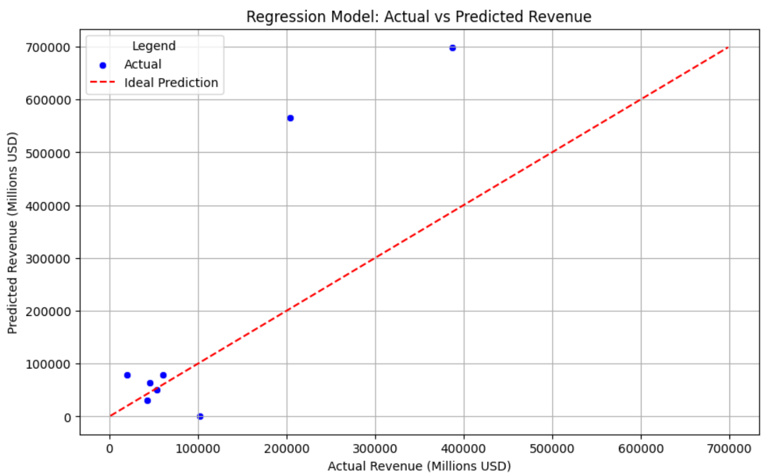
```
Mean Squared Error: 30254755134.03265
```

This Mean Squared Error is very high but this can possibly be explained due to the the scale of the revenue data being in millions. High values in the target variable can lead to high error values.

Lets visualize the model!

```
plot_data = pd.DataFrame({
    'Actual Revenue (Millions USD)': y_reg_test,
    'Predicted Revenue (Millions USD)': reg_predictions
})

plt.figure(figsize=(10, 6))
sns.scatterplot(x='Actual Revenue (Millions USD)', y='Predicted Revenue (Millions USD)', data=plot_data, color='blue', label='Actual')
```

```
max_value = max(plot_data['Actual Revenue (Millions USD)'].max(),
        plot_data['Predicted Revenue (Millions USD)'].max())
min_value = min(plot_data['Actual Revenue (Millions USD)'].min(),
        plot_data['Predicted Revenue (Millions USD)'].min())
plt.plot([min_value, max_value], [min_value, max_value], 'r--',
        label='Ideal Prediction')

plt.title('Regression Model: Actual vs Predicted Revenue')
plt.xlabel('Actual Revenue (Millions USD)')
plt.ylabel('Predicted Revenue (Millions USD)')
plt.legend(title='Legend')
plt.grid(True)
plt.show()
```



We can that towards the lower part of the line, there many actual values close to the line and as we increase in Revenue there are outliers. This model indicates that it is somewhat close. The discrepancies come from the lack of real time data as some data is not up to date, companies not updating their founding year on the Nasdaq, and some companies may identify as multiple sectors, these are some issues that may throw our model off.

Next lets apply our model to the Nasdaq tech stocks and find some winners!!!!

```
tech_companies_df = tech_companies_df.dropna(subset=['Market Cap (USD
        in Billions)', 'Annual Revenue 2022-2023 (USD in Millions)',
        'Employee Size'])

median_growth = tech_companies_df['Annual Revenue 2022-2023 (USD in
        Millions)'].median()
tech_companies_df['Growth Label'] = (tech_companies_df['Annual Revenue
        2022-2023 (USD in Millions)'] > median_growth).astype(int)

X = tech_companies_df[['Market Cap (USD in Billions)', 'Annual Revenue
        2022-2023 (USD in Millions)', 'Employee Size']]
y = tech_companies_df['Growth Label']

pipeline = make_pipeline(
    StandardScaler(),
    LogisticRegression()
)

pipeline.fit(X, y)
```

```
cross_val_scores = cross_val_score(pipeline, X, y, cv=10, scoring='ac-
        curacy')

print("Average Accuracy:", cross_val_scores.mean())
print("Accuracy Standard Deviation:", cross_val_scores.std())

predicted_growth = pipeline.predict(X)

tech_companies_df['Predicted_Growth'] = predicted_growth

high_growth_companies = tech_companies_df[tech_companies_df['Predict-
        ed_Growth'] == 1]

print(high_growth_companies['Company Name'])
```

```
Average Accuracy: 0.7596135265700481
Accuracy Standard Deviation: 0.09787234547737046
0                     Microsoft Corporation
2                        NVIDIA Corporation
3                             Alphabet Inc.
4                             Alphabet Inc.
6                      Meta Platforms, Inc.
                        ...
3031                    Earlyworks Co., Ltd
3119                           Amesite Inc.
3151    Integrated Media Technology Limited
3203                    Asset Entities Inc.
3289                    Versus Systems Inc.
Name: Company Name, Length: 141, dtype: object
```

```
<ipython-input-17-3da86f747e42>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Growth Label'] = (tech_companies_df['Annual Rev-
enue 2022-2023 (USD in Millions)'] > median_growth).astype(int)
<ipython-input-17-3da86f747e42>:23: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Predicted_Growth'] = predicted_growth
```

Above are the Nasdaq Tech companies the model classified as high growth from the classification machine learning model. It also gave us a accuracy of 75.96% which is great for limited information on very small companies with not much information.

Next, we know the top 50 tech stocks are all high growth, and are all in the Nasdaq as well. Lets see how many

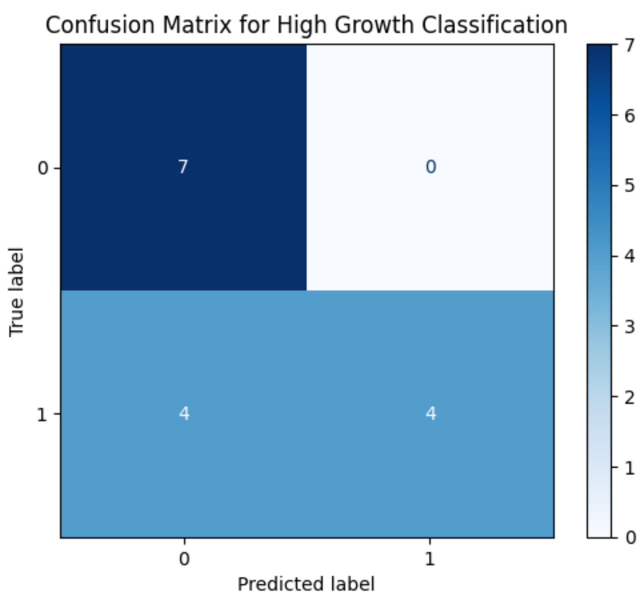
```
high_growth_tech = tech_companies_df[tech_companies_df['Predicted_-
        Growth'] == 1]
top_50_symbols = top_50_Tech_df['Stock Name']
```

```
# Find how many of the top 50 tech stocks are classified as high-
        growth
top_50_high_growth_count =
        high_growth_tech[high_growth_tech['Symbol'].isin(top_50_symbols)].shape[0]
high_growth_tech[high_growth_tech['Symbol'].isin(top_50_symbols)]
top_50_high_growth_count =
        high_growth_tech[high_growth_tech['Symbol'].isin(top_50_symbols)].shape[0]


print(f"Number of Top 50 Tech Stocks classified as High Growth:
        {top_50_high_growth_count}")
```

```
Number of Top 50 Tech Stocks classified as High Growth: 24
```

Our model predicted 24 out of 50 stocks correct which is not bad. To analyze this further lets visualize this with a confusion matrix.

```
# the confusion matrix
cm = confusion_matrix(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for High Growth Classification')
plt.show()
```



The confusion matrix shows that our classification model correctly identified 7 out of 7 companies as low-growth (True Negatives). However, it correctly identified only 4 out of 8 companies as high-growth (True Positives), with 4 false negatives. There are no false positives, where a low-growth company is incorrectly labeled as high-growth, which is good for avoiding overestimating growth. This suggests that while the model is very reliable at confirming companies that are not high-growth, it's somewhat conservative, potentially missing some high-growth companies. At least we know it can find some potential winners and is also accurate at identifying companies that do not have high growth potential.

```
tech_companies_df['Growth Label'] = (tech_companies_df['Annual Revenue
        2022-2023 (USD in Millions)'] > median_growth).astype(int)
X_nasdaq = tech_companies_df[['Market Cap (USD in Billions)', 'Found-
        ing Year']]


X_nasdaq_scaled = scaler.transform(X_nasdaq)
```

```
nasdaq_predictions = classifier.predict(X_nasdaq_scaled)
tech_companies_df['Predicted Growth'] = nasdaq_predictions

nasdaq_high_growth_companies =
        tech_companies_df[tech_companies_df['Predicted Growth'] == 1]

print(nasdaq_high_growth_companies[['Company Name', 'Predicted
        Growth']])

nasdaq_high_growth_features =
        tech_companies_df[tech_companies_df['Predicted Growth'] == 1]
        [['Market Cap (USD in Billions)', 'Founding Year']]
nasdaq_high_growth_features_scaled = scaler.transform(nasdaq_high_-
        growth_features)

nasdaq_revenue_predictions = regressor.predict(nasdaq_high_growth_fea-
        tures_scaled)

tech_companies_df.loc[tech_companies_df['Predicted Growth'] == 1,
        'Predicted Revenue (USD in Millions)'] = nasdaq_revenue_pre-
        dictions

print(tech_companies_df[tech_companies_df['Predicted Growth'] == 1]
        [['Company Name', 'Predicted Revenue (USD in Millions)']])
```

```
                                Company Name  Predicted Growth
0                      Microsoft Corporation                 1
2                         NVIDIA Corporation                 1
3                              Alphabet Inc.                 1
4                              Alphabet Inc.                 1
6                        Meta Platforms, Inc.                1
7                              Broadcom Inc.                 1
12              Advanced Micro Devices, Inc.                 1
23              Texas Instruments Incorporated               1
62                   Roper Technologies, Inc.                1
103                ON Semiconductor Corporation              1
160   Telefonaktiebolaget LM Ericsson (publ)                 1
164                          VeriSign, Inc.                  1
240                          Amdocs Limited                  1
265                       Match Group, Inc.                  1
307                      SPS Commerce, Inc.                  1
309                              Lyft, Inc.                  1
389                    Varonis Systems, Inc.                 1
398                                IAC Inc.                  1
402                   Commvault Systems, Inc.                1
534                    Lumentum Holdings Inc.                1
548                            Rapid7, Inc.                  1
650                       SiTime Corporation                 1
754                             Upwork Inc.                  1
859                               Angi Inc.                  1
1042          Kingsoft Cloud Holdings Limited                1
1073                    Thryv Holdings, Inc.                 1
1079                        EverQuote, Inc.                  1
1148        International Money Express, Inc.               1
1154     Alpha and Omega Semiconductor Limited               1
1157                     Perion Network Ltd.                 1
1206                         PowerFleet, Inc.                1
1278                  Daily Journal Corporation              1
1375                            Cerence Inc.                 1
1404                    Aviat Networks, Inc.                 1
1469                         AudioCodes Ltd.                 1
```

```
1665                         PaySign, Inc.                 1
1738                  Digital Turbine, Inc.                1
1750                          Datasea Inc.                 1
1774                         Iteris, Inc.                  1
1777                           Tucows Inc.                 1
1966           Everspin Technologies, Inc.                 1
2095             XBP Europe Holdings, Inc.                 1
2425           Akoustis Technologies, Inc.                 1
2461                  Ondas Holdings Inc.                  1
2603             Creative Realities, Inc.                  1
2663                         Neonode Inc.                  1
2746                 Data I/O Corporation                  1
2778             Sonim Technologies, Inc.                  1
2836                   Hitek Global Inc.                   1
2866                      Sphere 3D Corp.                  1
2900             Future FinTech Group Inc.                 1
2905             Exela Technologies, Inc.                  1
3089             Luokung Technology Corp.                  1
3102                   Digital Ally, Inc.                  1
3119                         Amesite Inc.                  1
3151     Integrated Media Technology Limited               1
3173                 Boxlight Corporation                  1
3360                   Siyata Mobile Inc.                  1
3381                       Cemtrex, Inc.                   1
                              Company Name  \
0                    Microsoft Corporation
2                       NVIDIA Corporation
3                            Alphabet Inc.
4                            Alphabet Inc.
6                     Meta Platforms, Inc.
7                            Broadcom Inc.
12             Advanced Micro Devices, Inc.
23             Texas Instruments Incorporated
62                  Roper Technologies, Inc.
103              ON Semiconductor Corporation
160    Telefonaktiebolaget LM Ericsson (publ)
164                         VeriSign, Inc.
240                         Amdocs Limited
265                      Match Group, Inc.
307                     SPS Commerce, Inc.
309                            Lyft, Inc.
389                  Varonis Systems, Inc.
398                              IAC Inc.
402                 Commvault Systems, Inc.
534                   Lumentum Holdings Inc.
548                           Rapid7, Inc.
650                     SiTime Corporation
754                            Upwork Inc.
859                              Angi Inc.
1042         Kingsoft Cloud Holdings Limited
1073                 Thryv Holdings, Inc.
1079                     EverQuote, Inc.
1148        International Money Express, Inc.
1154     Alpha and Omega Semiconductor Limited
1157                   Perion Network Ltd.
1206                     PowerFleet, Inc.
1278             Daily Journal Corporation
```

1375	Cerence Inc.
1404	Aviat Networks, Inc.
1469	AudioCodes Ltd.
1665	PaySign, Inc.
1738	Digital Turbine, Inc.
1750	Datasea Inc.
1774	Iteris, Inc.
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3089	Luokung Technology Corp.
3102	Digital Ally, Inc.
3119	Amesite Inc.
3151	Integrated Media Technology Limited
3173	Boxlight Corporation
3360	Siyata Mobile Inc.
3381	Cemtrex, Inc.

	Predicted Revenue (USD in Millions)
0	8.531750e+05
2	6.259981e+05
3	5.627632e+05
4	5.626642e+05
6	3.063170e+05
7	1.647778e+06
12	7.458251e+04
23	7.983959e+04
62	1.494579e+06
103	1.487586e+06
160	7.923318e+04
164	1.483937e+06
240	1.482015e+06
265	1.481644e+06
307	1.481210e+06
309	1.481187e+06
389	1.480649e+06
398	1.480598e+06
402	1.480588e+06
534	1.480093e+06
548	1.480063e+06
650	1.479881e+06
754	1.479733e+06
859	1.479624e+06
1042	1.479489e+06
1073	1.479478e+06
1079	1.479474e+06
1148	1.479444e+06

```
1154                        1.479442e+06
1157                        1.479441e+06
1206                        1.479424e+06
1278                        1.479410e+06
1375                        1.479385e+06
1404                        1.479377e+06
1469                        1.479363e+06
1665                        1.479336e+06
1738                        1.479327e+06
1750                        1.479325e+06
1774                        1.479324e+06
1777                        1.479323e+06
1966                        1.479305e+06
2095                        1.479297e+06
2425                        1.479285e+06
2461                        1.479283e+06
2603                        1.479279e+06
2663                        1.479278e+06
2746                        1.479275e+06
2778                        1.479275e+06
2836                        1.479274e+06
2866                        1.479273e+06
2900                        1.479273e+06
2905                        1.479273e+06
3089                        1.479270e+06
3102                        1.479270e+06
3119                        1.479270e+06
3151                        1.479270e+06
3173                        1.479270e+06
3360                        1.479269e+06
3381                        1.479268e+06

<ipython-input-20-ba69d3e89e52>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Growth Label'] = (tech_companies_df['Annual Rev-
enue 2022-2023 (USD in Millions)'] > median_growth).astype(int)
<ipython-input-20-ba69d3e89e52>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df['Predicted Growth'] = nasdaq_predictions
<ipython-input-20-ba69d3e89e52>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan-
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  tech_companies_df.loc[tech_companies_df['Predicted Growth'] == 1,
```

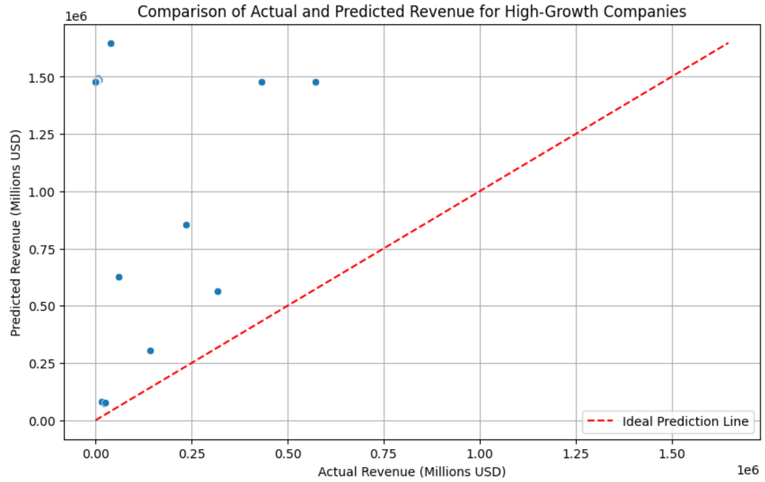
```
'Predicted Revenue (USD in Millions)'] = nasdaq_revenue_predictions
```

The code above tells us the future revenue of the high growth companies we identified in the Nasdaq by using the linear regression model to predict this. Next

Now lets visualize this!

```
tech_companies_df.loc[tech_companies_df['Predicted Growth'] == 1,
        'Predicted Revenue (USD in Millions)'] = nasdaq_revenue_predictions
high_growth_companies = tech_companies_df[tech_companies_df['Predicted
        Growth'] == 1]
predicted_revenues = tech_companies_df[tech_companies_df['Predicted
        Growth'] == 1]
tech_companies_df.loc[tech_companies_df['Predicted Growth'] == 1,
        'Predicted Revenue (USD in Millions)'] = nasdaq_revenue_predictions
high_growth_companies_with_revenue = tech_companies_df[tech_companies_df['Predicted Growth'] == 1]


plot_data = high_growth_companies_with_revenue[['Annual Revenue 2022-
        2023 (USD in Millions)', 'Predicted Revenue (USD in
        Millions)']]
plot_data.rename(columns={'Annual Revenue 2022-2023 (USD in
        Millions)': 'Actual Revenue'}, inplace=True)


plt.figure(figsize=(10, 6))
sns.scatterplot(data=plot_data, x='Actual Revenue', y='Predicted Revenue (USD in Millions)', marker='o')
plt.plot([plot_data.min().min(), plot_data.max().max()],
        [plot_data.min().min(), plot_data.max().max()], 'r--',
        label='Ideal Prediction Line')


plt.title('Comparison of Actual and Predicted Revenue for High-Growth
        Companies')
plt.xlabel('Actual Revenue (Millions USD)')
plt.ylabel('Predicted Revenue (Millions USD)')
plt.legend()
plt.grid(True)
plt.show()
```

```
<ipython-input-26-fd1aa0c54358>: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
  plot_data.rename(columns={'Annual Revenue 2022-2023 (USD in Millions)': 'Actual Revenue'}, inplace=True)
```



Well, our predictions for the future revenue are far off but we were somewhat close when the high growth stocks revenue is below 0.25 Million USD

Conclusion

All in all, this project embarked on a comprehensive exploration of the dynamics within the technology sector, specifically examining the performance and growth trajectories of leading tech companies listed on the Nasdaq. By integrating classification and regression models, this analysis aimed to not only segment these companies into high-growth and low-growth categories but also to predict their future financial outcomes based on historical data. Even though our model was not 100% accurate we were semiaccurate and hope to get better with more up to date data.