

Predicting Stock Prices after Earnings Calls



Team: Yearning for Earnings

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Overview

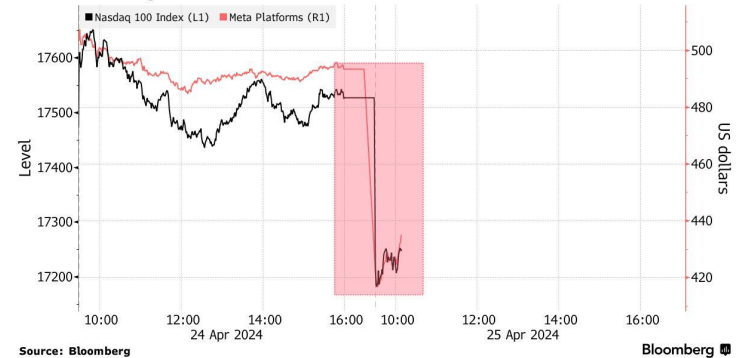
- Earnings calls often lead to **volatility in stock prices**.
- We want to create **machine learning models** that **predict percentage changes** in stock prices surrounding earnings calls based on
 - **sentiment analysis** of earnings call transcripts
 - earnings and revenue data
 - stock prices and volume before the earnings
- Detect factors which influence stock price the most

Nvidia's Remarkable Rally



NVDA earnings call working in favor of its stock price

Tech-heavy Nasdaq 100 Slumps Thursday Meta losses weighed on the index



META earnings call negatively impacts tech sector

Datasets

We selected **98 companies** from S&P 500 with a **6-year** earning period. In total we have **over 2000** data points. Sample companies include:



Data were gathered using Seeking Alpha API from rapidapi.com and Yahoo Finance.

Earnings Call Transcripts

Web Scraping using Seeking Alpha API obtained from Rapid API

Seeking Alpha^α



Earnings and Revenue Data

Web Scraping using Rapid API

1. Earnings per share (EPS)
2. Earning and revenue surprises



Stock Prices and Volume

Yahoo finance python package

1. Stock prices several time points before and after earnings
2. Average volume 50 days before each earning



Data Processing

- Instead of looking at **absolute changes**, we look at **percentage changes**.
- Key features include: **average_volume_50_days**, **% Change Revenue**, **% Change EPS Normalized** and several sentiment scores:
 - **Financial_performance_score**
 - **Market_position_score**
 - **Strategic_direction_score**
 - **Operational_aspects_score**
 - **Financial_indicators_score**
 - **Risks_challenges_score**
 - **Economic_factors_score**
- Target Feature: **perc_change_next_prev** (percentage of stock price changes next day to previous day of earnings call)

We label the data using
Symbol + Year + Quarter

AAPL2019Q1

AAPL2020Q1

AAPL2021Q1

AAPL2022Q1

AAPL2023Q1

...

XOM2019Q3

XOM2020Q3

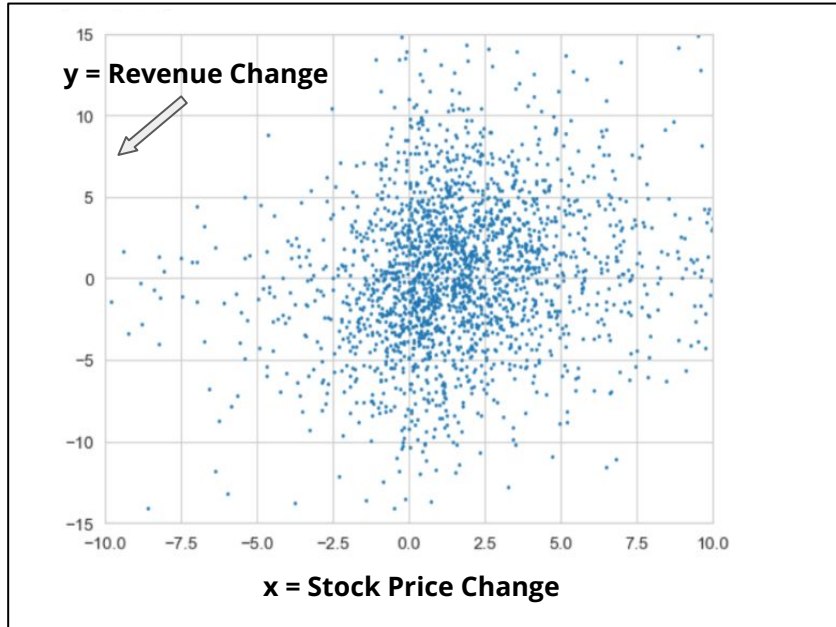
XOM2021Q3

XOM2022Q3

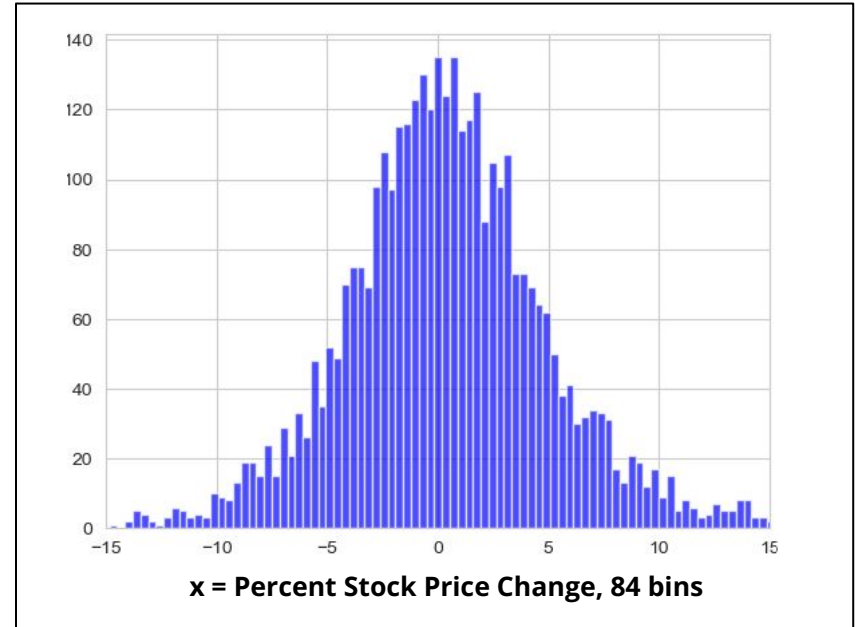
XOM2023Q3

Exploratory Data Analysis (EDA)

Scatter plot of percent change in **Revenue** vs **Stock Price** on earnings



Histogram of **percentage change in stock price** after earnings



Extracting Features from Earning Call Transcripts

Sentiment Scores

1. Organized keywords into seven categories.



Example:

```
financial_performance_keywords = {revenue, profit, loss, earnings, sales, expense, cost,...}
```

```
market_position_keywords = {market, share, grow, growth, decline, competitive, demand,...}
```

```
risks_challenges_keywords = {risk, challenge, uncertainty, regulation, legal, compliance, issue,...}
```

2. For each category, we extracted sentences (with context) and computed average sentiment scores using VADER.

Models

- **Baseline Model:** Predicts no change from previous day.
- **Linear Regression**

- **XGBoost** (parameters tuned using GridSearchCV)
- **Neural Network**

- Logistic Regression
- Neural Network (Classification)

Linear Regression

Training - Test Split: 0.8 - 0.2

Stratified by **symbol**



Run 1000 times, after scaling features



Record Actual and Predicted Values

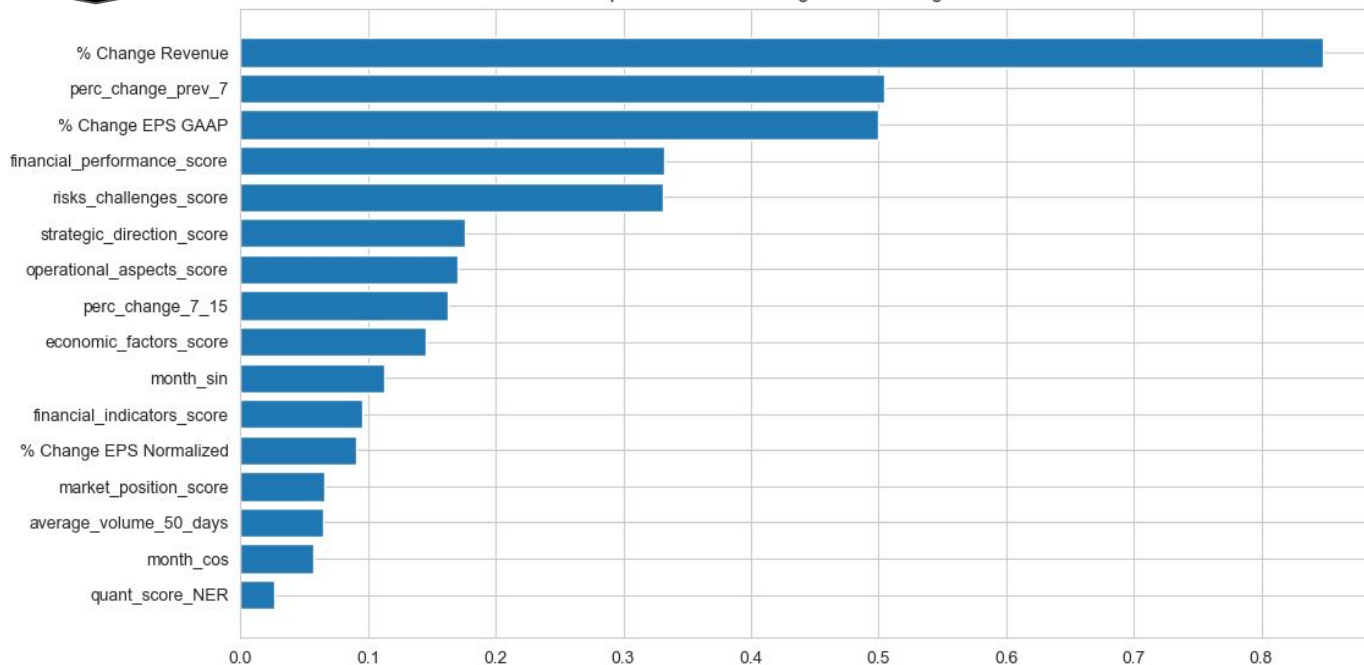
Remark:

Technically, we should only be doing a time based split. However, we found that the performance is similar by doing that.

Linear Regression

Feature Importance

Feature Importance for linear regression averaged over 1000 runs



XGBoost

Fine tune parameters using
GridSearchCV

```
graph TD; A[Fine tune parameters using GridSearchCV] --> B[Run 1000 times]; B --> C[Record Actual and Predicted Values];
```

Run 1000 times

Record Actual and Predicted
Values

Parameters tuned:

- alpha (L1 regularization)
- lambda (L2 regularization)
- n_estimators (number of trees used)
- max_depth of a tree
- learning_rate

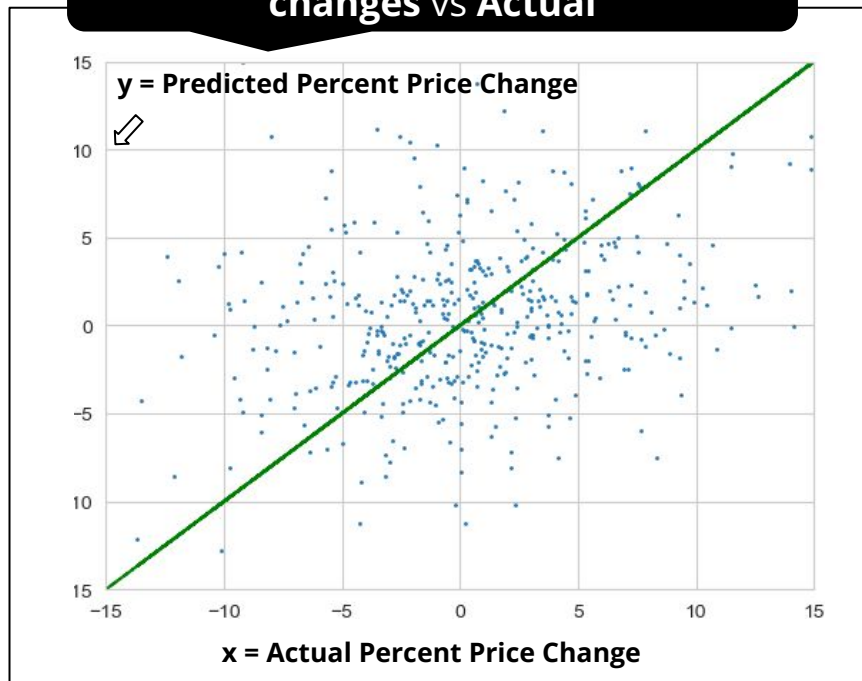
Results

The numbers are **means** of multiple runs

| | MSE | Correlation |
|-------------------|-------|-------------|
| Baseline | 31.16 | N/A |
| Linear Regression | 24.16 | 0.18 |
| XGBoost | 23.85 | 0.22 |
| Neural Network | 35.62 | 0.31 |

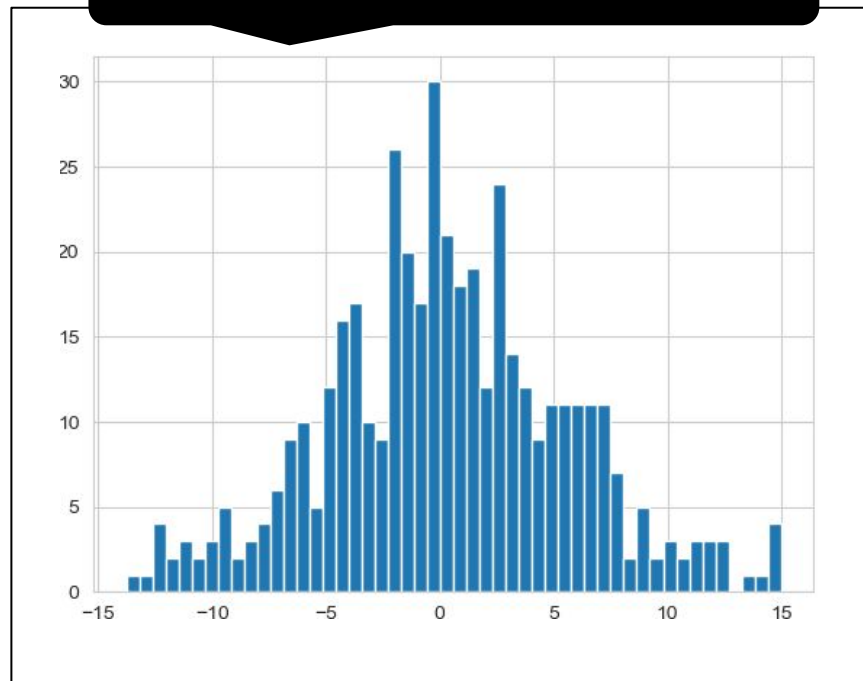
Results Visualization

Scatter plot **Predicted percent price changes vs Actual**



Both are based on **Neural Network**

Histogram of **Residuals**



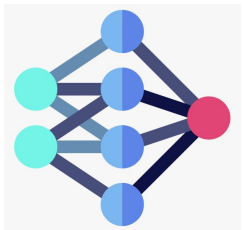
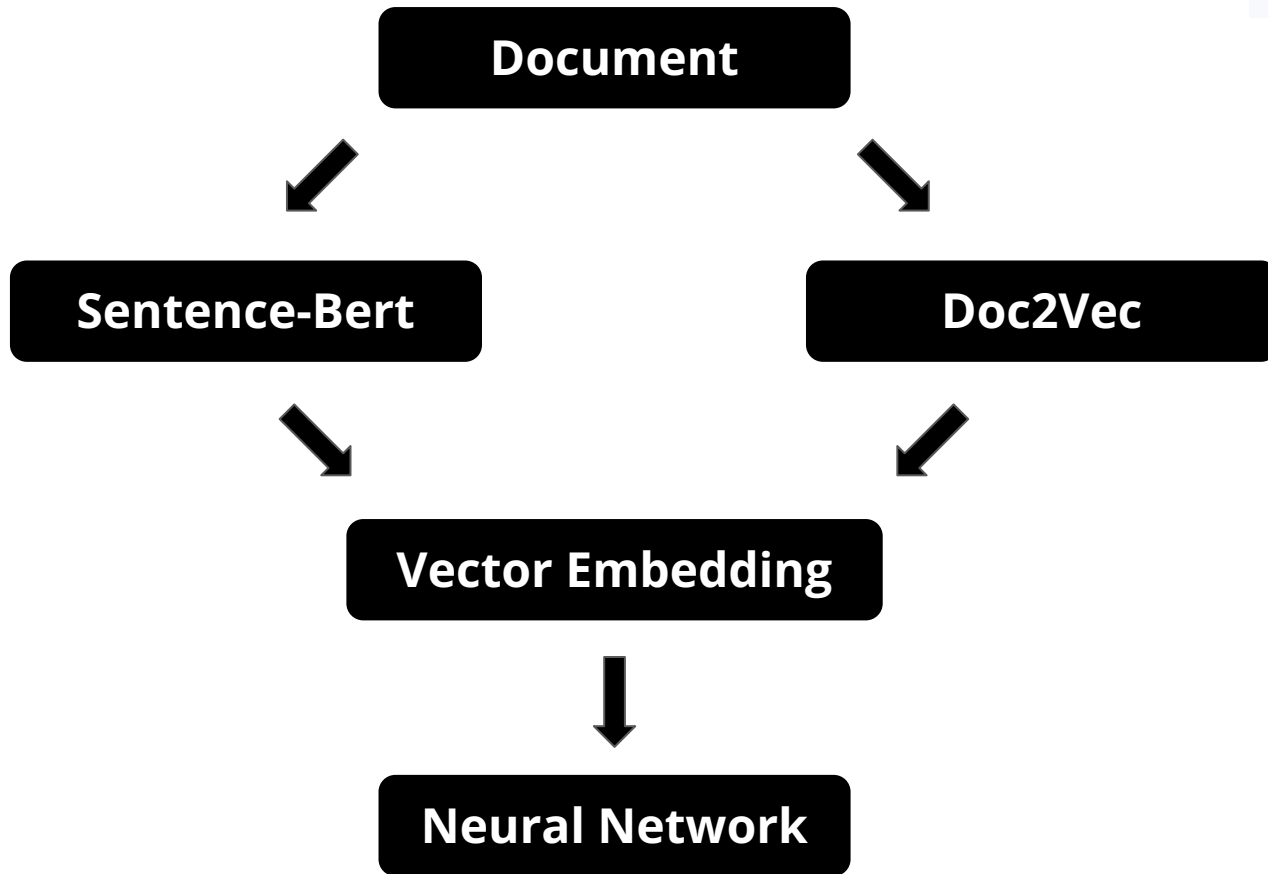
A Simple Trading Strategy



Results:

- We obtain **returns of 4.8%** over trades around 4 earnings call days.
- In comparison, blindly buying the stock on the day of earnings call and selling it the next day gives **a return of 2%**.

Future Research



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