Predict Stock Price From LinkedIn Profiles

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Motivation

Traditional stock trading techniques focus on the historical prices and volumes of stocks to predict the future price. Techniques methods have been widely used in high frequency trading and short term trading, and became less efficient since more and more people use similar features as stock price indicators. Here we use the social media information from LinkedIn Profiles to predict the stock prices. We are building models which use the expansion of the number of employees as an indicator, and predict the stock price of the corresponding company.

We find that the numbers of employees are leading the stock prices for many companies, and this indicator can be used to predict the market trending. For some of the companies, the number of employees has a large number of leading days (about several months) in front of the market, which means there are less people using this information. So this indicator is more or less a "private" information for the current market, and can be used to get profit in semi-strong or weak efficient markets.

Another interesting thing is that for many companies, the number of employers is far lagging (about 1 year) the stock price. This information can be used for employees and job seekers to make wise decisions of preparing to find a new positions.

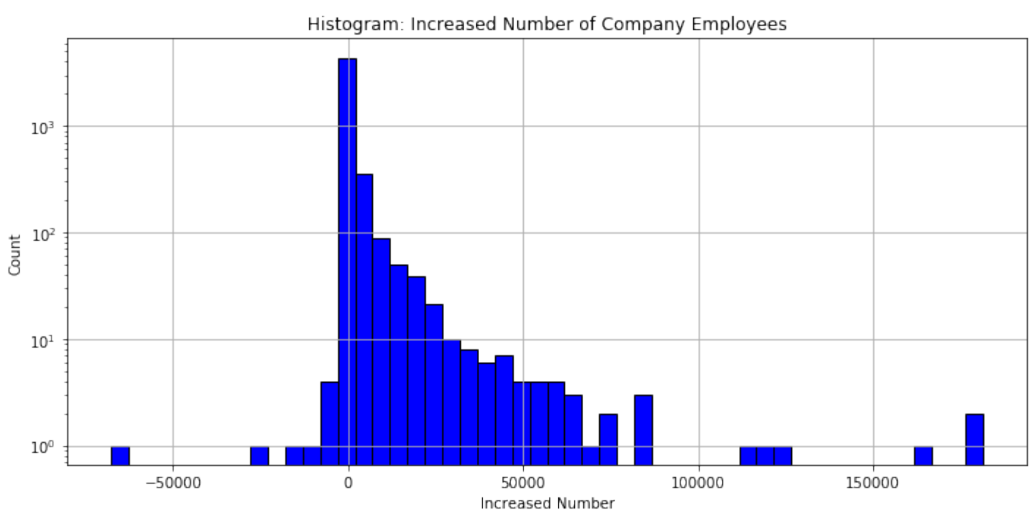
Data

- LinkedIn profile data set (954 MB, 2426196 records, in 2015/09/14 - 2018/07/17). It covers 5028 companies, and 141 industry types. Each record includes 14 variables. We mainly focus on 5 variables: [date, company_name, followers_count, employees_on_platform, industry]
- Stock price data from Yahoo Finance (https://finance.yahoo.com)

  From a company name of the previous dataset, we can find a stock name of that company. We download the stock price data in 2015/09/14 – 2018/07/17 from Yahoo Finance. We use the daily Adj Close price as our target.

Data Analysis

The histogram below counts the number of companies based on the increased number of employees from 2015/09/14 to 2018/07/17.



We can see that most of the companies in this dataset increased 0-50,000 employees in this period. There are 6 companies expanded more than 100,000 employees, while 4 companies decreased more than 10,000 employees. Below is the top 20 expansion companies in this period:

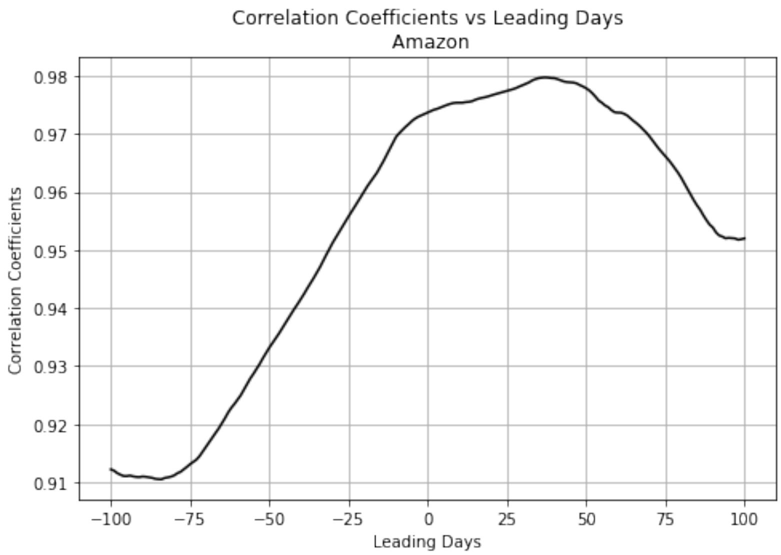
company_name	expand_num	expand_ratio
Walmart	181442.0	0.790146
Amazon	176769.0	2.087716
IBM	163813.0	0.395551
Accenture	122157.0	0.473460
McDonald's	119906.0	1.160497
Marriott International	115879.0	1.861959
Cognizant	85812.0	0.543995
Ford Motor Company	84251.0	1.024702
Apple	82126.0	0.790251
Google	72997.0	1.078529
JPMorgan Chase & Co.	71919.0	0.379084
HSBC	69610.0	0.501513
Vodafone	65685.0	0.839307
Citi	63873.0	0.441759
Bank of America	63626.0	0.321339
Sprint	61329.0	1.599484
Starbucks	60479.0	1.015907
GE	58862.0	0.332875
AT&T	58101.0	0.337875
Wells Fargo	56078.0	0.303592

We found that Walmart expanded the most in this period, while Amazon has the highest expansion ratio (2.087716) among the top 20 expansion companies.

Here is a simple example of comparing the number of employees and stock price for company Amazon. For the purpose of generalization, we scale the number of employees and stock prices by dividing the starting value (shown in the figure below):

We can see that the stock price of Amazon is highly correlated with the number of employees from 2015 to 2018.

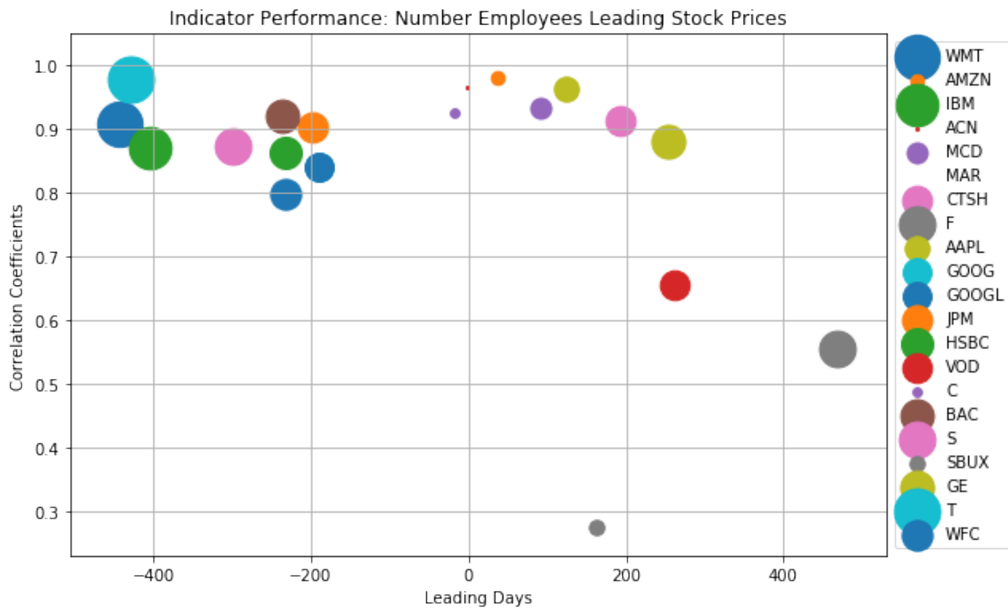
However, high correlation coefficient is not enough for a market indicator. Because we want the predictor in front of the market, thus we can use it to predict the stock price. We calculate the correlation coefficients on different the leading days of the number of employees for Amazon (figure below). We can find the number of employees is a quite good indicator (correlation coefficient = 0.97972886) to predict the stock price of Amazon 37 weekdays in the future.



Leading: If the date of indicator is leading the date of stock (as the figure of Amazon shown above), we say the leading days > 0, and high correlation leads to a good indicator to predict the stock price. Based on the efficient-market hypothesis (EMH), if less people use this indicator, the indicator is more likely a private information, and can be used to get profit in semi-strong or weak efficient markets.

Lagging: If the date of indicator is lagging the date of stock, we say the leading days < 0, and high correlation might be useless to predict the stock price. However, the stock price can be used to predict the company's expansion plan. A current employee knows that he/she may need to find another employer when the stock price goes down, while a job seeker knows that it is a good chance to join the company when the stock price goes up.

The figure below shows the indicator performance of the stocks of top 20 expansion companies.



Leading Indicator Companies: on the upper right of the graph, we find that the numbers of employees lead the stocks of { AMZN, MCD, APPL, CTSH, GE } for several months, with high correlation coefficients (>0.85). People can use this indicator for trading among these stocks.

Lagging Indicator Companies: on the upper left of the graph, we find that the stock prices of { T, WMT, IBM, BAC, S, HSBC, JPM, GOOGL, WFC } lead the number of employees of corresponding companies for nearly one year or even more, with high correlation coefficients (>0.8). The employees and job seekers can use this indicator to prepare to find new positions.

Further Steps and Approach:

- Exploratory Data Analysis: calculate the expansion amount, speed, and ratio of each company for feature selection. Focus on companies with long date range for machine learning modeling.
- Split the date range into in sample period (for training) and out of sample period (for testing)
- Predictive modeling (Naive Bayes, Random Forest, LSTM, etc.). Based on the expansion of a company is leading or lagging the stock price, we build 2 different type of models:
  - Leading model: select companies with high correlation coefficients leading indicators, and build a machine learning model to predict the stock price from the number of employees
  - Lagging model: select companies with high correlation coefficients lagging indicators, and build a machine learning model to predict the number of employees from the stock price
- Explore the followers_count, and add it as an additional indicator into the models
- Backtesting in sample and out of sample, fine tune the model
- The performance metric:
  - For regression model (e.g. predict the stock price values), we use Root Mean Square Error (RMSE)

    - For classification model (e.g. predict of the stock price goes up or down), we use Area Under the Receiver Operating Characteristics (AUROC)

Experimental Setup

The hardware for our experimental setup consists of a workstation with the following characteristics:

- CPU: 2.2 GHz Intel Core i7
- RAM: 6 GB 1600 MHz DDR3

The software environment includes:

- macOS Mojave 10.14.4
- Python 3.6 with current versions of the following libraries:
    - Numpy
    - Pandas
    - Matplotlib
    - Scikit-learn
    - Scipy
    - Deep Learning libraries: PyTorch, Keras

Timelines

The project timelines are listed below.

Table 1. Project timeline.

Date	Milestone
05/03	Data Selection and Preprocessing
05/05	Exploratory Data Analysis
05/06	**Submit Proposal**
05/10	Explore the indicator for all the 5028 companies in this dataset. Focus on companies with long date range to build predictive models
05/11	Leading modeling: predict the stock price from the number of employees
05/12	Lagging modeling: predict the number of employees from the stock price
05/20	Explore the followers_count, and add it as an additional indicator into the models
05/25	**Report Draft**
06/01	Backtesting in sample and out of sample, fine tune the model
06/15	Make the final version of the project code, make video presentation
06/25	**Final report**