# Research into the Modeling of Complex Systems Predicting the Stock Market

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### Abstract

The stock market is an immensely complex system made up of millions of interactions between different investors and affected by every action made by thousands of companies. However, economic theory decrees that the actions of most investors are governed by the actions of a few well informed primary investors and that those other investors primarily follow preexisting trends set by the well informed. Thus, as the primary catalyst for the well informed should be news reports, press releases, income reports, etc, (barring things like insider trading), it should be possible to predict the broad trends across the market and fairly detailed trends for specific stocks by analyzing the available news on stocks.

## Methodology

In order to gain the information necessary to analyze stocks, an XML parser is used to read financial news based websites (Such as Google Finance and Reuters). The information garnered by these data miners is stored into a MySQL database so that it is accessible to other aspects of the program. The news data is then analyzed with a program that takes the qualitative news renderred in text and assigns a signed floating point number to it so that the regressor has a qualitative value to base its analysis on . This, along with the stock price data which is taken from CSV (comma-seperated-value) files provided by Yahoo! Finance, is fed into an equation refiner, which generates equations describing the effect of news over time on stock prices using a genetic algorithm to refine the equations. The equations are then used to project the future price of stocks.

def regress(price\_data, news\_data,generations=100,children=4):
 start\_price = price\_data[min(price\_data.keys())]
 end price = price\_data[max(price\_data.keys())]

#### **Results and Findings**

Early tests using short term predictions and primitive artificial intelligence 'stock bots' proved to be successfully, especially given their low level of sophistication; however this was probably more likely to fortunate fluctuations in the stock market than anything else. Despite that, it did lead to some useful findings for later prediction algorithms as described above.

In terms of the results of the generated prediction equations, I found that the equations created by my algorithms tended to become less and less accurate the further away they were used from the timeframe they were generated for, implying that the effect of news on stock prices is constantly changing over time.

```
end_price = price_data[max(price_data.keys())]
end_time = max(price_data.keys())
equations = [equation() for x in range(children)]
target = end_price/start_price
mutations = .25
for generation in range(generations):
    output = [0 for x in range(children)]
    for i in range(children):
        for time in news_data.keys():
            if time > end_time:break
            output[i] += equations[i].calc(news_data[time],end_time-
```

#### time)

```
output[i] = (abs(1-output[i]/target),equations[i])
     output.sort()
     keep = children//2
     generate = children - keep
     equations = [output[k][1] for k in range(keep)]
     mutamt = output[keep-1][0]/keep
     for i in range(generate):
          b = random.choice(equations).decay_rate
         c = random.choice(equations).mult_const
         if random.random() < mutations:
              if random.random() < .5:
                   if random.random() < .5:b = b * (1+mutamt)
                   else:b = b * (1-mutamt)
              else:
                   if random.random() < .5:c = c * (1+mutamt)
                   else:c = c * (1-mutamt)
         equations.append(equation(b,c))
return output[0]
```

A part of the equation regression system