Trading Tips from Trump's Twitter

Named Entity Recognition and Sentiment Analysis on President Trump's Tweets to Test a Simple Stock Trading Strategy

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Project Overview

- Question, Background, and Hypothesis
- Approach
- Models
    - NER model
    - Sentiment Analysis model
- Trading Strategy
- Results
- Learnings and Future Work

Question

To what extent does President Trump's sentiment about a company, as reflected in his tweets, affect the stock price of that company? Can we make money trading the positive and negative sentiment toward companies of Trump's tweets?

Background

Yes, Trump's Tweets Move the Stock Market. But Not for Long. BARRON'S

Vox The Volfefe Index, Wall Street's new way to measure the effects of Trump tweets, explained

The president is tweeting more — and he's moving markets with it.

How Trump's Tweets Infect Your Stock Market Investing Forbes

MARKETPLACE

Meet the algorithms connecting Trump tweets and the stock market

FOX BUSINESS

Trump's tweets hurt stocks, research finds

Ritter, Alan, et al. Named Entity Recognition in Tweets: An Experimental Study. 2011.

Alexander Pak, Patrick Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining" May, 2010

Ream, Shannon. "Named Entity Recognition for Twitter." DigitalGlobe Blog, 2 Nov. 2017

Hypothesis

President Trump's tweets ***do have a significant impact*** on public perception of a company and should impact a company's stock price. So, ***there is opportunity to make money*** trading Trump's sentiment of these companies.

Approach

"Wow, Report Just Out! Google manipulated from 2.6 million to 16 million votes for Hillary Clinton in 2016 Election! This was put out by a Clinton supporter, not a Trump Supporter! Google should be sued. My victory was even bigger than thought! @JudicialWatch."

~ by Donald Trump, August 19, 2019 at 8:52 AM, Twitter

NER Model	Sentiment Model	Trading Strategy
↓	↓	↓
Google	**Negative**	**+$16K**

NER Models

Models

Stanford CoreNLP

Linear chain Conditional Random Field (CRF) sequence models

spaCy NER

LSTM + CNN using context-sensitive matrices for sentences from word embedding vectors

Training Data

Stanford CoreNLP

CoNLL 2003, Message Understanding Conference (MUC) 6 and 7, and Automatic Content Extraction (ACE) 2002

spaCy NER

Onto Notes 5

Performance

	Precision	Recall	F1
Stanford CoreNLP	**0.327**	**0.823**	**0.469**
spaCy NER	0.190	0.300	0.232
capitalized words - baseline	0.123	0.930	0.217

Sentiment Models

Data

Sentiment140 by Stanford

-Twitter corpus with 1.5MM training examples

-**Label**: 4 (Positive), 0 (Negative)

Data Cleansing

Remove stop words, Lower casing, Remove numbers and special characters, Canonicalization (stemming, lemmatization), Expand abbreviations, etc.

Data Formatting/Transformation

Tokenize
Convert to Sequence
Pad

Model Performance

Model	train	validation	test
TextBlob (NLTK)			80%
Naive Bayes			76%
CNN	**82%**	**81%**	**81%**
LSTM	78%	79%	79%

Trading Strategy

Test Period: 1/20/2017 ~ 10/25/2019

Experiment Portfolio

Positive Tweet

Buy at Today's Close Price

Sell at Next Day's Close Price

Negative Tweet

Sell at Today's Close Price

Buy at Next Day's Close Price

-Trade/Reverse 100% Share

-No Transaction Fees Assumed

Baseline Portfolio

Hold Shares Steady

Trading Results

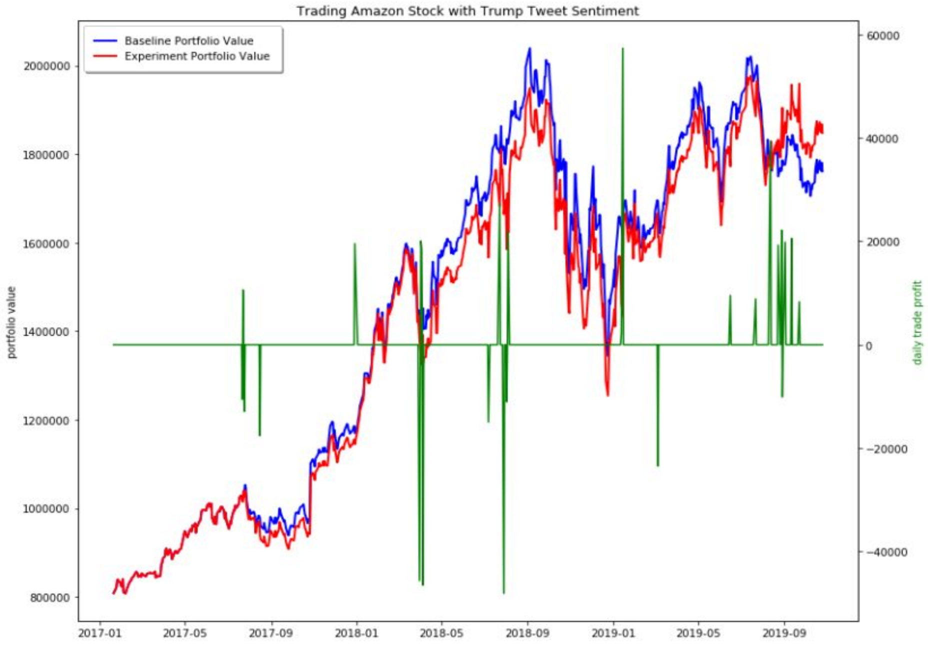
Trading Result Summary

		Amazon			
		Baseline	Experiment	NetTradeProfit	NetProfit%
begin	1/20/2017	808330	808330	0	
end	10/25/2019	1761329	1848120	86790	4.70

		Google			
		Baseline	Experiment	NetTradeProfit	NetProfit%
begin	1/20/2017	805020	805020	0	
end	10/25/2019	1265130	1287090	21960	1.71

		Facebook			
		Baseline	Experiment	NetTradeProfit	NetProfit%
begin	1/20/2017	127040	127040	0	
end	10/25/2019	187890	182930	-4960	-2.71

Amazon Trading Performance



Learnings & Future Work

Learnings

1. NER models require training on data in similar domain

2. Mapping holding companies to their subsidiaries a difficult task that constrained our analysis.

3. People tweet in different language style in witter. Do the standard text cleansings steps help or hurt for catching twitter sentiment?

Future Work

1. Train out-of-the box NER models using Twitter corpus.

2. Build or buy a mapping of subsidiary companies to their holding company.

3. We used most of the standard text cleansing techniques. Remove one at a time and assess how it may impact the model accuracy.

Thank you!
Questions?