

# Realestate Sentiment Analysis

## Intro

For this analysis we will be using Yahoo Financial News to see which Real Estate companies have had the most positive sentiments recently (January 16, 2018). We will be using the 'tm.plugin.webmining' package to search up articles from Yahoo Finance.

```
library(tm.plugin.webmining)
library(magrittr)
library(dplyr)
library(purrr)
library(tidyr)
library(tidytext)
library(ggplot2)

download_articles <- function(Symbol) {
  WebCorpus(YahooFinanceSource(Symbol))
}

real_state <- read.csv("~/desktop/realestate_landlords.csv", header = TRUE)

stock_articles <- real_state[real_state$Symbol != "", c("Company", "Symbol")] %>%
  mutate(corpus = map(Symbol, download_articles))

## Warning in strptime(val, format = "%a, %d %b %Y %H:%M:%S", tz = "GMT"):
## unknown timezone 'zone/tz/2017c.1.0/zoneinfo/America/New_York'
```

## Ngram Collection

Now that we have our corpus set up we will put each individual document into an observation in a dataframe. We could keep it as a character vector but I choose to convert it to a data frame because I feel that I work with data frames better and that functions can work through them faster.

```
ngram_tokens <- unnest(stock_articles, map(corpus, tidy))
ngram_tokens <- unnest_tokens(ngram_tokens, word, text)
ngram_tokens <- select(ngram_tokens, Company, datetimestamp, word, id, heading)
```

Now that we have our unigrams we can match it with a sentiment lexicon. For finance articles in particular we use a "loughran" sentiment because it is trained to specifically avoid giving negative and positive sentiments to words that hold a neutral value in finance.

```
sentiments <- ngram_tokens %>%
  count(word) %>%
  inner_join(get_sentiments("loughran"), by = "word") %>%
  group_by(sentiment) %>%
  top_n(5, n) %>%
  ungroup() %>%
  mutate(word = reorder(word, n))

ggplot(data = sentiments, aes(word, n, fill = sentiment)) +
  geom_col() +
  coord_flip() +
  facet_wrap(~ sentiment, scales = "free") +
  ggtitle("Frequency of This Word in Google Finance Articles") + theme_minimal() +
  theme(legend.position = "none")
```

## Frequency of This Word in Google Finance Articles



In the plot below shows us what are the most common words in each category of the “loughran” sentiment. It may not always be important for us to know which one of these categories the words are from, but as an example if a company is in legal trouble we may see that it has more words in the litigious category. For our purposes though we just want to know whether the company is generally being talked about more positively or negatively. Below I am going to call ‘inner\_join’ from the dplyr package and pipe it straight into count so we can see how many times each sentiment occurs for each company.

```
company_sentiment_freq <- ngram_tokens %>%
  inner_join(get_sentiments("loughran"), by = "word") %>%
  count(sentiment, Company) %>%
  spread(sentiment, n, fill = 0)
company_sentiment_freq
```

```
## # A tibble: 16 x 7
##               Company constraining litigious negative positive
##   *           <fctr>          <dbl>      <dbl>      <dbl>      <dbl>
## 1      Blackstone           11         52         60         64
## 2  Brixmor Property Group      7         22         89         87
## 3  Brookfield Properties      9          8         35         56
## 4  CBL & Associates Properties 10         19        112         88
## 5      DCT Industrial Trust    9         28        104        151
## 6 Developers Diversitfied Realty 19         40         98        108
## 7      Duke Realty           14         28         73        101
## 8  First Industrial Realty Trust 12         37         70         84
## 9   General Growth Properties  20         33        118         82
## 10      Kimco Realty          7         27         93         72
## 11   Liberty Property Trust     9         27         80        140
## 12      Macerich              3         14         70        121
```

```
## 13          Prologis          6      20      56      84
## 14      Simon Property Group      2       7      29      40
## 15      Vornado Realty Trust     13      36      81     111
## 16  Weingarten Realty Managment      4      35      92     111
## # ... with 2 more variables: superfluous <dbl>, uncertainty <dbl>
```

Now we can plot this data separating out only the columns labeled 'negative' and 'positive' and then follow by creating a score for each company that is based on the amount of positive and negative words in each article. To do this we will first subtract the number of positive words from the negative words to get our numerator, the sentiment score is completely dependent on this value. After we get the numerator we divide it by the total amount of words. After plotting we get our company sentiments.

```
company_sentiment_freq %>%
  mutate(score = (positive - negative) / (positive + negative)) %>%
  mutate(company = reorder(company, score)) %>%
  ggplot(aes(company, score, fill = score > 0)) +
  geom_col(show.legend = FALSE) + coord_flip() +
  theme_minimal() + ggtitle('Positive or Negative Scores for the Top Real Estate Companies')
```

