Sentiment Analysis in Finance:
Web Sources, Accuracy Analysis, and Python Implementation

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1. Introduction

Market sentiment significantly influences asset prices. Positive sentiment can drive asset prices up, while negative sentiment can lead to declines. Understanding and measuring market sentiment is crucial for making informed investment decisions, as it provides insight into the collective emotions and opinions of market participants.

Sentiment analysis, a subset of natural language processing (NLP), has emerged as a powerful tool to gauge market sentiment and predict asset movements. By analyzing text data from news articles, social media, and financial reports, sentiment analysis aims to quantify the emotions and opinions expressed, providing valuable insights for investors and analysts.

This report aims to evaluate some of the most commonly referred websites for sentiment analysis in the financial market, examining the assets they cover and the methods they use. Additionally, it explores the accuracy of these sentiment analyses, presenting available backtested results or statistical validations. Finally, the report delves into practical applications of sentiment analysis using Python. It provides an overview of relevant Python packages and modules, along with example code for generating sentiment scores for financial assets.

2. Sentiment Analysis Platforms

In the financial market, various platforms provide sentiment analysis services, helping investors and analysts gauge market sentiment and make informed decisions. These websites analyze textual data from news articles, social media, and financial reports to generate sentiment scores for different financial assets. Below, we explore some of the most commonly referred websites, the assets they cover, and the general calculation methods they use to derive sentiment insights.

2.1 AlphaSense

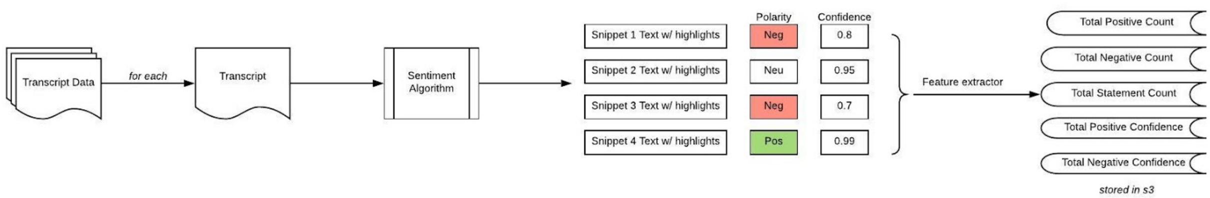
AlphaSense differentiates itself from other sentiment analysis products through its advanced search capabilities and comprehensive data sources. Unlike many competitors, AlphaSense offers real-time access to a vast repository of financial documents, including proprietary data that is not easily accessible elsewhere. Its AI-driven algorithms provide highly accurate sentiment analysis, contextual understanding, and entity recognition, enabling users to pinpoint relevant information quickly and accurately.

AlphaSense's approach to calculating sentiment for a specific document first entails counting the raw inputs. That includes counting:

- Total negative statements in the document;
- Total positive statements in the document;
- Total statements in the document.

The raw inputs drive the raw sentiment score for a document. The raw sentiment is the percentage of the document that is positive minus the percentage that is negative.

From there, the model calculates a normalized sentiment score. The normalized sentiment is the raw score normalized across all companies such that the mean sentiment is 0 and the scores are stretched between -99 and 99. This score matches what you see in the AlphaSense platform.



Each sentence in a transcript gets a prediction of positive, negative or neutral along with a confidence value (e.g. 99% confidence this statement is positive). Our sentiment model, which has been trained on a huge body of financial documents, first forms a contextual understanding of each sentence based on the surrounding context and what's important in that sentence or paragraph, and then uses it to make a sentence-level prediction and output a confidence value based on how confident our model is in its prediction. The model also highlights important phrases and sentences that are driving its predictions, generating a summary for our users.

For the doc-level score, we take the count of positive statements minus the count of negative statements divided by the total number of statements. We then normalize these scores by:

- The confidence of each prediction;
- The mean and standard deviation of scores across all transcripts in the last 2 years such that the average score is 0. Some examples of what this means: A score of 0 is average across all transcripts; A score of 40 (or -40) is in the top 20% (or bottom 20%) of all transcripts; A score of 99 (or -99) is in the top 2% (or bottom 2%) of all transcripts.

(Reference: How We Calculate Sentiment)

2.2 MarketPsych

MarketPsych Data stands out in financial sentiment analysis by integrating psychological insights with advanced data analytics. It covers a wide range of financial assets, including stocks, indices, commodities, currencies, and cryptocurrencies. This platform specializes in analyzing news and social media to extract sentiment data, providing a comprehensive understanding of market emotions and trends.

MarketPsych's methodology of calculating sentiment includes the following steps:

1. Investors form opinions about assets based on news, research, corporate documents, and online discussions;

2. Media Outlets such as traditional news and online social media amplify such opinions, creating feedback loops;

3. MarketPsych's NLP engines provide AI-assisted analytics across millions of media articles, documents, and online posts daily;

4. Datasets are created by aggregating topic and sentiment analytics data on millions of entities across time frames;

5. Workflows supported include alpha generation, research, ESG, monitoring, and risk management via APIs and Python notebooks;

6. Web App makes workflows and content easily accessible with visualizations, web tools, code samples, and research reports.

The model used in this process, the StarMine MarketPsych Media Sentiment (MMS) model, is a stock ranking system that provides a 1-100 daily percentile ranking for over 16,000 global stocks. MMS complements the StarMine suite of equity models and follows a similar methodology in research and implementation.

The output includes an overall score, as well as specific Equity, Business, and Management scores. The MMS scores are designed to predict the next month's relative share price returns, with higher-ranked stocks outperforming lower ones.

(Reference: MarketPsych Home; StarMine MarketPsych Media Sentiment Model)

2.3 Sentifi

Sentifi is an established fintech company and alternative data provider. They transform traditional and alternative raw data into investment analytics, supporting institutional investors across multiple stages of their decision-making process.

Sentifi ingests social media, news, and blogs, capturing and making sense of investment signals in unstructured data with a mature AI platform. Sentifi ESG alternative data-based analytics evaluate the environmental, social, and governance performance of companies, sectors, industries, based on insights reported by 15m+ influencers across tweets, news, and blogs real-time and surface material ESG events that can have an impact on the valuation of affected assets. They also provide ESG scores (for companies, sectors, and industries).

(Reference: Sentifi Quick Description)

2.4 RavenPack

RavenPack is a leading provider of big data analytics for financial services, specializing in transforming unstructured data into actionable insights. The platform focuses on analyzing news, social media, and other textual data to provide sentiment analysis, event detection, and predictive analytics for financial markets. RavenPack's tools are designed to help investors and analysts understand the impact of news on asset prices and market trends, thereby enhancing decision-making processes. Its sentiment analysis tool, the RavenPack Sentiment Index, is calculated as the difference between the average value-weighted return on the two low news beta portfolios (small or large) and the average value-weighted return on the two high news beta portfolios (small or large).

(Reference: Constructing a Sentiment Factor)

3. Sentiment Analysis Accuracy

In the financial markets, the accuracy of sentiment analysis is crucial for making reliable investment decisions. Accurate sentiment analysis can help predict asset price movements and market trends, thus providing a competitive edge to investors and analysts. This section examines the accuracy metrics used in sentiment analysis and evaluates the statistical proofs provided by the websites above.

3.1 Sentiment Analysis Accuracy in Mentioned Websites

AlphaSense provides the following information regarding their sentiment analysis accuracy:

"In AlphaSense's sentiment analysis tool, each sentence gets a prediction of positive, negative, or neutral along with a confidence value (i.e. 99% confidence this statement is positive). Overall, our sentiment analysis model has been shown to be over 90% accurate in its predictions."

MarketPsych provides the following information:

"The historical evaluation demonstrates significant outperformance of higher deciles versus lower ones, with the top-bottom decile spread averaging 10.4% annually from 2006 to October 2020, including 12.3% in the out-of-sample period. The MMS scores are uncorrelated with traditional market factors and complement fundamental models."

RavenPack provided the following information:

"From January 2000 to September 2011, the contemporaneous correlation between the RavenPack Sentiment Index and the S&P 500 Index is 79%; the RavenPack Sentiment index is consistently highly correlated with the S&P 500 Index across different market trends. Especially, we find an average correlation of almost 90% during bear markets.

Also, the RavenPack Sentiment Index is both statistically and economically significant:

- A causal relationship exists from market sentiment to stock market returns;

- The sentiment trading strategy based on monthly VAR(2) yields an annualized return of 10.2%;

- The recursive monthly VAR(2) model is able to generate an out-of-sample annualized return of 6.7% between April 2006 and September 2011;

- The sentiment based trading strategy based on weekly VAR(10) yields an annualized return of 13.4%;

- The recursive weekly VAR(10) model is able to generate an out-of-sample annualized return of 17.5% with an Information Ratio of 0.81."

(Reference: StarMine MarketPsych Media Sentiment Model; Introducing the RavenPack Sentiment Index; What Are Sentiment Scores and How Are They Calculated?)

3.2 General Sentiment Analysis Accuracy

The effectiveness of sentiment analysis models in the stock market is supported by academic research and empirical evidence. According to a study by the University of Michigan, integrating public sentiment data enhances the accuracy of stock price prediction models by up to 20%. This improvement not only boosts predictive capabilities but also provides a more nuanced understanding and quantification of market psychology.

Moreover, the use of sentiment analysis has been shown to improve the forecasting accuracy of financial models. For instance, a study using a word count approach evaluated the extent to which sentiment can be used to improve the accuracy of forecasting S&P 500 index returns. The study found that a model solely using financial variables had a forecasting accuracy of 54.12%. However, when incorporating sentiment measures from earnings releases, the accuracy increased to 59.52%, reflecting a 5.4% improvement in forecasting ability.

Other studies have similarly highlighted the potential of sentiment analysis to enhance predictive models. For example, research has demonstrated that incorporating sentiment data from social media and news sources can provide early warnings of market movements and enhance the performance of trading strategies. These findings underscore the value of sentiment analysis as an additional tool in the investor's toolkit.

However, it is important to note that while sentiment analysis can improve forecasting accuracy, the gains are often modest. This is because market sentiment, while influential, is just one of many factors that drive asset prices.

(References: Text-based Sentiment Analysis in Finance: Synthesizing the Existing Literature and Exploring Future Directions; Stock Market: How Sentiment Analysis Transforms Algorithmic Trading Strategies)

4. Conducting Sentiment Analysis in Python

Python has become a go-to language for sentiment analysis due to its powerful libraries, ease of use, and strong community support. It provides a comprehensive ecosystem for processing and analyzing text data, making it an ideal choice for sentiment analysis in the financial market. By leveraging Python's capabilities, investors and analysts can efficiently extract sentiment from large volumes of text data, such as news articles, social media posts, and financial reports, to gain actionable insights.

Several Python libraries are widely used for sentiment analysis:

- NLTK (Natural Language Toolkit): Provides a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning. One important aspect to note is that NLTK requires users to define their own sentiment weights. This means that users must create a sentiment dictionary, assigning positive, negative, or neutral weights to individual words.

- TextBlob: Built on top of NLTK and provides a simple API for diving into common NLP tasks; Includes tools for sentiment analysis, noun phrase extraction, classification, translation, and more;

- VADER (Valence Aware Dictionary and sEntiment Reasoner): Specifically designed for sentiment analysis of social media text; Provides a sentiment intensity analyzer that is sensitive to both polarity (positive/negative) and intensity (strength) of emotions;

- SpaCy: An advanced NLP library designed for efficient processing of large volumes of text; Offers pre-trained models for various NLP tasks, including sentiment analysis.

The report includes two attached code samples. The first code demonstrates how to use the TextBlob, VADER, and spaCy packages for sentiment analysis. It analyzes basic sentences using each package, generating sentiment scores for each sentence. The second code is a project sourced from GitHub that investigates the relationship between market sentiment and the S&P 500 index. This project utilizes real-time news data from various sources, including CNN, The New York Times, BBC News, ABC News, The Washington Post, Financial Times, and Bloomberg. It then conducts sentiment analysis on the subjectivity and polarity of the news using TextBlob and explores the correlation between these sentiment measures and the S&P 500 index.

5. Insights and Analysis

Upon evaluating the performance of various sentiment analysis tools and platforms, several key insights emerge regarding each package's effectiveness and reliability in analyzing sentiment throughout the financial market.

TextBlob and spaCy have demonstrated relatively higher accuracy in identifying positive sentiment. For example, the sentence "The stock market is doing great!" was accurately identified as a positive comment by both TextBlob and spaCy, each generating a sentiment value of 1.0. In contrast, VADER assigned a lower sentiment value of 0.6588, indicating a less pronounced positive sentiment.

However, VADER excels in detecting negative sentiment. In the sentence "I am worried about the economic downturn," VADER successfully generated a negative sentiment value of -0.296. On the other hand, both TextBlob and spaCy produced a positive sentiment value of 0.2 for the same sentence, failing to accurately capture the negative tone.

One significant limitation across all these sentiment analysis packages is their difficulty in recognizing sarcasm. For the sarcastic comment, "Oh great, the stock market is up again. I guess that means everything is perfect in the world and there are absolutely no underlying issues at all!" — which is intended to be negative — all three packages erroneously produced positive sentiment values (TextBlob & spaCy: 0.235; VADER: 0.6484). This underscores a common challenge in sentiment analysis, where the nuanced and context-dependent nature of sarcasm remains difficult to detect accurately.

6. Conclusion

Based on this comprehensive evaluation, sentiment analysis tools can offer valuable insights into market sentiment, potentially enhancing the accuracy of investment decisions. Platforms like AlphaSense and RavenPack have shown high accuracy rates and strong correlations with market indices, demonstrating their usefulness in financial analysis. Studies have indicated that integrating sentiment data can improve the accuracy of stock price prediction models and provide a more nuanced understanding of market psychology. However, the improvements, while significant, are often modest, suggesting that sentiment analysis should be used as a complementary tool rather than a standalone solution.

As natural language processing (NLP) and machine learning techniques continue to advance, the accuracy and reliability of sentiment analysis tools are likely to improve. Future developments may include better handling of complex linguistic phenomena like sarcasm, more sophisticated context analysis, and integration of a broader range of data sources. These advancements will make sentiment analysis an even more valuable asset for investors and analysts, helping them to better deal with the complexities of the financial market and make more informed decisions.

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What Are Sentiment Scores and How Are They Calculated?
https://www.alpha-sense.com/blog/engineering/sentiment-score/

This report utilizes ChatGPT for refining wording and generating comprehensive definitions of certain terms, such as quantitative and discretionary investing.