



Introduction

This white paper explains two key methodological concepts that we frequently discuss with clients:

1. How we build and update our lexicon through machine learning. The first section of this paper details this process.
2. Why our algorithm scores communications as it does. The second part of this paper explains the unbiased, high-speed nature of our data by highlighting two key communications and giving the rationale for their scores.

Understanding Our Lexicon: Building and Revising Through Machine Learning

To construct a lexicon for each bank, our algorithm is first trained on a series of published communications known as reference documents. These documents are central bank communications that have led to identifiable market reactions.

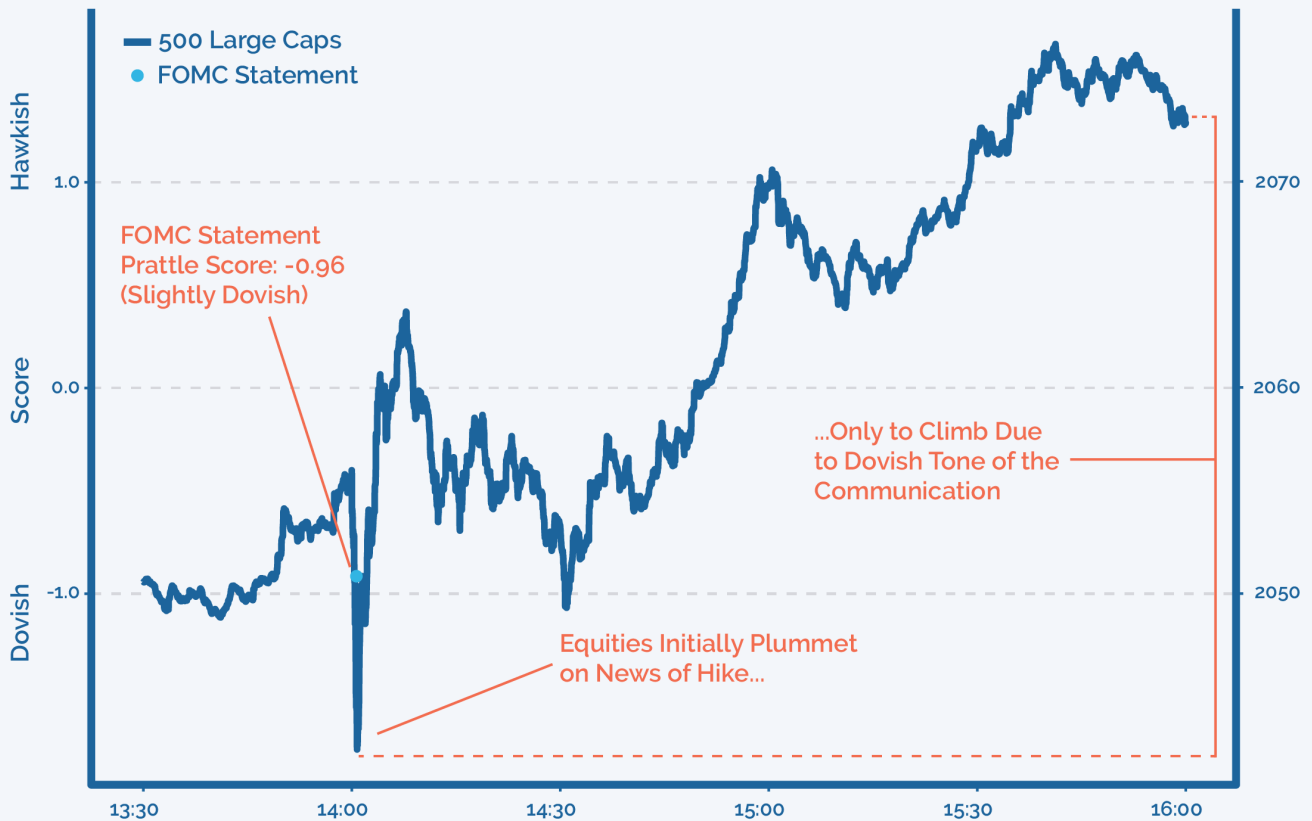
To identify the discrete market reaction to each reference document, we evaluate various markets including rates, forex, and equities. For example, the market impact of each Fed communication is measured based on fluctuations in overnight fixed income, 2 and 10 year treasuries, the trade-weighted dollar, and the 500 most commonly traded large cap stocks. Other banks are evaluated based on their specific area of influence, e.g. FTSE fluctuations are considered heavily when identifying Bank of England (BOE) reference documents. Each area of market impact is tested over short, medium, and long term periods, defined respectively as the remainder of the trading day, the rest of the week through the following week, and two weeks to six months from the communication date.

For an example of how the tone of a central bank communication can be identified as responsible for short term market impact independent of a given monetary policy decision, let's look at the Fed's December 2015 "dovish¹ hike." In this case, the opposing signals of the rate hike (hawkish) and the statement's tone (dovish) each impacted the market in discrete, identifiable ways. Considering that increasing interest rates consistently causes equity markets to drop, the sentiment contained in the statement can be positively attributed to the subsequent equity market upswing. As seen in Figure 1, many traders initially reacted to the

¹ Central bank communications (in general practice) are understood in terms of their "hawkishness" or "dovishness." A hawkish central bank views the economy as strong and growing and, because of this perception, will soon implement contractionary monetary policy—raising interest rates to ensure credit is less available—in an attempt to keep the market from overheating. A dovish central bank believes the economy is struggling and takes the corresponding strategy: lowering interest rates to encourage growth through a climate of easier credit.

hawkish policy move before eventually recognizing the statement's dovish language and reversing their positions throughout the day.

Figure 1: US Equity Price Movement and the Dec 16, 2015 FOMC Statement²



Using criteria such as this, we've directly connected the reference documents used to train our algorithm to varying degrees of market reaction (rather than policy change, which occurs too infrequently), making them a reliable, historically-rooted foundation of comparison.

With these reference documents, Prattle has mathematically linked specific words, phrases, sentences, and paragraphs—collectively referred to as “expressions”—to market reactions. Expressions linked to hawkish policy and the corresponding market reaction are assigned positive values, while dovish expressions are assigned negative values. These expressions and their corresponding weighting make up the initial lexicons for each bank.

The Federal Reserve Lexicon

For example, our Federal Reserve lexicon was originally built using a set of hawkish, dovish, and neutral reference documents over the time period of 1998-2005.

² Figure 1 sets the price movements of the 500 most commonly traded large cap equities on December 16, 2015 against our sentiment score for the FOMC meeting held that same day.

From there, each lexicon is then constantly updated through machine learning. After creating the initial lexicon for the Fed from the training documents, the algorithm then revised this lexicon by continually adding new expressions and altering the weighting of existing expressions based on the evolving use of those expressions.

When our system first encounters a new expression (such as newly-coined words like “Brexit”) in a central bank communication³, it does not weight that expression because it does not have a basis of evaluation. The second time that expression appears, however, the system is able to weight it based on how it was used previously. In a similar way, the weighting of existing expressions in the lexicon are constantly updated based on the evolving way in which they are used in communications.

In short, the weighting of expressions within the initial lexicon (the training set) are expertly determined by their association to market response. The weighting of new expressions is then determined by how they are used in relationship to the language in the training set. The weighting of the expressions in the initial lexicon evolve as the algorithm detects changes in their use over time.

We have found this process to be extremely accurate. For instance, we initially developed the Fed lexicon using communications from 1998-2005, then repeated this process from the period of 1998-2013 and found that the changes to our historical communication scores did not extend beyond the third decimal place. This lack of any statistically significant difference in scores suggests that the machine learning that took place from 2006-2013 succeeded in identifying and adapting to the Fed's changing linguistic patterns and their market impact.

Understanding Our Scores: Why Algorithms Outperform Analysts

To illustrate the accuracy of our scoring process, we'll explain our algorithm's perspective on two market-moving communications. We have included large portions of text from both communications because the algorithm takes a comprehensive, contextual approach rather than focusing exclusively on single words or phrases. The first example tackles Prattle's score of Mark Carney's July 5, 2016 speech, revealing why our system was able to correctly assess the tone of the communication when human analysts were not. The second explains how the algorithm was able to properly quantify the sentiment of Yellen's speech at the Jackson Hole Symposium in August of 2016.

Key Example 1: The BOE Rate Hold

While many analysts saw Mark Carney's [speech](#) on July 5 as a sign that the BOE would ease at the next policy meeting, Prattle's system was able to [correctly understand](#) the nuanced language of the speech and produce a more accurate interpretation. The system scored Carney's speech as fairly neutral to marginally hawkish (0.35) when compared to BOE communications as a whole—and marginally dovish (-0.45) when compared to other communications by Carney.

Let's take a look at why Prattle's algorithm scored this speech as it did.

³ Prattle scores all communications from a given bank, even those not directly related to monetary policy. This provides a more accurate representation of a bank's overall trend and reveals the communication patterns corresponding to various levels of economic strength. Excluding certain communications could obscure certain linguistic patterns in addition to introducing selection bias to the process.

The section on financial stability and the conclusion scored very dovish, while every other section of the speech scored either neutral or slightly hawkish. Those analysts who read only the first and last parts were likely to take a negative view and expect stimulus, but Prattle's system accurately gauged the overall neutral tone of the whole communication.

For instance, many analysts were likely caught up in the dovishness of the following portion...

"The concerns that the historically large current account deficit could be vulnerable to sudden shifts in foreign capital and sharp adjustments in sterling appear to have been borne out. Portfolio flows into UK equities and corporate debt appear to have slowed, and sterling experienced its largest two-day fall against the dollar since floating exchange rates were re-introduced almost half a century ago....In particular, there is growing evidence that uncertainty about the referendum has delayed major economic decisions, such as business investment, construction and housing market activity."

...while, primed by the previous negative sentiment, overlooked what directly followed it:

"More positively, sterling's sharp depreciation should, for given foreign demand, provide support to UK exporters, and the sharp fall in gilt yields has meant that all-in corporate borrowing costs actually fell modestly over the course of last week. In addition, financial markets have managed the volatility around the referendum well and have not added to stress."

In this case, analysts fell prey to confirmation bias by allowing their Brexit-fueled projections of a rate cut to skew their interpretation of Carney's speech. While this error is a constant threat to the integrity of human evaluation, it does not, however, apply to well-engineered programmatic analysis. In this instance and many others, Prattle's system was not subject to the cognitive biases that prevent the accurate interpretation of these texts.

Key Example 2: Yellen's Hawkish Signals

Prattle's score of Fed Chair Janet Yellen's speech at the August 2016 Jackson Hole Symposium perfectly quantified the moderate to slightly hawkish sentiment of the statement, as confirmed by [respected analyst reactions](#). The set of scores (raw 0.15, residual 0.38) numerically represent the tone and message of the speech: a hike by year-end is likely if economic data continues to look good.

To provide a rationale for this algorithmic interpretation, the following sections of the speech scored hawkish...

"U.S. economic activity continues to expand, led by solid growth in household spending. But business investment remains soft and subdued foreign demand and the appreciation of the dollar since mid-2014 continue to restrain exports...Looking ahead, the FOMC expects moderate growth in real gross domestic product (GDP), additional strengthening in the labor market, and inflation rising to 2 percent over the next few years. Based on this economic outlook, the FOMC continues to anticipate that gradual increases in the federal funds rate will be appropriate over time to achieve and sustain employment and inflation near our statutory objectives."

...while other more dovish sections, such as this excerpt where Yellen provides the rationale for the inherently dovish “lower for longer” rate path, helped shift the document score into more moderate territory:

“In part, current expectations for a low future federal funds rate reflect the FOMC’s success in stabilizing inflation at around 2 percent—a rate much lower than rates that prevailed during the 1970s and 1980s. Another key factor is the marked decline over the past decade, both here and abroad, in the long-run neutral real rate of interest—that is, the inflation-adjusted short-term interest rate consistent with keeping output at its potential on average over time. Several developments could have contributed to this apparent decline, including slower growth in the working-age populations of many countries, smaller productivity gains in the advanced economies, a decreased propensity to spend in the wake of the financial crises around the world since the late 1990s, and perhaps a paucity of attractive capital projects worldwide.”

Prattle’s algorithmic analysis of this speech was not only perfectly in tune with market response, it was delivered within seconds of the document’s release. This crucial time difference would have given market participants a distinct advantage over those relying on traditional human analysis.

Conclusion

This paper has clarified how our lexicons are created and maintained and how our algorithm breaks down and assesses communications. For more information, please feel free to reach out to our team.

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