Sentiment Analysis for Monetary Policy predictions: The case of Australia, Chile and Peru's Central Banks

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Abstract

This paper highlights the scope for using text data from central bank statements to improve predictions about policy rates. The problem is constructed as a classification into three potential outcomes: the rate in the next period goes up, goes down, or stays the same. We find that a random forest classifier trained only on economic data (e.g. inflation, growth) performs less well than when we also train it on sentiment scores for the bank statements. Although sentiment indicators are not high up on the feature importance of the model, we believe there is scope to refine this approach further.

Contents

1 Introduction

Most Central Banks issue quarterly or monthly statements to announce whether or not there will be a change in the policy rate, alongside some commentary on how the country's economy is doing. The aim of this project has been to use the text data obtained from these statements to help predict how a central bank might act in the next period. We simplify their action into three possibilities: increase the rate, lower it, or keep it the same.

In this paper we test our approach with data from the central banks of Australia, Chile and Peru, thus working with Spanish and English text.

1.1 Context: central bank rates

Monetary policy seeks to find the right balance between 'hawkish' aims of keeping inflation in check and 'dovish' concerns of stimulating spending. A dovish policy would see a fall in the central bank's interest rate to encourage spending and investment rather than saving. A hawkish policy would come into play when there are high levels of inflation, as is currently the case in many parts of the world.

What a central bank does to policy rates in the next month is of great importance to different economic agents. For commercial banks it dictates the cost of credit, but may also predict their clients' demand for cash and thus how liquid their assets should be. Companies care about the central bank rate because the cost of credit may get passed on to them, but also because it affects the likelihood of receiving private investment. If interest rates are high, private investors may prefer to keep savings in the bank rather than invest. Large central banks such as the Federal Reserve System of the USA also have impact way beyond their borders. The Fed's rate affects the demand for US dollars and thus the currency's international purchasing power. The exchange rate to the dollar may have great significance for emerging market economies, especially with regards to foreign direct investments. Therefore, their respective central banks may want to anticipate what comes next.

1.2 Paper outline

This paper is structured according to the stages in our project. Section 2 covers the process of gathering and pre-processing the data. In Section 3 we outline some of our exploratory data analysis, while in Section 4 we go on to explain the machine learning model applied. We compare the results from just training the model on economic data alone (our baseline model) versus adding the sentiment of the current statement to predict the change in rate in the next period (our augmented model). In the final section we summarise our findings and suggest next steps for further research. The appendices provide additional information referenced throughout the paper, including an overview of all notebooks submitted alongside this paper.

2 Data gathering and pre-processing

We worked with two sets of data for each of the three countries: economic indicator data and text data from the statements issued by the central banks. The text data was scraped from the banks' websites and subjected to three different approaches of pre-processing. We outline them briefly and argue which one we chose for the final model. The economic data was obtained from different sources and its completeness was mixed.

2.1 Obtaining Text Data

The approach to scraping the central bank websites differed between the countries and each site came with its own challenges. For all three we used a combination of the Selenium and BeautifulSoup libraries. Table 1 gives an overview of the number of text documents scraped for each country.

Country	Statements/year	Years scraped	Effective analysis	Total statements
Australia	11	2008-2023	2009-2023	166
Chile	12	1997-2023	2003-2023	277
Peru	12	2001-2023	2003-2023	242

Table 1: Table Overview of the text data obtained from the websites of three central banks. While the central banks of Chile and Peru publish monthly statements, Australia omits statements in the month of January.

In the Australian case, the data set was limited by the fact that until 2007, the Royal Bank of Australia (RBA) only issued statements whenever it made a change to the monetary policy rate. This meant we could only take into account the period from 2008 onward. The website itself would have been hard to click through, but we made use of the repetitive structure in the link of the landing page for each year to loop through different pages. We extracted the link to the relevant "media releases" for that year from the text on the site. Once we had obtained all the links we could open each of the statements and extract the text.

The Banco Central de Chile's (BCC) website had the most extensive set of usable data, giving us a total of 277 statements. The text of more recent statements (since 2005) was directly available on the site, however older years only has a single line next to the download link for the PDF file of the entire statement. Therefore we opted to download the files for all statements and process them that way to extract the text.

Obtaining the statements for Peru also involved downloading the "notas informativas" as PDF files from the Banco Central de Reserva del Peru (BCRP) website before being able to extract the text.

2.2 Pre-processing Text Data

Due to the heterogeneity between (and within) the statements of the three countries, we implement three different methods of sentiment analysis that are detailed below. Each approach gives us a sentiment indicator for each central bank statement.

1. **General (positive vs negative) dictionary:** In order to see if the official statements may contain some useful insight to predict policy changes, we used Loughran and McDonald's (2021) Sentiment Word List to measure the sentiment of each statement [1]. This dictionary contains several thousand words appearing in financial documents such as 10K, 10Q and earnings calls categorised into positive and negative. It includes words in different forms, therefore stemming or lemmatizing should not be used. We applied a simply technique to flip the sentiment when it is combined with a negation. Thus the positive word 'achieve' becomes negative when preceded by words such as 'cannot', 'won't', 'not', 'did't' or 'rarely'. We

[1] Source: https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

compute the index as the net sentiment (positive words minus negative words) over the total words in each statement. We refer to this indicator as $tone\_LM$.

2. **Domain-specific (hawkish vs dovish) vocabulary:** In this approach we analyze the statements by separating them into individual sentences. We follow the work and dictionaries developed in Gonzalez and Tadle (2021) who categorized words as hawkish and dovish for different central banks. For a given sentence, if it has a hawkish keyword and more positive than negative modifiers, then its sentiment is coded as hawkish and it is is given a score of '+1'. If the sentence that has a hawkish keyword, but has more negative than positive modifiers, then its sentiment is coded as dovish and is given a score of '-1' [2]. After conducting the sentence-level scoring, we aggregate the sentence scores for each document. We then divide the sum by the number of evaluated sentences, and scale the resulting value by a 100. We refer to this indicator as $tone\_GT$.

3. **Tf-idf - cosine similarity:** This approach seeks to capture a local change in sentiment from one statement to the next rather than giving a static measure like the other approaches above. The texts are vectorized by tf-idf using the aforementioned Loughran and McDonald dictionary. However, this time we apply tokenization, stopwords removal and lemmatization to both the dictionary and the text to reduce dimensionality. [3] From applying tf-idf we get a positive and a negative vector for each statement. Then we calculate the cosine similarity between two consecutive statements. This value represents the degree of change in the sentiment direction, i.e. how close a statement's positivity and negativity vectors are to the the respective sentiment vectors of the preceding statement.

For modeling purposes, we will include all sentiment indicators derived from the three approaches described above.

2.3 Obtaining Economic Data

For our baseline model we compiled economic data for each country, matching the years for which we could find central bank statements. We selected five economic features:

- Central Bank Rate: the actual monetary policy set by the bank for that month.
- Inflation Expectations: the 1-year horizon expectations averaged across the available groups (e.g. consumers, union officials and market economists).
- Gross Domestic Product (GDP): level and growth.
- Consumer Price Index (CPI): once with and once without food and energy.
- Unemployment rate: as a percentage.

In the case of Peru and Chile, this information was neatly provided by the central bank page of each country on a monthly basis. However, for Australia the data was significantly harder to compile. It had to be brought together from different sources and was often only provided on a quarterly basis.

2.4 Pre-processing Economic Data

For the Australian data, the first step was to extrapolate from quarterly to monthly data. We chose to split the difference between the quarterly intervals evenly across the three months. This may only be a poor approximation of what actually happened and means we have lower data quality for the Australian economy. It should also be noted that we discard Australian economic data for January as we do not have a statement to match it.

Overall the cleaned data looks as expected. Figure 1 illustrates a selection of the economic data obtained for all three countries. The impact of Covid is clearly visible with central banks dropping the rate to revive the economy while GDP dropped and unemployment spiked around 2020. For the longer timelines of Chile and Peru, the financial crisis of 2008/2009 also shows.

The most critical part of pre-processing the economic data was encoding the target variable. It takes on the value 1 when rates were raised in the next period, 0 when rates stayed the same, and -1 when they were lowered

[2] For instance, the keyword 'growth' is categorized as a hawkish term since it signals more support for contractionary policy. This is because when 'growth' is attached to a positive modifier, such as 'higher', we have the phrase 'higher growth', which signals higher inflationary pressures. In contrast, when 'growth' is attached to the negative modifier 'weak', we obtain 'weak growth', which relates to more subdued inflationary pressures.

[3] For this purpose, the Spacy and NLTK packages were used both in their Spanish and English versions.

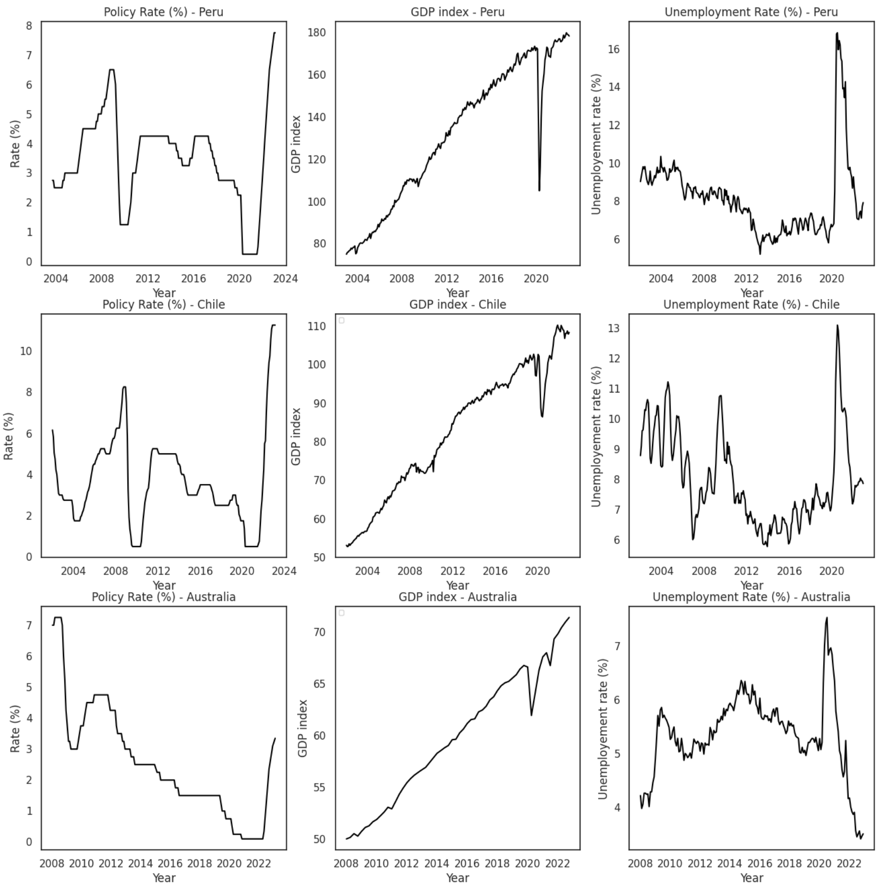


Figure 1: Economic indicators of GDP and unemployment alongside the monetary policy rate for Peru, Australia and Chile.

the next month.

In the pre-processing step we additionally created lags as well as changes in time for some of our variables to be able to analyze potential dynamic effects. For example, we have several CPI-related features: the current value, lagged with one year, the percentage change from the past month and the annual growth. Our section on the machine learning model elaborates which variables we ended up including in our baseline and augmented models.

At the end of the pre-processing stage we had two joint data frames: one of all three countries' monthly economic indicator data (634 rows), and one with the economic indicators alongside on sentiment indicators (614 rows). The discrepancy in rows comes from the lack of Australian statements for January. Furthermore, one statement from Australia was dropped as the RBA issued two statements in March 2020.

3 Exploratory analysis

Having obtained the data we started to look at how the different sentiment indicators behave relative to the economic data. For example, Figure 2 shows the (re-scaled) policy rate of Chile (shown in blue dots) alongside the LM_tone indicator from the general dictionary approach applied to the Chilean central bank statements.

The green line is the net sentiment score from the LM_tone indicator. The red line represents the average sentiment from the statements in year up to that point in time, which reduces fluctuations and improves readability. The policy rate seems to follow a somewhat inverse pattern: if the rolling sentiment was becoming more negative, the monetary policy became more hawkish, increasing the policy rate.

There may also be a heightened amount of co-movement in the policy sentiments during the global financial crisis and the 2020 pandemic period, which is more clearly seen in the juxtaposition of all three countries in Figure 14 in the appendix. Importantly, the image also conveys that the sentiment data has high variability from one statement to the next, and thus may have limited predictive power for a variable such as the policy rate, which rarely moves.

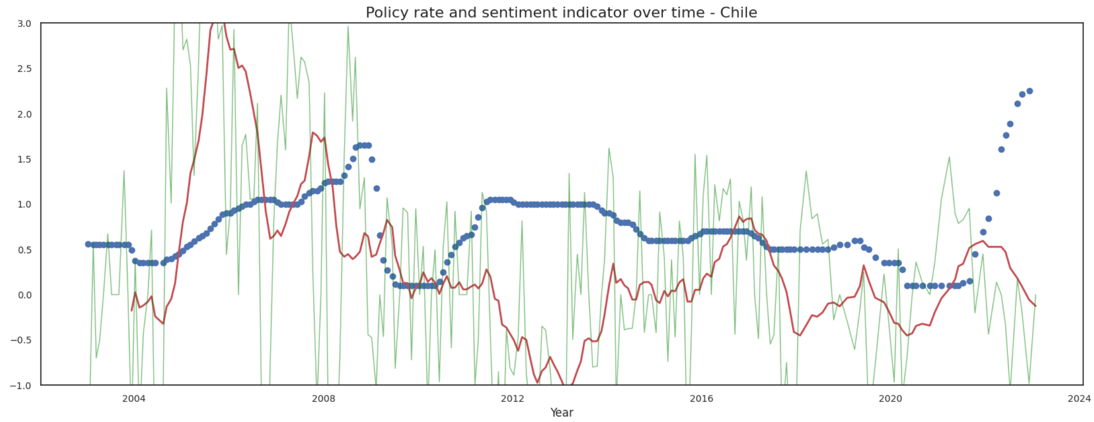


Figure 2: The blue dotted line shows the movements of the (re-scaled) monetary policy rate of Chile. The green line is the net sentiment score from the LM_tone indicator. The red line represents the average sentiment from the statements in year up to that point in time.

Similarly, we find a strong relationship between the dynamics of the GT_tone indicator and the policy rate, with particular emphasis on Chile and Peru. This could shed light on the predictive capacity of latent sentiment variables on the policy decisions of central banks.

Using correlation matrices we could investigate which parameters were moving most closely with the target. Correlation does not imply causation and the Random Forest classifier used for our predictions is not a linear model, so any insights could not be interpreted as definite guidance of what to include in the final model. Nonetheless it was of interest for us to see that for the joint data set of all three countries, the GT_tone was most strongly correlated with the target, as shown in Figure 3.

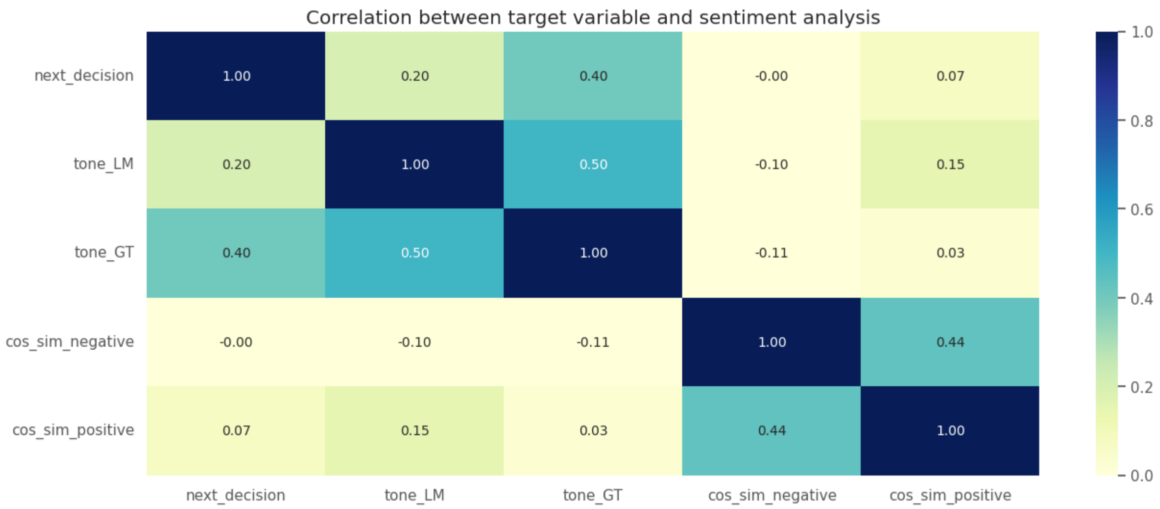


Figure 3: Correlation matrix between the target (the central bank lowering, holding or raising the policy rate in the next period) and the different sentiment indicators for the aggregated data frame across three countries.

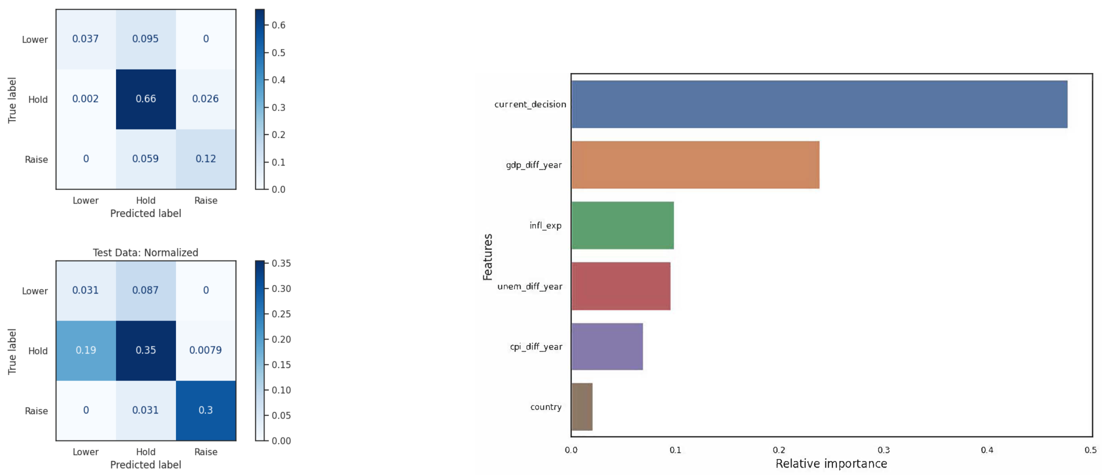
While data exploration indicated that the sentiment data may be related to our target variable, it also showed us that there may be a lot of noise and the prediction task may be hard.

4 Machine learning model

We worked with Random Forest Classifier from the scikit learn library for our model. The main benefit of such a tree-based model is that it is easy to obtain the importance attributed to each feature when making the classification. The target variable was encoded as three classes representing what the central bank could do with the policy rate in the next period: raise, hold or lower.

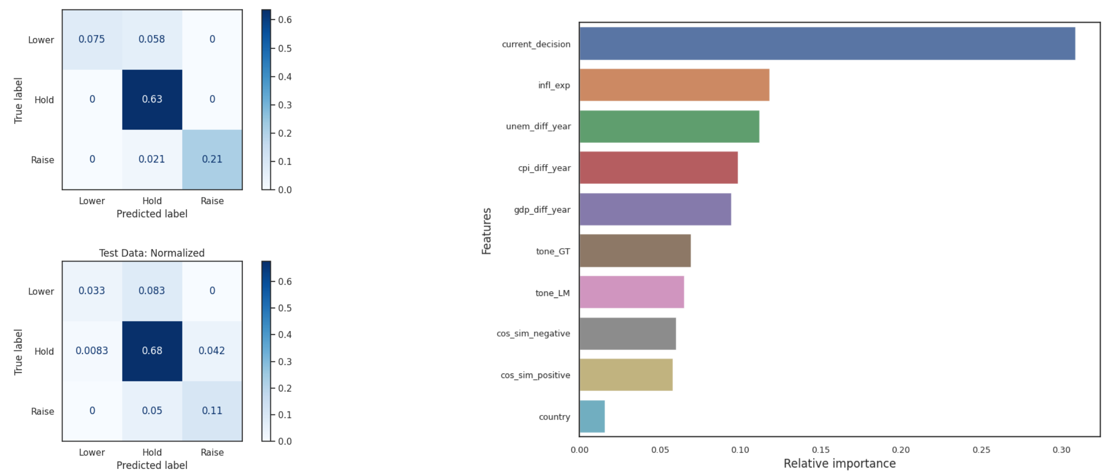
To find out to what extent adding sentiment data can help to improve predictions, we fit two models. The baseline model only has economic features as its input, while the augmented model received those same features alongside the sentiment indicators.

We originally ran the models for each country but were concerned about the relatively small data sets not being very insightful. We therefore present the results for the combined data set of all three countries. This combination came with its own problems as the data values are much further apart as they come from different contexts. For example, unemployment rates are typically lower in Australia than in Peru or Chile. To aid the model in making 'sense' of the data we added a dummy variable for each of the countries.



(a) Confusion Matrix (b) Feature Importance

Figure 4: Baseline Model: The upper confusion matrix refers to the training set while the lower matrix corresponds to the out-of-sample predictions. 68.1% of the test set targets correctly identified (sum of diagonal).



(a) Confusion Matrix (b) Feature Importance

Figure 5: Augmented Model: The upper confusion matrix refers to the training set while the lower matrix corresponds to the out-of-sample predictions. 82.3% of the test set targets correctly identified (sum of diagonal).

4.1 Baseline Model

To predict the next monetary policy decision (target: next_decision), it is crucial to understand the theoretical foundations of the Central Banks' reaction function. In most macroeconomic models, the transmission mechanism of monetary policy is modelled as an interest rate transmission process. The central bank sets the short-term interest rate in order to maintain price stability, keep unemployment low and sustain economic growth. Therefore, we model the Central Bank next decision as a function of the current: (i) annual inflation; (ii) 1-year inflation expectations; (iii) annual unemployment growth; (iv) annual GDP growth; and, (v) the decision of the current period (to capture the inertia of the target).

As an estimation strategy, we opted for a methodology that is flexible and captures possible non-linear relationships between the variables, as well as potential structural breaks in periods of crisis (for example, the 2008 financial crisis or the 2020 pandemic). A test run of different machine learning models, showed that the Random Forest was at least as good as other options; and it was essential for the project's objective to determine the importance of different features.

4.1.1 Random Forest Model

We built a Random Forest model to solve our machine learning classification problem. To optimize performance, we defined a grid of hyper-parameter ranges, performing a StratifiedKFold for the cross validation. We ensured that the maximum depth was capped in order to prevent over-fitting. After fitting the model with the optimal set of parameters, we computed the predictions in the corresponding testing set (randomly generated). In order to visualize the performance of our Baseline Model, we generated a confusion matrix where each row represents the actual category of our target (raise, hold or lower), while each column represents the instances in a predicted class.

The results are shown in Figure 4a. Note that the values inside the confusion matrix are normalized, so their sum is equal to 1. The matrix located at the top corresponds to the training set while the lower matrix corresponds to the out-of-sample predictions. From to the results of the baseline model we conclude that 0.681 of the decisions were predicted correctly. This corresponds to the sum of the diagonal, so the fraction of correctly predicted outcomes. The results shown in Figure 4b suggest that the feature with the most influence in the prediction on the next policy decision is the bank's decision (to lower, hold or raise) in the current period. This is unsurprising as central banks do not tend to change their rates that often. The GDP difference to last year is the second most important feature. The remaining economic variables follow by a margin.

4.2 Augmented model

Next, we went on to to evaluate the gains (in terms of predictive power) of adding latent textual features derived from monetary policy statements to the baseline model that only considers traditional macroeconomic variables. We wanted to know whether we can improve on the baseline model and also which approach to sentiment indicators adds the most value.

4.2.1 Sentiment Analysis

As we said in Section 2 we based our sentiment analysis on three different approaches. Before exploring the data, we thought that the cosine similarities would be the most helpful addition. This is because this sentiment indicates how much the sentiment has changed compared to the positive and negative vectors of the previous statement. However, given the volatility in sentiments from one period to another seen above, it is perhaps less surprising that this does not give it an advantage over the other sentiment approaches. Instead, the domain-specific dictionaries developed by Gonzalez and Tadle (2021) turn out to be more useful. They categorized words as hawkish and dovish for different central banks, thus giving the sentiment indicator a touch of human intelligence.

4.2.2 Random Forest Model

We follow the steps as in the baseline model, applying GridSearchCV to find optimal hyper parameters, avoiding over-fitting through limited depth of trees, and using StratifiedKFold for cross validation. The results of the confusion matrix are shown in Figure 5a.

By summing the diagonal, we can see that 0.823 of the decisions were predicted correctly. If we compare these results with those obtained in the baseline model, we can see an improvement of 0.142 more of the target values correctly classified. Also, by looking at the confusion matrix, the model is more accurate in predicting 'hold' and ‘lower’ events. Therefore, we have some evidence that adding sentiment indicators improves the predictive power of the model.

In Figure 5b we see the feature importance of the model. Just as seen for the baseline model, the current decision is the feature that has the most predictive power in our model. We observe that the order in which the economic features appear has slightly changed. While the difference in GDP compared to the previous year was in second position for the baseline model, it is now the lowest ranking of the four, with inflation expectations taking its place.

None of the sentiment indicators are able to beat the economic indicators in terms of importance for the model. We have already pointed out why this might be. However, among the sentiment indicators, GT_tone is the one with the highest relevance, followed by LM_tone and the cosine similarity vectors.

5 Conclusion and Next Steps

We have examined whether central bank statements contain useful insight to predict the next monetary policy decision (i.e. to raise, hold or lower the policy rate). We implemented intensive web scraping and text pre-processing tasks to obtain sentiment indicators that help us improve the predictive capacity of traditional models.

Using machine learning techniques, we found evidence that official policy statements do indeed contain relevant information to better predict monetary decisions. In particular, we find that incorporating sentiment indicators significantly improves the prediction of ‘hold’ and ‘lower’ events in the next period compared to a baseline macroeconomic model. However, it should be noted that in terms of feature importance, macroeconomic variables continue to be the most relevant.

These results shed light on the suitability of incorporating sentiment indicators to enrich and improve existing analytical models, in this case in the field of economic policy.

5.1 Scope and limitations of sentiment data

A key feature of our chosen target variable is that it does not move much. Central banks aim to keep the economy steady and have no desire to upset the economy through erratic behaviour. Meanwhile the sentiment data gleaned from the very same banks’ statements fluctuates a lot more. This alone implies that there must be limitations to the usefulness of this data in prediction.

Nonetheless, adding this information improves the prediction of our target class, implying that it has value. Although the sentiment scores have the lowest feature importance, the gap between them and the more relevant economic features is not that large - given how much more important the current decision is.

5.2 Looking ahead

With more time at hand, we would have liked to experiment with training on different sets of economic indicators. In particular, we wonder whether having more data that indicates trends from the recent past for each row would improve our ability to predict future. We could for example include a difference from the most recent, second most recent and third most recent period for multiple indicators.

A similar logic could be applied to the extra cosine similarity values for the same reason. This would imply calculating similarity scores for statements further in past to make use of the trends in the sentiment. From the simple plotting exercise we saw that the volatile month-on-month sentiments become much smoother once we average over a year. Likewise, the performance of the indicators that use the LM dictionary as input could be improved. A potential drawback of the two approaches that rely on the dictionary is that it is highly imbalanced. While is contains 2,353 negative words, only 354 are encoded as positive.

We would also ideally like to include data for more countries. At the same time we would consider keeping sub-groups of countries in separate data frames. The prediction accuracy could be compared for different splits. For example, language groups could be kept separately in case some languages lend themselves more to some sentiments than others. Alternatively or additionally, we might want to keep more similar economies together. In particular, we wonder whether our model may have found it hard to make sense of data that was systematically higher (e.g. unemployment rate) for some countries than others. There is also scope in more pre-processing of the economic data here, as more systematically translating the data into indices could help to address some of these issues.

A Appendices

A.1 Guidance to the notebooks

There are notebooks for each country for the first parts of the process. Then we pull the data sets into a joint notebook to run the models. Below are the five types of notebooks submitted with how many versions of each one to expect.

1. Scraping: one notebook for each country to obtain the text data.
2. Generating dictionaries: two notebooks, one for English and one for Spanish.
3. Sentiment analysis: one notebook for each country to run the text data through the three approaches of getting sentiment values.
4. Cleaning economic data: one notebook for each country to add features to the economic data.
5. Modelling: single notebook in which data for all countries is joined together and a baseline model is trained on the economic data while an augmented model is trained on economic and text data.

A.2 Bank website structures

The different site structures required different approaches to scraping the text. The images below indicate the layout of the main landing page from which statements or links to statements could be obtained.

Figure 6: Reserve Bank of Australia's website.

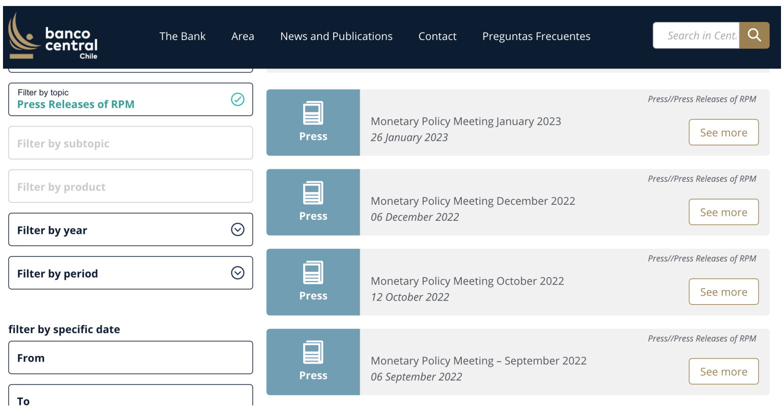


Figure 7: Central Bank of Chile's Website.

Figure 8: Central Bank of Peru's Website.

A.3 General dictionary results

The images below show the results from the most simple of the three sentiment approaches. The y-axis is a net word count: when it is above zero the overall sentiment of the statement is considered positive, when it is below zero it is negative. It seems the Australian central bank is particularly sparse in its use of positive words, although we also need to remember that the dictionary itself is skewed by containing more negative words. The dictionary was also translated for the two Spanish speaking countries, although it is not clear that this would result in a different emotional bias.

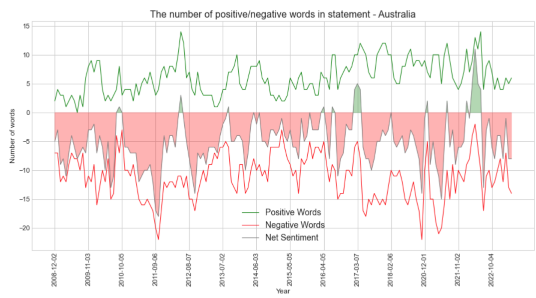


Figure 9: Positive and Negative words - Australia.

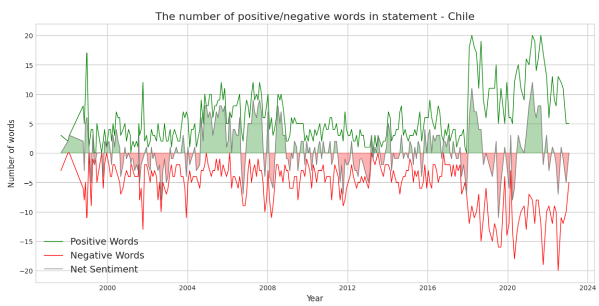


Figure 10: Positive and Negative words - Chile.

The remaining graphs in figure 14 show the equivalent to Figure 2 where the LM_tone scores are shown alongside the monetary policy rate of the respective countries.

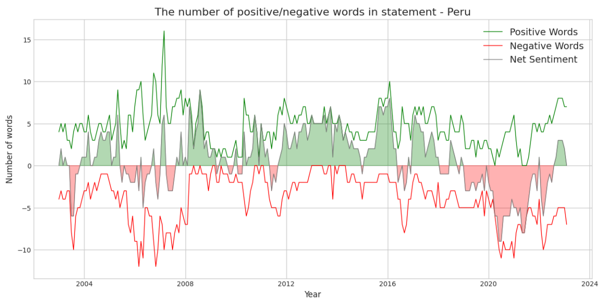


Figure 11: Positive and Negative words - Peru.

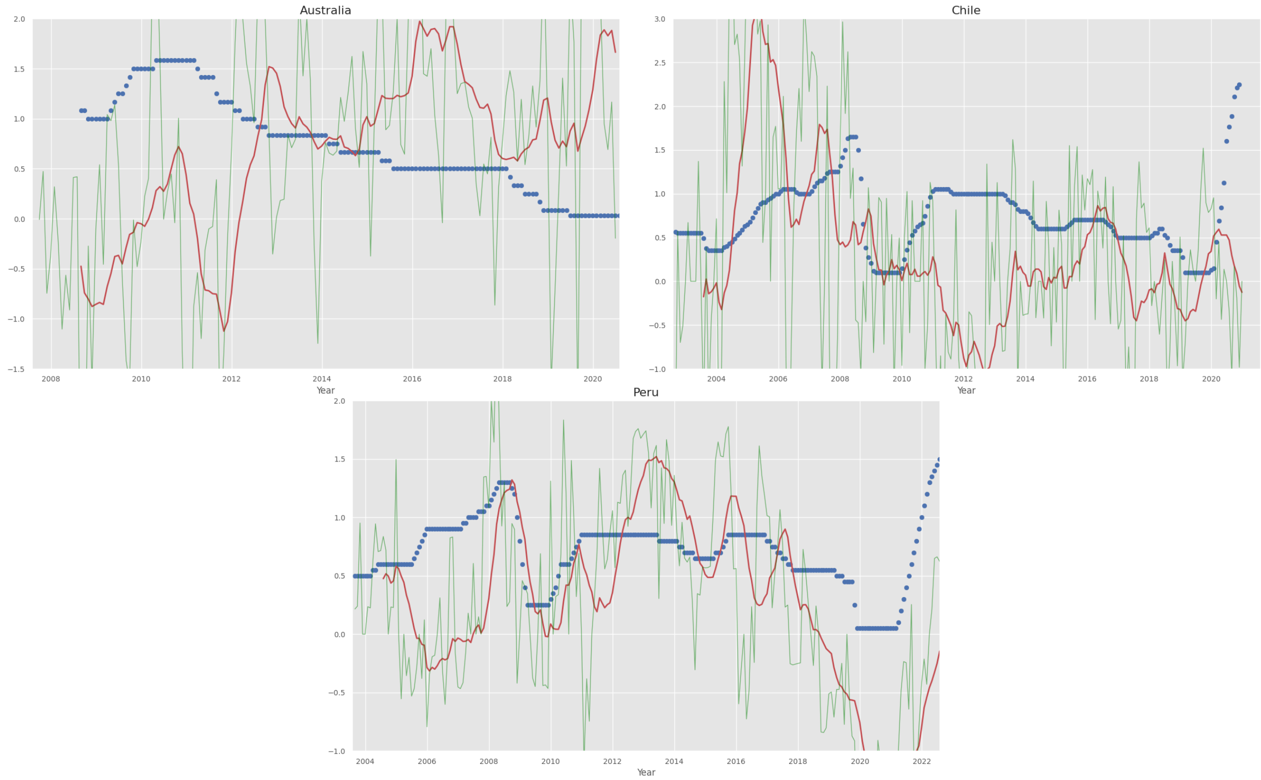


Figure 12: The blue dotted line shows the movements of the (re-scaled) monetary policy rate of the respective country. The green line is the net sentiment score from the LM_tone indicator. The red line represents the average sentiment from the statements in year up to that point in time.

A.4 Domain specific vocabularies

Here we show the examples of hawkish and dovish vocabulary used for the GT_tone approach, alongside the positive and negative modifiers.

```
#Australia

hawkish_AUS = ['business', 'businesses','commodity price', 'condition', 'confidence', 'credit', 'demand', 'economic', 'economy',
               'employment', 'exchange rate', 'expansion', 'expect', 'expected', 'expectation','financial market', 'global',
               'growth', 'household', 'housing', 'housing market', 'inflation', 'international', 'investment', 'lending', 'market',
               'pressure', 'price', 'prospect', 'recovery', 'spending', 'stance', 'trade', 'trend', 'wage', 'world']

dovish_AUS = ['risk', 'spare capacity', 'uncertainty']
```

Figure 13: Hawkish and Dovish vocabularies for Australia in the the GT_tone approach.

```
positive = ['above', 'accelerate', 'accelerated', 'accelerates', 'accelerating', 'accommodate','accommodated', 'accommodates',
            'accommodating', 'added', 'augment', 'augmented', 'augmenting', 'augments', 'benign', 'best', 'better', 'biggest',
            'boost', 'boosted', 'boosting', 'boosts', 'brighter', 'buoy', 'buoyant', 'buoyed', 'buoying', 'buoys', 'calm', 'calmed',
            'calming', 'calms', 'climb', 'climbed', 'climbing', 'climbs', 'depreciate', 'depreciated', 'depreciates', 'depreciating',
            'dynamic', 'elevate', 'elevated', 'elevates', 'elevating', 'encouraging', 'escalate', 'escalated', 'escalates', 'escalating',
            'exceed', 'exceeded', 'exceeding', 'exceeds', 'expand', 'expanded', 'expanding', 'expands', 'expansionary', 'expansive',
            'fast', 'faster', 'fastest', 'favorable', 'favourable', 'firmer', 'good', 'great', 'greater', 'greatest', 'grew', 'grow', 'growing',
            'grown', 'grows', 'healthier', 'high', 'higher', 'highest', 'improve', 'improved', 'improves', 'improving', 'impulse', 'impulsed',
            'impulses', 'impulsing', 'increase', 'increased', 'increases', 'increasing', 'inflationary', 'large', 'larger', 'largest',
            'lift', 'lifted', 'lifting', 'lifts', 'loose', 'loosen', 'loosened', 'loosening', 'loosens', 'looser', 'maximum', 'mitigate',
            'mitigated', 'mitigates', 'mitigating', 'more', 'mount', 'mounted', 'mounting', 'mounts', 'optimistic', 'outperform',
            'outperformed', 'outperforming', 'outperforms', 'peak', 'peaked', 'peaking', 'peaks', 'pick', 'picked', 'picking', 'picks',
            'positive', 'raise', 'raised', 'raises', 'raising', 'ramp', 'ramped', 'ramping', 'ramps', 'rapid', 'recover', 'recovered',
            'recovering', 'recovers', 'reinforce', 'reinforced', 'reinforces', 'reinforcing', 'restore', 'restored', 'restores',
            'restoring', 'rise', 'risen', 'rises', 'rising', 'rose', 'satisfactory', 'skyrocket', 'skyrocketed', 'skyrocketing',
            'skyrockets', 'spike', 'spiked', 'spikes', 'spiking', 'spur', 'spurred', 'spurring', 'spurs', 'stabilise', 'stabilised',
            'stabilises', 'stabilising', 'stabilize', 'stabilized', 'stabilizes', 'stabilizing', 'stable', 'steady', 'stimulate',
            'stimulated', 'stimulates', 'stimulating', 'stimulative', 'stimulatory', 'strengthen', 'strengthened', 'strengthening',
            'strengthens', 'strong', 'stronger', 'strongest', 'successful', 'surge', 'surged', 'surges', 'surging', 'swifter', 'upper',
            'upside', 'upswing', 'upswinging', 'upswings', 'upswung', 'uptrend', 'upturn', 'upturned', 'upturning', 'upturns', 'upward',
            'vigorous', 'widen', 'widened', 'widening', 'widens', 'wider']

negative = ['adverse', 'aggravate', 'aggravated', 'aggravates', 'aggravating', 'appreciate', 'appreciated', 'appreciates',
            'appreciating', 'appreciatory', 'bad', 'bottom', 'bottomed', 'bottoming', 'bottoms', 'concern', 'concerned',
            'concerning', 'concerns', 'conservative', 'constrain', 'constrained', 'constraining', 'constrains', 'contract',
            'contracted', 'contracting', 'contractionary', 'contracts', 'cut', 'cuts', 'cutting', 'dampen', 'dampened',
            'dampening', 'dampens', 'decelerate', 'decelerated', 'decelerates', 'decelerating', 'decline', 'declined', 'declines', 'declining',
            'decrease', 'decreased', 'decreases', 'decreasing', 'deepen', 'deepened', 'deepening', 'deepens', 'deflationary',
            'descend', 'descended', 'descending', 'descends', 'destabilizing', 'deteriorate', 'deteriorated', 'deteriorates',
            'deteriorating', 'difficult', 'diminish', 'diminished', 'diminishes', 'diminishing', 'disappointing',
            'disinflationary', 'dovish', 'down', 'downside', 'downsize', 'downsized', 'downsizes', 'downsizing', 'downward',
            'downwards', 'drop', 'dropped', 'dropping', 'drops', 'erode', 'eroded', 'erodes', 'eroding', 'fade', 'faded', 'fades',
            'fading', 'fail', 'failed', 'failing', 'fails', 'fall', 'fallen', 'falling', 'falls', 'fell', 'fewer', 'flatten', 'flattened',
            'flattening', 'flattens', 'fluctuate', 'fluctuated', 'fluctuates', 'fluctuating', 'fragile', 'harm', 'harmed', 'harming',
            'harms', 'inconsistent', 'jeopardise', 'jeopardised', 'jeopardises', 'jeopardising','jeopardize', 'jeopardized',
            'jeopardizes', 'jeopardizing', 'lackluster', 'least', 'less', 'low', 'lower', 'lowered', 'lowering', 'lowers', 'lowest',
            'mild', 'minimal', 'minimum', 'minor', 'moderate', 'moderated', 'moderates', 'moderating', 'modest', 'negative',
            'pessimistic', 'poor', 'recessionary', 'reduce', 'reduced', 'reduces', 'reducing', 'restrictive', 'riskier', 'risky',
            'sank', 'shorten', 'shortened', 'shortening', 'shortens', 'shrink', 'shrinking', 'shrinks', 'shrunk', 'shrunken', 'sink',
            'sinking', 'slow', 'slowed', 'slower', 'slowest', 'slowing', 'slows', 'sluggish', 'small', 'smaller', 'smallest', 'soften',
            'softened', 'softening', 'softens', 'speculate', 'speculated', 'speculates', 'speculating', 'stress', 'stressed',
            'stresses', 'stressing', 'stringent', 'subdued', 'subprime', 'sunk', 'suppress', 'suppressed', 'suppresses',
            'suppressing', 'threaten', 'threatened', 'threatening', 'threatens', 'tighten', 'tightened', 'tightening',
            'tightens', 'tighter', 'tougher', 'turbulent', 'uncertain', 'unclear', 'undermine', 'unfavorable', 'unfavourable',
            'unstable', 'volatile', 'vulnerable', 'wane', 'waned', 'wanes', 'waning', 'weak', 'weaken', 'weakened', 'weakening',
            'weakens', 'weaker', 'weakest', 'worse', 'worsen', 'worsened', 'worsening', 'worsens', 'worst']
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Figure 14: Positive and negative modifiers for English language countries in the the GT_tone approach.

References

GONZALEZ, M. TADLE, R.C. (2021).Monetary Policy Press Releases: An International Comparison, *Working Papers Central Bank of Chile 912, Central Bank of Chile*. https://ideas.repec.org/p/chb/bcchwp/912.html

LOUGHRAN, T. & MCDONALD, B. (2011). When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance, 66:1, 35-65*. http://ssrn.com/abstract=1331573

VEGA, M. & LAHURA, E. (2020). Assessing central bank communication through monetary policy statements: Results for Colombia, Chile and Peru. *Working Papers 2020-017, Banco Central de Reserva del Perú*. https://ideas.repec.org/p/rbp/wpaper/2020-017.html