

**The Psychological Underpinnings of
Conservative/Liberal Ideology in the Australian Federal Parliament: A Computational
Linguistic Analysis**

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Michael Coleman Dalvean

School of Politics and International Relations

Australian National University

Haydon-Allen Building #22, The Australian National University, Acton ACT 0200

michael.dalvean@anu.edu.au

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Abstract

The purpose of this article is to examine the psychological elements of the ideology of members of the major parties in the Australian federal parliament using computational linguistics. The cohort consists of the 485 Labor, Liberal and National parliamentarians who were in parliament over the period April 1996 to July 2014. I use computational linguistics to extract linguistic variables from first speeches in parliament of those in the cohort. I draw from methods used in machine learning to develop a classifier which has a 74% out of sample (leave-one-out cross validation) accuracy in classifying parliamentarians as liberal (ALP) or conservative (Liberal/National Party Coalition). I then examine the salient variables and find that there are only six linguistic markers of conservative/liberal ideology. Of these, two are consistent with the previous findings that liberals tend to display more psychological 'openness' than conservatives and less psychological 'conscientiousness'. However, one of these variables strongly challenges the idea that conservatives look to the past and liberals to the future. Two of the six linguistic variables are 'suppressor' variables and I discuss these variables in the context of their role in suppressing 'irrelevant' variance in the other independent variables.

Key Words: Text Analysis, Australian Politics, Machine Learning, Ideology, Suppressor Variable

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1. Introduction

In recent years there has been an increase in the use of ideology to explain the political behaviour of voters, legislators and other political agents. As Diermeyer et al (2012) point out, an individual's view on various issues is structured by ideology. This means that attitudes on certain issues will covary between individuals who share the same ideology. This does not necessarily mean that those who share an ideology share a logically consistent world view. Nor does it mean that the association between issues may not be influenced by experience or culture. The important point is that 'ideologies constrain' (Diermeyer et al 2012: 32).

The purpose of this paper is to examine the psychology behind the ideology of Australian federal politicians. We have a broad understanding of the concepts of 'liberal' and 'conservative'. We also have a reasonable understanding of how they differ. Consider that Carney et al (2008) found that Republican (conservative) students organised their dormitories and possessions in quite a different way in comparison with Democrat (liberal) students. Republican students were more likely to have a picture of a sporting star or an American flag on their dormitory walls (indicating support for traditional pursuits and traditional institutions) while Democrat students were more likely to have a map of a foreign country (indicating a higher level of psychological openness). The idea of this article is to use the speeches of Australian federal politicians to look for similar types of differences in speech acts.

Speech acts betray proclivities that are not necessarily evident in the surface semantic content of utterances. While both sides of the political spectrum express the need to address the negative elements of society and promote the positive elements, very few will openly admit that they are less conscientious than members of the opposing party or that they are willing to tolerate a high level of social inequality. Yet these characteristics of respectively liberal and conservative ways of thinking are implicit in their speech acts. The primary purpose of this paper is to mine the speech acts of parliamentarians to make explicit the elements of their ideologies.

The basic raw material for this analysis is the maiden or first speech in parliament. Using text analysis to examine differences between individuals of different ideological orientations is not new. However, the use of the first parliamentary speech in examining political orientation has not been attempted for this purpose. For example, in studies of political orientation using text analysis undertaken by Yu et al (2008), Riabinin (2009) and Diermeier et al (2012), the speeches used were general speeches on policy matters in the respective legislatures. Such speeches are likely to be heavily loaded with the ideological biases of representatives' parties because they are likely to be speaking for the party rather than themselves or reading speeches or questions prepared for them. Indeed, due to the party discipline in the Australian system, the vast majority of parliamentarians merely vote along party lines and as such have very little individual input into parliamentary debate. However, all parliamentarians deliver a substantial first or 'maiden' speech. In the Westminster system there is a tradition of a parliamentarian introducing herself to the parliament in a 'maiden speech' which has more personal content than the standard policy-based speech. It is my contention that the neophyte parliamentarian delivering a personalised first speech provides a text sample that carries sufficient signal to enable a classification of a neophyte parliamentarian as a conservative/liberal. This is a contention that is borne out in that, as I demonstrate below, a classification accuracy of 75% can be achieved using the maiden speech.

Although not examined in this paper, it is worthwhile noting two other advantages of using the maiden speech to classify parliamentarians. The first is that an individual's specific position on the ideological spectrum can be attributed to the specific variables underlying a given score. Two individuals may score similarly but the values for constituent independent variables underlying the scores may be quite different. This can potentially provide insight into individual differences within the same general ideological sphere. The second advantage is that the maiden speech is delivered early in a parliamentarian's career and can therefore be used to score individuals soon after they enter parliament. Thus, a lobbyist, for example, could use the speech to identify potentially

ideologically sympathetic neophyte politicians while they are relatively accessible rather than having to wait until they are relatively prominent in the public arena and are likely to be less accessible. The results in this study show that this is a feasible application.

2. The Conservative-Liberal Spectrum

Before embarking on the linguistic analysis it is worthwhile considering how valid the conservative-liberal construct is. Can we still speak of a one dimensional spectrum for ideology?

Poole and Rosenthal used roll call voting data to estimate that 85% of the voting decisions made by members of Congress between 1789 and 1985 can be accounted for on a Left-Right scale (Poole & Rosenthal, 1991, cited in Diermeyer et al 2012,; 32). Similarly, a single dimension accounts for approximately 90% of the variance in Congressional roll-call voting (Poole, 2005). Thus, there is good evidence that a single dimension does explain a large proportion of the behaviour of members of Congress.

In the current study, party affiliation is used as a proxy for ideology. Voting records are not the ideal measurement of ideology in the Australian system because party discipline dictates that, with few exceptions such as the case of with 'conscience votes', parliamentarians vote along party lines. By using party membership as a proxy, the assumption is that party identification indicates a parliamentarian's ideology. This should not be too controversial as we would expect that a person of a given ideology would choose a party that most closely represents those values.

There is evidence of a historically stable 'liberal' – 'conservative' way of looking at the world. In ancient Rome, for example, the Optimates had an essentially 'conservative' outlook in that they tried to uphold their oligarchy while the 'liberal' Populares used the popular support of the plebeians to challenge the orthodoxy (Parenti 2003: 59-83). In any relatively complex political system a similar system has emerged such that the politically dominant parties can be put on a broadly left-right spectrum. It is a contention of this study that this is because individuals

themselves can be placed on such a spectrum. There is a well-documented literature on the psychological association between political orientation and certain psychological constructs. For example, there is good evidence that those who are broadly liberal are less conscientious and more open to new experiences than those who are broadly conservative (Jost 2003; Carney 2008). In short, what we call political orientation may be a manifestation of a particular constellation of psychological constructs. In as much as individuals can be placed on a spectrum in regard to the constituent psychological constructs, this means that they can be placed on an ideological spectrum. The essential idea here is that ideology is a latent variable which can be approximated by using a number of related constructs.

Further support for the idea that individuals can be placed on a broadly left-right spectrum comes from biological studies. The biological basis for ideology has been recognized by studies that show a higher correlation between the ideological beliefs of monozygotic twins than that between dizygotic twins (Alford, Funk and Hibbing, 2005). This holds even when controlling for situations in which twins are brought up different families (Bouchard et al 2003). The idea here is that there is a heritable component of ideological orientation. Thus, the idea of placing individuals on a left-right spectrum is not a project that comes from a parochial conception of party politics or a socially defined set of circumstances. It has a basis in measurable biological phenomena. The psychological and genetic evidence is that a liberal-conservative orientation is more than a result of local and contextualized perceptions. That is, it is not solely the result of purely environmental factors.

3. Previous Work

In recent years the growth of the use of text analysis has been associated with a number of studies involving classifying individuals as liberal or conservative in using their speech acts. Laver et al's (2003) Wordscores approach is useful as a starting point for the discussion because it is a highly successful method of using language to classify political texts. The idea is that the frequencies of

particular words in archetypal liberal/conservative documents will be indicative of a liberal/conservative way of perceiving the world and any political document with similar word frequencies is likely to have a liberal/conservative author. Archetypal liberal/conservative 'reference texts' are sourced using *a priori* judgments of their liberal/conservative representativeness. These are then used as indicative ends of a spectrum upon which other texts can be placed.

By far, the most common method of ideology classification involves supervised training in which exemplars are provided to guide a learning algorithm. Wordscores is of this nature in that it requires the identification of reference texts. The problem with this is that the identification of such polar exemplars on a priori grounds can be difficult. A procedure that does not require this kind of supervised training is the approach used in Slapin and Proksch (2008). 'Wordfish'. The 'Wordfish' algorithm they employed uses word frequencies to score party manifestos using an unsupervised scaling method.

Wordscores and Wordfish approach the identification of ideological orientation using respectively supervised and unsupervised methods. An approach that uses a supervised method as with Wordscores but which avoids the problems associated with identifying polar exemplars using a priori methods is Diermeier et al (2012). This study used roll-call data to classify members of the US Senate as liberal or conservative. Classification was based on the extent to which members voted in support of conservative (Republican) or liberal (Democrat) motions. They then choose the 25 most liberal and 25 most conservative senators and analysed their speeches from the 101st to 107th Congress. They use the classifier built using this data to classify 50 speeches of the 25 most liberal and 25 most conservative members of the Senate from the 108th congress. They achieve 94% accuracy on this set of 50 'held-out' cases. There is a problem trying to apply this methodology to the Australian setting in that, due to party discipline, parliamentarians do not tend to depart from the standard party positions on the vast majority of issues and as such an Australian analogue of roll-call scores would merely mirror the party vote.

Instead of using roll-call data values to classify the members as liberal and conservative, Yu et al (2008) use party affiliation to determine members' ideological stances. As mentioned earlier, the idea here is that party affiliation is a good proxy for ideological orientation, with Democrats being identified as liberals and Republicans as conservatives. They found that classifiers trained on House speeches performed better in classifying speeches in the Senate than classifiers trained on Senate speeches and tested on House speeches. They also found there was a high degree of variation in the classification accuracy of a classifier trained on 2005 House data in classifying Senate speeches from 60% in 1989 to 80% in 2006 with a trough of 41% - 43 % in the early 1990s. A Classifier trained and tested on Senate speeches from 1989 – 2006 attained an accuracy of 77.24%. The important point here is that, notwithstanding variations in accuracy as between the Senate and House speeches and over time, using party affiliation as a proxy for ideology can yield classification accuracies well beyond the baseline.

Riabinin (2009) used parliamentary speeches to attempt to place individuals on a spectrum of liberal – conservative in the Canadian parliament. Party membership was used as a proxy for ideological orientation and a number of text analytic variables were extracted from parliamentary speeches to be used as the independent variables. In this paper it was concluded that a high degree of accuracy could be achieved in classifying parliamentarians as conservative-liberal using their speech acts. However, a subsequent study (Hirst, Riabanin and Graham, 2010) found that, because the speeches were selected from the same parliamentary session (the 36th session) the speeches of all the liberals had been collected at a time when the liberals were in power while all the speeches of the conservatives were from a time in which the conservatives were in opposition. Subsequent analysis revealed that the model was actually picking up the language of government (relatively positive) and opposition (relatively negative and aggressive) rather than liberalism and conservatism.

4. The Current Approach

Word Categories vs n-grams

The current study uses word categories rather than individual words or n-grams as independent variables. One of the problems of using words rather than word categories is that it is difficult to get an insight into the drivers of ideology from words or groups of words. of individual words. For example, Iyyer et al (2014) found that the following list of words was significantly associated with conservative speech: 'salt', 'Mexico', 'housework', 'speculated', 'consensus', 'lawyer', 'pharmaceuticals', 'ruthless', 'deadly', 'Clinton' and 'redistribution'. Certainly we could construct a theoretical reason why conservatives might use such words. But this does not help us with getting new insights into the psychological drivers of ideology. In the case of word categories we have a greater opportunity to work out the ideological drivers because word categories have been studied extensively. If a particular word category is associated with an ideological stance we need only to look at the research into that category to determine what the psychology behind the use of that word category is. It has been found that in on-line chat forums, conservatives tend to use more 'anxiety'-related words while liberals use more 'anger'-related words (Robinson et al 2014). This identification of differences the word group choice is facilitates the subsequent discussion of the psychology of conservatives and liberals. This would be significantly more difficult with uncategorised groups of words.

Another problem with using words rather than word categories in the current study is that the corpus is drawn from a wide period and over that period there are likely to have been changes in word use and meaning. The way words change over time means that there can be problems comparing a speech from the 1960s with one from 2015 using individual words alone. Nuclear weapons would be referred to as 'atomic' in an earlier age whereas the words 'thermonuclear' and 'nuclear' were used more recently. The n-gram approach treats these as different words whereas the word category approach means they are treated as essentially the same.

The Sample

The basic sample of parliamentarians consists of all Liberal, National and ALP parliamentarians who were in parliament at any time over the period following the election of March 1996 to the period following the election of July 2014. This yields a sample of 485 individuals, 269 members of the Liberal National Party Coalition and 216 members of the ALP.

However, we need to account for an element of the selection method that proved to be a problem in Riabinin (2009): speeches are likely to differ according to whether the speaker's party was in government or opposition at the time the speech was delivered. The evidence is that government/opposition status can influence the way a parliamentarian speaks. Essentially, those who delivered their speech when their party was 'in-power' use more positive and fewer aggressive terms than those whose party was not in-power when they delivered their speech. In the current study the selection is spread over a large proportion of parliamentarians with and without 'In-power' status. Table 1 shows the distribution of InPower as opposed to not InPower parliamentarians in the sample.

Table 1 about here

Given the distribution across the sample, the InPower language is unlikely to be a problem. However, in order to address any possible doubt, a dummy variable is included in the modelling to control for whether a speech was delivered while the speaker's party was in power.

The Dependent Variable

The current approach uses party membership as a proxy for ideology. As mentioned above this is a standard way of approaching the problem and has been shown to account for up to 90% of Congressional roll-call voting (Poole 2005). It also avoids the problem associated with Wordscores of having to identify by *a priori* means a set of exemplar extremes of the spectrum. This is not to suggest that ideology might not be better represented by more dimensions. For example, there is evidence that ideology is made up of three factors: individualism; authoritarianism; and inequality tolerance. However, we have no means of efficiently determining these categories. Determining the broad categories of liberal and conservative based on party membership, on the other hand, is relatively straightforward.

The method for classifying Australian Federal Parliamentarians is to use party membership as a means of determining ideological stance. The three major political parties were used. These three parties are the Liberal Party, the National Party and the Australian Labor Party. The Liberal Party and the National Party have formed governments and oppositions since 1945 as a conservative coalition (the LNPC), while the liberal ALP has, until the 2010 election, formed governments and oppositions in its own right, with a minor deviation from this mode of operation in the period 2010 to 2013 when the ALP governed in association with two independent MPs in the House of Representatives and an alliance with the Greens. Given the essentially polar nature of the two major parties it seems reasonable to take party membership of the major parties as being a good proxy for ideological stance. As such, the ALP (liberal) members are coded as 1 while members of the Liberal National Coalition are coded as 0 (conservative).

The Independent Variables

The source of the data is the first speeches of parliamentarians who were in parliament at any time over the period April 1996 - March 2014. Maiden speeches were used because they are likely to be able to provide linguistic clues to the cognitive makeup of parliamentarians (Dalvean 2012: 139).

The first or 'maiden' speeches of parliamentarians all occur in a similar manner, format and context and are therefore a good source for these speech acts. Furthermore, maiden speeches are designed to introduce the new parliamentarian to parliament and as such cover a broad spectrum of topics such as biography, political concerns, economic interests and social attitudes.

To extract linguistic data from the speeches, the speeches were broken down into linguistic variables using Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al, 2007). This system has become very common in the content analysis field. Using content coding dictionaries, it breaks text down into a number of linguistic variables designed to cover a number of basic psychological and social processes. There are also variables measuring the rate of references to self (first person), other (second and third person) as well verb tenses and several other variables measuring linguistic phenomena. LIWC also provides structural variables such as words per sentence and several measures of punctuation. If documents are collected from different settings there may be idiosyncratic uses of punctuation and this could obscure any potential signal. However, in the current study the sample is drawn from Hansard. There are strict guidelines given to Hansard recorders in relation to all elements of the recording process, including punctuation use. For this reason, punctuation variables were included in the basic set of independent variables.

The variable 'ingest' which measures references to ingestion such as food, drink and other words related to eating and drinking was removed from the variable list. The reason for this is that it was found in preliminary modeling that this was a highly predictive variable but upon inspection it was found that this individuals scoring high on this variable were highly likely to be members of the National Party who represent the predominantly rural constituencies with agrarian interests. As such they were prone to refer to agricultural issues in their maiden speeches which meant that they were often referring to food, wine, coffee etc. Thus this variable directly linked these individuals to their party membership and as such needed to be excluded so that variables that picked up ideological orientation alone could be identified.

5. Machine Learning

The purpose of this section is to determine whether the variables under consideration contain enough strong correlations to enable us to use those correlations to classify parliamentarians. As we will see, there is a robust relationship between the variables and party affiliation such that it is possible to use the data to correctly classify approximately 75% of parliamentarians correctly.

It should be noted that the aim of machine learning is classification rather than interpretation. As such, it is customary to focus on the classification accuracy rather than the importance of individual variables. Indeed, the ‘black-box’ nature of two of the techniques described below, the multilayer perceptron and the support vector machine using the SMO algorithm, means that the importance and directional influence of the independent variables are significantly more difficult to determine than is the case with logistic regression. Even with logistic regression used in a machine learning setting the coefficients often difficult to interpret because the number of variables included means that there may be high levels of multicollinearity as well as suppressor variables. This presents a problem to some extent because we wish to gain an insight into which variables are the most important so that we can determine the psychological drivers of ideology. In order to overcome this problem I shall undertake a subsequent exercise which uses logistic regression in such a way as to eliminate all but the most important variables. The method is to use forward variable selection to create a series of models which are tested against independent and external set of cases. I will discuss this further in the next section. At this stage I will focus on the ability of the entire set of independent variables to classify parliamentarians.

Machine Learning Experiments

The modeling procedure was undertaken using the Weka Environment for Knowledge Analysis, version 3.3.6 (Hall et al 2009). Weka defaults were used except that for the SMO algorithm

different kernels were used (polykernel and RBF kernel) and for the multilayer perceptron the number of hidden layers tried was 1 and 42 (the latter derived from the Weka default).

All LIWC variables excluding 'ingest' were used as well as the InPower variable. The validation method was leave-one-out validation (485-fold validation) . This procedure works by creating a model with 484 cases and testing this model against the 1 case 'held out'. This procedure is repeated 485 times with a different case held out each time. The accuracy is the percentage of correctly classified cases over the 485 models.

Table 2 shows the results of the experiments. The best overall accuracy was the multilayer perceptron with 42 hidden layers (accuracy = 75.88%). Here, the number of layers was determined by the Weka default ($[\text{number of attributes} + \text{the number of classes}] / 2$). The second best overall result was logistic regression (accuracy = 75.26%). The third most accurate was the SMO — polykernel (accuracy = 71.55%).

Table 2 about here

From the modeling we see that there is good evidence that speech acts alone can be used to classify Australian federal parliamentarians as liberal or conservative with a 75% overall accuracy.

Extracting Important Variables

In this section I will extract salient variables using machine learning techniques but the technique will enable us to get an insight into what the most important variables are in the dataset. We have seen that there is sufficient signal in the data to enable efficient classification. However, we still do not have a transparent insight into what the important variables are. We will see in this section that only seven variables are required to correctly classify the sample at a rate of approximately 74%.

The method used here is 10-fold cross validation. The idea here is to divide the dataset of 485 into 10 'folds' and for each disjunct dataset a model is built using 90% of the data and is tested

on the remaining 10%. This is repeated for each fold so that we have 10 models with 10 independent test samples. Importantly, all the data has been used to both build and test the models.

The procedure used to build to model is stepwise logistic regression. This procedure involves adding variables which are assessed by the algorithm as increasing the model fit. The algorithm adds or subtracts variables according to whether they increase the fit of the data. The algorithm stops when there are no variables that can be added or subtracted to increase model fit. This procedure, if used without a held out test sample, can lead to overfitting in which the model simply learns the noise in the data and obscures the signal. This means that the observations made in relation to the given data set cannot be extrapolated to 'unseen' data. The purpose of the 10 held out test samples is to assess how well a given model is likely to classify data not used to create the model. The reported accuracy is the accuracy in classifying the held-out samples.

What we get from this exercise is 10 models which taken together provide a ten-model classifier. Table 3 shows the coefficients and accuracy statistics for the 10 folds. Note that, for readability, coefficients with $p < .01$ are in bold.

Table 3 about here

The most prominent word category variables in the classifier, appearing in all 10 folds, are work (words such as 'income', 'salary' and 'service'), money (words such as 'audit', 'sales' and 'wages') and past (use of the past tense). The variable ipron (impersonal pronouns such as 'it', 'somebody' and 'who') appears in 7 folds while discrep (discrepancy words such as 'should', 'could' and 'ought') appears in five folds. The variable sad (sadness words such as 'grief' unhappy and 'doom') is relatively unimportant, appearing in only one fold. The forced InPower variable is not significant in any fold ($p > .1$). There are no variables with significance at the $p < .05$ level. In short, all variables other than InPower are significant at the $p < .01$ level.

The average accuracy of the 10 folds is 74% (95% CI: 69.88% – 77.87%) The sensitivity, that is, the ability to correctly classify ALP parliamentarians, is 66.83% (95% CI: 59.95% – 72.92%) while the specificity, the ability to correctly classify LNPC parliamentarians is 79.93% (95% CI: 74.63% – 84.54%). The Kappa statistic is .4698 ($p < .01$).

At 74%, the ensemble classifier has a slightly lower classification accuracy than the best classifier in the previous section. The multilayer perceptron with 42 hidden layers had an overall classification accuracy of 75.88% and the logistic model with all variables achieved an accuracy of 75.26%. However, as discussed above, the purpose of the current exercise was to extract the salient variables.

Having identified the important variables in the set of 80 under consideration the next step is to attempt to explain how these variables might be linked to ideology.

6. Regression Analysis

In the previous section 7 independent variables, including one control, were isolated as explaining most of the predictive power of the models created in the machine learning experiments. The next stage is to interpret the relationships between the independent variables and the dependent variable. The standard approach to this procedure is to look at the strength and direction of the coefficients for each variable and then try to determine possible reasons why each variable has its particular coefficient. However, in recent years it has become apparent that this approach is not sufficient for a correct interpretation because in a model with more than one variable, it is possible that the phenomenon known as 'suppression' is taking place and this can drastically affect the interpretation of coefficients (Nimon & Reio 2011; Nimon & Oswald 2013; Ray-Mukherjee et al 2014). A systematic discussion of suppressor effects is outside the scope of this paper. However, I will provide a basic outline of the phenomenon below.

Suppressor Effects

Of the 7 variables in the model, only four — work, past, discrep and sad — are 'predictors' in the standard sense. The independent variable InPower is a control, while the remaining variables, money and ipron are suppressor variables. A suppressor variable is an independent variable that is not correlated with the independent variable but 'suppresses' irrelevant variance in another independent variable so that the inclusion of the suppressor gives greater strength to the coefficients of both the suppressor and the predictor variables.

Consider Horst's (1966) finding that trainee pilots who scored well in mechanical aptitude tests were likely to complete their training successfully while there was no correlation between high scores on literacy tests and successful completion of training. When both variables were entered into a regression equation, the literacy test scores became significant and had a negative coefficient and the strength of mechanical aptitude test scores as a predictor increased. The reason for this was that the inclusion of literacy test scores in the equation reduced or 'suppressed' the influence of those high scores on mechanical aptitude which were due merely to the ability to read the instructions and answer the questions. Thus, the literacy score variable was not a predictor but a suppressor.

With this background, we need to consider the results of a 'commonality analysis' which allows us to determine which variables are suppressors and which are predictors. The analysis here is performed using an algorithm described in Ray-Mukherjee et al (2014). This algorithm is designed to examine the influence of the variables in a given model both individually and in combination with the other variables in a model. It should be noted that the analysis is undertaken in this case using linear regression. This does not mitigate the applicability of the findings despite the fact that logistic regression is usually applied to binary analyses. Indeed, given that the R^2 of the linear regression model with 7 variables is .2537 and that of the logistic regression model is .2130, there is no reason for preferring the logistic to the linear model. Further support for this proposition

comes from the fact that the coefficients in both the linear and logistic models have the same signs and the same levels of significance.

Table 4 shows the results of the linear regression commonality analysis for all 7 variables identified in the previous section.

Table 4 about here

With a beta of 2.792 ($p < .01$), work is the biggest influence on the dependent variable. The zero order correlation between work and the independent variable is 0.276 ($p < .01$). Thus, the beta and correlation are positive and significant indicating that this variable is not a suppressor. The structure coefficient, which is calculated by dividing the squared zero order correlation by the R^2 of the model ($R^2 = .2537$), shows how much variance is shared between the independent variable and the predicted outcome (\hat{Y}). Thus, work accounts for 30% of the R^2 of the model without taking into account its affect on other variables in the model. The unique effect of the variable is 0.165 indicating that this variable makes up $0.165/0.2537 = 65\%$ of the overall effect on the model R^2 . The variable's common effect (that is, it's effect in association with other variables) is -.089 indicating that it does have some roll in suppressing irrelevant variance in other variables. However given its positive association with the dependent variable it is essentially a predictor.

The variable money, unlike work, functions as a suppressor. It has a relatively high and significant beta of -1.774 ($p < .01$). However, its zero order correlation with the dependent variable is close to zero. The structure coefficient of .004 indicates that as an individual contributor to R^2 its influence negligible. It's unique contribution to R^2 is .065 but the common contribution of -.064 indicates that this is almost entirely made up of its action as a suppressor.

With these observations in mind we can now interpret the coefficients with better insight into coefficients of the individual variables. I will consider the predictors work, past, discrep and

sad and then go on to the more difficult task of attempting to unravel the suppression effects of the variables money and ipron.

work

The variable work is the most important variable in the model. The beta of 2.792. is the highest in the model and, as discussed above, although it has some suppression effects, it has the characteristics of a predictor.

On the face of it, the finding is not surprising given that the ALP is traditionally the party of the workers. However, to better understand what is going on it is worthwhile looking at how the term is used in speeches. The parliamentarian with the highest score on this measure is Bruce Childs (ALP) who scores 9.69 (Parliamentary average =5.00 stdev = 1.33). The following is an extract from his first speech:

Let us look at some detailed figures which support my argument that the Government favours the corporate sector at the expense of wage and salary earners. What has happened to individual taxpayers since this Government began its strategy in 1975? Looking at individual taxation alone, we find that while wages and salaries have gone up by only 71 per cent, tax paid by those workers has risen by 101 per cent. On the other hand, while wealthy non-pay-as-you-earn taxpayers' income from rent, interest, dividends, et cetera, has risen by over 80 per cent over the period, tax paid rose by only 55 per cent. As an example, let us take two workers at opposite ends of the scale. In 1975 one worker earned \$3,700 and the other \$30,000. How have these two taxpayers fared under this Government? The first is now earning \$6,000 a year and has had his after tax income cut by \$113 in

1981 terms. Twenty-eight per cent of our citizens are receiving salaries of \$6,000 or less.

The first interesting observation here is that Childs makes a distinction between the relative wealth of the corporate sector and the relative poverty of wage and salary earners. This is archetypal liberal concern for inequality. Interestingly, there is no mention of the fact that the income of the workers may be dependent on the health of the corporations and institutions, which would indicate a conservative orientation. In contrast, in the first speech of the parliamentarian with the lowest score on work (1.91), LNPC member Philip Ross Lightfoot, we can see that income inequality is not an issue. His speech is highly 'top down' in that he refers to the institutions of government and society but does not specifically refer to individuals. His speech deals with the High Court, the Monarchy, republicanism, mining, the Privy Council, cabinet and states' rights but he does not consider the welfare of individuals in the concrete way that Childs does. Lightfoot chooses not to discuss these issues because, as a conservative, he reasons that a prosperous society is dependent on the society's constituent institutions functioning properly. The conservative idea is that the worker will not prosper unless the institutions are protected. Inequalities that occur as a result of this top down approach are a necessary element of this arrangement (Jost et al. 2003).

The influence of these relative perceptions of the world is that the liberal ALP members will tend to focus on the sources and solutions to inequality, which will entail the use of the kind of vocabulary in the extract from Childs while conservative LNPC members will tend to see inequality as an unavoidable outcome of the system. This is in contrast to the liberal ALP parliamentarians who will focus on the less fortunate individuals who fail to benefit from the system. Thus, ALP members will discuss issues relating to individual workers such as work, tax, income and earnings to a greater extent than LNPC parliamentarians.

past

The traditional stance on temporal orientation and ideology is that conservatives hark back to the past and liberals are 'progressive' and therefore look to the future. The finding that ALP 'progressives' use the past tense more than LNPC members contradicts this.

Much of the traditional view of conservatives/liberals being past/future focused is supported by the interpretation of the relationship between psychological variables and ideology. In a large scale metastudy of the psychology of conservatives and liberals (Jost et al. 2003) it was found that there were strong associations of a number of psychological phenomena with conservatism. These were: death anxiety ($r = .50$); system instability ($r = .47$); dogmatism–intolerance of ambiguity ($r = .34$); openness to experience ($r = -.32$); uncertainty tolerance ($r = -.27$); needs for order, structure, and closure ($r = .26$); integrative complexity ($r = -.20$); fear of threat and loss ($r = .18$); and self-esteem ($-.09$). Because many of these variables focus on what might happen in the future it is held that conservatives wish to maintain a strong association with the past because the past is somehow safer. In contrast, it is held that liberals are willing to downplay the importance of tradition and stability and focus more on progress and flexibility. This strongly implies that the conservative will look to the past for security while liberals, with their emphasis on change, will look to the future. However, the above modeling shows that this time orientation is not apparent in the data.

There are contradictory findings about ideology and time orientation. Robinson et al (2015) found that in social media postings, conservatives use more past references than liberals in political blog postings. In contrast, Tumasjan et al (2010) examined the use of twitter in the 2009 German election and found that tweets mentioning all 6 party leaders and/or parties across the spectrum used the past tense at equal rates except for the Greens candidate for which the use of the past tense was slightly higher.

Given these contradictory finding in social media postings it is worthwhile to consider a study by Thornhill and Fincher (2007) which looked directly at how conservatives and liberals

regard time. They found that on psychological tests of time preference (positive versus negative attitudes to the past present and future), liberals and conservatives do not differ.

One way to get an insight into time orientation in the current study is to look at the speeches and try to determine what they are focusing on. However, inspection of the speeches shows that even those that use high levels of past references are referring to the recent past, particularly recent events and general conditions in their electorates. Thus, the ALP propensity to use the past tense is not related to the dynamics of the traditionalism/progressivism.

One possible explanation is that time orientation is functioning as a proxy for conscientiousness. Conservatives score higher on tests of conscientiousness than liberals. Zimbardo and Boyd (1999) found that those who emphasise the past tend to be less conscientious than those who emphasise the present and the future. Thus, the past tense may be functioning as a proxy for conscientiousness. Further support for this idea is given by the fact that Boyd and Zimbardo found that conscientious people use references to the future more than less conscientious people. If use of the past tense in the current study is a proxy for conscientiousness, then we should see LNPC parliamentarians using references to the future more than ALP members. The results show that this is the case: LNPC members use LIWC future terms at a higher rate of 1.07 than ALP members who averaged 0.98 (stdev = .328) and this difference is significant ($p < .01$). Thus, drawing on Boyd and Zimbardo's (2005) study and the known association between conservatism and conscientiousness, we can conclude that time references in this dataset are related to conscientiousness.

Before we leave this issue it is worth considering why conservatives have a reputation for 'looking back'. The answer is that we have been living in a period of increasing liberalism and therefore, to espouse conservative values is to desire a social structure that existed in our past. For a counterexample, consider that in 1777 Frederick the Great of Prussia, not known as a liberal, argued that beer was a healthier drink than coffee and that the consumption of coffee should be discouraged

and that of beer encouraged (Vallee 1998). The conservative disdain for alcohol is relatively recent and reached a peak in the US in the 1930s with their support for the prohibition of alcohol. This prohibition was therefore not a case of conservatives 'turning back the clock' but a radical reaction to a perceived social issue. The rather contentious point I am making here is that the putative association between conservatives and the past is mediated by our own recent history.

discrep

This variable includes the use of words such as 'could', 'ought', 'would' and 'must'. It has a negative association with ALP and has only minimal suppression effects. As such we can focus on its unique or 'predictor' effects.

The variable seems to tap into the strong sense of morality that is inherent in the conservative personality. Graham et al (2009) undertook four separate studies of the differences between liberals and conservatives in terms of their fundamental value systems and concluded that, while there was overlap in the moral bases of decisions used by both, the conservatives raised a larger set of moralistic concerns:

'In all four studies we found that liberals showed evidence of a morality based primarily on the individualizing foundations (Harm/care and Fairness/reciprocity), whereas conservatives showed a more even distribution of values, virtues, and concerns, including the two individualizing foundations and the three binding foundations (Ingroup/loyalty, Authority/respect, and Purity/sanctity) (Graham et al 2009: 1031).

Thus, in any moral issue, it is not the case that liberals use more of a particular way of looking at the world and conservatives use less, or vice versa; it is that conservatives bring to bear on a given issue a set of values that are not considered by liberals. In this context, it is easy to see that conservatives would have a greater propensity to look at the world in terms of 'shoulds', 'oughts' and

'musts'. They see a greater number of obligations and as such their speech is peppered with the language of those obligations.

sad

This is not an important variable in the classifier. It appears in only one model of the 10 constituent models. Nevertheless, it has a positive association with ALP and as such it is worthwhile mentioning some of the associations that have been found between this emotion and ideology.

Dodd et al (2012) found that conservatives were more likely than liberals to be distracted by negative or threatening images. Furthermore, they have a propensity to see the world as a dangerous place (Shook & Fazio 2009). However, the issue of overall sadness suggests that conservatives are generally happier than liberals. This is despite some the fact that 'conservatives report but liberals display greater happiness' (Wojcik et al 2012). Interestingly, Choma et al (2009) found that happiness for a liberal is defined as the presence of positive affect whereas happiness for the conservative is defined as the absence of negative affect. With this in mind we can see that the sad variable is picking up the general lack of sadness in the LNPC members and its relative presence in ALP members. The variable on its own does not tell us which of the two groups has a higher level of overall positive or negative affect made up of both happiness and sadness. In short, the albeit minor presence of LIWC sad in the ensemble confirms Choma et al's (2009) finding that conservatives are characterised by a relative lack of sadness.

money

The second most powerful variable is money (beta = -1.774). However, the evidence is that money is a suppressor variable.

The first indication that money is a suppressor variable is that it has no zero order correlation with the dependent variable ($r = -0.033$, $p > .1$) but is significant in the regression equation.

As discussed above, the structure coefficient shows that the individual contribution to the R^2 of the model is negligible. As such, its strength in the regression equation must be due to its common effect.

In Table 4 the unique effect of money on R^2 is 0.065 while the common effect is -0.064 giving a total effect of 0.001. What this indicates is that the common effect almost entirely negates the unique effect. That is, the suppression effects of money are a more important influence on the R^2 of the full model than the unique effect.

In order to better understand what is going on here we need to look at Table 5 which shows the commonalities for all 7 variables.

Table 5 about here

The suppression effect of money on work is the highest in the commonalities table. This suppression effect accounts for 25.12% of the R^2 of the model. The variable money also has suppressor effects on other variables such as ipron which accounts for 4.78% of the effect on R^2 . However, inspection of the commonalities shows that, by far, the greatest amount of suppression by money occurs between money and work. The question is, how do we interpret this?

It should be recalled that money terms are used equally by both ALP and LNPC parliamentarians, hence the lack of correlation between money and ALP. However, it seems that when ALP parliamentarians use money terms, they are generally talking about work whereas when LNPC parliamentarians use money terms they are generally not talking about work. In other words, money is suppressing irrelevant variance in work terms. Consider the extract from Child's speech

above. In that speech, the money terms are intimately associated with the world of work. Conversely, in Lightfoot's speech money terms are used to refer to the wealth generated by mining and how tax incentives have affected investment. There is a little discussion of work terms. Including the money variable in the equation reduces (suppresses) the use of work terms by those, such as Lightfoot, who do not use money words in association with work terms. In other words, ALP parliamentarians tend to use work and money terms together while LNPC parliamentarians use money terms with less reference to work.

We can therefore conclude that, despite money playing a significant role in the classifier, it is not because the use of such terms is associated with being an ALP or LNPC parliamentarian.

ipron

This is a suppressor variable. It has a high beta of 1.107 ($p < .01$) but it is not correlated with the dependent variable. Furthermore, its structure coefficient is approximately 1/12 of that for past and 1/25th of that for work. These factors indicate that it does not, on its own, have more than a negligible influence on the R^2 of the model. This is reflected in the low unique effect of .033 on the R^2 of .2537. This unique effect consists almost entirely of the common effect of -.027. Thus, excluding its actions as a suppressor variable *ipron* contributes only 0.006 to the R^2 of .2537.

Having established *ipron* as a suppressor variable, we need to consider what variables it is suppressing. Unlike money, which focused most of its suppression on one variable – work – the suppression action of *ipron* is spread over several variable so it is very difficult to discern its actions.

Table 5 in the Appendix shows that the strongest suppression effect of *ipron* is on work, which accounts for 9.16% of the total suppression in the model. I will therefore focus on the work – *ipron* interaction.

The main reason for the suppression effects on work seem to be that the ALP members use work terms in broad 'impersonal' ways while LNPC parliamentarians speak of work in more personal terms. This may be because the worker, for the liberal ALP member, is a general category about which the parliamentarian is concerned while for the conservative LNPC, the worker is merely an element of an overarching system. Ironically, this means that ALP members cannot afford the luxury of thinking of workers in individual terms because they are concerned with the plight of the worker as a class whereas the LNPC member can afford to think of individual workers in more personal terms because they are less focused on the workers as a whole. As such, references to work by ALP members are, on average, more impersonal than those by LNPC members because they cannot get personally involved with all those parties in relation to which they discuss work. Thus, LIWC ipron is a positive suppressor in that it enhances the effect in the model of work terms used by ALP parliamentarians and reduces the effect of work terms used by LNPC parliamentarians.

7. Conclusion

In this paper I have attempted to determine the psychological drivers of the broadly liberal-conservative ideology of parliamentarians of the left and right of the Australian federal parliament. Text analysis based on the first parliamentary speech a cohort of 485 parliamentarians was used to develop a classifier which with an accuracy of approximately 75%, indicating that there is a strong ideological signal in the data. I then went on to isolate the most salient variables. This procedure yielded 7 variables, of which four were predictors of the dependent variable, two were suppressors and one was a control. All four predictors were associated with factors that are generally associated with liberalism-conservatism. One interesting result was that references to the past are not positively associated with conservatism, as we might have expected, but with liberalism (membership of the ALP). I explained this being due to past references functioning as a proxy for

conscientiousness. I explain the putative association between the past and conservatism as being due to historical rather than ideological phenomena.

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Tables

Table 1: Distribution of InPower/not InPower Values for ALP and LNPC

	ALP	LNPC	Total
In Power	110	151	261
Not In Power	106	118	224
Total:	216	269	

Table 2: Results for Machine Learning Experiments

	Logistic Ridge = 1.08E	SMO RBF Kernel	SMO Polykernel	MLP HL = 42	MLP HL = 1
Accuracy	75.26	67.01	71.96	75.88	69.90
95% CI Lower	71.17	62.63	67.73	71.81	65.60
95% CI Upper	79.04	71.18	75.92	79.62	73.95
Sensitivity	70.37	60.65	66.67	69.91	66.20
95% CI Lower	63.80	53.79	59.95	63.32	59.47
95% CI Upper	76.37	67.21	72.92	75.94	72.48
Specificity	79.18	72.12	76.21	80.76	72.86
95% CI Lower	73.83	66.35	70.66	75.44	67.13
95% CI Upper	83.87	77.39	81.17	85.21	78.08
Kappa	0.4973	0.3292	0.4303	0.5088	0.3907
Kappa p	<.01	<.01	<.01	<.01	<.01

Table 3: Results for 10 Folds - Logistic Classifier

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10
Coeff										
InPower	-0.100	-0.203	-0.129	-0.113	-0.183	-0.104	-0.196	-0.109	-0.147	-0.117
discrep			-1.101			-1.125	-1.144	-1.102	-1.280	
ipron	0.338		0.543		0.387	0.510	0.450	0.516	0.522	
money	-0.971	-0.770	-0.888	-0.778	-1.102	-0.800	-0.916	-0.844	-0.947	-0.797
past	0.831	0.782	0.699	0.841	0.831	0.787	0.798	0.724	0.858	0.829
sad									2.172	
work	1.049	0.918	0.980	0.915	1.085	1.036	1.079	1.014	0.991	0.971
Constant	-7.401	-5.236	-6.459	-5.398	-7.625	-6.864	-6.549	-6.680	-7.151	-5.606
Acc' %										
Sensitivity	72.73	68.18	68.42	60.87	50.00	78.95	65.00	66.67	80.95	56.52
Specificity	70.37	85.19	93.33	80.77	89.66	72.41	60.71	85.71	85.19	76.00
Accuracy	71.43	77.55	83.67	71.43	73.47	75.00	62.50	75.00	83.33	66.67

Table 4: Regression Results

	B	Beta	Sig	Zero Order R	Struc' Coeff ²	Unique	Common	Total
ipron	0.529	1.107	0.000	0.078	0.024	0.033	-0.027	0.006
past	0.784	1.232	0.000	0.187**	0.140	0.047	-0.012	0.035
sad	1.933	0.695	0.004	0.102*	0.042	0.014	-0.004	0.010
work	1.045	2.792	0.000	0.276**	0.305	0.165	-0.089	0.076
InPower	-0.040	-0.040	0.857	-0.052	0.011	0.000	0.003	0.003
money	-0.977	-1.774	0.000	-0.033	0.004	0.065	-0.064	0.001
discrep	-1.316	-1.058	0.000	-0.157**	0.099	0.032	-0.007	0.025
Constant	-7.192		0.000					

Table 5: Commonality Analysis for 7 Variable Model

Variables	Coeff'	Percent	Variables	Coeff'	Percent
Unique: ipron	0.0334	13.18	ipron past money sad	0.0001	0.05
Unique: past	0.0474	18.68	ipron past work sad	-0.0001	-0.04
Unique: money	0.0651	25.65	ipron money work sad	-0.0004	-0.15
Unique: work	0.1649	65.00	past money work sad	-0.0012	-0.46
Unique: sad	0.0141	5.57	ipron past money InPower	-0.0002	-0.07
Unique: InPower	0.0001	0.03	ipron past work InPower	0.0001	0.02
Unique: discrep	0.0316	12.45	ipron money work InPower	0.0013	0.50
ipron past	0.0108	4.25	past money work InPower	-0.0002	-0.07
ipron money	-0.0121	-4.78	ipron past sad InPower	0.0001	0.02
past money	0.0008	0.33	ipron money sad InPower	-0.0003	-0.13
ipron work	-0.0232	-9.16	past money sad InPower	0.0001	0.02
past work	-0.0220	-8.69	ipron work sad InPower	-0.0005	-0.18
money work	-0.0637	-25.12	past work sad InPower	-0.0001	-0.04
ipron sad	-0.0004	-0.14	money work sad InPower	0.0007	0.27
past sad	-0.0019	-0.76	ipron past money discrep	0.0002	0.07
money sad	-0.0058	-2.27	ipron past work discrep	0.0013	0.50
work sad	0.0051	2.01	ipron money work discrep	-0.0022	-0.86
ipron InPower	0.0019	0.73	past money work discrep	-0.0001	-0.03
past InPower	0.0000	-0.01	ipron past sad discrep	0.0001	0.04
money InPower	0.0000	-0.02	ipron money sad discrep	-0.0008	-0.32
work InPower	0.0013	0.53	past money sad discrep	0.0004	0.14
sad InPower	0.0006	0.22	ipron work sad discrep	-0.0005	-0.20
ipron discrep	-0.0150	-5.90	past work sad discrep	-0.0001	-0.03
past discrep	0.0119	4.68	money work sad discrep	-0.0011	-0.42
money discrep	0.0034	1.32	ipron past InPower discrep	-0.0003	-0.10
work discrep	0.0030	1.18	ipron money InPower discrep	0.0002	0.10
sad discrep	-0.0051	-2.00	past money InPower discrep	0.0001	0.02
InPower discrep	-0.0001	-0.03	ipron work InPower discrep	-0.0002	-0.08
ipron past money	-0.0020	-0.79	past work InPower discrep	-0.0001	-0.02
ipron past work	-0.0048	-1.89	money work InPower discrep	-0.0002	-0.07
ipron money work	0.0118	4.66	ipron sad InPower discrep	-0.0002	-0.08
past money work	0.0008	0.30	past sad InPower discrep	0.0000	-0.01
ipron past sad	-0.0002	-0.09	money sad InPower discrep	0.0001	0.05
ipron money sad	0.0006	0.23	work sad InPower discrep	-0.0002	-0.09
past money sad	0.0004	0.16	ipron past money work sad	-0.0001	-0.05
ipron work sad	-0.0002	-0.06	ipron past money work InPower	0.0000	0.01
past work sad	0.0000	-0.02	ipron past money sad InPower	0.0000	0.00
money work sad	0.0046	1.82	ipron past work sad InPower	0.0000	0.01
ipron past InPower	0.0003	0.13	ipron money work sad InPower	0.0005	0.20
ipron money InPower	-0.0014	-0.54	past money work sad InPower	-0.0002	-0.09
past money InPower	0.0001	0.02	ipron past money work discrep	-0.0003	-0.11
ipron work InPower	-0.0001	-0.04	ipron past money sad discrep	-0.0001	-0.03
past work InPower	-0.0002	-0.08	ipron past work sad discrep	0.0002	0.09
money work InPower	-0.0003	-0.10	ipron money work sad discrep	0.0007	0.27
ipron sad InPower	0.0012	0.47	past money work sad discrep	-0.0003	-0.11
past sad InPower	-0.0001	-0.05	ipron past money InPower discrep	0.0000	0.01
money sad InPower	-0.0006	-0.22	ipron past work InPower discrep	0.0001	0.05
work sad InPower	0.0013	0.53	ipron money work InPower discrep	-0.0002	-0.09
ipron past discrep	-0.0046	-1.83	past money work InPower discrep	0.0000	-0.01
ipron money discrep	0.0023	0.90	ipron past sad InPower discrep	-0.0001	-0.04
past money discrep	0.0008	0.30	ipron money sad InPower discrep	-0.0002	-0.07
ipron work discrep	0.0068	2.70	past money sad InPower discrep	0.0001	0.02
past work discrep	-0.0029	-1.15	ipron work sad InPower discrep	0.0000	-0.01
money work discrep	-0.0029	-1.15	past work sad InPower discrep	0.0000	-0.02
ipron sad discrep	0.0013	0.51	money work sad InPower discrep	-0.0002	-0.10
past sad discrep	-0.0006	-0.22	ipron past money work sad InPower	0.0000	-0.01
money sad discrep	0.0010	0.38	ipron past money work sad discrep	0.0001	0.03
work sad discrep	-0.0011	-0.44	ipron past money work InPower discrep	0.0000	0.00
ipron InPower discrep	-0.0008	-0.33	ipron past money sad InPower discrep	0.0000	0.00
past InPower discrep	0.0000	0.01	ipron past work sad InPower discrep	0.0001	0.03
money InPower discrep	0.0002	0.08	ipron money work sad InPower discrep	0.0001	0.03
work InPower discrep	-0.0003	-0.13	past money work sad InPower discrep	-0.0001	-0.02
sad InPower discrep	-0.0003	-0.11	ipron past money work sad InPower discr	0.0000	0.00
ipron past money work	0.0019	0.77	Total	0.2537	100.00

Note: The first seven entries in the table are unique effects. All other values are common effects.