Report

Zhiyi Jin

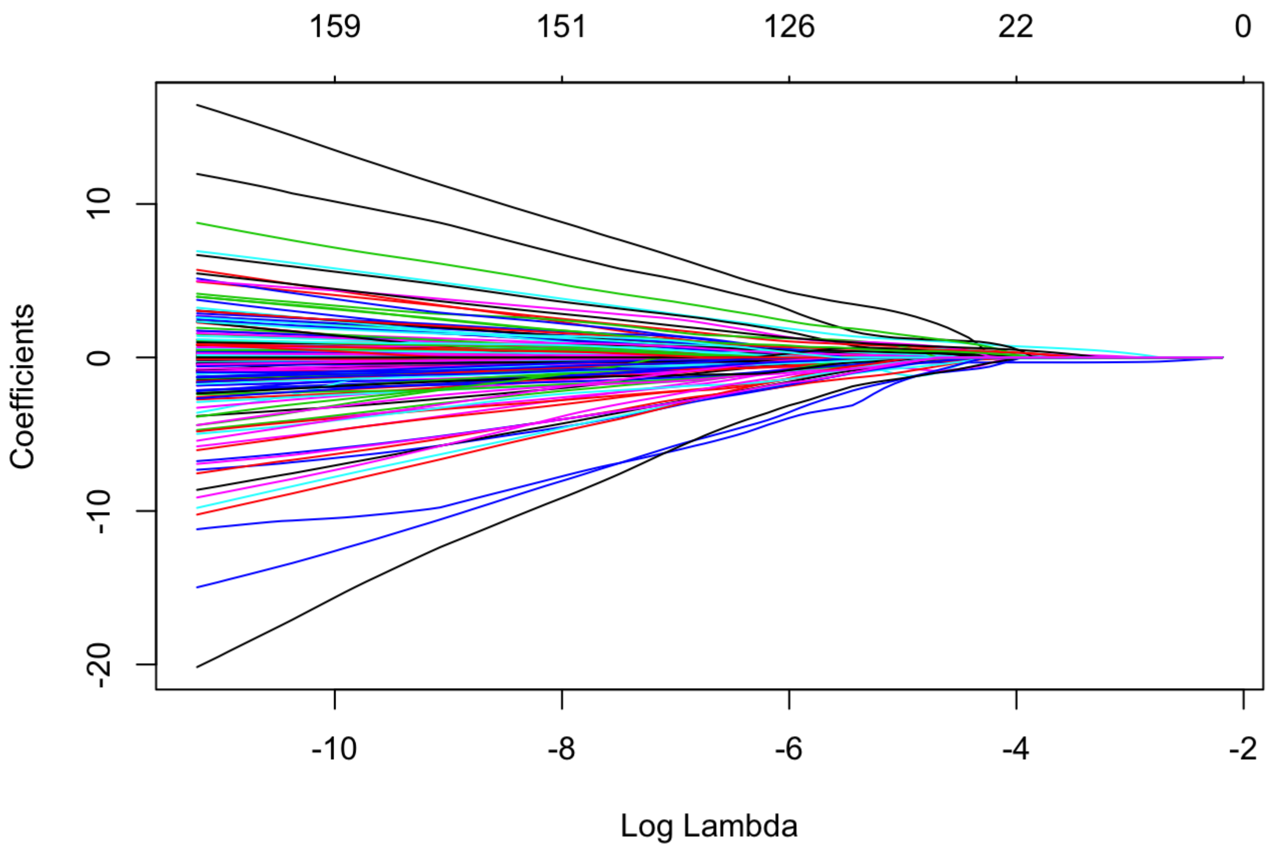
1. Possible predictors of voting for the Sweden Democrats

In recent years, many populist parties are rising in European countries. Sweden is no exception. The Sweden Democrats(Sverigedemokraterna SD), founded in 1918, now is a popular party in Sweden. The reason behind this growing electoral supports for these populist parties has been studied by many researchers from both economic and cultural perspectives. Specifically, employment and occupation seem to be qualified indicators of voting behavior. Unemployed people could be more likely to vote for the populist party. People with unstable occupations could have stronger economic security, further strengthens the likelihood of voting for SD. Attitudes towards immigrants and ethnicities can also be an indicator. People who anti-immigrants could be more likely to vote for SD.

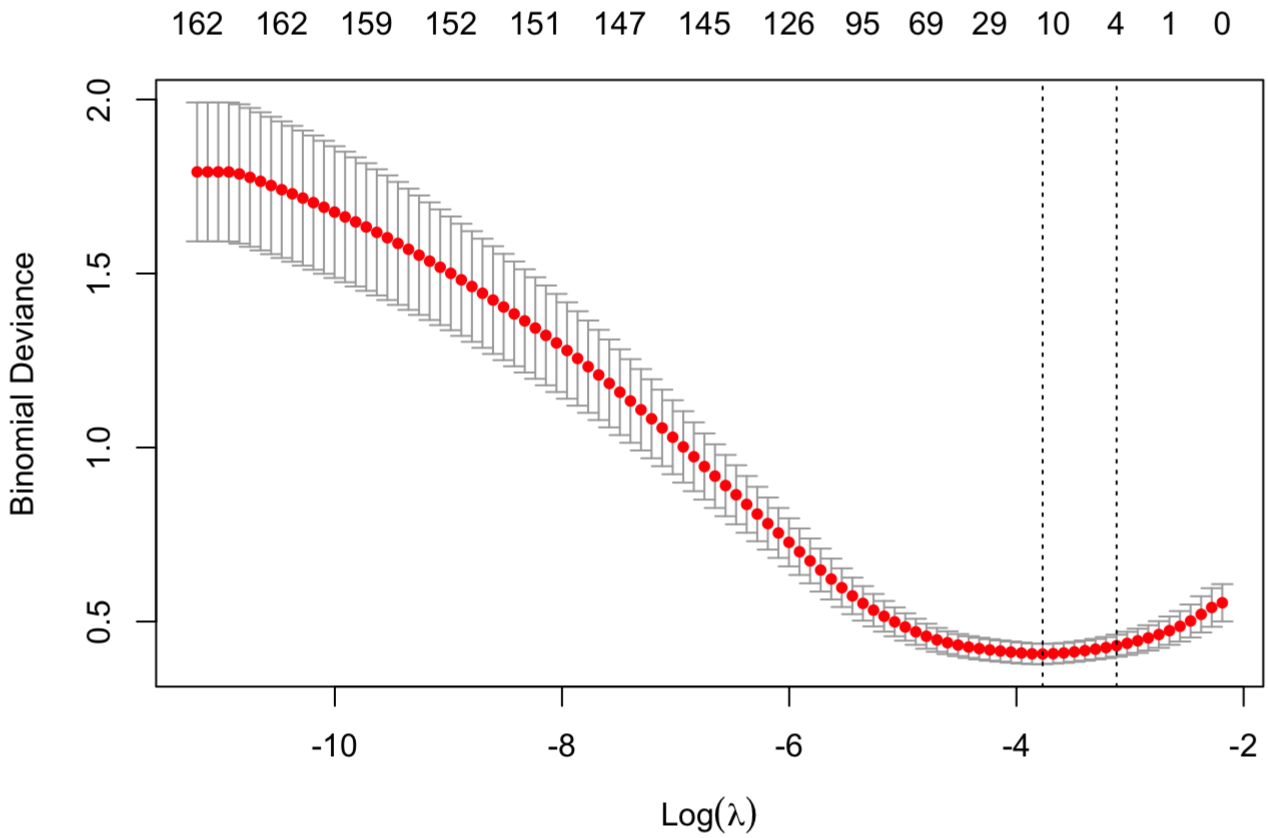
Considering the ESS data protocol, I assume that “imwbcnt”, which measures beliefs on immigrants making a country a worse or better place to live, could be one of the predictors. Though other immigrant-related variables could also be the predictors. “pdjob” could be another indicator, which indicates whether a respondent ever had a paid job. Finally, the occupation variable, “occgrp” is likely to be an indicator as well.

2. Logistic regression models with a lasso penalty

To make the logistic regression with a lasso penalty, I exclude the irrelevant ID variable, “idno”, and include all other variables. The coefficient paths as a function of λ values are plotted as follows:



3. Predictive accuracy of the lasso penalized models



It can be seen from the following table that there are seven variables are within one standard error of the model with the minimum error, as follows: (1)stfgov: How satisfied with the national government; (2)imbgeco: Immigration bad or good for the country's economy; (3)imueclt: Country's cultural life undermined or enriched by immigrants; (4)gvrfgap: Government should be generous in judging applications for refugees status; (5)rfgbfml: Granted refugees should be entitled to bring close family members; (6)vteurmmb2.Leave the EU: Would vote for Sweden to leave the EU (7)occgrp7.Craft and Trades: occupation group.

In summary, many of these variables are about immigration and refugees, which confirms my assumption to some extent although the imwbcnt variable is not included in the model. Occupation also turns out to be a prominent indicator. It confirms the influence of an economic-related factor on voting for SD that I assumed before.

Table: Minimum predictive error coefficients

row	column	coef	oddsrat	oddspct
(Intercept)	s1	-0.966	0.381	-61.929
imbgeco	s1	-0.308	0.735	-26.540
imueclt	s1	-0.039	0.962	-3.836
rfgbfml	s1	0.080	1.084	8.357
vteurmmb2. Leave the European Union	s1	0.354	1.424	42.406

4. Estimate an ordinary glm model

After fitting an ordinary glm model with seven variables, the coefficient values change a little bit and some variables become insignificant, while the direction of the influence does not change at all. The following table shows the results. Specifically, in both models, “imbgeco” and “imueclt” are negatively correlated with voting for SD. The better influence of immigration on the economy and cultural life the respondents feel, it’s more unlikely that they vote for SD. Specifically, in the lasso regression model, one unit increase in “imbgeco” and “imueclt” will result in a 27% and 5% decrease in the odds of voting for SD. However, in the glm model, the values slightly increase to 33% and 6%, respectively. And the “imueclt” becomes insignificant. Likewise, the “gvrfgap” and “occgrp7” also become insignificant. But originally in the lasso model, the “gvrfgap” and “occgrp7” are associated with around 2.6% and 3% higher odds of voting for the SD.

Table: Logistic Regression Result

	Dependent variable:
	votesd
stfgov	-0.082
	(0.095)
imbgeco	-0.413***
	(0.106)
imueclt	-0.068
	(0.087)
gvrfgap	0.215
	(0.200)
rfgbfml	0.396**
	(0.193)
vteurmmb2. Leave the European Union	1.149***
	(0.374)
occgrp10. Armed Forces	-12.679
	(1,172.102)
occgrp2. Professionals	-1.446
	(1.077)
occgrp3. Technicians	-0.503
	(0.886)
occgrp4. Clerical	0.174
	(0.994)
occgrp5. Services	-0.382
	(0.873)
occgrp6. Skilled Agricultural	-1.349
	(1.426)
occgrp7. Craft and Trades	0.528
	(0.889)
occgrp8. Plant and Machine Operators	0.926
	(0.890)
occgrp9. Elementary	0.114
	(1.231)
Constant	-2.097
	(1.280)
Observations	750
Log Likelihood	-118.030
Akaike Inf. Crit.	268.061
Note:	*p<0.1;* ***p<0.05;*** p<0.01