Voting Patterns in the 32nd Dáil Éireann

Ireland is a parliamentary democratic country; it has Dáil Éireann as the lower house and Seanad Éireann as the upper house of the Oireachtas. The elected members of Dáil Éireann are called TDs – *Teachta Dála* (or Deputies). The people directly elect TDs to the Dáil in a general election. The Dáil is part of the legislative (or lawmaking) branch of the Irish State.

In this short research, we want to investigate the voting patterns in the 5th session of the 32nd Dáil Éireann using poLCA function in R. There were several votes in Dáil Éireann by the set of elected TDs. The summary of the main topic for each vote as below.

Table 1. Voting Topics Details

Topic	Detail	Result
Environment	Environmental Policy: Motion (Resumed)	LOST
Rent Freeze	Rent Freeze (Fair Rent) Bill 2019: Second Stage (Resumed)	CARRIED
Social Welfare	Social Welfare (Payment Order) (Amendment) Bill 2018: Second Stage (Resumed)	CARRIED
Gambling and Lotteries	Gaming and Lotteries (Amendment) Bill 2019 [Seanad]: Order for Report Stage	CARRIED
Housing Minister	Confidence in the Minister for Housing, Planning and Local Government	LOST
First Time Buyers	Planning and Development (Amendment) (First-Time Buyers) Bill 2019: Second Stage (Resumed)	CARRIED

How do we Manipulate the Data?

The term 'poLCA' stands for Polytomous Latent Class Analysis, and it generally is used to a categorical data. A latent class model uses different response patterns in the data to find similar groups. The model aims to identify groups that are 'conditionally independent.' In these groups, there is zero correlation between the variables (meanwhile sometimes a relationship can be explained by examining the group membership). For example, there will be a tendency for TDs from a particular party will vote 'yes' or 'no' based on their party's manifestos.

As a result of analyzing the data, there are two latent classes can be identified.

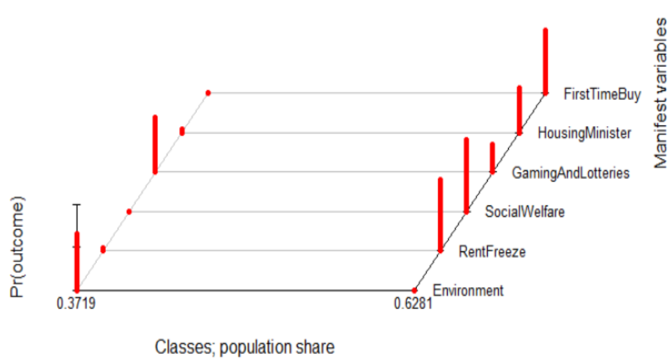

Figure 1. Estimated Two Latent Classes Model using the Bin.votes Data

Out of the total 156 TDs in this voting data, the first latent class contains 37.2% of the members (56 to be precise), and the second latent class includes the rest (62.8%, 100 members). Each group of red bars in Figure 1 represents the conditional probabilities of a topic being voted 'yes' (in favor of), by a latent class. Taller bars indicate the conditional probabilities are closer to 1.

In Figure 2, we can compare the probabilities of further discussion on topics by each class. 'Gambling and Lotteries' topic has an equal probabilities accumulation between the two classes. However, since the population of the second class is larger and more members voted for 'no', it will not be discussed any further.

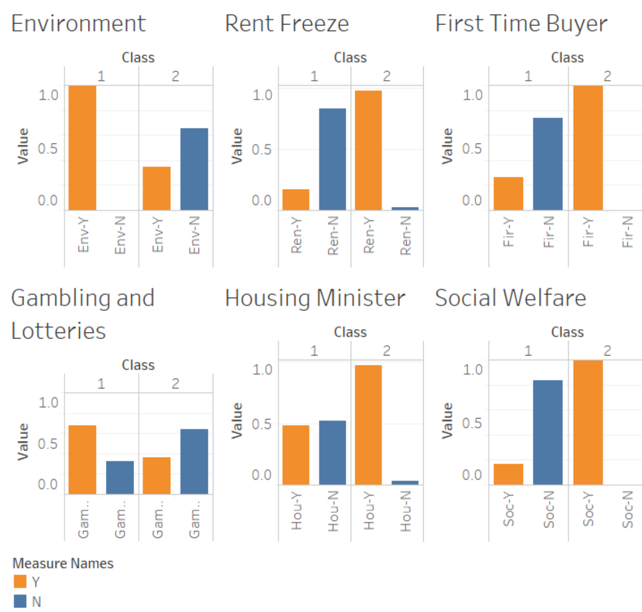

Figure 2. Probabilities of Yes and No for Selection Topic

The first latent class tends to vote 'yes' for the further discussion of 'Environment topic', while 'Rent Freeze ', 'Housing Minister ', 'First Time Buyer ', and 'Social Welfare' topics tend to be voted yes for further discussion by the members of the second latent class. These last four topics were carried (see table 1) because they were considered as important by most of the TDs. Let us examine the membership of each class.

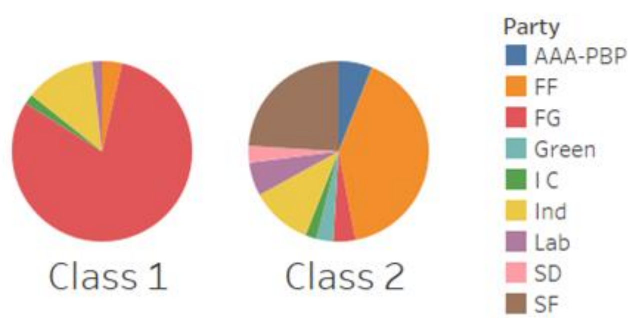

Figure 3. Class Memberships

In the first class containing 56 members, FG (Fine Gael) accounts for most of the membership, with 45 out of 49 FG representatives present. As for the second class consisting of 100 members, including all of the SF (Sinn Féin) representatives, and 41 out of 43 of the FF (Fianna Fáil) representatives are included. This data shows a higher tendency probability that the SF and FF parties have similar manifestos influencing their voting.

Now from the report of function:

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Estimated class population shares
 0.6281 0.3719

Predicted class memberships (by modal posterior prob.)
 0.641 0.359

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Fit for 2 latent classes:
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number of observations: 156
number of estimated parameters: 13
residual degrees of freedom: 50
maximum log-likelihood: -462.0166

AIC(2): 950.0332
BIC(2): 989.6813
G^2(2): 58.95794 (Likelihood ratio/deviance statistic)
X^2(2): 67.89262 (Chi-square goodness of fit)
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Figure 4. poLCA Output

Figure 4 provides the estimated class population shares, corresponding to the percentage of observations belonging to each latent class. The other way to determine this is through its 'modal posterior probability', the result of which is provided as 'predicted class memberships'. Both results have close resemblance and indicate a good fit of the model to the data.

The rest of the report discloses the number of observations, the number of estimated parameters, residual degrees of freedom, and maximum log-likelihood. Lastly, is the output of goodness of fit statistics. Before two latent classes is chosen for further analysts, there were pre-analysis on a few models.

Table 3. Models containing 2 - 6 Clusters

Model	BIC	AIC
Model 2	989.68	950.03
Model 3	1004.96	943.96
Model 4	1017.07	934.73
Model 5	1047.84	944.14
Model 6	1076.97	951.92

In this case, a model with 2 clusters has the lowest BIC, and the model with 4 clusters has the lowest AIC. In general, it might be best to use AIC and BIC together in model selection. Here, in selecting the number of latent classes in a model, if BIC points to a two-class model and AIC points to a four-class model, it makes sense to select from models with 2, 3, and 4 latent classes. In this research, the lowest 'Bayesian Information Criterion' (BIC) is then employed to choose the optimal model, since it induces a higher penalization for models with an intricate parametrization of the value 989.68 (model with 2 clusters). Based on Occam's razor, the best pattern can always be seen in a general way with the simplest model.