Modelling voting behaviour during a general election campaign using dynamic Bayesian networks

Patrício Costa[1234] [0000-0002-1201-9177], Ana Rita Nogueira[56][0000-0002-2005-1943], João Gama[16][0000-0003-3357-1195]

[1] Faculty of Economics – University of Porto, Portugal
[2] Life and Health Sciences Research Institute (ICVS), School of Medicine, University of Minho, Braga, Portugal
[3] ICVS / 3B's–P.T. Government Associate Laboratory, Braga / Guimarães, Portugal,
[4] Faculty of Psychology and Education Sciences, University of Porto, Porto, Portugal
pcosta@med.uminho.pt
[5] Faculty of Sciences of the University of Porto, Porto, Portugal
[6] LIAAD - INESC TEC, Porto, Portugal

Abstract. This work aims to develop a Machine Learning framework to predict voting behaviour. Data resulted from longitudinally collected variables during the Portuguese 2019 general election campaign. Naïve Bayes (NB), and Tree Augmented Naïve Bayes (TAN) and three different expert models using Dynamic Bayesian Networks (DBN) predict voting behaviour systematically for each moment in time considered using past information. Even though the differences found in some performance comparisons are not statistically significant, TAN and NB outperformed DBN experts' models. The learned models outperformed one of the experts' models when predicting abstention and two when predicting right-wing parties vote. Specifically, for the right-wing parties vote, TAN and NB presented satisfactory accuracy, while the experts' models were below 50% in the third evaluation moment.

Keywords: Machine Learning, Voting behaviour, Dynamic Bayesian Networks, Causality.

1 Introduction

The study of the determinants of voting behaviour is one of the main topics of research in the political science domain. The development of theoretical models to explain and predict voters' decisions started in 1940 at Columbia University, with a team of social scientists led by Paul Lazarsfeld. He applied sophisticated survey research methods to the study of electoral behaviour.

Nowadays, political scientists face new challenges, considering the declining voter turnout, the increasing volatility or the emergence of new political parties, which have introduced new electoral realignments, leading to the emergence of new theories. With the decline of the traditional (structural, class) determinants of voting, it becomes necessary to find new axes that explain voting behaviour.

With the decline of party identification and other traditional long-term anchors in voting decisions, short-term factors are being increasingly relevant [1]. These short-term factors include party leaders' traits, economic growth and campaign issues. Nowadays, party leaders are assuming a central role in contemporary Western Democracies, independently of their political system. However, strong empirical evidence is needed. This phenomenon, described as the personalisation of politics, accounts for the ascending importance of the politician as an individual actor [2], being an important determinant on voting decisions [3].

Langer [4] divides personalisation into three categories: *presidentialization* of power, leadership focus and politicisation of private persona. There is an inconsistent definition of the personalisation of politics phenomenon. It is considered the process of increasing the prominence of the politician as an individual [2]. Briefly, personalisation is changing the focus of politics from issues to people and from parties to politicians [5].

This new role of the party and political leaders enhances the need for political campaign staff and polls' companies to adapt to a new reality. It is also an opportunity to reflect on the boundaries of political marketing strategies, particularly political campaigns and their effects.

ML allows the researcher to drive new theory by uncovering hidden complexities, to elucidate blind spots between theory and reality, and it also leads to new measures for analytical modelling with smaller samples [6].

We seek to extend the traditional analytical tools/methodologies applied in the Political Science research domain. Accompanying the recent developments within other research areas, to predict voting behaviour, mainly turnout and main party choices (left-wing and right-wing parties). Our main goal is to develop and test different Bayesian Networks (BNs) based on the main predictors of voting behaviour collected during the Portuguese 2019 general election campaign. We explore the influence of political leaders' personality traits and campaign tone on implicit and explicit measures of voting behaviour longitudinally. Thus, we propose the use of Dynamic Bayesian Networks (DBNs) to explore the underlying causal mechanisms that drive voters' decisions in different situations during a campaign period.

Our primary research hypotheses consist in studying voting behaviour main determinants (sociodemographic characteristics such as sex, age and education), political attitudes (such as party identification and political interest), party leaders' traits and campaign tone perceptions. We also aim to test the stability of voting behaviour during the campaign period and what are the main drivers for change. We will test the campaign effects and how the mentioned variables affect voting behaviour. Finally, and the most relevant for this work, we aimed to compare the performance of voting behaviour predictions of the NB and TAN ML algorithms with the three different expert models using DBN. This paper is organised as follows: Section 2 describes some essential definitions. Section 3 describes data and the proposed approach, Section 4 the results obtained in the tests, and Section 5 contains the main conclusions and some limitations of this work.

2 Background

In this section, we briefly describe some of the Bayesian learning methods used in data mining for classification problems. We start by presenting the NB classifier. Then, we introduce BNs [23], emphasising the TAN [24], which is an extension of the NB classifier. Finally, we present DBNs, which are BNs that allow incorporating a temporal component, besides the causal model.

The NB classifier uses probabilistic methods and assumes that all the attributes' values are independent between them. This method allows calculating the conditional probability of the object belonging to the class C is given by the following expression (1) [9].

$$\mathrm{P}(C|A_1, \ldots, A_n) = \alpha \,.\, \mathrm{P}(\mathrm{C}) \,.\, \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}(A_i|\mathrm{C}) \; (1)$$

The NB classifier learns from "training data the conditional probability of each attribute A_i given the class label C. Classification is then done by applying Bayes rule to compute the probability of C given the particular instance of A_1, …, A_n, and then predicting the class with the highest posterior probability [8, pp. 131–132].

Furthermore, the described independence assumption is problematic to observe in real-world situations. In many cases, we cannot ignore the theoretically-supported relations between some relevant variable used for modelling.

Thus, a BN model consists of a directed acyclic graph of 'nodes', in which its values are defined in terms of different, mutually exclusive, 'states', and 'links' that conceptualise a system. The edges of the graph form a directed acyclic graph (DAG), which is a graph with no cyclic paths (no loops), allowing for efficient inference and learning [10].

The BNs rely on Bayes' theorem in the sense that it describes how prior knowledge about a given hypothesis H is updated by the observation of the evidence E.

The Bayesian networks are factored representations of probability distributions that generalise the NB classifier and allow to represent and manipulate independence assumptions effectively. Although, while BNs require space of all possible combinations of edges, TAN examine a restricted form of correlation edges, approximating the interactions between attributes by using a tree structure imposed on the NB [8]. TAN is based on the supposition that a classifier with less restrictive assumptions could outperform the NB classifier.

TAN classifiers allow to form a tree structure and consequently reduce the NB bias. The K-Dependence Bayesian Classifier (K-DBC) consists in a BN, containing the structure of an NB and allowing each feature to have a maximum of k-feature nodes as parents [11].

The BNs that allows incorporating a temporal component, besides the causal model, are called DBNs. These graphical model-based methods allow time-series modelling, and their static component (nodes, edges and probabilities) interpretation is similar to the one of BNs. They can find probabilistic models representing a system's causal structure [12] and allow for detailed voting behaviour predictions.

Some assumptions should be ensured when applying and analysing a constraint-based algorithm [13]:

a. Causal sufficiency: the set of observed variables satisfies the causal sufficiency assumption;
b. Faithfulness and Markov condition: the states of a DBN satisfy the (first-order) Markov condition (the state of a system at time *t* depends only on its immediate past, the state at time *t-1*): *the future is independent of the past given the present* [14, p. 2];
c. Reliable independence tests.

With DBNs, a dynamic system is modelled, and the underlying process is stationary (the assumption that the data are generated by a distribution that does not change with time; the structure and parameters of DBN are fixed over time). Different approaches have been proposed to relax this restriction [15], [16].

On the other hand, the use of BNs has some substantial advantages such as:

a. It facilitates learning causal relationships between variables [17], and can easily be converted into decision support systems [18];
b. Its graphical capabilities display the links between different system components, thus facilitating the discussion of the system structure [19];
c. They may be interpreted as a causal model which generated the data. The arrows in the DAG can represent causal relations/dependencies between variables. However, to assume causality, association data is not enough [10].

In the next section, we explore the variables that will be modelled, and we implement the described learning algorithms.

3 Data

3.1 Data Collection

This project uses longitudinal data collected in four different moments concerning the Portuguese 2019 general election (t_0 - approximately two weeks before the campaign period – selection study; t_1 - pre-campaign; t_2 - campaign; and t_3 - post-election.

3.2 Participants

The study sample size comprises of 236 participants. From which 61% are female (n=145), 13% (n=31) aged between 18 and 24 y.o., 36% (n= 85) aged between 25 and 34 y.o., 33% (n=77) aged between 35 and 44 y.o. and 18% (n=43) older than 44 y.o. The majority of the participants have higher education (59%; n=140).

3.3 Variables

Absolute frequencies and percentages for all the measured variables are presented in Table 1. Left-right ideology and party identification were only measured at the baseline since they can be considered long-term factors for voting behaviour prediction. The majority of our sample voters revealed not being identified with a particular party (58%), positioning themselves on the centre in the left-right ideology scale. The importance of voting, the interest in politics, the campaign tone and leaders' evaluations for left and right parties were collected in the four time points.

Table 1. Study population by political attitudes variables in different moments in time

Variables		***t*₀**		***t*₁**		***t*₂**		***t*₃**	
		N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Left-right ideology	Left	62	26.3%						
	Center	126	53.4%						
	Right	48	20.3%						
Party identification	No party identification	136	57.6%						
	Left parties	65	27.5%						
	Right parties	35	14.8%						
Importance of voting	It does not make any difference	52	22.0%	29	12.3%	36	15.3%	31	13.1%
	It does make the difference	184	78.0%	207	87.7%	200	84.7%	205	86.9%
Interest in politics	Not interested in politics	42	17.8%	28	11.9%	21	8.9%	19	8.1%
	Interested in politics	194	82.2%	208	88.1%	215	91.1%	217	91.9%
CT_left Left parties campaign tone	Negative	48	20.3%	49	20.8%	55	23.3%	62	26.3%
	Neutral	113	47.9%	123	52.1%	134	56.8%	118	50.0%
	Positive	75	31.8%	64	27.1%	47	19.9%	56	23.7%
CT_right Right parties campaign tone	Negative	118	50.0%	59	25.0%	79	33.5%	89	37.7%
	Neutral	62	26.3%	107	45.3%	93	39.4%	107	45.3%
	Positive	56	23.7%	70	29.7%	64	27.1%	40	16.9%
PL_left Left parties leaders	Low	50	21.2%	42	17.8%	56	23.7%	61	25.8%
	Medium	116	49.2%	139	58.9%	121	51.3%	112	47.5%
	High	70	29.7%	55	23.3%	59	25.0%	63	26.7%
PL_right Right parties leaders	Low	90	38.1%	77	32.6%	101	42.8%	103	43.6%
	Medium	89	37.7%	108	45.8%	84	35.6%	99	41.9%
	High	57	24.2%	51	21.6%	51	21.6%	34	14.4%
VOTE Voting behaviour	Abstention	62	26.3%	59	25.0%	56	23.7%	28	11.9%
	Left parties	120	50.8%	125	53.0%	117	49.6%	131	55.5%
	Right parties	54	22.9%	52	22.0%	63	26.7%	77	32.6%

3.4 Data Modelling

The first approach for data modelling consisted of the application of the NB learning algorithm. The second algorithm was TAN. Finally, considering the temporal dependencies of our data, a third learning algorithm was applied, the DBN, which is a BN that relates variables to each other over adjacent time steps [20]. Three experienced PhD researchers and specialists in the political science research domain were invited to build connections between the variables following the assumption that the aim was to predict voting behaviour (abstention, left and right). The three conceptualised models were tested using DBN (EXP_1, EXP_2, and EXP_3).

3.5 Comparison of models

To assess if there are significant differences in the performance of the five different approaches, we followed recommendations in the literature [21]. We had used the corrected Friedman test [22], followed by *Nemenyi* test or Friedman's Aligned Ranks test, with *Shaffer* procedure to correct the p-values [23], [24], when significant differences were found. The results from the *post-hoc* tests are presented with average rank diagrams.

4 Results and Discussion

For the importance of voting and interest in politics, we used Cochran's Q test to compare the proportion of voters considering that voting does make the difference and voters interested in politics across the four measurement moments. Significant differences were found in both variables (importance, $\chi2(3) = 17.2$, $p = .001$; interest $\chi2(3) = 30.1$, $p < .001$). Pairwise comparisons were then performed, and p-values were adjusted using the Bonferroni correction method. Regarding the importance of voting, significant differences were found between baseline (t_0) and measurement moments t_1 ($p=.004$) and t_3 ($p=.001$). No significant differences were observed between t_0 and t_2 (middle campaign period; $p=.057$) and all the other pairwise comparisons. As for the interest in politics, differences were found only between the baseline (t_0) and all the other measurement moments (p's <.05). No significant differences were detected for all the other pairwise comparisons. These results demonstrate that the proportion of voters considering that voting does make the difference and voters interested in politics changed significantly over time.

The majority of participants (54%) maintained their option from t_0 to t_3. For those who changed across the campaign period, 8% returned to their baseline option. The most relevant change occurred from abstention in t_0 to voting in a left party (12%).

The real 2019 election abstention was 51.4%. The reported abstention in the post-election poll was approximately 12%, which is significantly different from the real one ($\chi2(1) = 148$, $p<.001$). The reported turnout rates are frequently higher than the real ones. On the one hand, people who vote and who are willing to answer surveys are likely to be correlated, leading to an under-representation of abstainers in surveys [25].

On the other hand, the pressure of social norms leads individuals to over-report voting in an attempt to conform to socially desirable behaviour [26], particularly when they are asked about voting in a survey. However, if we only consider turnout and the distribution of left and right parties, vote results from this study (63% and 37%, respectively) are similar to the real ones (62% and 38%, respectively; considering the same parties about whom were obtained voting intentions in the study), $\chi 2(1) = 0.183$, p=.669.

Before modelling data, it is crucial to capture the relations between the variables. Since we have dichotomous, polytomous, dichotomised and polytomized data, different coefficients were computed (Pearson's Phi, Cramer's V, tetrachoric and polychoric, respectively). Generally, the highest correlations observed were within the same variables across time (the highest observed value was between Interest t_1 and Interest t_3; .932). The campaign tone was also highly correlated with the party leaders' evaluations.

Regarding voting behaviour, the highest correlation was between Vote t_1 and Vote t_2 (Cramer's V = .747). The highest observed correlations were between time t and t-1, the immediate past. However, there are also considerable correlations between other moments in time. This might indicate that the assumption that t+1 is independent of t-1 given that t is not fully accomplished. We performed a few multinomial logistic regressions and detected the violation of this assumption in some cases.

The correlation between the baseline and the reported vote after the election was only Cramer's V =.399, meaning that voting behaviour changes across time.

Next, NB, TAN and the DBN models and their main results are described. The estimated probabilities presented in Table 2 correspond to the model predicting the reported vote in t3 (post-election survey), using all the previous information. This estimation is the main outcome of this work. For NB and TAN, we do not have results for t0 to t2 because, in these cases, all the information was used to model t3. For the experts' models, since the DBN is the temporal component that is considered, the probabilities for all moments in time points are presented.

Table 2. Voting behaviour (temporal) probability distributions

Model	VOTE Voting behaviour	t_0	t_1	t_2	t_3
NB	Abstention				0.120
	Left parties				0.554
	Right parties				0.326
TAN	Abstention				0.120
	Left parties				0.554
	Right parties				0.326
EXP_1	Abstention	0.260	0.198	0.181	0.176
	Left parties	0.490	0.515	0.522	0.524
	Right parties	0.250	0.287	0.297	0.301
EXP_2	Abstention	0.263	0.201	0.184	0.179
	Left parties	0.491	0.512	0.519	0.521
	Right parties	0.246	0.287	0.297	0.301

	Abstention	0.271	0.194	0.169	0.161
EXP_3	Left parties	0.450	0.526	0.547	0.555
	Right parties	0.278	0.280	0.284	0.285

NB and TAN models present similar class proportions for t3, which correspond to the obtained result in our sample. Regarding the experts' models, these models differ significantly from the observed proportions in t3 (for EXP_1 and EXP_2, $\chi2(2) = 59.7$, $p < .001$; and for EXP_3, $\chi2(2) = 80.4$, $p < .001$). EXP_1 and EXP_2 revealed to be similar models. NB and TAN models predictions do not differ significantly from the real reported values ($\chi2(2) = 5.79$, $p = .055$ and $\chi2(2) = 2.82$, $p = .244$, respectively). Experts models tend to overestimate the abstention proportion and to underestimate the vote in the right parties. However, as shown in Table 2, there is a trend to diminish the abstention probabilities and to increase the vote for the right parties.

We developed and tested five different models (EXP_1, EXP_2, EXP_3, NB and TAN) for the prediction of a multiple class outcome (abstention, left and right) in three different predictions across time (predicting vote at time point 1 (t_1) using the information gathered in time point 0 (t_0); predicting vote at time point 2 (t_2) using the information gathered in t_0 and t_1; and, finally, predicting vote at time point 3 (t_3) using the information gathered in t_0, t_1 and t_2).

The method used in this project was the leave-one-out cross-validation (LOOCV), which is a particular case of k-fold cross-validation, where k is the number of samples [27]. The method consists of repeating the holdout method for the total sample size (N, where parameter k is equal to N). Basically, in each fold, the model trains with all participants except for the one (N-1) who is used to test (prediction). This approach has the advantage of using all participants for training and testing the model, which is particularly relevant, considering our study sample size.

For validation purposes three different models were performed. We develop a model:

1. in t_0 and predict for t1 (m1);
2. with t_0 and t_1 and predict for t_2 (m2);
3. with t_0, t_1 and t_2 and predict for t_3 (m3).

The obtained results for the LOOCV method, using DBNs, are presented in Table 3.

Table 3. Performance measures

Outcome	Model	Measure	EXP_1	EXP_2	EXP_3	NB	TAN
Abstention	m1	Accuracy	0.720	0.720	0.653	0.775	0.763
		Precision	0.462	0.462	0.391	0.547	0.525
		Recall	0.729	0.729	0.695	0.593	0.525
		Specificity	0.718	0.718	0.638	0.836	0.842
		AUC	0.766	0.766	0.682	0.834	0.825
	m2	Accuracy	0.805	0.805	0.809	0.843	0.852
		Precision	0.561	0.561	0.562	0.651	0.714
		Recall	0.821	0.821	0.893	0.732	0.625
		Specificity	0.800	0.800	0.783	0.878	0.922
		AUC	0.858	0.858	0.893	0.900	0.888

	m3	Accuracy	0.725	0.725	0.695	0.847	0.873
		Precision	0.215	0.215	0.194	0.400	0.450
		Recall	0.500	0.500	0.500	0.571	0.321
		Specificity	0.755	0.755	0.721	0.885	0.947
		AUC	0.652	0.652	0.646	0.768	0.743
Left	m1	Accuracy	0.771	0.771	0.716	0.767	0.763
		Precision	0.820	0.820	0.796	0.792	0.785
		Recall	0.728	0.728	0.624	0.760	0.760
		Specificity	0.820	0.820	0.820	0.775	0.766
		AUC	0.807	0.807	0.782	0.877	0.880
	m2	Accuracy	0.843	0.843	0.856	0.839	0.839
		Precision	0.851	0.851	0.881	0.856	0.821
		Recall	0.829	0.829	0.821	0.812	0.863
		Specificity	0.857	0.857	0.891	0.866	0.815
		AUC	0.901	0.901	0.905	0.927	0.920
	m3	Accuracy	0.750	0.750	0.763	0.831	0.831
		Precision	0.795	0.795	0.832	0.864	0.827
		Recall	0.740	0.740	0.718	0.824	0.878
		Specificity	0.762	0.762	0.819	0.838	0.771
		AUC	0.824	0.824	0.855	0.917	0.895
Right	m1	Accuracy	0.881	0.881	0.860	0.881	0.847
		Precision	0.875	0.875	0.788	0.731	0.643
		Recall	0.539	0.539	0.500	0.731	0.692
		Specificity	0.978	0.978	0.962	0.924	0.891
		AUC	0.839	0.839	0.860	0.925	0.923
	m2	Accuracy	0.852	0.852	0.877	0.886	0.886
		Precision	0.850	0.850	0.947	0.790	0.781
		Recall	0.540	0.540	0.571	0.778	0.794
		Specificity	0.965	0.965	0.988	0.925	0.919
		AUC	0.872	0.872	0.847	0.933	0.927
	m3	Accuracy	0.746	0.746	0.763	0.839	0.839
		Precision	0.673	0.673	0.706	0.775	0.753
		Recall	0.429	0.429	0.468	0.714	0.753
		Specificity	0.899	0.899	0.906	0.899	0.881
		AUC	0.812	0.812	0.805	0.894	0.883

Considering the overall accuracy of the three predictions (vote at t_1, t_2 and t_3), no significant differences were found between the five models tested (corrected Friedman's $\chi 2(4, 8) = 2.93$, p=.091). Since we have a multiple class outcome (abstention, left and right), we also compared the accuracy for each outcome in the five models, and no significant differences were found for the vote in right-wing parties (corrected Friedman's $\chi 2(4, 8) = 3.47$, p=.483). The *Nemenyi* test, considering a 0.05 significance level, proves to be conservative, not identifying the obtained differences. The Friedman's Aligned Ranks test (with Shaffer correction) was applied, but the result also proves to be conservative. The solution was to use Friedman's Aligned Ranks test results with no p-value correction method, presented in the model graph in Fig. 1.

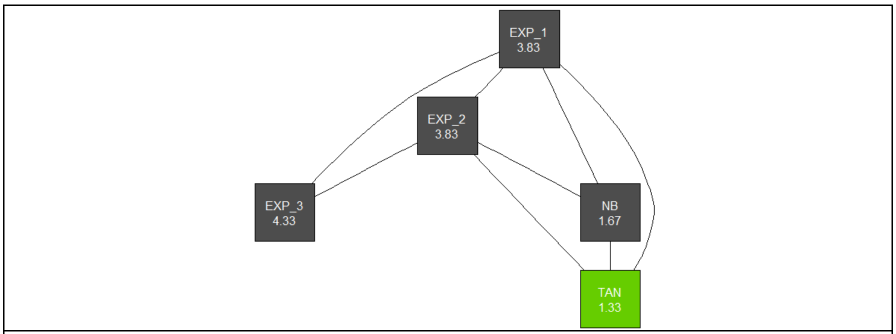

Fig. 1. Models average rankings and significant differences for the prediction of abstention

The models are the nodes, and if two nodes are linked, we cannot reject the null hypothesis of being equal. TAN and NB models perform significantly better than EXP_3 in predicting abstention behaviour.

5 Conclusion

The present study aimed to develop an ML framework to predict voting behaviour during the Portuguese 2019 general election. Data was collected longitudinally in four moments in time, and two different modelling approaches were used, depending on the inclusion or not of the temporal dynamic component.

The majority of the participants (54%) maintained their opinions across data collection in different periods. The most relevant change occurred from abstention in the baseline for voting in a left-wing party (12%) in the post-election survey.

NB, TAN and DBN models were implemented. Three DBNs were developed considering the opinion of three experts in the Political Science research domain.

Interest in politics and party identification presented the most substantial influence on voting behaviour. The major influences detected were from party identification to ideology and campaign tone to party leaders' evaluations, mainly in the right-wing parties.

Despite not having significant differences in some performance comparisons, TAN and NB outperformed DBN experts' models. Generally, experts' models were less accurate predicting abstention, and the learned models outperformed EXP_3 predicting this outcome. No significant differences were found for left or right-wing parties vote prediction.

The participants who were responsible for the significant shift observed in our data (non-voters to voting left-wing parties) were also examined. They reveal to lack proximity to any particular party, and they ideologically position themselves in the centre; also, they present lower proportions of a higher education and report increasing positive evaluations of left-wing parties leaders and campaign tone during the campaign period. Younger voters present lower turnout rates and older people with higher education levels present a higher probability of voting in right-wing parties. The "education effect" [28] was also observed in our models. There was a positive effect of education on participation, suggesting additional evidence for a causal interpretation. It was also clear that age affects party identification, with young voters not identifying themselves with any particular party.

Using self-reported measures is a limitation since it was clear that turnout was higher than the one in real-life. Social desirability and the compromise assumed when participating in surveys may help to explain such low abstention rates. The distribution left-right parties in our sample were similar to the real election results in 2019.

Despite potential limitations of this work, it is essential to highlight that, to the best of our knowledge, this study represents the first panel study covering pre, during and post-campaign in which ML techniques were implemented. The collaboration of experts to develop the models is also a relevant strength of this work.

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References

[1] R. J. Dalton and M. P. Wattenberg, *Parties without partisans: Political change in advanced industrial democracies*. Oxford: Oxford University Press, 2002.

[2] G. Rahat and T. Sheafer, “The personalization(s) of politics: Israel, 1949-2003,” *Polit. Commun.*, vol. 24, no. 1, pp. 65–80, 2007, doi: 10.1080/10584600601128739.

[3] P. Van Aelst, T. Sheafer, and J. Stanyer, “The personalization of mediated political communication: A review of concepts, operationalizations and key findings,” *Journalism*, vol. 13, no. 2, pp. 203–220, 2012.

[4] A. I. Langer, “A historical exploration of the personalisation of politics in the print media: The British Prime Ministers (1945--1999),” *Parliam. Aff.*, vol. 60, no. 3, pp. 371–387, 2007.

[5] S. Adam and M. Maier, “Personalization of Politics A Critical Review and Agenda for Research,” vol. 8985, no. May, 2016, doi: 10.1080/23808985.2010.11679101.

[6] B. R. Spisak, P. A. Van Der Laken, and B. M. Doornenbal, “Finding the right fuel for the analytical engine : Expanding the leader trait paradigm through machine learning ?,” *Leadersh. Q.*, no. May, pp. 0–1, 2019, doi: 10.1016/j.leaqua.2019.05.005.

[7] J. Pearl, *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Elsevier, 2014.

[8] N. Friedman, D. Geiger, and M. Goldszmidt, “Bayesian Network Classifiers,” *Mach. Learn.*, vol. 29, no. 2, pp. 131–163, 1997, doi: 10.1023/A:1007465528199.

[9] J. Gama, A. C. P. de L. F. de Carvalho, K. Faceli, A. C. Lorena, and M. Oliveira, *Extração de conhecimento de dados: data mining*. Edições Sílabo, 2015.

[10] C. J. Needham, J. R. Bradford, A. J. Bulpitt, and D. R. Westhead, “A primer on learning in Bayesian networks for computational biology,” *PLoS Comput. Biol.*, vol. 3, no. 8, pp. 1409–1416, 2007, doi: 10.1371/journal.pcbi.0030129.

[11] Z. Duan and L. Wang, “K-dependence Bayesian classifier ensemble,” *Entropy*, vol. 19, no. 12, 2017, doi: 10.3390/e19120651.

[12] N. Heintzman and S. Kleinberg, "Using uncertain data from body-worn sensors to gain insight into type 1 diabetes," *J. Biomed. Inform.*, vol. 63, pp. 259–268, 2016, doi: 10.1016/j.jbi.2016.08.022.

[13] K. Yu, J. Li, and L. Liu, "A Review on Algorithms for Constraint-based Causal Discovery," pp. 1–17, 2016, [Online]. Available: http://arxiv.org/abs/1611.03977.

[14] K. Murphy and S. Mian, "Modeling gene expression data using dynamic Bayesian networks BT - Technical Report, Computer Science Division," Berkeley, CA: University of California, 1999.

[15] S. Zhu and Y. Wang, "Hidden markov induced dynamic Bayesian network for recovering time evolving gene regulatory networks," *Sci. Rep.*, vol. 5, no. December, pp. 1–17, 2015, doi: 10.1038/srep17841.

[16] Y. Jia and J. Huan, "Constructing non-stationary Dynamic Bayesian Networks with a flexible lag choosing mechanism," *BMC Bioinformatics*, vol. 11, no. SUPPL. 6, pp. 1–13, 2010, doi: 10.1186/1471-2105-11-27.

[17] L. Uusitalo, "Advantages and challenges of Bayesian networks in environmental modelling," *Ecol. Modell.*, vol. 203, no. 3–4, pp. 312–318, 2007, doi: 10.1016/j.ecolmodel.2006.11.033.

[18] B. G. Marcot, R. S. Holthausen, M. G. Raphael, M. M. Rowland, and M. J. Wisdom, "Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement," *For. Ecol. Manage.*, vol. 153, no. 1–3, pp. 29–42, 2001, doi: 10.1016/S0378-1127(01)00452-2.

[19] F. J. Martín De Santa Olalla, A. Domínguez, A. Artigao, C. Fabeiro, and J. F. Ortega, "Integrated water resources management of the Hydrogeological Unit 'Eastern Mancha' using Bayesian Belief Networks," *Agric. Water Manag.*, vol. 77, no. 1–3, pp. 21–36, 2005, doi: 10.1016/j.agwat.2004.09.029.

[20] P. Dagum, A. Galper, and E. Horvitz, "Dynamic network models for forecasting," in *Uncertainty in artificial intelligence*, 1992, pp. 41–48.

[21] J. Demšar, "Statistical comparisons of classifiers over multiple data sets," *J. Mach. Learn. Res.*, vol. 7, pp. 1–30, 2006.

[22] R. L. Iman and J. M. Davenport, "Approximations of the critical region of the fbietkan statistic," *Commun. Stat. Methods*, vol. 9, no. 6, pp. 571–595, 1980.

[23] S. García and F. Herrera, "An extension on 'statistical comparisons of classifiers over multiple data sets' for all pairwise comparisons," *J. Mach. Learn. Res.*, vol. 9, pp. 2677–2694, 2008.

[24] J. P. Shaffer, "Modified Sequentially Rejective Multiple Test Procedures," *J. Am. Stat. Assoc.*, vol. 81, no. 395, pp. 826–831, 1986, doi: 10.1080/01621459.1986.10478341.

[25] F. F. da Silva and P. Costa, "Do we need warm leaders? Exploratory study of the role of voter evaluations of leaders' traits on turnout in seven European countries," *Eur. J. Polit. Res.*, vol. 58, no. 1, 2019, doi: 10.1111/1475-6765.12273.

[26] B. D. Silver, B. A. Anderson, and P. R. Abramson, "Who Overreports Voting?," *Am. Polit. Sci. Rev.*, vol. 80, no. 2, pp. 613–624, 1986, doi: 10.2307/1958277.

[27] M. Kuhn and K. Johnson, *Applied predictive modeling*, vol. 26. Springer, 2013.

[28] J. A. Henderson, "Hookworm eradication as a natural experiment for schooling and voting in the American South," *Polit. Behav.*, vol. 40, no. 2, pp. 467–494, 2018.