Detection of Region-Specific Voting Patterns in Eurovision Song Contest

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***Abstract*— When Eurovision Song Contest (ESC) first adopted the voting system in which citizens could vote by telephone, also known as televoting, it became possible for large population subgroups with similar biases to directly influence the voting outcome. As a result, region-specific voting trends emerged. In this paper, findings about ESC voting patterns based on data from the televoting period (1998–2008) are presented. Countries were partitioned into eight different regions based on their geographic, demographic, economic and cultural characteristics. Agglomerative hierarchical clustering and visualization of voting distribution using a circos plot were performed to check for the existence of inter-region and intra-region favoritism. Distinct decision tree models were built for votings of countries from different regions. Region-specific voting patterns, connected with demographic, religous, linguistic, economic and geographic relationships between the countries, were examined by analyzing structure of decision tree models. Results indicate that the intra-region favoritism exists in most of the regions, while inter-region favoritism exists between some pairs of regions. Differences in voting patterns between richer and poorer regions were noticed. Countries from richer regions tend to favor countries from which they have numerous economic immigrants, probably due to patriotic voting of these immigrants. Countries from poorer regions tend to give more points to other countries with similar demographic and cultural structure.**

I. Introduction

Eurovision Song Contest (ESC) is an international, annual, music competition in which every participating country is represented by one performer. The best-known voting rules were probably those from 1998 to 2008, when every voting country distributed 1, 2, 3, 4, 5, 6, 7, 8, 10 and 12 points among ten distinct countries, and gave 0 points to the rest, based on the results of telephone voting (televoting) of its citizens [1].

With the introduction of televoting, speculations arose that there are country-specific patterns in voting [2, 3]. Such voting patterns may be explained, at least partially, by different demographic, geographic and cultural qualities of countries, and biases in their populations toward other countries and populations [4].

Based on these patterns, it is possible to derive interesting sociological conclusions about the collective attitude of some population. Also, by knowing patterns in voting between countries, it might be possible to predict the results of some countries. By comparing the actual with the predicted result, each country may evaluate its performance and classify it as success or failure. Having accurate predictions of future results can increase the chances of making a profit in case of betting on competition results, which is today also available [5]. Data confirming the existence of patterns that do not depend on song quality but rather on other factors can be a stimulus for changing the rules. New rules could equalize countries' chances to win and make the competition more interesting for viewers by making results more unpredictable.

The goal of the present study is to answer the following questions about the existence of voting patterns specific to some groups of countries. What are the key factors based on which it could be expected that one country, belonging to a certain region, would favor another country during the voting process? Is it possible to notice intra-region and inter-region favoritism, i.e. do countries from a particular region tend to favor countries from the same region or countries from some other region?

In order to answer these questions, data about votings and some demographic, economic, religious, linguistic and geographic relations between countries were collected and processed. Votings were partitioned into several groups based on the region associated with the voting country. Inter-region favoritism was examined by visualizing number of points on average shared between countries from different regions. Intra-region favoritism was tested by hierarchical clustering of countries based on their mutual votings. Two clusters were merged if the averagely given number of points in votings from countries belonging to one of these clusters to countries belonging to another one is the highest among all possible pairs of clusters. Votings from each partition were used to create one decision tree model trying to predict the voting outcome based on factors representing relations between the voting and the voted country. Structural analysis of decision tree models uncovered some determinants of the high-value outcome in particular votings.

II. Related Work

Some researchers attempted to identify pairs or groups of countries that favor each other during the voting process in ESC [6]. Others defined measurements of mutual support between countries and degree of voting polarization, e.g. mutual sharing of a large number of points between countries belonging to a certain cluster [2]. Also, there is an evidence for the existence of asymmetric voting patterns where one country favors another, but not vice versa [4].

Researchers tried to create predictive models that give expectations for voting results. Some of these models are formed based solely on the structure of previous votings

[7], while others depend more on factors describing linguistic and cultural relations between the voting and the voted country [8].

The present study is a continuation of our previous work, in which a regression model for predicting voting outcome was created. Independent variables in the model included measurements of some relations between the voting and the voted country and aggregate results about their previous votings [9]. Analysis of the model coefficients revealed that most loyal voters for one country are probably people born in it, but living outside for economic reasons.

III. MATERIALS

This chapter presents sources from which data were collected and the process of transforming source data into the resulting data set, which was used for further analysis.

A. Sources of Data

Data about each voting from 1998 to 2008 were collected from the Eurovision Song Contest Database [10]. For every voting, there were recorded names of the country that voted (voting country) and the country that was voted for (voted country), song and performer name, year and phase (semi-final or final). Trees representing the development of languages and religions dominant in participating countries, as well as the list of the neighboring countries with the type of border (maritime, land or both) have been based on information available publicly on the Internet [11, 12, 13]. The tree representing the separation of countries into regions was the same as the one given in a Kaggle competition [14], but enriched with nodes grouping countries that were formed after the breakup of the same country. For each country, data about annual gross domestic product (GDP) per capita and dominant religions and languages were retrieved from the Nation Master web site [15]. Data about the flow of immigrants between countries were retrieved from the UN Data web site [16].

B. Data Processing

If country data about GDP per capita or a number of immigrants from some county were missing for a particular year, they were estimated based on an interpolation function obtained using available data. Economic differences between the two countries were calculated as the natural logarithm of GDP per capita of the voting country divided by GDP per capita of the voted country. The intensity of immigration from the voted country into the voting country is equal to the number of immigrants born in the voted country but living in the voting country divided by the total number of immigrants in the voting country.

The closeness between two languages was defined as the number of all languages outside of the smallest group containing both of them, divided by the total number of considered languages. The linguistic closeness between the two countries was defined as the highest achieved closeness between languages linked with the voting country and languages linked with the voted country. A similar method was used to define religious and geographic closeness between the two countries.

C. Resulting Data Set

The resulting data set has 12435 records and comprises all ESC from 1998 to 2008. Votings were described by 14 organized into the groups of auxiliary, independent and dependent attributes. The group of auxiliary attributes contains six attributes: *voting*, *voted*, *year*, *phase*, *singer* and *song*. They are used only for understanding the context of voting and they represent the name of the voting country, name of the voted country, year of voting, competition phase (semifinal or final), name of the performer who represented the voted country and name of the song performed by that performer, respectively. The group of independent attributes contains seven attributes, later used as independent variables while building decision tree models [17]: *religion_closeness*, *language_closeness*, *geography_closeness*, *border*, *familiarity*, *gdp_ratio* and *immigration*. Attributes *immigration*, *religion_closeness*, *language_closeness* and *geography_closeness* represent the intensity of immigration from the voted country into the voting country, and closeness of the voting and the voted country based on their religious, linguistic and geographic similarities, respectively. Attribute *border* takes value 0 if the two countries do not share a mutual border, 1 if they share only a maritime border, 2 if they share only a land border, and 3 if they share both a maritime and a land border. Attribute *familiarity* takes value 1 if the voted country’s song was performed in the semifinal, and 2 if, additionally, the voting country’s song was also performed in the same semifinal, otherwise, it takes value 0. Attribute *gdp_ratio* represents the economic difference between the voting and the voted country. The group of dependent attributes contains only attribute *point*, which represents the actual voting outcome, i.e. the given number of points, and it has been used as the dependent variable while forming models.

IV. METHODS

All countries were partitioned into eight regions based on their sociological, cultural and geographic characteristics: **Balkans**, **Scandinavia**, **Western Central Europe (German-speaking)**, **Eastern Central Europe**, **Northwestern Europe**, **Western Mediterranean**, **Eastern Mediterranean,** and **Ex-USSR**. All votings were partitioned into eight groups, based on the region of the voting country, and each group of votings was used for building a separate decision tree model.

Methods for analysis of intra-region and inter-region favoritism are presented in the first subsection. Decision tree models were used for the analysis of voting patterns characteristic for that region, as described in the second subsection. Programming language *R* with its libraries *sqldf*, *stats*, *circlize* and *tree* [18, 19, 20, 21] was used for data transformation, analysis, visualization and model construction.

A. Intra-Region and Inter-Region Favoritism

A matrix whose values are numbers of points that countries from one region averagely give to countries from another region was formed. In order to check for the existence of differences in voting distribution considering the voting region, the chi-square test of independence was performed on the formed matrix [22]. The distribution of votings between regions was visualized using a circos plot

[20]. In that plot, a link between two regions is shown only if the number of points that countries from the first region averagely give to countries from the second region is higher than the number of points that countries from the first region averagely give each other [20].

Agglomerative hierarchical clustering of countries was performed based on their mutual votings [17]. The closeness between two clusters was defined as the averagely given number of points in votings from countries belonging to one of these clusters to countries belonging to the other.

B. Region-Specific Patterns Based on Country Relations

All votings where the voting countries were in the same region were used to form one decision tree. Based on the structural analysis of the formed trees region-specific voting patterns were identified. Additionally, pairs of countries whose mutual votings were frequently associated with tree paths with the highest outcomes are shown. Paths associated with high-value outcomes are especially interesting because they might indicate potential favoritism. If some country receives a small number of points from another country, this should not be regarded as some antipathy between the two countries, because most countries always get zero points from that particular voting country.

Mean absolute error (MAE) and mean square error (MSE) were used to evaluate model accuracy. Performance of the decision tree models was compared to that of the overall best regression model from [9]. The data set was split in the manner used in [9], i.e. the test set contained all votings from final rounds between 2006 and 2008, and the training set contained the remaining votings. The regression model contained an additional attribute named *pastAvg*, which represented the number of points averagely given in previous votings from the voting to the voted country. Model performance was measured both when the attribute *pastAvg* was included in the trained models and when it was omitted.

V. RESULTS

Results of intra-region and inter-region favoritism analysis are presented in the first subsection. The second subsection presents some of the results obtained using the methodology described in subsection IV-B, as well as the results of model evaluation.

A. Intra-Region and Inter-Region Favoritism

The p-value of a chi-square test of independence conducted on the matrix representing the averagely given number of points between every two regions is less than 0.01. This indicates there are differences in the distribution of points between the regions.

The distribution of points shared between regions is visualized using a circos plot [20] shown in Fig. 1. Every region was assigned a different color. Links between the voting and the voted region are shown only if the number of points that countries from the voting region averagely give to countries from the voted region is higher than the number of points that countries from the voting region mutually share on average. The color of a link is the same as the color of the voting region. The width of a link is proportional to the number of points averagely given from the voting to the voted region. The circos plot contains hillocks surrounded with black border, one per each region. The color of a hillock matches the color of the region to which it refers. The width of a hillock's base is proportional to the number of points averagely shared between the countries from the region to which the hillock refers. For example, the width of the brown hillock is proportional to the number of points that Western Central Europe countries on average mutually share and the width of brown link at its ends is proportional to the number of points that these countries averagely give to countries from the Eastern Mediterranean region.

Fig. 2 presents the result of hierarchical clustering. The country names shown at the bottom of the dendrogram are colored according to the region to which the country belongs, using the same colors as in Fig. 1.

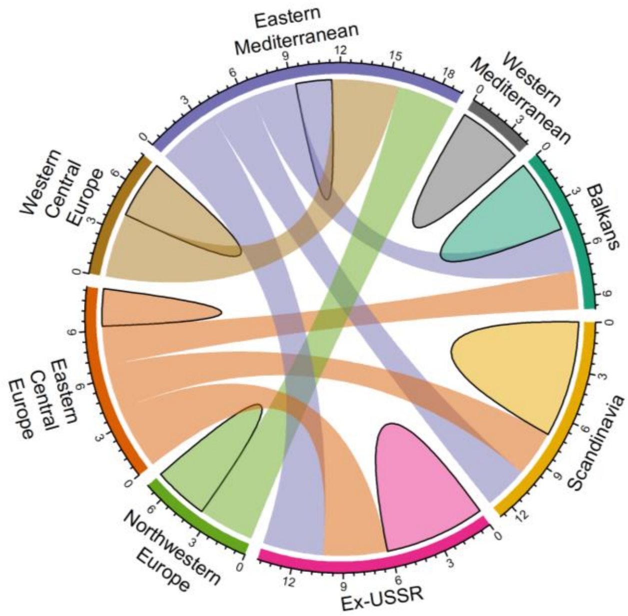

Figure 1. Circos plot representing the distribution of points between country regions

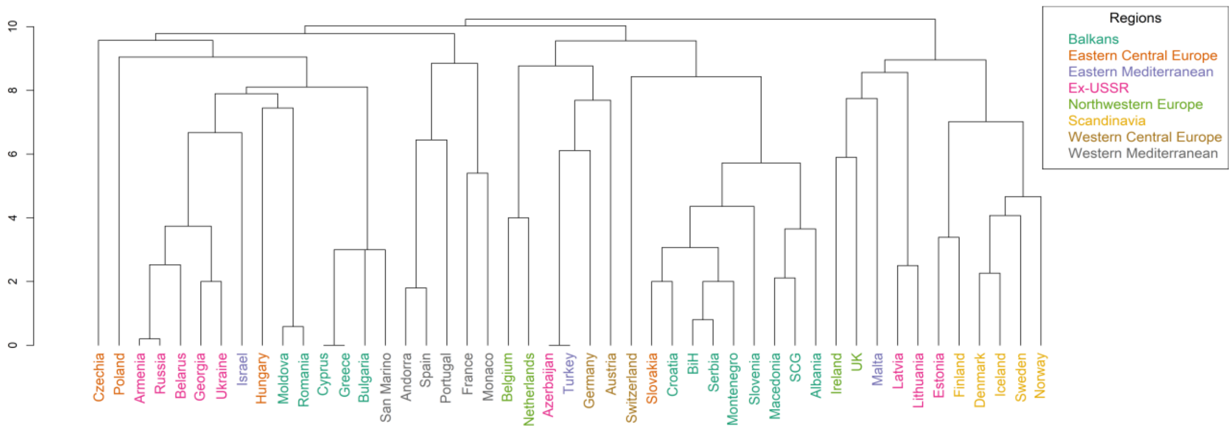

Figure 2. Hierarchical clustering of countries based on the number of points they share in their mutual votings

B. Region-Specific Patterns Based on Country Relations

Due to limited space, only trees for two regions of countries are presented and discussed here: Balkans (Serbia, Montenegro, Serbia and Montenegro [SCG], Bosnia and Herzegovina [BIH], Croatia, Slovenia, Macedonia, Albania, Bulgaria, Greece, Cyprus, Romania and Moldova) and Western Central Europe (Austria, Switzerland, Germany). Countries from the Western Central Europe region have more economic immigrants and higher GDP than the Balkans countries. Analysis of the decision tree models of these two regions reveals different patterns, which are discussed in chapter VI. The decision trees of these regions are shown in Figs. 3 and 4. Inner nodes of a decision tree have the split criterion shown in bold face. During the process of voting outcome prediction, it is needed to go to the node's right child if the current split criterion is satisfied, otherwise to the left child. For each shown tree node, there are the number of samples associated with it (samples) and their average value of attribute *point* (value).

Tables I and II show pairs of countries whose votings are most frequently associated with high outcome paths of decision trees presented in Figs. 3 and 4, respectively. For each pair, the following data are presented: the name of the voting and the voted country (columns Voting and Voted), predicted and actual average number of points given in votings (columns Predicted and Real), as well as the number of occurrences of this pair on paths with highest outcomes (column Count).

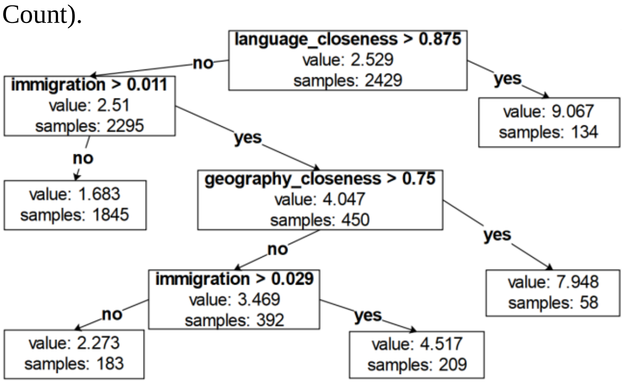

Figure 3. Decision tree for Balkans

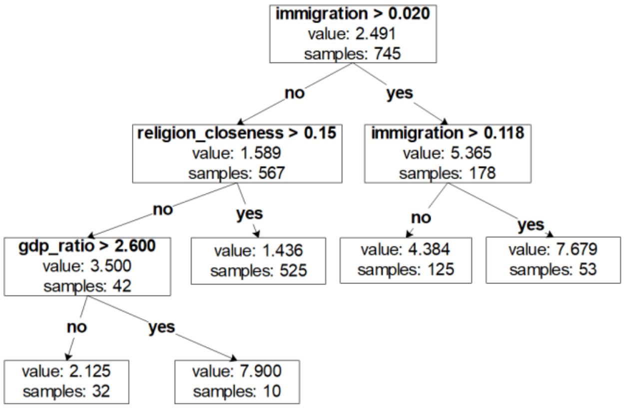

Figure 4. Decision tree for Western Central Europe

TABLE I.
LIST OF THE MOST FREQUENT PAIRS ON HIGH OUTCOME PATHS IN THE DECISION TREE SHOWN IN FIG. 3

Voting	Voted	Predicted	Real	Count
Slovenia	Croatia	9.07	9.10	10
BIH	Croatia	9.07	8.55	9
BIH	Slovenia	9.07	5.78	9
Croatia	Slovenia	9.07	7.00	9
Slovenia	BIH	9.07	7.89	9
Greece	Cyprus	9.07	12.00	8
Croatia	Macedonia	7.95	7.80	10
Macedonia	Croatia	7.95	8.22	9
Slovenia	Macedonia	7.95	5.86	8
BIH	Macedonia	7.95	8.33	6

TABLE II.
LIST OF THE MOST FREQUENT PAIRS ON HIGH OUTCOME PATHS IN THE DECISION TREE SHOWN IN FIG. 4

Voting	Voted	Predicted	Real	Count
Switzerland	Albania	7.90	9.00	6
Germany	Turkey	7.68	9.30	10
Germany	Poland	7.68	6.00	9
Austria	Turkey	7.68	6.00	7
Austria	BIH	7.68	8.83	6
Austria	Germany	7.68	5.67	6
Switzerland	Portugal	7.68	7.67	6
Switzerland	Germany	7.68	7.40	5
Germany	Croatia	4.38	4.73	11
Switzerland	Macedonia	4.38	3.60	10

Performance of the evaluated decision trees and regression models [9] is shown in Table III. Both types of predictive models were tested when independent attribute *pastAvg* was included and when it was omitted from the model. Performances are measured using mean absolute error and mean square error.

Table III.
PERFORMANCE OF EVALUATED MODELS

Predictive model	MAE	MSE
Decision tree models with *pastAvg*	2.310	8.161
Regression model with *pastAvg*	2.383	9.443
Decision tree models without *pastAvg*	2.500	9.375
Regression model without *pastAvg*	2.650	10.832

VI. DISCUSSION

This chapter contains a discussion about results presented in chapter V. Subsection VI-A contains a discussion on the results of the chi-square test of independence, circos plot in Fig. 1 and dendrogram in Fig. 2. Subsection VI-B contains a discussion about patterns noticed during the analysis of decision trees and pairs of countries most frequently associated with high outcome tree paths. This subsection, also, contains a discussion of model evaluation results shown in Table III.

A. *Intra-Region and Inter-Region Favoritism*

The p-value of the conducted chi-square test indicates that there are differences in the distribution of points between the regions. As shown in Fig. 1, there are four regions (Ex-USSR, Balkans, Western Mediterranean and Scandinavia) whose countries give more points, on average, to each other, than to countries belonging to any other region. Countries from other regions averagely give more points than they mutually share only to countries from few regions. Countries from Northwestern Europe and Western Central Europe have numerous Turkish minority and they are only associated with the region of Eastern Mediterranean countries, to which Turkey belongs.

Many countries that are closely related in the dendrogram in Fig. 2 also belong to the same region. Examples for that are two clusters consisting just of five Ex-USSR and five Western Mediterranean countries. Also, there is a cluster consisting of nine countries, of which eight countries belong to the Balkans region. There is a cluster of six countries that comprises five Scandinavian countries and Estonia, which exhibits intensive favoring of Finland. This favoritism may be related to the Estonian language, which is very similar to Finnish. For these reasons, Estonia can be regarded as both a Scandinavian and an Ex-USSR country. Similar to Estonia and Finland, it is noticeable that there are a few pairs of countries which share the same language and favor each other more than any other country. Examples for that are pairs Greece-Cyprus, Romania-Moldavia, Netherlands-Belgium, UK-Ireland, and Turkey-Azerbaijan.

Existence of intra-region favoritism and differences in the distribution of points with respect to the region of the voting country indicate that presented partition of countries into regions is not meaningless. Also, there could be some another reasonable partition of countries.

B. *Region-Specific Patterns Based on Country Relations*

Decision trees shown in Figs. 3 and 4 both give higher outcomes if there are a lot of immigrants from the voted to the voting country, which might indicate that the most loyal voters are emigrants who vote for their homeland. As shown for the Balkans tree, higher outcomes might be expected if linguistic and geographic similarities between countries are high. This is most often happening between countries formed after the breakup of the common predecessor country, e.g. BIH and Croatia, formed after the breakup of Yugoslavia, and countries with very similar national structure, e.g. Greece and Cyprus. In the Western Central Europe region, there is noticeable favoring between demographically and geographically related countries, e.g. from Austria and Switzerland to Germany. The tree structure shown in Fig. 4, which exhibits voting patterns of richer countries, better illustrates the case when there are substantial economic differences between the voting and the voted country. If the voted country is much poorer than the voting country, higher outcome could be expected. This suggests that people coming from much poorer countries are often coming solely for economic reasons. These people might stay less assimilated and more focused on their homelands. Moreover, the less similar the religion of immigrants from the voted country is to the religion of the domestic population, the more points would be assigned to the voted country. Examples for that are votings from Switzerland, Germany and Austria to Albania, Turkey and BIH. In the region of Balkan countries, only favoring between demographically and geographically related countries could be observed, which may be also explained by the generally lower level of economic immigration in these countries.

Evaluation of model performance reveals that inclusion of the additional attribute *pastAvg* improves model accuracy. However, decision tree models from this study are formed primarily for the analysis of voting patterns. Attribute *pastAvg* was deliberately excluded in order to avoid splits based on its value. All splits are based on values of factors covering demographic, religious, linguistic and economic relations between the populations of the voting and the voted country. By excluding attribute *pastAvg*, a cleaner insight into the impact of other attributes was obtained. Another important observation is that predictions based on a system of decision tree models have higher accuracy than the regression model formed in [9]. An advantage of using regression models is that they give a wider range of different outcomes for a different combination of independent variables. That enables post-processing of predictions, as done in [9] where predictions of one country are adjusted for each voting round. After post-processing, that country gives only once twelve points to a country for which the largest number of predicted points is assigned, ten points to a country to which the second largest number of predicted points is assigned, and so on. Decision tree models have as many possible predictions as they have leaf nodes, which is less than ten in the present study, so the post-processing algorithms presented in [9] cannot be applied.

VII. CONCLUSION

Based on the presented analysis, it is reasonable to conclude that patterns in voting in Eurovision Song

Contest exist, and that they differ from region to region. Countries from all regions are more likely to give a large number of points to countries from which they have high immigration. The difference is that countries belonging to rich regions are more likely to give a large number of points to countries much poorer and culturally different than they are. That might be explained by the phenomenon of patriotic voting [4], where economic immigrants regularly vote for the country of their origin because they are not sufficiently assimilated in their new country. Countries from poorer regions are more prone to give a large number of points to countries whose ethnical structure is similar to theirs. Also, intra-group favoritism was noticed both in some rich and in some poor regions.

The present study could be improved by the introduction of additional attributes. Interesting attributes could be the closeness of countries based on a relative number of their inhabitants speaking languages or practicing religions present in more than one country. With these data, it would be possible to introduce an attribute representing the degree of familiarity of the population of the voting country with the language in which a performer representing the voted country sang. Introduction of an attribute representing exact numbers of the telephone votes in each voting between two countries could cause additional improvements.

One possible direction of further research on this topic could be an analysis of the impact of song presentation on voting results. Measured parameters of performance could be song genre, song length, performer gender, performer type (group or solo performer), the language in which the song is sung, and schedule of song performances and pauses. These factors are more controllable than the factors examined in the present study, so performers could adjust their performances accordingly. In such a study, a similar approach to modeling separate decision tree models for different groups of votings could be applied. For example, votings could be grouped based on the criterion whether the language of a song is an official language in the voting country. Also, after grouping countries based on music genres preferred by their citizens [23], votings could be separated into different groups based on the group associated with the voting country.

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