

# Analysing the structure of high-dimensional opinion spaces - the example of Swiss popular votes

*issue bundles, correlated class analysis, belief networks, political polarization*

## Extended Abstract

Data for understanding opinion dynamics arise in a variety of contexts: from voting patterns and multi-item surveys to hashtags use and user participation in different online groups. Despite their different origins they have a similar mathematical structure: a matrix  $X = \{x_{ij}\}$  with rows representing members of a population and columns representing e.g. items of a survey or political issues. Recently various novel methods employing methods from network science have been proposed to make sense of correlational patterns in such data in order to identify them with cultural schemata [2] or dimensions of an underlying political space [6]. In this contribution we will explore different such methods including belief modules [3] or issue bundles (IB) [6] and correlational class analysis (CCA) [2]. Both methods IB and CCA start with matrices of correlation coefficients.

In order to identify issue bundles we consider the correlations between issues and represent them as a signed and weighted network called inter-issue consistency network (IICN) with the correlation coefficients being the edge weights. The issue bundles are then identified by maximizing a coherence measure that tries to group positively correlated issues in the same bundle and negatively correlated issues in different ones [6].

The basic idea of CCA is to divide the population (of data points) into sub-populations motivated by the observation that attitudes on different attitude objects might be organized according to different cultural schemas for different groups and that these schemas correspond to different “logics” in evaluating the attitude objects. In this contribution we combine both methods: In a first step we use t-distributed stochastic neighbor embedding [7] to identify the relevant sub-populations. In the second step we use inter-issue consistency networks (IICN) and (IB) to represent the main conflict lines within these subpopulations. This contribution is work in progress and we presents results for Swiss popular votes. In Switzerland every three month the public votes on different issues. Here we analyze a data set containing the ratio of yes votes for each vote from all 2222 communities. Thus the members of the populations are communities and the issues are the topics of the single votes, respectively. The full data set contains all 325 nation wide votes from 1981 till 2018. The data were provided by [SOTOMO](#) (see also [4] for an analysis of the older part of the data set). The selected time spans shown in the figures contain 79 (2010 - 2018) or 36 (2015 - 2018) votes, respectively. Embedding the communities using t-SNE with the correlation distance (Fig. 1 A) we find that the communities cluster according to their cantonal affiliation while differences such as the difference between urban and rural communities occur only within the clusters (not shown). In the second step we create the inter-issue consistency networks for the communities from the single cantons and estimate the corresponding issue bundles. Figs. 1 B and C show two examples: one from the German speaking canton Zürich and one from the French speaking canton Waadt. It turns out that the issue bundles are quite similar in both cantons. We observe a more “conservative” bundle (blue nodes), a big “progressive” bundle (yellow for Zürich and green for Waadt) and a smaller intermediate one. However, Figs. 1B and C also show significant differences in the correlation structures. In the

canton Zürich we see a clear bi-polarization between the “conservative” and the “progressive” cluster. In the french speaking canton Waadt we see instead two divides corresponding to a split of the “progressive” cluster therefore not a simple bi-polarization. Looking more closely at the issues one could characterize the two axis as a economic-technological axis (e.g. nuclear power, mobility, genetic engineering or green economy) and the other more related to cultural and societal issues (migration, family, or national sovereignty).

We expect that understanding these “cultural differences” will also help to understand the dynamics of political cleavages and could add new aspects to the debate about new cleavages and political realignments in Swiss and, beyond, in European politics [1].

Combining correlational class analysis with t-SNE embeddings (or similar methods such as UMAP [5]) to identify sub-populations and using inter-issue consistency networks to analyze the correlation structure within them seems to be a promising framework for the exploration of the structure of high dimensional opinion spaces. Cultural network analysis is a growing field in Sociology. It aims at analysing how different cultural schemata are shared across different segments of a population by usually exploiting the correlational patterns in survey data [2, 3]. To our knowledge, this is the first application of belief network analysis to *behavioral* voting data.

## References

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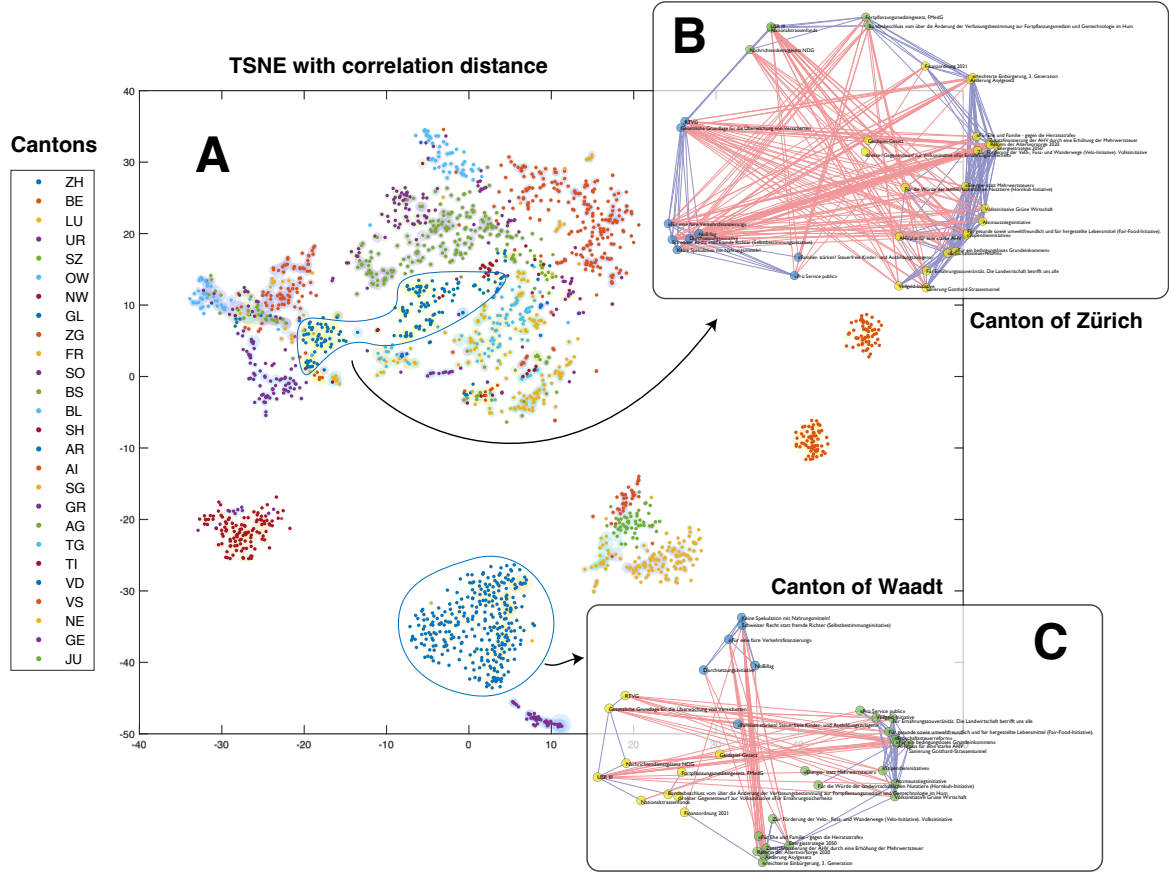


Figure 1: **A** t-SNE embedding [7] of popular votes of Swiss communities between 2010 and 2018. Colors encode the canton. The big cluster in the upper left mainly German speaking cantons. The Italian speaking Tessin (TI) is the single cluster in the left middle, while the down right clusters are French speaking cantons. **B** Inter-issue consistency network (IICN) for Zürich for votes between 2015 and 2018 only for better readability. Node colors indicate issue bundles. Edges are shown for correlations larger than 0.4. Blue edges indicate positive, red negative correlations. **C** Same as in B, but for the French speaking canton Waadt. Note, that the node colors do not match for corresponding bundles in both networks.