How do we think? - Reassessing construal clusters with bipolar data

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Introduction

Empirical knowledge on **construal classes**, or “social affinity groups of individuals who share similarities in how they organize their outlooks on a collection of issues”, has significantly expanded in recent years. These discoveries have been enabled by a family of methods that make use of community-detection algorithms to cluster survey respondents according to how similarly their answers change among questions. The use of these methods, which we will refer as **Construal Clustering Methods** (**CCMs**), has produced seminal information about the number, relative population, and characteristics of construal classes for issues as diverse as artistic consumption, political orientations, attitudes towards religion and science, and opinions on the role of the market in social life.

Most of these findings are based on the use of Relational Class Analysis (RCA) [4]. Furthermore, on 2017 Boutyline introduced Correlational Class Analysis (CCA) [2]. And, finally, on 2023 Sotoudeh and Dimaggio [5] presented a new version of RCA (NRCA) that constitutes the state of the art regarding CCMs. All these methods share the same schema: first, they compute a *similarity function* between pairs of respondents, and, second, apply a community-detection algorithm in order to obtain the construal classes. All the previous mentioned methods differ in how they calculate the first step and only N-RCA uses a different community-detection algorithm.

After testing the existent CCMs, we concluded they carry some structural deficiencies. The most important one is that they are not designed for *bipolar questions*, the most common questions in opinion surveys. Bipolar questions are characterized as the union of two sets (*positive and negative opinion semispace*) of possible answers to that question with, at most, non empty intersection in a *neutral option*. For example, an `agree-disagree` question would be a bipolar one: $\mathcal{P} = \{\texttt{Agree}, \texttt{Neither agree nor disagree}\}$, $\mathcal{N} = \{\texttt{Disagree}, \texttt{Neither agree nor disagree}\}$ with neutrality option `Neither agree nor disagree`.

In this poster, we present **Bipolar Class Analysis** (BCA) to address the problems identified in previous CCMs and provide a more accurate method for analyzing bipolar data.

Bipolar Class Analysis (BCA)

Let $u = (u_1, \dots, u_Q)$ and $v = (v_1, \dots, v_Q)$ be two respondents to certain poll and $u_{kl} = (u_k, u_l)$ a pair of answers. Then, we compute the similarity function between u, v following the next formula:

$$B_j(u, v) = \frac{2}{Q(Q-1)} \sum_{k=1}^{Q-1} \sum_{l=k+1}^{Q} \omega(u_{kl}, v_{kl}) \mu_j(u_{kl}, v_{kl}),$$

for $j = 1, 2$ depending on either μ_1 or μ_2 we will introduce.

Polarity function ω

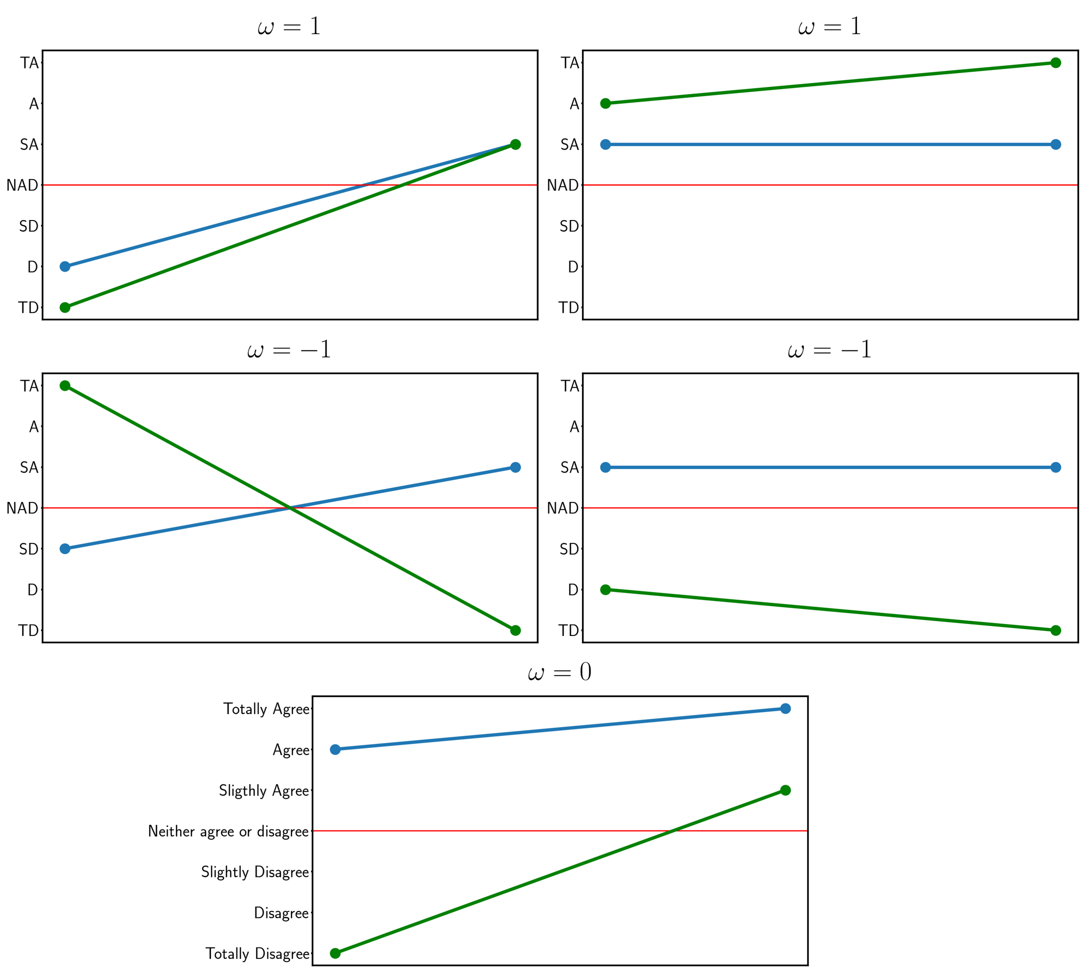

Fig. 1: Values of $\omega(u_{kl}, v_{kl})$ when $u_{kl}, v_{kl} \neq n_{kl} = (n_k, n_l)$

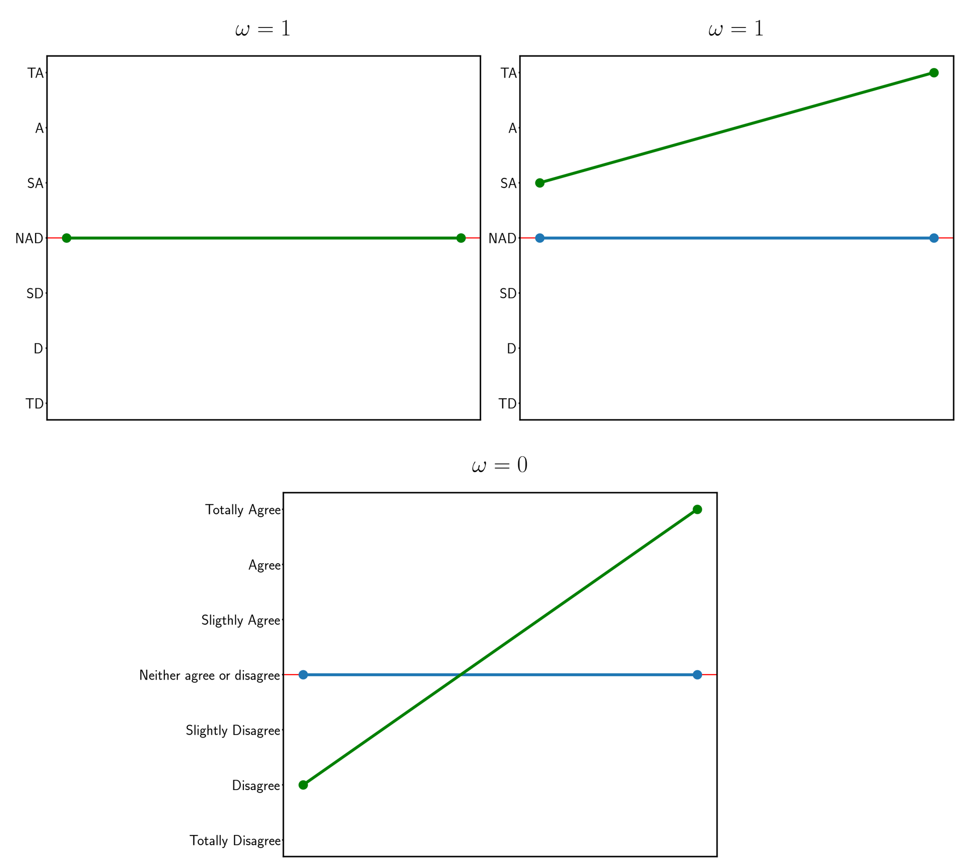

Fig. 2: Values of $\omega(u_{kl}, v_{kl})$ when u_{kl} or $v_{kl} = n_{kl} = (n_k, n_l)$

Magnitude term μ_j

We fix two diferent magnitudes μ_1 and μ_2.

$$\mu_1(u_{kl}, v_{kl}) = 1.$$

Given the bipolar structure of the data, this option is always feasible without requiring additional assumptions. Therefore, we consider it a suitable benchmark. Comparing results obtained using μ_1 with those from other functions can help assess their robustness. We will denote BCA with this magnitude as **BCA$_1$**.

$$\mu_2(u_{kl}, v_{kl}) = 1 - \frac{|\Delta(u_{kl}) - \Delta(v_{kl})|}{\max_q(D_q)},$$

where

$$\Delta(u_{kl}) = |dist_k(u_k, n_k) - dist_l(u_l, n_l)|,$$

$dist_i(\cdot, \cdot)$ denotes a metric function that measures the distance from answer u_i to the neutrality element n_i and $D_q = \max_{q \in Q}\{dist(a_q, n_q)\}$ where a_q is a possible answer of question q.

μ_2 needs the existence of a distance function in every question q (not necessarily the same) between any option and the neutrality n_q and it must be an explicit option. This method avoids comparing answers across different questions and provides an implicit normalization. This approach allows BCA to address more effectively the variation in response numbers compared to other CCMs. We will denote BCA with this magnitude as **BCA$_2$.**

Simulations

We define a new simulation method that accounts for the structure of opinion polls with bipolar questions. The modeling strategy incorporates **ordered choice and multivariate dependency**. Respondents hold a specific latent position towards each question, which they use to select opinion values from a finite set of alternatives. The positions of respondents across questions are constrained through a specific dependency structure. This structure, interpretable as a construal, is predetermined by design.

We present three different *performance metrics* (CPA, CD and M-SNMI) for three different experiments (**E1**, **E2** and **E3**) where BCA performs from 2 to 10 times better than the other CCMs in terms of *right number of classes* and at least as well as them in the other two metrics.

	(1)	(2)	(3)	(4)	(5)
	RCA	CCA	NRCA	BCA$_1$	BCA$_2$
E1					
CPA	0.028	0.061	0.227	0.387	0.405
CD	11.149	13.631	10.340	6.668	6.565
M-SNMI	0.187	0.284	0.310	0.292	0.312
E2					
CPA	0.065	0.065	0.224	0.388	0.386
CD	7.605	10.533	6.740	4.986	5.018
M-SNMI	0.158	0.198	0.255	0.246	0.253
E3					
CPA	0.046	0.203	0.298	0.410	0.397
CD	5.891	5.424	4.950	4.012	4.028
M-SNMI	0.136	0.220	0.206	0.214	0.217

Experiments:

E1 *Fixed opinion parameters:* Same number of options per question and same thresholds for questions and respondents.

E2 *Heterogeneous answer points:* Different number of options per questions but same thresholds.

E3 *Het. answer points and thresholds:* Heterogeneity in number of options and thresholds.

Performance metrics:

CPA = Construal partition accuracy.

CD = Correlation dissimilarity.

M-SNMI = Mean Scaled NMI.

References

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