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Exploration of Preference Models using Visual Analytics

Raphael Buchmüller[1], Mark-Matthias Zymla[1], Daniel Keim[1], Miriam Butt[1] and Rita Sevastjanova[2]

University of Konstanz[1], ETH Zurich[2]

Abstract

The identification and integration of diverse viewpoints are key to sound decision-making. This paper introduces a novel Visual Analytics technique aimed at summarizing and comparing perspectives derived from established preference models. We use 2D projection and interactive visualization to explore user models based on subjective preference labels and extracted linguistic features. We then employ a pie-chart-like exploration design to enable the aggregation and simultaneous exploration of diverse preference groupings. The approach allows rotation and slicing interactions of the visual space. We demonstrate the technique's applicability and effectiveness through a use case in exploring the complex landscape of argument preferences. We highlight our designs potential to enhance decision-making processes within diverging preferences through Visual Analytics.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization design and evaluation methods;***

1. Introduction

Effective decision-making depends on the ability to identify and handle a diversity of perspectives such as the exploration of individual preferences. Incorporating diverse opinions towards a decision-making process prooves to be challenging while dealing with complex, qualitative data that can be both vast and multidimensional [EAJS*19]. The use of Visual Analytics (VA) enables experts to explore individual preference models [HA07], more specifically seeking common ground in using collaborative frameworks [BMZ*06] and visual dashboards [PSG*18, GPEA*18, GHJH16, BGHJ*14] to find preference patterns and understand singular opinion dynamics.

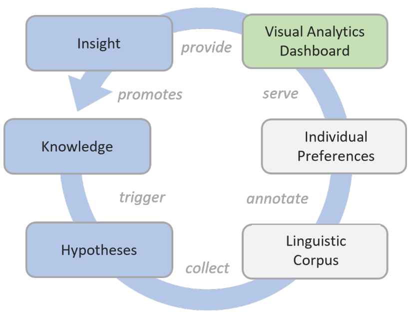

Figure 1: *Our framework for preference exploration derived from the Knowledge Generation Model [SSS*14].*

Mentioned approaches present a need for methods to summarize preference models to find joint tendencies and compare group-based viewpoints [FH11]. Such preferences are often articulated through nuanced expressions within natural language which we set as a focus in this work [WNH*17]. Navigating the complexity of linguistic data presents unique challenges for preference modeling [LNNT20]. This channel, rich and varied, encapsulates a broad spectrum of subjective opinions while drawing challenges by the subtlety and nuancedness of human communication. Variability in language use, including semantics, syntax, and pragmatics, introduces additional layers of complexity, necessitating sophisticated analysis techniques to decipher and especially combine the underlying patterns of preference [RLM16, HJCM22].

However, existing visualization techniques fall short of explaining the feature space behind interactively combined preference models in linguistic contexts limiting the visual exploration of common perspectives and opinions.

We present a novel Visual Analytics (VA) technique designed to a) examine the distribution of individual preference models, b) aggregate them to selected groupings and c) explore and compare such groupings based on formerly extracted, linguistic features. Specifically, we enable visual exploration of model projections to analyze combined feature spaces making use of a pie chart, boxplots, visual markings, and interaction methods. Our approach (green) is embedded into our preference exploration pipeline, as illustrated in Figure 1 derived from the knowledge generation model proposed by Sacha et al. [SSS*14]. We specifically focus on the linguistic field of argumentation as it presents the richness and complexity of individual preferences towards arguments which can highly influence the perception and effectiveness of communication.

We apply multiple steps towards the exploration of preference models focusing on linguistic argumentation. Initially, we compile a specialized corpus comprising individual arguments, each presented with nuanced variations to capture the persuasive effects of different formulations. The corpus is labeled by users to accurately

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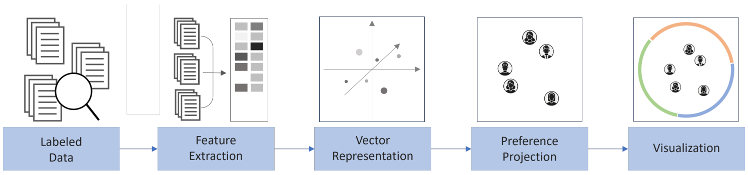

Figure 2: *Multi-staged process towards building our visual analytics design.*

reflect a range of individual preferences as further discussed in Section 4. In the final step as presented in this work, we facilitate the exploration of these preferences through visual exploration and interactive engagement.
In the following, Section 2 reviews related work, while Section 3 describes our methodology. Section 4 presents a use case to demonstrate our technique's benefits. Finally, Section 5 concludes.

2. Related Work

Preferences in VA Despite its increasing relevance, Visual Analytics (VA) for preference model exploration is still in need of comprehensive frameworks [HJCM22]. However, Bernard et al. [BZSA17, BZSA18] emphasize VA's role in handling user-specific preferences, offering a taxonomy foundational to our further discussion. The challenge of representing and exploring collective preferences is discussed by Hindalong et al. [HJCM22], underscoring the need for comparative visualization techniques. Similarly, the work of Bautista et al. [BC06] and the EMA framework by Cashman et al. [CHH*19] align VA tools with decision-making, stressing the exploration of language corpora and the necessity of personalized models to grasp shifting perspectives, as seen in Progressive Learning of Topic Modeling by El-Assady et al. [EASS*18] and TopicDrivers by Lu et al. [LWLM18]. Wall et al. [WDC*18] and Schmid et al. [SCHB22] demonstrate practical applications of VA in preference-based ranking and decision-making. Innovative approaches, such as BaobabView by Van den Elzen et al. [vdEvW11] for constructing decision trees, and the Visual-Interactive Similarity Search by Bernard et al. [BRS*17] for analyzing complex objects, further illustrate the utility of VA in preference exploration. Sevastjanova et al.'s incorporation of gamification [SHDEA23] introduces an engaging method to explore personal preferences.

Visualizing Combinations The visualization of combined models is directly related to the field of overlapping sets visualizations. In particular, a great challenge exists when complex datasets of higher dimensionality should be combined and visually analyzed. Matrix-based approaches [EDG*08] and parallel coordinates [FMH08] offer improved scalability but can become cluttered and less intuitive for identifying self-selected combinations in large datasets with small space for individual feature presentation. *Radial Sets*, introduced by Alsallakh et al. [AAMH13] and *Set'o'Grams* by [FMH08], innovate by providing a scalable, interactive method to visualize and analyze large overlapping sets using a radial layout, focusing on the intersections and unions within the dataset. This technique allows for efficient exploration of complex set relationships and overlaps.

Contribution for VA Our work is based on the designs of *Radial Sets* [AAMH13] and *Set'o'grams* [FMH08]. Instead of overlapping sets present in the data, we use a similar approach to interactively investigate high-dimensional projection spaces with user-defined groupings. We further extend the design in feature exploration by making use of boxplots [Mar52] to display set variations and add visual markings for a direct comparison as an extension to existing designs to fit our need for combined feature exploration of user preferences.

3. Methodology

We design our Visual Analytics (VA) technique through a multi-stage process, as illustrated in Figure 2: For our analysis, we utilize a dataset $\mathcal{D}$ consisting of user-generated labels over a corpus of textual arguments, where each label corresponds to a preference vector $\mathbf{p}_i$ in an n-dimensional feature space $\mathcal{F}$. Initially, individual data items are labeled to gather the preferences of multiple users. We extract feature vectors based on selected linguistic features and generate vector representations for each user, which are interpreted as preference models. The importance of various features within these models is determined by feature weights, which are derived from extensive empirical data (based on [SG18, SG20]). To effectively handle sparse data sets and construct predictive models, we apply Gaussian Process Preference Learning (GPPL) to predict and complement missing argument labels. Subsequently, we employ Principal Component Analysis (PCA) [MR93] to project these high-dimensional preference vectors onto a two-dimensional, radial visualization space. Finally, we apply our visualization for the interactive exploration of the given space, thereby transforming complex, subjective content into accessible, interpretable visual formats.
Our objective is to aggregate these individual preference vectors to identify common patterns and divergences across different user groups. Specifically, the mapping facilitated by PCA allows us to interpret and delineate clusters of similar preferences within the adjusted groupings visually, providing insights into collective decision-making processes. For example, we may find that groupings adjusted for readability and argument complexity consistently show a preference for concise and straightforward argumentation styles, in contrast to other clusters favoring more complex, nuanced language use. Ultimately, our visualization applies this framework for the interactive exploration of the given space, thereby transforming complex, subjective content into accessible, interpretable visual formats.

Visual Design

Our visual dashboard as depicted in Figure 3 is built around the projection of preference models. The visualization space is encir-

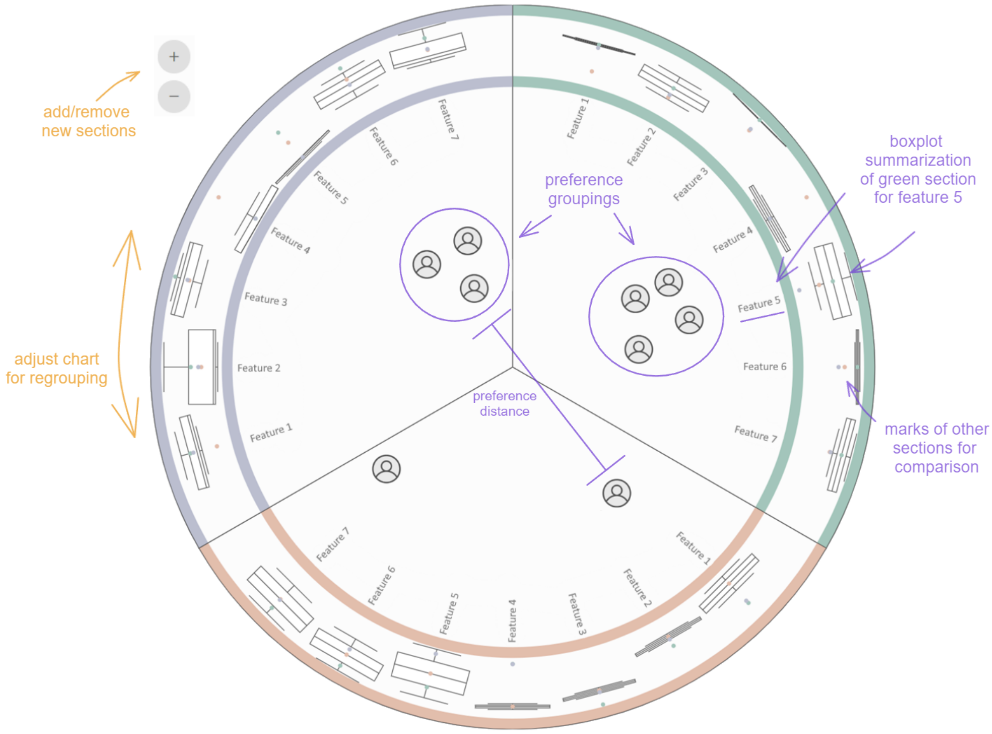

Figure 3: *Explanation of visualization design describing visual artifacts (purple) and interaction methods (orange).*

cled by a boundary, segmented into sections of consistent size by black grid lines, with colored arcs delineating two concentric outer rings. Preference projections from individual users within the same section are aggregated. Enclosed between the two rings, boxplots represent the aggregated data for each feature, based on the chosen feature set to show homogeneity and variance of the related preference model grouping.

As highlighted in Figure 3 and marked in purple, the projection space is partitioned into three sections. These sections are designed to encapsulate different groupings of user preferences, with each section representing a distinct grouping strategy based on seven selected features such as readability, argument strength, and emotional appeal, among others. Two of these sections demonstrate notable groupings based on the similarity of preferences across these features, while the third appears more disparate. Each section's aggregated feature information is visually represented, with boxplots illustrating the mean value and variability. Additionally, the mean values of alternate sections are color-coded on each boxplot, allowing for swift comparative analysis between the sections.

Our design integrates interactive elements to enhance exploration within this space, as indicated in orange: Users can rotate the visualization to form new groupings or adjust the number of sections to tailor the granularity of groupings according to the exploration task at hand. The visual dashboard and additional functionalities can be used . *Use "mlvis24" as username and password for restricted access.*

4. Use Case: Argument Preferences in Comprehensibility

Our case study is based on exploring the feature preferences of ten participants. Concretely, we focus on features about the domain of comprehensibility including readability scores and other metrics of linguistic complexity. This approach has been chosen under the consideration that complex language can be a barrier in argumentation and preference articulation (e.g., [Doe12, CD14, Bec86]).

Following the presented pipeline (see Section 3), we collected a dataset comprised of 520 arguments focusing on linguistic integrity and coherence to prepare for future studies. We specifically aimed to assemble a corpus that accurately represents a range of argumentative structures and linguistic expressions from varying sources. We extract a set of 70 linguistic features that we use for visual exploration. For this case study, we selected a subset of features related to linguistic complexity.

Preference labels were gathered from the ten participants. This involved conducting pairwise comparisons of arguments (similar to [SG18]). Through evaluating 50 argument pairs each, we accumulated information to explore each participant's argument preferences. Specifically, models that predict user preferences. Each user receives their model capturing their personal preferences.

Assuming the reliability of these models, their output — feature importance vectors [SG18] — becomes the input for our visual analytics dashboard. The model reliability is evaluated by measuring the model's performance on the seen data set. Thus, they capture task-specific preferences.

As illustrated in Figure 4 on the left, the attributes examined include the ratio of verb phrases (VPsconsRat) to total constituents, indicating action or state density; vocabulary diversity (richness),

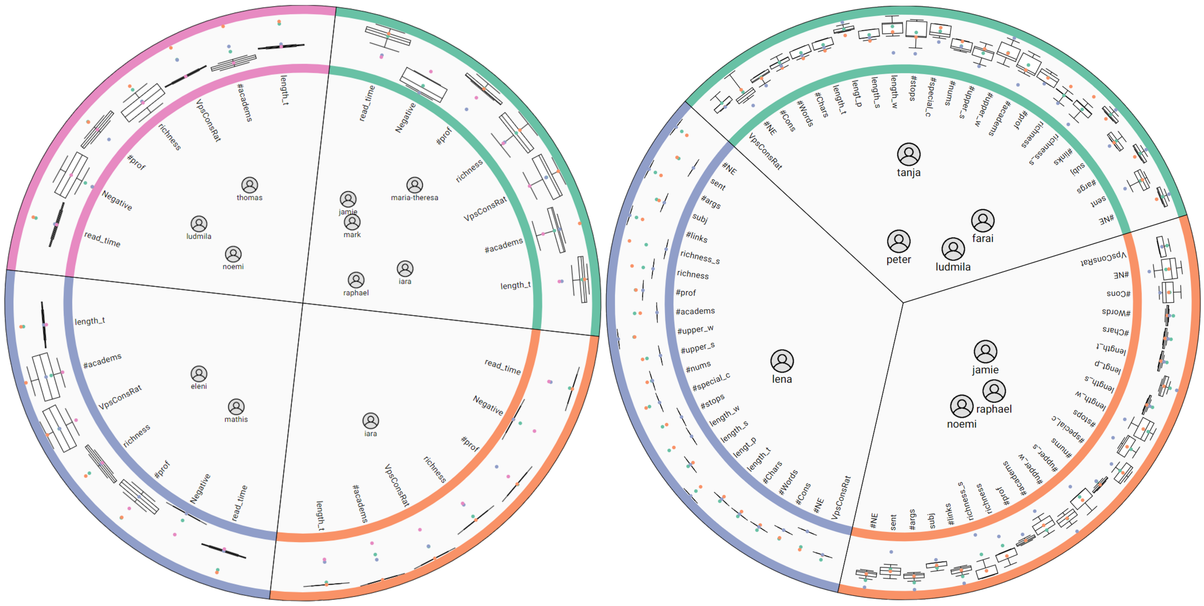

Figure 4: *Two visualization states during the exploration of argument preferences in comprehensibility as described in the Use Case. The set sections are adjusted based on the visual projection groupings e.g. showcasing diverse feature importances towards the use of academic terms in the adjusted groupings on the left.*

highlighting the breadth of language used; the proportion of profane (#prof) and academic words (#academs), signifying the tone and target audience of the text; along with the text's overall length (length_t) and the estimated reading time (read_time). On the right, we extend this investigation of user preferences toward text comprehensibility by exploring lengths of textual parts and ratios of specific terms relative to the text's length. We chose to demonstrate two states with varying numbers of sections and preference models to demonstrate the versatility of the visualization.

Exploring the PCA projections of user models reveals three visually distinct preference clusters—three on the left and two on the right. Each model comparison features one outlier, namely *iara* and *lena* respectively. These outliers are effectively segregated into their respective sections through interactive adjustments based on the visual projections. The delineation of sections is dynamically determined, allowing for realignment to suit specific exploratory tasks.

A closer examination of the preference differences between outliers and the broader user group highlights *iara*'s pronounced valuation of the selected feature set, with a particular emphasis on the use of academic language (#academs), distinguishing her preferences from others. Conversely, on the right, *lena*'s model reveals lower importance to the applied feature set in general, albeit with a marked preference for the presence of links and sources (#links), an aspect that contrasts with the rest of the group.

Across the analysis on the left graphic, reading time (read_time) and the correlated attribute of text length (length_t) emerge as universally relevant for user preferences. Conversely on the right, the use of negative expressions appears to hold less sway, especially noted in the largest cluster on the right. The variability in the use of Named Entities (#NE) is most pronounced, indicating a diverse range of user interest in this feature.

In this section, we have exemplified a potential use case of the visual analytics technique presented in this paper. While the use case focused on analyzing individual arguments, it can be extended towards more application cases on preference model exploration.

5. Conclusion

This paper presents a Visual Analytics (VA) technique for exploring the feature space of combined preference models, specifically aiming at enhancing the understanding of diverse preferences and opinions applied in the field of argumentation. Through interactive visualization and model projection, our method allows a feature space exploration of combinations of projected user preference models. Specifically, we base our approach on former literature and combine established visual designs such as a pie chart, boxplots, and visual markings.

Our approach illustrates the application of Visual Analytics (VA) to explore how linguistic features shape collective opinion. In our presented use case, we facilitate a detailed exploration of linguistic complexity in argumentation, allowing for a more comprehensive understanding of diverse viewpoints and the exploration of different user groupings.

Sections were uniformly sized to ensure equitable comparisons. Navigating the projection space poses challenges, particularly for models clustering towards the center, which might unintentionally merge into groupings. Future iterations could incorporate a designated "middle" area and apply projection techniques more apt for the radial configuration. The radial layout's spatial limitations restrict the number of features and slices that can be displayed. Additionally, the effectiveness of exploration and the ability to compare results hinge on the projection's precision and how the radial arrangement affects boxplot readability. In future developments, there's an opportunity to enhance our methodology to more broadly apply model exploration.

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