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RankASco: A Visual Analytics Approach to Leverage Attribute-Based User Preferences for Item Rankings

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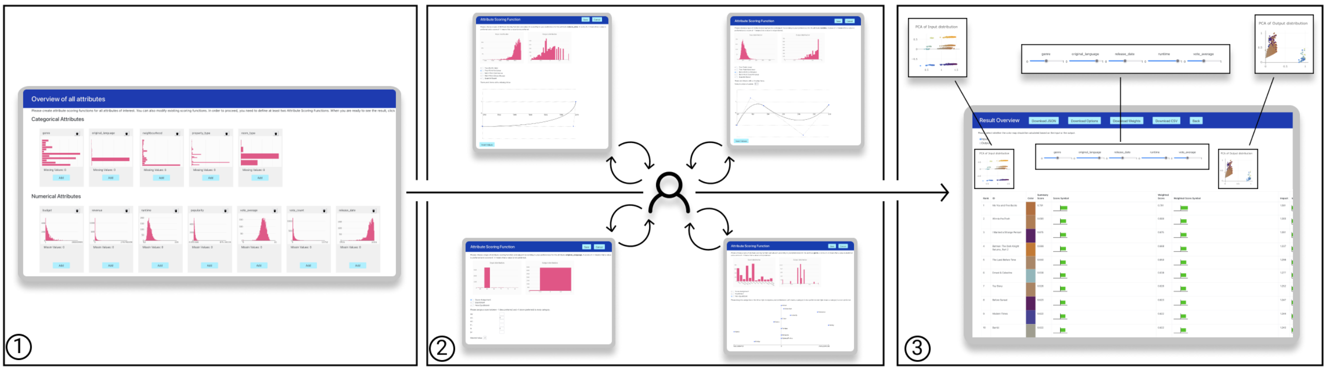

Figure 1: *Overview of the RankASco visual analytics workflow. (1) Users can gain an overview of multiple categorical and numerical attributes and (2) create attribute scorings for relevant attributes based on their preferences by using interactive visual interfaces. Finally, (3) users can configure attribute weights, analyze and refine ranking results, and make informed multi-criteria decisions.*

Abstract

Item rankings are useful when a decision needs to be made, especially if there are multiple attributes to be considered. However, existing tools either do not support both categorical and numerical attributes, require programming expertise for expressing preferences on attributes, do not offer instant feedback, or lack flexibility in expressing various types of user preferences. In this work, we present RankASco: a human-centered visual analytics approach that supports the interactive and visual creation of rankings. RankASco leverages a series of visual interfaces, enabling broad user groups to a) select attributes of interest, b) express preferences on attribute scorings based on different mental models, and c) analyze and refine item ranking results.

1. Introduction

In our everyday and professional lives, we are increasingly faced with large collections of items. Prioritizing items over others is an important task. The resulting rankings are a valuable basis for decision making, particularly where many, potentially conflicting data attributes are to be considered. Interacting with item rankings is desirable for everyone, whether to choose the best product in an online shop or the best hotel for a holiday stay based on our preferences. The notion of goodness, relevance, or preference of data items cannot always be made explicit in an objective function (a-priori). Instead, preferences are often highly subjective, involving the human decision-maker. The life-cycle of item rankings includes a *creation*, a *refinement*, and a *usage* phase. The *creation* and *refinement* phases are highly suitable for visual analytics (VA) support because user actions can be visualized in feedback loops. While the *refinement* phase is already well supported with VA techniques, ranking *creation* still lacks visual analysis support.

Strategies for an interactive *creation* of rankings are two-fold. *Item-based* approaches allow users to express feedback about the perceived order and relevance of data items [BOH12, KVD*18, PP20]. *Attribute-based* approaches allow users to express feedback by mapping attribute values to preference scores. These data mappings can be represented through different types of Attribute Scoring Functions (ASFs) [SB21]. In this work, we limit the scope to the attribute-based ranking creation strategy for two reasons. First, we believe that its scalability is mainly agnostic to the number of items, making it more applicable for large item sets. Second, it should often be easier for users to express preferences for individual attributes than between items as a whole.

While there are already approaches that support the creation of attribute-based rankings, reflection on related work reveals three shortcomings. First, existing solutions do not yet offer the full flexibility users may require to express their preferences on attribute scorings. No existing tool supports the creation of all eight types of

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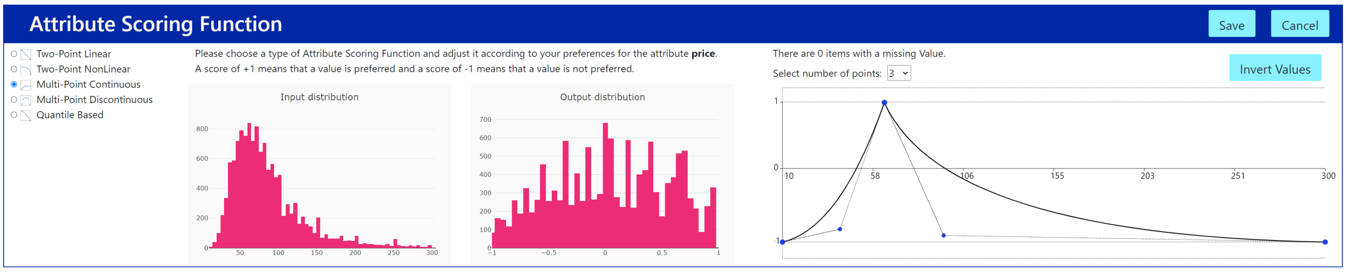


Figure 2: *One of five visual interfaces for the creation of numerical ASFs. Here, a Multi-Point Continuous function is used to help a user express the preference for prices around 60€ (drag-and-drop interface on the right). On the left, two histograms show the distribution of input values and output scores. This instant feedback also helps to achieve balanced scores, compared to the left-skewed input values.*

possible ASFs [SB21]. In specific, we identify a lack of tools that support both categorical and numerical ASFs. Second, most existing tools require programming when it comes to ASF creation. Therefore, these tools can only be steered by math experts or computer scientists but not by non-experts. Third, the black-box nature of the programming paradigm does not offer instant feedback about how a created ASF behaves for a given distribution of attribute values. A pioneer VA approach for multi-attribute ranking is *LineUp* [GLG*13], offering a visual interface that allows users to define such data mappings, even if *LineUp* does not offer full coverage of possible types of user preferences.

We present **Rank**ing based on **A**ttribute **Sco**rings (RankASco), a VA approach that supports the interactive visual creation of rankings based on attribute scores. To address the human-centered component of ranking creation, users can express preferences for attribute values through interactive interfaces, which are coupled with different ASF models and offer instant feedback for user-based scoring refinement. Our primary contributions are:

- The iterative design and development of eight interactive visual interfaces for the creation of the eight different types of ASFs.
- The integration of the eight interfaces into a web-based VA environment that implements the workflow for the creation and analysis of item rankings.

We validate RankASco through a usage scenario on accommodations for rent in the city of Rome, showing that it only takes several minutes to create a personal ranking based on multiple criteria.

2. Related Work

Our interactive visual contributions on attribute scoring are based on a taxonomy of eight different types of ASFs [SB21]. Three types of functions refer to categorical attributes, differing in their mode of operation. Five types of functions exist for numerical attributes, ranging from simple linear models to higher-order functions including multi-point piece-wise defined functions.

Inspiration can be found in medical visualizations where transfer functions (TF) map raw volume data to visual properties [GLY14]. Dedicated interfaces enable users to create and modify TFs from several default functions. Approaches range from a) steering trapezoids or ramps in a step-wise manner [KG01] over b) sketch-based user input [LPM*18] and c) parallel coordinates as a means [ZK10] for higher-dimensional input to d) the visual exploration of collections of TFs using a map metaphor [GLY14]. Downsides of tools for TF design are three-fold. First, they lack support for categorical attributes. Second, often there is only limited interaction support. Finally, TFs do not carry semantic meaning in the form of user preferences that contribute to creating a ranking.

Most attribute-based approaches to specifying preferences either support only predefined linear functions [BMPM12, CMMK20] and/or focus on the weighting of ASF outputs [PSTW*17, WDC*18]. Soo Yi et al. use a magnet metaphor to attract items according to a user's attribute-based preferences [SYMSJ05]. Fuzzy filters can be used to express soft user preferences [LHZ15]. However, such systems are typically limited with respect to the complexity of (weighting) functions and do not support unordered categorical features. Most importantly, they do not allow for interactive manipulation of the attribute value mappings. An inspiring approach is *LineUp* [GLG*13], a multi-attribute ranking approach with a visual interface that allows users to define such data mappings. However, the capabilities of *LineUp* do not include the creation of a ranking using unordered categorical attributes and discontinuous functions for numerical attributes.

To conclude, tools that allow users to specify attribute mappings typically support a limited number of mapping functions, require programming expertise, or do not provide instant feedback. Interactive visual editors that enable non-expert users to create and combine diverse categorical and numerical ASFs are missing.

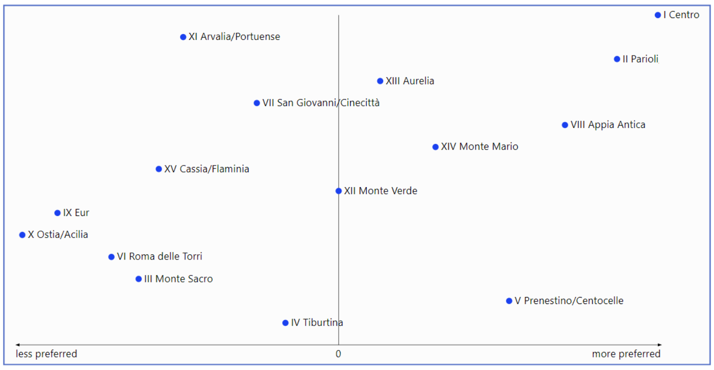
3. RankASco

RankASco is a VA approach for the human-centered ranking of item sets based on attribute preferences. We first describe the requirements that motivated the design of RankASco, before we introduce RankASco's main views, in the order of the three phases of the VA workflow shown in Figure 1. In particular, we discuss our primary contribution: visual interfaces for the creation of ASFs. RankASco is publicly available [†] and implementation details are described in the supplemental material.

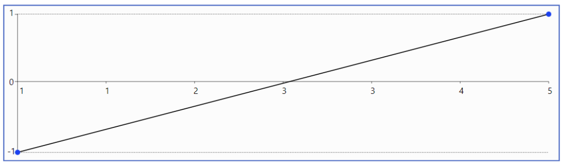
Requirements We define requirements for the system based on the problem statement, the reflection on related works, and by following a conceptual workflow for attribute-based item-ranking [SB21].

- R1: **Attribute Overview**: To make an informed selection on attributes, users should be provided with an overview of all attributes existing in the dataset, including detailed information about value distributions.
- R2: **User Preferences**: To account for individual user preferences, systems should support the creation of various ASF types.
- R3: **Instant Feedback**: Users should be able to instantly assess the effect of ASFs on underlying data distribution for validation and refinement purposes.
- R4: **Straight-Forward ASF Creation**: Attribute scorings should be open to a broad spectrum of users.
- R5: **Ranking Overview**: The system should support the analysis of the ranking result, including influencing scores.

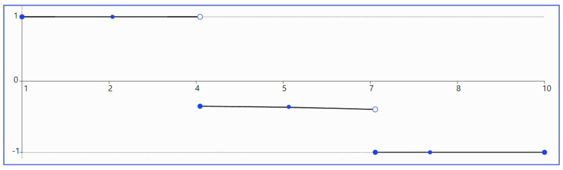
† https://www.ifi.uzh.ch/en/ivda/research/ranking.html



(a) *Non-Equidistant ASF, used to prefer some holiday regions over others.*



(b1) *Two-Point Linear ASF, here to prefer higher user ratings.*



(b2) *Multi-Point Discontinuous ASF, preferences of nights to stay.*

Figure 3: *Three interfaces for ASF creation, cropped out of the web-based ASF creation view for (a) categorical and (b) numerical attributes.*

- R6: **Attribute Weighting**: Users should be able to define and refine the importance of attributes through weights, to achieve user-centered rankings.
- R7: **Ranking-Data Comparison**: Users should be able to assess how the ranking relates to the underlying item distribution.

3.1. Phase 1: Attribute Overview and Selection

At the start of the analysis, RankASco provides a view showing all categorical and numerical attributes of the dataset as shown in Figure 1 (left). This view enables users to get an overview of the available attributes, their types, and value distributions (R1). For every attribute, bar charts show the value distribution, which also eases the informed selection of attributes for the ranking process.

3.2. Phase 2: Creation of Attribute Scoring Functions

RankASco supports users in the expression of preferences for categorical and numerical attributes with ASFs. Overall, RankASco offers eight different interfaces to support every type of ASF that has been characterized so far [SB21], each supporting a different mental model of the user. For both categorical and numerical attributes, users can decide on which scoring function matches their mental model best (R2). To improve the user experience, visual fingerprints explain the functional behaviors of the scoring function interfaces and guide users in the choice of meaningful ASF types (cf. Figure 2 left). The design of all eight visual interfaces reflects the idea to show the input value distribution and the output score distribution for attributes. Moreover, the interfaces are designed in a simplistic way to enable the creation of a visual literacy and support non-expert users in the interaction with different ASFs. The visual output score distribution is automatically updated in real-time with every change made to the ASF allowing users to instantly assess the effect of changes made (R3), as the histograms in Figure 2 show.

3.2.1. Categorical Attributes

The *Score Assignment* ASF lets a user assign a numerical score to every attribute category based on absolute preferences. The interface of this function contains a numerical input field for each category. Unassigned categories receive a user-definable neutral score. A real-world example would be the assignment of scores to languages of movies according to the languages that a user speaks.

The *Equidistant* and *Non-Equidistant* ASFs are based on relative preferences. Both interfaces are two-dimensional, where categories are shown as points on the y-axis. Users can drag categories along the x-axis according to their preferences from left to right (less to more preferred), an interaction inspired by the dis-function approach [BLBC12]. Here, the interaction allows to create an order across categories and to express relative preferences, in the notion of attribute quantification approaches [JJJ08]. The interfaces for equidistant and non-equidistant ASFs differ in the discrete and continuous point placement strategy along the x-axis, with the continuous (non-equidistant) variant offering more flexibility. An example of the equidistant ASF would be if a user prefers certain movie genres but cannot express, how much a genre is preferred over another. Figure 3a on the other hand shows a non-equidistant ASF for the neighborhood of an accommodation where users prefer certain regions and also know how much they prefer them.

3.2.2. Numerical Attributes

For numerical attributes, a user can choose between five types of ASFs: two-point linear, two-point non-linear, multi-point continuous, multi-point discontinuous, and quantile based ASFs, covering all functional behaviors observed so far [SB21]. The default theme for all interfaces is a coordinate system where the attribute values are shown on the x-axis and the scores are represented by the y-axis (cf. Figure 2). This design choice is based on visualizations of math functions $f(x) = y$ in 2D. Default functions for all five types can be modified by users to account for individual preferences (R4). For that purpose, each numerical function is depicted with draggable points and line segments in between, representing the user-steerable mapping from x (input values) to y (output scores) allowing users to only design valid ASFs.

Figure 3b1 shows a *Two-Point Linear* ASF for accommodation ratings with a linear preference for higher-rated accommodations. This is the most simplistic numerical ASF and visual interface. *Two-Point Non-Linear* ASFs with a non-linear segment are based on Bézier curves [Won03]. One control point lets users control the curvature of the line segment. An example of a two-point non-linear ASF could be the exponentially higher preference for movies that were released more recently.

Multi-Point ASFs offer more than two points. They enable users to steer multiple (curved) line segments to design more complex functions. In particular, they allow for "roof-functions" that have a peak, e.g., in the middle of the value domain, as opposed to a peak only at the left or right border of the domain, or polynomial functions with higher degrees such as cubic functions. Figure 2 shows a *Multi-Point Continuous* ASF for the price attribute of accommodations, with a preference for prices around 60€. The

Multi-Point Discontinuous ASF type additionally allows for mathematical discontinuities. Figure 3b2 shows a discontinuous ASF for the attribute minimum nights of the booking. The example function prefers accommodations available for a short trip (up to 4 nights) over week stays (up to 7 nights), over long-term bookings.

Finally, *Quantile Based* ASFs apply a quantile normalization [HOP*17] to the raw input values. The user can define the degree of quantile normalization through a slider (0% to 100% of intensity). This ASF operates on the order instead of the values of the input and is thus useful if the input data contains many outliers.

3.3. Phase 3: Ranking Analysis

Based on all ASFs, a weighted score is calculated for each item. For the weighted item score, every attribute score is multiplied by a user-defined weight and then all weighted attribute scores are summed up. The ranking view mainly consists of a list-based interface showing the ranked items from top to bottom, as can be seen in Figure 4 (bottom). Every item is represented by its rank, id, color, weighted score, as well as visual cues for the individual weighted scores (R5). Global weights per attribute can be steered by the user with sliders at the top of the view [PSTW*17], allowing the user to assign preferences also between selected attributes (R6). Weight changes automatically trigger the ranking model and refined results are delegated to the ranking list so that users get instant feedback from weighting interactions. To facilitate the comparison between the ranking result and the underlying data, color-coding can be used: Users can link the colors of ranked items to dimensionality-reduced representations (scatterplots) of all items of the dataset. The scatterplot on the left shows the items using all attributes of the dataset (categorical attributes were turned into numbers through one-hot encodings), allowing the assessment of input data characteristics. The scatterplot on the right shows the items only by the scores produced by created ASFs, which enables users to assess the distribution of items in the output data spaces produced by ASFs (R7). The color coding uses a 2D colormap [BSM*15], either applied on the left or the right scatterplot for item linking purposes.

4. Usage Scenario

We demonstrate the usefulness and applicability of RankASco to support multi-criteria ranking problems with a usage scenario on the Airbnb dataset containing information about accommodations in Rome [Cox]. A second usage scenario is described in the supplemental material based on the TMDB Movie dataset [Dat]. We will be talking about Federico, a fictive non-expert user that wants to go on a holiday trip to Rome with his family, therefore, he wants to book an accommodation. Federico first needs to gain an overview of the dataset. He uses the attribute overview page in Figure 1 (left) and gains interest into the attributes neighborhood, price, bedrooms, and review scores. Federico starts by formalizing his preferences for the price attribute. He creates the multi-point continuous ASF from Figure 2, reflecting his preferences for accommodations with a price of around 60€. Next, Federico chooses the score assignment ASF for the number of bedrooms (preferably 2 or 3). Also, Federico creates a non-equidistant ASF for the neighborhood, where he assigns highest scores to districts in the center of Rome. Lastly, Federico includes the review rating by leveraging a two-point linear ASF, which assigns the highest scores to the highest ratings. After creating all ASF, Federico proceeds to the ranking view where he assigns weights according to his attribute preferences as seen in Figure 4 (top). He then receives a ranked list of items based on his preference as shown in Figure 4 (bottom). He uses the input space coloring and makes an interesting observation: despite some top-ranked accommodations having different colors in the table and thus not being similar, they share strong scores among the attributes of interest.

Figure 4: *Ranking refinement with color-coding across views: attribute weighting and comparison of input data space with output score data space (top), ranking overview (bottom).*

5. Discussion and Future Work

User Studies The iterative design of RankASco included feedback rounds with visualization experts and non-experts alike, however, we do not yet report on user studies. A qualitative user study could be conducted by observing a small group of participants solving a ranking task using RankASco. Quantitative results could be based on the comparison with other tools and many participants.

Multi-Dimensional Attribute Scoring Functions RankASco only facilitates $1:1$ relations between one input attribute and its corresponding output scores. Future work involves the introduction of multi-dimensional ASFs that allow multiple attributes as input ($n:1$), such as: "low risk but high performance".

Sensitivity Analysis With RankASco, users can instantly observe the effect of weight changes on the ranking. Changes in individual ASFs could be observed in the ranking, even if not through direct feedback. Also, the comparison of different ranking states was beyond the scope. Future work might include means to conduct a sensitivity analysis [BMPM12, TASM18] in RankASco.

Integration with Existing Tools RankASco is a standalone solution for the human-centered creation of ASFs. However, the variety of interactive visual interfaces could also be intertwined with other approaches. Examples are *PAVED* [CMMK20], where ASF creation interfaces could be triggered at each criterion axis to specify user preferences that go beyond the current two-point linear functions, and LineUp [GLG*13], to offer more flexibility for the creation of attribute mappings.

User Guidance While RankASco contains some visual cues that support users in the decision for different ASF types, no user guidance is given for the selection of interesting attributes apart from the attribute value distributions. Future work includes adding user guidance on the attribute selection e.g. through correlation matrices to help users find sets of uncorrelated attributes.

6. Conclusion

We have presented RankASco, a VA approach that enables users to create item rankings to support multi-criteria decision-making. RankASco is the first approach that lets users express preferences through eight scoring functions, each supported with an interactive visual interface. The design of RankASco is applicable for large user groups, following the idea of personal VA solutions.

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