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Comparative user feedback rating

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ABSTRACT

This disclosure describes comparative user feedback for products and services. Users are presented with choices of products and/or services and requested to make an ordered selection of their preferred choice(s). A user's spatial ordering of choices on a slider provides information about the degree of user preferences. The comparative user feedback data are analyzed and used to train a machine learning (ML) model using ordinal regression. Absolute training data are provided to the machine learning model as seed training data. Ordinal ML regression is used to generate a comparison metric based on the comparison data, and is utilized for ranking user preferences and providing recommendations. The comparative feedback is integrated into the user's profile that is utilized to generate user feedback candidates and provide recommendations.

KEYWORDS

- User feedback
- Review
- Rating
- Ordinal regression
- Comparison data

BACKGROUND

Currently, user feedback based rating systems are designed such that users provide ratings for goods and services based on absolute scales. These scales are usually discrete and can be descriptive (for example, "good," "bad," "great," etc.) or numeric (e.g., a scale of 1-5).

Rating information is lost when users classify products into discrete bins. All products with the same rating are considered as being equal for a particular user, even though users may have a preference ranking for products within the bin. Increasing the number of possible bins can mitigate this somewhat, but in practice, most users utilize a limited subset of the available rating bins.

When absolute scales are employed, ratings from different users cannot be easily compared. Some users habitually give high ratings as long as they are not dissatisfied, while other users withhold high ratings unless the product or service is truly exceptional. Some users only provide feedback when they're extremely upset or happy, causing ratings from such users to be highly polarized.

User's ratings may not scale the same way; for example, the difference between ratings of 4 and 5 can be different for different users. Further, users that provide feedback may also be rating different attributes of the same product. For example, a high quality phone could be provided a low rating by a user, e.g., because the phone was too large for the user's hands and inconvenient to use.

Currently, most systems do not obtain continued feedback that can reflect a user's evolving preference over time. For example, as a user experiences more of a certain type of cuisine, they become discerning and are better able to distinguish quality. A user may provide a lower rating to an experience at a later time that the user rated highly a first time.

DESCRIPTION

This disclosure describes techniques to acquire and utilize comparative feedback from users. With user permission and express content, comparative feedback data are acquired using different mechanisms and are used to derive the users' natural preference order for goods and services. Continual feedback gathering reflects the evolving user preferences in addition to first impressions. Rankings generated from comparative feedback retain more information than the ones generated from binned (absolute) feedback. With user consent, personalized recommendations for products and services can be generated using the comparative feedback data.

User preferences and attributes can assist in the generation of feedback candidates and recommendations based on other users' preferences, where the users share a similar profile. Comparative user feedback can be obtained for products, movies, videos and music streams, restaurants, tourist locations, sellers of products, etc.

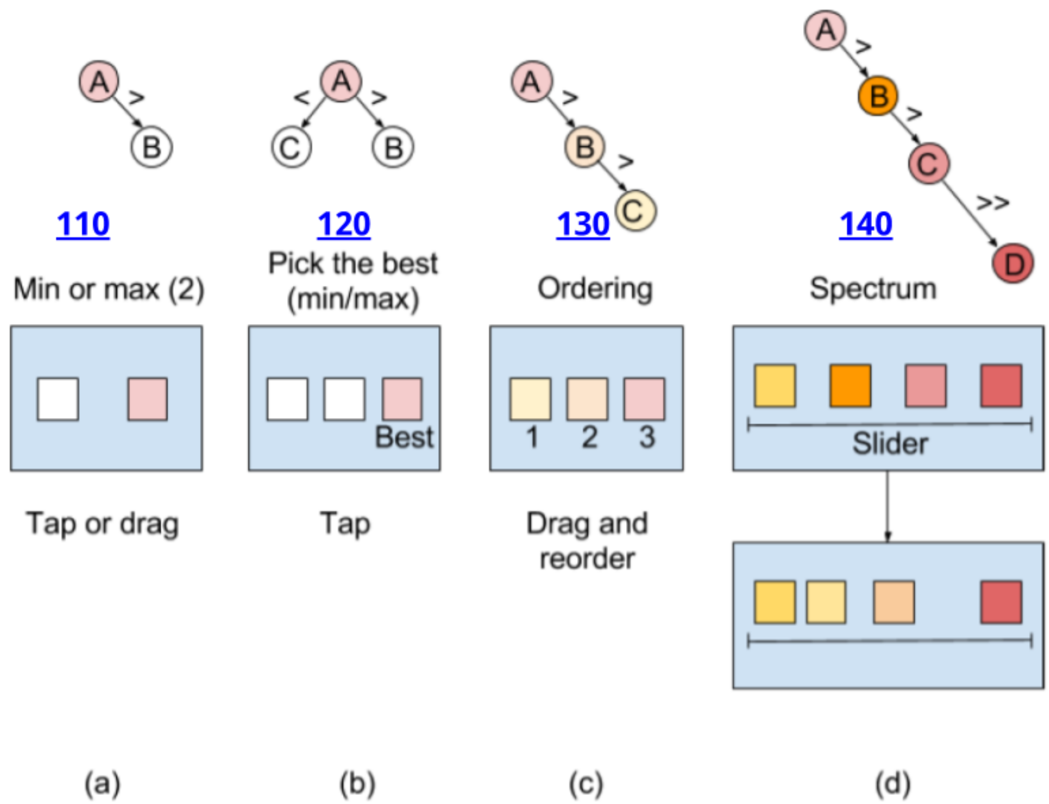

Fig. 1: Comparative user feedback acquisition

Fig. 1 illustrates examples of screenshots of a user interface that can be utilized for acquiring comparative feedback from users, when such a feature is expressly utilized by a user. As illustrated in Fig. 1(a), the user is presented with two choices, A and B (110), and is asked to choose the better (or worse) of the two. The user indicates their preference by indication (tapping or dragging) of their preferred choice. If the user is unable to decide between the options, this can be indicated. An option to skip selection is available to the user in case the user does not wish to make the comparison. The feedback provided by this selection allows a determination of whether the user considers A to be superior to B (A > B), of equal quality to B (A = B), or inferior to B (A < B).

In another example, illustrated in Fig. 1(b), the user is presented with three choices (120), A, B, and C, and is asked to choose the best option from among the three. The user indicates their preference by tapping or selecting the preferred choice. In this example illustration, if the user selects A to be the best, it can be inferred that A is superior to both B and C (A>B and A>C).

Thus, from the one tap, two comparisons are obtained. The user is enabled to indicate a tie between choices by tapping multiple items. For example, if a user indicates a tie between A and B, it can be inferred that A is perceived to be equal to B, that A is superior to C, and that B is superior to C (A=B, A>C and B>C). Three comparisons are obtained from the user selections. This process can be extended to multiple items.

In the example illustrated in Fig. 1(c), the user is presented with three choices, A, B, and C, and is asked to indicate an order (130) according to user preference. An initial ordering of the items can be predicted using data derived from discrete-scale feedback and previous comparative feedback obtained from the user. The user indicates their ordering of the choices by dragging the choices into place.

From this feedback, a strict ordering between A, B, and C is obtained (A > B > C). Three comparisons, (viz. A > B, A > C and B>C) are obtained. Users are enabled to stack their choices on top of one another to indicate a tie between choices. This process can be extended to multiple items.

In the example illustrated in Fig. 1(d), the user is asked to place the choices on a spectrum slider (140). For example, the user is presented with choices A, B and C displayed equidistant from each other on a slider. The user is allowed the option to reorder the choices. The user moves (slides) the choices into positions wherein the distance between the choices indicates the magnitude of the user’s preference for the choices.

For example, the user may order the choices as A>B>C, with A and B positioned proximally to one another on the slider and C positioned away from both A and B. From this user feedback, the relative magnitude of the comparison is obtained, namely, that A is superior to B, and that A and B are far superior to C, as perceived by the user (A>B, A>>C, and B>>C).

In addition to providing the weighting of each comparison, the magnitude can be used to infer the confidence level of the comparison. A strong preference of B over C is associated with a higher confidence score, which can serve as an indication that the user is less likely to change their mind. Multiple choices can be presented to the user utilizing a similar process.

Other mediums can be used to acquire comparative user feedback utilizing the techniques described in this disclosure. With user permission and express content, voice or conversational assistants can be employed to obtain user feedback using verbal interaction with the user. For example, a query posed to a user: “How does it compare to a similar product in the past?” can elicit a response from the user that is indicative of user preferences. A response from the user to the effect of “better”, “worse,” or “same,” provides an ordering of A>B, A<B, and A=B, respectively. The user can also provide magnitude information, for example, with a response such as: “much better.”

A query posed, for example: “Of the 3 options, which is your favorite?” can be used to obtain the user’s preferred choice. Alternate queries such as “Of the 3 options, which is your favorite and which is your least favorite?” can also be utilized.

During some user interactions, the user may also indicate, without being prompted by a voice assistant, for example, that A is "far better". Magnitude information can be derived from such user responses.

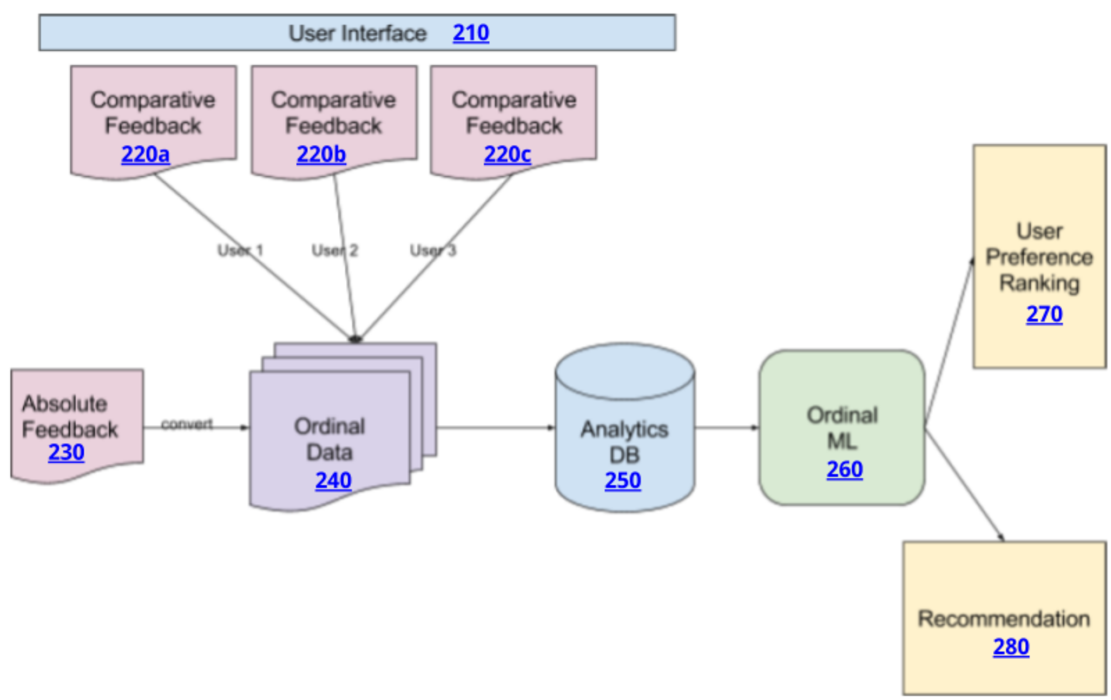

Fig. 2: Ordinal Machine Learning architecture

Fig. 2 illustrates an example architecture per techniques of this disclosure. With user permission and express content, a user interface (210) is utilized to obtain comparative feedback (220a, 220b, and 220c) from users and provided to an ordinal database (240). With user consent, the comparative feedback data are analyzed (250) and used to train a machine learning (ML) model using ordinal regression algorithms (260). The ordinal ML regression outputs a comparison metric based on the comparison data, which is utilized for ranking user preferences (270) and providing recommendations (280).

Absolute training data (230) are provided to the machine learning model as seed training data to create initial coarse rankings of the user preferences. Initial predictions and recommendations are generated from the coarse rankings and used to select candidates for obtaining additional feedback from users. With the additional feedback, the machine learning model receives inputs of ordinal data, and is less dependent on the absolute training data. New data from other applications that can utilize absolute rating systems are also continuously imported, converted and integrated with the ordinal feedback. With user permission and express content, user preference data are updated based on additional preferences provided by a user.

Techniques disclosed herein can be utilized in multiple contexts. Some example use cases are described below.

- *Confirmation feedback:* When a user preference for a new product compared to two products already in use is sought, an ordered choice sequence is predicted using the trained model, and the user is given the option to either accept the predicted preferences or to make adjustments.
- *Discovery feedback:* Questions are posed that obtain additional data about the most important preferences that enhance the understanding of the user preferences. For example, if the available user preference data lacks information about a particular aspect of a product, a comparison is sought from the user for products which mainly differ in that aspect.
- *Fine Tuning Feedback:* Products and services with comparable ratings are utilized when seeing comparative feedback from users. For example, if the model predicts that a new

product would rank in the 80-100 percentile category, products in that range are presented as candidates for user comparison. This generates more valuable data, conserves user time, and enhances the user experience.

- *Opportunistic Feedback:* Questions about higher ranked items are prioritized because the comparisons for highly ranked products contain more information about the user's top preferences. Preferences are also sought for low-ranked products and services to provide granularity within the low-ranked category.
- *Reflecting evolving user preference feedback:* At regular intervals, preferences are requested for previously rated products and/or services to discover any changes in the user preference and the user data is updated accordingly. With user permission and express content, the comparative feedback is integrated into the user’s profile.

Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs or features described herein may enable collection of user information (e.g., information about a user’s social network, social actions or activities, profession, a user’s preferences, or a user’s current location), and if the user is sent content or communications from a server. In addition, certain data may be treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user’s identity may be treated so that no personally identifiable information can be determined for the user, or a user’s geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level), so that a particular location of a user cannot be determined. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure describes the generation of comparative user feedback. With user permission and express content, users are presented with choices of products and/or services and asked to make an ordered selection of their preferred choice(s). A user's spatial ordering of choices on a slider provides magnitude information about the degree of user preferences. The comparative user feedback data obtained from the users are analyzed and used to train a machine learning (ML) model using ordinal regression. Absolute training data are provided to the machine learning model as seed training data. Ordinal ML regression is used to generate a comparison metric based on the comparison data, which is utilized for ranking user preferences and providing recommendations. With user permission and express content, the comparative feedback is integrated into the user's profile. When permitted by the user, the user profile is utilized to generate user feedback candidates and provide recommendations.