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ScrollyPOI: A Narrative-Driven Interactive Recommender System for Points-of-Interest Exploration and Explainability

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ABSTRACT

Recommender systems can help web users find more relevant content, improve their online experience, and support them in the discovery of new Points-of-Interest (POI). Yet, challenges persist in dealing with the cold-start problem and in recommendation explainability. To address these, we have created ScrollyPOI, an interactive POI recommender system based on Data Humanism principles. Utilizing scrollytelling, we address the cold-start problem by engaging users in reflecting on previous positive experiences. Additionally, ScrollyPOI enhances explainability through input and output explanations. The system uses stacked bar charts and word clouds to explain how user preferences inform recommendations (input). Finally, ScrollyPOI employs a multi-layered approach to explain why specific POIs are recommended (output). We have evaluated ScrollyPOI's interface and experience through a preliminary study, highlighting its potential for transparent explanations in the POI recommendation domain. Our findings underscore ScrollyPOI's efficacy in collecting preferences and enhancing recommendation transparency, positioning it as a platform for studying explainability goals in the POI domain.

CCS CONCEPTS

• **Human-centered computing** → **Visualization systems and tools**; **Interaction design**; • **Information systems** → **Web interfaces**; **Recommender systems**; **Personalization**.

KEYWORDS

Explainable Recommender Systems, Points-of-Interest Recommendations, Data Humanism

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1 INTRODUCTION

Recommender Systems (RecSys) are routinely applied in social media platforms, like Facebook or TikTok, streaming services, such as Spotify or Netflix, and location-based services (LBS), like Tripadvisor or Airbnb. Particularly in LBS, RecSys can support user decision-making by promoting personalized selections of Point-of-Interest (POI), like restaurants, art galleries, or outdoor activities [44, 58, 78]. Strategies for recommending POIs leverage user preferences [40, 68], POI information such as category, reviews [18, 28], and geographical data such as current location or distance to the POI [11, 84]. State-of-the-art POI RecSys combine multiple strategies to ensure accurate recommendations [25, 29, 74]. However, POI RecSys face two main challenges. First, the *cold-start problems*, i.e., recommending to *new users* or recommending *new POI items* [35, 45, 80]. For newly introduced items, existing solutions focus on content-based approaches or indicating which specific user group may like a new POI [10, 39]. In this work, we focus on the new user cold start problem and we follow the approach of asking users to signal their preferences by recalling a small number of POIs that they like [76, 83]. The remaining challenges center around the possible low level of user engagement and the improvement of the user experience when they are forced to elicit preferences in a time-intensive and potentially tedious process. Secondly, we address the *model explainability challenges*, i.e., making recommendations interpretable, transparent, and scrutinizable by the users [31, 58]. In general, state-of-the-art approaches differ in explaining the model input (i.e., the system's assumptions about users' interests) [6, 13, 24, 52, 63], the inner workings (i.e., the recommendation process) [72], and the model output (i.e., justifying why a particular recommendation has been provided without revealing the internal logic) [26, 38]. In addition to domain-independent and general solutions, we are aware of only one POI explanation approach for RecSys, leaving the space of explanation solutions in this domain mainly unexplored. The pioneering output-centered approach is LikeMind, utilizing look-alike user data to provide transparent POI recommendations tailored to individual users [49].

Our work draws inspiration from the Data Humanism (DH) [43] manifesto, connecting data to what they stand for (knowledge, behavior, and people) and arguing for the value of spending time with data, e.g., to amplify explanation experience. Similarly, we investigate the scrollytelling approach [64], to gather user input in a contextualized and engaging way. We started by deriving requirements to explainable POI RecSys at the intersection of DH and scrollytelling. Next, we have designed and developed a human-centered POI RecSys with different narrative steps of POI explanation at different levels of depth, enabling people to elicit context-sensitive preferences, and so providing a RecSys that dynamically responds to this valuable user input. In a user study, we have found that people engaged in scrollytelling experiences are more prompt to provide explicit preferences, mitigating the cold-start problem. Also, we have observed a perceived transparency increase when subjects are engaged with different levels of explanation details.

Our main contributions are: 1. Development of an interactive POI RecSys for the city of Zurich, utilizing scrollytelling to effectively gather user preferences, overcoming the cold-start issue, and leveraging the DH principle of multi-level (explanation) details to address input and output explainability challenges. 2. Evaluation of ScrollyPOI and its explanation strategies in a user study, to assess the effect of scrollytelling on the engagement level in gathering user preferences, and assess the utility of input and output explanations in a decision-making scenario.

2 RELATED WORK

We refer to the problem space of RecSys, before leading over to possible solution space, including DH and scrollytelling.

2.1 Recommender Systems

Cold-start Problem. The cold-start problem is a well-known issue in RecSys [37, 50, 82, 86]. It is generated by the sparsity of user and item information that is often usable by the recommendation algorithm. There are two main types of cold-start problems: (a) recommendations of *new items* [59, 85, 86], (b) recommendations for *new users* [8, 16], and its combination (c) recommendations of new items for new users [45, 49]. Previous works have either focused on purely algorithmic solutions [8, 33, 60, 85] or on using more human-centered approaches, i.e., by enabling the users to interact with a conversational RecSys [5, 36, 53]. Despite their benefit, human-centered approaches typically require users to spend more time and effort [14, 21, 45]. This is a negative effect that we counter-attack with scrollytelling [48, 64]. This design-driven approach facilitates user engagement, data collection, and self-reflection, and may be particularly useful when RecSys lack any prior information about users, a condition under which classical RecSys struggle. Our approach is more similar to Case-Based Reasoning RecSys [2, 41], where the recommendations are determined by their similarity to previously liked items, and RecSys based on Large Language Models, when used as zero-shot rankers [15, 27].

Explainability. Providing input explanations (i.e., the system's assumptions about users' interests) has been shown to help users build a more accurate mental model of the inner workings of the RecSys, leading to an increase in transparency and trust [22, 24]. Moreover, previous work highlights how providing this type of explanation enables users' self-reflection and self-actualization [23, 24, 67]. We build on top of previous work about *input explanation* and test two different visualizations (stacked bar chart and word cloud) in the context of POI recommendation to show how the model interprets the provided user input preferences. *Output explanations* have been more studied in the general field of RecSys [73, 81], but when it comes to POI, the study of input/output explanations is very limited. To the best of our knowledge, the only case where output explanations have been studied is in the work of Omidvar-Tehrani et al. [49], where explanations for recommended POIs are associated with the look-alike groups that the user identifies with.

2.2 Design-Driven Human-Centered Approaches

Data Humanism. *DH* is a design-driven principle that aims to challenge purely technical approaches to data visualization and connects data to knowledge, behaviors, and people [43, 55]. Lupi [43] presented a DH manifesto with 13 principles, including imperfect data, subjective data, data to depict complexity, spending time with data, data is people, sneak-in context, and data will make us more human. Previous studies have applied DH in fields like medicine [1] and climate change [17] but its use in RecSys, especially in explaining POI recommendations, remains unexplored.

Narrative Approaches. To encourage users to spend more time with data, visual narrative approaches such as storytelling [51, 56, 70] and data comics [3, 4, 75] have been shown to be effective. Segel and Heer [62] categorized visual narratives as author-driven and reader-driven. The former follows a linear path, while the latter offers flexibility and interactivity. Lupi [42] introduced a novel narrative static technique called *multi-layer storytelling*, which aligns both with the reader-driven approach and the DH manifesto. This technique integrates multiple layers of elements within visualizations, enabling rich narratives while preserving the complexity of data. An alternative interactive visual narrative technique combines scrolling and storytelling, i.e.,*scrollytelling*. Scrollytelling guides users through a dynamic sequence of visual and textual elements as they scroll down a web page [47, 48, 65, 77]. However, no research study has explored the use of different types of narrative-driven approaches to eliciting users' preferences and explaining POI recommendations.

3 SCROLLYPOI

ScrollyPOI is a human-centered interactive POI RecSys that combines DH [43] and scrollytelling [64] principles, tailored for individuals aware of some POI in the designed city. First, we introduce the requirements that have guided the design and development of ScrollyPOI, the dataset used by ScrollyPOI, and the algorithm employed to generate recommendations. Then, we offer a thorough overview of the tool through the lens of user navigation and interaction.

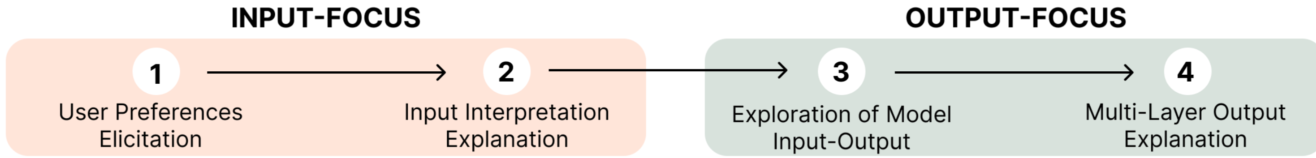

Figure 1: ScrollyPOI workflow - Four steps categorized into input-focused and output-focused. Input-focused steps rely on the elicitation of user input POIs and their exploration, while output-focused steps prompt different types of explanations of recommended POI.

3.1 Requirements

We draw guiding principles to develop ScrollyPOI, with strong inspiration from DH principles (in brackets).

- **REQ1:** Collect users' preferences (*subjective data*) while incorporating contextual data factors (*sneak-in context*) through a narrative-driven scrollytelling (*spend time with data*) and overcome the new-user cold-start problem.
- **REQ2:** Enable users to see how their input (*subjective data, small data*) is interpreted by the RecSys.
- **REQ3:** Foster user interactions to engage users in exploring input-output POI details and context enabling the user to explore the recommendations space (*spend time with data*).
- **REQ4:** Explain the complexity of recommendations at different levels of detail (*data to depict complexity, multi-layer storytelling*) highlighting model confidence, POI similarity (*imperfect data*), and adapt to users' needs.

3.2 Data and Recommender System Model

We have used the Open Data of Zurich POI V2 provided by Zurich Tourism [1]. This dataset includes 1444 data points on attractions, destinations, restaurants, and accommodations in the greater Zurich area. From these, we selected only the POIs in Zurich city, i.e., 991 data points. We clustered the original 150 POI categories by similarity into nine groups based on ChatGPT suggestions. Two authors evaluated the results. A table presenting the original and clustered categories is available in the Appendix A. Since the POIs dataset lacks user interaction logs, we opted for a similarity-based retrieval algorithm for our RecSys to generate a list of recommended POIs. Our model, based on the Doc2Vec embedding technique [34], leverages two key POI attributes: 'category' and 'disambiguatingDescription' due to their ability to generate reasonable recommendations, both providing 5 recommended POIs, 10 POIs in total per retrieval. The Doc2Vec model generates descriptive vectors based on these two key attributes of the user-inputted POIs, and this enables the computation of the cosine similarity between the POIs available in the dataset and the user-provided ones.

3.3 User Flow

The design of ScrollyPOI follows a narrative metaphor, separating user activities into four consecutive steps (Figure 1).

User Preferences Elicitation. Users are first invited to elicit their preferred POIs in the city of Zurich (**REQ1**). Our implementation combines an interactive city map with a scrollytelling-based guide, prompting users to recall places they have previously enjoyed. As users scroll, they are walked through a journey of restaurants, sports activities, bars, museums and galleries, and tourist attractions. For each category, the map dynamically displays color-coded points representing various POIs, contextualized within the city's urban landscape as shown in Figure 2 IN_01. This enriches users' understanding of their preferred locations *sneak-in context.* For each category, users are prompted to choose a specific POI they enjoyed (Figure 2 IN_02), fostering deeper engagement with the data, which aligns with Lupi [43]'s principle of *subjective data and spend time with data.* The result of the first step is a personalized set of POIs, summarising user's preferences and addressing the cold-start problem.

Input Interpretation Explanation. After completing the scrollytelling step, users transition to a summary view of their personal preferences as illustrated in Figure 2 IN_03. The main purpose of this view is to explain how these POIs collection is interpreted by the RecSys (**REQ2**), and it is realized with two commonly used visualizations: a stacked bar chart (top) and a word cloud (bottom) [7, 20, 24, 30, 71, 79]. The stacked bar chart illustrates the distribution of user category preferences associated with the chosen POIs. Users can hover over individual bars to inspect these details. The word cloud represents the frequency of words extracted from the descriptions of the selected POIs, aiding the user in grasping contextual interests and identifying key keywords influencing the system's understanding of their preferences. The result of this second step is an enhanced user's understanding of how personal POI-based preferences are interpreted.

Exploration of Model Input-Output. Once the initial steps are completed, the focus switches from a user-input to a model-output, enabled by ScrollyPOI through input-output exploration **REQ3**). A map of Zurich forms the main canvas, featuring previously user-selected POIs (heart icons) and ScrollyPOI-recommended POIs (circle icons) as illustrated in Figure 3 L0. To enhance input-output comparison, ScrollyPOI provides two stacked bar charts at the top, representing the distributions of categories for input POIs and recommended POIs, including name and percentage per category. Hovered categories are automatically highlighted in the city map, encouraging users to *spend time with data.* This interaction helps users to assess how well recommendations match their input and past experiences, deepening their understanding of preferences and interests and identifying new categories (serendipity) [19]. Hovering over any POI on the map reveals a card with a brief description and a list of associated categories. A click redirects users to the official POI website (if available), for further POI contextualization. A side panel on the left supports adding or removing POIs, and refreshing recommendations, respectively. Users can also manage a secondary set of preferred POIs for collaborative scenarios, marked with stars (input) and squares (output) on the map.

[1]https://zt.zuerich.com/en/open-data

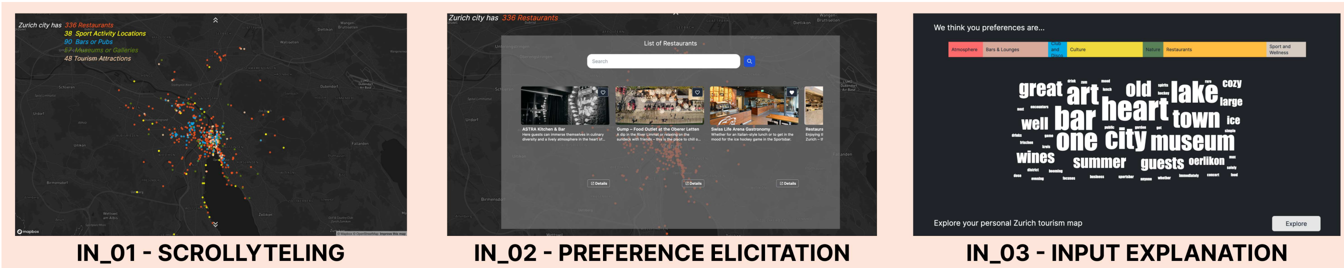

Figure 2: Summary of input-focus views for Step 1 and 2. Left: Contextualizing POIs in Zurich using scrollytelling. Center: Selecting an experienced POI of a category. Right: Visualizing the model interpretation of user input with a stacked bar chart and word cloud.

Multi-Layer Output Explanation. To explain the recommended POIs output, we adopted the multi-layer storytelling approach proposed by Lupi [42]. Our design rationale is to explain different types of output complexity on demand (**RQ4**). Users are encouraged to control this level of detail, by adding/removing three different layers of explanation complexity: the confidence of the model, relations between input and output POIs, and commonalities and differences of model outputs for two sets of input POIs. Building upon the visualization encodings and interactions of Step 3, the city map populated with visited and recommended POIs again serves are the main canvas, unifying data exploration and model explanation. Again, the 'Places Recommended' stacked bar chart at the top summarizes categories of both input POIs and recommended POIs, allowing users to understand thematic distributions.

Layer 1: Model Confidence This layer depicts the probabilistic output of the model, informing users about the likelihood of enjoying a recommended POI. We dynamically adjust the circle icon's size to represent the likelihood of enjoyment (magnitude channel [46]) as illustrated in Figure 3 L1. Furthermore, when users interact with an individual POI, the POI card now includes a sentence stating the estimated likelihood of enjoyment, represented as a percentage. This transparent sharing of model confidence empowers users to prioritize destinations likely to meet their expectations, fostering decision-making under uncertainty, and raising awareness for *imperfect data and models.*

Layer 2: Relation between input and output POIs. To explain the model output with respect to the elicited set of input POIs, users need to understand their relations. This layer adds a graph connecting each recommended POI to its corresponding input POIs on the city map. We use the thickness of connecting lines to depict the similarity scores between output and input POI relations, offering insights into the underlying logic of the recommendation algorithm. Users can click on any POI to instantly highlight the associated POI involved in the recommendation process. This interactive feature eventually mitigates 'hair ball' problems [61] for large sets of POIs as shown in Figure 3 L2.

Layer 3: Model Output Comparison. When users have defined two sets of input POIs, this layer allows direct comparisons between two sets of POIs recommended by the model. Activating this layer shows four stacked bar charts at the top of the city map, two for the sets of input POIs and two for the corresponding sets of recommended POIs. Moreover, the second set of POI will be shown on the map with a star icon (input) and an empty circle (output). An instance of this layer is visible in Figure 3 L3. This layer is especially helpful for collaborative exploration and decision-making, allowing two users to compare and make joint decisions about the next POI based on their visited locations.

4 USER STUDY

To evaluate the overall user interface (UI), user experience (UX), and to test the transparency explainability goal [69], we conducted a preliminary within-subject study with five participants. All participants had a higher level of education (ranging from Bachelor's to PhD) and their age was between 21 and 26 years old (Mean=23.2, SD=2.3). Participants were recruited through the network of one of the authors, and have explored the city of Zurich at least once. See Appendix B and C to see the complete questionnaire and the tasks.

UI and UX. In RecSys, UI and UX can be assessed across three categories: System Effectiveness (Sys-EXP), Choice Satisfaction (Cho-SAT), and Effort (EFF) [32]. To evaluate ScrollyPOI in these areas, we developed a questionnaire using a 5-point Likert scale for participant responses. This scale allows for neutral responses, reduces respondent frustration, and enhances response rates and quality [9, 12, 57]. Participants rated ScrollyPOI's UI, usability, effectiveness under Sys-EXP. Cho-SAT questions assessed the users' satisfaction with the 10 recommended POIs and the selected one as their next destination. EFF aspects were evaluated regarding preference input ease, tool usability learning curve, and overall navigation and interaction.

Explainability Goals. To evaluate the potential for testing explainability goals, we focused on transparency as one of the seven explainability goals in RecSys [54, 69]. Users were tasked with generating recommendations and exploring explanation layers to complete tasks like identifying the most or least similar POI and assessing alignment with input preferences. Additionally, participants rated perceived transparency questions using a 5-point Likert scale as more explanation layers were activated.

Results. The analysis of UI and UX questionnaire indicates that our tool excels in Cho-SAT, averaging 4.2 (SD = 0.837). Participants expressed overall satisfaction with recommended and selected POIs, averaging 4.2 (SD = 0.837) each. Sys-EXP feedback on general satisfaction was positive (MEAN = 4.4, SD = 0.548), with suggestions for aesthetic improvements. EFF scores for learning speed (MEAN = 3.8, SD = 0.37) and navigation (MEAN = 3.8, SD = 0.837) were moderate, while scrollytelling experience (MEAN = 4.6, SD = 0.548, AVERAGE TIME = 11:18, SD = 0.108) and preference elicitation (MEAN = 4.2, SD = 0.837) were highly rated. The analysis of users'

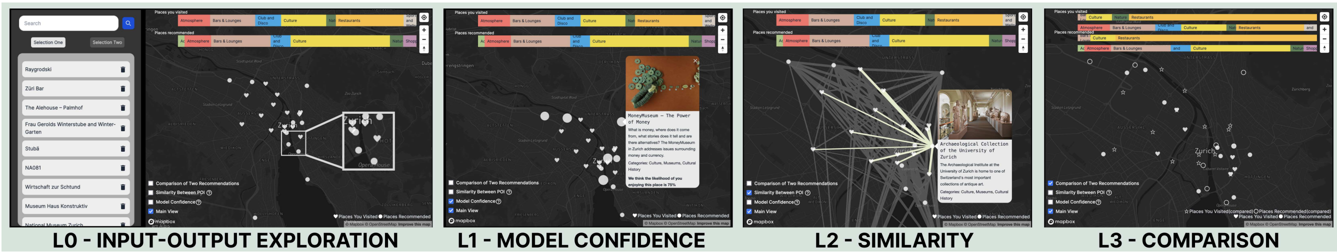

Figure 3: Summary of output-focus views. Exploration of the input-output POI (Step 3, L0), encoding of the model confidence to highlight the imperfection in the data model (Step 4, L1), visual indication of relations between input and output recommendation (Step 4, L2), and model comparison to allow collaborative POI decision making (Step 4, L3). More detailed views are in the Appendix.

responses regarding perceived transparency showed positive feedback. In particular, the input explanation (MEAN = 4.6, SD = 0.548) and the use of stacked bar charts (MEAN = 4.8, SD=0.447) were well-received. Output transparency exhibited an overall increasing trend as more layers were activated, indicating a preliminary positive correlation between adding explanation layers and perceived transparency. Excluding one exceptional case (a user in the first step selected over 30 POI compared to an average of 13 POI), the average transparency scores rose from 3.0 to 4.25 after participants interacted with all three layers.

5 REFLECTION AND CONCLUSION

We have presented ScrollyPOI, an interactive recommender system grounded in DH principles. It is designed to foster self-reflection on past Points-of-Interest experiences in the city of Zurich while facilitating transparent decision-making for future selections through input and output explanations. ScrollyPOI employs a narrative-driven approach (scrollytelling) to address the new user cold-start problem and enhance user engagement, prompting reflection on previous POI experiences. We also adapt a multi-layer storytelling strategy to explain recommendations, tailoring the explanation level of detail to match users' needs. Preliminary user feedback highlighted the effectiveness of scrollytelling in gathering preferences and the multi-layer approach's ability to enhance the perceived transparency of the recommendation process.

While ScrollyPOI and its results show promising potential as a tool for assessing explainability goals in the future, we recognize five main limitations of our approach. Firstly, the current RecSys model is not leveraging other users' input in the generation of recommendations for a target user, i.e., is not learning from the interaction data. Secondly, the similarity-based retrieval component leverages generic embeddings. Recent findings suggest that these are not optimized for assessing similarity in a way that matches human perceptions [66]. Thirdly, the size of our user study is small, and future work will focus on a larger user study with a more diverse user base, to make more generalizable statements. Fourthly, based on the results of our study, we noticed that users would like to adjust how the model interprets their preferences by the ratios of categories displayed in the stacked bar chart, aligning with the scrutability goal [54]. Lastly, out ScrollyPOI was designed for people who have visited the city of Zurich already once. We could expand the use of ScrollyPOI also to people who have not visited the city before by combining an exploratory analysis approach with asking users for preferences on categories that might be interesting.

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A CATEGORIZATION OF POI CATEGORIES

FINAL CATEGORY	ORIGINAL CATEGORY
Restaurants	Restaurants, Gastronomy, American, Asian, Sushi, BBQ, Bistro, Coffee Houses & Tea Rooms, Coffee, Cakes, Confectionery, Tea, Winery, Spanish, Fish, French, Gourmet, International, Italian, Pasta, Pizza, Mediterranean, Mexican, Oriental, Swiss Specialties, Zürcher Geschnetzeltes, Fondue, Hashbrown (Rösti), Raclette, Vegan friendly, Vegetarian, Breakfast, Brunch, Lunch, Family-friendly, Garden Terrace, Online Bookings
Shopping	Fashion& Accessories, Made in Zurich, Sustainable Production, Bike Hire, Shopping Mall, Christmas Market, Department store, Fashion & Accessories, Food & Delicacy, Markets, Watches & Jewelry, Souvenirs & Gifts, Swissness, Tourist Information
Accomodation	Apartments, Vacation, Apartments, Hostels, B&Bs, Campsites, Hotels
Atmosphere	Lively and Cheerful, Place, Alternative and Arty, Cool and Trendy, Cultural and Inspiring, Relaxed and Cozy, Glamorous and Chic, LGBTQ+, LGBTQ+*, Traditional and Down-to-earth, Exhibitions, Children and Families, Classical, Comedy, Conferences and Congresses, Parties, Festivals, Trade Fair / Market, Sports Events, Pop, Rock, Jazz, Theater, Traditional
Bars & Lounges	After-work, Choice Spirits, Cocktail Bar, Music Bar / Live Music, Wine Bar, Neighborhood Bar, Hotel Bar, Cultural Locale, Open-air Area, Restaurant & Bar
Nightlife	Afterhours, Hip-Hop / Rap / Reggae, House / Techno / Electro, Jazz / World Music, Latin / Salsa, Live Music, Party Beats, Rock / Alternative, Nightlife
Culture	Stages, Opera, Theater, Movie, Galleries, Music, Museums, Child-friendly, Art, Science & Technology, Cultural History, Design & Architecture, Photography, Architecture, Vantage Points, Churches, Monuments, Works of Art, Squares & Streets
Nature	Water, Mountains, Parks & Gardens, Zoos & Animals, Tours & Excursions, By foot
Sport	Summer Tobogganing, Climbing, Bike Tours, Running, Cross-Country Skiing, Ice Skating, Tobogganing, Sailing, Inline Skating, Hikes, Golf, Motor Boat Hire, Mountain Biking, Means of locomotion, Swimming, Walks, Pedalos, Snowshoe Trekking, Skiing/Snowboarding, Ski Touring, Waterskiing/Wakeboarding, SUP Stand Up Paddling, Surfing, Wellness

Table 1: Comprehensive breakdown of clustered categories of points of interest, highlighting the diverse range of establishments and experiences available in Zurich. The final categories provide the foundation for further visualization, and the corresponding original categories being grouped with them are listed.

B QUESTIONNAIRE

C TASKS

- Reflect on how you usually find activities or POIs in a new/old city.
- Consider a scenario where you need to discover new POIs in the city of Zurich.
- Go through the first phase of the tool you are testing and provide some POI preferences.
- Analyze and comment on the results of your input preferences.
- Generate your set of personalized POI recommendations.
- Identify on the screen how the recommendations align with your input and preferences.
- With only the first layer activated, explore the map and the recommendations.
- Select a point on the map from your output data and explain out loud why it has been recommended based on your input.
- Activate the second layer.

PERSPECTIVE	QUESTION	MEAN	SD
System Effectiveness (Sys-EXP)	On a scale of 1-5, how would you rate the overall aesthetics of the ScrollyPOI?	3.6	0.548
	On a scale of 1-5, to what extent are you satisfied with ScrollyPOI?	4.4	0.548
	On a scale of 1-5, how easy was to provide your preference to ScrollyPOI?	4.2	0.837
	On a scale 1-5, how easy was to provide your preference to ScrollyPOI?	4.2	0.837
	On a scale of 1-5, how useful is it to see how your preference relates to the recommendations?	4.6	0.548
	On a scale of 1-5, how much having the multi-layer explanations facilitate your understanding of how the recommender system works?	4	1.0
Choice Satisfaction (Cho-EXP)	On a scale of 1-5, how satisfied are you with the overall recommended point-of-interest?	4.2	0.837
	On a scale of 1-5, how satisfied are you with your POI decision?	4.2	0.837
Effort (EFF)	On a scale of 1-5, how quickly were you able to learn how to use ScrollyPOI?	3.8	0.837
	On a scale of 1-5, how easy was to provide your preference to ScrollyPOI?	4.2	0.837
	On a scale of 1-5, how much did you like the narrative about the city of Zurich and its points-of-interests?	4.6	0.548
	On a scale of 1-5, how would you rate the overall navigation experience?	3.8	0.837
	On a scale of 1-5, how much the developed ScrollyPOI supports your decision-making process in making a better decision?	4.2	0.447
	On a scale of 1-5, how well does ScrollyPOI solve your problems when it comes to selecting the next point-of-interest in Zurich?	4.6	0.548
	On a scale of 1-5, how well would you rate your knowledge about the point of interest recommendation process after interacting with ScrollyPOI?	4.8	0.447

Table 2: Comprehensive overview of the questions participants of the user study were tasked to answer using a 5-points Linker Scale. Question aimed at assessing System Effectiveness, Choice Satisfaction, and Effort. On the left the average score and standard deviation is available.

- Identify the POI that the algorithm believes you will most likely enjoy.
- Identify the POI that the algorithm believes you will least like.
- Activate the third layer.
- Select the same output data on the map as before and identify which input data affects this point.
- Identify the most similar item.
- Identify the least similar item.
- Add two items from the menu on the left.
- Identify where these new selections are reflected in the UI and the recommendation process.

D EXTRA FIGURES

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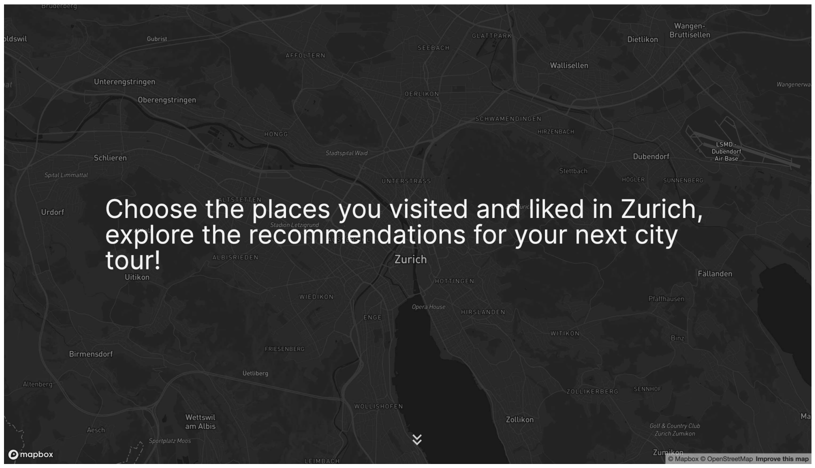

Figure 4: Upon opening ScrollyPOI, users are greeted with this welcoming view, prompting them to engage in self-reflection on past points-of-interest they've enjoyed while exploring Zurich.

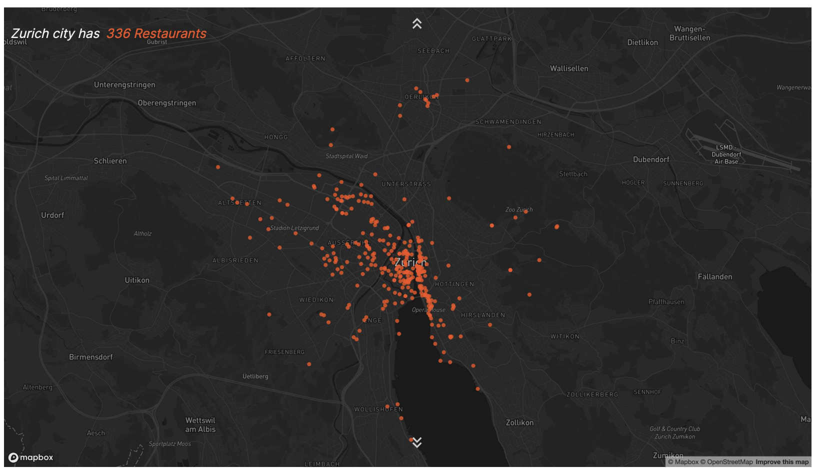

Figure 5: An example of the scrollytelling narrative pahse. The restaurant category is presented with insightful information (number of restaurant in the city of Zurich, top left) and the various restaurants are positioned within the city map for contextualization.

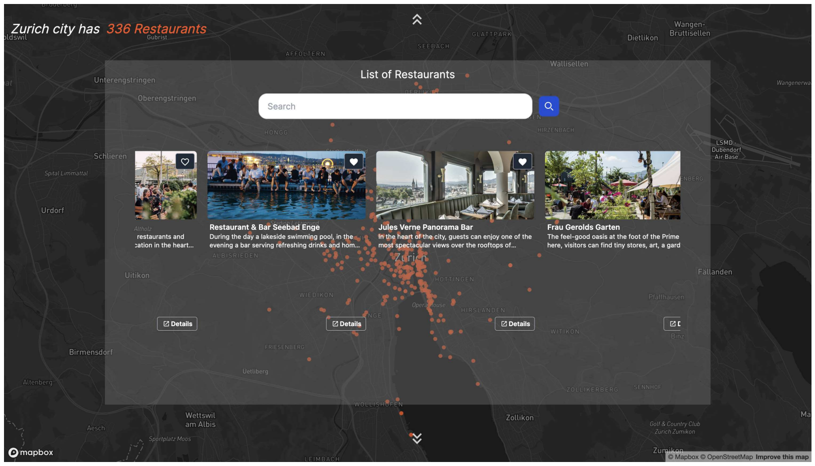

Figure 6: The prompt window for the restaurant category enables users to select previously visited and favored restaurants. This feature is designed to gather user preferences and address the new-users cold start problem where no information are available in advance.

Figure 7: Explanation Input View - Users are presented with two visualizations summarizing how their preferences are interpreted by the recommendation models. At the top, a stacked bar chart provides a summary distribution of selected points-of-interest categories. Below, a word cloud illustrates the frequency of words found within the descriptions of the selected points-of-interest.

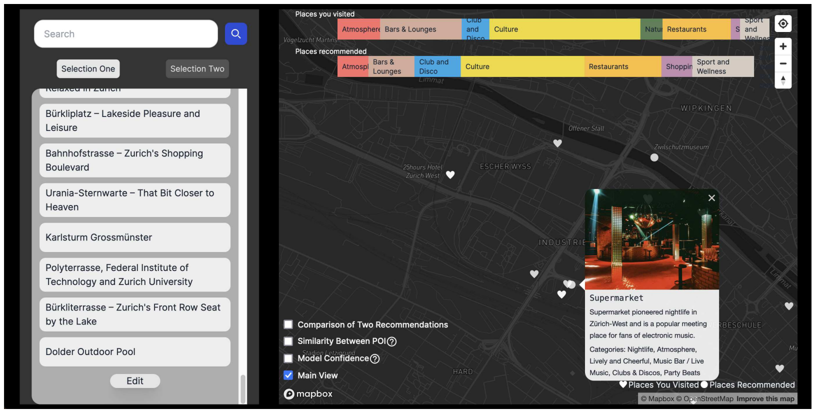

Figure 8: Input-Output Exploration - Users have the option to click on recommended points-of-interest, indicated by circles, to access further details, including a brief description and specific categories.

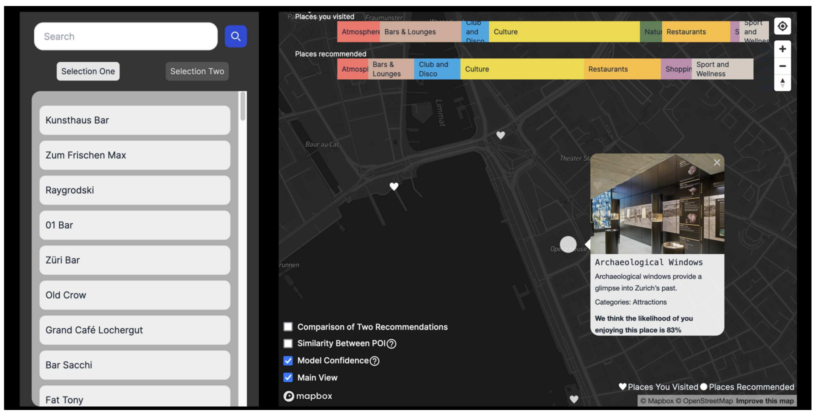

Figure 9: First layer "Model Confidence" activated - The size of the circles indicates the likelihood that users will enjoy the recommended point-of-interest. When users hover over a point, the card now includes a sentence detailing the precise score.

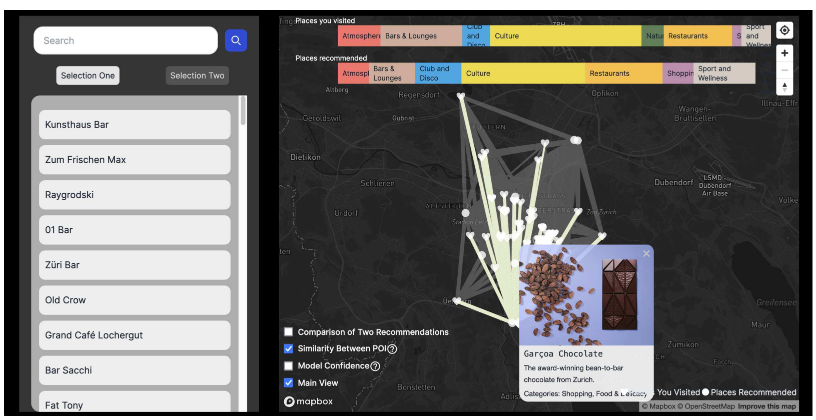

Figure 10: Second layer "Similarity Between POI" activated - Input and output points-of-interest are linked, with the thickness of the lines representing their similarity. Users can click on recommended points-of-interest to highlight the relevant connections.

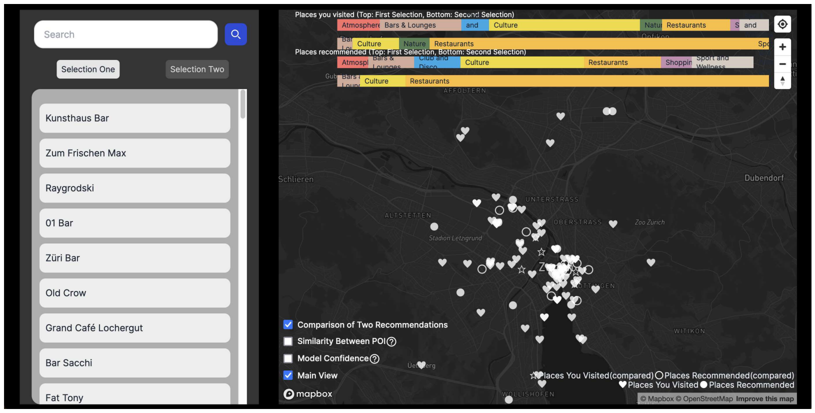

Figure 11: Third layer ”Comparison of Two Recommendations” activated - A second pair of stacked bar charts is now accessible at the top, allowing users to compare two sets of recommendations.