A Neural Embedding-based Recommender System to Get the Most out of EV Recharge Times

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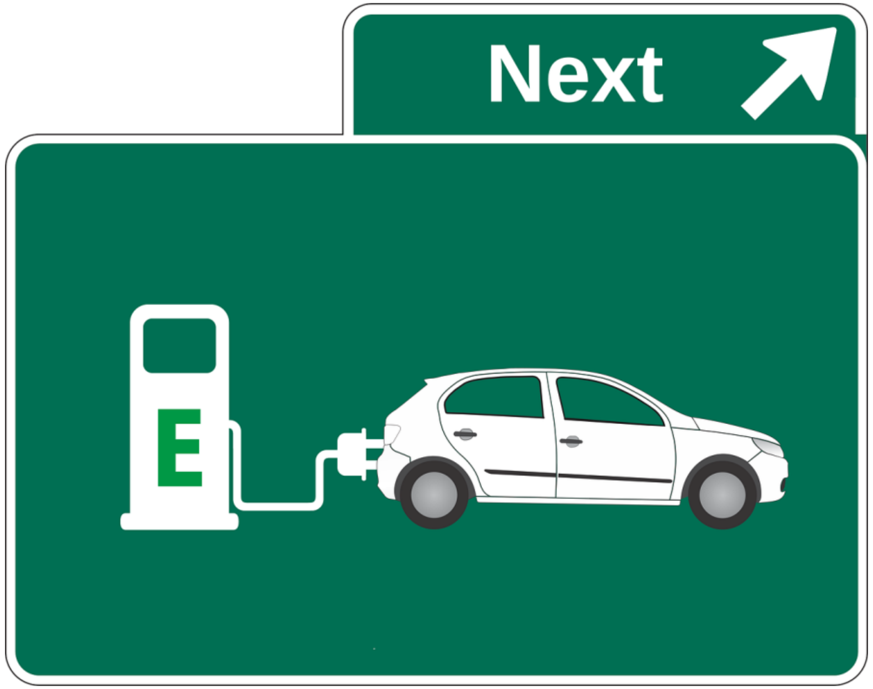
The EV Charging Problem

- **Recharge times** are one of the main challenges in providing a seamless experience for EV drivers
- Drivers might have to **wait** for their turn to use a charging station
- The charging process itself requires time



Recommender Systems

- **Recommender Systems** have been proposed to alleviate this issue
- These systems support drivers by recommending which charging stations to use or which route to drive by to **minimize wait times**

Proposal: Activity Recommender

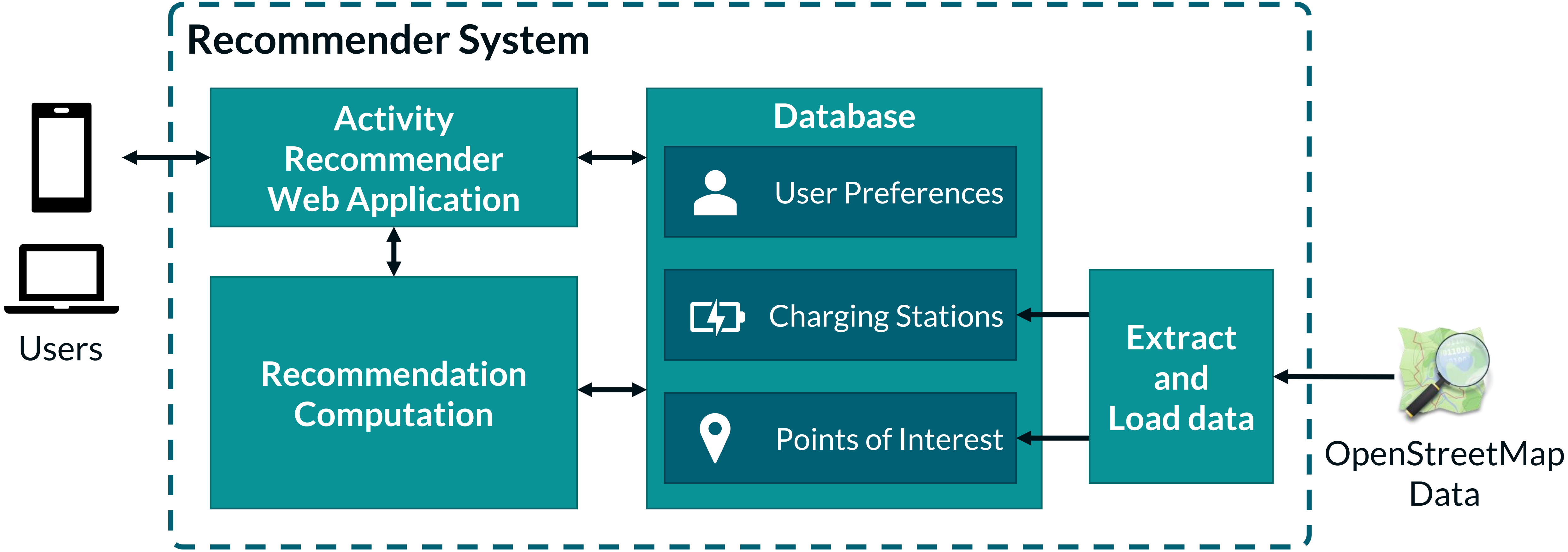
- Still, wait times might be **unavoidable**
- We tackle the charging problem from a **different** and **complementary** perspective

- **What can EV drivers do the get the most out of their recharge wait times?**

Contributions

- A Recommender System that suggests relevant activities users can perform during recharge times
- Based on **open data** from the OpenStreetMap project
- Leverages **Neural Embeddings** to provide accurate recommendations
- The System is **open-source** and **freely available** to interested practitioners and researchers

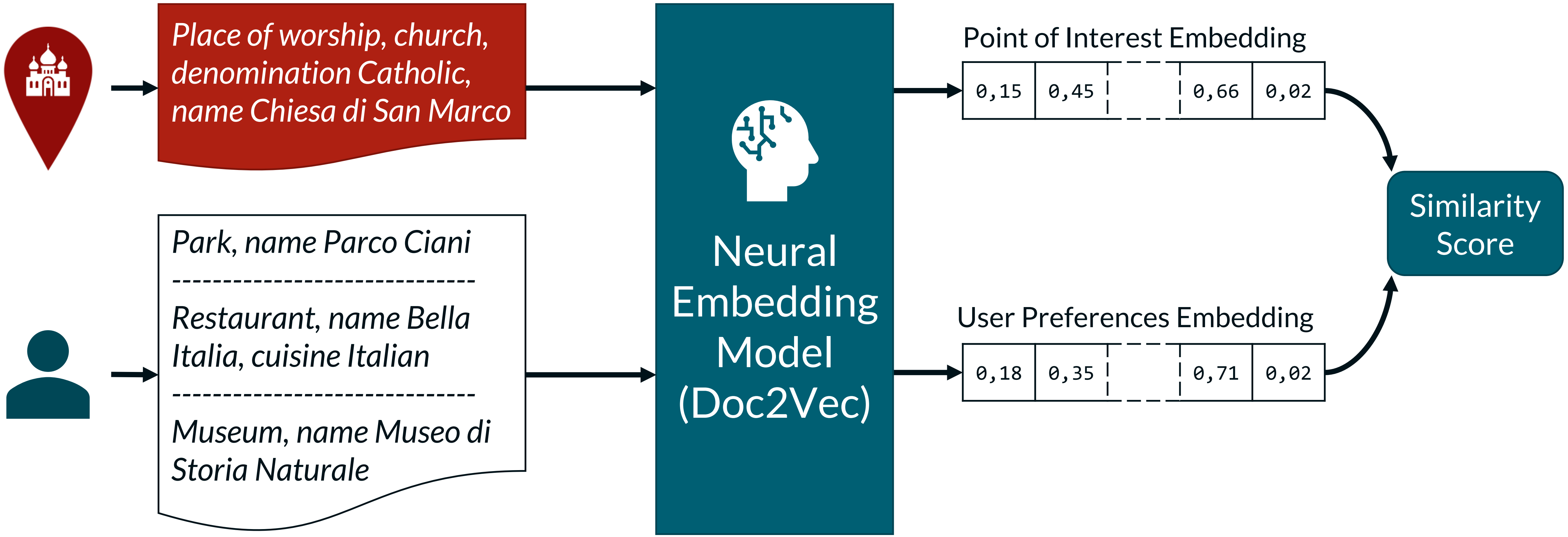
Overall System Architecture



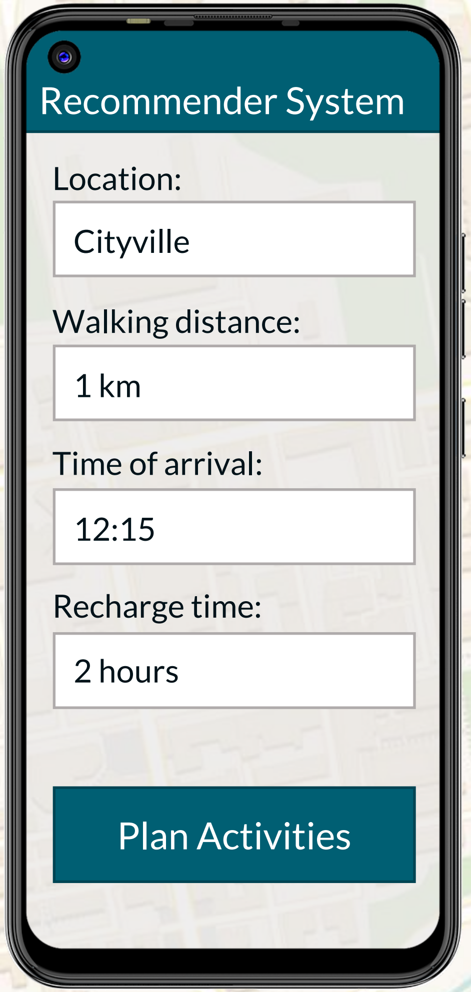
Recommendation Computation

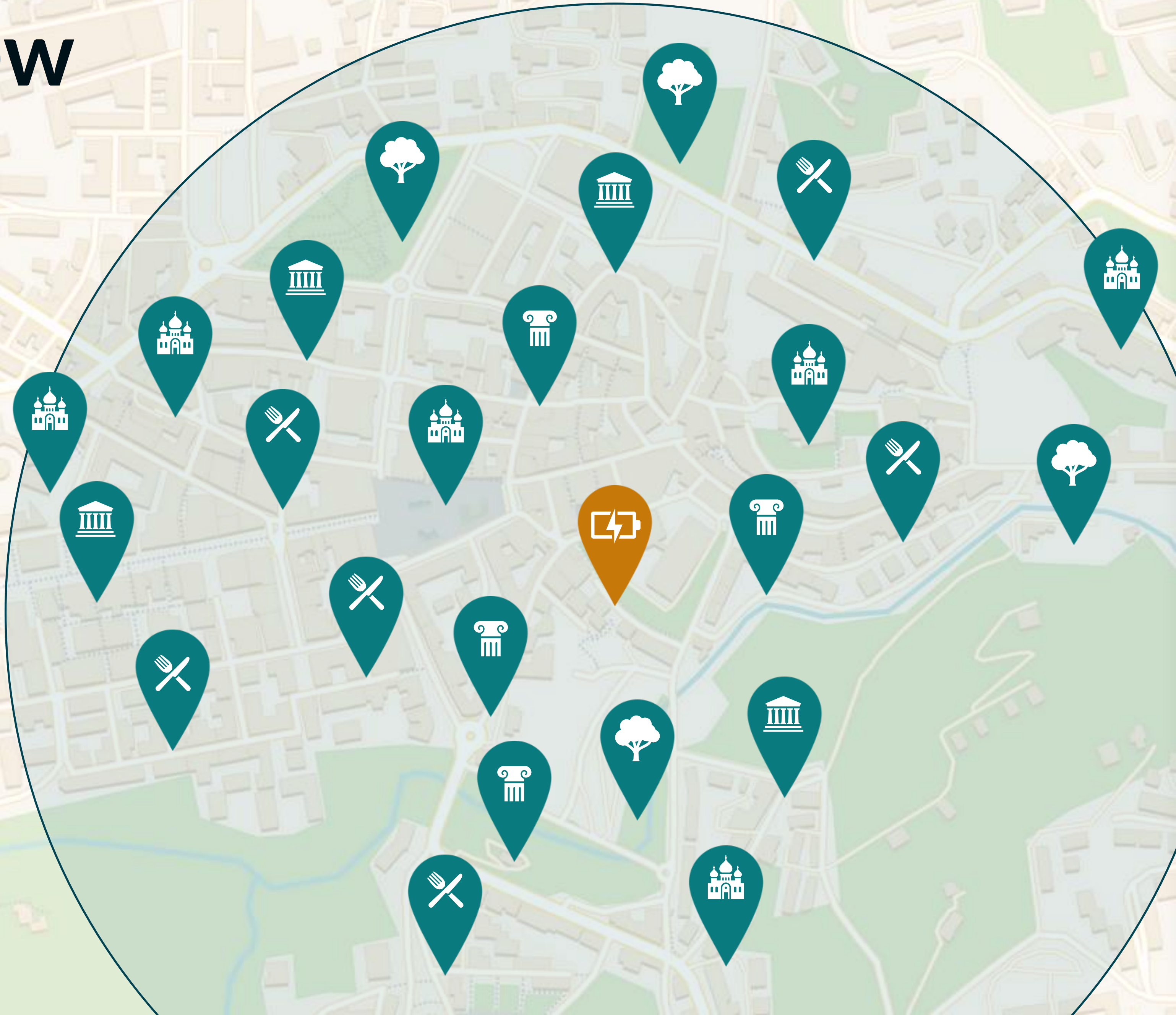
- **Key idea**: represent both **Points of Interest (PoIs)** and **User preferences** as **text** docs
- Use a **specifically-trained** neural embedding model to **measure** semantic similarity between them
- These models leverage **neural networks** to learn a **meaningful** mapping from documents to vectors (***embeddings***)
- Similar documents are mapped to points in the vector space that lie close together
- Similarity between docs can then be measured by considering the distance between the corresponding embeddings

Recommendation Computation



System Overview





System Overview

- Available PoIs are first ranked by decreasing affinity with user preferences
- PoIs are then selected until the wait time is entirely spent
- Users have the final say
- The system keeps track of user choices and *learns* from them for future recommendations

Empirical Evaluation

- Assessed the effectiveness with an empirical study
- Involving **six** potential users, from different backgrounds and demographics
- Participants were asked to rate (0-10) the pertinence of recommendations and ease of use of the system

	Pertinence of Recommendations	Ease of Use
U1	8,5	9
U2	8,5	9
U3	9	10
U4	8,5	8,5
U5	7,5	9
U6	8,5	9,5
AVG	8,4	9,2

Future Research

- Integrate **power grid status** information
- Integrate **more details** in the text representations
- Consider a **wider range of possible activities**
  - E.g.: Watch a new episode of a TV show on a streaming service
  - Watch a movie you might like in the local cinema

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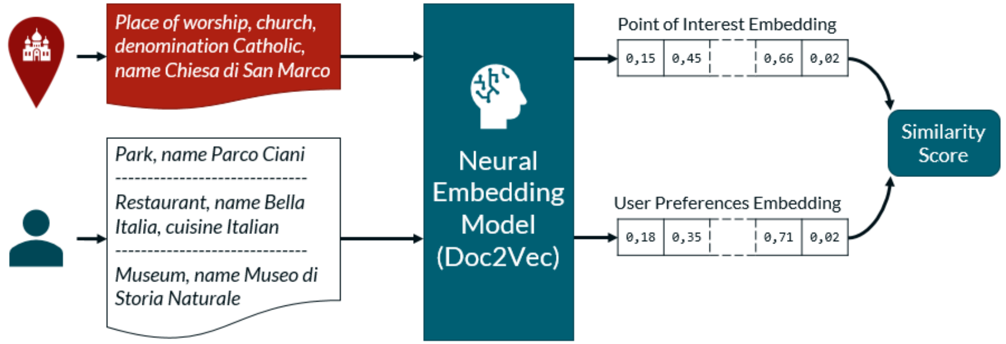

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