Accommodation Review Ranking for Tourism Recommendation

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Outlines of the Presentation

- Definition of the problem
- Motivation
- Traditional approach and challenges
- Experiments and Results
- Conclusion

Problem definition

- Accommodation Review Ranking
- Rank Top 10 reviews for each accommodation
- Return the corresponding review Ids for each user-accommodation pair

user_id	Acco_id	rev_1	rev_2	….	rev_10
1	1	73	3	56	18

Photo is taken from booking.com

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Motivation

- Reviews are considered as an important aspect of a product or service because user makes decisions based on reviews
- Top reviews influence the user’s decision
- Reviews play an important role in user’s interaction experience

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Traditional approaches

- **Review Score**: Highest rating score is ranked at the top
- **Helpness vote:** Top reviews receive the highest helpfulness vote counts
- **Time-based**: Recent reviews are placed at the top positions

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Limitation of the traditional method

- Sparse data-Most of the reviews don’t receive the helpfulness vote or review scores

- Time-based ranking doesn’t reflect the users’ true preferences.

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Proposed Method

User and Item similarity search for ranking review

- **User profile**: User information, e.g., guest_country, guest_type, etc.
- **Item profile**: “ccommodation_type”, “review_title”, etc.
- **Feature extraction**- Sentence Transformer
- **Similarity search**- Cosine Similarity
- **Sorting-** sort reviews according to the similarity

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Feature Extraction

Sentence Transformer (SBERT)

- Transformer based sentence or text encoder model that represents the text as dense vector
- “all-MiniLM-L6-v2”: 6 attention layers, and 768 dim
- Contextual representation of the text

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Similarity Measure

Cosine Similarity

- Score ranges from 0 to 1
- V and U user and item vectors

$$\mathrm{sim}(u, v) = \frac{u \cdot v}{|u||v|}$$

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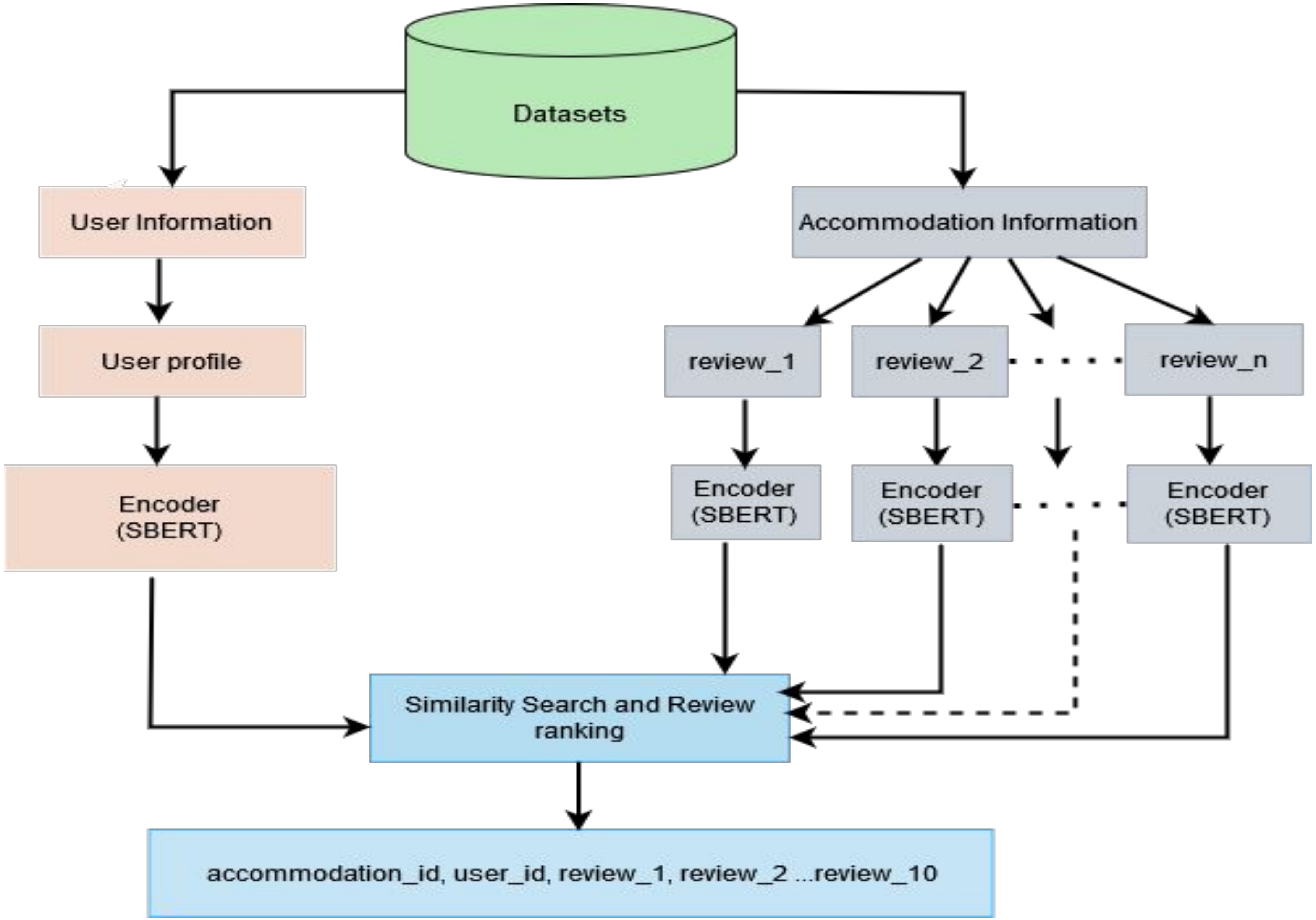
Workflow of the proposed method



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Experiments

Exp No.	User information	Accommodation Information
1	NA	Helpfulness votes
2	NA	Review Score
3	“guest_type”, “guest_country”, “room_nights”, “month”, “acco_type”,“acco_country”, “acco_score”, “acco_star_rating”, “location_is_beach ”, “location_is_ski”, and “location_is_city_center”	“review_title”, “review_positive”, “review_negative”, “re-view_score”, and “review_helpful_votes”.
4	“guest_type” and “guest_country”	Same as experiment 3
5	“guest_type” and “guest_country”	“acco_type”, “acco_country”, “acco_score”, “acco_star_rating”, “ location_is_beach ”, “location_is_ski”, and “location_is_city_center”

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Evaluation Metrics

- MRR (Mean Reciprocal Rank)@K
- Precision@K

$$\text{MRR@K} = \frac{1}{|U|} \sum_{u=1}^{|U|} \frac{1}{\text{rank}_u}$$

$$\text{Precision@K} = \frac{\text{Total Number of relevant items in the top K}}{|K|}$$

Results

Experiment No.	**MRR@10**	**Precision@10**
Exp 1	0.0735	0.2511
Exp 2	0.0735	0.2511
Exp 5(Proposed) Method	**0.0787**	**0.2605**

Ablation Studies

Features	MRR@10	Precision@10
Exp 3	0.0775	0.2582
Exp 4	0.0735	0.2511
Exp5 (Proposed Method)	**0.0787**	**0.2605**

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Conclusion and Discussion

- We propose a review ranking method by leveraging user and item features
- Feature selection plays an important role in semantic similarity search
- Diverse set of features can provide better user and item representation
- Advanced embedding Model, e.g. LLM

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Thank You!

Questions?

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