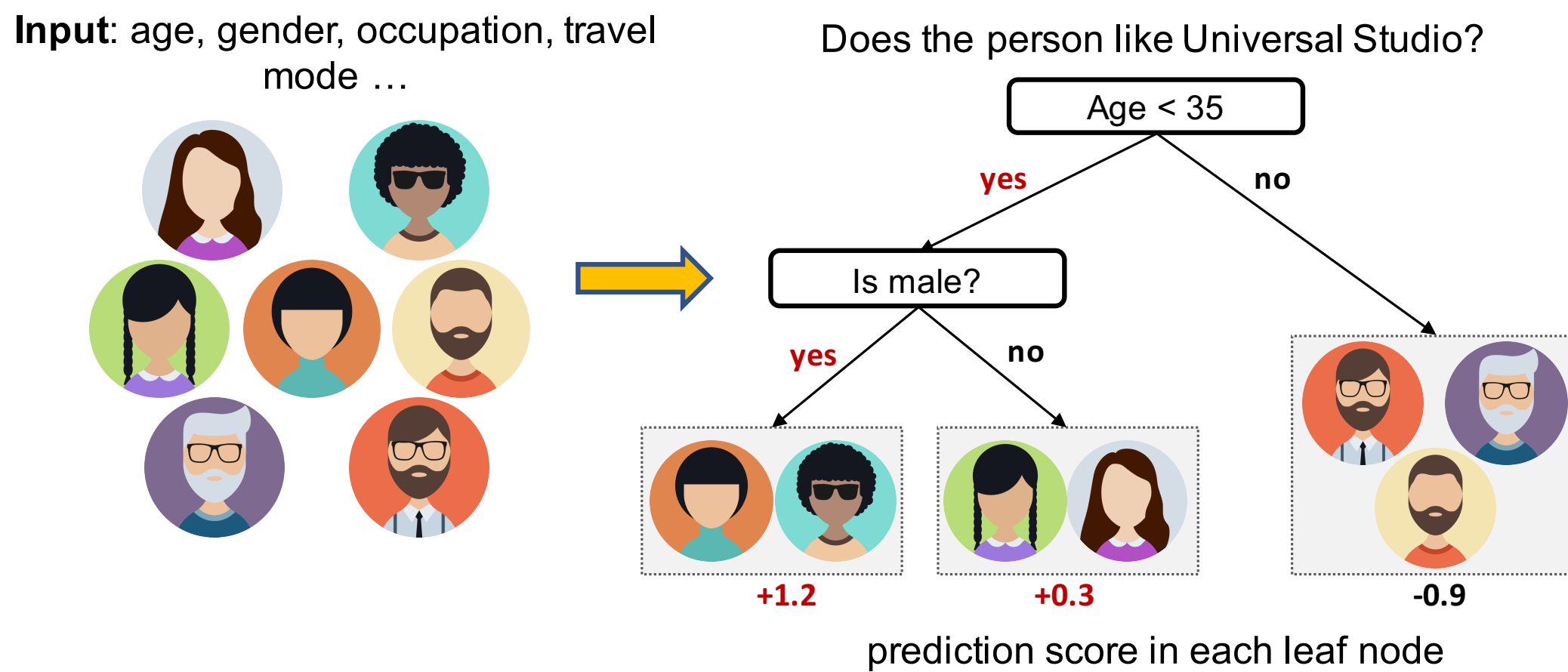


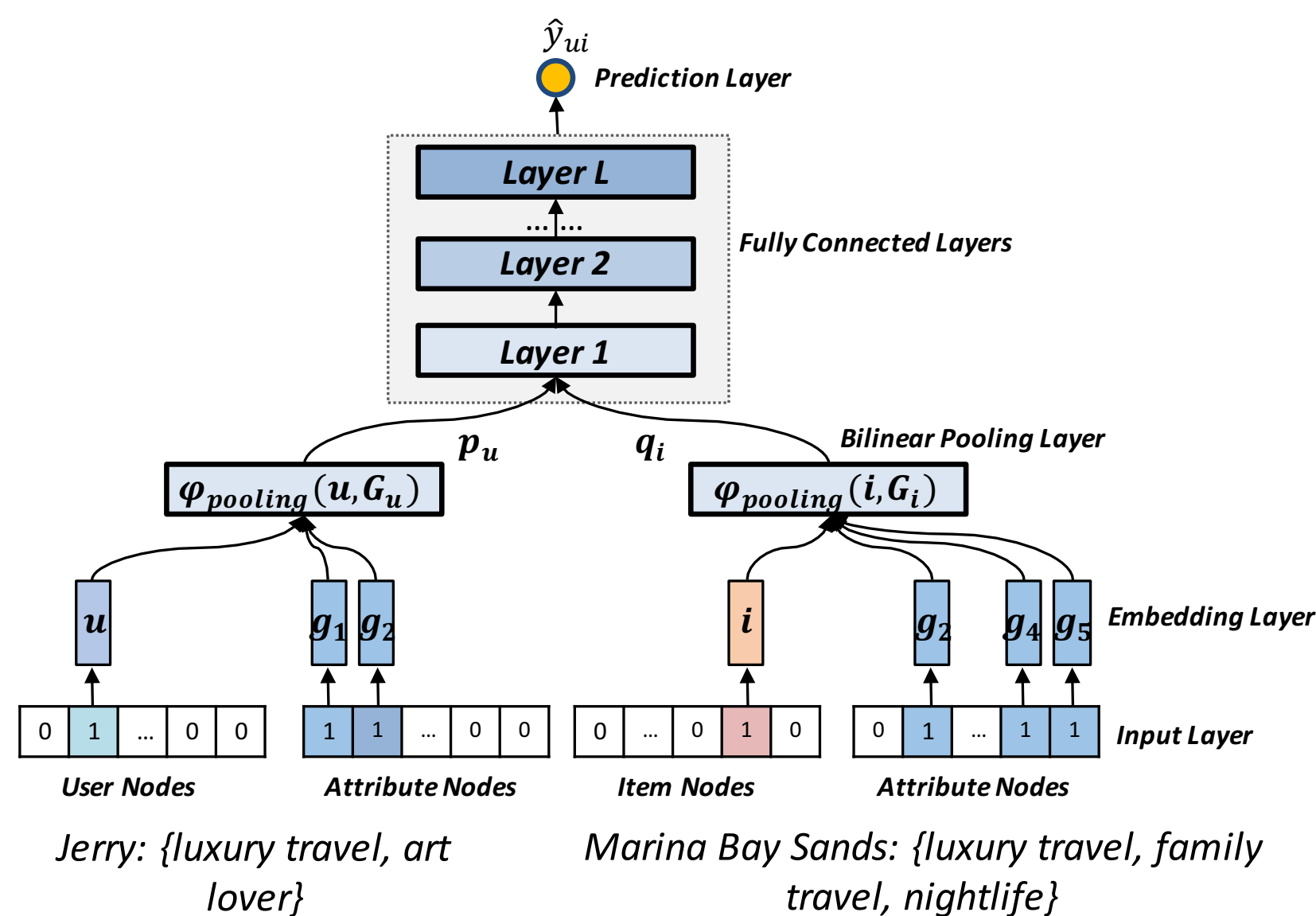
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## Background

- Tree-based models are easily explainable, but they have limited representation power.



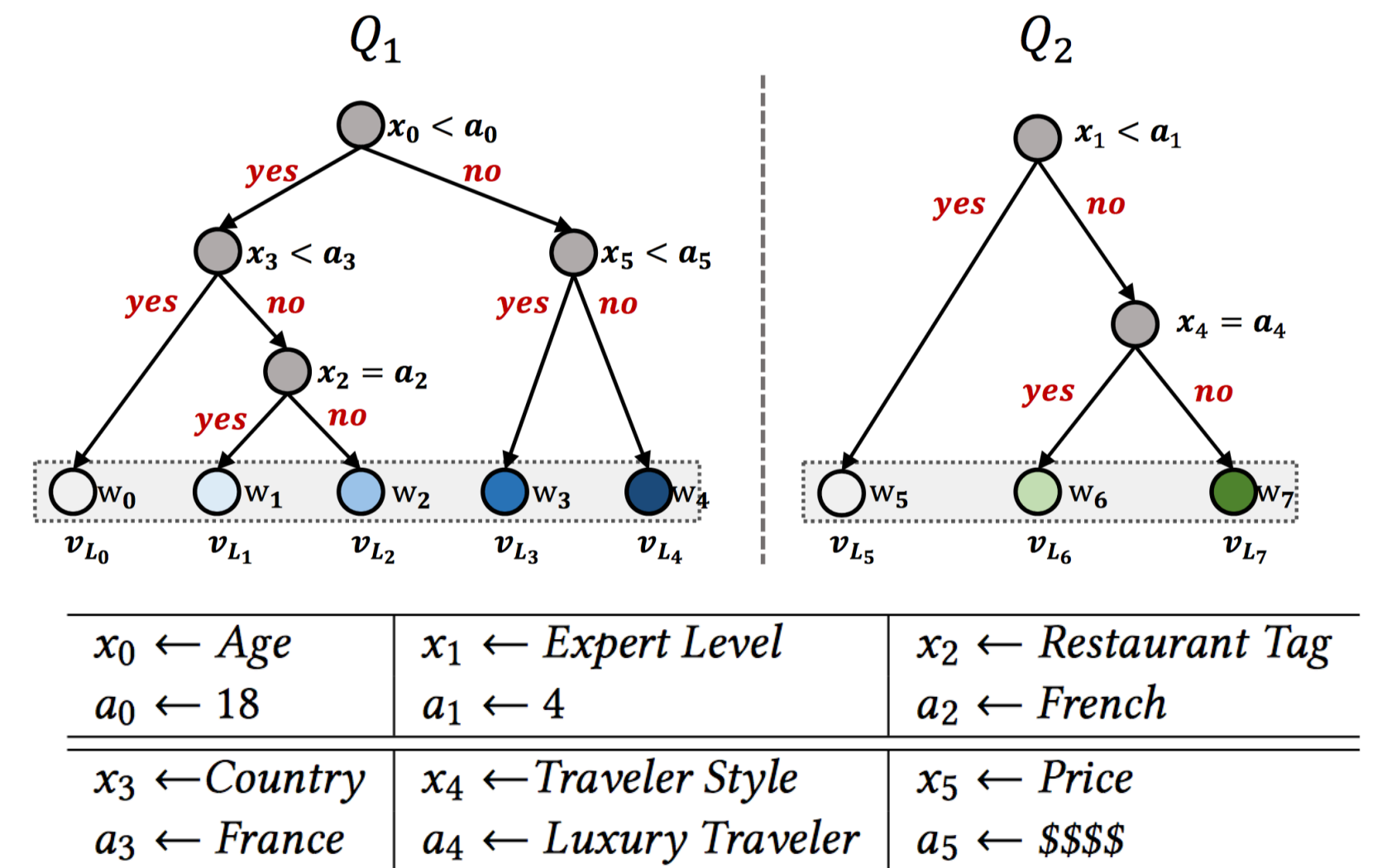
- Neural recommendation methods (e.g., NCF and NFM) operate as a black-box, very expressive yet hardly understood by end users.



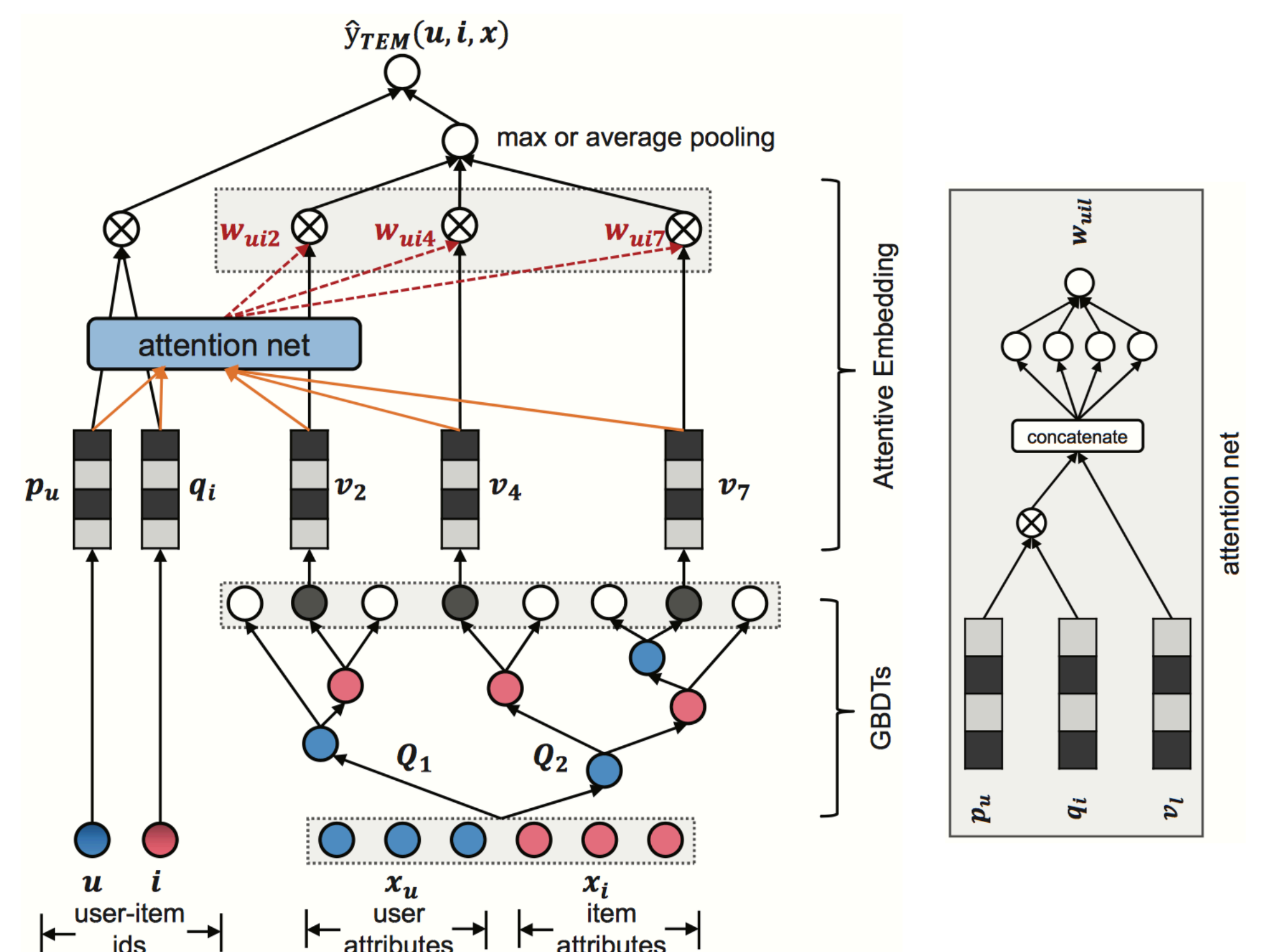
- Promising applications
  - Recommender systems provide sound reasons on why the product is suitable choice.
  - Injecting explainability, recommendations will assist merchants to make informed decisions.

## Explainable Recommendation

- We first employ a tree-based model to learn explicit decision rules (aka. cross features) from the rich side information



- We next design an embedding model that can select the most predictive cross features based on the user-item attention scores.



## Experimental results

### >> Dataset Statistics

- TripAdvisor
- Attraction Recommendation in London
- Restaurant Recommendation in New York City

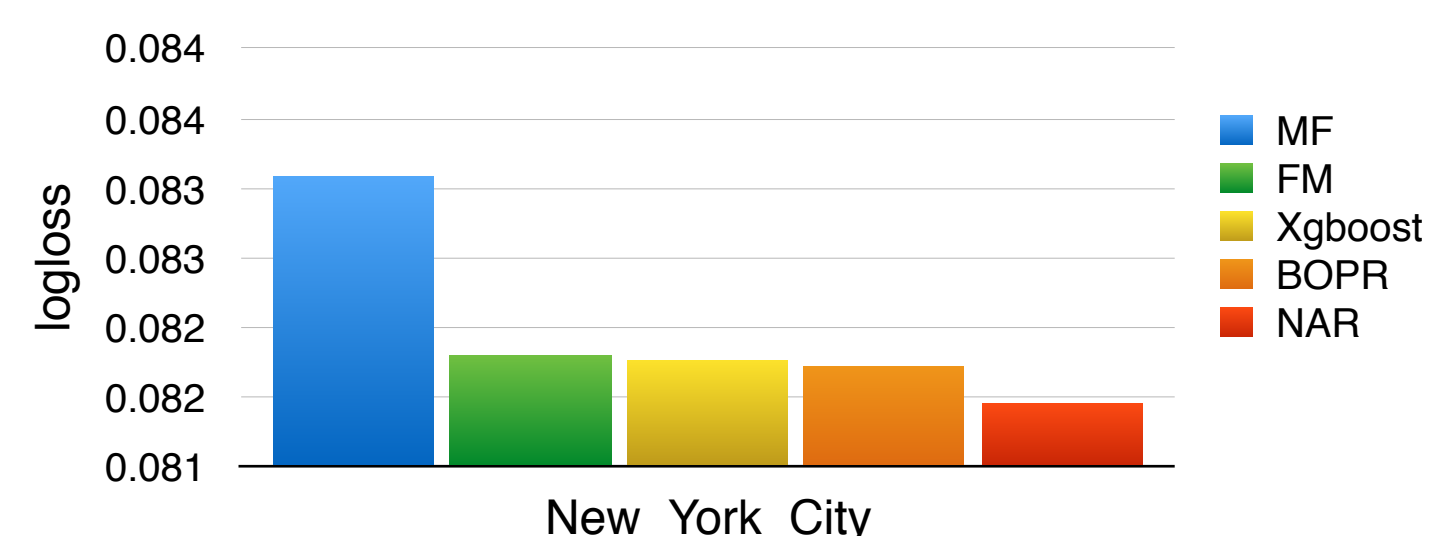
Table 2: Statistics of the datasets.

Dataset	User#	User Feature#	Item#	Item Feature#	Interaction#
LON-A	16, 315	3, 230	953	4, 731	136, 978
NYC-R	15, 232	3, 230	6, 258	10, 411	129, 964

Table 3: Statistics of the side information, where the dimension of each feature is shown in parentheses.

Side Information	Features (Category#)
LON-A/NYC-R User Feature	Age (6), Gender (2), Expert Level (6), Traveler Styles (18), Country (126), City (3, 072)
LON-A Attraction Feature	Attributes (89), Tags (4, 635), Rating (7)
NYC-R Restaurant Feature	Attributes (100), Tags (10, 301), Price (3), Rating (7)

### >> Restaurant Recommendation



### >> Restaurant Recommendation

- <City: Florida, Style: Nightlife Seeker, Age: 50-64> will visit <Per Se>
- <City: SanFrans, Style: Family Travel, Age: 65+> will visit <Gabriel Kreuther>