Matrix Factorization with Domain Knowledge and Behavioral Patterns for Intent Modeling

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The Task

- Motivations
  - An typical SDS has two main challenges:
    1) **Predefined ontology**: the domain ontology is required to support the corresponding functions
    2) **Language ambiguity**: same utterance may infer different intents during different situations
  - Structured knowledge resources are available (e.g. Freebase, Wikipedia, FrameNet) and may provide semantic information
  - Users' behavioral patterns may help disambiguate the current intents
  - Hidden semantics help infer the relation between different features
- Approaches: **Feature-Enriched MF-SLU**
  - Enrich semantics with the structured knowledge or behavioral patterns for improving intent prediction
  - Unify the human written knowledge and automatically inferred information in a matrix and predict user intents in the mean time
- Results
  - Feature-enriched MF-SLU benefits from hidden information and rich features, and then outperforms the baselines for both single-turn requests and multi-turn interactions.

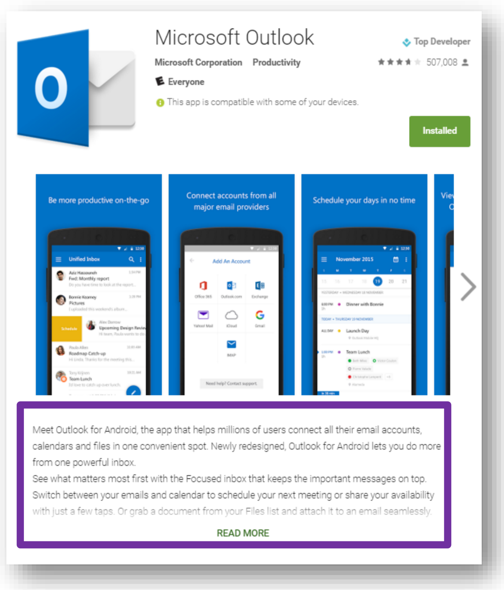
Feature-Enriched MF-SLU: Spoken Language Understanding by Matrix Factorization

Experiment 1: Single-Turn Request

- **Data**: speech data collected from the users with the intents from 13 frequently accessed domains in Google Play (WER = 19.8%)

Lexical Matrix

- **Main idea: utilize manual written app description because it should describe the app's functionality**

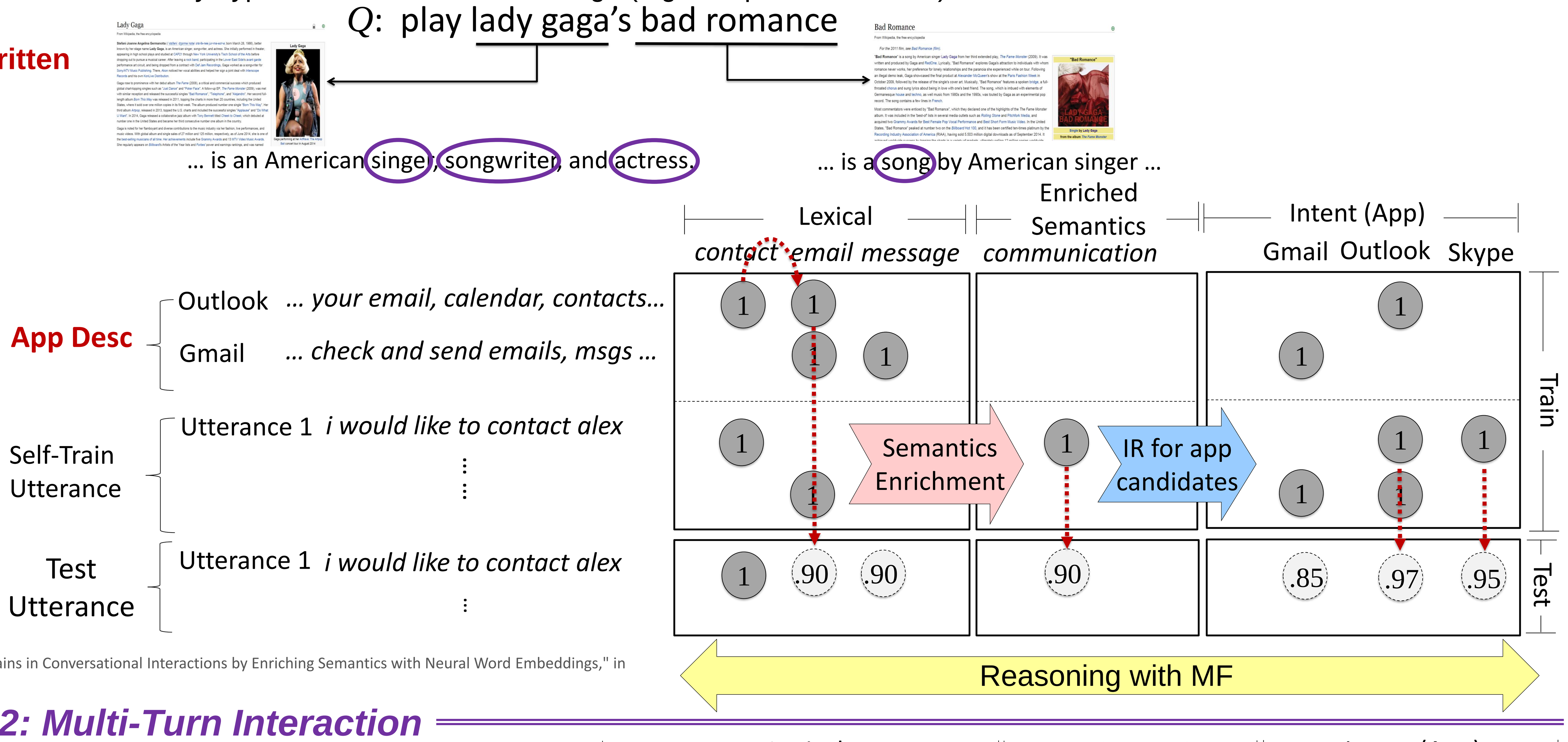


Enriched Semantics Matrix

- **Main idea: slot types and word embeddings help imply semantics for expanding domain knowledge**
  - Entity Type from Structured Knowledge (e.g. Wikipedia/Freebase)

Intent Matrix

- **Main idea: retrieve the apps that are more likely to support users' requests for self-training**

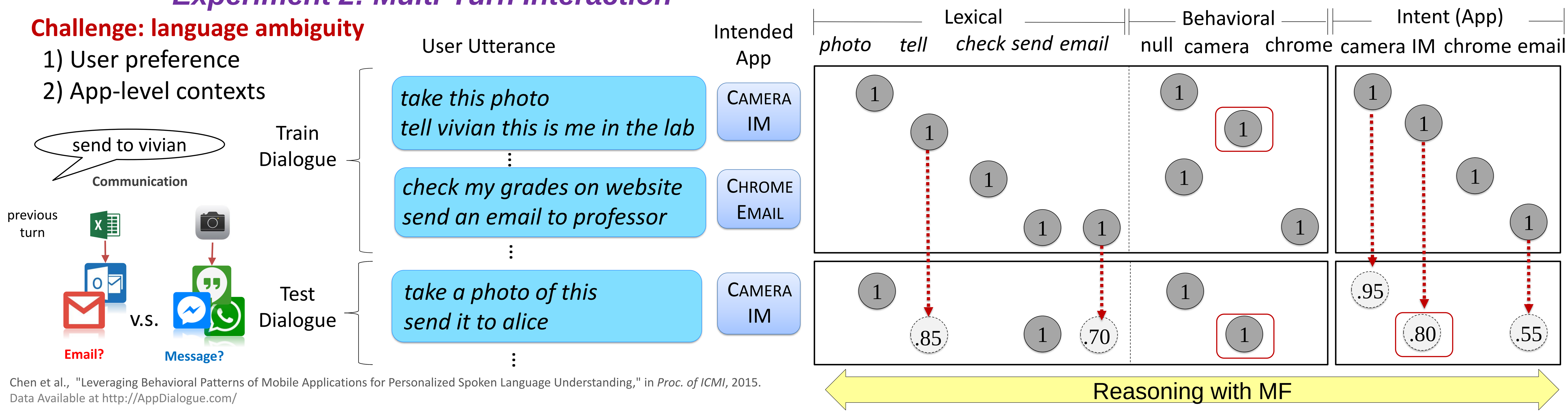


Chen and Rudnicky, "Dynamically Supporting Unexplored Domains in Conversational Interactions by Enriching Semantics with Neural Word Embeddings," in *Proc. of SLT*, 2014.

Experiment 2: Multi-Turn Interaction

Challenge: language ambiguity

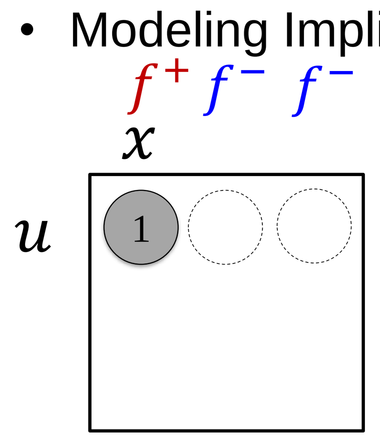
1) User preference
2) App-level contexts



Chen et al., "Leveraging Behavioral Patterns of Mobile Applications for Personalized Spoken Language Understanding," in *Proc. of ICMI*, 2015.
Data Available at http://AppDialogue.com/

Matrix Factorization

- Modeling Implicit Feedback:



$$f^+ = \langle u, x^+ \rangle \quad f^- = \langle u, x^- \rangle \Rightarrow p(f^+) > p(f^-)$$

$$p(M_{u,x} = 1 \mid \theta_{u,x}) = \sigma(\theta_{u,x}) = \frac{1}{1 + \exp(-\theta_{u,x})}$$

- Objective: $\sum_{f^+ \in \mathcal{O}} \sum_{f^- \notin \mathcal{O}} \ln \sigma(\theta_{f^+} - \theta_{f^-})$

> MF learns a set of well-ranked intents per utterance.

Experiments

Feature Matrix		ASR		Transcripts	
		LM / MLR	MF-SLU	LM / MLR	MF-SLU
Single-Turn	Word Observation	25.1	29.2 (+16.2%)	26.1	30.4 (+16.4%)
	+ Type-Enriched Semantics	31.5	**32.2 (+2.1%)**	32.9	**34.0 (+3.4%)**
Multi-Turn	Word Observation	52.1	52.7 (+1.2%)	55.5	55.4 (-0.2%)
	+ Behavioral Patterns	53.9	**55.7 (+3.3%)**	56.6	**57.7 (+1.9%)**

> The *feature-enriched MF-SLU* can benefit from both hidden information modeled by MF and enriched semantics including structured knowledge and behavioral patterns to improve Intent prediction.

Conclusions

- In a smart-phone intelligent assistant setting (e.g. requesting an app), the feature-enriched MF-SLU can handle users' open domain intents by returning relevant apps that provide desired functionality either locally available or by suggesting installation of suitable apps and doing so in an unsupervised way.
- The framework can extend to incorporate personal behavior history for improving a system's ability to assist users pursuing personalized multi-app activities.
- The effectiveness of the feature-enriched MF-SLU model can be shown in different domains, indicating good generality and providing a reasonable direction for the future work.