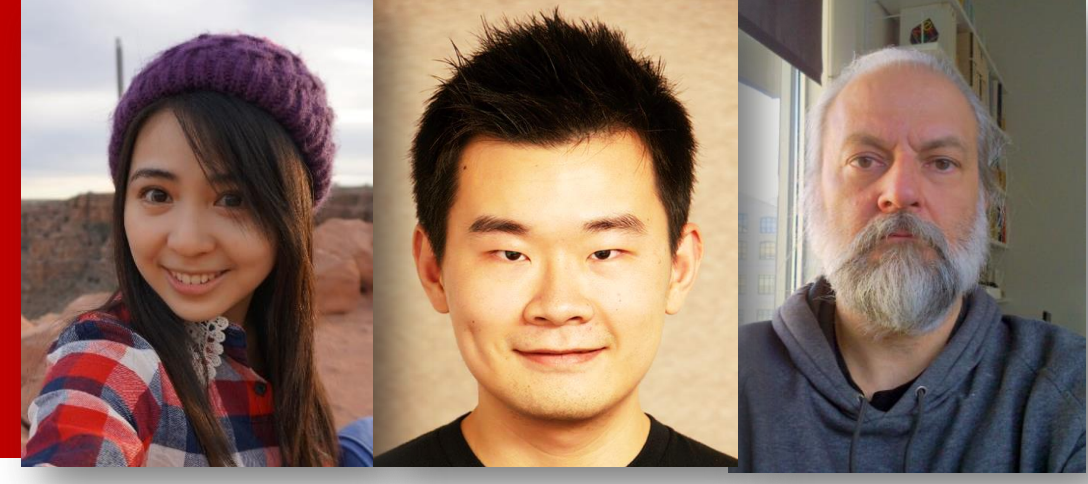




Learning Semantic Hierarchy with Distributional Representations for Unsupervised Spoken Language Understanding

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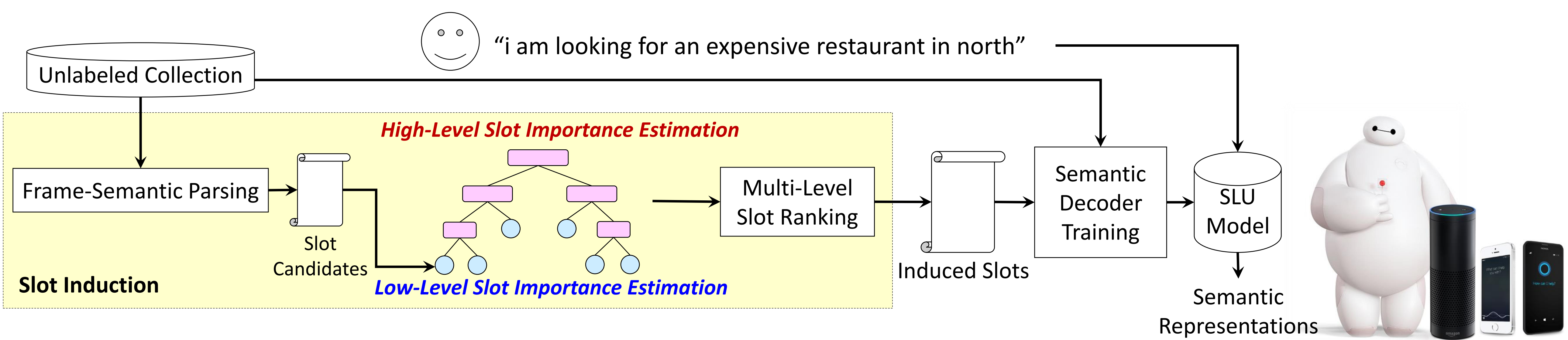
Can a dialogue system automatically learn open domain knowledge?

Summary

- Motivation
 - Dialogue systems require a predefined semantic ontology; can it be learned from data?
 - A hierarchical ontology containing cross-slot information is crucial to SLU.
 - Word embeddings carry robust semantics.
- Approach
 - 1) HAC learns a hierarchical ontology based on FrameNet-parsed slot candidates and word embeddings.
 - 2) The slot importance estimated for different levels is integrated together to induce the ontology.
 - 3) The induced slots are used for training an SLU model.
- Result
 - With high-level information, the SLU model achieves 13% relative improvement on F1.
 - The learned hierarchy aligns well with the hand-craft mapping.

Low-Level Slot Importance Estimation

- Frame semantics parsing generates slot candidates (Chen et al., 2013; 2014)
- can i have a cheap restaurant
- Frame: capability Frame: expensiveness Frame: locale by use
 FT LU: can FE Filler: i FT LU: cheap FT/FE LU: restaurant
- generic semantic concept (useless for SDS) domain-specific concept
- **Idea: rank domain-specific concepts higher than generic semantic concepts**
- $$w^0(s) = (1 - \alpha) \log f(s) + \alpha \log h(s)$$
- $f(s)$: the slot frequency in the parsed corpus
 - slots with higher frequency → more important
 - $h(s)$: the coherence of slot-fillers
 - domain-specific concepts focus on fewer topics → coherence can help measure slot prominence

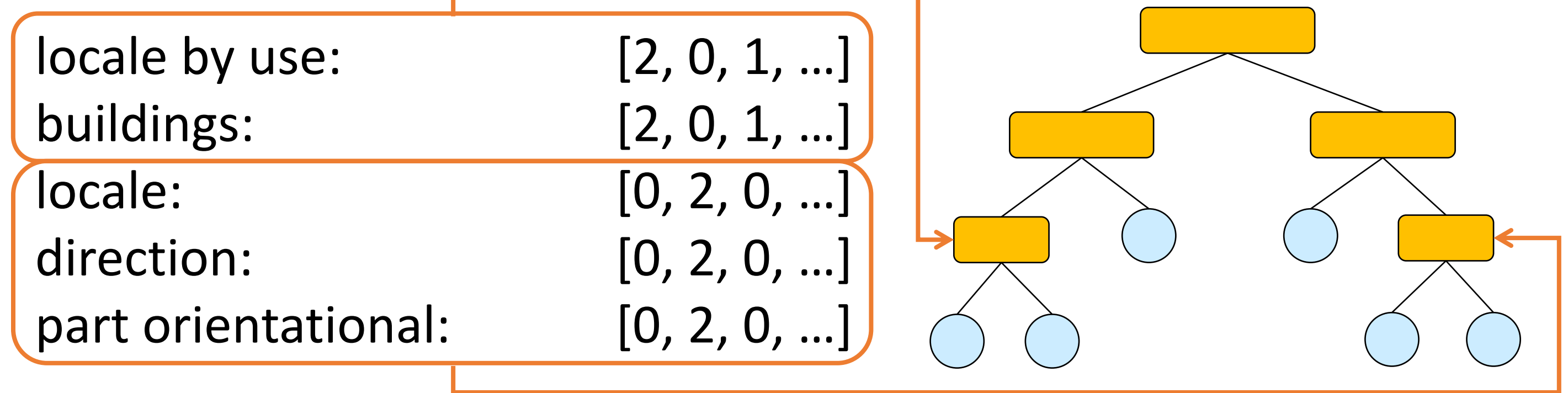
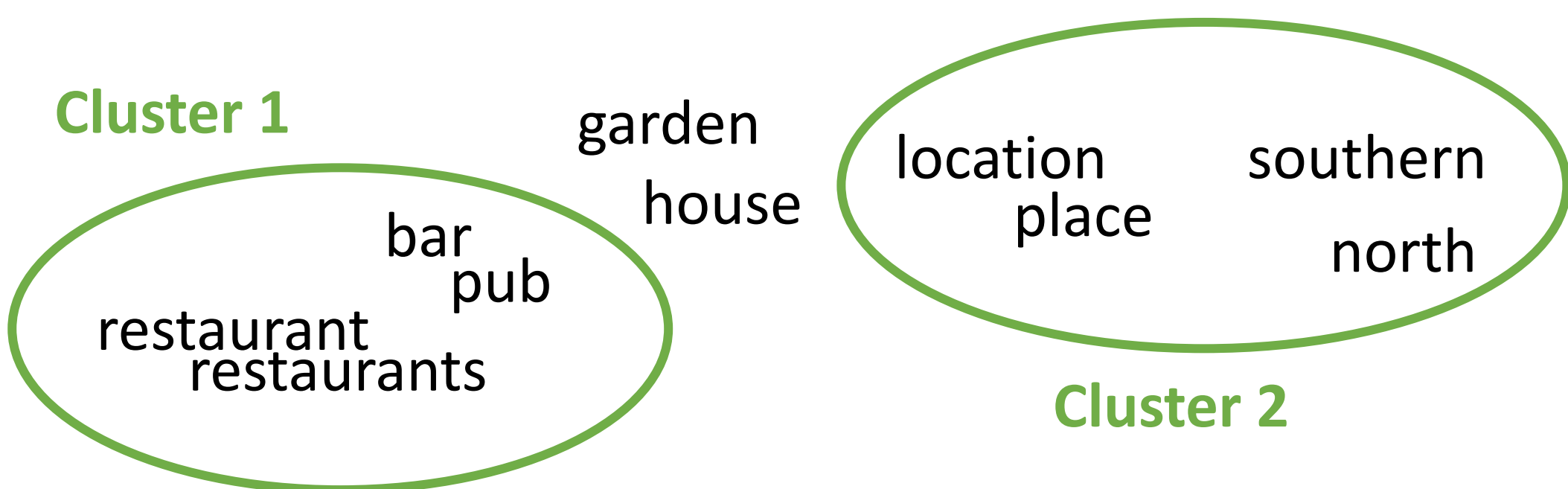


High-Level Slot Importance Estimation

- **Hierarchical Agglomerative Clustering (HAC)** performs a bottom-up clustering approach by successively merging similar clusters together.

- The distance between two clusters A and B is defined as $\frac{1}{|A||B|} \sum_{a \in A} \sum_{b \in B} d(a, b)$

- **Word-level clustering** groups the words with closer embeddings since they have similar contexts
- **Slot-level clustering** groups the slots with closer vectors built by the word-level clustering results



➤ Word embeddings help merge semantically similar words together.

➤ Different slot candidates generated by the frame semantic parser can be merged because they share similar clustering distribution.

- **Bottom-up slot importance estimation** estimates the high-level slot importance by aggregating the low-level importance:

$$w^{h+1}(s) = \frac{1}{|C^h(s)|} \sum_{c(s_k)=c(s)} w^h(s_k)$$

Multi-Level Slot Ranking

- **Idea: rank slots considering all different levels of the hierarchy**

$$w(s) = \sum_{h=0}^H \lambda_h w^h(s)$$

➤ The final slot importance contains hierarchical information.

Experiments

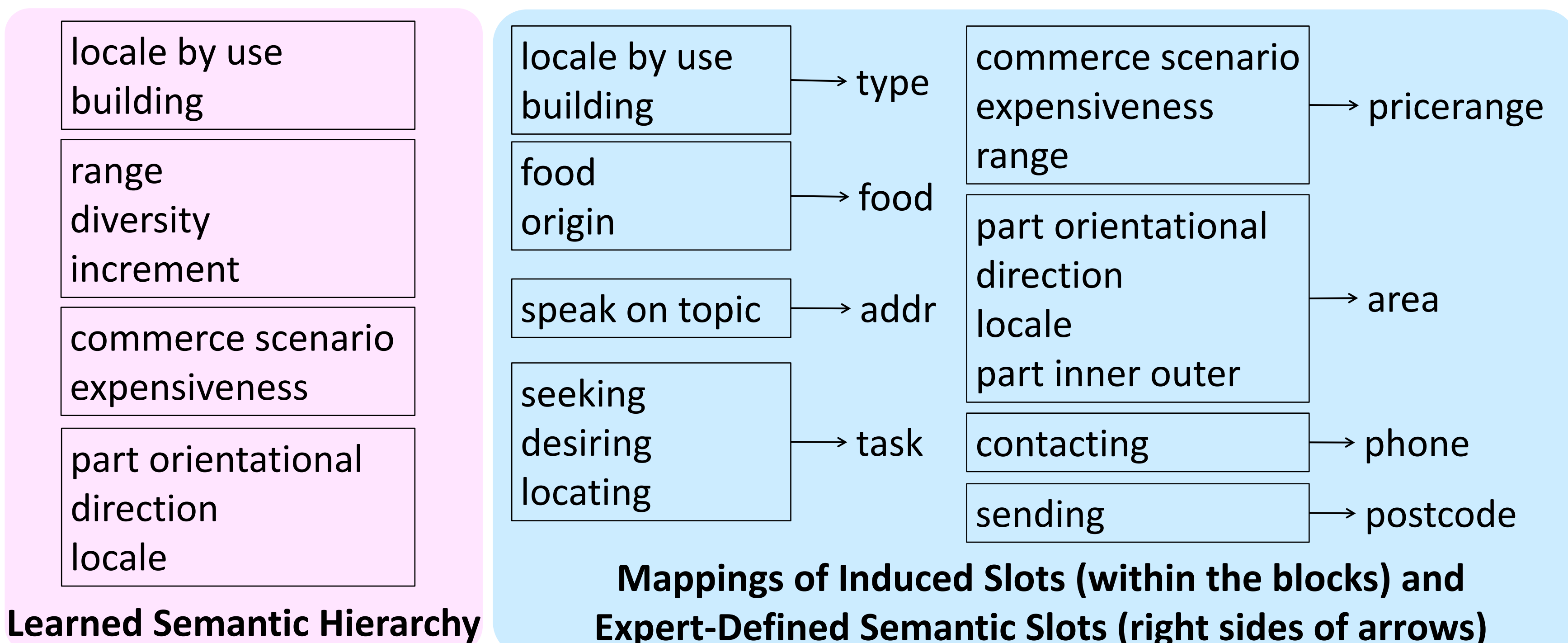
- **Domain:** restaurant recommendation in an in-car setting in Cambridge (Word Error Rate = 37%)

- Dialogue slots: **addr, area, food, phone, postcode, price range, task, and type**

Approach	Slot Induction AUC (%)	SLU F1 (%)
Baseline	79.50	60.27
Proposed	High-Level	67.94
	Multi-Level	68.13

Conclusion

- We propose an **unsupervised approach** unifying semantics from a **hierarchical structure** to improve slot induction and SLU modeling.
- Our automatically induced semantic slots align well with reference slots.
- We show the feasibility of training an SLU model based on automatically induced slots and its promising performance for practical usage.



➤ High-level information helps both slot induction and SLU performance, where the learned hierarchy aligns well with the manual mapping.

