1. The Task

- **Motivations**
  - SDSs require predefined semantic slots to support parsing users’ input into semantic representations.
  - Frame semantics theory provides generic semantics.
  - Distributional semantics capture contextual latent semantics.

- **Approaches**
  - Generate slot candidates using a frame-semantic parser.
  - Propose a re-ranking model to differentiate domain-specific concepts from generic semantic concepts using word representations.

- **Results**
  - Automatically induced semantic slots have average precision (AP) of 76% for ASR-transcribed data.

2. Probabilistic Frame-Semantic Parsing

- **Frame Semantics**: the meaning of most words can be expressed as semantic frames.
- **SEMAFOR** is a state-of-the-art parser for frame semantic parsing, trained on a linguistically-principled semantic resource, FrameNet.

- **How to adapt the FrameNet-style frame-semantic parses to the semantic slots in the target semantic space for practical use in spoken dialogue systems?**
  - We parse ASR-decoded utterances using SEMAFOR and extract all frames from semantic parsing results as slot candidates; LUs that correspond to the frames are used for slot-filling.

- **Approach**
  - Slot candidate: Frame: capability.
  - Slot filler: FT LU: can FE Filler: i.

- **Framework**
  - Can i have a cheap restaurant

3. Word Representations

- **Distributional Semantics** hypothesizes that words occurring in the same contexts may have similar meanings.
- **Recurrent neural network language models** use the context history to include long-distance information, capturing both syntactic and semantic regularities.

- **Allows the use of large external data sets to differentiate semantic concepts and help the adaptation process.**

- **Pre-trained distributed word embedding vectors:**
  - Word/Phrase Vectors from Google News
  - Entity Vectors with Freebase Naming

4. 4. Slot Ranking Model

- **Main idea**: rank domain-specific concepts higher than generic semantic concepts.
- **Motivations**
  - Rank the slot candidates by integrating two scores
  - Measure coherence by pair-wised similarity of slot-fillers
  - SDSs require predefined semantic slots to support parsing

- **Approaches**
  - Generate slot candidates using a frame-semantic parser
  - Propose a re-ranking model to differentiate domain-specific concepts from generic semantic concepts using word representations.

- **Results**
  - Automatically induced semantic slots have average precision (AP) of 76% for ASR-transcribed data.

5. Experiments

- **Domain**: restaurant recommendation in an in-car setting in Cambridge (Word Error Rate = 37%)
- **Slot Induction Evaluation**: AP of the slot ranking model used to measure the quality of induced slots via the mapping table.
- **Slot Filling Evaluation**: AP-F/H/S: weight the AP score with F-measure of two slot filler lists.

6. Conclusions

- **We propose an unsupervised approach unifying frame and distributional semantics for automatic induction and filling of semantic slots.**
- **Our work makes use of a state-of-the-art semantic parser**, and adapts the linguistically principled generic FrameNet-style outputs to the target semantic space that corresponds to a domain-specific SDS setting.
- **With the incorporation of word embeddings**, our experiments show that automatically induced semantic slots align well with the reference slots created by domain experts.
- **Automatically induced semantic slots achieve AP of 76% for ASR-transcribed data.**

- **Approach**
  - Adding distributional information outperforms our baselines
  - Neighbor-derived similarity performs better because it considers more semantically-related words (instead of two tokens)
  - Neighbor-derived similarity requires less space for computational procedure

- **Combining two datasets to integrate the coverage of Google and precision of Freebase can rank correct slots higher and provides the best MAP scores.**