1. The Task

- **Motivations**
  - SDSs require predefined semantic slots to parse users’ language input into unified semantic representations.
  - Defining semantic slots requires the involvement of a domain expert.
  - Frame semantics theory provides generic semantic information.

- **Approaches**
  - Obtain slot candidates using a state-of-the-art frame-semantic parser.
  - Propose a clustering-based ranking model to distinguish generic semantic concepts and domain-specific concepts.

- **Results**
  - Automatically induced semantic slots have MAP of 69.36% for ASR-transcribed data.

2. Probabilistic Frame-Semantic Parsing

- **Frame Semantics theory** states that the meaning of most words can be expressed on the basis of semantic frames:
  - frame (F): the frame “food” contains words referring to items of food
  - frame elements (FE): a descriptor frame element within the “food” frame indicates the characteristic of the food.
  - lexical units (LU): the values of the corresponding frame element, such as “milk”

- **SEMAFOR** is a state-of-the-art semantic parser for frame semantic parsing trained on a linguistically-principled semantic resource FrameNet.

- **How to map and adapt the FrameNet-style frame-semantic parses to the semantic slots in the target semantic space for practical use in the spoken dialogue systems?**

  - We parse all ASR-decoded utterances using SEMAFOR and extract all frames from semantic parsing results as slot candidates, where the LUs that correspond to the frames are extracted for slot-filling.
  - Frame: capability | Frame: expensiveness | Frame: locale by use
    - can have a cheap restaurant

3. Slot Ranking Models

- **Main idea**: rank domain-specific concepts higher than generic semantic concepts.
  - Rank the slot candidates by integrating two scores
    \[ w(s_i) = \log f(s_i) + \alpha \cdot h(s_i) \]
    - \( f(s_i) \): the frequency of each candidate slot in the SEMAFOR-parsed corpus
    - \( h(s_i) \): the coherence of values the slot corresponds to
  - Measure coherence by word-level context clustering
    - For each slot \( s_i \), \( V(s_i) = \{ v_{1i}, \ldots, v_{ji}, \ldots, v_{Vj} \} \)
      - slot candidate: corresponding value vectors: “cheap”, “not expensive” (from the domain concepts with \( s_i \) in the parsing results)
    - We have corresponding cluster vectors
      \[ C(s_i) = \{ c_1, \ldots, c_j, \ldots, c_J \} \]
      - the frequency of words in \( v_i \) clustered into cluster \( k \)
    - Measure coherence measure by pair-wise cosine similarity
      \[ h(s_i) = \frac{\sum_{c_n,c_k} C(c_n,c_k) \cdot \cosim(c_n,c_k)}{|C(s_i)|^2} \]
  - The slot with higher \( h(s_i) \) usually focuses on fewer topics, which are more specific, which is preferable for slots of SDS.

4. Experiments

- **Domain**: recommendation in an in-car setting in Cambridge* (WER = 37%)
  - Dialogue slot (total #slot = 10):
    - addr, area, food, name, phone, postcode, price range, signature, task, and type

- **Slot Induction Evaluation**
  - MAP of the slot ranking model: measure the quality of induced slots based on induced and reference slots via the mapping table

- **Slot Induction and Slot Filling Evaluation**
  - MAP-F1-Hard/Soft: weight the MAP score with F1-Hard or F1-Soft scores

5. Conclusions

- We propose an unsupervised approach 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 the domain-specific SDS setting.
  - Our experiments show that automatically induced semantic slots align well with the reference slots created by domain experts.
  - We focus on the slot-filling tasks that extract the slot-filler information from those automatically induced slots.

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