Summary

Motivation
- SDSs require a predefined semantic ontology; can it be learned from data?
- Inter-slot relations can provide a coherent ontology
- Typed dependencies enable learning of ontology structure

Approach
1. Construct two-layer knowledge graph represent slots, words, and relations
2. Compute scores for edges (relations) and nodes (slots) by random walk
3. Identify important slots associated with relations

Result
- Using embedding similarity, we achieve 70% AP for slot induction and 48% AF for SLU
- The automatically acquired slot set enhances the interpretability of semantic slots

Step 1: Knowledge Graph Construction

Structure can be constructed via the unlabeled collection with frame-semantic parsing and syntactic dependency parsing.

Step 2: Weight Measurement

Idea: the edge weights can represent the relation importance
- We train dependency-based word/slot embeddings [1].

Then the relation matrices can be built
- Slot-to-slot relation $L_{ss}$: similarity between slot embeddings
- Word-to-slot relation $L_{ws}$ or $L_{sw}$: frequency of the slot-word pair
- Word-to-word relation $L_{ww}$: similarity between word embeddings

Assumption: the slots with more dependencies to more important slots should be more important

The random walk algorithm computes the importance for each slot

\[
L_{ss}(t+1) = (1 - \alpha) L_{ss}(0) + \alpha L_{ss} L_{sw} L_{ws}(t)
\]

\[
L_{ws}(t+1) = (1 - \alpha) L_{ws}(0) + \alpha L_{ww} L_{ws} L_{sw}(t)
\]

Scores propagated from word-layer then propagated within slot-layer

\[
L^*_{ss} = L_{ss} L_{sw} L_{ws}
\]

\[
L^*_{ws} = L_{ww} L_{ws} L_{sw}
\]

The converged scores suggest whether the slots are important for this domain based on the automatically built structure [2].

Step 3: Domain Slot/Relation Identification

Converged slot importance helps us identify domain ontology:
1. Rank slot pairs by summing up their converged scores
2. Select slot pairs with higher scores according to a threshold

Experimental Results

- Domain: restaurant recommendation in an in-car setting (WER = 37%)
  - Dialogue slots: addr, area, food, phone, postcode, pricerange, task, type
  - SLU (AF)
    - Slot Induction (AP)
      - Baseline: 56.69
      - Single-Layer RW: 43.28
      - Double-Layer RW: 69.04
    - SLU (AF)
      - Baseline: 43.28
      - Single-Layer RW: 48.89
      - Double-Layer RW: 71.48

- AP: Average Precision given a ranked list of induced slots and associated scores
- AF: Average micro F-measure of SLU models at all cut-off positions in the ranked list

Can a dialogue system automatically learn open domain knowledge?

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References: