Learning Bidirectional Intent Embeddings by Convolutional Deep Structured Semantic Models for Spoken Language Understanding

Yun-Nung (Vivian) Chen, Dilek Hakkani-Tür, and Xiaodong He

- **Motivation:** *Inflexible Intent Schema*
  - Intents are usually *predefined* and *inflexible* to expand and transfer across domains and genres
  - Re-designing a semantic schema requires manual annotation and model re-training.

- **Approach:** *Learning Intent Representation*
  - Learn *high-level semantic representations* to bridge the semantic relation across domains and across genres

- **Cross-domain:** intent expansion
- **Cross-genre:** actionable item detection

Find Calendar Entry

Will Vivian come here for the meeting?

Carnegie Mellon

Microsoft Research
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- **Model Architecture**
  - Semantic Layer: $y$
  - Semantic Projection Matrix: $W_s$
  - Max Pooling Layer: $l_m$
  - Max Pooling Operation
  - Convolutional Layer: $l_c$
  - Convolution Matrix: $W_c$
  - Word Hashing Layer: $l_h$
  - Word Hashing Matrix: $W_h$
  - Word Sequence: $x$

  ![Model Architecture Diagram]

  **Max Pooling Operation**

  ![Max Pooling Operation Diagram]

- **Training Procedure**

  $\Lambda(\theta_1) = \log \prod_{(U, I^+)} P(I^+ | U)$

  $\Lambda(\theta_2) = \log \prod_{(I^+, U)} P(U^+ | I)$

  **Predictive Model**: maximizes the likelihood of associated intents given utterances

  **Generative Model**: maximizes the likelihood of generated utterances given user intents

- **How about we discuss this later**