COMP90042 Web Search & Text Analysis

Workshop Week 12

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Outlines

Machine Translation

- Statistical MT - IBM I
- Phrase Translation
- Neural MT
- Evaluation

IBM I - Concept

$$P(f, a|e) = \frac{\epsilon}{(1+I)^J} \prod_{j=1}^{J} t(f_j|e_{a_j})$$

Components in IBM I

- E: Original language
- F: Target language
- A: Alignments from F to E

Why normalize by $(1+I)^J$?
What is e_{a_j} representing ?

IBM I - Training

Expectation Maximisation

- Widely used in unsupervised learning
- Topic modeling (Latent Dirichlet Allocation)
- Clustering (Gaussian Mixture Model)

Intuition

- E-Step: Estimate distribution based on current parameters θ.
- M-Step: Update parameters θ based on the estimated distribution.

How is it applied in IBM I?

IBM - E-Step

So how do we estimate the alignments?

- What is not observed? (So we need to estimate them)
- What are the variables θ in this case?

$$P(a|f,e) = \frac{P(f,e,a)}{P(f,e)} = \frac{P(f,a|e)P(e)}{P(f|e)P(e)} = \frac{P(f,a|e)}{P(f|e)}$$

Looks familiar?

$$P(a_j|f,e) = \frac{t(f_j|e_{a_j})}{\sum_j t(f_j|e_{a_j})}$$

IBM - M-Step

Now, use the expectation of alignments to train our parameters θ.

Recall training for generative models (N-grams, HMM, etc).

$$t(f_j|e_{a_j}) = \frac{count(f_j, e_{a_j})}{count(e_{a_j})}$$

$$count(f_j, e_{a_j}) = count(f_j, e_{a_j}) + P(a_j|f, e)$$

What is the next step?

Phrase Translation - Key points

Steps for Phrase Translation

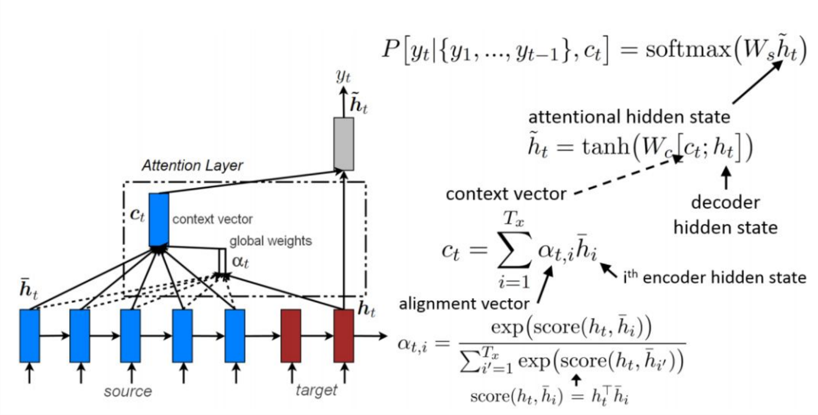
1. Learn word alignments (e.g. A in IBM I)
2. Extract phrase from the co-occurrence matrix
3. Train language model with phrase structures

Inference

- Beam search.
- Dynamic programming - e.g. the Viterbi algorithm

RNN-Based seq2seq models, using encoder-decoder structure.

- Use the final representation from encoder as first input to the decoder.
- Global attention.



Transformers (Vaswani et al., 2017)

Evaluation - BLEU

Widely used evaluation method for MT, Image Captioning, Summarisation.

Measuring discrepancy between human/machine outputs.

$$BLEU = bp \times exp(\frac{1}{N}\sum_{n=1}^{N} log(p_n))$$

- N: # of sentences
- $bp = min(1, \frac{len(machine)}{len(reference)})$
- $p_n = \frac{min(correct, len(reference))}{len(machine)}$

Criticism: *BLEU at your own risk*

Indexing

- Data Structure
  - Document-Term Matrix
  - Inverted Index
- Compression
  - Variable Byte Compression
  - OptPFor Delta Compression
- Index Construction
  - Invert Batch Indexing
  - Auxiliary Indexing
  - Logarithmic Indexing

Road Map - Web Search

Search

- Vector Space Models
  - TF-IDF
  - BM25
- Efficient Query Processing
  - Operation GEQ
  - WAND
- Query Completion
  - Prefix Trie
  - Range Maximum Query
- Query Expansion
  - Relevance Feedback
  - Semantic-Based Methods
- Phrase Search
  - Inverted Index + Positional Information
  - Suffix Array
- Evaluation and Re-rank

Roadmap - Text Analysis

Features

1. Word Semantics
    - Lexicon semantics
    - Distributional semantics
2. Sequence Labeling
    - Part-of-speech tagging
    - Named entity recognition
3. Parsing
    - Dependency parsing
    - Phrase-structure parsing

Roadmap - Text Analysis

Applications

1. Text classification
2. Question answering
3. Discourse tasks
4. Machine translation
5. Summarization

   . . .

Exam

Concept questions

- Concrete concept of any given topic, one sentence.

Method questions

- Describe general approach to given task.

Algorithm questions

- Methods in action. What we know how to train and infer.

Essay questions

- Can be boarder topics, application of NLP.