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?

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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?

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

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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

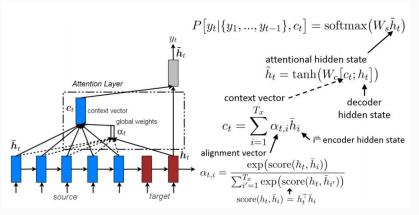
Inference

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

Neural LM

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

- Weighted average of 1-4 grams precision.
- $bp = min(1, \frac{len(machine)}{len(reference)})$
- $p_n = \frac{min(correct, len(reference))}{len(machine)}$

Criticism: BLEU at your own risk

Road Map - Web Search

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.