Machine Learning Final Project

Learning Continuous Phrase Representations for Translation Modeling

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Problem introduction

Deep learning

- Multiple processing layers
  - Layers of abstraction
- Neural networks
- State-of-the-art
  - Visual object recognition
  - Object detection
  - Speech recognition
  - Drug discoveries, genomics
- Statistical machine translation?

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Problem introduction

Learning Continuous Phrase Representation for Translation Modeling - *Gao et. al. 2013*

This paper tackles the sparsity problem in estimating phrase translation probabilities by learning continuous phrase representations, whose distributed nature enables the sharing of related phrases in their representations.

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- Phrases as translation units
  - Not linguistic notion
  - Sequence of words
- Longer phrases
  - Better translations
  - Less likely seen
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Dataset

TED talk transcripts (English and Chinese)

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- Source sentences (Chinese)

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- Source sentences (Chinese)
- Target sentences (English)

Dataset

TED talk transcripts (English and Chinese)

- Source sentences (Chinese)
- Target sentences (English)
- N-best-list (N translation hypotheses per sentence)
  - Generated by Moses: open source statistical machine translation system

The log-linear model for SMT

Standard statistical machine translation (SMT) systems are based on linear combinations of different features:

- Phrase translation table
- Reordering model
- Language model
- Many extensions:
  - Bidirectional translation probabilities
  - Word penalty
  - Phrase penalty
  - Continuous-space Phrase Translation Model (CPTM)

N-best (translation hypothesis) list generated for each source sentence

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Continuous-space Phrase Translation Model (CPTM)

- Addresses the data sparsity problem
- Score translation pair based on notion of similarity
- Dimensionality reduction
  - Raw phrase → Bag-of-words (word vector)
  - Neural network
    - Shared vocabulary for both languages
    - Same neural network for both languages
    - Helps discovering latent features
  - Output: lower dimension feature vector
- Similarity is measured by dot product of output feature vectors
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Overview

Learning Continuous Phrase Representation for Translation Modeling - *Gao et. al. 2013*

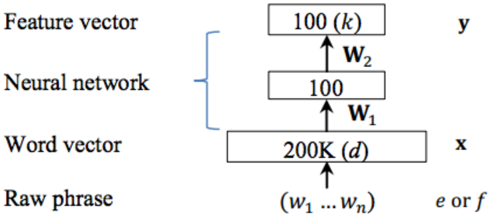

Figure 2. A neural network model for phrases giving rise to their continuous representations. The model with the same form is used for both source and target languages.

Objective function / Loss function

$$L(\theta) = -xBLEU(\theta)$$

$xBLEU$ - N-best list expected BLEU score

BLEU score

BLEU - Bilingual Evaluation Understudy

It is the most widely used automated method of determining the quality of machine translation. The BLEU metric scores a translation on a scale of 0 to 1, but is frequently displayed as a percentage value. The closer to 1, the more the translation correlates to a human translation.

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Objective function

$$\mathrm{xBleu}(\boldsymbol{\theta}) = \sum_{E \in \mathrm{GEN}(F_i)} P(E|F_i)\,\mathrm{sBleu}(E_i, E)$$

sBLEU - sentence level BLEU

$P(E|F_i)$ - translation probabilty using *softmax*

$$P(E|F_i) = \frac{\exp(\gamma \boldsymbol{\lambda}^{\mathrm{T}} \mathbf{h}(F_i, E, A))}{\sum_{E' \in \mathrm{GEN}(F_i)} \exp\left(\gamma \boldsymbol{\lambda}^{\mathrm{T}} \mathbf{h}(F_i, E', A)\right)}$$

Similarity

$$\mathbf{y} \equiv \phi(\mathbf{x}) = \tanh\left(\mathbf{W_2}^{\mathrm{T}}(\tanh(\mathbf{W_1}^{\mathrm{T}}\mathbf{x}))\right) \quad (2)$$

$$\mathrm{score}(f,e) \equiv \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f,\mathbf{x}_e) = \mathbf{y}_f^{\mathrm{T}}\mathbf{y}_e$$

Parameters

Parameters: $\theta = \{W_1, W_2\}$

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1. We use a baseline phrase-based SMT system to generate for each source sentence in training data an N-best list of translation hypotheses[4].
2. We set $\boldsymbol{\lambda}$ to that of the baseline system and let $\lambda_{M+1} = 1$, and optimize $\boldsymbol{\theta}$ w.r.t. a loss function on training data[5].
3. We fix $\boldsymbol{\theta}$, and optimize $\boldsymbol{\lambda}$ using MERT (Och 2003) to maximize BLEU on dev data.

Learning θ

- We learn θ by using gradient based numerical optimization algorithm (L-BFGS)
- We compute the gradient of the loss function

$$\frac{\partial \mathcal{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \sum_{(f,e)} \frac{\partial \mathcal{L}(\boldsymbol{\theta})}{\partial \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f, \mathbf{x}_e)} \frac{\partial \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f, \mathbf{x}_e)}{\partial \boldsymbol{\theta}}$$

$$= \sum_{(f,e)} -\delta_{(f,e)} \frac{\partial \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f, \mathbf{x}_e)}{\partial \boldsymbol{\theta}} \qquad (7)$$

COMPUTING $\delta sim_\theta(x_f, x_e)/\delta\theta$

$$\frac{\partial \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f, \mathbf{x}_e)}{\partial \mathbf{W}_1}$$

$$= \mathbf{x}_f \left(\mathbf{W}_2 \left(\mathbf{y}_e^2 \circ \sigma'(\mathbf{z}_f^2) \right) \circ \sigma'(\mathbf{z}_f^1) \right)^{\mathrm{T}}$$

$$+ \mathbf{x}_e \left(\mathbf{W}_2 \left(\mathbf{y}_f^2 \circ \sigma'(\mathbf{z}_e^2) \right) \circ \sigma'(\mathbf{z}_e^1) \right)^{\mathrm{T}}$$

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$$\frac{\partial \mathrm{sim}_{\boldsymbol{\theta}}(\mathbf{x}_f, \mathbf{x}_e)}{\partial \mathbf{W}_2} = \frac{\partial (\mathbf{y}_f^2)^{\mathrm{T}}}{\partial \mathbf{W}_2} \mathbf{y}_e^2 + (\mathbf{y}_f^2)^{\mathrm{T}} \frac{\partial \mathbf{y}_e^2}{\partial \mathbf{W}_2}$$

$$= \mathbf{y}_f^1 \left(\mathbf{y}_e^2 \circ \sigma'(\mathbf{z}_f^2) \right)^{\mathrm{T}} + \mathbf{y}_e^1 \left(\mathbf{y}_f^2 \circ \sigma'(\mathbf{z}_e^2) \right)^{\mathrm{T}} \quad (9)$$

Computing the error term $\delta_{(f,e)}$

$$\delta_{(f,e)} = \sum_{(E,A)\in GEN(F_i)} \mathrm{U}(\boldsymbol{\theta}, E) P(E|F_i) \lambda_{M+1} N(f, e; A) \tag{14}$$

where

$$\mathrm{U}(\boldsymbol{\theta}, E) = \mathrm{sBleu}(E_i, E) - \mathrm{xBleu}(\boldsymbol{\theta}).$$

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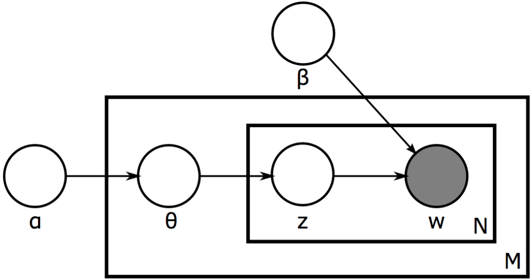
Learning θ

- The parameters are trained using **Stochastic gradient descent**
- Initialize

  W_1 bilingual topic model trained on parallell data

  W_2 identity matrix

Latent Dirichlet Allocation



Latent Dirichlet Allocation

Preprocessing:

- Stop words

Latent Dirichlet Allocation

Preprocessing:

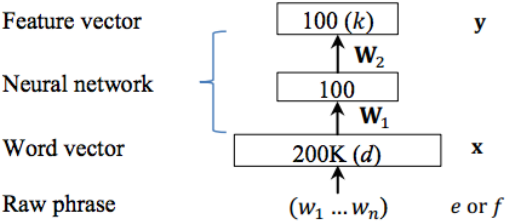
- Stop words

Output: W_1 - 100 x 50,000

Results

After multiple overnight test runs, our implementation of the CPTM algorithm conducted into satisfiable results.

Summary



$$\theta = \{W_1, W_2\}$$

Gradient descent:

$$\theta_{n+1} = \theta_n - \eta \frac{\partial L(\theta)}{\partial \theta} = \theta_n - \eta \left[\sum_{(f,e)} -\delta_{(f,e)} \right.$$

Results

In order to test the theoretical validity of our system, a plot over the loss function was made.

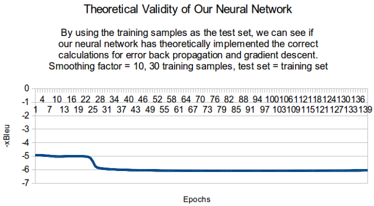


Figure: Theoretical validty of our neural network

Results

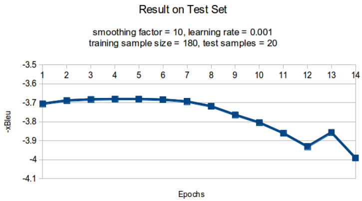


Figure: Result on test set

The results seem to suggest that the system is indeed performing a correct gradient descent.

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- We have been learning continuous phrase representations for a SMT system.
- Using a neural network, we have projected both source and target sentences into a real-number vector space.
- Loss function of the NN has been the negative expected BLEU score for a source sentence and it's possible translation.
- We also tested the validity of our system, showing that the loss function decreases.

Finally

Thank you for listening! It has been an adventurous journey.