Unsupervised Learning of Neural Network Lexicon and Cross-lingual Word Embedding

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Abstract

neural machine translation systems(NMT) beyond traditional statistical machine translation(SMT) in

This thesis start from unsupervised word translation,

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Chapter 1

Introduction

1.1 Neural Network Lexicon

1.2 Cross-lingual Word Embedding

Chapter 2

Word Embedding

2.1 Monolingual Embedding

Word embeddings is distributed representation of words in a vector space. With the learning algorithm it can capture the contextual or co-occurrence information. The word embedding has an interesting and important property: similar words will have similar distribution in the embedding space, with that property, we can find meaningful near-synonyms or Some successful methods for learning word embeddings like word2vec Mikolov et al. [2013] Continuous Bag-of-Words model(CBOW) and Skip-Gram model CBOW model and Skip-Gram model are currently the common structures to learn the word embedding. Algorithmically, CBOW tries to predict the current word based on the context while Skip-Gram model tries to maximize classification of a word based on another word in the same sentence. The neural probability language model defines the prediction probability using the softmax function:

$$p(w_t|w_s) = \text{softmax}(s(w_t, w_s)) \tag{2.1}$$

$$= \frac{\exp\{s(w_t, w_s)\}}{\sum_{w' \in W} \exp\{s(w', w_s)\}} \tag{2.2}$$

where w_t is target word)label word), w_s is the source word(input word), for Skip-Gram model, the target word refers to the context words, the source word refers to the current word, for CBOW model is simply inverted. W denotes the whole vocabulary. Then the training objective of the model is to maximize the log-likelihood on the training dataset, i.e. by maximizing:

$$J_{ML} = \log p(w_t|w_s) \tag{2.3}$$

$$= s(w_t, w_s) - \log(\sum_{w' \in W} \exp\{s(w', w_s)\}) \tag{2.4}$$

However the normalization on the whole vocabulary is very expensive because it is conducted for all words at every training step. The problem of predicting words

can be considered as an independent binary classification task. For example in the Skip-Gram model, we consider all the context words as positive samples and the words randomly sampled from the dictionary as the negative ones. Then the training objective is

$$J_{NEG} = \log Q_\theta(D = 1|w', w_s) + \sum_{w' \sim W} \log Q_\theta(D = 0|w', w_s)$$

where $Q_\theta(D = 1|w'w_s)$ is the binary logistic regression probability. In practice, we draw k contrastive words from the noise distribution. Since we only calculate the loss function for k samples instead the whole vocabulary, it becomes much faster to train.

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c<j<c, j\neq 0} \log p(w_{t+j}|w_t)$$

where c is the size of training context, larger context size make the results more precise at the cost of training time. Suppose we are give a scoring function to evaluate the word pair(word, context), the Skip-Gram model

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c<j<c, j\neq 0} \log p(w_t|w_{t+j})$$

According to empirical results, CBOW works better on smaller datasets because CBOW smoothes over a lot of the distributional information while Skip-Gram model performs better when we have larger datasets

Noise-Contrastive Training

fastText The training methods above treat each word as a distinct word embedding, however intuitively we can obtain more information from the morphological information of words. A subword model was proposed to try to fix such problem.The training network is similar, the model design a new presentation of the word: it adds speicial symbols $<, >$ as boundary information at the beginning and the end of a word. Then a normal word is represented as a bag of character n-grams . For example the word "where" and n equals 3, the it can be represented as the following 5 tri-grams:

$$< wh, whe, her, ere, re >$$

Suppose in this way we denote a word w as G_w the set of character n-grams, we assign for each character n-gram g in G_w, we assign a distinct vector z_g, we will finally represent the embedding of word w as the sum of these vector and also for the scoring function:

$$s(w, w_s) = \sum_{g \in G_w} z_g^T w_s$$

2.2 Cross-lingual Word Embedding

Cross-lingual word embedding is defined as word embedding of multiple languages in a joint embedding space. Mikolov first notice that the embedding distributions exhibit similar structure across languages. They proposed to use a linear mapping from the source embedding to target embedding.

In the thesis, I assume there are two set of embeddings E, F trained separately on monolingual data. The propose of cross-lingual word embedding training is to learn such a mapping $W \in$ from source embedding space to target embedding space, so WF, E in the same embedding space and

$$1$$

where d is the dimension of embeddings,

2.2.1 Supervised Learning

A dictionary is necessary for learning the cross-lingual word embedding. minimizing the distance in a bilingual dictionary.

Xing showed that the results are improved when we constrain the W to be an orthogonal matrix. This constraint, the optimal transformation can be efficiently calculated in linear time with respect to the vocabulary size.

The problem then is simplified as the Procrustes problem and there exists a closed-form solution obtained from the SVD of EF^T

2.2.2 Unsupervised Learning

However, large dictionary is also not readily available for many language pairs.

Several unsupervised learning algorithms are studies

Self-learning framework

Algorithm 1 Self-learning framework

Input: $\mathcal{F}$ (source embeddings)
Input: $\mathcal{E}$ (target embeddings)
Input: $\mathcal{D}$ (seed dictionary)
Result: $\mathcal{W}$ (embedding mapping)

Unsupervised Initialization

Iterative Closest Point Method

Adversarial Training

Discriminator is trained to discriminate between elements randomly sampled from WF and E and generator W is trained to prevent the discriminator from making accurate prediction

The training algorithm follows the standard procedure of deep adversarial networks(GAN) of Goodfellow **?**: the discriminator and generator are trained iteratively with the stochastic gradient descent to minimize the L_D and L_w

Cross-domain Similarity Local Scaling (CSLS) Since the embedding space is of high dimension and the nearest neighbour search is performed here, so that a few embeddings embedding will become the nearest neighbour of many data pointsto The obtained is known to suffer from the hubness problem,

Chapter 3

Sentence Translation

3.1 Context-aware Beam Search

3.1.1 Language Model

Language models are widely applied in natural language processing, especially machine translation which need frequent queries.

n-gram models
N-gram language models use the Markov assumption to break the probability of a sentence into the product of the probability of each word given a limit history of preceding words.

$$p(w_1^N) = \prod_{i=1}^{N} p(w_i|w_1, \cdots w_{i-1}) = \prod_{i=1}^{N} p(w_i|w_{i-(n-1)}, \cdots, w_{i-1})$$

The conditional probability can be calculated from n-gram model frequent counts:

$$p(w_i|w_{i-(n-1)}, \cdots, w_{i-1}) = \frac{count(w_{i-(n-1)}, \cdots, w_i)}{count(w_{i-(n-1)}, \cdots, w_{i-1})}$$

Language model tries to handling sparse data problem because some words or phrases have not been seen yet in the training corpus does not mean they are not impossible. Different smoothing techniques like back-off or interpolation are implemented to assign a probability mass to unseen cases.

3.1.2 Beam Search

The complexity of a search graph is exponential to the length of the given source sentence. Beam search is a heuristic search algorithm that explores a graph by expanding the most promising nodes. At each step of the search process, it will evaluate all the candidates together with the reserved translation results from last step, it will only stores a predetermined number (beam width) of translations for next step. The greater the beam width is, the fewer states will be pruned. So

it is suggested to prune these word translation candidates as soon as possible to reduce the search space and speed up the translation. According to the similarity of cross-lingual word embedding, we are able to find some meaningful for translation candidates for a given word. But there are also words that actually noise in the candidates or obviously incorrect because of grammar checking. With the support of language model, we can select the most probable words from previous word translation candidates.

Given a history h of target word before e, the score of e to be the translation of f is defined as:

$$L(e; f, h) = \lambda_{emb}q(f, e) + \lambda_{LM}p(e|h)$$

where the lexicon score $q(f, e) \in [0, 1]$ defined as:

$$q(f, e) = \frac{d(f, e) + 1}{2}$$

$d(f, e) \in [-1, 1]$ cosine similarity between f and e

In experiments, we find such lexicon score works better than others, e.g. *sigmoid* for *softmax*

3.2 Denoising Autoencoder

With the help of language model we have actually improved the quality of word-by-word translation but the results are still far from a acceptable one because of the drawback of the word-by-word mechanism, maybe to some degree we can infer the meaning of sentence, but the sequence of sentences depends on the specific language. We implement the sequential denoising autoencoder to improve the translation output.

An autoencoder is a neural network that is trained to copy its input to its output, autoencoders minimize the loss function like:

$$L(\boldsymbol{x}, g(f(\boldsymbol{x})))$$

where L penalizing the difference between the input and output. While a denoising autoencoder (DAE) instead minimizes

$$L(\boldsymbol{x}, g(f(\tilde{\boldsymbol{x}})))$$

where $\tilde{\boldsymbol{x}}$ is a noise transformation of $\boldsymbol{x}$ and denoising autoencoder will try to learn to ignore the noise in $\boldsymbol{x}$ reconstruct the correct one. Sequential denoising autoencoder will find robust representation of sentences. In practice, denoising autoencoder consists of two parts, namely encoder and decoder. The encoder processes noised

data and produces real-valued vectors as an encoding feature of the data. The computational graph of the denosing autoencoder, which attempt to reconstruct the normal input $\boldsymbol{x}$ from it corrupted version $\tilde{\boldsymbol{x}}$. The model is trained by minimize the loss.

For our sequential denoising model, the label sequences would be the monolingual data of the target language. However we do not have the noise input. In order to make the model run correctly, we should mimic the noise sentence of word-by-word translation on the target monolingual corpus.

We design different noise types w.r.t. the word-by-word translation. In the experiments, we inject the artificial noise into a clean sentence, the experiment results shows the noise is reasonable and suitable in this case.

3.2.1 Reordering Noise

The reordering problem is a common phenomenon in the word-by-word translation since the sequence in source language is not exact the sequence in target language. For example, in the grammar of German, the verb is often placed at the end of the clause. "um etwas zu tun". However in English it is not the case, the corresponding translation sequence is "to do something". The verb should always before the noun. In our beam search, language model only assisting in choosing more suitable word from the translation candidates, it cannot reorder the word sequence at all.

For a clean sentence from the target monolingual corpora, we corrupt the word sequence by permutation operation. We limit the maximum distance between the original position and its new position.

The design of reordering noise is as followed:

1. For each position i, sample an integer δ_i from $[0, d_{per}]$

2. Add δ_i to index i and sort $i + \delta_i$

3. Rearrange the words to be in the new positions, to which where indices have been moved

Reordering is actually depends on the specific language pair. However in the experiments we found the performance of the denoising network aimed at such noise is not obvious. The Bleu score before and after the process is close.

3.2.2 Insertion Noise

The word-by-word translation system predict the source word at every position of the sentence. However the vocabularies of different systems are not symmetric, for example, in German there are more compound words than that in English. So when translating cross languages, there are a plenty of cases that a single word will be

translated to multiple words and multiple words correspond to a single conversely. We focus on such a case: from a German sentence: "ich höre zu" to "i'm listening". A very frequent word "zu" which corresponds to "to" in English, is dropped from the sentence. The design of reordering noise is as followed:

1. For each position i, sample a probability $p_i \sim \text{Uniform}(0, 1)$

2. If $p_i < p_{ins}$, sample a word e from the most frequent $V_i ns$ target words and insert it before the position i

We limit the insertion word in a set consisting of the top frequent word in the target language $V_i ns$

3.2.3 Deletion Noise

The deletion noise is just a contrary case of insertion noise. Because different languages treat the prepositions or the articles differently. For example for "eine der besten" the corresponding translation is "one of the best". We need to add an extra preposition in the target sentence. The design of reordering noise is as followed:

1. For each position i, sample a probability $p_i \sim \text{Uniform}(0, 1)$

2. If $p_i < p_{del}$, drop the word in the position i

Appendix A

Appendix

List of Figures

List of Tables

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