Using Dependency Grammar Features in Whole Sentence Maximum Entropy Language Model for Speech Recognition

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Contents

Whole sentence language modeling

Statistical sentence modeling problem

- Given a finite set of observed sentences, learn a model which gives useful probability estimates for arbitrary new sentences

n-gram model: the standard approach

- Model language as a high-order Markov Chain; current word is dependent only on $n - 1$ of its preceeding words
- Sentence probability is obtained using chain rule; sentence probability is product of word probabilities
- Modeling is based on local dependencies of the language only; grammatical regularities learned by the model will be captured implicitly within the short word windows

Example: n-gram succeeds

- Stock markets **fell** yesterday.
  - Log probability given by trigram LM = -19.39
- Stock markets **fallen** yesterday.
  - Log probability = -21.26

Example: n-gram fails

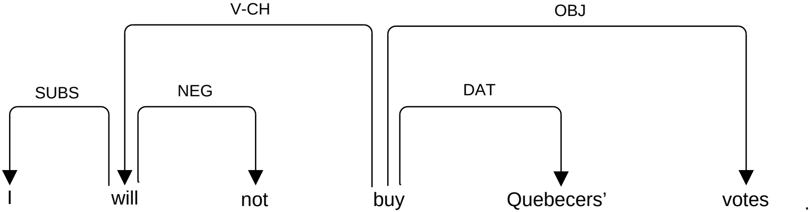
- Stocks **have** by and large **fallen**.
  - Log probability = -19.92
- Stocks **have** by and large **fell**.
  - Log probability = -18.82

Our aim

- Explicit modeling of grammatical knowledge over whole sentence
  - Dependency Grammar Features
  - Whole Sentence Maximum Entropy Language Model (WSME LM)
  - Experiments in a large vocabulary speech recognition task

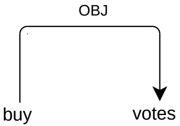
Dependency Grammar

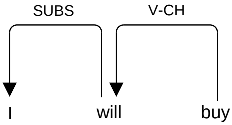
- Dependency parsing results in head-modifier relations between pairs of words, together with the labels of the relationships
- The labels describe the type of the relation, e.g. subject, object, negate
- These asymmetric bilexical relations define a complete dependency structure for the sentence



Extracting Dependency Grammar Features

- Dependencies are converted into binary features
  - Feature is or is not present in a sentence
- Dependency bigram features contain a relationship between a head and a modifier
- Dependency trigram features contain a modifier with its head and the head's head





Whole Sentence Maximum Entropy Language Model (WSME LM)

Principle of Maximum Entropy

- Model selection criterion
- From all the probability distributions satisfying known constraints, choose the one with the highest entropy

Maximum Entropy Model

- Constraints: expected values of features
- Form of the model satisfying the constraints: exponential distribution
- Within the exponential model family: maximum likelihood solution is the maximum entropy solution

WSME LM

- WSME LM is the exponential probability distribution over sentences which is closest to the background n-gram model (in Kullback-Leibler divergence sense) while satisfying linear constraints specified by empirical expectations of features
  - For uniform background model, the Maximum Entropy solution
- For testing data, the sentence probabilities given by the n-gram model are, effectively, scaled according to the features present in the sentence.

Practical issues

- Training WSME LM requires sentence samples from the exponential model
  - Markov Chain Monte Carlo sampling methods

Experiments

Experiment setup

- Train a baseline n-gram LM and WSME LM
- Obtain an N-best hypothesis list for a sentence from speech recognizer using the baseline n-gram and rescore them using WSME LM
- Compare model performance with speech transcript perplexity and speech recognition word error rate (WER)

Data

- Textual training corpus: Gigaword
  - English newswire articles of typical daily news topics; sports, politics, finances, etc.
  - 1M sentences (20M words)
  - Small subset of Gigaword
- Speech test corpus: Wall Street Journal
  - Dictated English financial newswire articles
  - 329 sentences (11K words)

Baseline LM

- Trigram model trained using Kneser-Ney smoothing
- Vocabulary size: 60K words

Dependency parsing

- Textual data was parsed using a freely distributed Connexor Machine Syntax parser

WSME LM training

- Sentence samples from the exponential model were obtained using importance sampling
- The L-BGFS algorithm was used for optimizing the parameters
- The parameters of the model were smoothed using Gaussian priors

Speech recognition system

- Large vocabulary speech recognizer developed at the Department of Information and Computer Science, Aalto University

Experiment results

- We observe a 19% relative decline in perplexity (PPL) when using the WSME LM compared to baseline trigram
- The WER drops by 6.1% relative (1.8% absolute) compared to the baseline
- Note: Results reported only for trigram Dependency Grammar features
- Performance gain is significant

Table: Perplexity (PPL) and word error rate (WER) when using different language models.

Language model	PPL	WER
Word trigram	303	29.6
WSME LM	**244**	30.6
Word trigram + WSME LM	255	**27.9**

Conclusions

- We described our experiments with WSME LM using binary features extracted with a dependency grammar parser
- The dependency features were in the form of labeled asymmetric bilexical relations
  - Experiments on bigram and trigram features
- The WSME LM was evaluated in a large vocabulary speech recognition

Conclusions (continued)

- We obtained significant improvement in performance using WSMELM compared to a baseline word trigram
- WSME LMs provide an elegant way to combine statistical models with linguistic information
- The main shortcoming of the method; extremely high memory consumption requirement during training of the model