Smoothing and Data Selection in Large SMT Systems

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Plan

- Introduction and motivation
- NIST task
- Baseline architecture
- Data selection/emphasizing
  - language modeling
  - translation models
- Smoothing techniques
  - language modeling
- Perspectives

Introduction

Statistical Machine Translation

- All knowledge is automatically extracted from representative data:
  - bitexts: existing human supplied translations (100k–200M)
  - monolingual data: used for the LM, usually journals or WEB data (10M–10G)
- Estimate probability distributions from this data:
  - phrase table with various scores
  - n-gram language model

Introduction

Probability estimation

- Relative frequency
  - high variance, low bias
  - overestimation of rare events
  - no generalization to unseen events
- Some kind of smoothing is needed
  - common practice in language modeling
  - but not (yet) frequently used for the translation model
  - some work has shown possible improvements
    for instance [Foster el al, EMNLP'06]

Introduction

Data selection/emphasizing

- Data often comes from a large variety of sources
  - in- versus out-of-domain
  - old versus recent sources
  - high quality human versus approximate translations
  - ...
- Large variations in size
- It seems suboptimal to mix all these data sources and to use them uniformly

⇒ How to weight the data sources in function of their relevance to the task ?

Task Description

NIST Open MT evaluation

- yearly evaluations performed by NIST since 2001
- focus on translation from Mandarin and Arabic to English
- large amounts of training data available:
  - 175M words of bitexts and 3.5G of newspaper texts
  - → considerable computational resources are needed
  - approaches that achieved improvements on smaller task may not help anymore or be to expensive to apply
- carefully selected test data with four high quality human translations

⇒ NIST evaluations have played a key role to advance the field by providing a common test bed and infrastructure to compare the most promising approaches

Data

Bitexts

- Various small corpora (9.1M words)
- Development data from previous evaluations (2M words)
- ISI automatically aligned data (35M words)
- UN corpus (130M words)

⇒ phrase-table with 228M entries (6.2G gzipped)

Monolingual data

- English part of bitexts (175M words)
- Gigaword corpus of newspaper texts (3.2G words)
- Parts of Google n-grams (139M out of 1T n-grams)

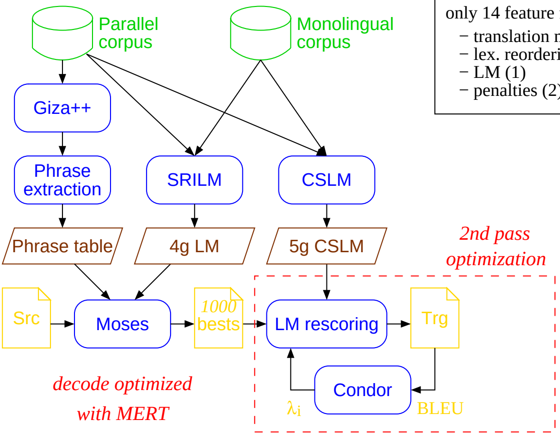
⇒ 4-gram back-off LM with 264M 4-grams, file size of 5.5GB

System Architecture

Design decisions of the system

- Pure statistical system without usage of linguistic knowledge (yet)
- Validate system architecture and algorithms that did work well on small (IWSLT) and medium sized tasks (Europarl)
- Build a state-of-the-art system based on open-source
- Single system without system combination
- Careful use of available data
  - do we need quality or quantity ?
  - reasonably compact representation of the data

System Architecture Overview



only 14 feature functions

- translation model (4)
- lex. reordering (7)
- LM (1)
- penalties (2)

Data Selection in the LM

Data selection

- Merge all data and build one LM
  $\rightarrow$ important but small data is outvoted by large corpora
- LM combination:
  - select common word list
  - train individual LM on each subcorpus
  - linear combination:

$$P_{LM}(w_3|w_1 w_2) = \sum_i \lambda_i P_{LM_i}(w_3|w_1 w_2)$$

  - log-linear: each LM is a feature function among others

$$P = \sum_j \log P_j + \underbrace{\sum_i \lambda_i \log P_{LM_i}(w_3|w_1 w_2)}_{P_{LM}}$$

Data Selection in the LM

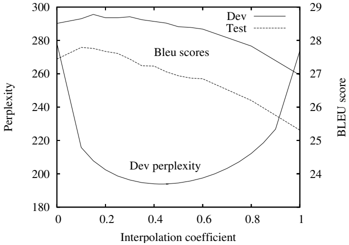
Theoretical comparison

	linear	log-linear
probabilities:	added	multiplied
criterion:	perplexity	BLEU
optimisation:	EM	numerical
# of models:	can be merged into one	as much as submodels

Data Selection in the LM

Experimental comparison

- Combining europarl and news-commentary LMs:



- Experimental comparison is not always clear
- Linear combination is usually as good and much easier to realize

Data Selection in the LM

Example: NIST task

- bitexts: 175M
  - Gale translations (1.1M words)
  - development data from previous years (0.9M words)
  - various news wire data (8.1M words)
  - automatically extracted parallel texts from ISI (35M words)
  - UN data (130M words)
- Gigaword newspaper corpus: 3.4G
  - divided into 7 subsets to keep estimation tractable
- Google *n*-grams: 1T
  - selected subset of 139M 4-grams

$\Rightarrow$ total of 12 submodels

Data Selection in the LM

Result summary

corpus	train #words	LM size	Px dev06 all	Px dev06 Nwire	Px dev06 WEB
bitexts pooled	175M	666M	189.3	145.7	351.3
idem w/o UN	45M	278M	183.0	140.2	343.7
bitexts ipol	175M	309M	161.7	131.0	266.2
+ GigaWord	3.4G	3.7G	128.1	104.7	206.5
+ Google	(1T)	5.5G	114.5	99.0	161.7

- Pooled LM is better without the UN data !
- It's very important to consider the heterogeneous data in the bitexts, in particular for the WEB part
- Google n-grams achieve decrease of 11%, mainly on WEB

Data Selection in the TM

How to account for the heterogeneous data ?

- multiple phrase tables
- linear interpolation of seperately trained phrase tables
- some kind of discriminative training

Data Selection in the TM

Multiple phrase tables

- build a phrase table per source and provide multiple tables to Moses
- log-linear combination
- MERT training should weight correctly the different models
- but each table provides 5 scores

  $\longrightarrow$ high dimensional optimisation problem
  (even worse when we also consider lexical reordering)
  - Unrealistic for more than three models
- alignments risk to be suboptimal for small corpora
- contradictory experimental results

Data Selection in the TM

Linear interpolation of seperately trained phrase tables

- motivated by the procedure used for LMs
- how to judge the quality of a phrase-table without runing a full system (something equivalent to perplexity) ?
- how to estimate the coefficients ?
- merging into one phrase table is not obvious
- alignments risk to be suboptimal for small corpora

$\Rightarrow$ often only one phrase table is estimated on the pooled data

Data Selection in the TM

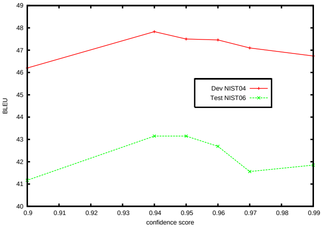
ISI automatically extracted parallel data

- found pseudo parallel data in the English and Arabic Gigaword corpus
- algorithm [Munteanu & Marcu, CL 2005]:
  - consider time window, word dictionnary, IBM1 alignements, max entropy classifier, ...
- 1.1M sentences were extracted (35M words)
- confidence scores are provided

Data Selection in the TM

How to best use the ISI automatically aligned bitexts ?

- Keep only sentences with a confidence score superior to a threshold
- Initial experiments with Gale manual translations only:



$\Rightarrow$ Gain of 2 points BLEU when not all ISI data is used

Data Selection in the TM

Result summary (LM trained on all bitexts + Gigaword)

Bitext	#words	Dev06
Gale+nw	9M	43.02
Gale+nw+ISI	35M	45.09
Gale+nw+ISI+dev	36M	45.38
Gale+nw+ISI+dev+un	165M	45.98

- Filtered ISI automatic texts are pretty useful
- Adding old Dev data gives 0.3 improvement

→ Pretty good result with core bitexts of 36M words only

- Only +0.6 BLEU with 129M words of UN data

→ High quality in-domain data seems to be more important than large amounts of general data

Continuous Space LM

Theoretical drawbacks of back-off LM:

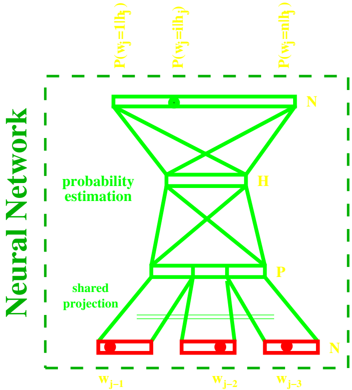
- Words are represented in a high-dimensional discrete space
- Probability distributions are not smooth functions
- Any change of the word indices can result in an arbitrary change of LM probability

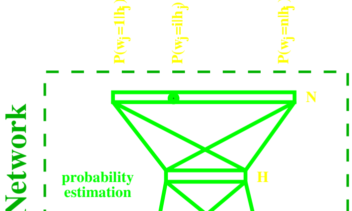
$\Rightarrow$ True generalization is difficult to obtain

Main idea [Bengio, NIPS'01]:

- Project word indices onto a continuous space and use a probability estimator operating on this space
- Probability functions are smooth functions and better generalization can be expected

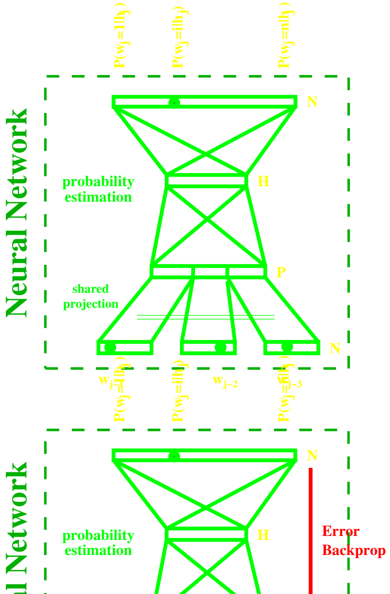
CSLM - Probability Calculation





- Outputs = LM posterior probabilities of all words: $P(w_j = i|h_j) \quad \forall i \in [1, N]$
- Context h_j = sequence of $n{-}1$ points in this space

CSLM - Training



- Backprop training, cross-entropy error

$$E = \sum_{i=1}^{N} d_i \log p_i$$

  $+$ weight decay

$\Rightarrow$ NN minimizes perplexity on training data

- continuous word codes are also learned (random initialization)

Continuous Space LM

Some details (Computer Speech and Language, pp 492–518, 2007)

- Projection and estimation is done with a multi-layer neural network
- Still an *n*-gram approach
- But LM probability for any *n*-gram can be calculated without backing off
- Usually trained on the same data than the back-off LM using a resampling algorithm
- Efficient implementation is very important
- Used in second pass as an additional feature function
- Quite succesful in several tasks and languages

CSLM - Training

Training Procedure

- Same training data than back-off LM (bibtexts + Giga)
- Resample algorithm (HLT/EMNLP'05 paper)
- Shortlist of length 8k
- Trained several networks with different context sizes
- Interpolated with 4-gram back-off LM

Incorporation into MT System

- *n*-best list rescoring
- Feature function coefficients are again optimized

CSLM

Result summary - perplexities

corpus	train #words	LM size	Px dev06 all	Nwire	WEB
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+ Google	(1T)	5.5G	114.5	99.0	161.7
+ CSLM	3.4G	+1G	98.3	85.3	137.4

- It seems to be very important to consider the heterogeneous data in the bitexts, in particular for the WEB part
- Google n-grams achieve decrease of 11%, mainly on WEB
- CSLM gives 14% improvement on top of this large LM

CSLM

Result summary - BLEU scores

System	Dev06 All	Dev06 NW	Dev06 Web	Eval08 All
Baseline	43.99	46.84	34.51	41.69
beam tuning	44.40	47.27	34.90	42.13
+ Google LM	44.70	47.22	36.11	41.90
+ CSLM	45.96	48.56	36.69	42.98

- Tuning of beam affects both subsets
- Filtered Google LM mainly improves BLEU on WEB data
- CSLM gives overall improvement of 1.1 BLEU on test data on top of the completely tuned system

Conclusion and Perspectives

Conclusion

- Data selection/emphasizing is very important
- There is a common practice for LM:
  - train individual models,
  - optimize perplexity with EM procedure
  - linear interpolation + merge into one model

  → apply this procedure consequently
- but there is no satistfactory straight-forward procedure for the translation model

⇒ Research in this direction is needed

Conclusion and Perspectives

Conclusion

- Automatically aligned data can be very helpful
- But it must be carefully selected
- Using too much can actually hurt

$\Rightarrow$ Continue to explore the usage of “found bitext”

- Nice result with CSLM: careful smoothing and good generalisation is important even with large amounts of training data

$\Rightarrow$ Can we do something similar with the translation model ?

Conclusion and Perspectives

Perspectives

- Phrase-based translation models are still too simple:
  - data emphasizing is difficult
  - no smoothing
  - bad generalization to unseen phrases (singular $\rightarrow$ plural)
- Possible research directions
  - factored representations of translation and language model
  - continuous space translation model
  - discriminative approaches