Language Model Adaptation for Statistical Machine Translation with Structured Query Models

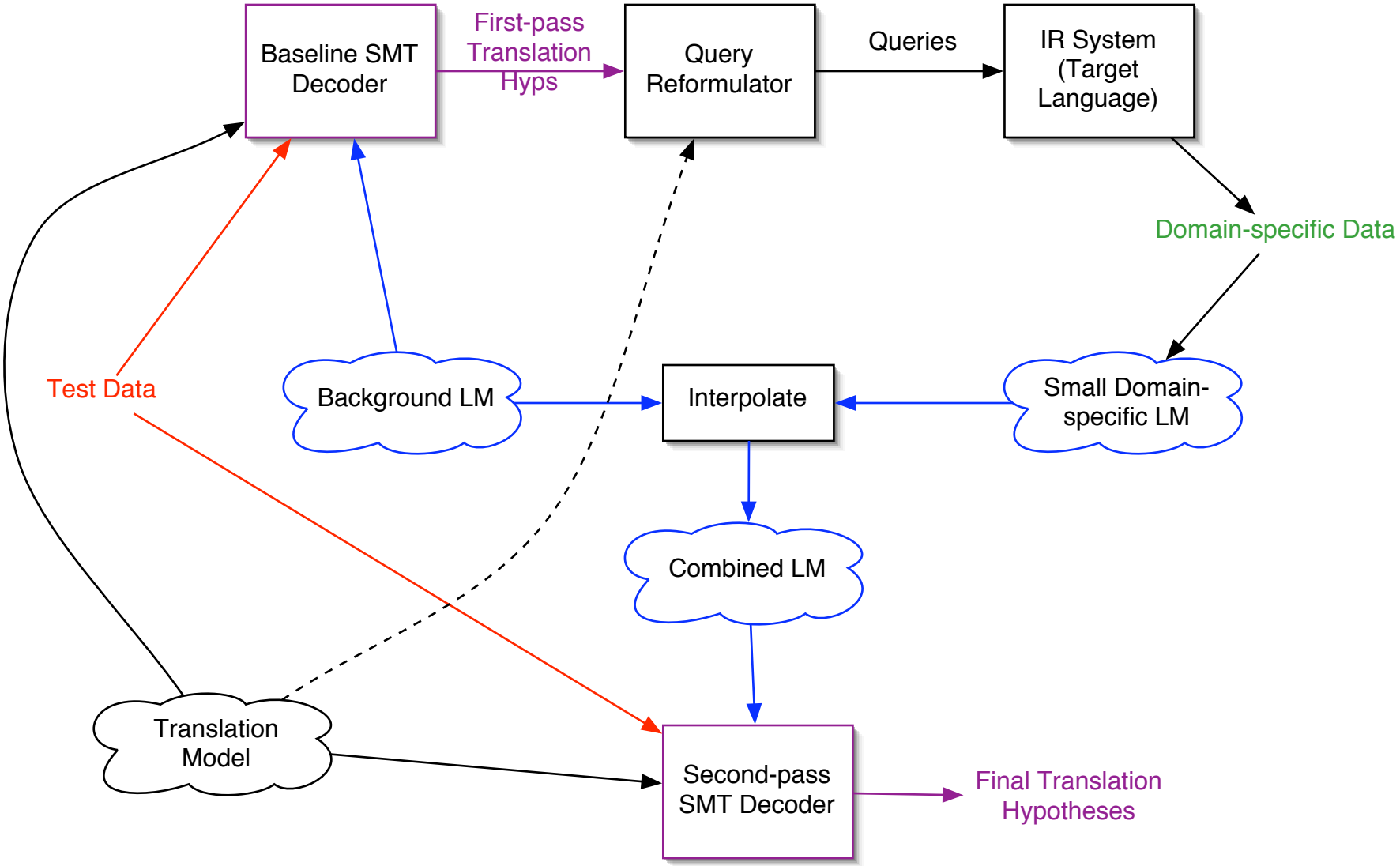
Bing Zhao, Matthias Eck, Stephan Vogel
CMU
Coling 2004

presented by Sarah Schwarm, 11/10/2004

Goal:
Language Model Adaptation

- Problem: Insufficient in-domain LM training data
- Approach: "unsupervised data augmentation by retrieval of relevant documents from large monolingual corpora..." and interpolation of model built from retrieved data with a background LM

Approach


Baseline SMT Decoder
First-pass Translation Hyps
Query Reformulator
Queries
IR System (Target Language)
Domain-specific Data
Test Data
Background LM
Interpolate
Small Domain-specific LM
Combined LM
Translation Model
Second-pass SMT Decoder
Final Translation Hypotheses

Questions to Address

- Should we use only 1-best, or n-best hyps for query generation?
- How should queries be constructed: bag-of-words, or more structured?
- How many documents should be retrieved, and what is the scope of a document?

Results from [Eck 2004]

- Used data retrieved from a local index (Lemur IR system) rather than the web
- Used Term Frequency /Inverse Document Frequency (tf/idf) for retrieval (outperformed two other IR techniques)
- Sentence-level retrieval outperforms story-level
- Big improvements in perplexity, smaller "actual" improvement
- Stemming and stopword removal were not helpful

Sentence Retrieval Process

- tf/idf queries built from translation hyps from first-pass decoder
- Consider each sentence as its own document
- Convert query and sentences in corpus into vectors
  - Assign term weight to each word
- Calculate cosine similarity between query and sentences in corpus
  - Select most similar 1-1000 sentences

Bag-of-words Query Models (1/3)

1-best hyp as query model

- w_i is a word in V_{T1}, the vocab of the top-1 hypothesis
- f_i is the frequency of w_i

$$Q_{T1} = (w_1, w_2, \ldots, w_l) = \{(w_i, f_i) | w_i \in V_{T1}\}$$

Bag-of-words Query Models (2/3)

N-best hyps as query model

$$Q_{TN} = (w_{1,1}, w_{1,2}, \ldots, w_{1,l_1}; \ldots; w_{N,1}, w_{N,2}, \ldots w_{N,l_N})$$

$$= \{(w_i, f_i) | w_i \in V_{TN}\}$$

- Benefits of Q_{TN}
  - Contains more translation candidates; more informative than Q_{T1}
  - Confident translations occur more, so they have a higher term frequency and more impact on retrival

Bag-of-words Query Models (3/3)

Translation model as query model

- Extract n-grams from source sentence
- Collect all candidate translations from TM

$$Q_{TM} = (w_{s_1,1}, w_{s_1,2}, \ldots w_{s_1,n_1}; \ldots; w_{s_I,1}, w_{s_I,2}, \ldots, w_{s_I,n_I})$$
$$= \{(w_i, f_i) | w_i \in V_{TM}\}$$

- No decoding, no use of background LM
  - Q_{TM} is a generalization of Q_{T1} and Q_{TN} (subject to more noise)

Structured Query Models

- Word order and word proximity:
  - Ignored by bag-of-words models
  - Convey syntactic and semantic information
  - Can be extracted from 1-best/n-best hyps and translation lattices

Structured Query Language InQuery (Lemur Toolkit)

- Four proximity operators (ordered and unordered windows) in queries
  - Sum: $\#sum(t_1, \ldots, t_n)$
    - all terms have equal influence, avg. belief values
  - Weighted sum: $\#wsum(w_1 : t_1, \ldots, w_n : t_n)$
  - Ordered distribution operator
  - $\#N(t_1 \ldots t_n)$
    - Terms must be within N word of each other
  - Unordered distribution operator
  - $\#uwN(t_1 \ldots t_n)$
    - Terms in any order within a window of N words

Structured Query Models (1/2)

- Collect target n-grams
  - For 1/n-best hyps, collect n-grams related to each source word
  - For TM, collect source n-grams and translate to target n-grams
- Model: collection of subsets of target n-grams
- $$Q_{st} = \{\overrightarrow{t_{s_1}}, \overrightarrow{t_{s_2}}, \ldots, \overrightarrow{t_{s_I}}\}$$
- $\overrightarrow{t_{s_i}}$ is a set of target n-grams for the source word s_i

$$\overrightarrow{t_{s_i}} = \{\{t_i, \ldots\}_{1-gram}; \{t_i t_{i+1}, \ldots\}_{2-gram}; \{t_{i-1} t_i t_{i+1}\}_{3-gram} \ldots\}$$

Structured Query Models (2/2)

- Example: sum of frequency-weighted sums

```
#q=#sum(#wsum(2 eu 2 #phrase(european union))
        #wsum(12 #phrase(the united states)
                1 american 1 #phrase(an american))
        #wsum(4 are 1 is)
        #wsum(8 markets 3 market))
        #wsum(7 #phrase(the main) 5 primary));
```

Experiments

- Test set: 878 sentences from NIST June 2002 Chinese to English MT evaluation
- Report NIST and BLEU scores with 4 refs for each sentence
- Baseline model:
  - TM training data: 284k parallel sentences
  - LM training data: 160 words of general English news text
- LM adaptation corpora: 4 collections from the GigaWord Corpora (English news text)
  - Preprocessing: lowercase, separate punctuation, no stopword removal

Results: Bag-of-words Models

- All adapted LMs outperformed the baseline
- Data from AFE corpus gave best improvement
- Used 100-best list for Q_{TN} model - only 9 times bigger than Q_{T1} (1-best)
- Retrieval of 100 sentences was best
- Overall, Q_{TN} gave best results
  - More alternatives than Q_{T1}
  - Q_{TM} probably contributed bad alternatives as well and good ones

Results: Structured Models

- Using more retrieved data (1000 sentences) gives better results
- Q_{TM} performs best - the structured model appears to reduce noise in the retrieved data

Oracle Experiment

- Use reference translations to retrieve adaptation data (4000 sentences)
- Higher BLEU and NIST scores show room for improvement
- Better 1st pass translations lead to better retrieved data which leads to better 2nd pass translations - could we iterate?
- Results are still limited by TM and decoder

Summary and Future Work

- LM adaptation by retrieving sentences similar to initial translations results in improved performance
- Structured queries which capture word order outperform bag-of-words queries
- Future work:
  - Will larger corpora for retrieval of adaptation data improve performance?
  - Can translation probabilities be included in queries?