Automatic Determination of Number of clusters for creating templates in Example-Based Machine Translation

Rashmi Gangadharaiah, Ralf D. Brown and Jaime Carbonell

Presentation: Bob Frederking

Outline of this talk

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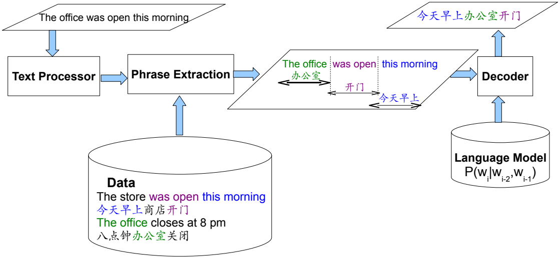
1. Our EBMT System
2. G-EBMT: Use of templates
3. Automatically determine the number of clusters
   - Word-Generalized Templates in TM
   - Word-Generalized Templates in LM
4. Results

EBMT System

R. D. Brown et. al., 2003



EBMT requires large amounts of data

- Decoding is expensive with long input sentences and short phrasal candidates.
  - Place restrictions on the decoder
  - Obtain local reordering information
    - Increase corpus size to obtain longer target phrasal matches.

Hence, EBMT requires large amounts of data to function well.

Sparse Data

- EBMT systems like other corpus-based methods require large amounts of data to function well.
  - *But*, obtaining parallel text is time-consuming, expensive and difficult.
  - Effect of less data on EBMT:
    - Reduces translation quality due to absence of longer phrasal matches.

How do we obtain longer phrasal matches in data sparse conditions?

Outline of this talk

How do templates help in data sparse conditions

S1: The session opened at 6 pm . ⟷ La séance est ouverte à 6 heures .
T1: The ***<event>*** opened at ***<time>*** . ⟷ La ***<event>*** est ouverte à ***<time>*** .

- If, "session(séance)", "seminar(séminaire)" belong to ***<event>*** and, "6 pm(6 heures), 2pm(2 heures), 9am(9 heures)" belong to ***<time>*** class.
- T1 can now translate:
  - The *session* opened at *2 pm* .
  - The *seminar* opened at *9 am* .

Templates in TM

- Example training corpus:
  - S_1:The Minister gave a speech on Wednesday .
    T_1:Le ministre a donné un discours mercredi .
  - S_2:The President gave a speech on Monday .
    T_2:Le président a donné un discours lundi .
- Example word-pair Clusters:
  - <CL0>: Minister-*ministre*,President-*président*,..
  - <CL1>: Wednesday-*mercredi*,Monday-*lundi*,..
- Generalized template (T):
  - The <CL0> gave a speech on <CL1> .
    Le <CL0> a donné un discours <CL1> .
- *I*:The President gave a speech on Wednesday .

Templates in TM

- *I*:The President gave a speech on Wednesday .

- Example word-pair Clusters:
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  - The <CL0> gave a speech on <CL1> .
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Templates in TM

- *I*:The President gave a speech on Wednesday .

- *ITS*:The <CL0> gave a speech on <CL1> .
  ITT:*Le <CL0> a donné un discours <CL1>* .

- Example word-pair Clusters:
  - <CL0>: Minister-*ministre*,President-*président*,..
  - <CL1>: Wednesday-*mercredi*,Monday-*lundi*,..
- Generalized template (T):
  - The <CL0> gave a speech on <CL1> .
    Le <CL0> a donné un discours <CL1> .

Templates in TM

- *I*:The President gave a speech on Wednesday .
- *ITS*:The <CL0> gave a speech on <CL1> .
  ITT:*Le <CL0> a donné un discours <CL1>* .
- *O*:*Le président a donné un discours mercredi* .

- Example word-pair Clusters:
  - <CL0>: Minister-*ministre*,President-*président*,..
  - <CL1>: Wednesday-*mercredi*,Monday-*lundi*,..
- Generalized template (T):
  - The <CL0> gave a speech on <CL1> .
    Le <CL0> a donné un discours <CL1> .

Usefullness of templates in G-EBMT systems that use Statistical decoders

- EBMT systems that use statistical decoders.
  - Constraints on decoder.
  - extract longer phrasal matches.

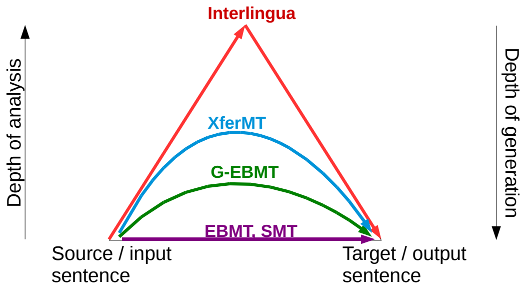
"Le président a donné un discours mercredi" vs.
"Le président a donné" and *"mercredi"*

Related Work: Templates resemble Transfer Rules

- Traditional Rule-based MT (trad. RBMT)
  - includes Xfer-based MT and interlingua-based MT
  - transformations based on structural rules or interlingua
  - manually built transfer rules made up of non-terminal (NT) labels with constraints and lexicon to translate source words.
- Xfer-based MT (Lavie, 2008)
  - similar to trad. RBMT with manually/automatically built transfer rules containing T and NT labels with constraints.
  - rules extracted by aligning source and target parse trees.
- Syntax-based SMT
  - Yamada and Knight (2001) statistical model containing transfer rules of NT labels to reorder child nodes, insert extra words and translate leaf words in the source parse tree.
  - Heiro (Chiang et. al., 2005) is a stochastic synchronous CFG consisting of pairs of CFG rules with aligned NT labels.

Templates: Resemble Transfer Rules

- EBMT templates provide more flexibility
  - Flat (not nested) structural templates contain both T and NT labels with fewer or no constraints
  - NT labels not necessarily linguistics-based syntactic phrases
  - any sequence of one or more words forms a phrase



Related Work

- Methods that generalize differences and similarities
  - ([Cicekli and Guvenir, 2001];[McTait, 2001]) use only similar and dissimilar portions limiting the amount of generalization
  - Recursive transfer-rule induction process (Brown, 2001) combining (Cicekli and Guvenir, 2001) and word clustering (Brown, 2000) based on context, but finds the number of clusters empirically.
- Methods that generalize chunk translations
  - (Kaji et al., 1992) extract phrase pairs from parse trees hence, templates created are less controllable
  - (Block, 2000) extracts chunk pairs from word alignments, can cause over-generalization increasing decoding time
  - (Carl, 2001) similar to (Block, 2000) but use bracketing Gaijin (Veale and Way, 1997) uses only marker hypothesis

Outline of this talk

Clustering Algorithm to obtain templates

- Automatically cluster words based on context
  - Selecting a clustering algorithm
    - simple in design
    - automatically determine the number of clusters
    - high quality clusters

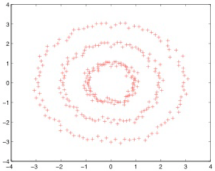
Clustering Algorithm

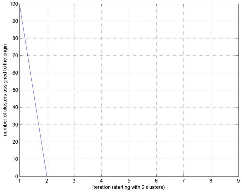
- Automatically cluster words based on context
  - Spectral Clustering (NJW algorithm)
    - Cluster points using the eigenvectors of distance matrices obtained from data.
      Features: form *term vectors* for each word-pair by accumulating counts for tokens in its context.
    - Superior to Group Average Clustering (Gangadharaiah et. al., 2006)
    - Automatically determine the number of clusters [modified (Sanguinetti et al., 2005)].

Finding number of clusters (N)

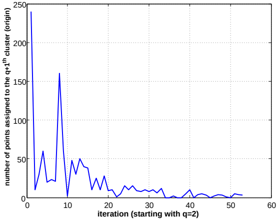
Modified algorithm of (Sanguinetti et al., 2005):

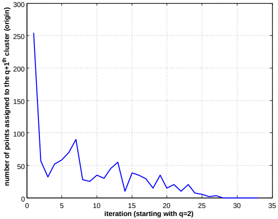
Artificially generated data





Real data





Cluster Purity

Impure clusters	Pure clusters
(“almost” *“presque”*)	
(“certain” *“certains”*)	
(“his” *“sa”*)	(“his” *“sa”*)
(“his” *“son”*)	(“his” *“son”*)
(“its” *“sa”*)	(“its” *“sa”*)
(“its” *“ses”*)	(“its” ‘ *‘ses”*)
(“last” *“hier”*)	
(“my” *“mes”*)	(“my” *“mes”*)
(“my” *“mon”*)	(“my” *“mon”*)
(“our” *“nos”*)	(“our” *“nos”*)
(“our” *“notre”*)	(“our” *“notre”*)
(“their” *“leur”*)	(“their” *“leur”*)
(“their” *“leurs”*)	(“their” *“leurs”*)
(“these” *“ces”*)	(“these” *“ces”*)
(“too” *“trop”*)	
(“without” *“sans”*)	
	(“his” *“ses”*)

Table: Cluster purity before and after removal of oscillating points with 10k Eng-Fre ($th_1 > 9$)

Previous Approaches

- Data sparsity is a big challenge in statistical LM.
- n-gram Class-based (CB) Language Models (Brown et al., 1992)

$$p(w_i|h) = p(w_i|c_i) \;\times\; p(c_i|c_{i-1}, \ldots, c_{i-n+1})$$

  - words grouped based on POS tags or automatically clustered
  - require all words present in the training data to be clustered
    - Unreliable clusters if errors in the data (eg. segmentation)
- Factored Language Models (Kirchhoff and Yang, 2005)
  - word represented by linguistic features
  - extremely large model space with many backoff paths

Our approach: Template-based (TB)

- Alternate approach
  - based on using short reusable sequences or 'templates' made up of words and class labels
  - Does not require all words to be clustered
    - Helpful when a small set of manually built clusters are present
  - How to form reliable clusters when manually built clusters are not available?
    - use clustering approach adopted in the TM

Note: CB can be made equivalent to TB

- when unreliable words are treated as singleton clusters.

Template-based Model

- Assume corpus C contains S1 and S2

  S1: the school reopens on Monday

  S2: the office is too far

Template-based Model

- Assume corpus C contains S1 and S2
  S1: the school reopens on Monday
  S2: the office is too far
- Assume <ORG> and <WEEKDAY> are obtained either manually or automatically
  <ORG>: school, company, office
  <WEEKDAY>: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.

Template-based Model

- Assume corpus C contains S1 and S2
  S1: the school reopens on Monday
  S2: the office is too far
- Assume <ORG> and <WEEKDAY> are obtained either manually or automatically
  <ORG>: school, company, office
  <WEEKDAY>: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.
- Templates T1 and T2 are obtained from S1 and S2
  T1: the <ORG> reopens on <WEEKDAY>
  T2: the <ORG> is too far

Template-based Model

- Assume corpus C contains S1 and S2

  S1: the school reopens on Monday
  S2: the office is too far

- Assume <ORG> and <WEEKDAY> are obtained either manually or automatically

  <ORG>: school, company, office
  <WEEKDAY>: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday.

- Templates T1 and T2 are obtained from S1 and S2

  T1: the <ORG> reopens on <WEEKDAY>
  T2: the <ORG> is too far

- If "p(reopens | the office)" is encountered during decoding
  - Word-based model: backs-off to unigram score, p(reopens)
  - Template-based model: gives a more reliable score, p(reopens | the <ORG>)

Formal Description

$$p(w_i|h) \approx xp(f_i|f_{i-1}, ..., f_{i-n+1})$$

$$f_j = \begin{cases} c(w_j), & \text{if } w_j^{th} \text{ class is present} \\ w_j, & \text{otherwise} \end{cases}$$

$$x = \begin{cases} p(w_i|c(w_i)), & \text{if } w_i^{th} \text{ class is present} \\ 1, & \text{otherwise} \end{cases}$$

- The probability of the i^{th} word (w_i) given its history h is represented as the probability of feature f_i corresponding to w_i given its previous history of features.
- Each f_i can represent a word w_j or its class $c(w_j)$.

Incorporating Template-based models

- EBMT engine assigns a quality score (q_i) to phrasal translations
  - Log-linear combination of alignment and translation score
- Our decoder works on a lattice of phrasal translations
  - total score for a path

$$total\ score = \frac{1}{n}\sum_{i=1}^{n}[wt_1 * log(b_i) + wt_2 * log(pen_i) + wt_3 * log(q_i) + wt_4 * log(P(w_i|w_{i-2}, w_{i-1})]$$

n: number of target words in the path, wt_j: importance of each score, b_i: bonus factor, pen_i: penalty factor, $P(w_i|w_{i-2}, w_{i-1})$: LM score.

- Template-based and word-based language model scores are interpolated

Outline of this talk

Experimental Setup(1)

- English-Haitian: The English–Haitian medical domain data (Haitian Creole, CMU, 2010)
  - Training Data : 1219 sentence pairs.
  - Tune Set: 200 sentence pairs, Test Data: 200 sentence pairs.
- English–Chinese: FBIS (NIST 2003)
  - Training Data: 15k, 30k and 200k sentence pairs.
  - Tune Set: 200 sentence pairs, Test Data: 4000 sentence pairs.
- English-French: Hansard Corpus (LDC)
  - Training Data: 10k, 30k and 100k sentence pairs.
  - Tune Set: 200 sentence pairs, Test Data: 4000 sentence pairs.

Experimental Setup(2)

- Language Models:
  - the target half of the training data.
  - 5-grams Language Models
- Statistical significance: Wilcoxon Signed-Rank Test.

Results

Lang-Pair	data	Manual	SangAlgo	Mod Algo
Eng-Fre(TM)	10k	0.1777 (10 clusters)	0.1641 (35 clusters)	0.1790 (27 clusters)
Eng-Chi(LM)	30k	0.1290 (110 clusters)	0.1257 (82 clusters)	0.1300 (75 clusters)

Table: BLEU scores with templates created using manually, SangAlgo and the modified algorithm to find N on 10k English-French and 30k English-Chinese training data.

Results

Lang-Pair		Baseline	LM	TM
Eng-Chi	15k	0.1076	0.1098	0.1102
Eng-Chi	30k	0.1245	0.1300	0.1338
Eng-Chi	200k	0.1905	0.1936	0.1913
Eng-Haitian		0.2182	0.2370	0.229

Table: BLEU scores with templates applied in LM and TM with 15k, 30k and 200k English-Chinese, and English-Haitian training data.

Conclusion and Future Work

- introduced a method for automatically finding the number of clusters (N) for a real world problem.
- refined the clustering process by removing incoherent points and showed that discarding these points boosts the translation quality.
- showed significant improvements by adding generalized templates.

Future Work:
Template-based systems with larger training data sets.

Backup Slides:Term Vectors

S1: $< NULL >< NULL >$ Le cinq jours depuis la
T1:$< NULL >< NULL >$ The five days since the elles
S2: elles commenceront en cinq jours . $< NULL >$
T2: They will begin in five days . $< NULL >$

- A rough mapping between source and target words is created
- For each word pair accumulate counts for each word in the surrounding context of its occurrences (N=3)
- Weigh the counts w.r.t distance from occurrence with a linear decay

word	occur	weight
<NULL>(-3)	1	0.333
<NULL>(-2)	1	0.667
commenceront(-2)	1	0.667
Le(-1)	1	1.000
en(-1)	1	1.000
jours(1)	2	2.000
depuis(2)	1	0.667
.(2)	1	0.667
la(3)	1	0.333
<NULL>(3)	1	0.333

Backup Slides:Clustering Algorithm

- Automatically determine the number of clusters: Modified algorithm of (Sanguinetti et al., 2005):
  - runs iteratively starting with three clusters and performs a modified version of k-means clustering to detect if points are assigned to the origin
  - When q is less than best, points that are not close to any of the q centers, get assigned to the origin.
  - $q = q + 1$ if points assigned to the origin and repeat
  - Halt if there are no points assigned to the origin