Statistical Machine Translation
Part I - Introduction

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NSSNLP, University of Kathmandu
About the course

• This is a course on statistical machine translation, but from three perspectives
  – First perspective: basic statistical machine translation (as explained in Koehn textbook)
  – Second perspective: how to integrate linguistic information into basic statistical MT
    • Statistical MT for many languages cannot work without such linguistic processing!
  – Third perspective: resources required for Nepali, Pashto, Punjabi, Sinhala, Tamil, Urdu
    • Others?
About the instructor

• Dr. Alexander “Alex” Fraser
  – Dissertation in computer science on statistical machine translation at University of Southern California, Information Sciences Institute
  – Developed first commercial statistical machine translation system: Language Weaver Arabic/English
  – Cross-language retrieval and resource construction at BBN Technologies
  – Senior researcher, leading research group at Stuttgart: Morphosyntactic Modeling for Statistical Machine Translation (located inside Hinrich Schuetze’s department)
  – Also interested in statistical parsing, terminology
PhD students

Fabienne Braune: Tree-based models for Statistic Machine Translation
   (Also works with Andreas Maletti on Tree Transducers for SMT)
Fabienne Cap: Compound words and derivational morphology for SMT
Nadir Durrani*: New statistical models for SMT
Anita Ramm (no picture): Word reordering in translation and verbal phenomena
Hassan Sajjad*: Transliteration mining and modeling
Marion Weller: Inflectional morphology and lexical semantics for SMT
   (Primary advisor: Sabine Schulte im Walde, lexical semantics)
*: jointly supervised w/ Helmut Schmid;  Masters with Prof. Sarmad Hussain

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Outline

- Part 1: introduction, resources, machine translation evaluation
- Part 2: word alignment
- Part 3: basic phrase-based model, decoding
- Part 4: discriminative phrase-based modeling
- Part 5: basic ideas for integrating linguistic knowledge, including syntactic models and morphology
- Part 6: utilizing linguistic resources: case study on German

Comments:
- Parts 2 and 4 have lots of math
- Part 3 includes a complex search algorithm
- I will separate into main ideas (easily accessible to everyone) and details (CS/math background helpful, important to study Koehn book)
• Slides will be on the course web page

• Other resources: Philipp Koehn’s book ->

• Kevin Knight’s tutorial on word alignment is long, but it is good!
Assignments

• There will be three assignments
• First assignment will involve using Google Translate
  – If there is anyone who does not know the basics of any language other than English supported by Google Translate, please talk to me after class today
• Any basic questions before we start?
Lecture 1 – Introduction + Eval

- Machine translation
- Data driven machine translation
  - Parallel corpora
  - Sentence alignment
  - Overview of statistical machine translation
- Evaluation of machine translation
A brief history

• Machine translation was one of the first applications envisioned for computers

• Warren Weaver (1949): “I have a text in front of me which is written in Russian but I am going to pretend that it is really written in English and that it has been coded in some strange symbols. All I need to do is strip off the code in order to retrieve the information contained in the text.”

• First demonstrated by IBM in 1954 with a basic word-for-word translation system

Modified from Callison-Burch, Koehn
Interest in machine translation

• Commercial interest:
  – U.S. has invested in machine translation (MT) for intelligence purposes
  – MT is popular on the web—it is the most used of Google’s special features
  – EU spends more than $1 billion on translation costs each year.
  – (Semi-)automated translation could lead to huge savings

Modified from Callison-Burch, Koehn
Interest in machine translation

- Academic interest:
  - One of the most challenging problems in NLP research
  - Requires knowledge from many NLP sub-areas, e.g., lexical semantics, syntactic parsing, morphological analysis, statistical modeling,…
  - Being able to establish links between two languages allows for transferring resources from one language to another

Modified from Dorr, Monz
Machine translation

• Goals of machine translation (MT) are varied, everything from *gisting* to rough draft

• Largest known application of MT: Microsoft knowledge base
  – Documents (web pages) that would not otherwise be translated at all
A description of the American president George W. Bush elections—Iraq, which will take place on the thirtieth session of the month—as a historic moment, acknowledging that the organization of elections in the current difficult circumstances. Bush said in press statements that it is possible to organize elections in most regions of Iraq to the deadline and I wish that the turnout are high. He added that "14 governorates of Iraq's 18 appeared in relative calm".

v.2.0 – October 2003

US President George W. Bush described Iraq elections—which will take place on the 30th of this month—as a historic moment, acknowledging that the elections in the current situation is difficult. Bush said in a press statement that it be possible to organize elections in most regions of Iraq in time and hoped that the rate of participation in the high. He added that "Iraqi 14 of the provinces of 18 appears to be relatively calm."

v.2.4 – October 2004

v.3.0 - February 2005

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Document versus sentence

• MT problem: generate high quality translations of documents
• However, all current MT systems work only at sentence level!
• Translation of independent sentences is a difficult problem that is worth solving
• But remember that important discourse phenomena are ignored!
  – Example: How to translate English *it* to French (choice of feminine vs masculine *it*) or German (feminine/masculine/neuter *it*) if object referred to is in another sentence?
Machine Translation Approaches

- Grammar-based
  - Interlingua-based
  - Transfer-based

- Direct
  - Example-based
  - Statistical

Modified from Vogel
Statistical versus Grammar-Based

- Often statistical and grammar-based MT are seen as alternatives, even opposing approaches – wrong !!!

- Dichotomies are:
  - Use probabilities – everything is equally likely (in between: heuristics)
  - Rich (deep) structure – no or only flat structure

- Both dimensions are continuous

- Examples
  - EBMT: flat structure and heuristics
  - SMT: flat structure and probabilities
  - XFER: deep(er) structure and heuristics

- Goal: structurally rich probabilistic models

<table>
<thead>
<tr>
<th></th>
<th>No Probs</th>
<th>Probs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat Structure</td>
<td>EBMT</td>
<td>SMT</td>
</tr>
<tr>
<td>Deep Structure</td>
<td>XFER, Interlingua</td>
<td>Holy Grail</td>
</tr>
</tbody>
</table>

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Statistical Approach

• Using statistical models
  – Create many alternatives, called hypotheses
  – Give a score to each hypothesis
  – Select the best -> search

• Advantages
  – Avoid hard decisions
  – Speed can be traded with quality, no all-or-nothing
  – Works better in the presence of unexpected input

• Disadvantages
  – Difficulties handling structurally rich models, mathematically and computationally
  – Need data to train the model parameters
  – Difficult to understand decision process made by system

Modified from Vogel
Outline

• *Machine translation*

• Data-driven machine translation
  – Parallel corpora
  – Sentence alignment
  – Overview of statistical machine translation

• Evaluation of machine translation
### Parallel corpus

- **Example from DE-News (8/1/1996)**

<table>
<thead>
<tr>
<th>English</th>
<th>German</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diverging opinions about planned tax reform</td>
<td>Unterschiedliche Meinungen zur geplanten Steuerreform</td>
</tr>
<tr>
<td>The discussion around the envisaged major tax reform continues.</td>
<td>Die Diskussion um die vorgesehene grosse Steuerreform dauert an.</td>
</tr>
<tr>
<td>The FDP economics expert, Graf Lambsdorff, today came out in favor of advancing the enactment of significant parts of the overhaul, currently planned for 1999.</td>
<td>Der FDP - Wirtschaftsexperte Graf Lambsdorff sprach sich heute dafuer aus, wesentliche Teile der fuer 1999 geplanten Reform vorzuziehen.</td>
</tr>
</tbody>
</table>

Modified from Dorr, Monz
Most statistical machine translation research has focused on a few high-resource languages (European, Chinese, Japanese, Arabic). (≈200M words)

Various Western European languages:
- parliamentary proceedings,
- govt documents (~30M words)

Bible/Koran/
- Book of Mormon/
- Dianetics (~1M words)

Nothing/
- Univ. Decl. Of Human Rights (~1K words)

Modified from Schafer&Smith
How to Build an SMT System

• Start with a large parallel corpus
  – Consists of document pairs (document and its translation)
• Sentence alignment: in each document pair automatically find those sentences which are translations of one another
  – Results in sentence pairs (sentence and its translation)
• Word alignment: in each sentence pair automatically annotate those words which are translations of one another
  – Results in word-aligned sentence pairs
• Automatically estimate a statistical model from the word-aligned sentence pairs
  – Results in model parameters
• Given new text to translate, apply model to get most probable translation
Sentence alignment

• If document $D_e$ is translation of document $D_f$ how do we find the translation for each sentence?
• The $n$-th sentence in $D_e$ is not necessarily the translation of the $n$-th sentence in document $D_f$
• In addition to 1:1 alignments, there are also 1:0, 0:1, 1:n, and n:1 alignments
• In European Parliament proceedings, approximately 90% of the sentence alignments are 1:1

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Sentence alignment

• There are several sentence alignment algorithms:
  – Align (Gale & Church): Aligns sentences based on their character length (shorter sentences tend to have shorter translations than longer sentences). Works well
  – Char-align: (Church): Aligns based on shared character sequences. Works fine for similar languages or technical domains
  – K-Vec (Fung & Church): Induces a translation lexicon from the parallel texts based on the distribution of foreign-English word pairs
  – Cognates (Melamed): Use positions of cognates (including punctuation)
  – Length + Lexicon (Moore; Braune and Fraser): Two passes, high accuracy, freely available

Modified from Dorr, Monz
Word alignments

• Given a parallel sentence pair we can link (align) words or phrases that are translations of each other:

Diverging opinions about the planned tax reform

Unterschiedliche Meinungen zur geplanten Steuerreform

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How to Build an SMT System

• Construct a function $g$ which, given a sentence in the source language and a hypothesized translation into the target language, assigns a goodness score
  
  – $g(\text{die Waschmaschine läuft }, \text{the washing machine is running}) = \text{high number}$
  
  – $g(\text{die Waschmaschine läuft }, \text{the car drove}) = \text{low number}$
Using the SMT System

- Implement a **search algorithm** which, given a source language sentence, finds the target language sentence which maximizes $g$

- To use our SMT system to translate a new, unseen sentence, call the search algorithm
  - Returns its determination of the best target language sentence

- To see if your SMT system works well, do this for a large number of **unseen** sentences and evaluate the results
SMT modeling

• We wish to build a machine translation system which given a Foreign sentence “f” produces its English translation “e”
  – We build a model of $P(\text{e} | \text{f})$, the probability of the sentence “e” given the sentence “f”
  – To translate a Foreign text “f”, choose the English text “e” which maximizes $P(\text{e} | \text{f})$
Noisy Channel: Decomposing \( P(e|f) \)

\[
\arg\max_{e} P(e|f) = \arg\max_{e} P(f|e) P(e)
\]

- \( P(e) \) is referred to as the “language model”
  - \( P(e) \) can be modeled using standard models (N-grams, etc)
  - Parameters of \( P(e) \) can be estimated using large amounts of monolingual text (English)
- \( P(f|e) \) is referred to as the “translation model”
SMT Terminology

- **Parameterized Model**: the form of the function $g$ which is used to determine the goodness of a translation

  $g(\text{die Waschmaschine läuft, the washing machine is running}) = P(e \mid f)$

  $P(\text{the washing machine is running} \mid \text{die Waschmaschine läuft}) =$
SMT Terminology

- **Parameterized Model**: the form of the function $g$ which is used to determine the goodness of a translation
  
  $g(\text{die Waschmaschine läuft, the washing machine is running}) = P(e | f)$
  
  $P(\text{the washing machine is running|die Waschmaschine läuft}) = \text{What??}$

  Unless we have seen exactly the input sentence in our training data, we can’t GENERALIZE.

  So we will decompose this translation into parts, so that we can generalize to new sentences.
SMT Terminology

- **Parameterized Model**: the form of the function \( g \) which is used to determine the goodness of a translation

\[
g(\text{die Waschmaschine läuft, the washing machine is running}) = P(e \mid f) 
\]

\[
P(\text{the washing machine is running} \mid \text{die Waschmaschine läuft}) = 
\]

Suppose we translate:

“die” to “the”

“Waschmaschine” to “washing machine”

“läuft” to “is running”

(and further suppose we don’t worry about word order…)

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SMT Terminology

- **Parameterized Model**: the form of the function $g$ which is used to determine the goodness of a translation

  $$g(\text{die Waschmaschine läuft, the washing machine is running}) = P(e \mid f)$$

  $$P(\text{the washing machine is running} \mid \text{die Waschmaschine läuft}) =$$

  $$n(1 \mid \text{die}) \ t(\text{the} \mid \text{die})$$

  $$n(2 \mid \text{Waschmaschine}) \ t(\text{washing} \mid \text{Waschmaschine})$$

  $$t(\text{machine} \mid \text{Waschmaschine})$$

  $$n(2 \mid \text{läuft}) \ t(\text{is} \mid \text{läuft}) \ t(\text{running} \mid \text{läuft})$$

  $$l(\text{the} \mid \text{START}) \ l(\text{washing} \mid \text{the}) \ l(\text{machine} \mid \text{washing}) \ l(\text{is} \mid \text{machine})$$

  $$l(\text{running} \mid \text{is})$$
SMT Terminology

• **Parameters:** lookup tables used in function $g$

  \[
P(\text{the washing machine is running} | \text{die Waschmaschine läuft}) =
  n(1 | \text{die}) \ t(\text{the} | \text{die})
  n(2 | \text{Waschmaschine}) \ t(\text{washing} | \text{Waschmaschine})
  t(\text{machine} | \text{Waschmaschine})
  n(2 | \text{läuft}) \ t(\text{is} | \text{läuft}) \ t(\text{running} | \text{läuft})
  l(\text{the} | \text{START}) \ l(\text{washing} | \text{the}) \ l(\text{machine} | \text{washing}) \ l(\text{is} | \text{machine})
  l(\text{running} | \text{is})
  \]

  \[
  0.1 \times 0.1 \\
  \times 0.5 \times 0.8 \\
  \times 0.7 \\
  \times 0.1 \times 0.1 \times 0.1 \\
  \times 0.0000001
  \]
SMT Terminology

- **Parameters**: lookup tables used in function $g$

  \[
  P(\text{the washing machine is running} | \text{die Waschmaschine läuft}) = \\
  n(1 | \text{die}) \ t(\text{the} | \text{die}) \\
  n(2 | \text{Waschmaschine}) \ t(\text{washing} | \text{Waschmaschine}) \\
  t(\text{machine} | \text{Waschmaschine}) \\
  n(2 | \text{läuft}) \ t(\text{is} | \text{läuft}) \ t(\text{running} | \text{läuft}) \\
  l(\text{the} | \text{START}) \ l(\text{washing} | \text{the}) \ l(\text{machine} | \text{washing}) \ l(\text{is} | \text{machine}) \\
  l(\text{running} | \text{is})
  \]

  Change “washing machine” to “car”

  \[
  0.1 \times 0.1 \\
  \times 0.5 \times 0.8 \\
  \times 0.7 \\
  \times 0.1 \times 0.1 \times 0.1 \\
  \times 0.0000001
  \]

  0.1 \times 0.1 \\
  \times 0.1 \times 0.0001 \ n(1 | \text{Waschmaschine}) \\
  t(\text{car} | \text{Waschmaschine}) \\
  \times 0.1 \times 0.1 \times 0.1 \\
  \times \text{also different}
SMT Terminology

- **Training**: automatically building the lookup tables used in g, using parallel sentences
- **One way to determine** $t(\text{the} | \text{die})$
  - Generate a word alignment for each sentence pair
  - Look through the word-aligned sentence pairs
  - Count the number of times „die“ is translated as „the“
  - Divide by the number of times „die“ is translated.
  - If this is 10% of the time, we set $t(\text{the} | \text{die}) = 0.1$
SMT Last Words

- Translating is usually referred to as **decoding** (Warren Weaver)
- SMT was invented by automatic speech recognition (ASR) researchers. In ASR:
  - $P(e) = \text{language model}$
  - $P(f|e) = \text{acoustic model}$
  - However, SMT must deal with word reordering!
Outline

- **Machine translation**
- **Data-driven machine translation**
  - Parallel corpora
  - Sentence alignment
  - *Overview of statistical machine translation*
- **Evaluation of machine translation**
Evaluation driven development

– Lessons learned from automatic speech recognition (ASR)
  • Reduce evaluation to a single number
    – For ASR we simply compare the hypothesized output from the recognizer with a transcript
    – Calculate similarity score of hypothesized output to transcript
    – Try to modify the recognizer to maximize similarity
  • Shared tasks – everyone uses same data
    – May the best model win!

– These lessons widely adopted in NLP and Information Retrieval
Evaluation of machine translation

• We can evaluate machine translation at corpus, document, sentence or word level
  – Remember that in MT the unit of translation is the sentence

• Human evaluation of machine translation quality is difficult

• We are trying to get at the abstract usefulness of the output for different tasks
  – Everything from gisting to rough draft translation
Sentence Adequacy/Fluency

- Consider German/English translation
- **Adequacy**: is the meaning of the German sentence conveyed by the English?
- **Fluency**: is the sentence grammatical English?
- These are rated on a scale of 1 to 5

Modified from Dorr, Monz
## Human Evaluation

<table>
<thead>
<tr>
<th>Input: Ich bin müde.</th>
<th>(OR Input: Je suis fatigué.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tired is I.</td>
<td>Adequacy: 5, Fluency: 2</td>
</tr>
<tr>
<td>Cookies taste good!</td>
<td>Adequacy: 1, Fluency: 5</td>
</tr>
<tr>
<td>I am tired.</td>
<td>Adequacy: 5, Fluency: 5</td>
</tr>
</tbody>
</table>

Modified from Schafer, Smith

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Further slides on manual evaluation
Automatic evaluation

- **Evaluation metric**: method for assigning a numeric score to a hypothesized translation
- Automatic evaluation metrics often rely on comparison with previously completed human translations
Word Error Rate (WER)

- **WER**: edit distance to reference translation (insertion, deletion, substitution)
- Captures fluency well
- Captures adequacy less well
- Too rigid in matching

Hypothesis = „he saw a man and a woman“
Reference = „he saw a woman and a man“
WER gives no credit for „woman“ or „man“!
Position-Independent Word Error Rate (PER)

- **PER**: captures lack of overlap in *bag of words*
- Captures adequacy at single word (unigram) level
- Does not capture fluency
- Too flexible in matching

Hypothesis 1 = „he saw a man“
Hypothesis 2 = „a man saw he“
Reference = „he saw a man“

Hypothesis 1 and Hypothesis 2 get same PER score!
BLEU

• Combine WER and PER
  – Trade off between rigid matching of WER and flexible matching of PER

• **BLEU** compares the 1,2,3,4-gram overlap with one or more reference translations
  – BLEU penalizes generating short strings with the brevity penalty, precision for short strings is very high
  – References are usually 1 or 4 translations (done by humans!)

• BLEU correlates well with average of fluency and adequacy at corpus level
  – But not at sentence level!
BLEU discussion

- BLEU works well for comparing two similar MT systems
  - Particularly: SMT system built on fixed training data vs. Improved SMT system built on same training data
  - Other metrics such as METEOR extend these ideas and work even better – ongoing research!

- BLEU does not work well for comparing dissimilar MT systems

- There is no good automatic metric at sentence level

- There is no automatic metric that returns a meaningful measure of *absolute* quality
Description of the Iraqi President George Bush American elections— which will follow in the current month of the thirty—that they constitute a historic moment, recognizing that the organization of elections in current circumstances difficult issue.

It was considered Bush in the press that the pronouncements of the possible organization of elections in most regions of the Iraqi punctually wish that the turnout where high. He added that "Iraqi 14 "appear in the relative calm 18 governores.

v.2.0 – October 2003

A description of the American president George W. Bush elections— Iraq, which will take place on the thirtieth session of the month—as a historic moment, acknowledging that the organization of elections in the current difficult circumstances.

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v.3.0 - February 2005

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• Next time we will look at word alignment models
  – Next lecture will be more mathematical
  – If you are highly motivated, take a look at Kevin Knight’s excellent tutorial (not required!)
• Thank you for your attention!