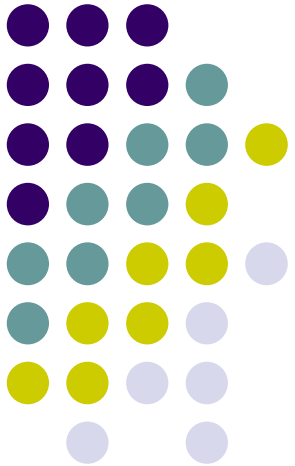
MACHINE TRANSLATION EVALUATION

Advanced Signal Processing Seminar

Emine Zerrin SAKIR

Stefan Petrik

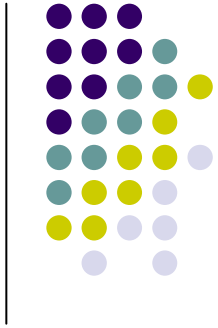


Overview

- Introduction to machine translation
- N-gram based methods
- BLUE
- NIST
- Word error rate based methods
- Minimum error rate training

A Brief Description of Machine Translation

Introduction



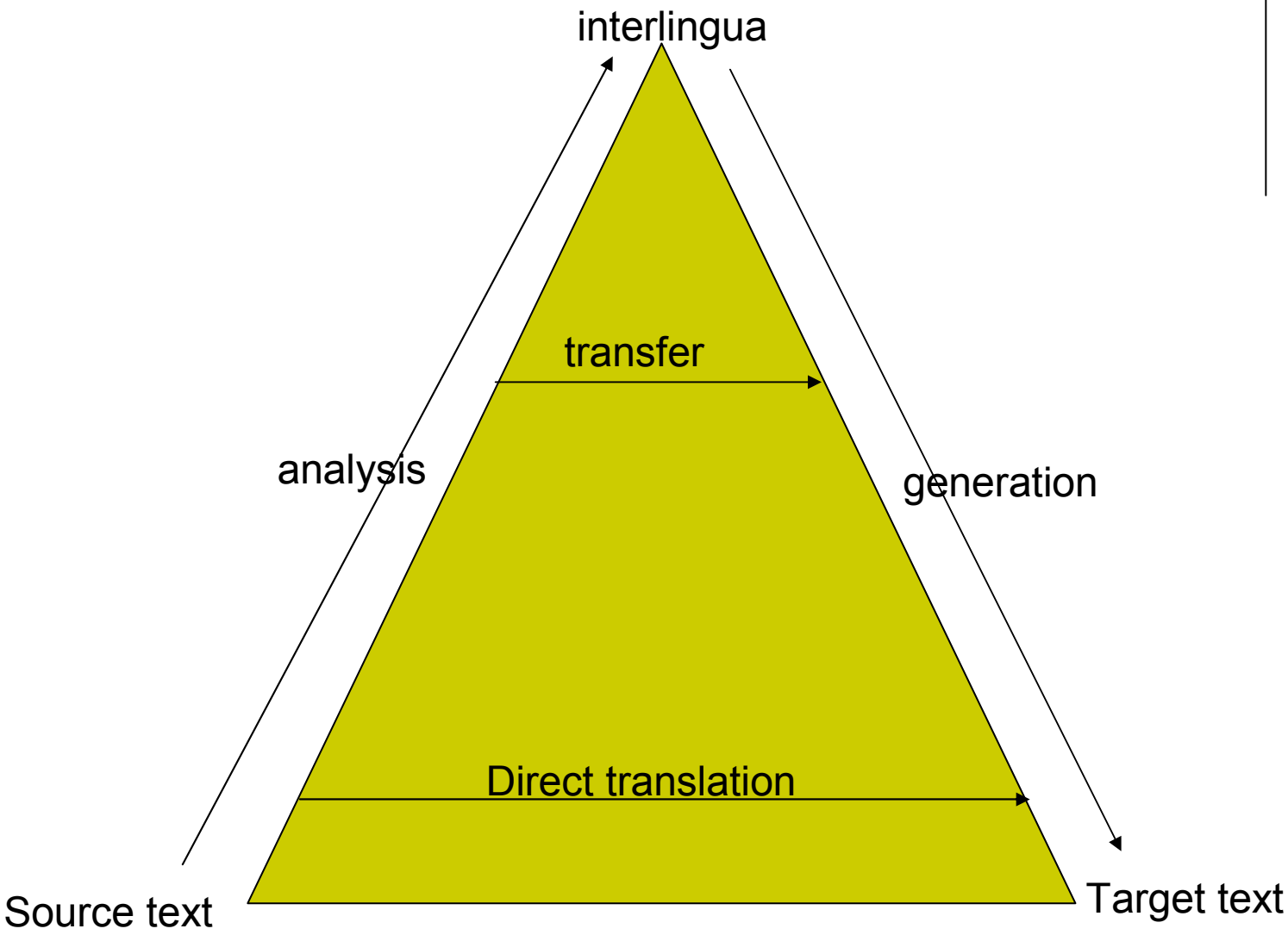
- Machine Translation (MT) is a subfield of computational linguistics.
- It investigates the use of computer software to translate text or speech from one natural language to another.
- The translation process, basically, includes two steps:
  1. Decoding the meaning of the source text
  2. Re-encoding this meaning in the target language

The Challenges of Machine Translation

- How to program a computer to understand a text as a human being does!
- To create a new text in the target language that sounds as if it has been written by a human being!

Approaches

- Lexicon-based machine translation
- Statistical machine translation
- Example-based machine translation
- Interlingual machine translation


interlingua
transfer
analysis
generation
Direct translation
Source text
Target text

Evaluation of MT Systems

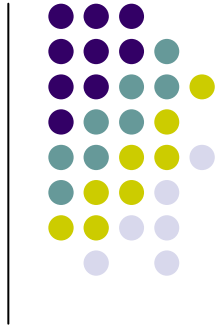
Pros and Cons of Human Evaluation of Machine Translation

- Human evaluations of MT are extensive but expensive.
- Human evaluations of MT are too much time consuming which is not practical for developers.
- Human evaluations of MT take human labor which can not be reused.
- Human evaluations of MT weigh many aspects of translation: adequacy, fidelity, fluency

Some Methods of Automatic Evaluation of MT

- BLEU
- NIST
- METEOR

Descriptions



- N-Gram: It is a sub-sequence of n items from a given sequence.
- Unigram: n-gram of size 1.
- Bigram: n-gram of size 2.
- Trigram: n-gram of size 3.

BLEU

- BLEU:***B***i***L***ingual ***E***valuation ***U***nderstudy
- The quality of translation is indicated as a number between 0 and 1.
- It is measured as statistical closeness to a given set of good quality human reference translations.
- it does not directly take into account translation intelligibility or grammatical correctness.

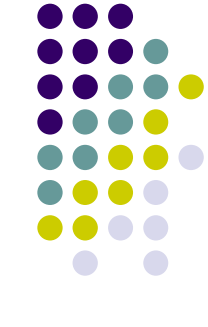
Viewpoint of „BLEU“ Method

- The criteria of translation performance measurement is:

  The closer a machine translation is to a professional human translation, the better it is.

- So, the MT evaluation system requires two ingredients:
  1. A numerical „translation closeness“ metric
  2. A corpus of good quality human reference translations

The Baseline BLEU Metric



- Example 1:
  - *Candidate 1*: It is a guide to action which ensures that the military always obeys the commands of the party.
  - *Candidate 2*: It is to ensure the troops forever hearing the activity guidebook that party direct.
  - Reference 1: It is a guide to action that ensures the military will forever heed Party commands.
  - Reference 2: It is the guiding principle which quarantees the military forces always being under the command of the party.
  - Reference 3: It is the practical quide for the army always to heed the directions of the party.

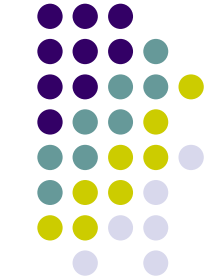
The Baseline BLEU Metric

- The primary programming task in BLEU implementation is:

  *To compare **n-grams** of the candidate with the n-grams of the reference translation and count the number of matches.*

- These matches are position independent.
- The more the matches, the better the candidate translation.

Modified Unigram Precision

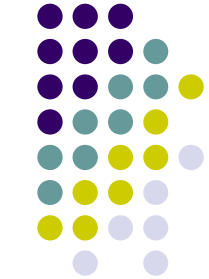


- Example2:
  - Candidate: the the the the the the the
  - Reference 1: The cat is on the mat.
  - Reference 2: There is a cat on the mat.
- The max. number of “the” is 2 in any single reference (Reference 2). So this number is clipped.
- Resulting modified unigram precision is: 2/7.

Modified n-gram Precision

- Modified n-gram precision computation for any n:
  - All candidate n-gram counts and their corresponding max. reference counts are collected.
  - The candidate counts are clipped by their corresponding reference max. value.
  - These values are summed and divided by the total number of candidate n-grams.

Modified n-gram Precision on Blocks of Text

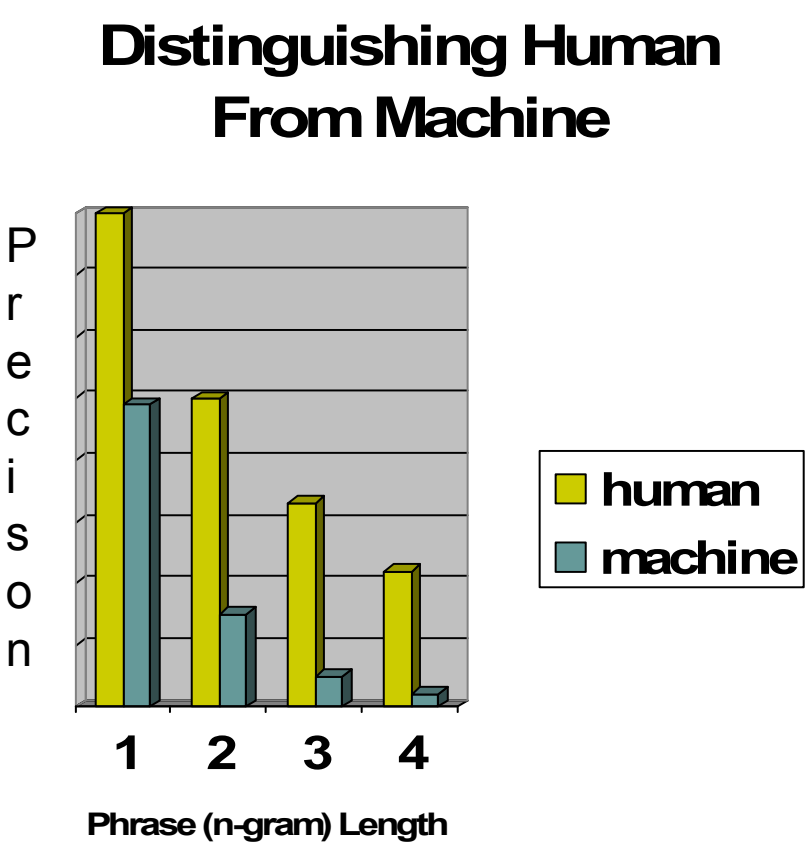


- The modified n-gram precision on a multi-sentence test set is computed by the formula:

$$pn = \frac{\sum_{c \in \{Candidates\}} \sum_{n-gram \in C} Countclip(n-gram)}{\sum_{c \in \{Candidates\}} \sum_{n-gram \in C} Count(n-gram)}$$

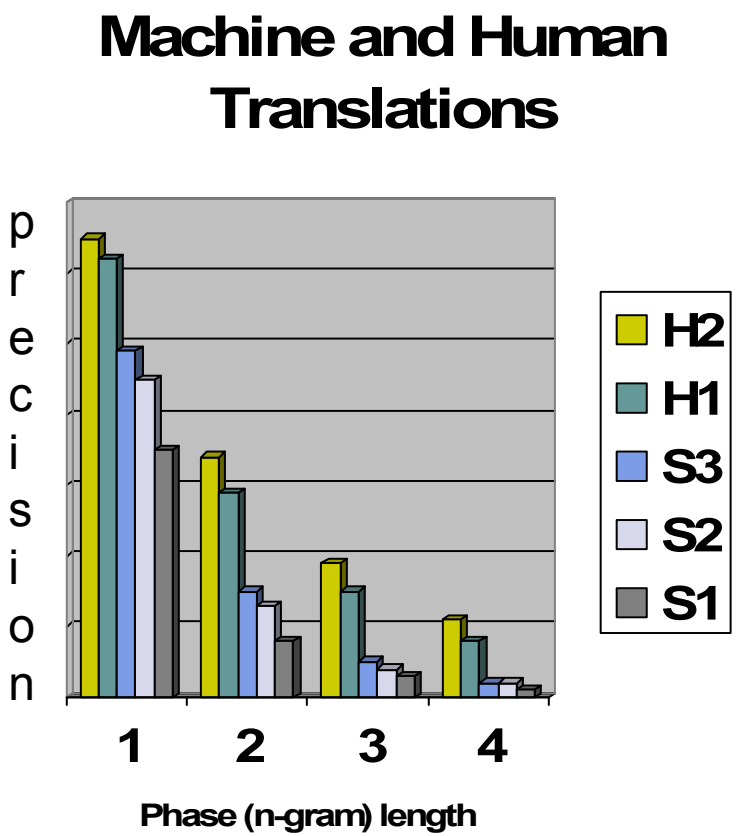
- This means that a word-weighted average of the sentence-level modified precision is used rather than a sentence-weighted average!

Ranking Systems Using Only Modified n-gram Precision



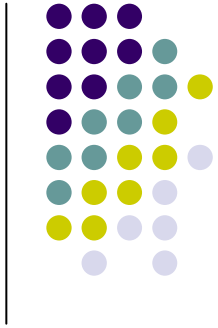
- The average modified precisions on the output of a human and machine translators.
- There are 4 reference translations for each of 127 source sentences.

Combining the n-gram Precisions



- As seen from the figure, the modified n-gram precision decays roughly, exponentially with n.
- BLEU uses the average logarithm with uniform weights, which is equivalent to using the geometric mean of the modified n-gram precisions.

Sentence Length



- A candidate translation length should not be too long or too short.
- Even though n-gram precision accomplishes this by penalizing using a word more times than it occurs in any of the reference, it alone fails to enforce the proper translation length.

- Example 3:
  - Candidate: of the
  - Reference 1: It is a guide to action that ensures that the military will forever heed the party commands.
  - Reference 2: It is the guiding principle which quarantees the military forces always being under the command of the party.
  - Reference 3: It is the practical guide for the army always to heed the directions of the party.

The Trouble with Recall

- Reference translations may choose different words to translate the same source word and the candidate should not recall all the references.
- Example 4:
  - Candidate 1: I always invariably perpetually do.
  - Candidate 2: I always do.
  - Reference 1: I always do.
  - Reference 2: I invariably do.
  - Reference 3: I perpetually do.

Sentence Brevity Penalty

- Brevity penalty factor penalizes candidates that are shorter than their reference.
- With this parameter in place, a high scoring candidate translation must match the reference translations in:
  - Length
  - Word choice
  - Word order
- Both n-gram precision length effect and brevity penalty considers the reference translation lengths in the target language.

Brevity Penalty

- Brevity penalty is a multiplicative factor, modifying the overall BLEU score.
- Brevity penalty is a decaying exponential in r/c, where:
  - r: test corpus's effective reference length. It is computed by summing the best match lengths for each candidate sentence in the corpus.
  - c: total length of the candidate translation corpus.

BLEU DETAILS

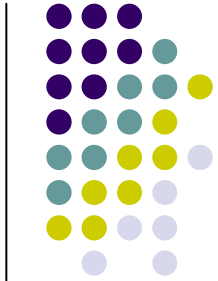
- The ranking behavior:

  N=4, w_n=1/N

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}$$

$$BLEU = BP * exp\left(\sum_{n=1}^{N} w_n log p_n\right)$$

The BLEU Evaluation

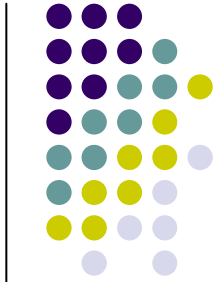


- The BLUE scores of the five systems against two references on the test corpus of 500 sentences.

S1	S2	S3	H1	H2
0.0527	0.0829	0.0930	0.1934	0.2571

  - How reliable is the difference in BLUE metric?
  - What is the variance of BLUE score?
  - If another random set of 500 sentences were taken, would the results be same?

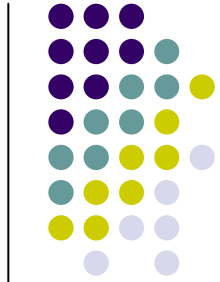
BLEU Evaluation



- The test corpus is divided into 20 blocks of 25 sentences and for each the BLEU metric is computed.

	S1	S2	S3	H1	H2
Mean	0.051	0.081	0.090	0.192	0.256
StdDev	0.017	0.025	0.020	0.030	0.039
t	-	6	3.4	24	11

NIST



- NIST is another method for evaluating the quality of the text translated using machine translation.
- NIST is based on BLEU metric with some alterations:
  - NIST calculates how informative a particular n-gram is.
  - When calculating brevity penalty small variations in translation length do not impact overall score very much.

The NIST Score Formulation

- Computation of information weights:

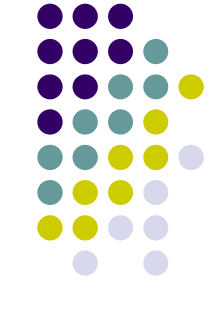
$$Info(w_1 \ldots w_n) = \log_2 \left(\frac{\text{the number of occurrences of } w_1 \ldots w_{n-1}}{\text{the number of occurrences of } w_1 \ldots w_n} \right)$$

$$Score = \sum_{n=1}^{N} \left\{ \frac{\sum_{\substack{\text{all } w1 \ldots wn \\ \text{that co-occur}}} Info(w_1 \ldots w_n)}{\sum_{\substack{\text{all } w1 \ldots wn \\ \text{in sys output}}} (1)} \right\} * \exp\left\{ \beta \log^2 \left[\min\left(\frac{L_{sys}}{L_{ref}}, 1 \right) \right] \right\}$$

Performance vs. Parameter Selection

- Performance as a function of source
- Performance vs. number of references
- Performance vs. segment size
- Performance with more language training
- Performance with preservation of case
- Performance with reference normalization

Conclusion



- The progress made in automatic evaluation of machine translation
  - helps the developers.
  - provides MT a significant progress.
- Automatic machine translation evaluation can be developed for a more accurate estimator of translation based on current techniques.

References

- Papineni, K.A.,Roukus,S., Ward, T., Zhu, W.J.: Bleu: a method for automatic evaluation of machine translation. Technical Report RC22176 (W0109-022), IBM Research Division, Thomas J. Watson Research Center, 2001.
- G.Doddington, Automatic evaluation of machine translation quality using n-gram cooccurrence statistics. ARPA Workshop on Human Language Technology, 2002.
- http://en.wikipedia.org/wiki/Machine_translation
- Arnold, D.,: Machine Translation:an Introductory Guide.University of Essex, 2002

Thanks for your attention…