Evaluation

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(adapted from the original slides
of Prof. Philipp Koehn)

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Evaluation

- How good is a given machine translation system?
- Hard problem, since many different translations are acceptable
  $\rightarrow$ semantic equivalence / similarity

Ten Translations of a Chinese Sentence

这个 机场 的 安全 工作 由 以色列 方面 负责 .

Israeli officials are responsible for airport security.
Israel is in charge of the security at this airport.
The security work for this airport is the responsibility of the Israel government.
Israeli side was in charge of the security of this airport.
Israel is responsible for the airport's security.
Israel is responsible for safety work at this airport.
Israel presides over the security of the airport.
Israel took charge of the airport security.
The safety of this airport is taken charge of by Israel.
This airport's security is the responsibility of the Israeli security officials.

(a typical example from the 2001 NIST evaluation set)

Evaluation

- Evaluation metrics
  - subjective judgments by human evaluators
  - automatic evaluation metrics
  - task-based evaluation, e.g.:
    - how much post-editing effort?
    - does information come across?

Manual evaluation

- Bilingual evaluators are preferable, but not always available
- Alternatively, monolingual evaluators, if a reference translation is available

- Evaluation can be on sentence level, but the context should be checked as well.

Manual evaluation

- Human judgment
  - given: machine translation output
  - given: source and/or reference translation
  - task: assess the quality of the machine translation output

Adequacy and Fluency

- Metrics

  Adequacy: Does the output convey the same meaning as the input sentence?
  Is part of the message lost, added, or distorted?

  Fluency: Is the output good fluent English?
  This involves both grammatical correctness and idiomatic word choices.

Fluency and Adequacy: Scales

Adequacy	
5	all meaning
4	most meaning
3	much meaning
2	little meaning
1	none

Fluency	
5	flawless English
4	good English
3	non-native English
2	disfluent English
1	incomprehensible

Annotation Tool

Judge Sentence

You have already judged 14 of 3064 sentences, taking 86.4 seconds per sentence.

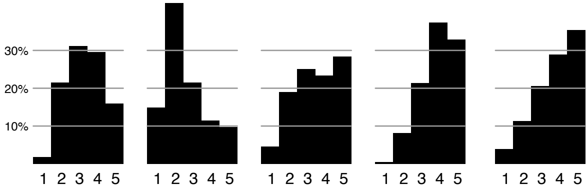
Source: les deux pays constituent plutôt un laboratoire nécessaire au fonctionnement interne de l ' ue .

Reference: rather , the two countries form a laboratory needed for the internal working of the eu .

Translation	Adequacy	Fluency
both countries are rather a necessary laboratory the internal operation of the eu .	1 2 3 4 5	1 2 3 4 5
both countries are a necessary laboratory at internal functioning of the eu .	1 2 3 4 5	1 2 3 4 5
the two countries are rather a laboratory necessary for the internal workings of the eu .	1 2 3 4 5	1 2 3 4 5
the two countries are rather a laboratory for the internal workings of the eu .	1 2 3 4 5	1 2 3 4 5
the two countries are rather a necessary laboratory internal workings of the eu .	1 2 3 4 5	1 2 3 4 5
Annotator: Philipp Koehn **Task:** WMT06 French-English	Annotate	
Instructions	5= All Meaning 4= Most Meaning 3= Much Meaning 2= Little Meaning 1= None	5= Flawless English 4= Good English 3= Non-native English 2= Disfluent English 1= Incomprehensible

Evaluators Disagree

- Histogram of adequacy judgments by five different human evaluators



(from WMT 2006 evaluation)

Measuring Agreement between Evaluators

- Kappa coefficient

$$K = \frac{p(A) - p(E)}{1 - p(E)}$$

  - $p(A)$: proportion of times that the evaluators agree
  - $p(E)$: proportion of time that they would agree by chance (5-point scale $\rightarrow$ $p(E) = \frac{1}{5}$)

- Example: Inter-evaluator agreement in WMT 2007 evaluation campaign

Evaluation type	$P(A)$	$P(E)$	K
Fluency	.400	.2	.250
Adequacy	.380	.2	.226

Ranking Translations

- Task for evaluator: Is translation X better than translation Y? (choices: better, worse, equal)
- Evaluators are more consistent:

Evaluation type	$P(A)$	$P(E)$	K
Fluency	.400	.2	.250
Adequacy	.380	.2	.226
Sentence ranking	.582	.333	.373

Goals for Evaluation Metrics

Low cost: reduce time and money spent on carrying out evaluation

Tunable: automatically optimize system performance towards metric

Meaningful: score should give intuitive interpretation of translation quality

Consistent: repeated use of metric should give same results

Correct: metric must rank better systems higher

Other Evaluation Criteria

When deploying systems, considerations go beyond quality of translations

- **Speed:** we prefer faster machine translation systems
- **Size:** fits into memory of available machines (e.g., handheld devices)
- **Integration:** can be integrated into existing workflow
- **Customization:** can be adapted to user's needs or to other domains

Automatic Evaluation Metrics

- Goal: computer program that computes the quality of translations
- Advantages: low cost, tunable, consistent

- Basic strategy
  - given: machine translation output
  - given: human reference translation
  - task: compute similarity between them

Precision and Recall of Words

SYSTEM A: Israeli officials ~~responsibility~~ ~~of~~ airport ~~safety~~

REFERENCE: Israeli officials are responsible for airport security

- Precision
$$\frac{correct}{output\text{-}length} = \frac{3}{6} = 50\%$$

- Recall
$$\frac{correct}{reference\text{-}length} = \frac{3}{7} = 43\%$$

- F-measure
$$\frac{precision \times recall}{(precision + recall)/2} = \frac{.5 \times .43}{(.5 + .43)/2} = 46\%$$

Precision and Recall

Metric	System A	System B
precision	50%	100%
recall	43%	86%
f-measure	46%	92%

flaw: no penalty for reordering

Word Error Rate

- Minimum number of editing steps to transform output to reference

match:	words match, no cost
substitution:	replace one word with another
insertion:	add word
deletion:	drop word

- Levenshtein distance

$$\mathrm{WER} = \frac{\textit{substitutions} + \textit{insertions} + \textit{deletions}}{\textit{reference-length}}$$

Example

		Israeli	officials	responsibility	of	airport	safety
	0	1	2	3	4	5	6
Israeli	1	0	1	2	3	4	5
officials	2	1	0	1	2	3	4
are	3	2	1	1	2	3	4
responsible	4	3	2	2	2	3	4
for	5	4	3	3	3	3	4
airport	6	5	4	4	4	3	4
security	7	6	5	5	5	4	4

		airport	security	Israeli	officials	are	responsible
	0	1	2	3	4	5	6
Israeli	1	1	2	2	3	4	5
officials	2	2	2	3	2	3	4
are	3	3	3	3	3	2	3
responsible	4	4	4	4	4	3	2
for	5	5	5	5	5	4	3
airport	6	5	6	6	6	5	4
security	7	6	5	6	7	6	5

Metric	System A	System B
word error rate (WER)	57%	71%

BLEU (A Bilingual Evaluation Understudy)

- N-gram overlap between machine translation output and reference translation
- Compute precision for n-grams of size 1 to 4
- Add brevity penalty (for too short translations)

$$\text{BLEU-4} = \min\left(1, \frac{\textit{output-length}}{\textit{reference-length}}\right) \left(\prod_{i=1}^{4} \textit{precision}_i\right)^{\frac{1}{4}}$$

- Typically computed over the entire corpus, not single sentences

Example

SYSTEM A: $\boxed{\text{Israeli officials}}$ responsibility of $\boxed{\text{airport}}$ safety

2-GRAM MATCH 1-GRAM MATCH

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: $\boxed{\text{airport security}}$ $\boxed{\text{Israeli officials are responsible}}$

2-GRAM MATCH 4-GRAM MATCH

Metric	System A	System B
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0%	52%

Multiple Reference Translations

- To account for variability, use multiple reference translations
  - n-grams may match in any of the references
  - the closest and smallest reference length is used
- Example

SYSTEM: Israeli officials responsibility of airport safety
2-GRAM MATCH 2-GRAM MATCH 1-GRAM

REFERENCES:
Israeli officials are responsible for airport security
Israel is in charge of the security at this airport
The security work for this airport is the responsibility of the Israel government
Israeli side was in charge of the security of this airport

Multiple Reference Translations

Metric	Single reference		Multiple reference	
	System A	System B	System A	System B
precision (1gram)	3/6	6/6	5/6	6/6
precision (2gram)	1/5	4/5	2/5	4/5
precision (3gram)	0/4	2/4	0/4	2/4
precision (4gram)	0/3	1/3	0/3	1/3
brevity penalty	6/7	6/7	6/7	6/7
BLEU-1	42%	86%	71%	86%
BLEU-2	9%	69%	29%	69%
BLEU-3	0%	34%	0%	34%
BLEU-4	0%	11%	0%	11%

METEOR: Flexible Matching

- Partial credit for matching stems

SYSTEM	Jim went home
REFERENCE	Joe goes home

- Partial credit for matching synonyms (e.g., Wordnet)

SYSTEM	Jim walks home
REFERENCE	Joe goes home

Critique of Automatic Metrics

- They ignore relevance of words
  - names and core concepts more important than determiners and punctuation
  - negation cues (e.g., not) should not be missed

Critique of Automatic Metrics

- Operate on local level
  - do not consider overall grammar of the sentence
  - do not consider sentence meaning
  - it is supposed to favor phrase-based statistical systems

Critique of Automatic Metrics

- Scores are meaningless
  - very test-set specific, absolute value not informative
  - scores depend on many features:
    - number of reference translations
    - language pair
    - domain
    - tokenization scheme

Critique of Automatic Metrics

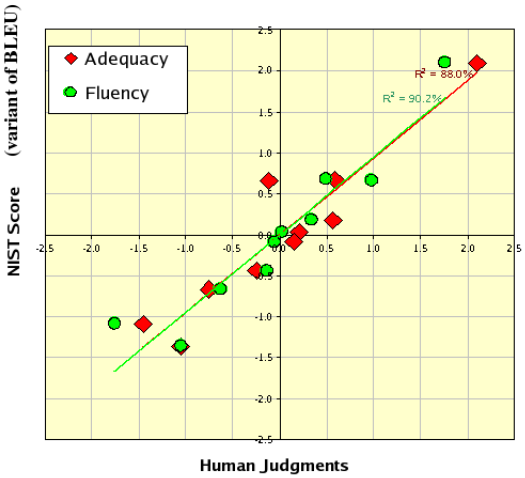
- Human translators score low on BLEU
  - possibly because of higher variability
  - different word choices

Evaluation of Evaluation Metrics

- Automatic metrics are low cost, tunable, consistent
- But are they correct?

→ Yes, if they correlate with human judgment

Correlation with Human Judgment (NIST'02, Arabic-English)



Pearson Correlation Coefficient

- Two variables: automatic score x, human judgment y
- Multiple systems (x_1, y_1), (x_2, y_2), ...
- Pearson's correlation coefficient r_{xy}:

$$r_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{(n-1)\, s_x\, s_y}$$

- Note:

$$\text{mean} \;\; \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

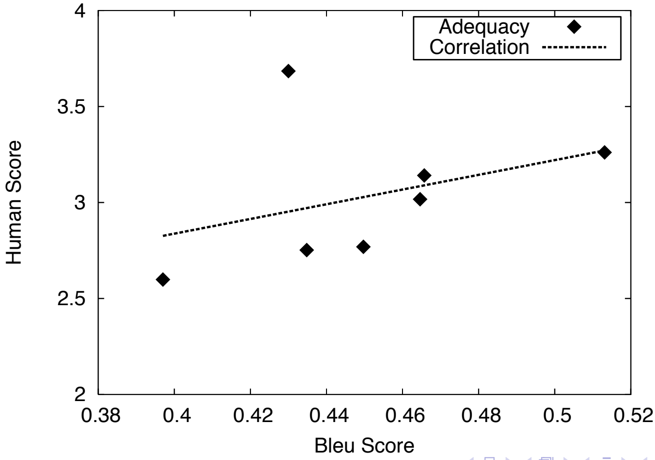
$$\text{variance} \;\; s_x^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$$

Pearson Correlation Coefficient

Correlation	Negative	Positive
low	-0.29 to -0.10	0.10 to 0.20
medium	-0.49 to -0.30	0.30 to 0.49
high	-1.00 to -0.50	0.50 to 1.00

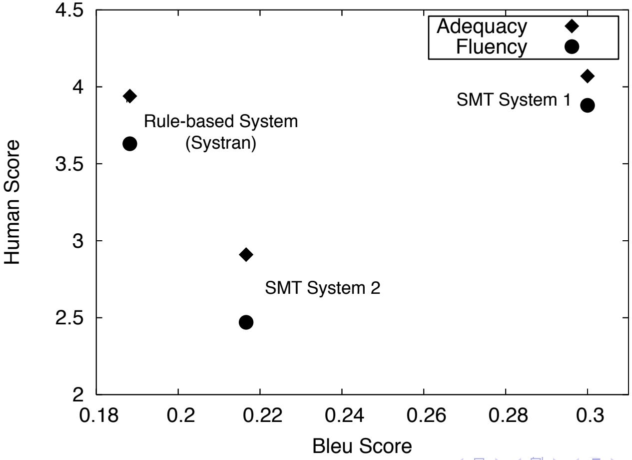
Evidence of Shortcomings of Automatic Metrics (NIST'05, Arabic-English)

Post-edited output vs. statistical systems



Evidence of Shortcomings of Automatic Metrics (NIST'05, Arabic-English)

Rule-based vs. statistical systems



Metric Research

- Active development of new metrics
  - syntactic similarity
  - semantic equivalence or entailment
  - metrics targeted at reordering
  - trainable metrics
  - etc.

- Evaluation campaigns that rank metrics (using Pearson correlation coefficient)

Automatic Metrics: Conclusions

- Automatic metrics are essential tools for system development
- Not fully suited to rank systems of different types
- Evaluation metrics still open challenge

Hypothesis Testing

- Situation
  - system A has score x on a test set
  - system B has score y on the same test set
  - $x > y$
- Is system A really better than system B?
- In other words:
  Is the difference in score **statistically significant**?

Core Concepts

- Null hypothesis
  - assumption that there is no real difference
- P-Levels
  - related to probability that there is a true difference
  - p-level $p < 0.01 =$ more than 99% chance that difference is real
  - typically used: p-level 0.05 or 0.01
- Confidence Intervals
  - given that the measured score is x
  - what is the true score (on a infinite size test set)?
  - interval $[x - d, x + d]$ contains true score with, e.g., 95% probability

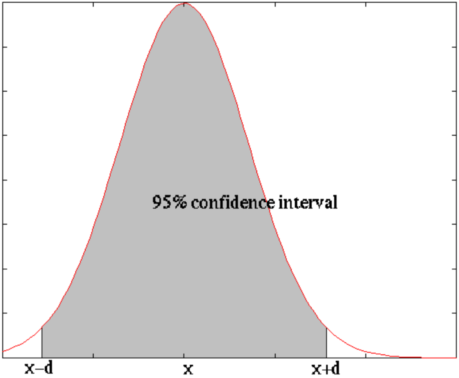
Computing Confidence Intervals

- Example
  - 100 sentence translations evaluated
  - 30 found to be correct

- True translation score?

  (i.e. probability that any randomly chosen sentence is correctly translated)

Normal Distribution



true score lies in interval $[\bar{x} - d, \bar{x} + d]$ around sample score $\bar{x}$ with probability 0.95

Confidence Interval for Normal Distribution

- Compute mean $\bar{x}$ and variance $\bar{s^2}$ from data of size n

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$$

- True mean μ?

Student's t-distribution

- Confidence interval $p(\mu \in [\bar{x} - d, \bar{x} + d]) \geq 0.95$ computed by

$$d = t \frac{s}{\sqrt{n}}$$

- Values for t depend on test sample size and significance level:

Significance Level	**Test Sample Size**			
	100	300	600	∞
99%	2.6259	2.5923	2.5841	2.5759
95%	1.9849	1.9679	1.9639	1.9600
90%	1.6602	1.6499	1.6474	1.6449

Example

- Given
  - 100 sentence translations evaluated
  - 30 found to be correct
- Sample statistics
  - sample mean $\bar{x} = \frac{30}{100} = 0.3$
  - sample variance $s^2 = \frac{1}{99}(70 \times (0 - 0.3)^2 + 30 \times (1 - 0.3)^2) = 0.2121$
- Consulting table for t with 95% significance $\rightarrow$ 1.9849
- Computing interval $d = 1.9849 \frac{0.2121}{\sqrt{100}} = 0.042 \rightarrow [0.258; 0.342]$

Pairwise Comparison

- Typically, absolute score less interesting
- More important
  - Is system A better than system B?
  - Is change to my system an improvement?
- Example
  - Given a test set of 100 sentences
  - System A better on 60 sentence
  - System B better on 40 sentences
- Is system A really better?

Sign Test

- Using binomial distribution
  - system A better with probability p_A
  - system B better with probability p_B $(= 1 - p_A)$
  - probability of system A better on k sentences out of a sample of n sentences

$$\binom{n}{k} \, p_A^k \, p_B^{n-k} = \frac{n!}{k!(n-k)!} \, p_A^k \, p_B^{n-k}$$

- Null hypothesis: $p_A = p_B = 0.5$

$$\binom{n}{k} \, p^k \, (1-p)^{n-k} = \binom{n}{k} \, 0.5^n = \frac{n!}{k!(n-k)!} \, 0.5^n$$

Examples

n	$p \leq 0.01$		$p \leq 0.05$		$p \leq 0.10$	
5	-	-	-	-	$k = 5$	$\frac{k}{n} = 1.00$
10	$k = 10$	$\frac{k}{n} = 1.00$	$k \geq 9$	$\frac{k}{n} \geq 0.90$	$k \geq 9$	$\frac{k}{n} \geq 0.90$
20	$k \geq 17$	$\frac{k}{n} \geq 0.85$	$k \geq 15$	$\frac{k}{n} \geq 0.75$	$k \geq 15$	$\frac{k}{n} \geq 0.75$
50	$k \geq 35$	$\frac{k}{n} \geq 0.70$	$k \geq 33$	$\frac{k}{n} \geq 0.66$	$k \geq 32$	$\frac{k}{n} \geq 0.64$
100	$k \geq 64$	$\frac{k}{n} \geq 0.64$	$k \geq 61$	$\frac{k}{n} \geq 0.61$	$k \geq 59$	$\frac{k}{n} \geq 0.59$

Given n sentences,
the system has to be better in at least k sentences
to achieve statistical significance at specified p-level

Sampling

- Described methods require score at sentence level
- But: common metrics such as BLEU are computed for whole corpus
- Sampling
  1. test set of 2000 sentences, sampled from large collection
  2. compute the BLEU score for this set
  3. repeat step 1–2 for 1000 times
  4. ignore 25 highest and 25 lowest obtained BLEU scores

  → 95% confidence interval

Bootstrap Resampling

- Bootstrap resampling: sample from the same 2000 sentences, with replacement

- For pairwise comparison, which check which system is better on each sample

$\rightarrow$ if a system is better on at least 950 samples, it is better under a statistically significance of $p \leq 0.05$.

Task-Oriented Evaluation

- Machine translations is a means to an end
- Does machine translation output help accomplish a task?
- Example tasks
  - producing high-quality translations post-editing machine translation
  - information gathering from foreign language sources

Post-Editing Machine Translation

- Measuring time spent on producing translations
  - baseline: translation from scratch
  - post-editing machine translation

  But: time consuming, depend on skills of translator and post-editor
- Metrics inspired by this task
  - TER (translation edit rate): based on number of editing steps
    Levenshtein operations (insertion, deletion, substitution) plus movement
  - HTER (human translation edit rate): manually construct reference translation for output, apply TER
    (very time consuming, used in DARPA GALE program 2005-2011)

Content Understanding Tests

- Given machine translation output, can monolingual target side speaker answer questions about it?
  1. basic facts: who? where? when? names, numbers, and dates
  2. actors and events: relationships, temporal and causal order
  3. nuance and author intent: emphasis and subtext
- Evaluation is based on the ratio of correctly answered questions and the time spent

Suggested reading

- Statistical Machine Translation, Philipp Koehn (chapter 8).