

Need for evaluation

What counts as a good translation?

The cat sat on the mat	(reference)
T 1	_
The cat sat on mat the	1
On the mat sat the cat	2
The cat on the floor	3
A cat sat on the mat	4
the cat sat on the mat	5
The cat sat on the straw mat	6

• What is wrong with the current system?

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Central to progress in any field is good evaluation • How do we know if we are doing a good job?

• Are we the best in the world?

Evaluating MT is hard ...

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Subjective Evaluation

One could argue that a good translation is one that people like:

The cat sat on the mat	(reference)
The cat sat on the floor On the mat sat the cat The cat on the floor A cat sat on the floor the cat sat on the mat The cat sat on the straw mat	1 2 3 4 5 6

Subjective Evaluation

One approach is to have people rate candidates

- Which candidate sentence captures most of the meaning?
 Adequacy
- Which candidate sentence is most readable?
 - Fluency

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Evaluation is hard Subjective evaluation			
Automatic metrics			
Cubicative Freelection			
Subjective Evaluation			

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Evaluation is hard	
Subjective evaluation Automatic metrics	
Subjective Evaluation	

- People have difficulties carrying out this task:
 - There is a preference for fluency.
 - People tend not to agree with each other.
- It is time consuming.
- Subjective evaluation is hard to reuse.

An alternative is to rank sentences:

• Do you prefer sentence *A* to sentence *B*?

Sentence ranking is faster and more reliable than sentence rating

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Automatic Evaluation

Since people are expensive, *automatic* methods have become popular

- Create a set of *reference* translations.
- Design a *similarity metric* to measure sentence closessness.
- Apply that metric between the candidate and the set of references.

There are many automatic methods

First attempt

- We want to be rewarded if we produce output that is present within a reference.
 - This aspect deals with word choice.
- We should be rewarded if that output is in the correct order.
 - This aspect deals with word order.

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First attempt	

Count ngrams appearing in the candidate and in a reference

- An ngram of order one (unigram) rewards word choice.
- Higher order ngrams reward word order.
- (Four is a useful maximum order)

The cat sat	(reference)
The cat	(The cat) (The) (cat)
sat the cat	(sat) (the) (cat)

Counting these ngrams tells us what we have found

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First attempt	

Count ngrams appearing in the reference but not in the candidate

The cat sat (reference)

The cat (^{*} sat the cat (^{*}

(The cat sat) (cat sat) (sat) (The cat) (The) (The cat sat)

Counting these ngrams tells us what we have missed

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First attempt

Putting it together:

- Sum-up the ngram hits (order n) in candidate translation c_i
 Call this h_{ci}
- Sum-up the ngram hits for all candidate translations.
- Sum-up the total number of possible order *n* ngrams in reference *r*
 - Call this t_{r_i}
- Sum-up the total possible hits over all reference translations.

ΜТ

$$p_n = \frac{\sum_i h_{c_i}}{\sum_i t_{r_i}}$$

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Second attempt

We can *game* the metric:

- Produce lots of function words.
- Produce all possible ngrams!
 - The The The The cat cat cat cat ...
- Counts are *clipped* to prevent double counting.

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Automatic metrics	
Third attempt	

How well does this do?

Second attempt

• IBM took output from a human translator.

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• IBM also took output from a poor machine translator.

Ngram order	Human	Machine
1	.8	.5
2	.5	.1
3	.3	.05
4	.2	.01

 \rightarrow Easy to tell people from machines

We do not deal with candidate translations that are too short

- The *Brevity Penalty* (BP) punishes translations that are too short.
- The BP is document-based.
- Ngram hits punish translations if they are too long (produce spurious ngrams)



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Third attempt

The BP:

$$BP = \begin{cases} 1 & \text{if } C' \ge R' \\ \exp(1 - \frac{R'}{C'}) & \text{if } C' < R' \end{cases}$$

Here R' is the total length (in words) of all selected references (ie the document) and C' is the sum of all candidate translations (ie the translated document)

Third attempt

$$BP = \left\{ egin{array}{cc} 1 & ext{if } C' \geq R' \ \exp(1 - rac{R'}{C'}) & ext{if } C' < R' \end{array}
ight.$$

• By construction the BP is a probability.

• As translations get shorter the BP decreases

C'	R'	BP	
5	10	0.37	Too short
8	10	0.78	Too short
10	10	1	Same length
12	10	1	Too long

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	Comments on BLEU			

$$\mathsf{BLEU} = \mathsf{BP} \cdot \exp(\sum_{n=1}^{N} w_n \log p_n)$$

- The first part is our brevity penalty
- The second part is a geometric mean of ngram matches
- (Each match is weighted if for example we prefer four-gram hits)

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This is the BLEU metric and it is widely used in MT research

- BLEU generally correlates with subjective evaluation.
- It is hard to interpret.
- BLEU cannot be used across language pairs.
- It should be used with caution since good translations not in the reference set are punished

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Summary

- Subjective evaluation is the best way to measure progress
- Automatic metrics are useful for day-to-day evaluation
- Care must be taken interpreting BLEU scores

