Natural Language Understanding, Generation, and Machine Translation

Lecture 17: Evaluating Machine Translation Systems

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Based on slides by Adam Lopez, Rico Sennrich, Philipp Koehn

Previous lectures have surveyed all of the tools we need to *implement* a machine translation system: data, effective models, and learning algorithms.

This lecture: How do we know whether what we've implemented is useable?

Evaluating machine translation

    Evaluation is important and difficult

    Evaluation by people

    Evaluation by machine

Evaluating machine translation

Testing is crucial to good engineering

Suppose I give you a program to compute Fibonacci numbers. Suppose I give you a python interpreter. Suppose I give you a speech recognizer. Suppose I give you a self-driving car. Suppose I give you a machine translation system.

How would you decide if the implementation is correct?

What does is mean for an implementation to be correct?

Why do we need to evaluate machine translation systems?

- Decide which of two (or more) systems to use.
- Evaluate incremental changes to systems.
  - Does a new idea make it better or worse?
  - Does it change things in the intended way?
- Decide whether a system is appropriate for a given use case.
  - Understanding a restaurant menu.
  - Understanding a news about safety of a city you are visiting.
  - Translating legal notices of a product you are selling.
  - Negotiating a peace treaty.

Key questions. Are you trying to *assimilate* or *disseminate* information? Who is affected by the system, and what at are the consequences of errors for each of them?

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 good translation is both adequate and fluent

People can (and do) evaluate MT on many different dimensions. Two crucial ones:

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? Is is grammatically correct? Does it use appropriate words and idioms?

Can we even measure adequacy and fluency?

Typical scales for adequacy and fluency

	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	dis-fluent English
1	incomprehensible

Source. Avauspelin voitto on aina tärkeä.

Reference. It is always important to win the opening match.

System 1. Victory for the game is always important.

System 2. The victory of the opening game is always important.

System 3. Victory in the opening game is always important.

Evaluate some translations

Source:

ઘટનાની જાણકારી મળતા જ ઘરે જોવાવાળાનો જમાવડ

Reference: As people came to know of this, they started gathering to see this spectacle.

System 1. As soon as the incident was known, the house was flooded.

System 2. As soon as the information of the incident came to pass, there was a group of people who saw it at home.

System 3. As soon as the incident was reported, there was a meeting of people who saw it at home.
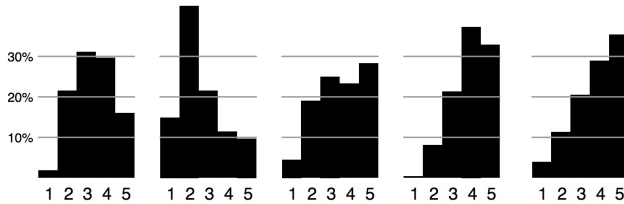
We can measure agreement between evaluators

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

- $p(A)$ is proportion of times that evaluators agree.
- $p(E)$ is proportion of times that they would agree by chance.

Empirically, agreement on fluency and adequacy is low, but positive. Agreement on rating (which of two translations is better?) tends to be higher, but still not very high.

Adequacy and fluency are very abstract, difficult to measure.

Direct Assessment

3/10 blocks, 10 items left in block	NewsTask #13:Segment #1278	Czech (čeština) → English

How do you rate your Olympic experience?
— Reference

How do you value the Olympic experience?
— Candidate translation

— How accurately does the above candidate text convey the original semantics of the reference text? Slider ranges from Not at all (left) to Perfectly (right).

Reset   Submit

From Findings of the 2017 conference on machine translation (wmt17) Bojar et al. (2017)

- 100-point Likert scale allowing fine grained statistical analysis
- Normalise individual annotators, quality control with references
- Intra-annotator agreement is higher
- Continuous measurement scales in human evaluation of machine translation Graham et al. (2013)

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A very specific use case: evaluating *incremental* changes to systems. This typically requires something automatic, due to the cost of human evaluation.

How would you decide whether to deploy a change to Google translate, which supports over 100 languages in any direction?

Idea. Human evaluators compare with a *reference translation* when they don't know the source language. We can automate this comparison.

Q. What are the pros and cons of this idea?

Idea: count all of the words that match

System 1. Victory in the opening game is always important

Reference. It is always important to win the opening match

System 2. the it opening important is match always win to

Precision. $\frac{\text{\# of correct words}}{\text{\# of output words}} = \frac{5}{8}$

Recall. $\frac{\text{\# of correct words}}{\text{\# of reference words}} = \frac{5}{9}$

F-measure. $\frac{\text{precision} \times \text{recall}}{(\text{precision} + \text{recall})/2}$

System	Precision	Recall	F-measure
System 1	.623	.55	.58
System 2	1.0	1.0	1.0

Problem. Does not account for word order.

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New idea: count all of the *n*-grams that match

System. Victory in the opening game is always important

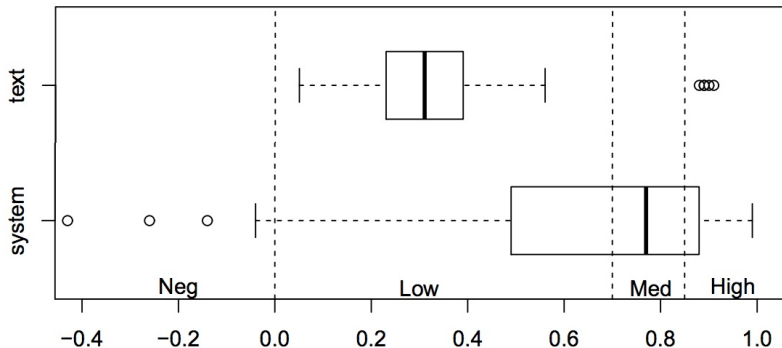**Reference 1.** It is always important to win the opening match

Reference 2. Opening game wins are always important.

Compute precision for n-grams of size 1 to 4 against multiple references.

Recall not well-defined in this setting. *BLEU* compares system length to an *effective reference length* and penalize if too short.

$$\text{BLEU} = \min\left(1, \frac{\text{output length}}{\text{reference length}}\right)\left(\prod_{n=1}^{4}\text{precision}_i\right)^{\frac{1}{4}}$$
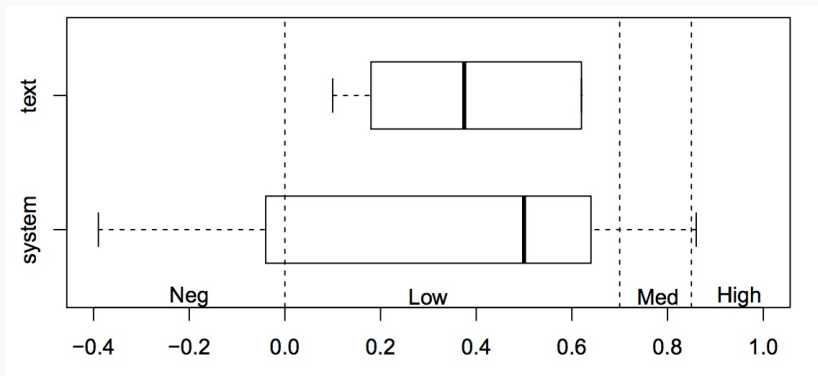
BLEU is reasonably correlated with human ratings of MT

Many studies have, over time, shown *some* correlation between BLEU and human ratings.

No studies have shown relationship to real applications.

Bleu is less correlated with human ratings of NLG

Source: Ehud Reiter, A Structured Review of the Validity of Bleu

In brief: Take Bleu with skepticism

Bleu is generally a crude measure of accuracy

- Not all words are equally important! BLEU treats determiners and punctuation the same as names and other content words.
- BLEU is a poor proxy for both adequacy and fluency.
- BLEU isn't interpretable across datasets.
- BLEU often scores human translation low.

- Transformers can be used to encode, decode and evaluate!
- Have 16 years of human evaluation data from WMT tasks
- COMET (Rei et al. 2020): Crosslingual Optimized Metric for Evaluation of Translation.
- Pretrain cross-lingual language model
- Fine-tune on human evaluations eg. Direct Assessments
- SOTA results for correlation with human judgements WMT 2019 Metrics shared task
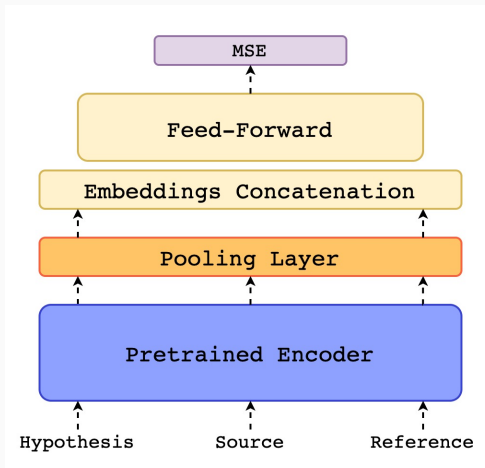
From Rei et al. (2020)
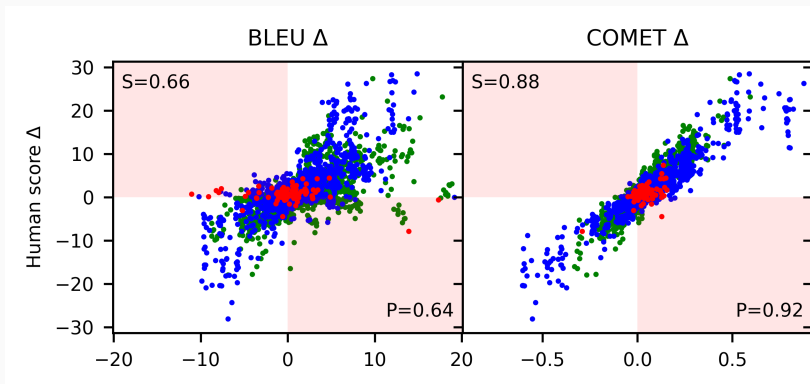
To Ship or Not to Ship: An Extensive Evaluation of Automatic Metrics for Machine Translation Kocmi et al. (2021)

Sole use of BLEU is impeding development of better MT systems and leading to bad deployment decisions.

Be skeptical of hype

▲ Programmering 11 points · 4 years ago · edited 4 years ago
↓ What do you believe that AI capabilities could be in the close future?

   ▲ wojzaremba **OpenAI** 17 points · 4 years ago
   ↓ Speech recognition and machine translation between any languages should be fully solvable.

≡ 🔍 **Microsoft**

Research ⌄

Achieving Human Parity on Automatic Chinese to English News Translation

Summary of key points (i.e. examinable content)

- Good evaluation of machine translation (or NLG in general) is both *really, really important* and *really, really difficult*.
- We can distinguish between two crucial concerns in MT systems: *adequacy* and *fluency*.
- Automatic evaluation metrics for iterative system development eg. BLEU score
- Typical evaluation metrics measure *n*-gram overlap with a human *reference translation*. Has many problems.
- Trained metrics correlate better with humans
- Understanding which phenomena your system handles well, and which it doesn't, requires you to *look at the data*.
- Be skeptical of claims of human-level accuracy.

Next lecture: Look at the problem of modelling large vocabularies

Bojar, O., Chatterjee, R., Federmann, C., Graham, Y., Haddow, B., Huang, S., Huck, M., Koehn, P., Liu, Q., Logacheva, V., et al. (2017). Findings of the 2017 conference on machine translation (wmt17). In *Proceedings of the Second Conference on Machine Translation*, pages 169–214.

Graham, Y., Baldwin, T., Moffat, A., and Zobel, J. (2013). Continuous measurement scales in human evaluation of machine translation. In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse*, pages 33–41.

Kocmi, T., Federmann, C., Grundkiewicz, R., Junczys-Dowmunt, M., Matsushita, H., and Menezes, A. (2021). To ship or not to ship: An extensive evaluation of automatic metrics for machine translation. *arXiv preprint arXiv:2107.10821*.

Rei, R., Stewart, C., Farinha, A. C., and Lavie, A. (2020). Comet: A neural framework for mt evaluation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2685–2702.