Evaluating text generation

CS685 Spring 2024
Advanced Natural Language Processing

Mohit Iyyer
College of Information and Computer Sciences
University of Massachusetts Amherst

some slides from Marine Carpuat & Marzena Karpinska
So far...

• We’ve seen *perplexity* as an automatic measure to evaluate language models.

• However, perplexity alone is insufficient to tell us about how well a model is solving some downstream task (e.g., translation or summarization).

• Today: BLEU score for MT, ROUGE for summarization, BERT-based improvements, LLM judges, and human evaluation.
Reporters learned from the Ministry of Environmental Protection, "Water 10" requirements before the end of this year before the municipality, the provincial capital city, plans to build a separate city to solve the basic black and black water. Up to now, the country's 224 prefecture-level and above cities were identified to confirm the black and white water 2082, of which 34.9% to complete the renovation, 28.4% is remediation, 22.8% is carrying out the project early.
How Good is Machine Translation?
French > English

A l'orée de ce débat télévisé inédit dans l'histoire de la Ve République, on attendait une forme de «Tous sur Macron» mais c'est la candidate du Front national qui s'est retrouvée au cœur des premières attaques de ses quatre adversaires d'un soir, favorisées par le premier thème abordé, les questions de société et donc de sécurité, d'immigration et de laïcité.

At the beginning of this televised debate, which was unheard of in the history of the Fifth Republic, a "Tous sur Macron" was expected, but it was the candidate of the National Front who found itself at the heart of the first attacks of its four Opponents of one evening, favored by the first theme tackled, the issues of society and thus security, immigration and secularism.
What is MT good (enough) for?

• **Assimilation:** reader initiates translation, wants to know content
  • User is tolerant of inferior quality
  • Focus of majority of research

• **Communication:** participants in conversation don’t speak same language
  • Users can ask questions when something is unclear
  • Chat room translations, hand-held devices
  • Often combined with speech recognition

• **Dissemination:** publisher wants to make content available in other languages
  • High quality required
  • Almost exclusively done by human translators
How good is a translation?
Problem: no single right answer

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.
Evaluation

• How good is a given machine translation system?

• Many different translations acceptable

• Evaluation metrics
  • Subjective judgments by human evaluators
  • Automatic evaluation metrics
  • Task-based evaluation
Adequacy and Fluency

• Human judgment
  • Given: machine translation output
  • Given: input and/or reference translation
  • Task: assess quality of MT output

• Metrics
  • Adequacy: does the output convey the meaning of the input sentence? Is part of the message lost, added, or distorted?
  • Fluency: is the output fluent? Involves both grammatical correctness and idiomatic word choices.
Fluency and Adequacy: Scales

<table>
<thead>
<tr>
<th>Adequacy</th>
<th>Fluency</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>all meaning</td>
</tr>
<tr>
<td>4</td>
<td>flawless English</td>
</tr>
<tr>
<td>3</td>
<td>most meaning</td>
</tr>
<tr>
<td>3</td>
<td>good English</td>
</tr>
<tr>
<td>2</td>
<td>much meaning</td>
</tr>
<tr>
<td>3</td>
<td>non-native English</td>
</tr>
<tr>
<td>2</td>
<td>little meaning</td>
</tr>
<tr>
<td>2</td>
<td>disfluent English</td>
</tr>
<tr>
<td>1</td>
<td>none</td>
</tr>
<tr>
<td>1</td>
<td>incomprehensible</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th>Translation</th>
<th>Adequacy</th>
<th>Fluency</th>
</tr>
</thead>
<tbody>
<tr>
<td>both countries are rather a necessary laboratory the internal operation of the eu.</td>
<td>![Adequacy Icon]</td>
<td>![Fluency Icon]</td>
</tr>
<tr>
<td>both countries are a necessary laboratory at internal functioning of the eu.</td>
<td>![Adequacy Icon]</td>
<td>![Fluency Icon]</td>
</tr>
<tr>
<td>the two countries are rather a laboratory necessary for the internal workings of the eu.</td>
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<td>![Adequacy Icon]</td>
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Annotator: Philipp Koehn Task: WMT06 French-English

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
Let’s try:
rate fluency & adequacy on 1-5 scale

– Source:
  N’y aurait-il pas comme une vague hypocrisie de votre part ?
– Reference:
  Is there not an element of hypocrisy on your part?
– System1:
  Would it not as a wave of hypocrisy on your part?
– System2:
  Is there would be no hypocrisy like a wave of your hand?
– System3:
  Is there not as a wave of hypocrisy from you?
what are some issues with human evaluation?
Automatic Evaluation Metrics

• Goal: computer program that computes quality of translations

• Advantages: low cost, optimizable, consistent

• Basic strategy
  • Given: MT 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
\[
\frac{\text{correct}}{\text{output-length}} = \frac{3}{6} = 50\%
\]

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

F-measure
\[
\frac{\text{precision} \times \text{recall}}{(\text{precision} + \text{recall})/2} = \frac{.5 \times .43}{(.5 + .43)/2} = 46\%
\]
Precision and Recall of Words

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

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: **airport security** **Israeli officials are responsible**

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<thead>
<tr>
<th>Metric</th>
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<th>System B</th>
</tr>
</thead>
<tbody>
<tr>
<td>precision</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>recall</td>
<td>43%</td>
<td>100%</td>
</tr>
<tr>
<td>f-measure</td>
<td>46%</td>
<td>100%</td>
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flaw: no penalty for reordering
BLEU
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)

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

Typically computed over the entire corpus, not single sentences
Multiple Reference Translations

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

Example

SYSTEM:

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
BLEU examples

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

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security Israeli officials are responsible
2-GRAM MATCH 4-GRAM MATCH

<table>
<thead>
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<th>System B</th>
</tr>
</thead>
<tbody>
<tr>
<td>precision (1gram)</td>
<td>3/6</td>
<td>6/6</td>
</tr>
<tr>
<td>precision (2gram)</td>
<td>1/5</td>
<td>4/5</td>
</tr>
<tr>
<td>precision (3gram)</td>
<td>0/4</td>
<td>2/4</td>
</tr>
<tr>
<td>precision (4gram)</td>
<td>0/3</td>
<td>1/3</td>
</tr>
<tr>
<td>brevity penalty</td>
<td>6/7</td>
<td>6/7</td>
</tr>
<tr>
<td>BLEU</td>
<td>0%</td>
<td>52%</td>
</tr>
</tbody>
</table>
**BLEU examples**

SYSTEM A: Israeli officials responsibility of airport safety

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security Israeli officials are responsible

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why does BLEU not account for recall?
what are some drawbacks of BLEU?

• all words/n-grams treated as equally relevant
• operates on local level
• scores are meaningless (absolute value not informative)
• human translators also score low on BLEU
Yet automatic metrics such as BLEU correlate with human judgement.
ROUGE - a recall-based counterpart to BLEU

• Idea: what % of the words or n-grams in the reference occur in the generated output?

• ROUGE and its variants are often used to evaluate text summarization systems
Traditional string-matching metrics don’t work

Q. Why are almost all boats white?

A. Why are almost all boats white?

Input copying

Krishna et al., NAACL 2021. “Hurdles to Progress in Long-form Question Answering”
### Traditional string-matching metrics don’t work

**Q. Why are almost all boats white?**

<table>
<thead>
<tr>
<th>Method</th>
<th>ROUGE-L</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input copying (↓)</td>
<td>20.0</td>
</tr>
<tr>
<td>RAG (Lewis et al. 2020)</td>
<td>16.1</td>
</tr>
<tr>
<td>RT (Krishna et al. 2021)</td>
<td>24.4</td>
</tr>
<tr>
<td>Human answers (↑)</td>
<td>21.2</td>
</tr>
</tbody>
</table>

Input copying

Krishna et al., NAACL 2021. “Hurdles to Progress in Long-form Question Answering”
Can we include *learned* components in our evaluation metrics?
BLEURT (BLEU + BERT)

- Take a pretrained BERT, and fine-tune it on a variety of synthetic tasks with perturbed data
- Synthetic data involves a sentence $z$ and “perturbed” version $z'$
- Objectives include many regression tasks (e.g., predict BLEU, ROUGE, backtranslation likelihood)
- Then, fine-tune the resulting model on small supervised datasets of human quality judgments
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• Then, fine-tune the resulting model on small supervised datasets of human quality judgments

Higher correlation with human judgments than just BLEU, but has limitations…
COMET (now recommended for MT evaluation over BLEU)

Rei et al., EMNLP 2020
How do we evaluate open-ended text generation?
**Writing Prompts** (Fan et al., 2019)

**PROMPT:** You, a video game character, just died. You had no spare lives left.

**STORY:** Link woke in a panic, gasping and flailing wildly at the air above him. The panic quickly turned to confusion, wasn't he just...? He heard footsteps approaching from behind. Link leapt up from the floor and drew his sword, ready to strike. The sight of a slight man in a suit added to Link's already mounting confusion. Is this another trap set by Ganondorf?
PROMPT: You, a video game character, just died. You had no spare lives left.

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~150 words

STORY: *The US Space Station exploded with automatic fire in preparation for tonight's nuclear strike on Earth. This is video from the control center inside the Space Station*

*‘A figure wearing a manilla envelope falls off of the back of the space station, detonating a nuclear device. **An audio file is made of the sirens, and some screams (…)*
AMAZON MECHANICAL TURK

How grammatically correct is the text of the story fragment?

How well do the sentences in the story fragment fit together?

How enjoyable do you find the story fragment?

How relevant is the story fragment to the prompt?
AMAZON MECHANICAL TURK

1. GRAMMAR
   How grammatically correct is the text of the story fragment?

2. COHERENCE
   How well do the sentences in the story fragment fit together?

3. LIKABILITY
   How enjoyable do you find the story fragment?

4. RELEVANCE
   How relevant is the story fragment to the prompt?
Human evaluators struggle to read long texts

- To evaluate a 250-word generation:
  - Crowdworkers take ~10 sec
  - English teachers take ~70 sec
- High variability across runs, low agreement

Question: If under anesthesia do you get your sleep needed for the day?

Answer 1:
No. The unconsciousness induced by both IV anesthetics and inhaled anesthetics is very different from restorative sleep. In fact, patients in ICUs who are sedated for long periods of time with some of the same medications they use in anesthesia get delirium from both a lack of sleep and a lack of proper awake time. Sleep = charging your phone on airplane mode. Anesthesia = turning your phone off but not charging it.

Answer 2:
There is no clear consensus on whether or not people under anesthesia get the sleep they need for the day. Some studies suggest that people under anesthesia do get some sleep, but it is not clear how deep or restful this sleep is. Other studies suggest that people under anesthesia do not get any meaningful sleep at all. Therefore, it is difficult to say definitively whether or not people under anesthesia get the sleep they need for the day.

Which answer is better?
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Answer 1:
No. The unconsciousness induced by both IV anesthetics and inhaled anesthetics is very different from restorative sleep. In fact, patients in ICUs who are sedated for long periods of time with some of the same medications they use in anesthesia get delirium from both a lack of sleep and a lack of proper awake time. Sleep = charging your phone on airplane mode. Anesthesia = turning your phone off but not charging it.

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Which answer is better?
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No. The unconsciousness induced by both IV anesthetics and inhaled anesthetics is very different from restorative sleep. In fact, patients in ICUs who are sedated for long periods of time with some of the same medications they use in anesthesia get delirium from both a lack of sleep and a lack of proper awake time. Sleep = charging your phone on airplane mode. Anesthesia = turning your phone off but not charging it.

**Answer 2:**
There is no clear consensus on whether or not people under anesthesia get the sleep they need for the day. Some studies suggest that people under anesthesia do get some sleep, but it is not clear how deep or restful this sleep is. Other studies suggest that people under anesthesia do not get any meaningful sleep at all. Therefore, it is difficult to say definitively whether or not people under anesthesia get the sleep they need for the day.
Step 1: decompose long-form text into short units

Asa Graybar is a biological engineer who studies keeping Slider eggs alive and he is accused of a crime at the opening of the story. He thinks he was framed by Tom Dorr, Hazeltyne’s general manager. He was offered one year as a “changeling” on another planet or 5 years in rehabilitation on Earth. He elects to do the one year, and thinks that he will get into smuggling Slider eggs on Jordan’s planet. Being a changeling is not a highly sought after line of work, but it pays well, and the people who do it have organs and body parts regenerated to better suit specialized tasks. Asa travels to Jordan’s planet on a spaceship with a cellmate, Kershaw, who got caught stealing a Slider egg and is returning to serve more time...
Step 2: **verify** each atomic unit

Asa Graybar is a biological engineer who studies keeping Slider eggs alive and he is accused of a crime at the opening of the story. He thinks he was framed by Tom Dorr, Hazeltyn’s general manager. He was offered one year as a “changeling” on another planet or 5 years in rehabilitation on Earth. He elects to do the one year, and thinks that he will get into smuggling Slider eggs on Jordan’s planet. Being a changeling is not a highly sought after line of work, but it pays well, and the people who do it have organs and body parts regenerated to better suit specialized tasks. Asa travels to Jordan’s planet on a spaceship with a cellmate, Kershaw, who got caught stealing a Slider egg and is returning to serve more time...
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Compute the fraction of atomic units that were verified.

\[
F_{\text{summ}} = \frac{1}{|C_{\text{summ}}|} \sum_{c \in C_{\text{summ}}} F_c, \ F_c \in \{0, 1\}
\]

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Our approach, **LongEval**, provides scalable human evaluation for summarization faithfulness.

Asa Graybar is a biological engineer who studies keeping Slider eggs alive and he is accused of a crime at the opening of the story. He thinks he was framed by Tom Dorr, Hazeltyne’s general manager. He was offered one year as a “changeling” on another planet or 5 years in rehabilitation on Earth. He elects to do the one year, and thinks that he will get into smuggling Slider eggs on Jordan’s planet. Being a changeling is not a highly sought after line of work, but it pays well, and the people who do it have organs and body parts regenerated to better suit specialized tasks. Asa travels to Jordan’s planet on a spaceship with a cellmate, Kershaw, who got caught stealing a Slider egg and is returning to serve more time ...

Can we use LLMs to evaluate generated text?

**Task Introduction**
You will be given one summary written for a news article. Your task is to rate the summary on one metric.

**Evaluation Criteria**
Coherence (1-5) - the collective quality of all sentences. We align this dimension with the DUC quality question of structure and coherence.

**Evaluation Steps**
1. Read the news article carefully and identify the main topic and key points.
2. Read the summary and compare it to the news article. Check if the summary covers the main topic and key points of the news article, and if it presents them in a clear and logical order.
3. Assign a score for coherence on a scale of 1 to 5, where 1 is the lowest and 5 is the highest based on the Evaluation Criteria.

**Input Context**
Article: Paul Merson has restarted his row with Andros Townsend after the Tottenham midfielder was brought on with only seven minutes remaining in his team’s 0-0 draw with Burnley.

**Input Target**
Summary: Paul Merson was brought on with only seven minutes remaining in his team’s 0-0 draw with Burnley.

**Evaluation Form (scores ONLY):**
- Coherence:

- **GPTEval, Liu et al., 2023**
Most popular LLM judge: **win rate** against a base LM’s outputs

- **<Prefix>**
- **<Candidate generation #1>**
- **<Candidate generation #2>**

“Which candidate is a better completion of the prefix?”

**GPT-4**

1

https://tatsu-lab.github.io/alpaca_eval/
Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey’s Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and...

How factually correct is this biography?
**Decomposition**: Break the generation into atomic facts via few-shot prompting

Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey’s Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and...

- Bridget Moynahan is American.
- Bridget Moynahan is an actress.
- Bridget Moynahan is a model.
- Bridget Moynahan is a producer.
- Bridget Moynahan is best known for her roles in Grey’s Anatomy.
- Bridget Moynahan is best known for her roles in I, Robot.
- Bridget Moynahan is best known for her roles in Blue Bloods.
- Bridget Moynahan studied acting.
- Bridget Moynahan studied at the American Academy of Dramatic Arts.

Min & Krishna et al., EMNLP 2023. “FActScore: Fine-grained atomic evaluation of factual precision in long-form text generation”
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**Verification:** Retrieve Wikipedia passages for each atomic fact. Prompt LLM to generate True or False given top-k passages and fact.

Bridget Moynahan is best known for her roles in Grey’s Anatomy.

Min & Krishna et al., EMNLP 2023. “FActScore: Fine-grained atomic evaluation of factual precision in long-form text generation”
Bridget Moynahan is American.
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Bridget Moynahan is best known for her roles in Blue Bloods.
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6 of the 9 atomic facts are supported by Wikipedia.
**FActScore**: Implement verifier with LLaMA-7B, error rate of <2% compared to human annotations

Min & Krishna et al., EMNLP 2023. “FActScore: Fine-grained atomic evaluation of factual precision in long-form text generation”
**FActScore**: Implement verifier with LLaMA-7B, error rate of <2% compared to human annotations

$26K if done by humans!

Min & Krishna et al., EMNLP 2023. “FActScore: Fine-grained atomic evaluation of factual precision in long-form text generation”