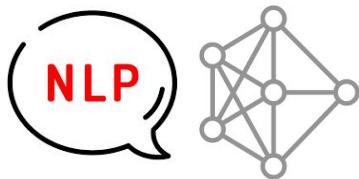




CHULA ENGINEERING
Foundation toward Innovation

COMPUTER



Neural Machine Translation (NMT)

2110572: Natural Language Processing Systems

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Credit: TA.Knight, TA.Pluem, and all TAs

Outline

- Part1) MT models
 - mBART (2020)
 - NLLB (started 2018)
 - m2m-100 (2020)
 - NLLB-200 (2022)
- Part2) MT data sets
 - WMT
 - OPUS
 - FLORES-200
- Part3) Evaluation
 - Accuracy-based score (BLEU, charF++)
 - Model-based score
 - COMET
 - Quality Estimation

Introduction

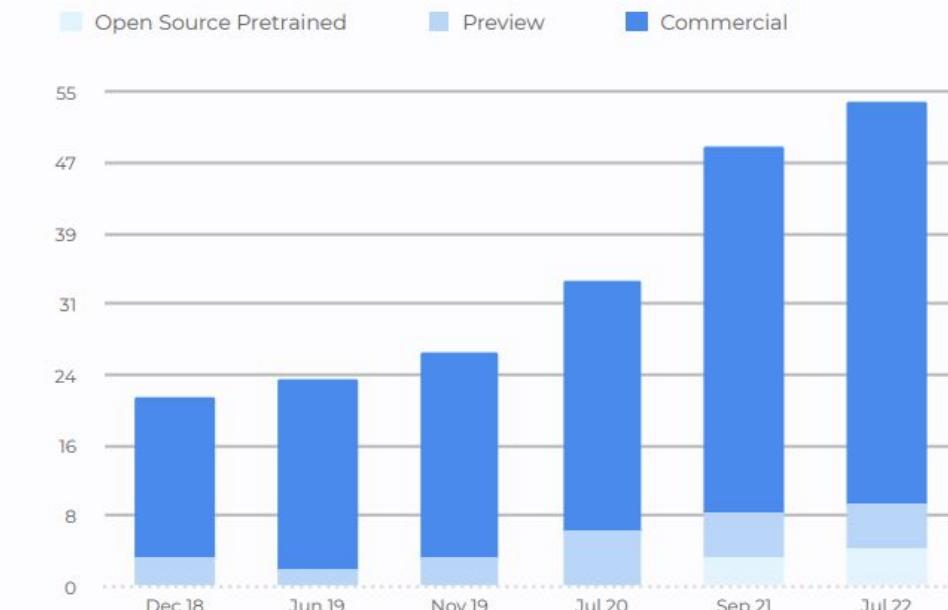
Machine Translation (MT) is a research field in NLP that aims to create a system that can translate text from one language to another.



Machine Translation Landscape

| | | | | | |
|--|---|--|--|---|--|
|  AISA Neural Machine Translation API |  Alibaba eCommerce MT |  Alibaba Cloud General |  Amazon Translate |  Apptek Neural Machine Translation | |
|  Baidu Translate API |  DeepL API |  Elia Elhuyarren itzultzale automatikoa |  Globalese Machine Translation |  Google Cloud Advanced Translation | |
|  GTCom YeeCloud MT |  IBM Watson eCommerce MT |  Meta AI NLLB |  Microsoft Language Translator |  ModernMT Realtime | |
|  Naver Papago NMT Commercial |  NiuTrans Translation Cloud Platform |  Pangeanic Machine Translation API |  PROMT Cloud API |  RoyalFlush Finance Translation | |
|  Rozetta T-400 Machine Translation API |  SYSTRAN PNMT |  Tilde Machine Translation API |  Tencent Cloud TMT API |  Ubiquis Translation API | |
|  Yandex Translate API |  Youdao Cloud Translation API |  XL8 Machine Translation | | | |

Cloud MT Vendors with Stock Models



Commercial (45)

AISA, Alibaba, Amazon, Apptek, Baidu, CloudTranslation, DeepL, Elia, Fujitsu, Globalese, Google, GTCom, IBM, iFlyTec, HiThink RoyalFlush, Lesan, Lindat, Lingvanex, Kawamura / NICT, Kingsoft, Masakhane, Microsoft, Mirai, ModernMT, Naver, Niutrans, NTT, Omniscien, Pangeanic, Prompsit, PROMT, Process9, Rozetta, RWS, SAP, Sogou, Systran, Tencent, Tilde, Ubiquis, Viscomtec, XL8, Yandex, YarakuZen, Youdao

Preview / Limited (5)

eBay, Kakao, QCRI, Tarjama, Birch.AI

Open Source Pretrained (3)

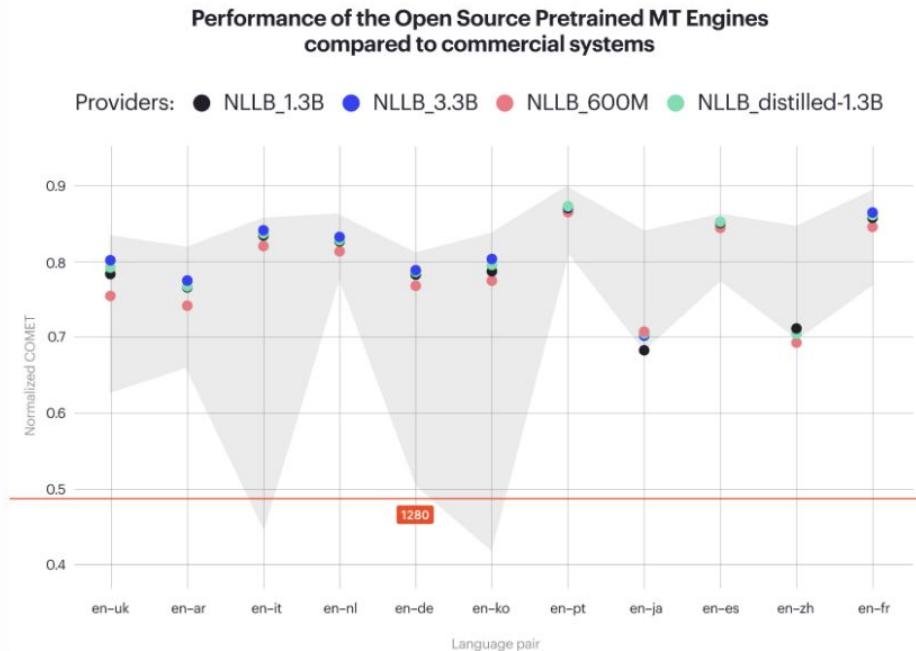
M2M-100, mBART, NLLB by Meta

Open Source MT Performance (COMET)

NLLB by Meta AI mostly show performance in the 2nd tier of commercial systems.

For **en-es (English-to-Spanish)**, NLLB scores are on par with the best commercial systems

For **en-zh (English-to-Chinese)** and **en-ja (English-to-Japanese)**, the scores are quite low



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Part1) MT models

- mBART (2020)
- NLLB (started 2018)
 - m2m-100 (2020)
 - NLLB-200 (2022)

History of Machine Translation

1. Rule-Based Machine Translation

- a. Manual, hand-crafted rules for vocabulary, grammar, etc.
- b. Low-quality translation and time-consuming.
- c. Cannot utilize context information!

2. Statistical Machine Translation

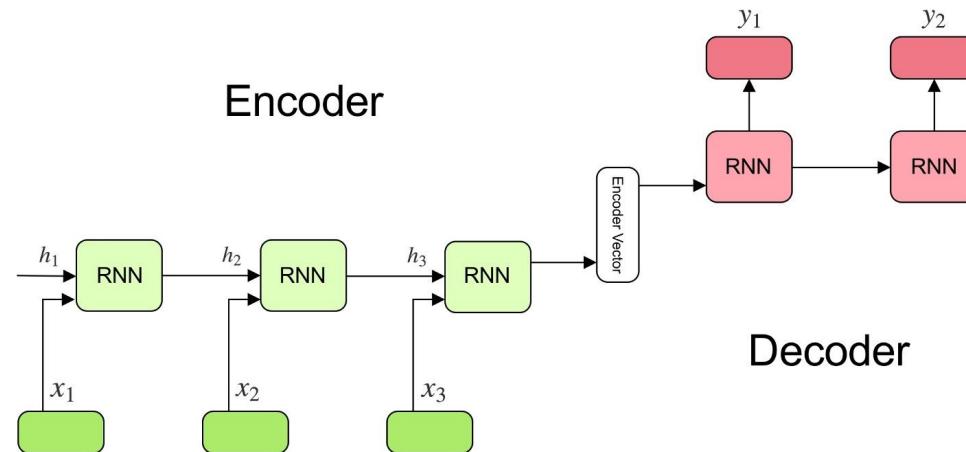
- a. Use statistics from a parallel corpus
- b. Google translate (from 2006 to 2016)

3. Neural Machine Translation

- a. Competitive performance but hard to debug
- b. Google translate (now)

Neural Machine Translation (NMT)

Prior to the Transformer, the dominant model in NMT was the RNN-based encoder-decoder.



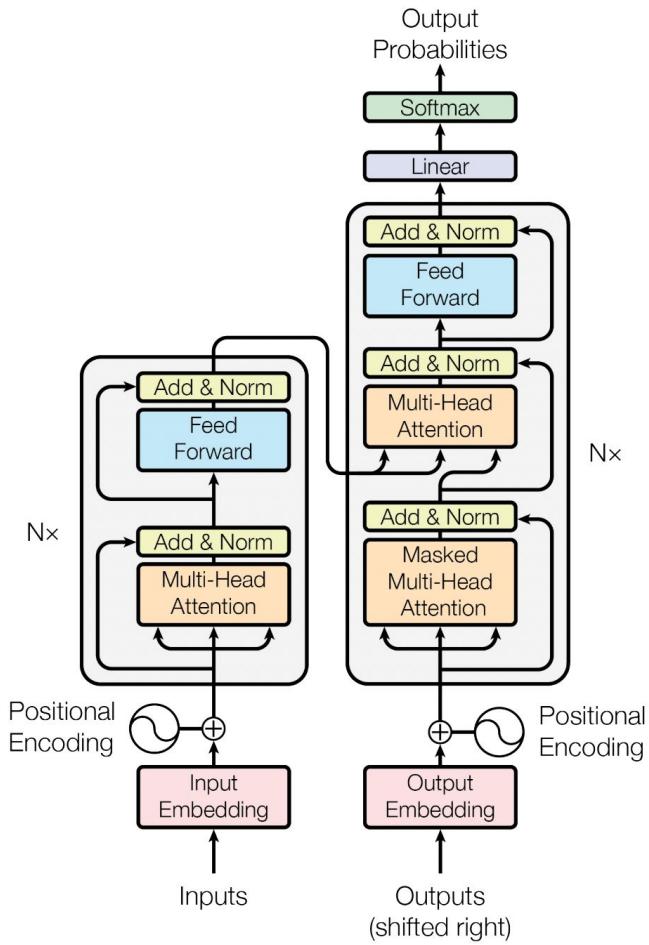
Transformer

The self-attention mechanism in the Transformer allows for better input representations and faster computation due to parallelization.

This brings big performance improvements and thus allows researchers to scale the model more efficiently.

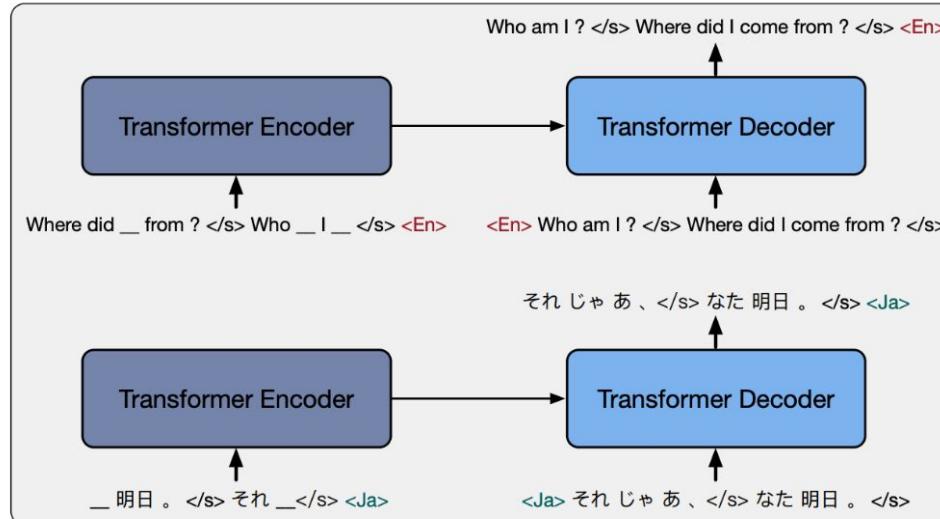
Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

| Model | BLEU | | Training Cost (FLOPs) | |
|---------------------------------|-------------|--------------|---------------------------------------|---------------------|
| | EN-DE | EN-FR | EN-DE | EN-FR |
| ByteNet [18] | 23.75 | | | |
| Deep-Att + PosUnk [39] | | 39.2 | | $1.0 \cdot 10^{20}$ |
| GNMT + RL [38] | 24.6 | 39.92 | $2.3 \cdot 10^{19}$ | $1.4 \cdot 10^{20}$ |
| ConvS2S [9] | 25.16 | 40.46 | $9.6 \cdot 10^{18}$ | $1.5 \cdot 10^{20}$ |
| MoE [32] | 26.03 | 40.56 | $2.0 \cdot 10^{19}$ | $1.2 \cdot 10^{20}$ |
| Deep-Att + PosUnk Ensemble [39] | | 40.4 | | $8.0 \cdot 10^{20}$ |
| GNMT + RL Ensemble [38] | 26.30 | 41.16 | $1.8 \cdot 10^{20}$ | $1.1 \cdot 10^{21}$ |
| ConvS2S Ensemble [9] | 26.36 | 41.29 | $7.7 \cdot 10^{19}$ | $1.2 \cdot 10^{21}$ |
| Transformer (base model) | 27.3 | 38.1 | $3.3 \cdot 10^{18}$ | |
| Transformer (big) | 28.4 | 41.8 | $2.3 \cdot 10^{19}$ | |



1) mBART

A standard encoder-decoder transformer model that pretrains on an input denoising objective. There are two steps: (1) pretrain on the denoising task and (2) finetune on the MT task.

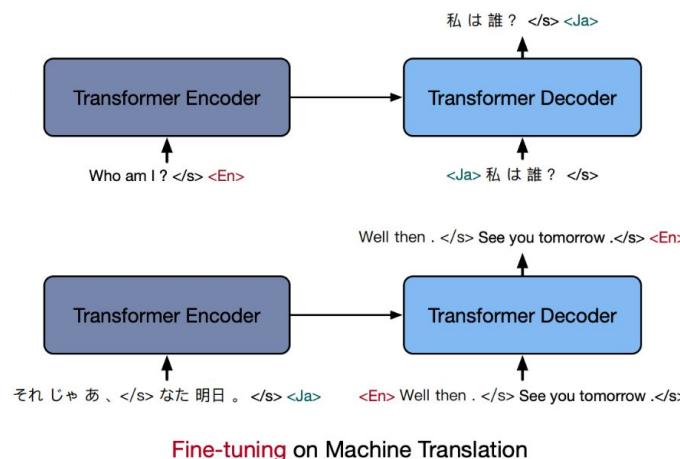


Multilingual Denoising Pre-Training (mBART)

improves

1) mBART (cont.)

Pretraining on multilingual data (~1TB) improve translation quality, especially for low-resource language pairs.



| Languages | En-Gu | En-Kk | En-Vi | En-Tr | En-Ja | En-Ko |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Data Source | WMT19 | WMT19 | IWSLT15 | WMT17 | IWSLT17 | IWSLT17 |
| Size | 10K | 91K | 133K | 207K | 223K | 230K |
| Direction | ← → | ← → | ← → | ← → | ← → | ← → |
| Random | 0.0 | 0.0 | 0.8 | 0.2 | 23.6 | 24.8 |
| mBART25 | 0.3 | 0.1 | 7.4 | 2.5 | 36.1 | 35.4 |
| Languages | En-Nl | En-Ar | En-It | En-My | En-Ne | En-Ro |
| Data Source | IWSLT17 | IWSLT17 | IWSLT17 | WAT19 | FLoRes | WMT16 |
| Size | 237K | 250K | 250K | 259K | 564K | 608K |
| Direction | ← → | ← → | ← → | ← → | ← → | ← → |
| Random | 34.6 | 29.3 | 27.5 | 16.9 | 31.7 | 28.0 |
| mBART25 | 43.3 | 34.8 | 37.6 | 21.6 | 39.8 | 34.0 |
| Languages | En-Si | En-Hi | En-Et | En-Lt | En-Fi | En-Lv |
| Data Source | FLoRes | ITTB | WMT18 | WMT19 | WMT17 | WMT17 |
| Size | 647K | 1.56M | 1.94M | 2.11M | 2.66M | 4.50M |
| Direction | ← → | ← → | ← → | ← → | ← → | ← → |
| Random | 7.2 | 1.2 | 10.9 | 14.2 | 22.6 | 17.9 |
| mBART25 | 13.7 | 3.3 | 23.5 | 20.8 | 27.8 | 21.4 |

Table 2: Low/Medium Resource Machine Translation Pre-training consistently improves over a randomly initialized baseline, with particularly large gains on low resource language pairs (e.g. Vi-En).

1) mBART (cont.)

It can also do **zero-shot MT (with some tricks)** that yields decent results.

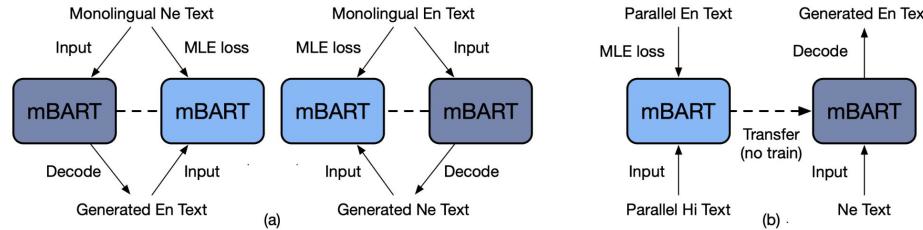


Figure 5: Illustrated frameworks for unsupervised machine translation via (a) back-translation (b) language transfer where Ne-En is used as an example. For both cases, we initialize from multilingual pre-training (e.g. mBART25).

| Model | Similar Pairs | | | | Dissimilar Pairs | | | |
|--------------------|---------------|---------------|--------------|---------------|------------------|---------------|--------------|---------------|
| | En-De | | En-Ro | | En-Ne | | En-Si | |
| | \leftarrow | \rightarrow | \leftarrow | \rightarrow | \leftarrow | \rightarrow | \leftarrow | \rightarrow |
| Random | 21.0 | 17.2 | 19.4 | 21.2 | 0.0 | 0.0 | 0.0 | 0.0 |
| XLM (2019) | 34.3 | 26.4 | 31.8 | 33.3 | 0.5 | 0.1 | 0.1 | 0.1 |
| MASS (2019) | 35.2 | 28.3 | 33.1 | 35.2 | - | - | - | - |
| mBART | 34.0 | 29.8 | 30.5 | 35.0 | 10.0 | 4.4 | 8.2 | 3.9 |

Table 10: **Unsupervised MT via Back-Translation.** En-De, En-Ro are initialized by mBART02, while En-Ne, En-Si are initialized by mBART25. Our models are trained on monolingual data used in pre-training.

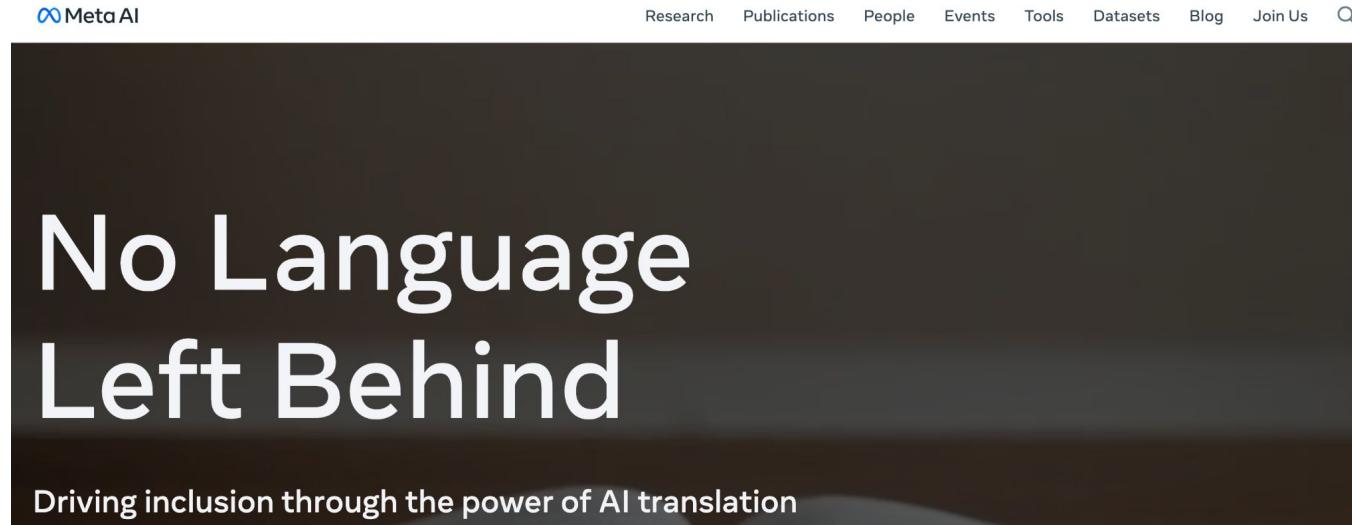
1) mBART (cont.)

- Originally trained on 25 languages, 25 more languages (50 total languages) were added via continual pretraining.
- Thai language included! The model is very large, though.

| Data size | Languages |
|-------------|---|
| 10M+ | German, Czech, French, Japanese, Spanish, Russian, Polish, Chinese |
| 1M - 10M | Finnish, Latvian, Lithuanian, Hindi, Estonian |
| 100k to 1M | Tamil, Romanian, Pashto, Sinhala, Malayalam, Dutch, Nepali, Italian, Arabic, Korean, Hebrew, Turkish, Khmer, Farsi, Vietnamese, Croatian, Ukrainian |
| 10K to 100K | Thai, Indonesian, Swedish, Portuguese, Xhosa, Afrikaans, Kazakh, Urdu, Macedonian, Telugu, Slovenian, Burmese, Georgia |
| 10K- | Marathi, Gujarati, Mongolian, Azerbaijani, Bengali |

2) No Language Left Behind (NLLB) [FB started in 2018]

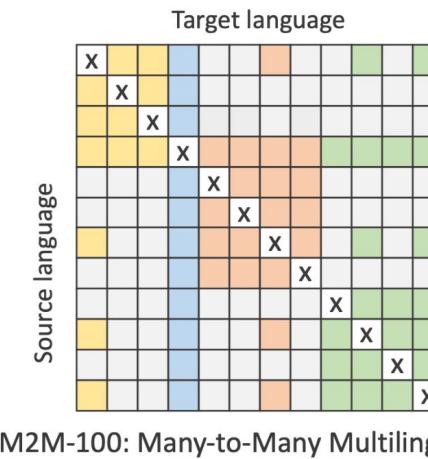
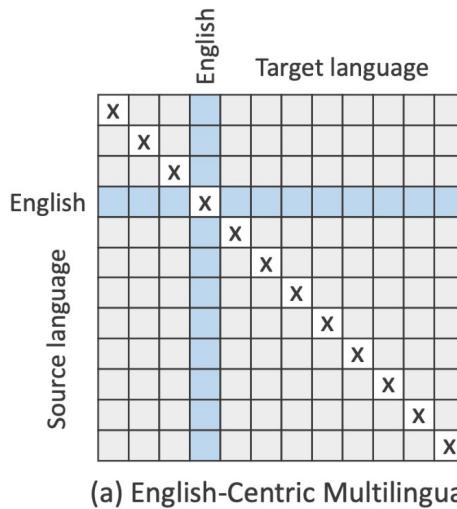
From the webpage - “No Language Left Behind (NLLB) is a first-of-its-kind, AI breakthrough project that open-sources models capable of delivering evaluated, high-quality translations **directly between 200 languages**”...



2.1) m2m-100

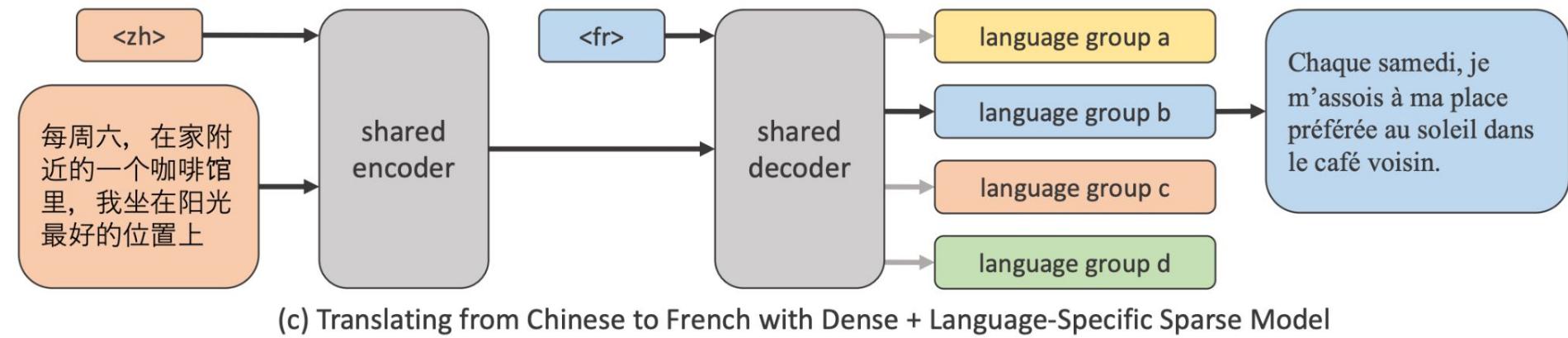
Previous works mostly focus on translation from/to English ([English-centric](#)).

This paper introduces a many-to-many translation model and dataset of 100 languages (that's 9900 directions!)



2.1) m2m-100 (cont.)

The model is also **an encoder-decoder model** with **additional language-specific (language token) sparse models**.



2.1) m2m-100 (cont.)

The model outperforms mBART even though it trains on 100 languages. Thai language is also covered by this model.

| Benchmark | Model | BLEU |
|-----------------|--------------------------------------|-------------|
| mBART | Previous Work (Liu et al., 2020) | 23.9 |
| | M2M-100 | 24.6 |
| CCMatrix | Previous Work (Schwenk et al., 2019) | 16.3 |
| | M2M-100 | 18.7 |
| OPUS100 | Previous Work (Zhang et al., 2020) | 14.1 |
| | M2M-100 | 18.4 |

Table 11: Comparison on various evaluation settings from previous work. We display the best performing model from the published work and report average BLEU on the test set. For these comparisons, we use the tokenization and BLEU evaluation script used by each work for comparability. Liu et al. (2020) report Low/Mid resource directions into and out of English and High resource directions into English, we average across all. Schwenk et al. (2019) report the full matrix on 28 languages, we average across all. Zhang et al. (2020) report results on non-English directions, we average across all.

2.2) NLLB-200

This model is capable of a total of 40,602 translation directions!

It is also an encoder-decoder transformer model.
However, it is a sparse model (**Mixture of Experts transformer**).

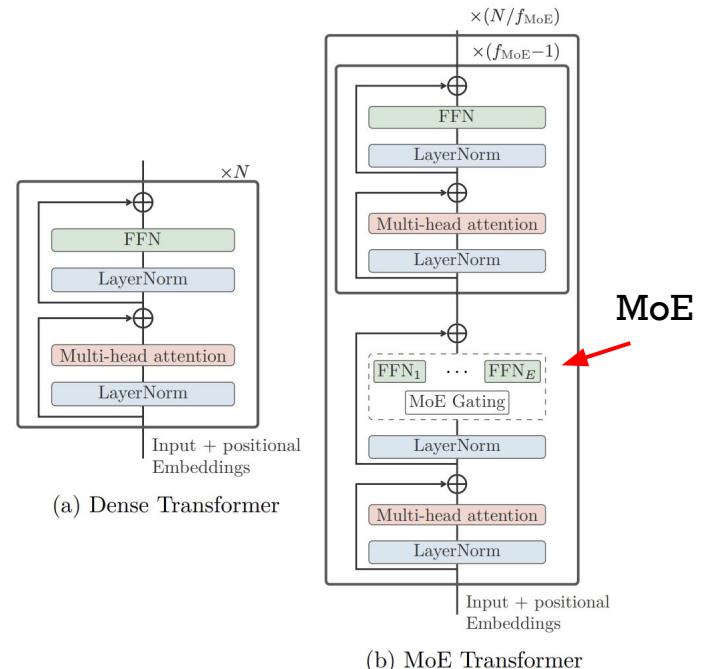
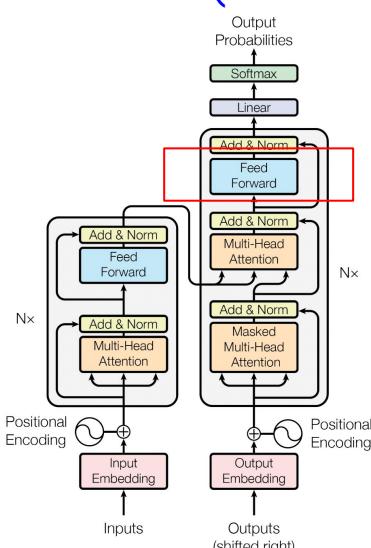


Figure 16: Illustration of a Transformer encoder with MoE layers inserted at a $1:f_{\text{MoE}}$ frequency. Each MoE layer has E experts and a gating network responsible for dispatching tokens.

2.2) NLLB-200 (cont.)

With just 1.3B parameters, it outperforms Google Translate in some language pairs.

(Distilled) weight available!

<https://huggingface.co/facebook/nllb-200-distilled-600M>

| | eng_Latn-xx | xx-eng_Latn | xx-yy | Avg. |
|---------------|-------------------|-------------------|-------------------|-------------------|
| 87 languages | | | | |
| M2M-100 | -/- | -/- | -/- | 13.6/- |
| Deepnet | -/- | -/- | -/- | 18.6/- |
| NLLB-200 | 35.4 /52.1 | 42.4 /62.1 | 25.2 /43.2 | 25.5 /43.5 |
| 101 languages | | | | |
| DeltaLM | 26.6/- | 33.2/- | 16.4/- | 16.7/- |
| NLLB-200 | 34.0 /50.6 | 41.2 /60.9 | 23.7 /41.4 | 24.0 /41.7 |

Table 30: Comparison on FLORES-101 devtest. We evaluate over full FLORES-101 10k directions. We report both spBLEU/chrF++ where available. All spBLEU numbers are computed with FLORES-101 SPM tokenizer. Scores for DeltaLM are taken from FLORES-101 leaderboard. M2M-100 and Deepnet average is only over 87 languages that overlap with FLORES-101, we also show NLLB-200 performance on that subset of languages. NLLB-200 outperforms previous state of the art models by a significant margin, even after supporting twice as many languages.

| | eng_Latn-xx | | xx-eng_Latn | | Average | |
|------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| | low | v.low | low | v.low | low | v.low |
| Google Translate | 32.3 / 50.3 | 27.0 / 46.5 | 35.9/57.1 | 35.8/57.0 | 34.1/53.7 | 31.3/51.7 |
| NLLB-200 | 30.3/48.2 | 25.7/45.0 | 41.3 / 60.4 | 41.1 / 60.3 | 35.8 / 54.3 | 33.4 / 52.6 |

Table 34: Comparison on 102 Low-Resource Directions on FLORES-200 devtest against commercial translation systems. We evaluate on all English-centric low-resource directions that overlap between FLORES-200 and Google’s Translation API as of this writing. We report both spBLEU/chrF++ and bold the best score. We observe that NLLB-200 outperforms significantly on xx-eng_Latn and overall average.

2.2) NLLB-200 (cont.)

This paper also explains how they created a parallel corpus (NLLB-SEED), including a multilingual sentence encoder and a language identification model.

The whole paper is 192 pages!

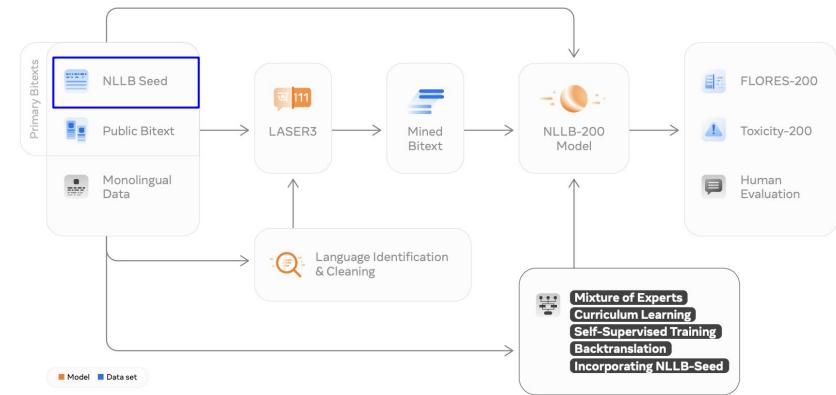


Figure 14: **Modeling Contributions of No Language Left Behind:** As highlighted, we describe several modeling techniques to enable coverage of hundreds of languages in one model. We focus on effectively scaling model capacity while mitigating overfitting, as well as how to improve backtranslation for low-resource languages and incorporate NLLB-SEED.

MT on LLM Performance

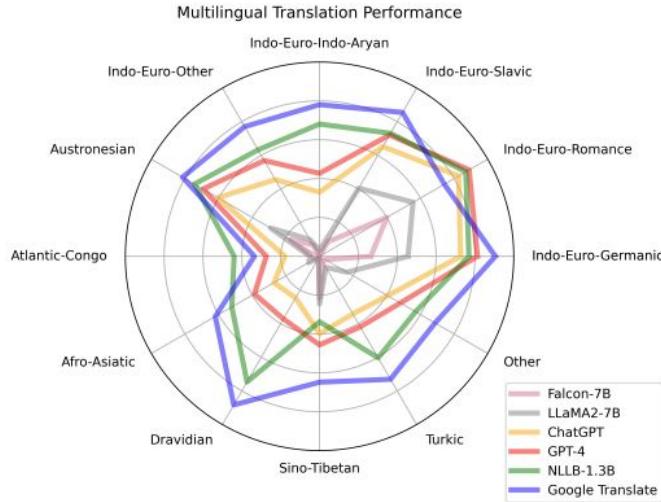


Figure 1: Multilingual translation performance (BLEU) of some popular LLMs and traditional supervised systems in translating from English to non-English. LLMs have demonstrated great potential in multilingual machine translation.

LLM capabilities are evolving

GPT-4 beat supervised baseline **NLLB** in 41% of translation pairs but still has large gap to **Google Translate**

But the advantage is LLM can acquire moderate translation ability in **zero-resource languages**.

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Part2) Notable datasets

WMT
OPUS
FLORES-200

1) WMT

- WMT (Workshop on Statistical Machine Translation)—This is a machine translation dataset composed of a collection of various sources, including (1) news commentaries and (2) parliament proceedings.
- It focuses mainly on European language pairs.
- There are many versions from 2008 to 2014.

| W M T | WMT 2020 | WMT 2020 is a collection of datasets used in shared tasks of the Fifth Conference on Machine Translation. 35 PAPERS • 1 BENCHMARK |
|-------|----------|---|
| W M T | WMT 2016 | WMT 2016 is a collection of datasets used in shared tasks of the First Conference on Machine Translation. The conference builds on ten previous Workshops on statistical... 136 PAPERS • 20 BENCHMARKS |
| W M T | WMT 2018 | WMT 2018 is a collection of datasets used in shared tasks of the Third Conference on Machine Translation. 35 PAPERS • 6 BENCHMARKS |
| W M T | WMT 2014 | WMT 2014 is a collection of datasets used in shared tasks of the Ninth Workshop on Statistical Machine Translation. 226 PAPERS • 12 BENCHMARKS |
| W M T | WMT 2015 | WMT 2015 is a collection of datasets used in shared tasks of the Tenth Workshop on Statistical Machine Translation. 32 PAPERS • 4 BENCHMARKS |

• Parallel data:

| File | Size | CS-EN | DE-EN | HI-EN | FR-EN | RU-EN | Notes |
|---------------------------------------|--------|-------|-------|-------|-------|-------|---|
| Europarl v7 | 628MB | ✓ | ✓ | | ✓ | | same as previous year, corpus home page |
| Common Crawl corpus | 876MB | ✓ | ✓ | | ✓ | ✓ | same as previous year |
| UN corpus | 2.3GB | | | | ✓ | | same as previous year, corpus home page |
| News Commentary | 77MB | ✓ | ✓ | | ✓ | ✓ | updated, data with document boundaries |
| 10 ⁹ French-English corpus | 2.3 GB | | | | ✓ | | same as previous year [md5 sha1] |
| CzEng 1.0 | 115MB | ✓ | | | | | same as previous year, corpus home page (avoids sections 98 and 99) |
| Yandex 1M corpus | 121MB | | | | | ✓ | corpus home page ; v1.3 now in original case |
| Wiki Headlines | 7.8MB | | | | ✓ | | Provided by CMU. The ru-en is unchanged from last year. |
| HindEnCorp | 25MB | | | ✓ | | | Collected by Charles University |
| The JHU Corpus | | | | ✓ | | | This is fully contained in HindEnCorp, so not made available here. |

• Monolingual language model training data:

| Corpus | CS | DE | EN | HI | FR | RU | All languages combined | Notes |
|--------------------------------|-------|-------|-------|-------|-------|-------|------------------------|-------|
| Europarl v7 | 32MB | 107MB | 99MB | | 107MB | | 446MB | |
| News Commentary | 11MB | 14MB | 15MB | | 13MB | 14MB | 64MB | |
| News Crawl: articles from 2007 | 3.7MB | 92MB | 198MB | | 6.0MB | | 302MB | |
| News Crawl: articles from 2008 | 191MB | 313MB | 672MB | 1.2MB | 244MB | 2.3MB | 1.5GB | |
| News Crawl: articles from 2009 | 194MB | 296MB | 757MB | 2.8MB | 233MB | 5.1MB | 1.6GB | |
| News Crawl: articles from 2010 | 107MB | 135MB | 345MB | | 99MB | 2.5MB | 727MB | |
| News Crawl: articles from 2011 | 389MB | 746MB | 784MB | 9.9MB | 317MB | 564MB | 3.1GB | |
| News Crawl: articles from 2012 | 337MB | 946MB | 751MB | 4.0KB | 218MB | 568MB | 3.1GB | |
| News Crawl: articles from 2013 | 395MB | 1.6GB | 1.1GB | 62MB | 474MB | 730MB | 4.3GB | |

News Crawl
Extracted article text from various online news publications.
The data sets from 2007-2012 are the same as [last year's](#).

2) OPUS

Opus - <https://opus.nlpl.eu/>



OPUS is a growing collection of translated texts from the web. In the OPUS project we try to convert and align free online data, to add linguistic annotation, and to provide the community with a publicly available parallel corpus. OPUS is based on open source products and the corpus is also delivered as an open content package. We used several tools to compile the current collection. All pre-processing is done automatically. No manual corrections have been carried out.

The OPUS collection is growing! Check this page from time to time to see new data arriving ...
Contributions are very welcome! Please contact <jorg.tiedemann@helsinki.fi>

Search & download resources: show all versions

3) FLORES-200

- **FLORES-200 (Few-Shot Learning Oriented Evaluation for Machine Translation)** is a large-scale multilingual dataset designed to evaluate machine translation (MT) models **across 200 languages**. It was developed by Meta AI (formerly Facebook AI) to benchmark multilingual models, such as mBART-50, NLLB (No Language Left Behind), and M2M-100.
- FLORES-200 consists of translations from **842 distinct web articles**, totaling 3,001 sentences. These sentences are divided into three splits: dev, devtest, and test (hidden). On average, sentences are approximately 21 words long.



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Part3) Evaluating a Translation

Syntactic Similarity (BLEU, ROUGE, METEOR, TER, chrF)

Semantic Similarity (BERTScore, COMET, BLEURT)

Human Judgement (HTER, DA, MQM)

Evaluation

Syntactic Similarity

BLEU

ROUGE

METEOR

TER

ChrF

Semantic Similarity

BERTScore

COMET

BLEURT

Human Judgement

HTER

DA

MQM

Syntactic Similarity

BLEU

BLEU is a precision focused metric that calculates n-gram overlap of the reference and generated texts (including brevity penalty—penalizing short sentences). Works well for structured content but struggles with paraphrasing.

ROUGE

Very similar to the BLEU definition, the difference being that Rouge is recall focused overlap. Often used for summarization but can apply to MT. ROUGE-N considers n-gram overlap. ROUGE-L considers longest common subsequence (LCS).

METEOR

Improves over BLEU by considering synonyms, stemming, and paraphrasing (WordNet). The metric is a harmonic mean of unigram precision and recall (recall weighted 9x higher than precision). Penalty is changed to be correlated to number of adjacent chunks.

TER

Translation Edit Rate: Measures the number of edits (insertions, deletions, shifts, and substitutions) required to transform a machine translation into the reference translation. Penalizes paraphrases/synonyms. Penalizes translations of different length.

ChrF

An F-score based on character n-gram precision and recall (instead of word or n-gram level). No need for tokenization. Better for highly inflected languages (e.g., Finnish, Turkish, Thai, Arabic) where words change forms frequently.

$$RECALL = \frac{\text{Overlapping number of } n\text{-grams}}{\text{Number of } n\text{-grams in the reference}}$$

$$PRECISION = \frac{\text{Overlapping number of } n\text{-grams}}{\text{Number of } n\text{-grams in the candidate}}$$

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

$$\begin{aligned} & \text{ROUGE-N} \\ &= \frac{\sum_{S \in \{\text{Reference Summaries}\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{\text{Reference Summaries}\}} \sum_{gram_n \in S} Count(gram_n)} \quad (1) \end{aligned}$$

$$\begin{aligned} F_{mean} &= \frac{10PR}{R + 9P} \quad p = 0.5 \left(\frac{c}{u_m} \right)^3 \\ M &= F_{mean}(1 - p) \end{aligned}$$

$$TER = \frac{\text{number-of-edits}}{\text{word-length-of-Reference-text}}$$

$$\text{CHRF}\beta = (1 + \beta^2) \frac{\text{CHRP} \cdot \text{CHRR}}{\beta^2 \cdot \text{CHRP} + \text{CHRR}}$$

BLEU (Bilingual Evaluation Understudy) [2002]

The most popular metric to (try to) measure the quality of predicted translations.

The idea is to measure **the similarity of the predictions with human references**.

"The BLEU metric ranges from 0 to 1. Few translations will attain a score of 1 unless they are identical to a reference translation. For this reason, even a human translator will not necessarily score 1. [...] on a test corpus of about 500 sentences (40 general news stories), a human translator scored 0.3468 against four references and scored 0.2571 against two references.

- BLEU: a Method for Automatic Evaluation of Machine Translation, 2002.

BLEU (cont.)

The score is calculated based on **clipped n-gram precision.**

Clipping prevents repetitive predicted sentence from getting a good score

For example, we could have

- Target Sentence: He eats an apple
- Predicted Sentence: He He He

This means that the 1-gram precision is 3/3 or 100% (**it shouldn't be like this!**)

BLEU (cont.)

The score is calculated based on **clipped n-gram precision**.

So we limit the count of each word to the maximum number of times that the word occurs in the target Sentence

- Target Sentence 1: He eats a sweet apple
- Target Sentence 2: He is eating a tasty apple
- Predicted Sentence: He He He eats tasty fruit

Now the 1-gram precision becomes 3/6
There are **6 words** in the predicted sentence

“He” occurs max. one time in 2 reference sentences. So we clip it to 1.

| Word | Matching Sentence | Matched Predicted Count | Clipped Count |
|-------|-------------------|-------------------------|---------------|
| He | Both | 3 | 1 |
| eats | Target 1 | 1 | 1 |
| tasty | Target 2 | 1 | 1 |
| fruit | None | 0 | 0 |
| Total | | 5 | 3 |

Note that precision now refers to the clipped precision

BLEU (cont.)

The score is calculated based on **clipped n-gram precision**.

Now we calculate the n-gram (clipped) precision for all N. The widely used number for **N** is 4 and a uniform weight w_n of $N/4$.

Let's look at all the 2-grams in our predicted sentence:

Target Sentence:  The guard arrived late because it was raining

Predicted Sentence: The guard arrived late because of the rain

$$\begin{aligned} \text{Geometric Average Precision } (N) &= \exp\left(\sum_{n=1}^N w_n \log p_n\right) \\ &= \prod_{n=1}^N p_n^{w_n} \\ &= (p_1)^{\frac{1}{4}} \cdot (p_2)^{\frac{1}{4}} \cdot (p_3)^{\frac{1}{4}} \cdot (p_4)^{\frac{1}{4}} \end{aligned}$$

The precision of 2-grams is 4/7.
(#correct/#total)

[$\text{pre(1-gram)} * \text{pre(2-gram)} * \text{pre(3-gram)} * \text{pre(4-gram)}$] $^{1/4}$

BLEU (cont.)

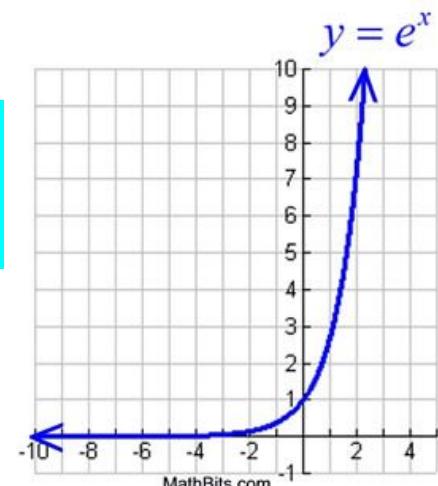
The score is calculated based on **clipped n-gram precision**.

Next, we compute the brevity penalty. This **penalizes predicted sentences that are too short**.

For example, a predicted sentence can contain only one word and get a perfect n-gram precision score

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

- c is *predicted length* = number of words in the predicted sentence and
- r is *target length* = number of words in the target sentence



BLEU (cont.)

The score is calculated based on **clipped n-gram precision**.

Finally, we can compute the BLEU score by

$$Bleu(N) = \text{Brevity Penalty} \cdot \text{Geometric Average Precision Scores}(N)$$

2
(larger is better)

1
(larger is better)

BLEU (cont.)

The score is calculated based on **clipped n-gram precision**.

Finally, we can compute the BLEU score by

$$\text{Bleu} (N) = \text{Brevity Penalty} \cdot \text{Geometric Average Precision Scores} (N)$$

Even though BLEU score is widely used, it has some important **weaknesses**:

- It does not consider words that have the **same meaning** to be correct. For example, for the word “dog,” we can either use “ໜາ” or “ສຸນໜີ”.
- It ignores the **importance of words**. With Bleu Score an incorrect word like “to” or “an” that is less relevant to the sentence is penalized just as heavily as a word that contributes significantly to the meaning of the sentence.
- Most importantly, **higher BLEU does not always mean a good score based on human judgment [1]**.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) [2004]

Introduced in 2004 Paper: Lin. ROUGE: a Package for Automatic Evaluation of Summaries.

<https://aclanthology.org/W04-1013/>

Instead of precision measures like BLEU, ROUGE is more focused on **recall**.

- Mostly used for **summarization**
- 4 Versions of ROUGE:
 - **ROUGE-N:** Measures the *n*-gram overlap between the generated text and reference text.
 - **ROUGE-L:** Takes the *longest common subsequences (LCS)*, useful for capturing structural similarity.
 - **ROUGE-W:** Weighs *contiguous matches* that are higher than other n-grams.
 - **ROUGE-S:** Measures *skip-bigram overlap*, where two words are considered but may not be adjacent.

Note: **ROUGE-1**, **ROUGE-2**, and **ROUGE-L** is mostly used

ROUGE-N

ROUGE-N is an n-gram **recall** between a candidate summary and a set of references.

N indicates the *number of N grams* which can be 1 (unigram) and 2 (bigram).

In the paper, ROUGE-N is only defined for **recall**.

In practice, the Python implementation shows **ROUGE-N F1**.

ROUGE-1

```
Candidate 1 : Summarization is cool
Reference 1 : Summarization is beneficial and cool
Reference 2 : Summarization saves time
```

Use only reference 1 since there are more overlapping words

$$\text{Recall} = 3/5 = 0.6$$

$$\text{Precision} = 3/3 = 1$$

$$\text{ROUGE-1 F1} = 2RP/(R+P) = 2*0.6/1.6 = \mathbf{0.75}$$

As defined in paper

$$\begin{aligned} \text{ROUGE-N} \\ &= \frac{\sum_{S \in \{\text{ReferenceSummaries}\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{\text{ReferenceSummaries}\}} \sum_{gram_n \in S} Count(gram_n)} \end{aligned}$$

$$RECALL = \frac{\text{Overlapping number of } n\text{-grams}}{\text{Number of } n\text{-grams in the reference}}$$

$$PRECISION = \frac{\text{Overlapping number of } n\text{-grams}}{\text{Number of } n\text{-grams in the candidate}}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

ROUGE-N

ROUGE-2

It's the same process as above, but right now bigrams are determined.

```
Candidate 1: (Summarization is),(is cool)
Reference 1: (Summarization is),(is beneficial),(beneficial and),(and cool)
Reference 2: (Summarization saves),(saves time)
```

$$\text{Recall} = 1/4 = 0.25$$

$$\text{Precision} = 1/2 = 0.5$$

$$\text{ROUGE-2 F1} = 2RP/(R+P) = 2*0.25*0.5/0.75 = \mathbf{0.33}$$

Huggingface Evaluate uses rouge-score package (replication of original perl package)

<https://pypi.org/project/rouge-score/>

```
candidates = ["Summarization is cool"]
references = [["Summarization is beneficial and cool","Summarization saves time"]]

results = rouge.compute(predictions=candidates, references=references)
print(results)

{'rouge1': 0.7499999999999999, 'rouge2': 0.3333333333333333, 'rougeL': 0.7499999999999999, 'rougeLsum': 0.7499999999999999}
```

ROUGE-L

ROUGE-L is **Longest Common Subsequence (LCS)** oriented. LCS is the longest sequence of words that appear in both the candidates and reference summaries, while keeping the order of the words intact.

Note that LCSEs are not necessarily consecutive but still in order

Candidate: A fast brown fox leaps over a sleeping dog.

Reference: The quick brown fox jumps over the lazy dog.

Recall = 4/9 = 0.44

Precision = 4/9 = 0.44

$$\text{ROUGE-L} = 2RP/(R+P) = 2 \cdot 0.44 \cdot 0.44 / 0.89 = \mathbf{0.44}$$

```
[6]: candidates = ["A fast brown fox leaps over a sleeping dog"]
      references = [{"The quick brown fox jumps over the lazy dog"}]

      results = rouge.compute(predictions=candidates, references=references)
      print(results)

→ { 'rouge1': 0.4444444444444444, 'rouge2': 0.125, 'rougeL': 0.4444444444444444, 'rougeLsum': 0.4444444444444444}
```

As defined in paper

$$R_{lcs} = \frac{LCS(X, Y)}{m}$$

$$P_{lcs} = \frac{LCS(X, Y)}{n}$$

$$F_{lcs} = \frac{(1 + \beta^2)R_{lcs}P_{lcs}}{R_{lcs} + \beta^2P_{lcs}}$$

The paper introduced β in F1-score.
 $\beta = 1$ means F1.

$\beta > 1$, recall is given more weight than precision.

Other ROUGE Flavours

ROUGE-L Sum

- Previous ROUGE-L is at the sentence level. In summary level, newlines are interpreted as sentence boundaries, and the LCS is computed between each pair of reference and candidate sentences, and something called union-LCS is computed.
- ROUGE-LSum evaluates LCS across multiple sentences, unlike ROUGE-L, which is sentence-level.

Reference Summary (Ground Truth) [20 tokens]

“The President held a press conference today. He discussed the economy and upcoming policies. Several journalists asked about inflation concerns.”

Generated Summary (Model Output) [19 tokens]

“The President spoke at a press conference. He mentioned new policies and economic conditions. Reporters questioned him about inflation.”

LCS length = 7

| Precision | Recall | F1 Score |
|---|---|---|
| $\text{ROUGE - L Precision} = \frac{\text{LCS Length}}{\text{Generated Summary Length}}$ $= \frac{7}{19} = 0.368$ | $\text{ROUGE - L Recall} = \frac{\text{LCS Length}}{\text{Reference Summary Length}}$ $= \frac{7}{20} = 0.35$ | $\text{ROUGE - L F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ $= \frac{2 \times 0.368 \times 0.35}{0.368 + 0.35} = \frac{0.257}{0.718} = 0.359$ |

Other ROUGE Flavours (cont.)

ROUGE-W

ROUGE-L LCS does not differentiate consecutiveness. In the following example, Y1 and Y2 will have the same ROUGE-L score. However, Y1 should be a better match than Y1 because it has consecutive matches. ROUGE-W improves the ROUGE-L by **assigning more weight to consecutive LCSEs**. More details in this [link](#).

ROUGE-S

ROUGE-S stands for **skip-grams**. The order of the words in each sequence is preserved, but arbitrary gaps are allowed between words.

Sentence : police killed the gunman

Skip-Grams : ("police killed", "police the", "police gunman",
"killed the", "killed gunman", "the gunman")

X: [A B C D E F G]
Y₁: [A B C D H I K]
Y₂: [A H B K C I D]

Formula of ROUGE-S is almost same as ROUGE-L with an addition of combination function(C).

$$R_{skip2} = \frac{SKIP2(X, Y)}{C(m, 2)}$$

$$P_{skip2} = \frac{SKIP2(X, Y)}{C(n, 2)}$$

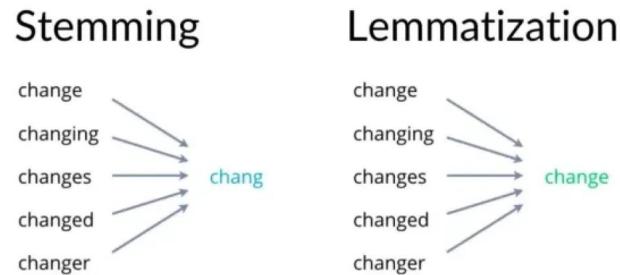
$$F_{skip2} = \frac{(1 + \beta^2)R_{skip2}P_{skip2}}{R_{skip2} + \beta^2 P_{skip2}}$$

METEOR [2005]

Introduced in 2005 Paper: Banerjee and Lavie. METEOR: An Automatic Metric for MT Evaluation with Improved Correlation with Human Judgments <https://aclanthology.org/W05-0909/>

It's a metric aimed to improve BLEU for machine translation based on the harmonic mean of unigram precision and recall (with recall weighted higher than precision).

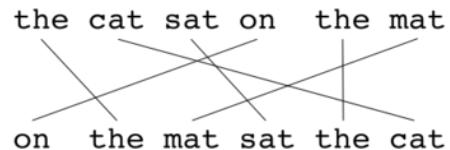
Several features that are not found in other metrics, such as **stemming** and **synonymy** matching, along with the standard **exact word** matching. (Uses WordNet)



METEOR has a correlation of up to 0.964 with human judgment at the corpus level, compared to BLEU's achievement of 0.817 on the same data set.

METEOR (cont.)

The algorithm creates an alignment between unigrams of the candidate string and the reference string.



We then calculate the precision P, recall R, and harmonic mean (with recall weighted 9x more than precision)

$$P = \frac{m}{w_t} \quad R = \frac{m}{w_r} \quad F_{mean} = \frac{10PR}{R + 9P}$$

m is the intersecting unigrams, w_t is candidate unigrams and w_r is reference unigrams

These measures account only for single words; they need to account for larger segments too! A penalty p is introduced for the grouping of the *fewest possible adjacent chunks* c in the candidate.

$$M = F_{mean}(1 - p)$$

The final score is F_{mean} with a penalty applied.

$$p = 0.5 \left(\frac{c}{u_m} \right)^3$$

- u_m is the number of unigrams that have been mapped.
- c is the number of chunks.
- This penalty has the effect of reducing F_{mean} by up to 50% without bigram or longer matches.

$$P = \frac{m}{w_t} \quad R = \frac{m}{w_r} \quad F_{mean} = \frac{10PR}{R + 9P}$$

METEOR (cont.)

Example 1

| | | | | | | |
|-------------|-----|-----|-----|-----|-----|-----|
| Candidate : | the | cat | sat | on | the | mat |
| Reference : | on | the | mat | sat | the | cat |

$$p = 0.5 \left(\frac{c}{u_m} \right)^3$$

$$M = F_{mean}(1 - p)$$

$$P = 6/6 = 1.0$$

$$R = 6/6 = 1.0$$

$$F_{mean} = 10 * 1.0 * 1.0 / (9*1.0 + 1.0) = 1.0$$

$$p = 0.5 * (3 / 6)^3 = 0.0625$$

Chunks : (the cat) (sat) (on the mat)

$$\boxed{\text{METEOR} = 1.0 * (1-0.0625) = 0.9375}$$

Example 2

| | | | | | | |
|-------------|-----|-----|-----|----|-----|-----|
| Candidate : | the | cat | sat | on | the | mat |
| Reference : | the | cat | sat | on | the | mat |

$$P = 6/6 = 1.0$$

$$R = 6/6 = 1.0$$

$$F_{mean} = 10 * 1.0 * 1.0 / (9*1.0 + 1.0) = 1.0$$

$$p = 0.5 * (1 / 6)^3 = 0.0023$$

Chunks : (the cat sat on the mat)

$$\boxed{\text{METEOR} = 1.0 * (1-0.0023) = 0.9977}$$

Translation Edit Rate (TER) [2006]

Introduced in 2006 Paper: Snover et. al. A Study of Translation Edit Rate with Targeted Human Annotation. <https://aclanthology.org/2006.amta-papers.25/>. This metric was introduced with the human-edited version (HTER), which will be introduced later.

It is an intuitive measure that measures the amount of editing that a human would have to perform to change a system output so it exactly matches the reference translation.

$$\text{TER} = \frac{\text{\# of edits}}{\text{average \# of reference words}}$$

Possible edits include the **insertion**, **deletion**, and **substitution** of single words as well as **shifts** of word sequences. A shift moves a contiguous sequence of words within the hypothesis to another location within the hypothesis.

Punctuation tokens are treated as normal words, and **miscalculation** is counted as an edit.

TER (cont.)

Reference Translation (Ground Truth) [14 tokens]

“The President held a press conference today to discuss the economy and upcoming policies.”

Generated (Hypothesis) Translation [13 tokens]

“The President spoke at a press conference about the economy and new policies.”

Step 1: Count Edits

1. “held” → “spoke” → Substitution (1 edit)
2. “today to discuss” → Removed → Deletion (2 edits)
3. “upcoming” → “new” → Substitution (1 edit)

Step 2: Compute TER Score

$$TER = \frac{\text{Total Edits}}{\text{Total Words in Reference Translation}}$$

$$TER = \frac{4}{14} = 0.429$$

| Metric | Value |
|---------------------------------|--------------|
| Total Edits | 4 |
| Total Words in Reference | 14 |
| TER Score | 0.429 |

chrF & chrF++

- A score based on **character n-gram precision and recall**.
 - No tokenization required!
- The score averages over all n-grams.
 - The widely used number is **6 characters**
- **Later, chrF++ adds word n-gram (2-gram) to the metric since it correlates more strongly with human judgement.**
 - Now tokenization is required.

$$\text{CHRF} \beta = (1 + \beta^2) \frac{\text{CHRP} \cdot \text{CHRR}}{\beta^2 \cdot \text{CHRP} + \text{CHRR}}$$

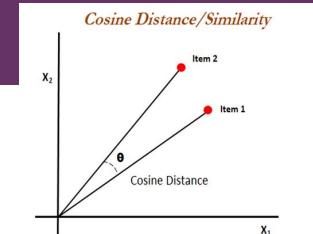
Recent experiments have shown that adding word 1-grams and 2-grams to the standard character 6-grams improves the Pearson correlation with direct human assessments. If you want to use only character n-grams, just set the word n-gram order to 0.

where CHRP and CHRR stand for character n -gram precision and recall arithmetically averaged over all n -grams:

- CHRP
percentage of n -grams in the hypothesis which have a counterpart in the reference;
- CHRR
percentage of character n -grams in the reference which are also present in the hypothesis.

and β is a parameter which assigns β times more importance to recall than to precision – if $\beta = 1$, they have the same importance.

Semantic Similarity



BERTScore

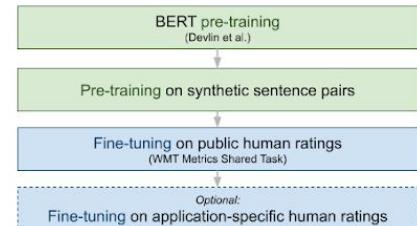
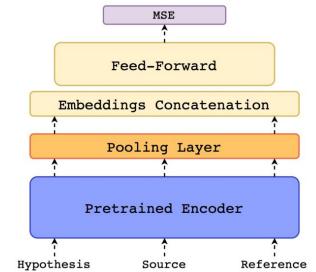
Analyzes cosine distances between BERT representations of machine translation and human reference. More robust against word reordering and paraphrasing. May be unreliable for terminologies underrepresented in BERT model.

COMET

Uses a neural model (i.e. XLM-RoBERTa + Pooling/Feed-Forward) to predict machine translation quality (use source input and reference translation). More correlated with human judgements than BLEU. May penalize paraphrases/synonyms.

BLEURT

Improves over BERTScore by fine-tuning on human evaluation scores (like MQM, DA) to predict translation quality with strong human correlation.



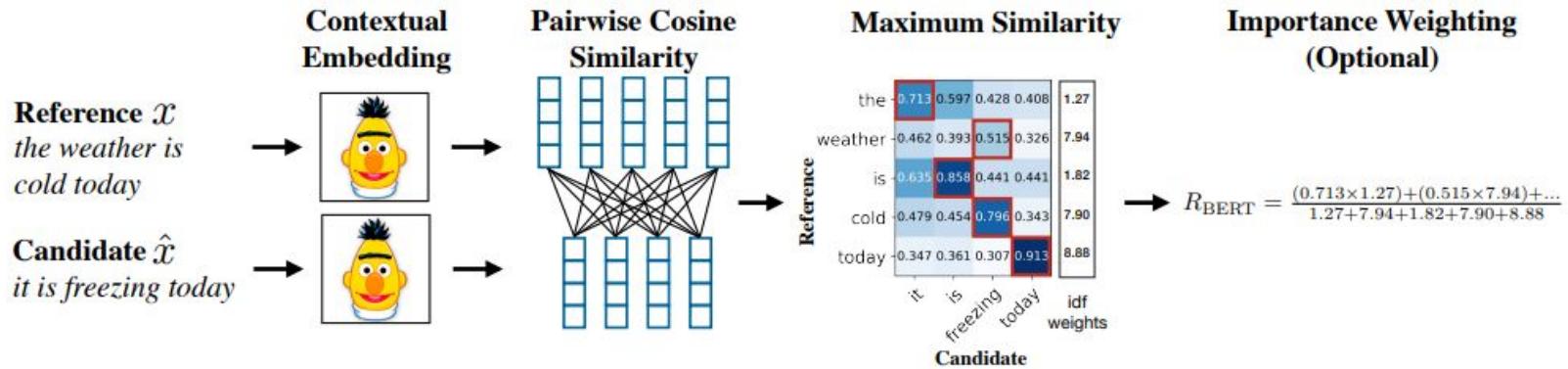
BERTScore

Introduced in 2020 ICLR Paper: Zhang et. al. [BERTScore: Evaluating Text Generation with BERT](#)

Uses **pre-trained BERT embeddings** to match words in candidate and reference with **cosine similarity**.

Shown to correlate with human judgment on sentence-level and system-level evaluation.

It's *semantic nature* can be useful for evaluating language generation tasks (instead of syntactic similarity).



BERTScore (cont.)

Matches each token x to \hat{x} to compute recall and \hat{x} to x to compute precision.
Uses greedy matching to maximize the matching similarity score (each token is matched to the most similar token in the other sentence).

F_1 is the harmonic mean of the two scores.

$$R_{\text{BERT}} = \frac{1}{|x|} \sum_{x_i \in x} \max_{\hat{x}_j \in \hat{x}} \mathbf{x}_i^\top \hat{\mathbf{x}}_j , \quad P_{\text{BERT}} = \frac{1}{|\hat{x}|} \sum_{\hat{x}_j \in \hat{x}} \max_{x_i \in x} \mathbf{x}_i^\top \hat{\mathbf{x}}_j , \quad F_{\text{BERT}} = 2 \frac{P_{\text{BERT}} \cdot R_{\text{BERT}}}{P_{\text{BERT}} + R_{\text{BERT}}} .$$

Importance Weighting

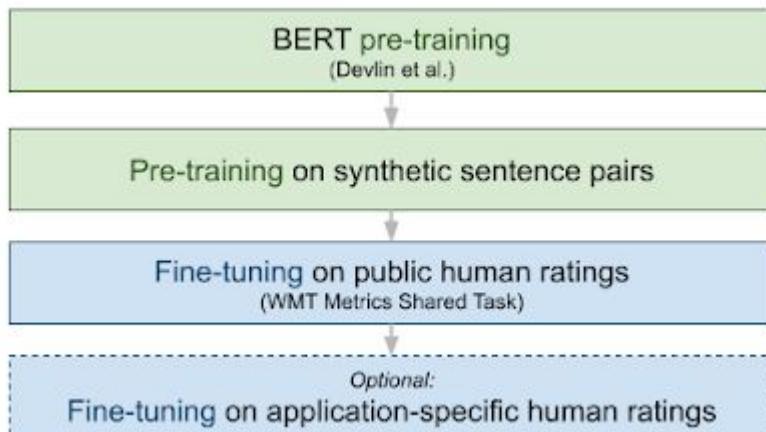
$$\text{idf}(w) = -\log \frac{1}{M} \sum_{i=1}^M \mathbb{I}[w \in x^{(i)}] ,$$

Rare words can be more indicative of sentence similarity than common words.

Inverse Document Frequency (IDF) score can be optionally used to put more weight on more rare words.

BLEURT (Bilingual Evaluation Understudy with Representations from Transformers)

Improves over BERTScore by fine-tuning on human evaluation scores (like MQM, DA) to predict translation quality with strong human correlation.



| Metric Name | Kendall Tau w. Human Ratings (mean of all to-English lang. pairs) |
|-----------------------------|--|
| sentenceBLEU | 22.7 |
| BERTscore w. BERT-large | 30.0 |
| YiSi1 SRL | 30.4 |
| ESIM | 31.6 |
| <i>BLEURT w. BERT-base</i> | 33.6 |
| <i>BLEURT w. BERT-large</i> | 33.8 |

BERTScore vs. BLEURT

- BERTScore: Computes cosine similarity between token embeddings in the reference and hypothesis.
- BLEURT: Uses a fine-tuned BERT model trained on human-rated translations, making it more aligned with human judgment.

| Feature | BERTScore | BLEURT |
|----------------------------|--|--|
| Full Name | BERT-based Sentence Similarity Score | Bilingual Evaluation Understudy with Representations from Transformers |
| Developed By | Columbia University | Google Research |
| Model Type | Uses pretrained BERT embeddings | Fine-tuned BERT with human ratings |
| Scoring Method | Measures cosine similarity between token embeddings | Uses a regression model trained on human evaluation data |
| Needs Fine-Tuning? | ✗ No | ✓ Yes (pretrained BLEURT models available) |
| Handles Synonyms? | ✓ Yes | ✓ Yes |
| Context-Aware? | ✓ Yes | ✓ Yes (More human-like) |
| Handles Fluency & Grammar? | ✗ No | ✓ Yes |
| Best For | General semantic similarity evaluation | Machine Translation (MT) & Text Generation evaluation |
| Performance | Works well for short sentences | Works well for longer texts |

Generated Translations:

1. Good Translation (High Similarity)

"The researcher released a pioneering study about global warming."

2. Bad Translation (Unrelated Meaning)

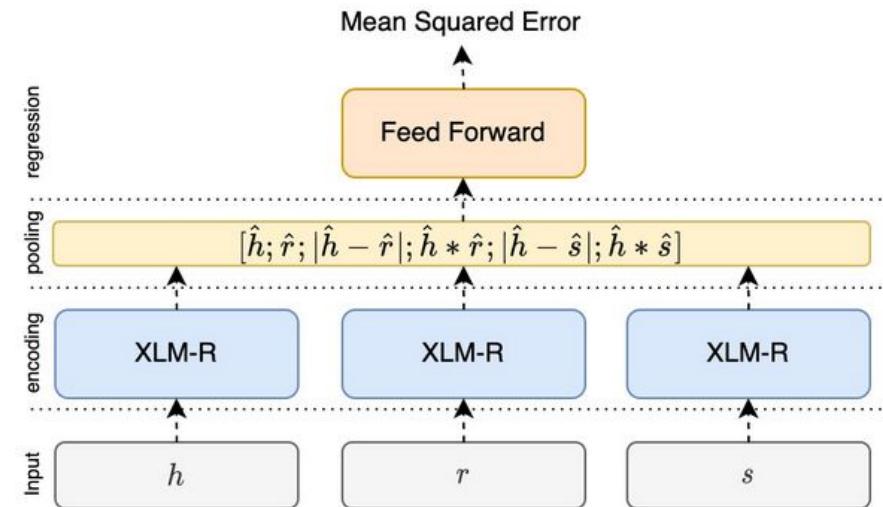
"A new book was written about space exploration."

(Expected Scores for Each Metric)

| Metric | Good Translation | Bad Translation |
|-----------|------------------|------------------|
| BERTScore | 0.92 (High) | 0.30 (Low) |
| BLEURT | 0.85 (High) | -0.20 (Very Low) |

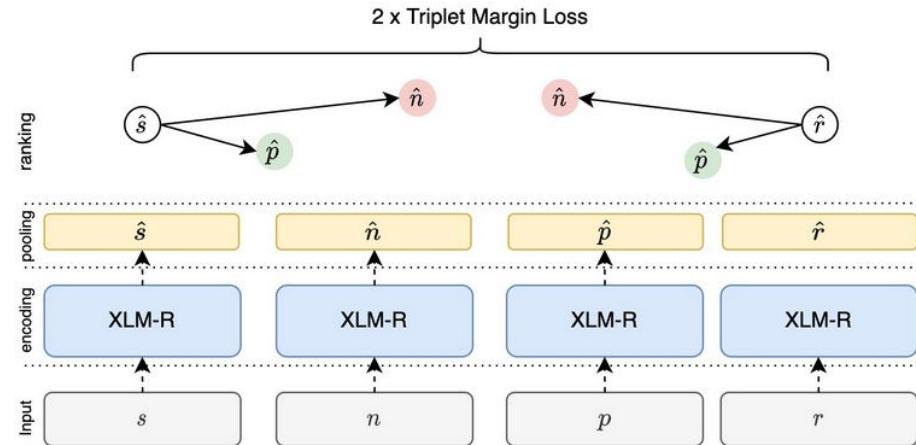
COMET (with reference): variation 1

- Given a hypothesis (prediction) h , a reference (answer) r , and a source s as inputs
- COMET uses a multilingual encoder (i.e. XLM-R) to extract the features from the inputs.
- Concatenate them and feed it to a feed-forward regressor.
- **The target score can be anything from humans, such as HTER or DA.**



COMET (with reference): variation 2

- With a different architecture, it can also **rank two different translations**
- Given a worse translation n , a better translation p , a reference (answer) r , and a source s as inputs
- COMET uses a multilingual encoder (i.e. XLM-R) to extract the features from the inputs.
- Optimizes on the triplet loss.



What if we don't have a reference (answer)?
Quality Estimation

Quality Estimation

An actively researched field where one attempts to **estimate the quality of a translation** *without* access to a reference translation.

This is a particularly hard task since neural networks are known to often be confident while giving wrong answers.

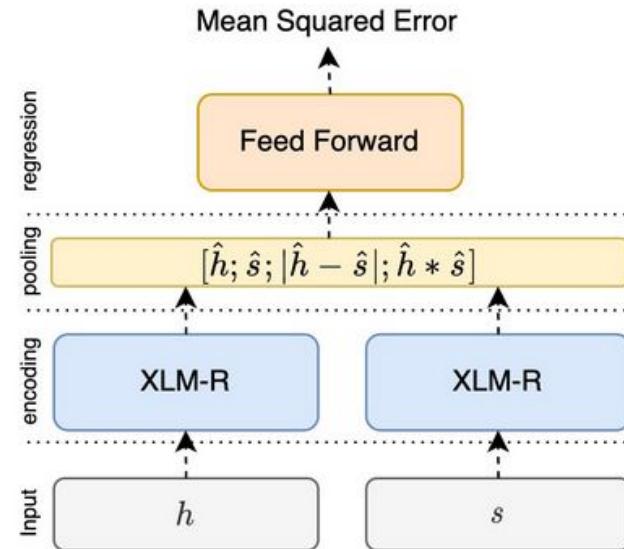
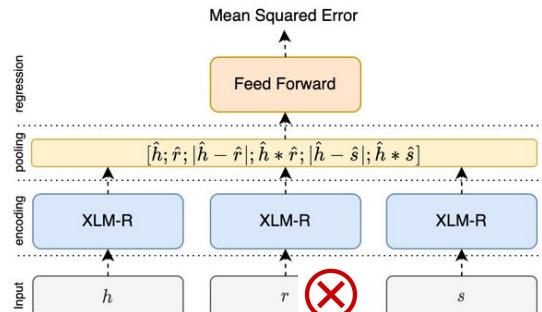
Even the best system does not exactly correlate with human judgement

| Encoder | Direct Assessment | | | | | | | | | | | | |
|---------------------------------------|-------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | km-en | ps-en | en-ja | en-cs | en-mr | ru-en | ro-en | en-zh | en-de | et-en | si-en | ne-en | avg. |
| <i>Baseline (Zerva et al., 2021)</i> | | | | | | | | | | | | | |
| XLM-R | 0.615 | 0.601 | 0.295 | 0.535 | 0.419 | 0.703 | 0.828 | 0.513 | 0.500 | 0.806 | 0.565 | 0.793 | 0.598 |
| <i>Pretrained models</i> | | | | | | | | | | | | | |
| InfoXLM | 0.619 | 0.603 | 0.328 | 0.510 | 0.462 | 0.731 | 0.829 | 0.554 | 0.516 | 0.803 | 0.561 | 0.777 | 0.608 |
| RemBERT | 0.600 | 0.621 | 0.338 | 0.525 | 0.447 | 0.680 | 0.818 | 0.487 | 0.491 | 0.810 | 0.525 | 0.747 | 0.591 |
| XLM-R | 0.610 | 0.579 | 0.325 | 0.503 | 0.405 | 0.715 | 0.832 | 0.541 | 0.514 | 0.782 | 0.540 | 0.740 | 0.591 |
| <i>Sentence-level only</i> | | | | | | | | | | | | | |
| XLM-R | 0.628 | 0.591 | 0.350 | 0.531 | 0.551 | 0.761 | 0.859 | 0.577 | 0.568 | 0.800 | 0.565 | 0.796 | 0.631 |
| InfoXLM | 0.629 | 0.623 | 0.348 | 0.515 | 0.574 | 0.747 | 0.858 | 0.586 | 0.551 | 0.828 | 0.568 | 0.790 | 0.635 |
| RemBERT | 0.634 | 0.631 | 0.346 | 0.570 | 0.564 | 0.754 | 0.862 | 0.534 | 0.531 | 0.822 | 0.550 | 0.782 | 0.632 |
| <i>Few-shot Language Adaptation</i> | | | | | | | | | | | | | |
| XLM-R | 0.650 | 0.619 | 0.352 | 0.551 | 0.546 | 0.753 | 0.852 | 0.571 | 0.554 | 0.813 | 0.562 | 0.798 | 0.635 |
| InfoXLM | 0.641 | 0.650 | 0.367 | 0.549 | 0.549 | 0.751 | 0.855 | 0.591 | 0.565 | 0.824 | 0.563 | 0.803 | 0.642 |
| RemBERT | 0.625 | 0.641 | 0.367 | 0.568 | 0.563 | 0.756 | 0.857 | 0.540 | 0.527 | 0.824 | 0.568 | 0.796 | 0.636 |
| <i>Sentence + word-level training</i> | | | | | | | | | | | | | |
| InfoXLM | 0.617 | 0.586 | 0.344 | 0.532 | 0.572 | 0.761 | 0.865 | 0.586 | 0.579 | 0.829 | 0.576 | 0.804 | 0.637 |
| RemBERT | 0.634 | 0.628 | 0.356 | 0.564 | 0.571 | 0.762 | 0.860 | 0.541 | 0.553 | 0.826 | 0.564 | 0.799 | 0.638 |
| <i>Few-shot Language Adaptation</i> | | | | | | | | | | | | | |
| InfoXLM | 0.643 | 0.632 | 0.335 | 0.557 | 0.560 | 0.766 | 0.860 | 0.575 | 0.582 | 0.833 | 0.578 | 0.809 | 0.644 |
| RemBERT | 0.644 | 0.645 | 0.356 | 0.567 | 0.568 | 0.759 | 0.856 | 0.545 | 0.552 | 0.835 | 0.561 | 0.804 | 0.641 |
| <i>Final Ensemble</i> | | | | | | | | | | | | | |
| Ensemble 6x | 0.664 | 0.669 | 0.380 | 0.591 | 0.593 | 0.782 | 0.871 | 0.597 | 0.593 | 0.845 | 0.588 | 0.820 | 0.666 |

Table 1: Results for sentence-level QE in terms of Spearman correlation for DA

COMET (without reference)

- Everything is the same with the first variation of COMET with reference, except you don't give it a reference text.
- Given a hypothesis h and a source s as inputs
- COMET uses a multilingual encoder (XLM-R) to extract the features from the inputs.
- Concatenate them and feed it to a feed-forward regressor.
- The target score can be anything from humans, such as HTER or DA.



Human Judgement

HTER

Human-targeted Translation Edit Rate: Similar to TER, but instead of using a fixed reference translation, it uses an edited version of the machine translation that has been manually corrected by a human.

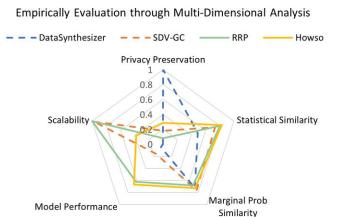
DA

Human annotators score translations on a continuous scale (0-100).

MQM

Multidimensional Quality Metrics is a more detailed framework used in professional translation assessment, assigning a score for each dimensions.

Although some of the loans did achieve their intended aims, many went to the funding of large projects that were not well matched to the needs of the countries in which the projects were undertaken. Moreover, the funds intended for development projects often were diverted either to local elites or to the operations of military dictatorships. Many of the loans had been made at floating interest rates, so their repayment became very difficult when worldwide interest rates rose circa 1980. Repayment was made even more difficult by falling commodity prices and by the fact that the loans themselves had often not been put to any productive use.



Human Evaluation

Human judgements of MT quality usually come in the form of segment-level scores, such as:

1. Human-targeted Translation Edit Rate (HTER) [1]

- a. the MT outputs are manually corrected (#edit)
- b. then the original outputs are compared to the edited ones by computing TER.

$$\text{TER} = \frac{\text{\# of edits}}{\text{average \# of reference words}}$$

2. Direct Assessment (DA)

- a. A quality score (satisfaction score) of 0 to 100 is given for a translation by human

3. Multidimensional Quality Metrics (MQM)

| A | B | C | D | E | F | G | H |
|------------------------|--|------------------------|--------------|-------|----------|--------------------------|-------|
| 1 | MQM Scorecard: Top-Level Error Typology with 4 Severity Levels | | | | | | |
| Error Severity Levels: | | | | | | | |
| 4 | Severity Penalty Multipliers: | Neutral | Minor | Major | Critical | Error Type Penalty Total | |
| 5 | ET Nos | Error Types | Error Counts | | | ET Weights | ETPTs |
| 6 | 1 | Terminology | 2 | 7 | 7 | 0 | 1.0 |
| 7 | 2 | Accuracy | 4 | 14 | 7 | 1 | 1.0 |
| 8 | 3 | Linguistic conventions | 1 | 23 | 9 | 0 | 1.0 |
| | | | | | | | 42.0 |
| | | | | | | | 74.0 |
| | | | | | | | 68.0 |

| A | B | C | D | E | F | G | H |
|----|--|--------------------------------|---------------------|-------|----------|--------------------------------------|--------|
| 1 | MQM Scorecard: Top-Level Error Typology with 4 Severity Levels | | | | | | |
| 2 | | | | | | | |
| 3 | <i>Error Severity Levels:</i> | Neutral | Minor | Major | Critical | <i>Error Type Penalty Total</i> | |
| 4 | <i>Severity Penalty Multipliers:</i> | 0 | 1 | 5 | 25 | | |
| 5 | ET Nos | Error Types | <i>Error Counts</i> | | | ET Weights | ETPTs |
| 6 | 1 | Terminology | 2 | 7 | 7 | 0 | 1.0 |
| 7 | 2 | Accuracy | 4 | 14 | 7 | 1 | 1.0 |
| 8 | 3 | Linguistic conventions | 1 | 23 | 9 | 0 | 1.0 |
| 9 | 4 | Style | 5 | 7 | 3 | 0 | 1.0 |
| 10 | 5 | Locale convention | 1 | 12 | 5 | 0 | 1.0 |
| 11 | 6 | Audience appropriateness | 0 | 2 | 1 | 0 | 1.0 |
| 12 | 7 | Design and markup | 0 | 6 | 1 | 0 | 1.0 |
| 13 | 8 | Custom | | | | | |
| 14 | | | | | | Absolute Penalty Total: | 261.00 |
| 15 | | | | | | | |
| 16 | | Evaluation Word Count: | 10184 | | | Per-Word Penalty Total: | 0.0256 |
| 17 | | Reference Word Count: | 1000 | | | Overall Normed Penalty Total: | 25.63 |
| 18 | | Scaling Parameter (SP): | 1.00 | | | Overall Quality Score: | 97.44 |
| 19 | | Max. Score Value: | 100.00 | | | | |
| 20 | | Threshold Value: | 85.00 | | | Pass/Fail Rating: | Pass |

Figure 1: Scorecard with Top-Level MQM Error Types

| MQM Scorecard: Top-Level Error Typology with 4 Severity Levels | | | | | | |
|--|--------------------------------|--------------|-------|-------|-------------------------|-----------------------------------|
| | Error Severity Levels: | Neutral | Minor | Major | Critical | Error Type Penalty Total |
| | Severity Priority Multipliers: | 0 | 1 | 5 | 25 | |
| ET Nos | Error Types | Error Counts | | | ET Weights | ETPTs |
| 1 | Terminology | 2 | 7 | 7 | 0 | 42.0 |
| 2 | Accuracy | 4 | 14 | 7 | 1 | 74.0 |
| 3 | Linguistic conventions | 1 | 23 | 9 | 0 | 58.0 |
| 4 | Style | 5 | 7 | 3 | 0 | 22.0 |
| 5 | Locale convention | 1 | 12 | 5 | 0 | 37.0 |
| 6 | Audience appropriateness | 0 | 2 | 1 | 0 | 7.0 |
| 7 | Design and markup | 0 | 6 | 1 | 0 | 11.0 |
| 8 | Custom | | | | | |
| | | | | | Absolute Penalty Total: | 261.00 |
| | | | | | Per Word Penalty Total: | 0.0256 |
| | Evaluation Word Count: | 10184 | | | | 261 / 10184 |
| | Reference Word Count: | 1900 | | | | Overall Normalised Penalty Total: |
| | Scaling Parameter (SP) | 1.00 | | | | 25.83 |
| | Max. Score Value: | 300.00 | | | | Overall Quality Score: |
| | Threshold Value: | 85.00 | | | | 97.44 |
| | | | | | | Pass/Fail Rating: |
| | | | | | | Pass |

Figure 5: Scorecard with Top-Level MQM Error Types

The scorecard can be confusing on first glance. It is important to understand how different values interact on the scorecard, how an evaluator uses the card, and how the math functions.

$$100 \times (1 - 0.0256)$$

Which Scores to Use?

- **BLEU & ROUGE (syntactic)** → If you need a quick, traditional metric.
- **METEOR (syntactic)** → If BLEU seems too rigid (captures synonyms), languages with WordNet support.
 - Language with WordNet support:
English, Spanish, French, German

| Language | Exact Match | Stem Match | Synonym Match | Paraphrase Match | Tuned Parameters |
|----------|-------------|------------|---------------|------------------|------------------|
| English | Yes | Yes | Yes | Yes | Yes |
| Arabic | Yes | No | No | Yes | Yes |
| Czech | Yes | No | No | Yes | Yes |
| French | Yes | Yes | No | Yes | Yes |
| German | Yes | Yes | No | Yes | Yes |
| Spanish | Yes | Yes | No | Yes | Yes |

- **ChrF (syntactic)** → F1-Score for unsupported languages & morphologically rich languages (Thai)
- **BERTScore / COMET / BLEURT (semantic)** → If you care about semantic meaning.
- **Human Evaluation** (HTER, MQM, DA) (human) → Best for high-quality MT assessment.

METEOR supported languages <https://www.cs.cmu.edu/~alavie/METEOR/README.html>

Which Scores to Use?

- A paper from Microsoft [1] advocates for **COMET** and **ChrF** (for automatic metrics).

To Ship or Not to Ship:
An Extensive Evaluation of Automatic Metrics for Machine Translation

| | | | | | |
|--|------------------------|-----------------------|---------------------------|------------------------|-----------------|
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Abstract

Automatic metrics are commonly used as the exclusive tool for declaring the superiority of one machine translation system's quality over another. The community choice of automatic metric guides research directions and industrial developments by deciding which models are deemed better. Evaluating metrics correlations with sets of human judgements has been limited by the size of these sets. In this paper, we corroborate how reliable metrics are in contrast to human judgements on – to the errors (Freitag et al., 2021), and thus may mislead system development by incorrect judgements. Therefore, it is important to study the reliability of automatic metrics and follow best practices for the automatic evaluation of systems.

Significant research effort has been applied to evaluate automatic metrics in the past decade, including annual metrics evaluation at the WMT conference and other studies (Callison-Burch et al., 2007; Przybocki et al., 2009; Stanojević et al., 2015; Mathur et al., 2020b). Most research has fo-

Based on our findings, we suggest the following best practices for the use of automatic metrics:

1. Use a pretrained metric as the main automatic metric; we recommend COMET. Use a string-based metric for unsupported languages and as a secondary metric, for instance ChrF. Do not use BLEU, it is inferior to other metrics, and it has been overused.