AutoML Translation (https://cloud.google.com/translate/automl/) Documentation

# Evaluating models

After training a model, AutoML Translation uses items from the VALIDATION and TEST sets (https://cloud.google.com/translate/automl/docs/prepare) to evaluate the quality and accuracy of the new model. AutoML Translation expresses the model quality using its BLEU (Bilingual Evaluation Understudy) score (#bleu), which indicates how similar the candidate text is to the reference texts, with values closer to one representing more similar texts.

The BLEU score provides an overall assessment of model quality. You can also evaluate the model output for specific data items by exporting the TEST set (#export) with the model predictions. The exported data includes both the reference text (from the original dataset) and the model's candidate text.

Use this data to evaluate your model's readiness. If you're not happy with the quality level, consider adding more (and more diverse) training sentence pairs. One option is to add more sentence pairs. Use the **Add Files** link in the title bar. Once you've added files, train a new model by clicking the **Train New Model** button on the **Train** page. Repeat this process until you reach a high enough quality level.

## Getting the model evaluation

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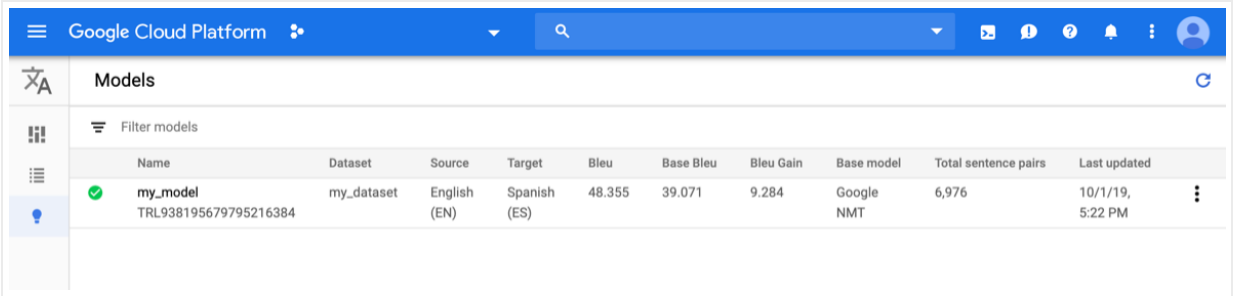
1. Open the AutoML Translation UI (https://console.cloud.google.com/translation) and click the lightbulb icon next to **Models** in the left navigation bar. The available models are displayed. For each model, the following information is included: Dataset (from which the model was trained), Source (language), Target (language), Base model (used to train the model).




To view the models for a different project, select the project from the drop-down list in the upper bar.

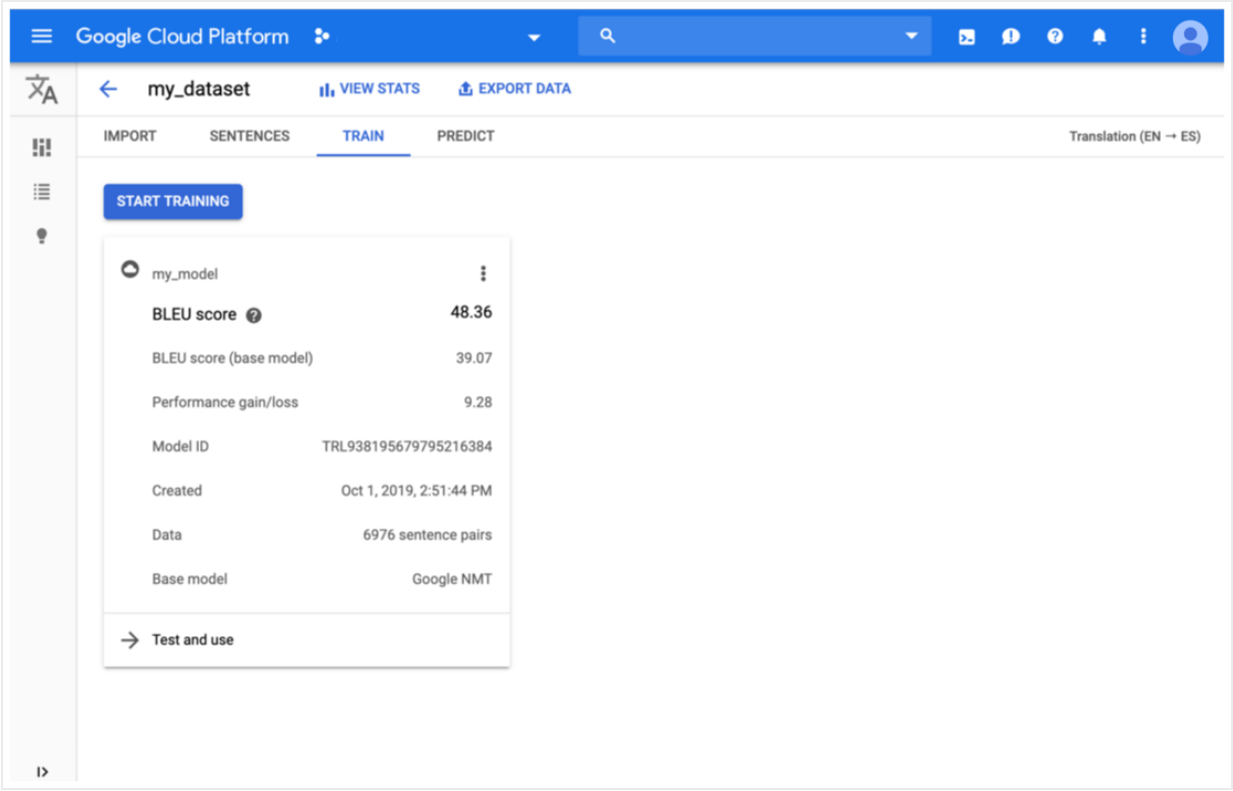
2. Click the row for the model you want to evaluate.

   The **Predict** tab operns.

   Here, you can test your model and see the results for both custom model and the base model you used to train with.

3. Click the **Train** tab just below the title bar.

   When training has completed for the model, AutoML Translation shows its evaluation metrics.



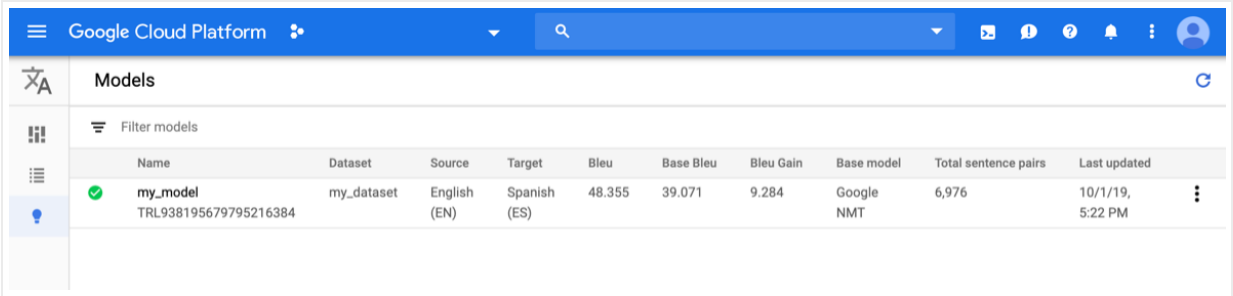

## Exporting test data with model predictions

After training a model, AutoML Translation uses items from the TEST set (https://cloud.google.com/translate/automl/docs/prepare) to evaluate the quality and accuracy of the new model. From the AutoML Translation UI, you can export the TEST set to see how the model output compares to the reference text from the original dataset. AutoML Translation saves a TSV file to your Google Cloud Storage bucket, where each row has this format:

`Source sentence` *tab* `Reference translation` *tab* `Model candidate translation`

WEB UI

1. Open the AutoML Translation UI (https://console.cloud.google.com/translation) and click the lightbulb icon to the left of "Models" in the left navigation bar to display the available models.




   To view the models for a different project, select the project from the drop-down list in the upper right of the title bar.

2. Select the model.
3. Click the **Export Data** button in the title bar.
4. Enter the full path to the Google Cloud Storage bucket where you want to save the exported .tsv file.

   You must use a bucket associated with the current project.

5. Choose the model whose TEST data you want to export.

   The **Testing set with model predictions** drop-down list lists the models trained using the same input dataset.

6. Click **Export**.

   AutoML Translation writes a file named ***model-name*`_evaluated.tsv`** in the specified Google Cloud Storage bucket.

## Understanding the BLEU Score

BLEU (**Bi**L**i**ngual **E**valuation **U**nderstudy) (https://en.wikipedia.org/wiki/BLEU) is a metric for automatically evaluating machine-translated text. The BLEU score is a number between zero and one that measures the similarity of the machine-translated text to a set of high quality reference translations. A value of 0 means that the machine-translated output has no overlap with the reference translation (low quality) while a value of 1 means there is perfect overlap with the reference translations (high quality).

It has been shown that BLEU scores correlate well with human judgment of translation quality. Note that even human translators do not achieve a perfect score of 1.0.

AutoML expresses BLEU scores as a percentage rather than a decimal between 0 and 1.

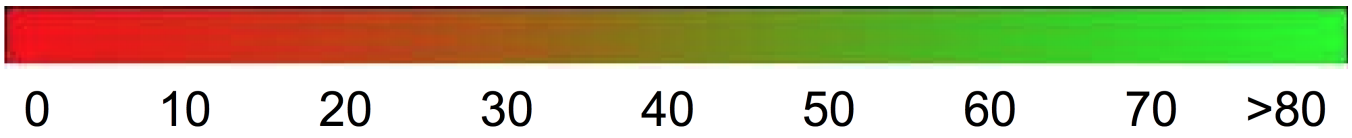
## Interpretation

Trying to compare BLEU scores across different corpora and languages is strongly discouraged. Even comparing BLEU scores for the same corpus but with different numbers of reference translations can be highly misleading.

However, as a rough guideline, the following interpretation of BLEU scores (expressed as percentages rather than decimals) might be helpful.

| BLEU Score | Interpretation |
|---|---|
| < 10 | Almost useless |
| 10 - 19 | Hard to get the gist |
| 20 - 29 | The gist is clear, but has significant grammatical errors |
| 30 - 40 | Understandable to good translations |
| 40 - 50 | High quality translations |
| 50 - 60 | Very high quality, adequate, and fluent translations |
| > 60 | Quality often better than human |

The following color gradient can be used as a general scale interpretation of the BLEU score (https://www.cs.cmu.edu/%7Ealavie/Presentations/MT-Evaluation-MT-Summit-Tutorial-19Sep11.pdf):




## The mathematical details

Mathematically, the BLEU score is defined as:

$$\text{BLEU} = \min\left(1, \exp\left(1 - \frac{\text{reference-length}}{\text{output-length}}\right)\right)\left(\prod_{i=1}^{4} precision_i\right)^{1/4}$$

$$\underbrace{\qquad\qquad}_{\text{brevity penalty}} \qquad\qquad \underbrace{\qquad\qquad}_{\text{n-gram overlap}}$$

Processing math: 100%

with

$$precision_i = \frac{\sum_{\text{snt} \in \text{Cand-Corpus}} \sum_{i \in \text{snt}} \min\left(m^i_{cand}, m^i_{ref}\right)}{w^i_t = \sum_{\text{snt}' \in \text{Cand-Corpus}} \sum_{i' \in \text{snt}'} m^{i'}_{cand}}$$

where

- $m^i_{cand}$ is the count of i-gram in candidate matching the reference translation
- $m^i_{ref}$ is the count of i-gram in the reference translation
- $w^i_t$ is the total number of i-grams in candidate translation

The formula consists of two parts: the brevity penalty and the n-gram overlap.

- **Brevity Penalty**
  The brevity penalty penalizes generated translations that are too short compared to the closest reference length with an exponential decay. The brevity penalty compensates for the fact that the BLEU score has no recall (https://developers.google.com/machine-learning/crash-course/glossary#recall) term.
- **N-Gram Overlap**
  The n-gram overlap counts how many unigrams, bigrams, trigrams, and four-grams ($i$=1,...,4) match their n-gram counterpart in the reference translations. This term acts as a precision (https://developers.google.com/machine-learning/crash-course/glossary#precision) metric. Unigrams account for *adequacy* while longer n-grams account for *fluency* of the translation. To avoid overcounting, the n-gram counts are clipped to the maximal n-gram count occurring in the reference ($m^n_{ref}$).

## Examples

### Calculating $precision_1$

Consider this reference sentence and candidate translation:

**Reference:** `the cat is on the mat`
**Candidate:** `the the the cat mat`

The first step is to count the occurrences of each unigram in the reference and the candidate. etric is case-sensitive.

| Unigram | $m^i_{cand}$ | $m^i_{ref}$ | $\min(m^i_{cand}, m^i_{ref})$ |
|---|---|---|---|
| the | 3 | 2 | 2 |
| cat | 1 | 1 | 1 |
| is | 0 | 1 | 0 |
| on | 0 | 1 | 0 |
| mat | 1 | 1 | 1 |

The total number of unigrams in the candidate ($w^1_t$) is 5, so $precision_1$ = (2 + 1 + 1)/5 = 0.8.

### Calculating the BLEU score

**Reference:** `The NASA Opportunity rover is battling a massive dust storm on Mars .`
**Candidate 1:** `The Opportunity rover is combating a big sandstorm on Mars .`
**Candidate 2:** `A NASA rover is fighting a massive storm on Mars .`

The above example consists of a single reference and two candidate translations. The sentences are tokenized prior to computing the BLEU score as depicted above; for example, the final period is counted as a separate token.

To compute the BLEU score for each translation, we compute the following statistics.

- **N-Gram Precisions**
  The following table contains the n-gram precisions for both candidates.
- **Brevity-Penalty**
  The brevity-penalty is the same for candidate 1 and candidate 2 since both sentences consist of 11 tokens.
- **BLEU-Score**
  Note that at least one matching 4-gram is required to get a BLEU score > 0. Since candidate translation 1 has no matching 4-gram, it has a BLEU score of 0.

| Metric | Candidate 1 | Candidate 2 |
|---|---|---|
| $precision_1$ (1gram) | 8/11 | 9/11 |
| Processing math: 100% | 4/10 | 5/10 |

| Metric | Candidate 1 | Candidate 2 |
|---|---|---|
| $precision_3$ (3gram) | 1/9 | 2/9 |
| $precision_4$ (4gram) | 0/8 | 1/8 |
| Brevity-Penalty | 0.83 | 0.83 |
| **BLEU-Score** | **0.0** | **0.27** |

## Properties

- **BLEU is a Corpus-based Metric**
  The BLEU metric performs badly when used to evaluate individual sentences. For example, both example sentences get very low BLEU scores even though they capture most of the meaning. Because n-gram statistics for individual sentences are less meaningful, BLEU is by design a corpus-based metric; that is, statistics are accumulated over an entire corpus when computing the score. Note that the BLEU metric defined above cannot be factorized for individual sentences.
- **No distinction between content and function words**
  The BLEU metric does not distinguish between content and function words, that is, a dropped function word like "a" gets the same penalty as if the name "NASA" were erroneously replaced with "ESA".
- **Not good at capturing meaning and grammaticality of a sentence**
  The drop of a single word like "not" can change the polarity of a sentence. Also, taking only n-grams into account with n≤4 ignores long-range dependencies and thus BLEU often imposes only a small penalty for ungrammatical sentences.
- **Normalization and Tokenization**
  Prior to computing the BLEU score, both the reference and candidate translations are normalized and tokenized. The choice of normalization and tokenization steps significantly affect the final BLEU score.

*Last updated January 9, 2020.*