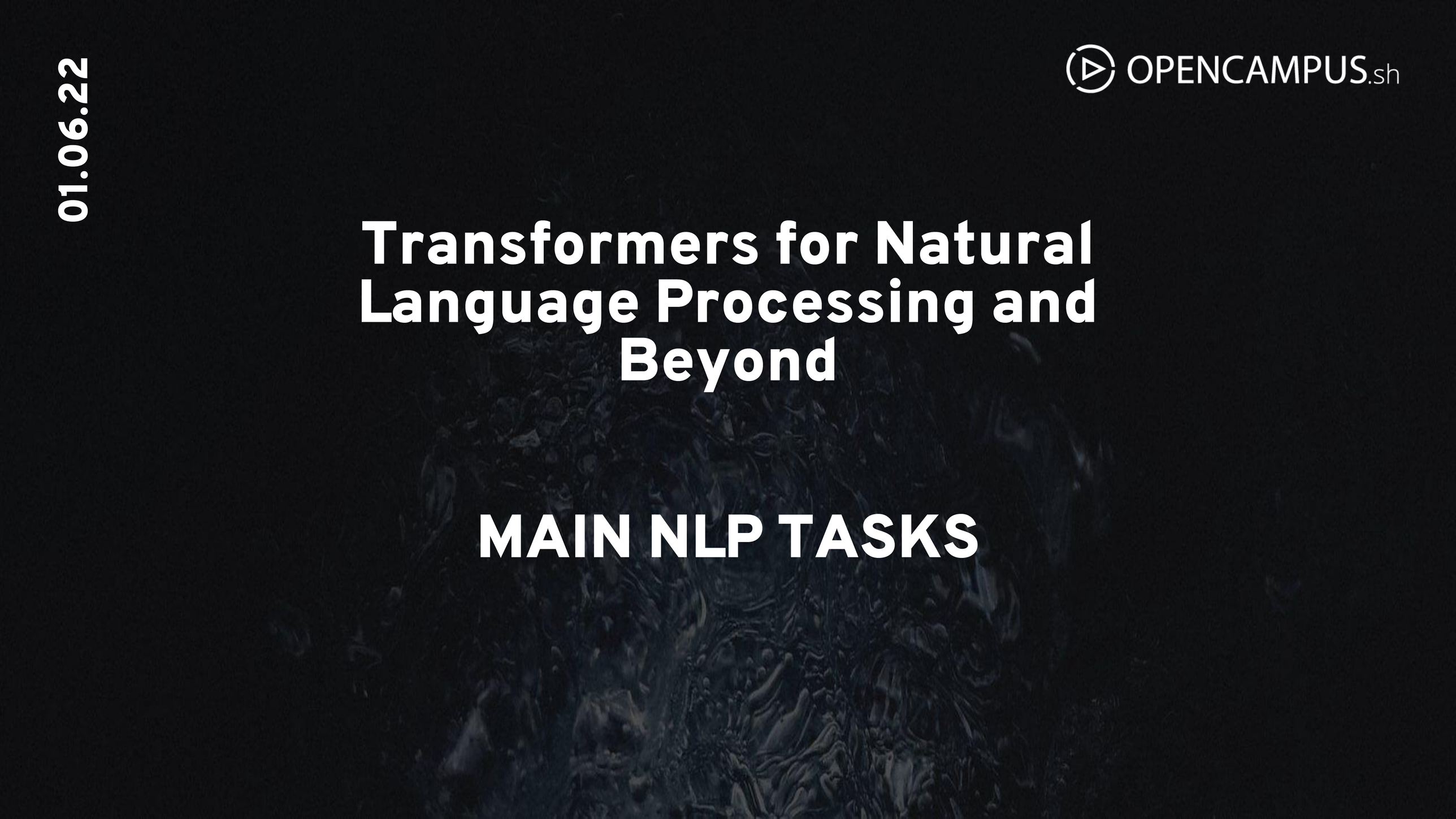
01.06.22

OPENCAMPUS.sh

Transformers for Natural Language Processing and Beyond

MAIN NLP TASKS



- Summary Main NLP Tasks
- Review Baseline Models
- Evaluation Metrics

MAIN NLP TASKS

- Token classification
- Fine-tuning a masked language model
- Translation
- Summarization
- Training a causal language model from scratch
- Question answering

TOKEN CLASSIFICATION

- Named entity recognition (NER)
- Part-of-speech tagging (POS)
- Chunking

PREPROCESSING

- Tell a tokenizer to ignore a word („0-Label“) by giving it a value of „-100“
- DataCollatorForTokenClassification():
  - Applies dynamic padding using the specified tokenizer
  - Default is to provide a value of -100 for each padded input
  - In comparison to DataCollatorForPadding() also pads the labels

Tokens assigned with the label “-100” are ignored when calculating the loss.
However, this is only true for the internal loss function of the chosen transformer model.

TRAINING THE MODEL

```
num_epochs = 3
num_train_steps = len(tf_train_dataset) * num_epochs

optimizer, schedule = create_optimizer(
    init_lr=2e-5,
    num_warmup_steps=0,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

FINE-TUNING A MASKED LANGUAGE MODEL

- Main purpose: Domain adaption
- Unsupervised Training on a large corpus from the more special domain
- Typically, training for 1 epoch

PREPROCESSING

- **A common step is to concatenate all examples (using a special EOS token between the actual samples) and then split the whole corpus into chunks of equal size.**
- **The size of the chunks depend on the amount of GPU memory available and on the model's maximum context size. (As, e.g., given by** `tokenizer.model_max_length()`**).**
- **After chunking** `DataCollatorForLanguageModeling()` **can be used to create randomly selected** `[MASKED]` **tokens**
- **For, e.g., whole word masking you have to implement you own data collator.**

TRAINING THE MODEL

```
num_train_steps = len(tf_train_dataset)

optimizer, schedule = create_optimizer(
    init_lr=2e-5,
    num_warmup_steps=1_000,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

TRANSLATION

A sequence-to-sequence task, similar to:

- Summarization
- Style transfer (e.g., formal to casual or Shakespearean English to modern English)
- Generative question answering (Generates answers to questions, given a context)

Used metric is typically the BLUE score (or sacreBLUE)

PREPROCESSING

- **Tokenization of input *and* targets using a Python context manager:**

```
en_sentence = split_datasets["train"][1]["translation"]["en"]
fr_sentence = split_datasets["train"][1]["translation"]["fr"]

inputs = tokenizer(en_sentence)
with tokenizer.as_target_tokenizer():
    targets = tokenizer(fr_sentence)
```

- **Using** `DataCollatorForSeq2Seq()`:
  - **Padding the encoder input sequence as usual**
  - **Padding the labels with “-100”**
  - **Setting the decoder input sequence equal to the labels but shifted one position to the left**

TRAINING THE MODEL

```
num_epochs = 3
num_train_steps = len(tf_train_dataset) * num_epochs

optimizer, schedule = create_optimizer(
    init_lr=5e-5,
    num_warmup_steps=0,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

SUMMARIZATION

- Preprocessing is equal to translation
- Seems to need fine-tuning for quite a few epochs (8 in the example)
- Used metric is typically the ROUGE score

TRAINING THE MODEL

```
num_train_epochs = 8
num_train_steps = len(tf_train_dataset) * num_train_epochs

optimizer, schedule = create_optimizer(
    init_lr=5.6e-5,
    num_warmup_steps=0,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

TRAINING A CAUSAL LANGUAGE MODEL FROM SCRATCH

- Any plain text dataset with a tokenizer can be used for training
- Common metrics are:
  - Perplexity
  - Cross Entropy

PREPROCESSING

- **Concatenate all examples and then split them into chunks of equal size (see “Fine-Tuning a Masked language Model”).**
- **Remove the last chunk if is shorter than max length to avoid padding issues**
- **After chunking** `DataCollatorForLanguageModeling()` **can be used with argument** `mlm=False`

TRAINING THE MODEL

```
num_train_steps = len(tf_train_dataset)
optimizer, schedule = create_optimizer(
    init_lr=5e-5,
    num_warmup_steps=1_000,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

QUESTION ANSWERING

- Encoder models are good for extractive question answering

- Alternative is generative question answering using:
  - a decoder model or
  - an encoder-decoder model (more similar to text summarization)

- Common metrics are:
  - Exact Match
  - F1-Score

PREPROCESSING

- **For training only one correct answer is defined.**
  (For evaluation multiple corrects answers are provided.)
- **Long contexts are split with about 50% overlap, the questions remain equal for all splits.**
- **Labels for the splits have to be provided via a custom function; thereafter the** `DefaultDataCollator()` **is used.**

TRAINING THE MODEL

```
num_train_epochs = 3
num_train_steps = len(tf_train_dataset) * num_train_epochs

optimizer, schedule = create_optimizer(
    init_lr=2e-5,
    num_warmup_steps=0,
    num_train_steps=num_train_steps,
    weight_decay_rate=0.01,
)
```

POSSIBLE TYPES OF BASELINE MODELS

- **Linear Regression**
  A solid first approach for predicting continuous values (prices, age, ...) from a set of features.
- **Logistic Regression**
  When trying to classify structured data or natural language, logistic regressions will usually give you quick, solid results.
- **Gradient Boosted Trees**
  A Kaggle classic! For time series predictions and general structured data, it is hard to beat Gradient Boosted Trees. While slightly harder to interpret than other baselines, they usually perform very well.
- **Simple Convolutional Architecture**
  Fine tuning VGG or re-training some variant of a U-net is usually a great start for most image classification, detection, or segmentation problems.

IF THERE IS NO EFFECTIVE BASELINE

- Instead of simplifying the model, simplify the data.
- Try to get your complex model to overfit to a very small subset of your data.

BASELINE MODEL RESULTS

Help you understand your data:

- **Which classes are harder to separate?**
- **What type of signal picks your model up on?**
  How is your model making decisions?
- **What signal is your model missing?**
  Is it possible to engineer an additional feature?

PROJECT MILESTONES

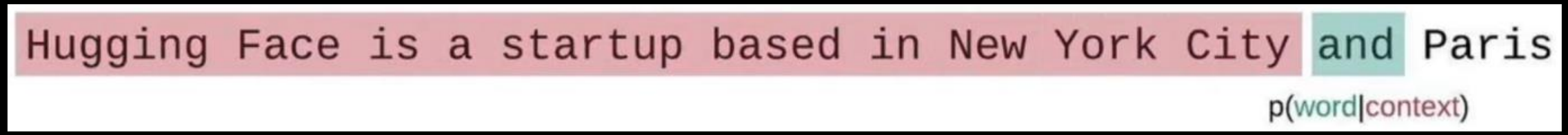
- 11.05. Form project groups
- 18.05. Literature review
- 25.05. Dataset characteristics
- 01.06. Baseline model
- 08.06. Model & model evaluation (Joint Coding)
- 15.06. Project presentations

EVALUATION METRICS FOR LANGUAGE MODELS

- BLUE Score
- ROUGE Score
- (Log-) Perplexity

LIKELIHOOD OF A SEQUENCE

$$P(X) = \prod_{i=0}^{t} p(x_i \mid x_{<i})$$



HuggingFace. (2021, November 15). *What is perplexity?* https://www.youtube.com/watch?v=NURcDHhYe98

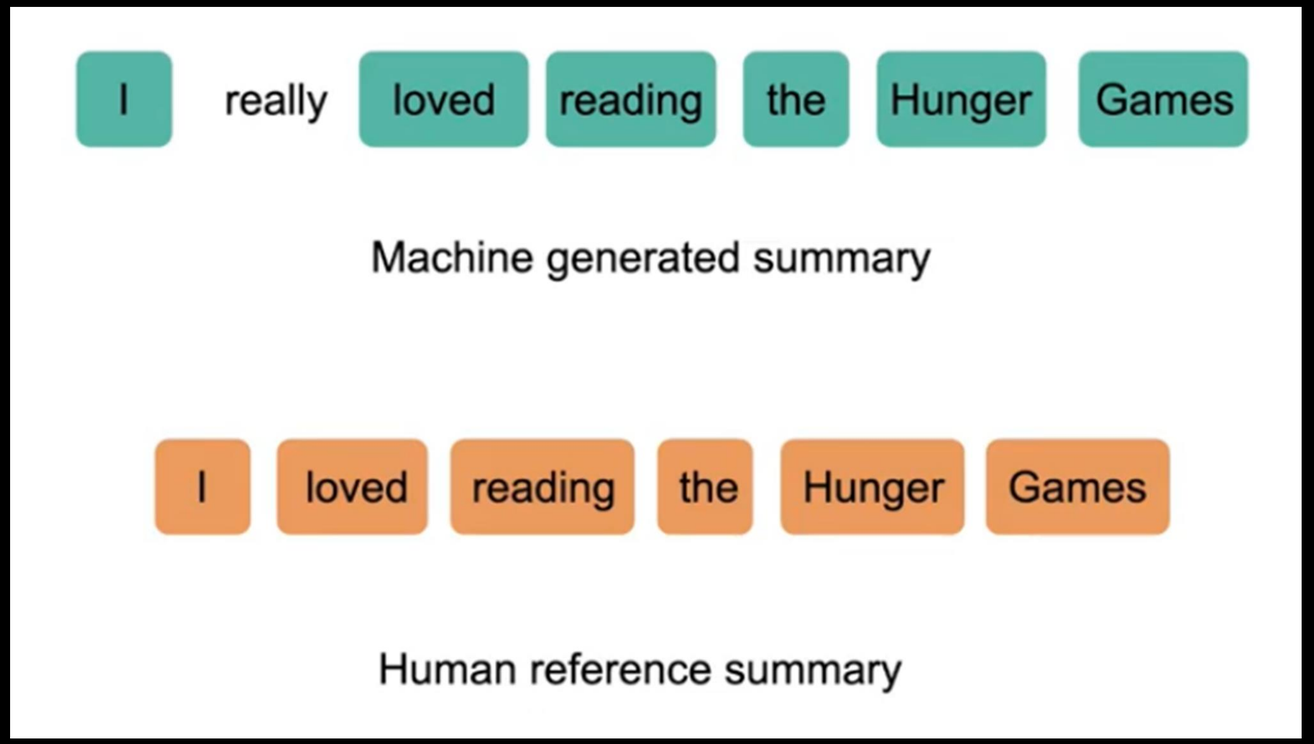
CROSS-ENTROPY

$$CE(X) = -\frac{1}{t}\log P(X)$$

LOG-PERPLEXITY

$$
\begin{aligned}
PPL(X) &= e^{CE(X)} \\
&= e^{-\frac{1}{t}\sum_{i=0}^{t}\log p(x_i|x_{<i})}
\end{aligned}
$$

ROUGE- 1 SCORE



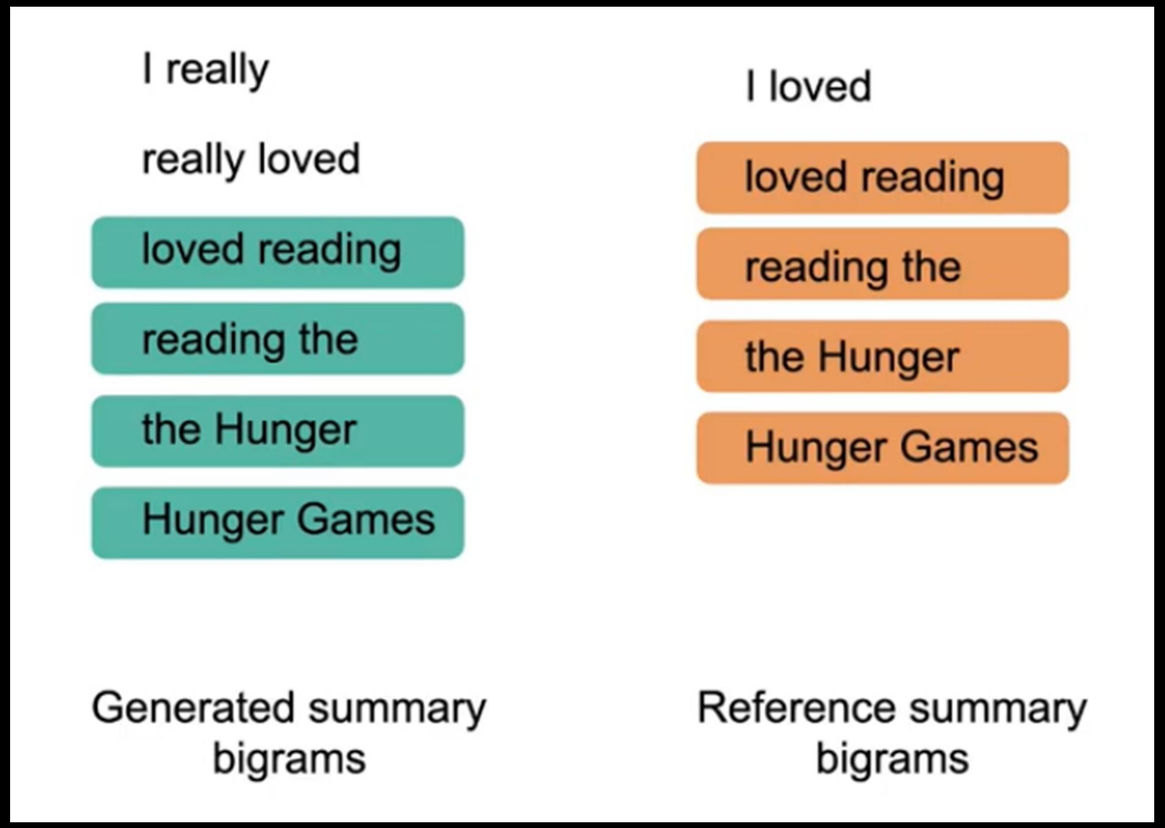
$$\text{ROUGE-1 recall} = \frac{\text{Num word matches}}{\text{Num words in reference}} = \frac{6}{6}$$

$$\text{ROUGE-1 precision} = \frac{\text{Num word matches}}{\text{Num words in summary}} = \frac{6}{7}$$

$$\text{ROUGE-1 F1-score} = 2\left(\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}\right)$$

HuggingFace. (2021, November 15). *What is the ROUGE metric?* https://www.youtube.com/watch?v=TMshhnrEXIg

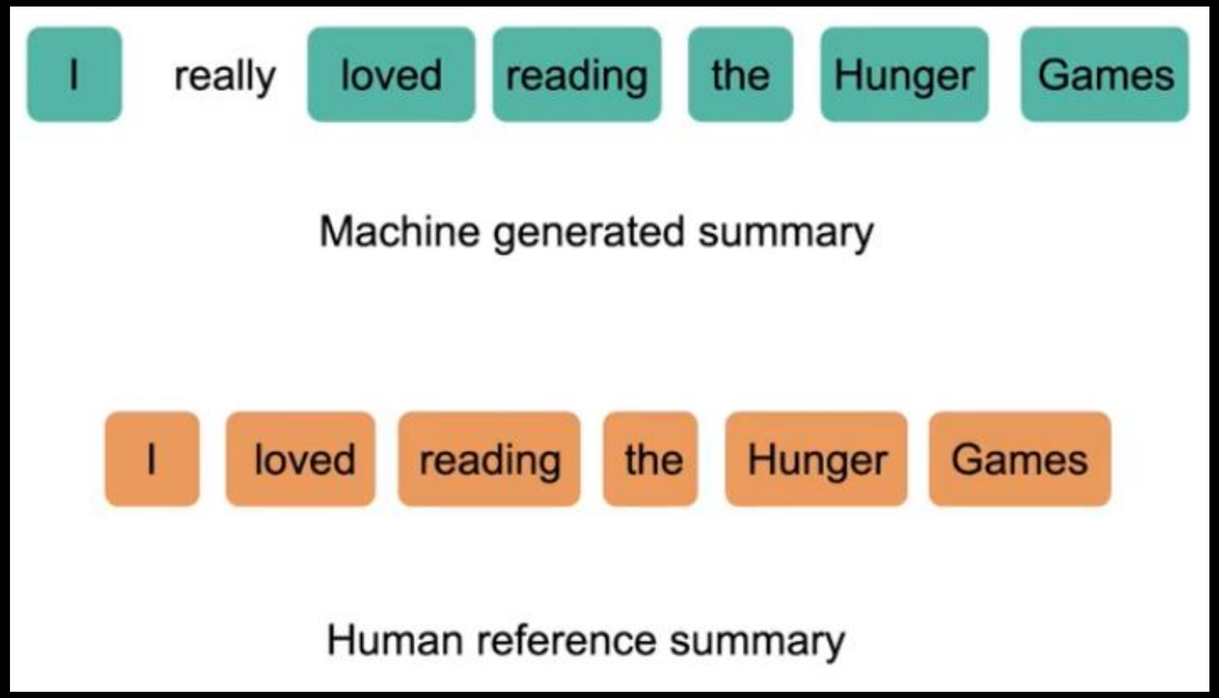
ROUGE-2 SCORE



$$\text{ROUGE-2 recall} = \frac{\text{Num bigram matches}}{\text{Num bigrams in reference}} = \frac{4}{5}$$

$$\text{ROUGE-2 precision} = \frac{\text{Num bigram matches}}{\text{Num bigram in summary}} = \frac{4}{6}$$

ROUGE-L SCORE



$$\text{ROUGE-L}_{\text{recall}} = \frac{\text{LCS(gen, ref)}}{\text{Num words in reference}} = \frac{6}{6}$$

$$\text{ROUGE-L}_{\text{precision}} = \frac{\text{LCS(gen, ref)}}{\text{Num words in summary}} = \frac{6}{7}$$


What is the BLEU metric?
with Lewis

MIXED PRECISION TRAINING

- **Use of both 16-bit and 32-bit floating-point types to train faster and use less memory.**
- **NVIDIA GPUs (20xx/V100 or newer) and TPUs are faster in float16. However, variables and a few computations should still be in float32 for numeric reasons so that the model trains to the same quality.**
- **If you’re using a Colab GPU or other GPU that does not have accelerated float16 support, you should rather not use it.**

```
# Train in mixed-precision float16
tf.keras.mixed_precision.set_global_policy("mixed_float16")
```

PROJECT PRESENTATIONS

- About 15 Minutes for each project

Content should be roughly equivalent to that of a “Model Card” (see this section for more details):

- Model description
- Intended uses & limitations
- How to use
- Limitations and bias
- Training data
- Training procedure
- Evaluation results

TODOS UNTIL NEXT WEEK

- Complete at least two sections from chapter 8 (How to ask for Help) of the Hugging Face course
- Further advance with your project
- Decide on your evaluation metric