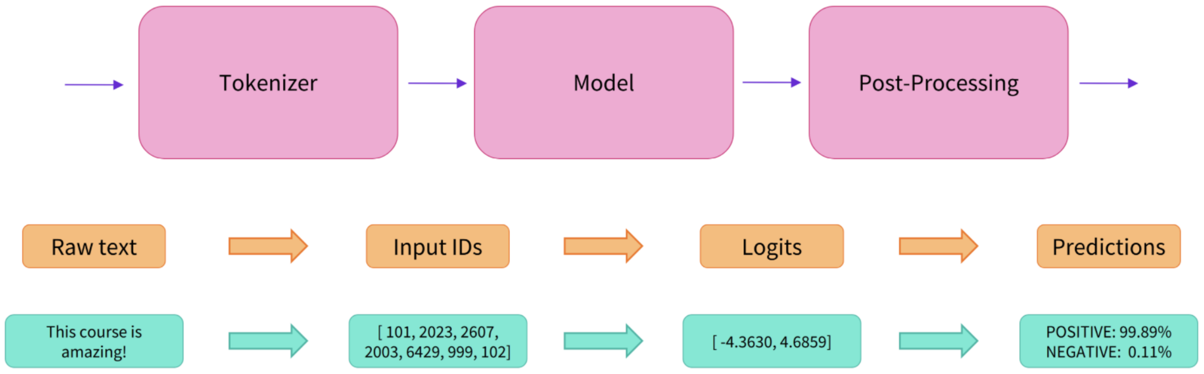
Using 🤗 Transformers

M2 I1. Behind the pipeline



When you use a pretrained Transformer for your down stream task, we have to make sure that the tokenizer used is same as the one which was used while building the pretrained model.

To do this, we can use the `AutoTokenizer` class and its `from_pretrained()` method. Using the checkpoint name of our model, it will automatically fetch the data associated with the model's tokenizer and cache it

```
from transformers import AutoTokenizer

checkpoint = "distilbert-base-uncased-finetuned-sst-2-english"
tokenizer = AutoTokenizer.from_pretrained(checkpoint)

# PreTrainedTokenizerFast(
# name_or_path='distilbert-base-uncased-finetuned-sst-2-english',
# vocab_size=30522, model_max_len=512, is_fast=True, padding_side='right',
# special_tokens={'unk_token': '[UNK]', 'sep_token': '[SEP]',
# 'pad_token': '[PAD]', 'cls_token': '[CLS]', 'mask_token': '[MASK]'})
```

The tokenizer now can be passed sentences and we get back a dictionary of list of ID's which need to be converted to tensors.

Example:

```
raw_input = [
    'Hey I am for a test',
    'All the best'
]
inputs = tokenizer(raw_input, padding=True, truncation=True,
                   return_tensors='tf'
                  )
print(inputs)
# {'input_ids': <tf.Tensor: shape=(2, 8), dtype=int32, numpy=
# array([[ 101, 4931, 1045, 2572, 2005, 1037, 3231,  102],
#        [ 101, 2035, 1996, 2190,  102,    0,    0,    0]], dtype=int32)>,
# 'attention_mask': <tf.Tensor: shape=(2, 8), dtype=int32, numpy=
# array([[1, 1, 1, 1, 1, 1, 1, 1],
#        [1, 1, 1, 1, 1, 0, 0, 0]], dtype=int32)>}
```

attention_mask will be explanined later.

Going through the model

```
model = TFAutoModel.from_pretrained(checkpoint)
```

This architecure contains only the base Transformer module, given some inputs it will output **hidden states/features** . For each model input, we'll retrieve a high-dimensional vector representing the **contextual understanding of that input by the Transformer model**.

The output high-dimensional Vector

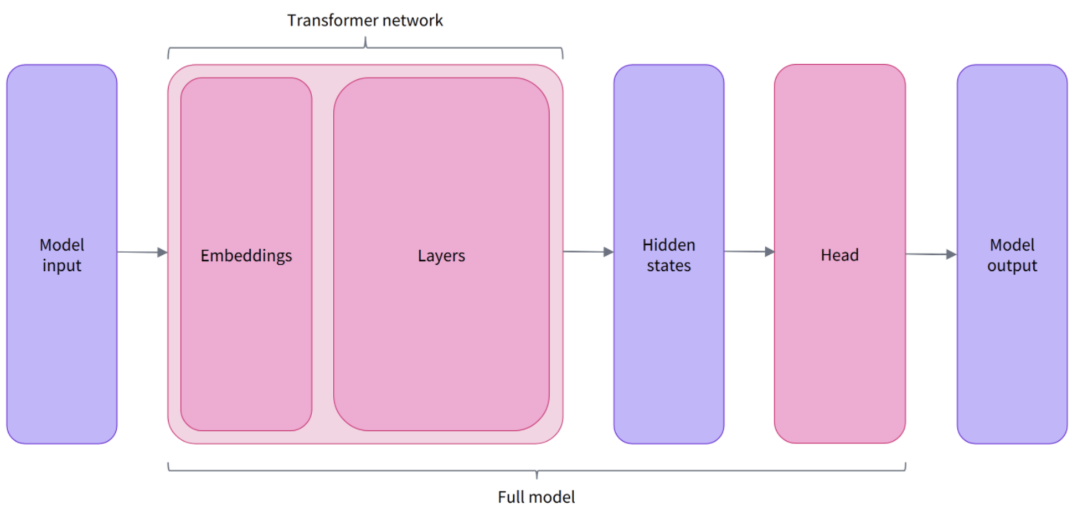
```
outputs = model(inputs)
print(outputs.last_hidden_state.shape)

#(2, 8, 768)
```

These vectors so returned are the input to the head of the Transformer.

The vector output by the Transformer module is usually large. It generally has three dimensions:

- **Batch size**: The number of sequences processed at a time (2 in our example).
- **Sequence length**: The length of the numerical representation of the sequence (8 in our example).
- **Hidden size**: The vector dimension of each model input.

Model heads



The output of the Transformer model is sent directly to the model head to be processed.

1. Our input sentence is broken down into and converted to input id's
2. Then these input id's are mapped to vectors (through dictonary look ups)

3. The subsequent layers manipulate those vectors using the attention mechanism to produce the final representation of the sentences.

For a text classification task like we have we won’t be using the TFAutoModel Class but we will use the TFAutoModelForSequenceClassification.

```
senti_model = TFAutoModelForSequenceClassification.from_pretrained(checkpoint)
outputs = senti_model(inputs)

# TFSequenceClassifierOutput(loss=None, logits=<tf.Tensor: shape=(2, 2),
# dtype=float32, numpy=
# array([[-1.4058973,  1.5513633],
#        [-4.28962  ,  4.6092067]], dtype=float32)>,
# hidden_states=None, attentions=None)
```

The output array so returned i.e :

For sentence 1 from our raw_input we get [-1.4058973, 1.5513633]

For sentence 2 from our raw_input we get [-4.28962 , 4.6092067]

These are logits and not the output probablities. To get the probablity score we have pass these logits through a softmax. We will use tensorflow for getting our probablity scores.

Postprocessing the output

```
print(outputs.logits)
# tf.Tensor(
# [[-1.4058973  1.5513633]
# [-4.28962    4.6092067]], shape=(2, 2), dtype=float32)
```

Now lets get our probablities:

```
import tensorflow as tf
predictions = tf.math.softmax(outputs.logits, axis=-1)
print(predictions)

# tf.Tensor(
# [[4.9394473e-02 9.5060551e-01]
# [1.3653041e-04 9.9986351e-01]], shape=(2, 2), dtype=float32)
```

The sentence 1 has probablites: [0.049, 0.950]

The sentence 2 has probablites: [0.0001, 0.998]

We can check the labels for the task using. the following code

```
model.config.id2label
# {0: 'NEGATIVE', 1: 'POSITIVE'}
```

Therefore our results are as follows:

First Sentence NEGATIVE: 0.049, POSITIVE: 0.950

Second Sentence NEGATIVE: 0.0001, POSITIVE: 0.998

M2 V2 Models:

There a couple of ways of Loading the Models:

1. **From the default config**

```
from transformers import BertConfig, TFBertModel

# Building the config
config = BertConfig()

# Building the model from the config
model = TFBertModel(config)
```

```
# Model is randomly intialized
```

In the above code a Bert Model is constructed from the config file that is loaded.

The configuration contains many attributes that are used to build the model:

```
print(config)

# Output
BertConfig {
  [...]
  "hidden_size": 768,
  "intermediate_size": 3072,
  "max_position_embeddings": 512,
  "num_attention_heads": 12,
  "num_hidden_layers": 12,
  [...]
}
```

This way of building model will intialize the BERT model with random weights and it won't be able to perform well. We can train the model and fine-tune it on our end task but that will require annotated dataset and sime time.

2. Loading the pretrained model

```
from transformers import TFBertModel
model = TFBertModel.from_pretrained("bert-base-cased")
```

Instead of using TFBertModel in the above code we can also use TFAutoModel. Using TFAutoModel is more preferred way as it produces checkpoint-agnostic code.

To know what the checkpoint model we passed do we can take a look at the **model card**.

The default weights are saved and cached under *~/.cache/huggingface/transformers*
You can customize your cache folder by setting the `HF_HOME` environment variable.

Saving a model:

```
model.save_pretrained("directory_on_my_computer")
```

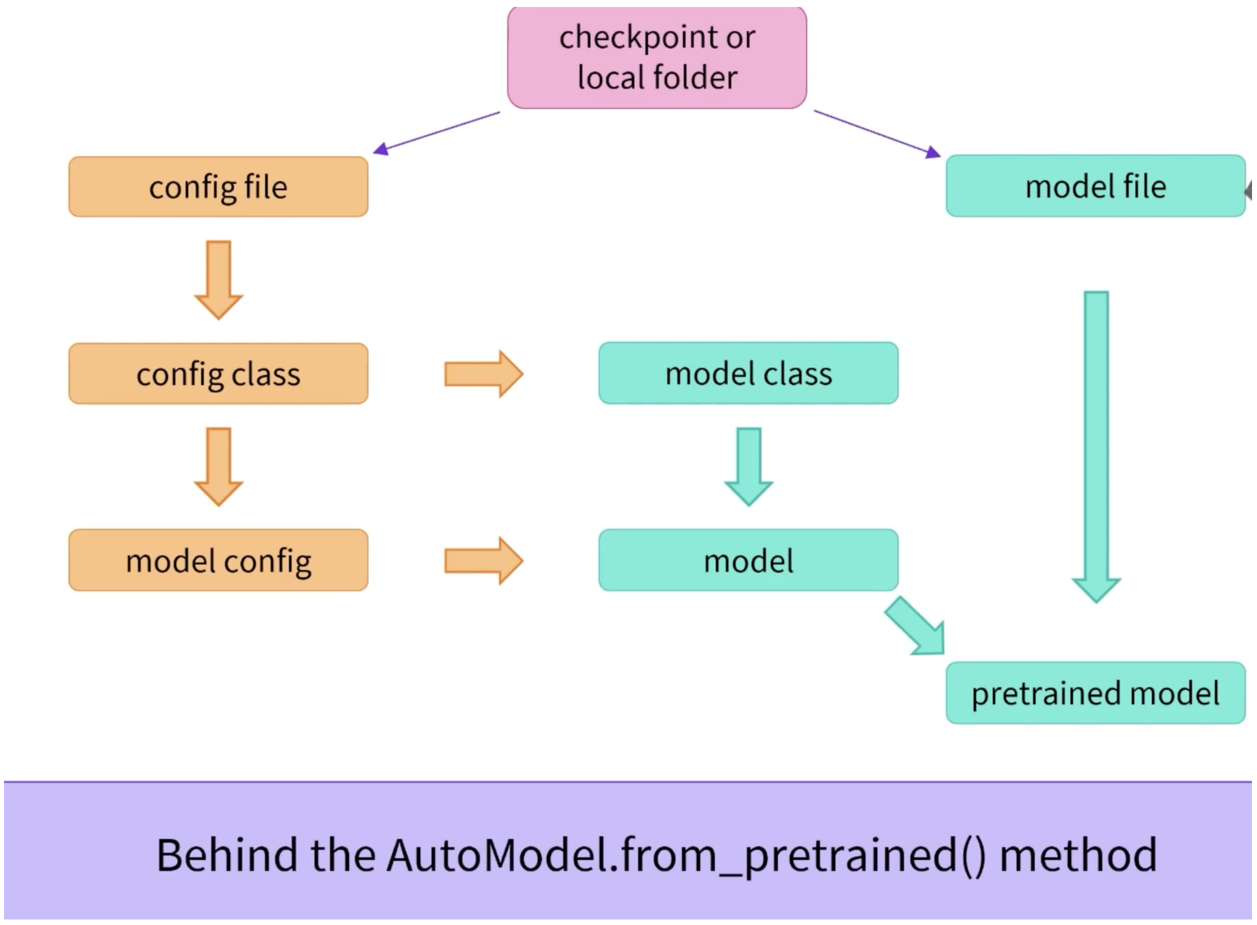
This will save 2 files on computer:
1. config.json
2. tf_model.h5

Lets use a Transformer model for inference:

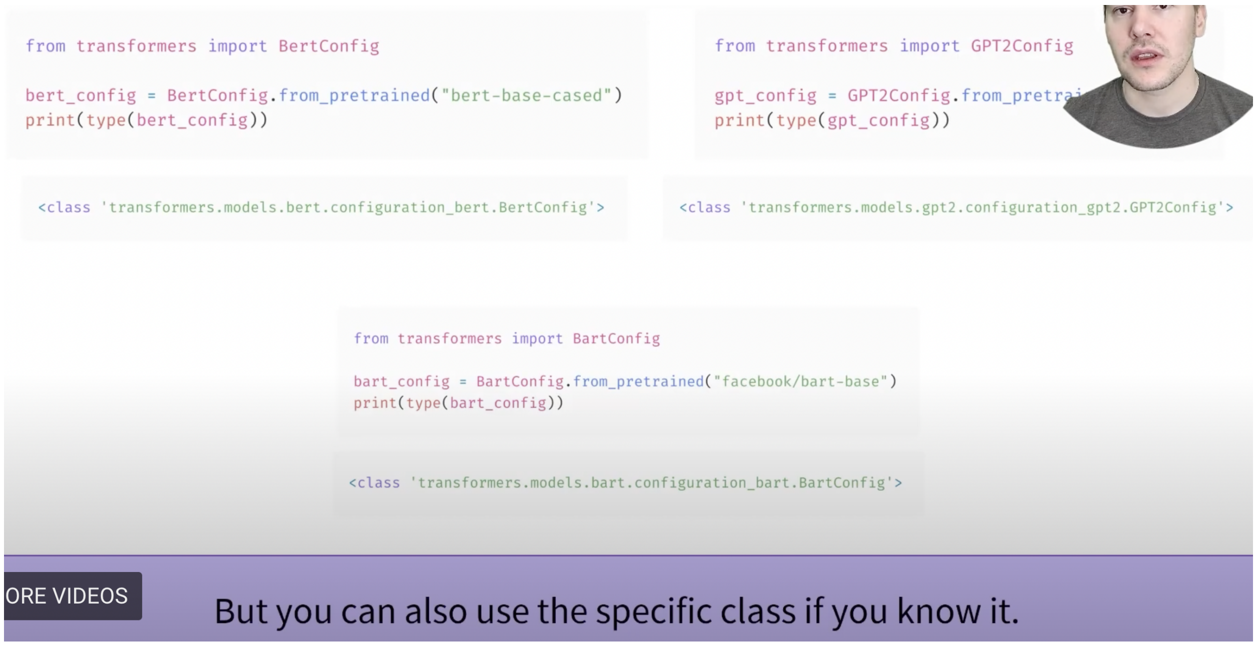
```
import tensorflow as tf

sequences = ["Hello!", "Cool.", "Nice!"]

encoded_sequences = [
    [101, 7592, 999, 102],
    [101, 4658, 1012, 102],
    [101, 3835, 999, 102],
]

model = TFAutoModel.from_pretrained("bert-base-cased")
model_inputs = tf.constant(encoded_sequences)

output = model(model_inputs)
print(output.last_hidden_state.shape)
# (3, 4, 768)
# (3 input senetences, sequence lenght of 4, vector size of 768)
```

The above code can't be used for a classification task. Because the model doesn't have a classification layer. In the previous example for this task we had used TFAutoModelForSequenceClassification instead of TFAutoModel

How does the AutoModels work? A high level overview of what goes under the hood.

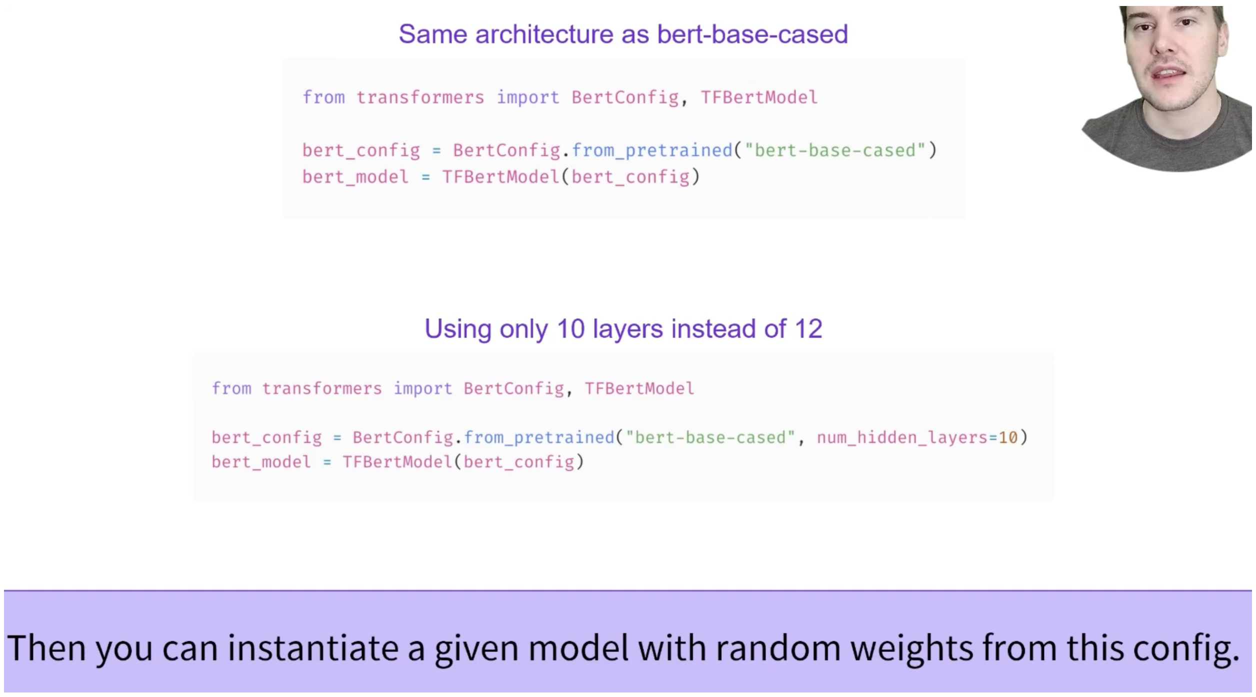


There are specific configs in Transformers library to load and build Transformer models


```
from transformers import BertConfig

bert_config = BertConfig.from_pretrained("bert-base-cased")
print(type(bert_config))
```
```
<class 'transformers.models.bert.configuration_bert.BertConfig'>
```
```
from transformers import GPT2Config

gpt_config = GPT2Config.from_pretra
print(type(gpt_config))
```
```
<class 'transformers.models.gpt2.configuration_gpt2.GPT2Config'>
```
```
from transformers import BartConfig

bart_config = BartConfig.from_pretrained("facebook/bart-base")
print(type(bart_config))
```
```
<class 'transformers.models.bart.configuration_bart.BartConfig'>
```

But you can also use the specific class if you know it.

We can build and tweak the transformer architecture using the keywords, check the sample code below:


Same architecture as bert-base-cased

```
from transformers import BertConfig, TFBertModel

bert_config = BertConfig.from_pretrained("bert-base-cased")
bert_model = TFBertModel(bert_config)
```

Using only 10 layers instead of 12

```
from transformers import BertConfig, TFBertModel

bert_config = BertConfig.from_pretrained("bert-base-cased", num_hidden_layers=10)
bert_model = TFBertModel(bert_config)
```

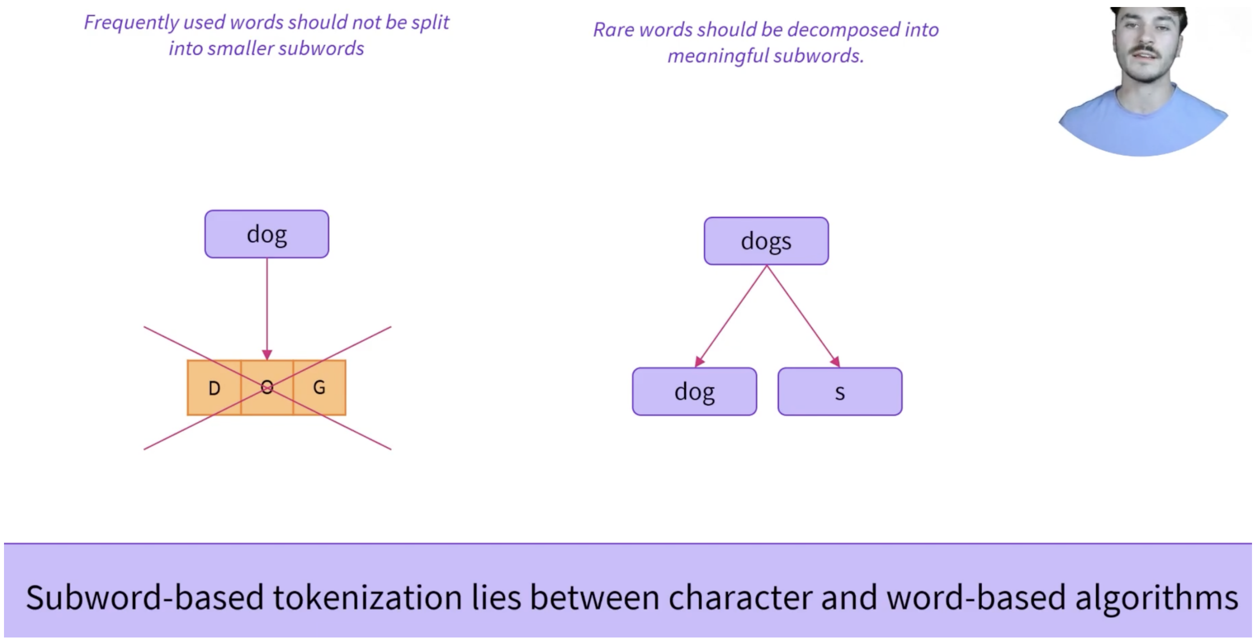
Then you can instantiate a given model with random weights from this config.

M2 V3: Tokenization

1. Word-Based
2. Character-Based
3. Subword tokenization:

It is finding middle ground between word and character based algorithms. The aim is to make the vocabulary better and not too big either.

Principles of Subword tokenization:


Frequently used words should not be split into smaller subwords
Rare words should be decomposed into meaningful subwords.
dog
D
O
G
dogs
dog
s

Subword-based tokenization lies between character and word-based algorithms

4. Encoding
5. Decoding

M2 V4: Handling multiple sequences

Questions while handling sequences:

- How do we handle multiple sequences?
- How do we handle multiple sequences *of different lengths*?
- Are vocabulary indices the only inputs that allow a model to work well?
- Is there such a thing as too long a sequence?

Models expect a batch of inputs

```
import tensorflow as tf
from transformers import AutoTokenizer, TFAutoModelForSequenceClassification

checkpoint = "distilbert-base-uncased-finetuned-sst-2-english"
tokenizer = AutoTokenizer.from_pretrained(checkpoint)
model = TFAutoModelForSequenceClassification.from_pretrained(checkpoint)

sequence = "I've been waiting for a HuggingFace course my whole life."

tokens = tokenizer.tokenize(sequence)
ids = tokenizer.convert_tokens_to_ids(tokens)

input_ids = tf.constant([ids])
print("Input IDs:", input_ids)

output = model(input_ids)
print("Logits:", output.logits)

# Input IDs: tf.Tensor(
# [[ 1045  1005  2310  2042  3403  2005  1037 17662
# 12172  2607  2026  2878
#   2166  1012]], shape=(1, 14), dtype=int32)
# Logits: tf.Tensor([[-2.7276208  2.8789377]],
# shape=(1, 2), dtype=float32)
```

Padding ids

Required to make every senetence of same size.

Attention masks:

Attention masks are tensors with the exact same shape as the input IDs tensor, filled with 0s and 1s:

1s indicate the corresponding tokens should be attended to, and

0s indicate the corresponding tokens should not be attended to
(i.e., they should be ignored by the attention layers of the model).

```
batched_ids = [
    [200, 200, 200],
    [200, 200, tokenizer.pad_token_id],
]

attention_mask = [
    [1, 1, 1],
    [1, 1, 0], # Zero since we are using a pad
]

outputs = model(tf.constant(batched_ids),
                attention_mask=tf.constant(attention_mask))
print(outputs.logits)
```

Longer Sequences:

With Transformer models, there is a limit to the lengths of the sequences we can pass the models. Most models handle sequences of up to 512 or 1024 tokens, and will crash when asked to process longer sequences. There are two solutions to this problem:

- Use a model with a longer supported sequence length.
- Truncate your sequences.

recommend to truncate the sequences by specifying the `max_sequence_length` parameter:

```
sequence = sequence[:max_sequence_length]
```

M2 V5: Putting it all together

Multiple objectives of using Padded:

```
# Will pad the sequences up to the maximum sequence length
model_inputs = tokenizer(sequences, padding="longest")

# Will pad the sequences up to the model max length
# (512 for BERT or DistilBERT)
model_inputs = tokenizer(sequences, padding="max_length")

# Will pad the sequences up to the specified max length
model_inputs = tokenizer(sequences, padding="max_length", max_length=8)
```

truncate sequences:

```
sequences = ["I've been waiting for a HuggingFace course my whole life.", "So have I!"]

# Will truncate the sequences that are longer than the model max length
# (512 for BERT or DistilBERT)
model_inputs = tokenizer(sequences, truncation=True)

# Will truncate the sequences that are longer than the specified max length
model_inputs = tokenizer(sequences, max_length=8, truncation=True)
```