Accelerating Machine Learning Predictions with NVIDIA TensorRT and Apache Beam

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BEAM SUMMIT
NYC 2023

Who is ML6?

Machine Learning services company.

We help our clients build machine learning applications using technologies such as Apache Beam.

Agenda

- Motivation
- Solution
  - **Beam RunInference:** Seamless integration of ML in a Beam pipeline for semantic enrichment
  - **Nvidia TensorRT**: Accelerated + Optimized ML Inference
- Example

Motivation

- Semantic Enrichment: ML models provide semantic information.
- Increasing scale and hardware requirements of ML models.

Semantic Enrichment of Data

- Categorise: Add specific label
- Summarize
- Sentiment Analysis
- Translate
- Extract important keywords
- Image Annotation
- Image Captioning
- Speech Recognition
- .....

Problem

Seamlessly integrate ML models in a Beam pipeline for semantic enrichment of data.

Increasing scale (longer inference times) and hardware requirements of models.

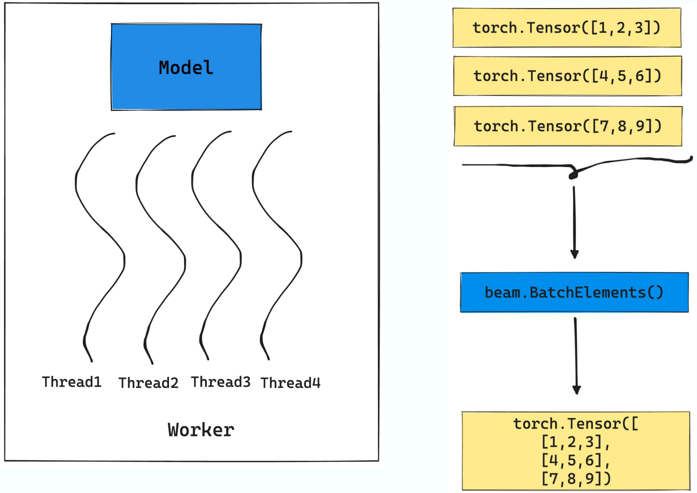
Solution

RunInference API = Inference with ML model in batch and streaming pipelines, without needing lots of boilerplate code.

Nvidia TensorRT = optimized + accelerated ML inference

RunInference >> Custom DoFn

Seamlessly integrate ML model in a Beam pipeline for semantic enrichment of data.



RunInference supports popular ML frameworks

PyTorch

TensorFlow

scikit learn

ONNX

NVIDIA TENSORRT

XGBoost

How to use RunInference?

```python
from apache_beam.ml.inference.base import RunInference
with pipeline as p:
 predictions = ( p | beam.ReadFromSource('a_source')
                   | RunInference(ModelHandler)
               )
```

ModelHandlers

```
from apache_beam.ml.inference.sklearn_inference import SklearnModelHandlerNumpy
from apache_beam.ml.inference.sklearn_inference import SklearnModelHandlerPandas
from apache_beam.ml.inference.pytorch_inference import PytorchModelHandlerTensor
from apache_beam.ml.inference.pytorch_inference import
PytorchModelHandlerKeyedTensor
model_handler = SklearnModelHandlerNumpy(model_uri='model.pkl',
 model_file_type=ModelFileType.JOBLIB)

model_handler = PytorchModelHandlerTensor(state_dict_path='model.pth',
 model_class=PytorchLinearRegression,
 model_params={'input_dim': 1, 'output_dim': 1})
```

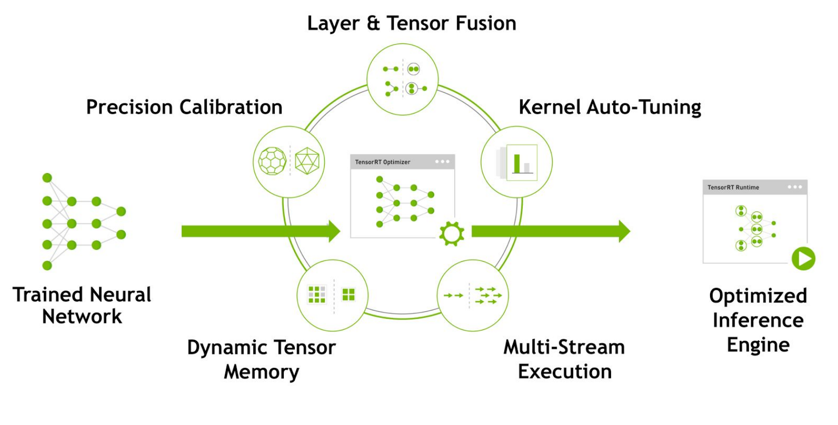
KeyedModelHandler

```
from apache_beam.ml.inference.base import
KeyedModelHandler
keyed_model_handler = \
KeyedModelHandler(PytorchModelHandlerTensor(...))

with pipeline as p:
 data = p | beam.Create([
 ('img1', np.array[[1,2,3],[4,5,6],...]),
 ('img2', np.array[[1,2,3],[4,5,6],...]),
 ('img3', np.array[[1,2,3],[4,5,6],...]),
 ])

 predictions = data | RunInference(keyed_model_handler)
```

Nvidia TensorRT

Flexible: An SDK designed to work with ONNX, TensorFlow, PyTorch, and others.

Optimizes a neural network for faster inference on NVIDIA GPUs, while preserving model accuracy.



Simplified and Accelerated Inference Pipelines

beam

RunInference API

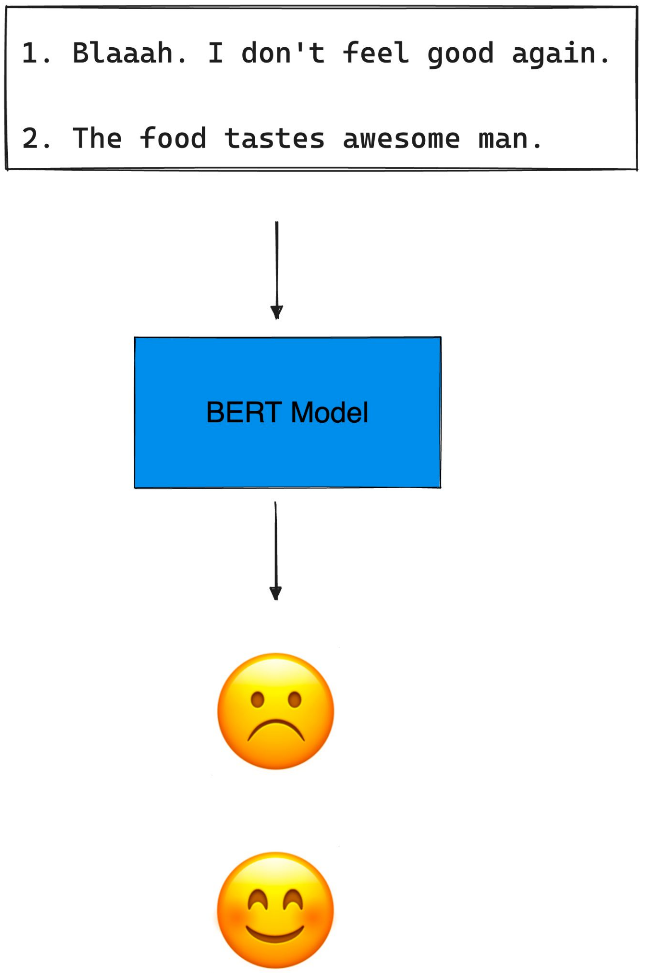
+

NVIDIA

TENSORRT

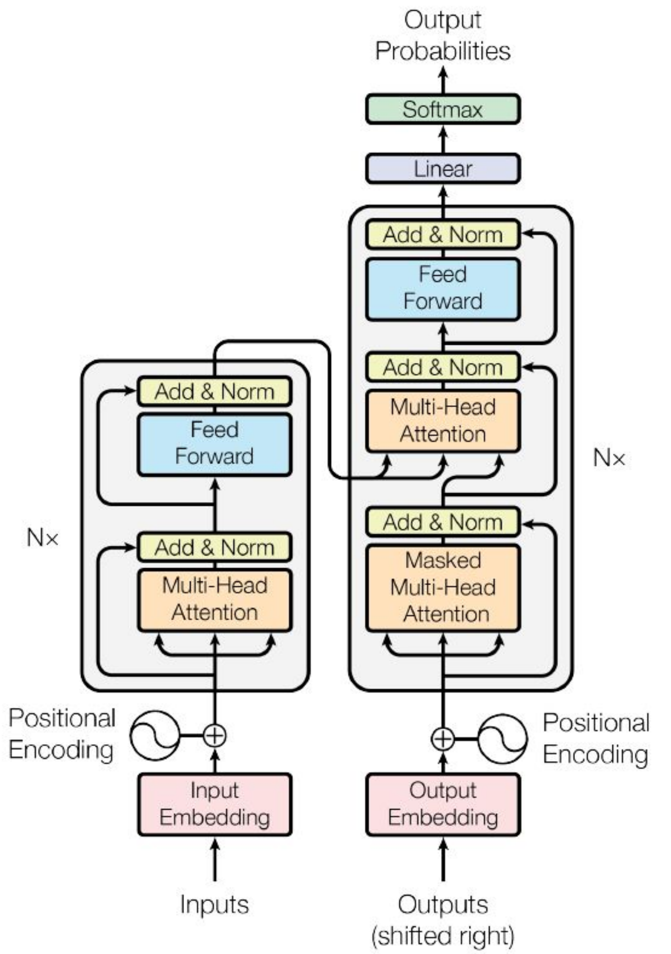
Example

Using a trained BERT-based (Transformer) text classification model for sentiment analysis in a Beam pipeline.

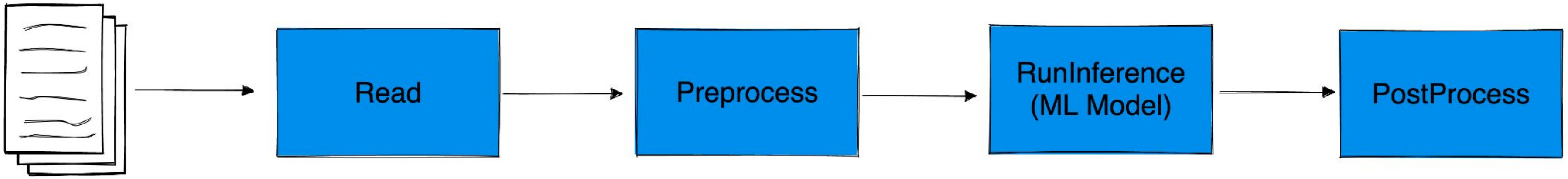


BERT

- A state-of-the-art (NLP) language model, Google.
- Can be fine-tuned for NLP tasks: text classification, named entity recognition, question answering, etc.
- textattack/bert-base-uncased-SST-2 finetuned on SST-2 for sentiment analysis.



ML Inference Pipeline in Beam as a DAG

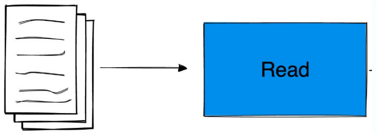


[File]

```python
with beam.Pipeline(options=pipeline_options) as pipeline:
  _ = (
      pipeline
      | "ReadSentences" >> beam.io.ReadFromText(known_args.input)
      | "Preprocess" >> beam.ParDo(Preprocess(tokenizer=tokenizer))
      | "RunInference" >> RunInference(model_handler=model_handler)
      | "PostProcess" >> beam.ParDo(Postprocess(tokenizer=tokenizer))
  )
```

Tutorial Link: [Apache Beam Documentation]()

Read Texts from File



[File]

1. Blaaah. I don't feel good again.

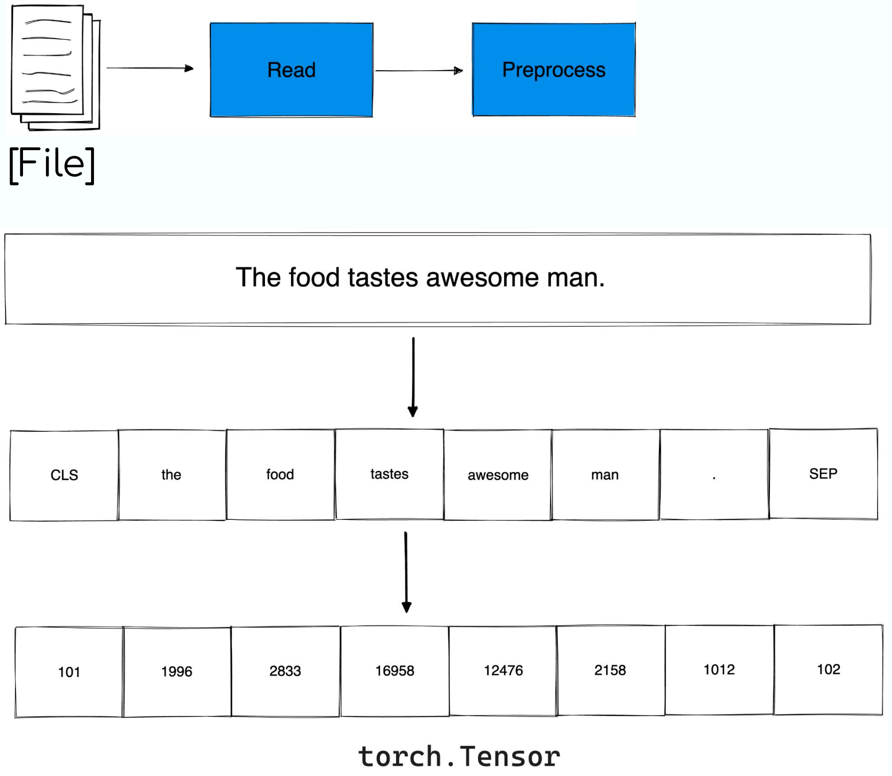
2. The food tastes awesome man.

.

.

```
with beam.Pipeline(options=pipeline_options) as pipeline:
  _ = (
      pipeline
      | "ReadSentences" >> beam.io.ReadFromText(known_args.input)
```

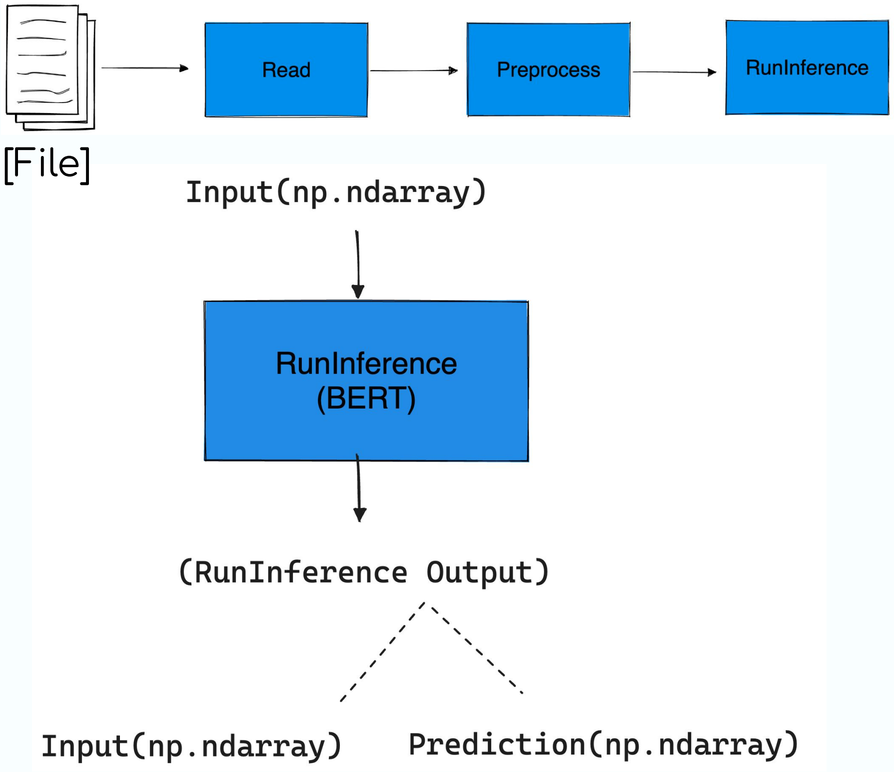
Preprocess(Tokenization)




```python
class Preprocess(beam.DoFn):
  def __init__(self, tokenizer: AutoTokenizer):
    self._tokenizer = tokenizer

  def process(self, element):
    inputs = self._tokenizer(
      element, return_tensors="np",
      padding="max_length",
      max_length=128)
    return inputs.input_ids

model_id = "textattack/bert-base-uncased-SST-2"
tokenizer = AutoTokenizer.from_pretrained(model_id)


| "Preprocess" >> beam.ParDo(Preprocess(tokenizer=tokenizer))
```

Hugging Face

TensorRT and RunInference



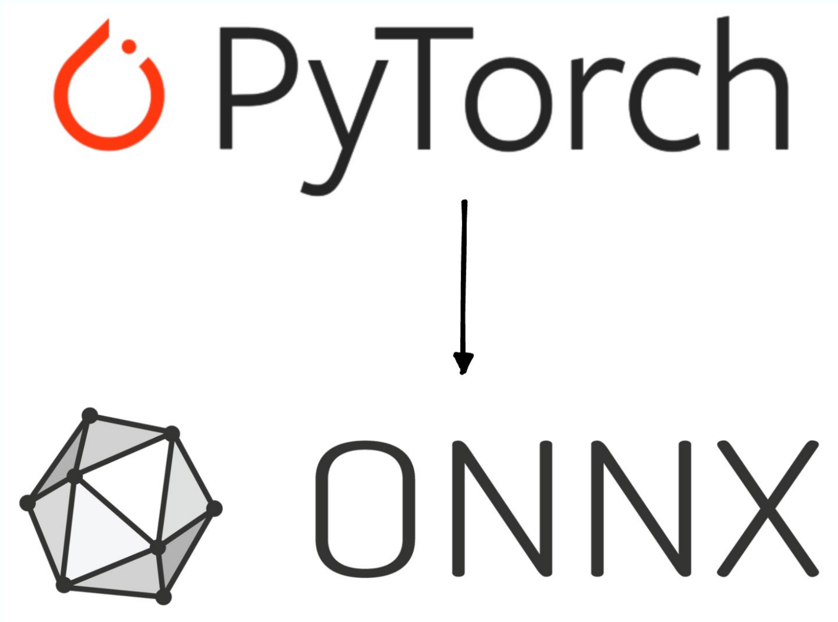

```
model_handler = TensorRTEngineHandlerNumPy(
    min_batch_size=1,
    max_batch_size=1,
    engine_path=known_args.trt_model_path,
)


| "RunInference" >> RunInference(model_handler=model_handler)
```

Hugging Face

Convert PyTorch model to a TensorRT Engine File

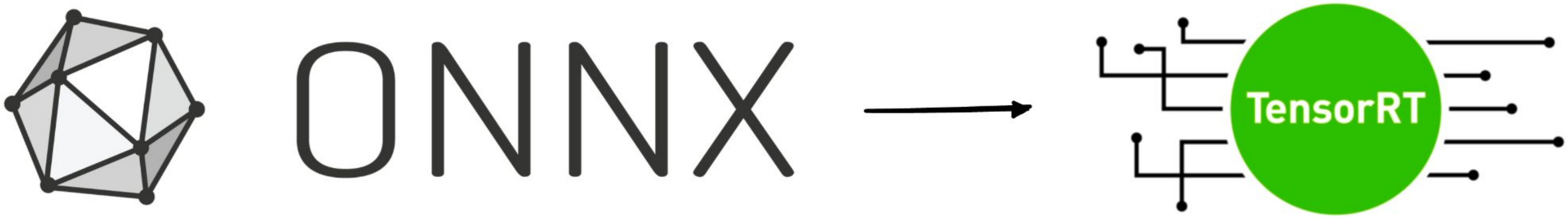
A common way to convert PyTorch model to TensorRT

PyTorch to ONNX




```python
from pathlib import Path
import transformers
from transformers.onnx import FeaturesManager
from transformers import AutoConfig
from transformers import AutoTokenizer
from transformers import AutoModelForMaskedLM
from transformers import AutoModelForSequenceClassification


# load model and tokenizer
model_id = "textattack/bert-base-uncased-SST-2"
feature = "sequence-classification"
model = AutoModelForSequenceClassification.from_pretrained(model_id)
tokenizer = AutoTokenizer.from_pretrained(model_id)

# load config
model_kind, model_onnx_config = FeaturesManager.check_supported_model_or_raise(model,
feature=feature)
onnx_config = model_onnx_config(model.config)

# export
onnx_inputs, onnx_outputs = transformers.onnx.export(
        preprocessor=tokenizer,
        model=model,
        config=onnx_config,
        opset=12,
        output=Path("bert-sst2-model.onnx")
)
```

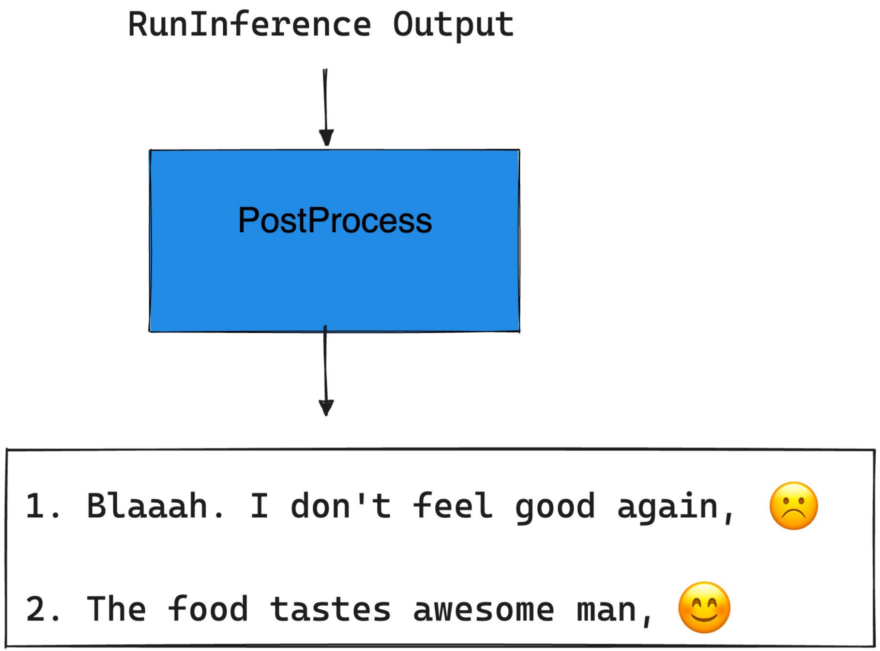
ONNX to TensorRT




```
trtexec --onnx=<path to onnx model> --saveEngine=<path to save TensorRT engine> --useCudaGraph --
verbose
```

trtexec - a command-line tool for Onnx to TensorRT Engine conversion

PostProcess RunInference Output




```python
class Postprocess(beam.DoFn):
  def __init__(self, tokenizer: AutoTokenizer):
    self._tokenizer = tokenizer

  def process(self, element):
    decoded_input = self._tokenizer.decode(
        element.example, skip_special_tokens=True)
    logits = element.inference[0]
    argmax = np.argmax(logits)
    output = "Positive" if argmax == 1 else "Negative"
    yield decoded_input, output


| "PostProcess" >> beam.ParDo(Postprocess(tokenizer=tokenizer))
```

TensorRT is 4.1x faster than PyTorch

Model	Mean Inference batch Latency (in microseconds)
PyTorch	15,176
TensorRT	3,685

Mean Inference batch Latency: Average time to perform the inference on a batch of examples.

GPU: T4, Batch-size = 1 to mimic streaming setup

Takeaways

- RunInference transform eliminates the need for extensive boilerplate code in pipelines with machine learning models.

- Beam and Nvidia TensorRT integration: Enhancing inference pipeline with improved GPU utilization, reduced production cost, and superior latency and throughput.

Code and Tutorial Link

Code: [GitHub Link]

Tutorial: [Apache Beam Documentation Link]

Slides: [GitHub Link]

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QUESTIONS?

in shubham-krishna-998922108

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