Accelerating Machine Learning Predictions with NVIDIA TensorRT and Apache Beam

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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
- .....
<table>
<thead>
<tr>
<th>Problem</th>
<th>Solution</th>
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<tr>
<td>Seamlessly integrate ML models in a Beam pipeline for semantic enrichment of data.</td>
<td><strong>RunInference API</strong> = Inference with ML model in batch and streaming pipelines, without needing lots of boilerplate code.</td>
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<tr>
<td>Increasing scale (longer inference times) and hardware requirements of models.</td>
<td><strong>Nvidia TensorRT</strong> = optimized + accelerated ML inference</td>
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RunInference >> Custom DoFn

Seamlessly integrate ML model in a Beam pipeline for semantic enrichment of data.
RunInference supports popular ML frameworks
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))
```
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})
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

```
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
1. Blaah. I don't feel good again.

2. The food tastes awesome man.

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

The food tastes awesome man.

```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

Input(np.ndarray) -> Preprocess -> RunInference

RunInference (BERT)

(RunInference Output)

Input(np.ndarray) → Prediction(np.ndarray)

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

"RunInference" >> RunInference(model_handler=model_handler)
```
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=nnx_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
1. Blaaah. I don't feel good again, 😞
2. The food tastes awesome man, 😊
TensorRT is 4.1x faster than PyTorch

<table>
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<tr>
<th>Model</th>
<th>Mean Inference batch Latency (in microseconds)</th>
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<tbody>
<tr>
<td>PyTorch</td>
<td>15,176</td>
</tr>
<tr>
<td>TensorRT</td>
<td>3,685</td>
</tr>
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</table>

**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: [GitHub Link](#)

Tutorial: [Apache Beam Documentation Link](#)

Slides: [GitHub Link](#)
QUESTIONS?

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