Apache Beam and Ensemble Modeling: A Winning Combination for Machine Learning

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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.

Credits

Philippe Moussalli
Machine Learning Engineer, ML6

Agenda

- Motivation
    - Ensemble Modeling for solving complex use-cases
- Solution
    - **Beam RunInference:**
        - Seamless integration of ML in a Beam pipeline for semantic enrichment
        - Use multiple Runinference transforms for pipelines with multiple ML models
- Example

Motivation

- Semantic Enrichment: ML models provide semantic information.
- Business needs often involve the use of multiple machine learning models, each addressing a specific subtask and contributing unique capabilities.

Semantic Enrichment of Data

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

Ensemble Modeling

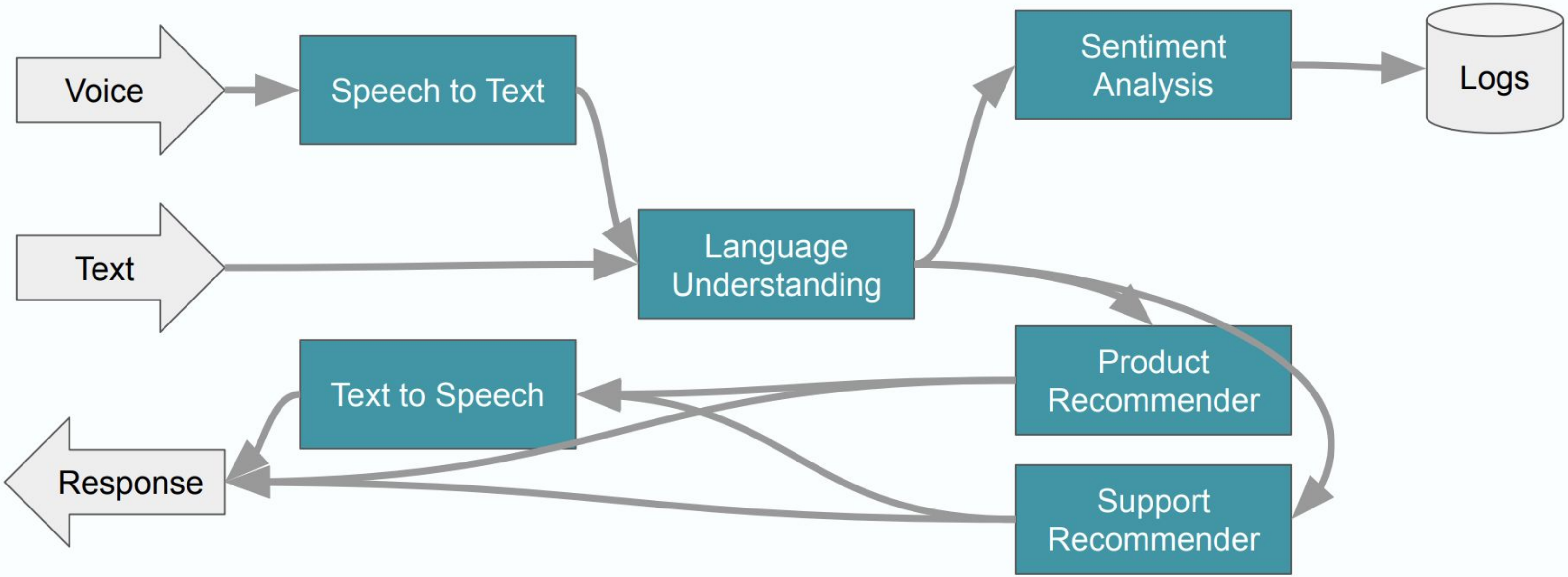
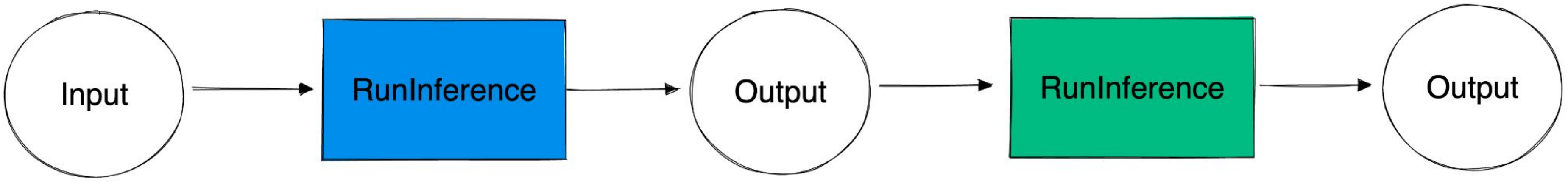
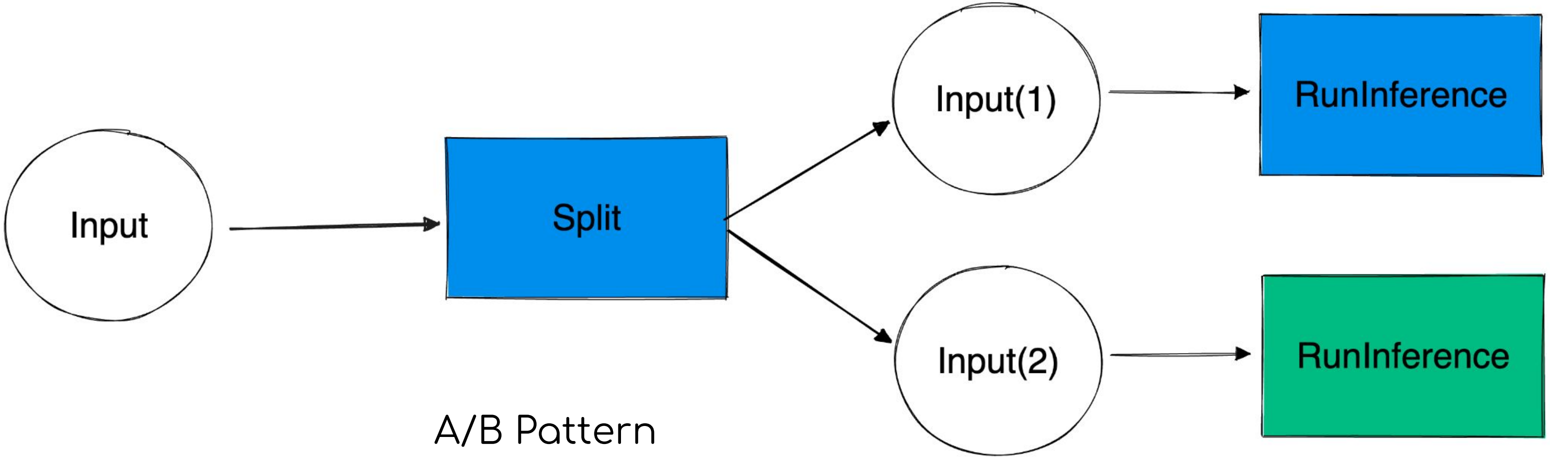


Fig.1. Example of a Multi model pipeline, taken from a tutorial on RunInference on Dataflow: [Link]()

Ensemble Modeling: Sequential vs A/B



Sequential Pattern



A/B Pattern

Problem

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

Business needs require combining multiple ML models. (Ensemble Modeling)

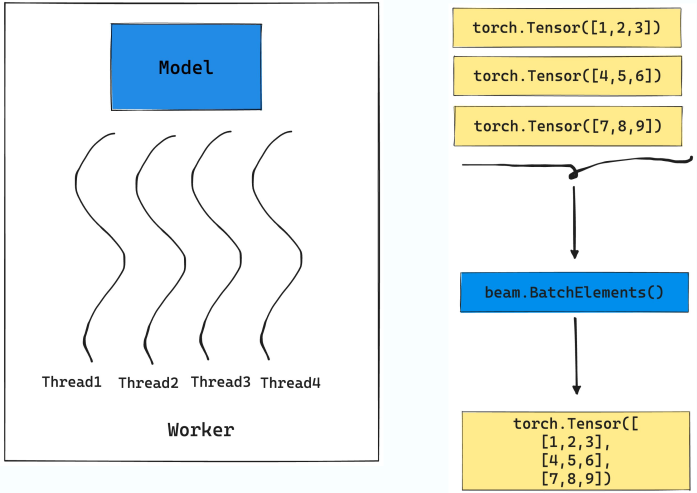
Solution

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

RunInference API = Using multiple RunInference transforms, build a pipeline that consists of multiple ML models.

RunInference >> Custom DoFn

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



```
torch.Tensor([1,2,3])
torch.Tensor([4,5,6])
torch.Tensor([7,8,9])
beam.BatchElements()
torch.Tensor([
[1,2,3],
[4,5,6],
[7,8,9])
```

RunInference supports popular ML frameworks

PyTorch

TensorFlow

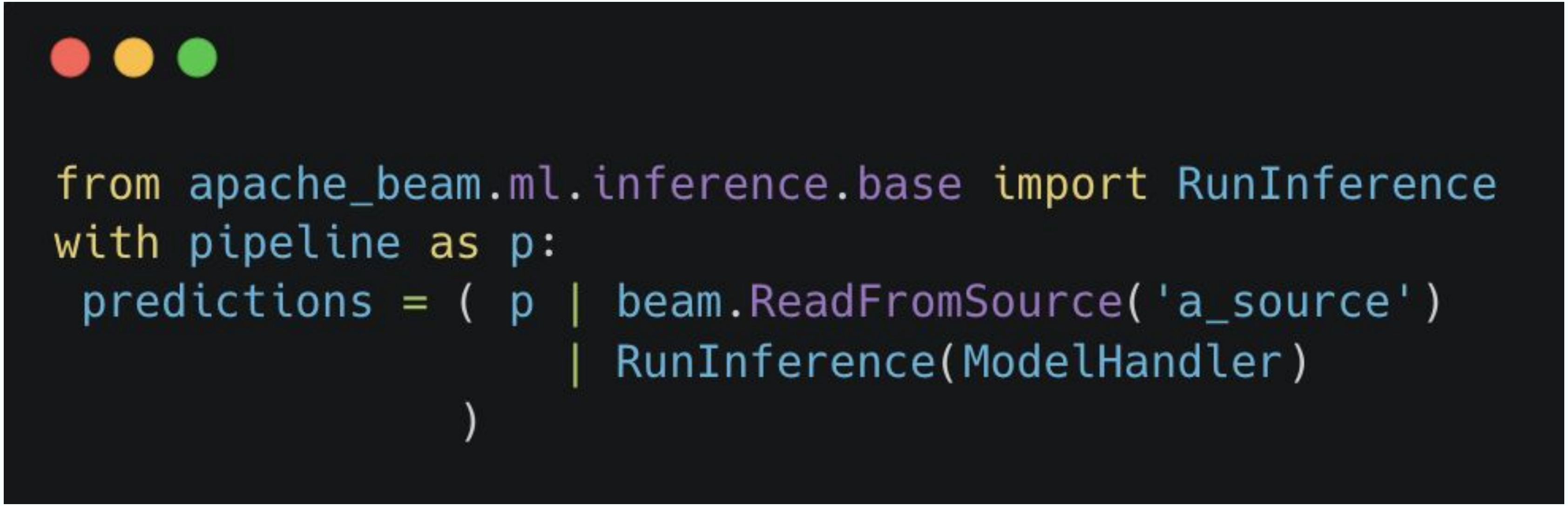
scikit learn

ONNX

NVIDIA TENSORRT

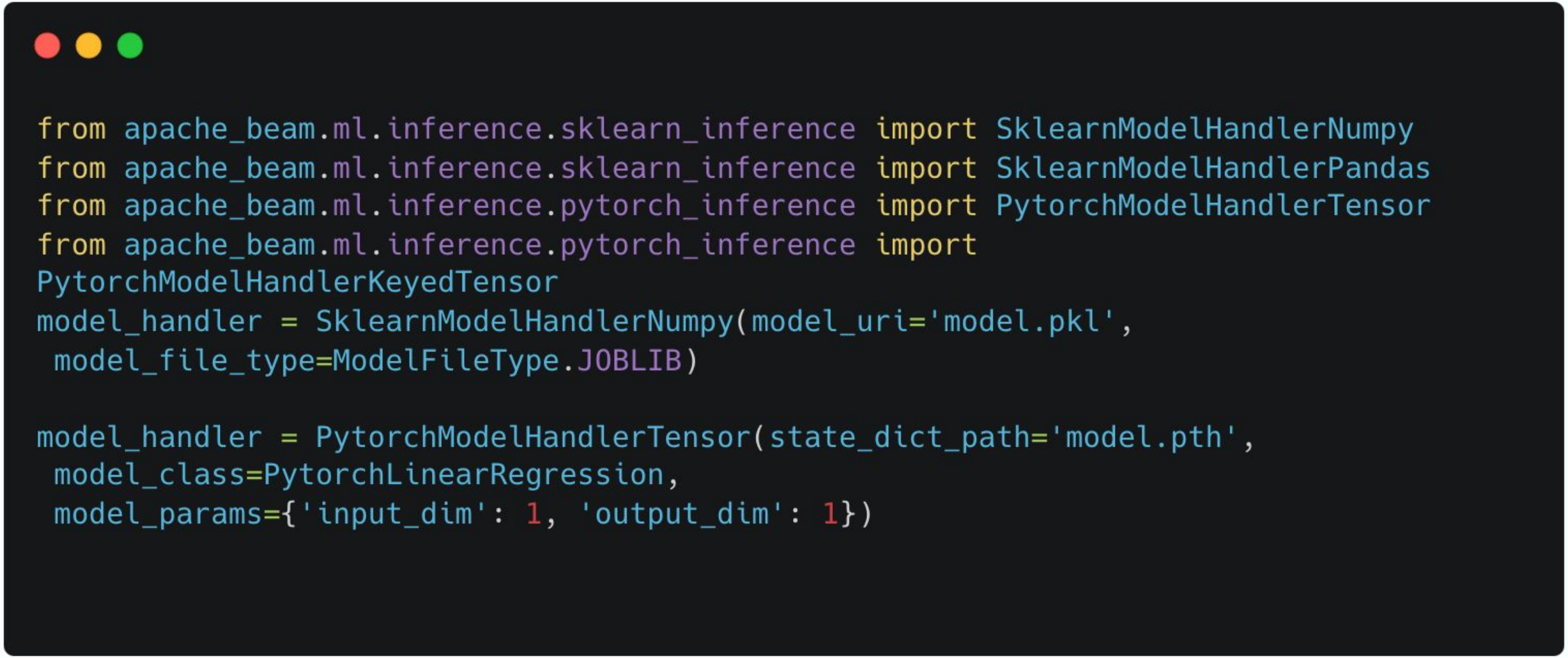
XGBoost

How to use RunInference ?



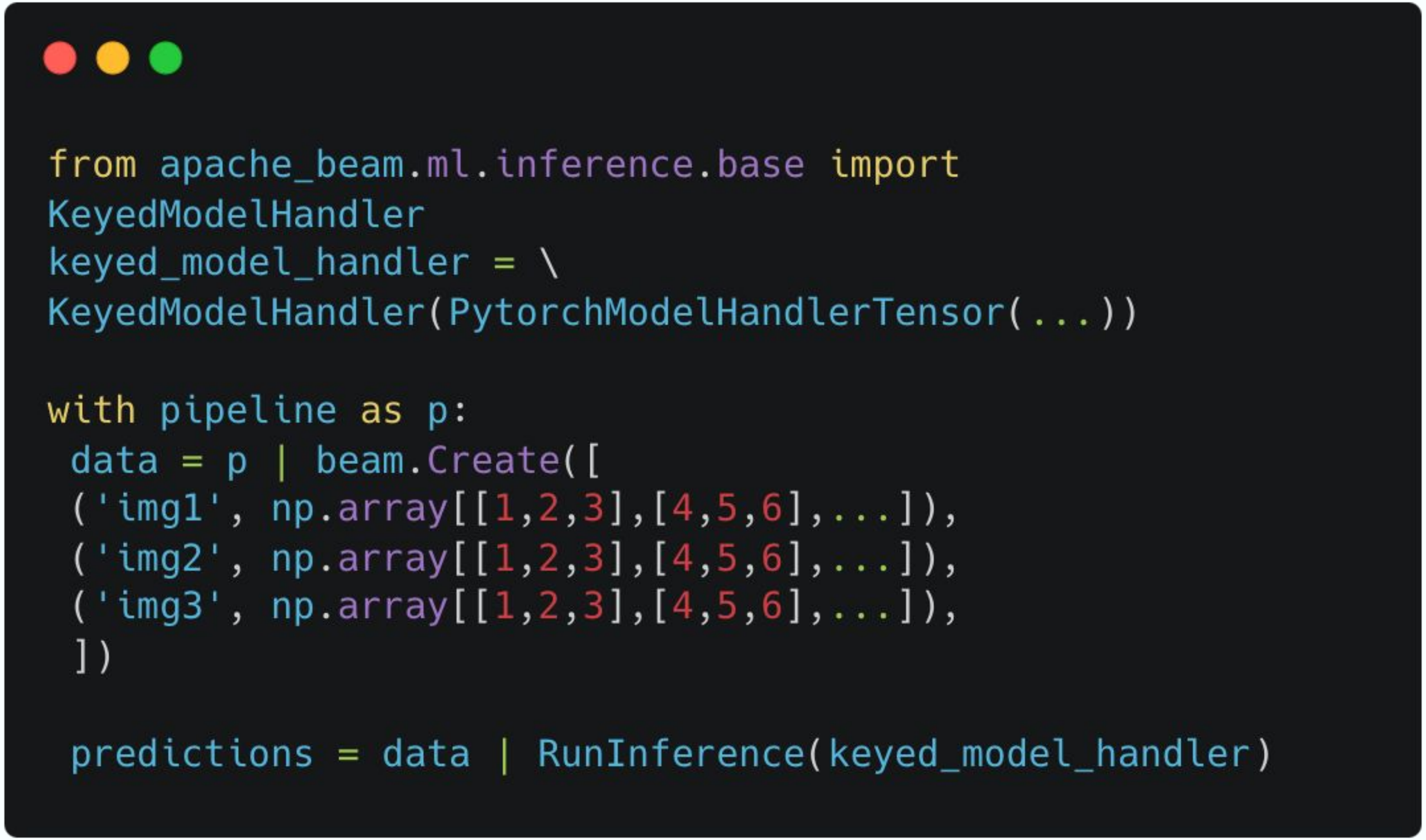
```
from apache_beam.ml.inference.base import RunInference
with pipeline as p:
 predictions = ( p | beam.ReadFromSource('a_source')
                   | RunInference(ModelHandler)
               )
```

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



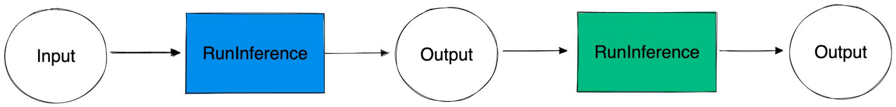
```
from apache_beam.ml.inference.base import
KeyedModelHandler
keyed_model_handler = \
KeyedModelHandler(PytorchModelHandlerTensor(...))

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)
```

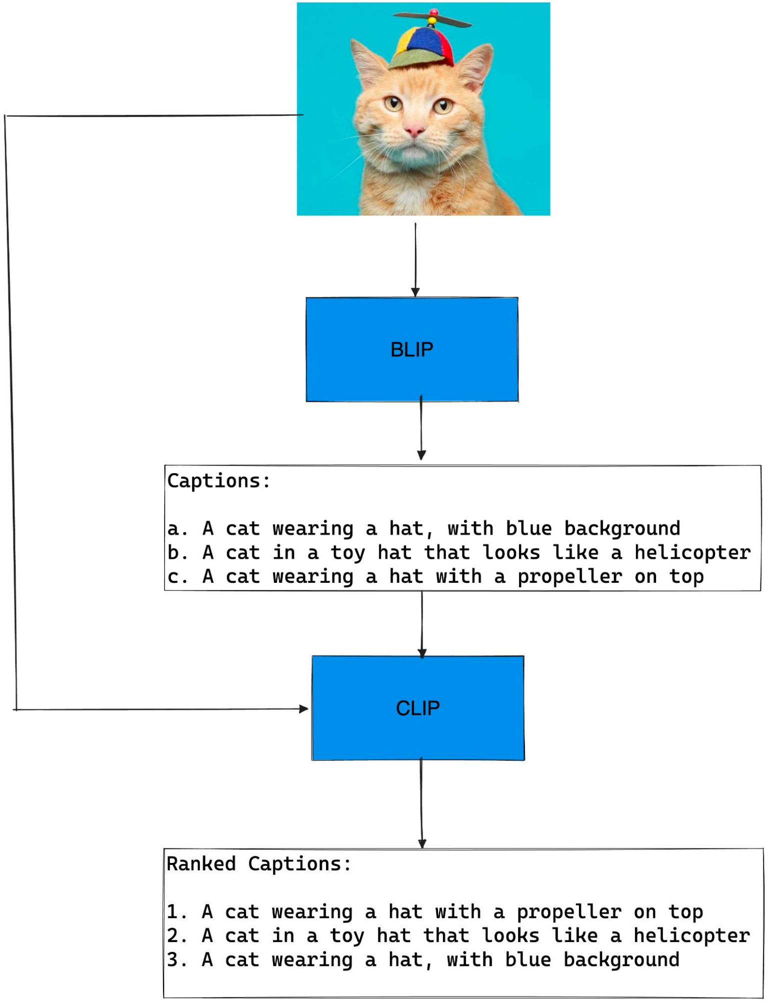
Example

Image captioning and ranking with Sequential Pattern:

1. **BLIP**: Image Captioning
2. **CLIP**: Ranking captions

Sequential Pattern





```
Captions:

a. A cat wearing a hat, with blue background
b. A cat in a toy hat that looks like a helicopter
c. A cat wearing a hat with a propeller on top
```

```
Ranked Captions:

1. A cat wearing a hat with a propeller on top
2. A cat in a toy hat that looks like a helicopter
3. A cat wearing a hat, with blue background
```

BLIP: Image Captioning

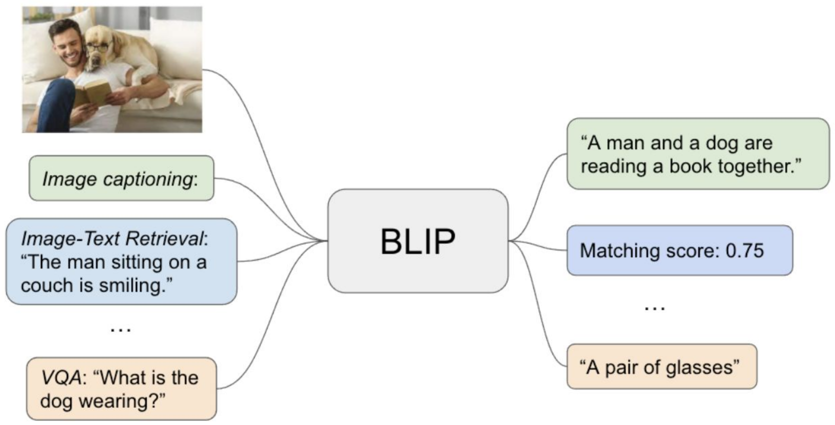


Image captioning:

Image-Text Retrieval: “The man sitting on a couch is smiling.”

…

VQA: “What is the dog wearing?”

BLIP

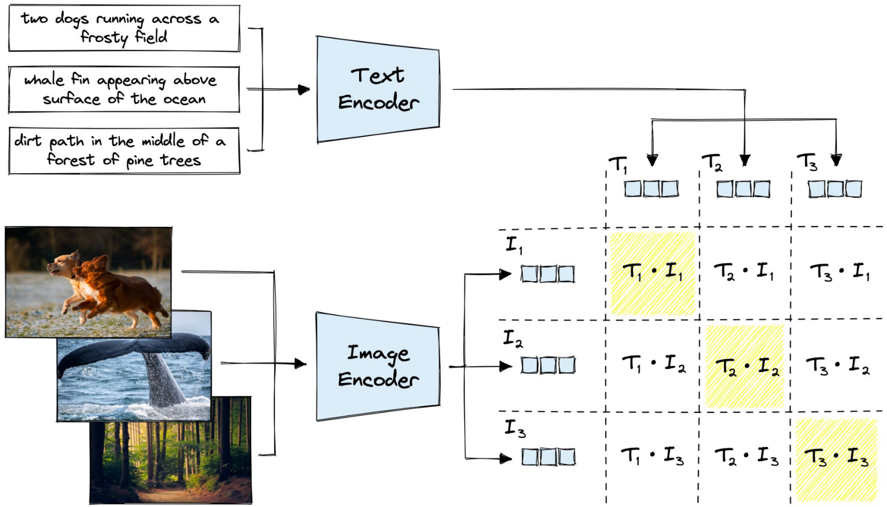
“A man and a dog are reading a book together.”

Matching score: 0.75

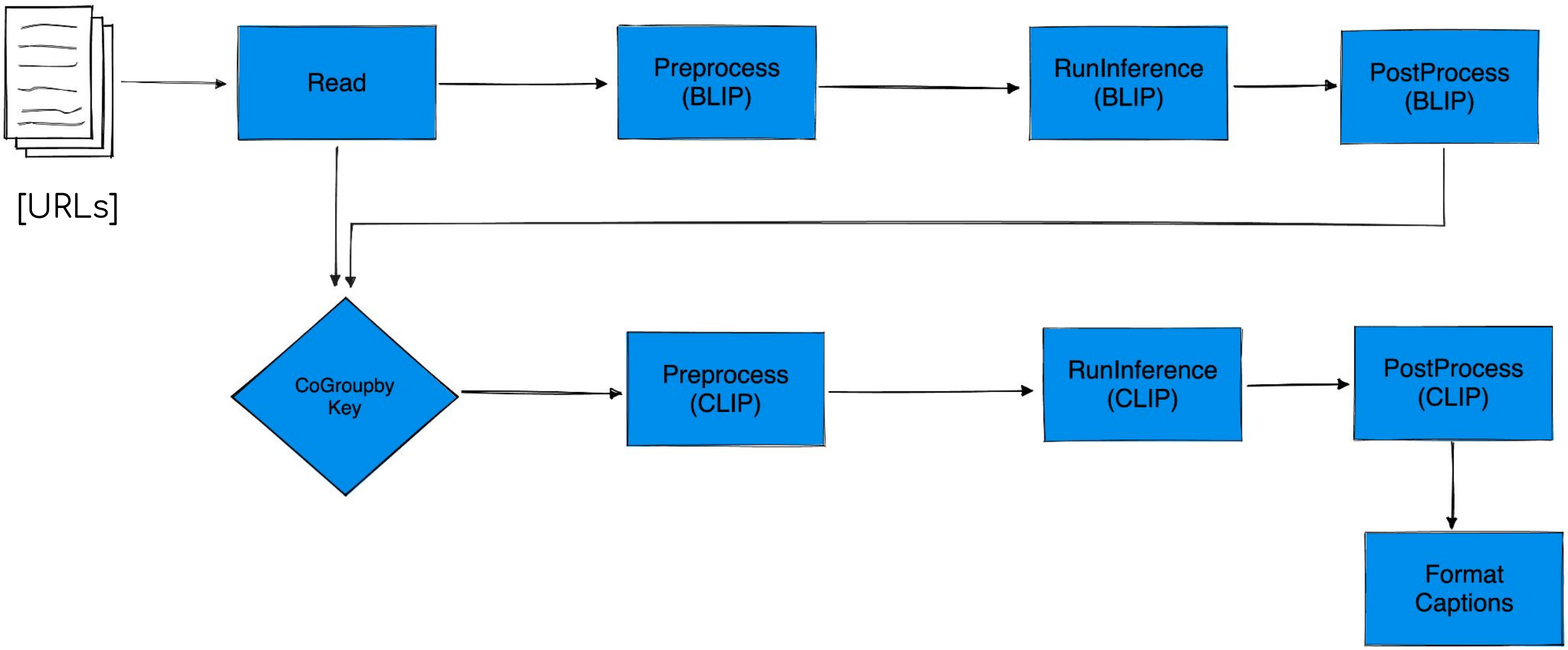
…

“A pair of glasses”

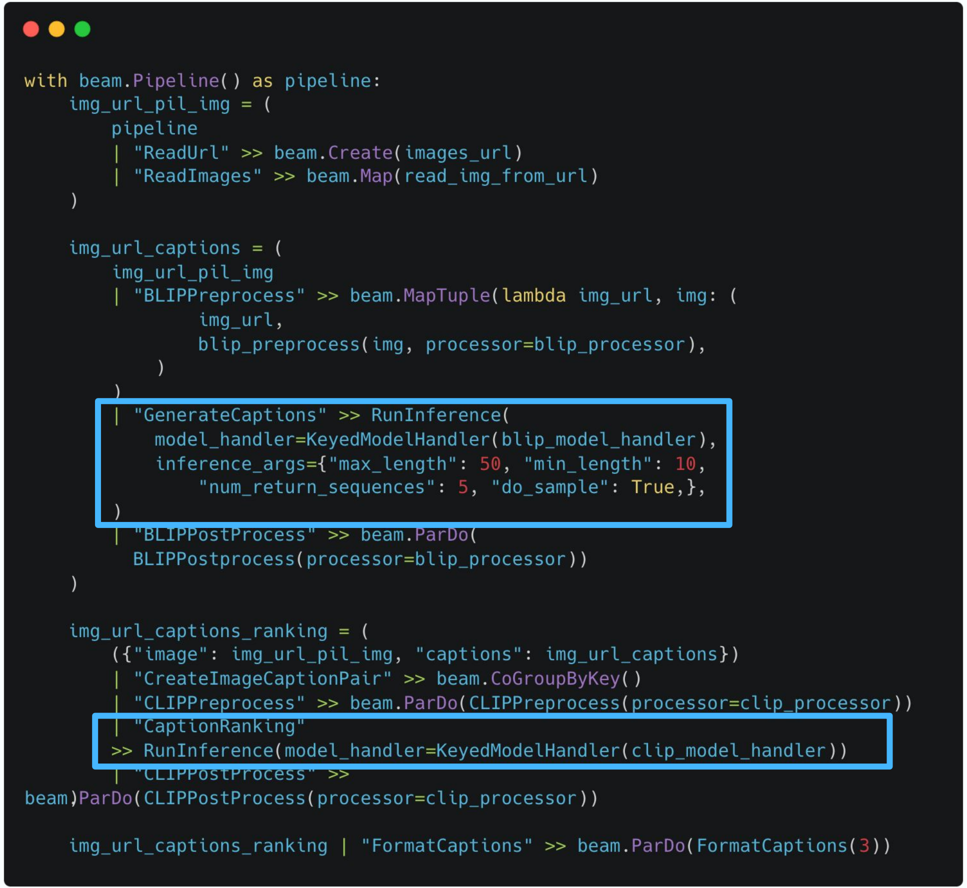
CLIP: Caption Ranking



ML Inference Pipeline in Beam as a DAG

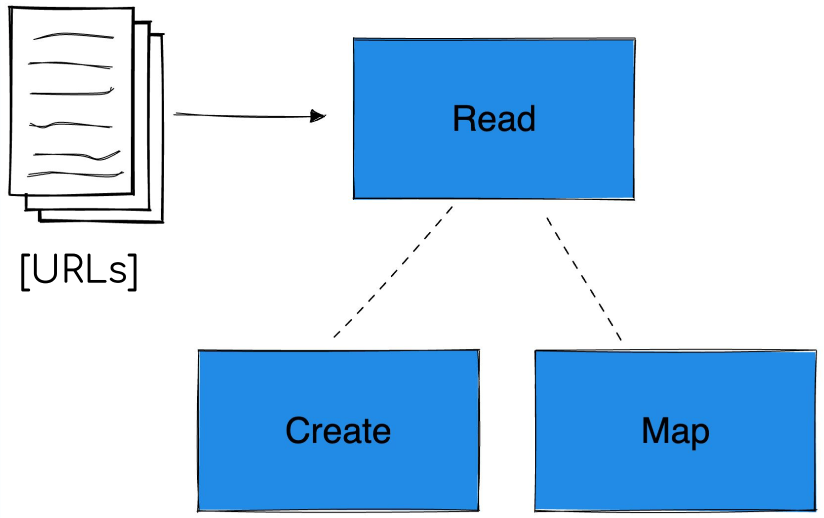


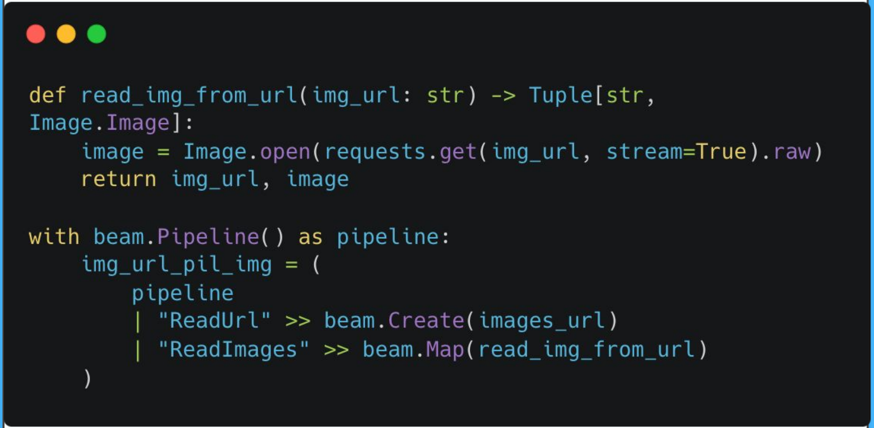
ML Inference Pipeline in Beam as a DAG



```
with beam.Pipeline() as pipeline:
    img_url_pil_img = (
        pipeline
        | "ReadUrl" >> beam.Create(images_url)
        | "ReadImages" >> beam.Map(read_img_from_url)
    )

    img_url_captions = (
        img_url_pil_img
        | "BLIPPreprocess" >> beam.MapTuple(lambda img_url, img: (
                img_url,
                blip_preprocess(img, processor=blip_processor),
            )
        )
        | "GenerateCaptions" >> RunInference(
            model_handler=KeyedModelHandler(blip_model_handler),
            inference_args={"max_length": 50, "min_length": 10,
                "num_return_sequences": 5, "do_sample": True,},
        )
        | "BLIPPostProcess" >> beam.ParDo(
          BLIPPostprocess(processor=blip_processor))
    )

    img_url_captions_ranking = (
        ({"image": img_url_pil_img, "captions": img_url_captions})
        | "CreateImageCaptionPair" >> beam.CoGroupByKey()
        | "CLIPPreprocess" >> beam.ParDo(CLIPPreprocess(processor=clip_processor))
        | "CaptionRanking"
        >> RunInference(model_handler=KeyedModelHandler(clip_model_handler))
        | "CLIPPostProcess" >>
beam)ParDo(CLIPPostProcess(processor=clip_processor))

    img_url_captions_ranking | "FormatCaptions" >> beam.ParDo(FormatCaptions(3))
```

Read Images from URLs

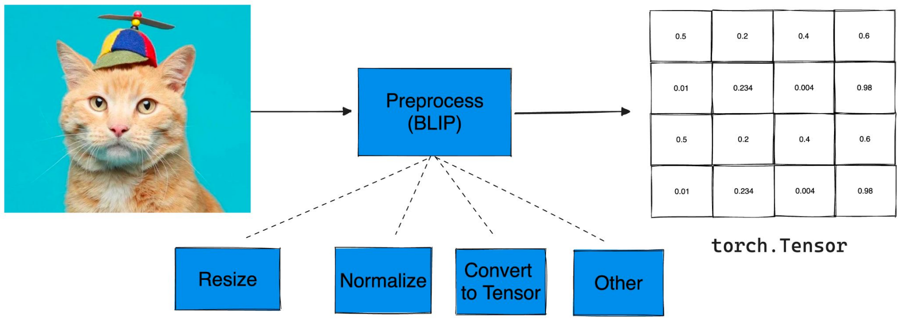




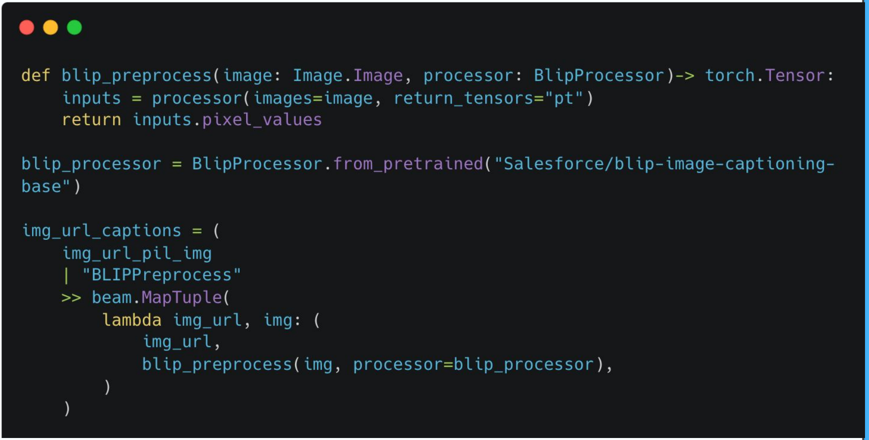
```python
def read_img_from_url(img_url: str) -> Tuple[str,
Image.Image]:
    image = Image.open(requests.get(img_url, stream=True).raw)
    return img_url, image

with beam.Pipeline() as pipeline:
    img_url_pil_img = (
        pipeline
        | "ReadUrl" >> beam.Create(images_url)
        | "ReadImages" >> beam.Map(read_img_from_url)
    )
```

(Img URL, Image)

Preprocess Inputs for BLIP



0.5	0.2	0.4	0.6
0.01	0.234	0.004	0.98
0.5	0.2	0.4	0.6
0.01	0.234	0.004	0.98

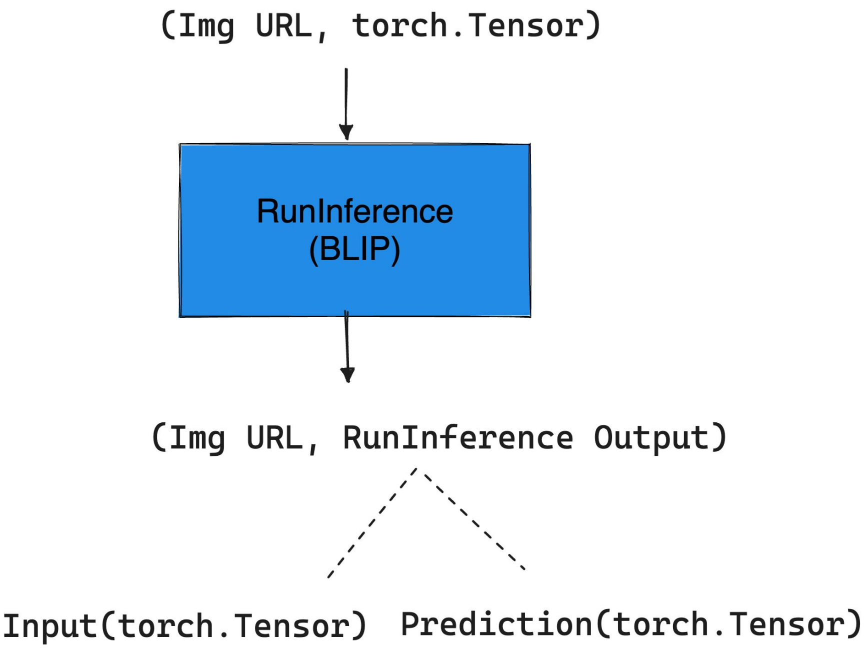


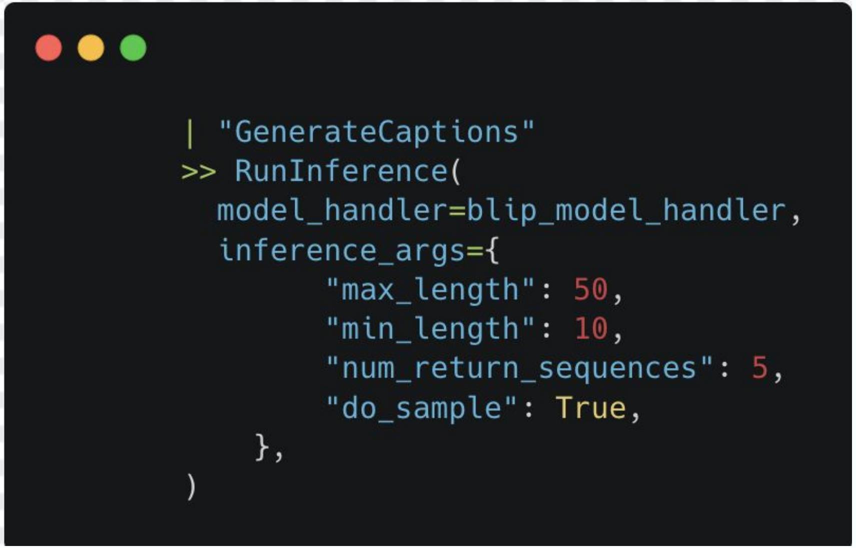
```python
def blip_preprocess(image: Image.Image, processor: BlipProcessor)-> torch.Tensor:
    inputs = processor(images=image, return_tensors="pt")
    return inputs.pixel_values

blip_processor = BlipProcessor.from_pretrained("Salesforce/blip-image-captioning-
base")

img_url_captions = (
    img_url_pil_img
    | "BLIPPreprocess"
    >> beam.MapTuple(
        lambda img_url, img: (
            img_url,
            blip_preprocess(img, processor=blip_processor),
        )
    )
```

(Img URL, torch.Tensor)

Hugging Face

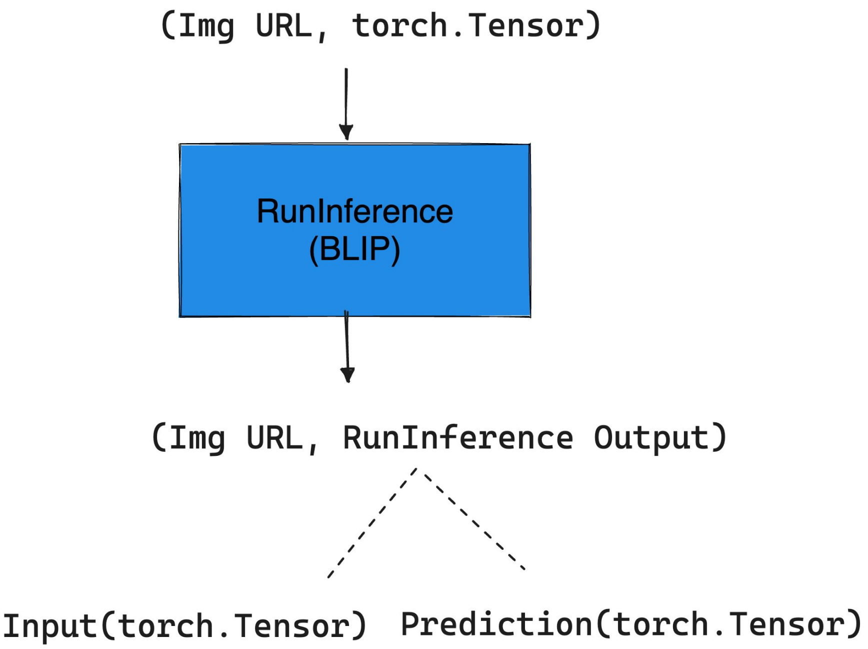
Inference using BLIP

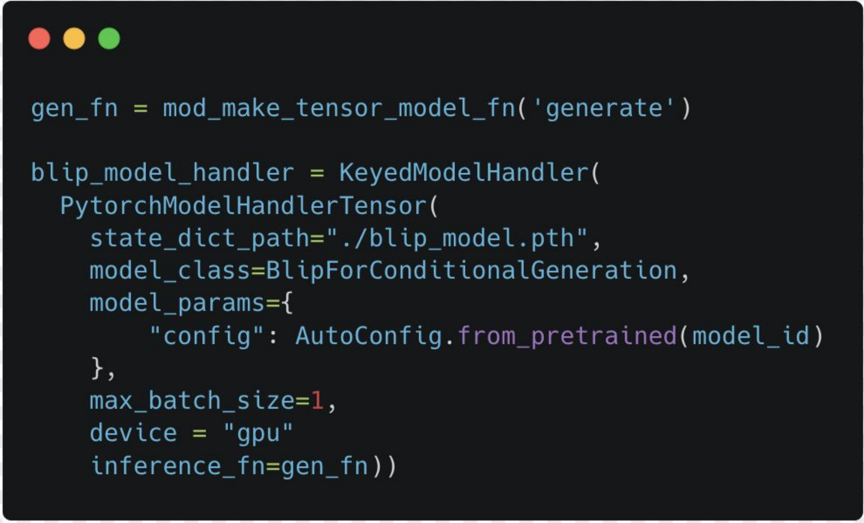




```
| "GenerateCaptions"
>> RunInference(
  model_handler=blip_model_handler,
  inference_args={
        "max_length": 50,
        "min_length": 10,
        "num_return_sequences": 5,
        "do_sample": True,
    },
)
```

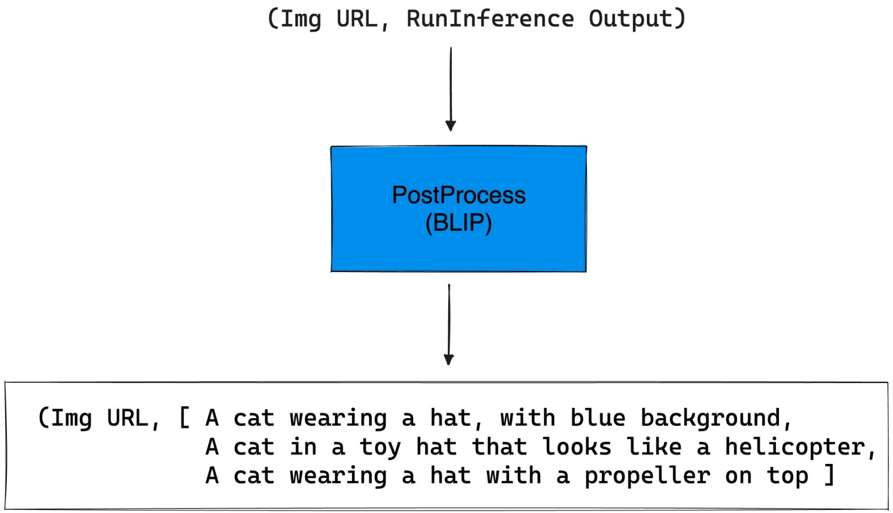
Inference using BLIP





```
gen_fn = mod_make_tensor_model_fn('generate')

blip_model_handler = KeyedModelHandler(
  PytorchModelHandlerTensor(
    state_dict_path="./blip_model.pth",
    model_class=BlipForConditionalGeneration,
    model_params={
        "config": AutoConfig.from_pretrained(model_id)
    },
    max_batch_size=1,
    device = "gpu"
    inference_fn=gen_fn))
```

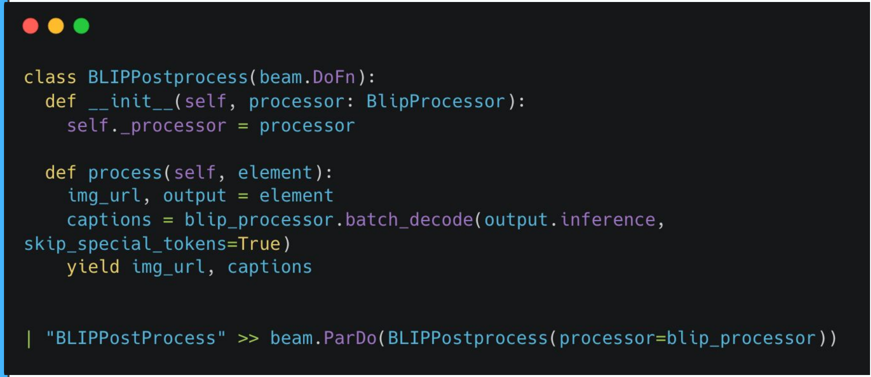
PostProcess BLIP Output



(Img URL, RunInference Output)

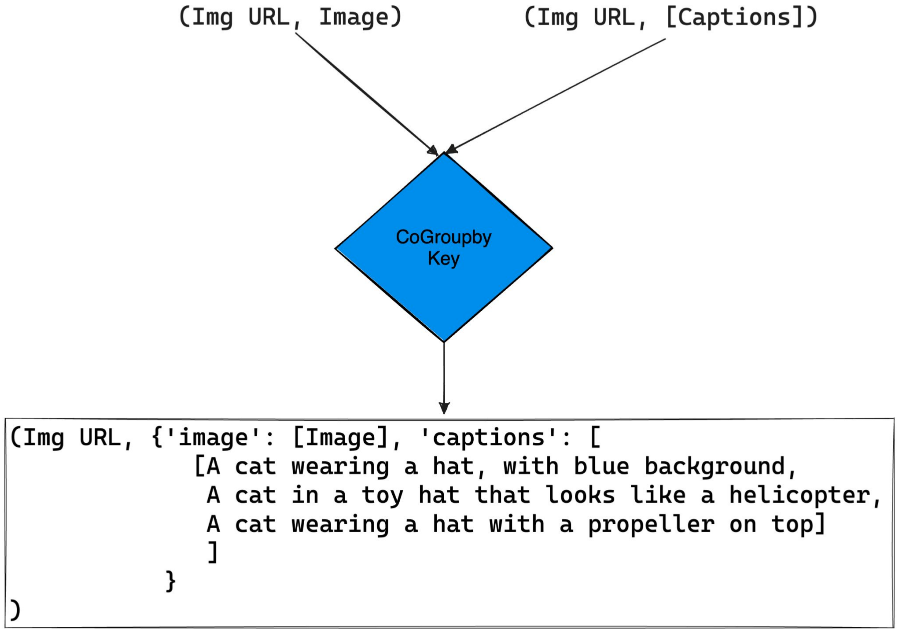
PostProcess
(BLIP)

```
(Img URL, [ A cat wearing a hat, with blue background,
            A cat in a toy hat that looks like a helicopter,
            A cat wearing a hat with a propeller on top ]
```



```
class BLIPPostprocess(beam.DoFn):
  def __init__(self, processor: BlipProcessor):
    self._processor = processor

  def process(self, element):
    img_url, output = element
    captions = blip_processor.batch_decode(output.inference,
skip_special_tokens=True)
    yield img_url, captions


| "BLIPPostProcess" >> beam.ParDo(BLIPPostprocess(processor=blip_processor))
```

Grouping Image and BLIP Output

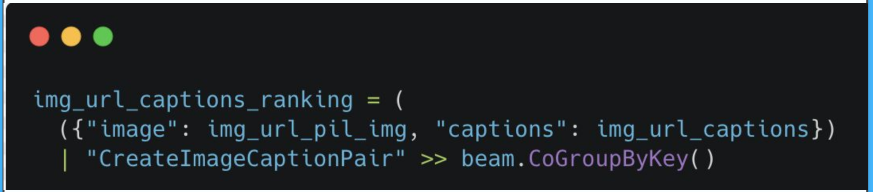


(Img URL, Image)

(Img URL, [Captions])

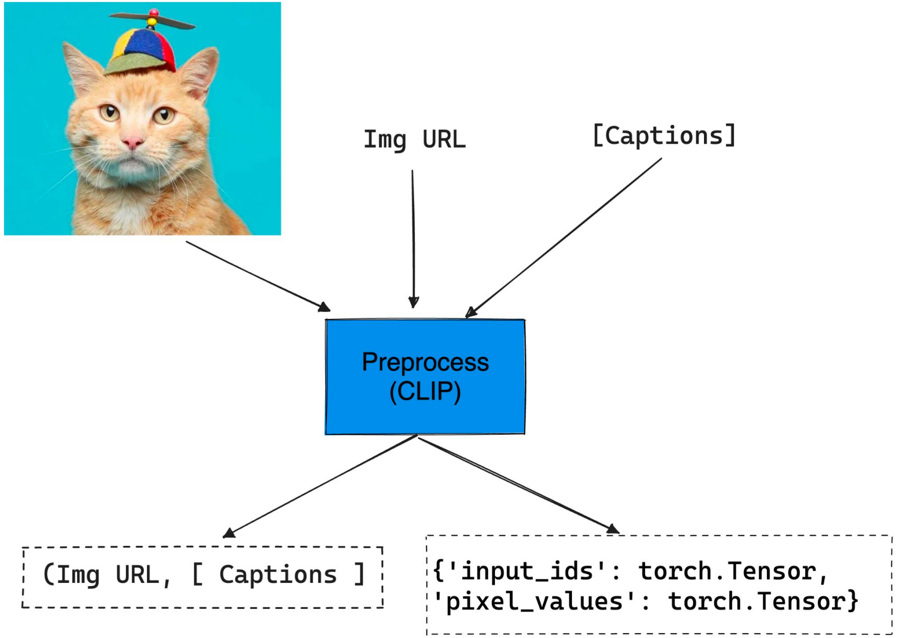
CoGroupby Key

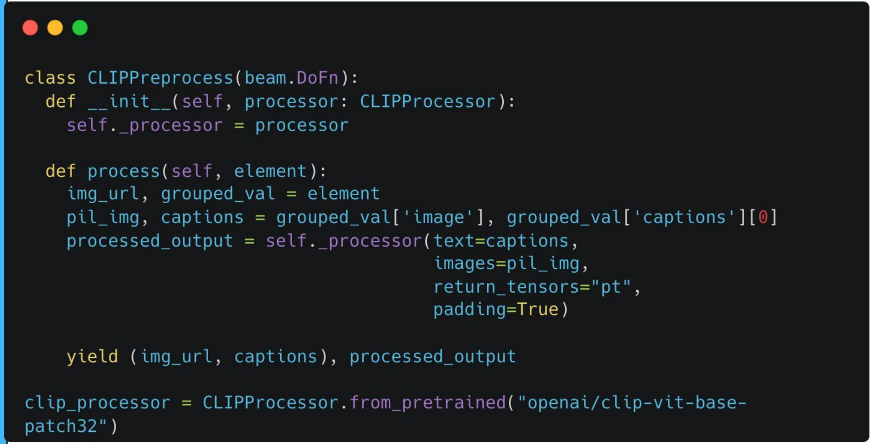
```
(Img URL, {'image': [Image], 'captions': [
                [A cat wearing a hat, with blue background,
                 A cat in a toy hat that looks like a helicopter,
                 A cat wearing a hat with a propeller on top]
                 ]
              }
)
```



```
img_url_captions_ranking = (
  ({"image": img_url_pil_img, "captions": img_url_captions})
  | "CreateImageCaptionPair" >> beam.CoGroupByKey()
```

Preprocess Inputs for CLIP

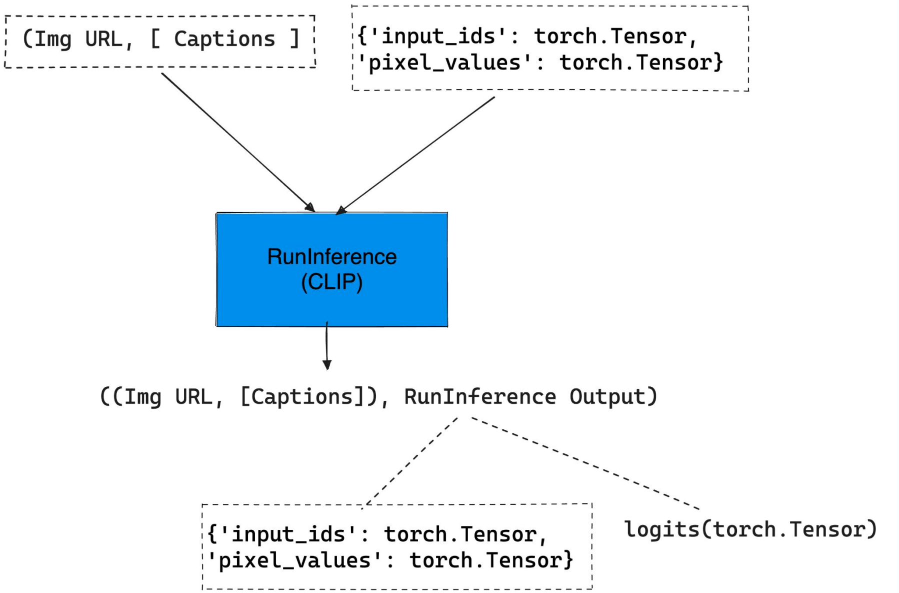


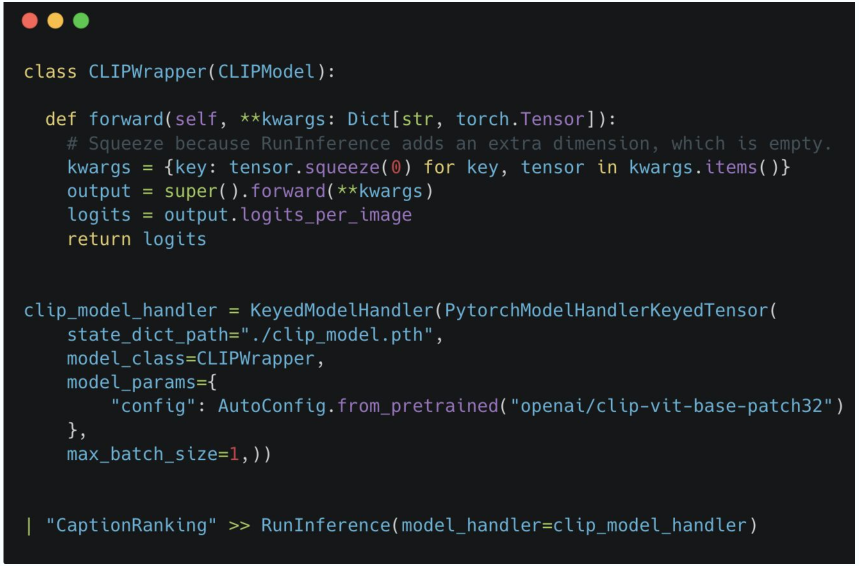


```python
class CLIPPreprocess(beam.DoFn):
  def __init__(self, processor: CLIPProcessor):
    self._processor = processor

  def process(self, element):
    img_url, grouped_val = element
    pil_img, captions = grouped_val['image'], grouped_val['captions'][0]
    processed_output = self._processor(text=captions,
                                       images=pil_img,
                                       return_tensors="pt",
                                       padding=True)

    yield (img_url, captions), processed_output

clip_processor = CLIPProcessor.from_pretrained("openai/clip-vit-base-
patch32")
```

Hugging Face

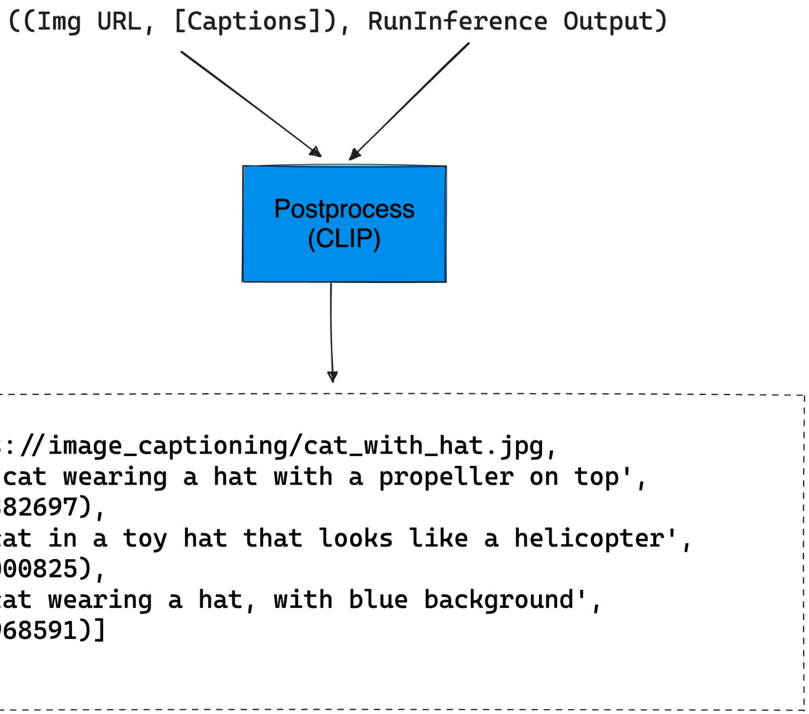
Inference using CLIP


(Img URL, [Captions]
{'input_ids': torch.Tensor,
'pixel_values': torch.Tensor}
RunInference
(CLIP)
((Img URL, [Captions]), RunInference Output)
{'input_ids': torch.Tensor,
'pixel_values': torch.Tensor}
logits(torch.Tensor)

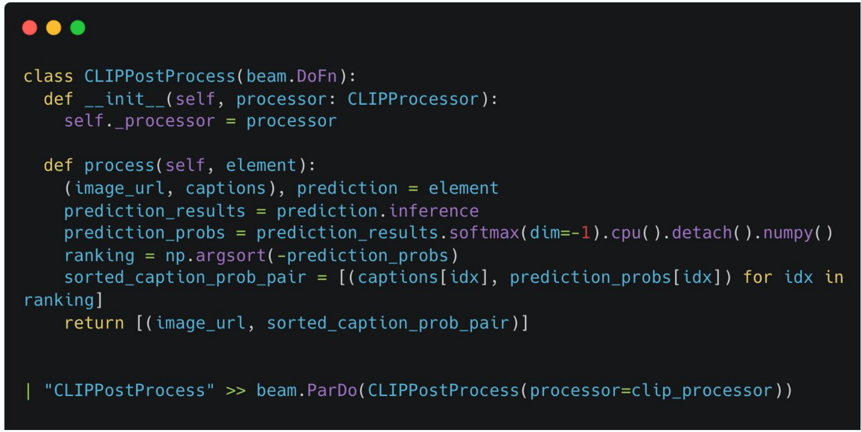


```
class CLIPWrapper(CLIPModel):

  def forward(self, **kwargs: Dict[str, torch.Tensor]):
    # Squeeze because RunInference adds an extra dimension, which is empty.
    kwargs = {key: tensor.squeeze(0) for key, tensor in kwargs.items()}
    output = super().forward(**kwargs)
    logits = output.logits_per_image
    return logits


clip_model_handler = KeyedModelHandler(PytorchModelHandlerKeyedTensor(
    state_dict_path="./clip_model.pth",
    model_class=CLIPWrapper,
    model_params={
        "config": AutoConfig.from_pretrained("openai/clip-vit-base-patch32")
    },
    max_batch_size=1,))


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

PostProcess CLIP Output

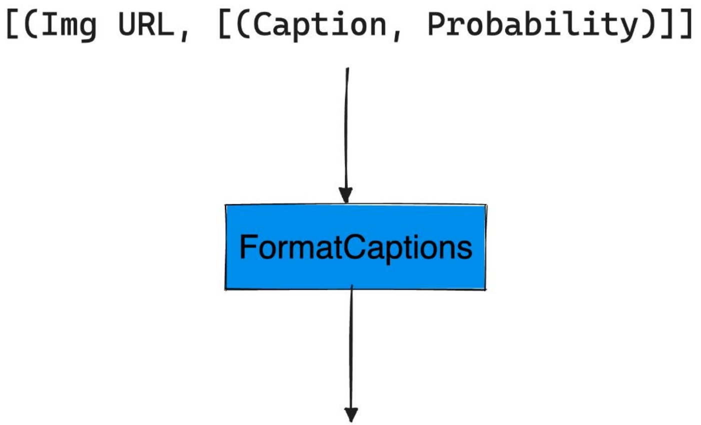


```
(
https://image_captioning/cat_with_hat.jpg,
[('A cat wearing a hat with a propeller on top',
0.43382697),
('A cat in a toy hat that looks like a helicopter',
0.32000825),
('A cat wearing a hat, with blue background',
0.16968591)]
)
```



```python
class CLIPPostProcess(beam.DoFn):
  def __init__(self, processor: CLIPProcessor):
    self._processor = processor

  def process(self, element):
    (image_url, captions), prediction = element
    prediction_results = prediction.inference
    prediction_probs = prediction_results.softmax(dim=-1).cpu().detach().numpy()
    ranking = np.argsort(-prediction_probs)
    sorted_caption_prob_pair = [(captions[idx], prediction_probs[idx]) for idx in
ranking]
    return [(image_url, sorted_caption_prob_pair)]


| "CLIPPostProcess" >> beam.ParDo(CLIPPostProcess(processor=clip_processor))
```

Printing the results nicely



[(Img URL, [(Caption, Probability)]]

FormatCaptions

```
Image: cat_with_hat
Top 3 captions ranked by CLIP:
1: A cat wearing a hat with a propeller on top
(Caption probability: 0.4338)
2: A cat in a toy hat that looks like a helicopter.
(Caption probability: 0.3200)
3: A cat wearing a hat, with blue background.
(Caption probability: 0.1697)
```

Takeaways

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

- Multiple RunInference transforms enable complex pipelines with minimal code for multi-ML models.

- Example pipeline can be used for captioning images for finetuning Stable Diffusion.

Code and Tutorial Link

Code: GitHub Link

Tutorial: Apache Beam Documentation Link

Slides: GitHub Link

Shubham Krishna

QUESTIONS?

in shubham-krishna-998922108

shub-kris

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Per Entity Training Pipelines in Apache Beam

Jasper Van den Bossche
ML6

BEAM SUMMIT
NYC 2023

About ML6

We are a group of AI and machine learning experts building custom AI solutions.

Amongst our engineers we have several Apache Beam contributors.

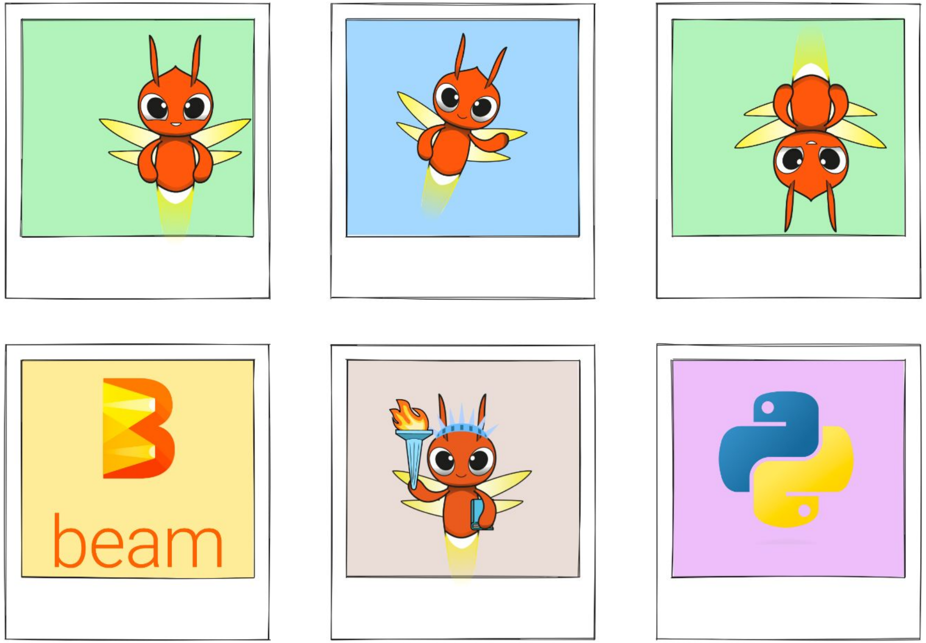
Agenda

- Development of ML applications
  - What is training?
  - What is MLOps?
- What does per entity training mean?
  - Training multiple models rather than a single model?
  - Why use a per entity strategy
- Example per entity training pipeline
- Bonus: Using trained models in a RunInference pipeline

What is machine learning model training?

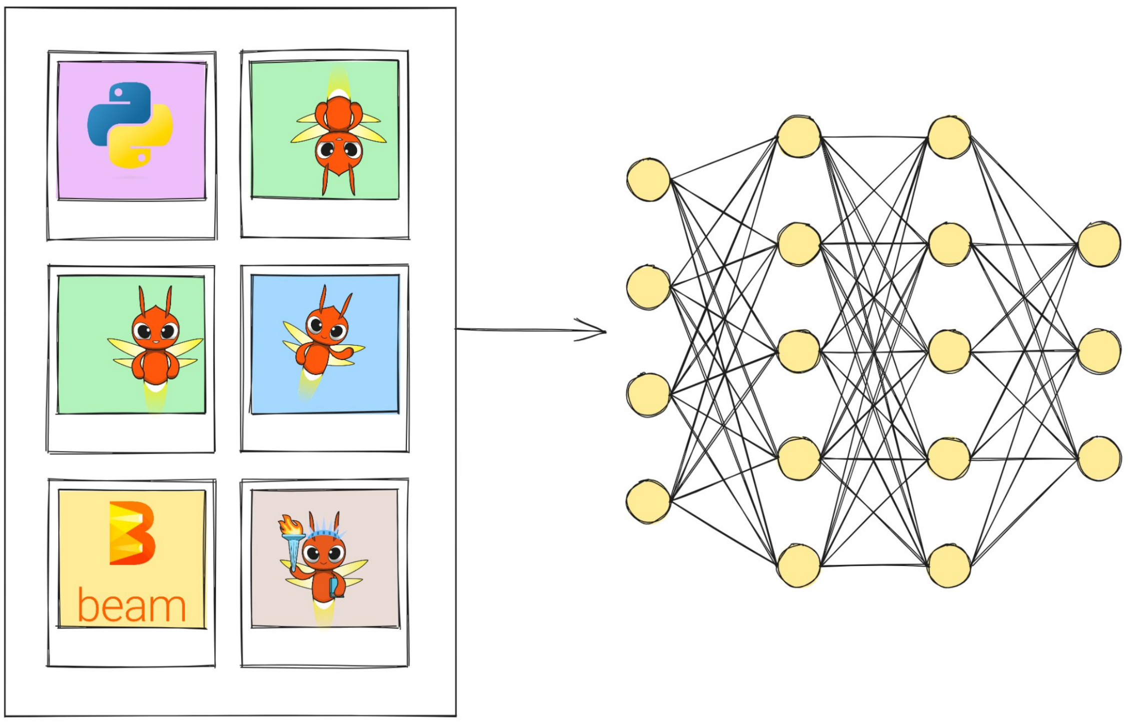
What is machine learning model training?

```
def contains_firefly():
    ...
```

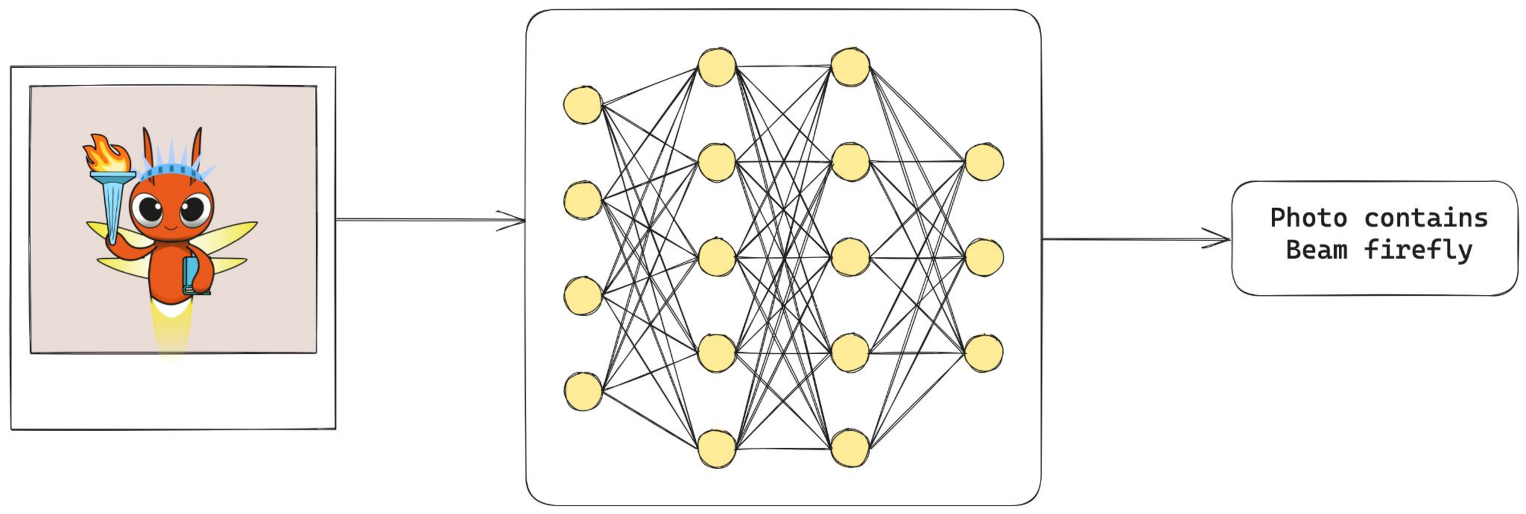


Writing logic to detect the Beam macot is almost impossible

What is training a machine learning model?

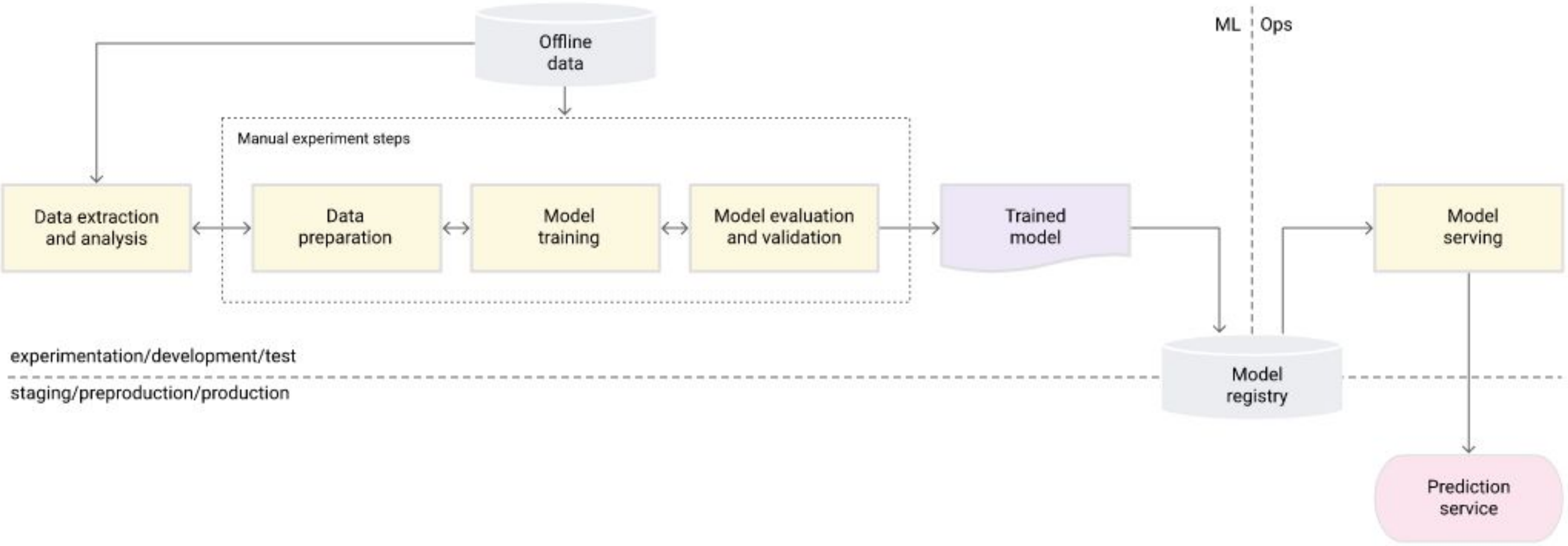


What is training a machine learning model?

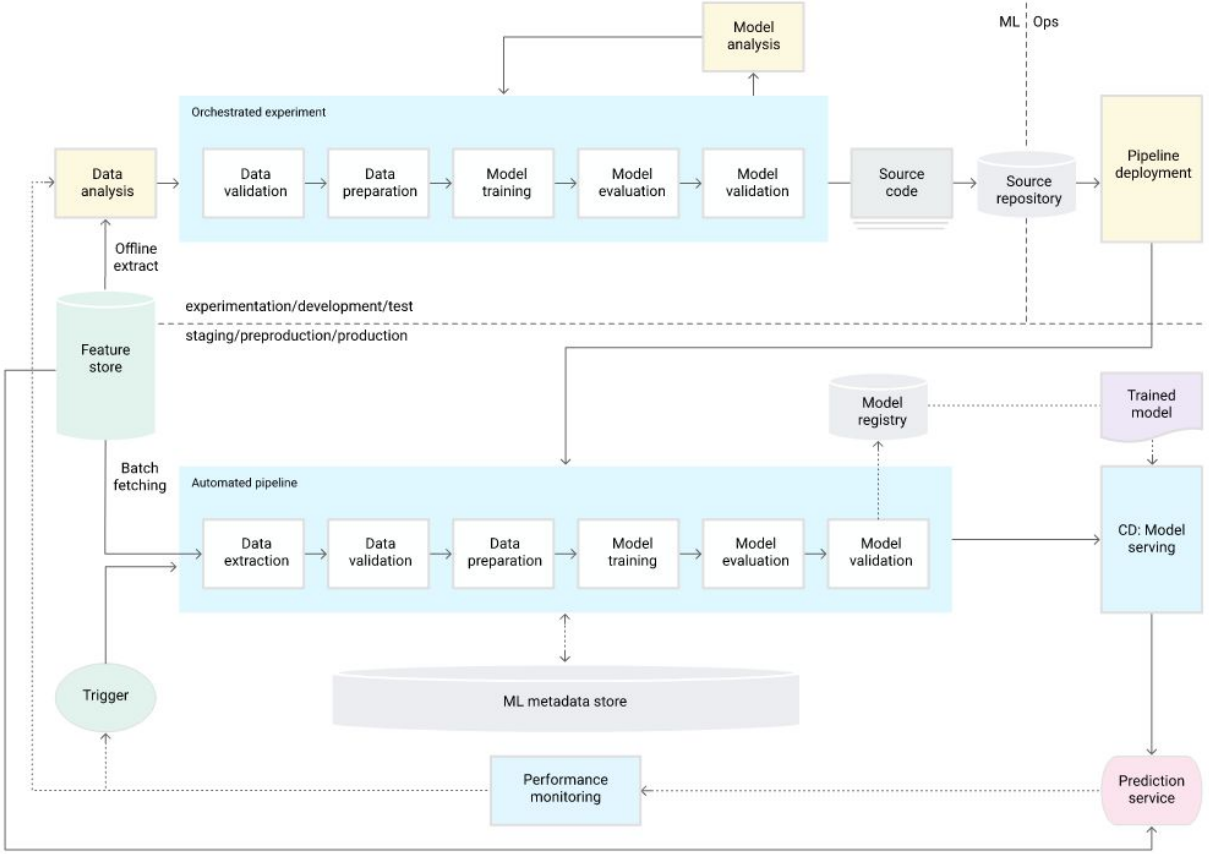


How are machine learning applications built and deployed?

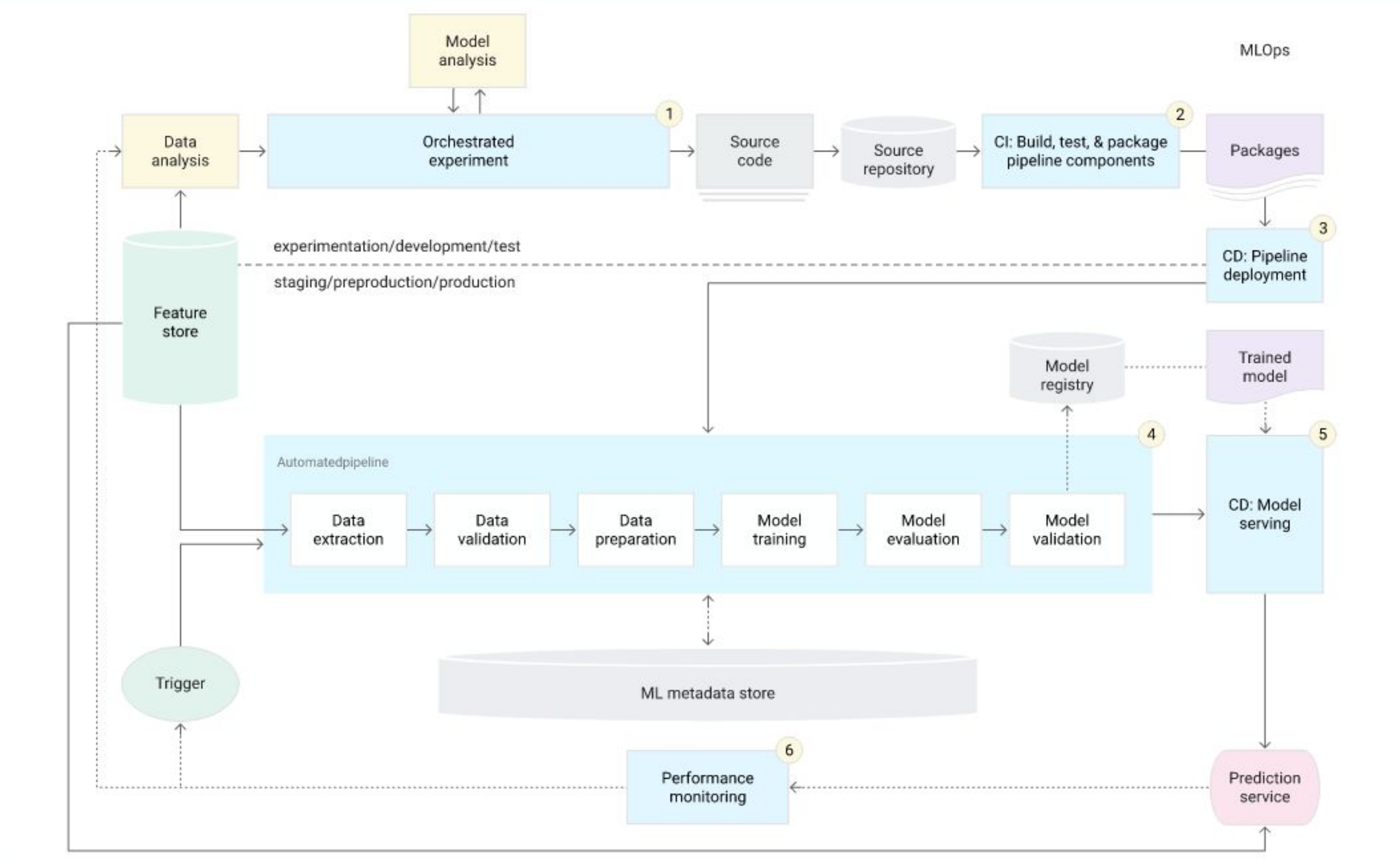
MLOps: Level 0



MLOps: Level 1

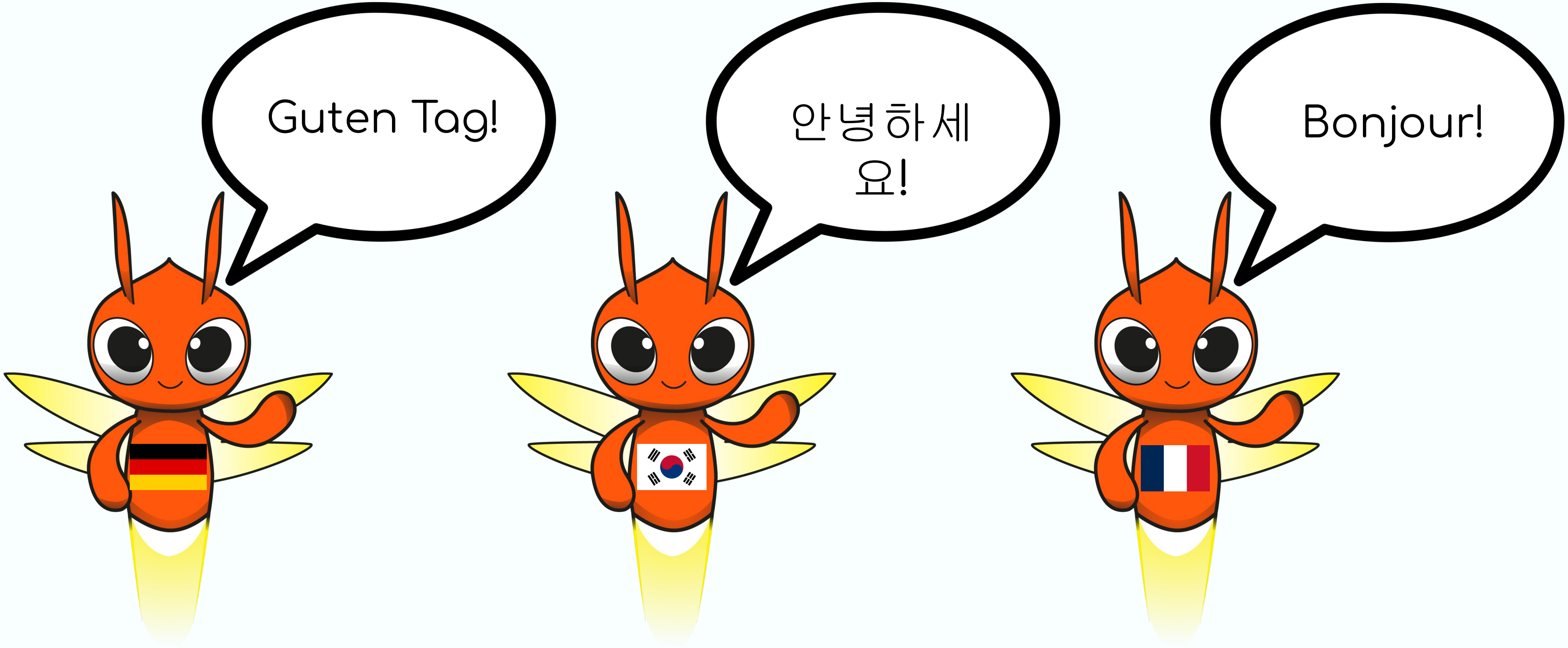


MLOps: Level 2

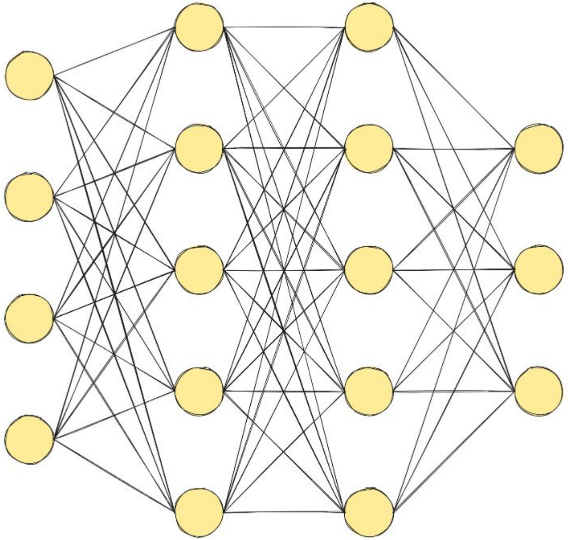


What is per entity training?

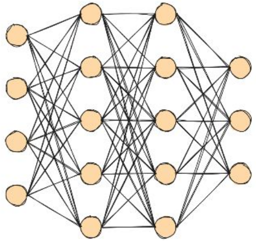
Example: Building multilingual chatbot



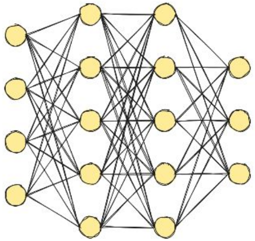
What is per entity training?



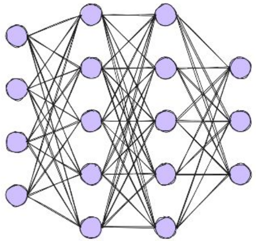
Multilingual Large Language Model



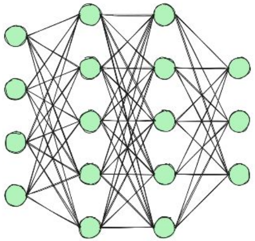
Dutch Language Model



Spanish Language Model

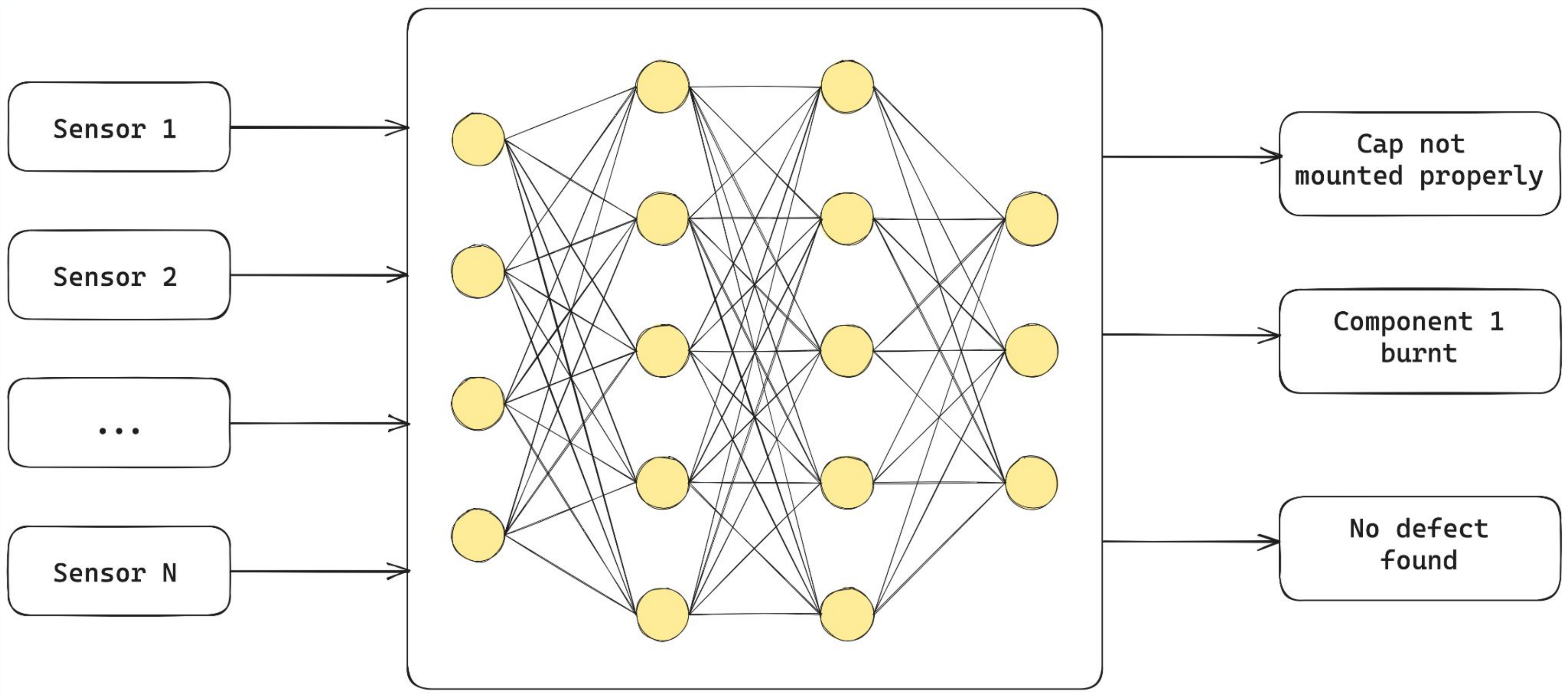


English Language Model

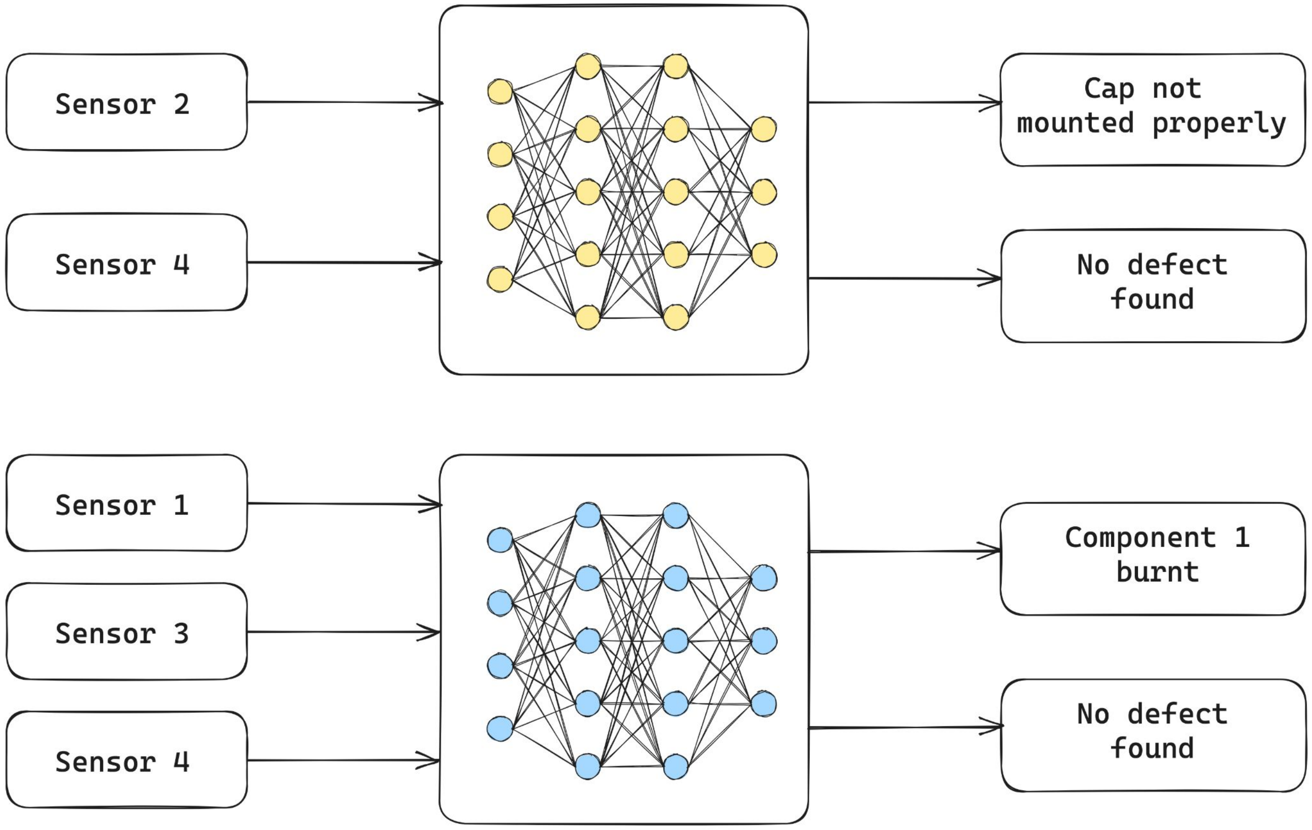


Italian Language Model

Example: Detect production defects using sensor data



Example: Detect production defects using sensor data



Sensor 2

Sensor 4

Cap not mounted properly

No defect found

Sensor 1

Sensor 3

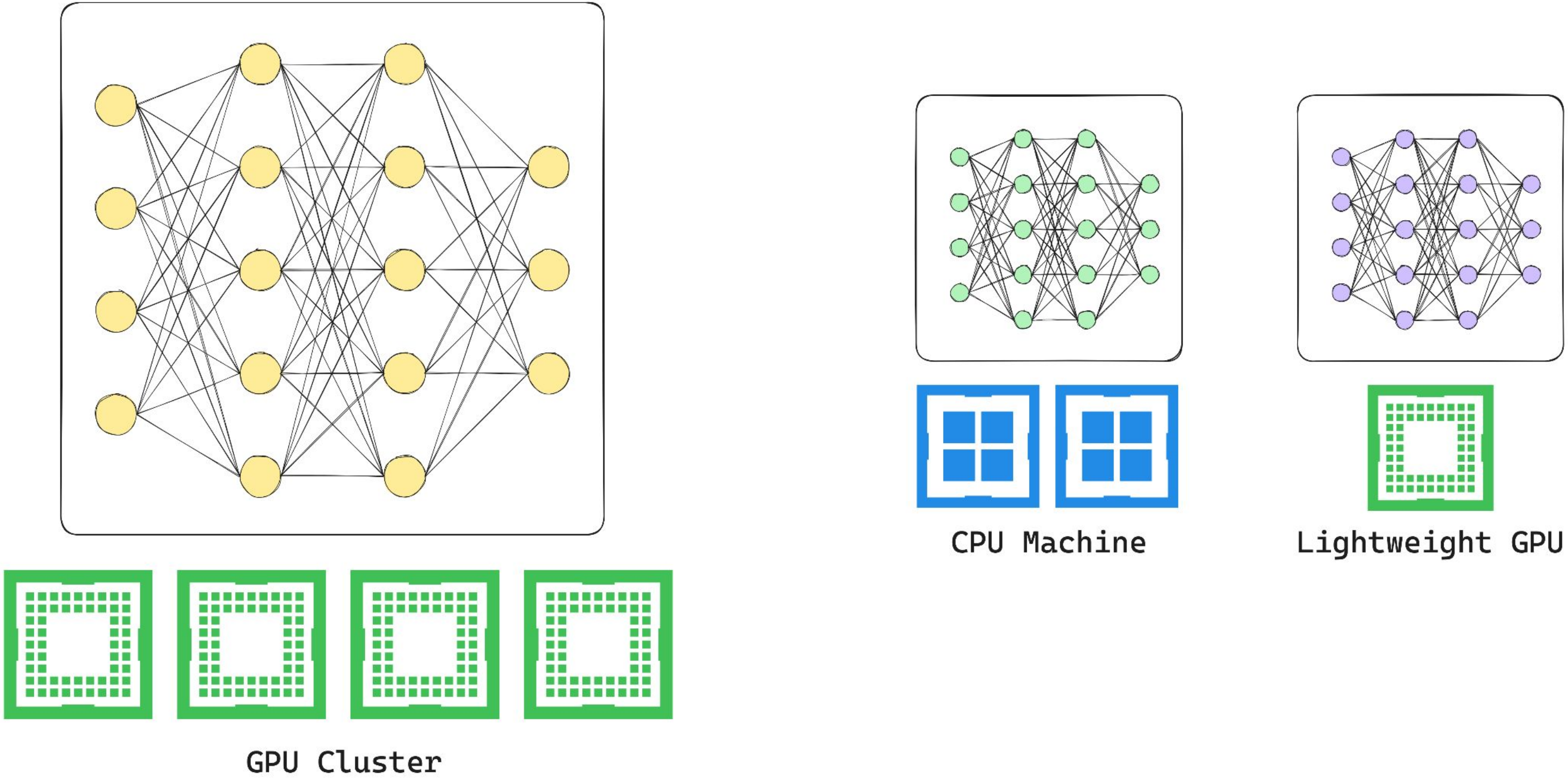
Sensor 4

Component 1 burnt

No defect found

Why use a per entity strategy?

Reduce Model Infrastructure Requirements

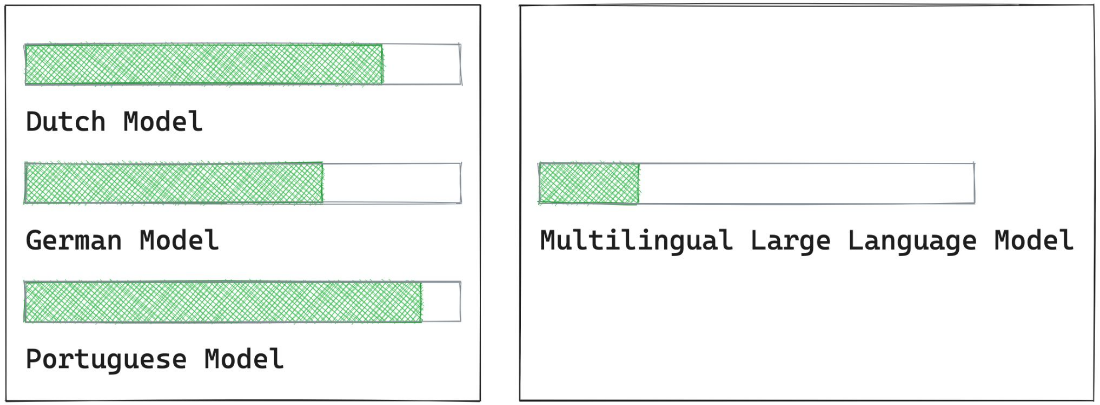


GPU Cluster

CPU Machine

Lightweight GPU

Faster training & inference

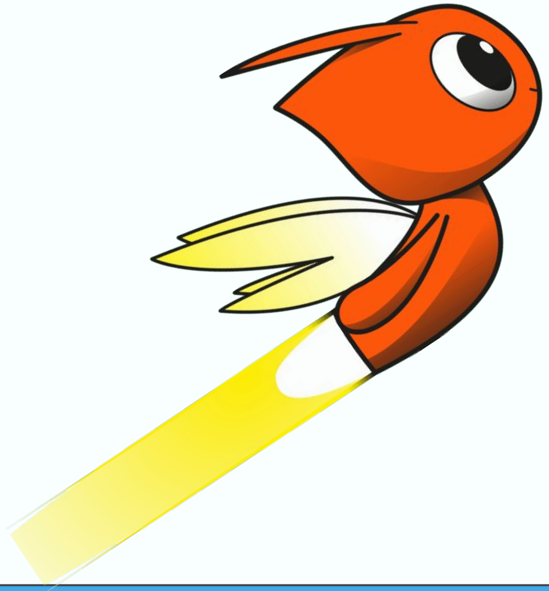


Dutch Model

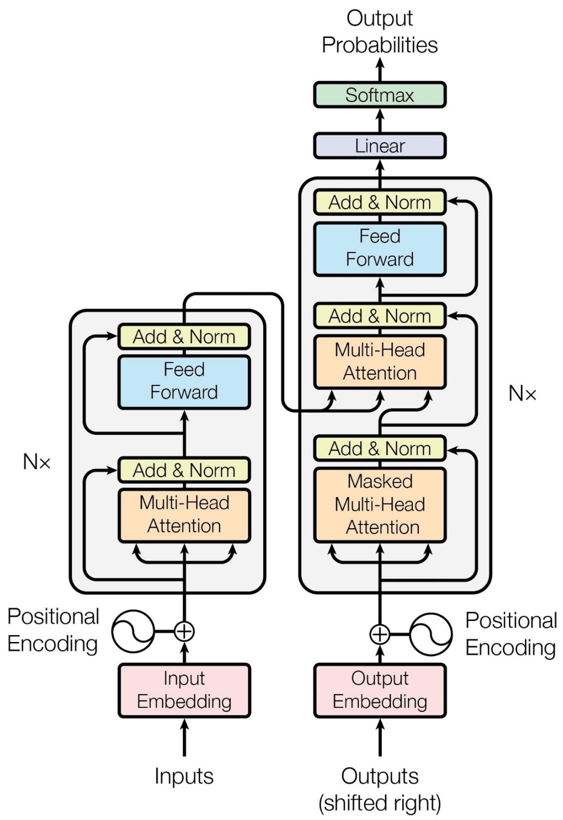
German Model

Portuguese Model

Multilingual Large Language Model



Address fairness and bias



Output Probabilities

Softmax

Linear

Add & Norm

Feed Forward

Add & Norm

Multi-Head Attention

Add & Norm

Masked Multi-Head Attention

Nx

Add & Norm

Feed Forward

Add & Norm

Multi-Head Attention

Nx

Positional Encoding

Positional Encoding

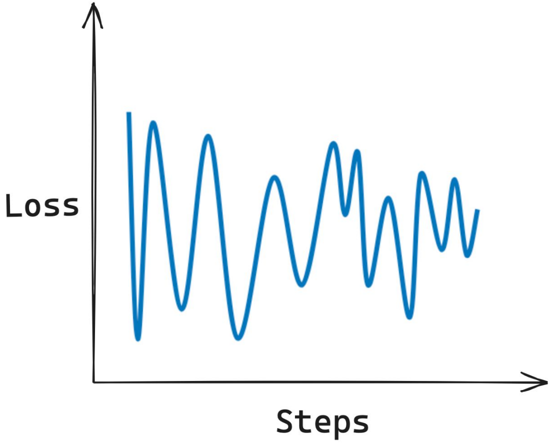
Input Embedding

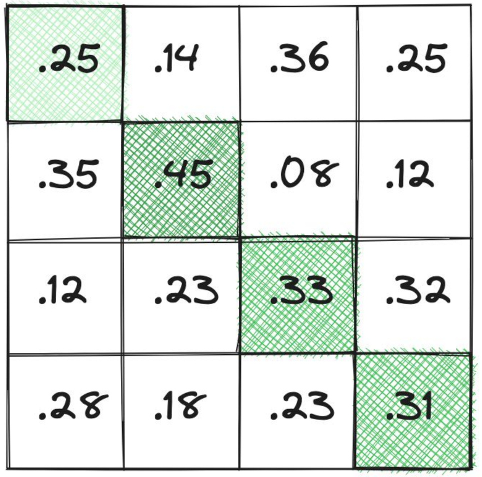
Output Embedding

Inputs

Outputs (shifted right)

Easier to detect problems

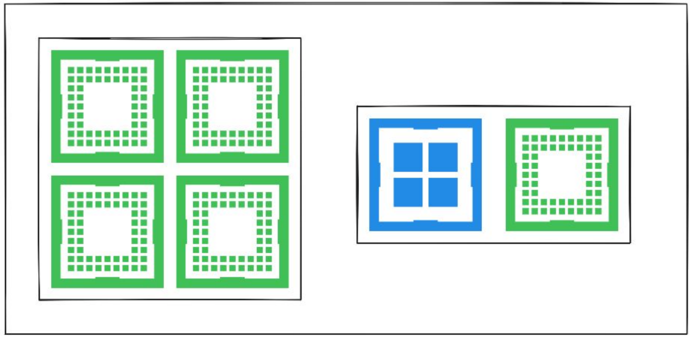




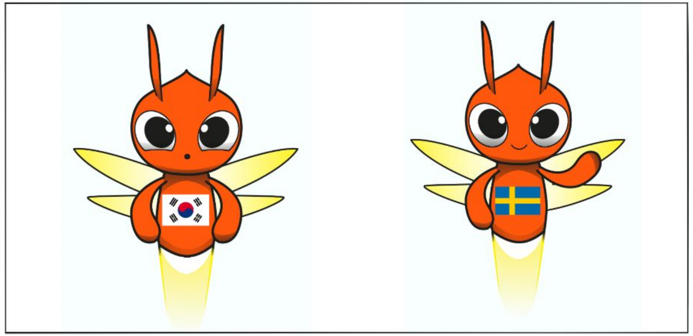
.25	.14	.36	.25
.35	.45	.08	.12
.12	.23	.33	.32
.28	.18	.23	.31

Confusion Matrix

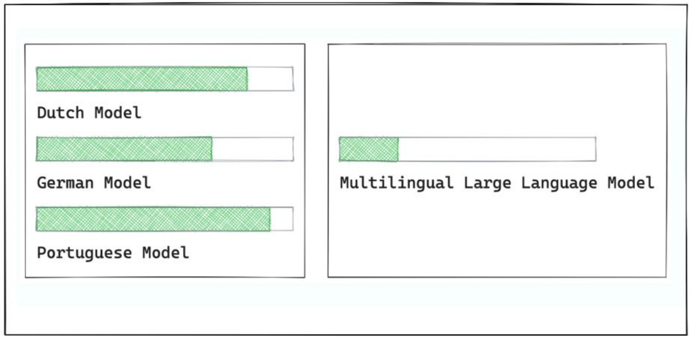
Simpler models have the following advantages



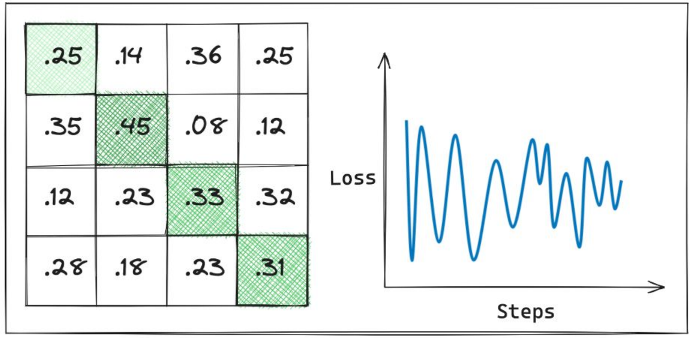
Less powerful hardware required



Easier to address bias



Faster training & inference

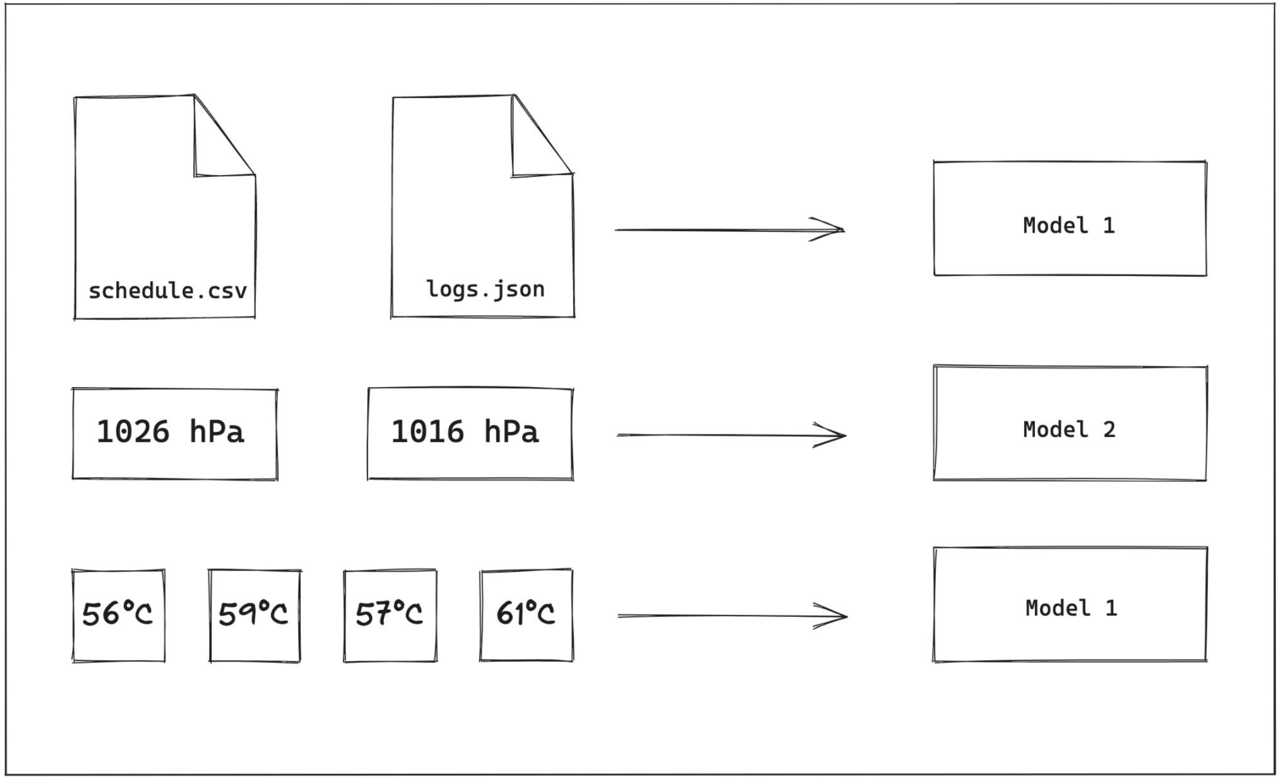


.25	.14	.36	.25
.35	.45	.08	.12
.12	.23	.33	.32
.28	.18	.23	.31

Easier debugging

But there is one big problem:
How do I manage the training of all of these models?

Manage training pipelines



The solution? Apache Beam!

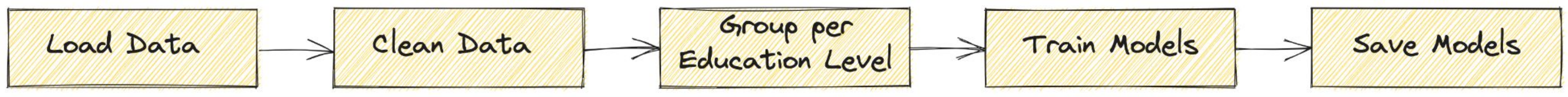
- Apache Beam can handle ***streaming*** and ***batch data***
- Apache Beam can easily ***prepare data*** for training
- Apache Beam can run on different ***runners*** depending on the model's ***requirements***
- ***Abstraction*** in ML libraries allows us to train models with few lines of code

Let’s look at an example of a per entity training pipeline

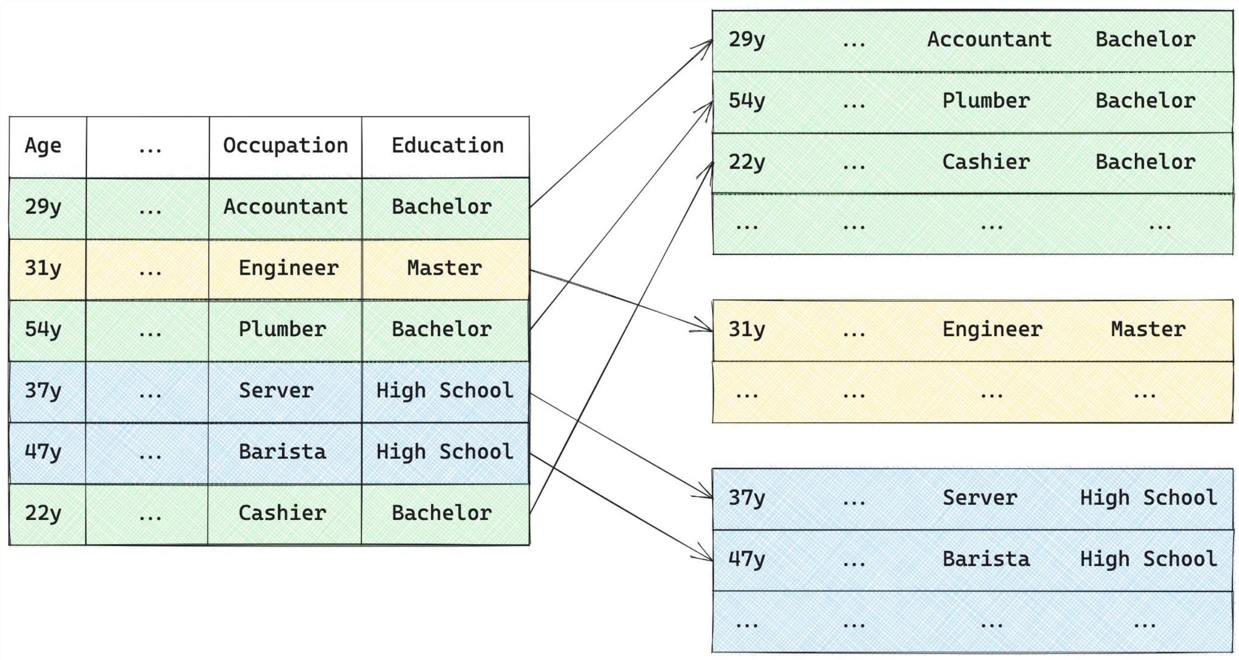
Predicting incomes per education level

Age	Workclass	Education	Marital Status	Occupation	Relationship	Race	Sex	Hours per Week	Native Country	Compensation
25	Private	11th	Never-married	Machine-op-inspct	Own-child	Black	Male	40	USA	<=50K.
38	Private	HS-grad	Married-civ-spouse	Farming-fishing	Husband	White	Male	50	USA	<=50K.
28	Local-gov	Assoc-acdm	Married-civ-spouse	Protective-serv	Husband	White	Male	40	USA	>50K.
44	Private	Some-college	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	40	USA	>50K.
18	?	Some-college	Never-married	?	Own-child	White	Female	30	USA	<=50K.

Pipeline overview



Split data per education level



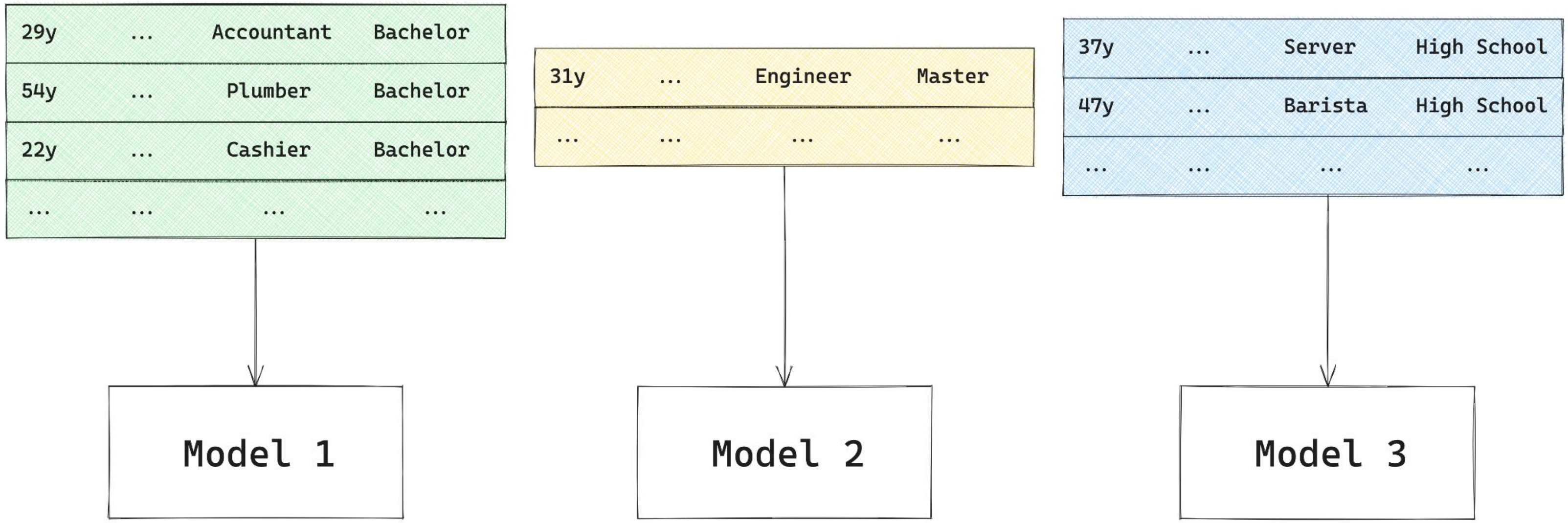
Age	...	Occupation	Education
29y	...	Accountant	Bachelor
31y	...	Engineer	Master
54y	...	Plumber	Bachelor
37y	...	Server	High School
47y	...	Barista	High School
22y	...	Cashier	Bachelor

29y	...	Accountant	Bachelor
54y	...	Plumber	Bachelor
22y	...	Cashier	Bachelor
...	...	...	...

31y	...	Engineer	Master
...	...	...	...

37y	...	Server	High School
47y	...	Barista	High School
...	...	...	...

Train model per dataset

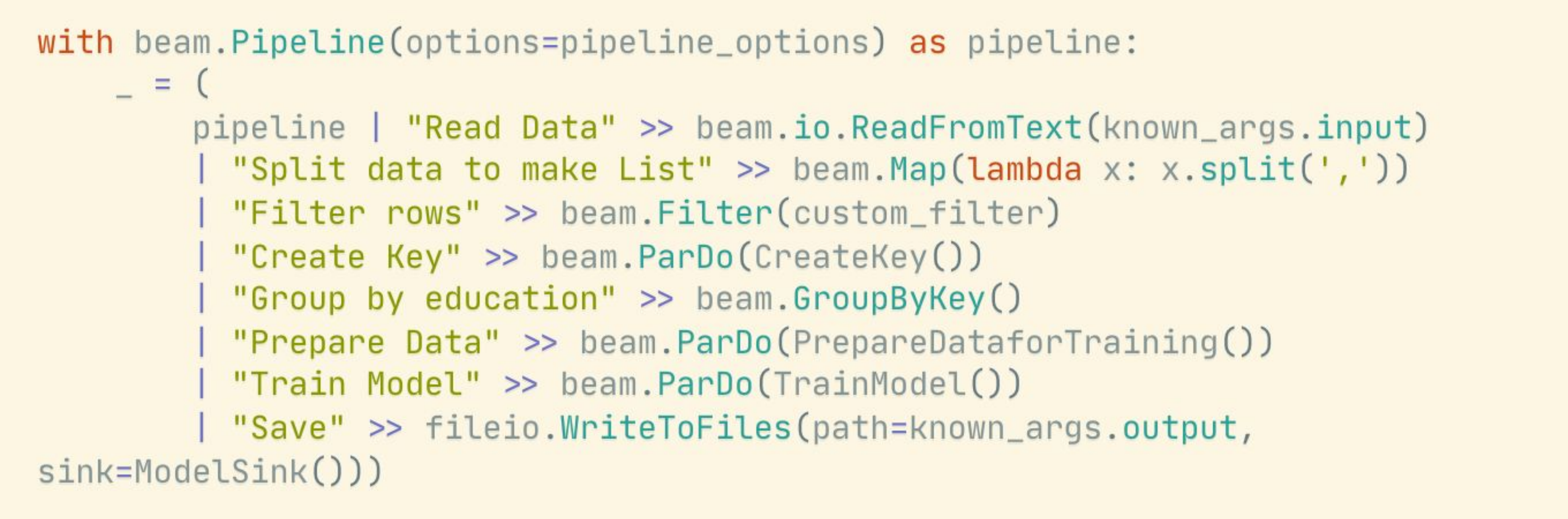


29y	...	Accountant	Bachelor
54y	...	Plumber	Bachelor
22y	...	Cashier	Bachelor
...	...	...	...

31y	...	Engineer	Master
...	...	...	...

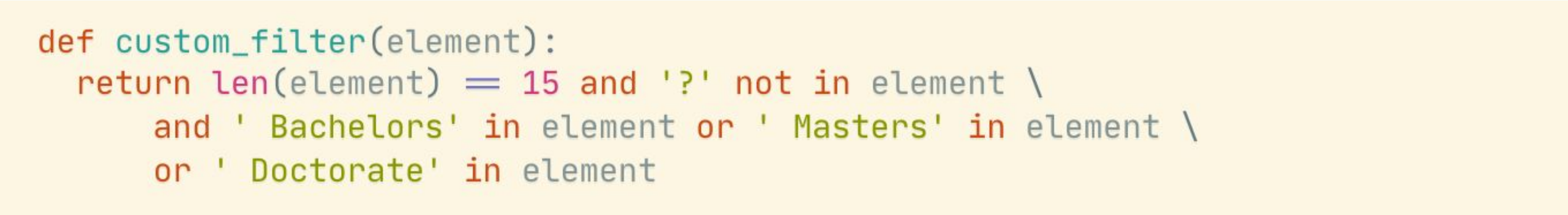
37y	...	Server	High School
47y	...	Barista	High School
...	...	...	...

Pipeline overview



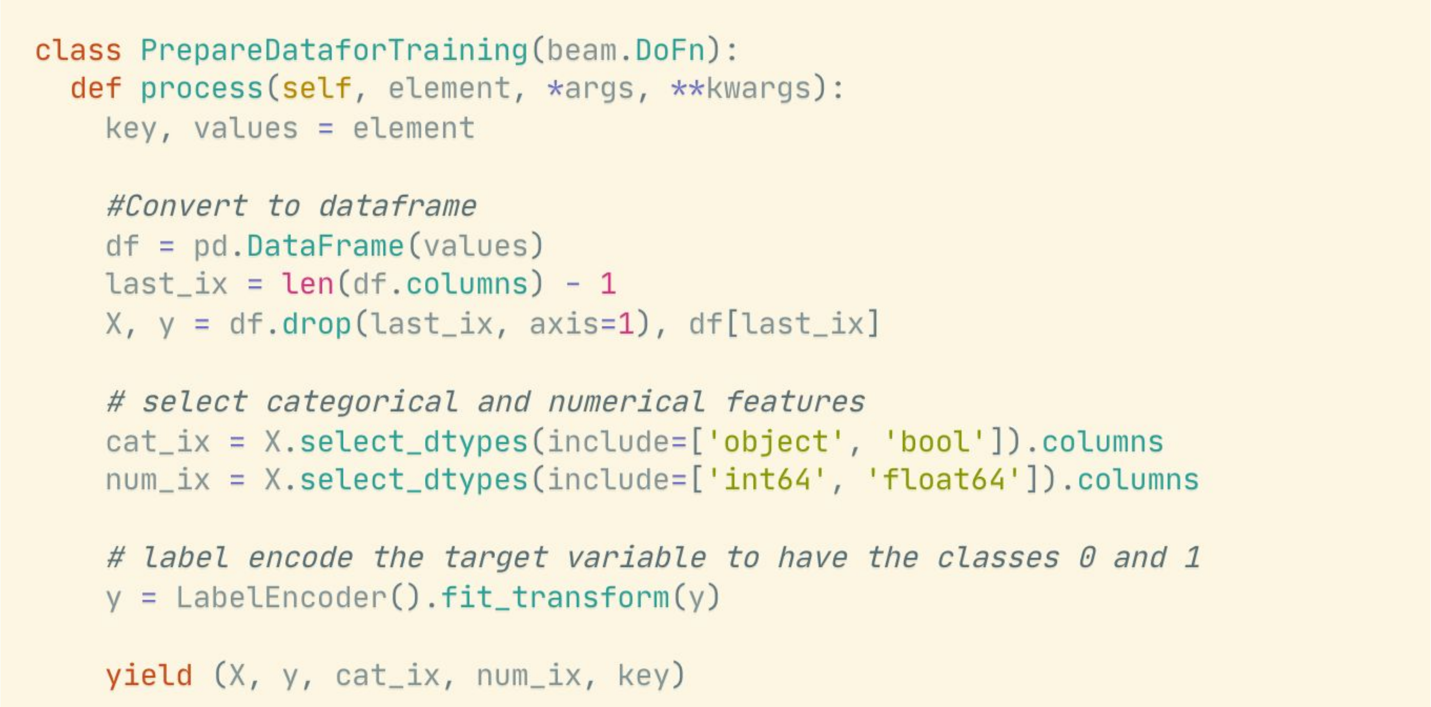
```
with beam.Pipeline(options=pipeline_options) as pipeline:
    _ = (
        pipeline | "Read Data" >> beam.io.ReadFromText(known_args.input)
        | "Split data to make List" >> beam.Map(lambda x: x.split(','))
        | "Filter rows" >> beam.Filter(custom_filter)
        | "Create Key" >> beam.ParDo(CreateKey())
        | "Group by education" >> beam.GroupByKey()
        | "Prepare Data" >> beam.ParDo(PrepareDataforTraining())
        | "Train Model" >> beam.ParDo(TrainModel())
        | "Save" >> fileio.WriteToFiles(path=known_args.output,
sink=ModelSink()))
```

Step 1: Data preparation



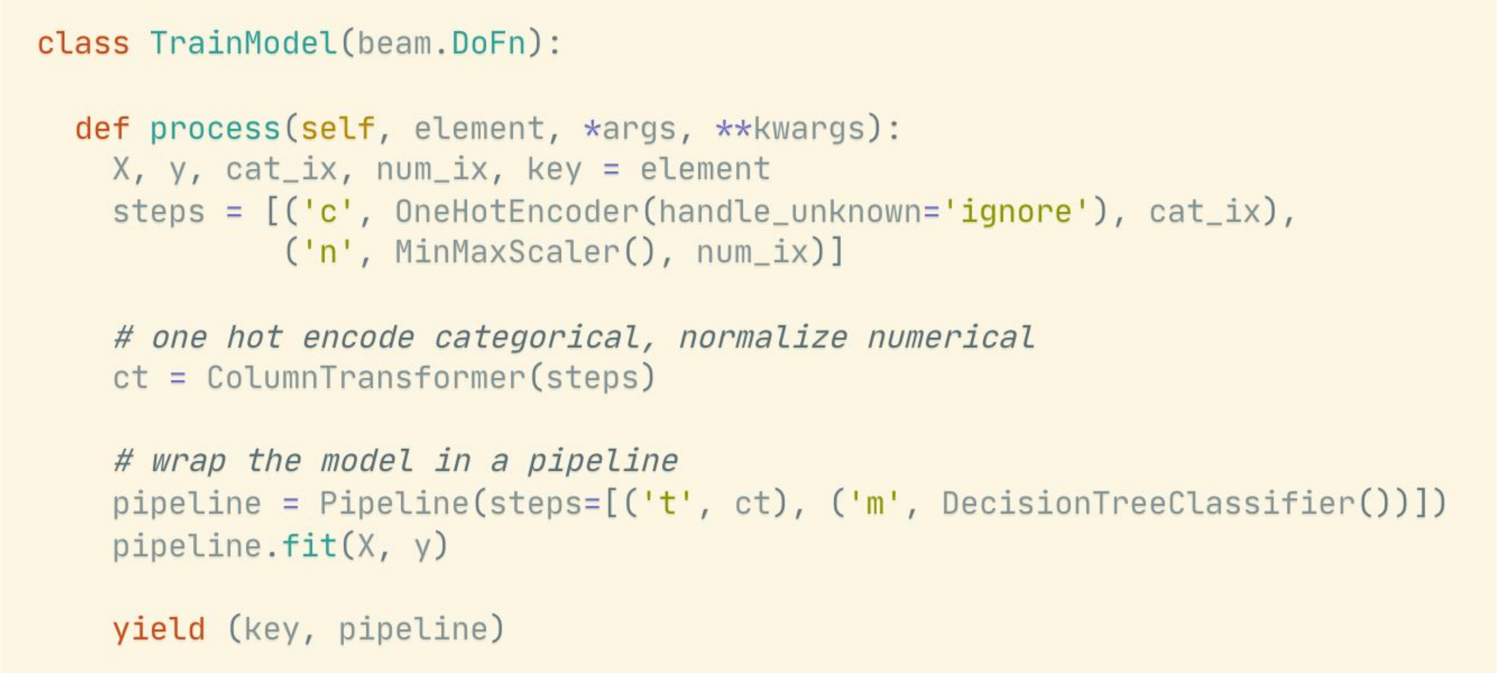
```python
def custom_filter(element):
  return len(element) == 15 and '?' not in element \
      and ' Bachelors' in element or ' Masters' in element \
      or ' Doctorate' in element
```

Step 1: Data preparation



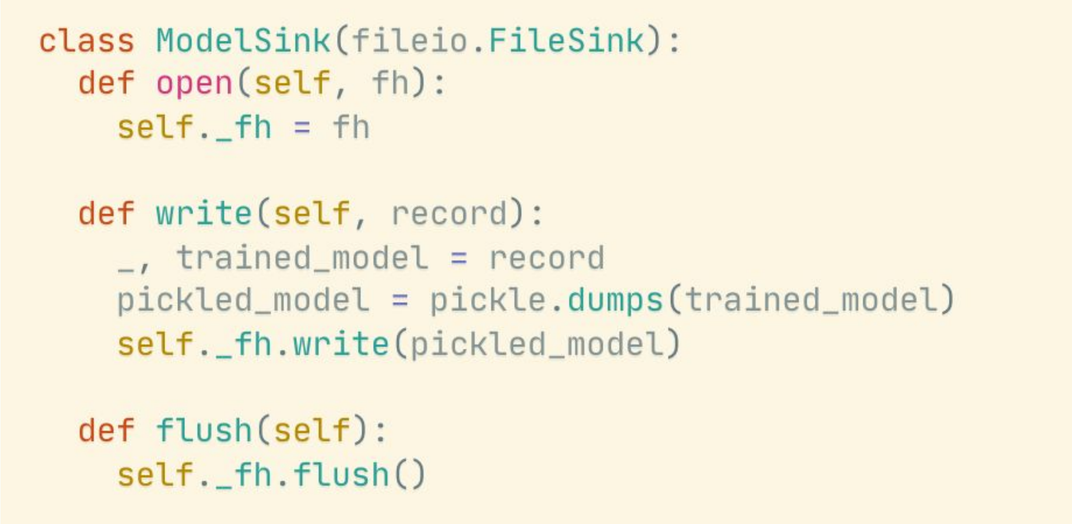
```
class PrepareDataforTraining(beam.DoFn):
  def process(self, element, *args, **kwargs):
    key, values = element

    #Convert to dataframe
    df = pd.DataFrame(values)
    last_ix = len(df.columns) - 1
    X, y = df.drop(last_ix, axis=1), df[last_ix]

    # select categorical and numerical features
    cat_ix = X.select_dtypes(include=['object', 'bool']).columns
    num_ix = X.select_dtypes(include=['int64', 'float64']).columns

    # label encode the target variable to have the classes 0 and 1
    y = LabelEncoder().fit_transform(y)

    yield (X, y, cat_ix, num_ix, key)
```

Step 2: Training the models



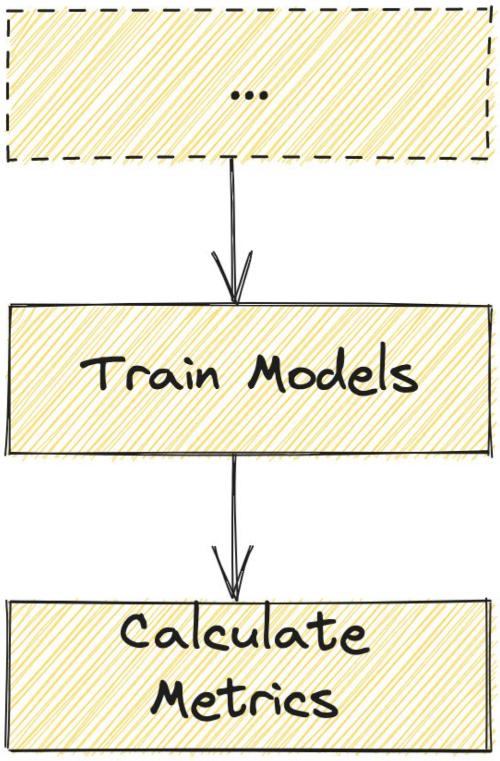
```python
class TrainModel(beam.DoFn):

  def process(self, element, *args, **kwargs):
    X, y, cat_ix, num_ix, key = element
    steps = [('c', OneHotEncoder(handle_unknown='ignore'), cat_ix),
             ('n', MinMaxScaler(), num_ix)]

    # one hot encode categorical, normalize numerical
    ct = ColumnTransformer(steps)

    # wrap the model in a pipeline
    pipeline = Pipeline(steps=[('t', ct), ('m', DecisionTreeClassifier())])
    pipeline.fit(X, y)

    yield (key, pipeline)
```

Step 3: Saving models

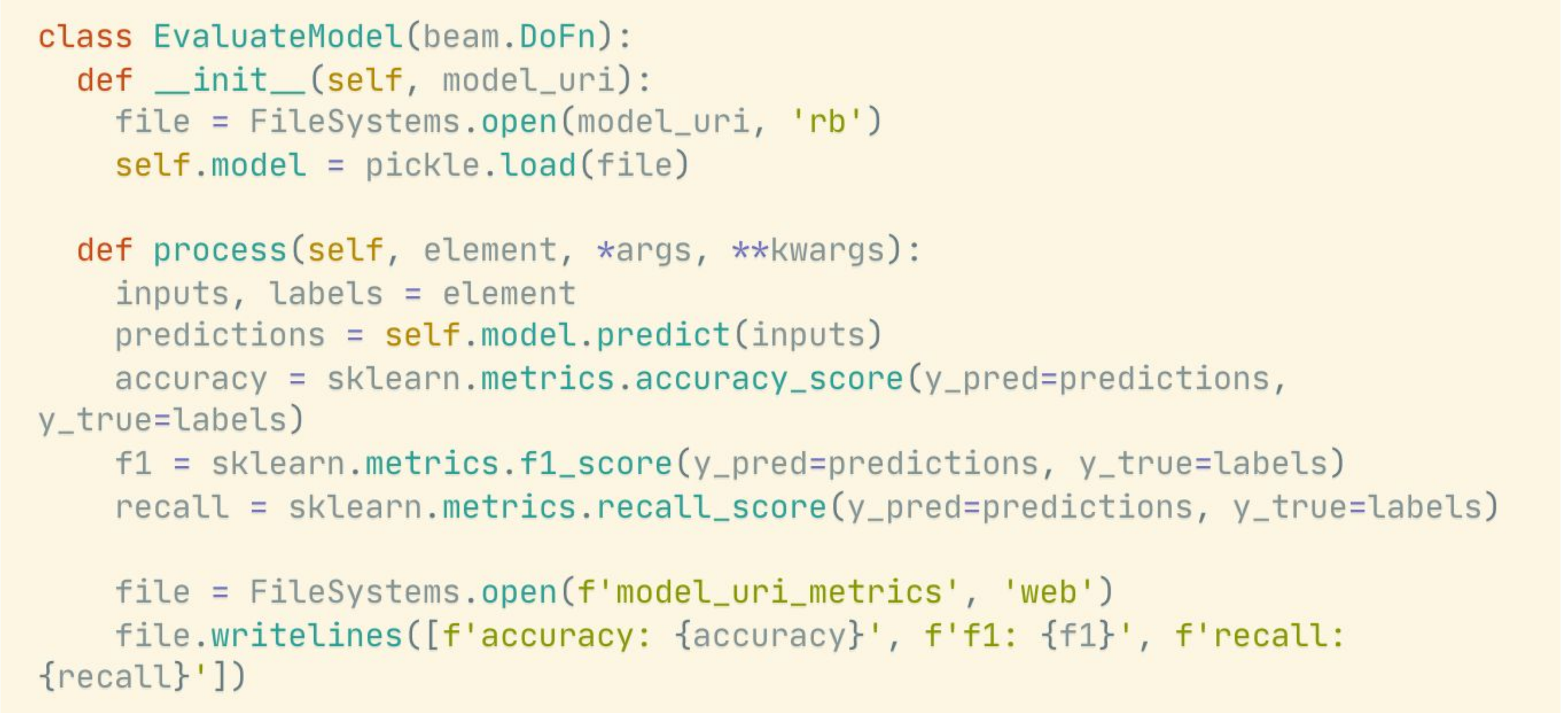


```python
class ModelSink(fileio.FileSink):
  def open(self, fh):
    self._fh = fh

  def write(self, record):
    _, trained_model = record
    pickled_model = pickle.dumps(trained_model)
    self._fh.write(pickled_model)

  def flush(self):
    self._fh.flush()
```

Extending the pipeline

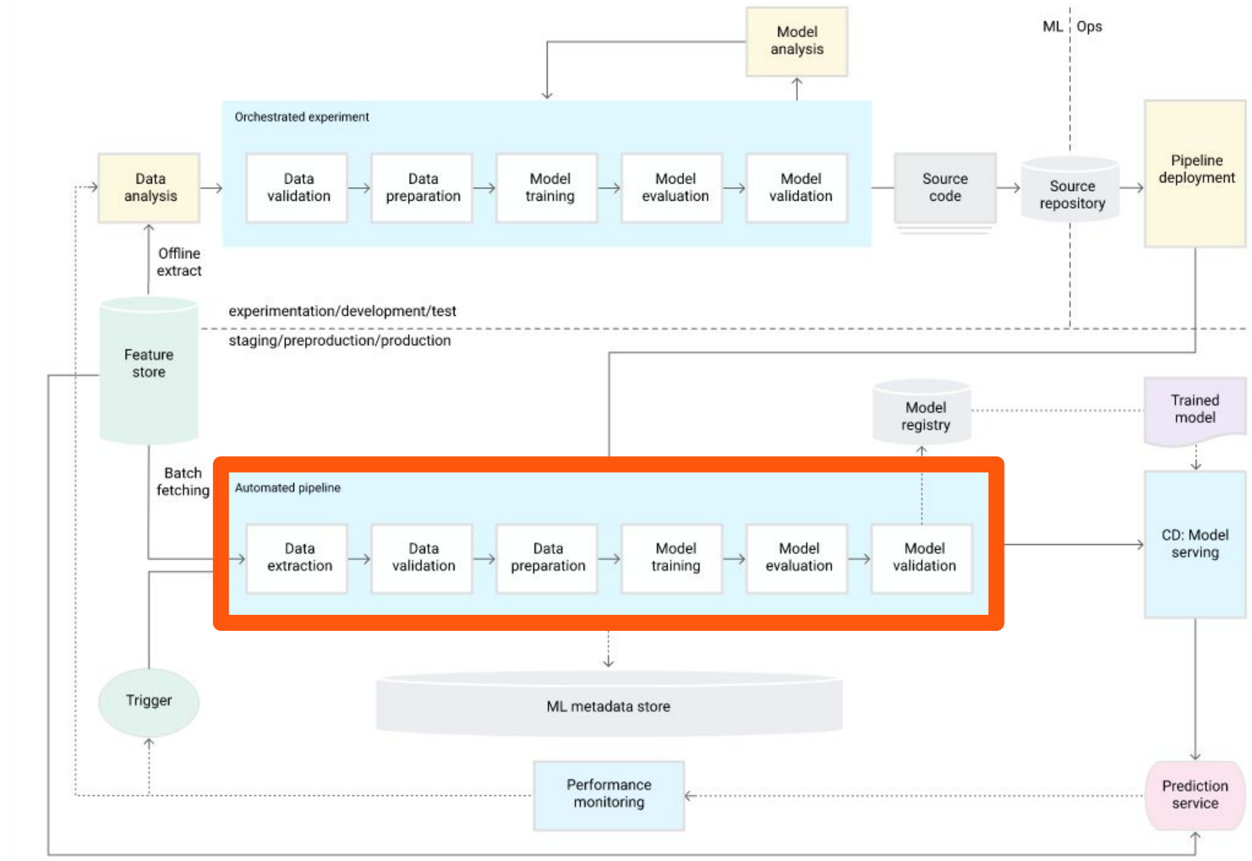


Extending pipeline with metrics



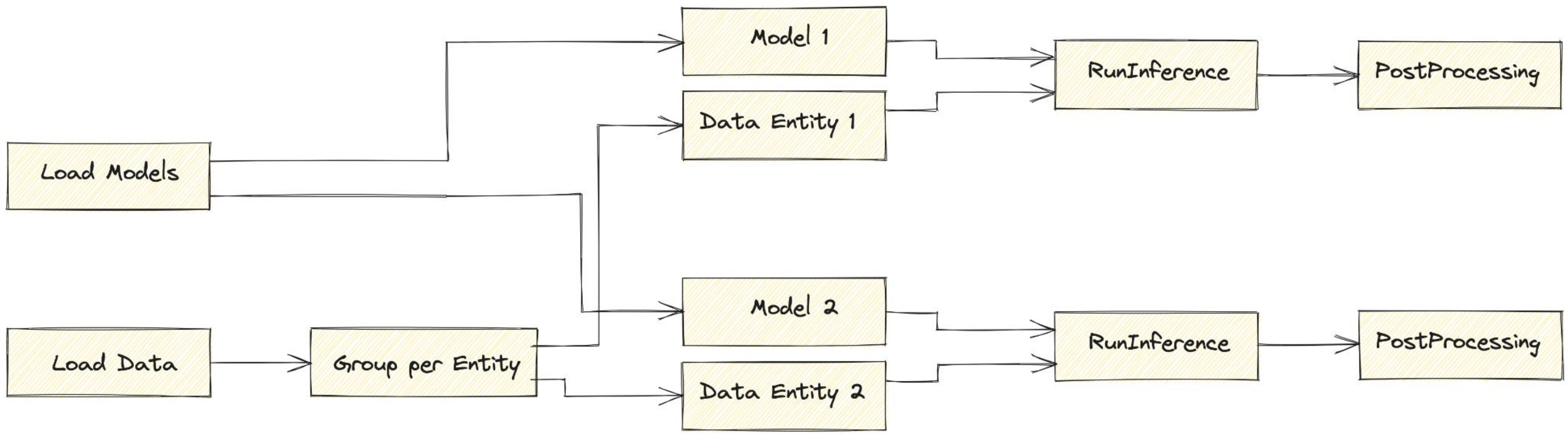
```
class EvaluateModel(beam.DoFn):
  def __init__(self, model_uri):
    file = FileSystems.open(model_uri, 'rb')
    self.model = pickle.load(file)

  def process(self, element, *args, **kwargs):
    inputs, labels = element
    predictions = self.model.predict(inputs)
    accuracy = sklearn.metrics.accuracy_score(y_pred=predictions,
y_true=labels)
    f1 = sklearn.metrics.f1_score(y_pred=predictions, y_true=labels)
    recall = sklearn.metrics.recall_score(y_pred=predictions, y_true=labels)

    file = FileSystems.open(f'model_uri_metrics', 'web')
    file.writelines([f'accuracy: {accuracy}', f'f1: {f1}', f'recall:
{recall}'])
```

How does this pipeline fit in the MLOps architecture?



Let’s try out our model using the RunInference trasform

Bonus: Inference in Apache Beam



Summary

- Apache Beam is more and more becoming technology that can be used in advanced MLOps setups
- Per entity strategy has several advantages
  - Requires less powerful hardware
  - Faster training and inference
  - Easier to address bias
  - Easier to debug
- Apache Beam a perfect candidate for per entity training pipelines thanks to
  - Excellent for data preprocessing and preparation
  - Different runners depending on model requirements
  - Abstraction in ML libraries that make it easy to train a model

Jasper Van den Bossche

QUESTIONS?

https://www.linkedin.com/in/jasper-van-den-bossche/
https://github.com/jaxpr
https://www.ml6.eu/

BEAM

SUMMIT

How many ways can you skin a cat, if the cat is a problem that needs an ML model to solve?

Kerry Donny-Clark

BEAM
SUMMIT

Write your own model handler for RunInference!

Ritesh Ghorse

BEAM SUMMIT
NYC 2023

BEAM
SUMMIT

Power Realtime Machine Learning Feature Engineering with Managed Beam at LinkedIn

David Shao
& Yanan Hao

BEAM SUMMIT
NYC 2023

BEAM

SUMMIT

Optimizing Machine Learning Workloads on Dataflow

Alex Chan

BEAM SUMMIT

NYC 2023

BEAM

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ML model updates with side inputs in Dataflow streaming pipelines

Anand Inguva

BEAM SUMMIT

NYC 2023

BEAM

SUMMIT

Use Apache Beam to build Machine Learning Feature System at Affirm

Hao Xu

BEAM SUMMIT

NYC 2023

Use Apache Beam To Build Machine Learning Feature System At Affirm

- Hao Xu

01

ABOUT ME

Earnest -> Fast -> Affirm -> JP Morgan & Chase

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- OOTB APIs

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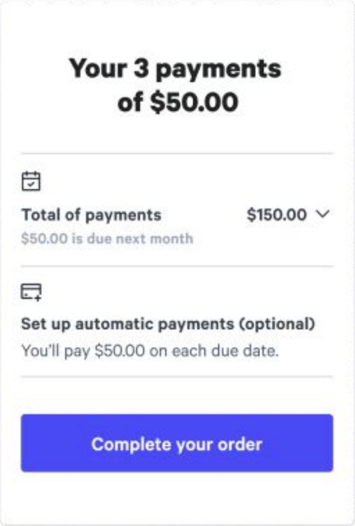
- Performance
- Dev Velocity

Background

- BNPL
- Machine learning feature store
- Streaming and Batch Compute Platform

The Story of BNPL



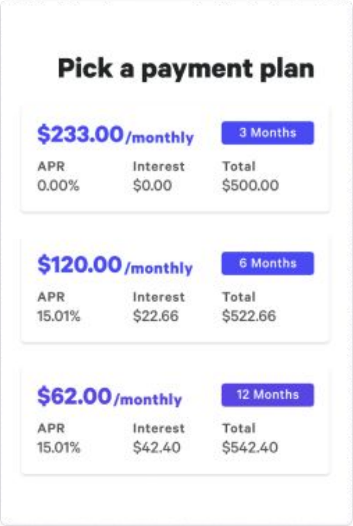
Your 3 payments of $50.00

Total of payments $150.00

$50.00 is due next month

Set up automatic payments (optional)

You'll pay $50.00 on each due date.



Pick a payment plan

$233.00/monthly — 3 Months

APR	Interest	Total
0.00%	$0.00	$500.00

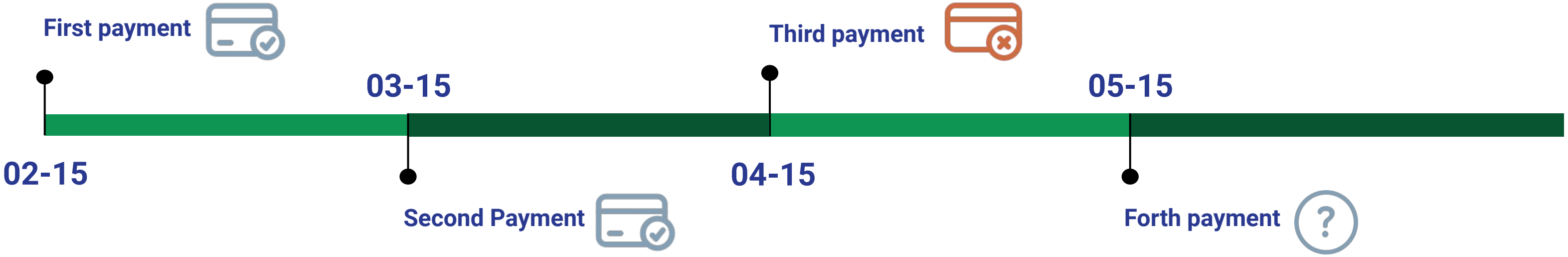
$120.00/monthly — 6 Months

APR	Interest	Total
15.01%	$22.66	$522.66

$62.00/monthly — 12 Months

APR	Interest	Total
15.01%	$42.40	$542.40

The Story of BNPL

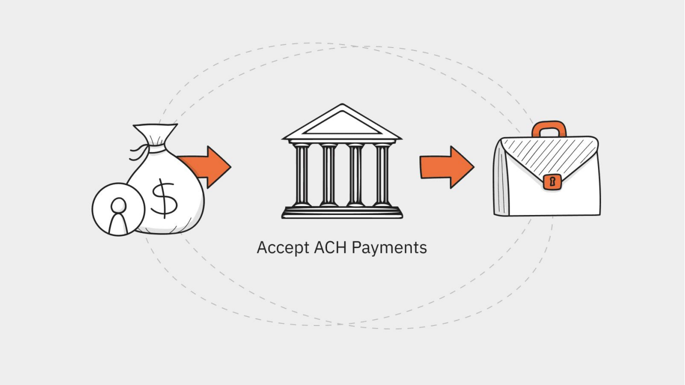


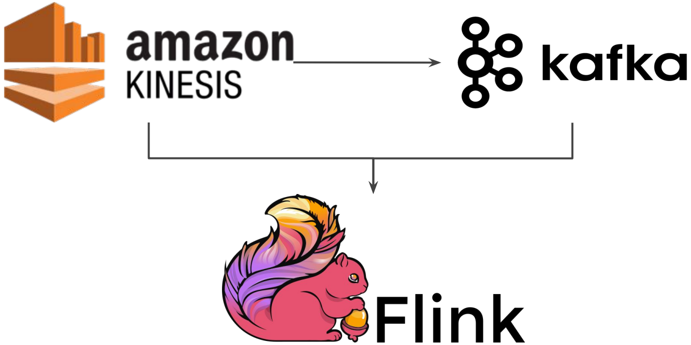
If a user failed the third payment, is it likely that they will also fail the fourth one?

Has the user failed to make a loan payment, and if so, have we identified the issue? Should we approve another loan for them?

Payment flow

The payment data was processed in batches, resulting in a delay of a couple of days. Utilizing stream data can help prevent such delays in the future.





Feature Store

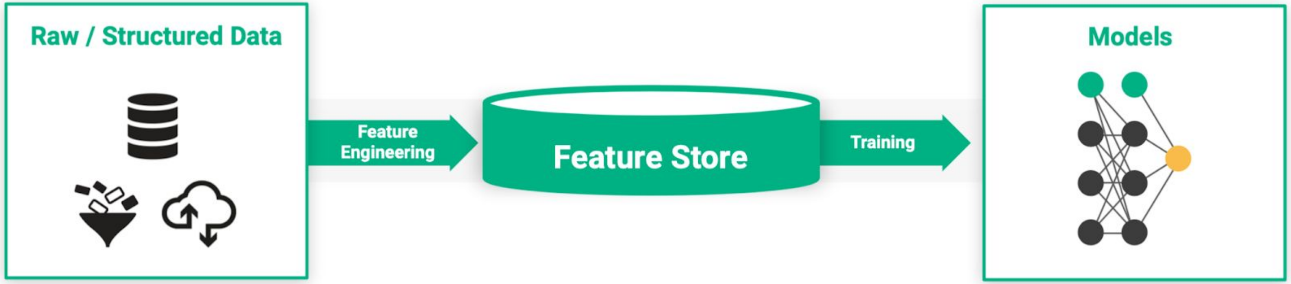


Figure 1. A feature store is the interface between feature engineering and model development.

Pain Points

Pain Points

Development Velocity

Slow backfilling of stream features.
Excessive code required to define a feature.

Variety

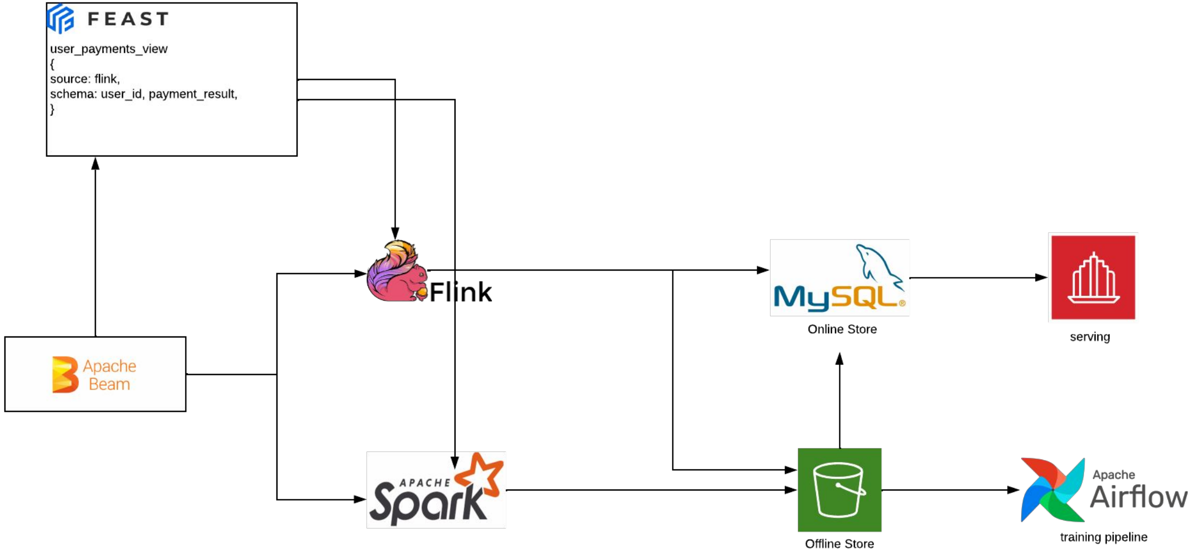
Inability to join two streams from Kinesis together, which is typically required for stateful processing.

Visibility

Lack of registry to quickly lookup data sources, features and metadata.

Solution

MLFS Architecture

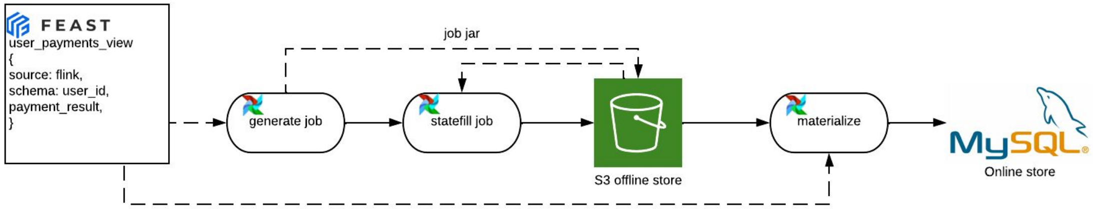


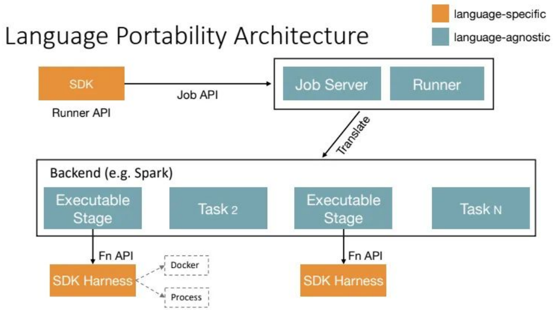
FEAST

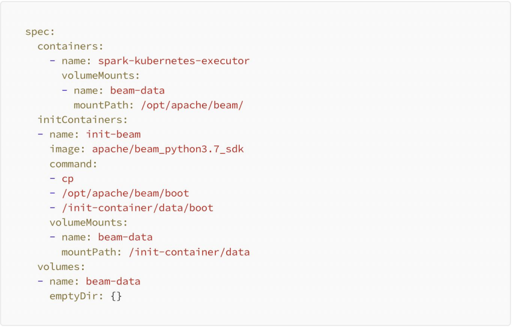
user_payments_view
{
source: flink,
schema: user_id, payment_result,
}

Complex of Backfilling

Backfilling is the process to backfill a feature data to the historical point in time







```
spec:
  containers:
    - name: spark-kubernetes-executor
      volumeMounts:
      - name: beam-data
        mountPath: /opt/apache/beam/
  initContainers:
  - name: init-beam
    image: apache/beam_python3.7_sdk
    command:
    - cp
    - /opt/apache/beam/boot
    - /init-container/data/boot
    volumeMounts:
    - name: beam-data
      mountPath: /init-container/data
  volumes:
  - name: beam-data
    emptyDir: {}
```

Unified Transformation Interface

```
class UnifiedTransformer(Transformer[beam.PCollection, beam.PCollection]):

    @property
    def window(self) -> beam.WindowInto:
        return self._window

    @property
    def event_transform(self) -> beam.PTransform:
        return self._event_transform

    @property
    def aggregator(self) -> beam.PTransform:
        return self._aggregator

    def run(self, inputs: beam.PCollection) -> beam.PCollection:
        if self.feast_context.runner == Runner.flink:
            if self.window:
                inputs = inputs | self.window
            return (
                inputs
                | self.event_transform.with_output_types(Tuple)
                | self.aggregator.with_output_types(Tuple)
            )
        elif self.feast_context.runner == Runner.spark:
            return (
                inputs
                | self.event_transform.with_output_types(Tuple)
                | self.aggregator.with_output_types(Tuple)
            )
        else:
            raise ValueError("Unsupported runner: {}.".format(self.feast_context.runner))
```

Unified Transformation Interface

```python
@stream_feature_view(
    entities=[entity_registry['user_ari']],
    ttl=timedelta(days=0),
    schema=[
        Field(name="user_ari", dtype=String),
        Field(name="timestamp", dtype=UnixTimestamp),
        Field(name="latest_payment_fail", dtype=UnixTimestamp),
        Field(name="latest_payment_fail_ach_nsf", dtype=UnixTimestamp),
    ],
    online=True,
    source=user_payment_fails_stream_source,
    timestamp_field="timestamp",
    tags={},
    mode="flink",
)
def user_last_payment_fail(feast_context: FeastContext, inputs: PCollection) -> PCollection:
    transformer = UnifiedTransformer(
        feast_context=feast_context,
        aggregator=LatestFeatureAggregator(feast_context, 'timestamp'),
        event_transform=extract_payment_fail_data,
    )
    return transformer.run(inputs)
```

Outcome

Performance boost

80%

Backfilling time

Backfilling time improved by 80%

60%

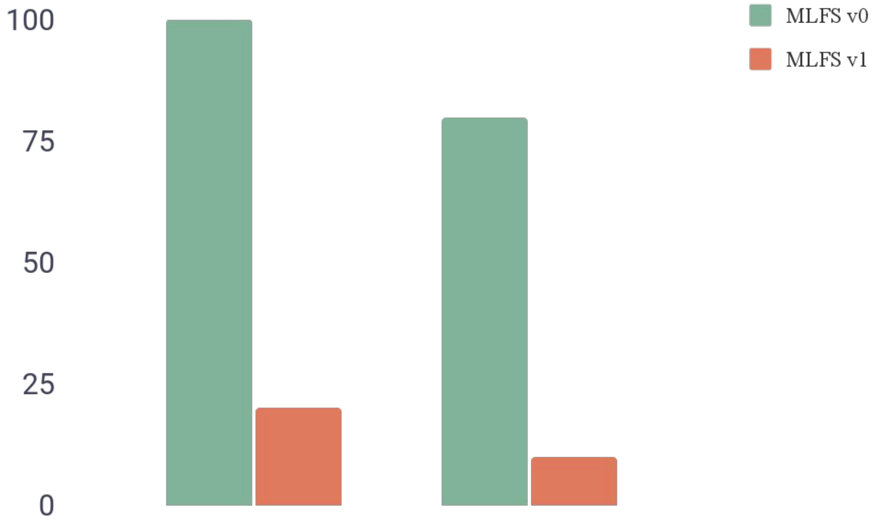
Code lines

Reduced 100+ lines to 20+ lines

40%

Registry

200+ data sources
100+ features



The time spent to backfill features for feature *time_since_user_checkout* and *tiem_since_user_last_payment_failure*

Future improvement

1. OOTB transformation interface
2. Transformation framework
3. Improvement on Beam Spark Runner