Use Apache Beam to build Machine Learning Feature System at Affirm

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ABOUT ME

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



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Background

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

The Story of BNPL



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



Complex of Backfilling

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



Unified Transformation Interface

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

```
@propertv
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

```
@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),
   1,
   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



Future improvement

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

