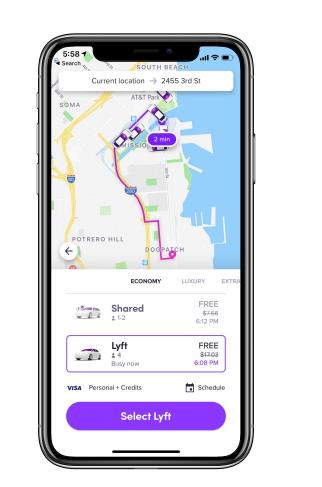
ML through Streaming at UpA







Stopping a Phishing Attack

Hello Alex, I'm Tracy calling from Lyft HQ. This month we're awarding \$200 to all 4.7+ star drivers. Congratulations!



Hey Tracy, thanks!



Np! And because we see that you're in a ride, we'll dispatch another driver so you can park at a safe location....

....Alright your passenger will be taken care of by another driver



Before we can credit you the award, we just need to quickly verify your identity.

We'll now send you a verification text. Can you please tell us what those numbers are.....



12345





Fingerprinting Fraudulent Behaviour

Sequence of User Actions

Request Ride

...

Driver Contact

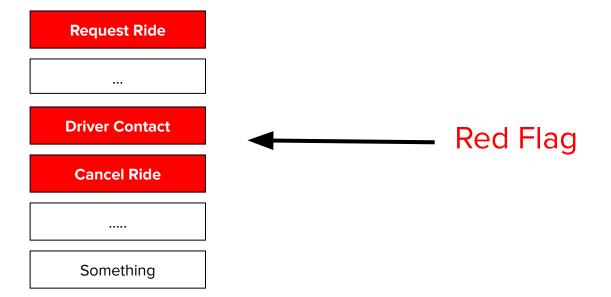
Cancel Ride

....

Something



Sequence of User Actions





```
SELECT
    user_id,
    TOP(2056, action) OVER (
        PARTITION BY user id
        ORDER BY event time
        RANGE INTERVAL '90' DAYS PRECEDING
    ) AS client action sequence
FROM event_user_action
```

```
SELECT
    user id.
                                                        Last x events sorted by time
    TOP(2056, action) OVER (
         PARTITION BY user id
         ORDER BY event_time
         RANGE INTERVAL '90' DAYS PRECEDING
     ) AS client action sequence
FROM event_user_action
```

```
SELECT
     user id,
     TOP(2056, action) OVER (
         PARTITION BY user id
         ORDER BY event time
                                                              Historic context is also important
         RANGE INTERVAL '90' DAYS PRECEDING
                                                                     (large lookback)
     ) AS client_action_sequence
FROM event user action
```

```
SELECT
    user id,
    TOP(2056, action) OVER (
         PARTITION BY user id
         ORDER BY event time
                                                        Event time processing
         RANGE INTERVAL '90' DAYS PRECEDING
    ) AS client action sequence
FROM event_user_action
```

Make streaming features accessible for ML use cases

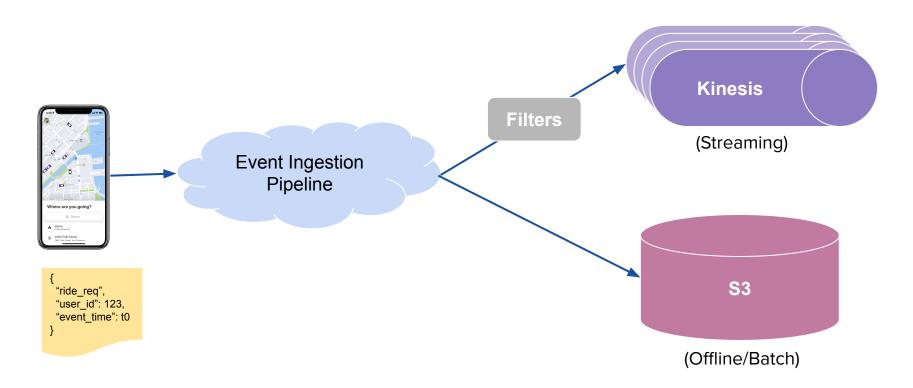


Flink

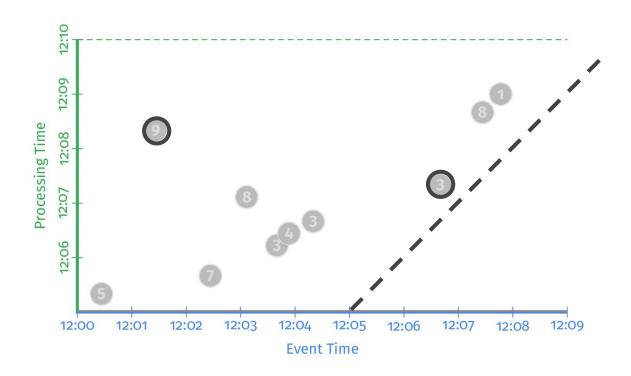
Apache Flink

- Low latency stateful operations on streaming data in the order or milliseconds
- Event time processing replayability, correctness
- Exactly once processing
- Failure recovery
- SQL Api

Event Ingestion Pipeline



Processing Time vs Event Time



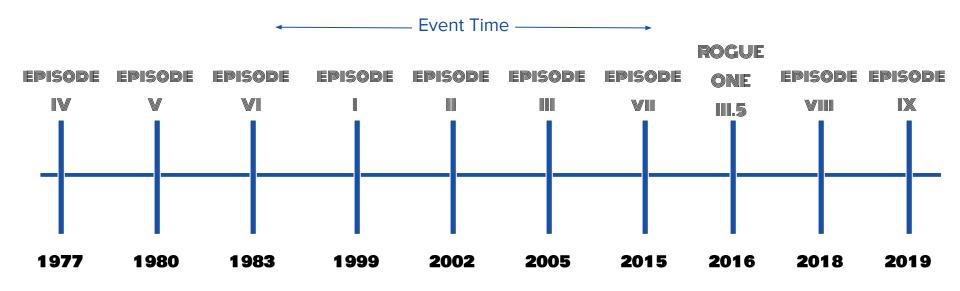
Processing time

System time when the event is processed -> determined by processor

Event time

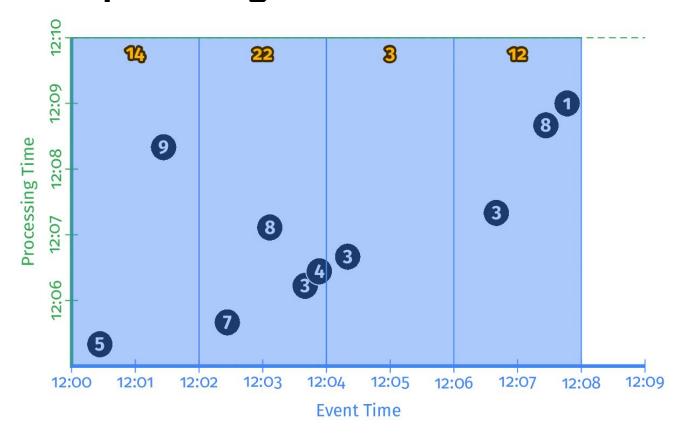
Logical time when the event occurred -> part of event metadata



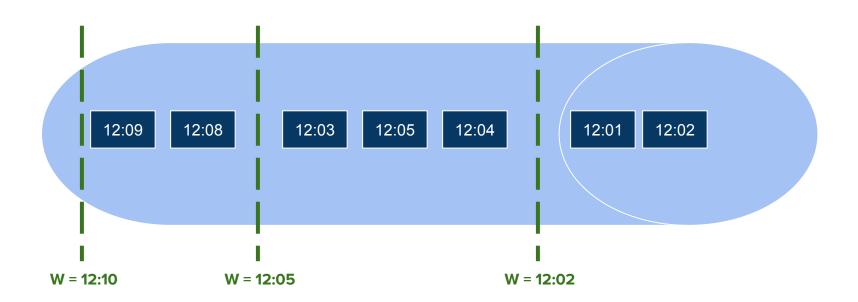


Processing Time —

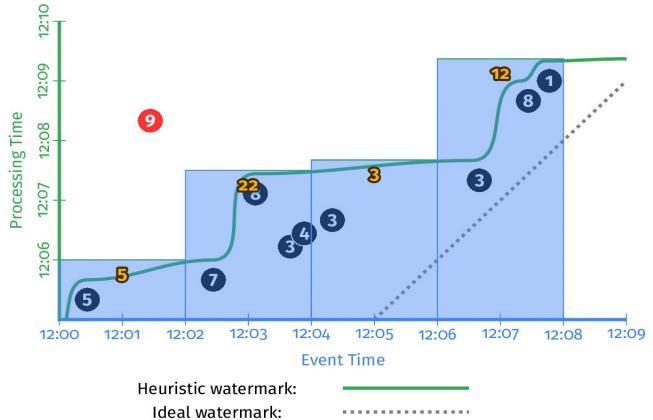
Example: integer sum over 2 min window



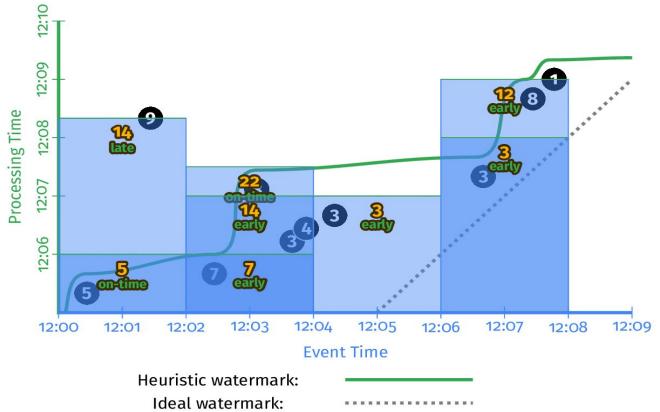
Watermark



Example: integer sum over 2 min window

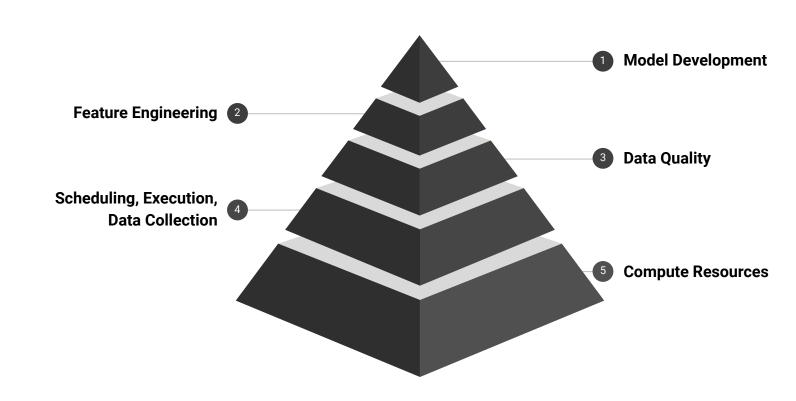


Example: integer sum over 2 min window

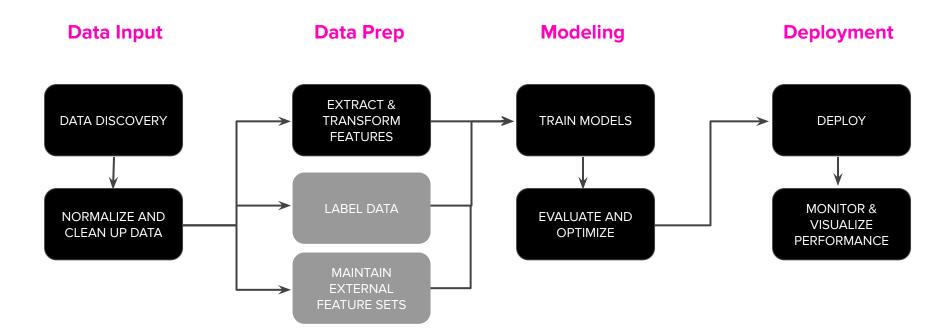


Usability

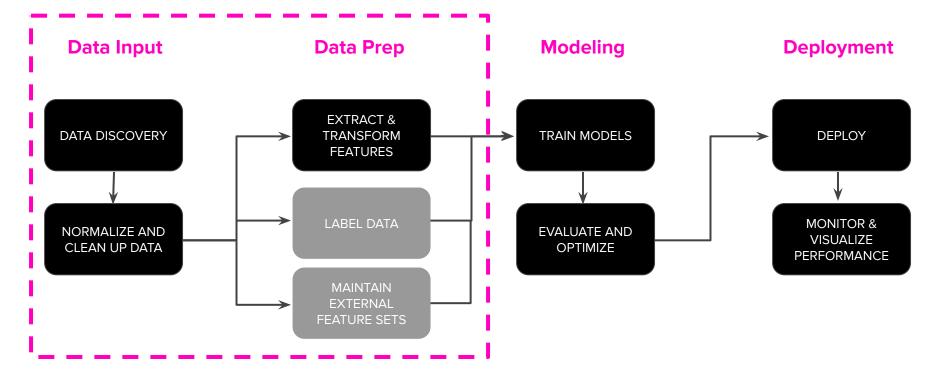
What Data Scientists care about



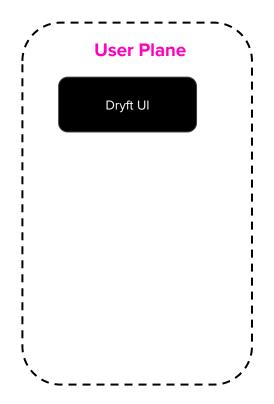
ML Workflow

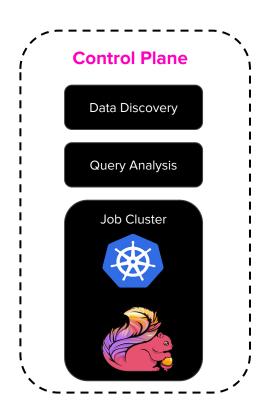


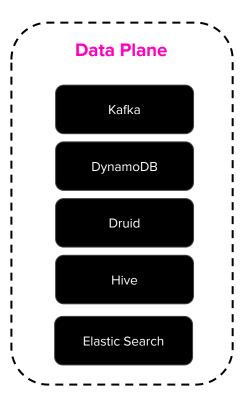
ML Workflow



Dryft! - Self Service Streaming Framework







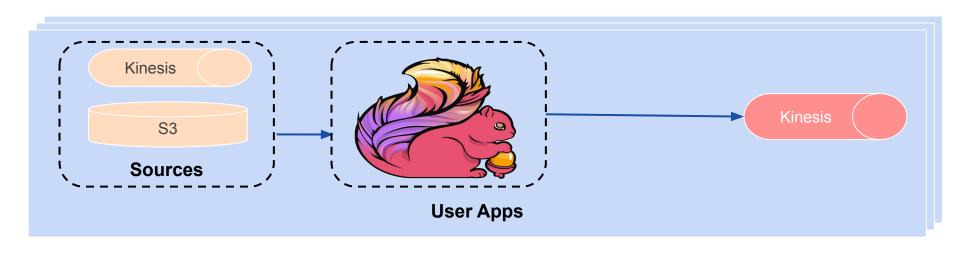
Declarative Job Definition

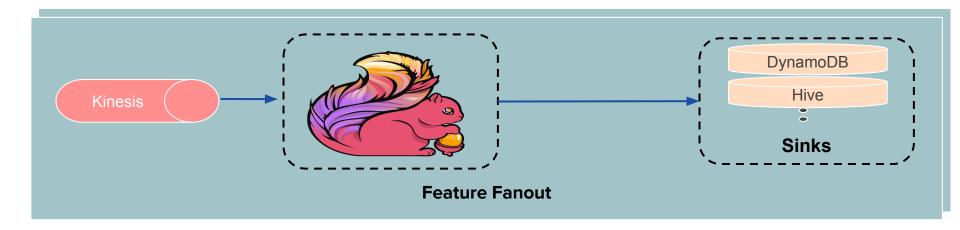
Flink SQL

```
SELECT
      geohash,
      COUNT(*) AS total_events,
      TUMBLE END(
        rowtime,
        INTERVAL '1' hour
FROM event user action
GROUP BY
      TUMBLE(
            rowtime,
            INTERVAL '1' hour
```

Job Config

```
"retention": {},
"lookback": {},
"stream": {
   "kinesis": user_activities
"features": {
   "user_activity_per_geohash": {
      "type": "int"
      "version": 1,
      "description": "user activities
             per geohash"
```





Eating our own dogfood

Feature Fanout App - also uses Dryft

```
SELECT
  -- this will be used in keyBy
  CONCAT_WS('_', feature_name, version, id),
 feature_data,
  CONCAT_WS('_', feature_name, version)
      AS feature_definition,
  occurred at
FROM features
```

```
"stream": {
   "kinesis": feature_stream
"sink": {
   "feature_service_dynamodb": {
      "write_rate": 1000,
      "retry count": 5
```

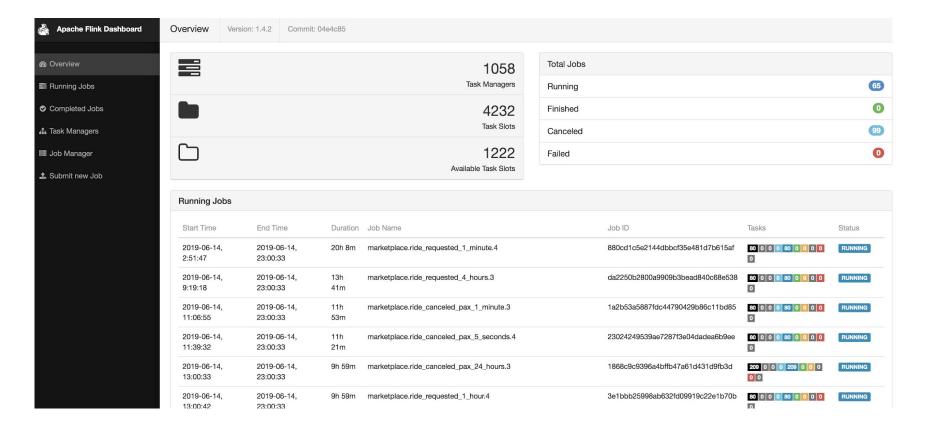


Deployment

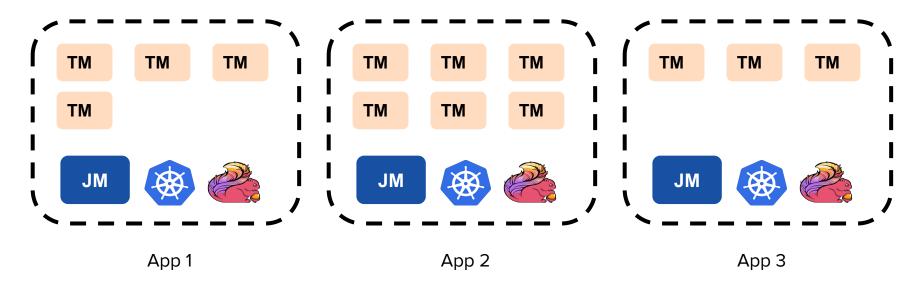
Previously...

- Ran on AWS EC2 using custom deployment
- Separate autoscaling groups for JobManager and Taskmanagers
- Instance provisioning done during deployment
- Multiple jobs(60+) running on the same cluster

Multi tenancy hell!!

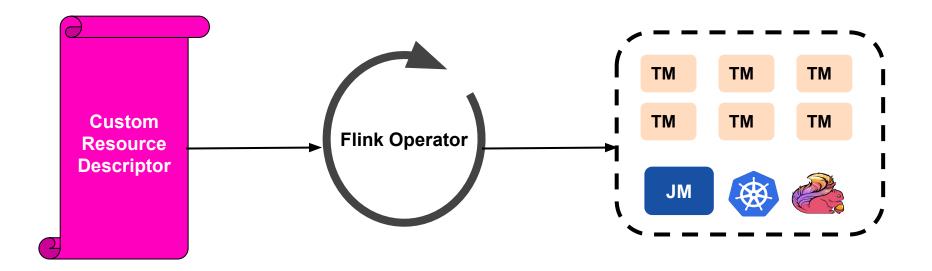


Kubernetes Based Deployment





Flink-K8s-Operator

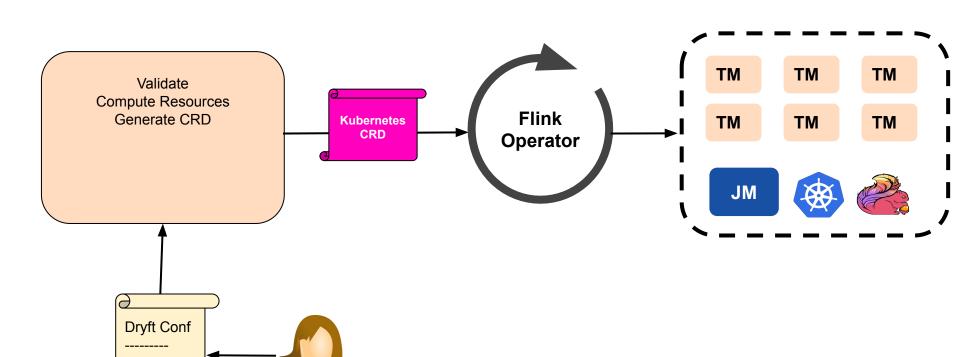




Custom Resource Descriptor

```
apiVersion: flink.k8s.io/v1alpha
kind: FlinkApplication
metadata:
        name: flink-speeds-working-stats
        namespace: flink
spec:
        image: '100,dkr.ecr.us-east-1.amazonaws.com/abc:xyz'
        flinkJob:
            jarName: name.jar
            parallelism: 10
taskManagerConfig: {
  resources: {
      limits: {
            memory: 15Gi,
            cpu: 4
  replicas: num task managers,
  taskSlots: NUM SLOTS PER TASK MANAGER,
  envConfig: {...},
```

- Custom resource represents Flink application
- Docker Image contains all dependencies
- CRD modifications trigger update (includes parallelism and other Flink configuration properties)



Flink on Kubernetes

- Separate Flink cluster for each application
- Resource allocation customized per job at job creation time
- Scales to 100s of Flink applications
- Automatic application updates

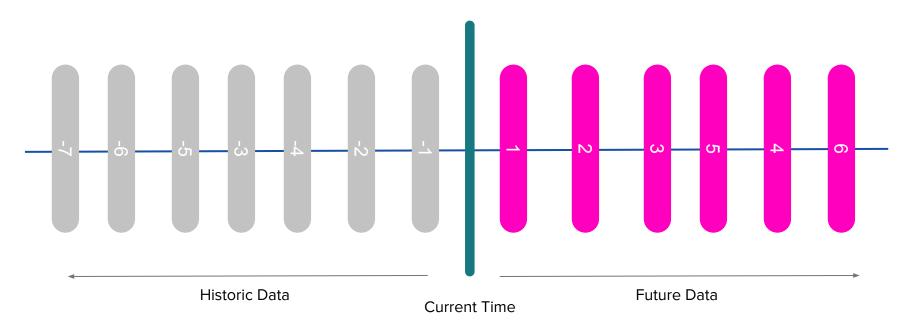


Bootstrapping

What is bootstrapping?

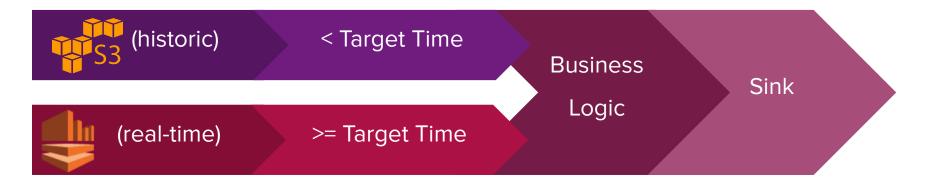
```
SELECT
     passenger_id,
     COUNT(ride id)
FROM event ride completed
GROUP BY
    passenger id,
    HOP(rowtime.
        INTERVAL '30' DAY,
        INTERVAL '1' HOUR)
```

Bootstrap with historic data



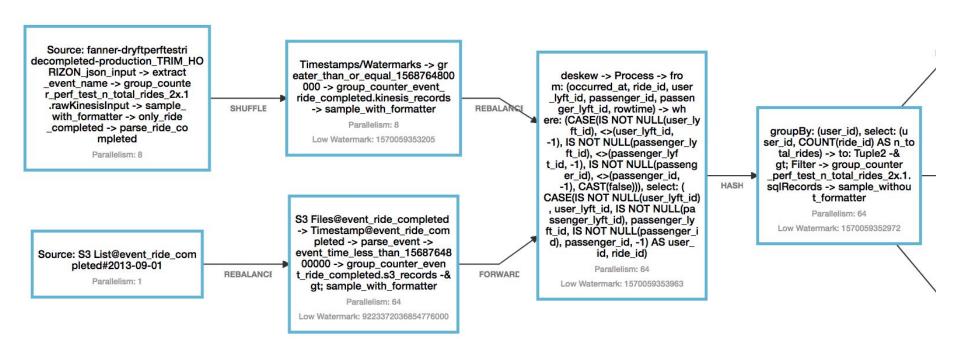
Read historic data to 'bootstrap' the program with 30 days worth of data. Now your program returns results on day 1. But what if the source does not have all 30 days worth of data?

Solution - Consume from two sources



Read historic data from persistent store(AWS S3) and streaming data from Kafka/Kinesis







an, ts(staging.app.dryft.task.numrecordsoutpersecond.rate.gauge.mean, job_name=fraud_perf_test_n_total_rides_2x_1 and task_name=s3_files)))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m , mean, ts(staging.app.dryf Warning: The expression: "default(0, align(1m, n t.task.numrecordsoutpersecond.rate.gauge.meart_lob_name=fraud_perf_test_n_total_rides_2x_1 and task_name=s3_files))))" in order to improve the performance of the max() aggregation operation. You can wrap the expression with align() to explicitly state the periodicity and desired summarization strategy.

Horizontal Scale: 781 point buckets across, 1 bucke ~ 900 sec (est)

Job starts

Queries v





max(default(0, align(1m , mean, ts(staging.app.dryft.task.numrecordsoutpersecond.rate.gauge.mean, job_name =fraud_perf_test_n_total_rides_2x_1 and task_name=s3_files))), job_name)









Warning: The expression: "default(0, align(1m, mean, ts(staging.app.dryft.task.numrecordsoutpersecond.rate.gauge.mean, job_name=fraud_perf_test_n_total_rides_2x_1 am task_name=s3_files)))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))" has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))") has been pre-aligned, making it equivalent to "align(900s, mean, default(0, align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft)) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) has been pre-aligned, making it equivalent to "align(1m, mean, ts(staging.app.dryft))) h t.task.numrecordsoutpersecond.rate.gauge.mean, job_name=fraud_perf_test_n_total_rides_2x_1 and task_name=s3_files))))" in order to improve the performance of the mat () aggregation operation. You can wrap the expression with align() to explicitly state the periodicity and desired summarization strategy.

Bootstrapping over

Queries v

✓ New Query



max(default(0, align(1m , mean, ts(staging.app.dryft.task.numrecordsoutpersecond.rate.gauge.mean, job_name =fraud_perf_test_n_total_rides_2x_1 and task_name=s3_files))), job_name)





Start Job

With a higher parallelism for fast bootstrapping

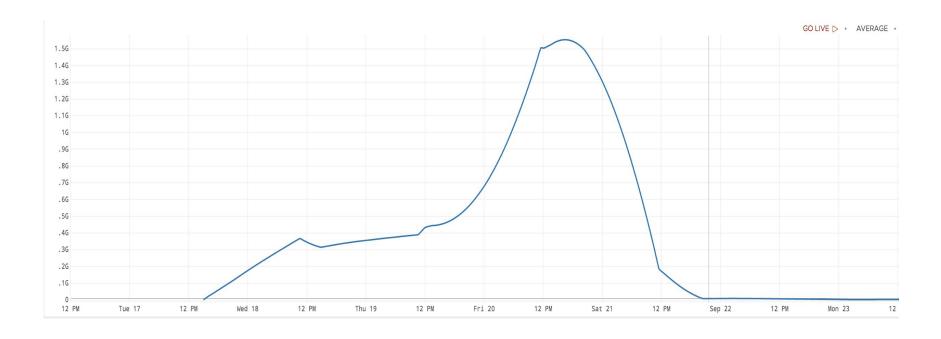
Detect Bootstrap Completion

Job sends a signal to the control plane once watermark has progressed beyond a point where we no longer need historic data

"Update" Job with lower parallelism but same job graph

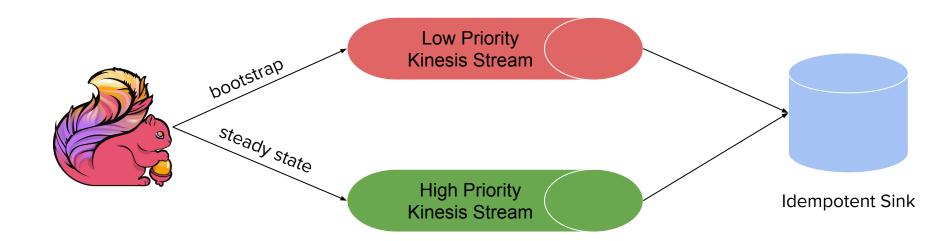
Control plane cancels job with savepoint and starts it again from savepoint but with a much lower parallelism

Output volume spike during bootstrapping



Output volume spike during bootstrapping

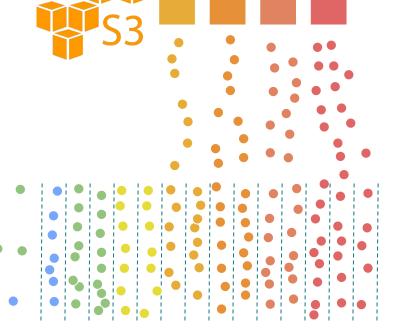
- Features need to be fresh but eventually complete
- Smooth out data writes during bootstrap to match throughput
- Write features produced during bootstrapping separately



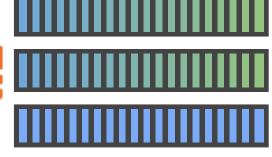
What about skew between historic and real-time data?

Skew

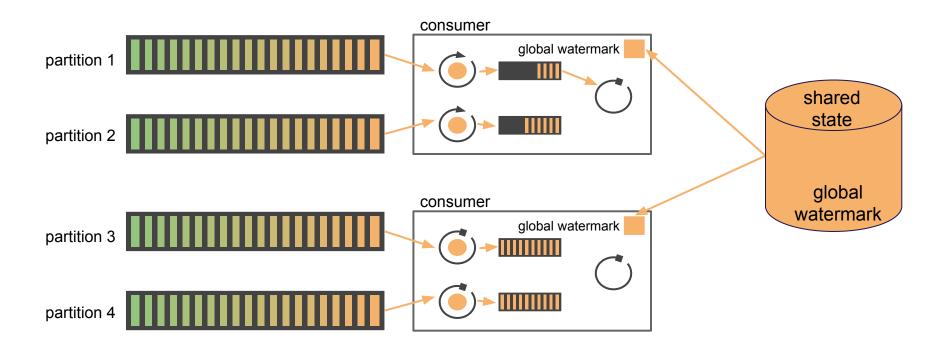
Watermark =







Solution: Source synchronization



Now...

- 120+ features
- Features available in DynamoDB(real time point lookup), Hive(offline analysis),
- Time to write, test and deploy a feature is < 1/2 day
- Time to write, test and deploy a reducte is 1/2 da

Druid(real time analysis) and more...

Coming Up - Python Support!

p99 latency <5 seconds

Thank you!



Later

Backfill

- What if one implementation could provide the training time and scoring time feature values?
 - o Batch processing mode to backfill historic values for training
 - Stream processing mode to generate values in real-time for model scoring
- Enable delivery of consistent features between training and scoring



Green/Blue deploy - zero downtime deploys

"Auto" scaling of Flink cluster and/or job parallelism

Feature library