# Streaming datasets for Personalization

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What is Netflix's Mission?

Entertaining you by allowing you to stream content anywhere, anytime



#### What is Netflix's Mission?

### Entertaining you by allowing you to stream personalized content anywhere, anytime



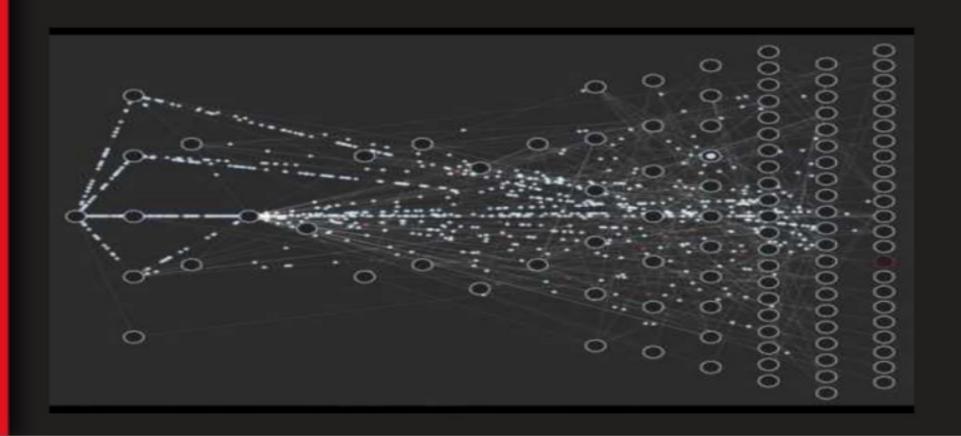


#### How much data do we process to have a personalized Netflix for everyone?

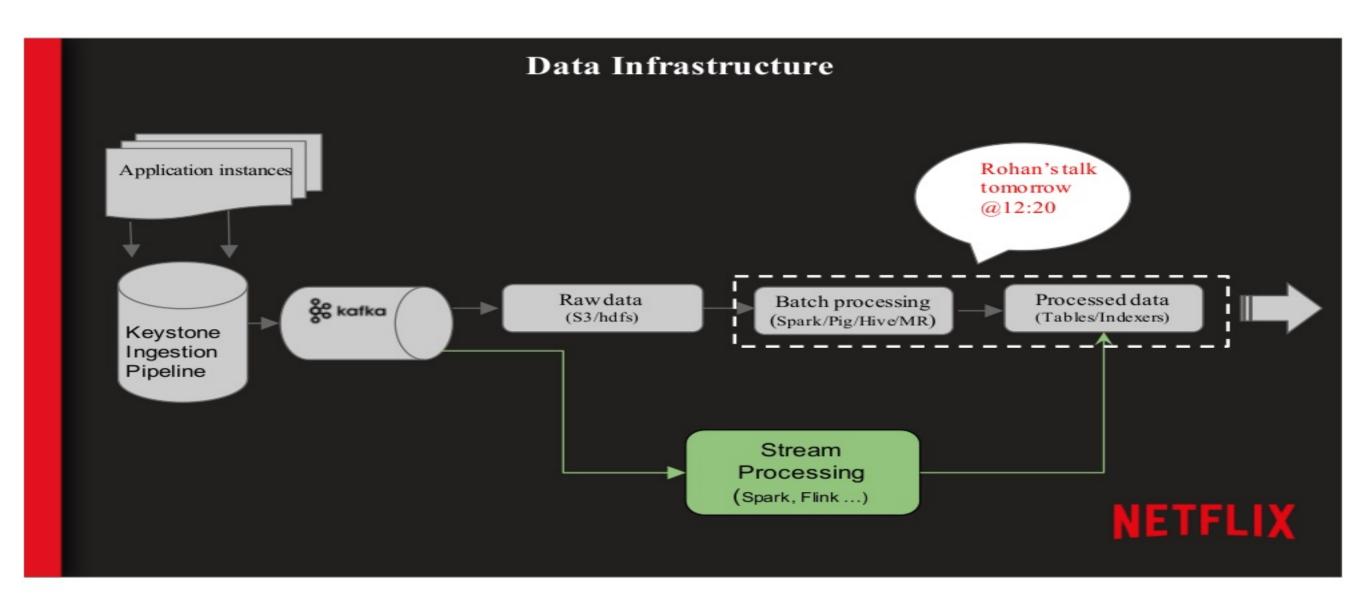
- 93M+ active members
- 125M hours/day
- 190 countries with unique catalogs
- 450B unique events/day
- 600+ Kafka topics



## A SERIES OF PLAYBACK EVENTS



NETFLIX



#### Our problem: Using user plays for feature generation, discovery, clustering ..



User watches a video on Netflix













#### Why have data later when you can have it now?

#### Business Wins

- Algorithms can be trained with the latest + greatest data
- Enhances research
- Creates opportunity for new types of algorithms

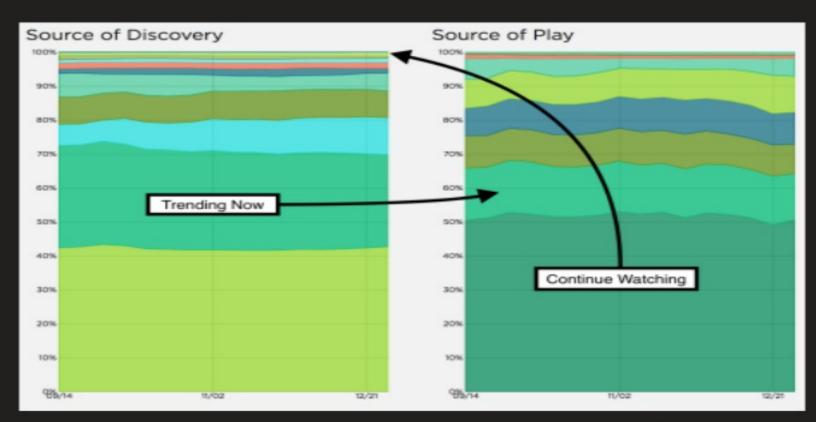
#### Technical Wins

- Save on storage costs
- Avoid long running jobs



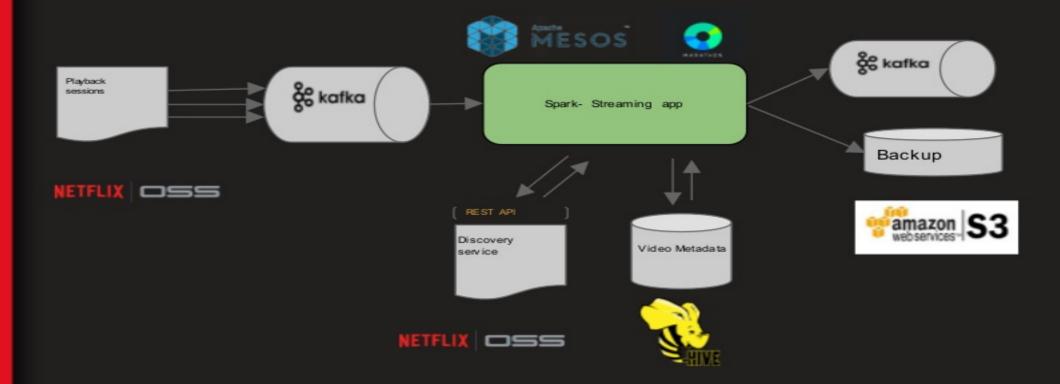
#### Source of Discovery / Source of Play







#### Source-of-Discovery pipeline





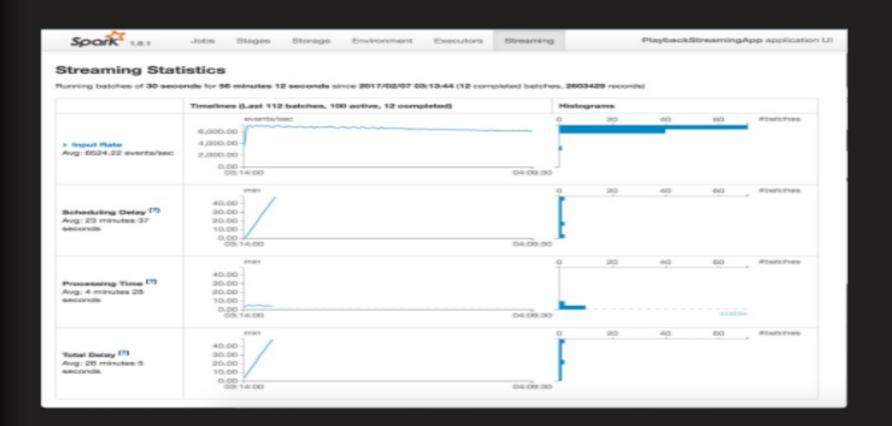
#### **Spark Streaming**



- Needs a StreamingContext and a batch duration
- Data received in DStreams, which are easily converted to RDDs
- Support all fundamental RDD transformations and operations
- Time-based windowing
- Checkpointing support for resilience to failures
- Deployment



#### Performance tuning your Spark streaming application



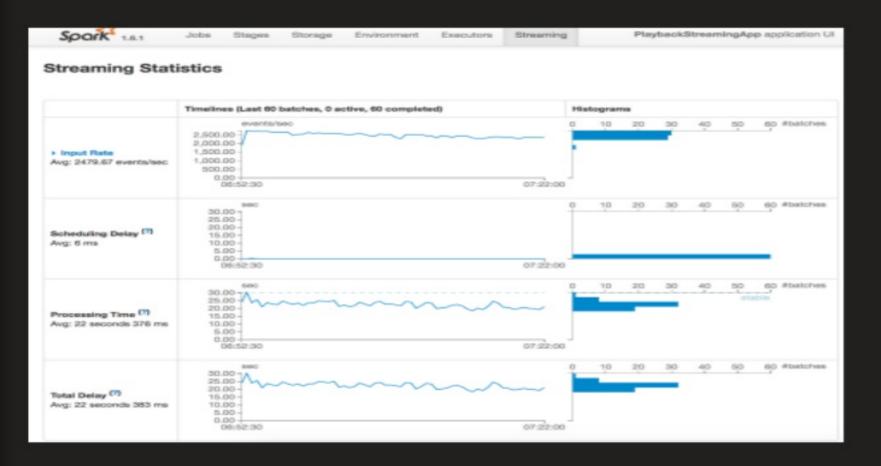


#### Performance tuning your Spark streaming application

- Choice of micro-batch interval
  - o The most important parameter
- Cluster memory
  - o Large batch intervals need more memory
- Parallelism
  - o DStreams naturally partitioned to Kafka partitions
  - Repartition can help with increased parallelism at the cost of shuffle
- # of CPUs
  - <= number of tasks</p>
  - o Depends on how computationally intensive your processing is



#### Performance tuning your Spark streaming application





#### Challenges with Spark

- Not a 'pure' event streaming system
  - Minimum latency of batch interval
  - Un-intuitive to design for a stream-only world
- Choice of batch interval is a little too critical
  - Everything can go wrong, if you choose this wrong
  - Build-up of scheduling delay can lead to data loss
- Only time-based windowing\*
  - Cannot be used to solve session-stitching use cases, or trigger based event aggregations

\* I used 1.6.1





- Pioneer Tax
  - Training ML models on streaming data is new ground
- Increased criticality of outages
  - Batch failures have to be addressed urgently, Streaming failures have to be addressed immediately.
- Infrastructure investment
  - o Monitoring, Alerts,
  - Non-trivial deployments

There are two kinds of pain...

#### **Questions?**

Stay in touch!



@NetflixData

