Creating an Extensible Big Data Platform

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Who am I

Reza Shiftehfar

- PhD in Computer Science from University of Illinois @Urbana-Champaign
- Working at Uber since 2014
- Founding engineer of the data platform team at Uber
- Currently managing the Hadoop Platform team at Uber
- Helped scale Uber's data from a few TB to 100+ PB
- Helped lower data latency from 24+ hrs to minutes

Agenda

1. **Intro to Data @ Uber**
2. **Data Platform - Past**
    - Traditional Big Data Platform
3. **Data Platform - Present**
    - Redesigned extensible Big Data Platform
4. **Data Platform - Future**
    - What’s coming next?
5. **Lessons learned**

Intro to Data @ Uber:

Uber's Mission

“Transportation as reliable as running water, everywhere, for everyone”

700+ Cities

75+ Countries

2M+ Driver Partners

And Growing...

The Impact of Data @ Uber

1. **City Operators (~1000s)**
    - On the ground team who run and scale uber's transportation network in each city

2. **Data Scientists and Analysts (~100s)**
    - Spread across various functional groups (e.g. Marketing Spend, Forecasting demand)

3. **Engineering Teams (~100s)**
    - Focused on building automated data applications (Fraud Detection, Incentive Payments, Driver onboarding,...)

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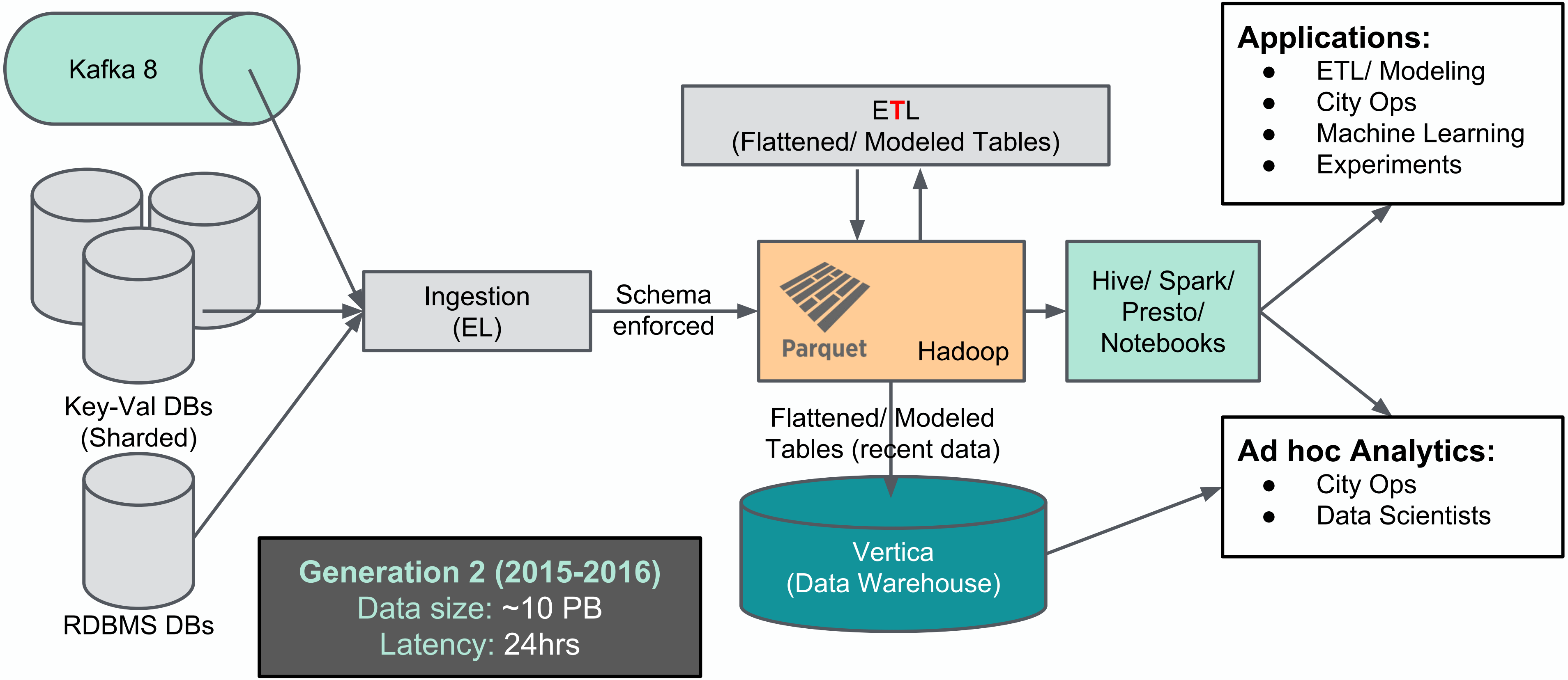
Past:
Traditional Big Data Platform
(2016)

Past: Traditional Big Data Platform (2015-2016)



Past: Traditional Big Data Platform (2015-2016)

Highlights:

- All raw data is stored in Hadoop Data Lake
- Data stored as Columnar Parquet format
    - More efficient storage
    - More efficient queries
- All ETL/Modeling happens in Hadoop
- Subset of data transferred to warehouse
    - Only flattened selected recent dates
- Presto added as interactive query engine
- Spark notebooks added to encourage data scientists to use Hadoop

Past: Traditional Big Data Platform (2015-2016)

Big Wins:

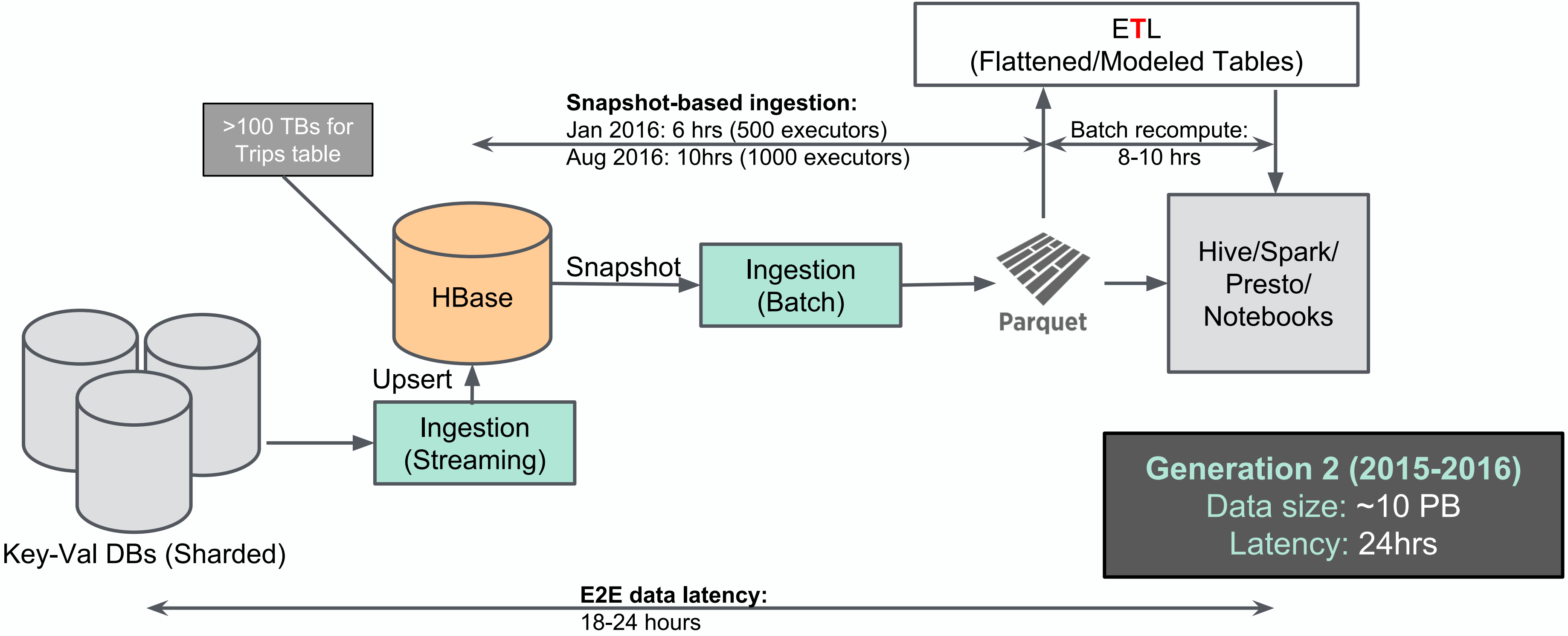
- Hadoop became the source-of-truth for all data
  - 100% of All analytical data in one place
- Hadoop powered critical Business Operations
  - Partner Incentive Payments, Fraud
- Unlocked the real power of data
- Gave us time to stabilize the infrastructure (Kafka,....) & think long-term

Some Numbers (early 2016):

- **~10 PB in HDFS**
- **~10 TB/day new data**
- **~10k vcores**
- **~100k daily batch jobs**
- **And growing...**

Past: Traditional Big Data Platform (2015-2016)

Why does data latency remain at 24 hours?



Past: Traditional Big Data Platform (2015-2016)

Problems/ Limitations:

Pain Point #1: Scalability:

- Too many small files in HDFS (required async stitcher)
- Source-specific data ingestion pipelines increased maintenance cost

Pain Point #2: Data Latency too high:

- snapshot based ingestion results in 24hrs data latency

Pain Point #3: Updates became a big problem:

- Updates/late-arriving-data are natural part of our data

Pain Point #4: ETL/ Modeling became the bottleneck:

- ETL/Modeling was snapshot based (running daily off raw tables)

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Present:
Redesigned extensible Big Data Platform

(2017-present)

Present: Redesigned extensible Big Data Platform (2017-present)

Some Numbers (early 2017):

- ~100+ PB in HDFS data
- ~100k vcores
- ~100k Presto queries/day
- ~1000+ Spark apps/day
- ~20k Hive queries/day
- And still growing...

Present: Redesigned extensible Big Data Platform (2017-present)

Motivation for rebuilding:

- Interactive Query engines -> Hadoop data extremely popular
- No more fire-fighting -> allowed study of our real needs
- **Let's build for long-term** (Generation 3 of our Big Data Platform)

Problems to solve:

- **Pain Point #1:** HDFS Scalability
  - Namenode will always be the bottleneck
  - Small files are the killer
  - Benefit from ViewFS and Federation to scale
    - Controlling small files and moving part of data to a separate cluster (e.g. HBase, Yarn app logs) can let you get to 100+ PB
    - See our recent [Engineering Blog post]() on this

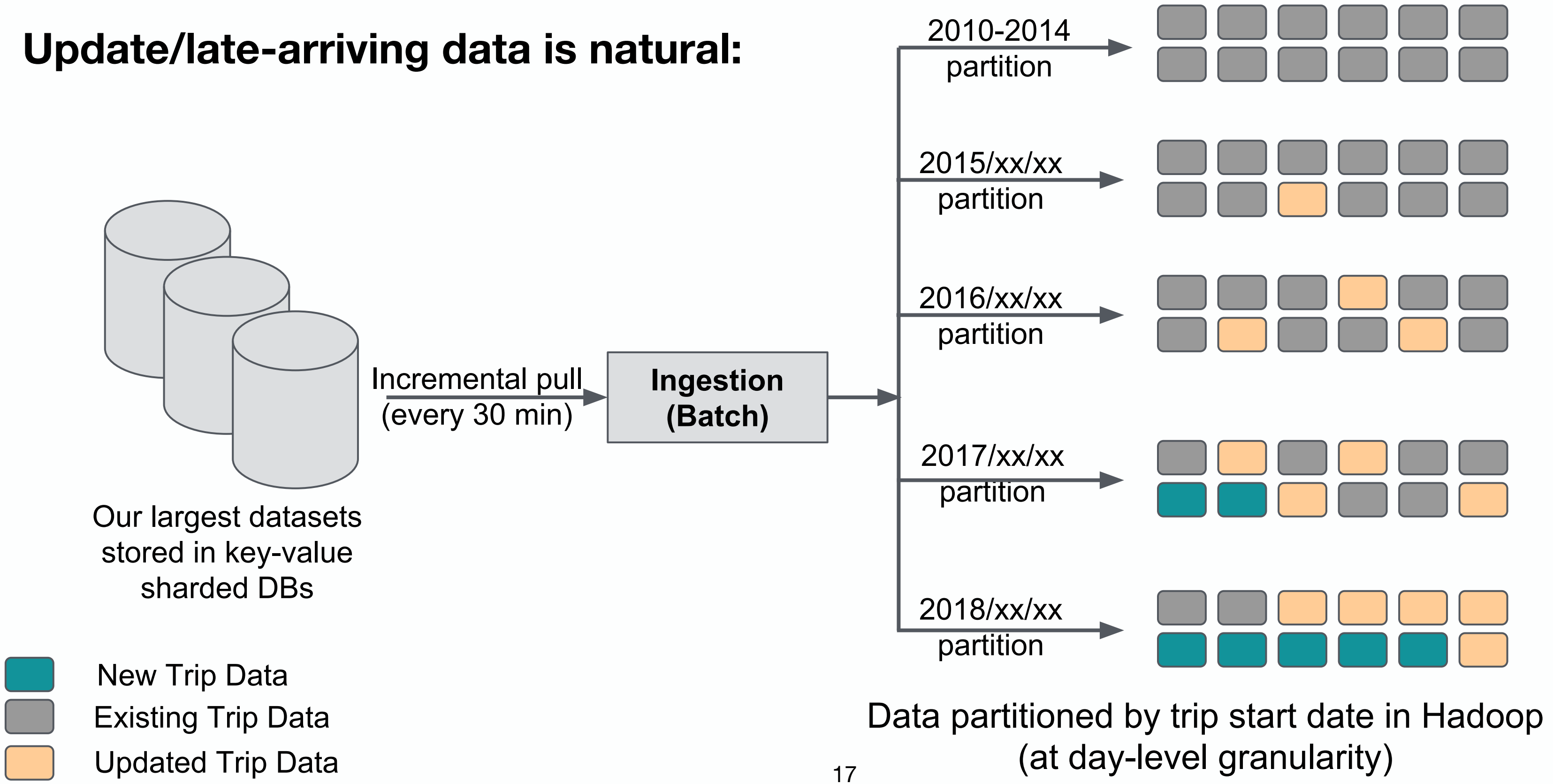
Present: Redesigned extensible Big Data Platform (2017-present)

Problems to solve:

- **Pain Point #2:** Faster data in Hadoop
    - Need fully incremental ingestion of data
- **Pain Point #3:** Support for Updates/Deletes in Hadoop/Parquet
    - Need to support Update/Deletion during ingestion of incremental changelogs
        - Our data has large number of columns with nested data support -> Parquet stays
- **Pain Point #4:** Faster ETL/ Modeling
    - ETL has to become incremental too
    - Need to allow users to pull out only changes incrementally
    - Have to support all different query engines (Hive, Presto, Spark,...)

Present: Redesigned extensible Big Data Platform (2017-present)

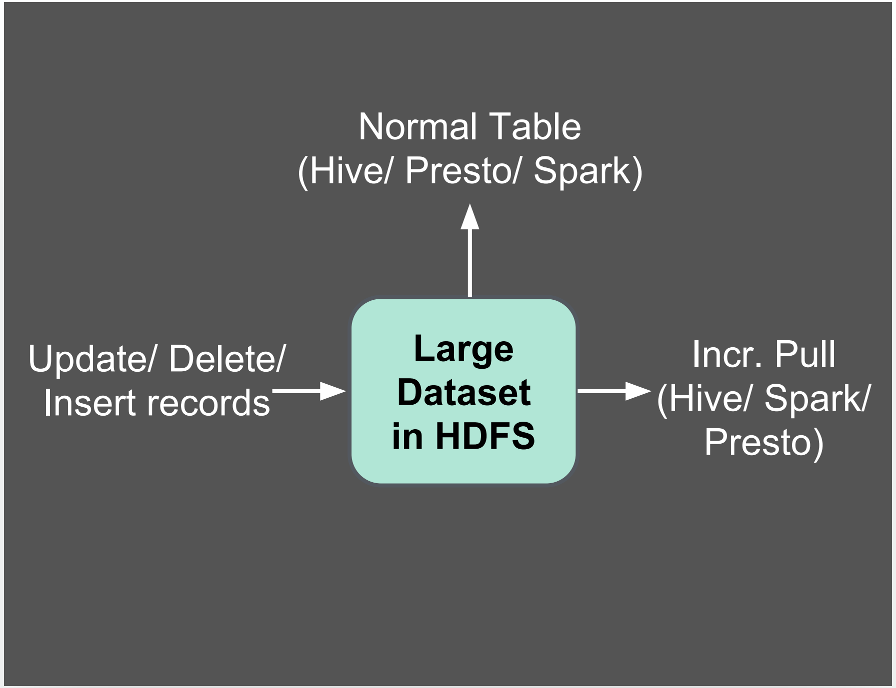
Update/late-arriving data is natural:



Present: Redesigned extensible Big Data Platform (2017-present)

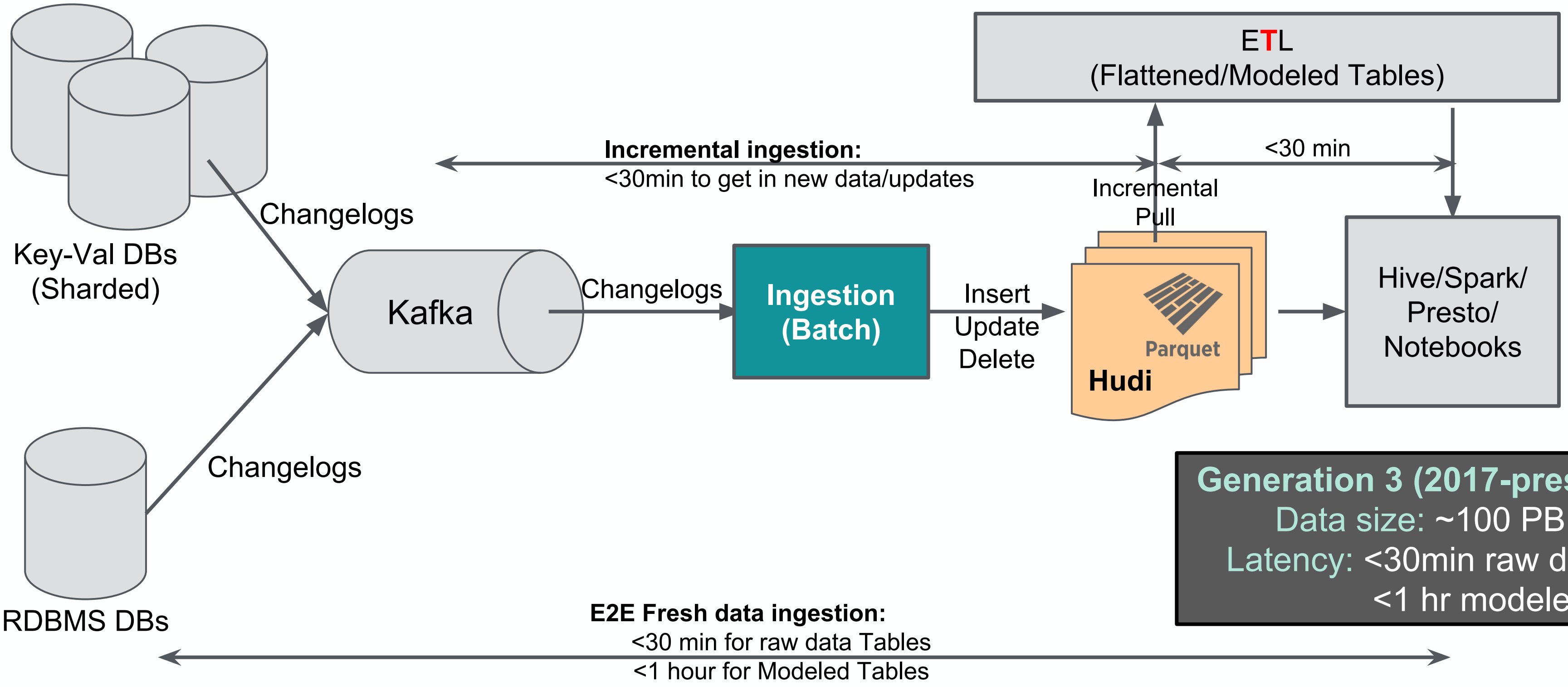
What did we build to address these needs?

- Built **Hudi**: **H**adoop **U**pserts an**D** **I**ncremental
- Storage abstraction to:
  - Apply upsert/delete on existing Parquet data in Hadoop
  - Pull out changed data incrementally
- Spark based library:
  - Scales horizontally like any Spark job
  - Only relies on HDFS
- It is open-sourced (Hudi on Github) (Hudi Eng Blog)



Present: Redesigned extensible Big Data Platform (2017-present)

Incremental ingestion:

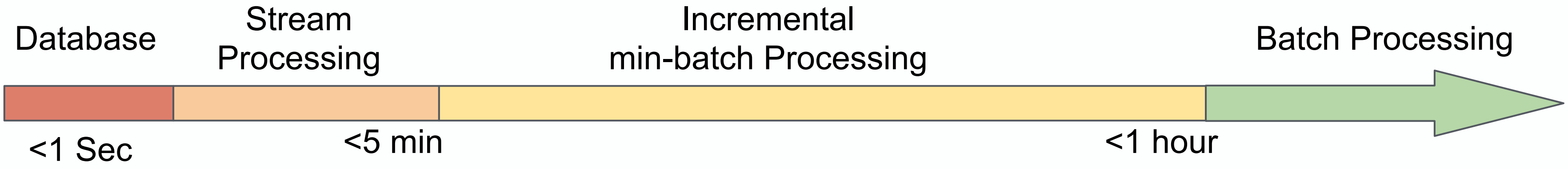


Generation 3 (2017-present)
Data size: ~100 PB
Latency: <30min raw data
<1 hr modeled

Present: Redesigned extensible Big Data Platform (2017-present)

What is Incremental Processing:

- Traditional λ architecture provides: Streaming vs Batch solutions
    - That assumes append-only immutable data
    - Processing based on timestamp (usually skips late-arriving data)
- Incremental Processing is mini-batch jobs that pulls out only changed data
    - This gets you all the recently appended data as well as old changed/updated records
    - Provides high completeness (compared to streaming mode)
    - Processing no longer limited by updates/deletes or late-arriving data
    - Is a batch job and supports full batch functionality (e.g. joins,....)

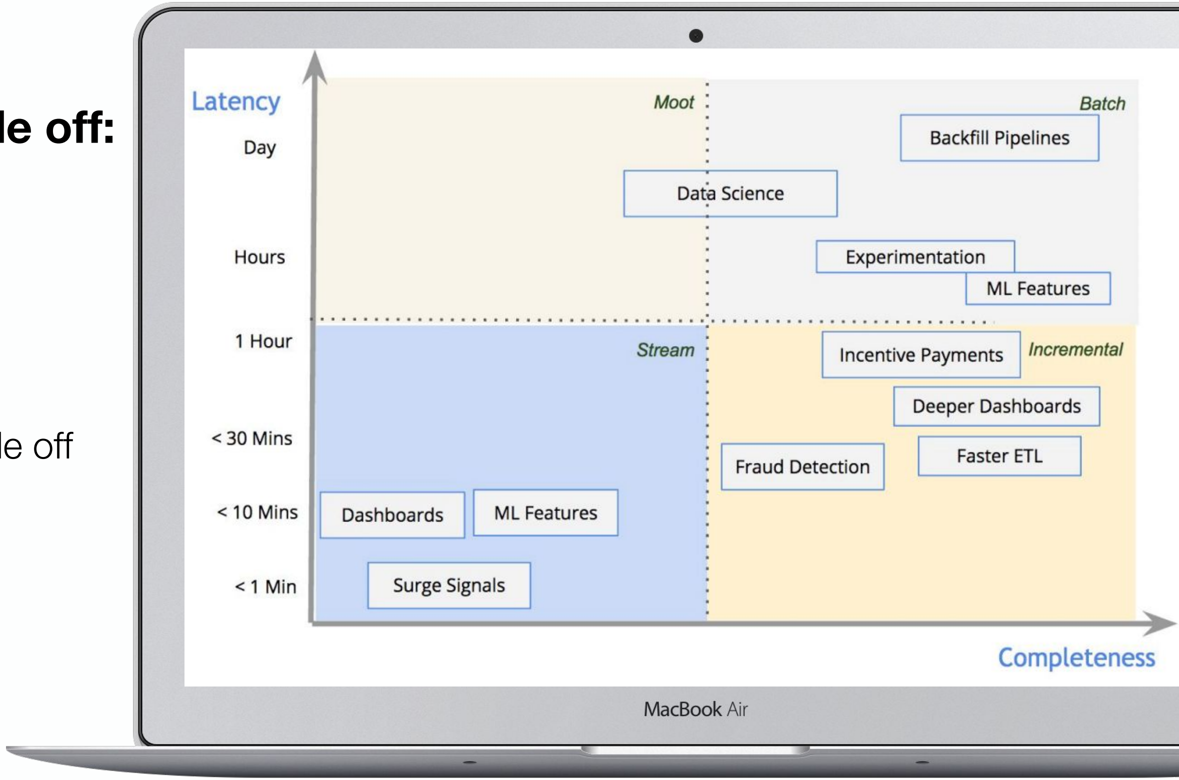


Present: Redesigned extensible Big Data Platform (2017-present)

Stream/Batch processing Trade off:

- Latency
- Completeness
- Cost (Throughput/efficiency)

Study your use case based on these trade off

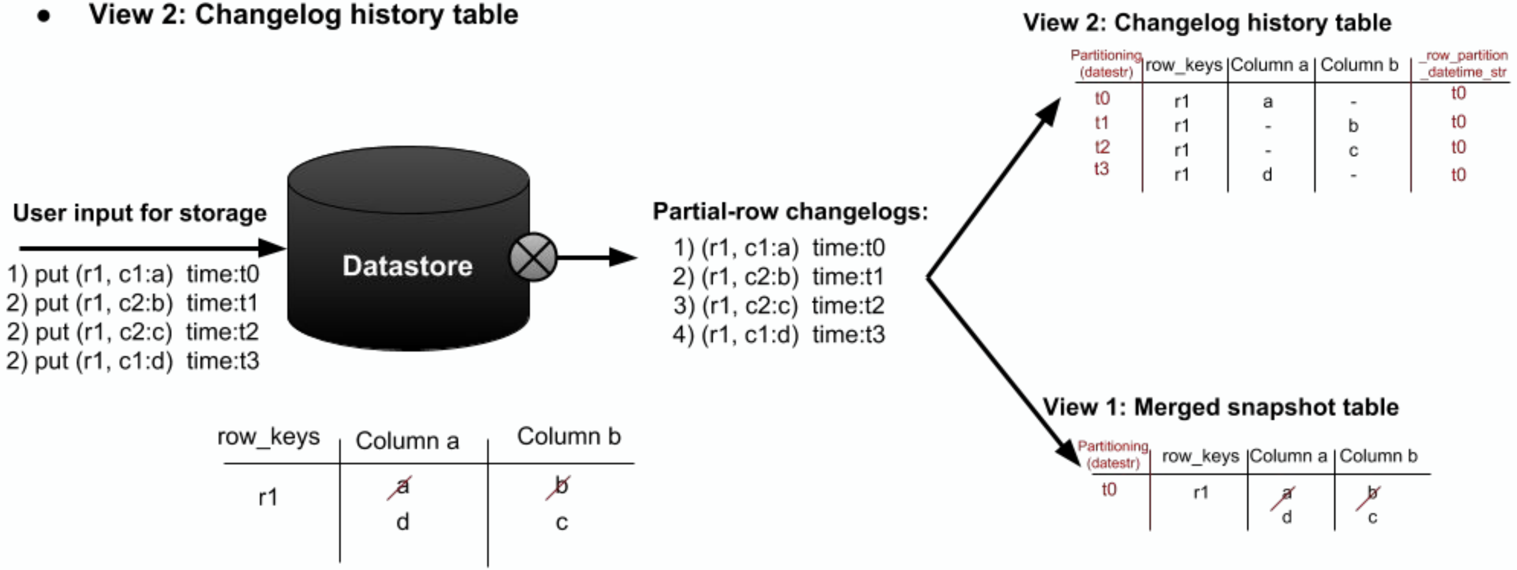


Present: Redesigned extensible Big Data Platform (2017-present)

Other Improvements: Standardized data model

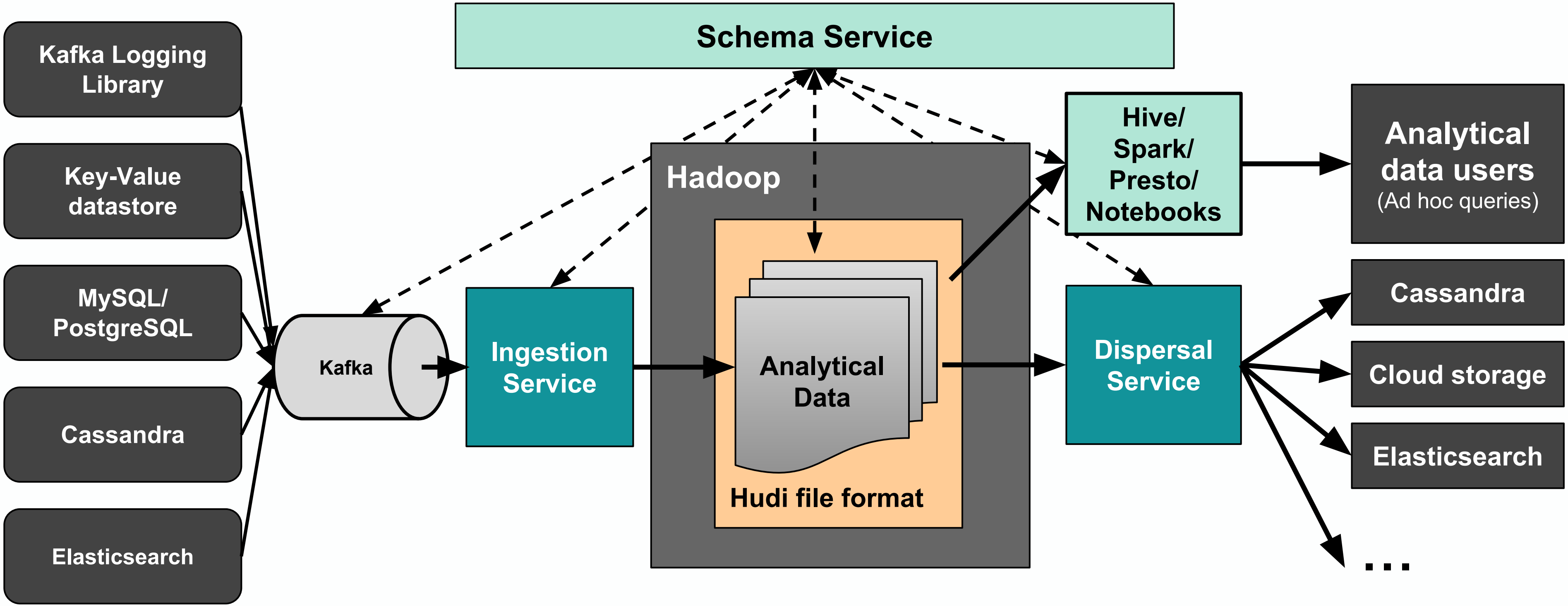
Standardized Hive raw data model:

- **View 1: Merged snapshot table**
- **View 2: Changelog history table**



Present: Redesigned extensible Big Data Platform (2017-present)

Other Improvements: Generic Any-to-Any Data platform



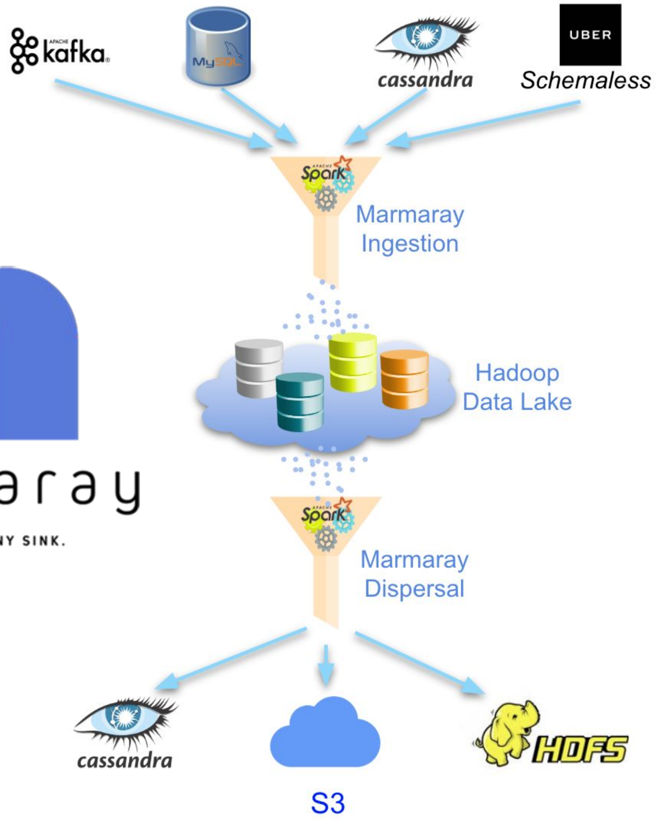
Present: Redesigned extensible Big Data Platform (2017-present)

Other Improvements: Generic Any-to-Any Data platform

- Built **Marmaray**:
    - Both Ingestion & Dispersal Framework/Library
    - Generic Any Source to Any Sink
- Spark based:
    - Scales horizontally like any Spark job
    - Sources and Sinks can easily be extended
- It is open-sourced ([Marmaray on Github]) ([Marmaray Eng Blog])

marmaray

ANY SOURCE, ANY SINK.



Future:
What’s coming next?

(Ongoing effort)

What’s coming next - Generation 4 (Ongoing effort)

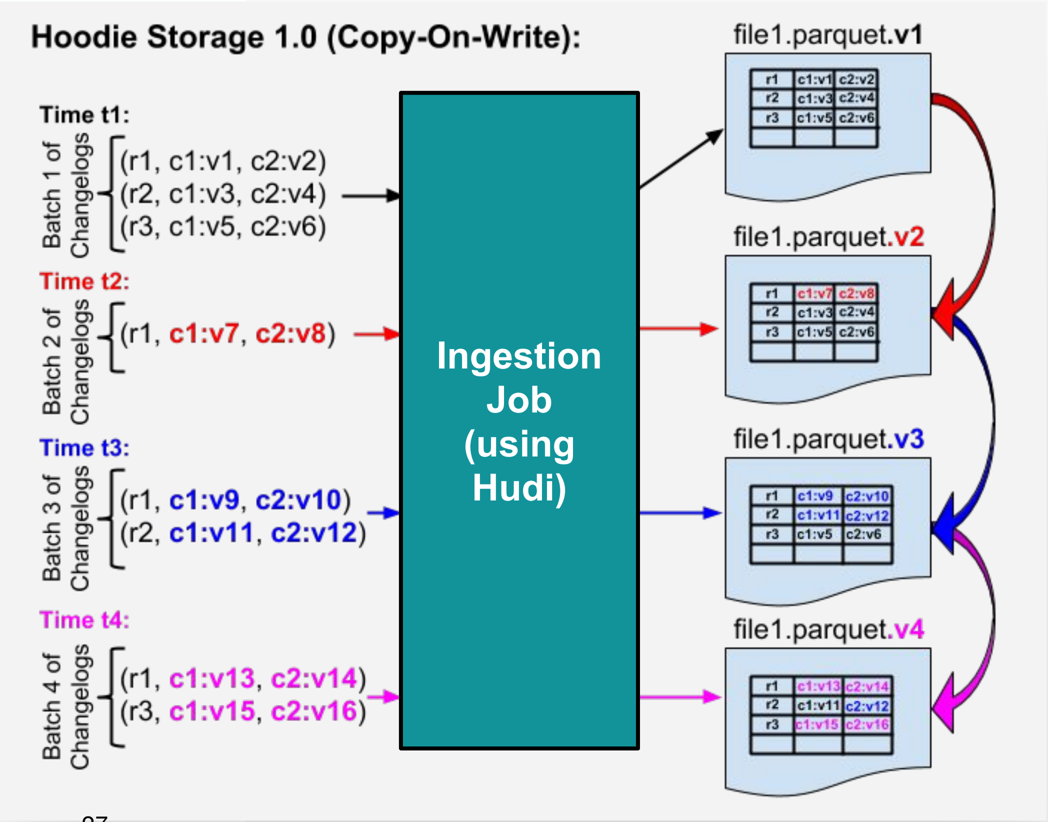
Are we done? Any remaining items?

1. **Data Quality is still a concern:**
   - Further unification of Hadoop Ingestion with strict contract with Storage team
   - Expand schema-service beyond type/structural check and into semantic checks
   - Unify RPC vs Analytical worlds (especially on data schema side)
2. **Still Need faster data access**
   - ~5-10 min Hadoop data for mini-batching to compete with Streaming
3. **Efficiency is the next big monster**
   - Don’t limit yourself to Hadoop. Go for the entire compute resources
   - Unified resource scheduler for Hadoop and beyond (Mesos, Yarn and now Peloton)
   - See our presentation at “Hadoop Infrastructure@Uber Past , Present and Future”
4. **Hudi is still actively being developed**
   - Get rid of sensitivity with respect to the ratio of update/delete vs insert
   - Provide large Parquet file (1+ GB) with data latency of 5-10min

What's coming next - Generation 4 (Ongoing effort)

Hudi Storage 1.0:

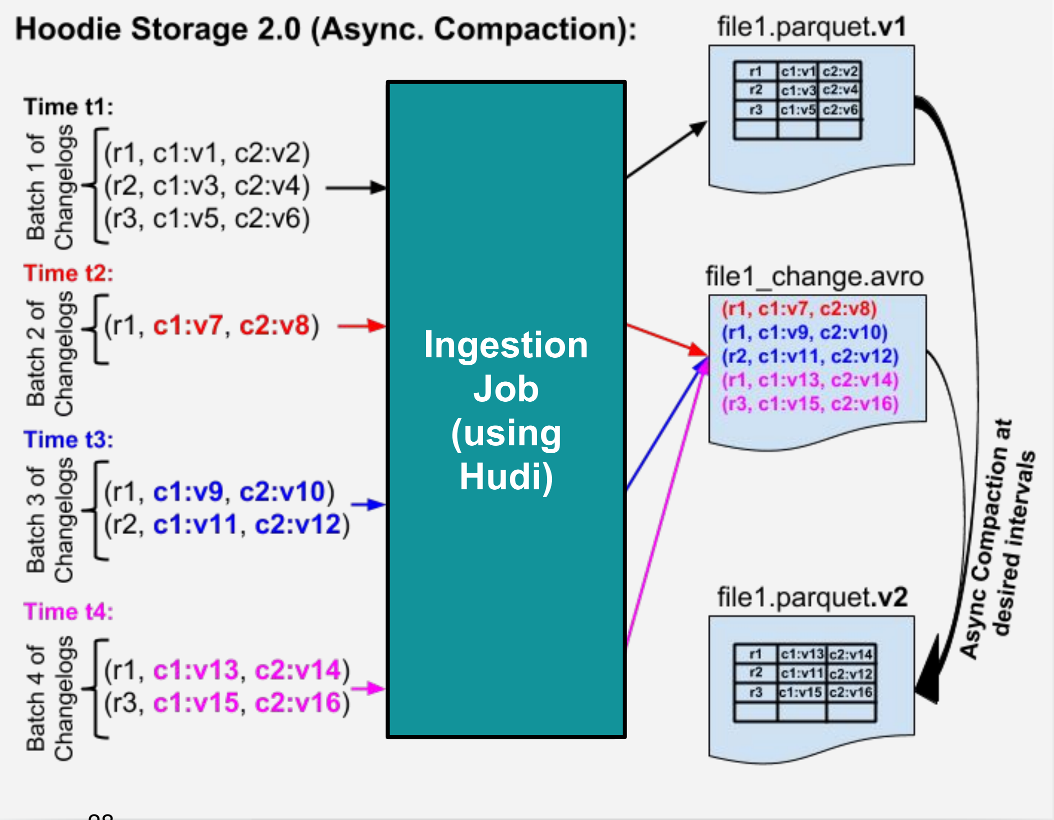
- Copy-on-write solution
- Rewriting Parquet files on updates/deletes
    - 1GB file very expensive
- Output Partition + Row_Key are required
    - Supports per partition index
    - Can we get rid of output partition?



What's coming next - Generation 4 (Ongoing effort)

Hudi Storage 2.0:

- Merge-on-Read solution
- Have row-based delta file + Parquet file
    - Merge only when the cost of rewrite is amortized
- Merge on Query side
    - Provides 5-10min hadoop data
- Add Global Index

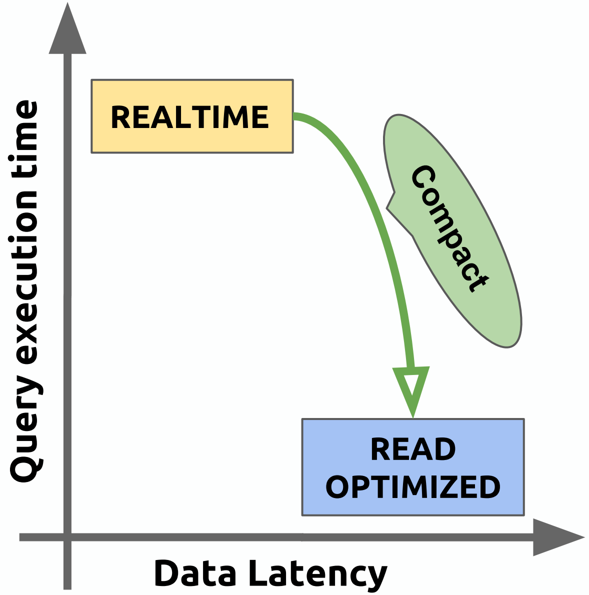


What's coming next - Generation 4 (Ongoing effort)

Be flexible with users:

- Hudi's supported different Storage Types and Views

Storage Type	Supported Views
Storage 1.0 (Copy On Write)	Read Optimized, ChangeLog View
Storage 2.0 (Merge On Read)	Read Optimized, RealTime, ChangeLog View



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Creating an Extensible Big Data Platform: Lessons learned

Creating an Extensible Big Data Platform: Lessons Learned

1. **Investigating your data/use cases and <u>finding the required primitives</u> pays back huge**
    - With <u>GDPR requirement</u>, Having Update/Delete on the entire Hadoop dataset is life-saving
2. **<u>Data Quality</u> will be an ongoing effort**
    - This is the key distinction between a <u>data swamp</u> and an <u>effective data lake</u>
    - <u>Enforce schema</u> (mandatory and pre-defined) as early as possible
    - Move beyond type checking and into <u>semantic checking</u>
    - Use "<u>enumerated values"</u> instead of Strings as much as possible
    - Enforce <u>mandatory documentation</u> for all fields
    - <u>Standardize schema name</u>, <u>field names</u> as well as define your <u>core entities as types</u>
3. **<u>Standardize</u> everything as soon as possible**
    - Don't make <u>exceptions</u> (it always comes back at you)
    - This is the key to having reliable Big data that can scale while being efficient
    - This is the key to have happy data users and to be able to educate them on how to use your data

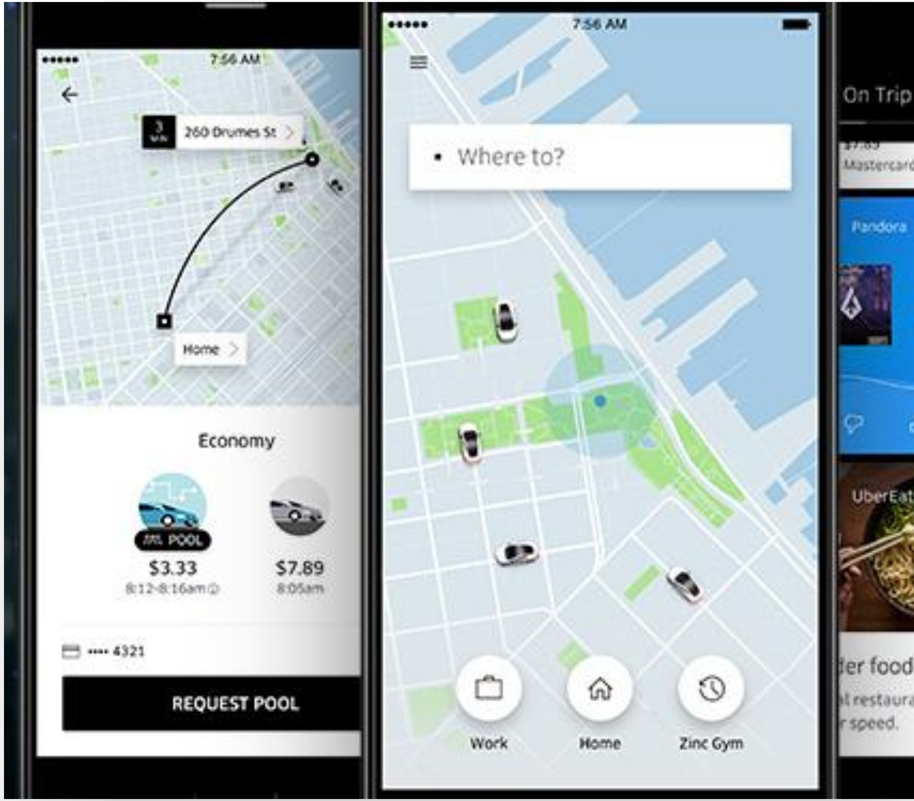
Creating an Extensible Big Data Platform: Lessons Learned

4. **Ensure you have a solid data <u>retention policy</u> as well as a standard <u>data model</u> as early as possible**
    - Retention from beginning saves you $ on wasted space and educates users on not wasting
5. **Track all related data <u>metadata</u>**
    - Who owns what data, data lineage, data content, data access,...
6. **Invest in a good <u>data pipeline monitoring</u>**
    - Define your terminology and stick to it (<u>Freshness</u>, <u>Latency</u>, <u>Completeness</u>, Late-arriving-data,...)
    - Detects many corner cases and lets you solve the issue before it affects your users
7. **Minimize your platform dependency on <u>user-defined values</u>**
    - User-defined values always break your Big data platform
    - Replace them by <u>system-defined values</u> as much as possible (e.g. user define ts vs system ts)
8. **Pay attention to the <u>notion of time in your data</u> and educate users on those**

Hadoop Platform @ Uber

Want to be part of our future effort?

- **Come talk to me**
    - Office Hours: 11:45am - 12:30 pm
- **Positions in both SF & Palo Alto**
    - email me: reza@uber.com



Creating an Extensible Big Data Platform

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Further references

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3. “Hudi: Uber Engineering’s Incremental Processing Framework on Hadoop”, Prasanna Rajaperumal, Vinoth Chandar, Uber Eng blog, 2017
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6. “Marmaray: An Open Source Generic Data Ingestion and Dispersal Framework and Library for Apache Hadoop”, Danny Chen, Omkar Joshi, Uber Eng blog, 2018
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Extra slides

Let’s rebuild for long term - Generation 3 (2017-present)

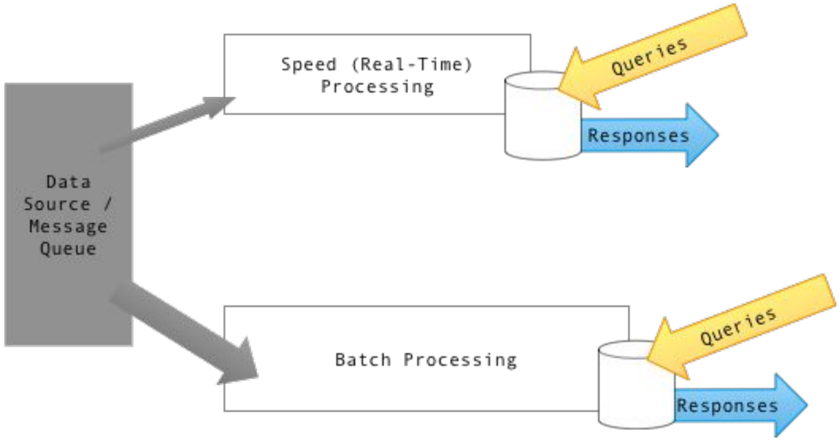
Any work-around for snapshot-based ingestion?

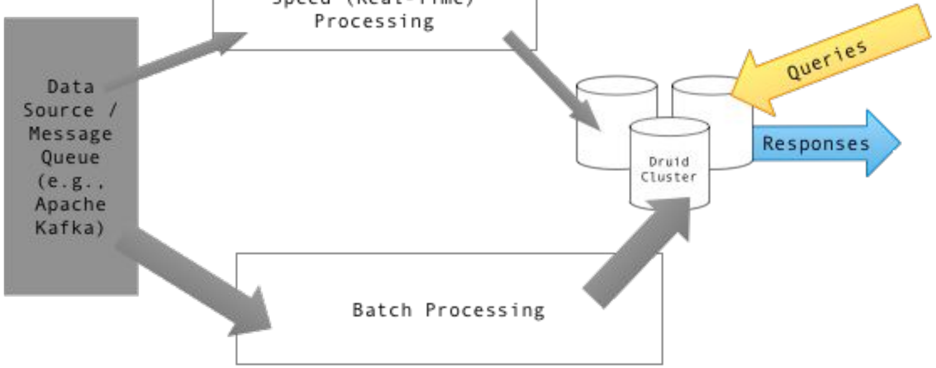
1. **Directly Query HBase**
    - Range scan will make it a bad fit
    - Lack of support for nested data
    - Significant operational overhead for 100 PB
2. **Don’t support Snapshot view and only provide logs**
    - Users need the merged view and will have to do it in their queries which makes it inefficient
    - Merging can be done inconsistency resulting in data correctness
3. **Use specialized analytical DBs**
    - Can’t bypass HDFS since we still need to join with other data in HDFS
    - Not all data fits into memory and many queries will fail
    - Leads to lambda architecture issue and multiple copies of the same data

Data @ Uber: Generation 3

What does Incremental Processing mean:

Lambda architecture:





Data @ Uber: Generation 3

Stream/Batch processing Trade off:

- Latency
- Completeness
- Cost (Throughput/efficiency)

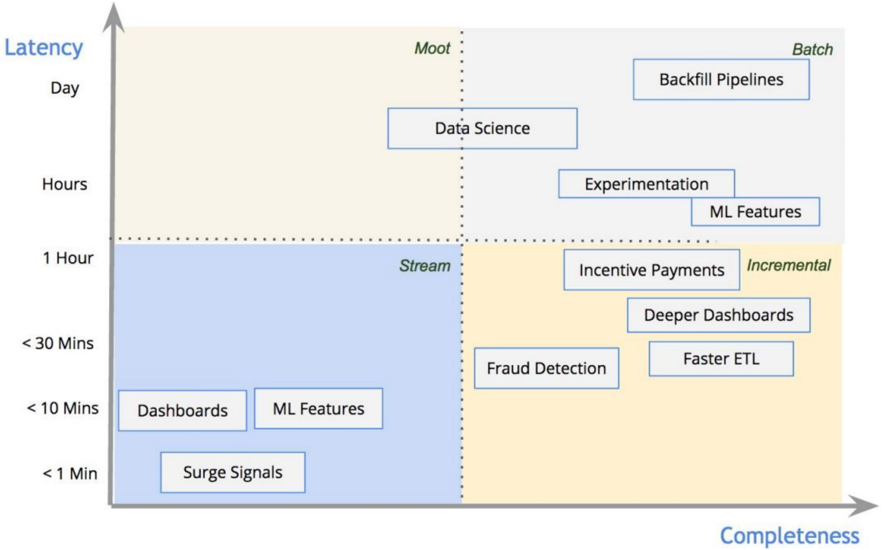
Operation challenges in Streaming & Batch:

- Projections (Streaming:Easy   Batch:Easy)
- Filtering (Streaming:Easy   Batch:Easy)
- Aggregations (Streaming:Tricky   Batch:Easy)
- Window (Streaming:Tricky   Batch:Easy)
- Joins (Streaming:HARD   Batch:Easy)

Data @ Uber: Generation 3

Do we need Streaming, Batch or Incremental?

- Need to investigate your use cases (based on latency vs Completeness)

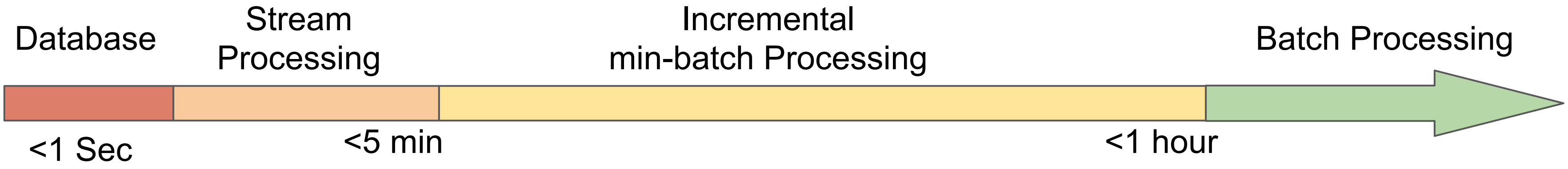


- Very distinct uses cases for Streaming
- Very distinct use cases for Batch
- A lot of use cases that can benefit from incremental mode

Data @ Uber: Generation 3: Provide Incremental processing

What exactly is Incremental mode?

- Mini-batch jobs that pulls out only changed data
- Provides high completeness (compared to streaming mode)
- Supports all hard operations as any other batch job (like multi-table joins,....)



Data @ Uber: Generation 3: Provide Incremental processing

How does Incremental mode help efficiency?

- Read only what you need by using Columnar file formats
- Simple solution for all types of queries (joins, …)
- Consolidation of Compute & Storage for all use case (exploratory, interactive,....)