Uber & Big Data
a case study

https://github.com/chgogos/big_data

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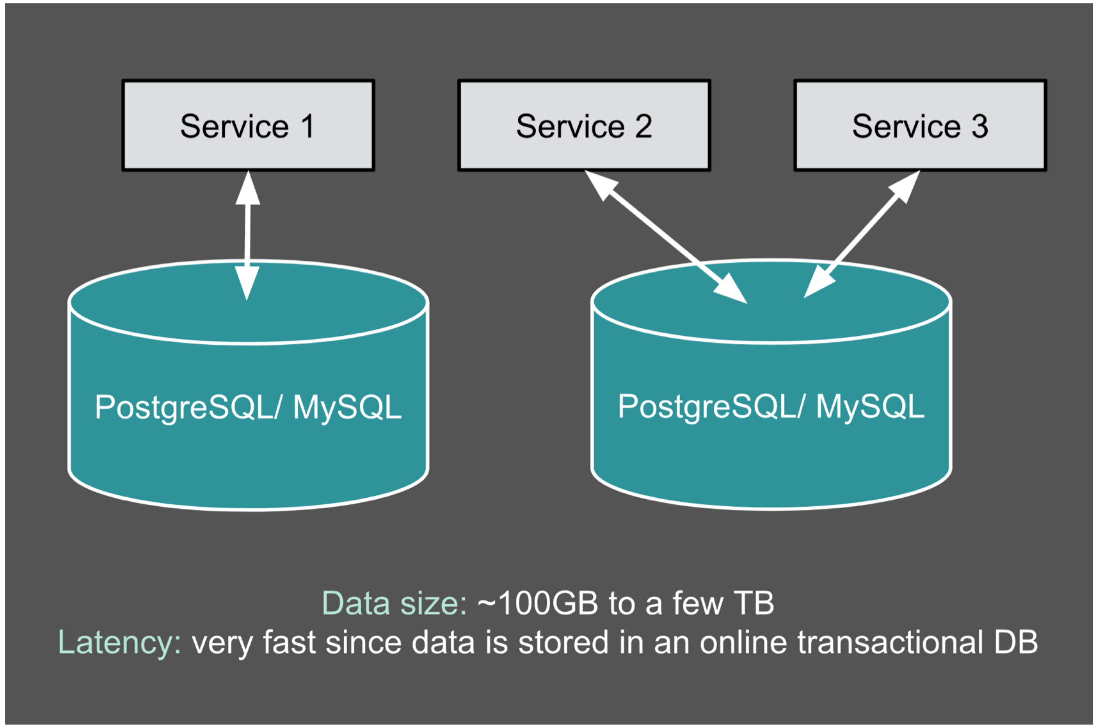
Uber

- Founded at 2009 by Travis Kalanick and Garrett Camp
- Peer to peer ridesharing, taxi cab, food delivery, bicycle sharing
- Uber's services and mobile app officially launched in San Francisco in 2011
- Operations in 785 metropolitan areas worldwide (Sept. 2018)
- 12000+ employees

Generation 0 (prior to 2014)

- data size = few terabytes
- latency < 1 min
- Online Transaction Processing (OLTP) databases
  - MySQL
  - PostgreSQL

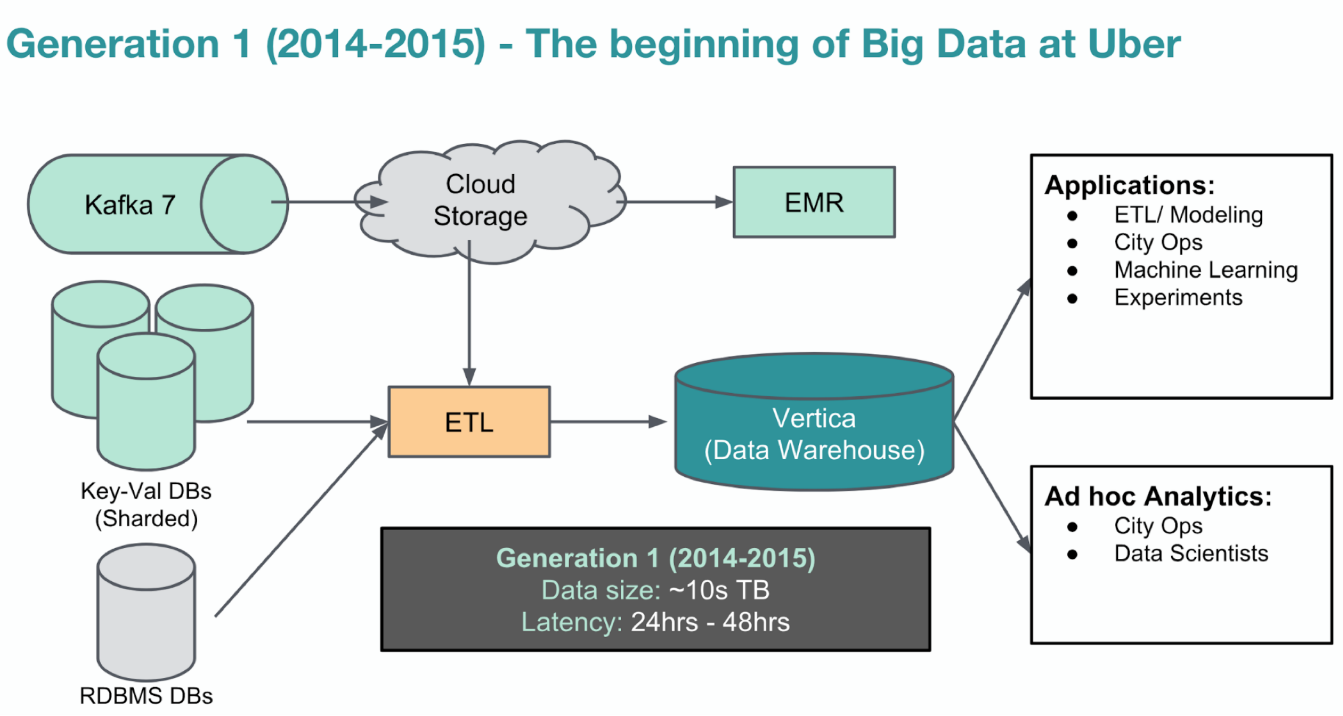


Data users

- **City operations teams (thousands of users)**
  On-the-ground crews that manage and scale Uber's transportation network in each market. Access data on a regular basis to respond to driver-and-rider-specific issues
- **Data scientists and analysts (hundreds of users)**
  Analysts and scientists spread across different functional groups that need data to help deliver high level transportation and delivery experiences to the users (e.g. forecasting rider demand)
- **Engineering teams (hundreds of users)**
  Engineers focused on building automated data applications, such as Fraud Detection and Driver Onboarding platforms

Generation 1 (2014-2015)

- Vertica: data warehouse software (column oriented)
- Extract Transform Load (ETL)
  - AWS S3 → Vertica
  - OLTP databases → Vertica
  - Logs → Vertica
  - …
- Online query system using SQL
  city operators could easily interact with the data without knowing about the underlying technologies



Limitations of Generation 1

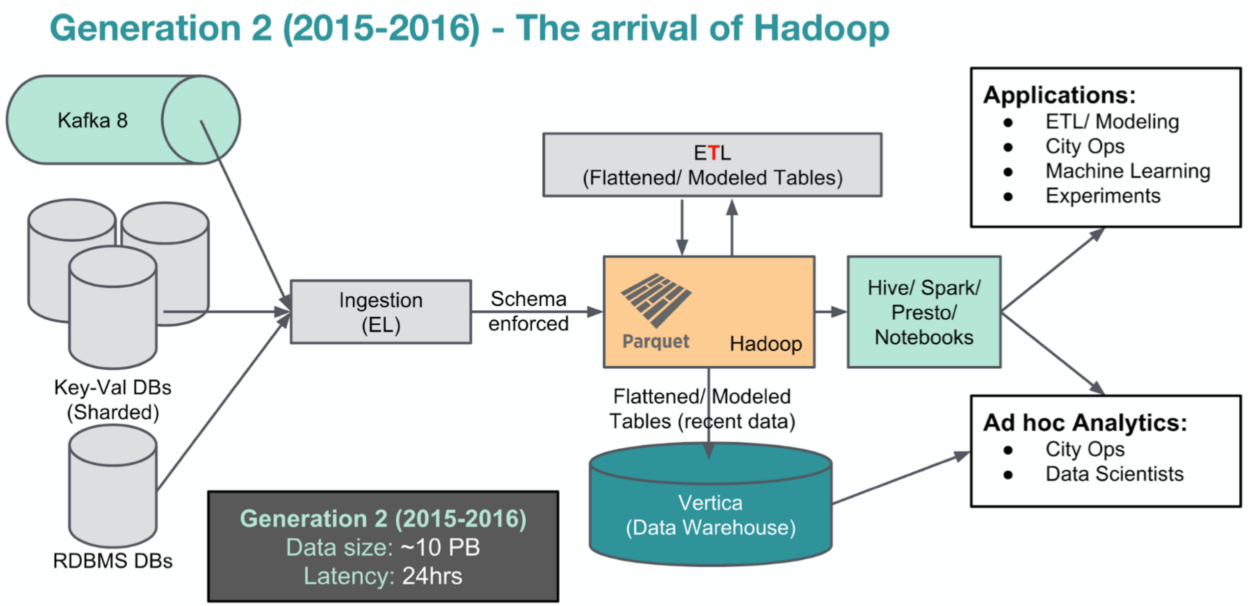
- Data (in JSON format) was ingested through ad hoc ETL jobs
- Lack of a formal schema communication mechanism → duplicate data
- Expensive scaling

Generation 2 (2015-2016)

- Hadoop data lake (all raw data was ingested from different online data stores only once and with no transformation during ingestion)
- Access data
  - Presto: interactive ad hoc user queries
  - Apache Spark: programmatic access to raw data
  - Apache Hive: heavy queries
- All data modeling and transformation only happened in Hadoop
- Critical tables were transferred to the data warehouse
  - → quick SQL queries
  - → lower operational cost
- Transition from JSON to Apache Parquet
  - → higher compression
  - → integration with Apache Spark

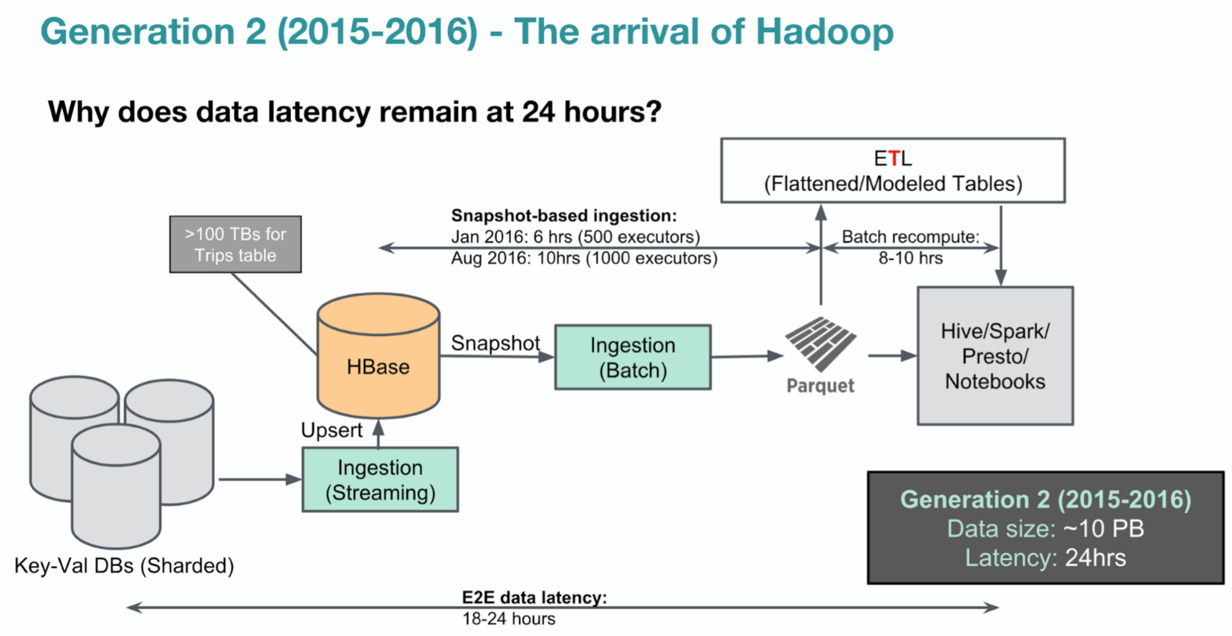
10,000 vcores

> 100,000 running batch jobs / day



Limitations of Generation 2

- Massive amount of small files stored in HDFS → pressure on HDFS NameNodes
- New data was accessible to users once every 24 hours → no real-time decisions
- HDFS and Parquet do not support data updates (all ingestion jobs needed to create new snapshots from the updated source data)
  1. ingest the new snapshot into Hadoop
  2. convert it into Parquet format
  3. swap the output tables
  4. view the new data



Pain points in gen2, solutions adopted in gen3

- **HDFS scalability limitation:** HDFS is bottlenecked by its NameNode capacity (if data size > 50-100 PB)
  Solution: control number of small files, move data to separate clusters
- **Faster data in Hadoop:** 24-hr data latency
  - **Solution:** incremental ingestion of only updated and new data
- **Support of updates and deletes in Hadoop and Parquet:** ingest all updates at one time, once per day
  - **Solution:** framework to support update/delete operations over HDFS
- **Faster ETL and modeling:** rebuild derived tables in every run
  - **Solution:** pull out only the changed data from the raw source table, update the previous derived output table

Hudi (Hadoop Upserts anD Incremental)

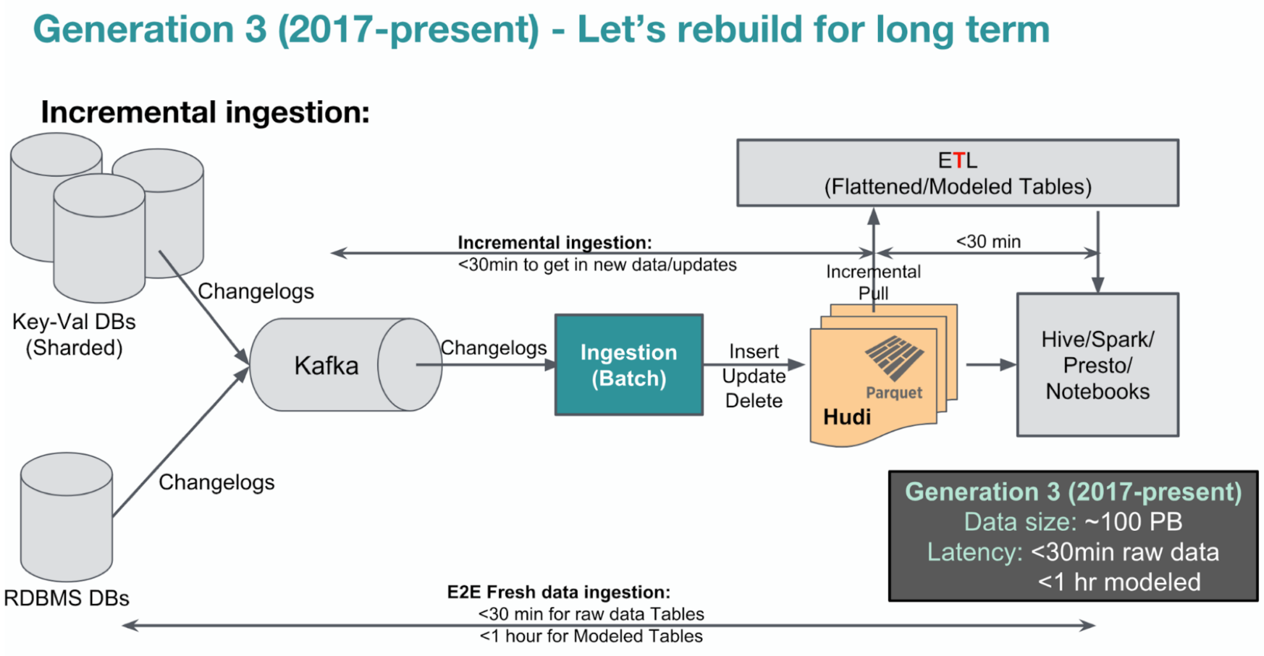
- Developed by Uber engineering in order to support Generation 3
- Open source Spark library that provides an abstraction layer on top of HDFS and Parquet to support the required update and delete operations
- Allows data users to incrementally pull out only changed data
  - Data users pass on their last checkpoint timestamp and retrieve all the records that have been updated since (without scanning the entire source table)
  - Snapshot-based ingestion of raw data to an incremental ingestion model: data latency 24 hours → < 1 hour

https://eng.uber.com/hoodie/

Generation 3 (2017 – present)

- Ingestion Spark jobs run every 10-15 minutes, providing a 30-minute raw data latency in Hadoop

100 PB data in Hadoop
100,000 vcores
~ 100,000 Presto queries / day
~ 10,000 Spark jobs / day
~ 20,000 Hive queries / day



Generation 4 (future work)

- Improved data quality through semantic checks
- Improved data latency (5 minutes)
- New version of Hudi
  - Generate larger parquet files (1GB vs 128MB)
  - Improve management of updates on parquet files through deltas

References

- https://eng.uber.com/
- https://eng.uber.com/uber-big-data-platform/
- https://eng.uber.com/hoodie/