



Beyond Lambda: Introducing Delta Architecture

Denny Lee, Developer Advocate

Who Am I?



Denny Lee is a Developer Advocate at Databricks. He is a hands-on distributed systems and data sciences engineer with extensive experience developing internet-scale infrastructure, data platforms, and predictive analytics systems for both on-premise and cloud environments.



Agenda

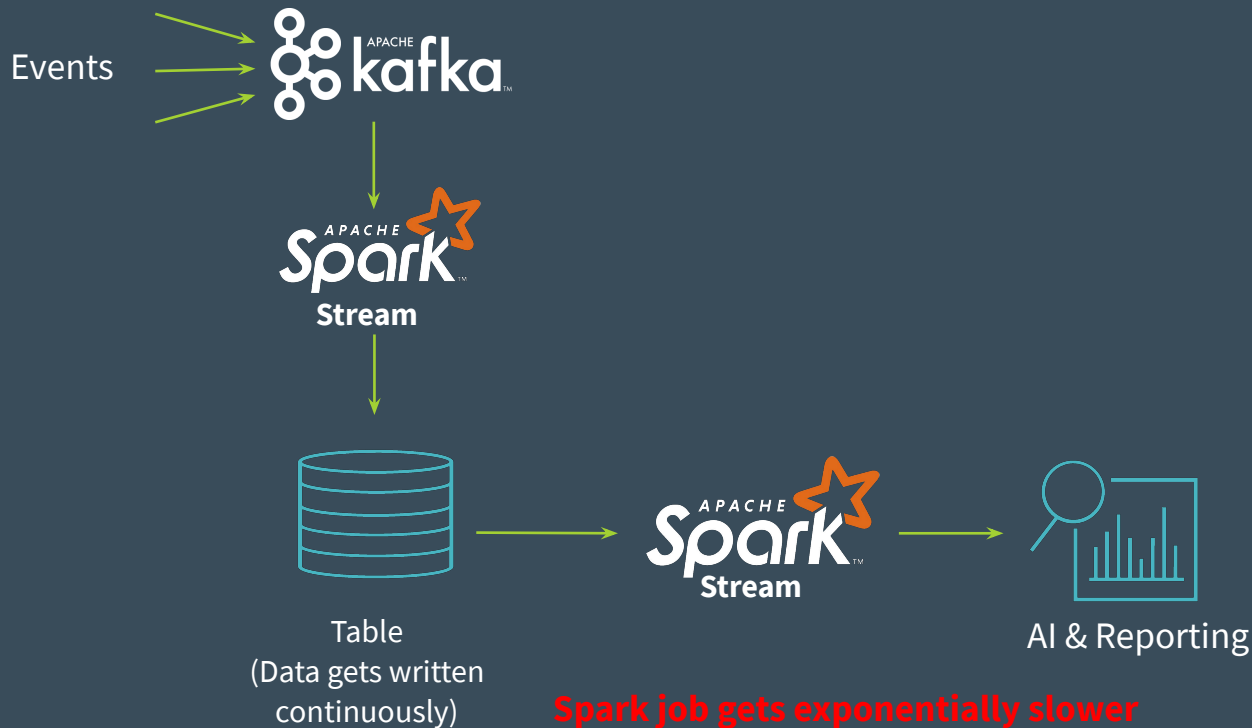
1. What are the complexities to build a simple data pipeline?
2. Why these complexities exist?
3. Delta Lake and How it works?
4. Delta Architecture: The pattern Databricks' customers follow to build continuous pipelines with Delta Lake
5. The key characteristics & benefits of the Delta Architecture.

A Data Engineer's Dream...

Process data **continuously** and **incrementally** as new data arrive in a **cost efficient way** without having to *choose* between batch or streaming



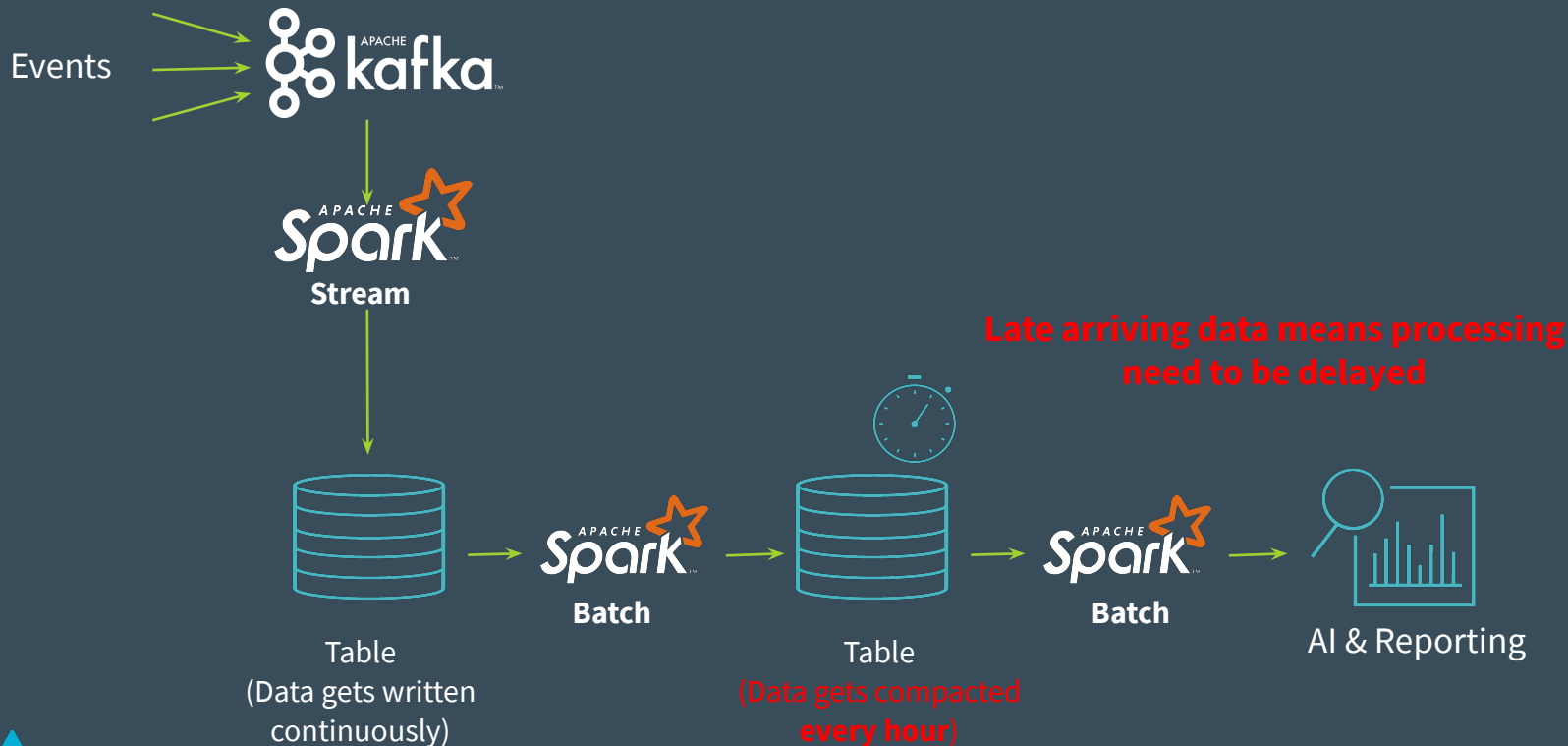
The Data Engineer's Journey...



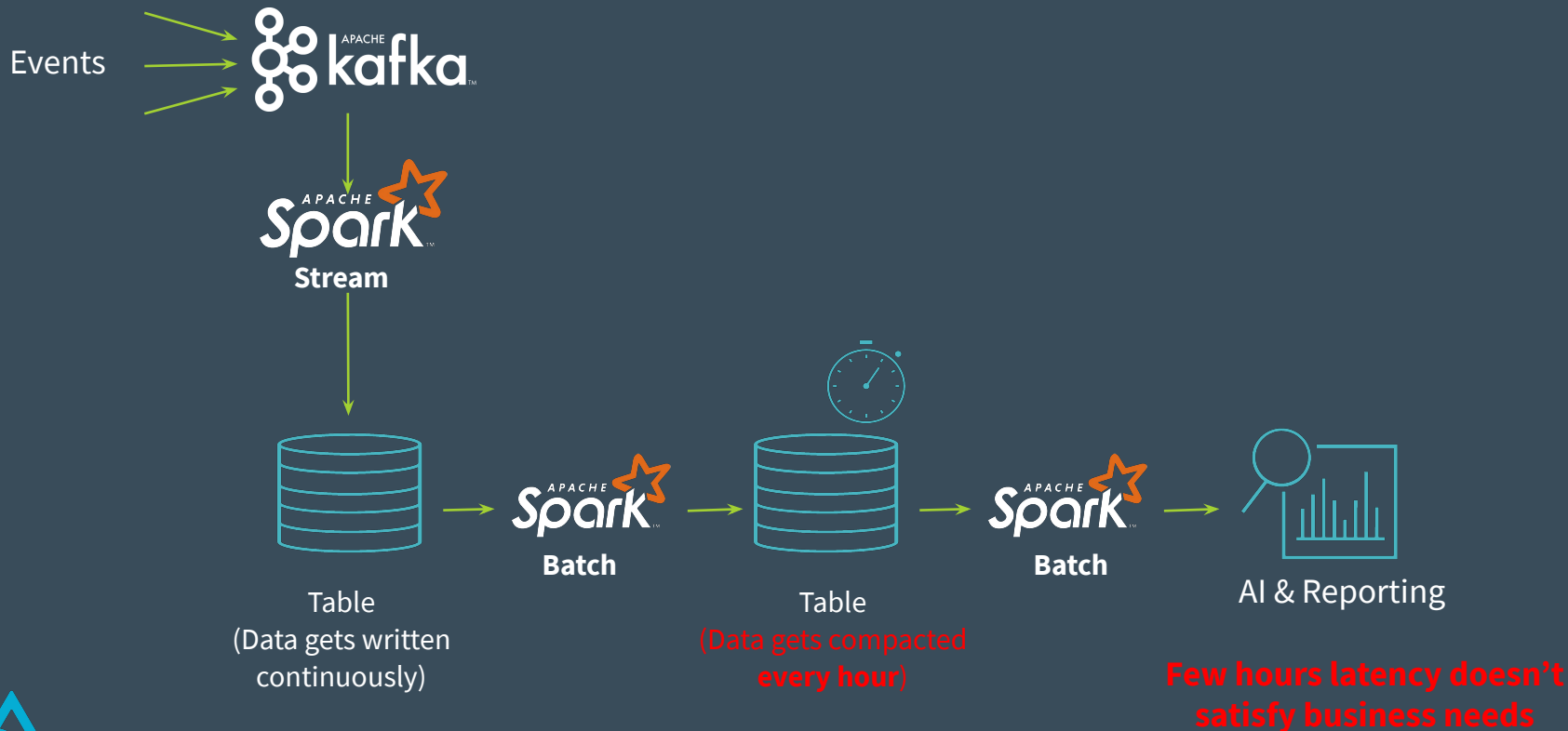
**Spark job gets exponentially slower
with time due to small files.**



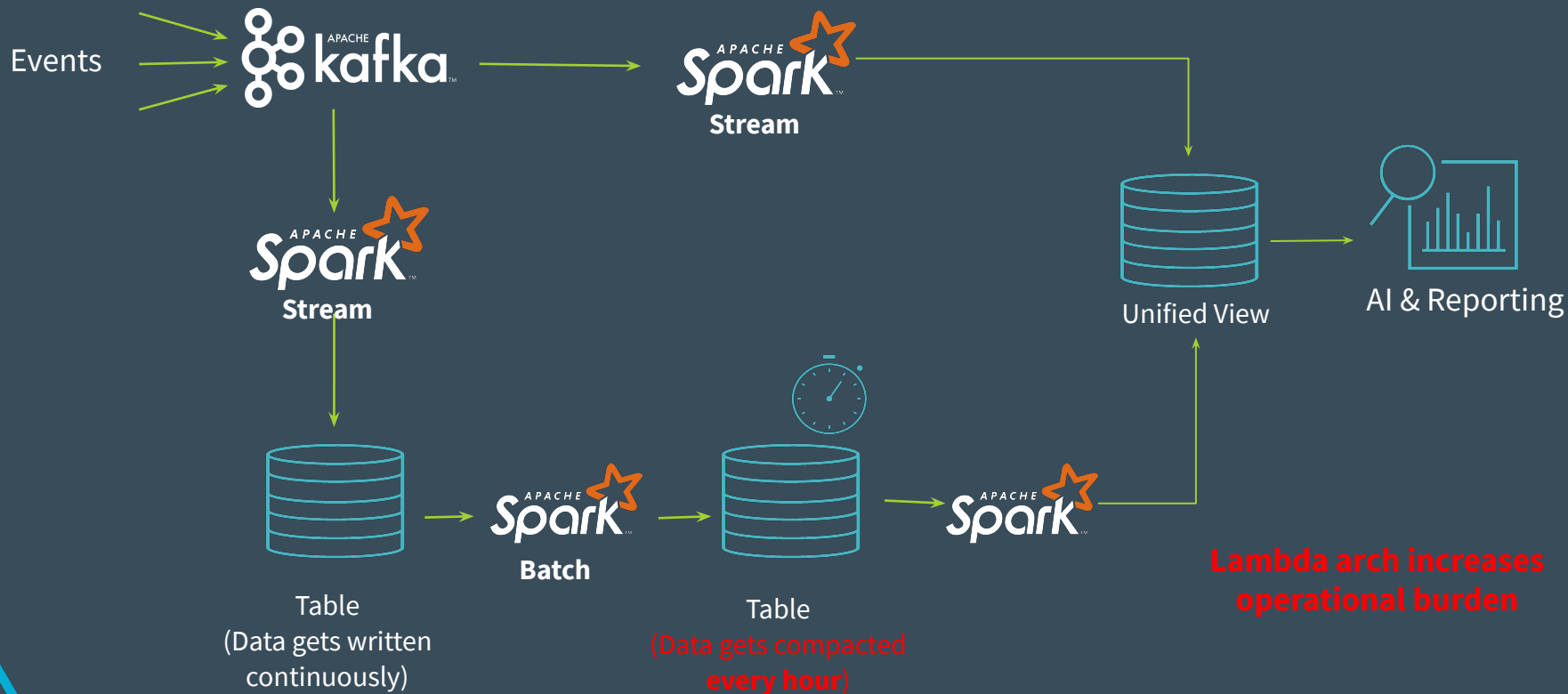
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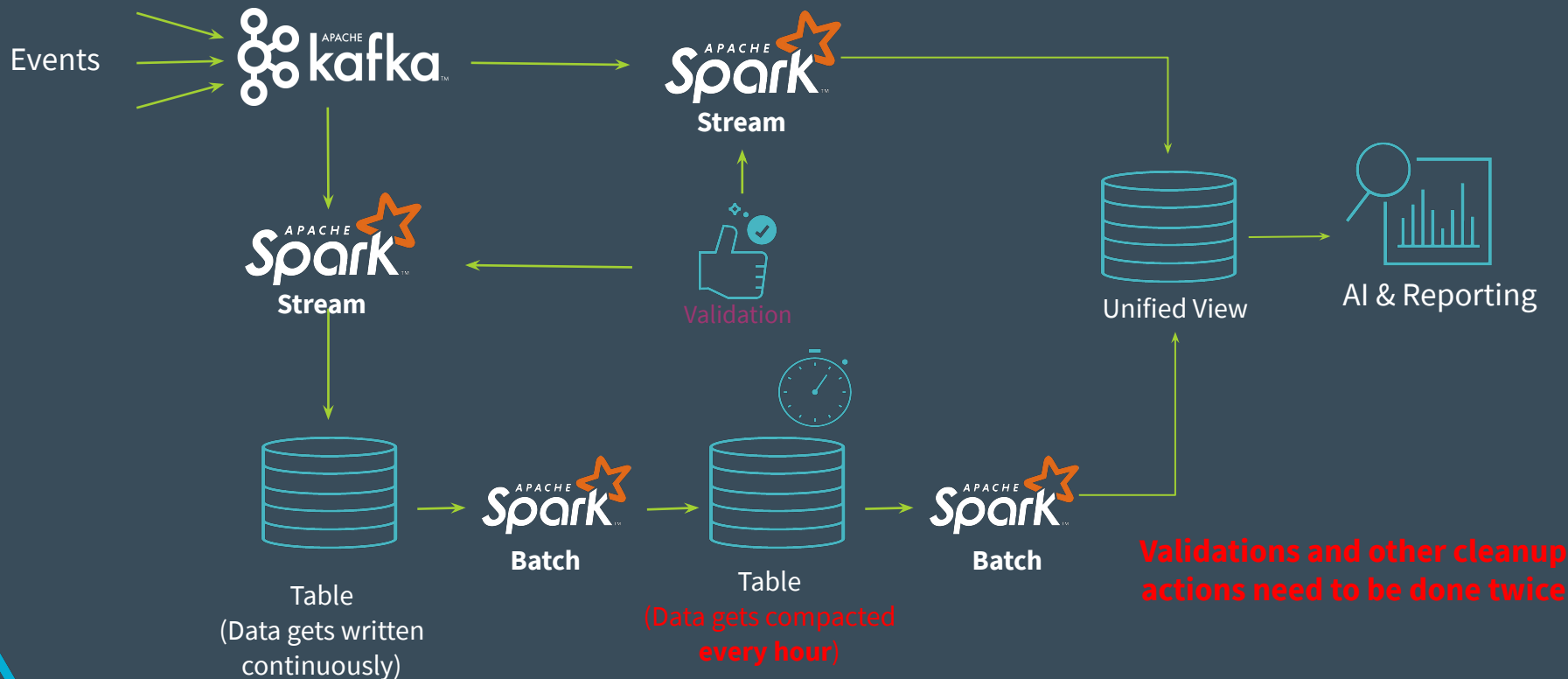
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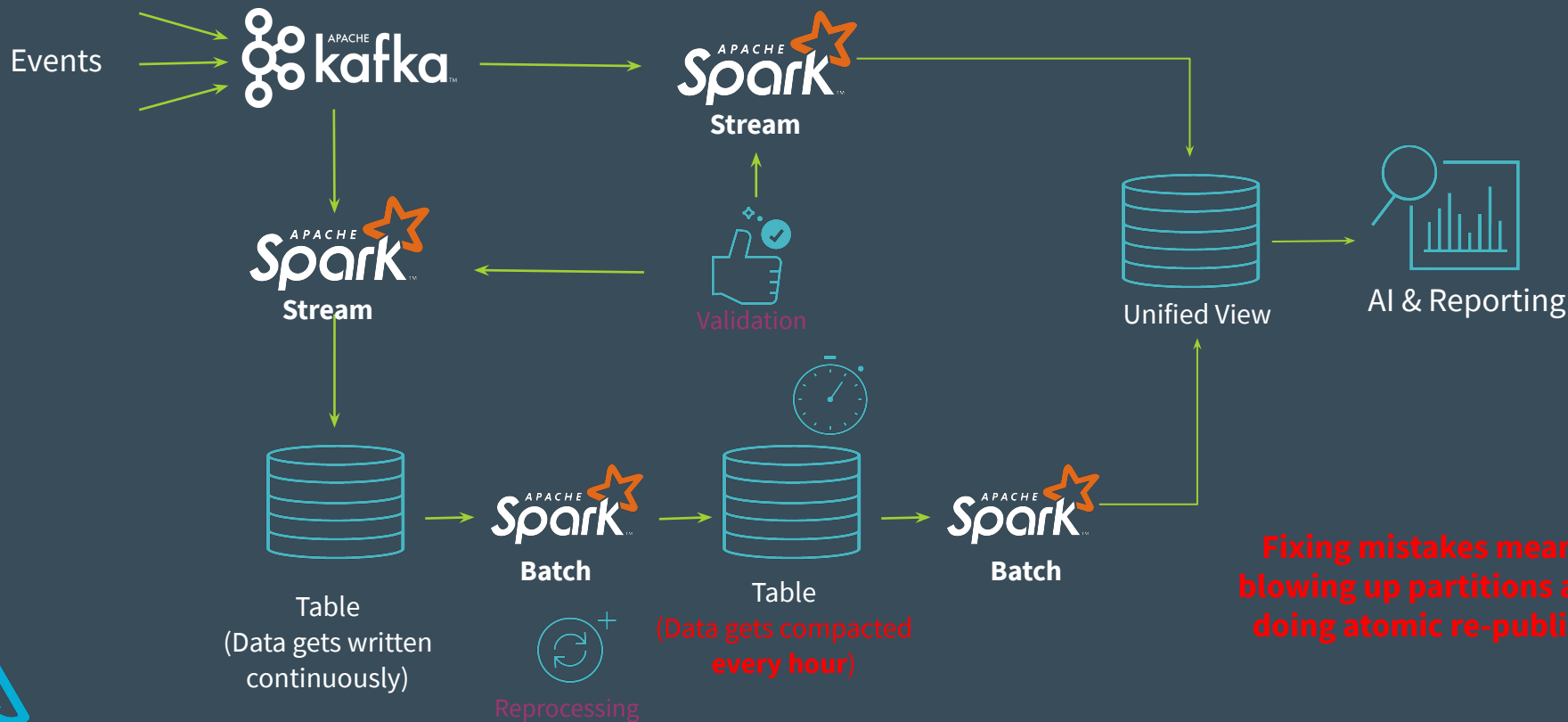
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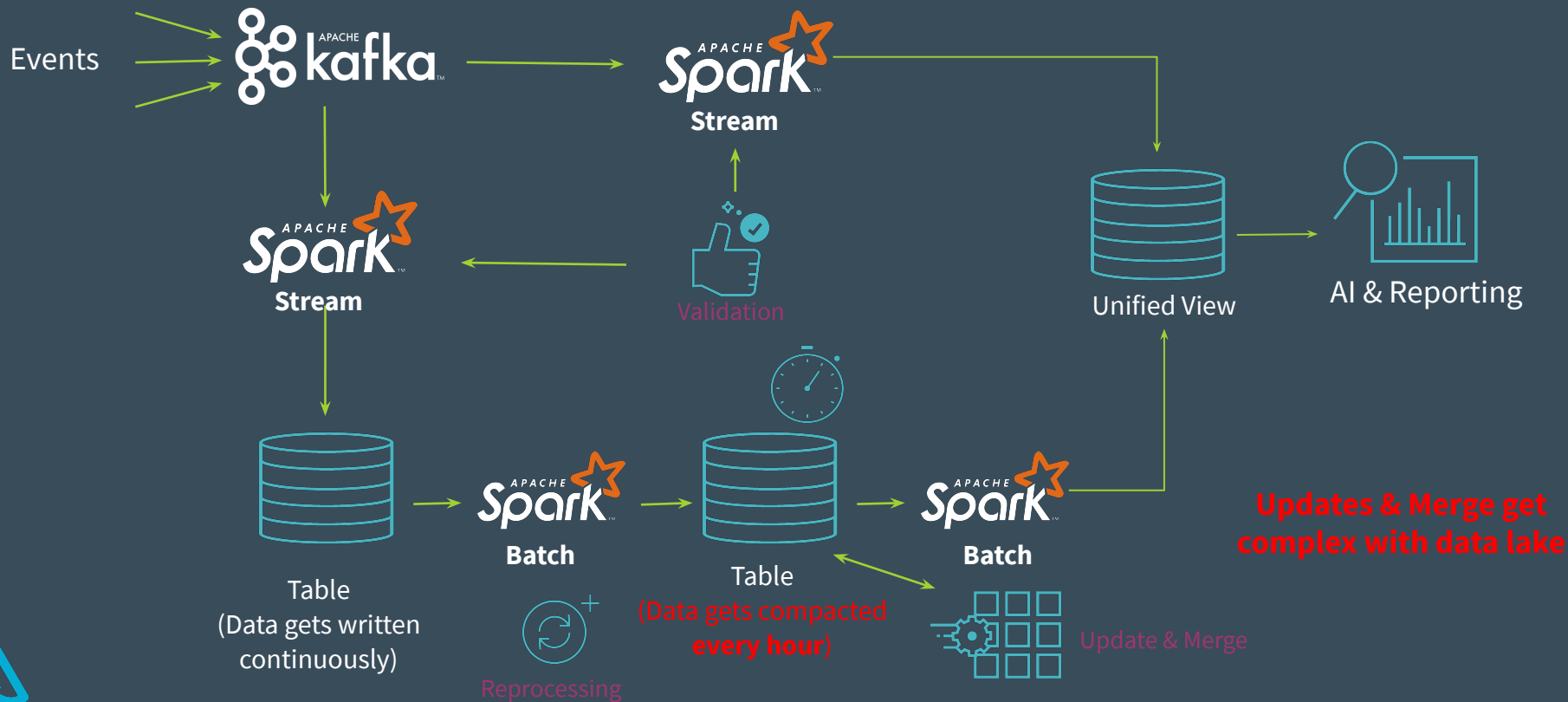
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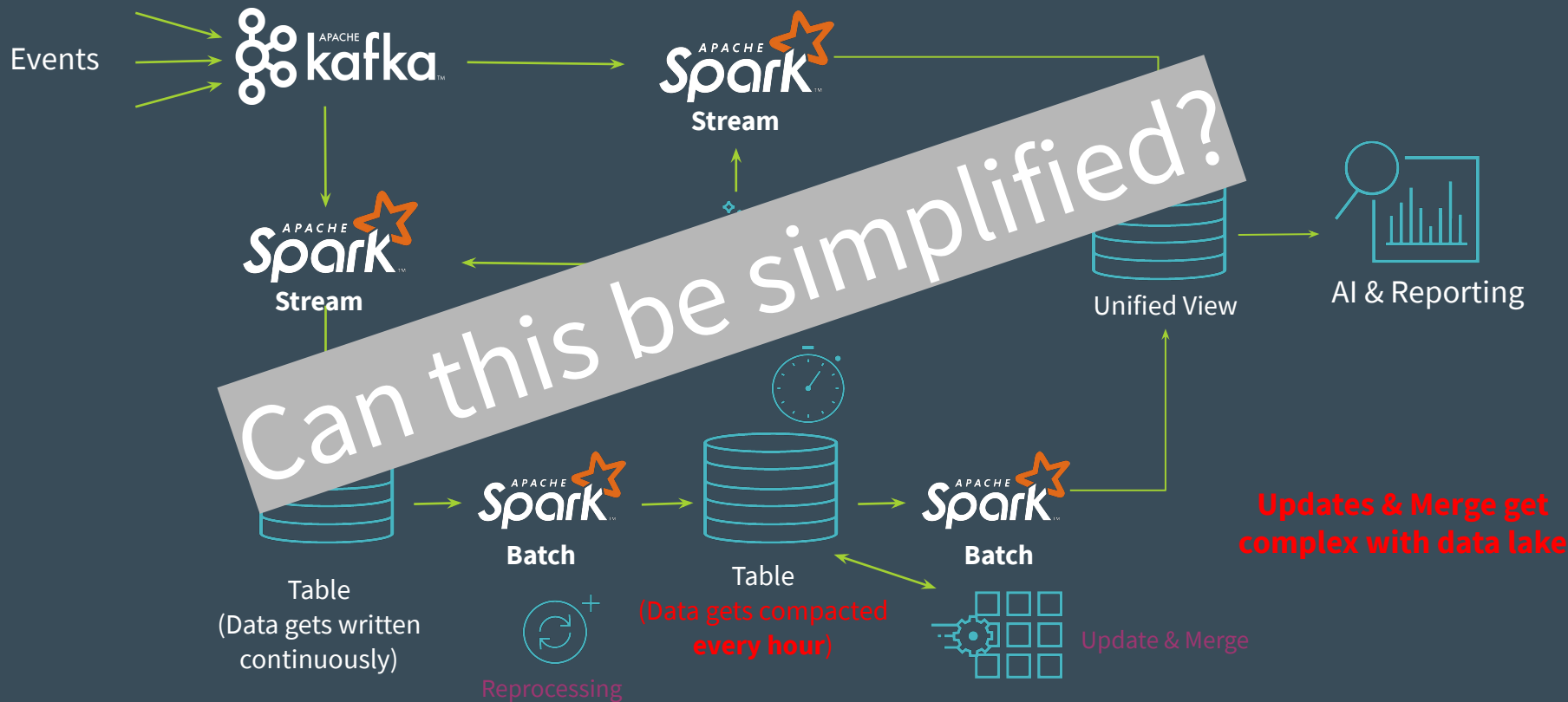
The Data Engineer's Journey...



The Data Engineer's Journey...



The Data Engineer's Journey...



What was missing?



1. Ability to **read consistent data** while data is being written
2. Ability to **read incrementally from a large table** with good throughput
3. Ability to **rollback** in case of bad writes
4. Ability to **replay historical data** along new data that arrived
5. Ability to **handle late arriving data** without having to delay downstream processing



So... What is the answer?



**STRUCTURED
STREAMING**

+



DELTA LAKE

=

**The
Delta
Architecture**

1. Unify batch & streaming with a continuous data flow model
2. Infinite retention to replay/reprocess historical events as needed
3. Independent, elastic compute and storage to scale while balancing costs

How Delta Lake Works?



Delta On Disk

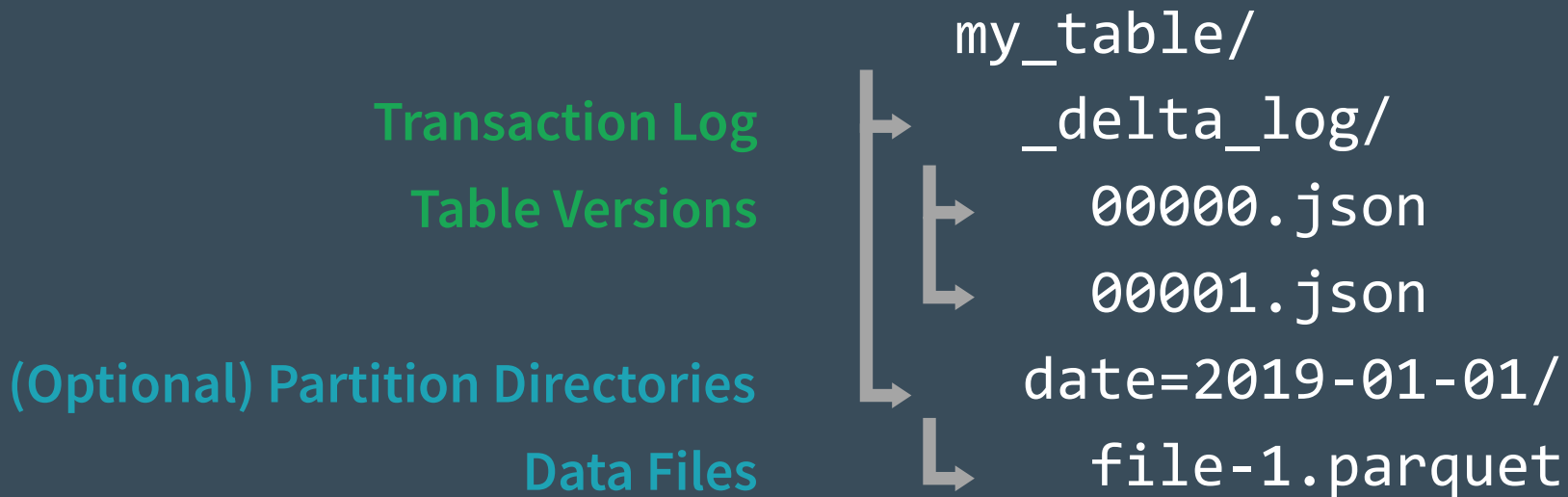


Table = result of a set of actions

Change Metadata – name, schema, partitioning, etc

Add File – adds a file (with optional statistics)

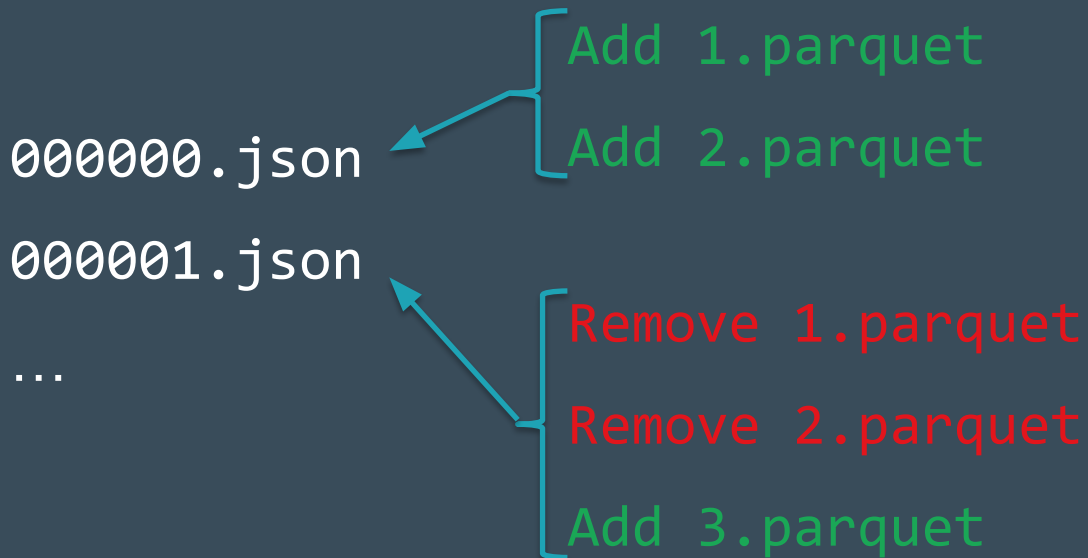
Remove File – removes a file

Result: Current Metadata, List of Files, List of Txns, Version



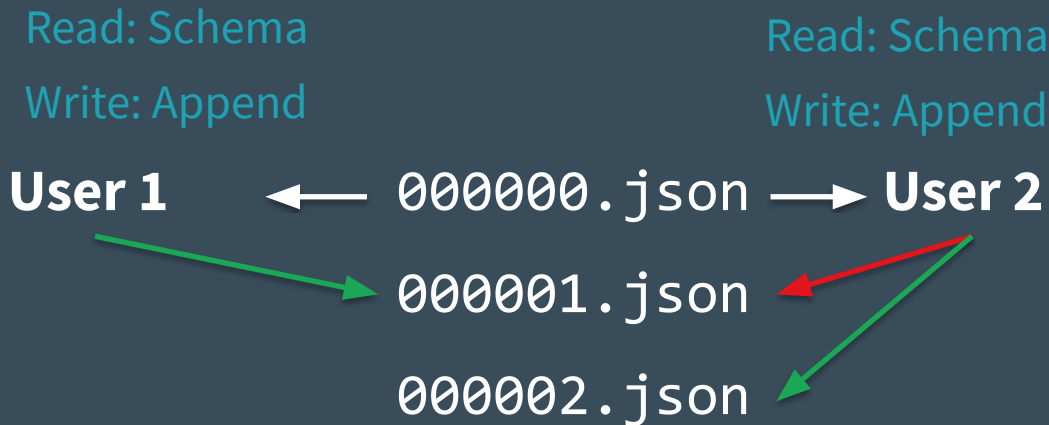
Implementing Atomicity

Changes to the table
are stored as
ordered, atomic units
called commits



Solving Conflicts Optimistically

1. Record start version
2. Record reads/writes
3. Attempt commit
4. If someone else wins, check if anything you read has changed.
5. Try again.



Handling Massive Metadata

Large tables can have millions of files in them! How do we scale the metadata? Use Spark for scaling!

Add 1.parquet

Add 2.parquet

Remove 1.parquet

Remove 2.parquet

Add 3.parquet



Checkpoint



Parquet



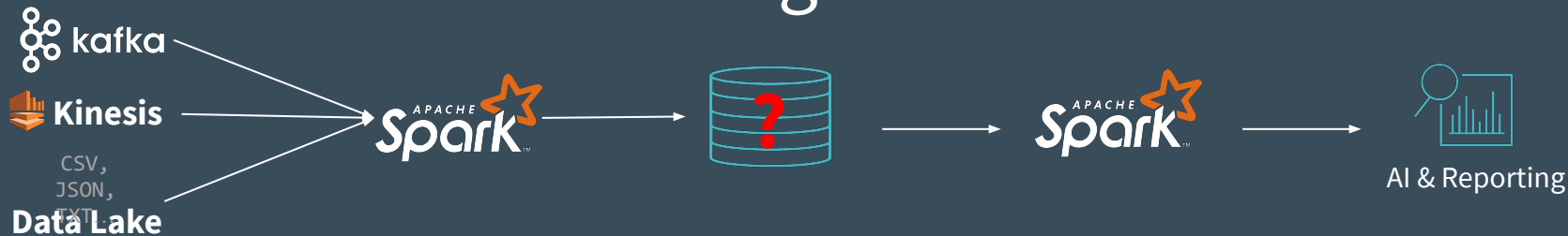
The Delta Architecture



Connecting the dots...



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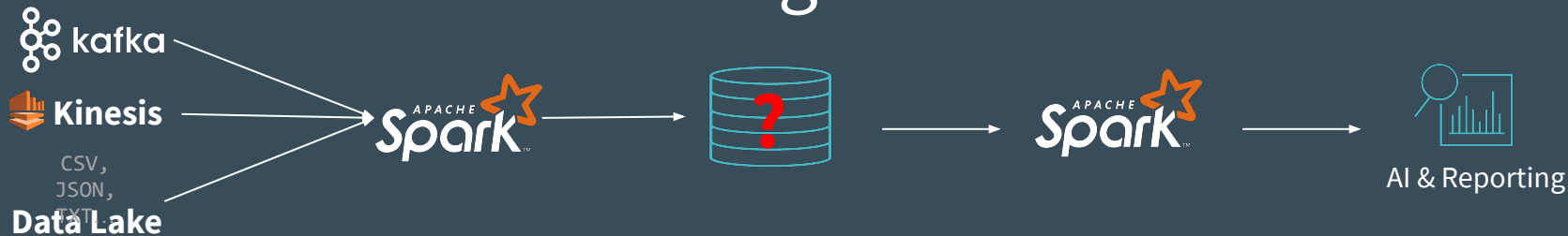
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Snapshot isolation between writers and readers



Connecting the dots...



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Snapshot isolation between writers and readers

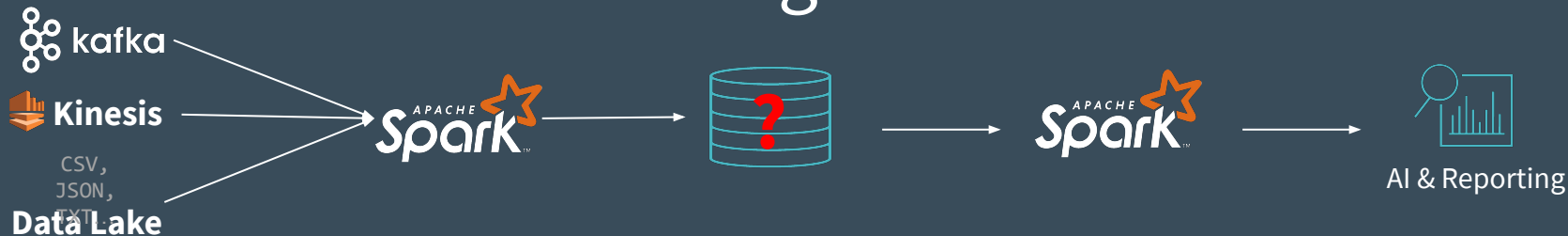
2. Ability to **read incrementally from a large table** with good throughput



Optimized file source with scalable metadata handling



Connecting the dots...



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Snapshot isolation between writers and readers

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Optimized file source with scalable metadata handling

3. Ability to **rollback** in case of bad writes







Time travel



Connecting the dots...



1. Ability to **read consistent data** while data is being written  Snapshot isolation between writers and readers
2. Ability to **read incrementally from a large table** with good throughput  Optimized file source with scalable metadata handling
3. Ability to **rollback** in case of bad writes  Time travel
4. Ability to **replay historical data** along new data that arrived  Stream the backfilled historical data through the same pipeline



Connecting the dots...

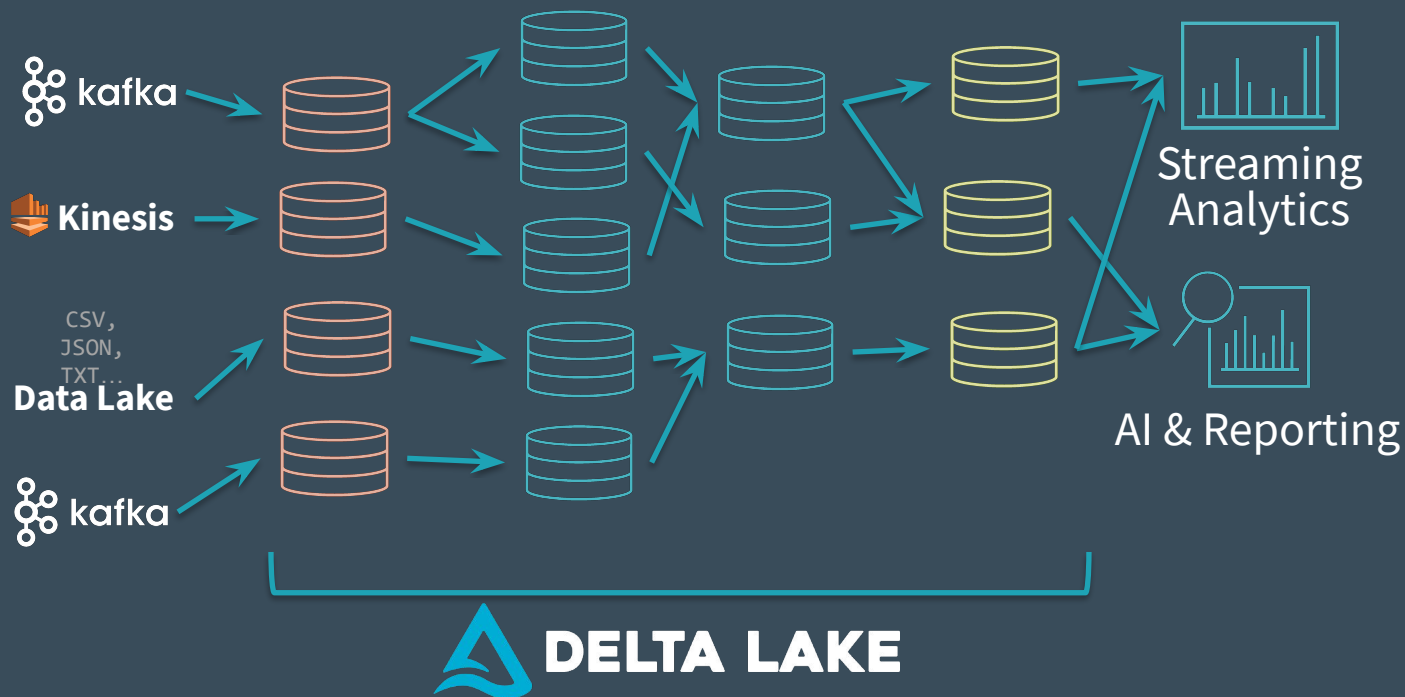


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The Delta Architecture

A continuous data flow model to unify batch & streaming



Connecting the dots...



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Characteristics of the Delta Architecture



#1. Adopt continuous data flow model

Stream to and from a Delta Lake table whenever possible.

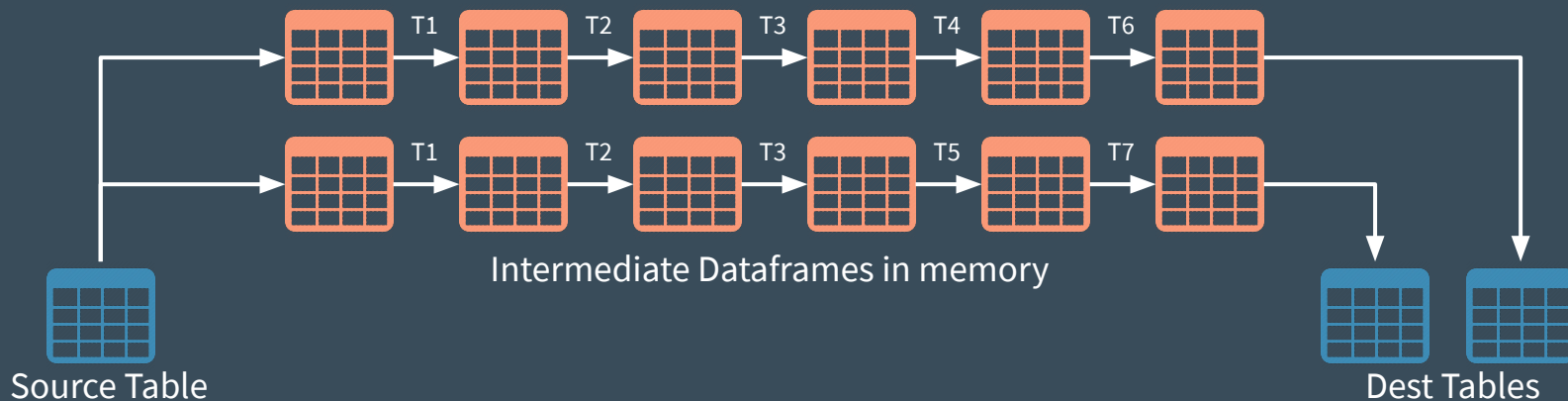
- **Unify batch and streaming.** Same engine. Same APIs. Same user code.
No need to reason about system complexities separately.
- **Incrementally load the new data efficiently.** No need to do state management on what are the new files added.
- **Process the data quickly as it arrives** without any delays.



#2. Use Intermediate Hops

Materialize DataFrames wherever applicable; especially when large number of transformations are involved. Materialization could be for:

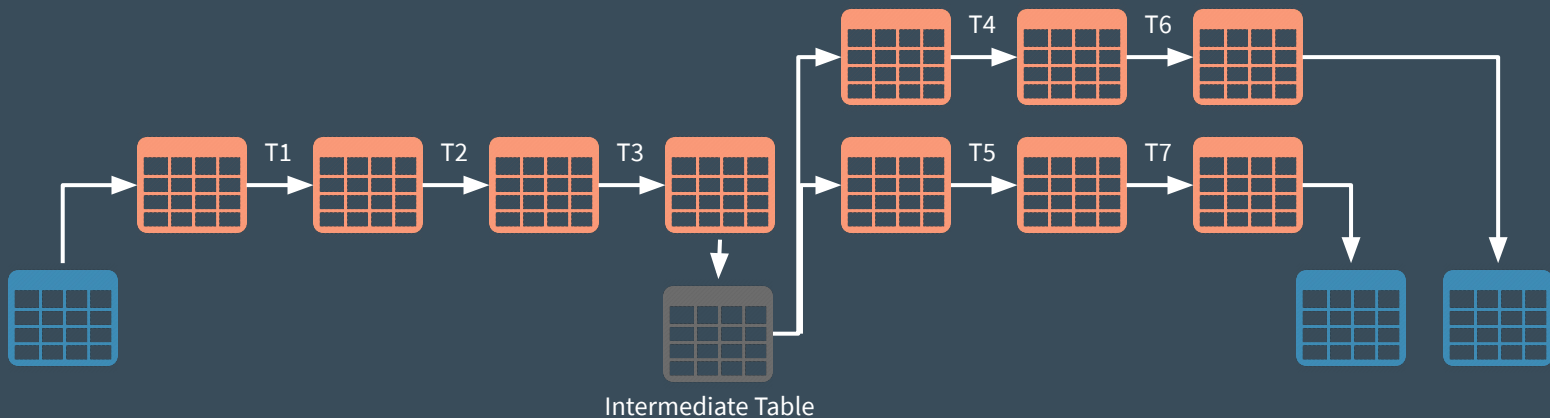
- Fault recovery
- Easy troubleshooting
- Multiple consumers expected



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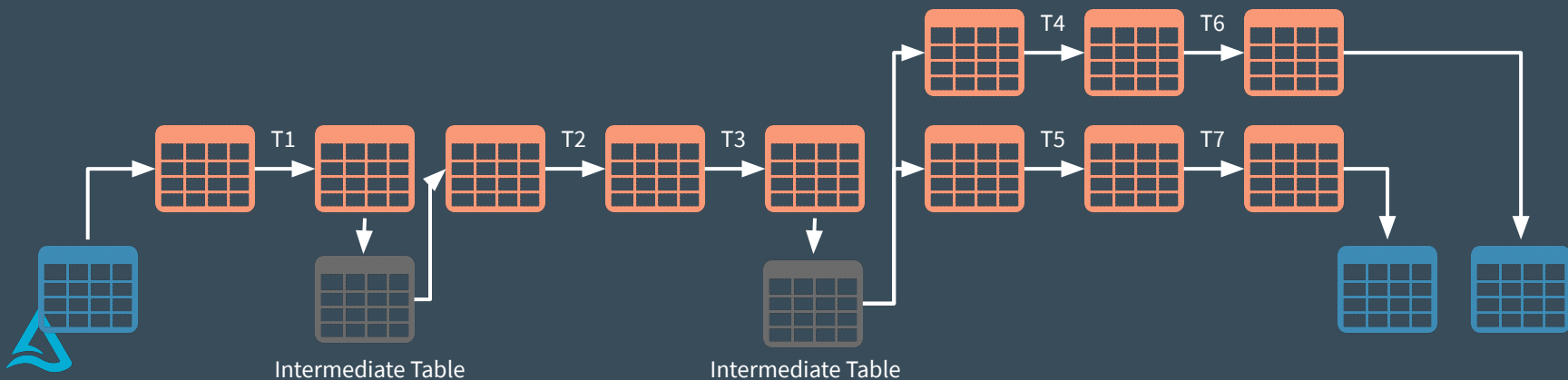
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#2. Use Intermediate Hops

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- Fault recovery
- Easy troubleshooting
- Multiple consumers expected

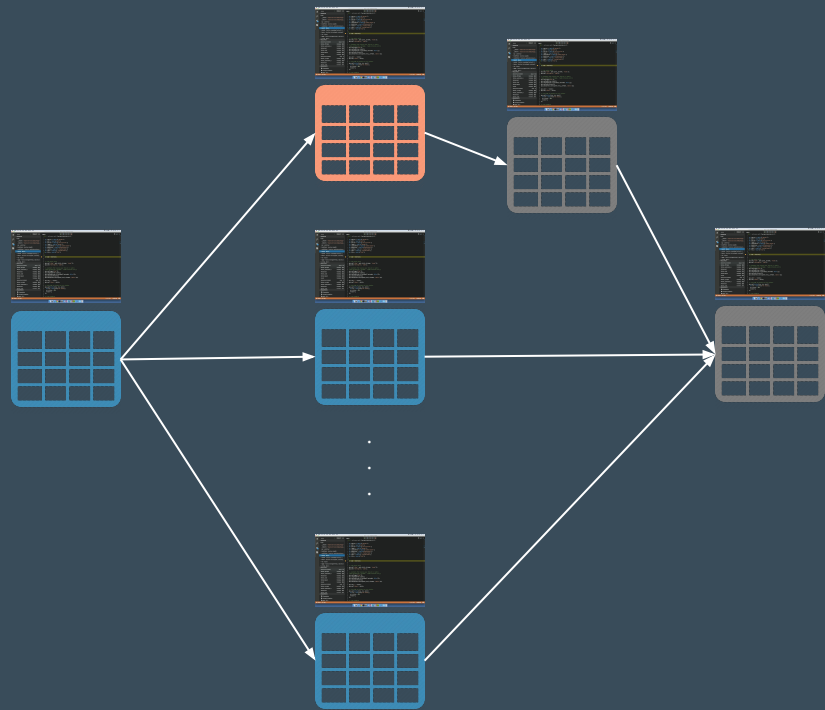


#3. Cost vs Latency Trade Off

1. **Streams; data arriving continuously:** Have an always-on cluster continuously processing data.
2. **Frequent batches; data arriving every few minutes (say 30 mins):** Use a warm pool of machines. Turn off the cluster when idle. Start the cluster when data needs to be processed. Use streaming `Trigger.Once` mode.
3. **Infrequent batches; data arriving every few hours or days:** Turn off the cluster when idle. Start the cluster when data needs to be processed. Use streaming `Trigger.Once` mode.



#4. Reprocessing



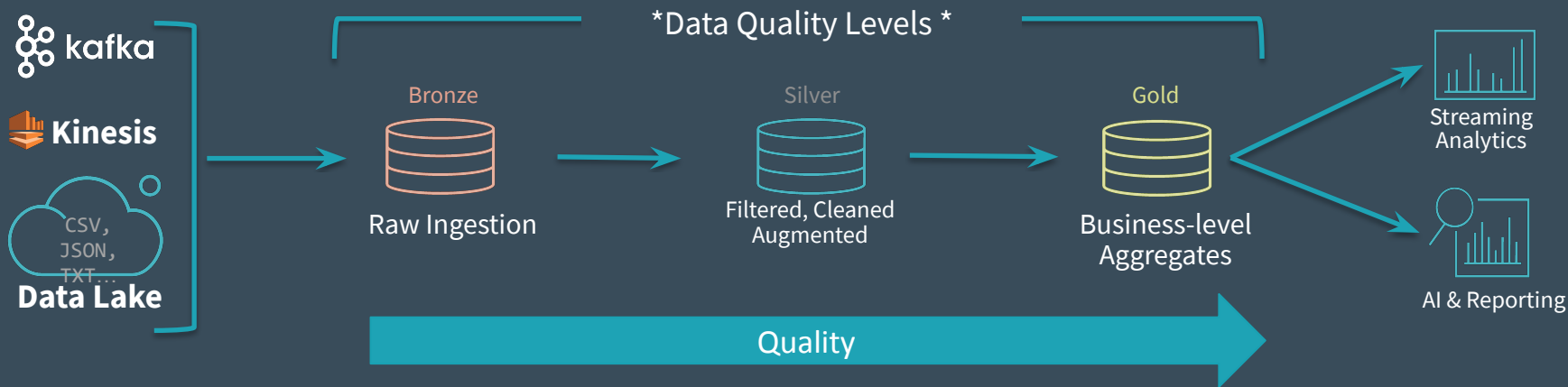
Infinite retention of raw data + stream = trivial recomputation

- Simply clear out the result table and restart the stream
- Leverage cloud elasticity to quickly process initial backfill



#5. Tune Data Quality

- **Merge schemas automatically for raw ingestion tables:** Make sure you capture all the raw events without ignoring any data.
- **Enforce Schema on write for high quality analytics tables:** Make sure the data is clean and ready for analytics by enforcing schema restrictions (and data expectations in future)



Summary of the key characteristics

1. **Adopt a continuous data flow model** to unify batch and streaming
2. **Use intermediate hops** to improve reliability and troubleshooting
3. **Make the cost vs latency trade off** based on your use cases and business needs
4. **Optimize the storage layout** based on the access patterns
5. **Reprocess the historical data as needed** by simply clearing the result table and restarting the stream
6. **Incrementally improve the quality of your data** until it is ready for consumption with schema management options and data expectations.



Benefits of the Delta Architecture

1. Reduce end-to-end pipeline SLA.
 - a. Organizations reduced pipeline SLAs from days and hours to minutes.
2. Reduce pipeline maintenance burden.
 - a. Eliminate lambda architectures for minute-latency use cases.
3. Handle updates and deletes easily.
 - a. Change data capture, GDPR, Sessionization, Deduplication use cases simplified.
4. Lower infrastructure costs with elastic, independent compute & storage
 - a. Organizations reduce infrastructure costs by up to 10x



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Delta Lake Connectors

Standardize your big data storage with an open format accessible from various tools



Delta Lake Partners and Providers

More and more partners and providers are jumping working with Delta Lake



Google Dataproc



Privacera



Informatica



WANDisco



Qlik



Streamsets



Users of Delta Lake

Tencent 腾讯



VIACOM

ciena.



Booz | Allen | Hamilton®



CONDÉ NAST

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Thank you



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