DATA+AI SUMMIT 2022

Evolution of Data Architectures

And building a Lakehouse



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ORGANIZED BY S databricks

in/vinijaiswal 💟 @vini_jaiswal

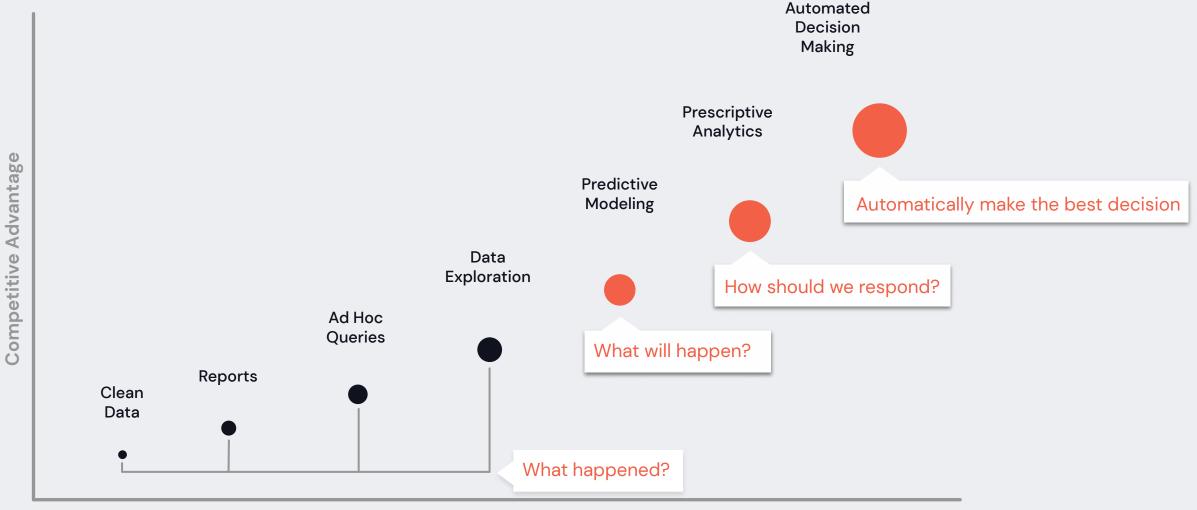
twitter Google Uber

Data, analytics, and AI enabled tech's leaders to disrupt industries

facebook NETFLIX Tヨニニ

Tech leaders are to the right of the Data Maturity Curve

From hindsight to foresight



Every company wants to leverage data and Al

COMCAST

Goldman Sachs

Use AI to approve and underwrite a new Apple Card in less than 5 minutes on iPhone

Uses ML and voice recognition to create a highly innovative, and an Emmy winning viewer experience.

AMCEN

Speed up the development of a groundbreaking cancer treatment

Lakehouse adoption across industries



Lakehouse Platform



Apache Spark Engine for massive data processing at scale

> **Delta Lake** Data reliability and performance

Cloud Data Lake All structured and unstructured data



aws Goog

Google Cloud

Lakehouse Platform

Simple

Unify your data warehousing and AI use cases on a single platform

Multicloud

One consistent data platform across clouds

Open

Built on open source and open standards

Most enterprises still struggle with data, analytics, and Al



Fivetran Data Analyst Survey

60% reported data quality as top challenge

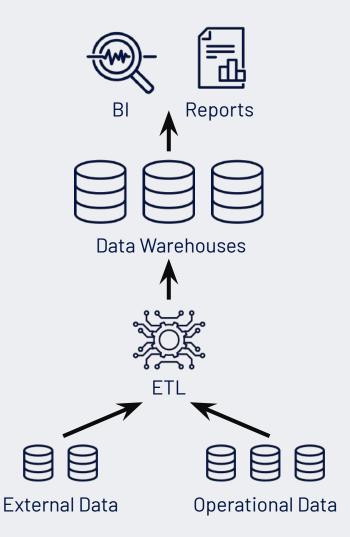
86% of analysts using stale data.

90% regularly had unreliable data sources



Getting high-quality, timely data is hard But it's also a problem with system architectures!





Data Warehouses

High quality, reliable dataGreat for Business Intelligence

Closed, proprietary format Only structured data

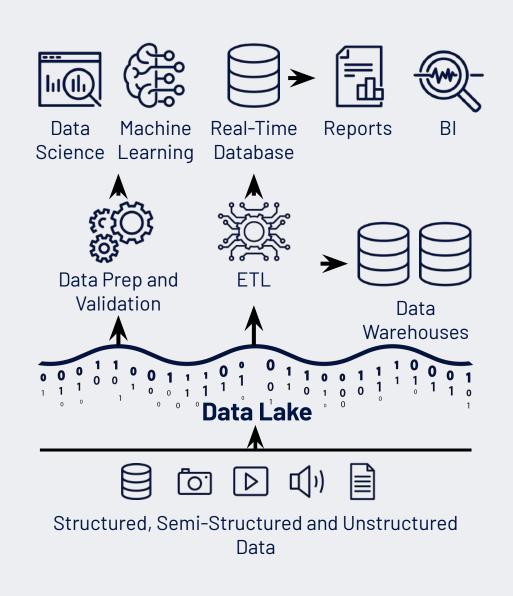
No support for data science, ML, streaming Expensive to scale out

DATA+AI SUMMIT 2022 Data Lakes
Open format
Scalability and Flexibility
All data types and use cases

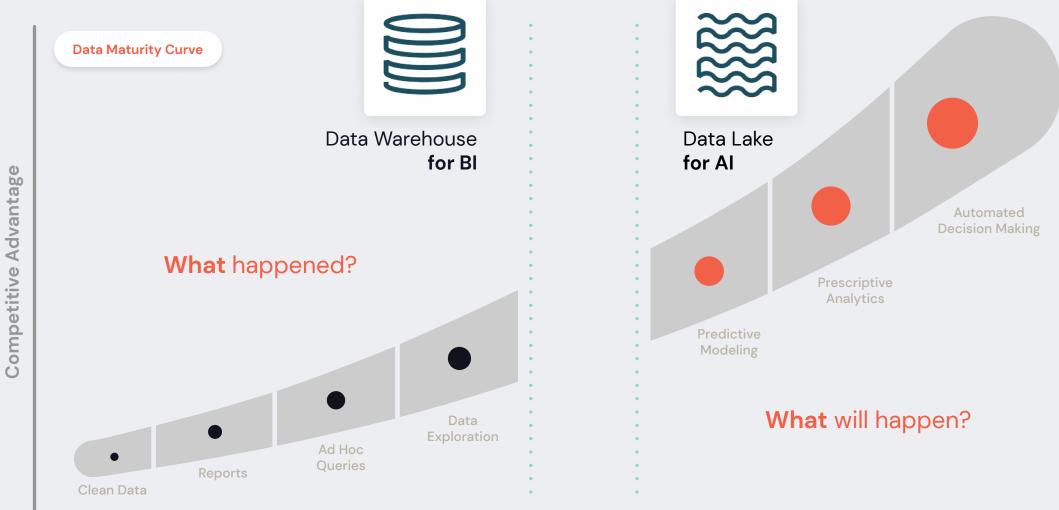
Low data quality



Complex to manage and govern Unreliable data swamps

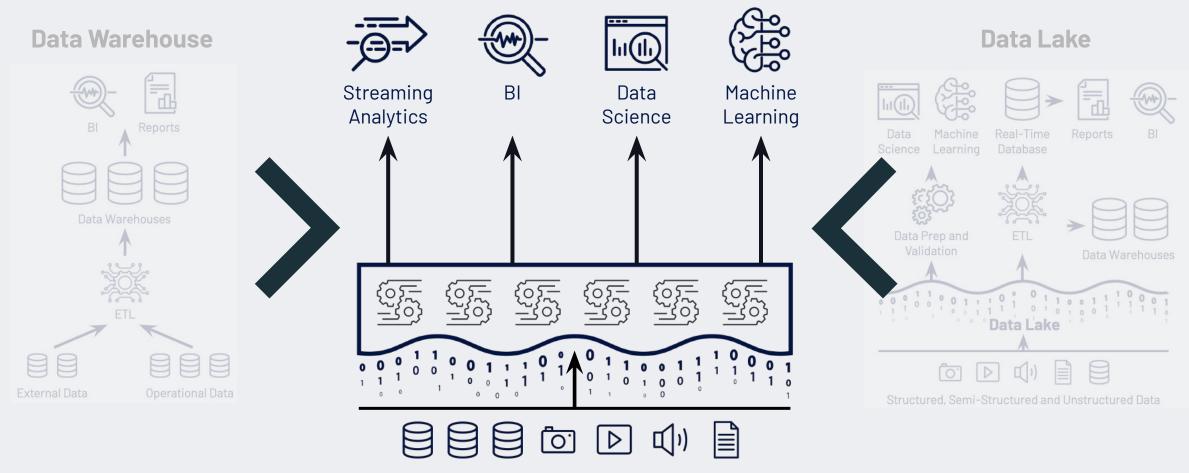


Realizing this requires two disparate, incompatible data platforms





Lakehouses – Best of Data warehouses + Data Lakes



Structured, Semi-Structured and Unstructured

Data



LAKEHOUSE

One platform to unify all of your data, and Al workloads



Evolution of Data Architectures

Data Warehouses

- High quality, reliable data
- Great for Business Intelligence

Data Lakes

- Open format
- Scalability and Flexibility
- All data types and use cases

Lakehouses

- Directly-accessible data in open formats
- Reliability and Performance
- Flexibility and Scalability
- Al and Bl workloads

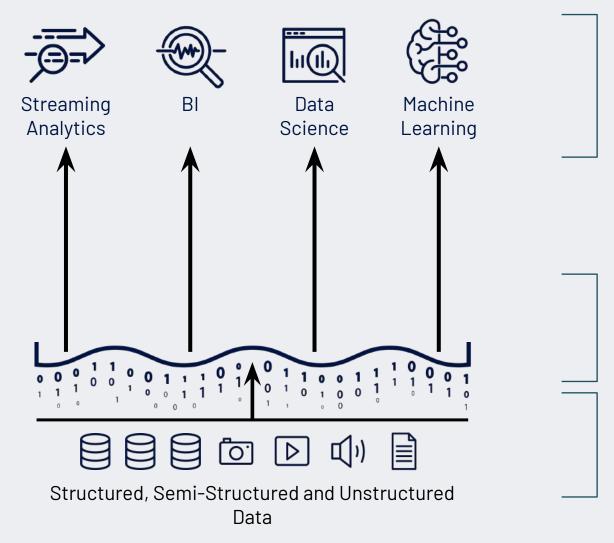
1980s: Datawarehouses	2010s: DW challenges	2010s: Data Lakes	Today's challenges	Today: Data Lakehouses
	Problems for Data Wareho	uses	Problems with today's architectures	
	 Closed, proprietary format Only structured data 		• Low data quality	

- Only structured data
 No support for data science, ML,
- streaming
- Expensive to scale out

- Low data quality
 Complex to manage
- Complex to manage and govern
- Unreliable data swamps



Lakehouse Architecture

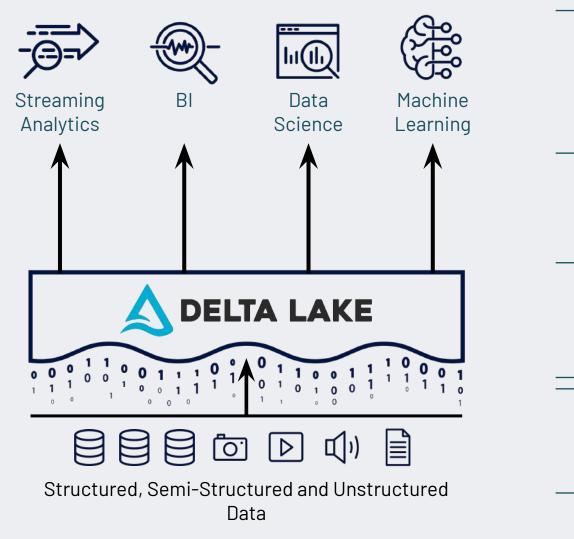


One platform for all Data use cases

Scalable, low-cost directly accessible Cloud Data Lakes



Lakehouse Architecture



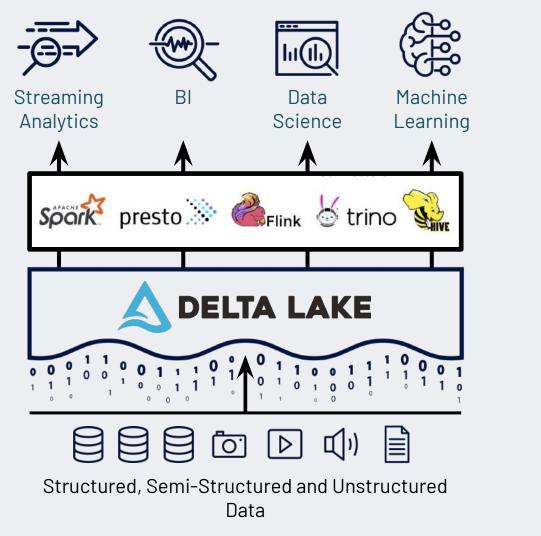
One platform for all Data Use Cases

Open, Transactional Layer for Curated Data

Scalable, low-cost directly accessible Cloud Data Lakes



Lakehouse Architecture



One platform for all Data Use Cases

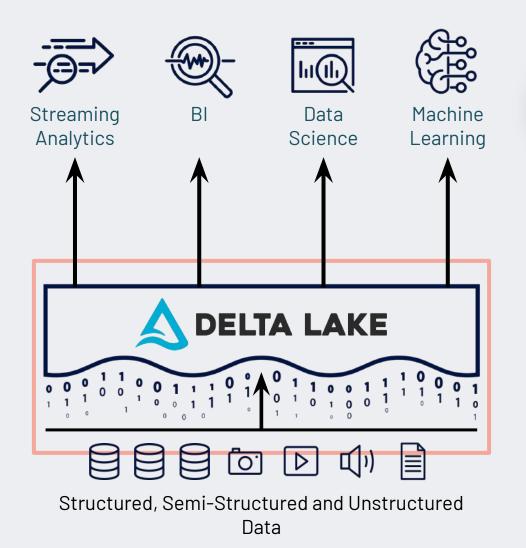
High perf query engine(s)

Open, Transactional Layer for Curated Data

Scalable, low-cost directly accessible Cloud Data Lakes



Delta Lake: The Foundation of Lakehouses



One Data Foundation for BI, Data Science & ML

- Adds reliability, performance, governance, and quality to existing data lakes
- Based on open data format (Parquet)
- Simplifies data engineering with a curated data lake approach

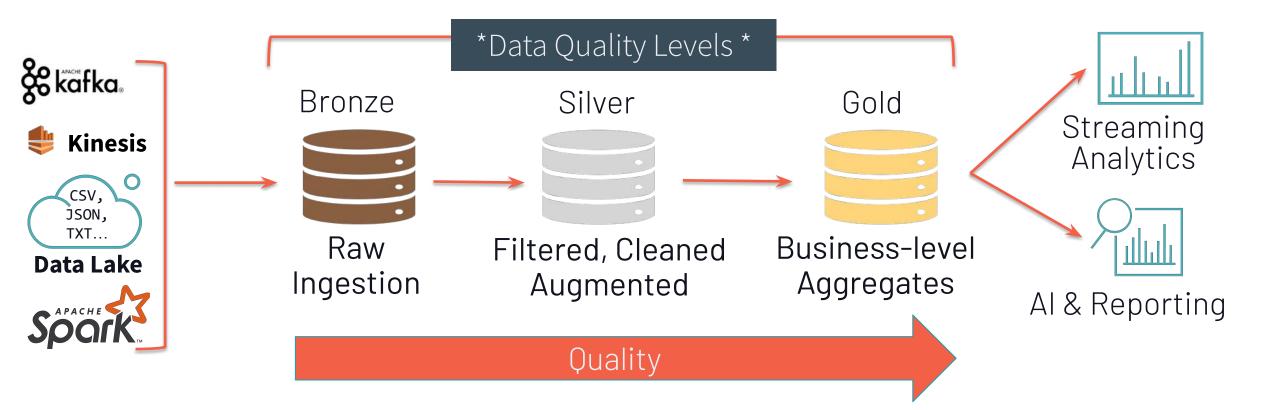




How to build a Lakehouse?

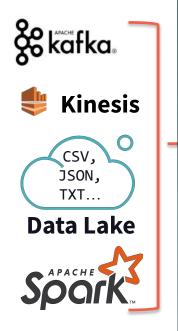


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Delta Lake allows you to *incrementally* improve the quality of your data until it is ready for consumption.





*Data Quality Levels *

parquet_path = "file:/dbfs/tmp/delta_demo/loans_parquet/"

df = (spark.read.format("parquet").load(parquet_path)
 .withColumn("type", lit("batch"))
 .withColumn("timestamp", current_timestamp()))

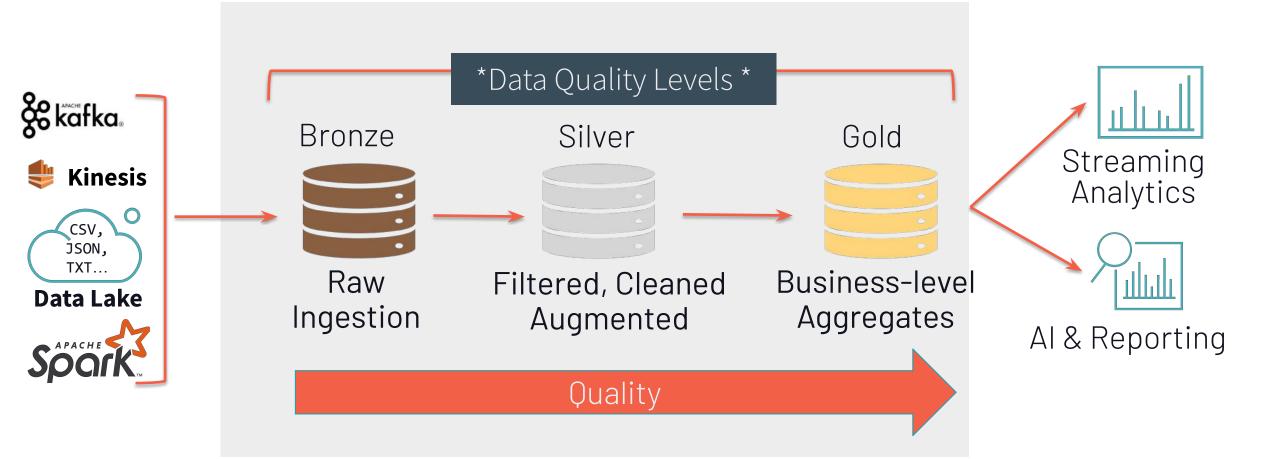
df.write.format("delta").mode("overwrite").saveAsTable("loans_delta")

Quality



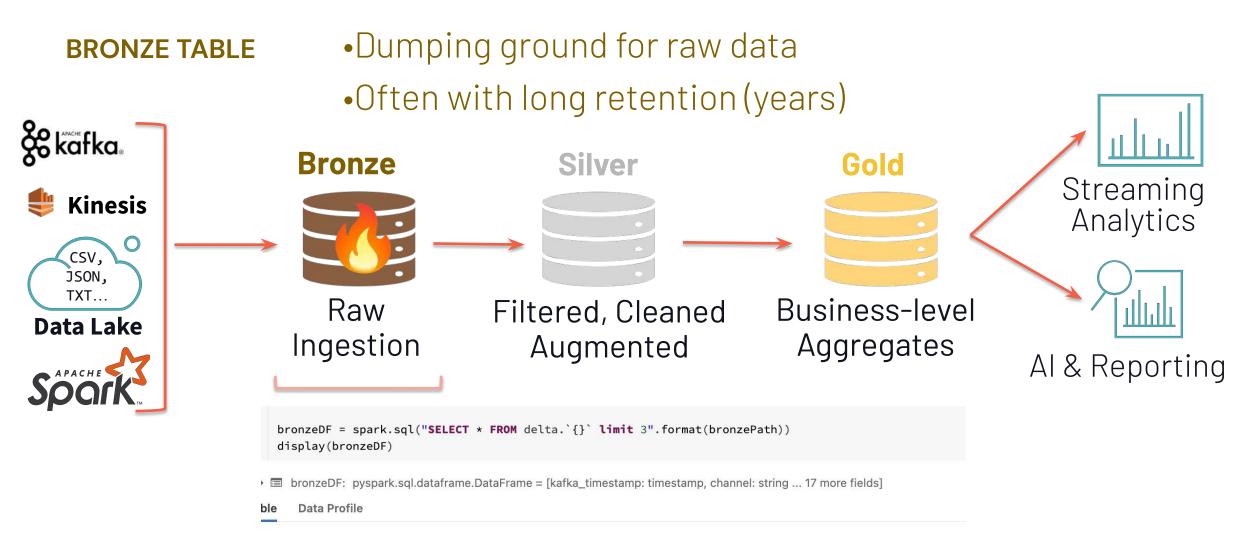
Delta Lake allows you to *incrementally* improve the quality of your data until it is ready for consumption.





Delta Lake allows you to *incrementally* improve the quality of your data until it is ready for consumption.



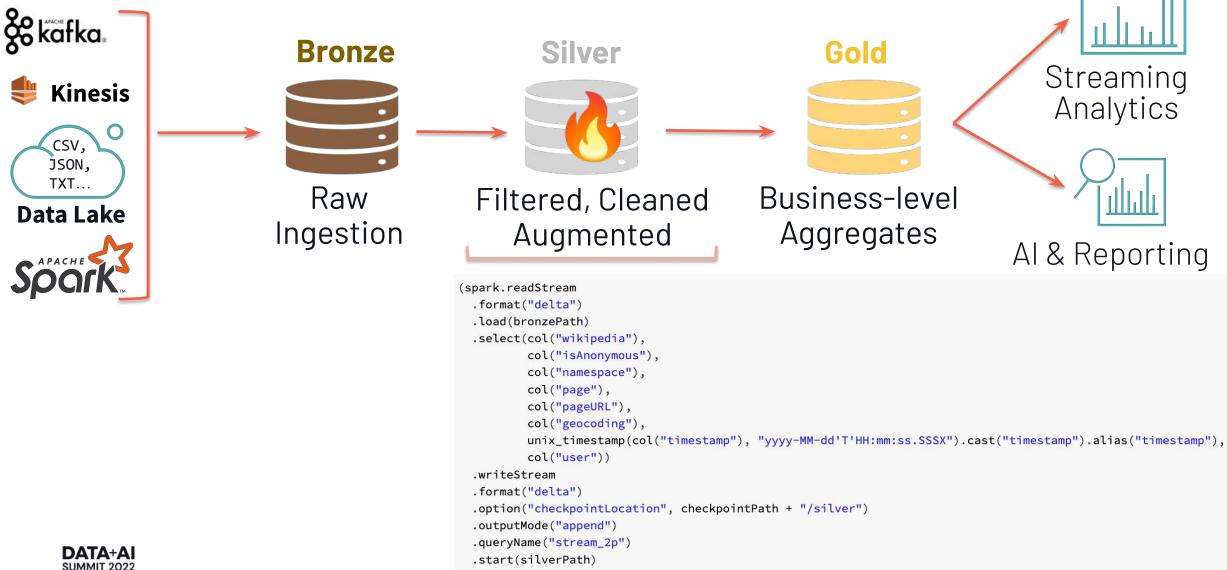


	kafka_timestamp	channel 🔺	comment	
1	1969-12-31T23:59:59.999+0000	#en.wikipedia	/* Update */	
2	1969-12-31T23:59:59.999+0000	#en.wikipedia	Rescuing 1 sources and tagging 0 as dead.) #IABot (v2.0.8	
3	1969-12-31T23:59:59.999+0000	#en.wikipedia	/* Continued discussion */ purpose of guidelines?	

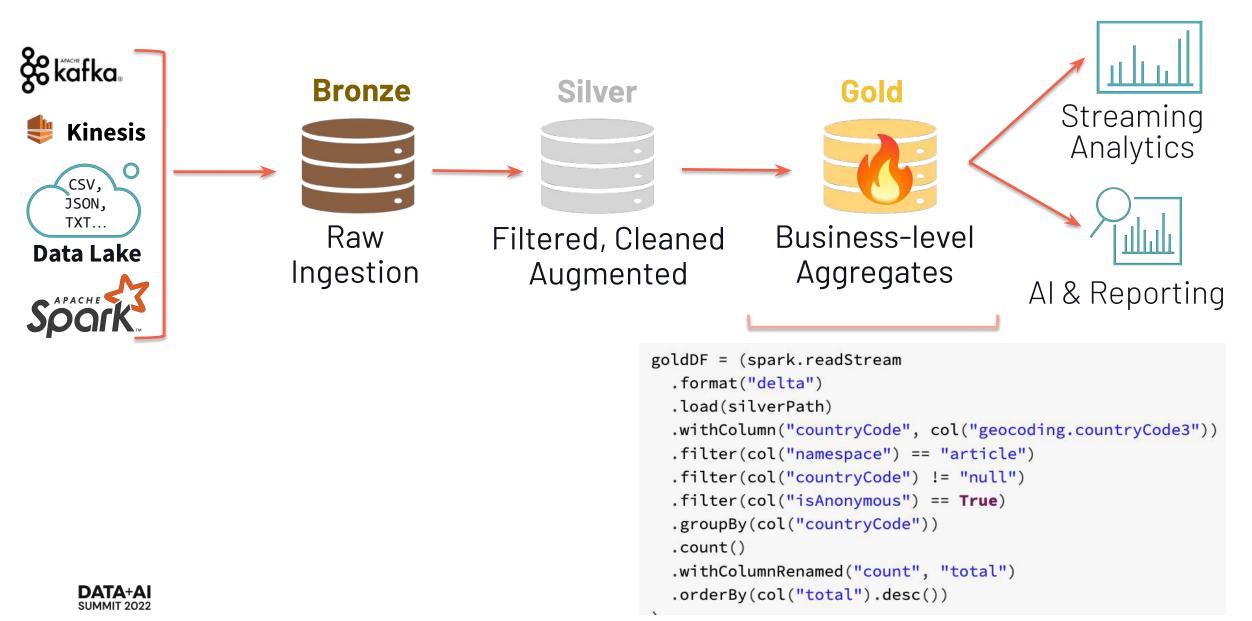


SILVER TABLE

- Intermediate data with some cleanup applied.
- Queryable for easy debugging!



GOLD TABLE Clean data, ready for consumption.



Internals of **DELTA LAKE**





Scalable storage

• table data stored as Parquet files on cloud storage

Scalable transaction log

- sequence of metadata files to track operations made on files in the table
- stored in cloud storage along with table
- read and process metadata in parallel

```
pathToTable/
      +---- 000.parquet
     +---- 001.parquet
002.parquet
     +---- delta log/
          +---- 000.json
          +---- 001.json
          • • •
```







Python

▶▼ lall ∨

- ×

1 %fs ls dbfs:/Users/vini.jaiswal@databricks.com/demo/customer_t2

	<u>ــــــــــــــــــــــــــــــــــــ</u>	name	size
1	demo/customer_t2/_delta_log/	_delta_log/	0
2	demo/customer_t2/part-00000-418067bd-bf5e-4d28-ac68-ea8cea49b956-	part-00000-418067bd-bf5e-4d28-ac68-ea8cea49b956-c001.snappy.parquet	542929260
3	demo/customer_t2/part-00000-45b799c4-6305-4c75-a3fd-fa1e840a8b99-	part-00000-45b799c4-6305-4c75-a3fd-fa1e840a8b99-c002.snappy.parquet	461126371
4	demo/customer_t2/part-00000-626b910a-882d-44ab-badf-756afde9f6e1-	part-00000-626b910a-882d-44ab-badf-756afde9f6e1-c000.snappy.parquet	54046800§
5	demo/customer_t2/part-00001-405b13dc-0f72-419a-ab75-ddf993ba51af-	part-00001-405b13dc-0f72-419a-ab75-ddf993ba51af-c002.snappy.parquet	541858629
6	demo/customer_t2/part-00001-a794b5c5-8876-4aa9-89c0-92bb15cf5055-	part-00001-a794b5c5-8876-4aa9-89c0-92bb15cf5055-c001.snappy.parquet	542859315
7	demo/customer_t2/part-00001-c3f739cd-e309-43de-ab84-d005efb6bb7a-	part-00001-c3f739cd-e309-43de-ab84-d005efb6bb7a-c000.snappy.parquet	541186721

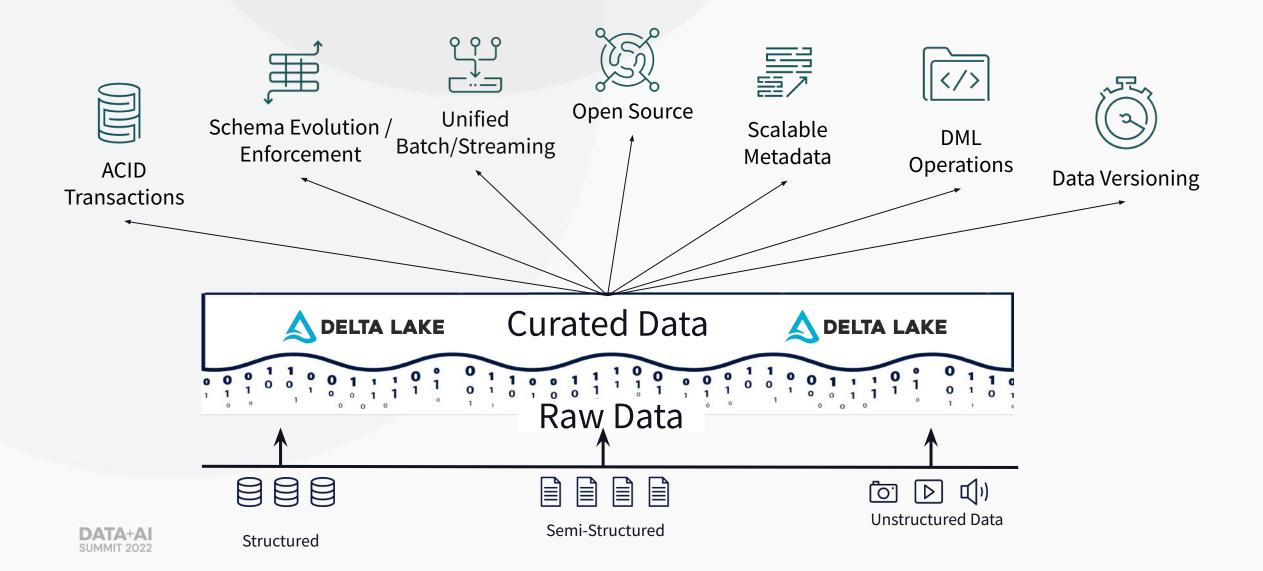
Delta Transaction logs



1 %fs ls dbfs:/Users/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log

		name 🔺	size 🔺
16	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/0000000000000000000016.json	000000000000000016.json	58080
17	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/0000000000000000000017.crc	000000000000000017.crc	95
18	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000017.json	0000000000000000017.json	21718
19	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/0000000000000000000018.crc	000000000000000018.crc	96
20	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000018.json	000000000000000018.json	46743
21	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/00000000000000000000019.crc	00000000000000000000000000000000000000	96
22	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000019.json	00000000000000000000000000000000000000	58080
23	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/0000000000000000000020.checkpoint.parquet	00000000000000000000000.checkpoint.parquet	94341
24	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000000000000000000000	00000000000000000000000000000000000000	97
25	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000000000000000000000	00000000000000000000000000000000000000	347291
26	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/0000000000000000000021.crc	00000000000000000000000000000000000000	95
27	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/000000000000000000021.json	00000000000000000000000000000000000000	41461
28	s/vini.jaiswal@databricks.com/demo/customer_t2/_delta_log/_last_checkpoint	_last_checkpoint	26

Delta Lake Features



Data reliability challenge # 1



Failed production jobs leave data in corrupt state requiring tedious recovery

Example: Data Corruption



Run result unavailable: job failed with error message Unexpected failure while waiting for the cluster (0422-091004-4zud3ebj) to be ready.Cause Unexpected state for cluster (hhij-02348-4zud3ebi): BOOTSTRAP_TIMEOUT(SUCCESS):[id: InstanceId(i-0f8a1c082d3aa434b), status: INSTANCE_INITIALIZING, workerEnvId:WorkerEnvId(workerenv-28425385-Idsajlf-34832-sdf33-fdgffvfbf), lastStatusChangeTime: 3794703740372, with threshold 700 seconds timed out after 704477 milliseconds. Please check network connectivity from the data plane to the control plane.,instance_id:i-7320kj2b3484

Data reliability challenge # 2



Lack of consistency makes it almost impossible to mix appends and reads, batch and streaming

Resolution of Consistency issues in Legacy Data Pipelines

- New rows to be inserted
- Rows that will be replaced
- Rows that are not impacted
- Create a new temp
- Delete the original table
- "Rename" the temp table
- Drop the temp table



How Delta Lake solves consistency and data corruption problems?



Transaction Log Commits DELTA LAKE **INSERT** actions Changes to the table Add 001.parquet are stored as *ordered*, *atomic* commits +---- delta log/ Add 002.parquet +---- 000.json +---- 001.json Each commit is JSON **UPDATE** actions file in _delta_log with a set of actions Remove 001.parquet Remove 002.parquet Add 003.parquet

Consistent Snapshots



Readers read the log in atomic units thus reading consistent snapshots



ACID via Mutual Exclusion on Log Commits

Concurrent writers need to agree on the order of changes (optimistic concurrency control)

New commit files must be created mutually exclusively using storage-specific API guarantees



only one of the writers trying to concurrently write 002.json must succeed

Data reliability challenge # 3



Lack of schema enforcement creates inconsistent and low quality data

Example: Lack of schema Enforcement in Parquet stream_query = generate_and_append_data_stream(

⇒		

table_format = "parquet", table_path = parquet_path)

1 spark.s	ql("select >	from loans_	parquet").sho
▶ (1) Spark J	lobs		
++	+-	+	+
loan_id fu	unded_amnt p	aid_amnt add	r_state
++	+-	+	+
0	1000	182.22	CA
1	1000	361.19	WA
2	1000	176.26	TX
3	1000	1000.0	OK
4	1000	249.98	PA
5	1000	408.6	CA
6	1000	1000.0	MD
7	1000	168.81	OH
8	1000	193.64	TX]
9	1000	218.83	CT]
10	1000	322.37	N С
11	1000	400.61	NY
12	1000	1000.0	FL
13	10001	165 88	ΝП

Total records = 14705

1 s	spark.re	ad.format("parquet	").loa	d(parquet_pa	th).show() # wrong	schema!
▶ (2)) Spark Jo	bs					
		timestamp	value l	pan_id	funded_amnt	paid_amnt	++ addr_state ++
2022	2-03-22	22:40:	36	10036	8894	8544.701793101429	CA
2022	2-03-22	22:40:	44	10044	7203	7143.422329828758	CA
2022	2-03-22	22:40:	52	10052	7113	6134.901645020872	TX
2022	2-03-22	22:40:	60	10060	5427	4402.746113849142	WA
2022	2-03-22	22:40:	68	10068	5850	4549.965501260052	NY
2022	2-03-22	22:40:	76	10076	7977	6774.398332299471	NY
2022	2-03-22	22:40:	84	10084	6576	5119.430008447199	WA
2022	2-03-22	22:40:	35	10035	5763	3947.6444236157877	CA
2022	2-03-22	22:40:	43	10043	8847	7344.280401545113	TX
2022	2-03-22	22:40:	51	10051	5117	4770.738672461943	NY
2022	2-03-22	22:40:	59	10059	6742	5882.987591904314	ТХ
2022	2-03-22	22:40:	67	10067	7144	6760.007491001625	CA
2022	2-03-22	22:40:	75	10075	6755	4809.795858246685	TX
2022	2-03-22	22:40:	83	10083	5817	4424.808390048687	WA
2022	2-03-22	22:40:	136	10136	9237	8319.033551236855	NY
2022	2-03-22	22:40:	144	10144	6953	6538.8935002252965	WA
2022	2-03-22	22:40:	152	10152	8212	8174.558041588866	NY
2022	2-03-22	22:40:	160	101601	6456	6059.975786688777	і тхі

TOTAL RECORDS = 51

Where did the two new columns `timestamp` and `value` come from? And where did my existing rows go?

How does Delta Lake enforce schema?



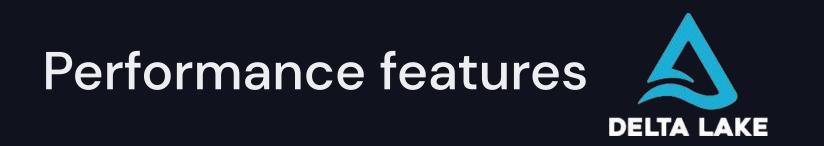
Example of schema handling in

		Intentional
2	rawDF = min	<pre>iDataDF.filter("CustomerID=20993").withColumn("Customer_ID", lit("8")) failure</pre>
3		
4		ected as enforcement of schema
5	(rawDF.write	e.format("delta").mode("append").saveAsTable('customer data_delta_mini'))
Ξo	rg.apache.sp	park.sql.AnalysisException: A schema mismatch detected when writing to the Delta table.
Py4	IJJavaError	Traceback (most recent call last)
/da	atabricks/spa	ark/python/pyspark/sql/utils.py in deco(*a, **kw)
	62	try:
	-> 63	return f(*a, **kw)
	64	except py4j.protocol.Py4JJavaError as e:
/da	atabricks/spa	ark/python/lib/py4j-0.10.7-src.zip/py4j/protocol.py in get_return_value(answer, gateway_client, target_id, name)
	327	"An error occurred while calling {0}{1}{2}.\n".
>	328	<pre>format(target_id, ".", name), value)</pre>
	329	else:
: c To	org.apache.s enable scher	An error occurred while calling o404.saveAsTable. park.sql.AnalysisException: A schema mismatch detected when writing to the Delta table. ma migration, please set: eSchema", "true")'.

Schema Evolution with



- Schema evolution allows users to easily change a table's current schema to accommodate data that is changing over time.
- Most commonly used operations for
 - append
 - overwrite
- Use .option('mergeSchema', 'true') to your .write or .writeStream
 Spark command.







- Column min/max values automatically collected when writing files and committing to log
- Read queries can skip files using min/max values

SELECT * FROM events

WHERE year=2020	uid=24000	
<u>file1.parquet</u>	year: min 2018, uid: min 12000,	

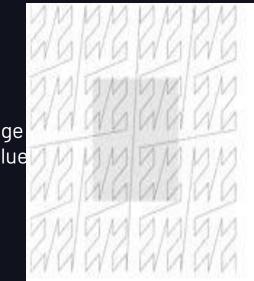
skipped as data range outside selected value

file2.parquet

year: min 2018, max 2020 uid: min 12000, max 14000

2019 23000

year: min 2020, max 2020 file3.parquet uid: min 23000, max 25000





- Automatically generate data for new columns using any expression on other columns
- Compliant with SQL standards
- Can be used for partitioning or bucketing
- Automatic filter generation and data skipping



	id	idBucket	eventTime	eventDate	
	1234	34	2021-05-24 09:00:00.000	2021-05-24	
CREA	TE T	ABLE ev	ents(
	id b	igint,			
5		cket bi % 100	gint GENER4	ATED ALWAY	SAS (
),	+Tima +	imestamp,		
					AC (
			ate GENERA T tTime AS DA		AS (
)				
)					
USIN	IG de	lta			
PART	ITI0	NED BY	(eventDate,	, idBucket)





Optimize data layout with Z-order

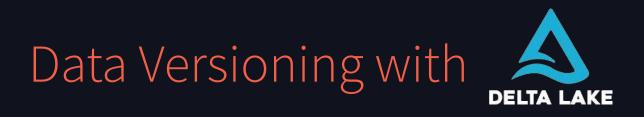
Multi-column data clustering that is better than simple multi-column sorting

OPTIMIZE deltaTable **ZORDER BY** (x, y)

With column stats, this enables better data skipping leading to faster queries

WHERE $x = 2$ OR $y = 3$							
9 files scanne 21 false pos					ed in total sitives 🍐		
Linear	Order			Z-0	rder		
⋈ ⋈ <mark>2,0</mark> 💓	4,0 (5,0) (6,0 (7,0)		0,0 1,0	2,0 30	4,0 (5,0	6,0 (7,0	
× × 2,1 ×	4,1 (5,1) (6,1) (7,1		0,1 (1,1	2,1 3,1	4,1 (5,1	6,1 (7,1	
× × 2,2 ×	4,2 (5,2 (6,2 (7,2		× ×	2,2 3,2	<u>4</u> ,2 5,2	× ×	
0,3 (1,3) (2,3) (3,3)	4,3 5,3 6,3 7,3	y=3	0,3 1,3	2,3 3,3	4,3 5,3	6,3 7,3	
× × × ×	4,4 (5,4) (6,4) (7,4		0,4 (1,4	2,4 3,4	4,4 (5,4	6,4 (7,4	
0,5 (1,5 2,5 3,5	4,5 (5,5) (6,5) (7,5)		0,5 (1,5)	2,5 3,5	4,5 (5,5	6,5 (7,5)	
) (6) (6) (2,6) (3)(6)	4,6 (5,6) (6,6) (7,6)		0,6 (1,6	2,6 3,6	4,6 (5,6	6,6 (7,6	
× × 2,7 ×	4,7 (5,7) (6,7) (7,7)		0,7 (1,7	2,7 3,7 x=2	4,7) (5,7)	6,7 (7,7	

SELECT * **FROM** points



- Audit
- Reproduce Experiments
- Rollbacks

SELECT * FROM my_table TIMESTAMP AS OF "2020-05-01"

DESCRIBE HISTORY flightdelays

(1) Spark Jobs

version 📼	timestamp	userId 🤝	userName w	operation 🤝	notebook 🤝
7	2019-10- 08T16:47:22	101543	@databricks.com	MERGE	▶ {"notebookId":"25"}
6	2019-10- 08T16:44:16	101543	@databricks.com	MERGE	▶ {"notebookId":"25"}
5	2019-10- 06T19:26:53	101543	@databricks.com	UPDATE	





Delta Lake Pace of Innovation Highlights

 Open Source Delta Lake ACID Transactions Schema Management Scalable Metadata Handling Time Travel Unified Batch and Streaming 	manifes Improve Improve Conver Experin Spectre	ed concurrency ed file compaction ed insert-only merge pe t-to-Delta using SQL mental Snowflake and R um support	engines (via erformance edshift	metastore Support for SQL DML Support for automatic and Presto/Athena manifest g Support for controlling the table history Support for adding user-d Delta table commits Support Azure Data Lake Improved support for stre triggers	d incremental eneration e retention of the lefined metadata in Storage Gen2 aming one-time	 Generated Colu Multi-cluster wr Cloud Independ Spark 3.1 Suppo PyPI Install Delta Everywhe 	rites dence ort ere Google Cloud storage support – GA
Apr 2019 (0.1) Sep 2019	0(0.4)	Dec 2019 (0.5)	Apr 2020 (0.6	5) Jun 2020 (0.7)	Feb 2021(0.8)	May 2021(1.0)	Dec 2021(1.1) April 2022(1.2)
 Scala/Java APIs for DML command Scala/Java APIs for query commit Scala/Java APIs for vacuuming old Python DML APIs Convert-to-Delta Python and SQL utility operations 	history I files	 Support for schema e operations Improved merge perfautomatic repartition Improved merge perfclause Operation metrics in Support for reading E file system 	ormance with ning ormance with no in: DESCRIBE HISTORY	 MERGE operation n evolution of nested MERGE INTO and UI nested struct colum Check constraints of Start streaming a tr 	ns (Scala, Java, Pytho ow supports schema columns PDATE operations no nns by name on Delta tables able from a specific v arallel deletes with V	version (auses Delta Delta Delta Delta Perfor MERG MERG	Standalone Writer Sink for Apache Flink Source for PrestoDB Source for Apache Pulsar rmance improvements in GE operation ort for Generated Columns in GE operation

• Support for defining tables in the Hive

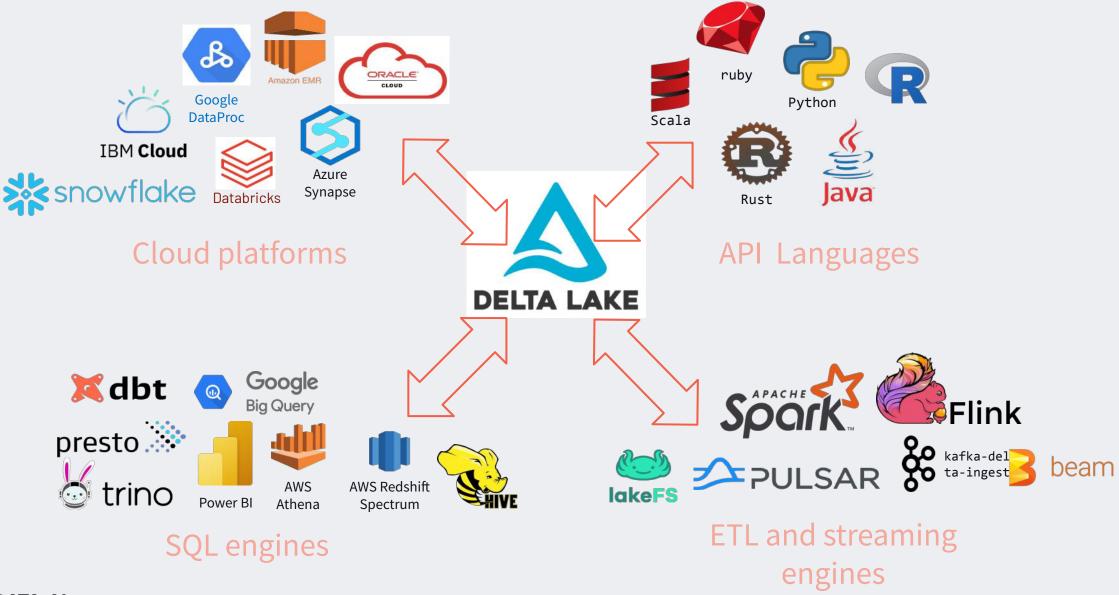
• Compacting small files (optimize)

into larger files

Delta Lake 2.0

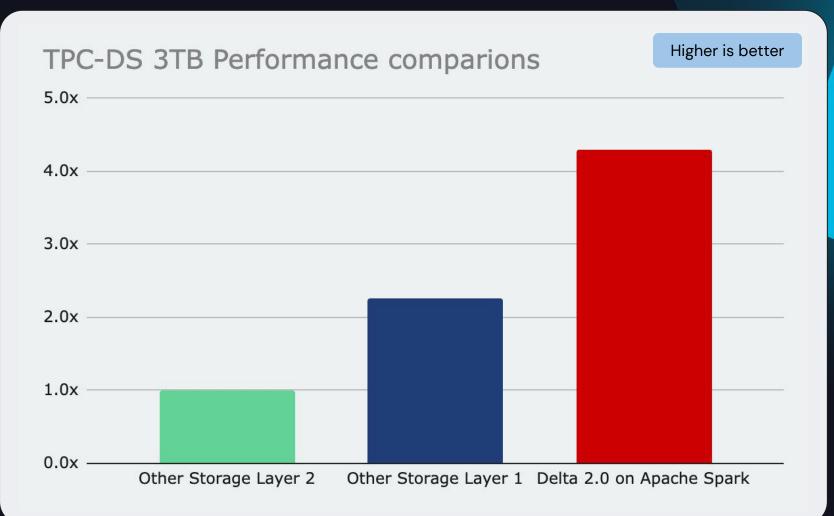


Delta Lake Ecosystem



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Delta Lake performance TPC-DS Benchmark Comparison (Higher is better)



Delta Lake is
1.9x faster than
Storage Format 1
4.3x faster than
Storage Format 2

Performance Optimizations roadmap https://github.com/delta-io/delta/issues/920

Issue	Description	Target CY2022
927	OPTIMIZE (file compaction) : Table optimize is an operation to rearrange the data and/or metadata to speed up queries and/or reduce the metadata size	Released in 1.2
923	File skipping using columns stats: This is a performance optimization that aims at speeding up queries that contain filters (WHERE clauses) on non-partitionBy columns.	Released in 1.2
931	Automatic data skipping using generated columns: Enhance generated columns to include automatic data skipping	Released in 1.2
1134	OPTIMIZE ZORDER : Data clustering via multi-column locality-preserving space-filling curves with offline sorting.	Q3/Q4
	MERGE Performance Improvements: We will be providing a project improvement plan (PIP) document shortly on the proposed design for discussion.	Q2/Q3





Community Adoption and Social Channels



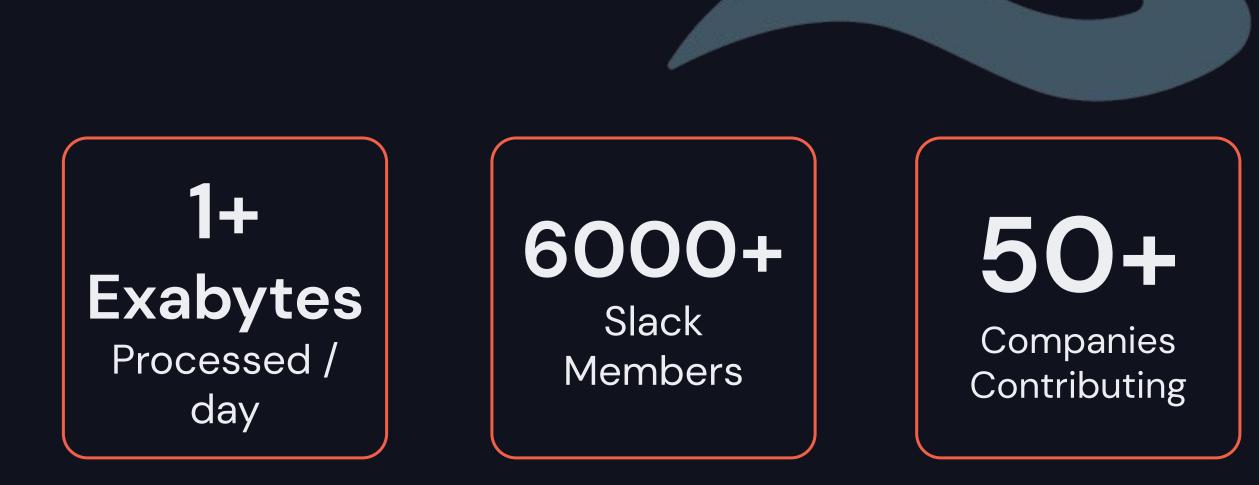


Adoption of Delta Lake

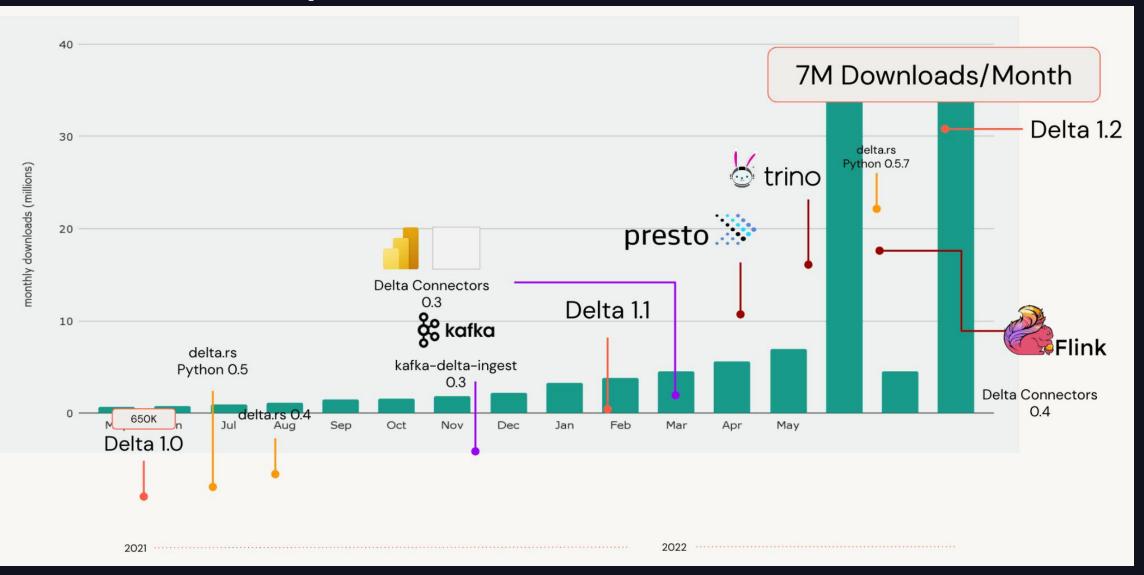


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Engage with Delta Lake community





delta-users Slack



Delta Lake YouTube channel



delta-users Google Group



Delta Lake GitHub Issues



Delta Lake Linkedin



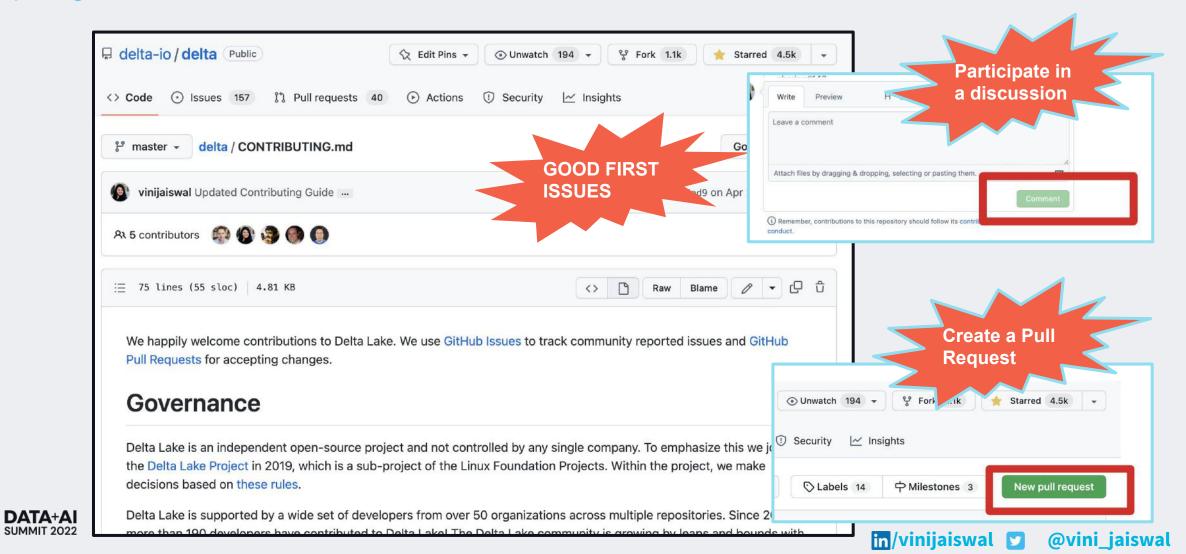
data-ai-online

@vini_jaiswal

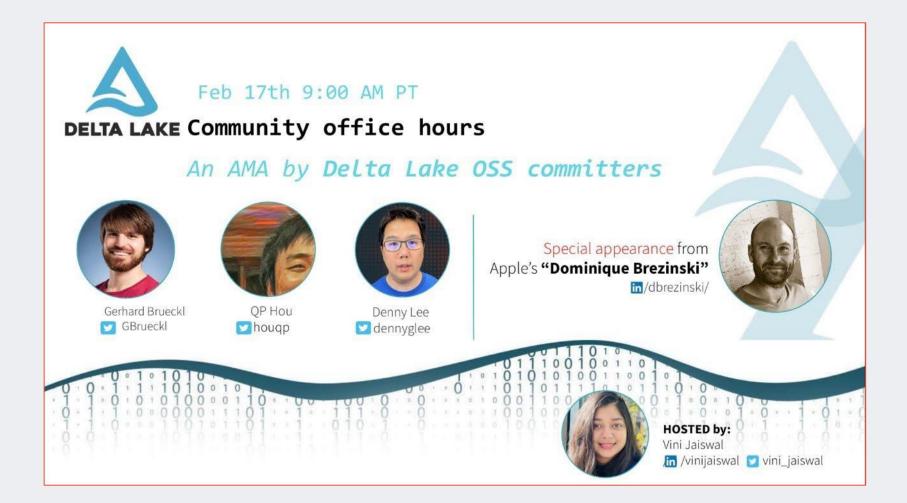
in/vinijaiswal 💟

Contributing to the Project

https://github.com/delta-io/delta/blob/master/CONTRIBUTING.md



Have questions, join our community AMAs every two weeks





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17+ Technical Sessions Delta Lake - Use Cases and Deep Dives

Come join the Delta Community at the Data and Al Summit

- We have exciting line up of technical sessions and events.
- You might also get a chance to meet some of the creators!!!

Ask Me Anything Delta Lake Panels

Panel 1: June 28 10:30 AM PST Panel 2: June 29 11:40 AM PST **Keynote** Delta Lake 2.0

June 28 10:30 AM PST DELTA LAKE

Thank you!



