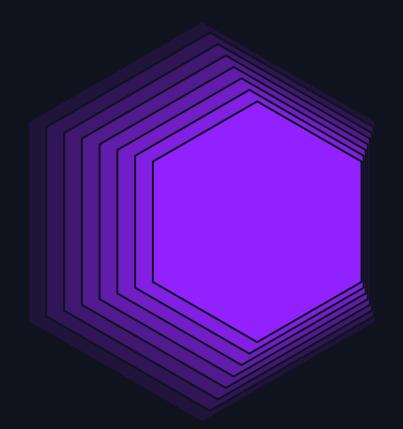


DATA QUALITY

The Greatest Challenge for GenAl Enterprise Adoption



Amy Reams and Taly Kanfi, Anomalo June 12, 2024

Enterprise Data Quality is Broken

91%

Think their company's data quality needs improvement

82%

IT decision-makers reworked data projects due to poor data quality





Amy Reams
VP, Business Development amy@anomalo.com



Taly KanfiDirector, Data Solutions Architect taly@anomalo.com

Come Visit Us at Booth 46



Anomalo

We Are Rethinking Data Quality

And We're Rethinking Data Quality With Databricks

Winner

2024 Databricks Partner Awards

Emerging Partner of the Year





- 1. High Quality Data is the New Gold
- 2. Anomalo and Databricks
- 3. Anomalo's Al-Powered Data Quality Monitoring
- 4. Data Quality for GenAl

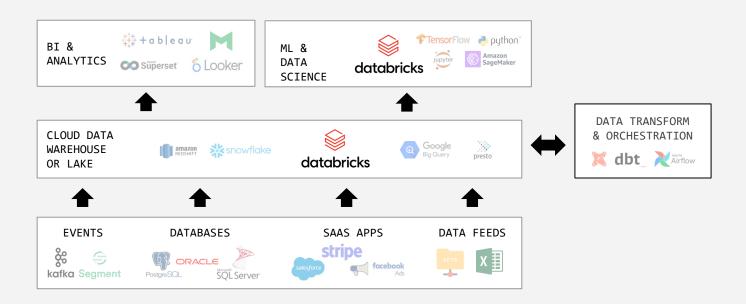


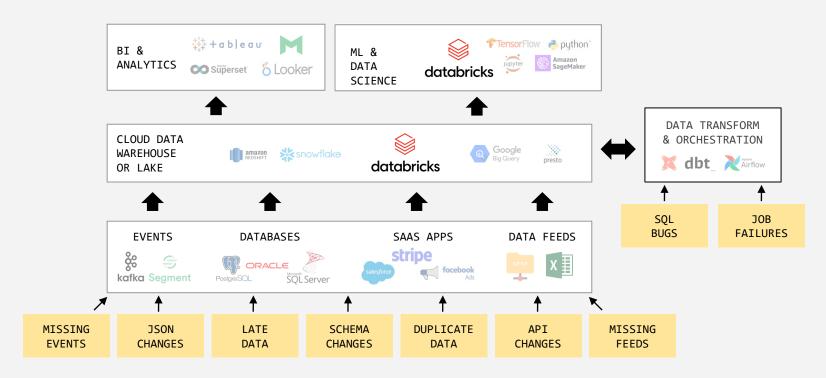


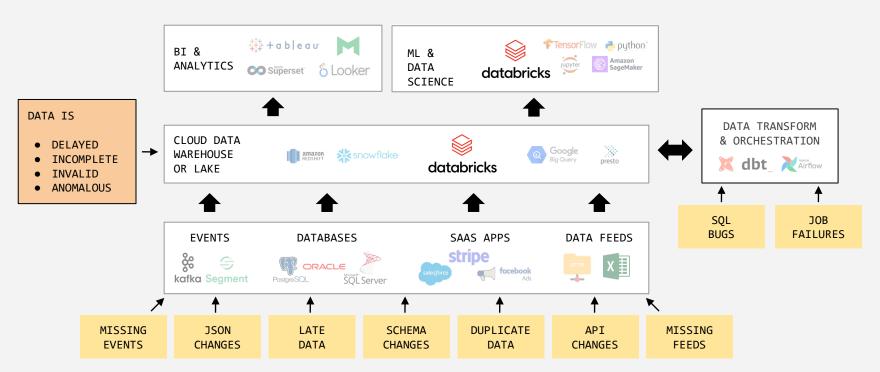
Data is the New Gold

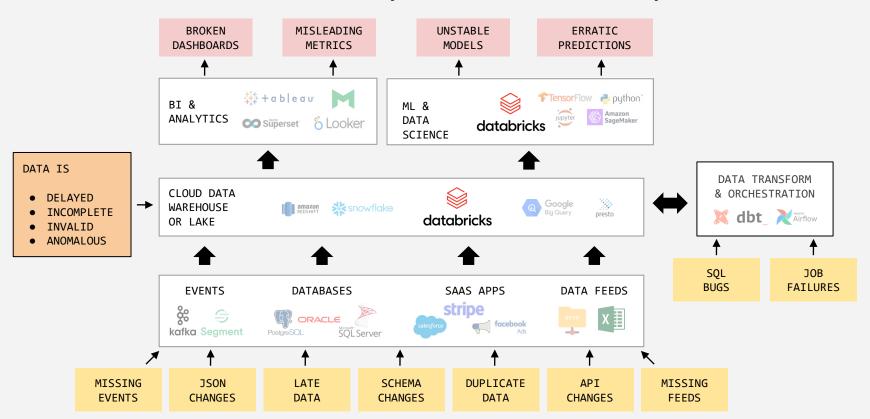


High Quality Data is the New Gold









Gen AI will only make these problems worse

Formatting

Does not comply with traditional standard formats





Storage

Sensitive Information

Affect specific value or cells of data







PII

Abusive Language

Inconsistences

Full of errors and duplicated content.



Incomplete



Duplicates



Temporal Inconsistency

Sentiment

How do you evaluate the tone of a document?







Document Characterteristics



Tone



Anomalo and Databricks

Winner

2024 Databricks Partner Awards

Emerging Partner of the Year





Data Observability

Is data moving through my warehouse in a timely manner?

- Catalog metadata
- Job monitoring
- Data lineage
- ✓ Catches data *movement* failures
- ⚠ Ignores data *contents*

Data Quality Monitoring

Is the data my warehouse produces of high quality?

- Queries the data
- Requires experts or ML
- Explainability is key
- Deep monitoring of data



Data Observability

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Is the data my warehouse produces of high quality?

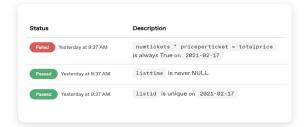
- Queries the data
- Requires experts or ML
- Explainability is key
- ✓ Deep monitoring of data



Anomalo Offers a Unique, Al-First Approach

Validation Rules

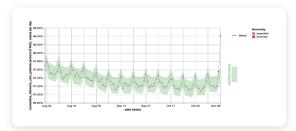
Experts specify hard and fast rules about the data



Easy to understand

Metric Anomalies

Monitor changes in key business or data quality metrics



Great for key KPIs

▲ Alert fatigue at scale

AI-Powered Monitoring

Automatically find significant changes in data contents



Exhaustive validation with no setup

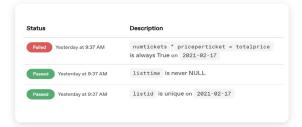
∧ Not as targeted as other methods



Anomalo Offers a Unique, Al-First Approach

Validation Rules

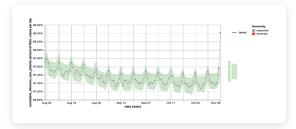
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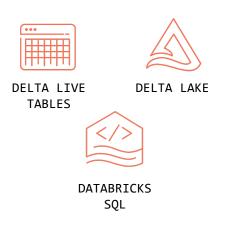
Exhaustive validation with no setup

∧ Not as targeted as other methods



Natively Integrated With Databricks

Monitor any Databricks table across the entire data and Al lifecycle



Extend the value of Unity Catalog with a native bidirectional integration

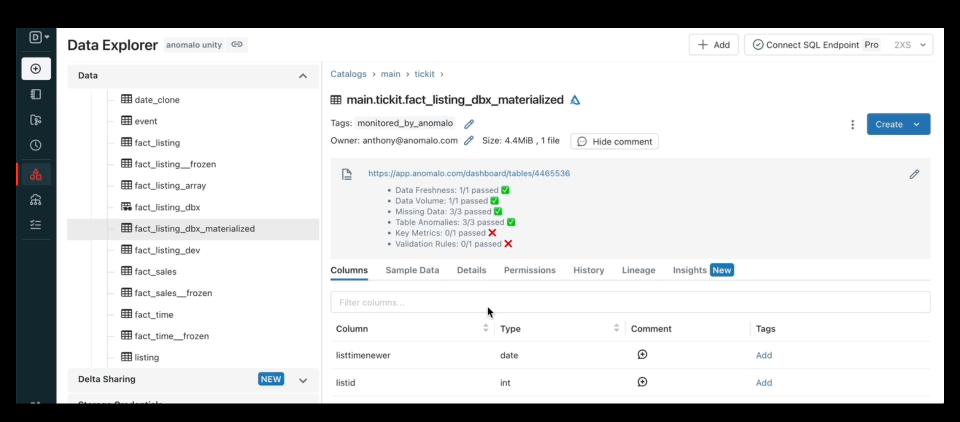


Access an exclusive free trial via Partner Connect





Databricks > Anomalo Demo



Using Anomalo + Databricks to Promote Data Trust

Anomalo has been the silver bullet in helping us promote trust in data across our organization. Since migrating to Anomalo, it is easy to detect false positives and has removed dependencies on data engineering. This makes both my data engineers and data consumers happy as it means less time fire-fighting issues, and more time using data to build products our customers love.

_

TIM NG
DATA PRODUCTS ENG LEAD, BLOCK







Using Anomalo + Databricks to Save Millions

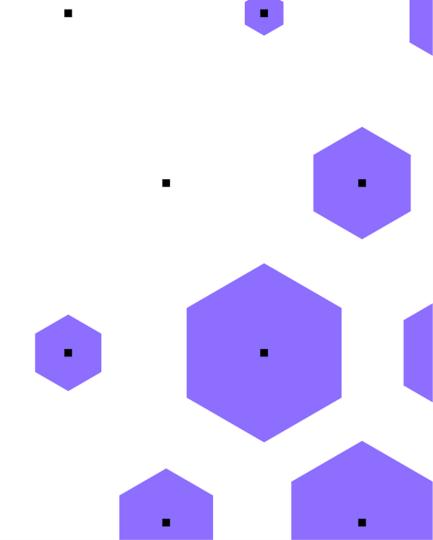
- → Dozens of teams onboarded
- → Thousands of automated checks
- → Over 100,000 hours saved
- → More than \$6MM dollars saved in < 1 year</p>

We have not only been able to replace manually created data quality checks with Anomalo's automated checks, but Anomalo's unsupervised machine learning has also found data quality issues that are hard to predict—thus savings us millions of dollars in a short period of time.

DATA GOVERNANCE PROGRAM LEAD



Deeper Dive





Easy

How easy is it for an end user to configure and execute the evaluation?



Sensitive

How small of a change can it find?



Interpretable

When differences are detected, how much work is required to understand them?



Comprehensive

Can it cover all of the columns, segments, metrics, relationships, values?



Scalable

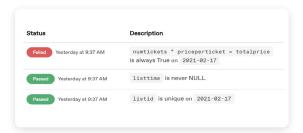
Can it scale to billions of rows and/or thousands of columns?





Is the data my warehouse produces of high quality?

User input required: Table and column(s), Rule type, Constraint



Easy to understand

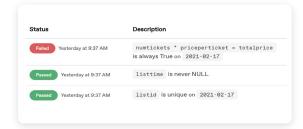
02

03



Is the data my warehouse produces of high quality?

User input required: Table and column(s), Rule type, Constraint



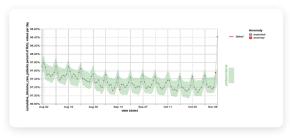
Easy to understand

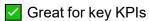
⚠ Hard to maintain at scale

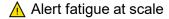
Metric Anomalies

Monitor changes in key business or data quality metrics

User input required: Table and column(s), Metric definition









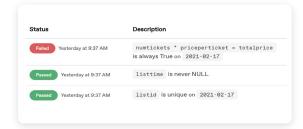


	Validation Rules	Metric Anomalies	
Easy	×	×	
Interpretable			
Scalable	×	×	
Sensitive		1	
Comprehensive	×	×	



Is the data my warehouse produces of high quality?

User input required: Table and column(s), Rule type, Constraint



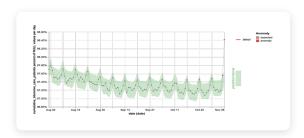
Easy to understand

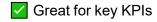
↑ Hard to maintain at scale

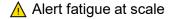
Metric Anomalies

Monitor changes in key business or data quality metrics

User input required: Table and column(s), Metric definition





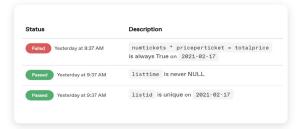






Is the data my warehouse produces of high quality?

User input required: Table and column(s), Rule type, Constraint

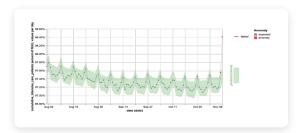


Easy to understand

Metric Anomalies

Monitor changes in key business or data quality metrics

User input required: Table and column(s), Metric definition



✓ Great for key KPIs

▲ Alert fatigue at scale

AI-Powered Monitoring

Automatically find significant changes inside the raw data

User input required: Table



Exhaustive validation with no setup

∧ Not as targeted as other methods



Is the data my warehouse produces of high quality?

User input required: Table and column(s), Rule type, Constraint

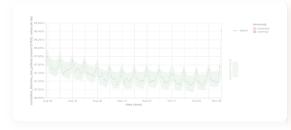


Easy to understand

Metric Anomalies

Monitor changes in key business or data quality metrics

User input required: Table and column(s), Metric definition



Great for key KPIs

▲ Alert fatigue at scale

Al-Powered Monitoring

Automatically find significant changes inside the raw data

User input required: Table



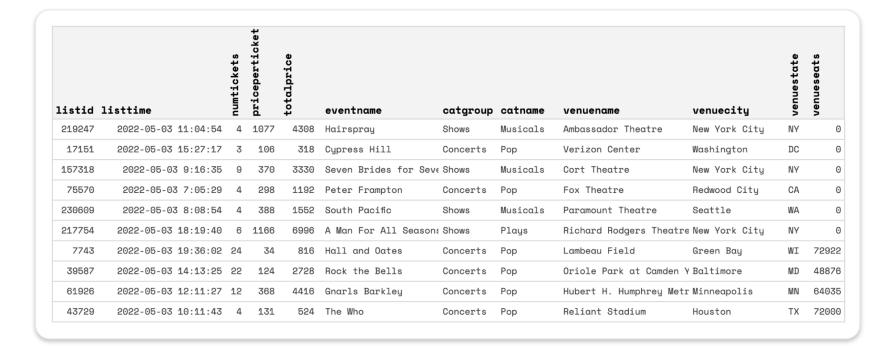
Exhaustive validation with no setup

∧ Not as targeted as other methods



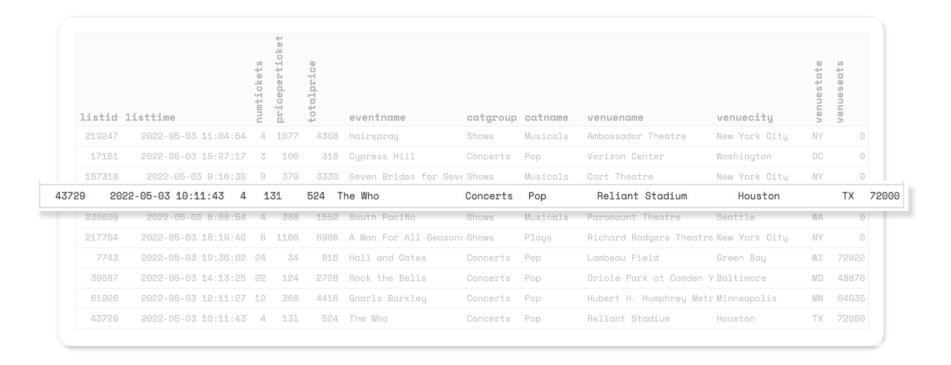
Easily Scale Data Quality Monitoring

Ticket Sales Data



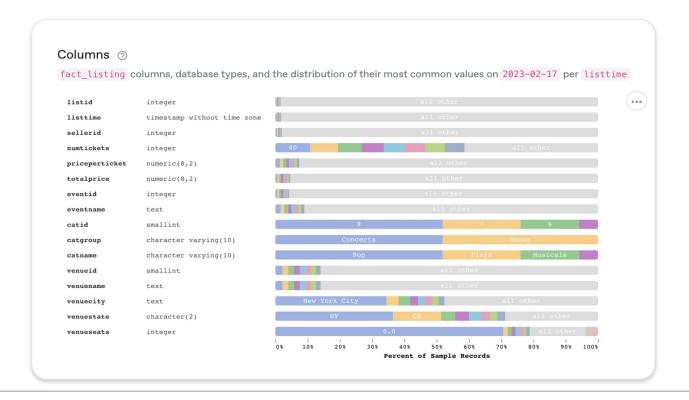


Ticket Sales Data



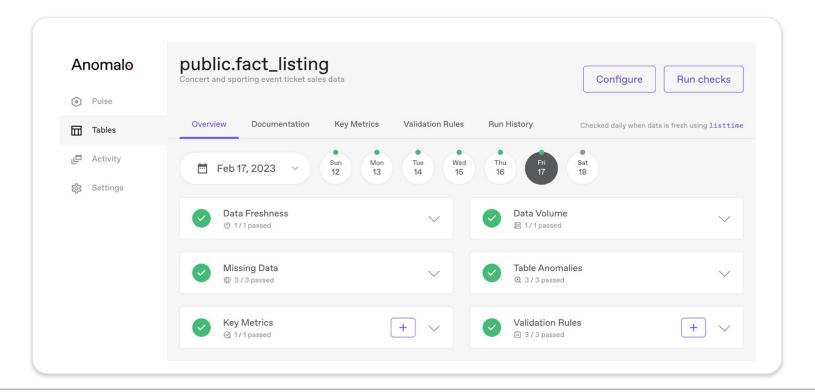


Data Profiling





Anomalo Monitoring





NETFLIX



Randomly terminates virtual machine instances

NETFLIX



Randomly terminates virtual machine instances

Anomalo



Randomly introduces data quality issues

Chaos Library

Anomalo >>> chaos help

Available Chaos Commands:

ColumnDropValue†

Drops all rows from table.column with a given value.

ColumnGrow†

Multiplies a column by a random value drawn uniformly from [low, high]. Use grow_sumbol='+' to achieve additive growth.

ColumnIdentity†

Does nothing to a Column (if a tree falls...).

ColumnInfrequentDropt

Drops rows with values equal to an infrequent randomly chosen value, which must represent between low_threshold and high_threshold fraction of records for a given column. If no such value exists, this check will throw an error.

ColumnModeDrop†

Drops rows with values equal to the mode of a given column. Requires that the mode represents at least threshold f raction of the data or else will throw an error. This is designed to prevent chaos where the mode is very rare.

• • •

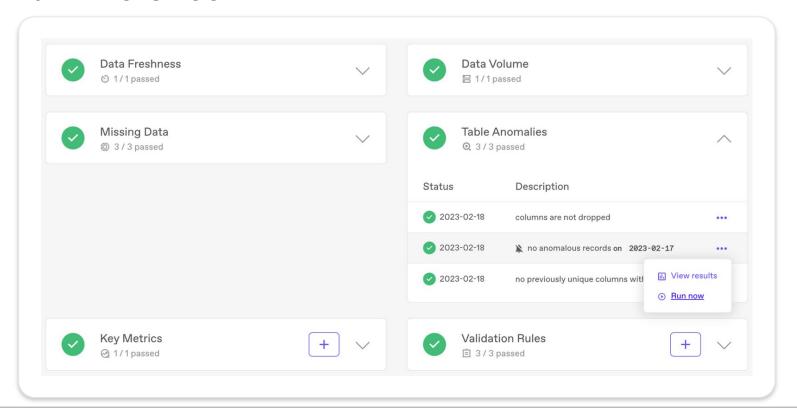


Introducing Chaos

```
Anomalo >>> chaos TimeColumnValue
                                        fact_listing
table:
column:
                              priceperticket
value:
                                  10
frac:
                                  .3
where_sql:
                              venuestate = 'NY'
time_col:
                              listtime
date:
                                  2023-02-17
```

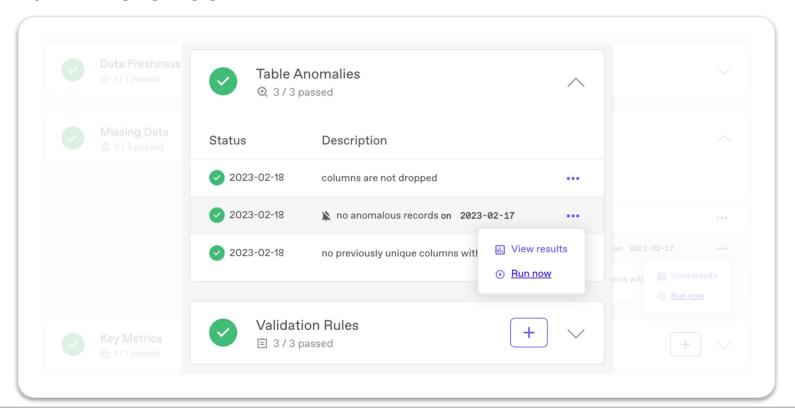


Re-Run The Check



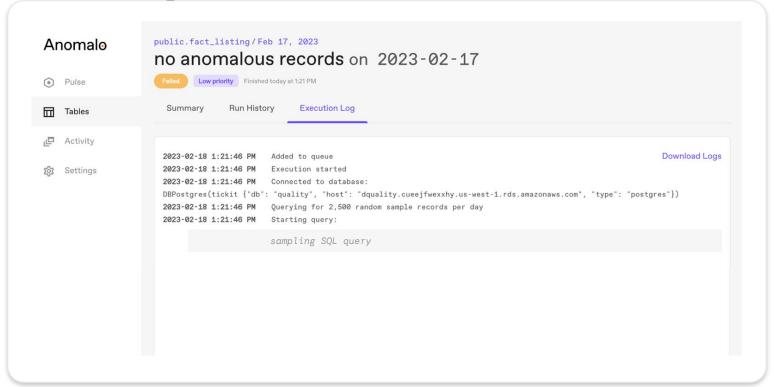


Re-Run The Check



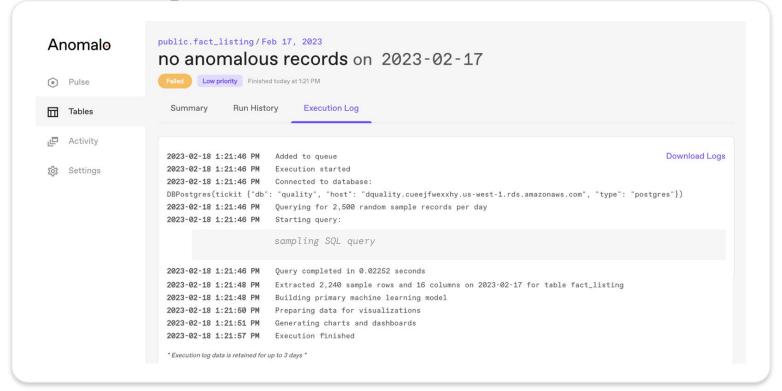


Watch The Log



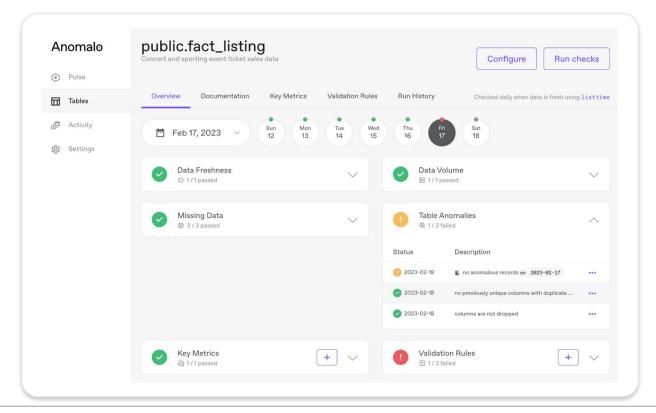


Watch The Log



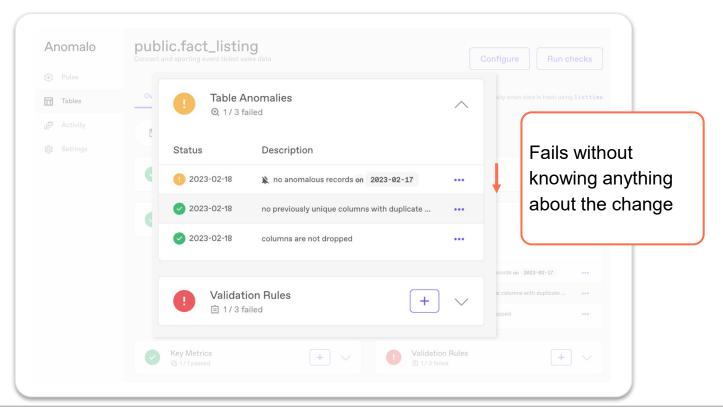


Check Fails



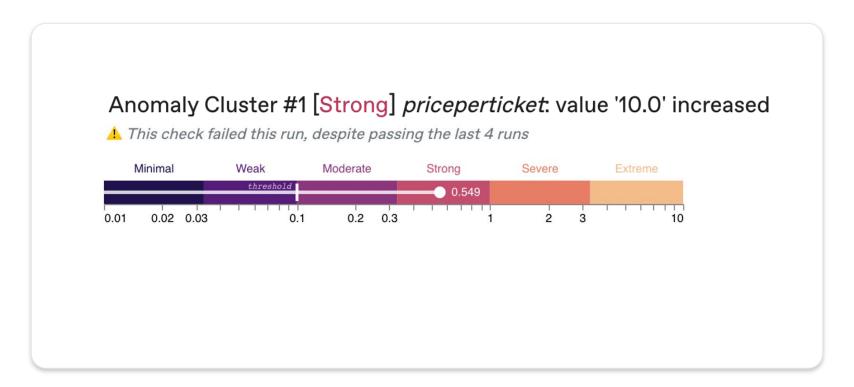


Check Fails



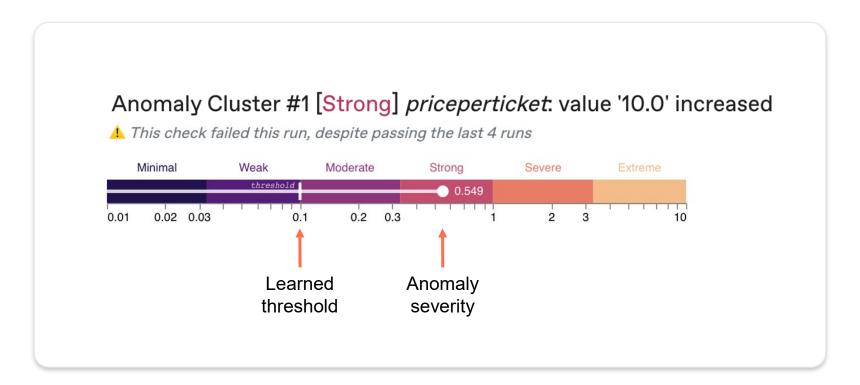


Severity and Explanation



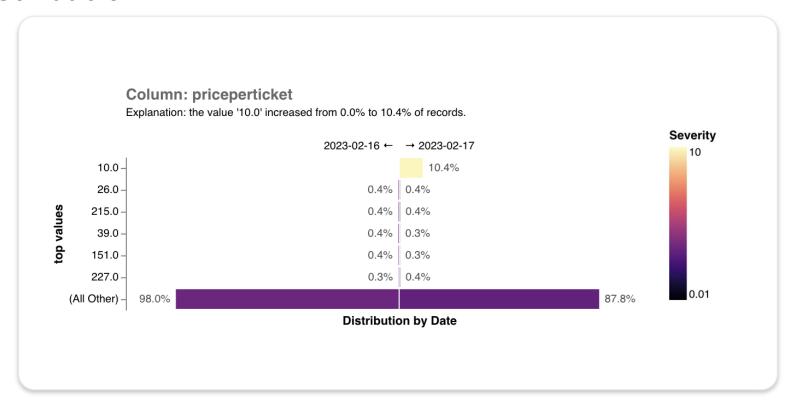


Severity and Explanation



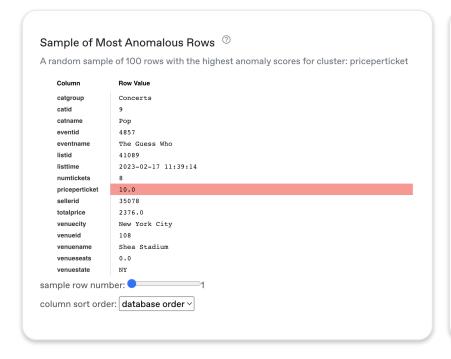


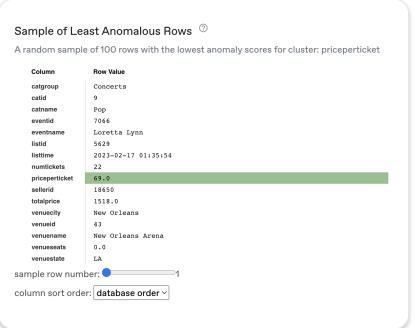
Distribution





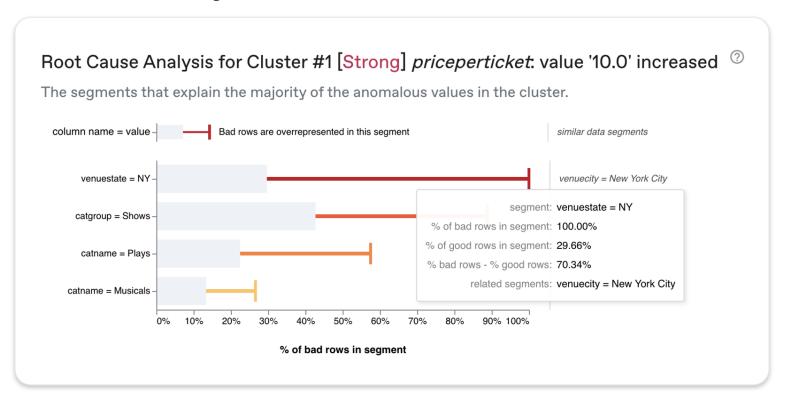
Good and Bad Records







Root Cause Analysis





DATA

listid listtime 219247 2022-05-03 11:04:54 12619 4 ... New York City 2022-05-03 15:27:17 27222 3 ... Washington 157318 2022-05-03 9:16:35 22899 9 ... New York City 2022-05-03 7:05:29 44301 4 ... Redwood City 4999 6 ... New York City 2022-05-03 19:36:02 4474 24 ... Green Bay WI 72922 2022-05-03 14:13:25 37990 22 ... Baltimore 39587 MD 48876 2022-05-03 10:11:43 39035 4 ... Houston TX 72000 listid listtime 2022-05-02 0:31:03 385 6 ... New York City 2022-05-02 14:19:31 1674 8 ... Mountain View 123523 2022-05-02 3:34:37 45271 8 ... Raleigh 11438 2022-05-02 11:20:46 38064 1 ... Dayton 118772 2022-05-02 9:51:39 41862 16 ... Kansas City 143671 4554 14 ... New York City 101427 3398 5 ... Philadelphia 228561 2022-05-02 3:40:54 4975 3 ... New York City 2022-05-02 20:25:23 47888 18 ... Milwaukee

Take random samples from today and yesterday

DATA

listid listtime 2022-05-03 11:04:54 12619 4 ... New York City 2022-05-03 15:27:17 27222 3 ... Washington 157318 2022-05-03 9:16:35 22899 9 ... New York City 2022-05-03 7:05:29 44301 4 ... Redwood City 6 ... New York Citu 2022-05-03 19:36:02 4474 24 ... Green Bay 39587 2022-05-03 14:13:25 37990 22 ... Baltimore MD 48876 2022-05-03 10:11:43 39035 4 ... Houston TX 72000 listid listtime 2022-05-02 0:31:03 385 6 ... New York City 2022-05-02 14:19:31 1674 8 ... Mountain View 123523 11438 2022-05-02 11:20:46 118772 2022-05-02 9:51:39 41862 16 ... Kansas City 4554 14 ... New York City 101427 3398 5 ... Philadelphia 228561 2022-05-02 3:40:54 4975 3 ... New York City 2022-05-02 20:25:23 47888 18 ... Milwaukee WI

Take random samples from today and yesterday

Is there any material change between the two dates?



DATA

listid listtime 2022-05-03 11:04:54 12619 4 ... New York City 2022-05-03 15:27:17 27222 3 ... Washington 157318 2022-05-03 9:16:35 22899 9 ... New York City 2022-05-03 7:05:29 44301 4 ... Redwood City 6 ... New York Citu 2022-05-03 19:36:02 4474 24 ... Green Bay 39587 2022-05-03 14:13:25 37990 22 ... Baltimore 2022-05-03 10:11:43 39035 4 ... Houston TX 72000 listid listtime 385 6 ... New York City 2022-05-02 0:31:03 123523 11438 118772 2022-05-02 9:51:39 41862 16 ... Kansas City 4554 14 ... New York City 101427 2022-05-02 3:40:54 4975 3 ... New York City 2022-05-02 20:25:23 47888 18 ... Milwaukee WI

Take random samples from today and yesterday

Is there any material change between the two dates?

Can we predict which day each record came from?





DATA

TODAY

YESTERDAY

listid	listtime	sellerid	numtickets	 venuecity	venuestate	venueseats	response
219247	2022-05-03 11:04:54	12619	4	 New York City	NY	0	1
17151	2022-05-03 15:27:17	27222	3	 Washington	DC	0	1
157318	2022-05-03 9:16:35	22899	9	 New York City	NY	0	1
75570	2022-05-03 7:05:29	44301	4	 Redwood City	CA	0	1
230609	2022-05-03 8:08:54	9663	4	 Seattle	WA	0	1
217754	2022-05-03 18:19:40	4999	6	 New York City	NY	0	1
7743	2022-05-03 19:36:02	4474	24	 Green Bay	WI	72922	1
39587	2022-05-03 14:13:25	37990	22	 Baltimore	MD	48876	1
43729	2022-05-03 10:11:43	39035	4	 Houston	TX	72000	1
listid	listtime	sellerid	numtickets	 venuecity	venuestate	venueseats	response
listid 227155	listtime 2022-05-02 0:31:03	sellerid 385	o numtickets	 venuecity New York City	Venuestate	venueseats	response 0
			_	_		-	
227155	2022-05-02 0:31:03	385	6	 New York City	NY	0	0
227155 41479	2022-05-02 0:31:03 2022-05-02 14:19:31	385 1674	6	 New York City Mountain View	NY	0 22000	0
227155 41479 123523	2022-05-02 0:31:03 2022-05-02 14:19:31 2022-05-02 3:34:37	385 1674 45271	6 8 8	 New York City Mountain View Raleigh	NY CA NC	0 22000 0	0 0 0
227155 41479 123523 11438	2022-05-02 0:31:03 2022-05-02 14:19:31 2022-05-02 3:34:37 2022-05-02 11:20:46	385 1674 45271 38064	6 8 8	 New York City Mountain View Raleigh Dayton	NY CA NC OH	0 22000 0	0 0 0
227155 41479 123523 11438 118772	2022-05-02 0:31:03 2022-05-02 14:19:31 2022-05-02 3:34:37 2022-05-02 11:20:46 2022-05-02 9:51:39	385 1674 45271 38064 41862	6 8 8 1	 New York City Mountain View Raleigh Dayton Kansas City	NY CA NC OH KS	0 22000 0 0	0 0 0 0
227155 41479 123523 11438 118772 143671	2022-05-02 0:31:03 2022-05-02 14:19:31 2022-05-02 3:34:37 2022-05-02 11:20:40 2022-05-02 9:51:39 2022-05-02 0:13:16	385 1674 45271 38064 41862 4554	6 8 8 1 16	 New York City Mountain View Raleigh Dayton Kansas City New York City	NY CA NC OH KS NY	0 22000 0 0	0 0 0 0
227155 41479 123523 11438 118772 143671 101427	2022-05-02 0:31:03 2022-05-02 14:19:31 2022-05-02 3:34:37 2022-05-02 11:20:46 2022-05-02 0:51:30 2022-05-02 0:13:16 2022-05-02 17:26:38	385 1674 45271 38064 41862 4554 3398	6 8 8 1 16 14 5	 New York City Mountain View Raleigh Dayton Kansas City New York City Philadelphia	NY CA NC OH KS NY	0 22000 0 0 0 0	0 0 0 0 0

Encode Response as 1 = Today, 0 = Yesterday



Encode features automatically

DATA

listid	listtime	sellerid	numtickets	 venuecity	venuestate	venueseats	response
219247	2022-05-03 11:04:54	12619	4	 New York City	NY	0	1
17151	2022-05-03 15:27:17	27222	3	 Washington	DC	0	1
157318	2022-05-03 9:16:35	22899	9	 New York City	NY	0	1
75570	2022-05-03 7:05:29	44301	4	 Redwood City	CA	0	1
230609	2022-05-03 8:08:54	9663	4	 Seattle	WA	0	1
217754	2022-05-03 18:19:40	4999	6	 New York City	NY	Θ	1
7743	2022-05-03 19:36:02	4474	24	 Green Bay	WI	72922	1
39587	2022-05-03 14:13:25	37990	22	 Baltimore	MD	48876	1
43729	2022-05-03 10:11:43	39035	4	 Houston	TX	72000	1
			w		0	w	

ES'		3 A	V
	I T		

listid	listtime	sellerid	numtickets	 venuecity	venuestate	venueseats	response
227155	2022-05-02 0:31:03	385	6	 New York City	NY	0	0
41479	2022-05-02 14:19:31	1674	8	 Mountain View	CA	22000	0
123523	2022-05-02 3:34:37	45271	8	 Raleigh	NC	0	0
11438	2022-05-02 11:20:46	38064	1	 Dayton	ОН	0	0
118772	2022-05-02 9:51:39	41862	16	 Kansas City	KS	0	0
143671	2022-05-02 0:13:16	4554	14	 New York City	NY	0	0
101427	2022-05-02 17:26:38	3398	5	 Philadelphia	PA	68532	0
228561	2022-05-02 3:40:54	4975	3	 New York City	NY	0	0
158082	2022-05-02 20:25:23	47888	18	 Milwaukee	WI	0	0

FEATURES

X_1	X_2	X_3	 X_n	response
Θ	0.07	17	 0.28	1
0	0.08	1	 0.27	1
Θ	0.61	2	 0.29	1
1	0.37	1	 0.27	1
1	0.44	9	 0.45	1
1	0.01	8	 0.88	1
1	0.16	1	 0.10	1
0	0.21	11	 0.58	1
1	0.73	3	 1.00	1

X_1	X_2	X_3	 X_n	response
0	0.85	17	 0.43	0
Θ	0.78	2	 0.49	0
1	0.79	2	 0.84	0
0	0.46	6	 0.93	0
0	0.91	3	 0.37	0
1	0.31	1	 0.51	0
1	0.52	13	 0.61	0
1	0.51	3	 0.35	0
1	0.60	7	 0.86	0



123523

11438

118772

Build a supervised learning model

GRADIENT BOOSTING DECISION TREE

DATA

listid listtime response 2022-05-03 11:04:54 12619 4 ... New York City 2022-05-03 15:27:17 27222 3 ... Washington 157318 2022-05-03 9:16:35 22899 9 ... New York City 2022-05-03 7:05:29 44301 4 ... Redwood City 230609 217754 2022-05-03 19:36:02 4474 24 ... Green Bay WI 72922 39587 2022-05-03 14:13:25 37990 22 ... Baltimore MD 48876 2022-05-03 10:11:43 39035 4 ... Houston TX 72000 listid listtime response 2022-05-02 0:31:03 385 1674 8 ... Mountain View

4554 14 ... New York City

4975 3 ... New York City

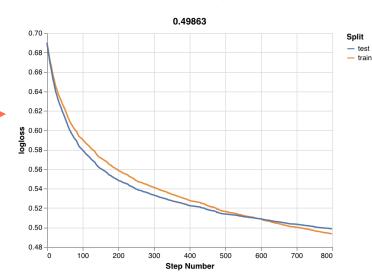
2022-05-02 9:51:39 41862 16 ... Kansas City

2022-05-02 20:25:23 47888 18 ... Milwaukee

2022-05-02 3:40:54

Model Train Test Split ②

Model performance over train and test split by iteration number

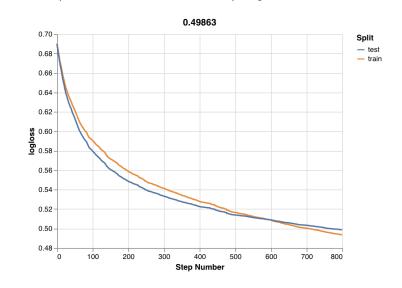


Use SHAP to credit changes to table values

GRADIENT BOOSTING DECISION TREE

Model Train Test Split ②

Model performance over train and test split by iteration number





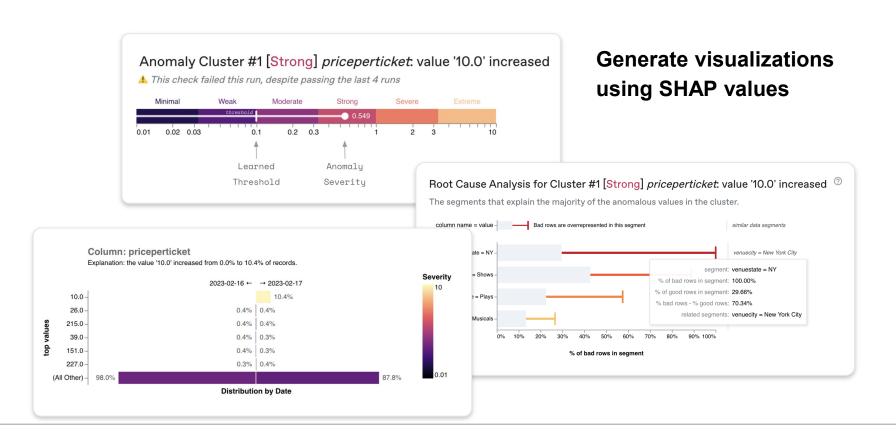
SHAP VALUES (ANOMALY SCORES)

Most Anomalous Rows ②

Shows the most anomalous rows of data, colored by anomaly scores and sorted by the maximum anomaly score in the row.

								column	1								
	- listid	- listtime	-sellerid	- numtickets	- priceperticket	-totalprice	- eventid	- eventname	-catid	-catgroup	- catname	-venueid	- venuename	-venuecity	-venuestate	venueseats	
1-	1060	2021-01-17	44798	28	1960.0	1568.0	8571	Vampire Weekend	9	Concerts	Pop	84	Soldier Field	Chicago	IL	63000.0	severity
2-	31413	2021-01-17	36758	1	1337.0	101.0	22	La Rondine	8	Shows	Opera	306	Lyric Opera House	Baltimore	MD	0.0	
3-	11686	2021-01-17	3739	3	2487.0	306.0	6427	America	9	Concerts	Pop	8	The Home Depot	Carson	CA	0.0	
4-	7207	2021-01-17	13517	16	1687.0	320.0	6210	Mos Def	9	Concerts	Pop	15	McAfee Coliseum	Oakland	CA	63026.0	1.5
5-	13558	2021-01-17	22420	16	2099.0	416.0	5341	Rock To Win At	9	Concerts	Pop	46	Nassau Veterans	Uniondale	NY	0.0	
6-	11693	2021-01-17	25615	28	2284.0	6916.0	862	A Catered Affair	6	Shows	Musicals	228	Eugene O'Neill		NY	0.0	
7-	24081	2021-01-17	8817	4	815.0	164.0	362	Tristan und Isolde	8	Shows	Opera	300	Kennedy Center	Washington	DC	0.0	
8-	14725	2021-01-17	27464	16	1656.0	1488.0	8086	Joe Satriani	9	Concerts	Pop	31	Pepsi Center	Denver	co	0.0	1.0
9-	40263	2021-01-17	27486	22	547.0	6138.0	3464	For Colored	7	Shows	Plays	228	Eugene O'Neill	New York City	NY	0.0	
10-	222909	2021-01-17	11687	7	69.0	17409.0	1122	Flower Drum Song	6	Shows	Musicals	231	Gerald	New York City	NY	0.0	
11 -	224164	2021-01-17	21252	6	29.0	5478.0	3273	A Streetcar	7	Shows	Plays	244	Royce Hall	Los Angeles	CA	0.0	0.5
12-	224347	2021-01-17	13152	7	244.0	12992.0	309	The Queen of	8	Shows	Opera	301	Ellie Caulkins	Denver	co	0.0	0.50.50
13-	16441	2021-01-17	25047	2	1794.0	106.0	3379	Othello	7	Shows	Plays	230	Richard Rodgers	New York City	NY	0.0	
14-	6132	2021-01-17	10704	5	1854.0	200.0	5324	Etta James	9	Concerts	Pop	60	Rexall Place	Edmonton	AB	0.0	
15-	42133	2021-01-17	2806	1	1247.0	216.0	919	The King and I	6	Shows	Musicals	222	Majestic Theatre	New York City	NY	0.0	
16-	234372	2021-01-17	18759	4	101.0	4988.0	8693	.38 Special	9	Concerts	Pop	122	Saratoga	Saratoga Springs	NY	0.0	
17-	233658	2021-01-17	25374	7	55.0	9044.0	3954	Echo & the	9	Concerts	Pop	24	Conseco Fieldhouse	Indianapolis	IN	0.0	
18-	123399	2021-01-17	30914	9	1278.0	432.0	1364	A Catered Affair	6	Shows	Musicals	245	The Guthrie	Minneapolis	MN	0.0	
19-	12686	2021-01-17	20138	8	1822.0	456.0	7240	Bette Midler	9	Concerts	Pop	61	Xcel Energy Center	St. Paul	MN	0.0	
20 -	212967	2021-01-17	41156	7	115.0	13531.0	7044	Dolly Parton	9	Concerts	Pop	87	Hubert H	Minneapolis	MN	64035.0	
21 -	8368	2021-01-17	1681	18	2488.0	3330.0	7456	Idina Menzel	9	Concerts	Pop	9	Dick's Sporting	Commerce City	co	0.0	
22-	1712	2021-01-17	21627	3	1158.0	207.0	4156	Kansas	9	Concerts	Pop	105	Safeco Field	Seattle	WA	47116.0	
23 -	40290	2021-01-17	20313	7	1867.0	301.0	1339	South Pacific	6	Shows	Musicals	227	New Amsterdam	New York City	NY	0.0	
24 -	48650	2021-01-17	7669	3	1191.0	267.0	5987	Rock The Bayou	9	Concerts	Pop	29	Amway Arena	Orlando	FL	0.0	
25 -	178489	2021-01-17	21218	24	830.0	576.0	3464	For Colored	7	Shows	Plays	228	Eugene O'Neill	New York City	NY	0.0	









Seasonality

This change happens every Monday



Clustering Across Columns

Groups of columns have the same change



Time-Correlated Features

ID or date columns always increase



Performance

Must scale to billions of rows, thousands of columns



Chaotic Tables

Some tables change 100x more often



Accuracy

Needs to be sensitive to real changes, but suppress false positives



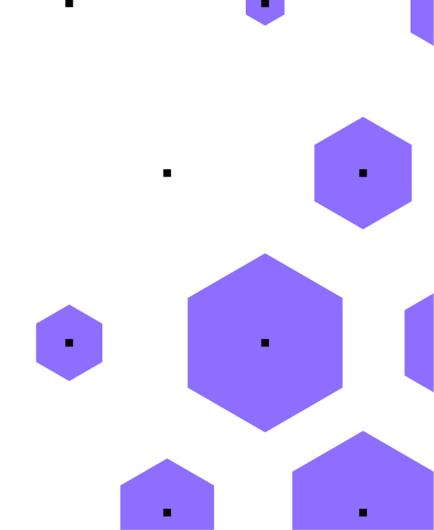
	Validation Rules	Metric Anomalies	
Easy	×	×	
Interpretable			
Scalable	×	×	
Sensitive		1	
Comprehensive	×	×	



	Validation Rules	Metric Anomalies	Al-Powered Monitoring
Easy	×	×	
Interpretable			
Scalable	×	×	
Sensitive			1
Comprehensive	×	×	



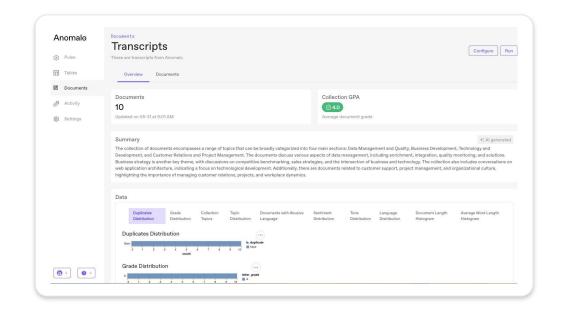
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Anomalo's Unstructured Monitoring Product

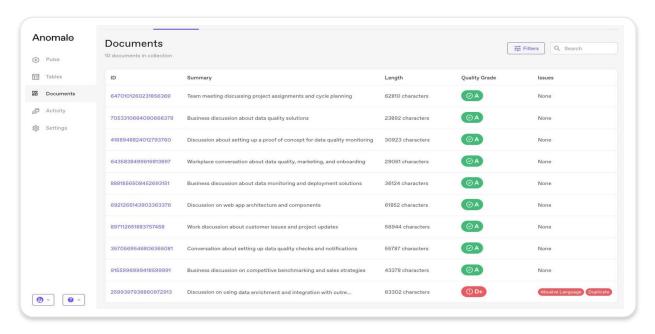
- 90% of Enterprise Data is Unstructrued
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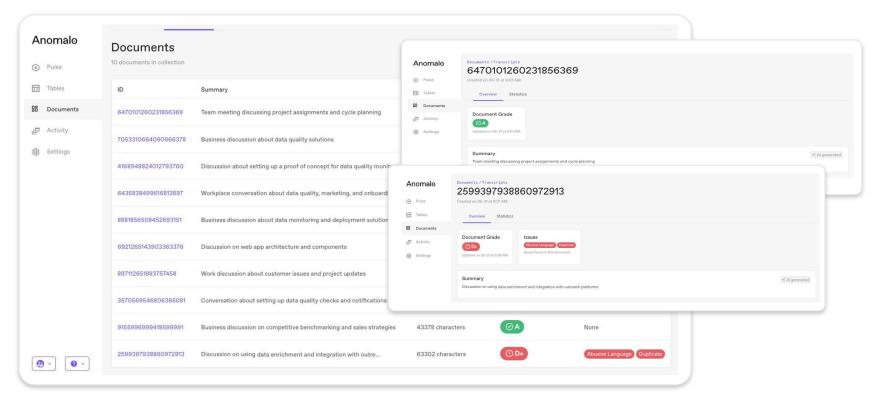


Monitor for length, duplicates, topics, tone, language, abusive language, PII and sentiment





Quickly evaluate the quality of a document





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