Data Warehouse Benchmark: Redshift

Me vs Snowflake

Vs BigQuery



CEO @ \\ Fivetran



Applications

Asana Bing Ads

Braintree Payments

Desk.com

DoubleClick

Dynamics (365, GP, AX) Eloqua

Facebook Ad Insights

Freshdesk

FrontApp

Github

Google Adwords
Google Analytics

Google Analytics 360

Google Play Help Scout

HubSpot

Hybris

Instagram Intercom

iTunes

Jira

Magento MailChimp

Mandrill Marketo

Mixpanel

NetSuite SuiteAnalytics

Stripe

Zendesk Chat (Zopim)

Xero Zendesk

7uora

Pardot

QuickBooks Online

Recurly Sailthru Salesforce SalesforcelO

SAP Business One

Shopify



Databases



Files

Amazon Aurora

Amazon RDS

Azure SQL Database

DynamoDB

Google Cloud SQL

Heroku

MariaDB MongoDB

MySQL

Oracle DB

PostgreSQL

SQL Server

.

Amazon Cloudfront

Amazon Kinesis Firehose

Amazon S3

Azure Blob Storage

CSV

Dropbox

FTP

FTPS

Google Cloud Storage

Google Sheets

JSON

SFTP



Events

Segment Snowplow Webhooks



Online Transaction Processing (**OLTP**)

```
select *
from github.commit
where sha = 'feeec5a81da13e95a1911b09773f8228f8c0db76'
```

is very different from Online Analytical Processing (**OLAP**)

```
select author_email, count()
from github.commit
group by 1
```

This talk is about **OLAP!**

Row Store:

commit	file	added	removed	changed	
xxx —	file1.txt	1	10		11
xxx -	file2.txt	100	0		100
xxx -	file3.txt	50	50		50
ууу	file1.txt	1	10	-	11

xxx, file1.txt, 1, 10, 11, xxx, file2.txt, 100, 0, 100, xxx, file3.txt, 50, 50, 50, yyy, file1.txt, 1, 10, 11

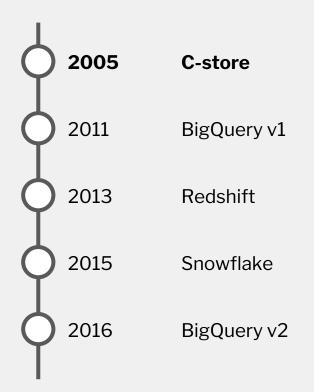
Column Store:

comm	it	file	added		removed	t	change	t
XXX	1	file1_txt	×	1	A	10	A	11
XXX		file2.txt		100		0		100
xxx		file3.txt		50		50		50
ууу	\	file1.txt	1	1	,	10	1	11

xxx, xxx, xxx, yyy, file1.txt, file2.txt, file3.txt, 1, 100, 50, 1, 10, 0, 50, 10, 11, 100, 50, 11

```
select file, sum(changed)
from github.commit
group by 1
```

C-store: the data warehouse that changed everything



C-Store: A Column-oriented DBMS

Mike Stonebraker*, Daniel J. Abadi*, Adam Batkin[†], Xuedong Chen[†], Mitch Cherniack[†], Miguel Ferreira*, Edmond Lau*, Amerson Lin*, Sam Madden*, Elizabeth O'Neil[†], Pat O'Neil[†], Alex Rasin[‡], Nga Tran[†], Stan Zdonik[‡]

*MIT CSAIL Cambridge, MA ⁺Brandeis University Waltham, MA †UMass Boston Boston, MA [‡]Brown University Providence, RI

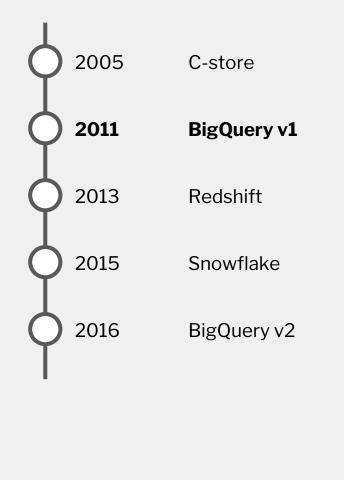
Abstract

This paper presents the design of a read-optimized relational DBMS that contrasts sharply with most current systems, which are write-optimized.

in which periodically a bulk load of new data is performed, followed by a relatively long period of ad-hoc queries. Other read-mostly applications include customer relationship management (CRM) systems, electronic library card catalogs, and other ad-hoc inquiry systems. In such anyironments, a column stars architecture, in which

2011: Early BigQuery

Not so great at joins



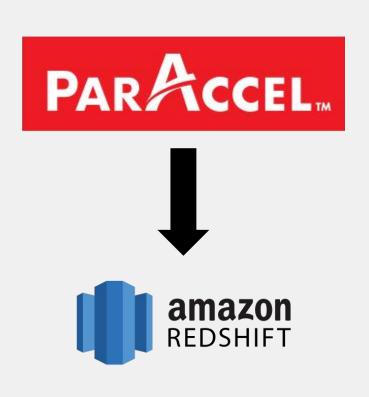
select foo, bar
from large_table
join other_large_table

Nonstandard SQL-like language

select why, did, you,
invent, your, own, sql
from google

2013: AWS Redshift takes off

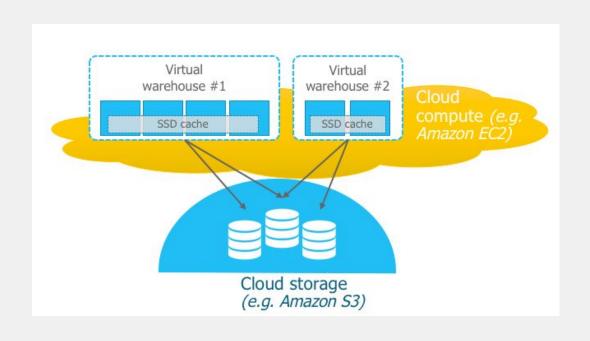
I	
2005	C-store
2011	BigQuery v1
	
2013	Redshift
2013	Redshift Snowflake



Snowflake: store the data in S3!

(similar to BigQuery)

20	005	C-store
20)11	BigQuery v1
20)13	Redshift
20)15	Snowflake
20	016	BigQuery v2



2016: BigQuery gets way better

2005 C-store 2011 BigQuery v1 2013 Redshift 2015 Snowflake 2016 BigQuery v2

Fact-to-fact joins work! Standard SQL! DELETE and UPDATE!

```
update mytable
set name = 'Hello world!'
where id = 1
```

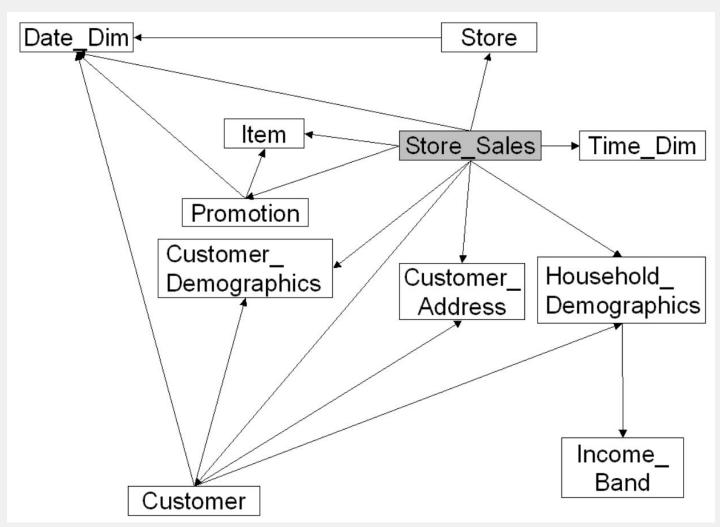
Benchmark time!







What data did we query?



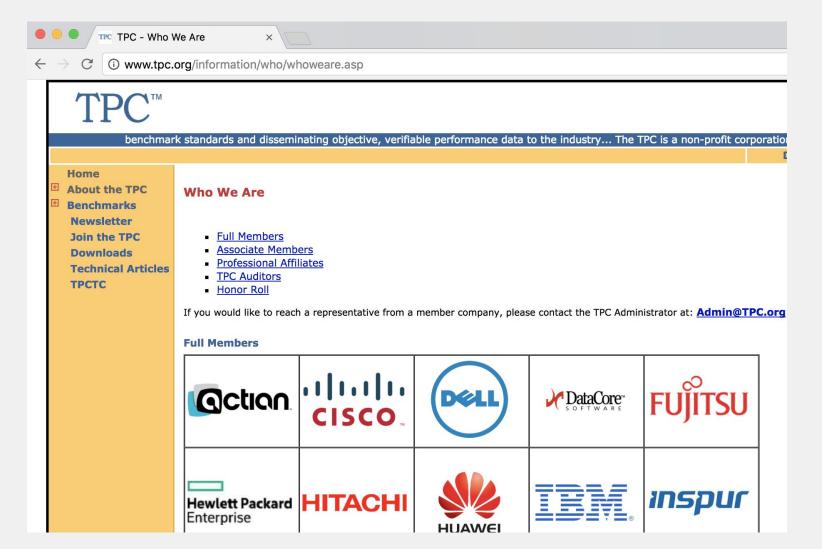
What queries did we run?

```
-- query12
SELECT
         i_item_id ,
         i item desc ,
         i category ,
         i_class ,
         i_current_price ,
         Sum(ws_ext_sales_price)
         Sum(ws_ext_sales_price)*100/Sum(Sum(ws_ext_sales_price))
         web sales,
FROM
         item ,
         date dim
         ws item sk = i item sk
WHERE
         i category IN ('Home',
AND
                        'Men'.
                         'Women')
AND
         ws_sold_date_sk = d_date_sk
         Cast(d_date AS DATE) BETWEEN Cast('2000-05-11' AS DATE)
AND
                  Cast('2000-06-11' AS DATE))
GROUP BY i item id ,
         i item desc ,
         i_category ,
         i_class ,
         i_current_price
ORDER BY i_category ,
         i class ,
         i_item_id ,
         i_item_desc ,
         revenueratio
LIMIT 100:
```

```
WITH ssr AS
        SELECT s_store_id,
                 Sum(sales_price) AS sales,
                 Sum(profit) AS profit,
                 Sum(return_amt) AS returns1,
                 Sum(net_loss) AS profit_loss
                        SELECT ss_store_sk
                                                      AS store_sk,
                                                      AS date_sk,
                              ss_sold_date_sk
                              ss_ext_sales_price
                                                      AS sales_price,
                              ss_net_profit
                                                      AS profit,
                              0 AS return_amt,
                              0 AS net_loss
                        FROM store_sales
                        LINTON ALL
                        SELECT sr_store_sk
                                                      AS store_sk,
                              sr_returned_date_sk
                                                      AS date_sk,
                              0 AS sales_price,
                              0 AS profit,
                                                      AS return_amt,
                              sr return amt
                              sr_net_loss
                                                      AS net_loss
                        FROM store_returns ) salesreturns,
                date_dim,
                 store
        WHERE
                date_sk = d_date_sk
                 Cast(d date AS DATE) BETWEEN Cast('2002-08-22' AS DATE) AND
                         Cast('2002-09-05' AS DATE))
                 store_sk = s_store_sk
        GROUP BY s_store_id) , csr AS
        SELECT cp_catalog_page_id,
                 sum(sales_price) AS sales,
                 sum(profit) AS profit,
                 sum(return_amt) AS returns1,
                 sum(net_loss) AS profit_loss
        FROM
                        SELECT cs_catalog_page_sk
                                                      AS page_sk,
                              cs sold date sk
                              cs ext sales price
                                                      AS sales_price,
                              cs_net_profit
                                                      AS profit,
                              0 AS return_amt,
                              0 AS net_loss
                        FROM catalog_sales
                        LINTON ALL
                        SELECT cr_catalog_page_sk
                              cr_returned_date_sk
                                                      AS date_sk,
                              0 AS sales_price,
                              0 AS profit,
                              cr_return_amount
                                                      AS return_amt,
                              cr_net_loss
                                                      AS net loss
                        FROM catalog_returns ) salesreturns,
                 date dim,
                catalog_page
                 Cast(d_date AS DATE) BETWEEN cast('2002-08-22' AS date) AND
                         Cast('2002-09-05' AS DATE))
                 page_sk = cp_catalog_page_sk
        GROUP BY cp_catalog_page_id) , wsr AS
        SELECT web_site_id,
                 sum(sales_price) AS sales,
                 sum(profit) AS profit,
                 sum(return_amt) AS returns1,
                 sum(net_loss) AS profit_loss
        FROM
                        SELECT ws_web_site_sk
                                                      AS wsr_web_site_sk,
                              ws_sold_date_sk
                                                      AS date_sk,
                              ws_ext_sales_price
                                                      AS sales_price,
```

AC profit

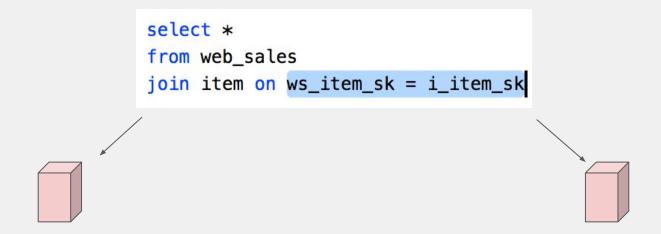
What is TPC-DS?



How to run TPC-DS without cheating

DON'T run the same query twice
DON'T use dist keys
DON'T use sort/partition keys
DO apply compression encoding
DO use a realistic (small) scale
DO compare cost

DON'T use dist keys



WEB_SALES			
ws_sold_date_sk	ws_sales_price	ws_item_sk	
Jan 1 2000	\$1	1	
Jan 2 2000	\$1	1	
Feb 1 2000	\$1	1	

ITEMS			
i_item_sk	i_product_name		
1	Rubber Ducks		

	WEB_SALES	
ws_sold_date_sk	ws_sales_price	ws_item_sk
Feb 1 2000	\$10	2
Aug 1 2000	\$10	2
Jan 1 2001	\$10	2

ITEMS				
i_item_sk	i_product_name			
2	Pinwheels			

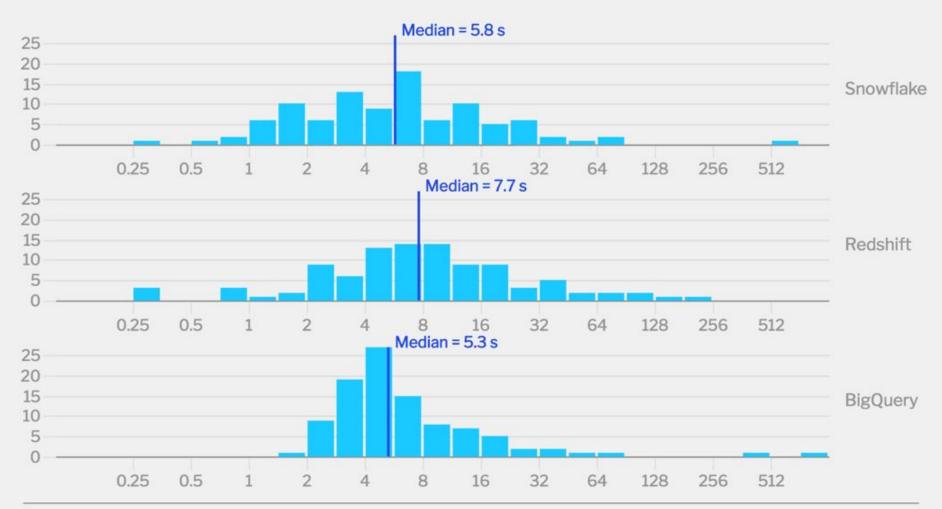
DON'T use sort/partition keys

```
select *
from web_sales
join item on ws_item_sk = i_item_sk
where d_date between '2000-05-11' and '2000-06-11'
```

	WEB_SALES	
ws_sold_date_sk	ws_sales_price	ws_item_sk
2000-01-01	\$1	1
2000-01-07	\$10	2
•••		•••
2000-05-11	\$1	1
2000-05-20	\$10	2
2000-05-30	\$1	1
2000-06-05	\$10	2
2000-06-11	\$10	2
	•••	
2000-12-01	\$1	1
2000-12-31	\$10	2

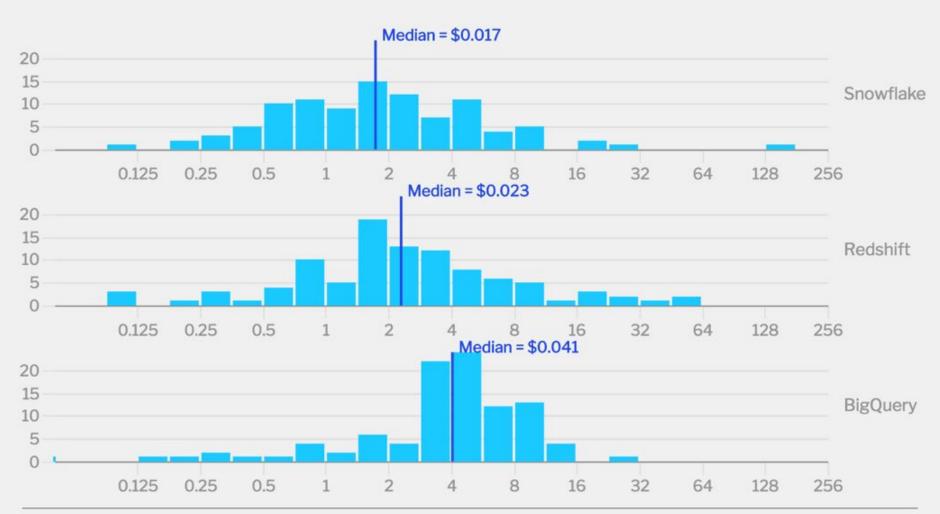
Which data warehouse is the fastest?

Histogram of execution times for 99 TPC-DS queries (seconds, log scale)



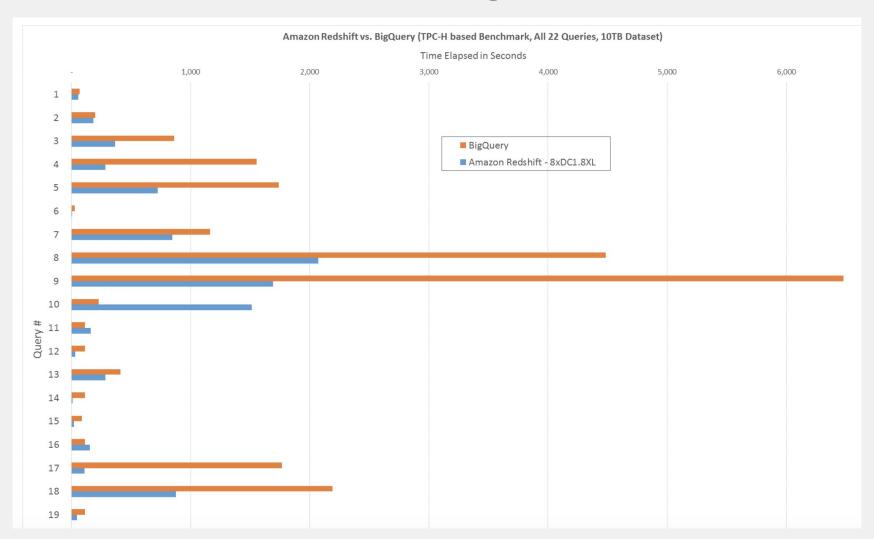
Which data warehouse is the cheapest?

Histogram of cost for 99 TPC-DS queries (cents, log scale)



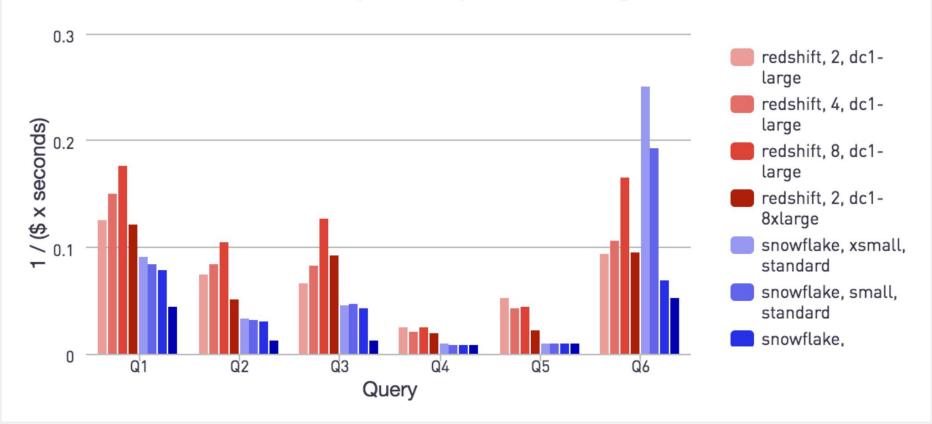
How does this compare to other benchmarks?

Amazon's Redshift vs BigQuery benchmark



Periscope's Redshift vs Snowflake vs BQ

Snowflake vs. Redshift: Computation per Dollar [Higher is Better]



Mark Litwintshik's 1.1 billion taxi-rides

Query 1	Query 2	Query 3	Query 4 Setup
0.005	0.011	0.103	0.188 BrytlytDB 2.1 & 5-node IBM Minsky cluster
0.009	0.027	0.287	0.428 BrytlytDB 2.0 & 2-node p2.16xlarge cluster
0.021	0.053	0.165	0.51 MapD & 8 Nvidia Pascal Titan Xs
0.027	0.083	0.163	0.891 MapD & 8 Nvidia Tesla K80s
0.028	0.2	0.237	0.578 MapD & 4-node g2.8xlarge cluster
0.034	0.061	0.178	0.498 MapD & 2-node p2.8xlarge cluster
0.036	0.131	0.439	0.964 MapD & 4 Nvidia Titan Xs
0.051	0.146	0.047	0.794 kdb+/q & 4 Intel Xeon Phi 7210 CPUs
0.762	2.472	4.131	6.041 BrytlytDB 1.0 & 2-node p2.16xlarge cluster
1.034	3.058	5.354	12.748 ClickHouse, Intel Core i5 4670K
1.56	1.25	2.25	2.97 Redshift, 6-node ds2.8xlarge cluster
2	2	1	3 <u>BigQuery</u>
4	4	10	21 Presto, 50-node n1-standard-4 cluster
6.41	6.19	6.09	6.63 <u>Amazon Athena</u>
8.1	18.18	n/a	n/a Elasticsearch (heavily tuned)
10.19	8.134	19.624	85.942 Spark 2.1, 11 x m3.xlarge cluster w/ HDFS
11	10	21	31 Presto, 10-node n1-standard-4 cluster
14.389	32.148	33.448	67.312 Vertica, Intel Core i5 4670K
34.48	63.3	n/a	n/a Elasticsearch (lightly tuned)
35	39	64	81 Presto, 5-node m3.xlarge cluster w/ HDFS
43	45	27	44 Presto, 50-node m3.xlarge cluster w/ S3
152	175	235	368 PostgreSQL 9.5 & cstore_fdw
264	313	620	961 Spark 1.6, 5-node m3.xlarge cluster w/ S3
1103	1198	2278	6446 Spark 2.2, 3-node Raspberry Pi cluster

20 points by georgewfraser 2 hours ago [-]

This is not a good benchmark. There are two problems:

- 1. It's a simple GROUP BY on a single table. You're basically just measuring the scan speed. Real queries are dominated by shuffles and the probe side of joins; these aren't even present in this benchmark.
- 2. He runs the query repeatedly and takes the fastest time. This is far too cache-friendly. In this example, the intermediate stages of the query or even the result are probably just sitting in memory on the nodes after the first couple runs.

If you want to measure the performance of a data warehouse, you need to use more complex queries and not run the *exact same* query repeatedly.

edit: Coincidentally, I am giving a talk about data warehouse benchmarking TONIGHT in NYC. If you're in NY and interested in this subject, please come! https://www.meetup.com/mysqlnyc/

marklit 2 hours ago [-]

The benchmarks are aimed at OLAP not OLTP workloads.

If I had a large query set to run on each vendor I'd be more likely to hit compatibility issues which could mean fewer benchmarks going out. As it is I spend a lot of time getting hardware and software vendors together for these benchmarks.

If caches were being hit I'd expect a lot more DBs hitting single millisecond times in my benchmarks but as far as I can see, there is a clear delta between the various setups I've tested:

http://tech.marksblogg.com/benchmarks.html

What really matters: ease of use









Applications

Asana Bing Ads

Braintree Payments

Desk.com

DoubleClick

Dynamics (365, GP, AX)

Eloqua

Facebook Ad Insights

Freshdesk

FrontApp

Github

Google Adwords

Google Analytics Google Analytics 360

Google Play Help Scout

HubSpot

Hybris

Instagram

Intercom iTunes

Jira

Magento

MailChimp

Mandrill Marketo

Mixpanel

NetSuite SuiteAnalytics

Stripe

Zendesk Chat (Zopim)

Xero Zendesk

7uora

Pardot

QuickBooks Online

Recurly Sailthru

Salesforce Salesforce Q

SAP Business One

Shopify



Databases



Files

Amazon Aurora

Amazon RDS

Azure SQL Database

DynamoDB

Google Cloud SQL

Heroku

MariaDB MongoDB

MySQL

Oracle DB

PostgreSQL

SQL Server

Amazon Cloudfront

Amazon Kinesis Firehose

Amazon S3

Azure Blob Storage

CSV

Dropbox

FTP

FTPS

Google Cloud Storage

Google Sheets

JSON

SFTP



Events

Segment Snowplow Webhooks

