

Get
Your
Guide

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June 12th 2017 - Berlin Buzzwords

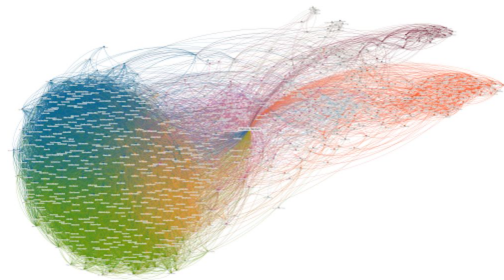
365 days of



BERLIN
BUZZWORDS
2017 JUNE 11-13

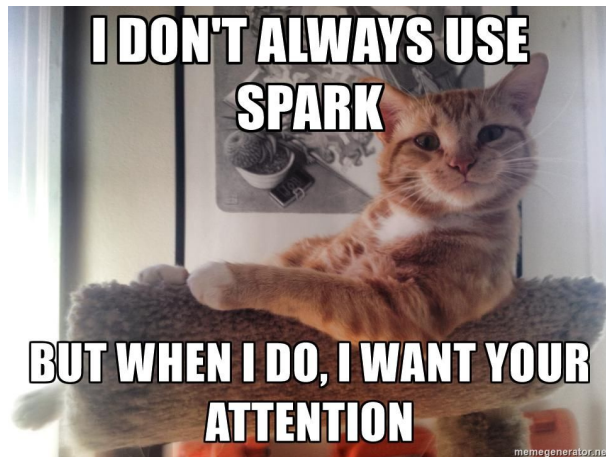
About me

- ❑ Data scientist and data engineer, all data matters!
- ❑ Paris → San Francisco → Berlin
- ❑ Led data products team at LinkedIn
- ❑ Co-founder of Gephi open-source software
- ❑ Head of Data at GetYourGuide



About this mission

- ❑ GetYourGuide is the leading global marketplace for tours and activities
 - ❑ Scale-up of 350+ employees, based in Berlin
- ❑ Types of datasets
 - ❑ User behavior (e.g. events)
 - ❑ Transactional data (e.g. bookings, payments)
 - ❑ Performance marketing (e.g. keywords, impressions)
 - ❑ Images, reviews, geolocations etc.
- ❑ Started at GetYourGuide in Feb 2016
 - ❑ Data mostly organized around single Data Warehouse
 - ❑ Your mission: Build a new data platform
 - ❑ Mission accepted! *Can I use Spark?*





A unified data platform

The end of the continental divide

Two fundamental goals



Data → decisions

- ❑ Metrics, reports and dashboards
- ❑ Deep-dive insights (exploratory)
- ❑ Data visualization



Building data products

- ❑ Algorithms and Machine Learning
- ❑ Many different sources and formats
- ❑ Fully automated and reliable

Also those goals...

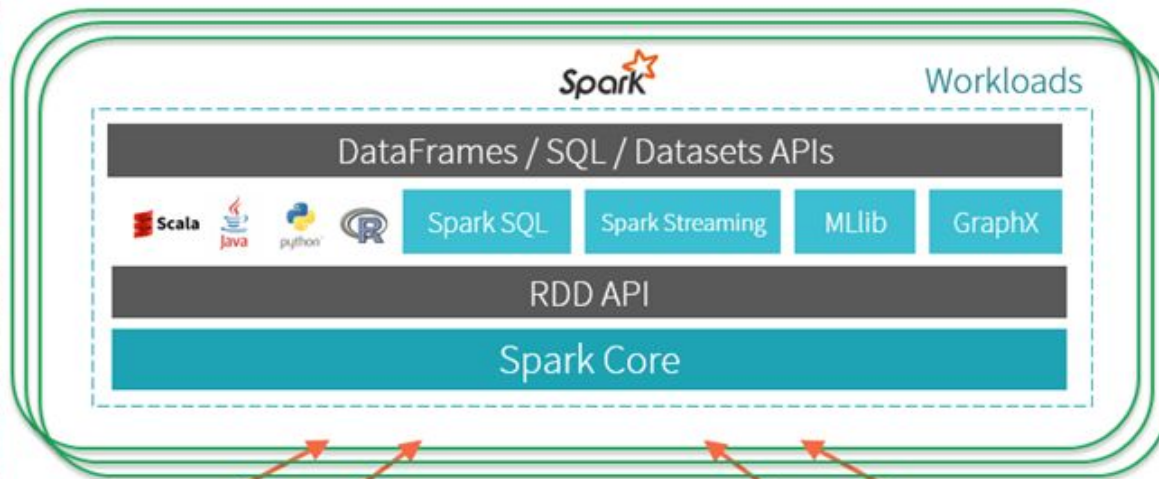
- ❑ Keep architecture future-proof
- ❑ Scale gracefully to large datasets and more complex use-cases
- ❑ Fast to setup (we're a startup!)
- ❑ Build infrastructure incrementally, while still delivering



We're aligned!

Goal: unified engine across data **sources**,
workloads and **environments**

Environments



Data Sources

Pick the right tool for the job

What do others say?

Spark



	Apache Hive	Apache Impala (incubating)	Apache Spark SQL
Audience	ETL Developers	Business Analysts	Data Engineers & Data Scientists
Strengths	<ul style="list-style-type: none"> Built for very long-running ETL, data preparation, or batch processing Supports custom file formats Handles massive ETL sorts with joins 	<ul style="list-style-type: none"> Scales to high-concurrency Supports high-performance interactive SQL Compatible with BI tools & skills Hadoop integration & usability 	<ul style="list-style-type: none"> Easily embed SQL into Java, Scala, or Python applications Simple language for common operations Seamlessly mix SQL and Spark code within a single application
New Features	<ul style="list-style-type: none"> Hive in the cloud (S3) Hive-on-Spark beta Governance & Lineage 	<ul style="list-style-type: none"> Nested data types Column-level security Integration with Kudu (beta) 	<ul style="list-style-type: none"> Support for Spark SQL & DataFrames Hive integration Automatic performance optimizations

Audience

Pick the right tool for the job



Data Scientist



Data Analyst



Data Engineer



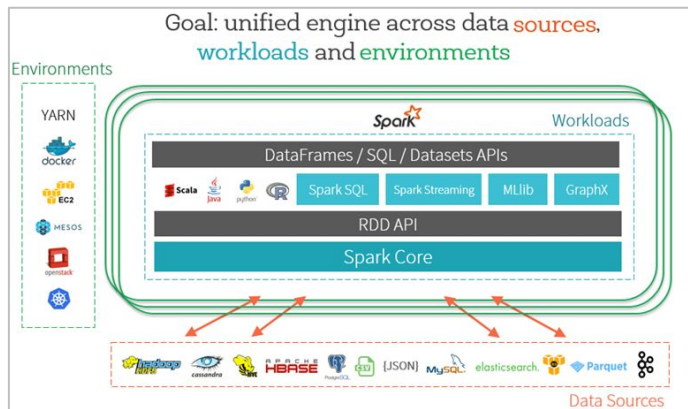
I WANT IT
ALL
AND
I WANT IT
NOW

The 3 reasons why it works

- ❑ Interactive querying
 - ❑ SQL (Ansi SQL)
 - ❑ Small task ~= Small runtime
 - ❑ Progress vs Spinner

- ❑ Standardized, rich API
 - ❑ From prototype to production
 - ❑ Standard machine learning library (distributed)

- ❑ Easy integration
 - ❑ Interoperability with other tools
 - ❑ Data sources and connectors
 - ❑ Streaming capabilities

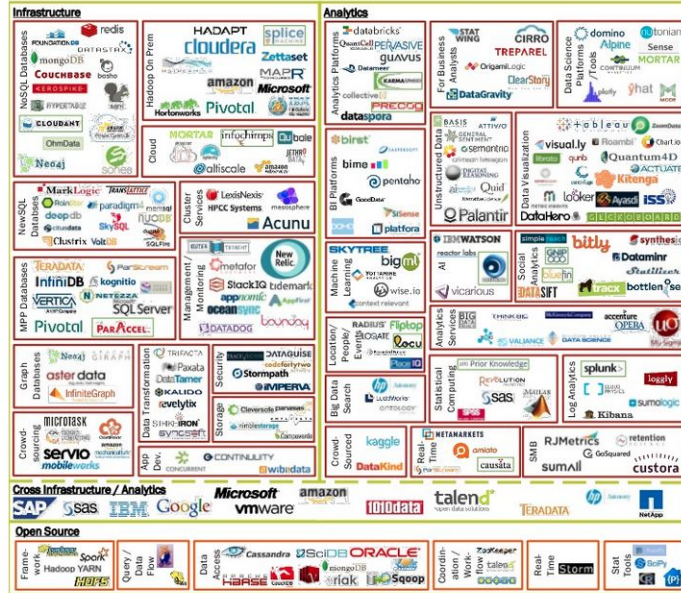


A nimble data platform

Simplicity and flexibility

When I think about big data platforms...

BIG DATA LANDSCAPE, VERSION 3.0



What I really want



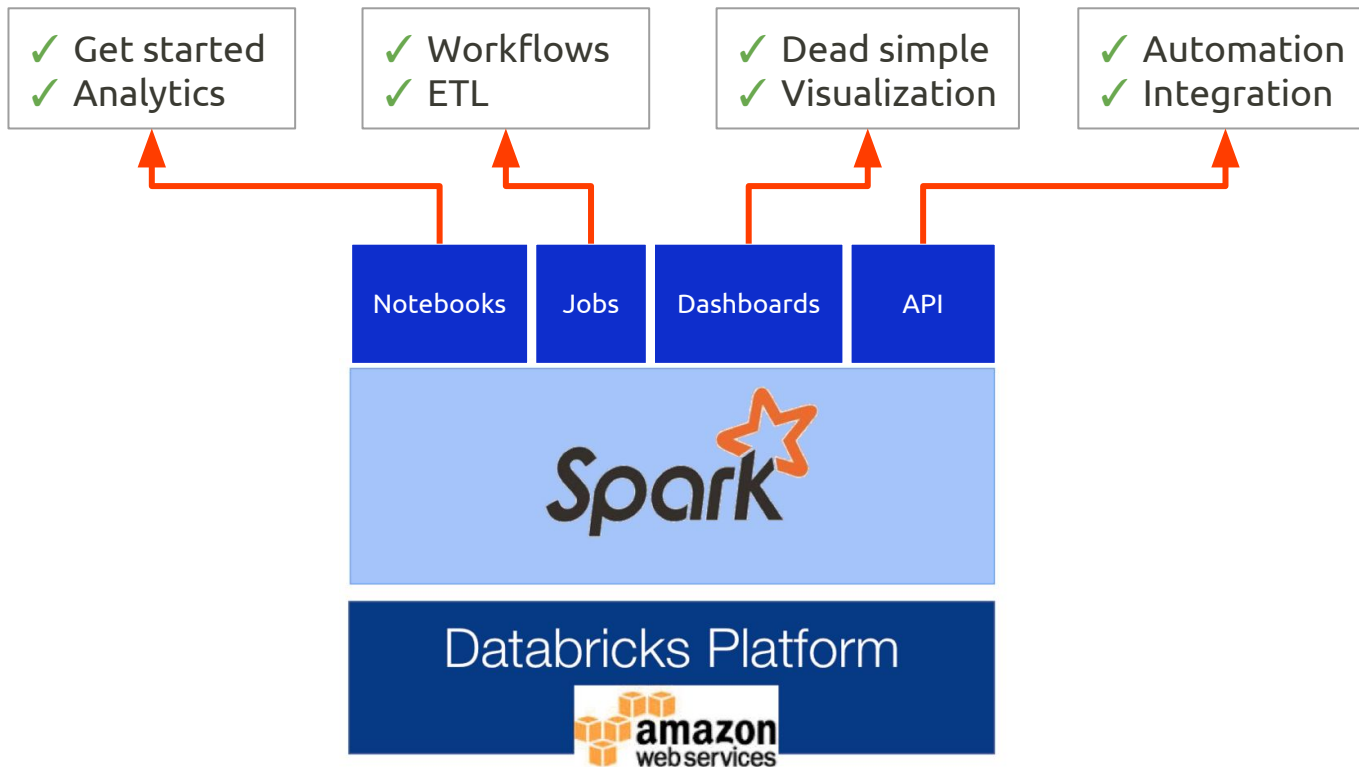
New data platform

- ❑ MVP mindset
 - ❑ Easy and quick to setup
 - ❑ Iterative improvements
- ❑ Databricks in the cloud
 - ❑ Cloud provider for Apache Spark
 - ❑ Founded by creators of Spark
 - ❑ Sits on top of AWS
 - ❑ Multiple clusters management

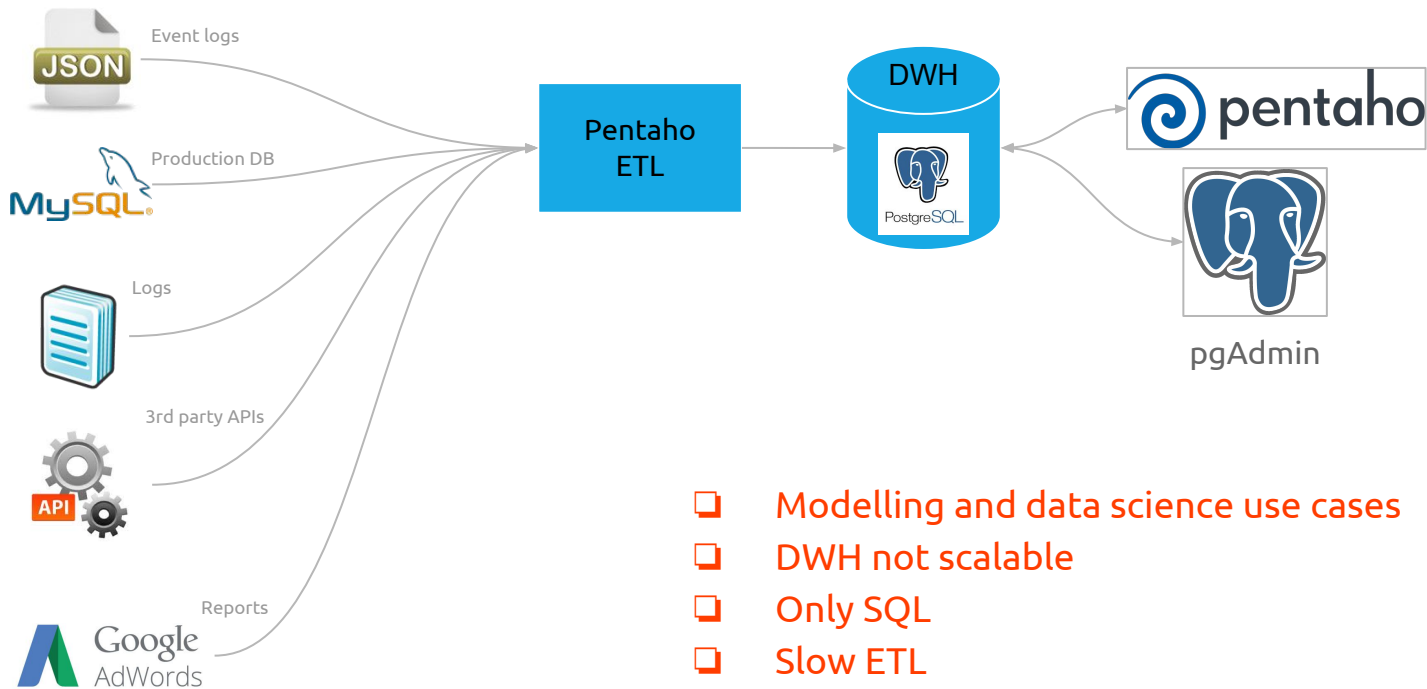
databricks™



Databricks

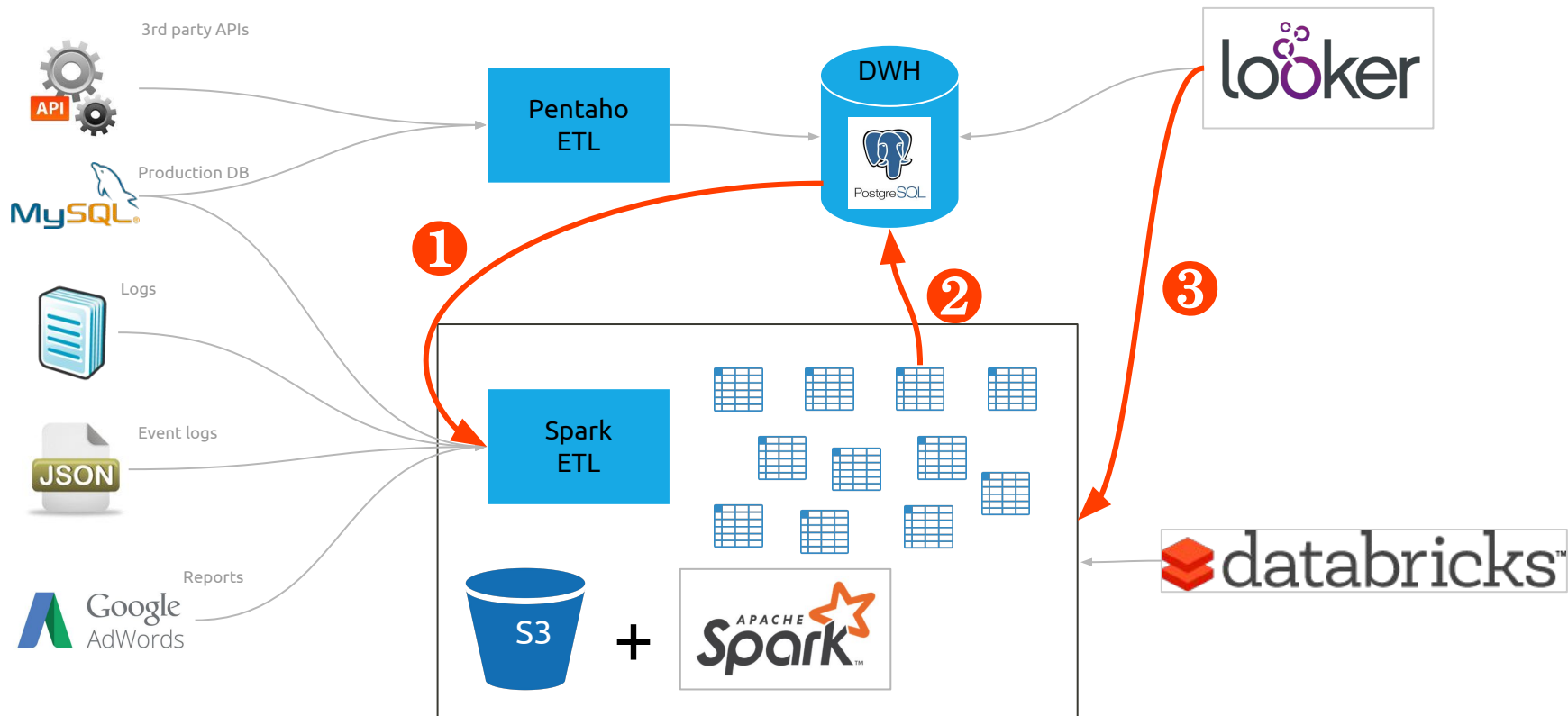


A while ago...



- ❑ Modelling and data science use cases
- ❑ DWH not scalable
- ❑ Only SQL
- ❑ Slow ETL

From good to great!



365 days of Spark use-cases

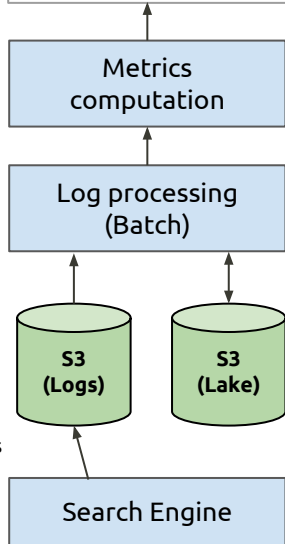
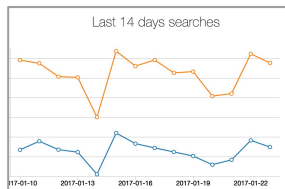
Search
Dashboarding

Performance
Management

Offloading
Aggregations

365 days of Spark use-cases

Search Dashboarding



15M impressions per day

365 days of Spark use-cases

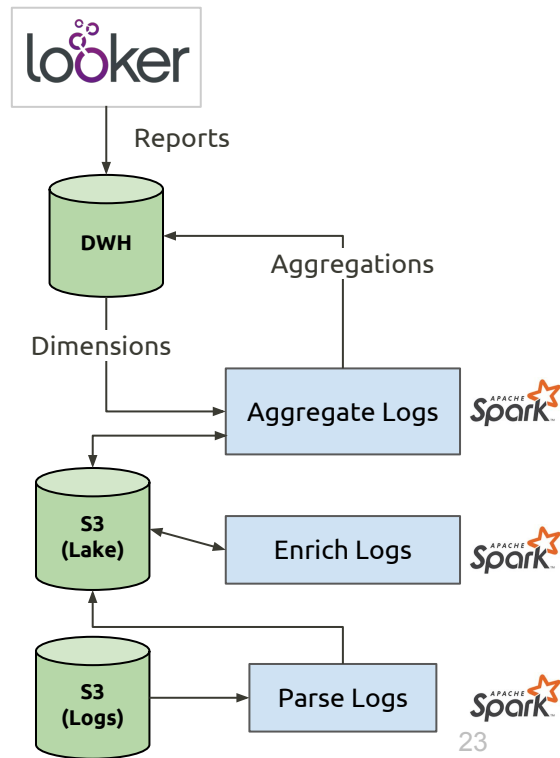
Performance Management

	Legacy	Now
Setup	On-premise server	Spark 2.1
Frequency	Once a week	Twice a day
Data size	1x	100x
Storage	PostgreSQL	Parquet



365 days of Spark use-cases

Offloading Aggregations



The storage question


- ❑ Anticipated growth pains with storage
 - ❑ Cost out of control
 - ❑ Lack of structure in formats and schemas (e.g. CSVs)
 - ❑ Redundant data for each use-case
 - ❑ Impact on Spark performance

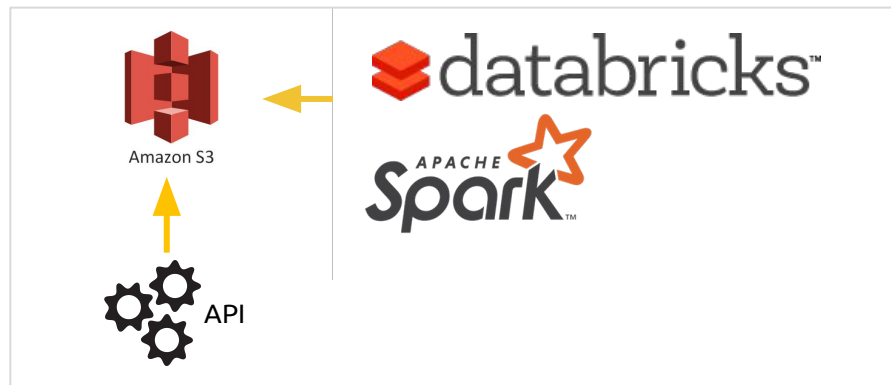


Data Lake!

- ❑ Data Lake philosophy
 - ❑ Save raw data now to analyze later
 - ❑ Centralisation brings efficiency
 - ❑ Access for everyone

❑ Spark ↔ Data Lake

- ❑ Parquet format 
 - ❑ Performance + Long-term storage
 - ❑ Interoperability (future proof)
- ❑ Tables === Files



Avoid data clutter

- ❑ Schemas!
- ❑ Data classification
- ❑ Discovery and search

Catalog &
Metadata

Flexible
Access

Security &
compliance



Parquet

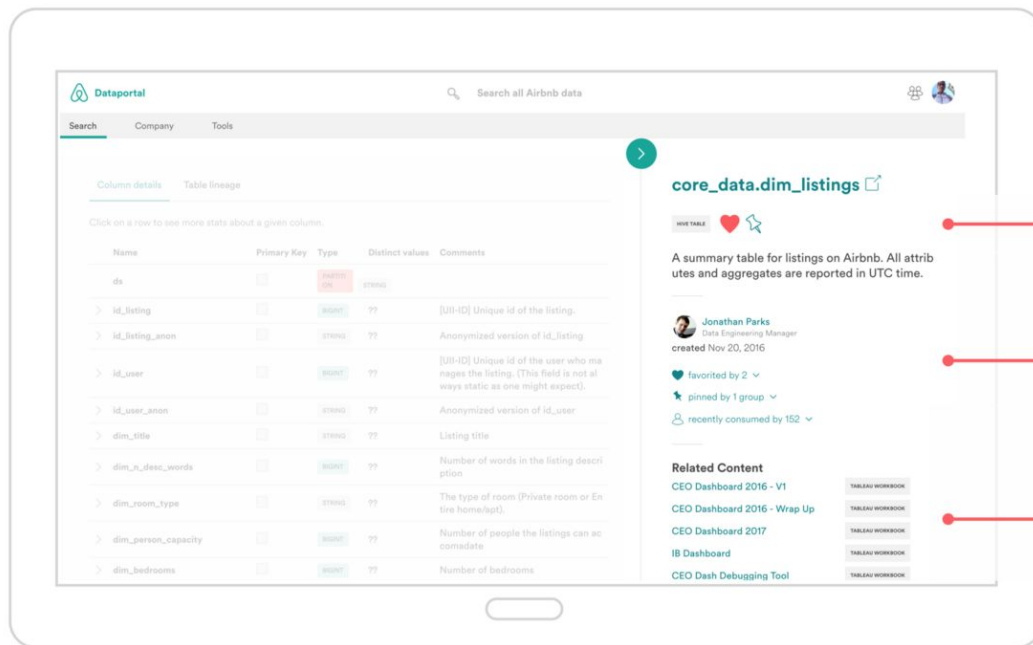
Storage



VS



Data discovery



Description, external link, social

Metadata & consumption

Surface relationships, everything's a link to promote exploration

AirBnB's dataportal

Future proof platform

“ Premature optimization is the root of all evil ” - *Donald Knuth*



☐ Solutions

- ☐ Rely on a unique open-source, standard technology
- ☐ Spark API, interoperable formats

Onboarding strategy

Let's talk about people!

What are our goals again?

❑ Goals

- ❑ People are **empowered** to make data-driven decisions
- ❑ People can find **clean data** to work with
- ❑ People can **innovate** rapidly in building data products

❑ Challenges

- ❑ Friction in accessing and analyzing data
- ❑ Eliminate the crutch, be truly self-service
- ❑ The vast majority of data users unfamiliar with Spark
- ❑ Anticipate data science needs



Lessons learnt



- ❑ Bring data
 - ❑ Data Warehouse tables early
 - ❑ Make it super easy and fast to add new tables (and avoid tickets)
- ❑ Early conventions
 - ❑ Parquet
 - ❑ Path structure
- ❑ Training and examples
 - ❑ Educational Scala notebooks

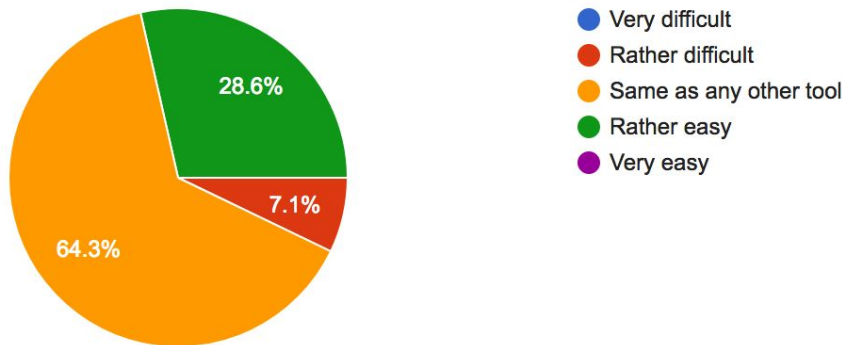


- ❑ Data source changes
 - ❑ Events restructure
 - ❑ Long-term history needed for analysis and insights
- ❑ Data quality
 - ❑ Trust is hard
 - ❑ Numbers won't match
- ❑ Mixing Python and Scala
 - ❑ Code duplication and libraries

Learning

Compared to other data tools you have worked with before, how difficult is it to learn Spark?

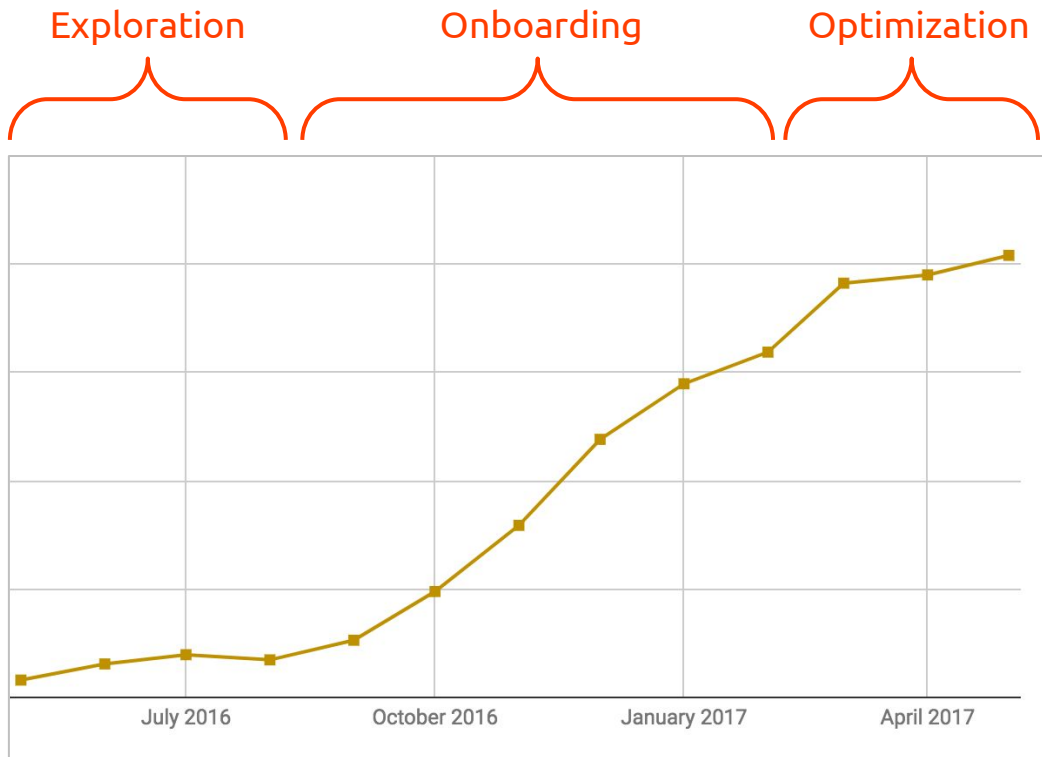
14 responses



The hard work

Post onboarding

Post onboarding



Monthly Spark Usage

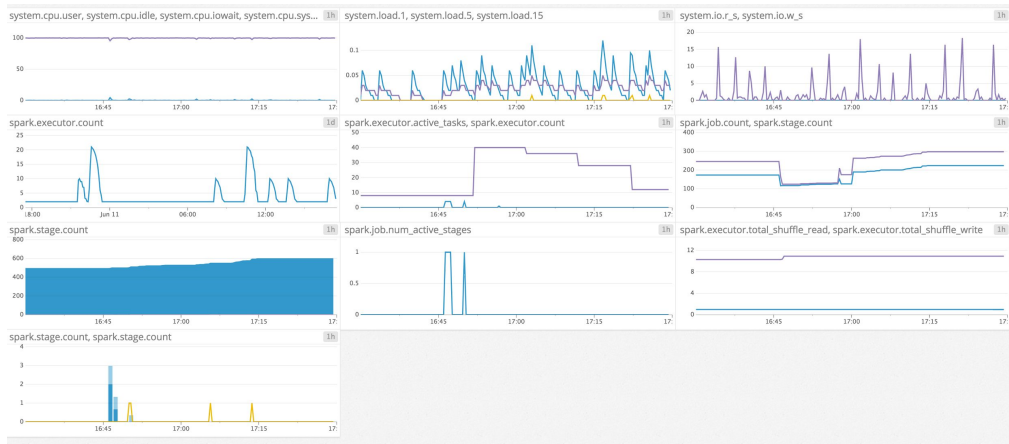
The main challenges we faced

- ❑ Getting real with cluster administration
- ❑ Deeper understanding of performance factors
- ❑ Understanding root causes
- ❑ Organizing data dependencies
- ❑ Ensuring data quality and standardization



Cluster administration

- ❑ Common issues
 - ❑ Driver crashing
 - ❑ Lost executors
- ❑ Built connector to DataDog
 - ❑ Hard to estimate capacity
 - ❑ Navigate into confusing metrics
- ❑ Cluster start/stop
 - ❑ Autoscaling



DataDog metrics cluster monitoring

Debugging inquiries

- ❑ Logs are hard to read/process
- ❑ SparkUI is useless for the most part
- ❑ Can't easily detect problems (e.g. memory problems)

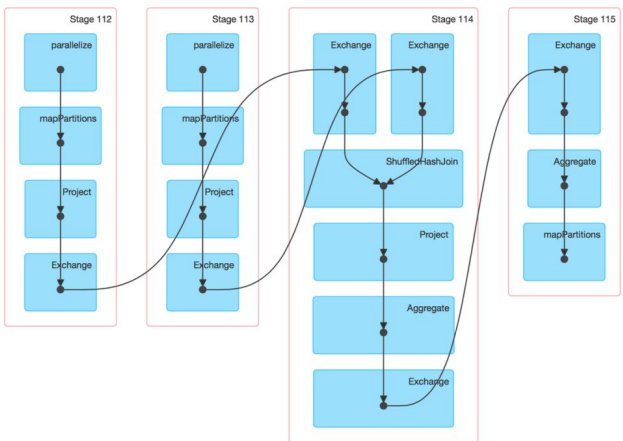
Details for Job 8

Status: SUCCEEDED

Completed Stages: 4

▶ Event Timeline

▼ DAG Visualization



Spark Stages

Total Duration: 1.5 m

Scheduling Mode: FIFO

Active Stages: 2

Completed Stages: 3

Failed Stages: 0

Active Stages (2)

Stage Id	Description	Submitted	Duration	Tasks: Succeeded/Total	Shuffle Read	Shuffle Write
3	flatMap at ALS.scala:326	2014/02/19 05:39:31	17.0 s	97/120		2.3 GB
6	map at ALS.scala:147	2014/02/19 05:39:30	18.0 s	77/183		33.7 MB

Completed Stages (3)

Stage Id	Description	Submitted	Duration	Tasks: Succeeded/Total	Shuffle Read	Shuffle Write
5	mapPartitionsWithIndex at ALS.scala:164	2014/02/19 05:39:30	1.0 s	120/120		662.9 MB
0	reduceByKeyLocally at ALS.scala:217	2014/02/19 05:39:20	10.0 s	120/120	63.2 MB	
1	map at ALS.scala:146	2014/02/19 05:38:50	29.5 s	183/183		79.0 MB

Failed Stages (0)

Stage Id	Description	Submitted	Duration	Tasks: Succeeded/Total	Shuffle Read	Shuffle Write
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Log processing on Spark

Legacy solution based on Pentaho Data Integration

Configuration vs Code

Scalability challenges

Migrate to Spark

Data quality challenges



Log parsing workflow in Pentaho

Log processing on Spark

- ❑ Scala library
 - ❑ Unit and integration testing
 - ❑ Easier to benchmark
- ❑ Validation, testing and errors
 - ❑ Incremental severity (warning, errors)
 - ❑ Edge cases
 - ❑ Track errors

client_ip	String	length<=50 255.255.255.255 (15 characters) ip6 2001:0db8:85a3:0000:0000:8a2e:0370:7334 (39 characters)	N	ERR	<field> is null or out of range
country_iso_code	String	length=2	Y	WAR	<field> is null or out of range
currency	String	length=3	Y	WAR	<field> is null or out of range
date_time	Timestamp	YYYY-MM-DDTHH24:MI:SS	N	ERR	<field> is null or out of range
partner_id	String	length<=32	Y	ERR	<field> is out of range
partner_src	Integer	IN (1,2,3,4,5,6)	Y	ERR	<field> is out of range
partner_cmp	String	length<=100	Y	ERR	<field> is out of range
platform	String	IN ('mobile','desktop') OR NULL	Y	ERR	<field> is out of range
request_url	String		N	ERR	<field> is null
referrer_url	String		Y	NONE	

error

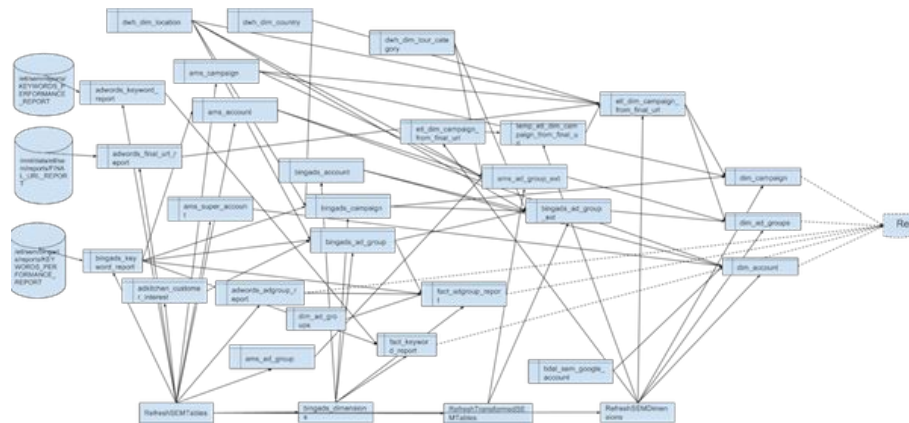
```

[{"column_name":"country_iso_code","error_type":"warning","error_message":"is_null"},{"column_name":"currency","error_type":"warning","error_message":"is_null"}]
[{"column_name":"country_iso_code","error_type":"warning","error_message":"is_null"},{"column_name":"currency","error_type":"warning","error_message":"is_null"},
{"column_name":"session_id","error_type":"error","error_message":"is_null"},{"column_name":"visitor_id","error_type":"error","error_message":"is_null"},
{"column_name":"locale_code","error_type":"warning","error_message":"is_null"}]

```

Workflow orchestration

- ❑ Data lineage
 - ❑ Recovery and SLAs
 - ❑ Data dependencies
- ❑ From 10 to 100 jobs
 - ❑ Self-service, undeclared consumers
 - ❑ Documentation and onboarding
 - ❑ Cluster utilization

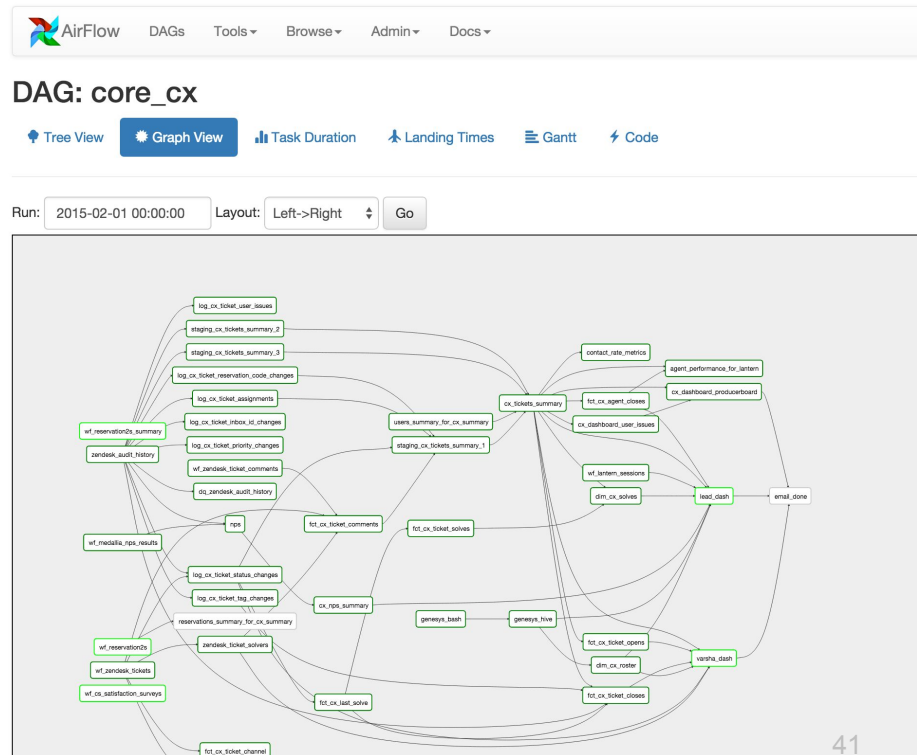


Workflow orchestration



Apache Airflow

- ❑ Map out data dependencies
- ❑ Flexible configuration
- ❑ Backfilling and data management
- ❑ Operators
 - ❑ Databricks
 - ❑ PostgreSQL
 - ❑ ...



Notebooks

The  and 

Notebooks

The screenshot shows a Databricks notebook titled "Sales Table Analysis (Scala)". The interface includes a sidebar with navigation options like "databricks", "Home", "Workspace", "Recent", "Tables", "Clusters", "Jobs", "Apps", and "Search".

The main content area displays a SQL query: `> %sql select * from sales_long`. Below the query, there are two Spark Jobs: Job 1306 and Job 1307. Job 1307 is expanded to show three stages: Stage 1965 (2/2, 0 running), Stage 1966 (48/200, 4 running), and Stage 1967 (0/1, 0 running).

Below the job progress, a bar chart titled "sales" is displayed. The y-axis represents sales from 0 to 60,000,000. The x-axis shows four categories: BRA, FRA, RUS state, and USA. The legend indicates three product types: MacBook (dark blue), Power Adapter (orange), and iPhone (teal).

On the right side of the notebook, there is a chat window with two messages:

- Chaoyu Yang: "Can you break down the revenue by type and country?"
- David: "Sure. Here you go."

Red circles highlight the SQL query input area, the job progress section, and the chart's plot options menu.

Contained collection of queries or code snippets



Data presentation and visualization



Tables



Visualization

The obvious advantages

- ❑ **Iterative development**
Chances you'll get your code or query right at the first try is close from zero
- ❑ **Exploratory data analysis**
Use simple visualizations (e.g. histogram, line chart) to ask questions to the data
- ❑ **Visible and collaborative**
Code and analysis aren't buried into Git repositories but easy to discover and review
- ❑ **Easy to get started and learn**
Online, safe environment to get started with Spark concepts and syntax
- ❑ **Also open-source**
Apache Zeppelin also easy to get started with



But you can also do...

- ❑ Run a notebook with parameters as part of a workflow

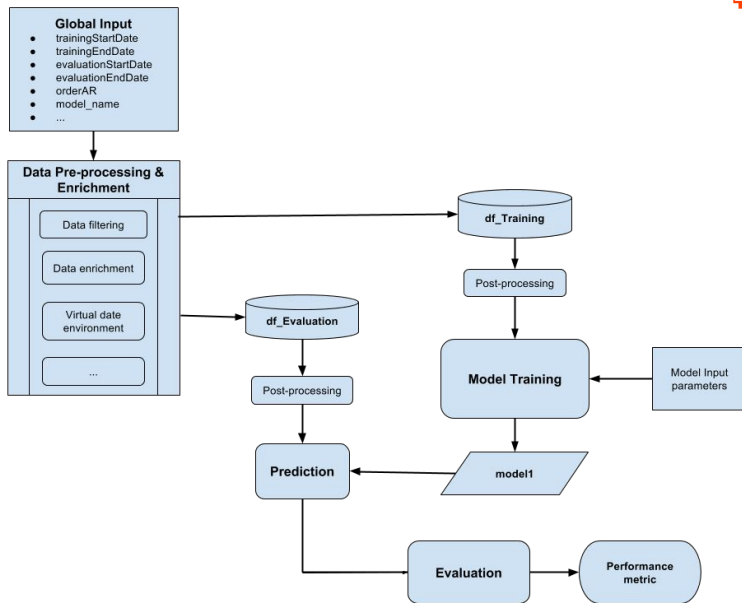
```
> var returnvalue = dbutils.notebook.run("./notebook2", 60, Map("data" -> "records"));
```

Notebook job #6120

- ❑ Run notebooks as part of other notebooks
- ❑ Develop utilities and libraries in notebooks
- ❑ Synchronize your notebook on Git repositories
- ❑ Use Databricks' notebook API
- ❑ Send execution logs to Sentry and by Email
- ❑ Use multithreading to run notebooks in parallel



Production workflows the right way



- ❑ Notebooks are too limited to scale production workflows
- ❑ Ability to design unit and integration tests
- ❑ Proper revision history and code review
- ❑ Global configuration
- ❑ Separate development from production environment
- ❑ Multi-module projects with dependencies
- ❑ Complete control on error handling and logging

Looking back...

Never been this easy to build large-scale production workflows!

❑ Compared to Hadoop

- ❑ Large overhead and complexities in testing locally
- ❑ No proper investment in unit-testing (MRUnit)
- ❑ Mix multiple languages (not only Java)



❑ Compared to Pig

- ❑ Built around simplistic data structures (Text vs Avro)
- ❑ Cumbersome mocking and testing



Wrapping-up

Thank you for your attention!

Get
Your
Guide

mbastian@getyourguide.com



We're hiring!

<https://careers.getyourguide.com/>