DigitalOcean

akass@ + dmi@

Building a Robust Analytics Platform

with an open-source stack

What's coming up:

1) DigitalOcean - a company background
2) Data @ DigitalOcean
3) The Big Data Tech Stack @ DO
4) Use-cases + Demo

What is DigitalOcean?

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- *700K Developer Users*
- ***30K Developer Teams***

Data @ DO - Participating Teams

- Data & Analytics ("DnA" - Analysts + Data Scientists/Engineering)
  - ***(Alex & Dao live here)***
- Platform/Infrastructure Engineering
- Product Engineering
- Security

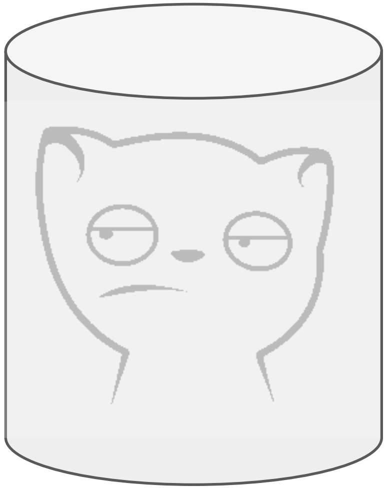
Data @ DO

- **Product Usage**

Data @ DO - **Product Usage**

- *Product Revenue Forecasting*
- *Churn Prediction*
- *User Segmentation*
- *Beta product uses and product cannibalization*
- *Support Team Efficacy*

Data @ DO - **Product Usage, v1.0**



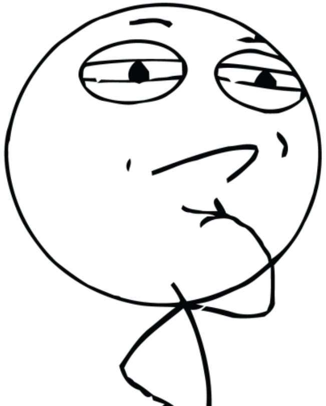
Pain Point 1: General Data Architecture

Huge, unwieldy SQL Tables → Slooooow, monolithic, unadaptive

Pain Point 2: Upstream Dependencies

E.g. Monthly Invoicing → Revenue analytics done on monthly basis

Data @ DO - **Product Usage, v2.0**



Revision 1: General Data Architecture

Microservices + Kafka pass application-level events →
Faster and more robust, but ***teams must build their own consumers***.

Revision 2: Active Downstream Consumption

E.g. Granular Billable Events → Daily, hourly, even near-RT processing of revenue for ingestion into analysis

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Data @ DO

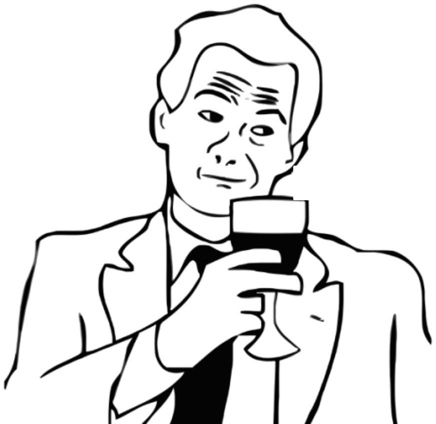
- Product Usage
- **Sales/Marketing Leads**

Data @ DO - **Sales/Marketing Leads**

Problem:

- *User behavioral data lives in AWS Redshift*

- *User metadata lives in MySQL on DO's cloud*



Data @ DO - **Sales/Marketing Leads**

Problem:

- *User behavioral data lives in AWS Redshift*
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Solution:

- *Migrate warehousing to our own cloud so that all data stays on-premise*

Data @ DO

- Product Usage
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- **Infrastructure**

Data @ DO - **Infrastructure**

Problem - nay - <u>Conundrum</u>:

- *Every 5 minutes, our entire active VM fleet is polled for OS and HW data using Prometheus and other in-house scraping solutions*

VMs

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S.M.A.R.T.ctl

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Problem - nay - Conundrum:

- *Every 5 minutes, our entire active VM fleet is polled for OS and HW data using Prometheus and other in-house scraping solutions*
- ***Significant scale (too big for RDBMS), inherent silos***

Nodes

PDU

To recap:

- Product Data in MySQL is **slow** and **isolated**
- Sales/Marketing data are **isolated** in different warehouses
- Infra data are **prohibitively large** and **isolated**

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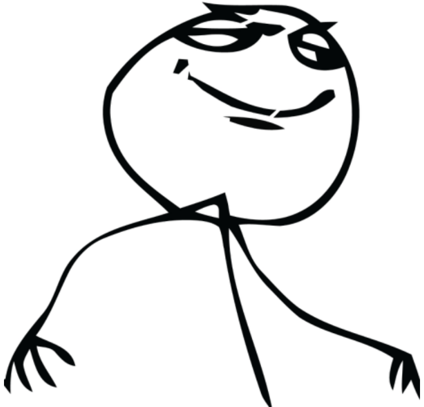

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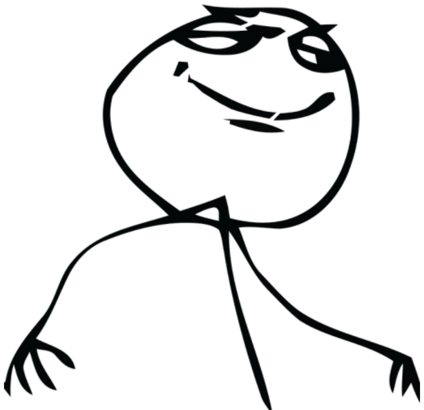

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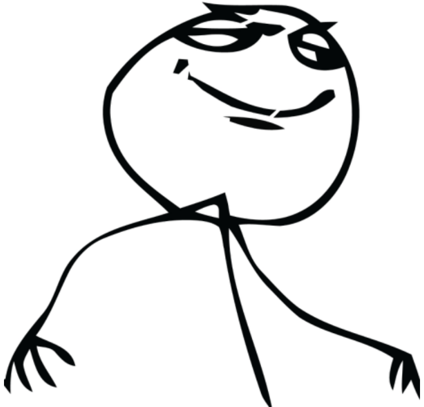

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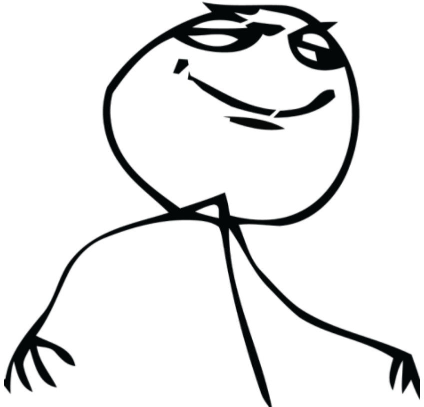

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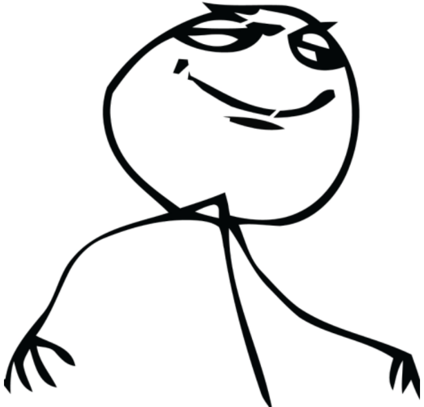

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The DO Big Data Stack

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MESOS

elasticsearch

jupyter

kafka

presto

Spark

The DO Big Data Stack

MESOS

1. **Distributed Systems Management**

The DO Big Data Stack

MESOS

1. Distributed Systems Management
2. **Parallel Compute**

Spark

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3. **Standardized Compute Environments**

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4. **Distributed Data Warehousing**

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5. **Distributed Streaming Events System**

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8. **Logging at Scale**

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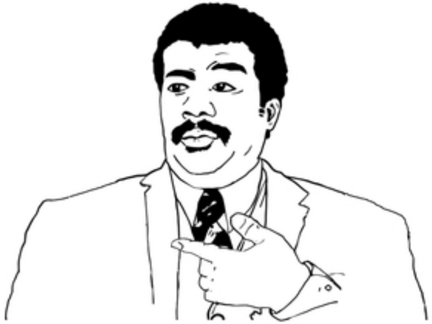

“Buzz.”

– Hive

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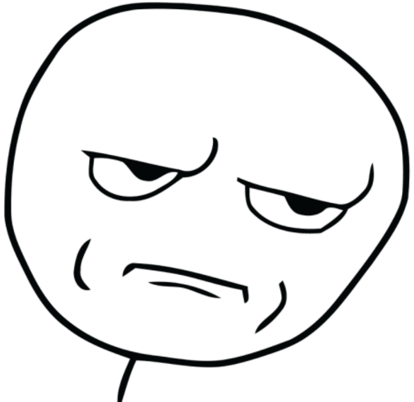

Use Case 1: A New ETL Pipeline for Support Ticket Events

Measuring Customer Satisfaction (CSAT)
Integration with Internal Ticketing
More transparency for Support Team

Use Case 1: A New ETL Pipeline for Support Ticket Events

Subscribe to new Kafka topic

```
akass@[redacted]$ python3 print_sample_event.py -t lifecycleevents
b'\n1\n$21c19a1f-3f3f-497c-a0d6-ba197c5bbfe6\x12\x06\x08\x8f\xa1\xaa\xc0\x05\x18\xfe\x01j\x
1e\x10\xe6\x88B\x18\xac\xaajR\x14\x10\xe6\x88B\x1a\x06\x08\xd1\xf3\xda\xba\x05"\x06\x08\x8f
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```

Use Case 1: A New ETL Pipeline for Support Ticket Events

Subscribe to new Kafka topic

Prototype reading of Kafka data within a Spark-enabled Jupyter Notebook

In [5]:
```
import lifecycle_events_pb2
from protobuf_to_dict import protobuf_to_dict

event = lifecycle_events_pb2.Event()
```

In [6]:
```
def decoder(s):
    """ Decode the object as bytes"""
    if s is None:
        return None
    return event.FromString(s)
```

Use Case 1: A New ETL Pipeline for Support Ticket Events

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Prototype reading of Kafka data within a Spark-enabled Jupyter Notebook

Update Spark Docker container to include new modules and configurations, if necessary

```
&& tar xf protobuf-$PROTOBUF_VERSION.tar.gz

COPY autogen.sh /protobuf-$PROTOBUF_VERSION/

RUN cd /protobuf-$PROTOBUF_VERSION && ./autogen.sh \
&& ./configure --prefix=/usr && make install \
&& cd / && rm /protobuf-$PROTOBUF_VERSION.tar.gz \
&& ./Anaconda3-$ANACONDA_VERSION-Linux-x86_64.sh -b -p /opt/anaconda3 \
&& rm Anaconda3-$ANACONDA_VERSION-Linux-x86_64.sh \
&& pip install protobuf==3.0.0 kafka-python protobuf3-to-dict
```

```
$ cat spark-defaults.conf | grep docker
spark.mesos.executor.docker.image
docker.internal.digitalocean.com/platform/spark:1929b8d
```

Use Case 1: A New ETL Pipeline for Support Ticket Events

- Subscribe to new Kafka topic
- Prototype reading of Kafka data within a Spark-enabled Jupyter Notebook
- Update Spark Docker container to include new modules and configurations, if necessary
- **Write Spark script & deploy onto Mesos**

Active Frameworks

Find...

ID ▼	Host	User	Name	Role	Principal	Active Tasks	CPUs	GPUs	Mem	Disk	Max Share
...975e-94a0cddebd60-1849	test-dna-kafka-lifecycle.nyc3.internal.digitalocean.com	root	product_lifecycle_etl	spark		1	8	0	4.4 GB	0 B	0.150%

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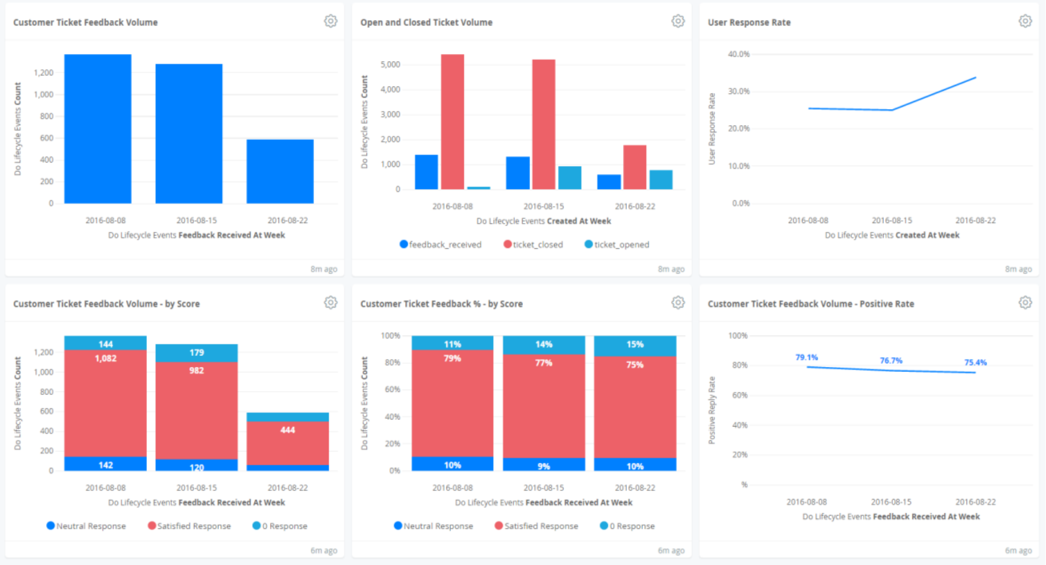

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Analyze!

Use Case 2: Billable Data, from Months to Minutes

Reminder:
Pain Point 2: Upstream Dependencies E.g. Monthly Invoicing → Revenue analytics done on monthly basis
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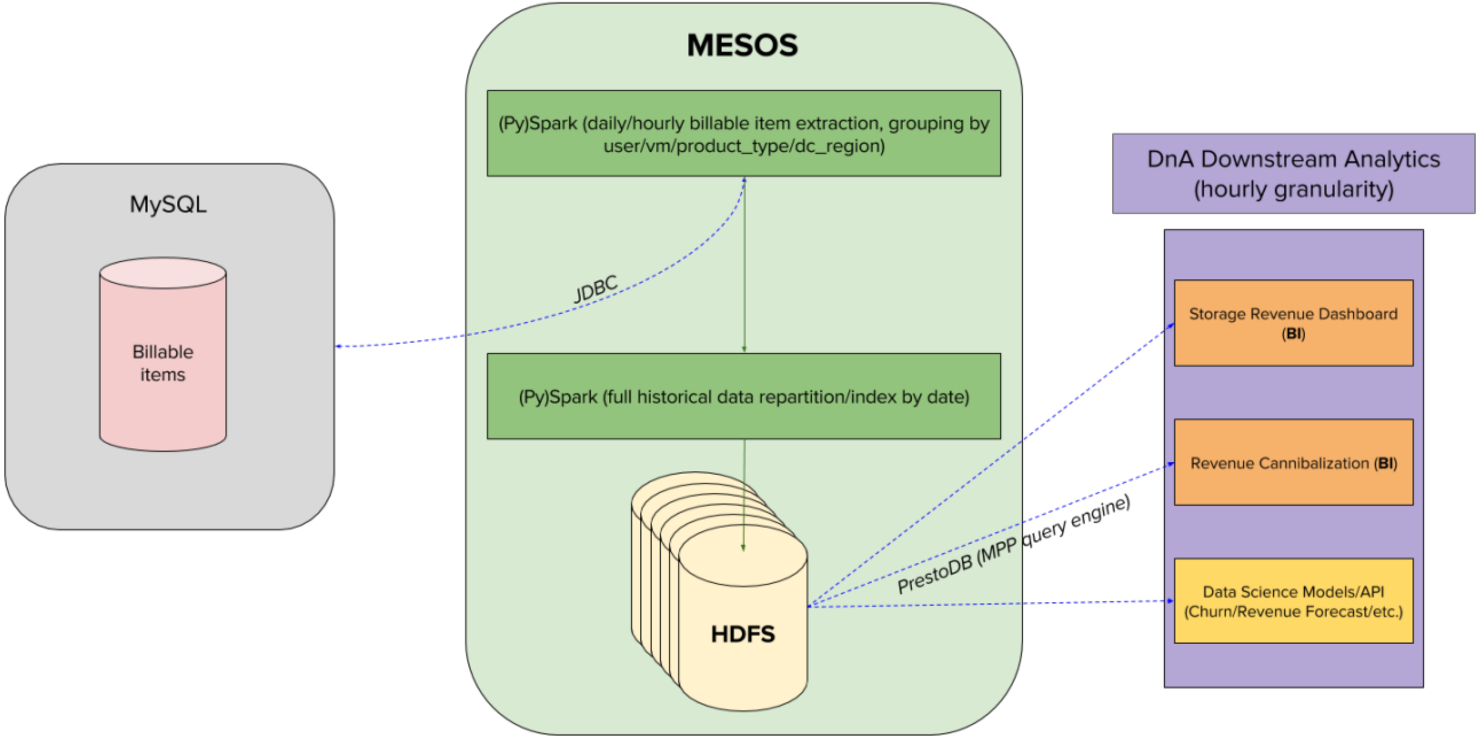

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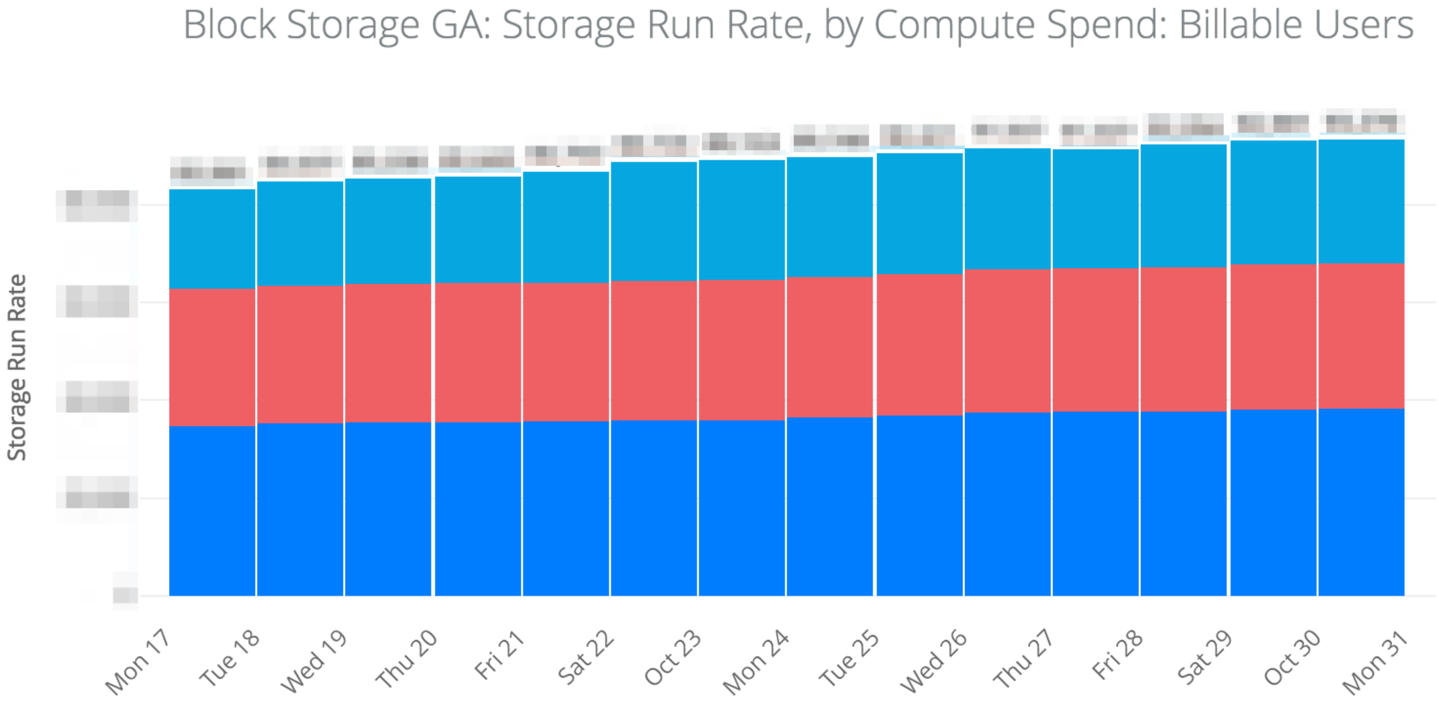

Use Case 3: Power Failure Detection + PDU Clustering

Real-World problem:

- **many** different drive models out in fleet…

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- **many** different drive models out in fleet…

- how to predict performance stability/failures with consistency?

Use Case 3: Power Failure Detection + PDU Clustering

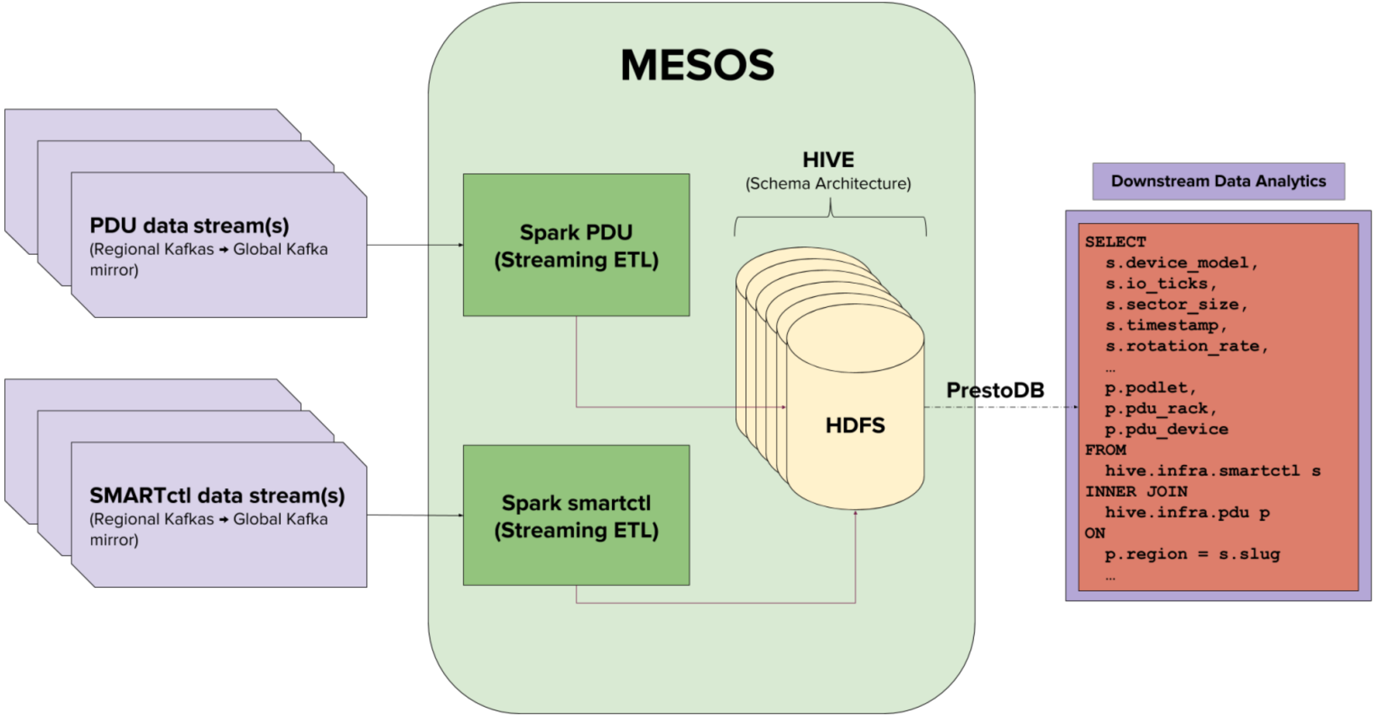
Solution:

1) Measure PDU patterns & fluctuations on a ***podlet/rack/device level***

2) Join to smartctl data to get vendor/drive-specific metadata

3) Mine for outliers to help DC teams react quicker to anomalies

Use Case 3: Power Failure Detection + PDU Clustering



Use Cases in Action:

Let’s have a DEMO...

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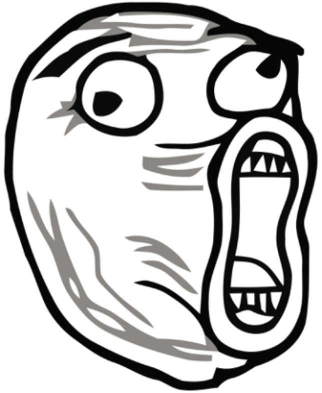

Lessons learned from work thus far...

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- Laying pipelines to connect Kafka to Spark to HDFS was challenging; **tuning** everything was often even harder!

Recapping…

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1) Consolidation/Centralization of data from across DO

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   Anyone can build reports/analyses

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4) Modern stack allows massive scale with small headcount

Gazing into the **Future**...

Future Work

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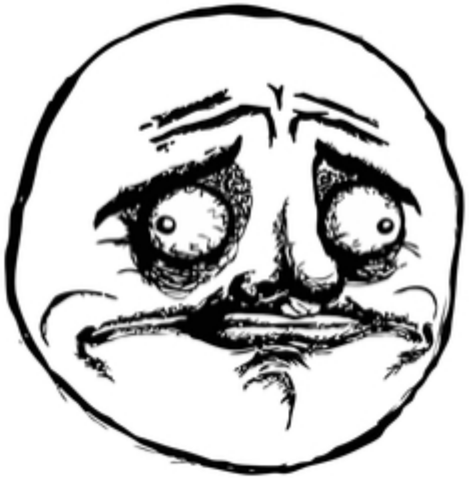
- Beta-test/prototype/dogfood future products.



Questions?

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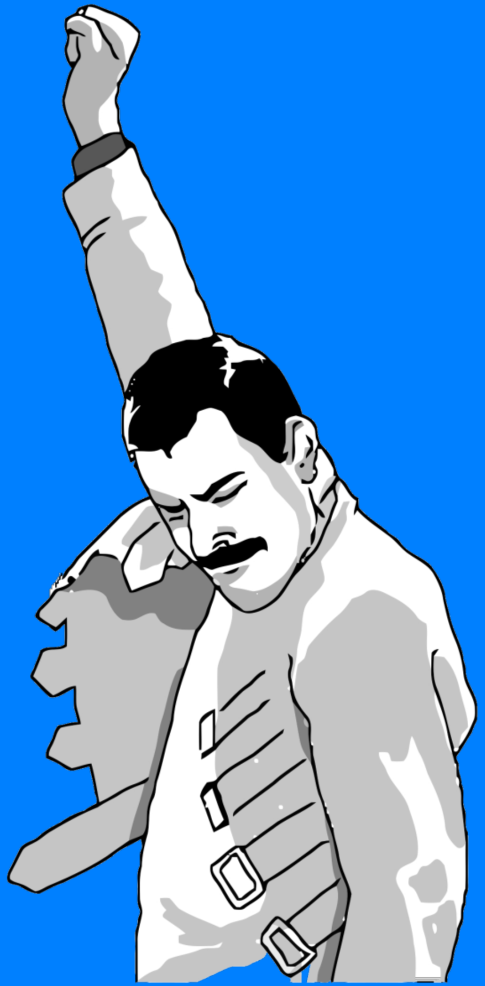

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