

# Think Big: Scale Your Business Rules Solutions Up to the World of Big Data

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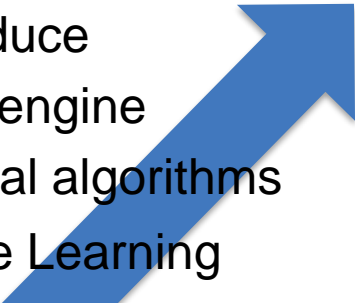
# Business Rules and Big Data

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- Where Business Rules fit in the World of Big Data & AI
- Think Big Use Case - Border Control
- Business Rules Blueprints
  - Landscape
  - in Hadoop MapReduce
  - in Apache Spark
- Rule coverage, Analytics and ML

# Big Data, Business Rules and ML

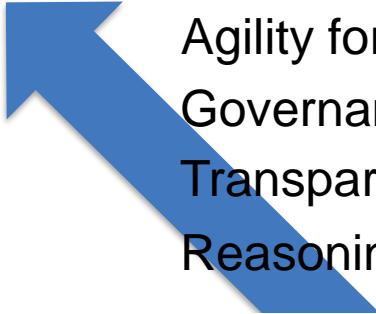
## Big Decision



Map/reduce  
Cluster engine  
Analytical algorithms  
Machine Learning

**Big data** is defined as extremely large data sets ... **analyzed computationally** to reveal patterns, trends, and associations, especially relating to human behavior.

*Google*



Agility for Business Users  
Governance  
Transparency  
Reasoning

A **BRMS** or Business Rule Management System is used to define, deploy, execute ... **decision logic**

*Wikipedia*

## Big Decision Use Cases at a glance

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- Automate massive decision making **batches**
- Running business policies **simulations** on large historical dataset
- **Detect situations** on data lakes
- **Invent** new algorithm combinations to solve new classes of enterprise problems at scale

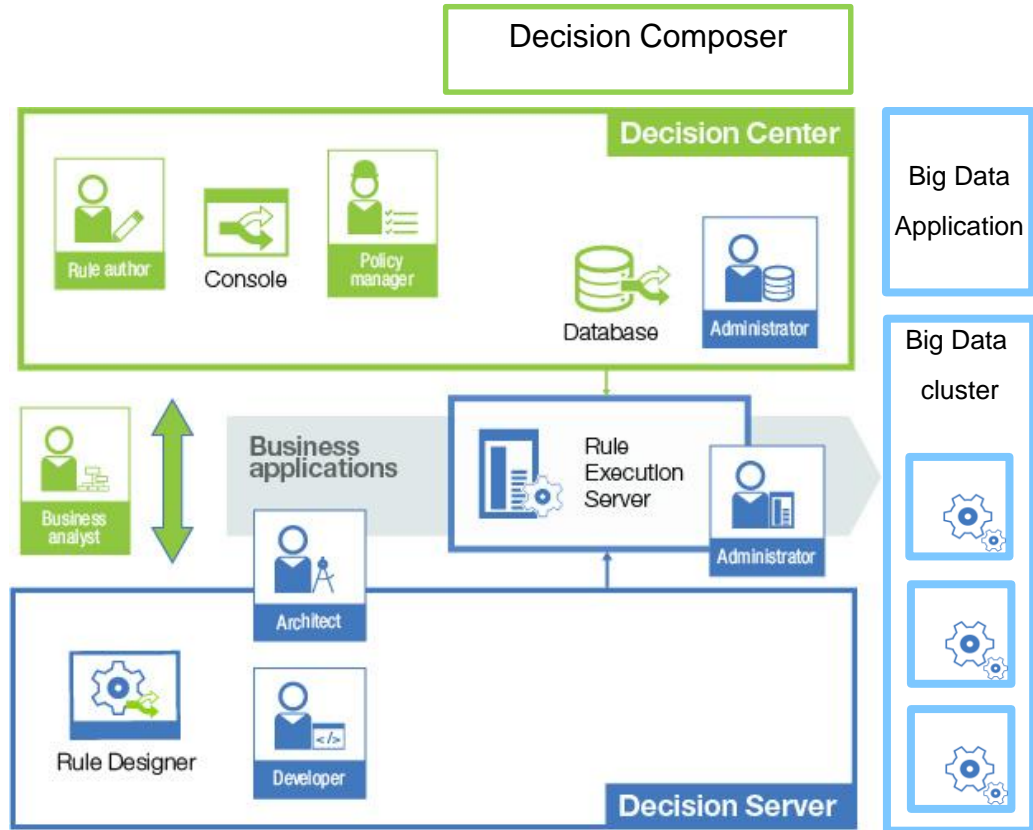
# Enterprise Use cases

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- A bank **simulates** new mortgage segmentation policies against ten million customers in under 3 minutes
- A credit/debit card tests new fraud **detection** rules on hundreds of millions of past transactions
- Recommend products based on regulations and client history
- A financial service company brings **together data science and operational decision teams** to build an end to end practice and platform
- A border control agency **simulates** and applies **profiling** rules on international travelers to detect terrorists

# Concept of Operations of ODM Rules in Big Data

- Rules are authored in Decision Composer, Decision Center or Rule Designer.
- Rules are versioned over HTTP(S) to a Rule Execution Server
- Big Data App fetches the latest deployed decision service
- At runtime the Big Data App applies the Decision Service against a large data set executing in parallel



# Business Rules and Big Data

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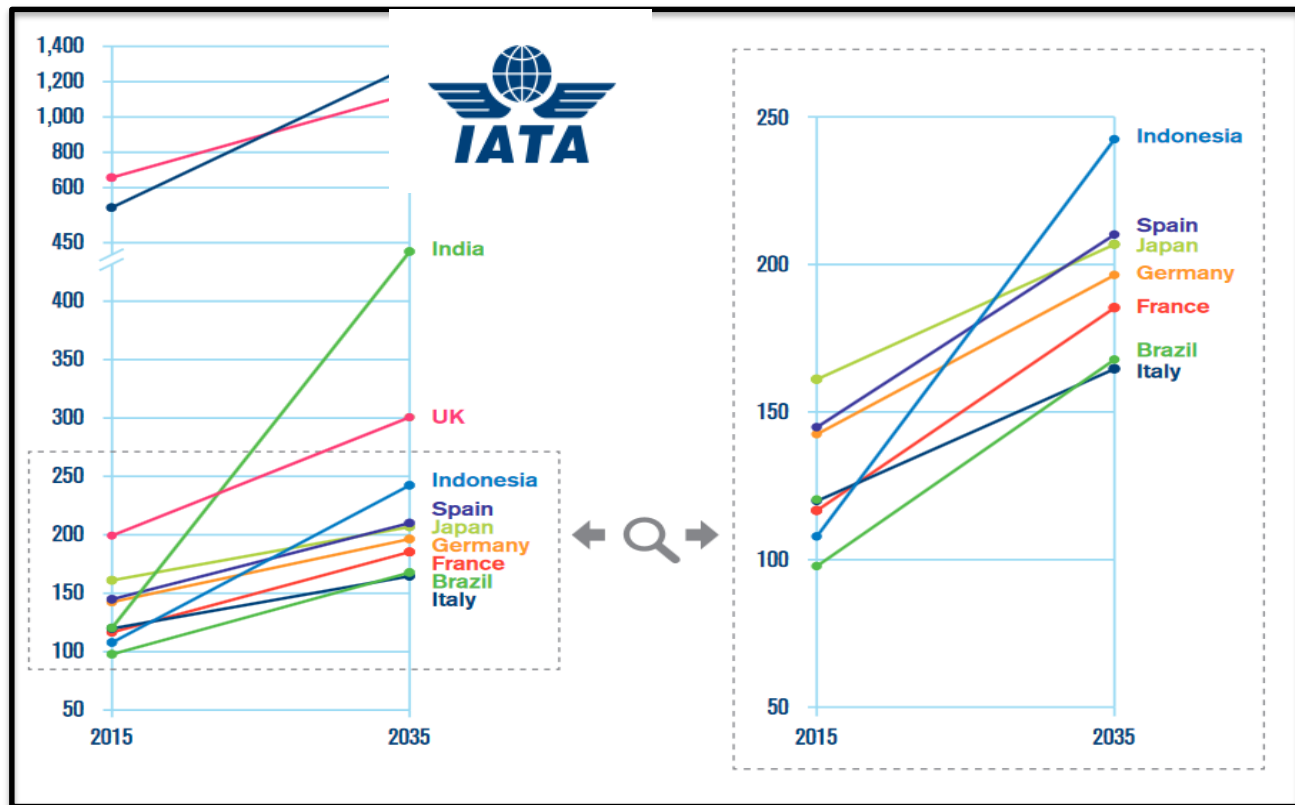
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# Think Big Use Case - Border Control

Passenger travel will double from 3.8 billion to 7.2 billion in 2035.  
20 Million per day.

Source: International Air Transport Association (IATA)

[IBM Case Study:](#)  
[The European Passenger Name Record Directive](#)  
[White Paper](#)





## Use Case - Border Control

By profiling passenger data, a tiny minority can be detected and prevented from flying

Passenger Profiling Existing World



National

< 1 M passengers per day

Passenger Profiling New World

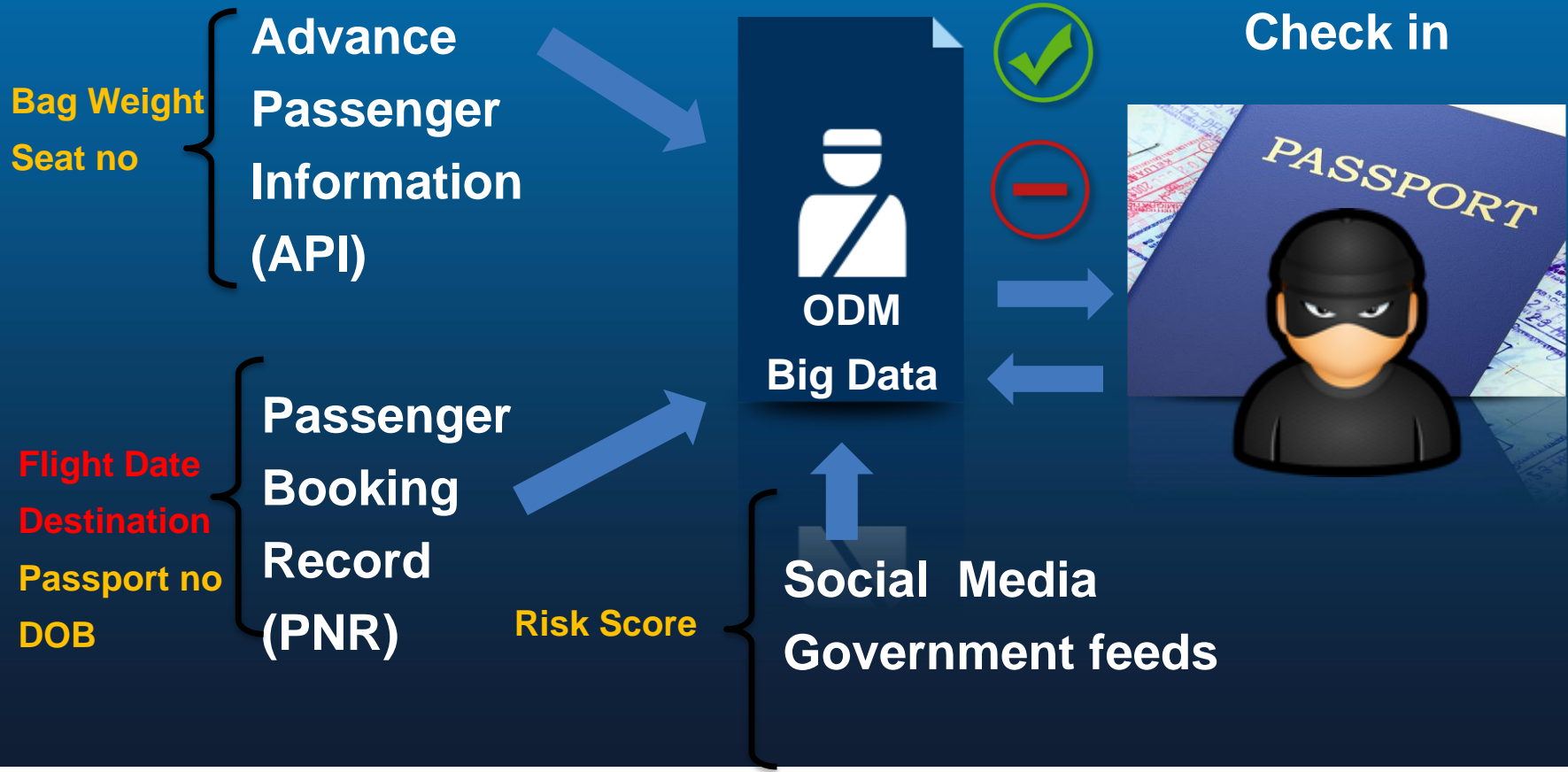


Cross Border

20 Million passengers per day

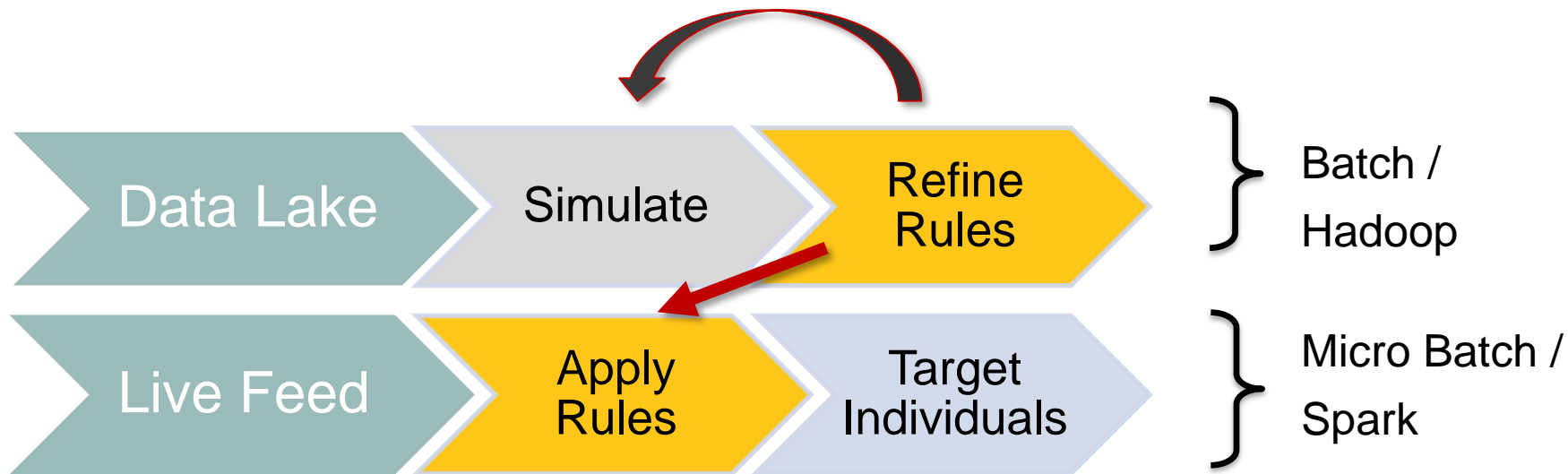
Advanced profiling

# THINK BIG USE CASE : BORDER CONTROL



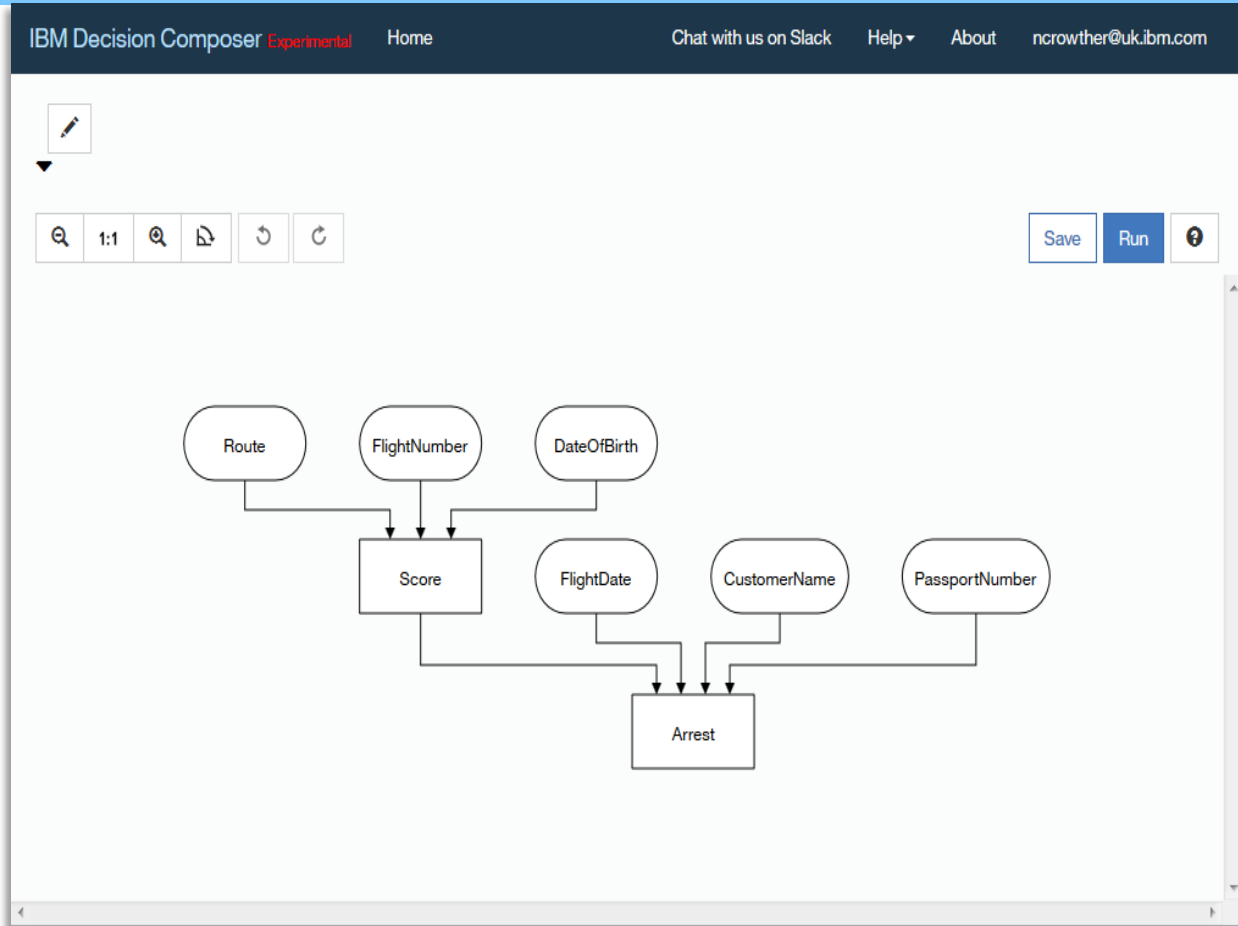
# Hadoop Enhances Conventional Architecture

Same rules used against data lake and live feed



# The DMN Model - Decision Composer

- Decision Composer is an experimental tool to generate rule projects
- Uses DMN (Decision Modelling Notation) to model decisions
- Build and deploy directly to Bluemix runtime
- Good for rapid prototyping and simple rulesets



# Example of Stateless Rules




```
if
  tweet contains "#DRUGS"
  and the age from 'date of birth' is between 18 and 30
then
  set score to score + 1 ;
```

Ben Smith **LASMEX** 16/08/1990 ME652 22/03/2017 **F607631362**

```
if
  'passport number' is one of {"U468924610", "F607631362"}
then
  set response to response + ", Passenger: " +
    'customer name' + " on watch list. Flight " +
    'flight number' + " flying at " + 'flight date';
```

# Example of Stateful Rules

**F607631362 Walter Black 16/08/1959 MA652 01/01/2017 LAXMEX**  
**F607631362 Walter Black 16/08/1959 MA445 22/03/2017 MEXLAX**

	Age 		Months Away	Score	Route	Response Code
	min	max				
1	16	60	$\geq 1$	$> 5$	LAXMEXMEXLAX	D254
2 <sub>13</sub>	12	50	$\geq 2$	$> 10$	LHRDAMDAMLHR	T023
3	16	60	$\geq 1$	$> 5$	LHRAMSAMSLHR	D345



# Business Rules and Big Data

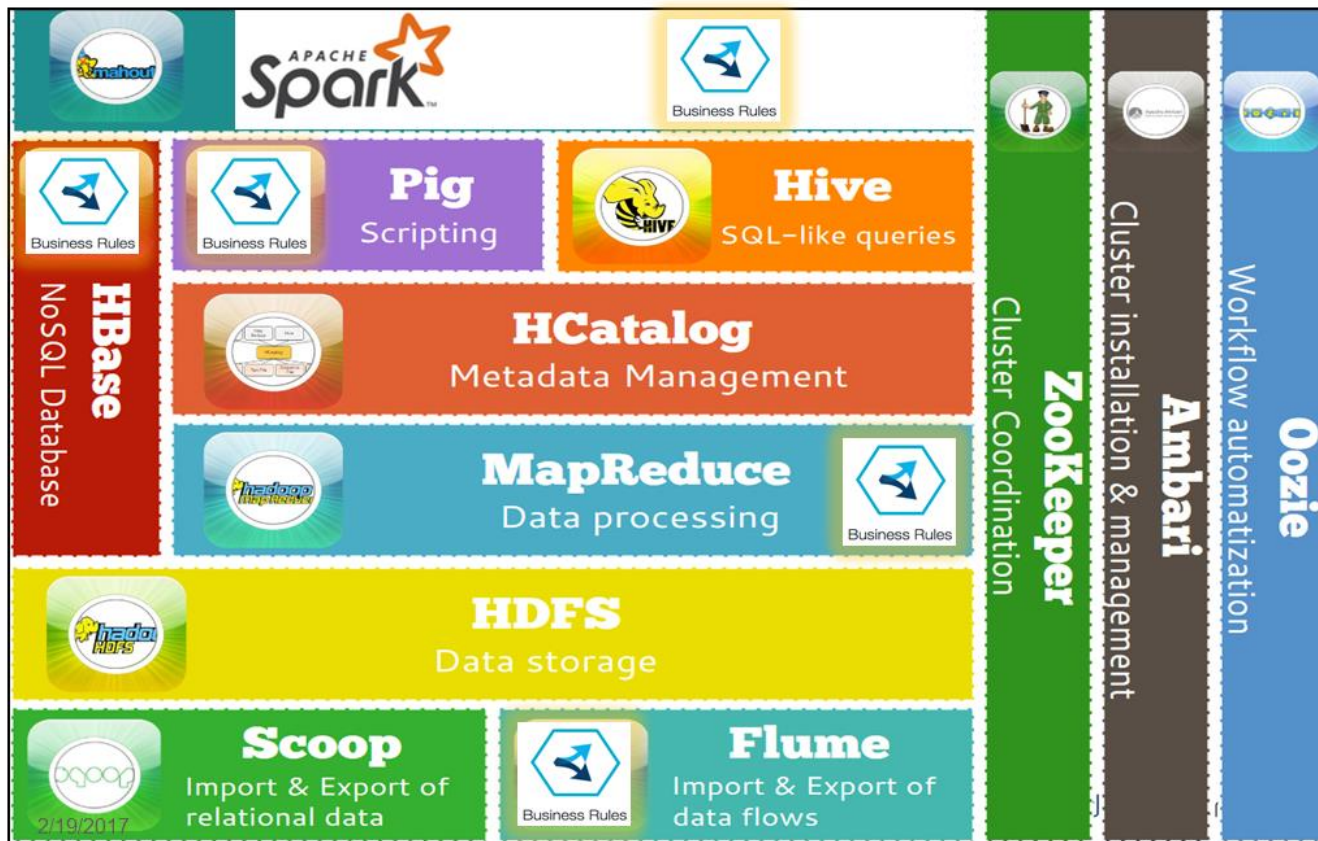
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# Landscape: Where ODM Rules fits in Big Data

Run ODM within:

- Apache Spark
- Hadoop map/reduce
- Flume





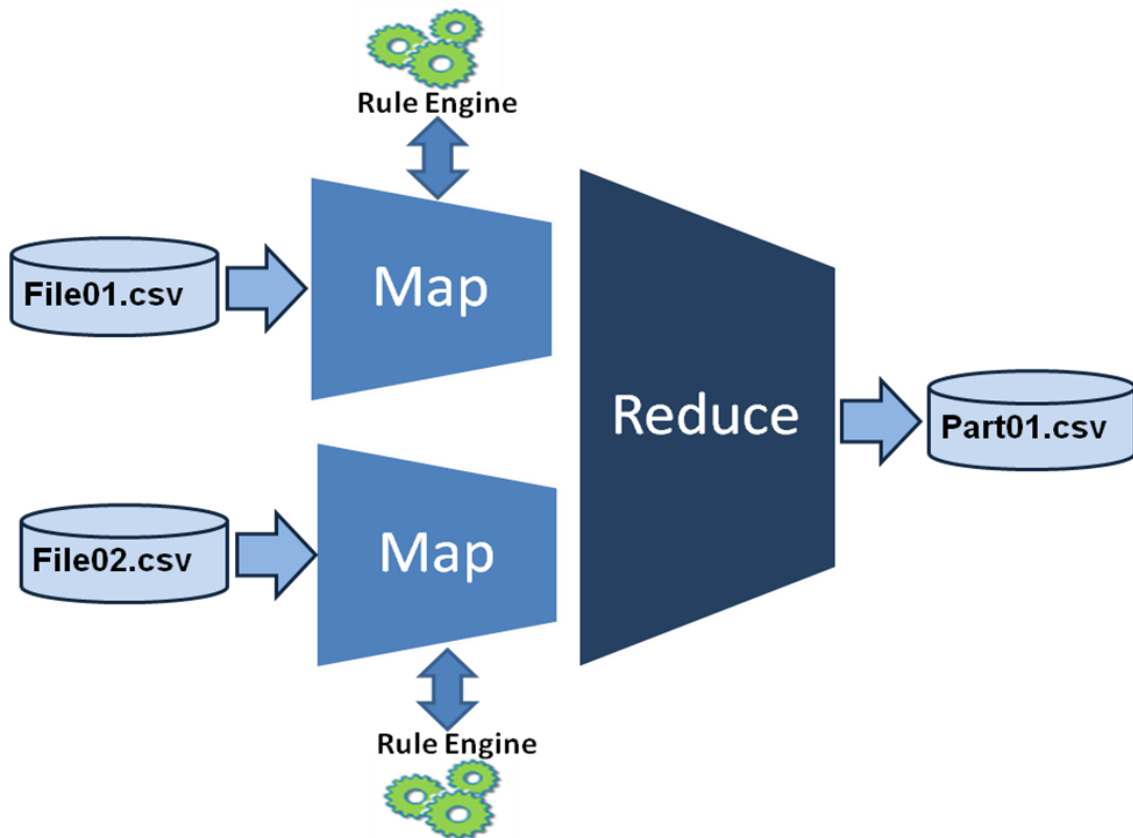
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# Rule Engine Integration in Hadoop

- Each Map job is given a part of the data (the split)
- The Map sends the split to an instance of the rule engine where it is processed.
- The Rule Engine can either be embedded within the Map job, or called externally.
- Data created by the rules are combined by the Reduce jobs.



# Execute with a local Rule Engine, Remote RES

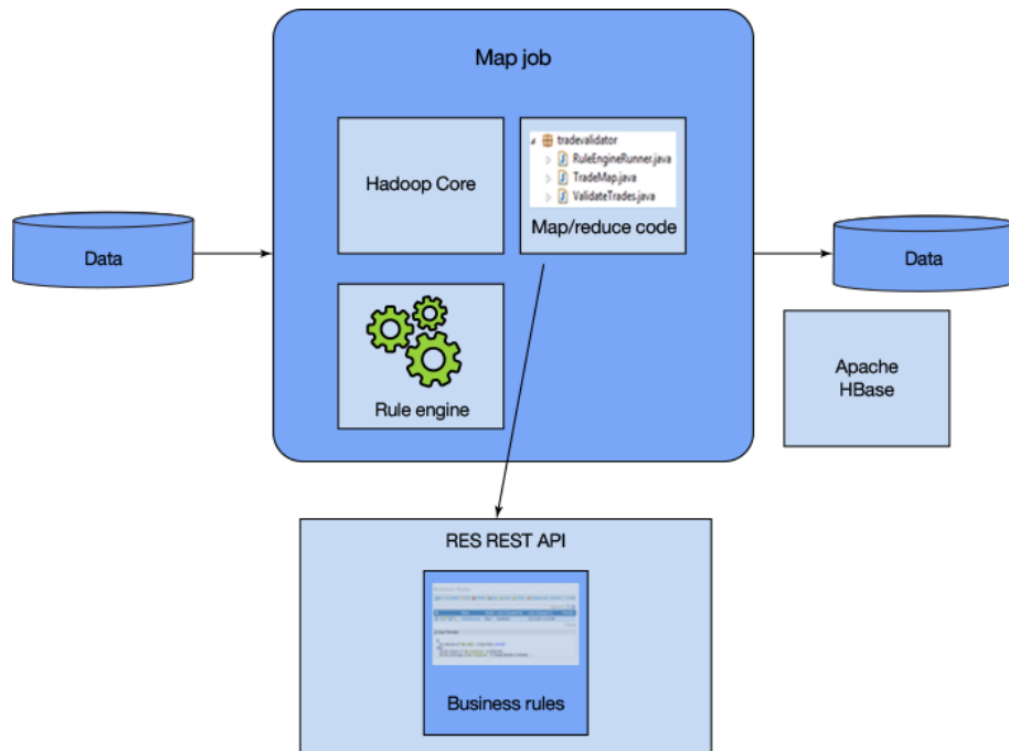
REST API extracts latest ruleset from RES.  
Ruleset executed against embedded engine in  
Map Job.

## Advantages:

- Versioning of rules within RES
- Avoid rebuilding Hadoop executable
- Embedded engine gives high performance
- Leverage full Hadoop stack – e.g. Hbase

## Disadvantages:

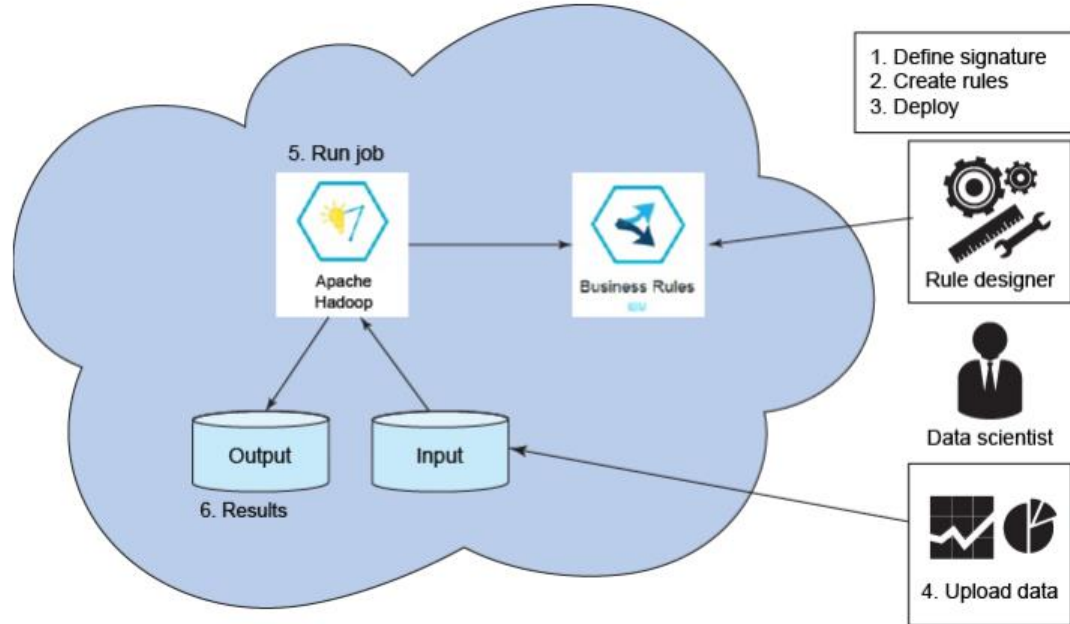
Need to manage engine license costs



# ODM/Hadoop Asset

Integration of ODM and Hadoop provided as a free asset:

1. Define ruleset signature
2. Create rule service
3. Deploy
4. Upload data
5. Configure and run job
6. Examine results



[Think Big! Developerworks article](#)

# Let's Create a Hadoop Super Computer on Bluemix!

## Provisioning



### Management Nodes

CPU (# of cores)      **24 Cores**  
2 X 12 = 24 Cores (2690v3)

RAM      **256 GB**  
16 X 16 GB = 256 GB

OS disk      **8 TB**  
4 X 4 TB = 16 TB (RAID 10)

Network      **10 GB**

### Compute Nodes

CPU (# of cores)      **24 Cores**  
2 X 12 = 24 Cores (2690v3)

RAM      **256 GB**  
16 X 16 GB = 256 GB

Data disk      **32 TB**  
8 X 4 TB = 32 TB

OS disk      **8 TB**  
4 X 4 TB = 16 TB (RAID 10)

Network      **10 GB**

## Performance

PNR Validation on BigInsights Apache Hadoop on Bluemix.

**One Day, 20 Million PNRs :**

- 3 compute nodes: *2min 46secs*
- **120,000 TPS**

**One Year, 7.2 Billion PNRs :**

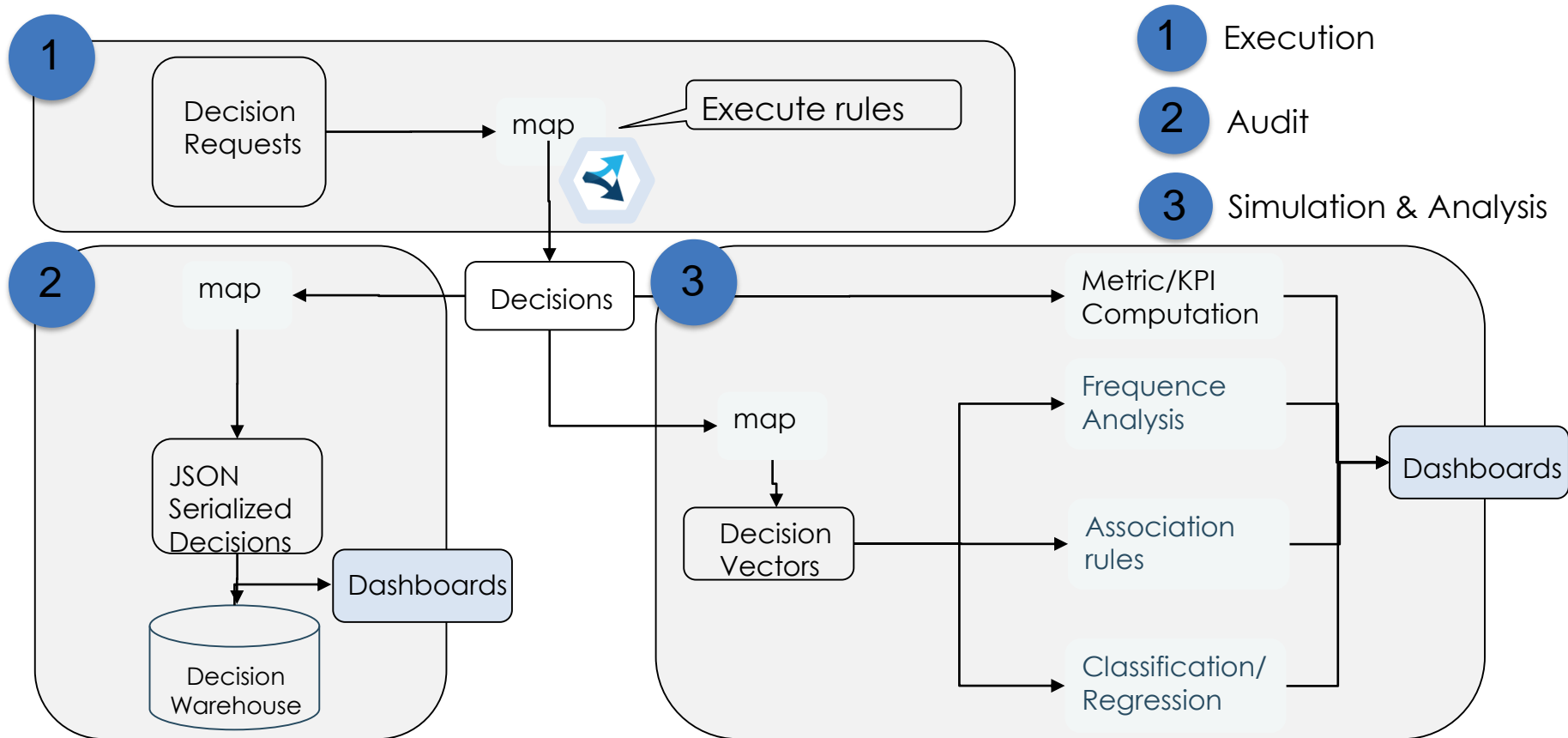
- 30 compute nodes: *1.5 hours*
- **1.2M TPS**

# Business Rules and Big Data

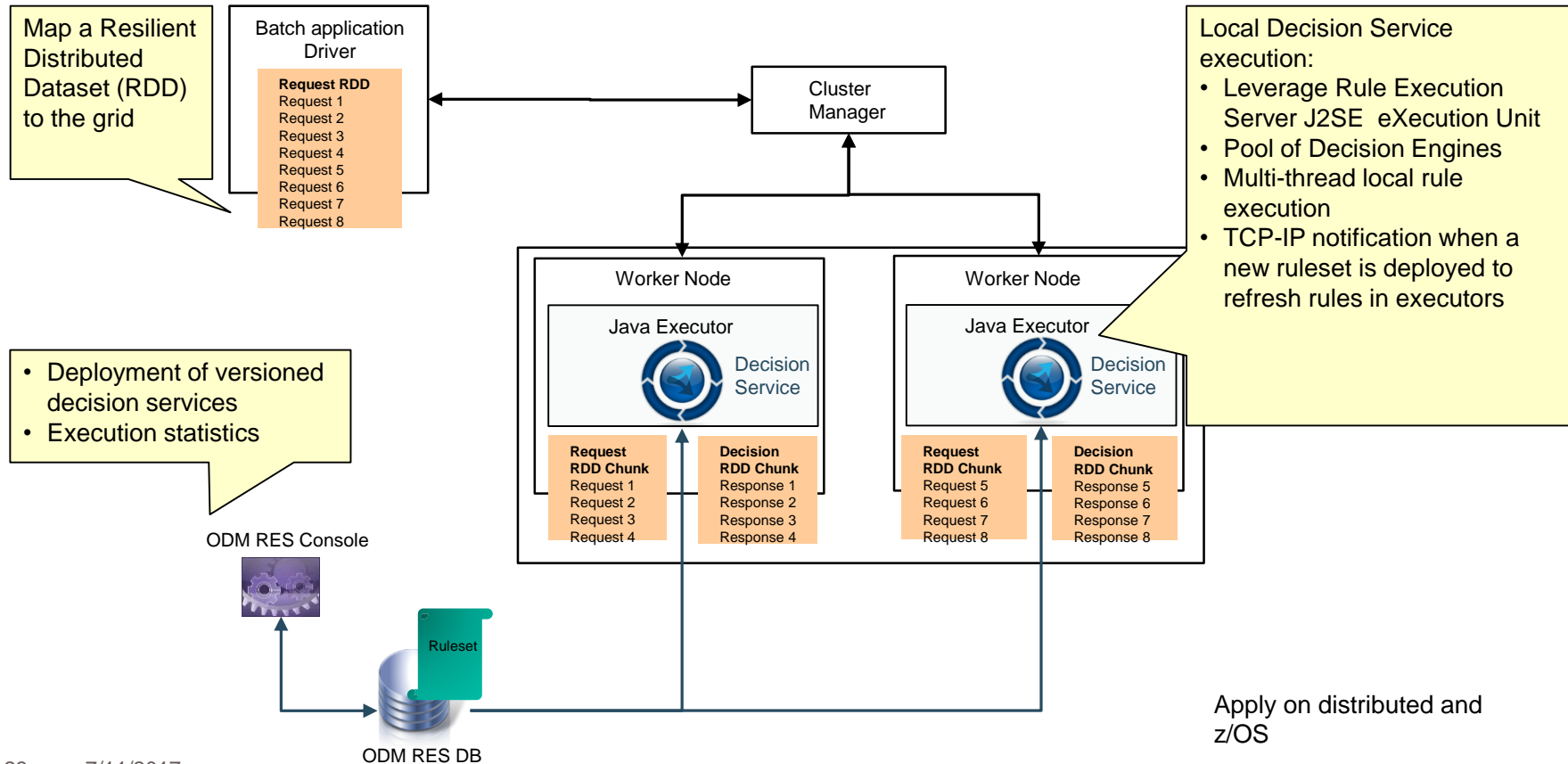
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# Automate, Audit and Analyze your decision making in Apache Spark



# Running a Decision service in an Apache Spark cluster





# Apache Spark Monitoring

- A Spark job is deployed on the master.
- Each cluster member starts an executor (JVM)
- Each JVM runs in multiple threads a rule engine of different chunks of the decision request dataset.

## Spark Master at spark://odm-ubuntu-15-10-spark-master:7077

URL: spark://odm-ubuntu-15-10-spark-master:7077  
REST URL: spark://odm-ubuntu-15-10-spark-master:6066 (cluster mode)  
Alive Workers: 2  
Cores in use: 4 Total: 0 Used  
Memory in use: 3.6 GB Total: 0.0 B Used  
Applications: 0 Running, 5 Completed  
Drivers: 0 Running, 0 Completed  
Status: ALIVE

### Workers

Worker ID	Address	State	Cores	Memory
worker-20151119020241-192.168.135.133-39081	192.168.135.133:39081	ALIVE	2 (0 Used)	1793.0 MB (0.0 B Used)
worker-20151119020242-192.168.135.134-35080	192.168.135.134:35080	ALIVE	2 (0 Used)	1932.0 MB (0.0 B Used)

### Running Applications

Application ID	Name	Cores	Memory per Node	Submitted Time	User	State	Duration
----------------	------	-------	-----------------	----------------	------	-------	----------

### Completed Applications

Application ID	Name	Cores	Memory per Node	Submitted Time	User	State	Duration
app-20151119020858-0004	MiniLoan Decision Service	4	1024.0 MB	2015/11/19 02:08:58	odm	FINISHED	6 s
app-20151119020845-0003	MiniLoan Decision Service	4	1024.0 MB	2015/11/19 02:08:45	odm	FINISHED	6 s
app-20151119020829-0002	MiniLoan Decision Service	4	1024.0 MB	2015/11/19 02:08:29	odm	FINISHED	6 s
app-20151119020751-0001	MiniLoan Decision Service	4	1024.0 MB	2015/11/19 02:07:51	odm	FINISHED	7 s
app-20151119020339-0000	MiniLoan Decision Service	4	1024.0 MB	2015/11/19 02:03:39	odm	FINISHED	7 s

## Spark Worker at 192.168.135.133:39081

ID: worker-20151119020241-192.168.135.133-39081  
Master URL: spark://odm-ubuntu-15-10-spark-master:7077  
Cores: 2 (0 Used)  
Memory: 1793.0 MB (0.0 B Used)

[Back to Master](#)

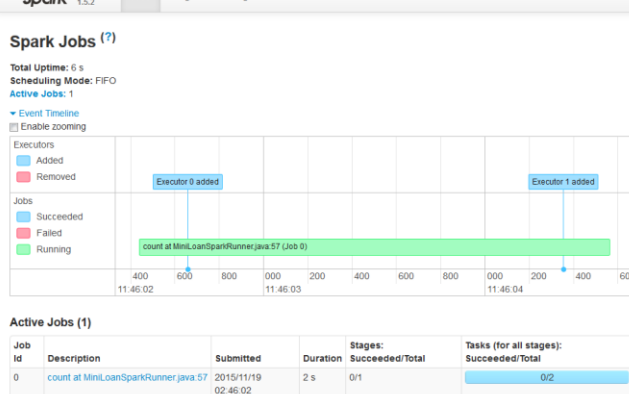
### Running Executors (0)

ExecutorID	Cores	State	Memory	Job Details	Logs
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### Finished Executors (5)

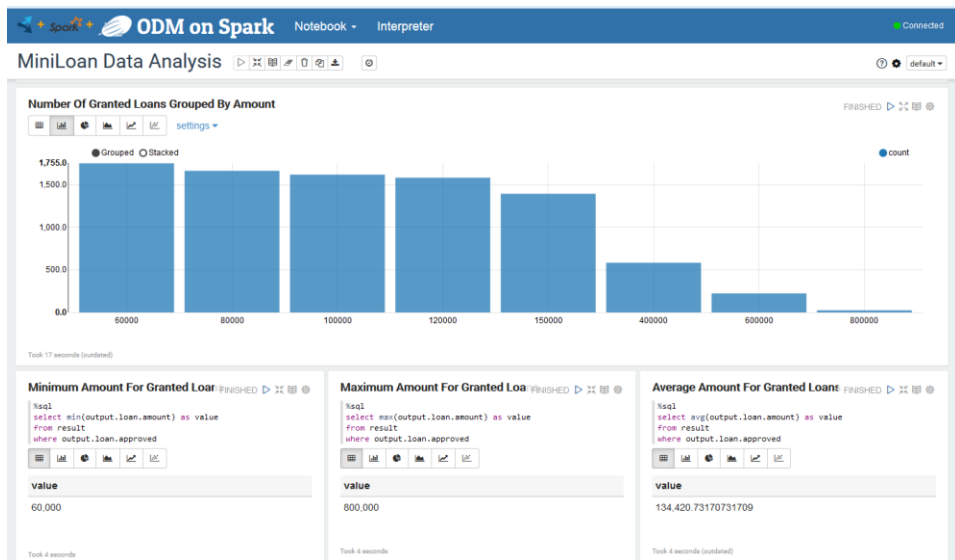
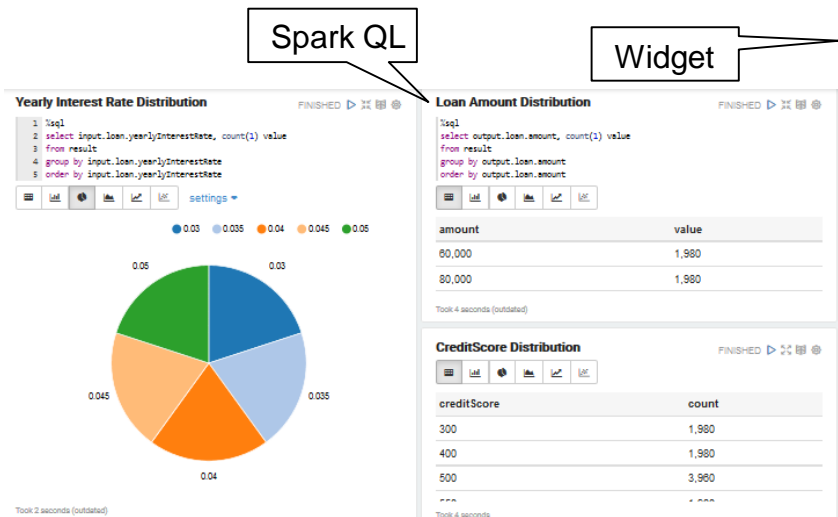
ExecutorID	Cores	State	Memory	Job Details	Logs
0	2	KILLED	1024.0 MB	ID: app-20151119020339-0000 Name: MiniLoan Decision Service User: odm	<a href="#">stdout stderr</a>
0	2	EXITED	1024.0 MB	ID: app-20151119020751-0001 Name: MiniLoan Decision Service User: odm	<a href="#">stdout stderr</a>
0	2	KILLED	1024.0 MB	ID: app-20151119020829-0002 Name: MiniLoan Decision Service User: odm	<a href="#">stdout stderr</a>
0	2	KILLED	1024.0 MB	ID: app-20151119020845-0003 Name: MiniLoan Decision Service User: odm	<a href="#">stdout stderr</a>
0	2	KILLED	1024.0 MB	ID: app-20151119020858-0004 Name: MiniLoan Decision Service User: odm	<a href="#">stdout stderr</a>

## Spark 1.5.2 Jobs Stages Storage Environment Executors



# Interactive Analytic Notebooks

- Interactive development with Zeppelin or Jupiter
- Manipulation of large dataset typically decisions
- Decision Service invocation possible through a Scala application
- Exploit Data results. (Metric & KPI computation & representation with Spark SQL )



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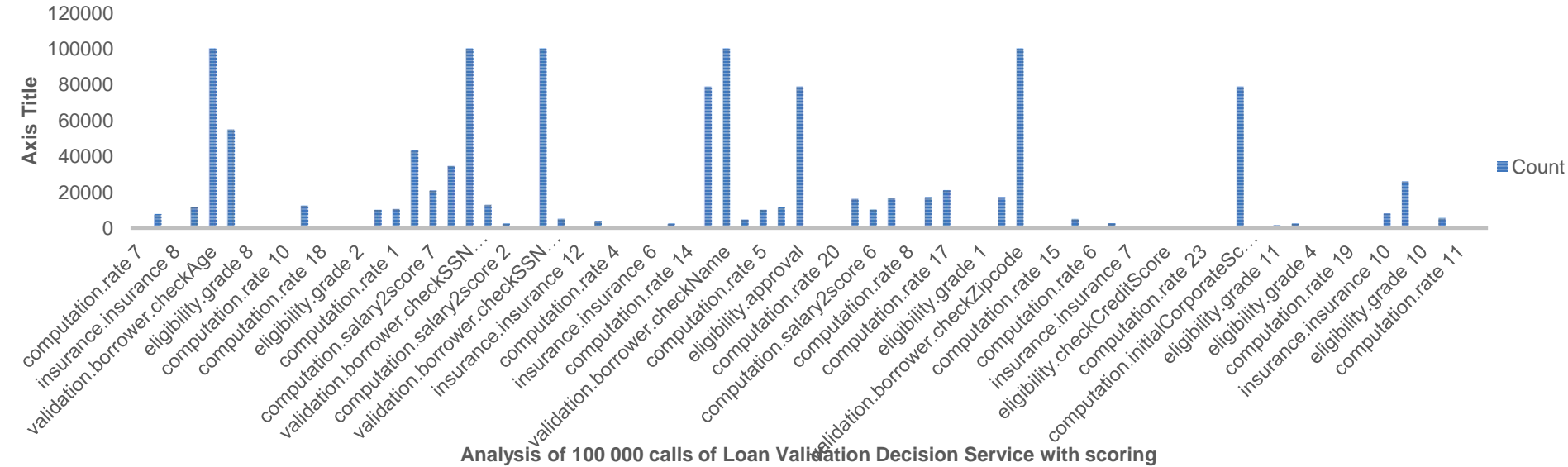
## Rule coverage for a Decision set

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- What is the rule distribution when running my test campaign? In my production?
- What is my data distribution for corresponding requests & answers?
- Are there rules never fired? Always fired?
- What are all the decisions that fired a particular rule?
- Can I check that an exception handling rule is only called with the expected data?
- How does data fit with my rules to achieve my business goals?

# Business Rule coverage

Analysis of 100 000 Loan validation decision set



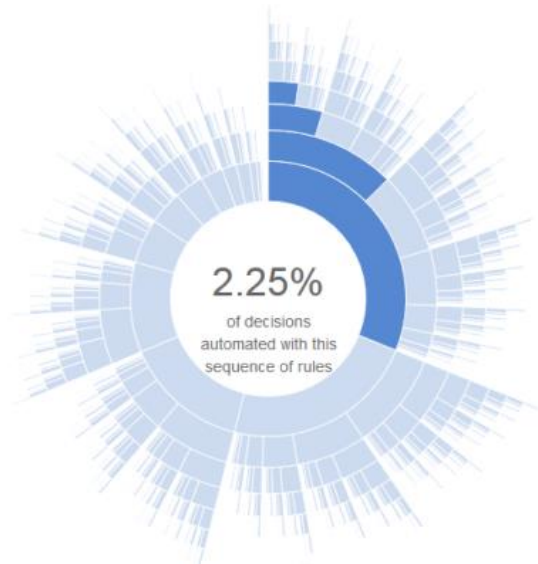
26 rules & Decision Table lines on a 74 total have no execution in the decision set

# Analyzing your automated decisions

- Frequency analysis

- View in large your sequences of executed rules in your decision set

eligibility.grade 12    eligibility.checkIncome    eligibility.approval    computation.repayment



- Conditional Rule appearance

- Likelihood that a rule comes executed after a specific sequence
- Indicate that some rules always go together and that their logic may be merged

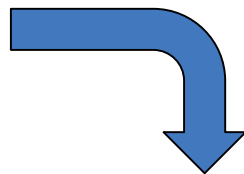
Executed Rule sequence	=>		%
validation. borrower. checkZipcode		validation.borrower.checkAge	1.0
		eligibility.approval	1.0
		eligibility.checkIncome	0.54
		approved=false	0.76

Loan validation associated rules generated on the 100 000 execution traces – Processed in Spark ML

# Serialize your rule based Decisions for Audit and Analytics

- Decision model
  - Decision = Request + Trace + response
  - Serializable in JSON, CSV or XML
  - Serializable into a numeric Vector

```
{
  "decision": {
    "id": "231422841",
    "request": {
      "borrower": {
        "name": "John Doe",
        "creditScore": 810,
        "yearlyIncome": 12000,
      },
      "loan": {
        "amount": 510000,
        "duration": 60,
        "yearlyInterestRate": 0.03,
        "yearlyRepayment": 10781,
      },
    },
    "response": {
      "loan": {
        "amount": 50000,
        "duration": 60,
        "yearlyInterestRate": 0.0255,
        "yearlyRepayment": 10781,
        "approved": false,
      },
    },
  },
}
```



eligibility is the boolean label

1 [1:810 2:120 3:510 4:60 5:255]

CreditScore

Yearly Income  
scaled in K

Loan amount  
scaled in K

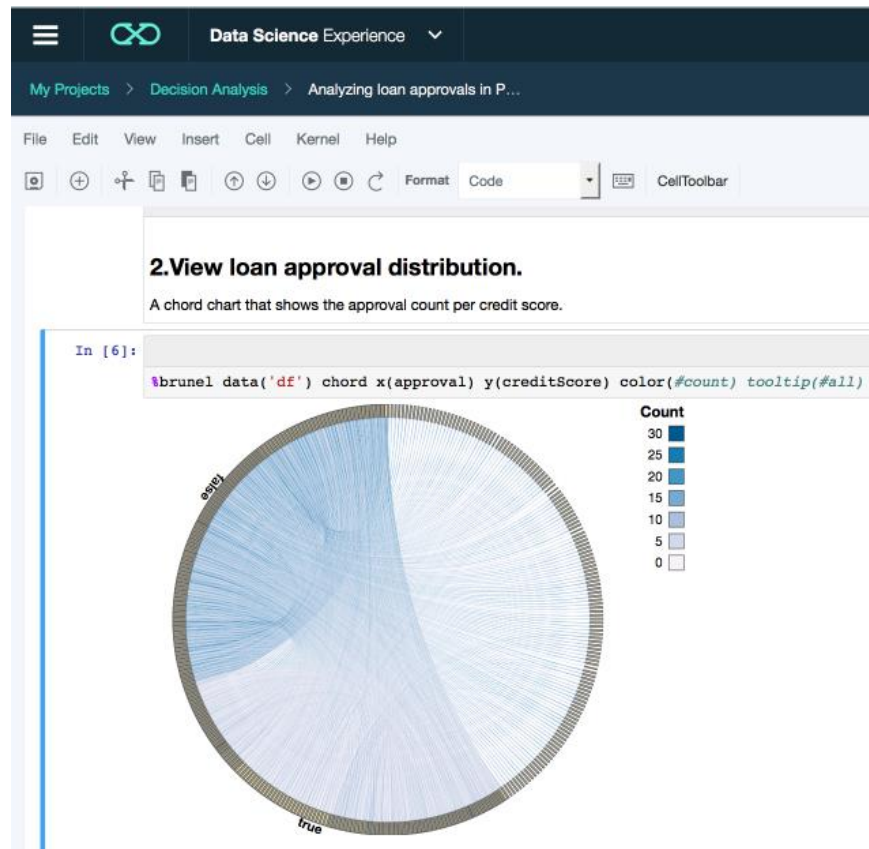
Duration in  
months

Interest rate  
scaled by 100

- From an object model to numeric vectors
- A past decision is a vector of features
- A feature has a numeric value
- For each feature vector you associate a label that is the expected variable value
- Value scaling to help numeric computation

# Business Rules in Data Science Experience

- Execute business rules in a Scala notebook
- Mix business rules with predictive model invocations
- Store serialized rule based decisions (JSON, CSV, XML)
- Query and analyze in your online decision warehouse
  - In Scala with Spark QL
  - In Python Panda or SparkSession dataframes
  - In R
- Visualize your decision insights in collaborative notebooks hosted in the IBM Cloud
- Publish your notebooks on Github and contribute to a community





# Rules & Machine Learning in Artificial Intelligence



## AI

- Symbolic Artificial Intelligence
- Structured data
- Formalized model with facts
- Causality
- Mainly Boolean logic
- Reasoning

- Non symbolic AI
- Unstructured data
- Signal processing
- Correlation
- Dealing with uncertainty
- Perception, Classification, Regression

## Wrap up

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- Combine **Today** business rules and Big Data into Big Decision in Hadoop and Apache Spark
- Bridge Predictive and Operation decision management technologies & teams together
- Automate **massive** decision making in standard OSS compute grids
- Running business policies **simulations** on large historical dataset with parallel metric and KPI computation
- **Store** your automated decisions and **Analyze** their efficiency against your business objectives
- **Optimize** the fitness between your decision logic and dataset
- **Detect situations** on data lakes
- **Invent** new algorithm combinations to solve new classes of enterprise AI at scale

# Wrap up

- ODM on Hadoop
  - [https://www.ibm.com/developerworks/bpm/library/techarticles/1411\\_crowther-bluemix/1411\\_crowther.html](https://www.ibm.com/developerworks/bpm/library/techarticles/1411_crowther-bluemix/1411_crowther.html)
- ODM on Spark article
  - <https://developer.ibm.com/odm/docs/solutions/odm-and-analytics/odm-business-rules-with-apache-spark-batch-operations/>
- Bluemix
  - <https://console.ng.bluemix.net/catalog/services/apache-spark>
  - <https://console.ng.bluemix.net/catalog/services/biginsights-for-apache-hadoop>
  - [Decision Composer](#)
- Data Science Experience
  - <http://datascience.ibm.com/>

Think big! Scale your business rules solutions up to the world of big data

Build an app that uses Business Rules and Apache Hadoop services on IBM Bluemix



Nigel Crowther

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