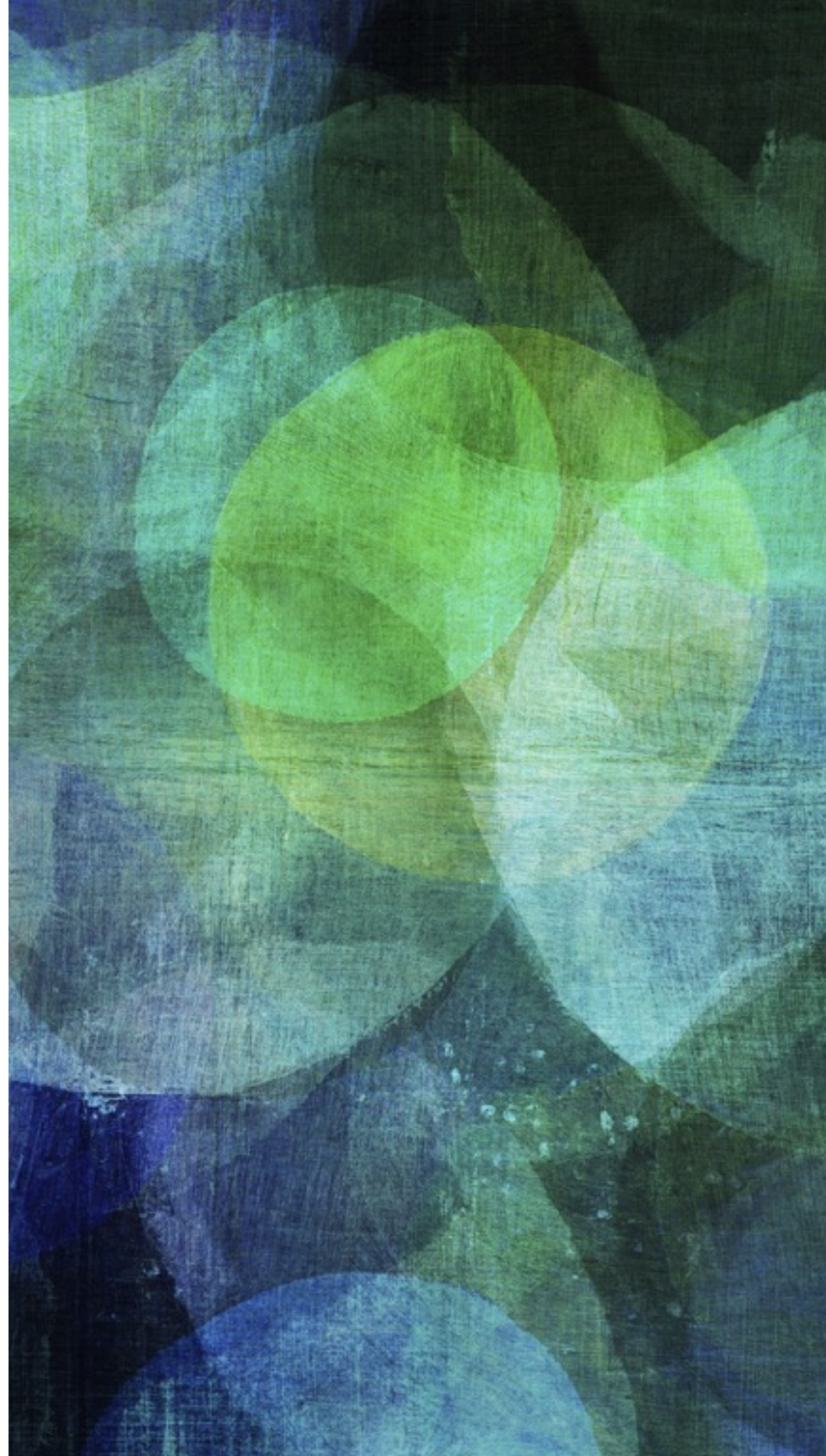


SPARK SQL

Shijie Zhang



OUTLINE

- Background
- Spark SQL overview
- Spark components
 - Data Source API
 - DataFrame API
 - Catalyst optimizer
- SparkSQL future
- Conclusion
- References

WHY BIG DATA WITH SQL

- SQL is compatible with tooling
 - e.g. Connect to existing BI tools via JDBC/ODBC
- Large pool of engineers proficient in SQL
- Compared with MapReduce, SQL is more expressive/succinct

“

Spark SQL is more than SQL

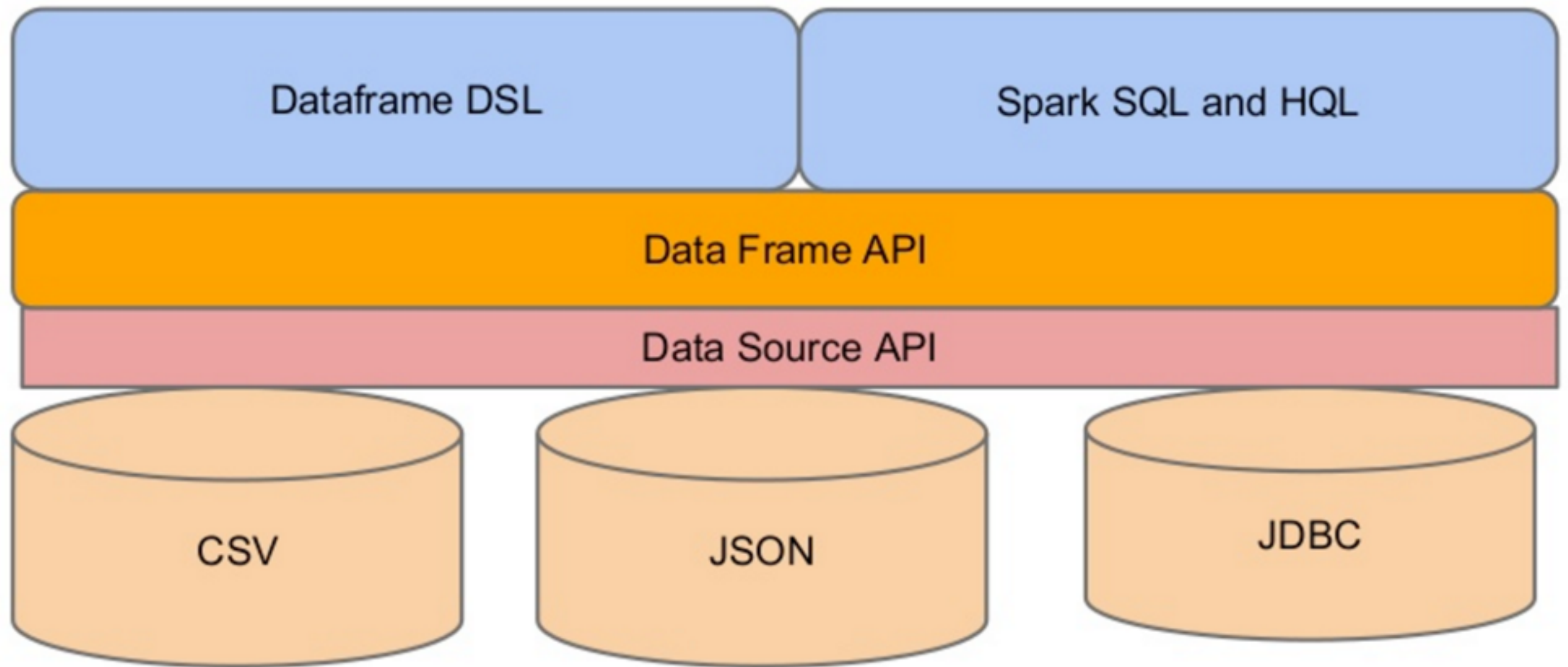
-not so top secret

CHALLENGES

- Spark needs to perform ETL on **various** data source formats
 - Solution: Data source APIs
 - Implement SQL for Spark
 - In an **extensible** way
 - Solution: DataFrame API
 - In an **efficient** way
 - Solution: Catalyst optimizer
-
- ```
graph LR; A["➤ Solution: Data source APIs"] --> D["Spark SQL
Major Components"]; B["➤ Solution: DataFrame API"] --> D; C["➤ Solution: Catalyst optimizer"] --> D;
```
- The diagram illustrates how specific solutions for Spark challenges converge on the Spark SQL Major Components. Three arrows point from the solutions 'Data source APIs', 'DataFrame API', and 'Catalyst optimizer' to the text 'Spark SQL Major Components' on the right side of the slide.

# SPARK SQL OVERALL ARCHITECTURE

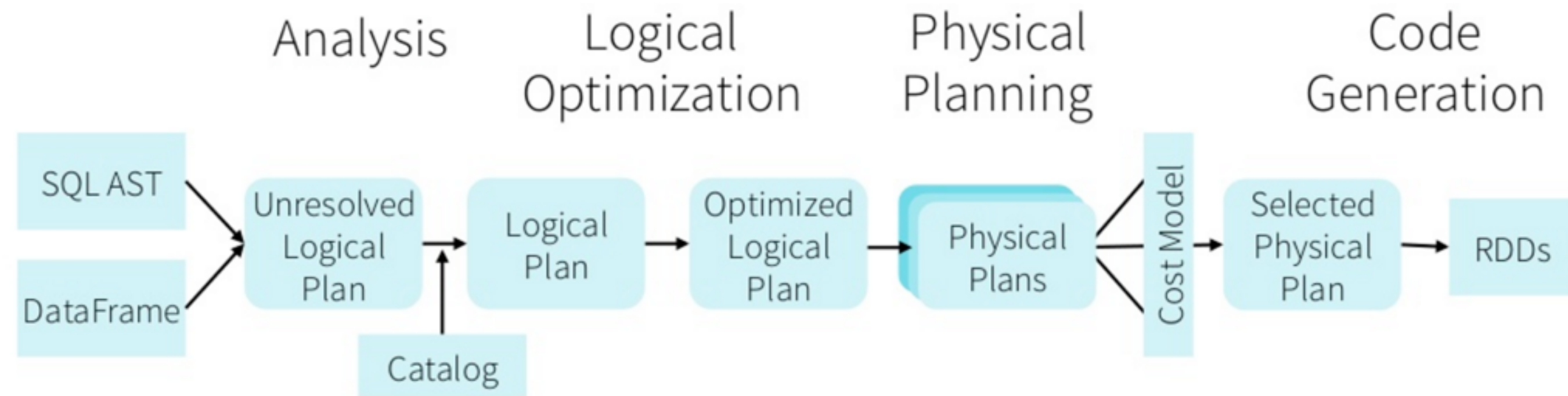
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# SPARK SQL WORKFLOW

---



# DATA SOURCE API

---

- Read and write with a variety of formats

Built-In



External





# DATA SOURCE API

---

- Unified interface to reading/writing data in a variety of formats

```
df = sqlContext.read \
 .format("json") \
 .option("samplingRatio", "0.1") \
 .load("/home/michael/data.json")
```

```
df.write \
 .format("parquet") \
 .mode("append") \
 .partitionBy("year") \
 .saveAsTable("fasterData")
```

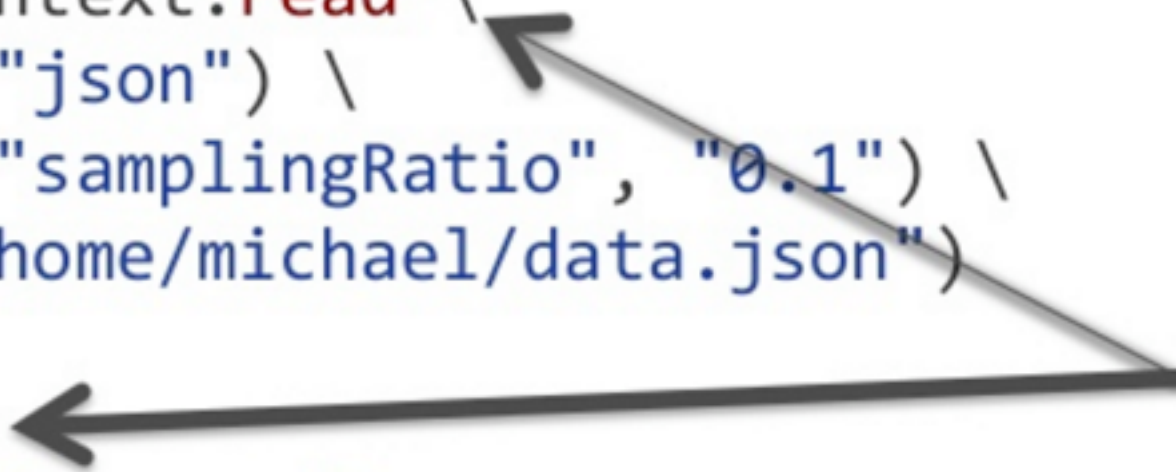
# DATA SOURCE API

---

- Unified interface to reading/writing data in a variety of formats

```
df = sqlContext.read \
 .format("json") \
 .option("samplingRatio", "0.1") \
 .load("/home/michael/data.json")
```

```
df.write \
 .format("parquet") \
 .mode("append") \
 .partitionBy("year") \
 .saveAsTable("fasterData")
```



**read** and **write**  
functions create  
new builders for  
doing I/O

# DATA SOURCE API

---

- Unified interface to reading/writing data in a variety of formats

```
df = sqlContext.read \
 .format("json") \
 .option("samplingRatio", "0.1") \
 .load("/home/michael/data.json")
```

```
df.write \
 .format("parquet") \
 .mode("append") \
 .partitionBy("year") \
 .saveAsTable("fasterData")
```



Builder methods  
are used to specify:

- Format
- Partitioning
- Handling of existing data
- and more



# DATA SOURCE API

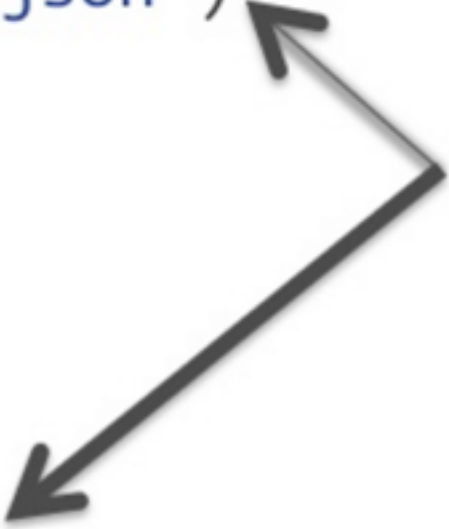
---

- Unified interface to reading/writing data in a variety of formats

```
df = sqlContext.read \
 .format("json") \
 .option("samplingRatio", "0.1") \
 .load("/home/michael/data.json")
```

```
df.write \
 .format("parquet") \
 .mode("append") \
 .partitionBy("year") \
 .saveAsTable("fasterData")
```

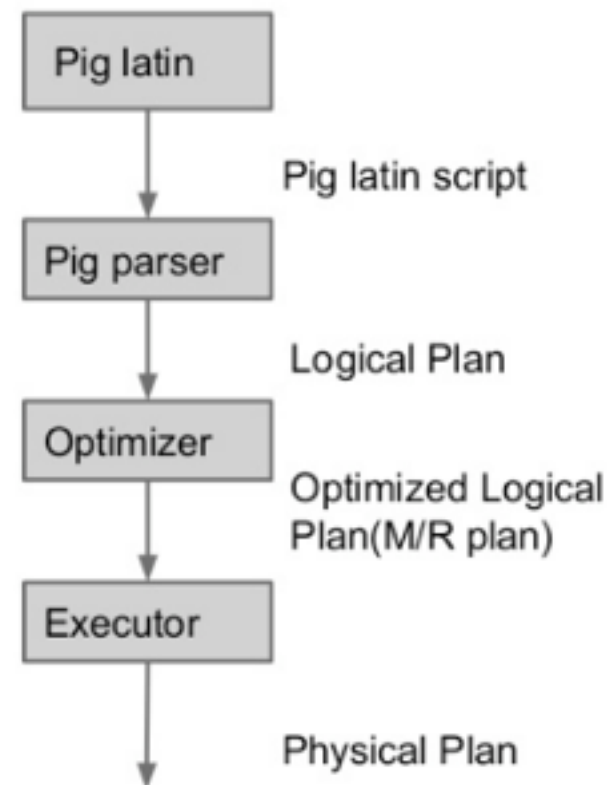
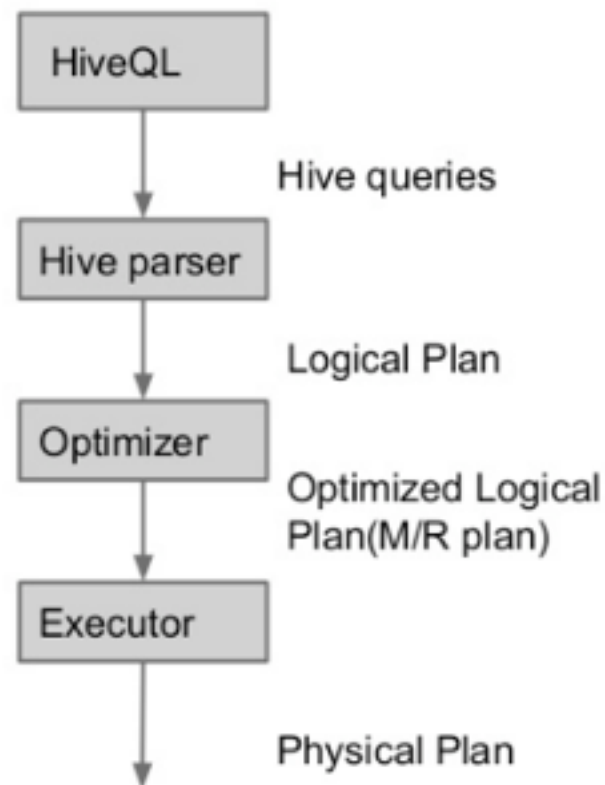
`load(...)`, `save(...)` or  
`saveAsTable(...)`  
functions create  
new builders for  
doing I/O



# SQL ON HADOOP

---

## ➤ Hive and Pig pipeline



## ➤ Problems

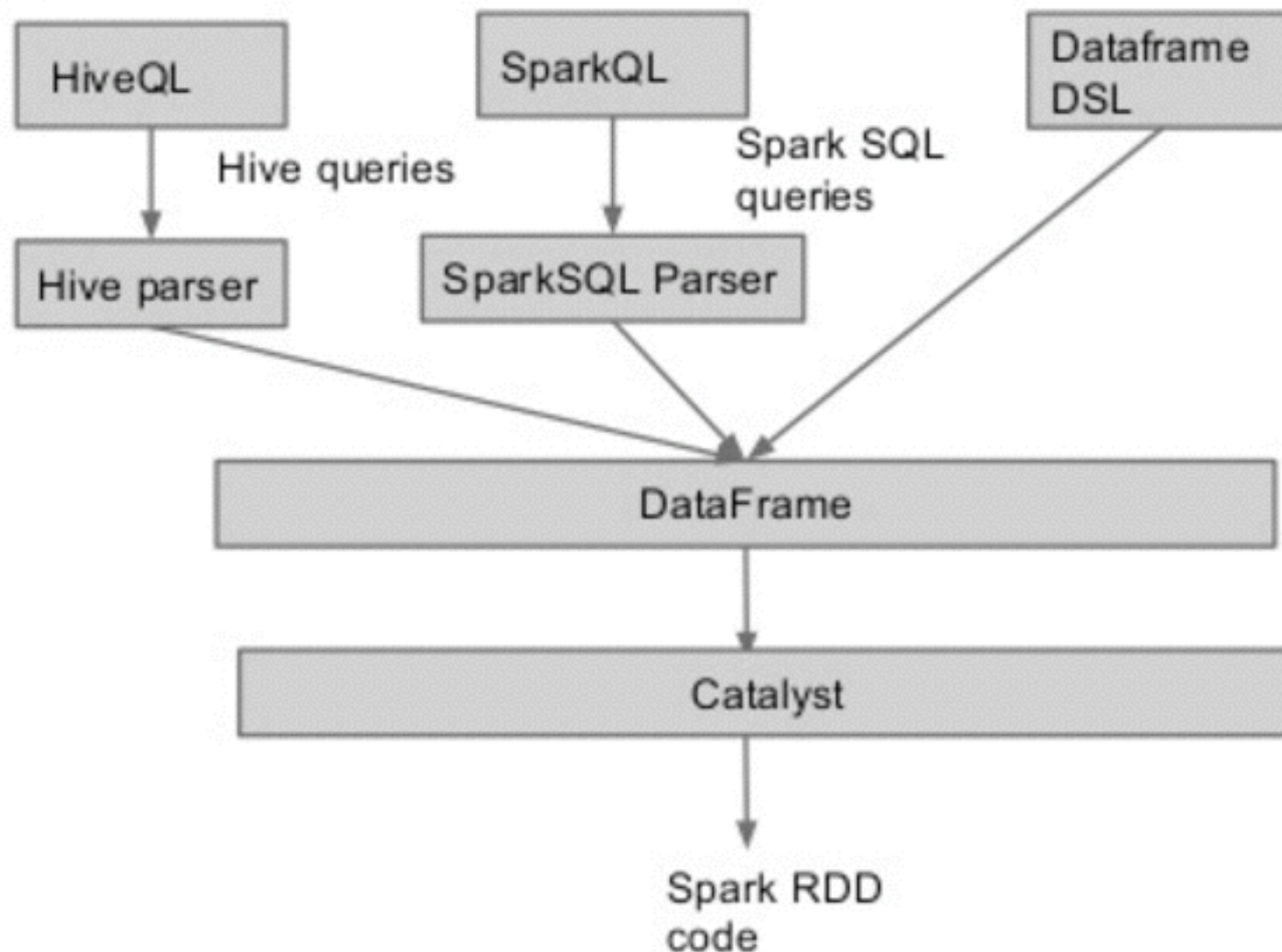
- Quite similar but implements its own optimizer/executor
- No common data structure to use both Hive/Pig/Other DSL



# DATAFRAME API

---

- DataFrame as a front end
- Multiple DSL share same optimizer and executor
- Plug your own DSL too

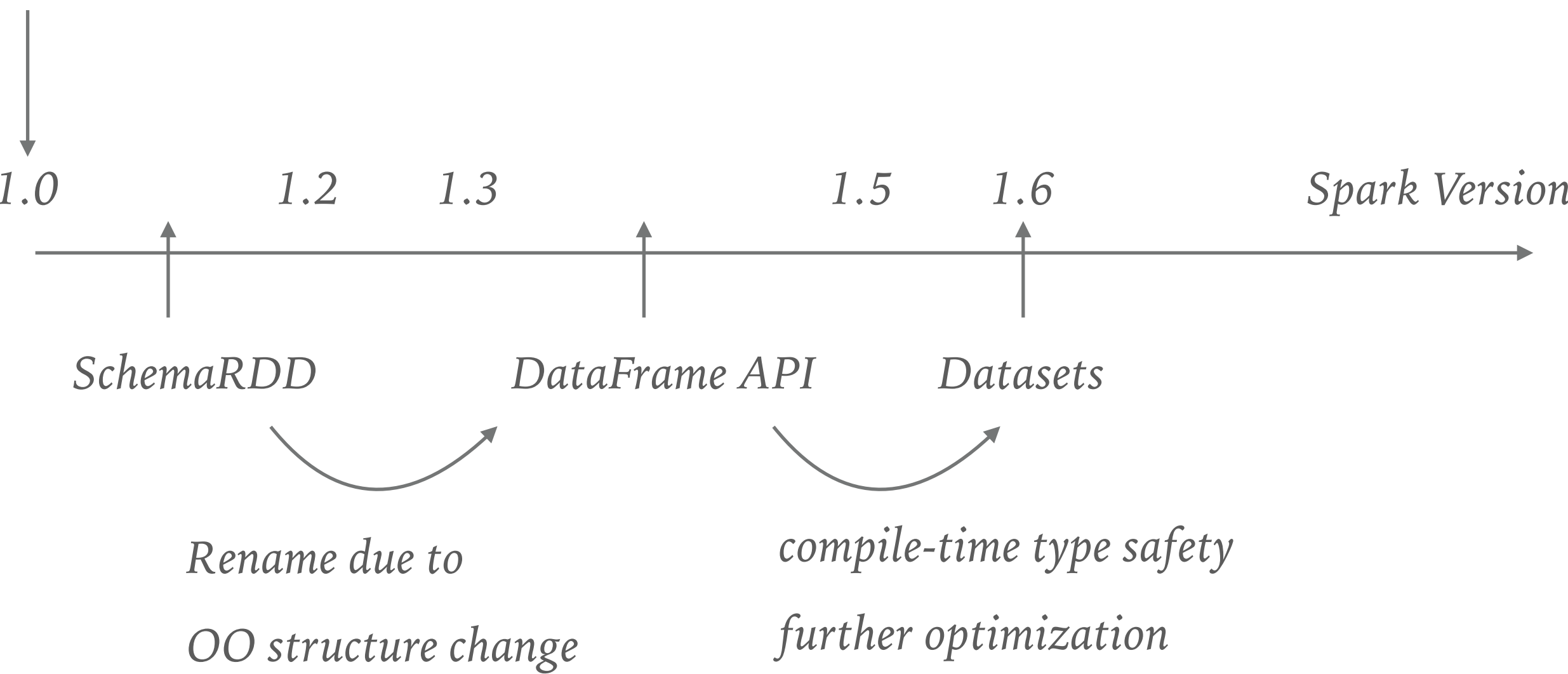




# MAJOR MILESTONE IN SPARK SQL

.....

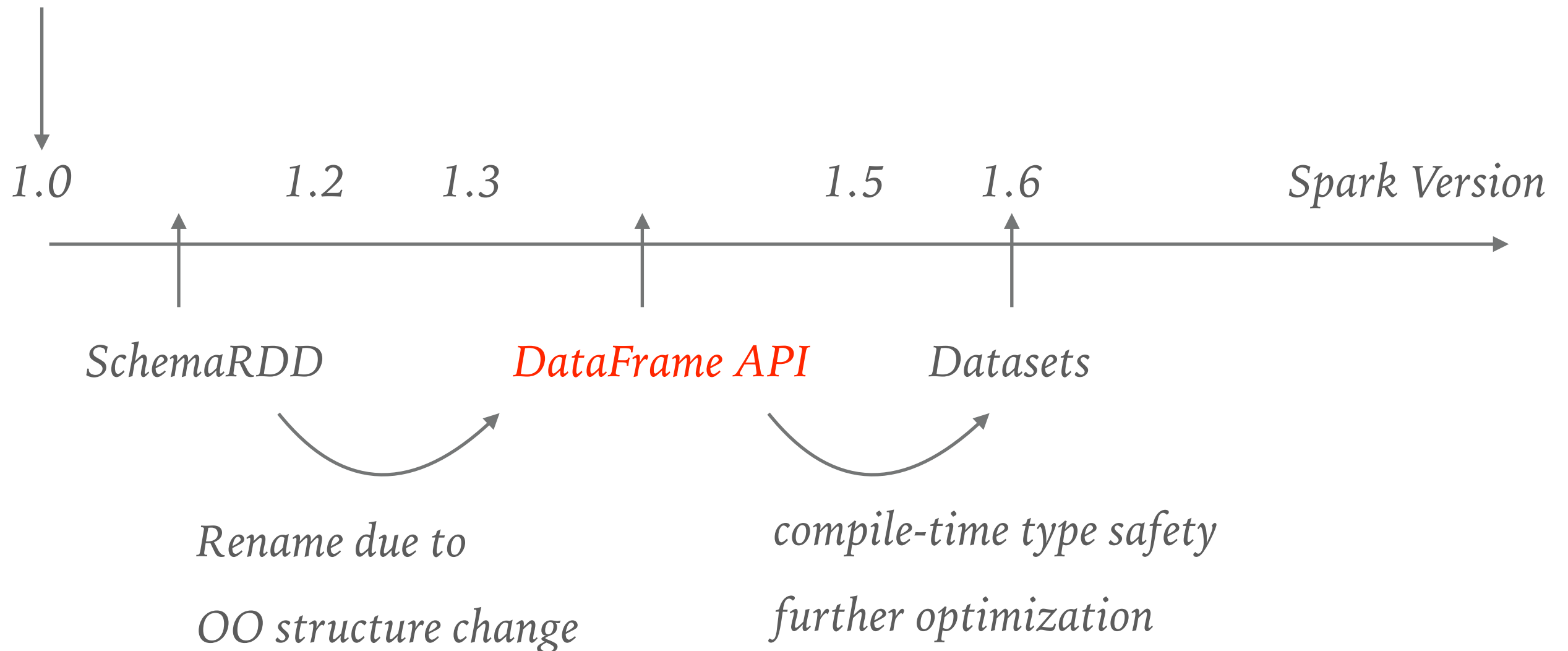
*SparkSQL becomes Spark core distribution*



# MAJOR MILESTONE IN SPARK SQL

---

*SparkSQL becomes Spark core distribution*



# DATAFRAME API

---

- Idea borrowed from Python Panda
  - single node tabular data with API for (math, stats, algebra...)
- Def:
  - RDD + Schema
  - RDDs with additional relational operators such as
    - selecting required columns
    - joining different data sources
    - aggregation
    - filtering

# DATAFRAME API

---

## ➤ Writing less code

### Using RDDs

```
data = sc.textFile(...).split("\t")
data.map(lambda x: (x[0], [int(x[1]), 1])) \
 .reduceByKey(lambda x, y: [x[0] + y[0], x[1] + y[1]]) \
 .map(lambda x: [x[0], x[1][0] / x[1][1]]) \
 .collect()
```

### Using SQL

```
SELECT name, avg(age)
FROM people
GROUP BY name
```

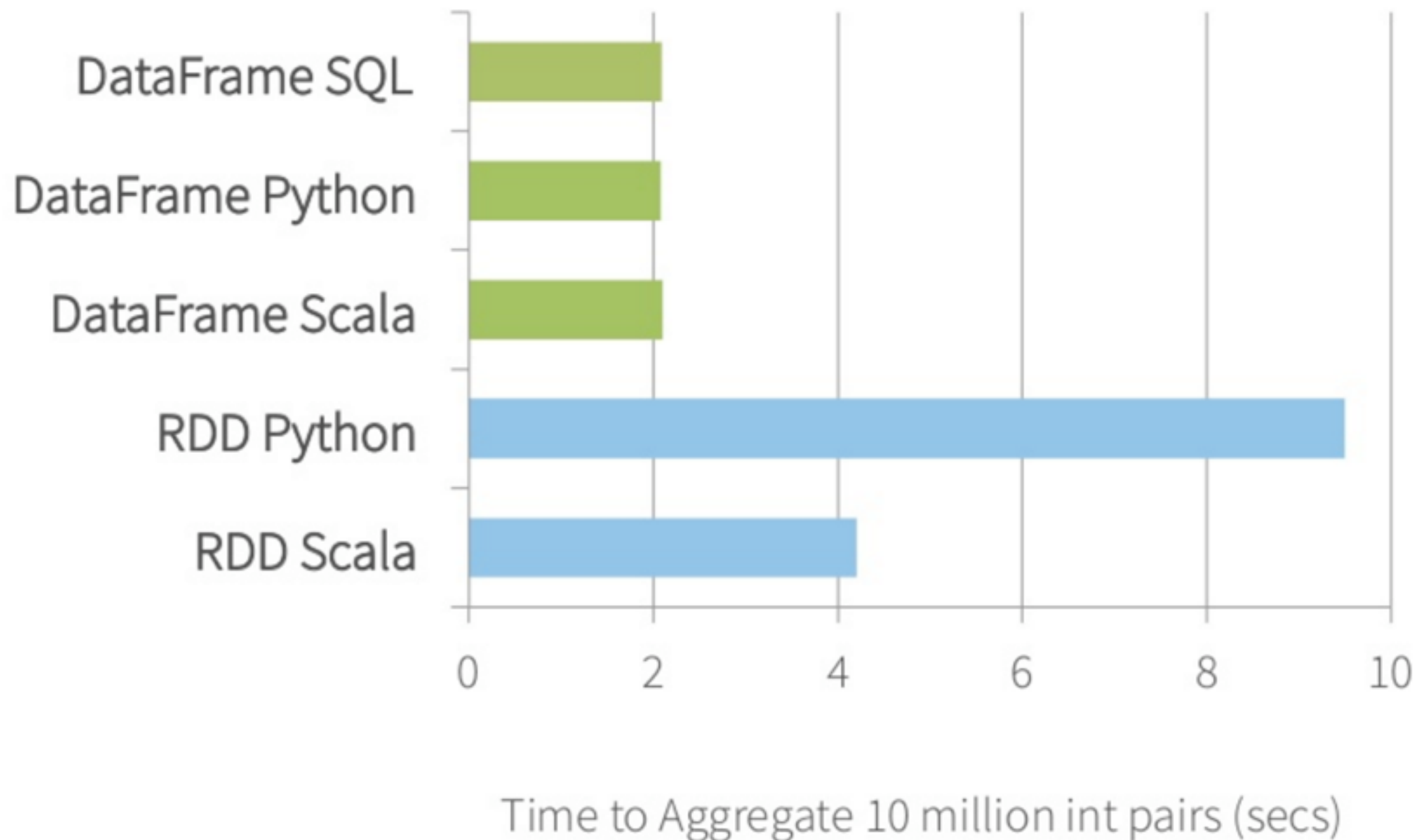
### Using DataFrames

```
sqlCtx.table("people") \
 .groupBy("name") \
 .agg("name", avg("age")) \
 .collect()
```

# DATAFRAME API

---

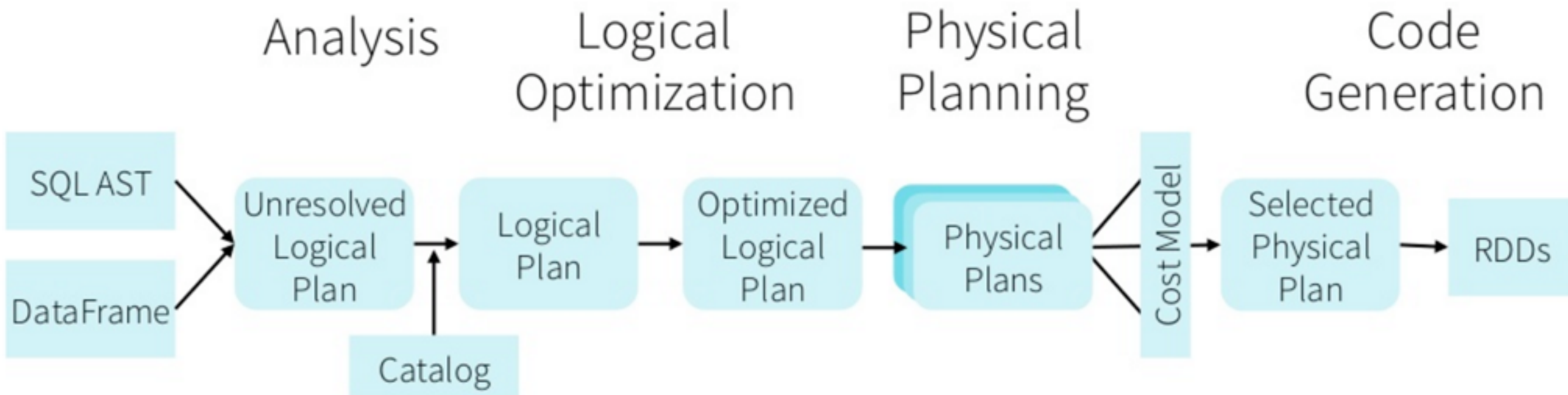
## ➤ Faster implementations



# CATALYST OPTIMIZER

---

- Goal: convert logical plan to physical plans
- Process:
  - Logical plan is a tree representing data and schema
  - The tree is manipulated and optimized by catalyst rules





# CATALYST OPTIMIZER

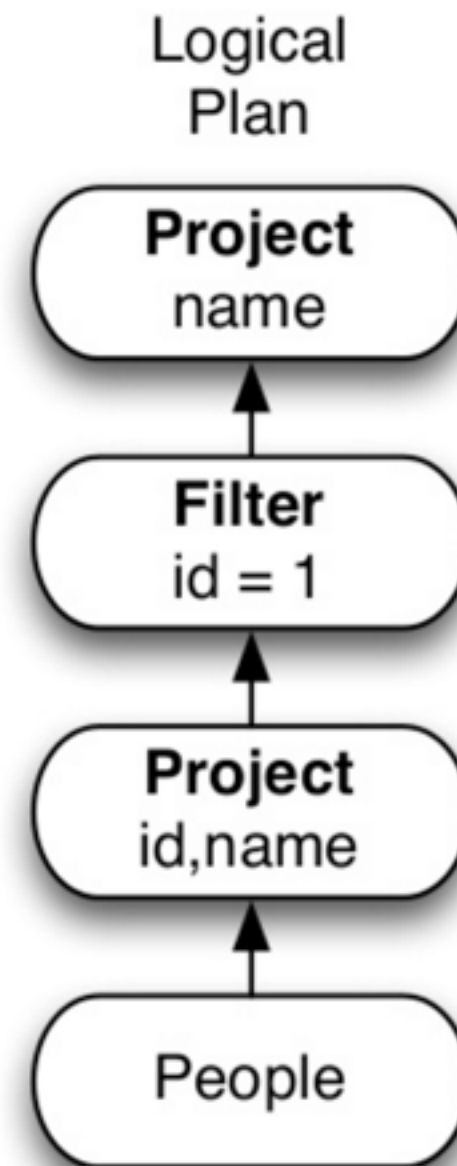
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- An example query

```
SELECT name

FROM (
 SELECT id, name
 FROM People) p

WHERE p.id = 1
```



# CATALYST OPTIMIZER

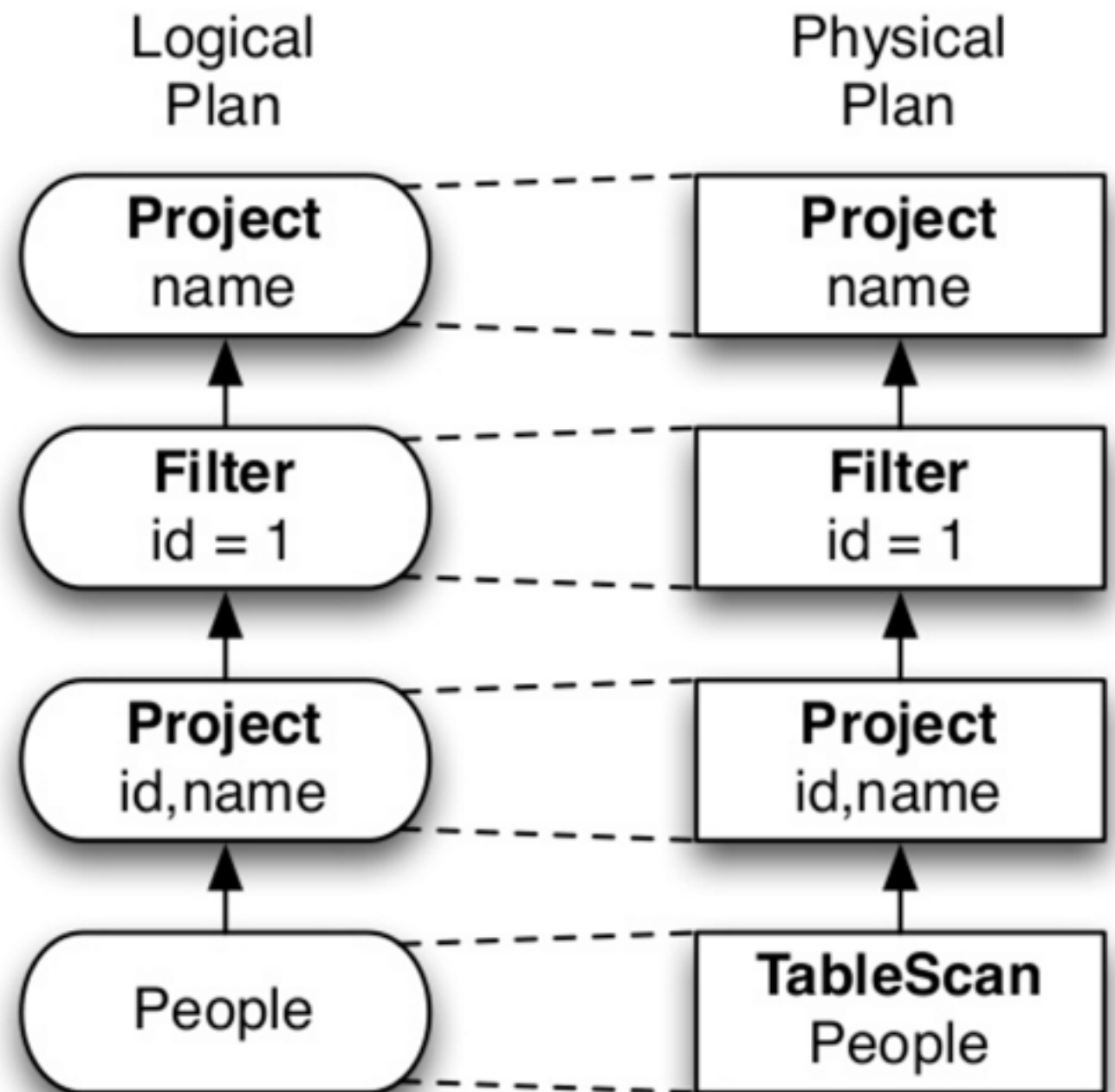
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## ► Native query planning

```
SELECT name

FROM (
 SELECT id, name
 FROM People) p

WHERE p.id = 1
```

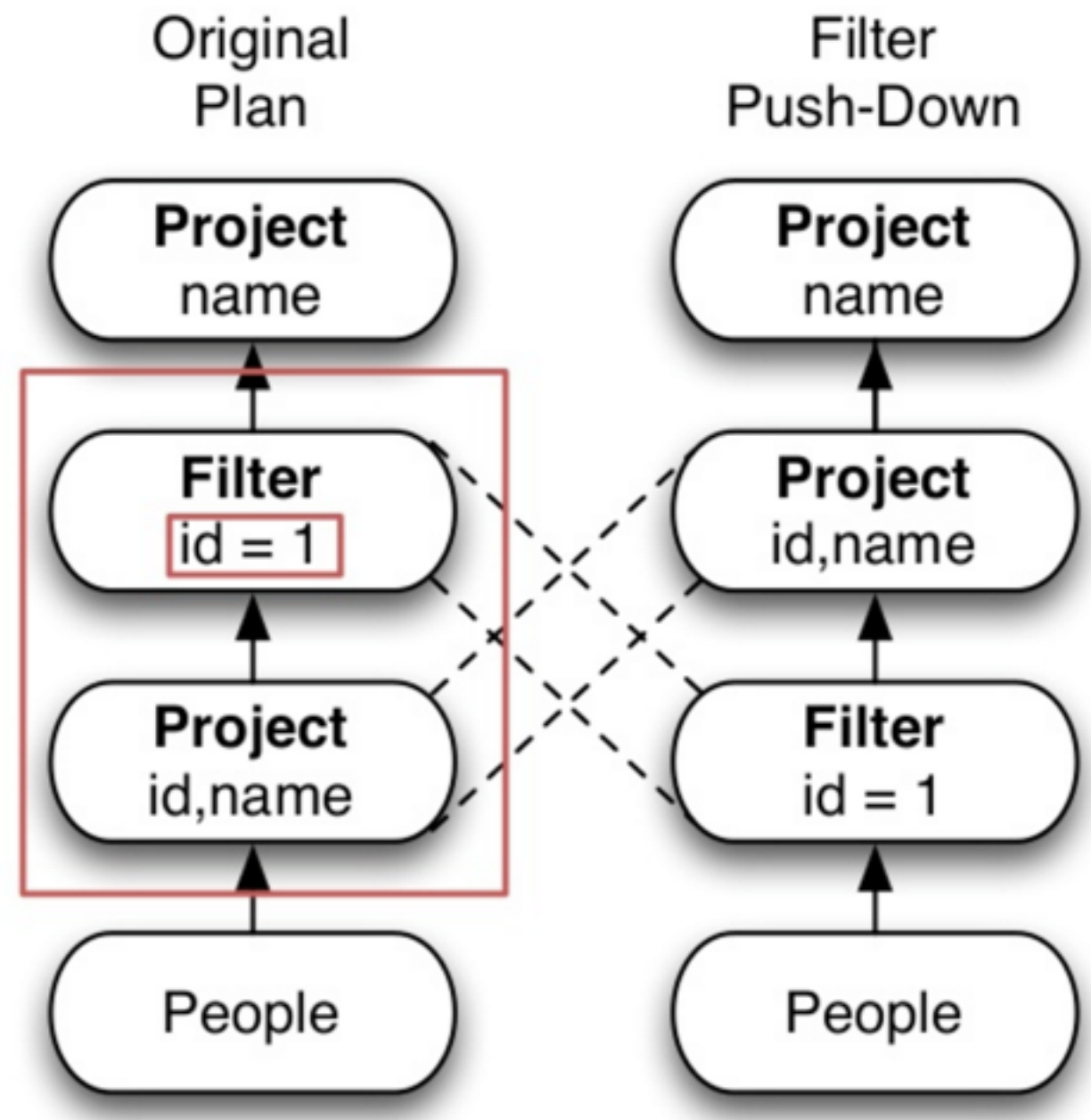


# CATALYST OPTIMIZER

---

## ► Optimization Rules example

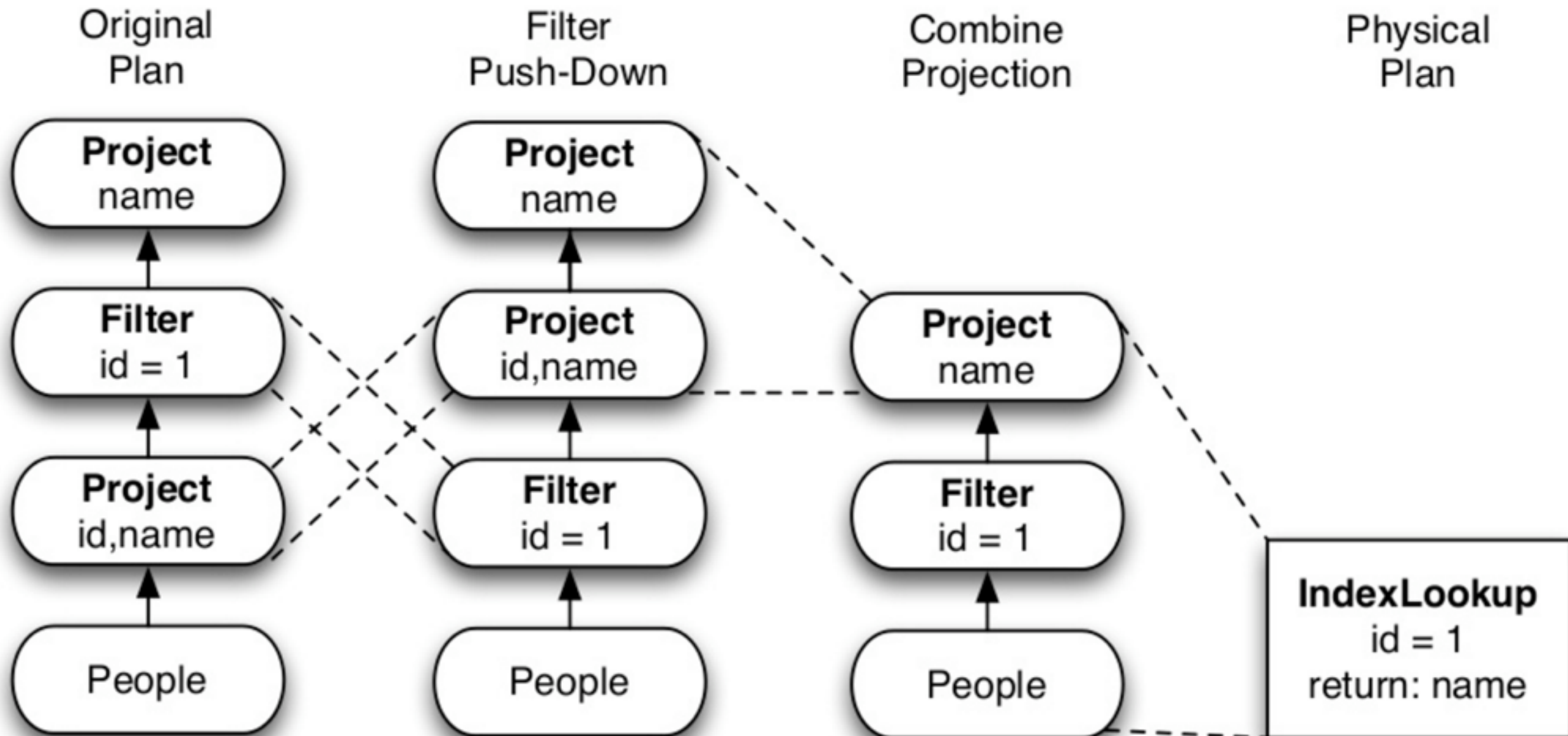
1. Find filters on top of projections.
2. Check that the filter can be evaluated without the result of the project.
3. If so, switch the operators.



# CATALYST OPTIMIZER

---

- Optimization Rules continued
  - Allow defining customized rules



# CATALYST OPTIMIZER

---

- Optimizing rules
  - Eliminate subqueries
  - Constant folding
  - Simplify filters
  - PushPredicate through filter
  - Project collapsing

# SPARK SQL FUTURE

---

- Tungsten - Optimization for the next few years
- Begin with hardware trends

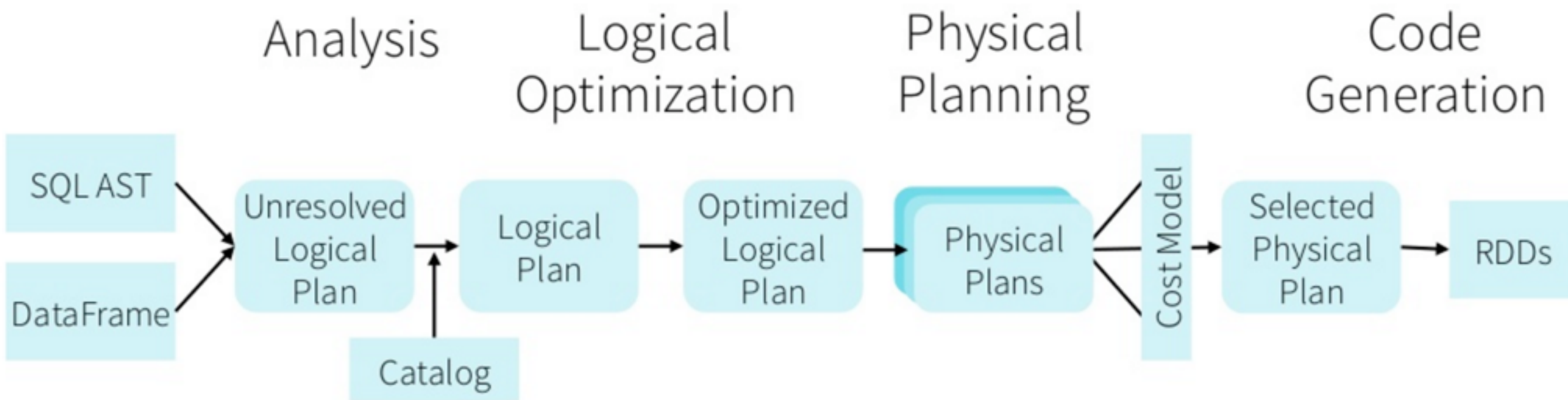
|         | 2010             | 2015              |     |
|---------|------------------|-------------------|-----|
| Storage | 50+MB/s<br>(HDD) | 500+MB/s<br>(SSD) | 10X |
| Network | 1Gbps            | 10Gbps            | 10X |
| CPU     | ~3GHz            | ~3GHz             | ☹   |



# SPARK SQL FUTURE

---

- Tungsten - Optimization for the next few years
- Recall our SparkSQL workflow



# SPARK SQL FUTURE

---

- Tungsten - Preparing Spark for next 5 years
- Begin with hardware trends

|         | 2010             | 2015              |     |
|---------|------------------|-------------------|-----|
| Storage | 50+MB/s<br>(HDD) | 500+MB/s<br>(SSD) | 10X |
| Network | 1Gbps            | 10Gbps            | 10X |
| CPU     | ~3GHz            | ~3GHz             | ☹   |

# SPARK SQL FUTURE

---

- Tungsten - Preparing Spark for next 5 years
- Substantially speed up execution by optimizing CPU efficiency via
  - Runtime code generation
  - Exploiting cache locality
  - Off-heap memory management



# CONCLUSION

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- SparkSQL intuition
- SparkSQL pipeline/  
architecture



# REFERENCES

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- <http://www.slideshare.net/datamantra/anatomy-of-data-frame-api>
- <http://www.slideshare.net/databricks/2015-0616-spark-summit>
- <http://www.slideshare.net/databricks/spark-sql-deep-dive-melbroune>
- <http://www.slideshare.net/databricks/spark-sqlsse2015public>
- <http://www.slideshare.net/datamantra/introduction-to-structured-data-in-spark>
- Data bricks official blog

# MY LEARNING WORKFLOW

---

- Recently I gradually set up my workflow and reduced learning cycle
- Everyone has different learning workflows
- But let's share and make progress together

*Knowledge  
collecting*

*Summarization*

*Sharing*

*Evernote web clipper*

*MindManager*

*Blog:Evernote+postach.io*

*Organize notes by tags*

*Evernote markdown doc  
with Marxico*

*Keynote/PowerPoint*