THE MAGIC OF PYSPARK

AN INTRODUCTION TO PYSPARK

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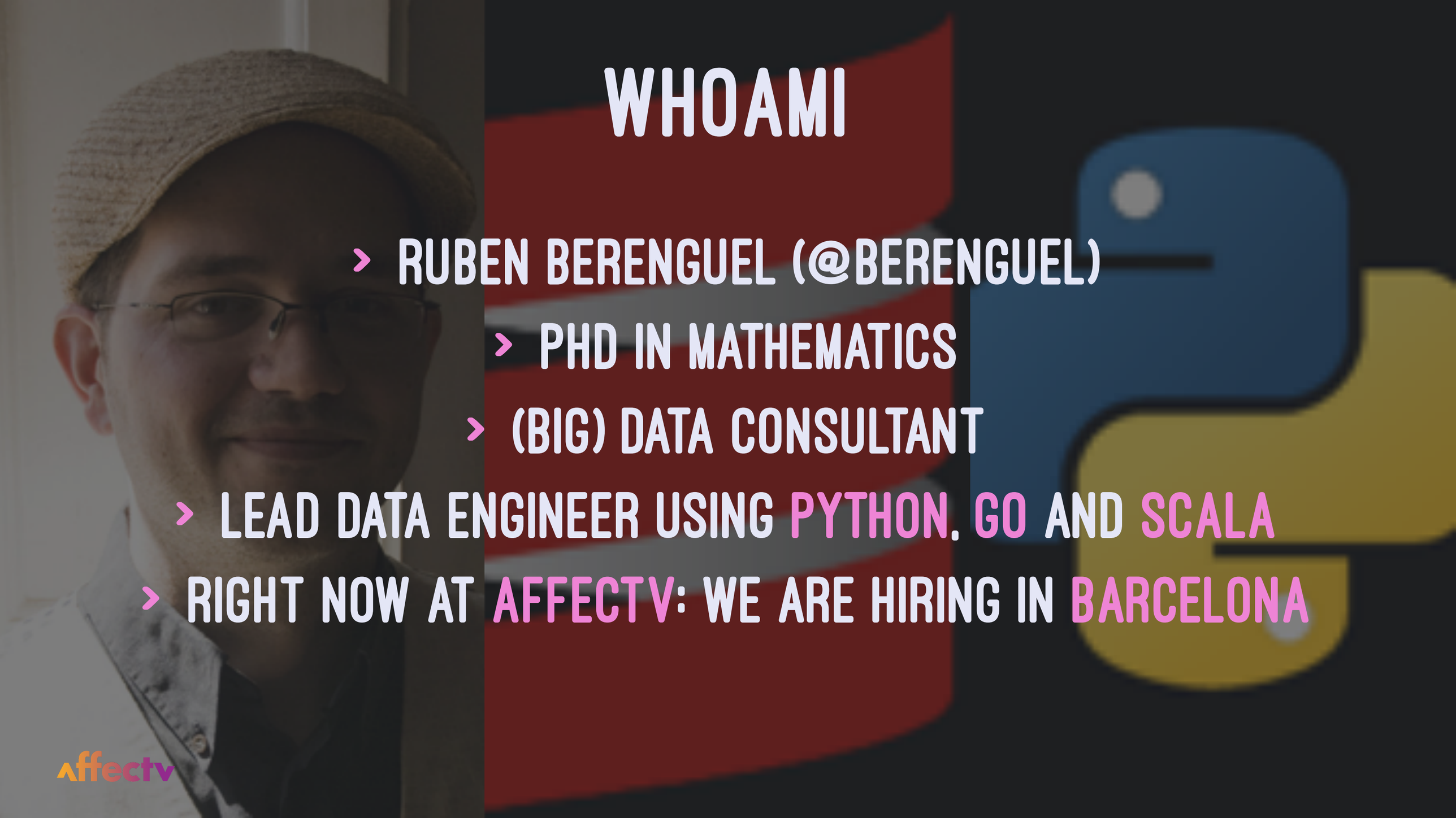

WHOAMI

- RUBEN BERENGUEL (@BERENGUEL)
- PHD IN MATHEMATICS
- (BIG) DATA CONSULTANT
- LEAD DATA ENGINEER USING PYTHON, GO AND SCALA
- RIGHT NOW AT AFFECTV: WE ARE HIRING IN BARCELONA

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WHAT IS SPARK?

WHAT IS SPARK?

- DISTRIBUTED COMPUTATION FRAMEWORK

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- OPEN SOURCE

WHAT IS SPARK?

- DISTRIBUTED COMPUTATION FRAMEWORK
  - OPEN SOURCE
  - EASY TO USE

WHAT IS SPARK?

- DISTRIBUTED COMPUTATION FRAMEWORK
  - OPEN SOURCE
  - EASY TO USE
- SCALES HORIZONTALLY AND VERTICALLY

HOW DOES SPARK WORK?

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SPARK USUALLY RUNS ON TOP OF A CLUSTER MANAGER

AND A DISTRIBUTED STORAGE

A SPARK PROGRAM
RUNS IN THE DRIVER

THE DRIVER REQUESTS RESOURCES FROM THE CLUSTER MANAGER TO RUN TASKS

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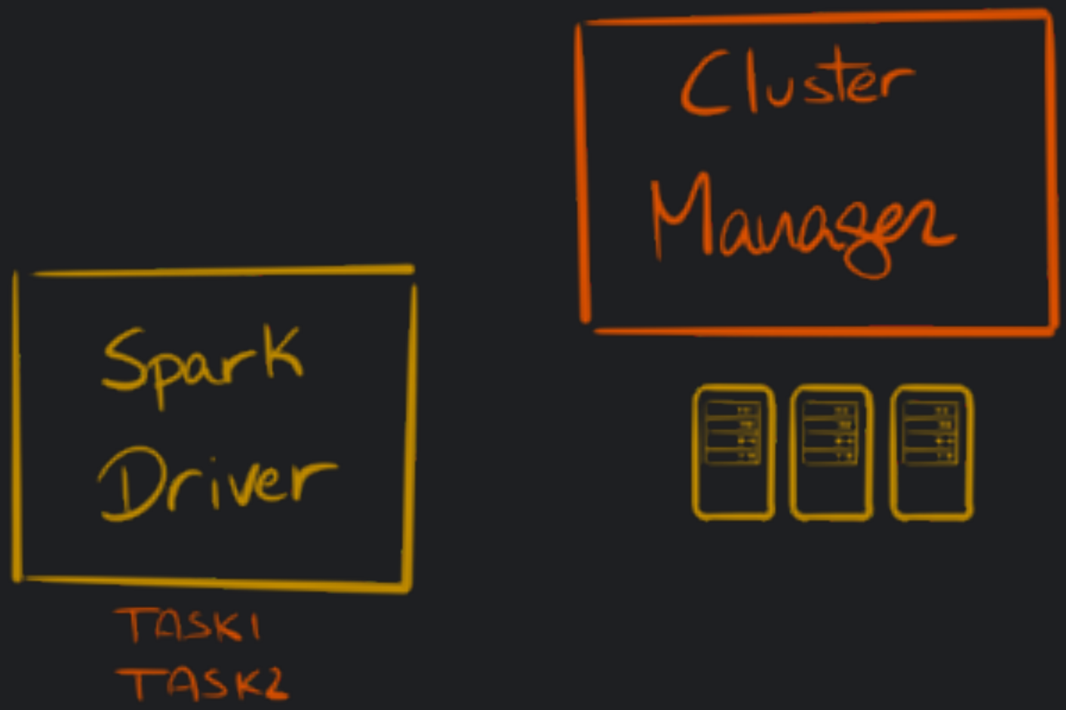

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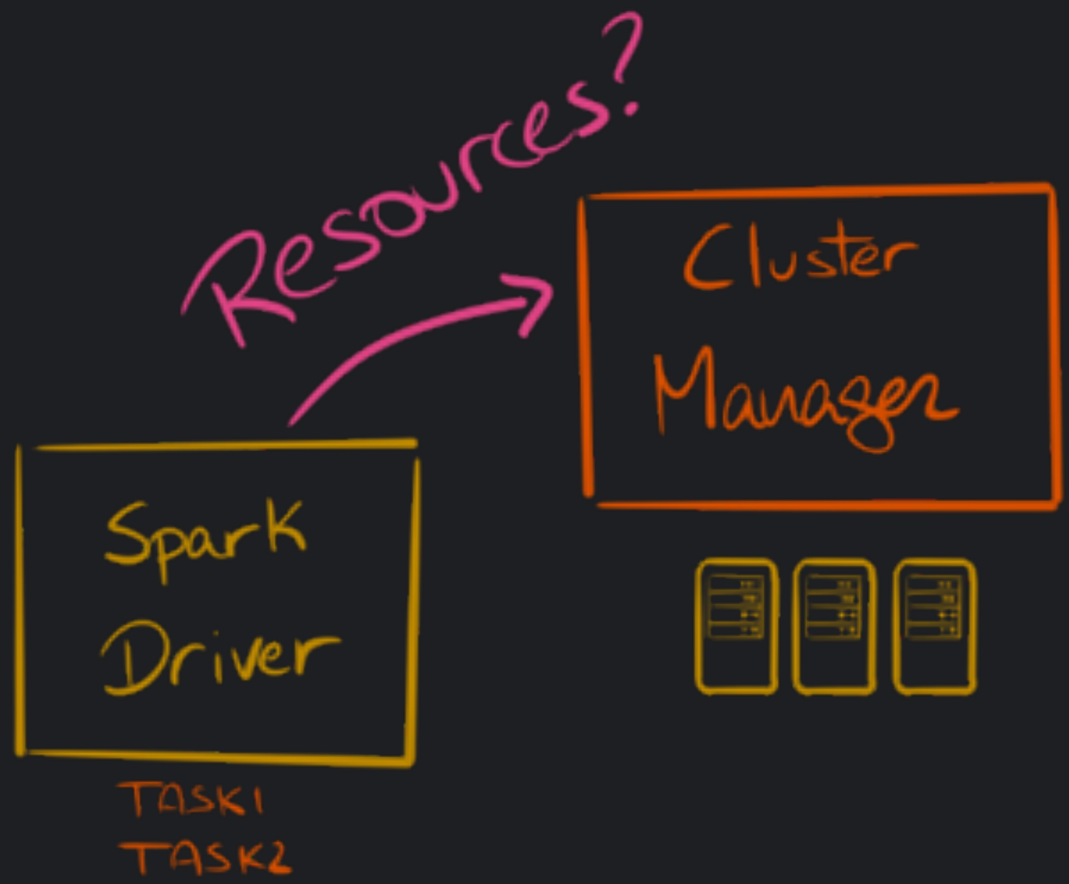

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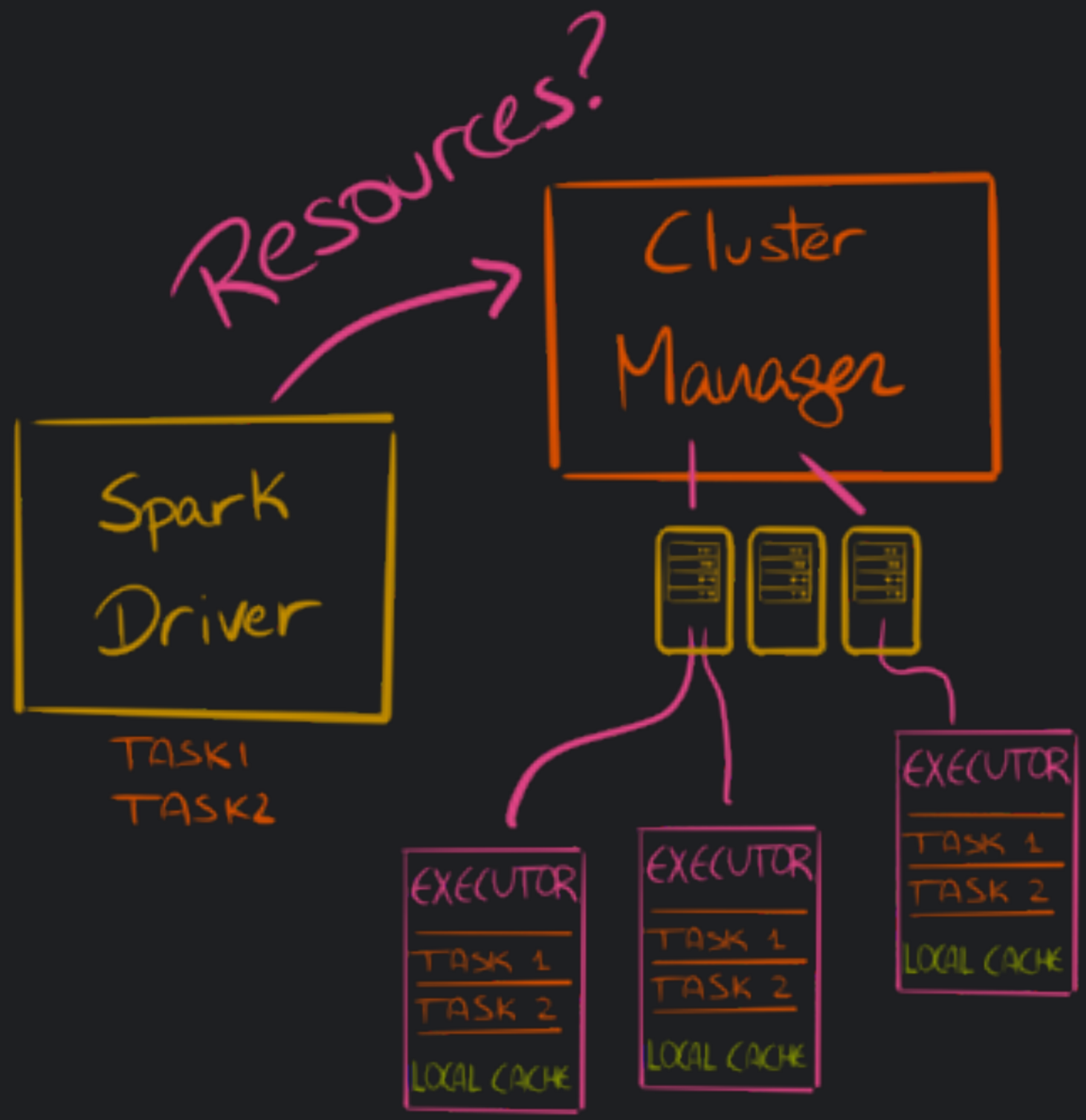

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THE MAIN BUILDING BLOCK IS THE RDD: RESILIENT DISTRIBUTED DATASET

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RDD

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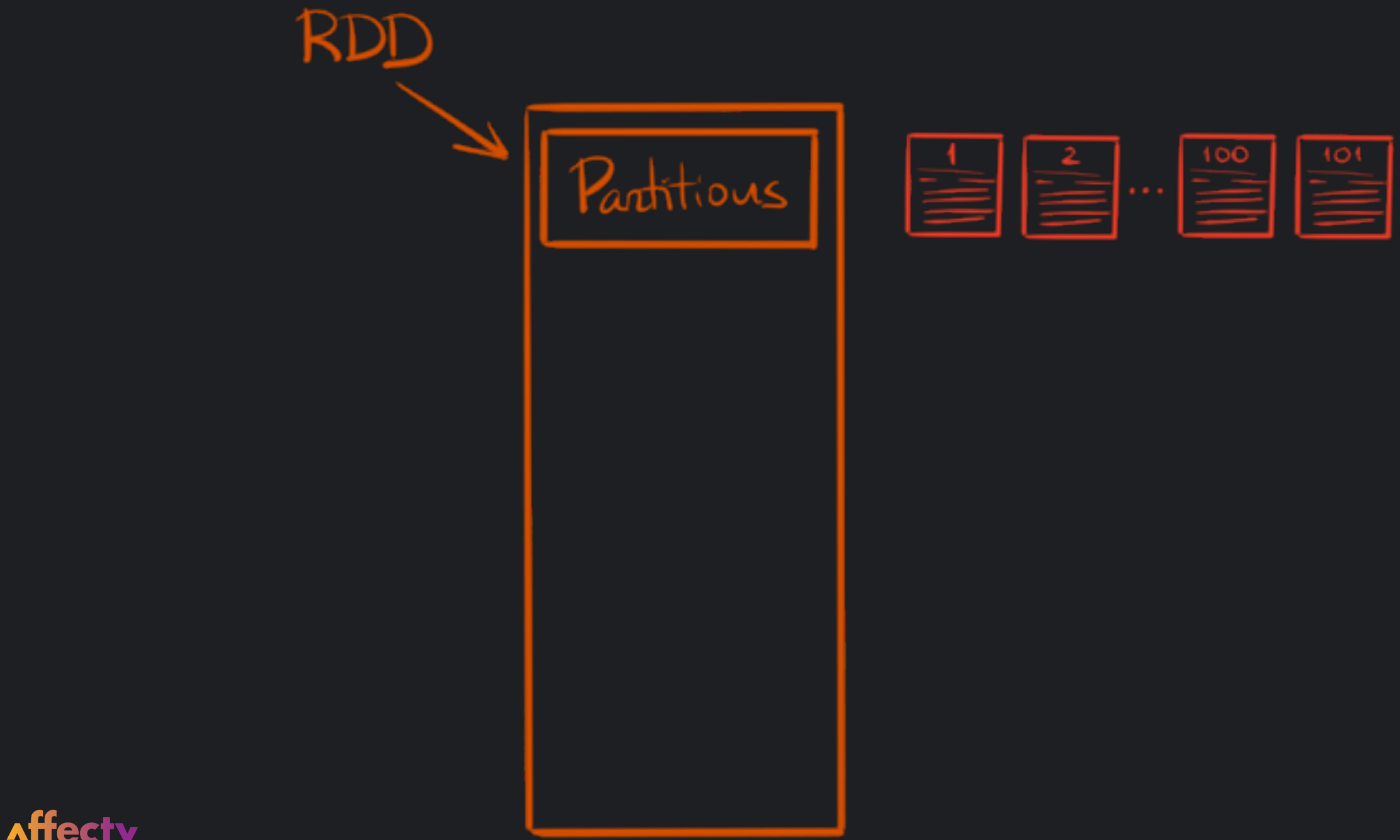

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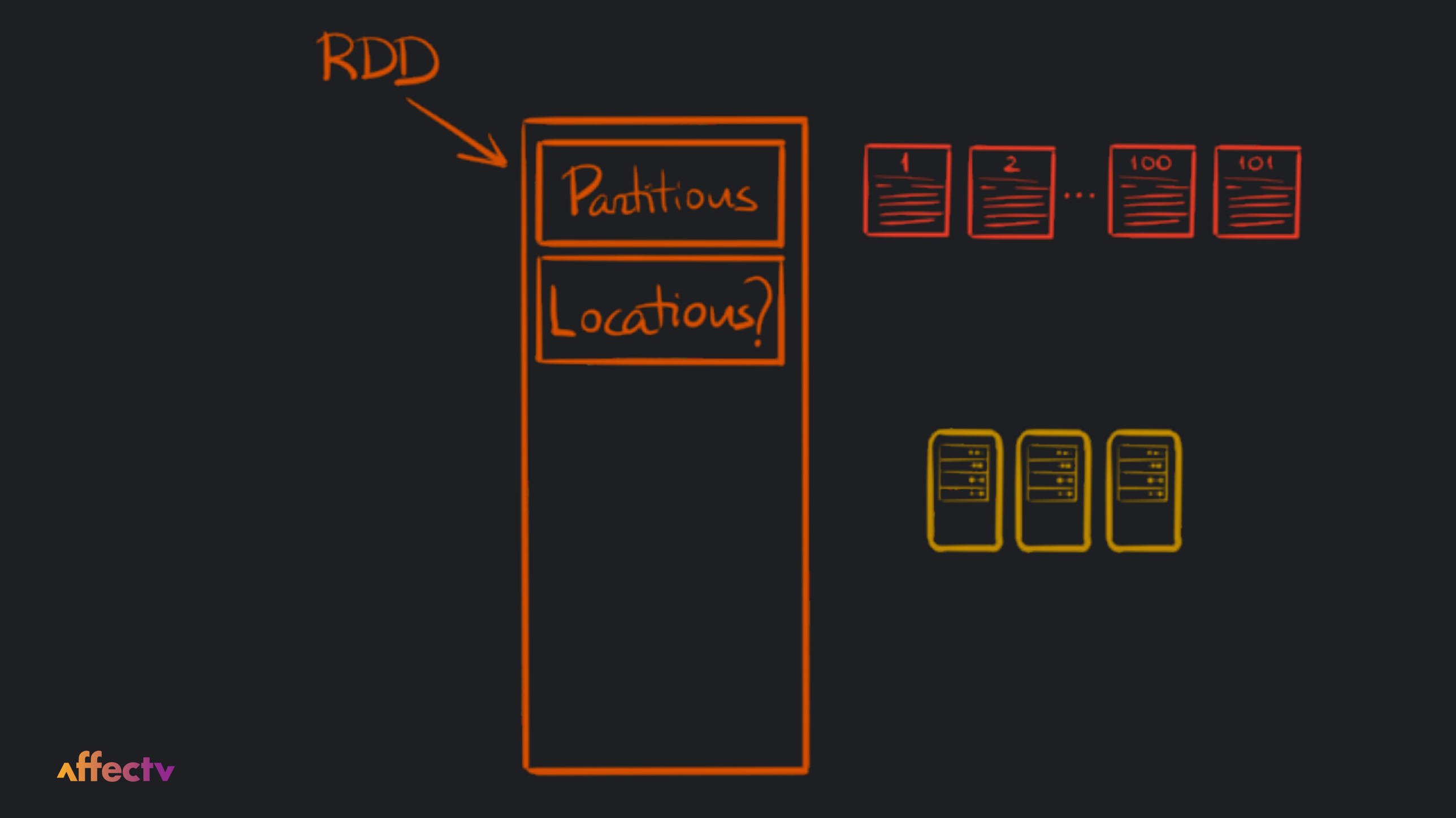
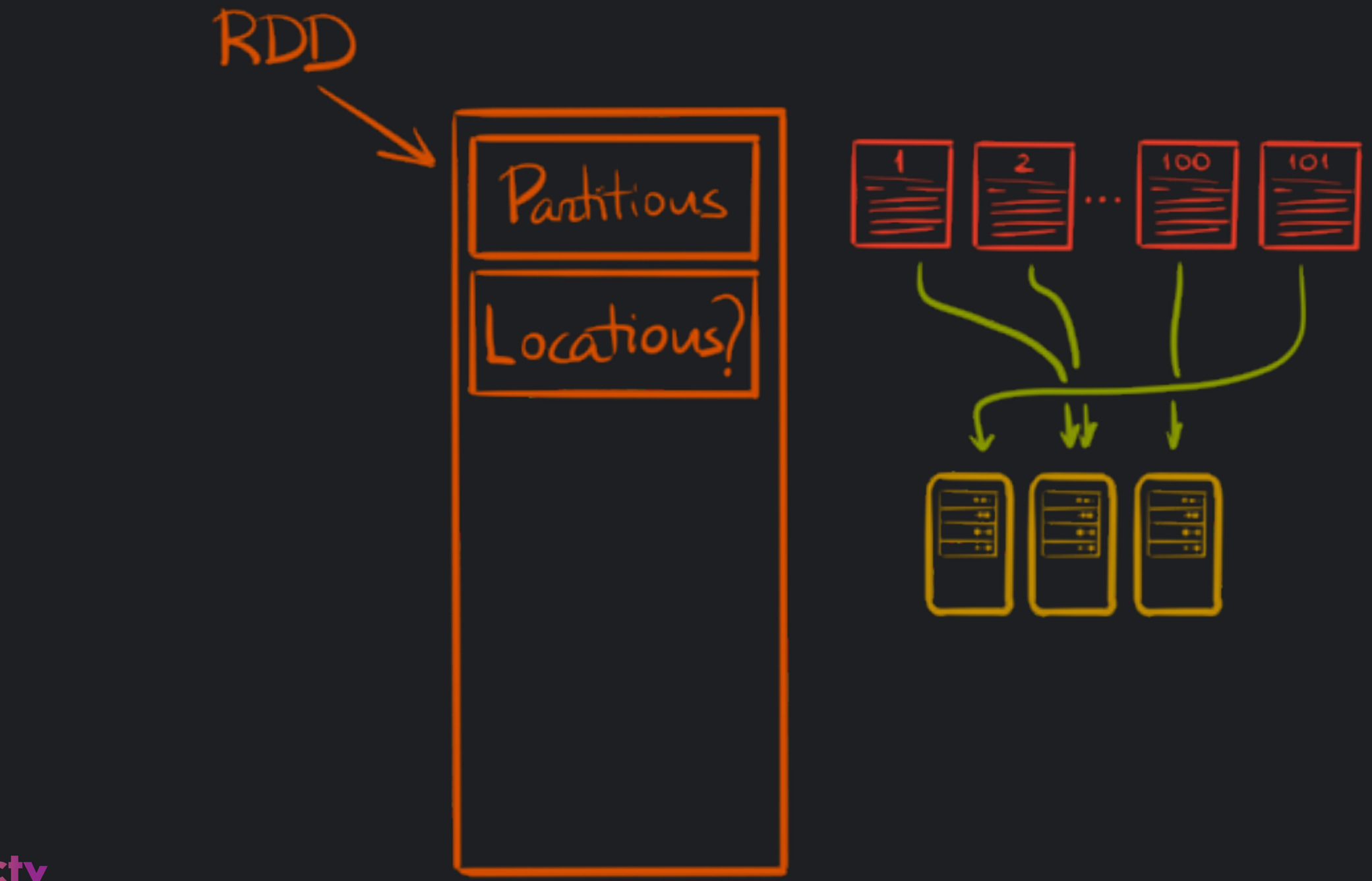

RDD
Partitions
Locations?
1
2
100
101



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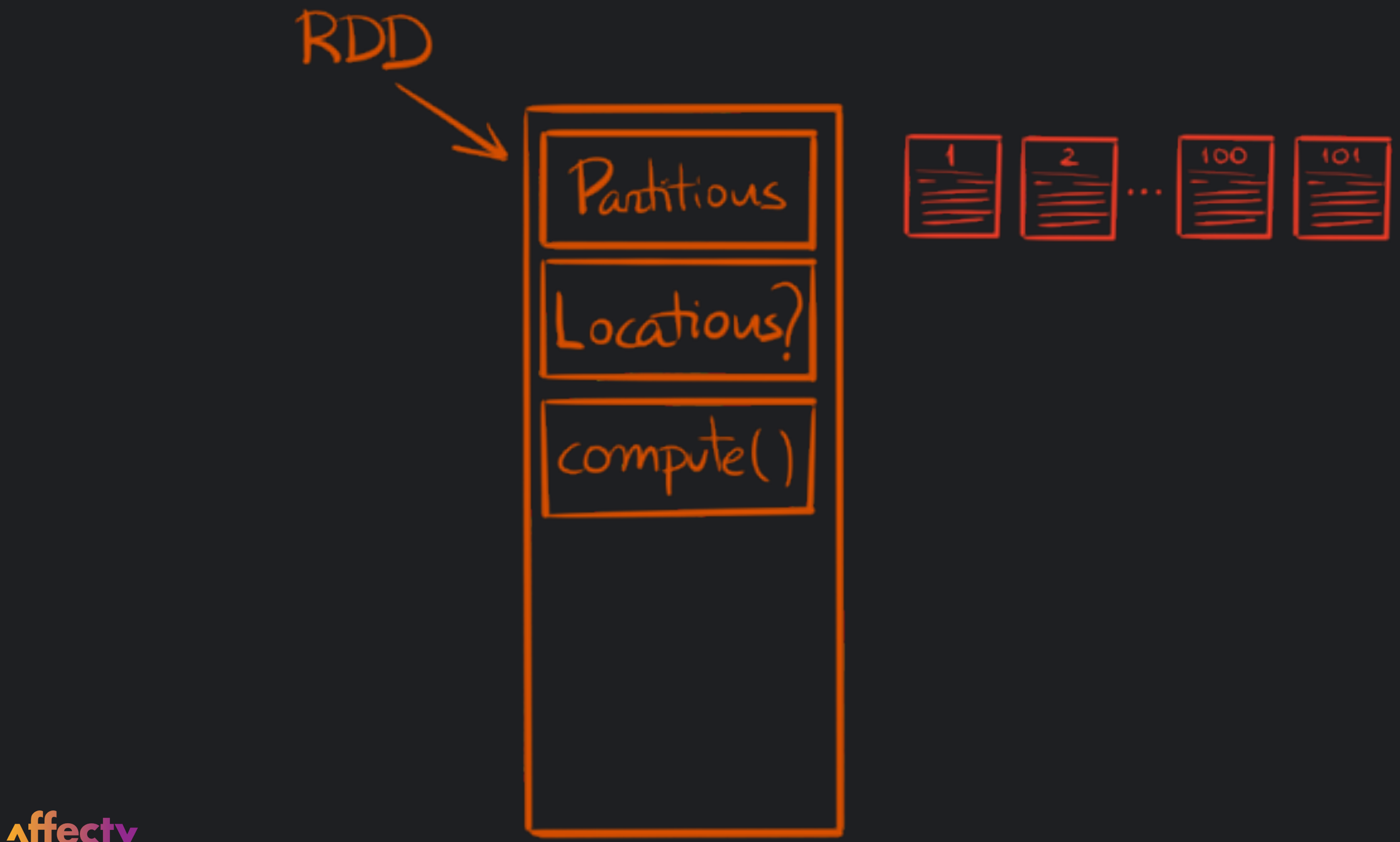

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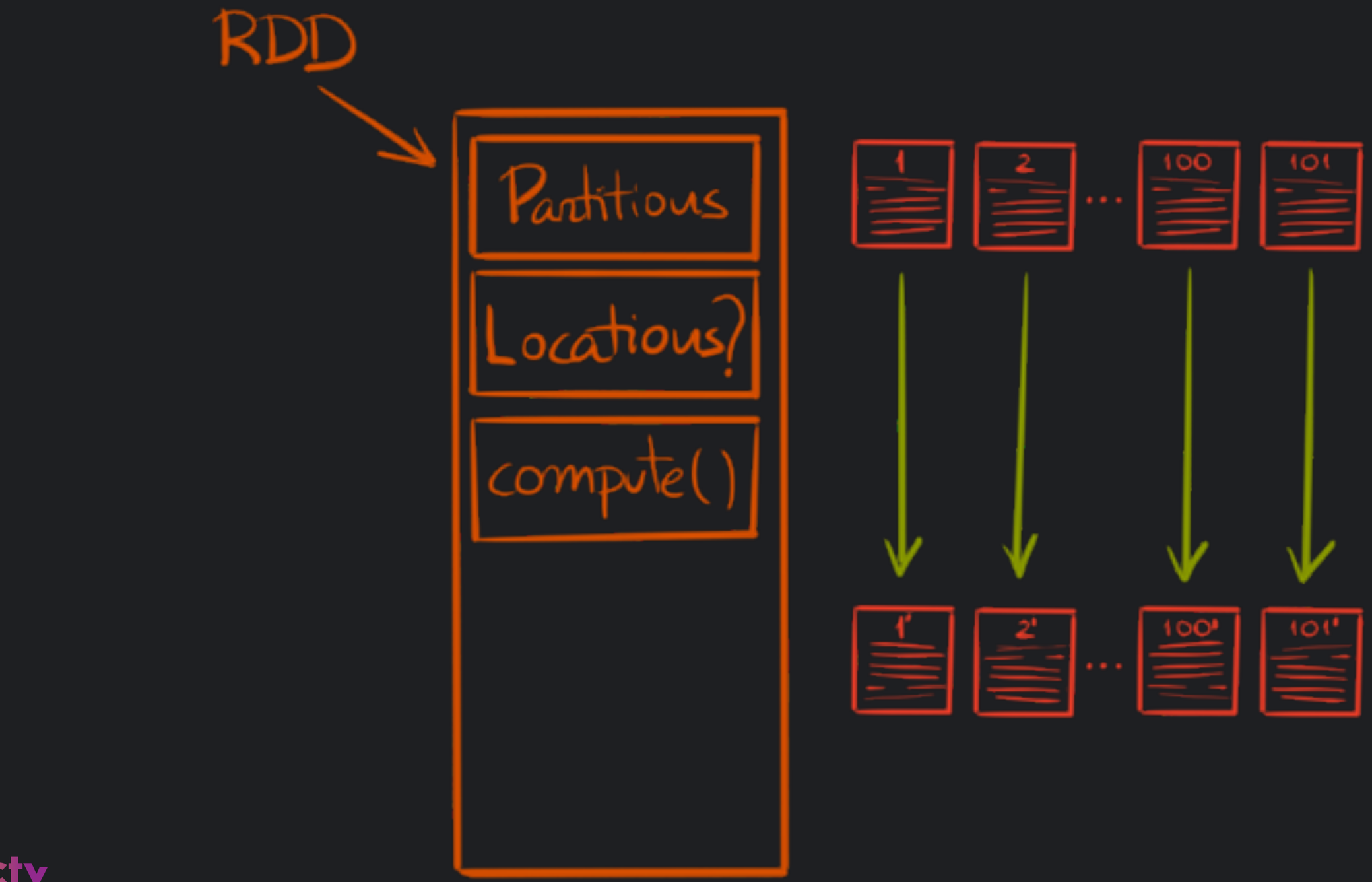

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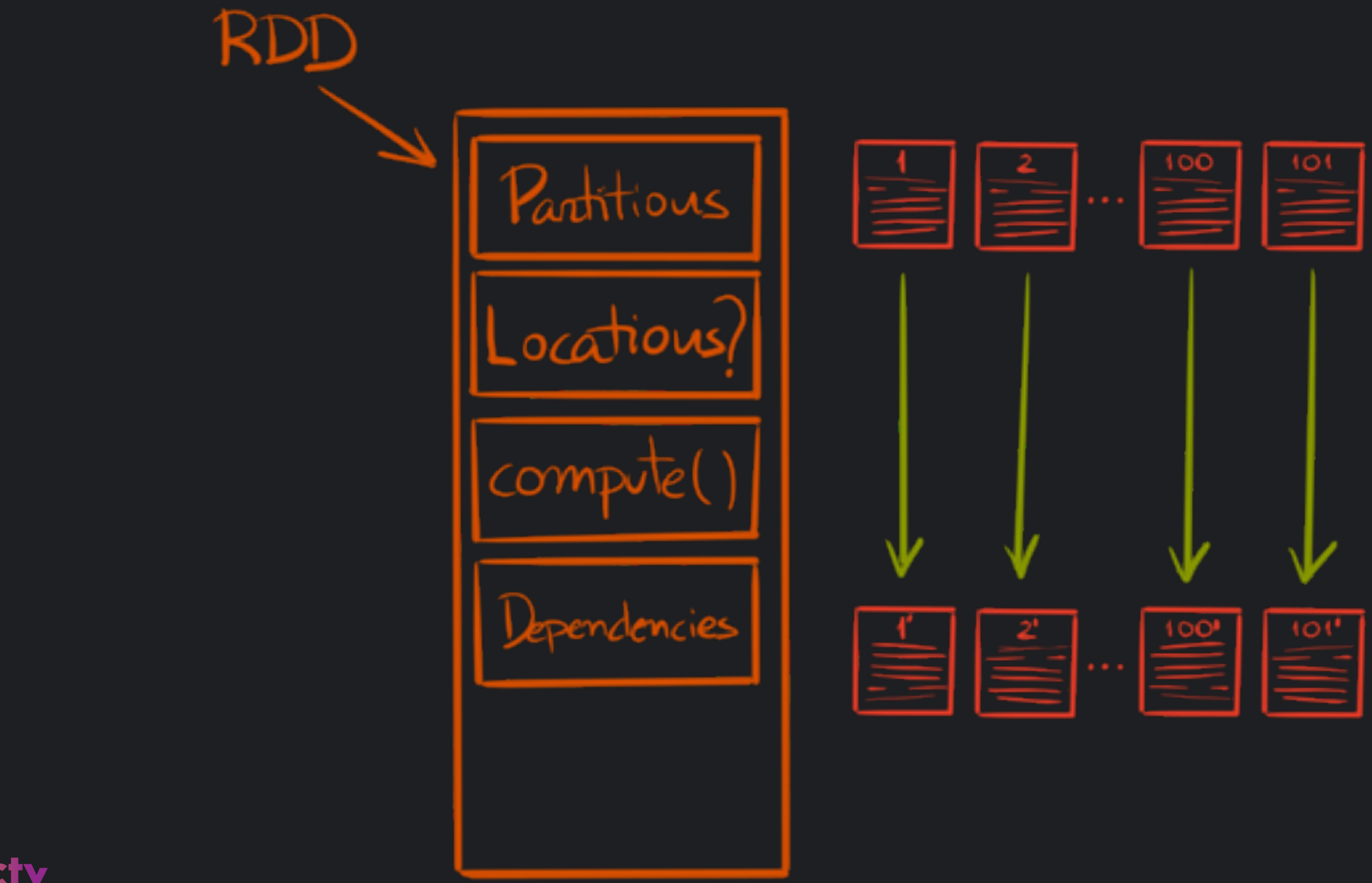
RDD
Partitions
Locations?
compute()
Dependencies
1
2
100
101
1'
2'
100'
101'

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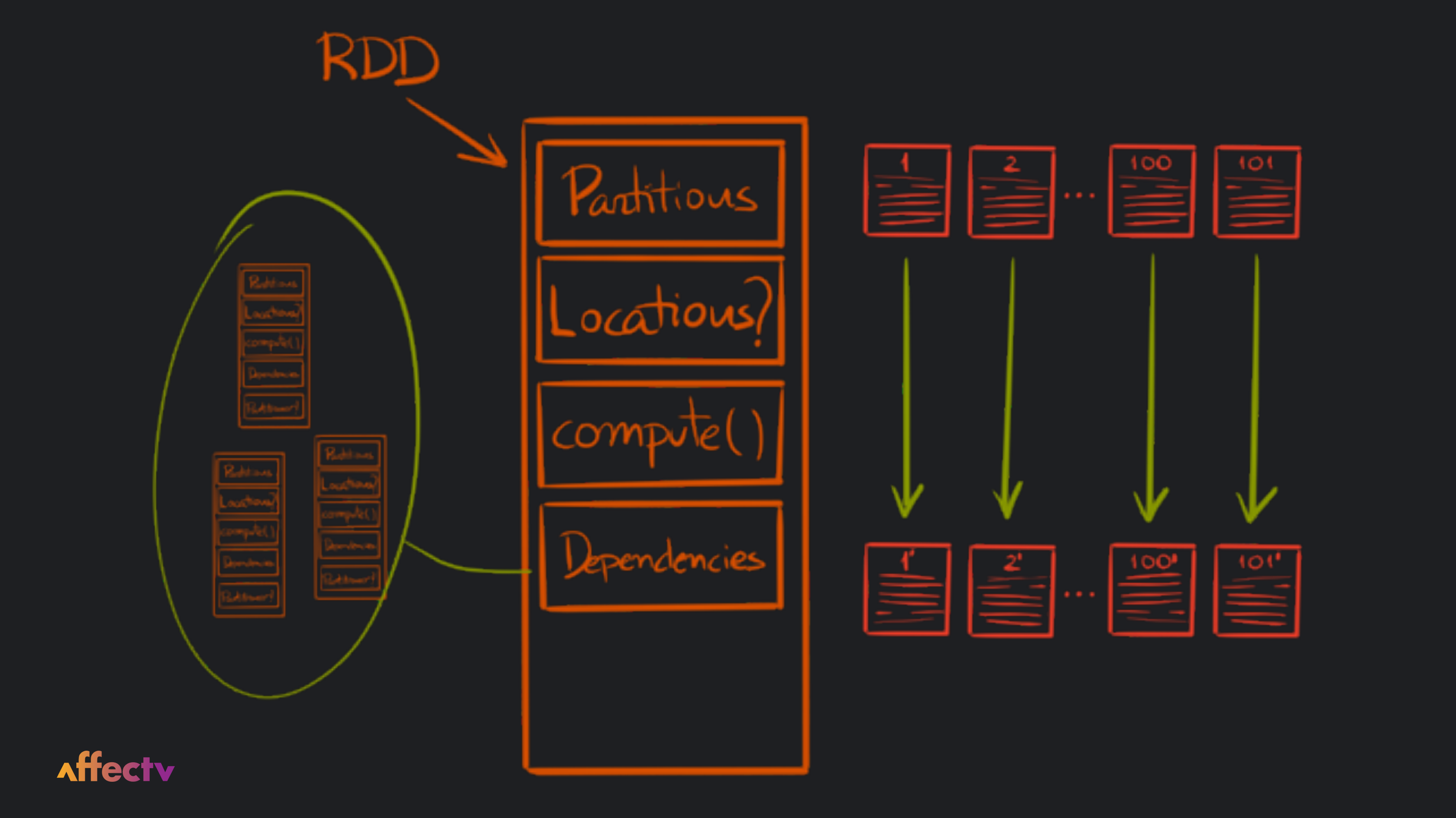
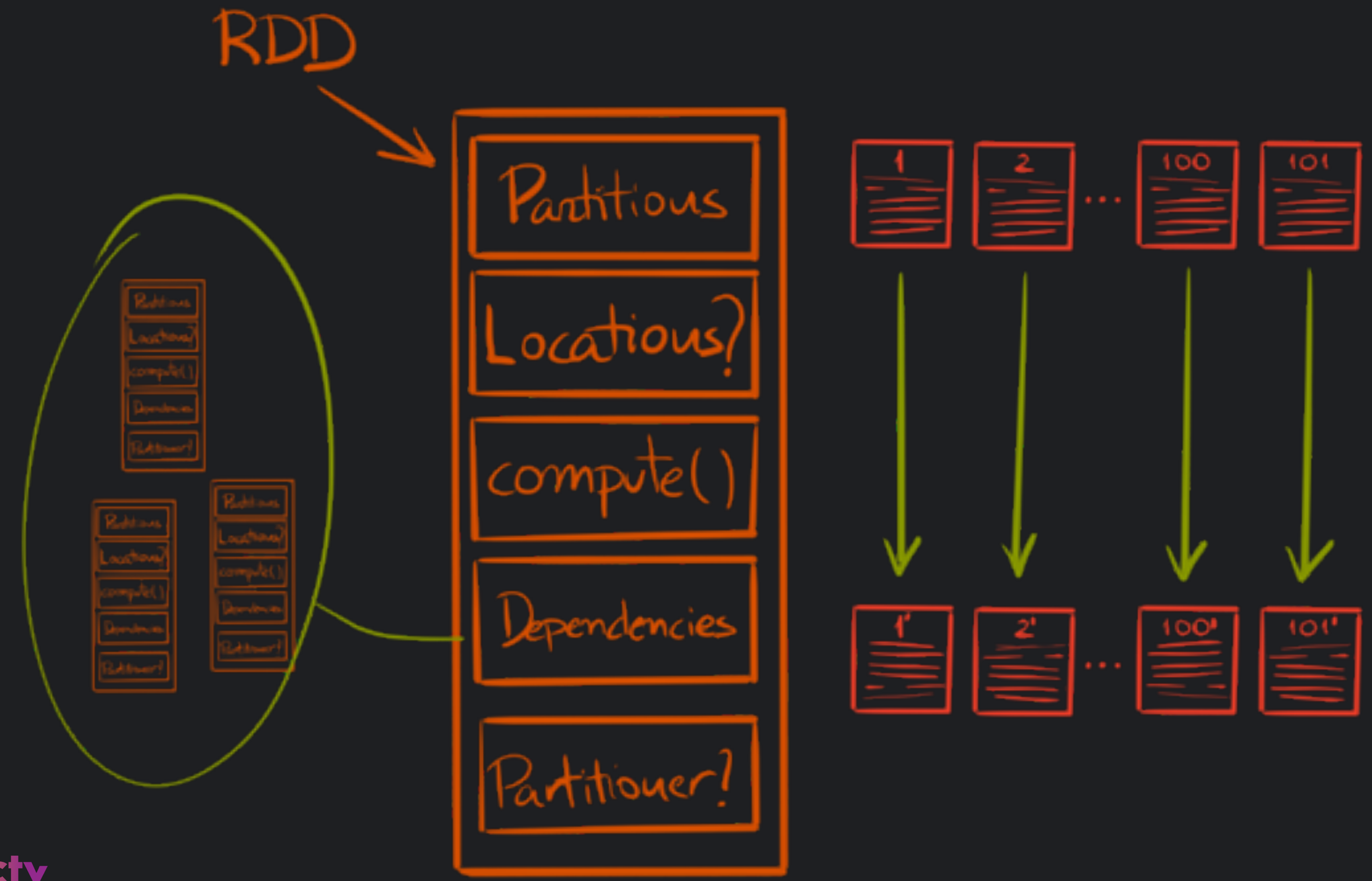

RDD
Partitions
Locations?
compute()
Dependencies
1
2
100
101
1'
2'
100'
101'


RDD
Partitions
Locations?
compute()
Dependencies
Partitioner?
1
2
100
101
1'
2'
100'
101'

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TWO KIND OF OPERATIONS:

TRANSFORMATIONS

&

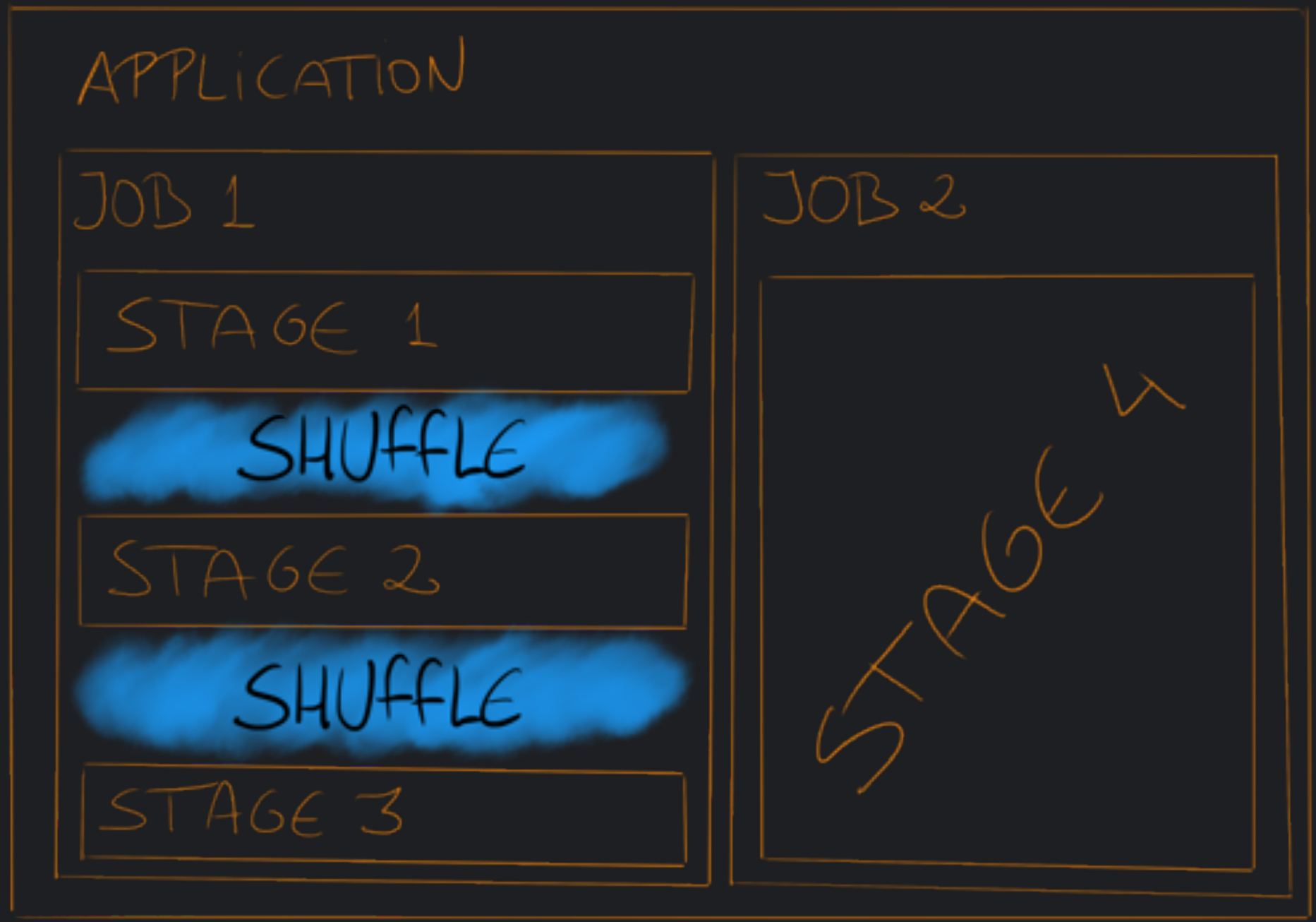
ACTIONS

TRANSFORMATIONS: RESHAPE THE DATA. THEY ARE PART OF STAGES

- FILTER
- MAP
- JOIN

ACTIONS: RETURN A RESULT. THEY DEFINE JOBS

- COUNT
- SHOW
- WRITE


APPLICATION
JOB 1
STAGE 1
SHUFFLE
STAGE 2
SHUFFLE
STAGE 3
JOB 2
STAGE 4

PYSPARK

PYSPARK OFFERS A PYTHON API TO THE SCALA CORE OF SPARK

IT USES THE PY4J BRIDGE

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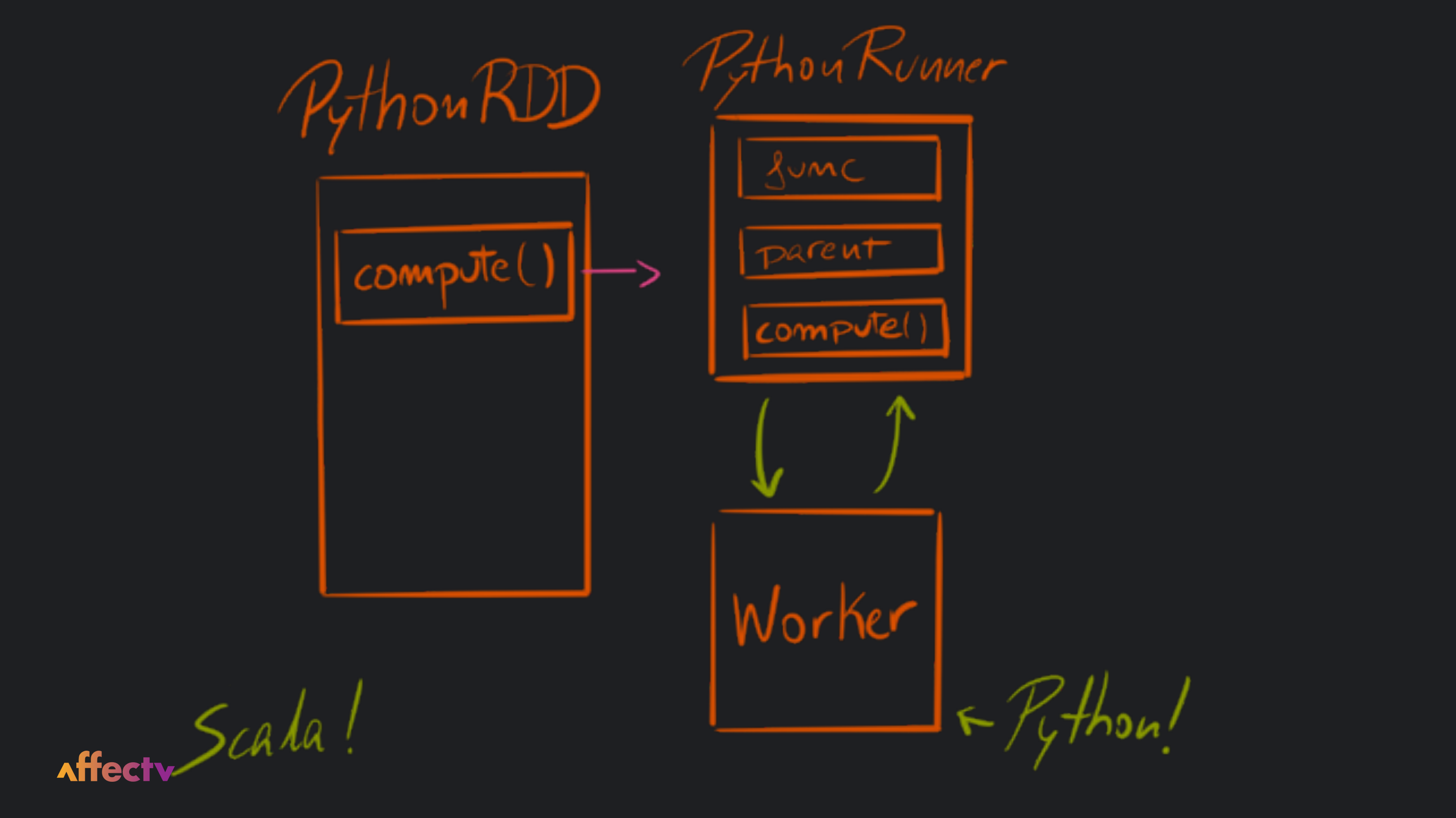
PythonRDD
compute()
PythonRunner
func
parent
compute()
Worker
Scala!
Python!
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WORKERS ACT AS STANDALONE PROCESSORS OF STREAMS OF DATA

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- CONNECTS BACK TO THE JVM THAT STARTED IT

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WORKERS ACT AS STANDALONE PROCESSORS OF STREAMS OF DATA

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- CONNECTS BACK TO THE JVM THAT STARTED IT
- LOAD INCLUDED PYTHON LIBRARIES
- DESERIALIZES THE PICKLED FUNCTION COMING FROM THE STREAM
- APPLIES THE FUNCTION TO THE DATA COMING FROM THE STREAM
- SENDS THE OUTPUT BACK

WHAT ABOUT DATAFRAMES?

THE RDD API EXPECTS YOU TO HANDLE EVERYTHING.

BUT SPARK CAN MAGICALLY OPTIMISE EVERYTHING..

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..IF YOU USE SPARK DataFrame

SPARK WILL GENERATE
A PLAN

(A DIRECTED ACYCLIC GRAPH)

TO COMPUTE THE
RESULT

AND THE PLAN WILL BE OPTIMISED USING CATALYST

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PLEASE. PLEASE. USE SPARK ≥ 2.3 (OR. THE LATEST YOU CAN)

YOU SHOULD TRY TO USE DataFrame UNLESS THERE IS A REASON NOT TO (LIKE SOME MLLIB METHOD)

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YOU SHOULD ALSO ENABLE ARROW OPTIMISATIONS TO SPEED UP THE DATA TRANSFER FROM THE JVM TO PYTHON

WE'LL SEE WHY AND HOW LATER DURING THE WORKSHOP

NEW PROJECT: KOALAS[1]

OFFERS A UNIFIED API BETWEEN PANDAS AND SPARK DATAFRAMES (AS MUCH AS POSSIBLE)

[1] HTTPS://GITHUB.COM/DASK/DASK

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PURE PYTHON ALTERNATIVE: DASK[1]

ANOTHER DISTRIBUTED FRAMEWORK

[1] HTTPS://GITHUB.COM/DASK/DASK

SHOULD YOU USE SPARK?

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YES IF

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YES IF

- THE DATA IS VERY LARGE (SIGNIFICANTLY LARGER THAN MEMORY)

YES IF

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- YOUR ORG ALREADY HAS SPARK CLUSTER OR CODEBASE

YES IF

- THE DATA IS VERY LARGE (SIGNIFICANTLY LARGER THAN MEMORY)
- YOUR ORG ALREADY HAS SPARK CLUSTER OR CODEBASE
- THERE IS NO BETTER ALTERNATIVE

NO IF

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NO IF

- YOU WANT TO ADD SPARK TO YOUR CV

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NO IF

- YOU WANT TO ADD SPARK TO YOUR CV
  - JAVA STACKTRACES SCARE YOU

RESOURCES

- SPARK DOCUMENTATION
- HIGH PERFORMANCE SPARK BY HOLDEN KARAU
- THE INTERNALS OF APACHE SPARK 2.4.2 BY JACEK LASKOWSKI
- SPARK'S GITHUB
- BECOME A CONTRIBUTOR


THANKS!
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WORKSHOP TIME!

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GET THE SLIDES AND NOTEBOOK WE WILL USE FROM MY GITHUB:

github.com/rberenguel/

THE REPOSITORY IS

pyspark_workshop

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FURTHER REFERENCES

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ARROW

ARROW'S HOME
ARROW'S GITHUB
ARROW SPEED BENCHMARKS
ARROW TO PANDAS CONVERSION BENCHMARKS
POST: STREAMING COLUMNAR DATA WITH APACHE ARROW
POST: WHY PANDAS USERS SHOULD BE EXCITED BY APACHE ARROW
CODE: ARROW-PANDAS COMPATIBILITY LAYER CODE
CODE: ARROW TABLE CODE
PYARROW IN-MEMORY DATA MODEL
BALLISTA: A POC DISTRIBUTED COMPUTE PLATFORM (RUST)
PYJAVA: POC ON JAVA/SCALA AND PYTHON DATA INTERCHANGE WITH ARROW

PANDAS

PANDAS' HOME
PANDAS' GITHUB
GUIDE: IDIOMATIC PANDAS
CODE: PANDAS INTERNALS
DESIGN: PANDAS INTERNALS
TALK: DEMYSTIFYING PANDAS' INTERNALS, BY MARC GARCIA
MEMORY LAYOUT OF MULTIDIMENSIONAL ARRAYS IN NUMPY

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SPARK/PYSPARK

CODE: PYSPARK SERIALIZERS
JIRA: FIRST STEPS TO USING ARROW (ONLY IN THE PYSPARK DRIVER)
POST: SPEEDING UP PYSPARK WITH APACHE ARROW
ORIGINAL JIRA ISSUE: VECTORIZED UDFS IN SPARK
INITIAL DOC DRAFT
POST BY BRYAN CUTLER (LEADER FOR THE VEC UDFS PR)
POST: INTRODUCING PANDAS UDF FOR PYSPARK
CODE: ORG.APACHE.SPARK.SQL.VECTORIZED
POST BY BRYAN CUTLER: SPARK TOPANDAS() WITH ARROW, A DETAILED LOOK

PY4J

PY4J'S HOME
PY4J'S GITHUB
CODE: REFLECTION ENGINE

EOF

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