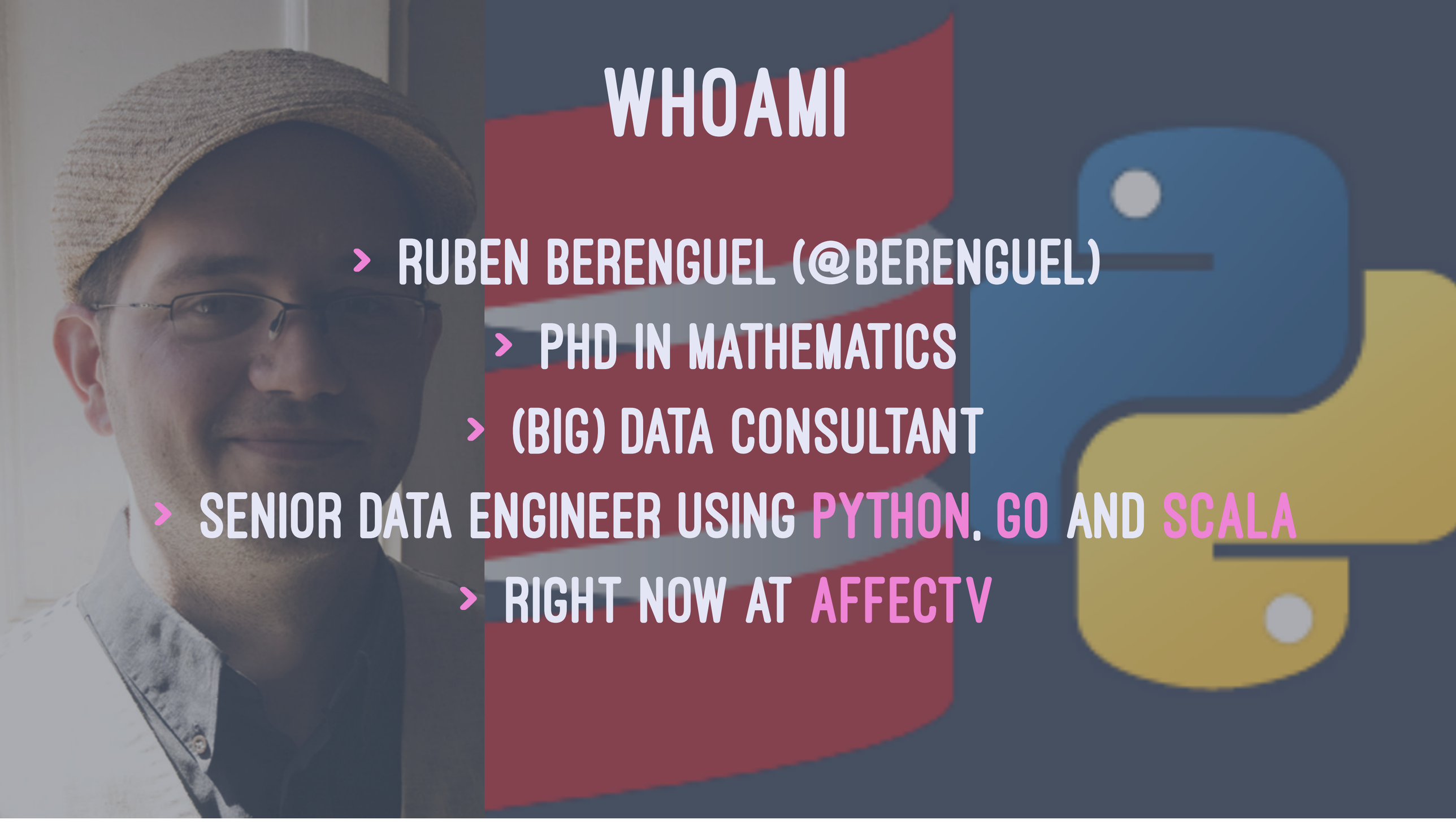
HOW DOES THAT PYSPARK THING WORK? AND WHY ARROW MAKES IT FASTER?



WHOAMI

- RUBEN BERENGUEL (@BERENGUEL)
- PHD IN MATHEMATICS
- (BIG) DATA CONSULTANT
- SENIOR DATA ENGINEER USING PYTHON, GO AND SCALA
- RIGHT NOW AT AFFECTV

WHAT IS PANDAS?

WHAT IS PANDAS?

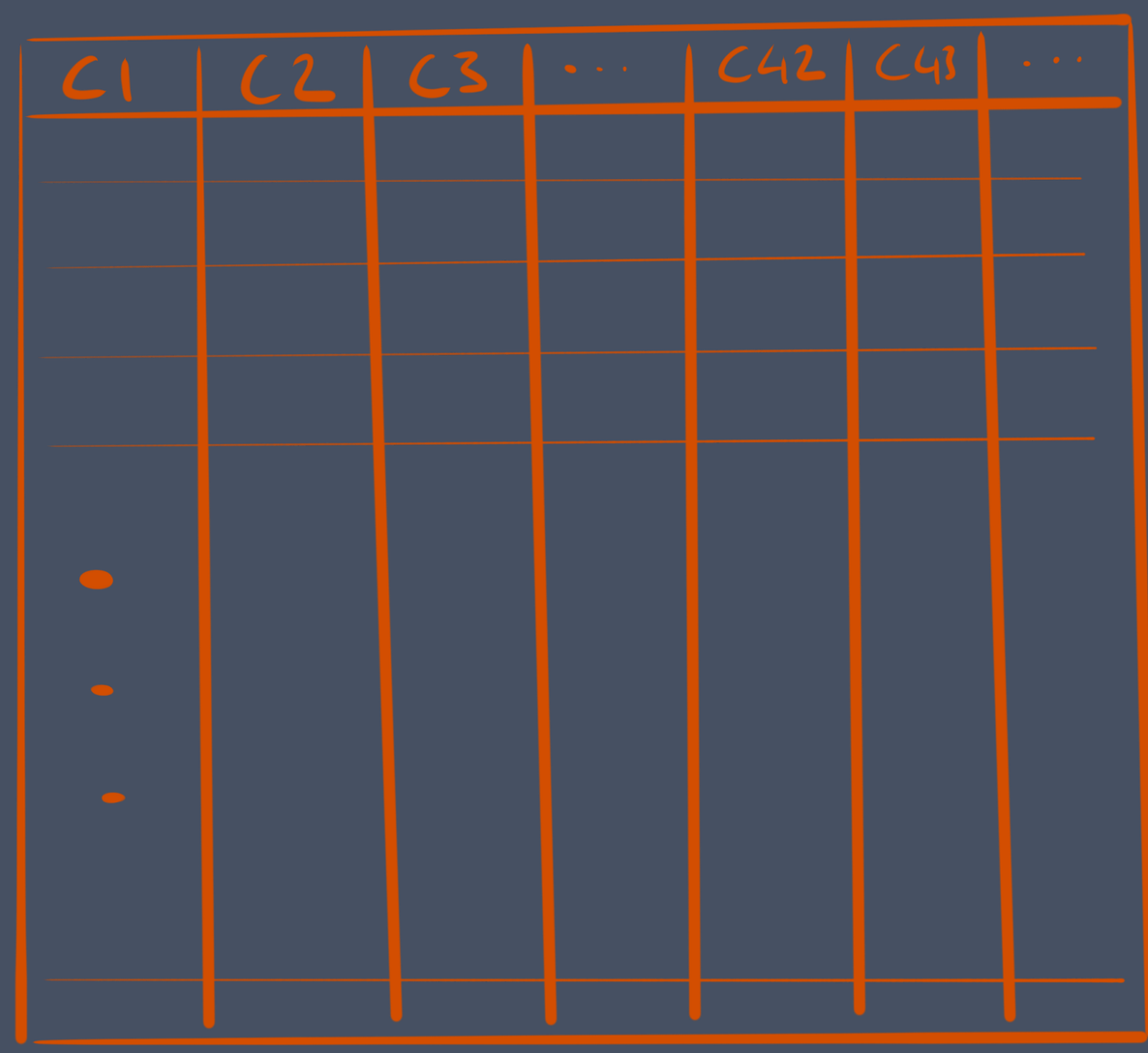
> PYTHON DATA ANALYSIS LIBRARY

WHAT IS PANDAS?

- PYTHON DATA ANALYSIS LIBRARY
- USED EVERYWHERE DATA AND PYTHON APPEAR IN JOB OFFERS

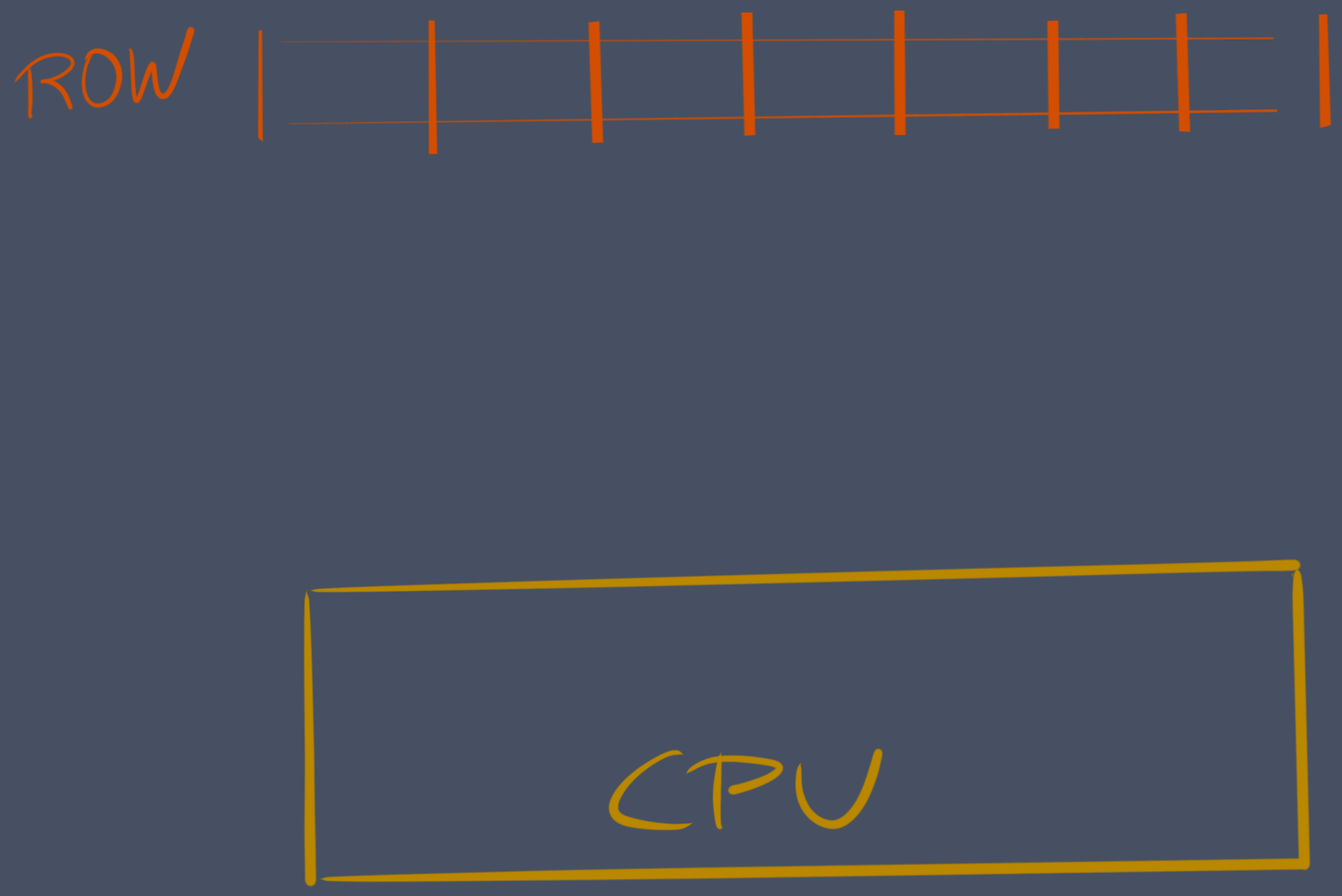
WHAT IS PANDAS?

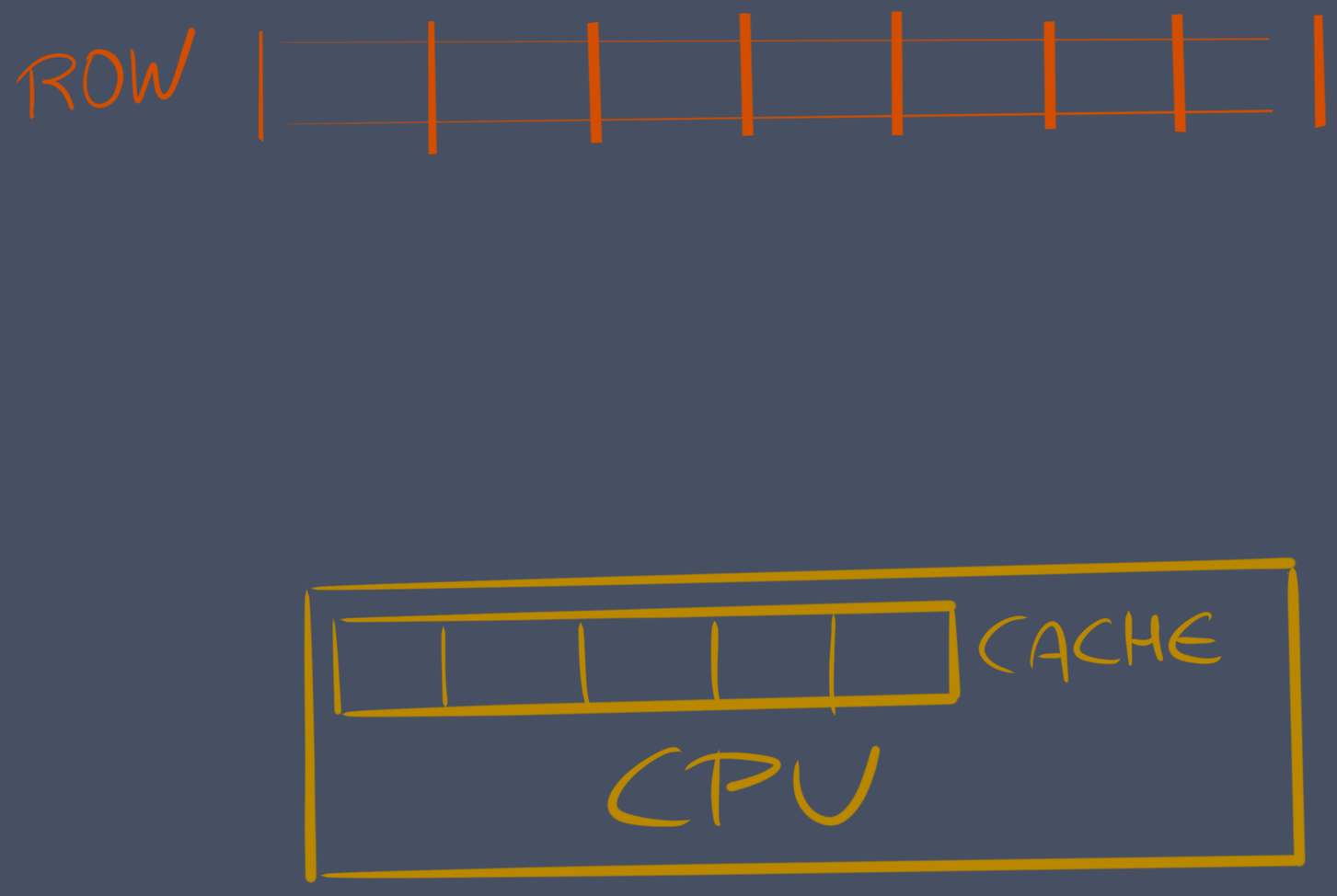
- PYTHON DATA ANALYSIS LIBRARY
- USED EVERYWHERE DATA AND PYTHON APPEAR IN JOB OFFERS
- EFFICIENT (IS COLUMNAR AND HAS A C AND CYTHON BACKEND)



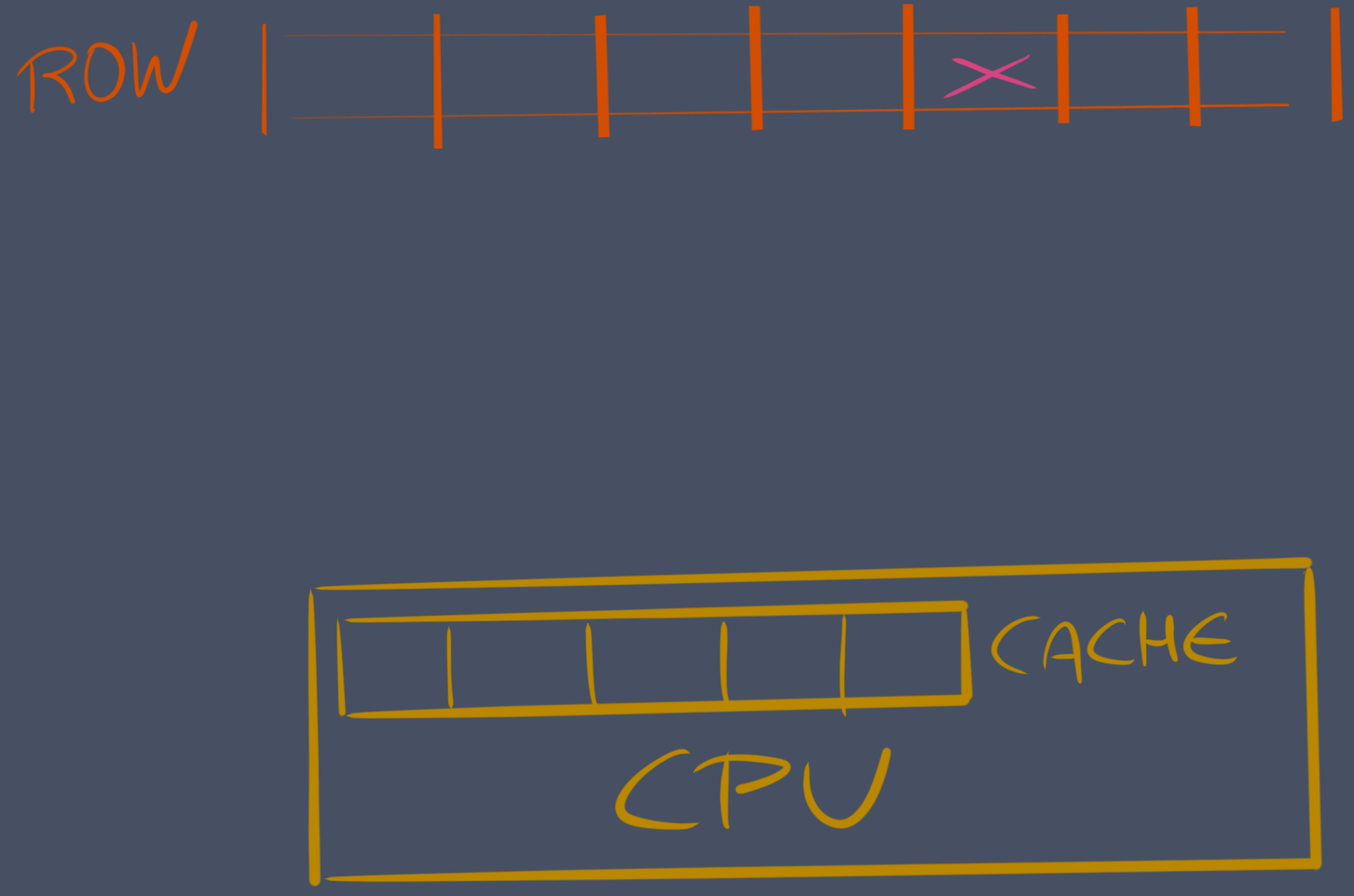
Have you ever asked yourself why "Columnar database" is so trendy?

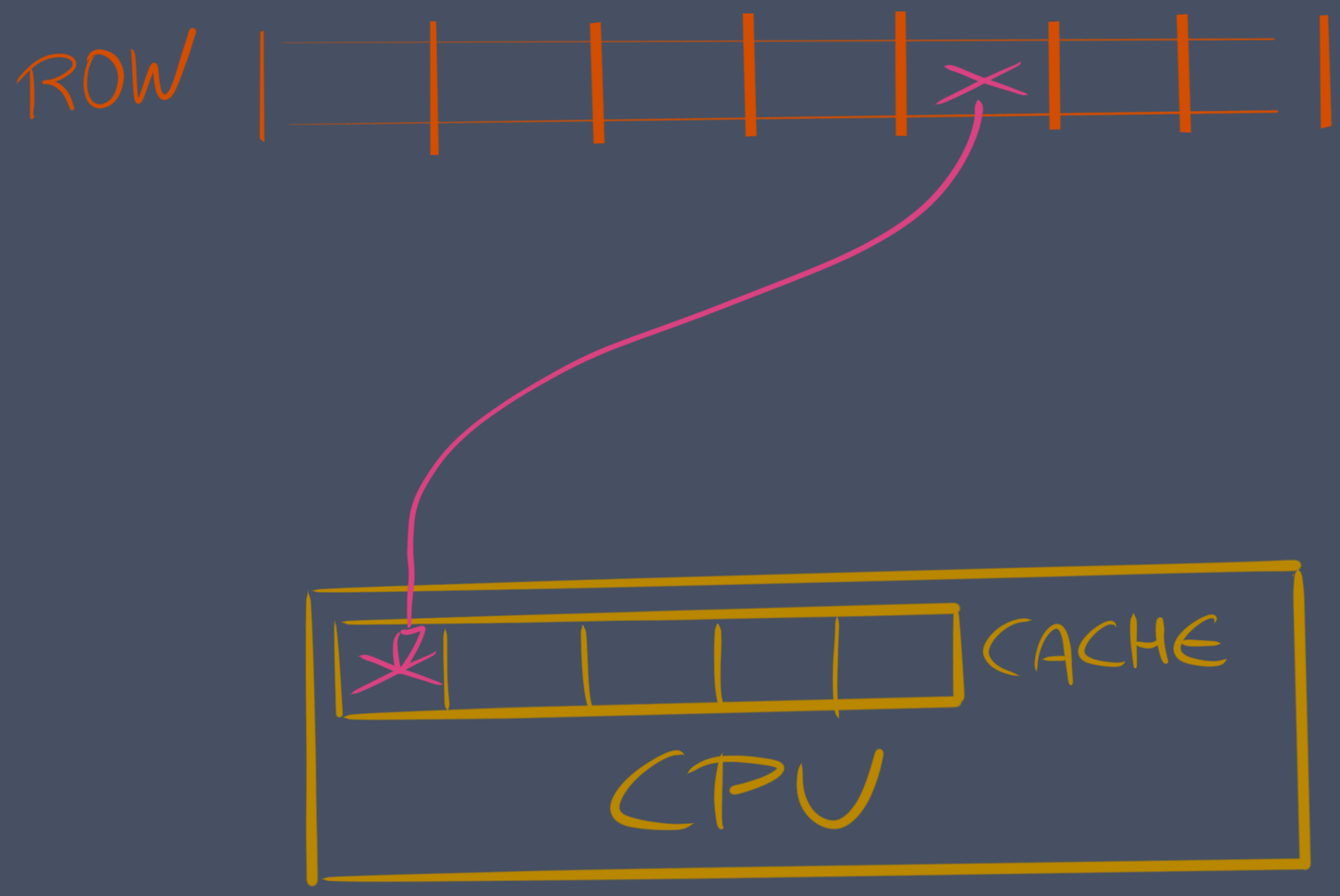

SUM
C1
C2
C3
...
C42
C43
...

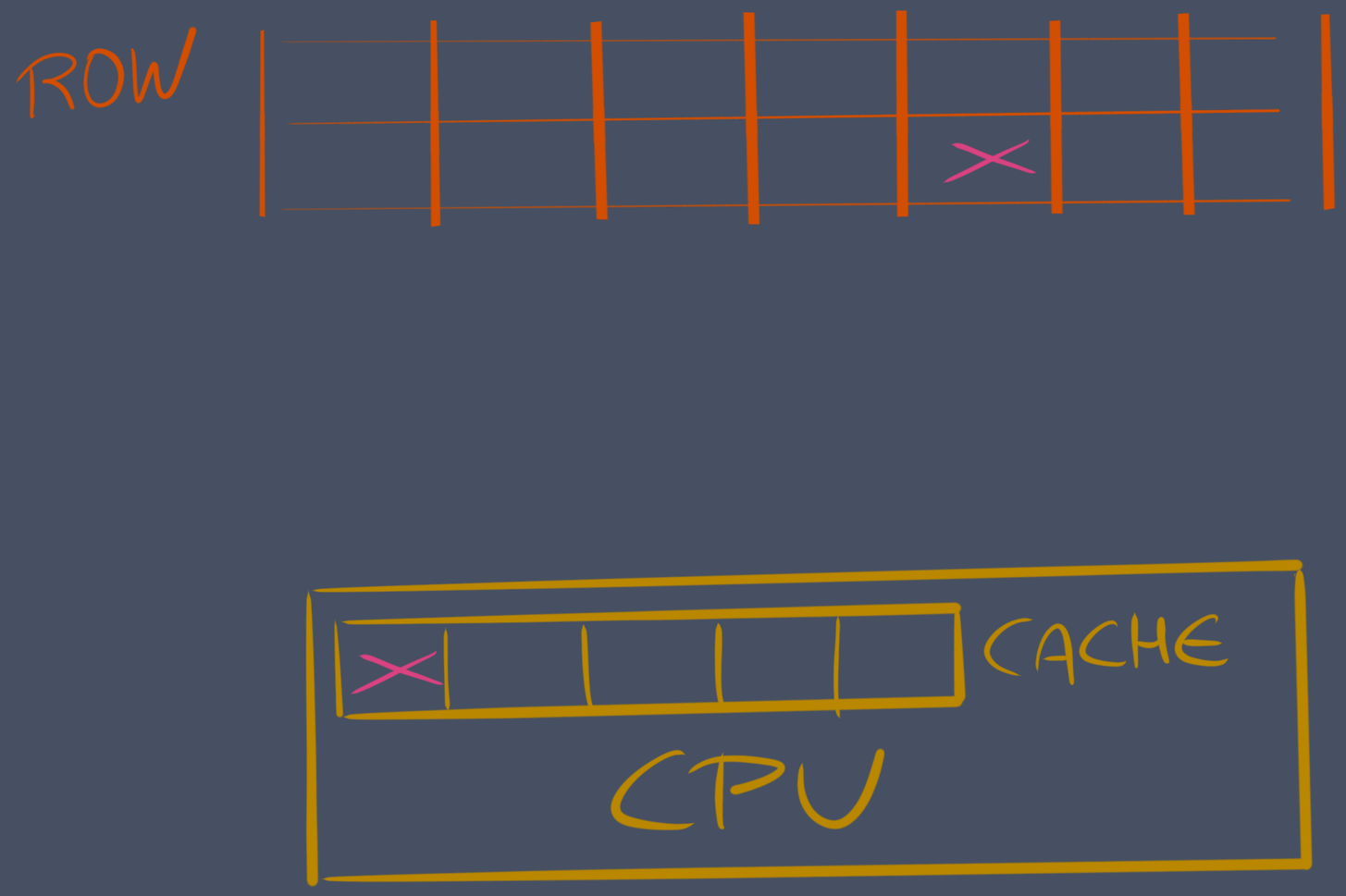

ROW
CPU

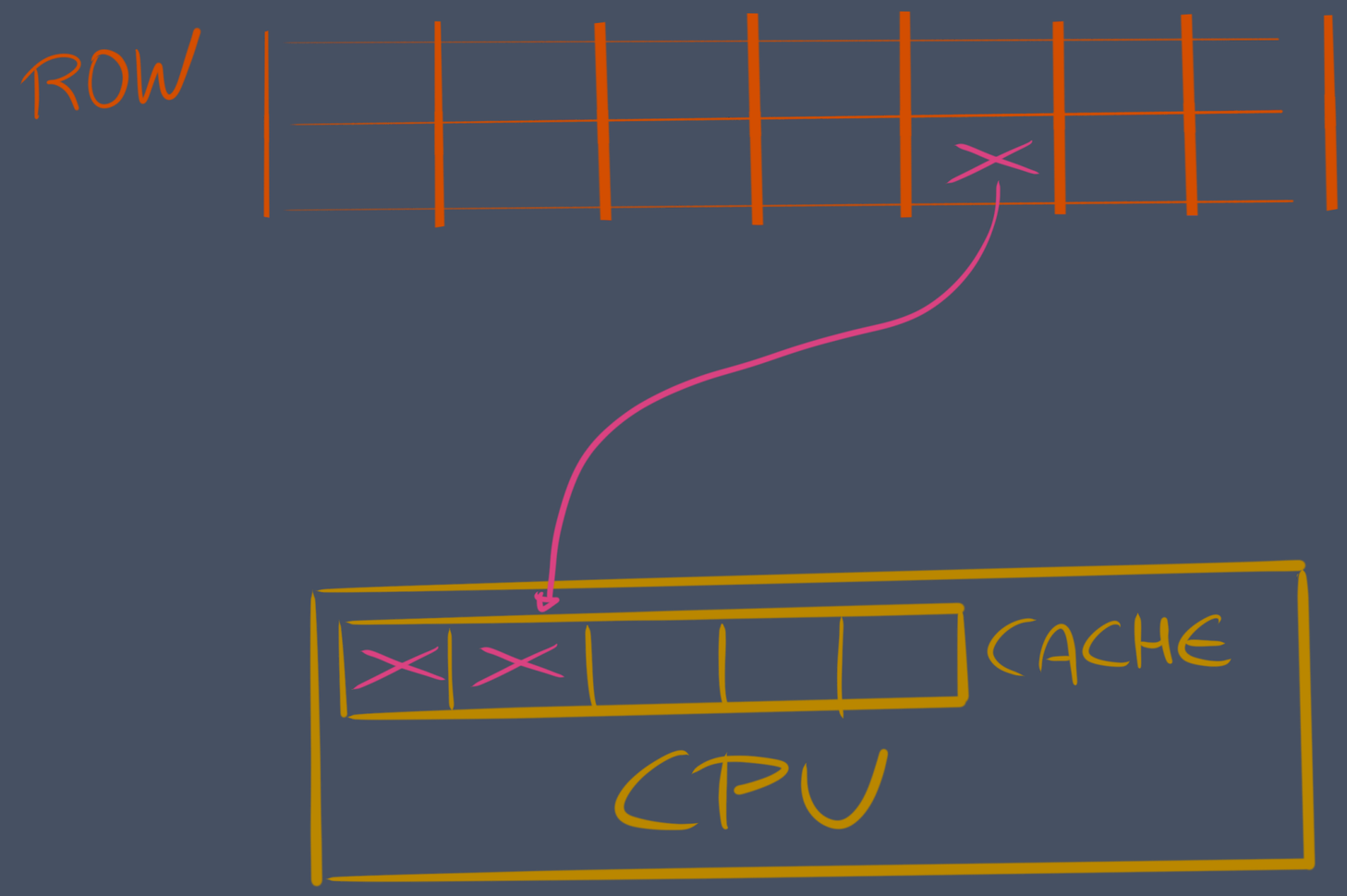


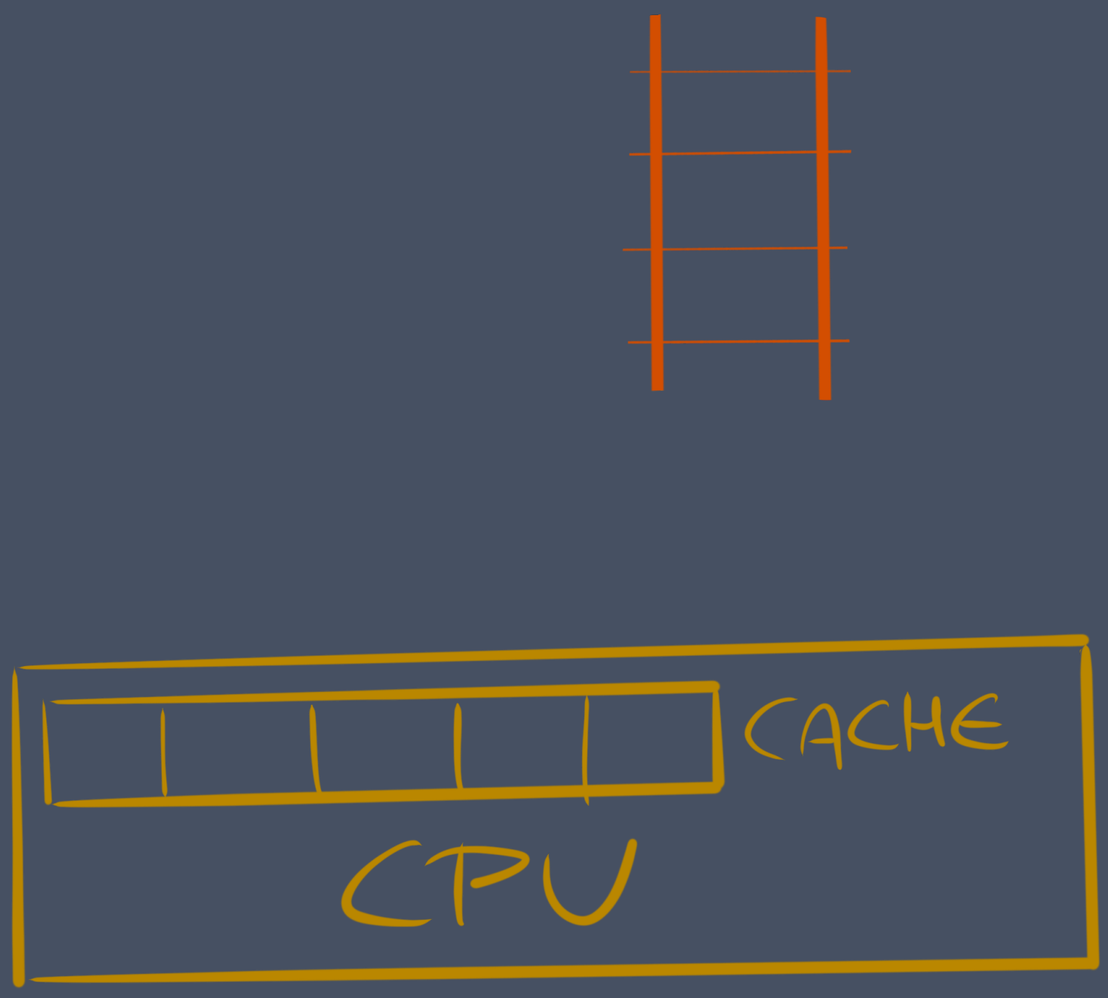
Moving data from memory to a cache line can be done in batches. If data is stored by column, we can load the whole column and operate straight with it with less memory fetching

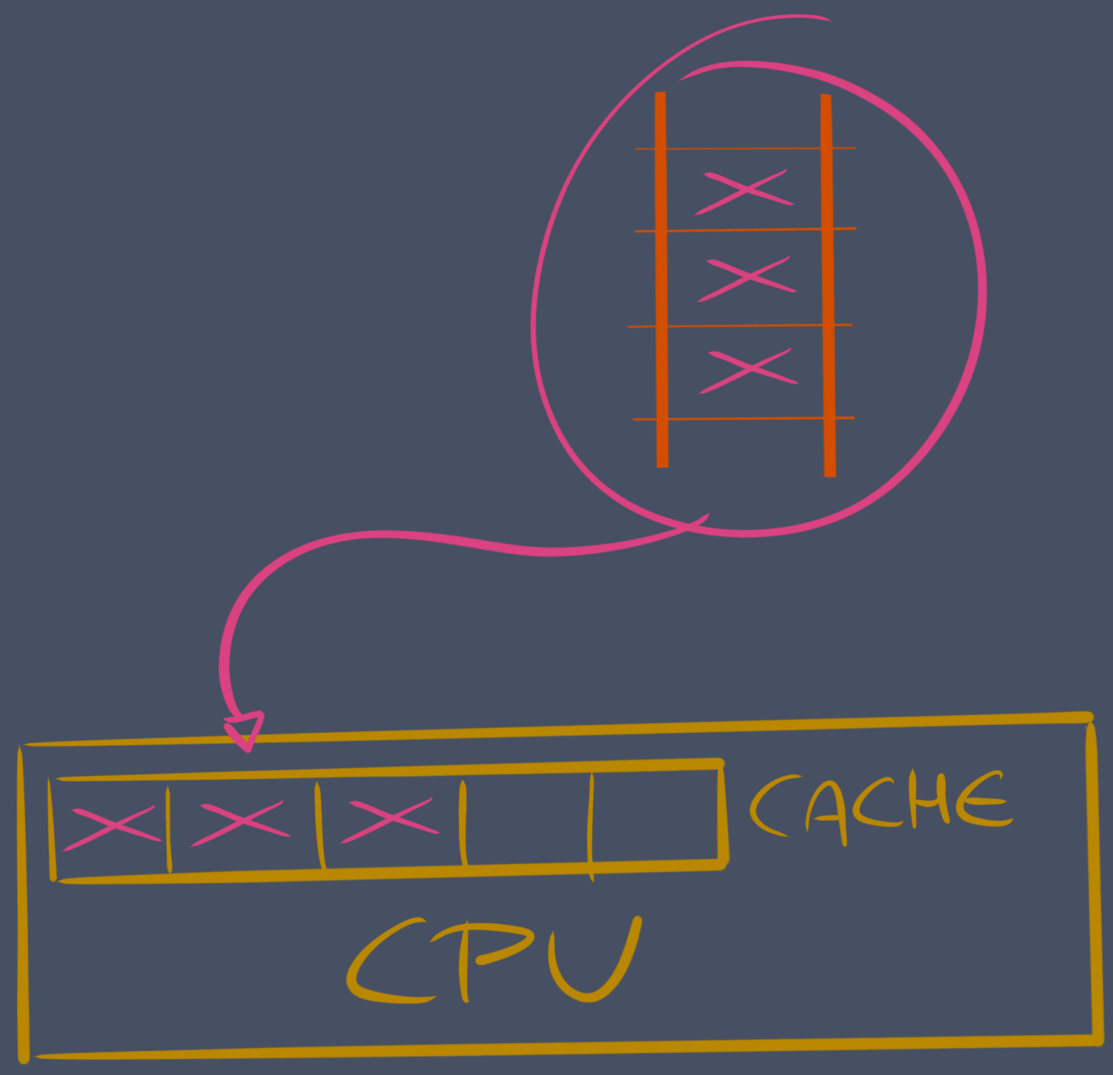

ROW
CACHE
CPU


ROW
CACHE
CPU


ROW
CACHE
CPU


ROW
CACHE
CPU


CACHE
CPU


CACHE
CPU

WHAT IS ARROW?

WHAT IS ARROW?

- CROSS-LANGUAGE IN-MEMORY COLUMNAR FORMAT LIBRARY

WHAT IS ARROW?

- CROSS-LANGUAGE IN-MEMORY COLUMNAR FORMAT LIBRARY
  - OPTIMISED FOR EFFICIENCY ACROSS LANGUAGES

WHAT IS ARROW?

- CROSS-LANGUAGE IN-MEMORY COLUMNAR FORMAT LIBRARY
  - OPTIMISED FOR EFFICIENCY ACROSS LANGUAGES
    - INTEGRATES SEAMLESSLY WITH PANDAS

The internal layouts are similar enough that transforming one into the other is close to being zero-copy. Since most of the code for this step is written in C and Cython, it is very fast.

🏹 ❤️ 🐼

> ARROW USES `RecordBatches`

The internal layouts are similar enough that transforming one into the other is close to being zero-copy. Since most of the code for this step is written in `C` and `Cython`, it is very fast.

- ARROW USES `RecordBatches`
- PANDAS USES BLOCKS HANDLED BY A `BlockManager`

The internal layouts are similar enough that transforming one into the other is close to being zero-copy. Since most of the code for this step is written in `C` and `Cython`, it is very fast.

- ARROW USES `RecordBatches`
- PANDAS USES BLOCKS HANDLED BY A `BlockManager`
- YOU CAN CONVERT AN ARROW `Table` INTO A PANDAS `DataFrame` EASILY

The internal layouts are similar enough that transforming one into the other is close to being zero-copy. Since most of the code for this step is written in `C` and `Cython`, it is very fast.

WHAT IS SPARK?

WHAT IS SPARK?

- **DISTRIBUTED COMPUTATION** FRAMEWORK

WHAT IS SPARK?

- DISTRIBUTED COMPUTATION FRAMEWORK
- 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?

SPARK USUALLY SITS ON TOP OF A CLUSTER MANAGER

This can be standalone, YARN, Mesos or in the bleeding edge, Kubernetes (using the Kubernetes scheduler)

AND A
DISTRIBUTED
STORAGE

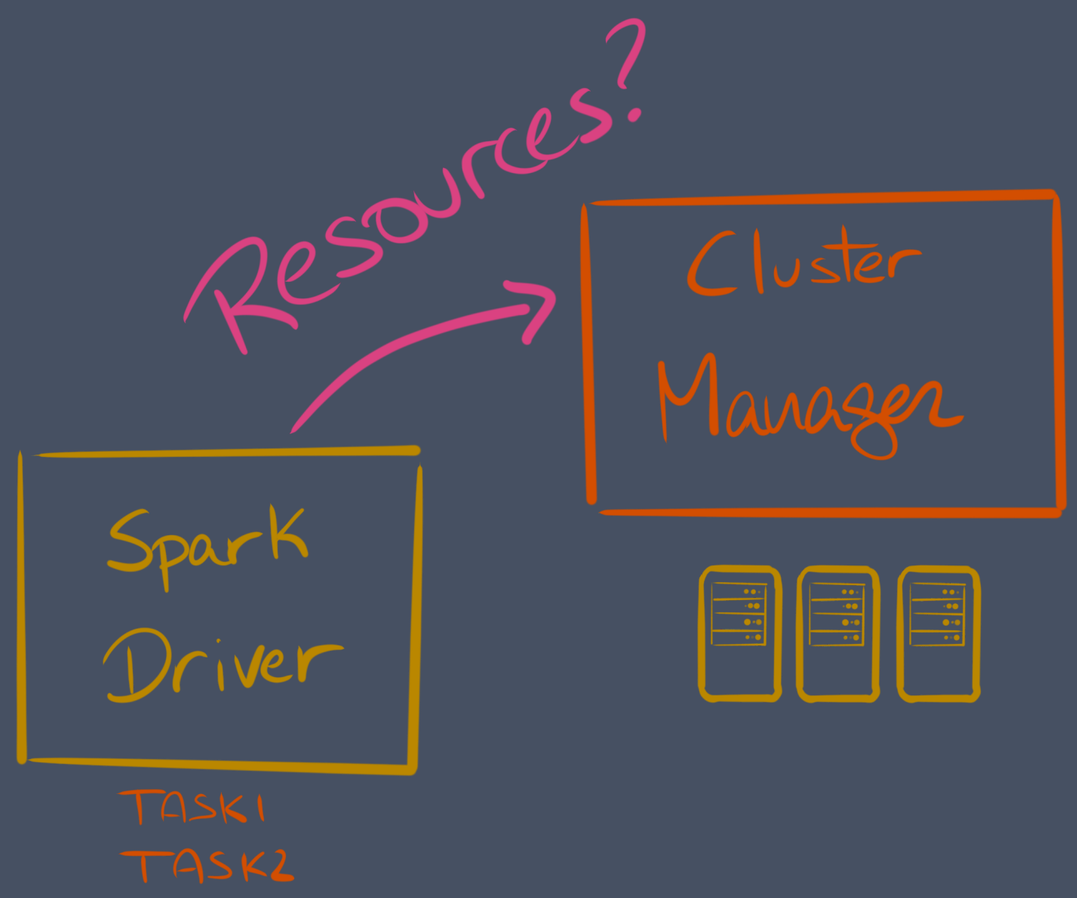
A SPARK PROGRAM RUNS IN THE DRIVER

THE DRIVER REQUESTS RESOURCES FROM THE CLUSTER MANAGER TO RUN TASKS

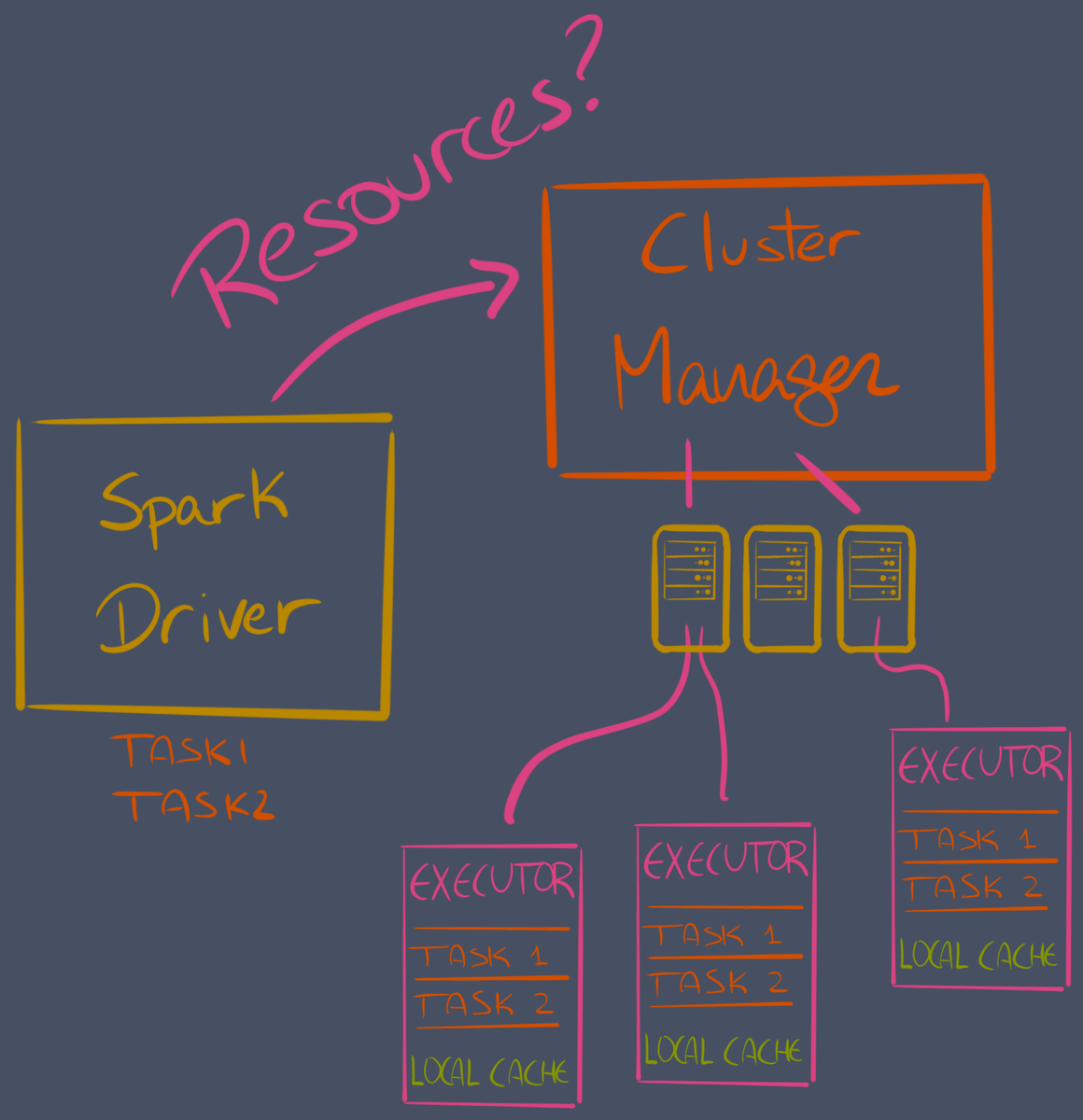
We usually don't need to worry about what the executors do (unless they blow up)

THE DRIVER REQUESTS RESOURCES FROM THE CLUSTER MANAGER TO RUN TASKS

THE DRIVER REQUESTS RESOURCES FROM THE CLUSTER MANAGER TO RUN TASKS



THE DRIVER REQUESTS RESOURCES FROM THE CLUSTER MANAGER TO RUN TASKS

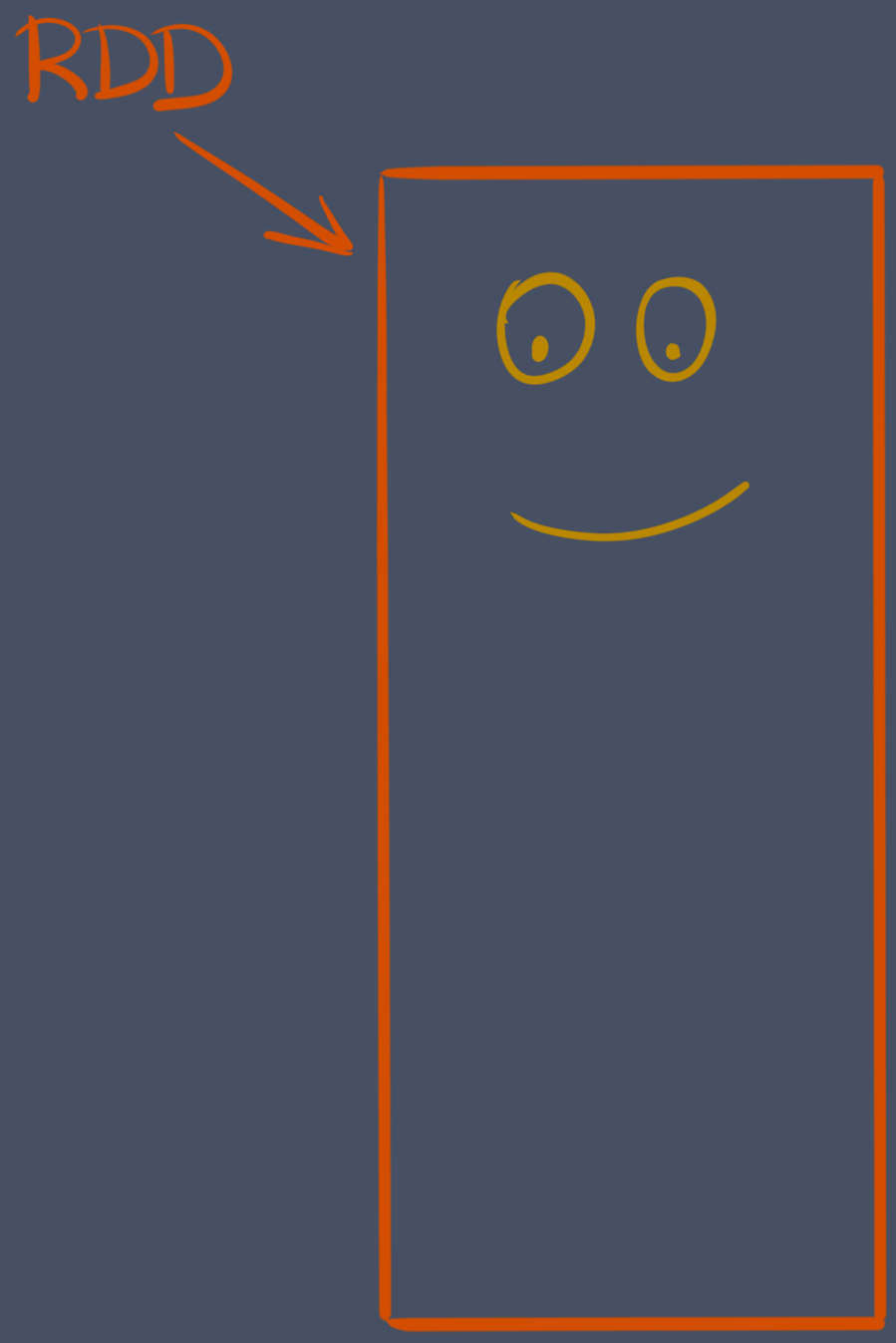


This is very nice, but what is the magic that lets us compute things on several machines, and is machine-failure safe?

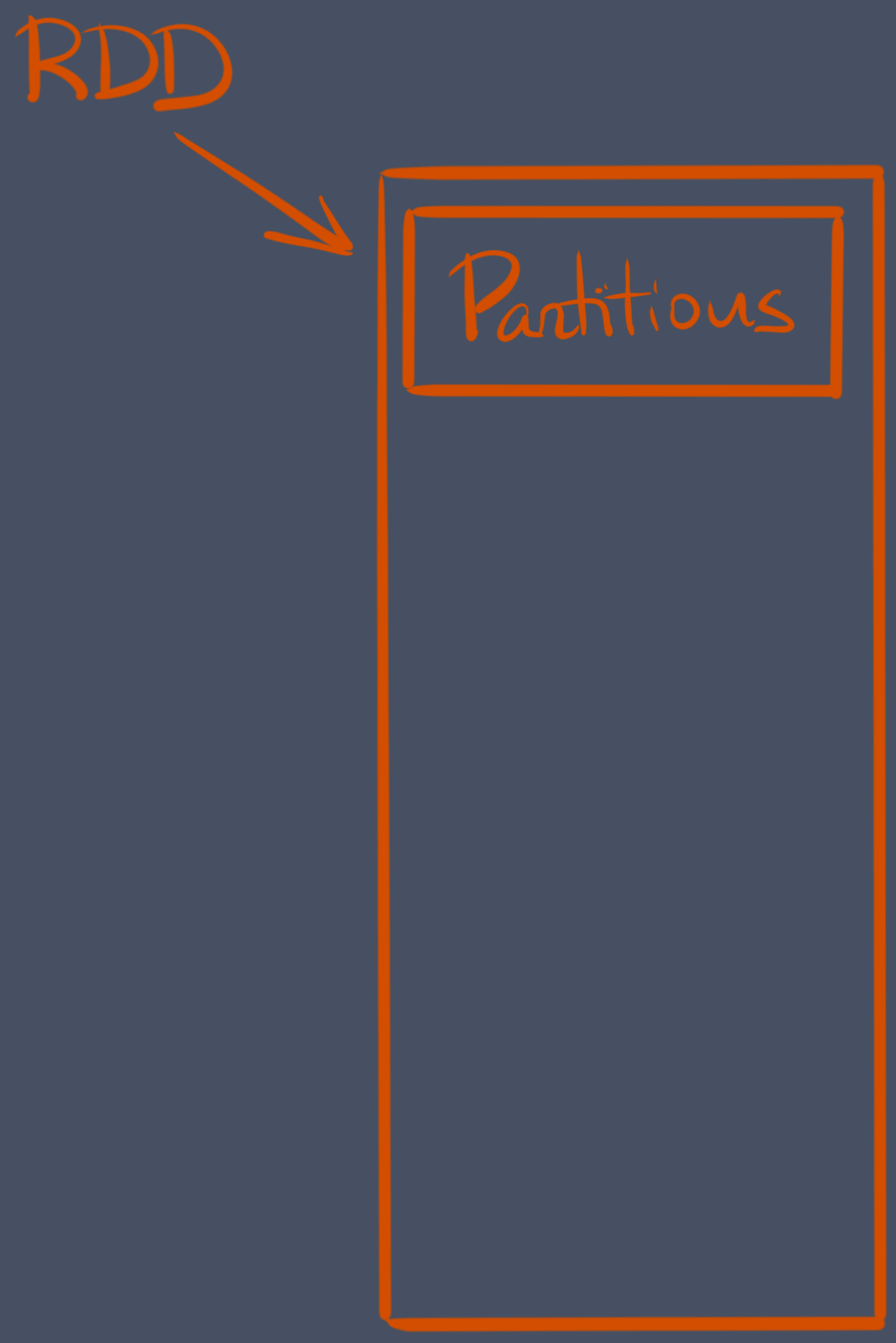
THE MAIN BUILDING BLOCK IS THE RDD: RESILIENT DISTRIBUTED DATASET

RDDs are defined in the Scala core. In Python and R we end up interacting with the underlying JVM objects

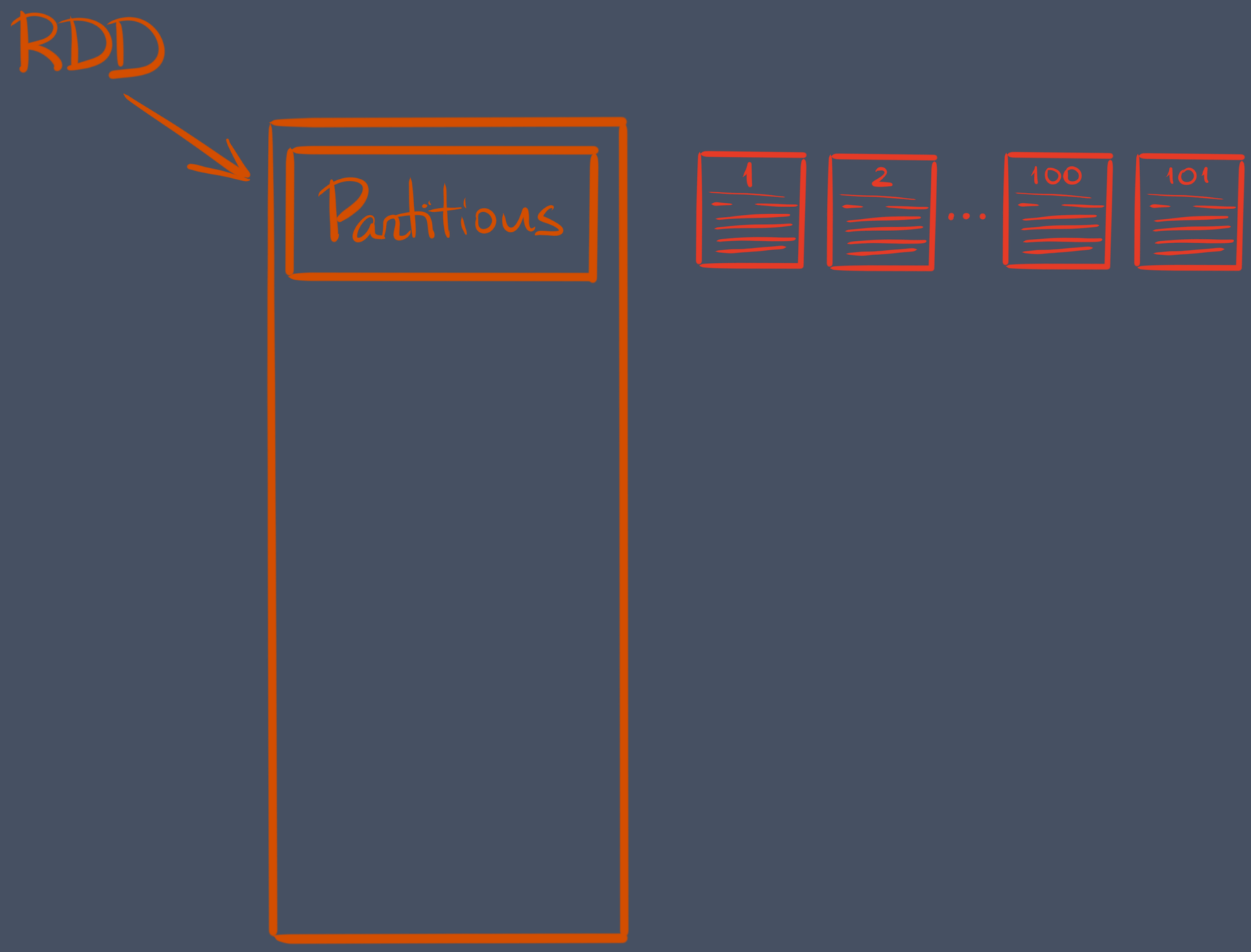
Happy RDD



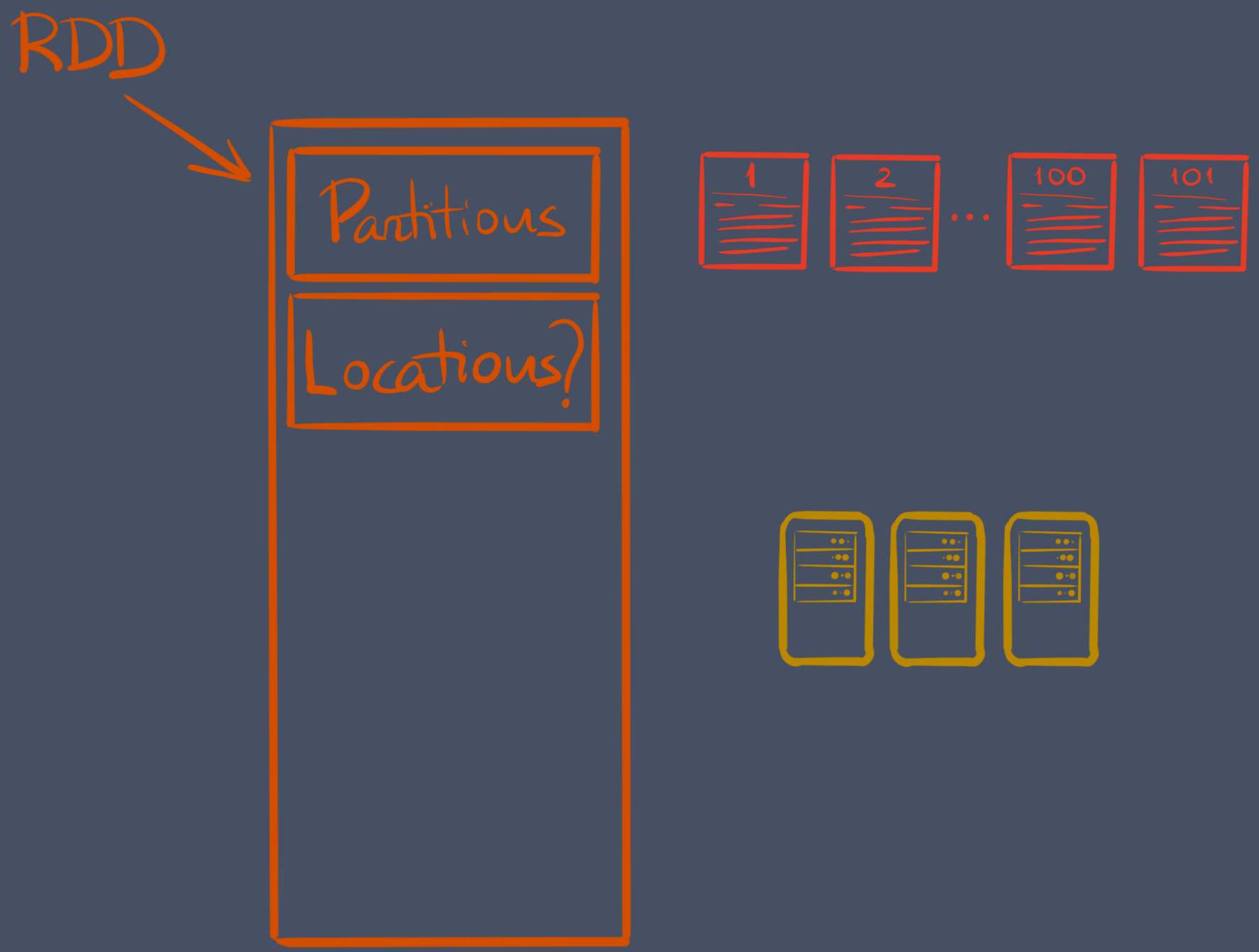
Happy RDD

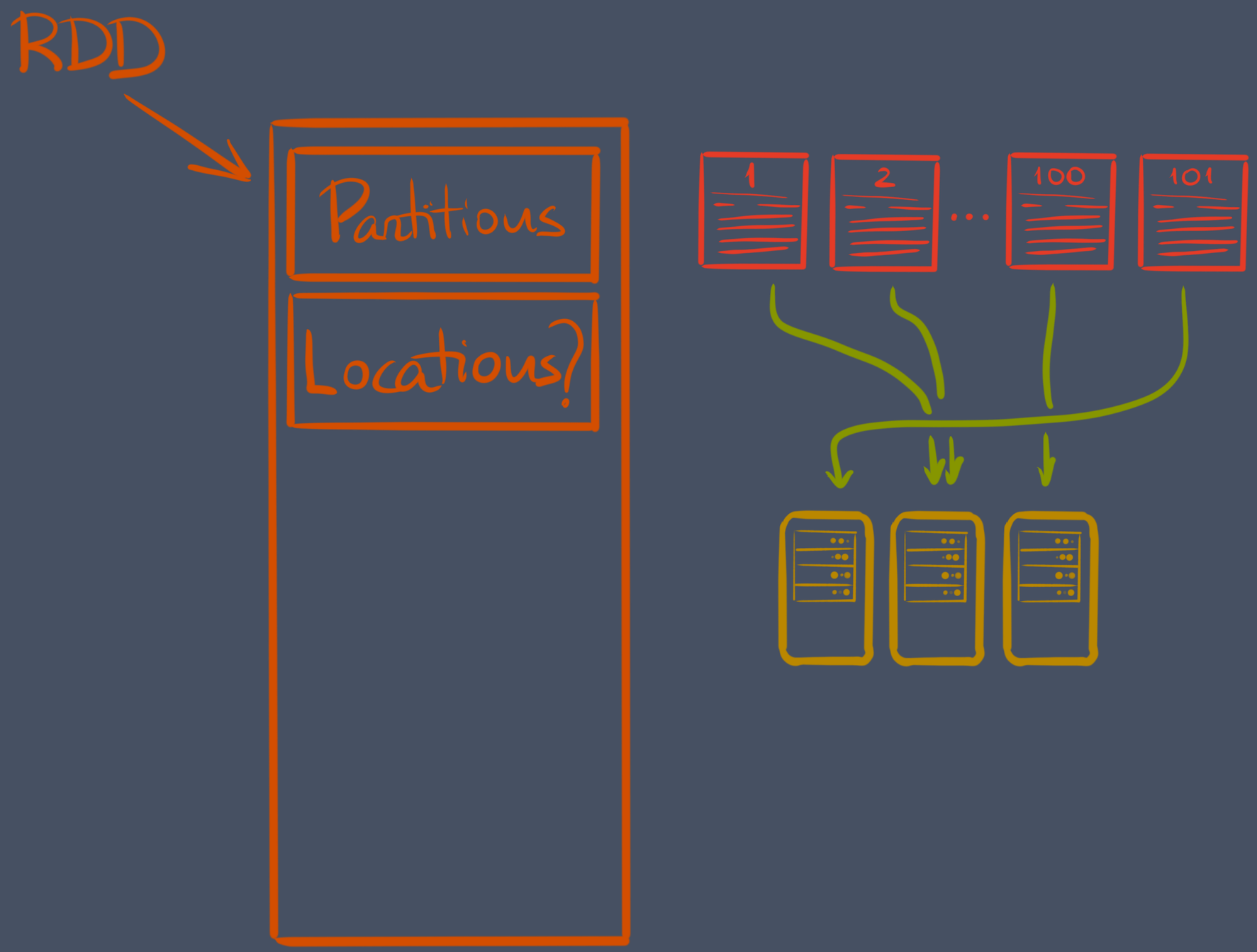


Partitions define how the data is *partitioned* across machines

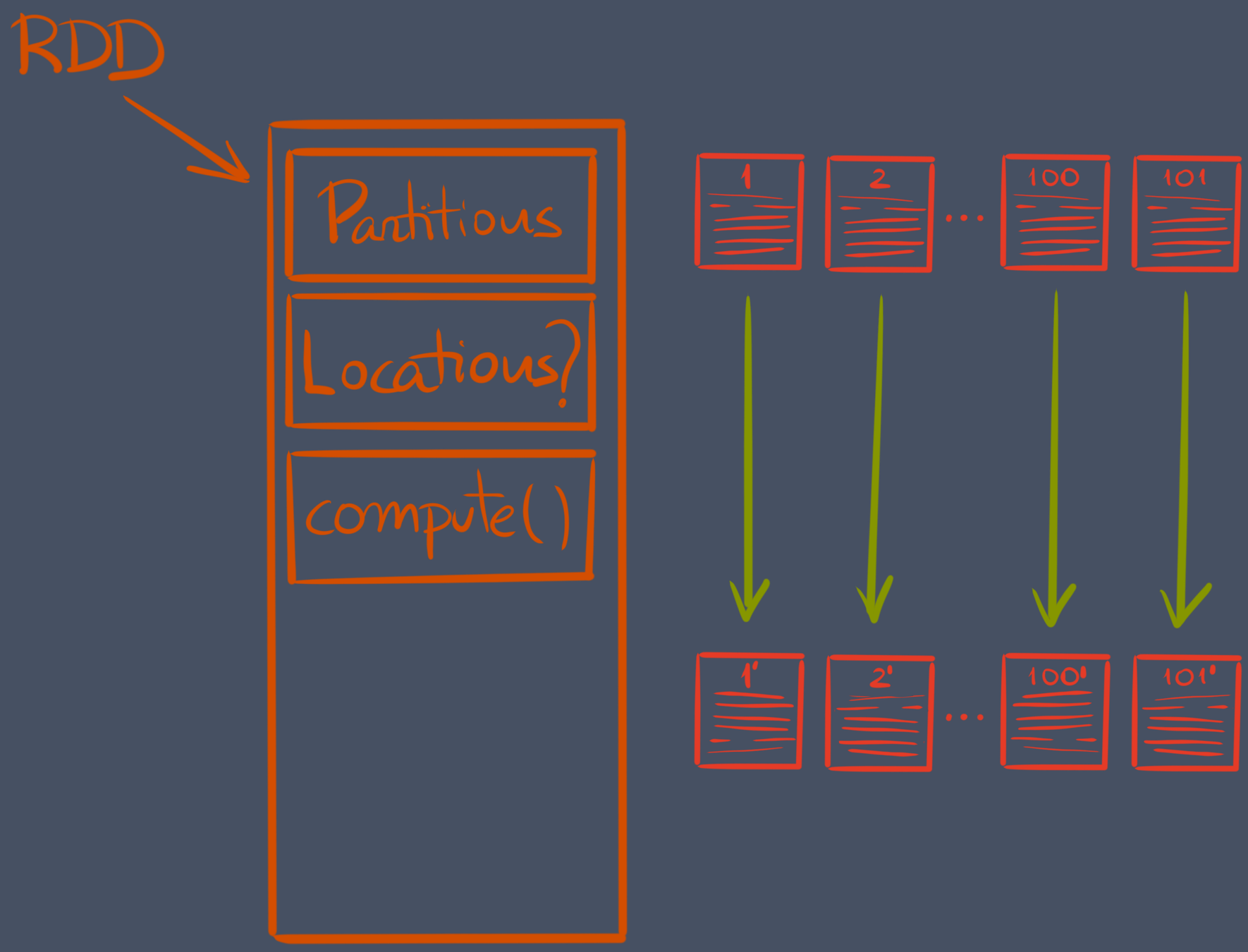


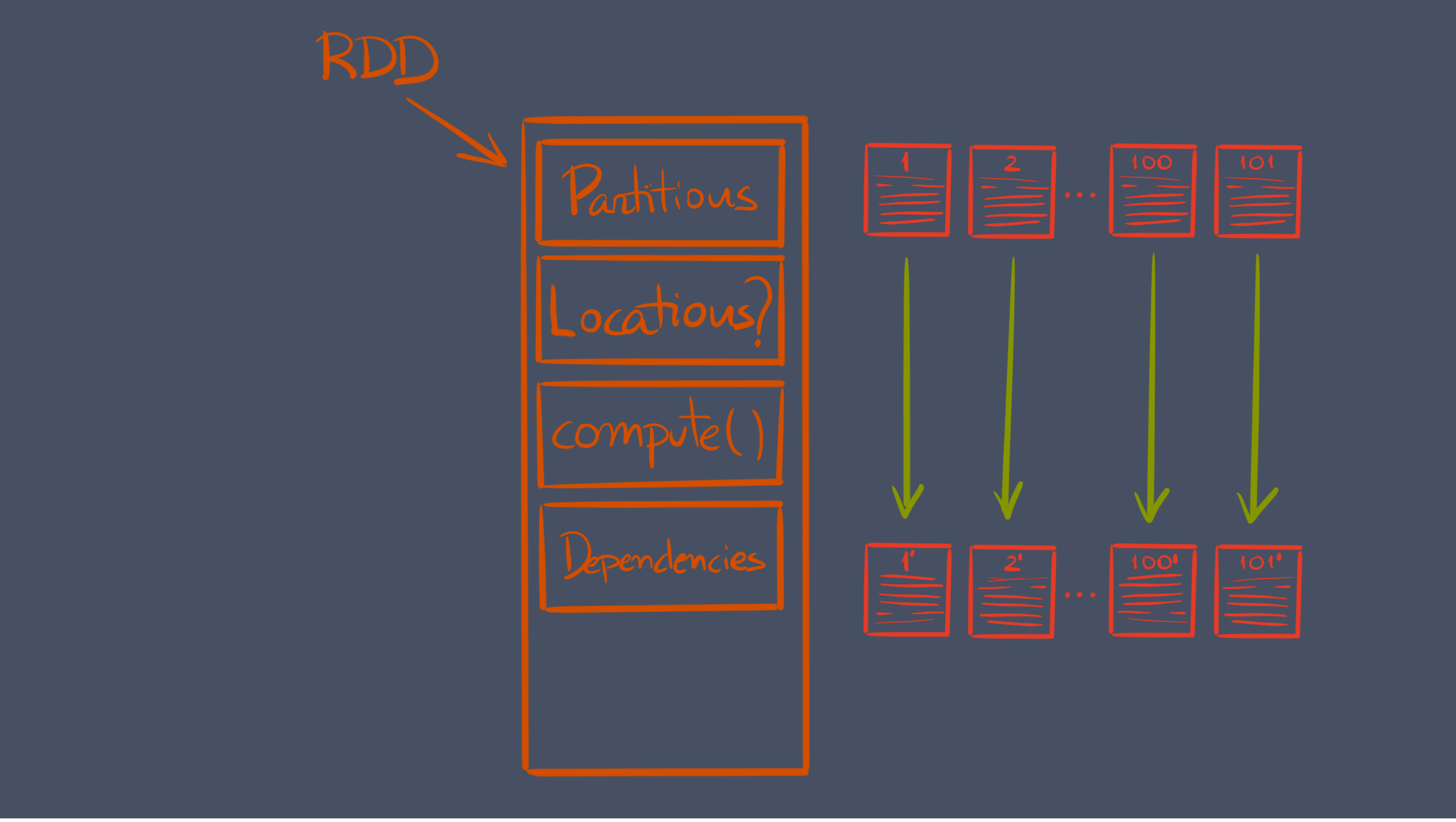
Locations (`preferredLocations`) are optional,
and allow for fine grained
execution to avoid shuffling data across the cluster


RDD
Partitions
Locations?
1
2
100
101

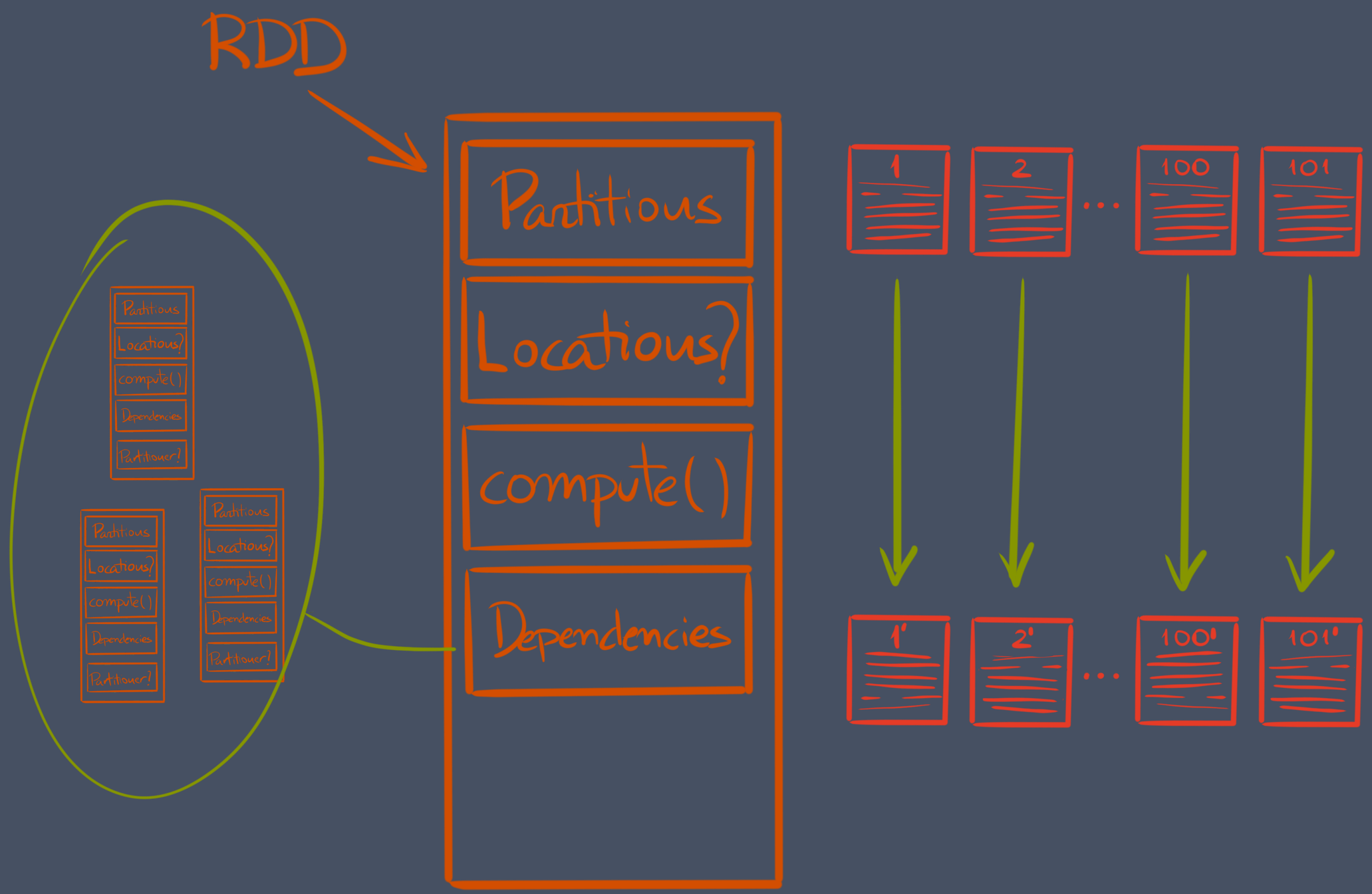

RDD
Partitions
Locations?
1
2
100
101

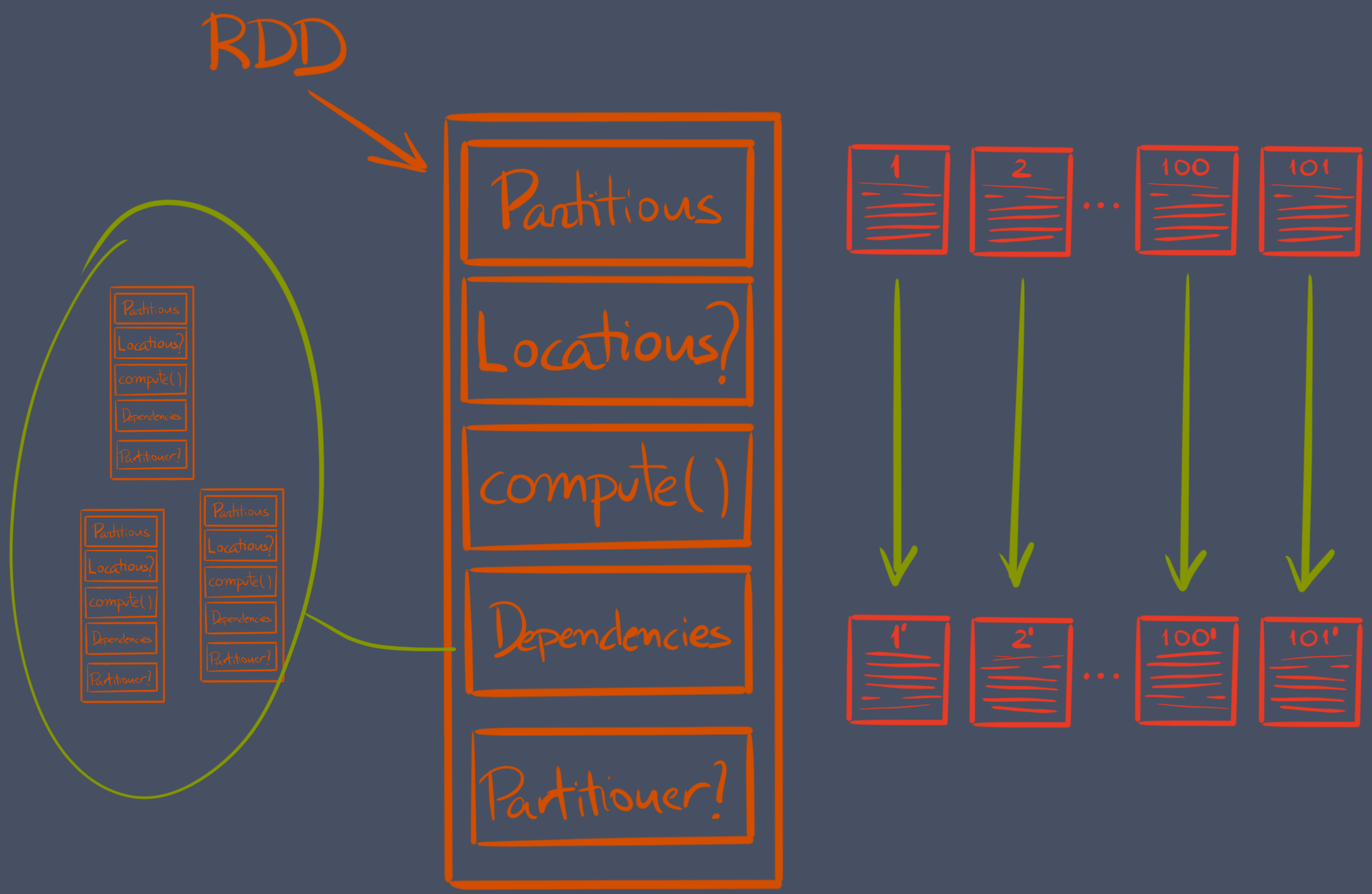
Compute is evaluated in the executors, each executor has access to its
assigned partitions. The result of compute is a new RDD, with different data


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



Dependencies are also called *lineage*. Each **RDD** (and by extension, each
partition) has a specific way to be computed. If for some reason one is lost
(say, a machine dies), **Spark** knows how to recompute *only* that


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



The partitioner needs to be a 1-1 function from keys/whatever to the data, to allow recomputing

PYSPARK

PYSPARK OFFERS A PYTHON API TO THE SCALA CORE OF SPARK

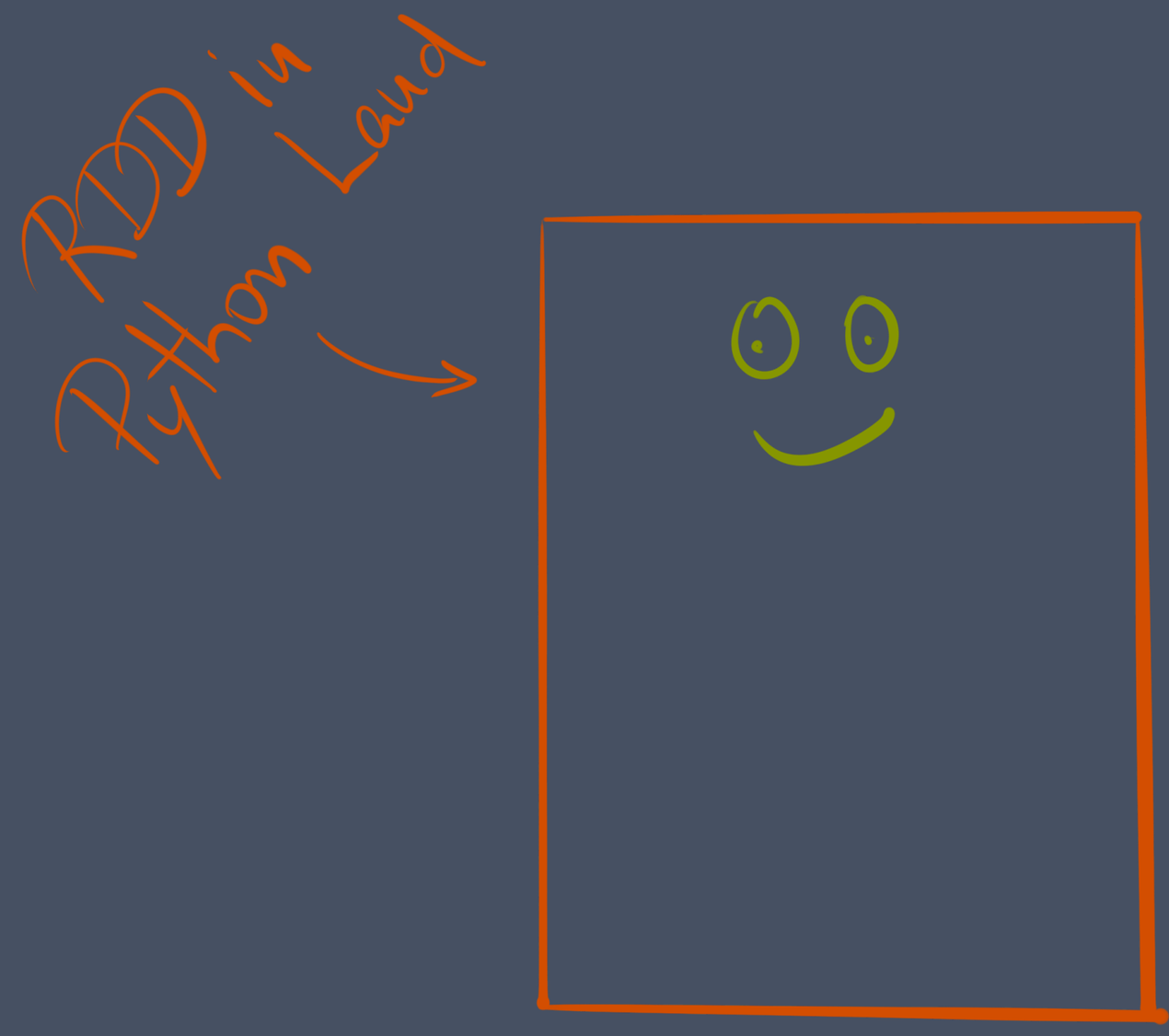
IT USES THE PY4J BRIDGE

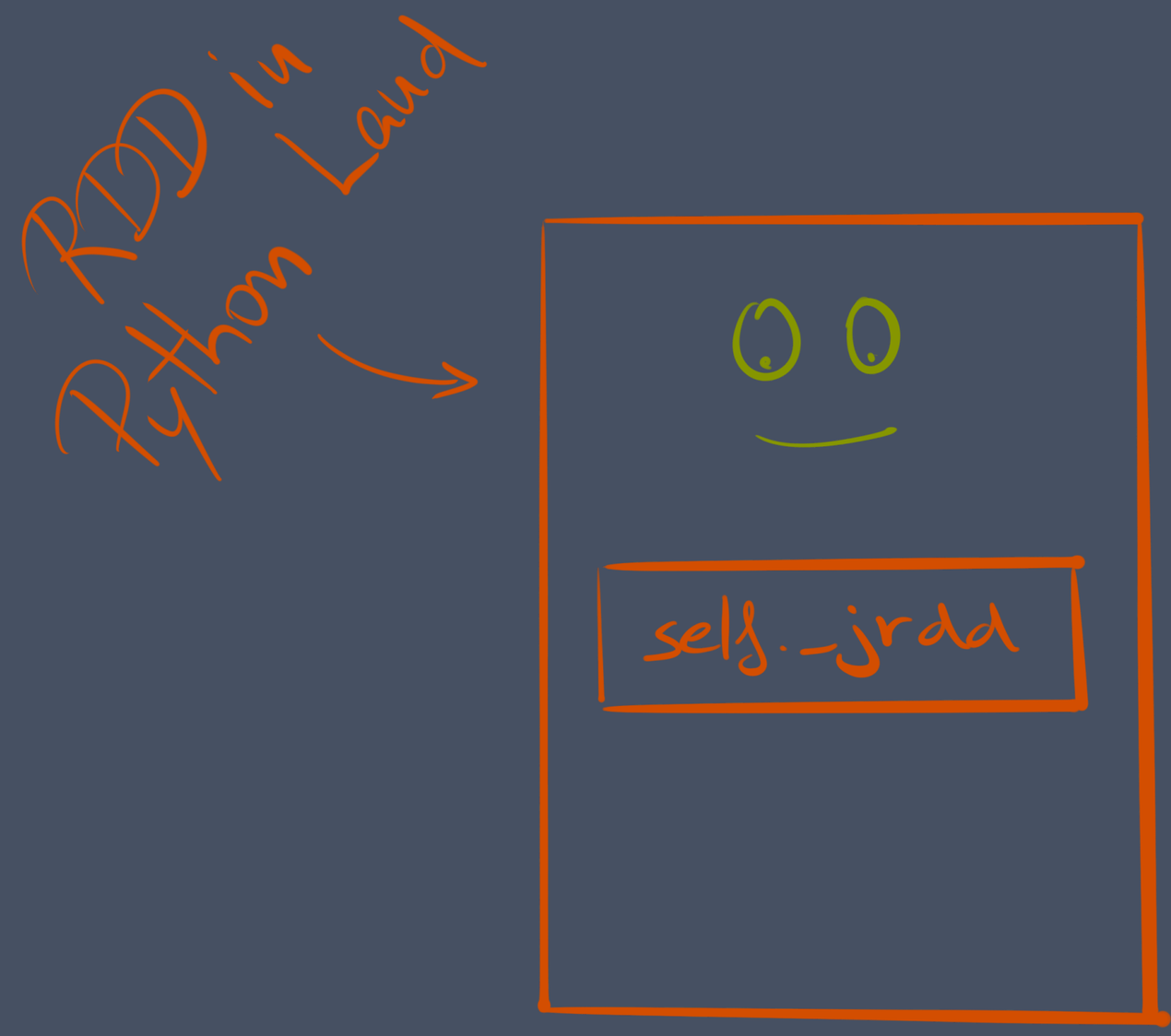
Each object in PySpark comes bundled with a JVM gateway (started when the Python driver starts). Python methods then act on the internal JVM object by passing serialised messages to the Py4J gateway

```
# Connect to the gateway
gateway = JavaGateway(
    gateway_parameters=GatewayParameters(
        port=gateway_port,
        auth_token=gateway_secret,
        auto_convert=True))

# Import the classes used by PySpark
java_import(gateway.jvm, "org.apache.spark.SparkConf")
java_import(gateway.jvm, "org.apache.spark.api.java.*")
java_import(gateway.jvm, "org.apache.spark.api.python.*")
.
.
.
return gateway
```

Happy RDD in Python

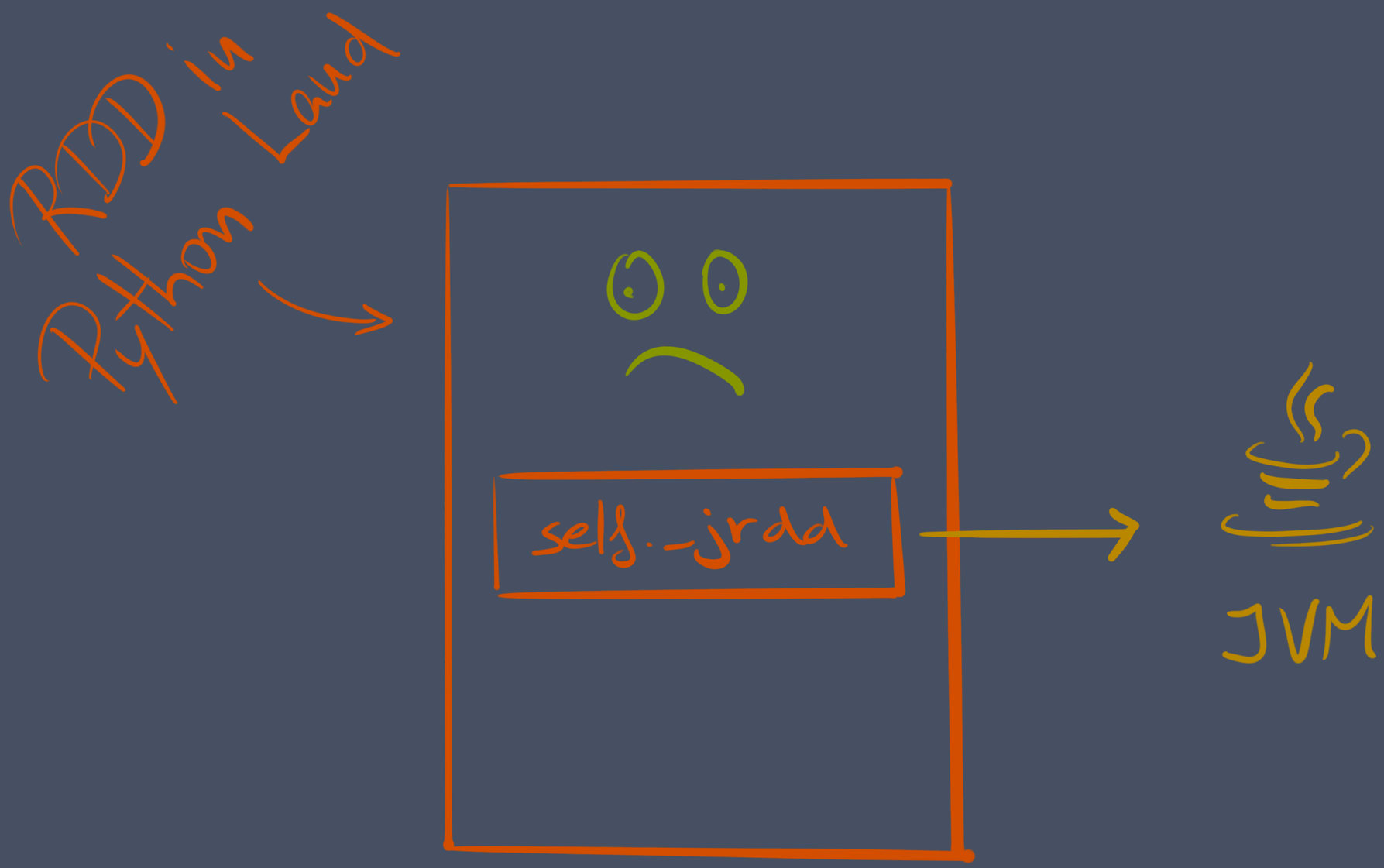

RDD in
Python Land

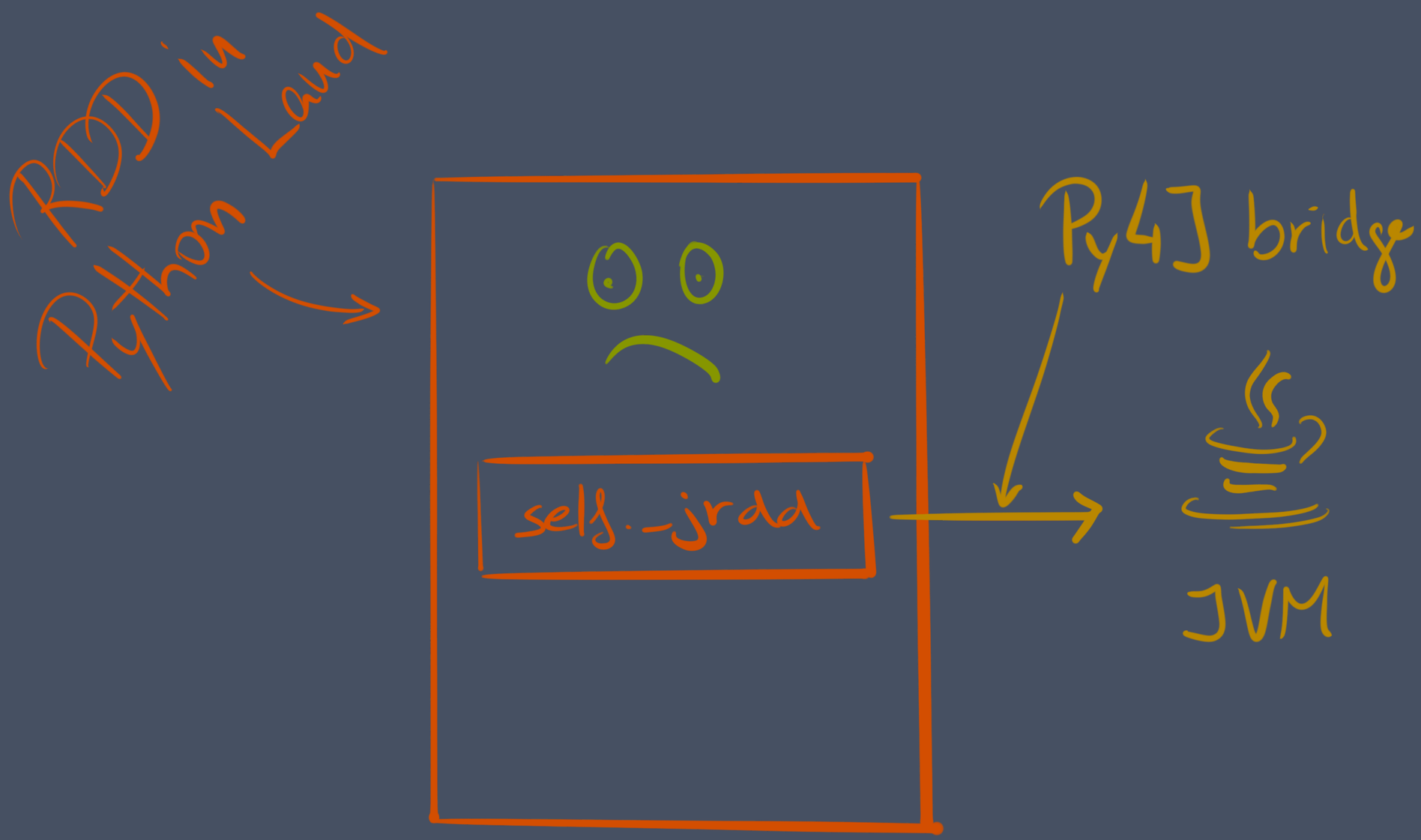


Some `_jrdd` appears. Each "Spark" related object has some internal
relationship with an equivalent JVM object. An RDD, for instance, has a `_jrdd`,
which refers to how the RDD was created in the JVM. By extension, if in Python
you create an RDD from a file, for instance, this will call the JVM method to do
so, and the resulting Python object will have a `_jrdd` pointing to that.

Just like M is for Murder...

J is for Java. There are *a lot* of properties prefixed with *j* in PySpark,
to denote they refer to a JVM object/property/class


RDD in Python Land
self._jrdd
JVM


RDD in Python Land
Py4J bridge
self._jrdd
JVM

THE MAIN ENTRYPOINTS ARE RDD AND PipelinedRDD(RDD)

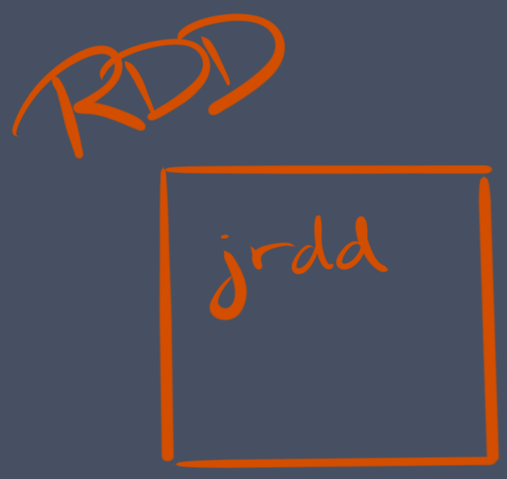
In Python land. The first exposes the API of Scala RDDs (by interacting with
the JVM connected to the RDD), the second defines how to apply a Python function
to an RDD. For instance, all map methods on RDDs defer to the
`mapPartitionsWithIndex` method, which builds a PipelinedRDD wrapping the Python
function to map, and then does some other things I'll explain later

PipelinedRDD

BUILDS IN THE JVM A

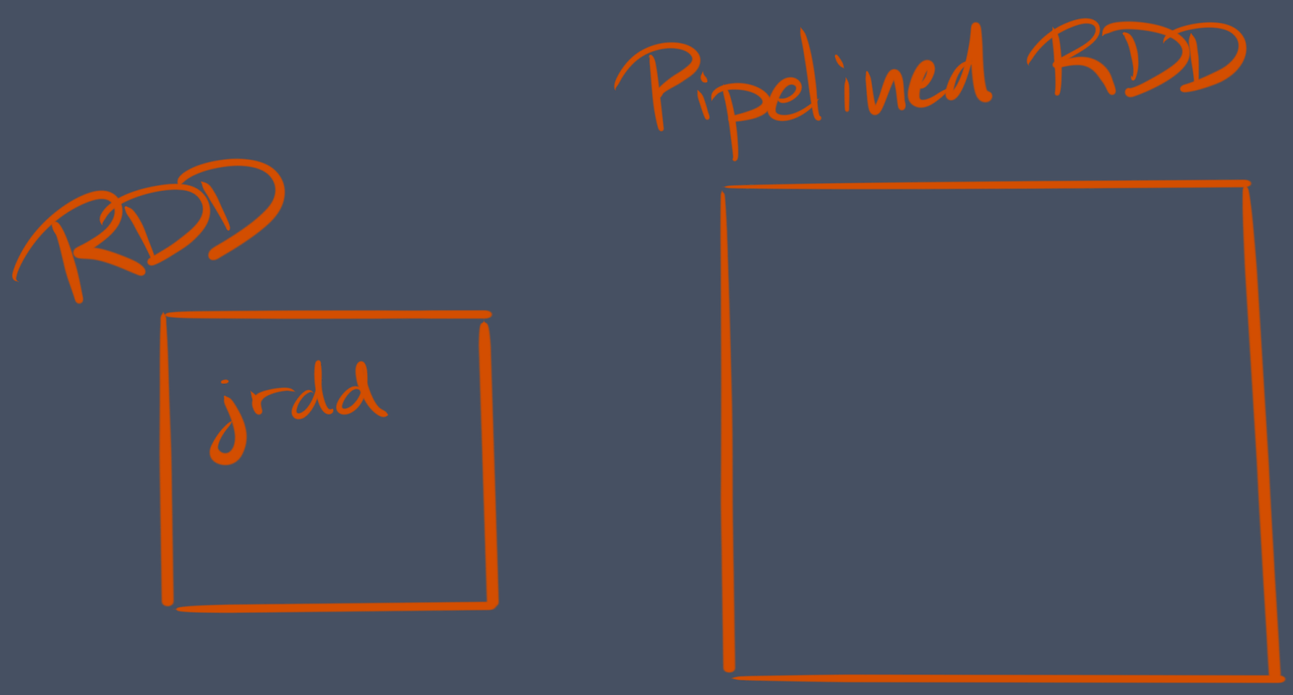
PythonRDD

Angry RDD

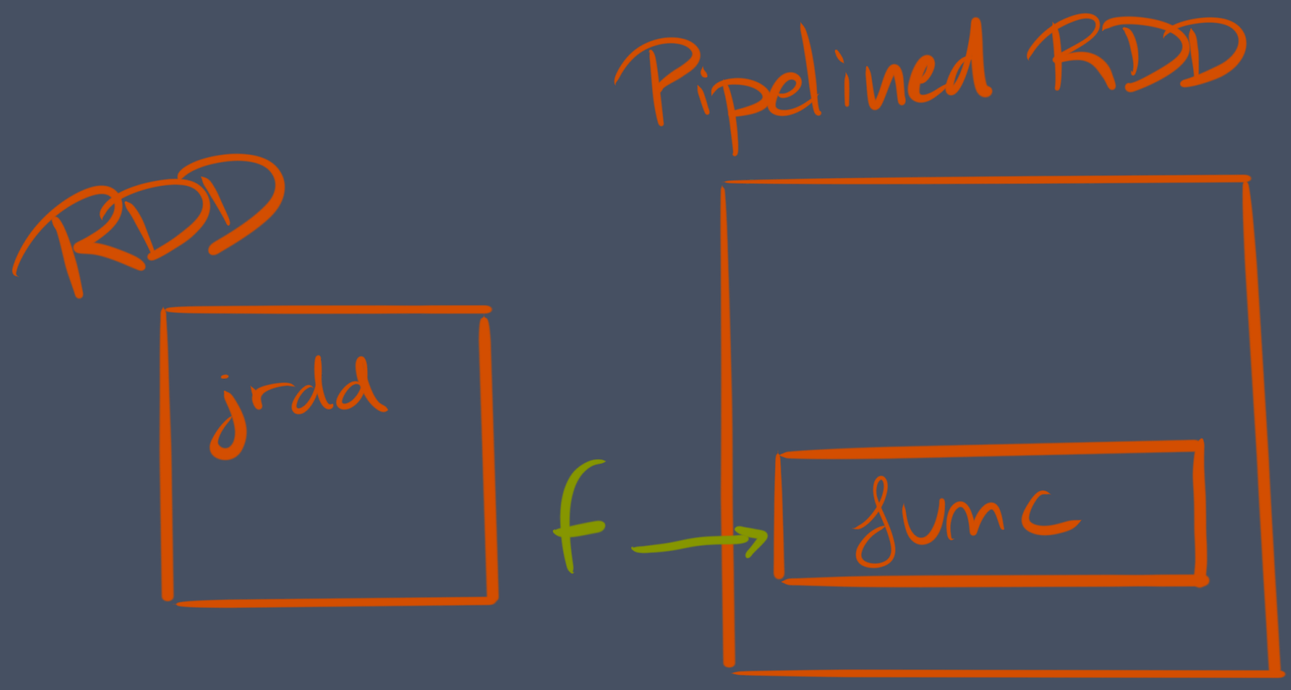


With its `jrdd` (so, it's in Python land)

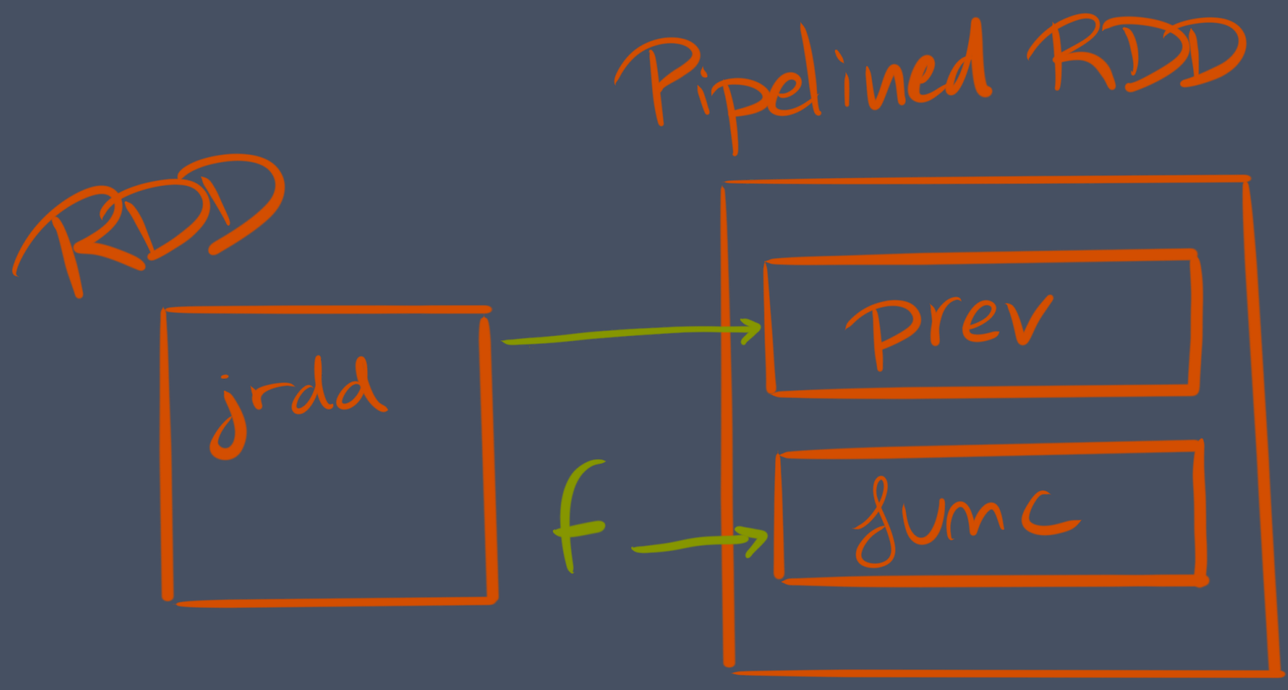
Let's map over this RDD!



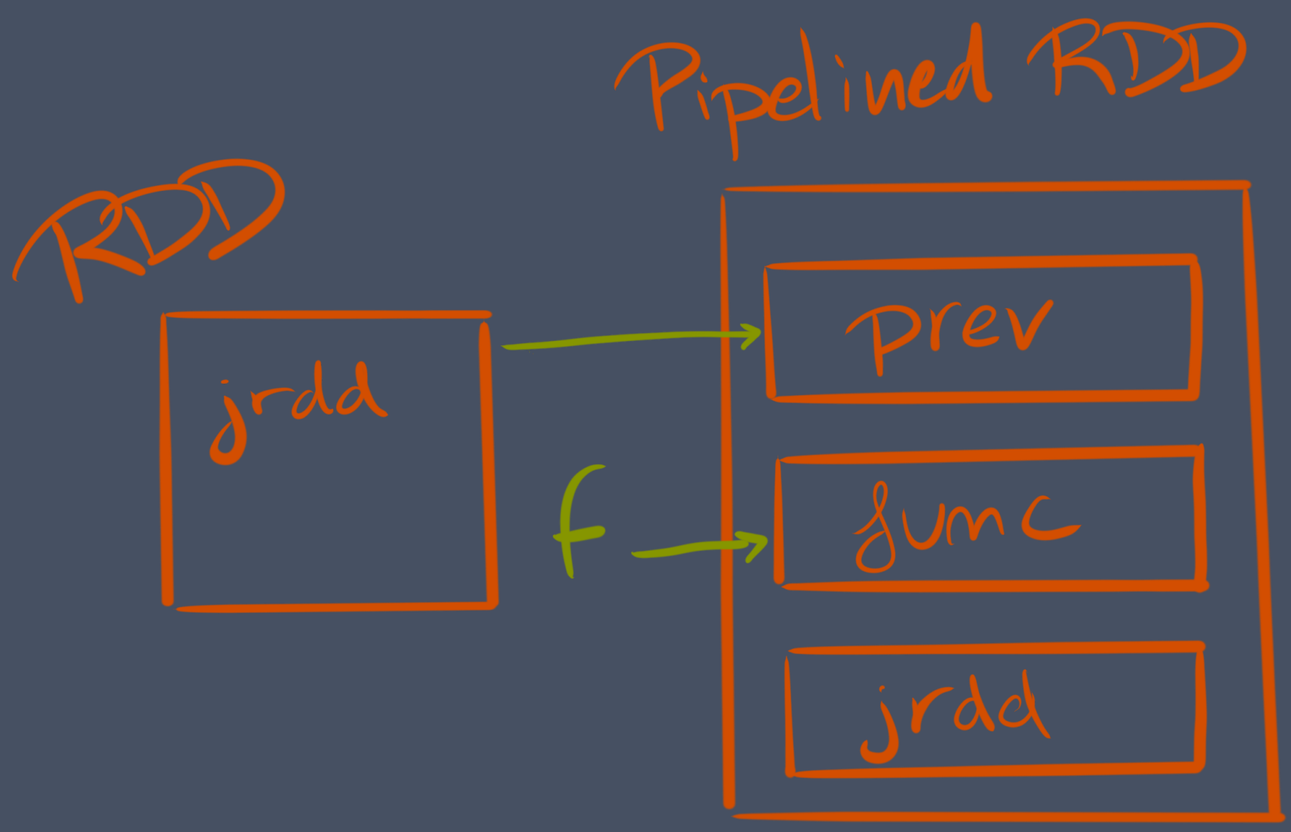
RDD's `map` will create a `PipelinedRDD`



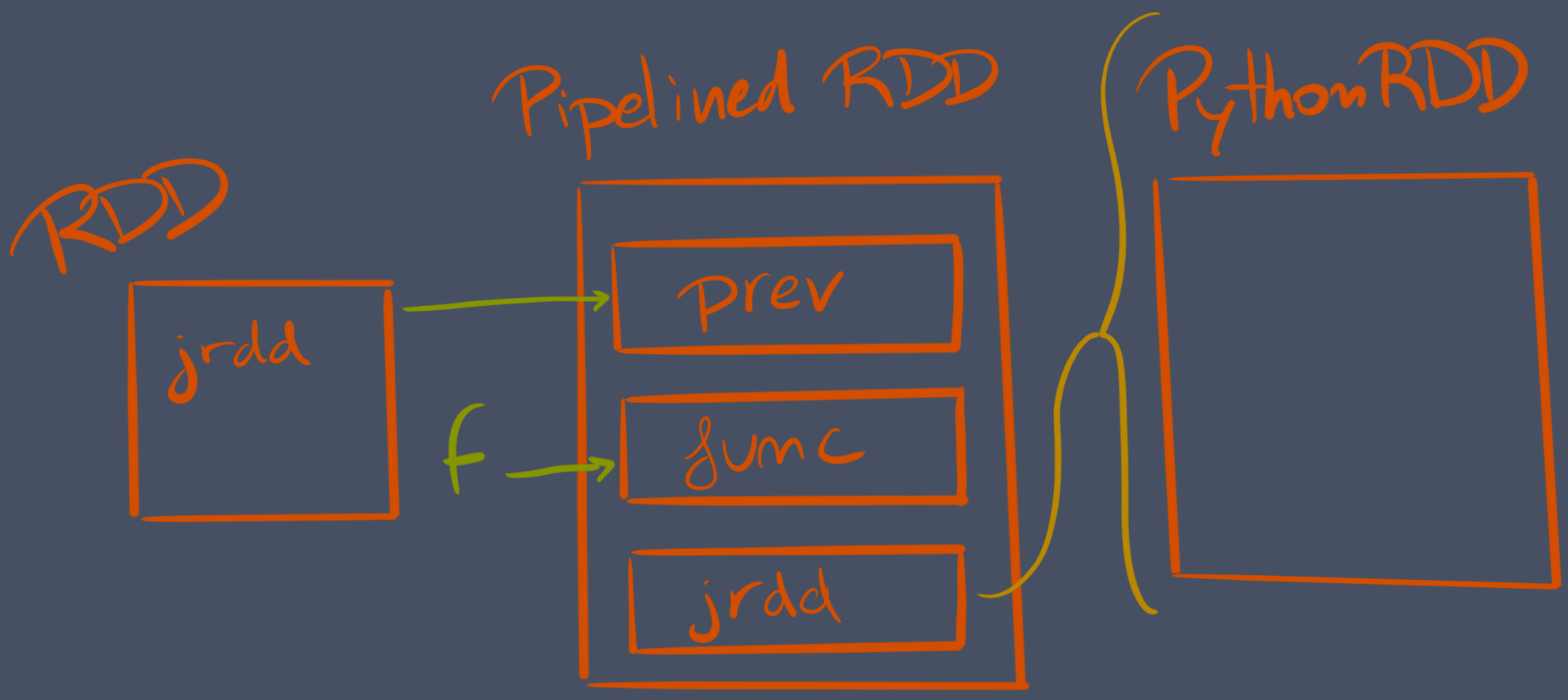
Will put the function in the `func` field



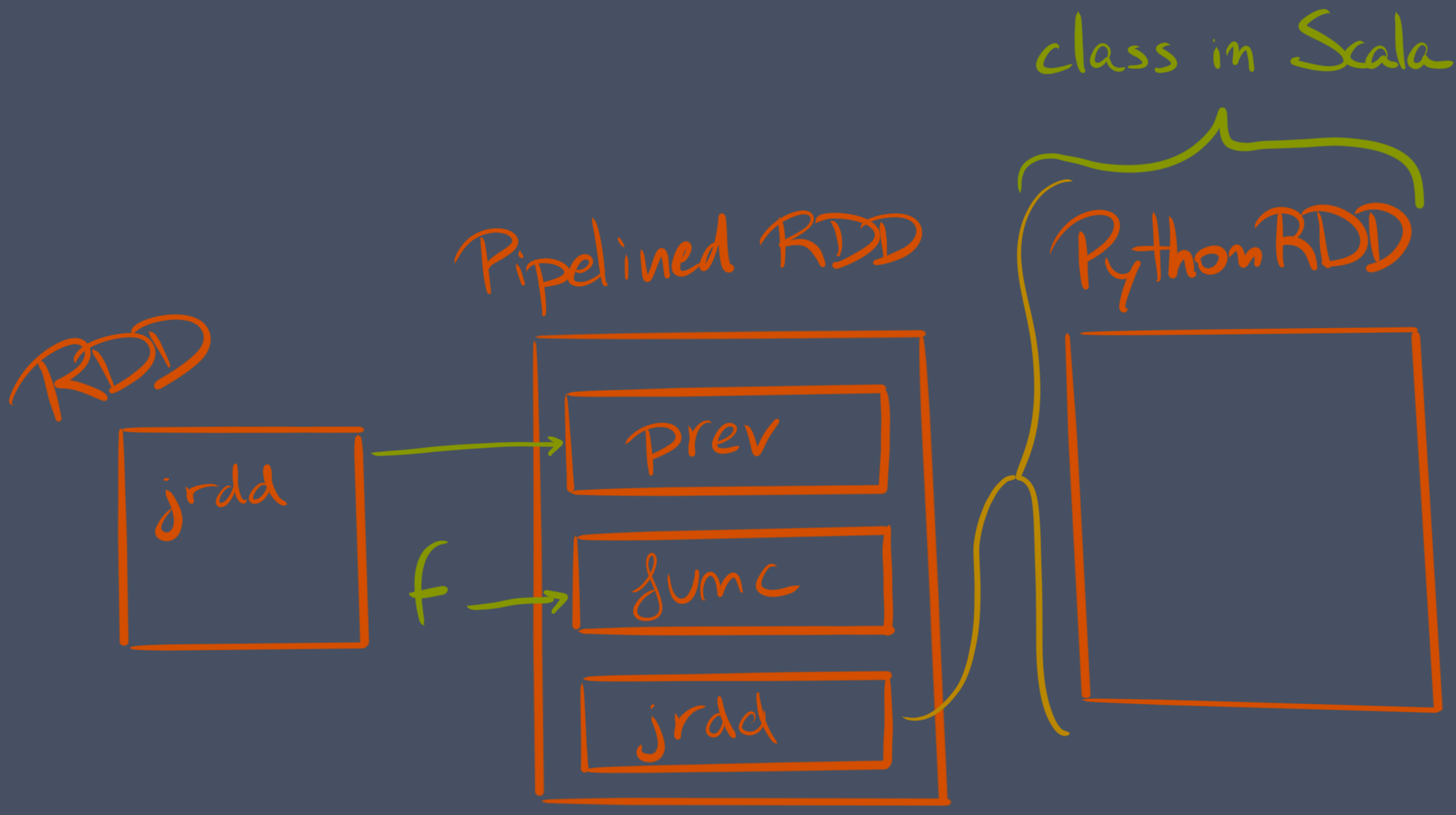
And will point `prev` to the RDD. Missing anything?

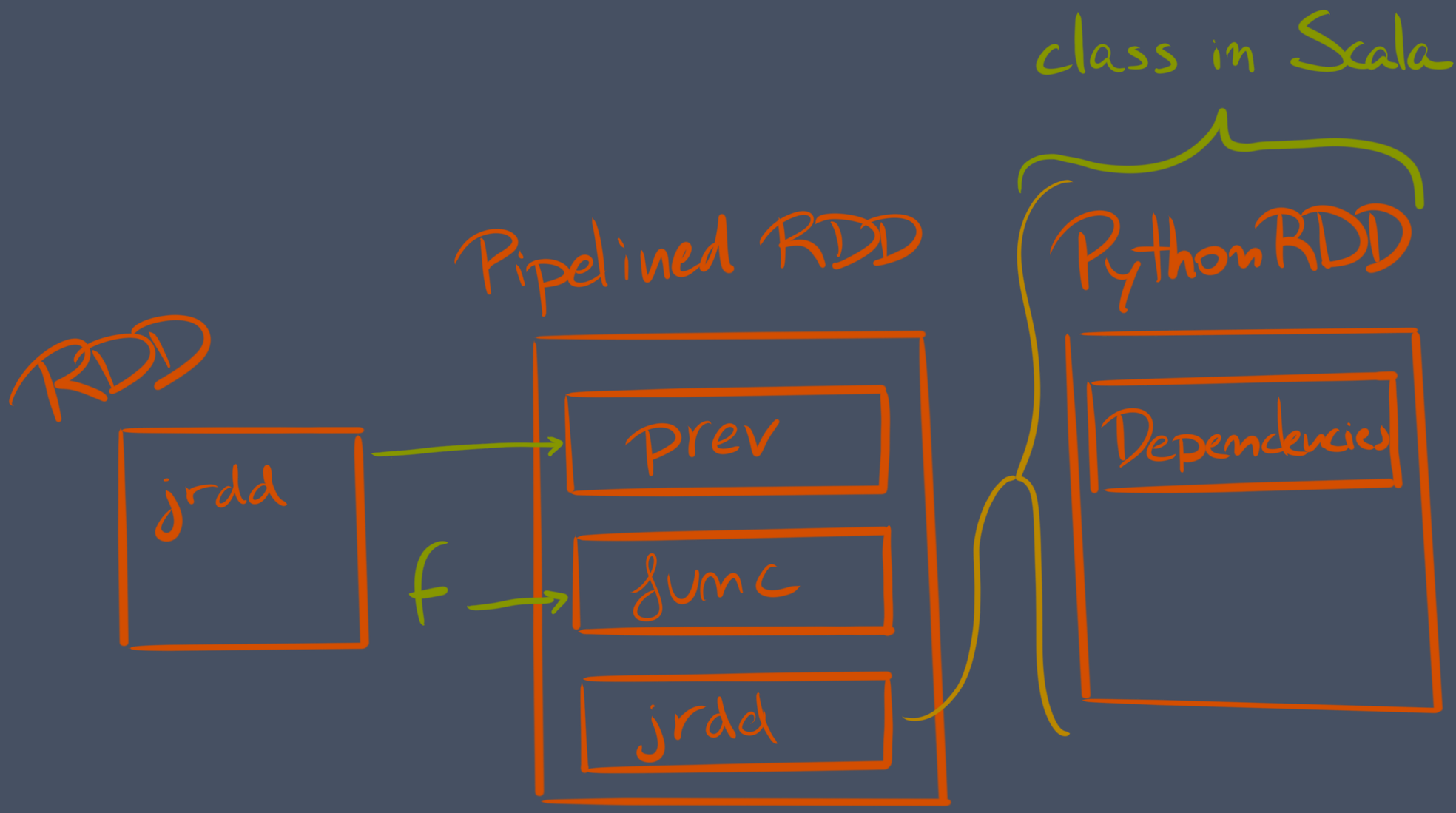


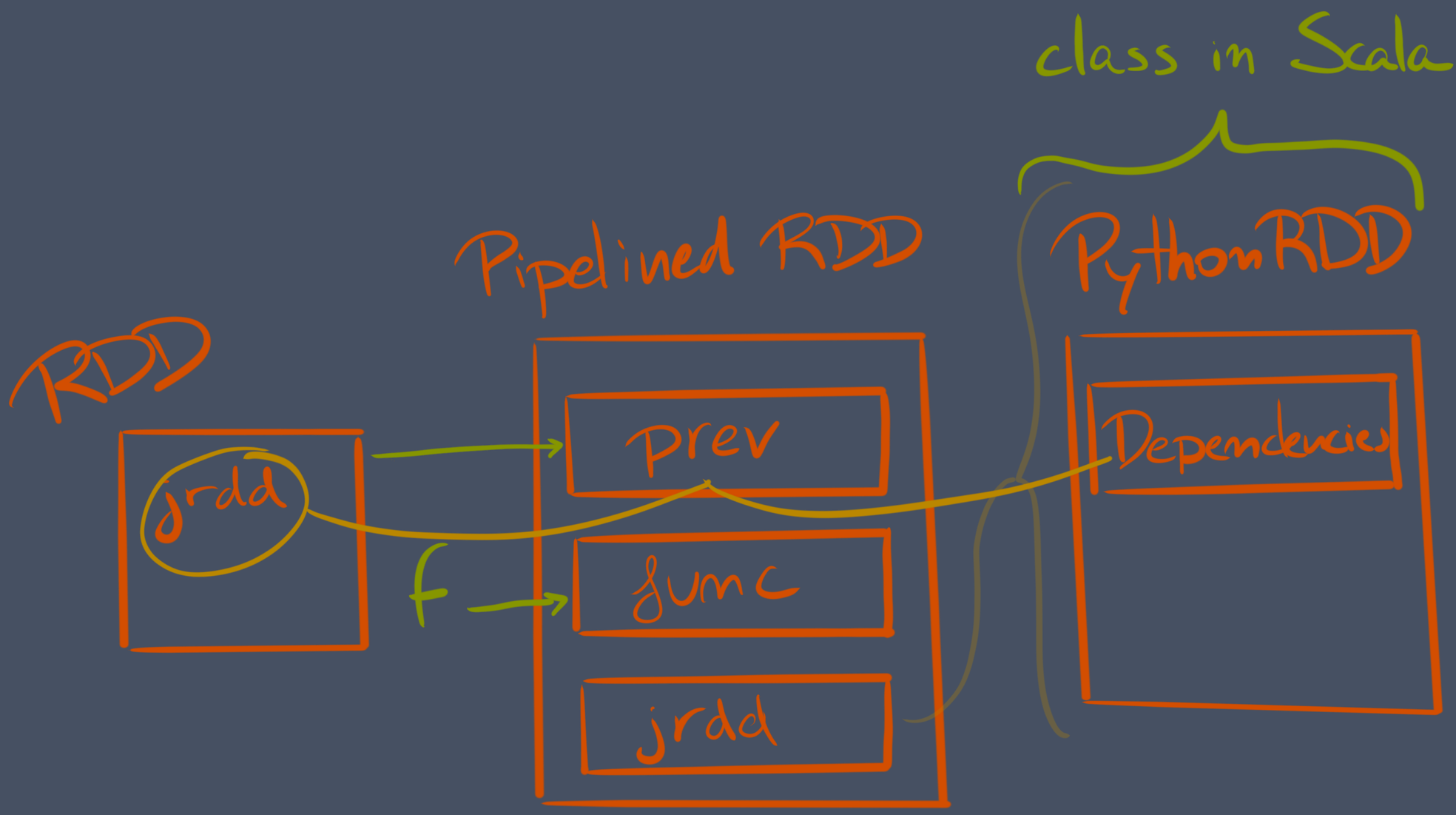
And now, what is the `_jrdd` of the PipelinedRDD?



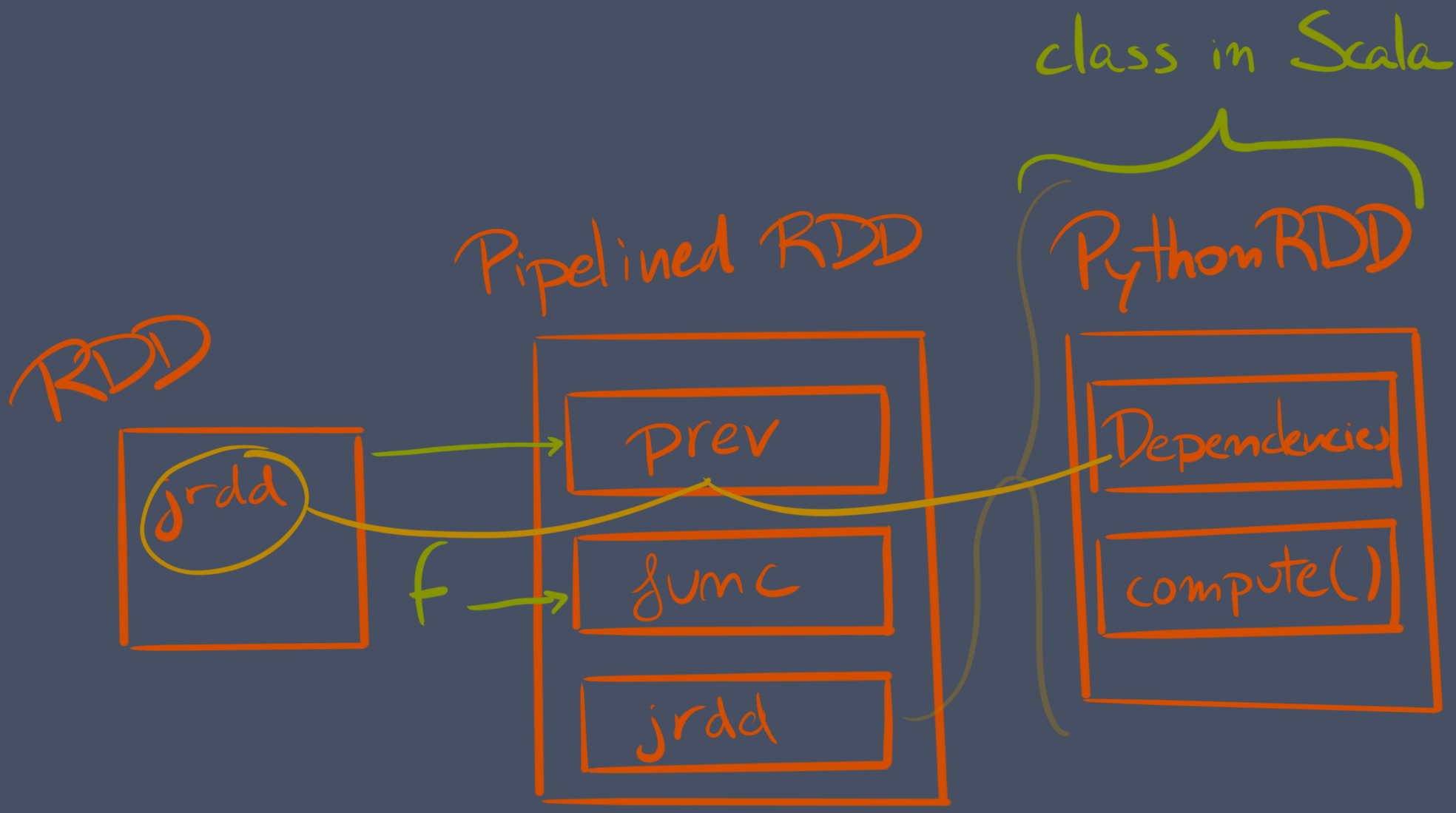
It's a PythonRDD (built via Py4J of course, this is in the Scala code), which is a sub-class of RDD

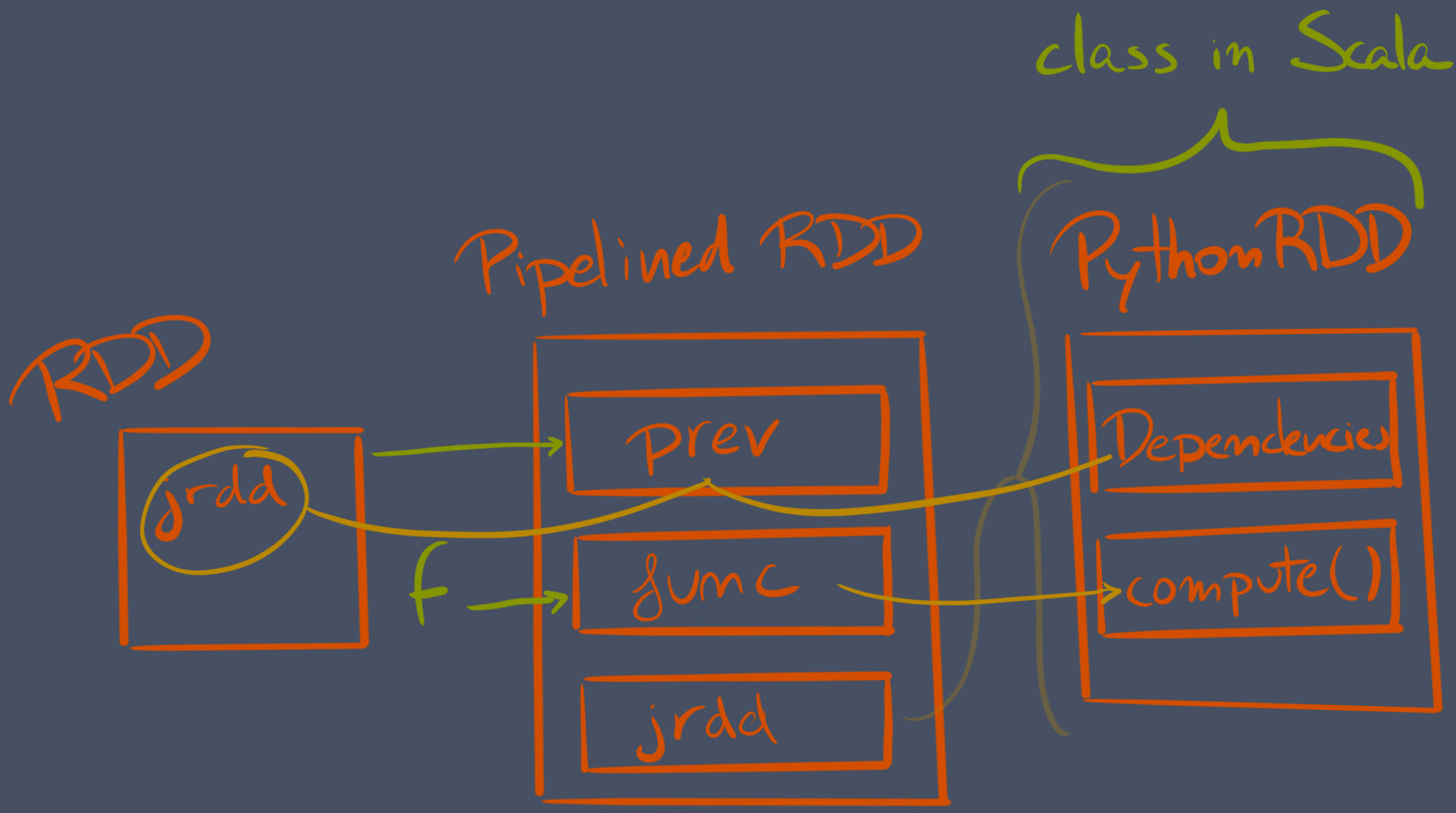

class in Scala
Pipelined RDD
PythonRDD
RDD
jrdd
prev
f
func
jrdd


class in Scala
Pipelined RDD
PythonRDD
RDD
jrdd
prev
f
func
jrdd
Dependencies



The dependencies of this RDD will point to the original `_jrdd`


class in Scala
RDD
jrdd
f
Pipelined RDD
prev
func
jrdd
PythonRDD
Dependencies
compute()



The compute method will wrap the function defined in `func`

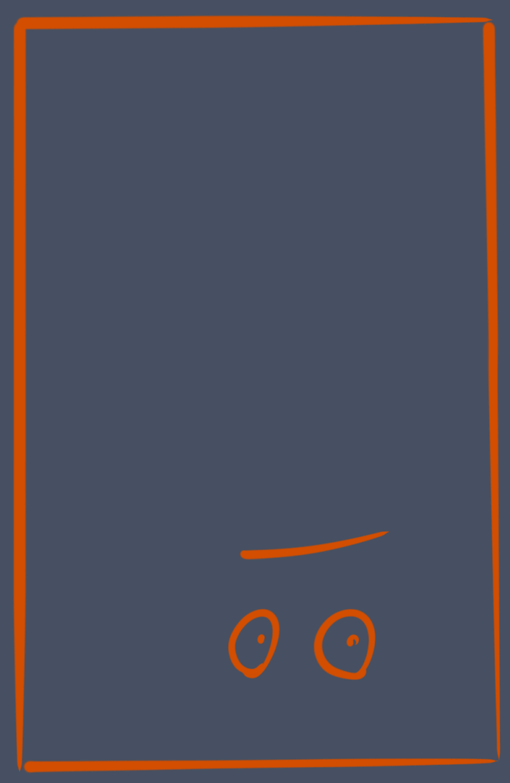
THE MAGIC IS IN compute

of PythonRDD It's where something gets eventually done to the RDD *in* Python

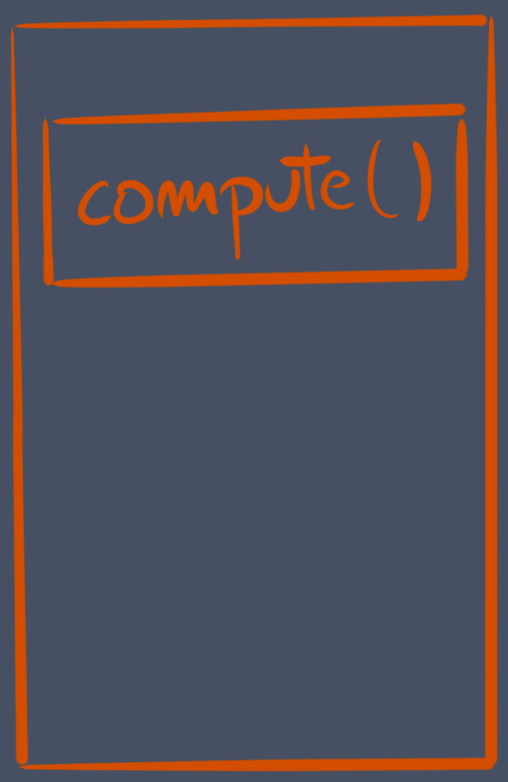
compute

IS RUN ON EACH EXECUTOR AND STARTS A PYTHON WORKER VIA PythonRunner

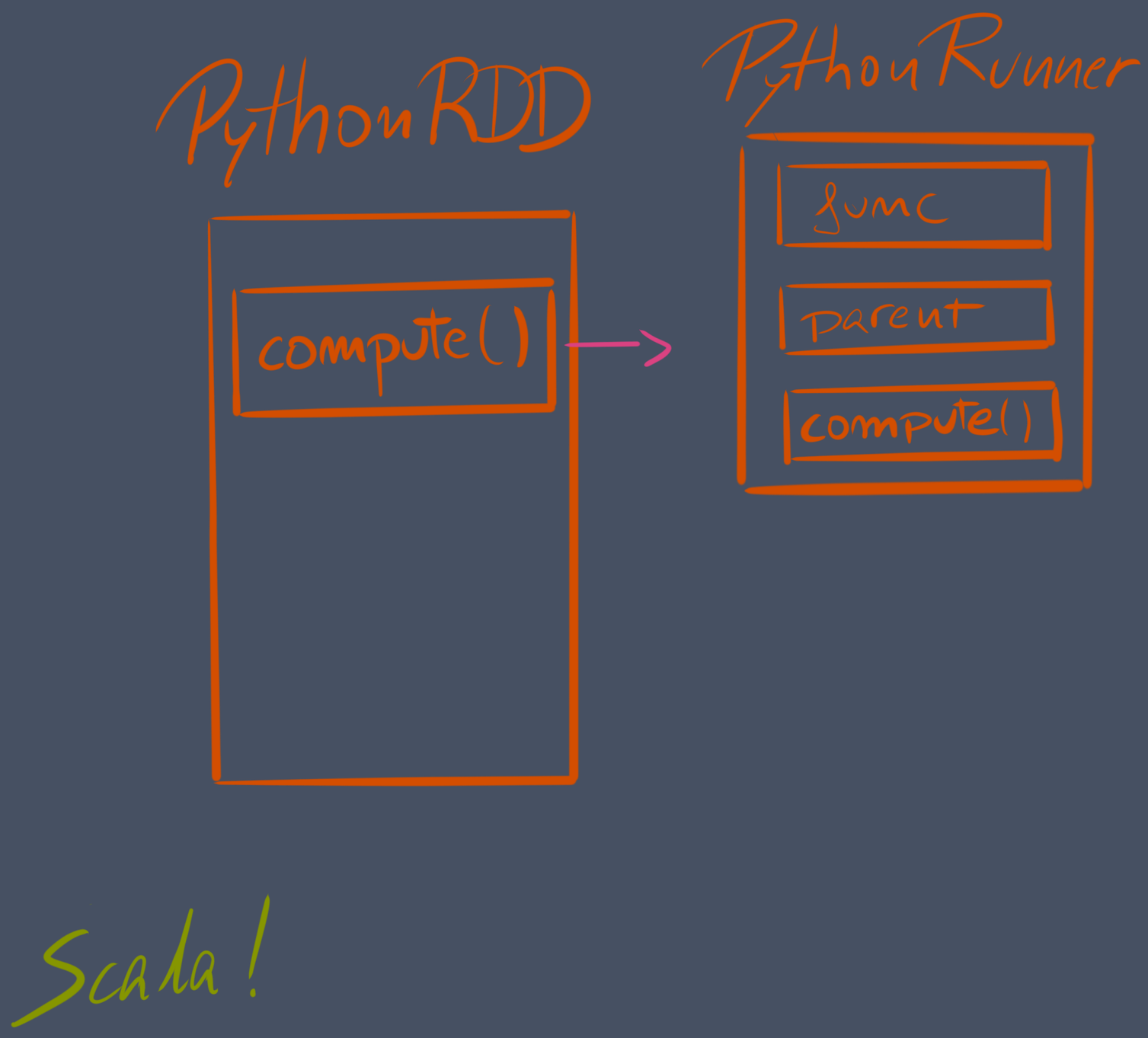
It will send all includes, broadcasts, etc through the stream. And actually the order of the data sent is important

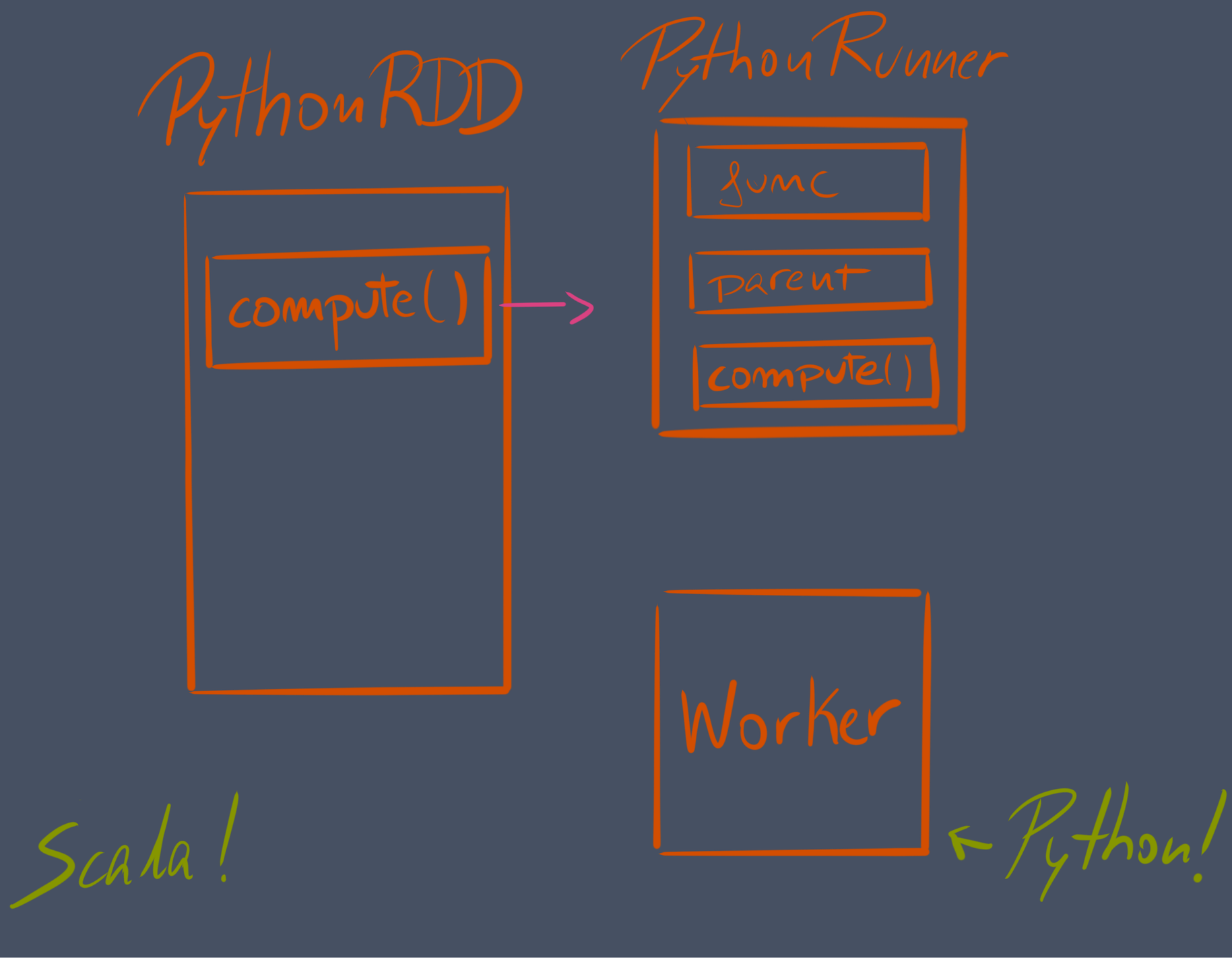


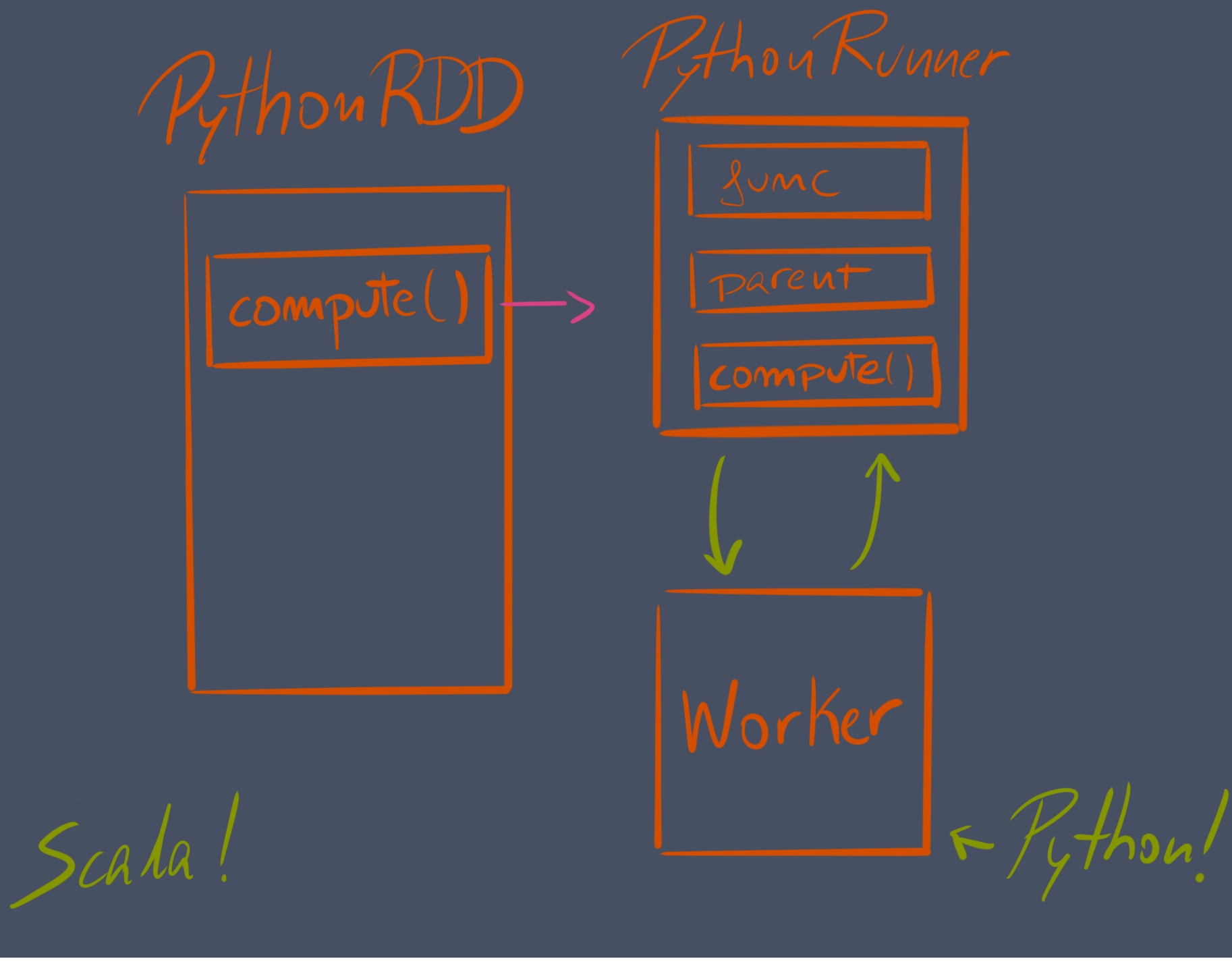
PythonRDD



Scala!


PythonRDD
compute()
PythonRunner
func
parent
compute()
Scala!


PythonRDD
compute()
PythonRunner
func
parent
compute()
Worker
Scala!
Python!


PythonRDD
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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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- 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

But, maybe you are missing something here, isn't Spark supposed to be pretty magic and plan and optimise stuff?

BUT... WASN'T SPARK MAGICALLY OPTIMISING EVERYTHING?

YES. FOR SPARK

DataFrame

You can think of `DataFrames` as RDDs which actually refer to tables. They
have column names, and may have types for each column

SPARK WILL GENERATE A PLAN

(A DIRECTED ACYCLIC GRAPH)

TO COMPUTE THE RESULT

When you operate on DataFrames, plans are created magically. And actually it
will generate a logical plan, an optimised logical plan, an execution plan...

AND THE PLAN WILL BE OPTIMISED USING CATALYST

The Catalyst optimiser. There's also a code generator in there (using Janino to compile Java code in real time) It prunes trees

DEPENDING ON THE FUNCTION, THE OPTIMISER WILL CHOOSE

PythonUDFRunner

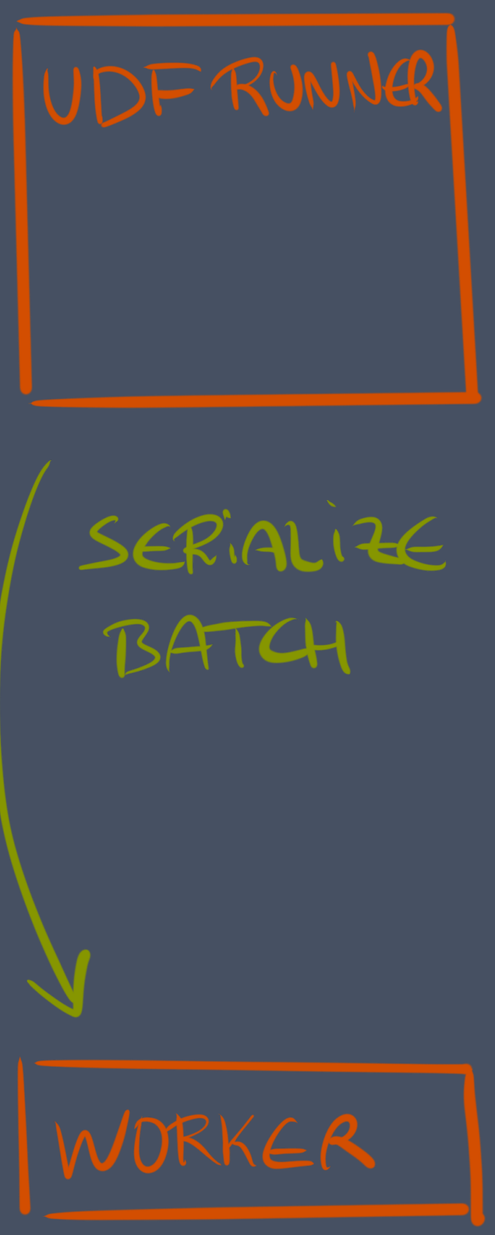
OR

PythonArrowRunner

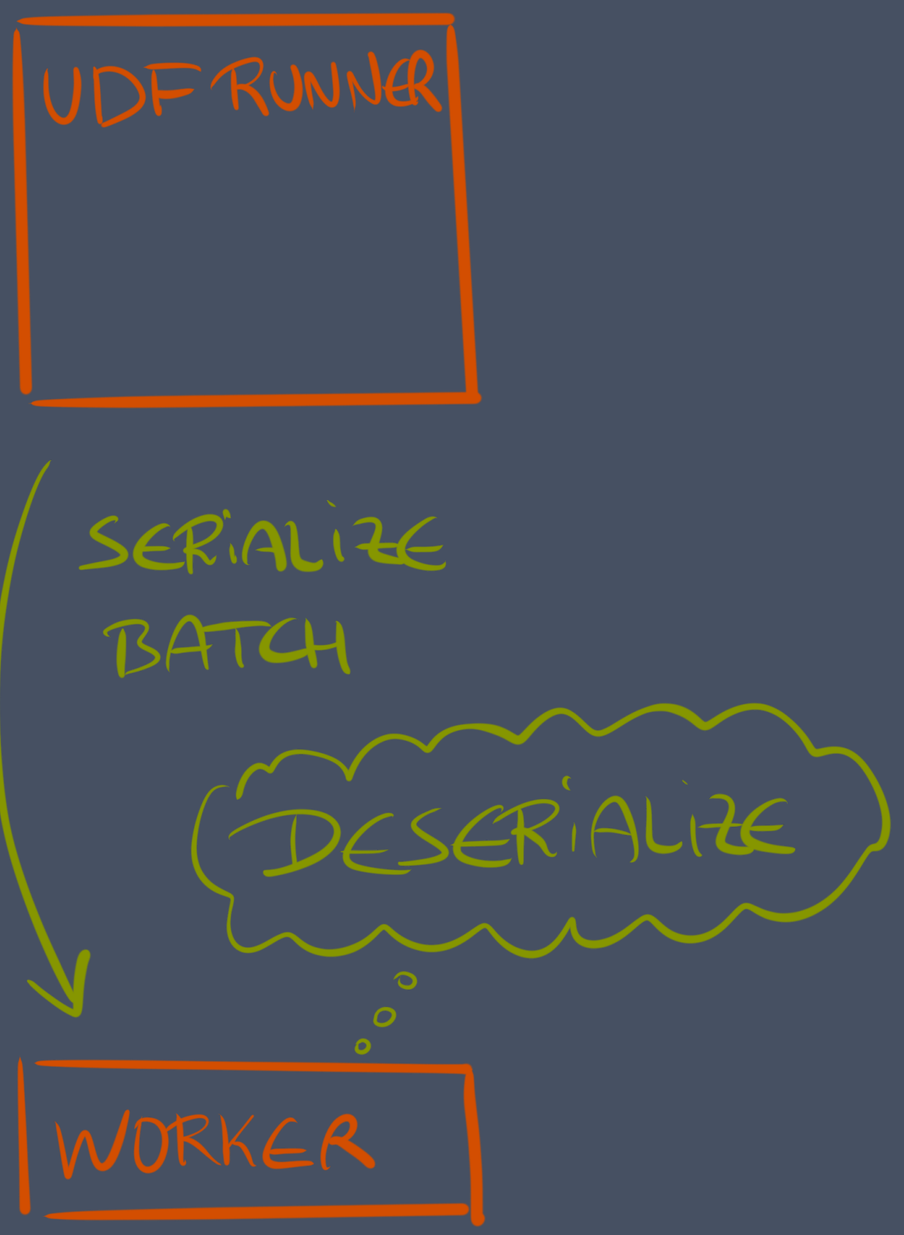
(BOTH EXTEND PythonRunner)


UDF RUNNER

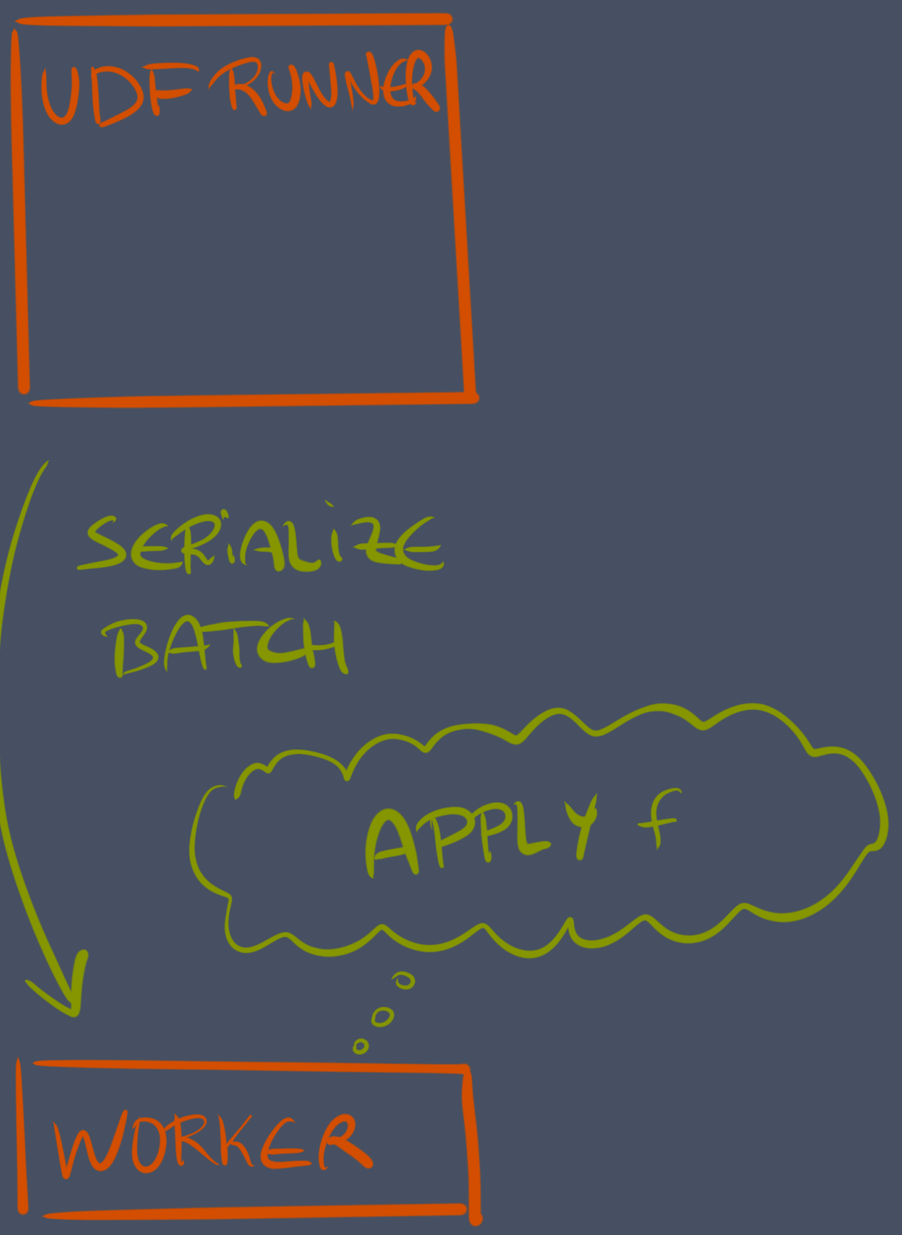

WORKER



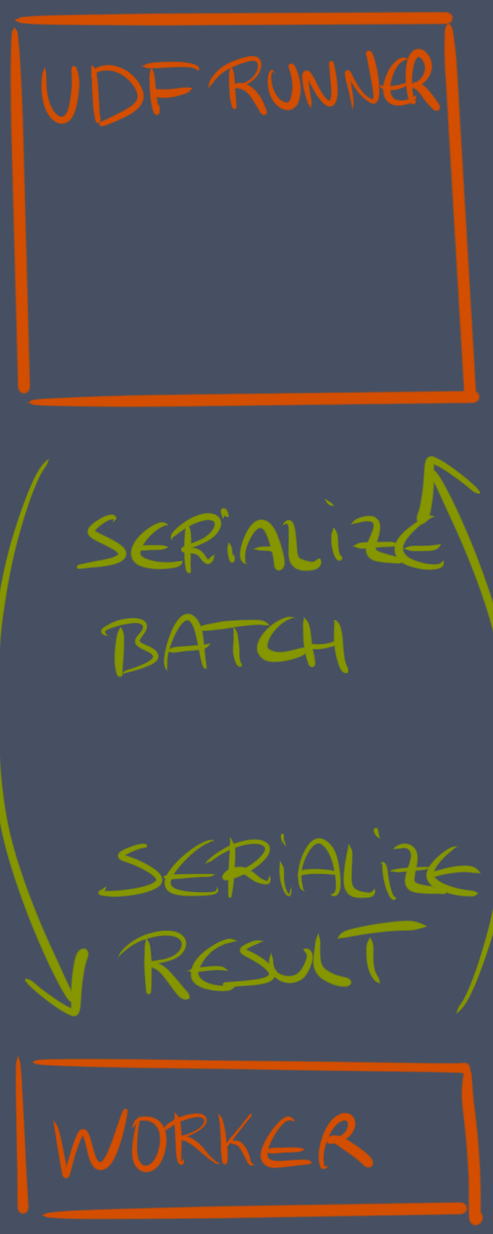
In the stream information about environment, length of data, versions, etc
will be sent first. Then data will be serialized in batches (of 100 rows I
think) using a Pickle implementation in Java (net.razorvine.pickle.{Pickler, Unpickler})



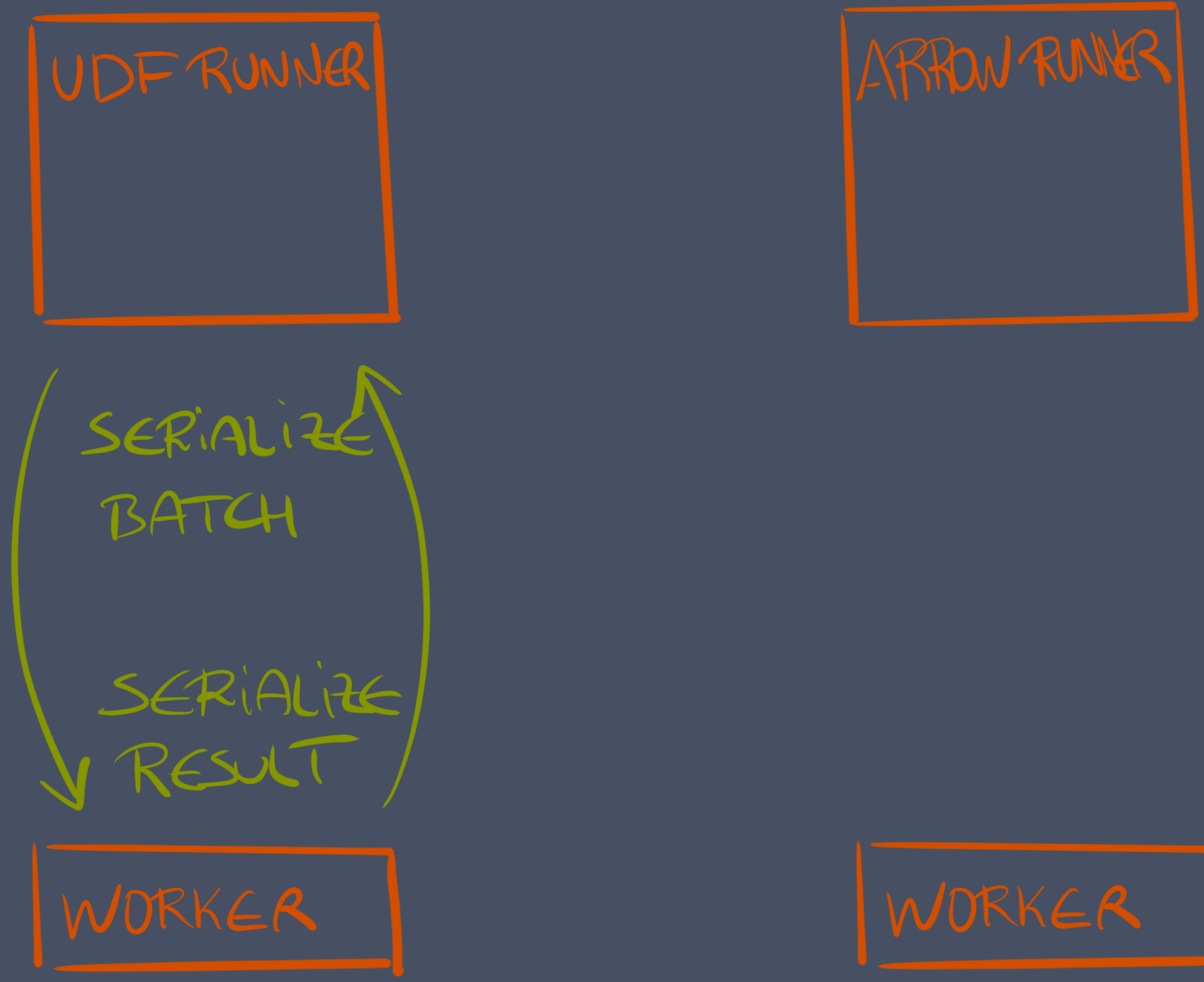
In Python land, after loading all the configuration and startup stuff, the data is unpickled



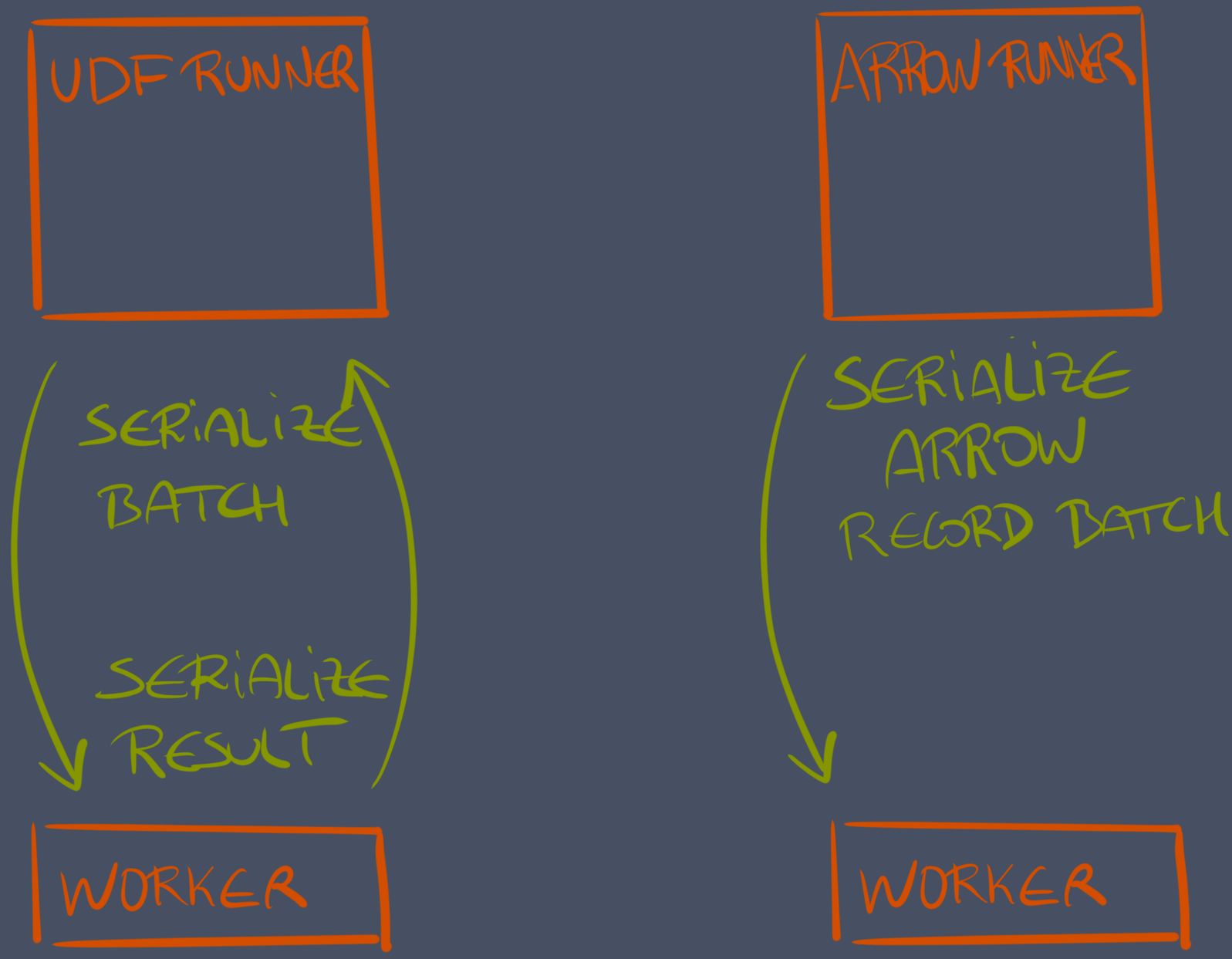
The stream is loaded as an iterator, and the function is applied to each item in the batch



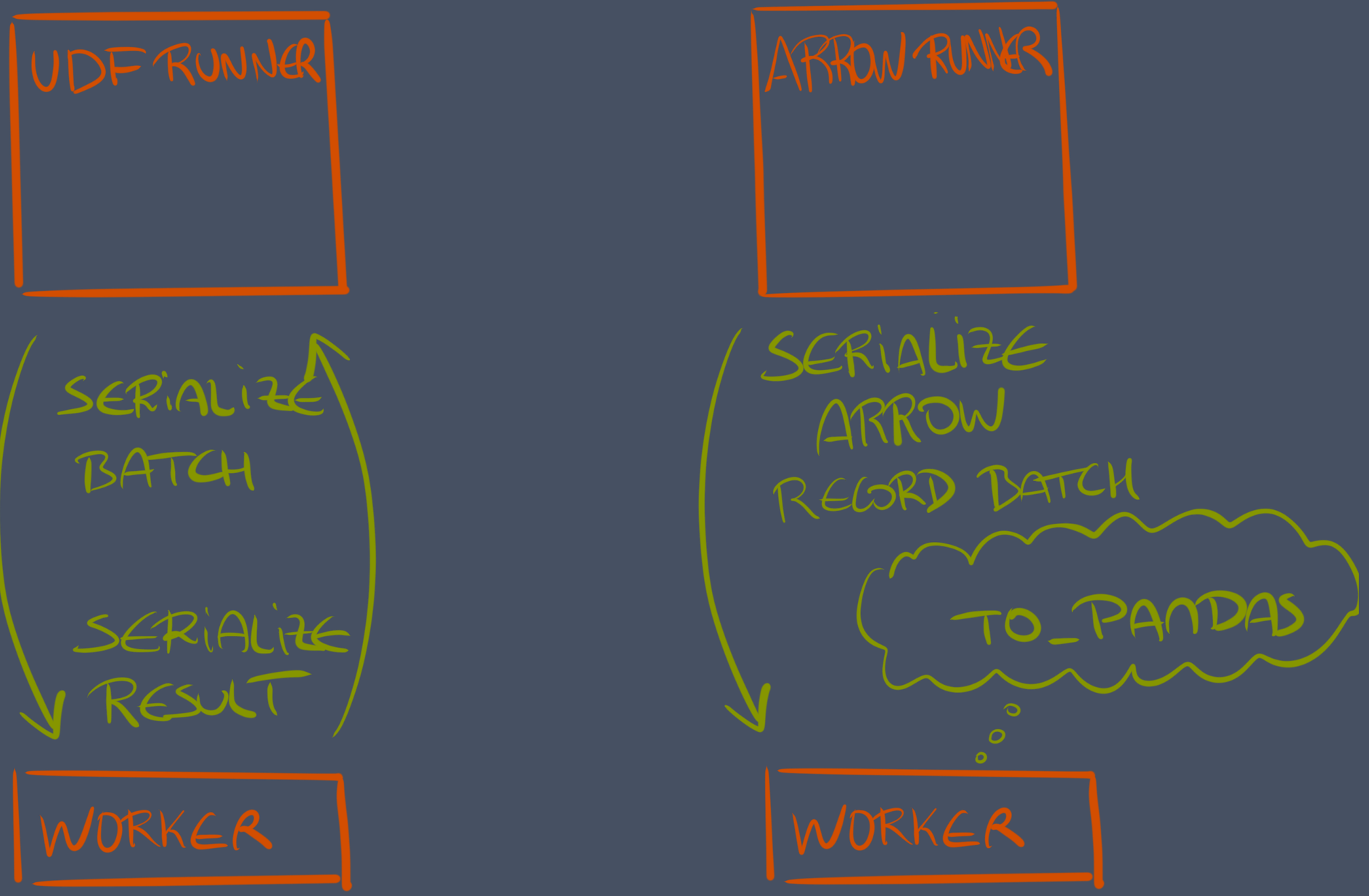
Then the data is serialized back to send to the JVM



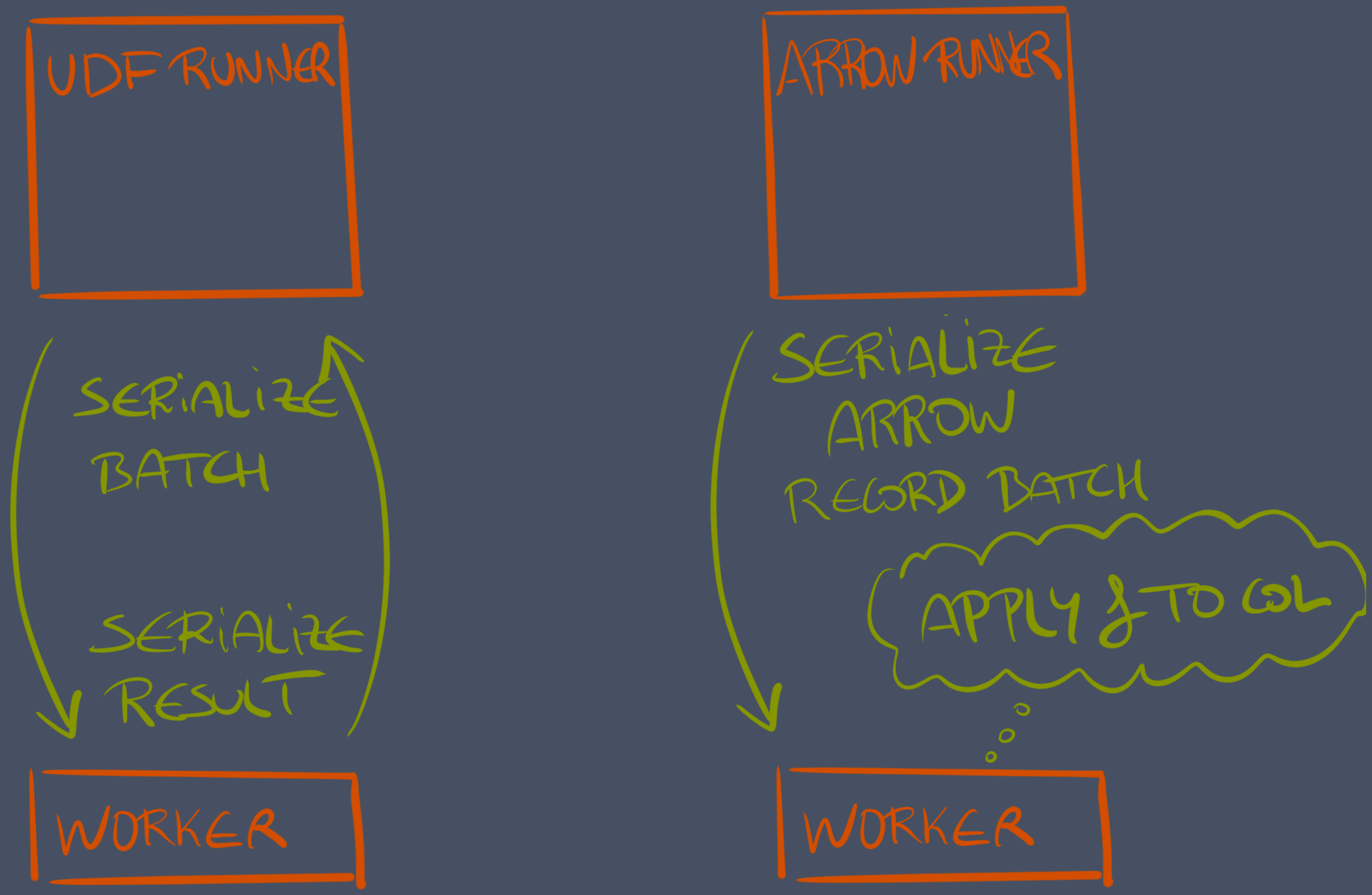
Arrow works a bit different, but not much



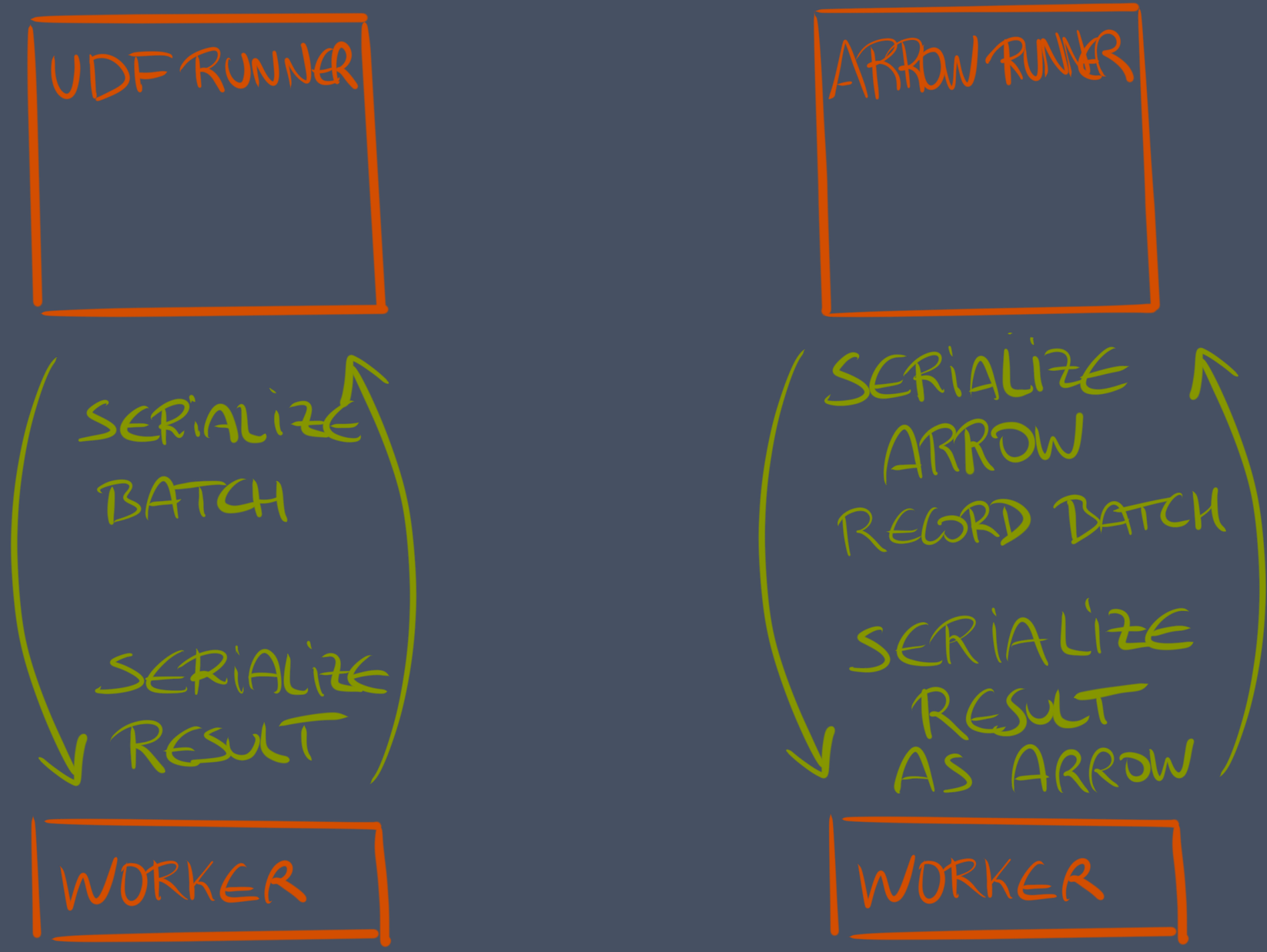
Data is sent as Arrow RecordBatch-es



Converting RecordBatches to a Pandas dataframe is essentially cost 0 (specially compared with pickling)



Applying a function to a column is super-fast, since it involves only running through all elements of the column. And the data has been loaded columnar already!



Data is sent back in Arrow columnar format,
which again is pretty much
cost-free in the Python side

IF WE CAN DEFINE OUR FUNCTIONS USING PANDAS `Series` TRANSFORMATIONS WE CAN SPEED UP PYSPARK CODE FROM 3X TO 100X!

See here: https://databricks.com/blog/2017/10/30/introducing-vectorized-udfs-for-pyspark.html

RESOURCES

- SPARK DOCUMENTATION
- HIGH PERFORMANCE SPARK BY HOLDEN KARAU
- MASTERING APACHE SPARK 2.3 BY JACEK LASKOWSKI
- SPARK'S GITHUB
- BECOME A CONTRIBUTOR

QUESTIONS?


THANKS!

FURTHER REFERENCES

ARROW

ARROW'S HOME
ARROW'S GITHUB
ARROW SPEED TESTS
ARROW TO PANDAS CONVERSION SPEED
STREAMING COLUMNAR DATA WITH APACHE ARROW
WHY PANDAS USERS SHOULD BE EXCITED BY APACHE ARROW
ARROW-PANDAS COMPATIBILITY LAYER CODE
ARROW TABLE CODE
PYARROW IN-MEMORY DATA MODEL

PANDAS

PANDAS' HOME
PANDAS' GITHUB
IDIOMATIC PANDAS GUIDE
PANDAS INTERNALS CODE
PANDAS INTERNALS DESIGN
DEMYSTIFYING PANDAS' INTERNALS (TALK BY MARC GARCIA)

SPARK/PYSPARK

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

PY4J

PY4J'S HOME
PY4J'S GITHUB
REFLECTION ENGINE

EOF