UMD DATA605 - Big Data Systems

Python Dask

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v1.1

SCIENCE
ACADEMY

Dask: Resources

- Web resources:
  - Dask project
  - Dask examples
- Tutorial
  - Dask_tutorial
  - Dask_advanced_tutorial
- Class project
- Mastery
  - Data science with Python and Dask, 2019
    - Amazon

Dataset Size Issues

- **Small datasets ($<$ 1 GB)**
  - Fits into RAM
  - Manipulation doesn't require paging to disk
- **Medium dataset ($<$ 1TB)**
  - Doesn't fit into RAM
  - Fits into local disk
    - Performance penalty imposed by using local disk
  - Need multiple CPU cores
    - Difficult to take advantage of parallelism with Python / Pandas
- **Large dataset ($>$ 1TB)**
  - Doesn't fit into RAM
  - Doesn't fit into local disk
  - Need multiple servers
    - Python / Pandas were not built to operate on distributed datasets
    - Use frameworks for massive datasets
    - E.g., Hadoop, Spark, Dask, Ray

Dataset Size Issues

- **Small datasets**
  - < 1 GB
- **Medium dataset**
  - < 1TB
- **Large dataset**

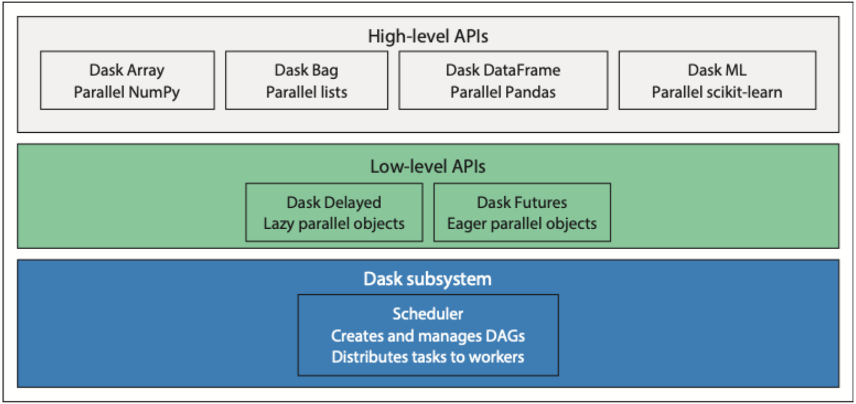
- *1TB*

- **The thresholds are fuzzy and changing over time**
  - E.g., you can scale the computer 10x and get 10x bigger data sets
- **Problem with scaling datasets**
  - Long run times
  - Rewriting code in different language / API for datasets of different size
  - Need to think about *what to do* it and *how to do* it efficiently
  - Cumbersome framework (Pandas easy, Hadoop difficult)

Dask

- Dask is written in Python
    - It scales natively Numpy, Pandas, sklearn
    - Dask objects are wrappers (don't just mirror the interface) objects from the respective libraries (e.g., Pandas DataFrame, numpy array)
    - Parallel parts are called "chunks" or "partitions"
        - Are queued to be worked on
        - Shipped between machines
        - Worked locally on a machine
- Pros
    - Users don't need to learn a new language, but can use familiar interfaces
    - Can focus on writing code that is optimized for parallelism
        - Dask does the heavy lifting
- Scaling Dask is easy
    - Users can write a prototype task on a local machines and use a cluster when needed
    - No need to refactor existing code
    - No need to handle cluster-specific issues
        - E.g., resource management, data recovery, data movement
    - Dask runs on multi-core
    - Dask can use cluster managers
        - E.g., Yarn, Mesos, Kubernetes, AWS ECS

Dask Layers



High-level APIs

Dask Array
Parallel NumPy

Dask Bag
Parallel lists

Dask DataFrame
Parallel Pandas

Dask ML
Parallel scikit-learn

Low-level APIs

Dask Delayed
Lazy parallel objects

Dask Futures
Eager parallel objects

Dask subsystem

Scheduler
Creates and manages DAGs
Distributes tasks to workers

Figure 3: alt_text

Scaling Up vs Scaling Out

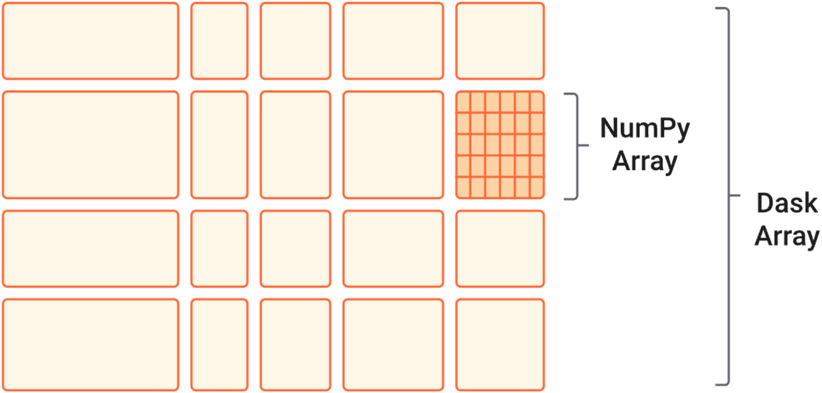
- **Scaling up**
  - = replace equipment with larger, faster equipments
    - E.g., buy a larger pot, replace knife with food processor
  - **Pros**
    - You got better hardware, nothing else needs to change (e.g., code)
  - **Cons**
    - There will be a time where you exceed the capacity of the current machines
    - Cost: more powerful machines are expensive
- **Scaling out**
  - = divide the work between many workers in parallel
    - E.g., buy more pots and hire more cooks
  - **Pros**
    - Task scheduler organizes computation, assigning workers to each task
    - More cost-effective solution since no specialized hardware is needed
  - **Cons**
    - Need to write code to expose parallelism
    - Costs of maintaining a cluster

Dask: Computation

- **Lazy computations**
  - User defines the transformations on the data
  - No need to wait for one computation to finish before defining the next
  - Avoid loading the entire data in memory by operating in chunks
  - E.g.,
    - Split a 2GB file into 32 64MB chunks
    - Operate on 8 chunks at a time on each server
    - The max memory consumption doesn’t exceed 512MB = (8 x 32)
  - Each task tracks object dimensions and data types
    - No code is executed
- **compute()**
  - Running a computation (aka materializing) ”’ python missing_count_pct = missing_count.compute()”’
- **persist()**
  - As soon as a node in the graph emits results, its intermediate work is
  - discarded to minimize memory usage
  - If we need to do additional computation on intermediate nodes we need to re-run the graph
  - **persist()** tells Dask to keep the intermediate result in memory
  - This speeds up a large and complex DAG that needs to be reused many times

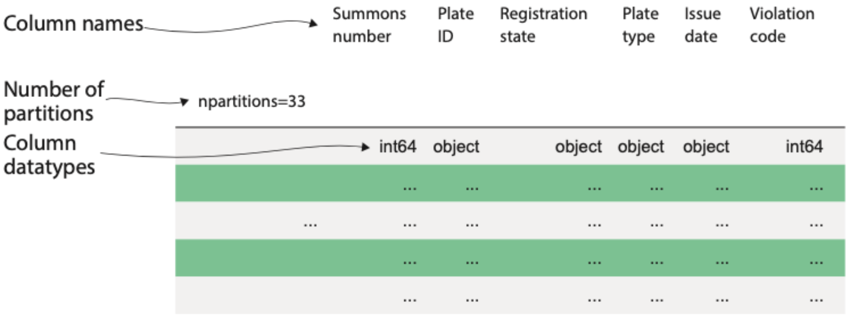
Dask: Data Structures

- **Dask DataFrame** implements Pandas DataFrame
  - Tabular / relational data
- **Dask Array** implements numpy ndarray
  - Multidimensional array**
- **Dag Bag** coordinates Python lists of objects
  - Parallelize computations on unstructured or semi-structured data



Dask Reading Data

- dask.dataframe.read_csv()
  - Doesn't load the data in memory with
  - Tries to infer the types of the columns
    - By randomly sampling some data
    - Best to set the data types
    - Even better is to use Parquet since it stores data and types together
- Partitions = chunks of data that can be worked independently
  - E.g., 33 partitions
  - Graph is composed of 99 tasks
  - Each partition reads data, splits data, initializes df object



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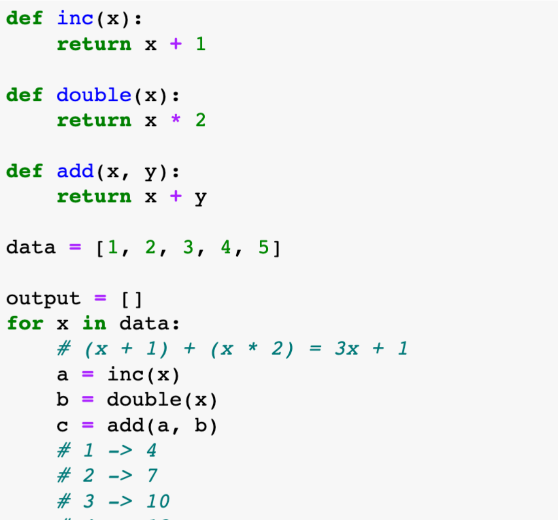
Low Level APIs: Delayed

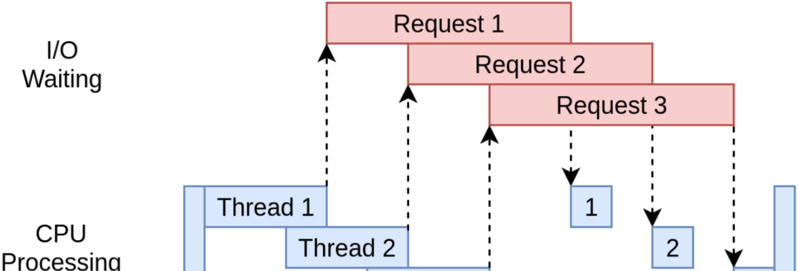
- Handle computations that don't fit in native Dask data structures (e.g., Dask DataFrame)
- In the example below there is parallelism that can be exploited



```
def inc(x):
    return x + 1

def double(x):
    return x * 2

def add(x, y):
    return x + y

data = [1, 2, 3, 4, 5]

output = []
for x in data:
    # (x + 1) + (x * 2) = 3x + 1
    a = inc(x)
    b = double(x)
    c = add(a, b)
    # 1 -> 4
    # 2 -> 7
    # 3 -> 10
```

Low Level APIs: Futures

- In parallel programming, a “future” encapsulates the asynchronous execution of a callable, representing the eventual result of the operation
- Futures is the most general way of specifying concurrency in Dask
  - Everything can be expressed in terms of futures
  - User can specify what’s blocking and what’s not blocking
- Python**concurrent.futures**
  - High-level interface for asynchronously executing callables
  - Thread pool or Process pool (same interface **Executor**)
- Dask extends **concurrent.futures**
  - Dask client can be used anywhere **concurrent.futures** can be used

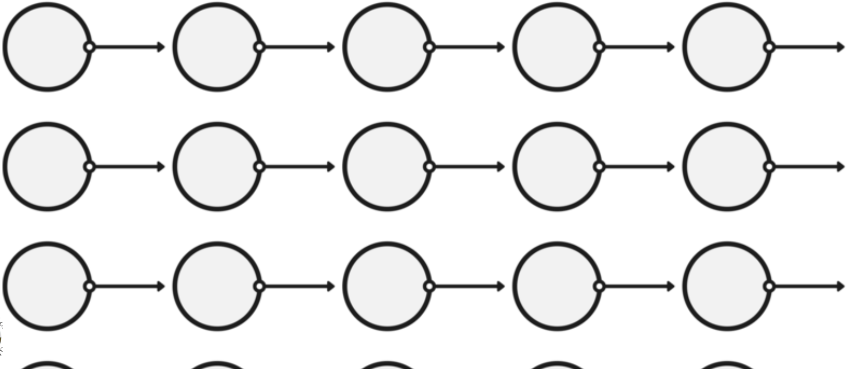


Different Types of Parallel Workload

- Break program in medium-size tasks of computation
    - E.g., a function call

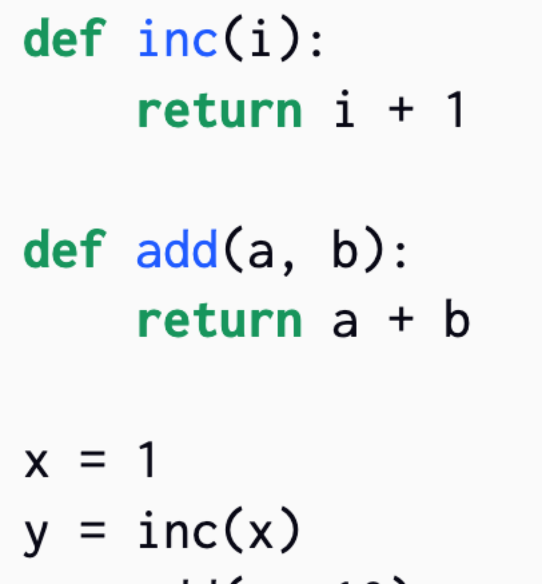
Embarrassingly Parallel

Hadoop/Spark/Dask/Airflow/Prefect



Encoding Task Graph

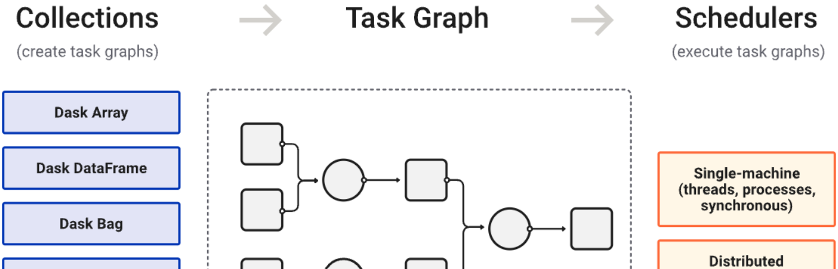
- Dask encodes tasks in terms of Python dicts and functions



```
def inc(i):
    return i + 1

def add(a, b):
    return a + b

x = 1
y = inc(x)
```

Task Scheduling

- Data collections (Bags, Arrays, DataFrame) and their operations create task graphs
  - Nodes in the task graph are Python functions
  - Edges are dependencies (e.g., output from one task used as input in another task)
- Task graphs are scheduled for execution
- Single-machine scheduler
  - Use local process or thread pool
  - Simple but it can only run on a single machine
- Distributed scheduler
  - It can run locally or distributed across a cluster



Collections → Task Graph → Schedulers

(create task graphs)

(execute task graphs)

Dask Array

Dask DataFrame

Dask Bag

Single-machine (threads, processes, synchronous)

Distributed

Task Scheduling

- **Dask task scheduler orchestrates the work dynamically**
  - Not a static scheduling of operations like a relational DB
  - When the computation takes place, Dask dynamically assesses:
    - What tasks has been completed
    - What tasks is left to do
    - What resources (CPUs) are free
    - Where the data is located
- **This dynamic approach handles a variety issues:**
  - Worker failure
    - Just re-run
  - Workers completing work at different speeds because of:
    - Different computation
    - Different hardware
    - Different workloads on the servers
    - Slower access to the data
  - Network unreliability
    - Just re-run or remove the isolated nodes

Dask vs Spark

- Spark has
- **Pros**
  - Popular framework for analyzing large datasets
  - In-memory alternative to MapReduce / Hadoop
- **Cons**
  - Spark is a Java library, supporting Python through PySpark API
    - Python code is executed on JVM through `py4j`
    - Difficult to debug since execution occurs outside Python
  - Different DataFrame API than Pandas
    - Learn how to do things "the Spark way"
    - You might need to implement things twice to go from exploratory analysis to large experiments / production
  - Optimized for MapReduce operations over a collection
  - Difficult to set-up and configure

Tutorial

Tutorial - From the official documentation
https://docs.dask.org/en/stable/10-minutes-to-dask.html