UMD DATA605 - Big Data Systems

Python Dask

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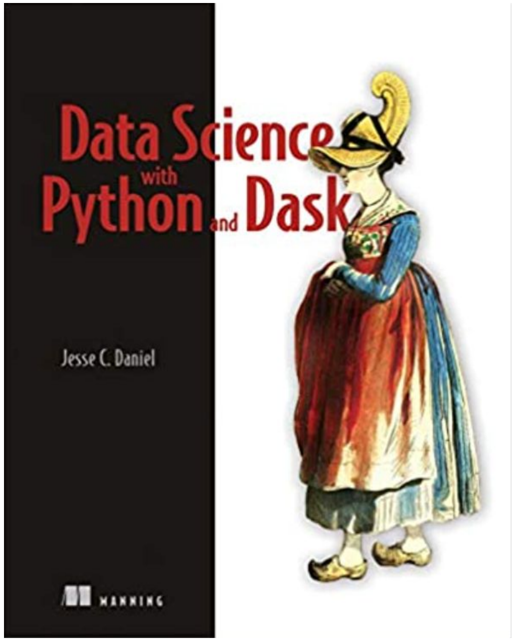
Dask: Resources

- 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

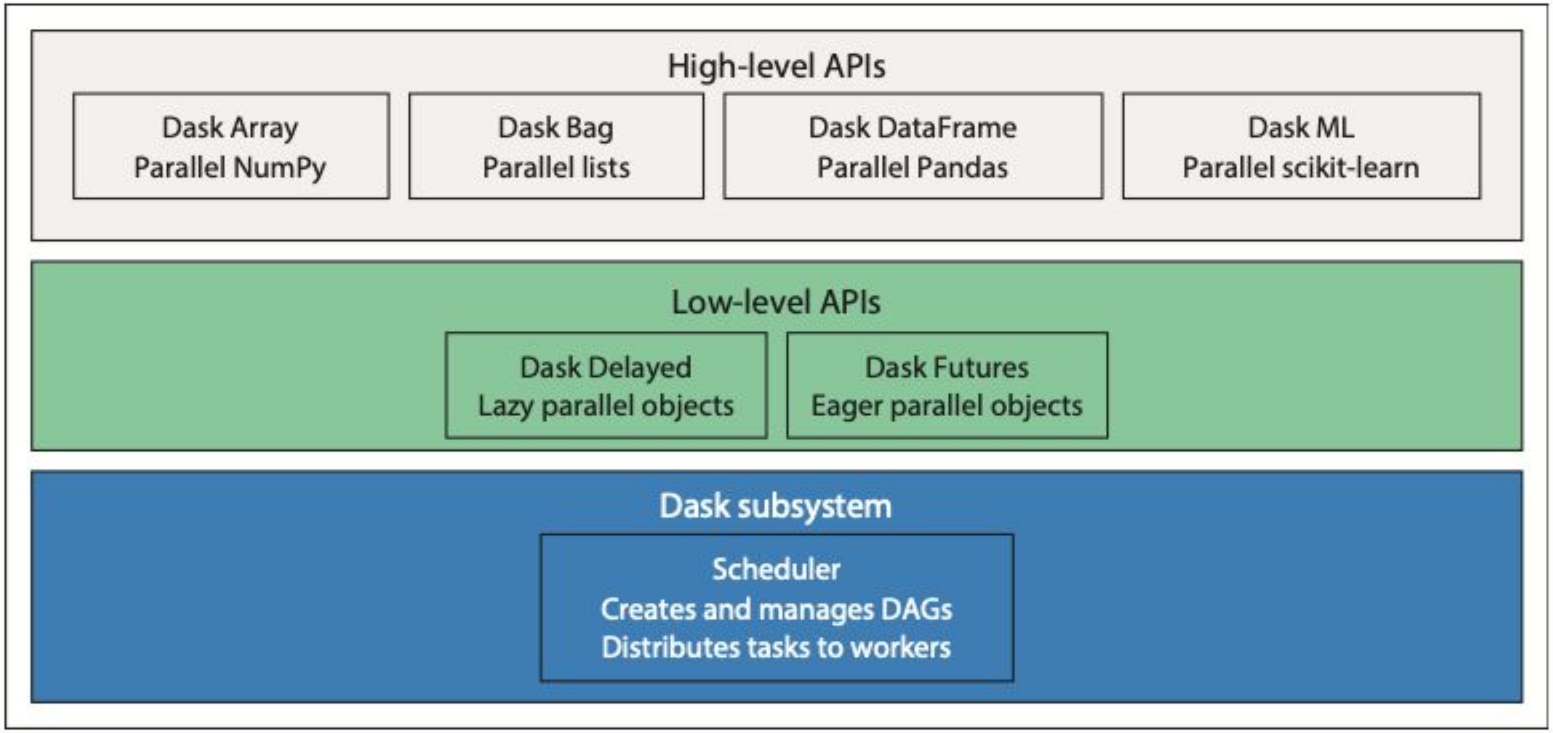
Dataset Size Issues

- **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

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

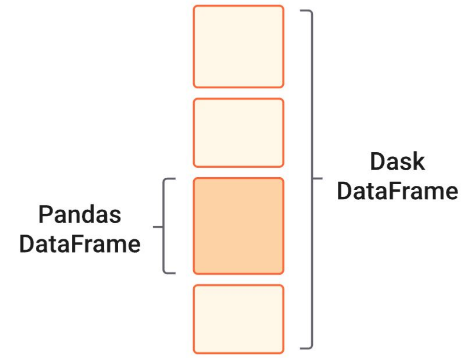
Dask: Computation

- **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)

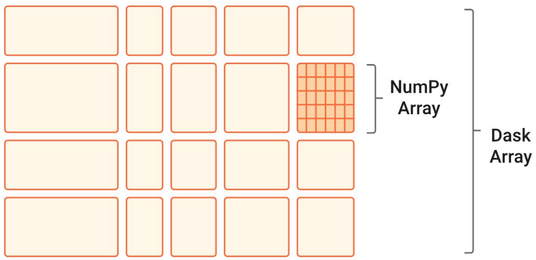
  ```
  missing_count_pct = missing_count.compute()
  ```
- `persist()`
  - As soon as a node in the graph emits results, its intermediate work is
  - discarded to minimize memory usage
  - If we need to do additional computation on intermediate nodes we need to re-run the graph
  - `persist()` tells Dask 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

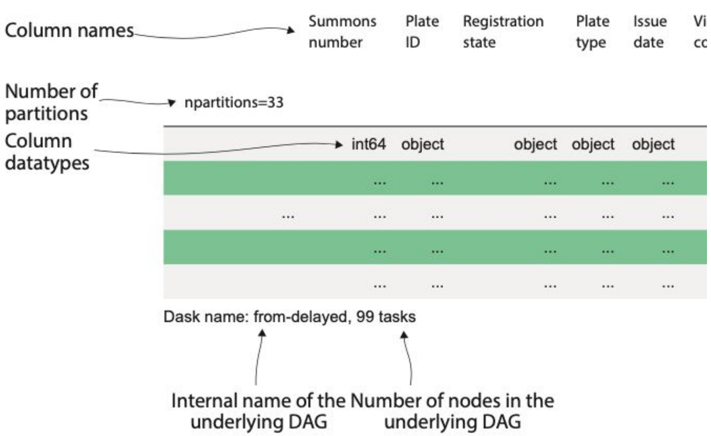


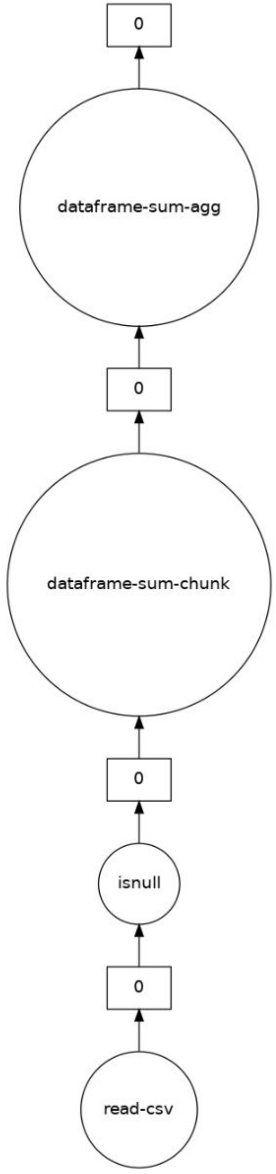
- **Dag Bag** coordinates Python lists of objects
  - Parallelize computations on unstructured or semi-structured data

Dask Reading Data

```python
import dask.dataframe as dd
df = dd.read_csv('nyc-parking-tickets-2017.csv')
missing_values = df.isnull().sum()
missing_values
```

- `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

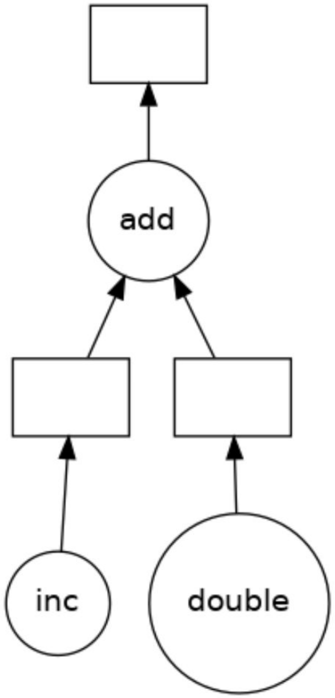




Low Level APIs: Delayed

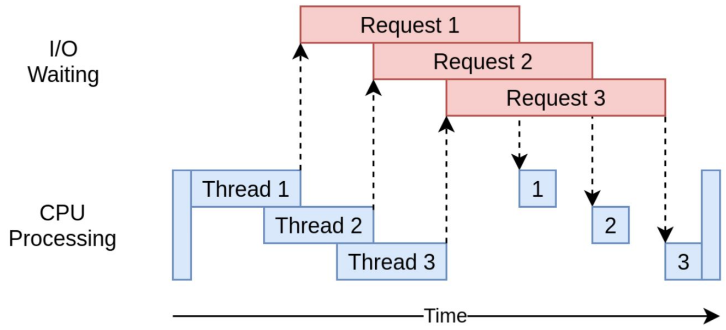
- Handle computations that don’t fit in native Dask data structures (e.g., Dask DataFrame)
- In the example below there is parallelism that can be exploited

```
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
    # 4 -> 13
    # 5 -> 16
    output.append(c)

# 4 + 7 + 10 + 13 + 16 = 20 + 20 + 10 = 50
total = sum(output)
print(total)
```



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




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

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

a = client.submit(inc, 10)
b = client.submit(inc, 20)
```

```
>>> a
<Future: status: pending, key: inc-b8aaf26b99466a7a1980efa1ade6701d>
```

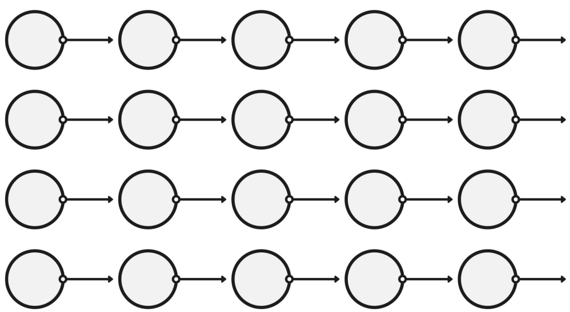
```
>>> a
<Future: status: finished, type: int, key: inc-b8aaf26b99466a7a1980efa1ade6701d>

>>> a.result()  # blocks until task completes and data arrives
11
```

Different Types of Parallel Workload

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

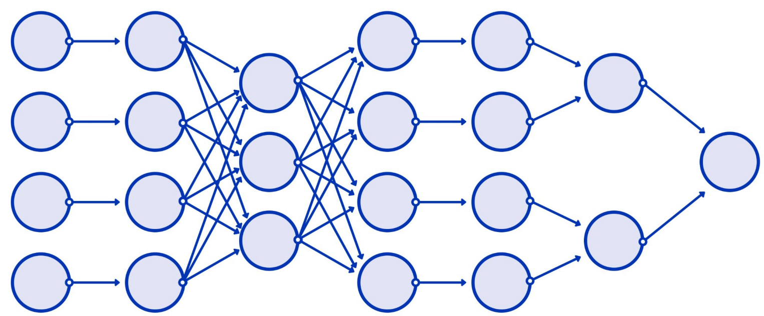
Embarrassingly Parallel

Hadoop/Spark/Dask/Airflow/Prefect



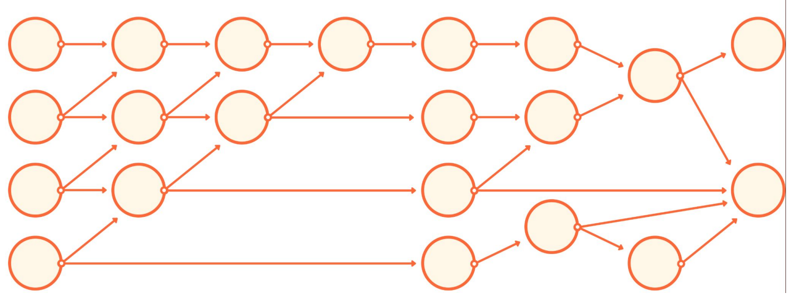
MapReduce

Hadoop/Spark/Dask



Full Task Scheduling

Dask/Airflow/Prefect

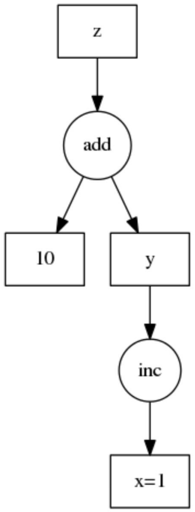


Encoding Task Graph

- Dask encodes tasks in terms of Python dicts and functions

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

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

x = 1
y = inc(x)
z = add(y, 10)
```

```python
d = {'x': 1,
     'y': (inc, 'x'),
     'z': (add, 'y', 10)}
```

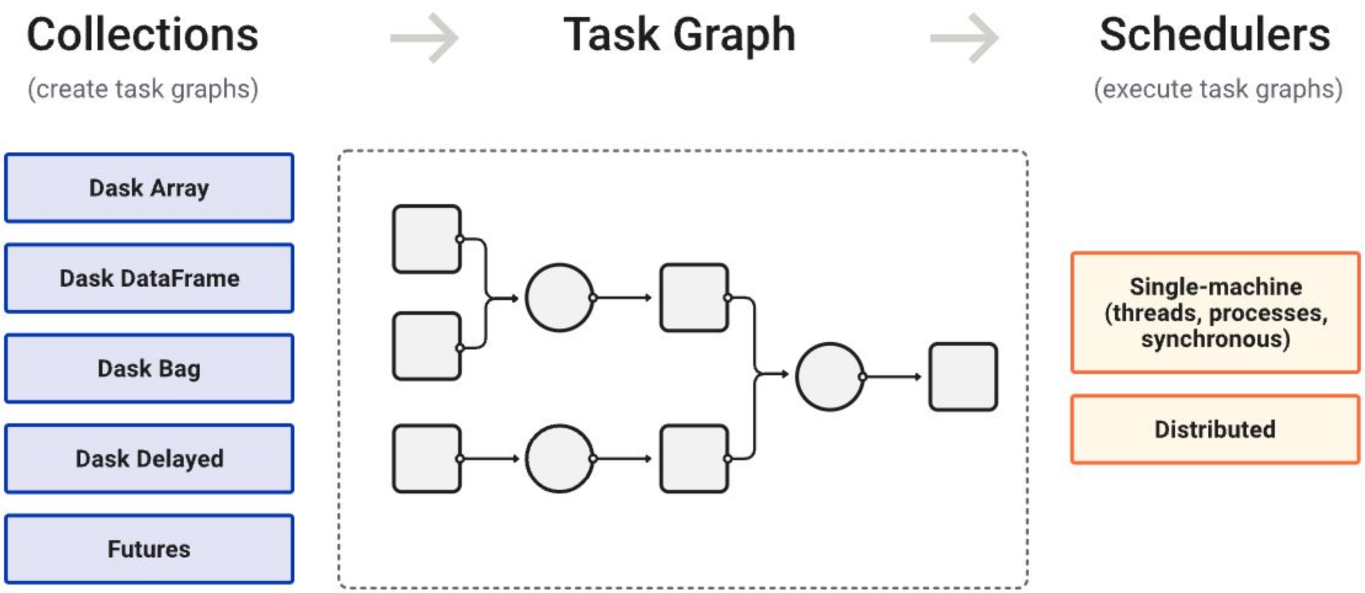



```python
import dask.dataframe as dd

df = dd.read_csv('myfile.*.csv')
df = df + 100
df = df[df.name == 'Alice']
```

```python
{
 # From the dask.dataframe.read_csv call
 ('read-csv', 0): (pandas.read_csv, 'myfile.0.csv'),
 ('read-csv', 1): (pandas.read_csv, 'myfile.1.csv'),
 ('read-csv', 2): (pandas.read_csv, 'myfile.2.csv'),
 ('read-csv', 3): (pandas.read_csv, 'myfile.3.csv'),

 # From the df + 100 call
 ('add', 0): (operator.add, ('read-csv', 0), 100),
 ('add', 1): (operator.add, ('read-csv', 1), 100),
 ('add', 2): (operator.add, ('read-csv', 2), 100),
 ('add', 3): (operator.add, ('read-csv', 3), 100),

 # From the df[df.name == 'Alice'] call
 ('filter', 0): (lambda part: part[part.name == 'Alice'], ('add', 0)),
 ('filter', 1): (lambda part: part[part.name == 'Alice'], ('add', 1)),
 ('filter', 2): (lambda part: part[part.name == 'Alice'], ('add', 2)),
 ('filter', 3): (lambda part: part[part.name == 'Alice'], ('add', 3)),
}
```

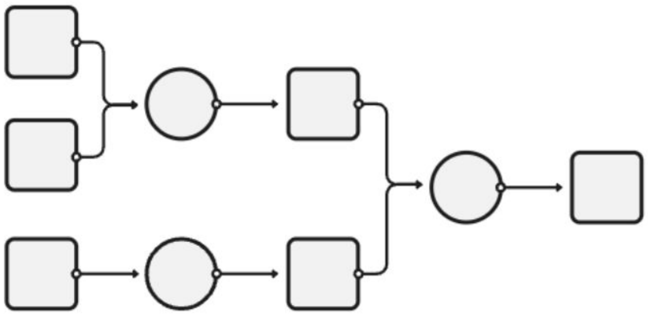
Task Scheduling

- 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



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](https://docs.dask.org/en/stable/10-minutes-to-dask.html)

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