# AUTOMATING AI LIFECYCLE: THE DDOS USE CASE

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# PROJECT GOALS

**CICDDoS2019**

Explore a new dataset for DDoS attacks

**DNN**

Develop a detection system using the dataset

**Kubeflow**

Design and develop a ML pipeline

# WHY

AI solutions have a typical lifecycle

**Preprocessing**
: Convert data into a suitable format for the problem under study

**Hyper-parameter tuning**
: Search the best model configuration for the task

**Testing**
: Measure the model performances on unseen data

*Problem* - Resource and time demanding

# WHAT

Find a way to automate and speed up this lifecycle

**Idea**

Distribute the workload among different units

- Identify any independent part of the execution flow
- Parallelize tasks when possible

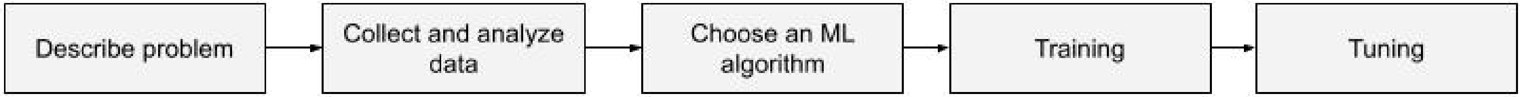
# HOW

**Kubeflow**

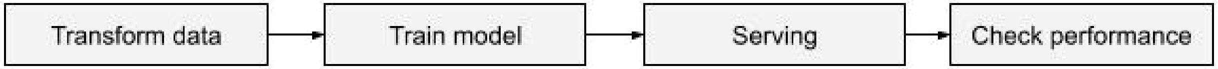
Deployment of ML workflows on Kubernetes

- Toolkit for K8s
- Simple, portable and scalable
- Development, testing, and production-level serving

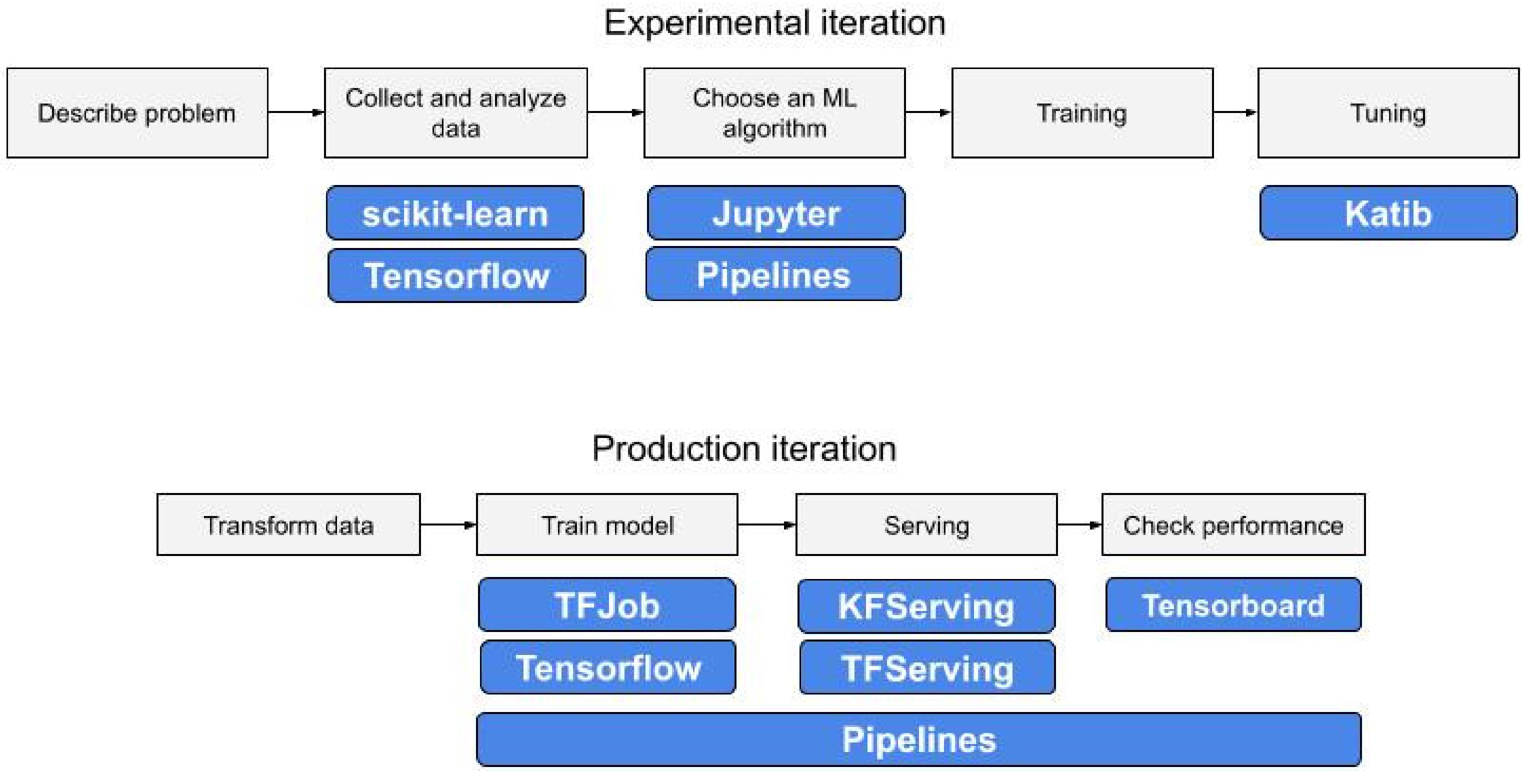
Experimental iteration




Production iteration



Kubeflow


Experimental iteration
Describe problem
Collect and analyze data
Choose an ML algorithm
Training
Tuning
scikit-learn
Tensorflow
Jupyter
Pipelines
Katib
Production iteration
Transform data
Train model
Serving
Check performance
TFJob
Tensorflow
KFServing
TFServing
Tensorboard
Pipelines

# CICDDOS2019 - DATASET

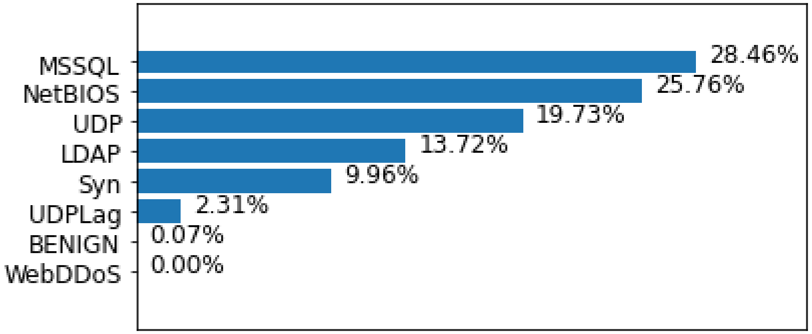
**Raw data**

With network traffic and event logs

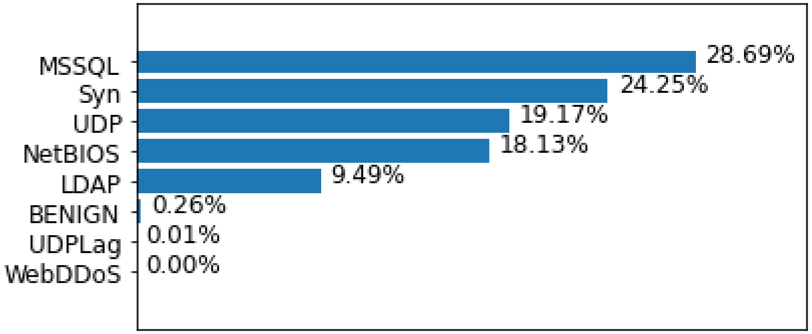
**CSV files**

More than 80 traffic features extracted from the raw data

# DATASETS FOR DNN

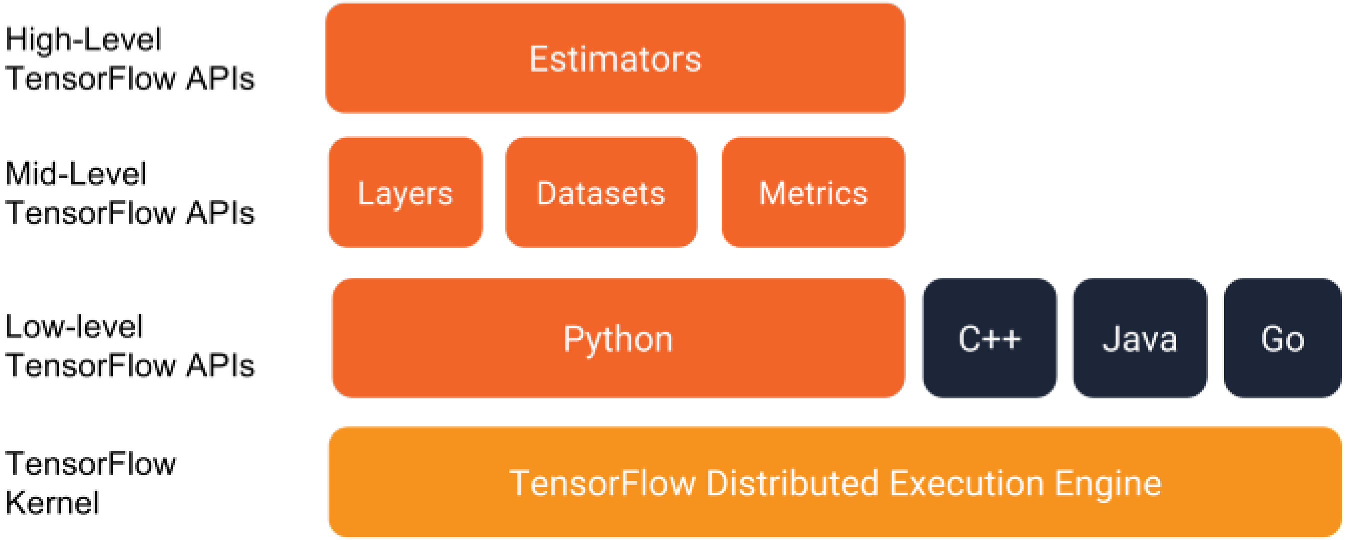



Training dataset




Testing dataset

# TENSORFLOW ESTIMATORS




Tensorflow API stack

# DESIGN

- Network
  - Dense, feed-forward neural network
- Multiclassification
  - 8 classes
- Features
  - 20 most useful features
- Batch normalization
- Adam optimizer

# HYPERPARAMETER TUNING

- Number of hidden units
  - [60, 30, 20]
  - [60, 40, 30, 20]
- Dropout rate
  - 0.1
  - 0.2
- Learning rate
  - 0.1
  - 0.3

# PIPELINE DEVELOMENT

- Docker 18.09.7
- Kubernetes v1.15.3
- Kubeflow v1.0
    - Kubeflow Pipeline SDK v1.0.0

# RESOURCES

**Master node**

- 4 VCPUs, 8GB RAM, 100GB of storage

**2 x Slave nodes**

- 4 VCPUs, 16GB RAM, 100GB of storage

**OS**

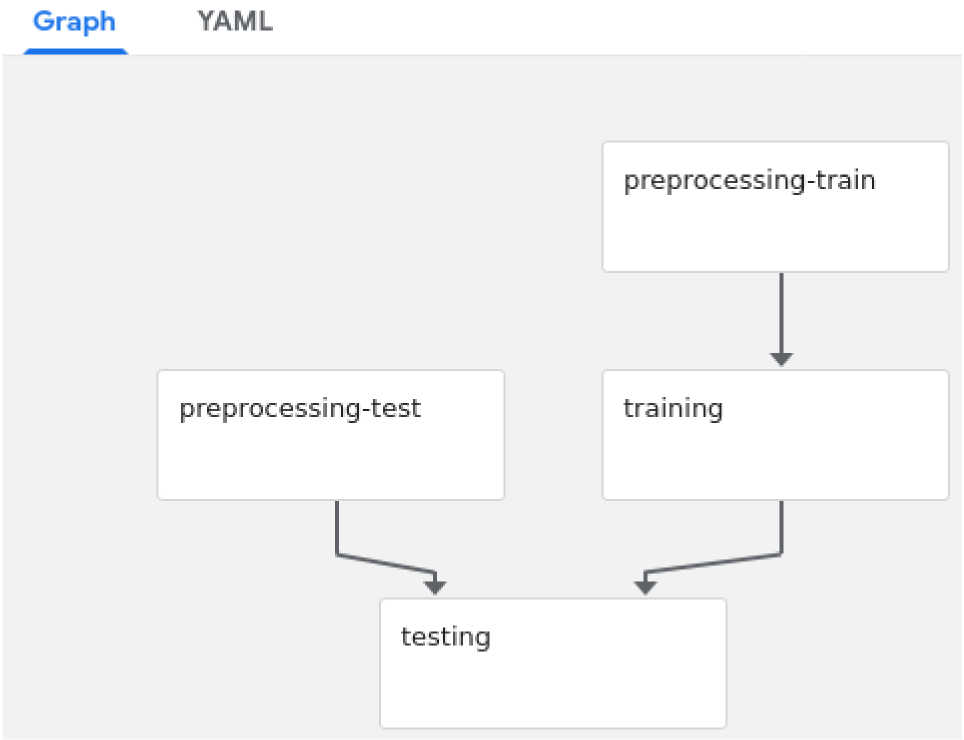
- Ubuntu 16.04 LTS

# PIPELINES

Description of an ML workflow, which

- Components, and how they combine in the form of a graph
- Inputs required for a run
- Inputs and outputs of each component

# PIPELINES



Graph
YAML
preprocessing-train
preprocessing-test
training
testing

# COMPONENTS

**Base image**

All the shared dependencies

**Preprocess-train**

Training dataset + Source code

**Preprocess-test**

Testing dataset + Source code

**Train**

Source code

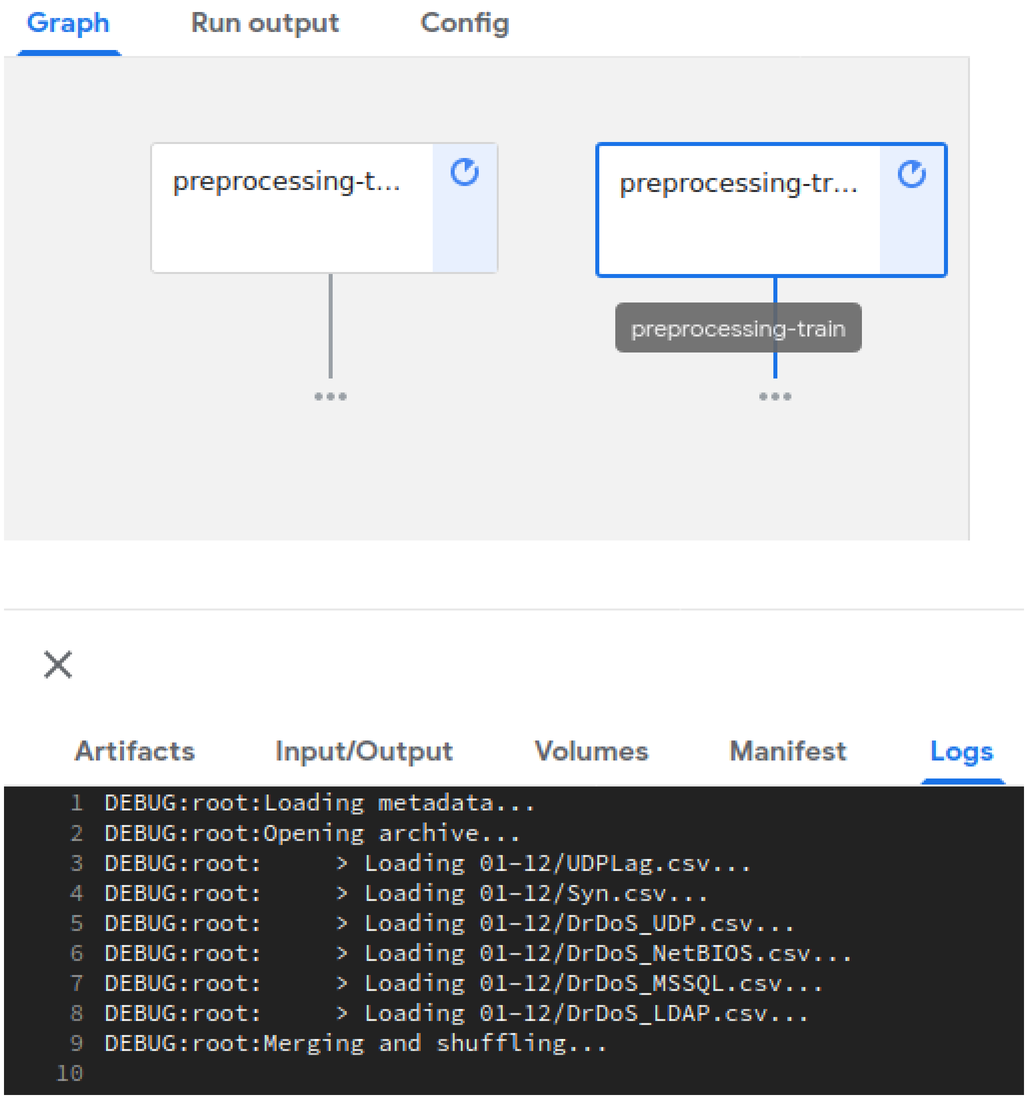
**Test**

Source code

# EXPERIMENTS

- Workspace to try different configurations of pipelines
- Organize runs into logical groups

# EXPERIMENTS



# BEHAVIOUR

**Load is distributed**

Components are executed according to the available resources

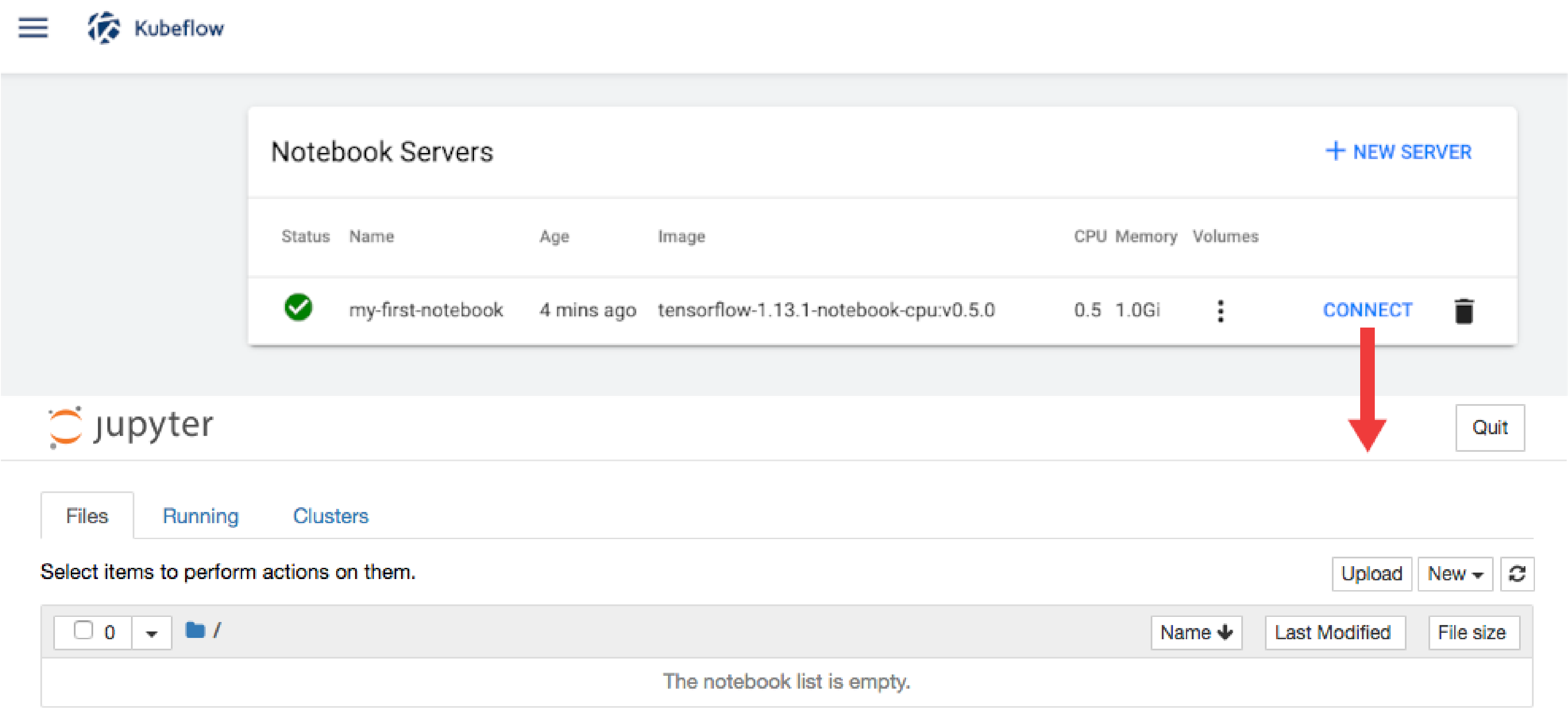
**Failure**

If any node fails, the experiment is resumed as soon as the node is again available

# SOLUTION 1

- Jupyter notebook, implementing all the phases
- Run on a notebook server instance (2CPU, 10GB)

# SOLUTION 1

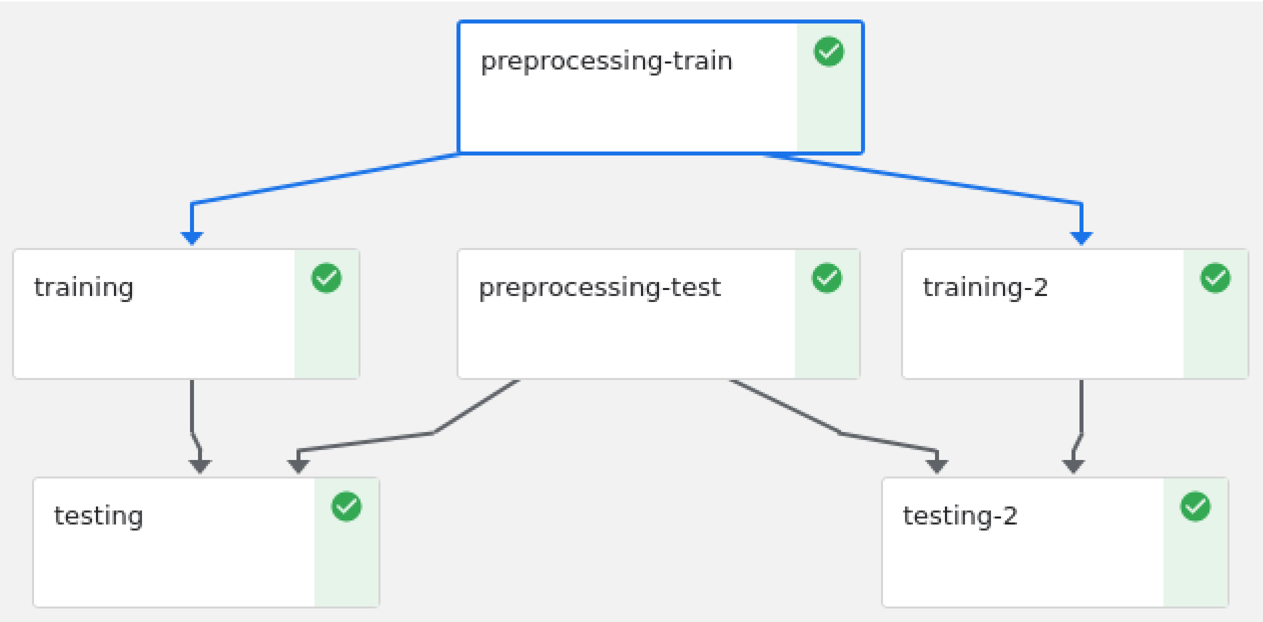

Kubeflow
Notebook Servers
+ NEW SERVER
Status Name Age Image CPU Memory Volumes
my-first-notebook 4 mins ago tensorflow-1.13.1-notebook-cpu:v0.5.0 0.5 1.0Gi
CONNECT
jupyter
Quit
Files Running Clusters
Select items to perform actions on them.
Upload New
0 /
Name Last Modified File size
The notebook list is empty.

# SOLUTION 2A

Concurrent, with two branches (with training and testing) executing the hyper-parameter tuning for dropout rate and learning rate

- Branch 1 on a [60, 30, 20] structure
- Branch 2 on a [60, 40, 30, 20] structure.

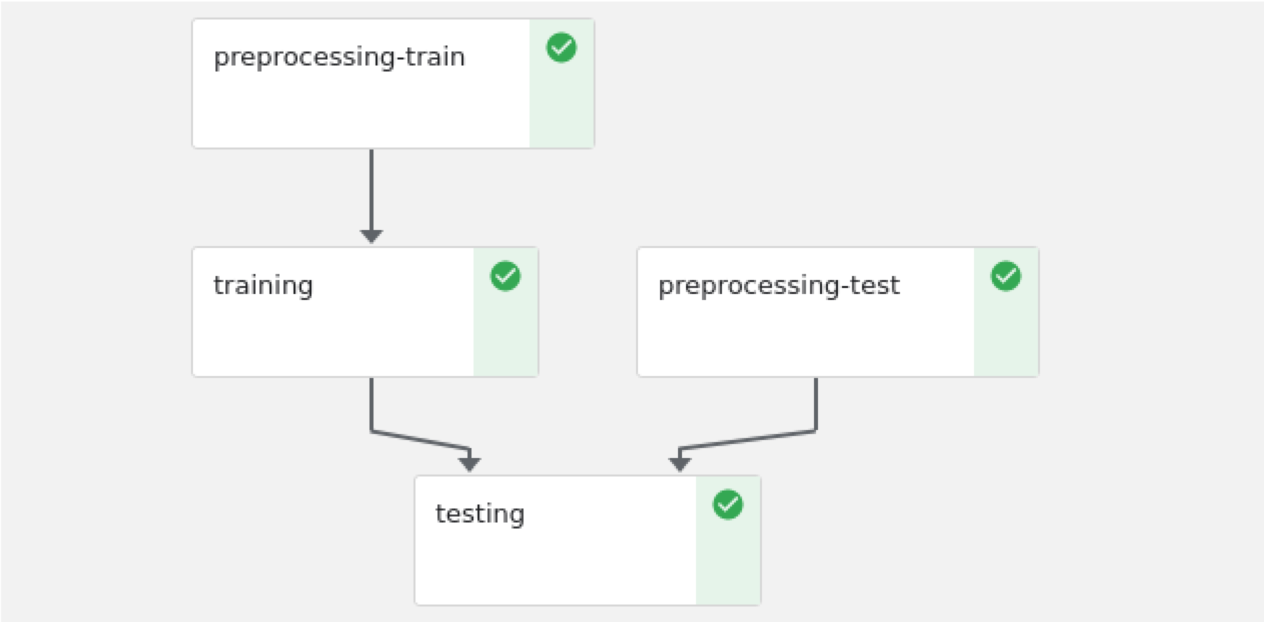
# SOLUTION 2A


preprocessing-train
training
preprocessing-test
training-2
testing
testing-2

# SOLUTION 2B

Non-concurrent, with just one branch that executes hyper-parameter tuning on number of hidden units, learning rate and dropout rate

# SOLUTION 2B


preprocessing-train
training
preprocessing-test
testing

# PERFORMANCE

$$Pr = \frac{TP}{TP + FP}, Rc = \frac{TP}{TP + FN}, F1 = \frac{2 * (Pr * Rc)}{Pr + Rc}$$

```
              precision  recall  f1-score support

BENIGN        0.00       0.00     0.00         1
LDAP          0.94       0.96     0.95        96
MSSQL         0.91       0.94     0.93       270
NetBIOS       1.00       0.97     0.99       183
Syn           1.00       0.96     0.98       243
UDP           0.93       0.92     0.92       207
UDPLag        0.00       0.00     0.00         0

accuracy                          0.95      1000
macro avg     0.68       0.68     0.68      1000
weight. avg   0.95       0.95     0.95      1000
```

Listing 3. Example of a typical report executed over 1000 samples

# TIMING

| Phases | 1a | 2a | 2b |
|---|---|---|---|
| Preprocessing | | | |
| - Training dataset | 0:03:36 | 0:09:19 | 0:08:34 |
| - Test dataset | 0:07:08 | 0:11:26 | 0:09:10 |
| Training | 4:42:25 | | 9:10:22 |
| - [60, 30, 20] | | 3:45:04 | |
| - [60, 40, 30, 20] | | 3:41:46 | |
| Testing | 0:23:06 | | 0:42:57 |
| - [60, 30, 20] | | 0:35:58 | |
| - [60, 40, 30, 20] | | 1:06:37 | |
| Overall | 5:22:04 | 5:40:21 | 10:17:47 |

TABLE 2. TIMES COMPARISON BETWEEN DIFFERENT SOLUTIONS (EXPRESSED IN H:MM:SS)

# COMMENTS

- Significant reductions in times with concurrency
- Small overhead on component initialization and management
- Pipeline implementations are overall slower than the notebook execution

  **Warning**

  > Your CPU supports instructions that this TensorFlow binary was not compiled touse: SSE4.1 SSE4.2

# CONCLUSIONS - DATASET

- Highly inbalanced
    - Deal with the inbalance (e.g. resampling)
- More potential to be discovered
    - Use of raw data (and custom exctraction of features)

# CONCLUSIONS - KUBEFLOW

Portability, reusability, concurrency

- TensorFlow with full instruction set support
  - May significantly reduce training times
- Increase the level of concurrency
  - Scaling with the amount resources
- Kubeflow Katib for hyperparameter tuning
  - Beta/alpha stage, focus on optimization