Asynchronous Hyperparameter Tuning and Ablation Studies with Apache Spark

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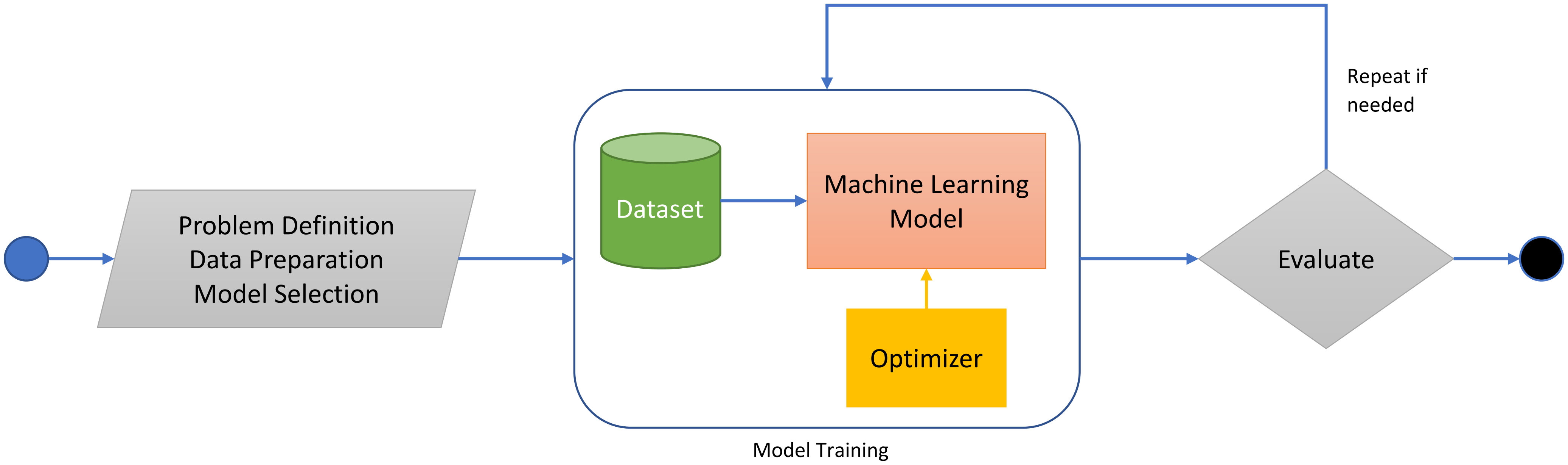
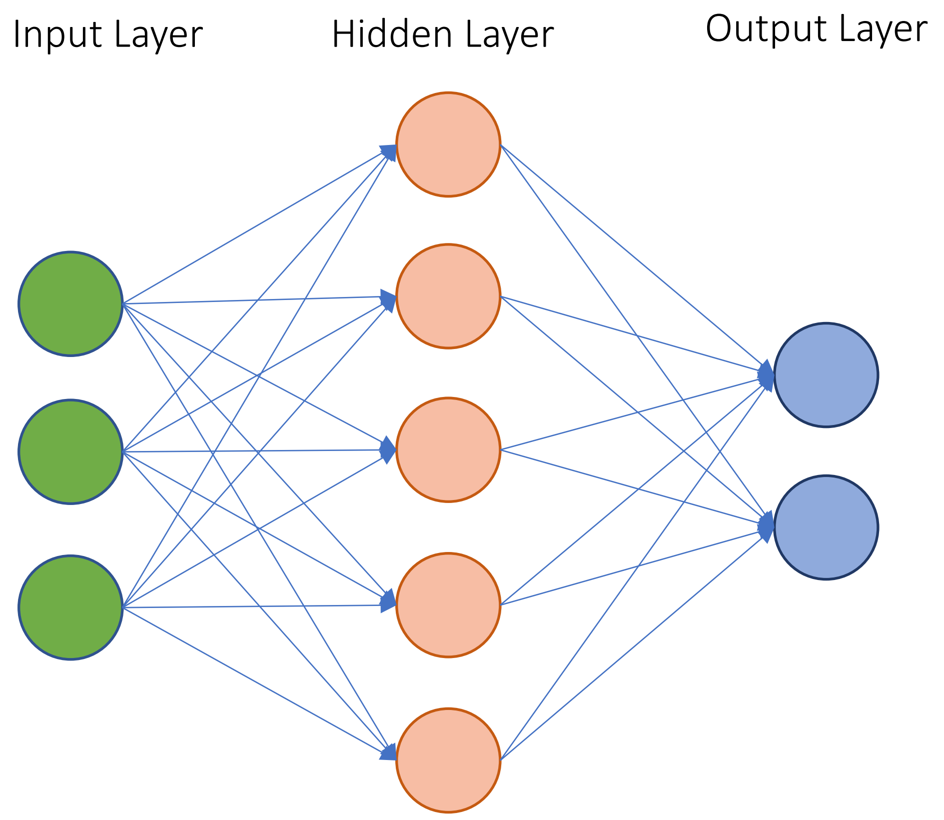
CASTOR Software Days 2019

The Machine Learning System

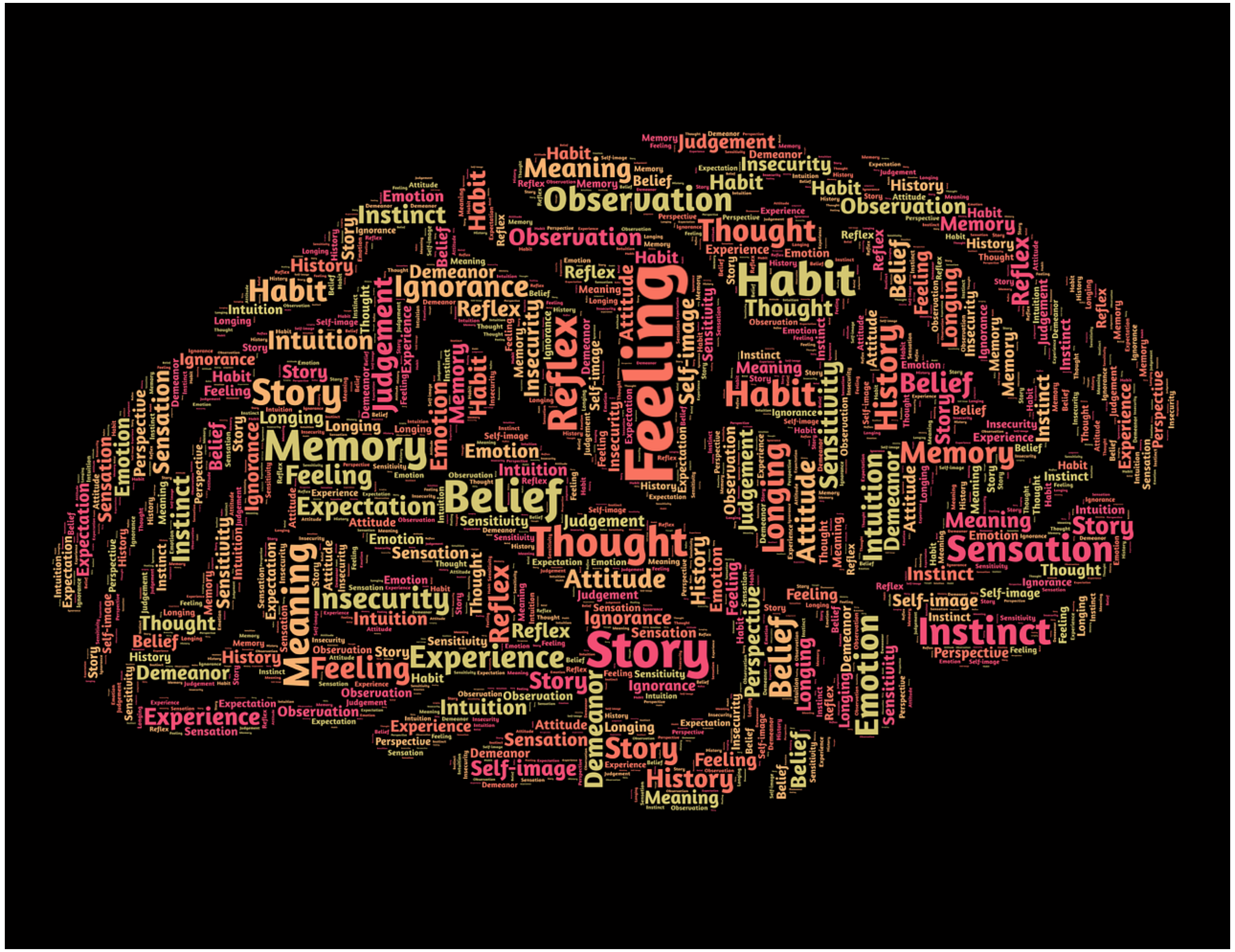


Artificial Neural Networks

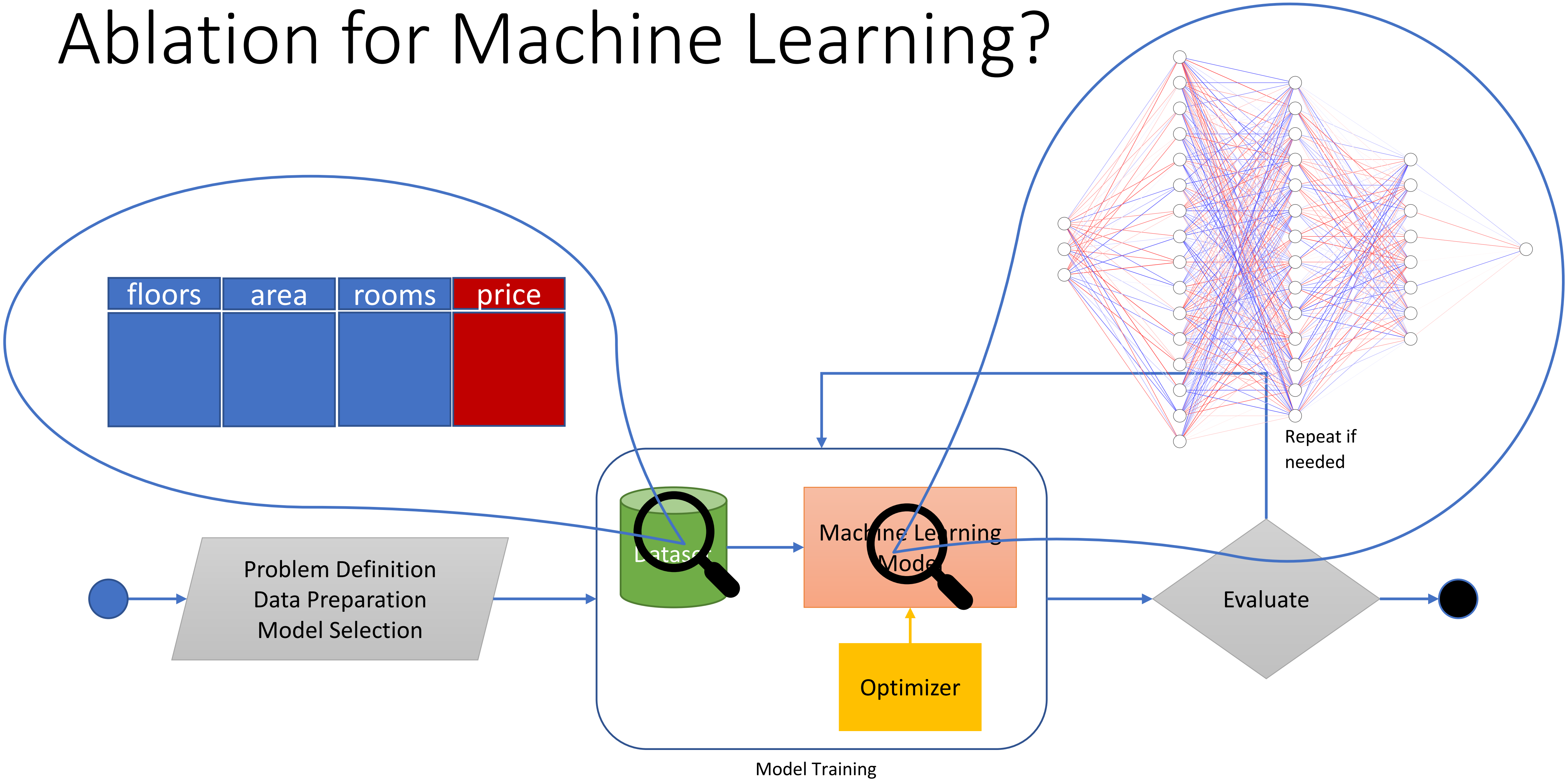


How We Study the Brain

- Early 19th Century, *ablative brain surgeries* by Jean Pierre Flourens (1794 - 1867)



Ablation for Machine Learning?



Talk of the Town

mat kelcey @mat_kelcey · Apr 11, 2017

i wish people did **ablation studies** more. they give me the most intuition (apart from coding myself) e.g. from cyclegan

Loss	Per-pixel acc.	Per-class acc.	Class IOU
Cycle alone	0.22	0.07	0.02
GAN alone	0.52	0.11	0.08
GAN + forward cycle	**0.55**	**0.18**	**0.13**
GAN + backward cycle	0.41	0.14	0.06
CycleGAN (ours)	0.52	0.17	0.11

Table 4: Ablation study: FCN-scores for different variants of our method, evaluated on Cityscapes labels→photos.

Loss	Per-pixel acc.	Per-class acc.	Class IOU
Cycle alone	0.10	0.05	0.02
GAN alone	0.53	0.11	0.07
GAN + forward cycle	0.49	0.11	0.07
GAN + backward cycle	0.01	0.06	0.01
CycleGAN (ours)	**0.58**	**0.22**	**0.16**

1 5 20

François Chollet @fchollet · Jun 29, 2018

Ablation studies are crucial for deep learning research -- can't stress this enough.

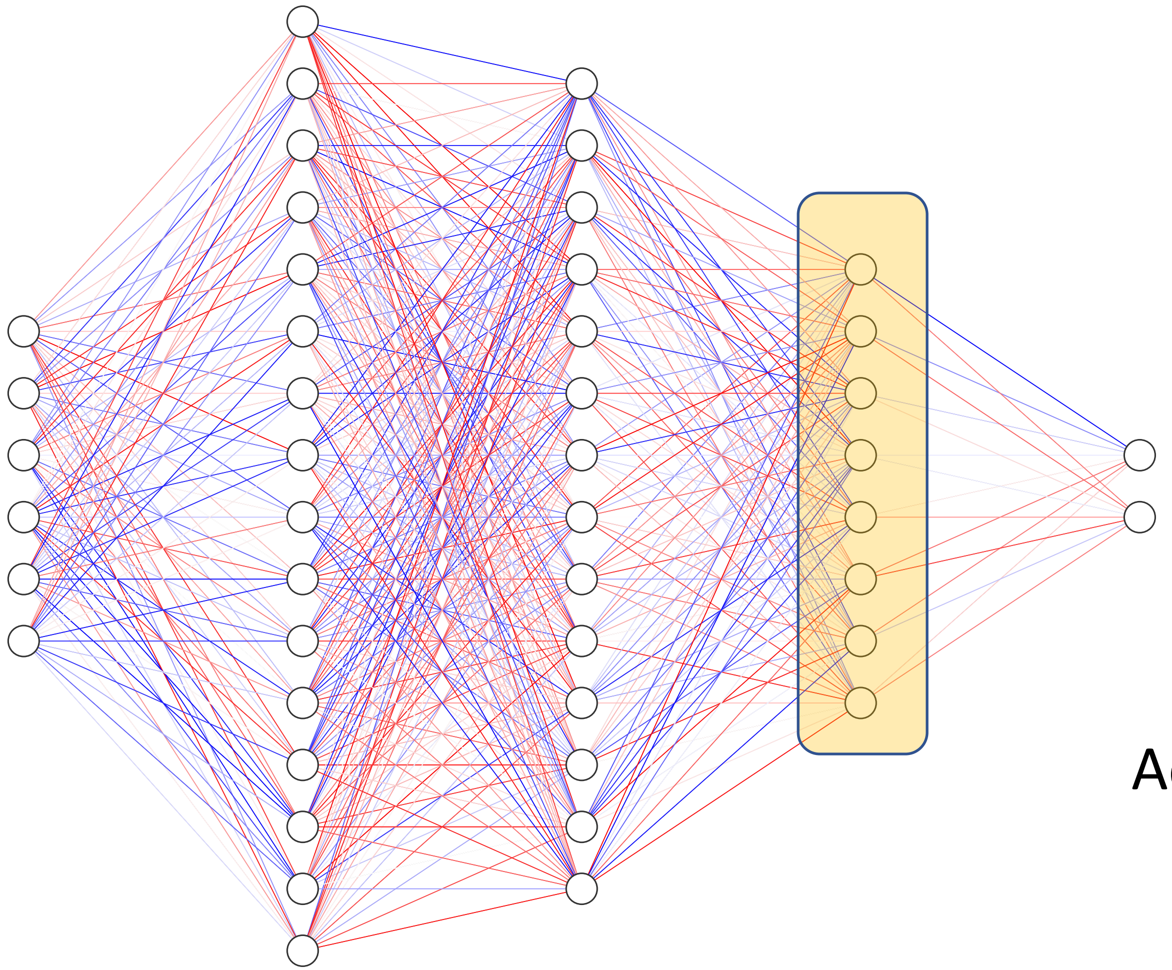
Understanding causality in your system is the most straightforward way to generate reliable knowledge (the goal of any research). And **ablation** is a very low-effort way to look into causality.

8 83 330

"Too frequently, authors propose many tweaks absent proper **ablation studies** … Sometimes just one of the changes is actually responsible for the improved results … this practice misleads readers to believe that all of the proposed changes are necessary."

(Lipton & Steinhardt, "*Troubling Trends in Machine Learning Scholarship*")

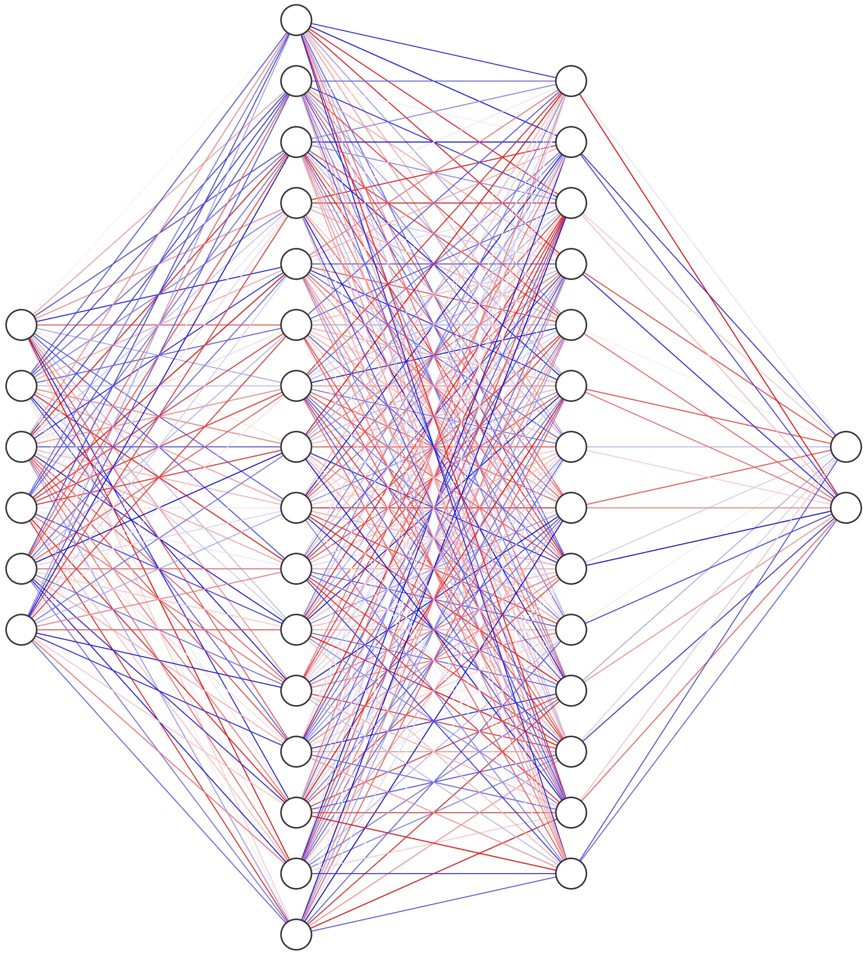
Example: Layer Ablation (1/6)



Accuracy: 78%

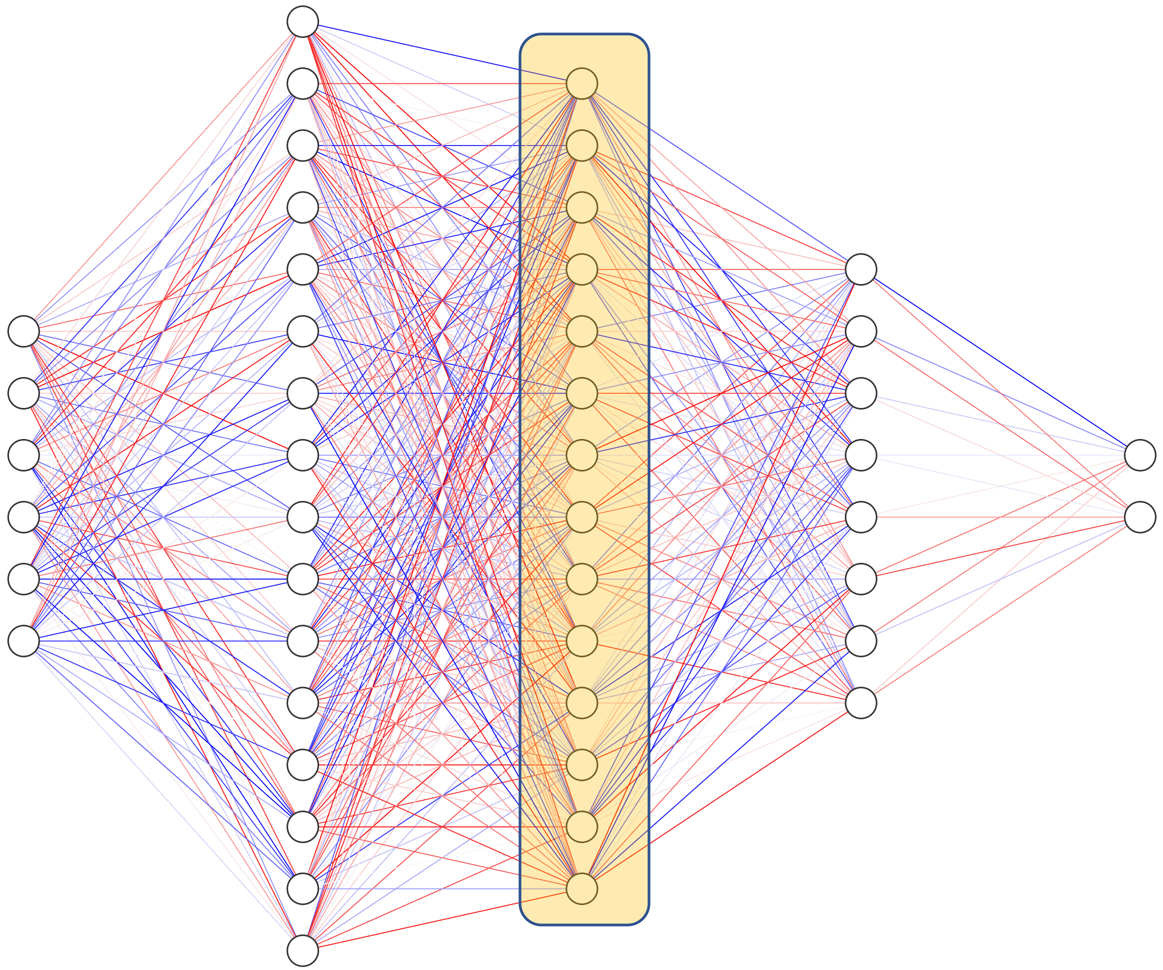
The Base Model

Example: Layer Ablation (2/6)



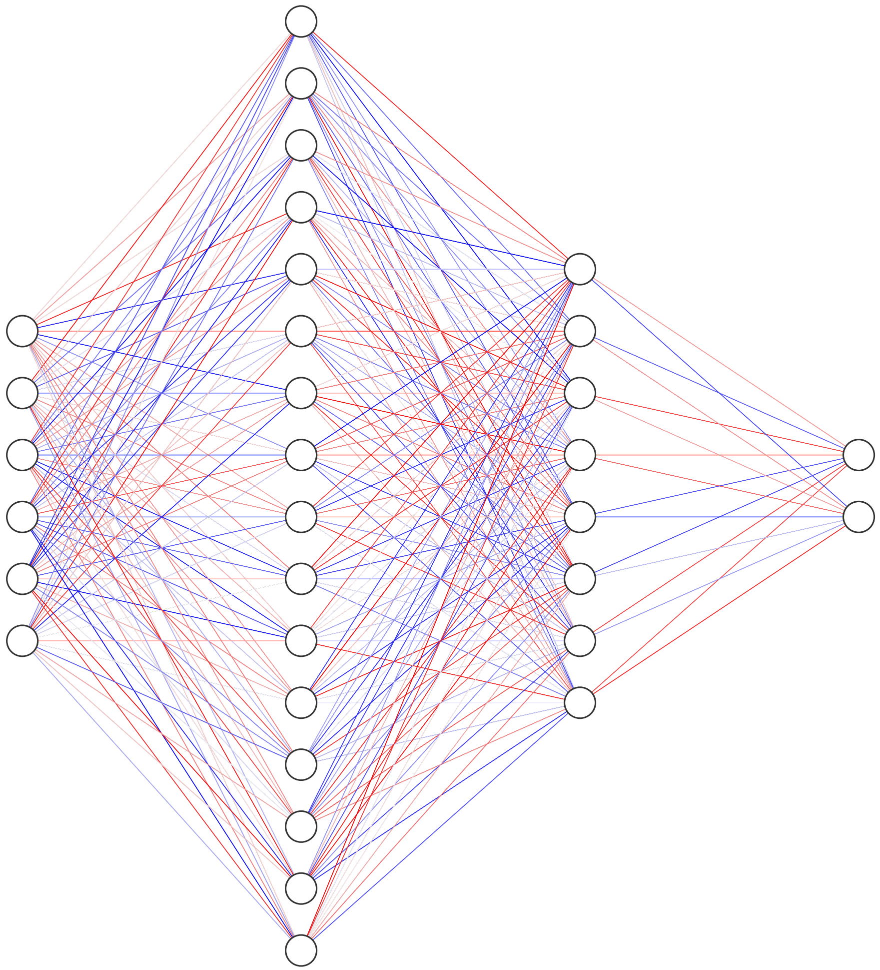
Accuracy: 73%

Example: Layer Ablation (3/6)



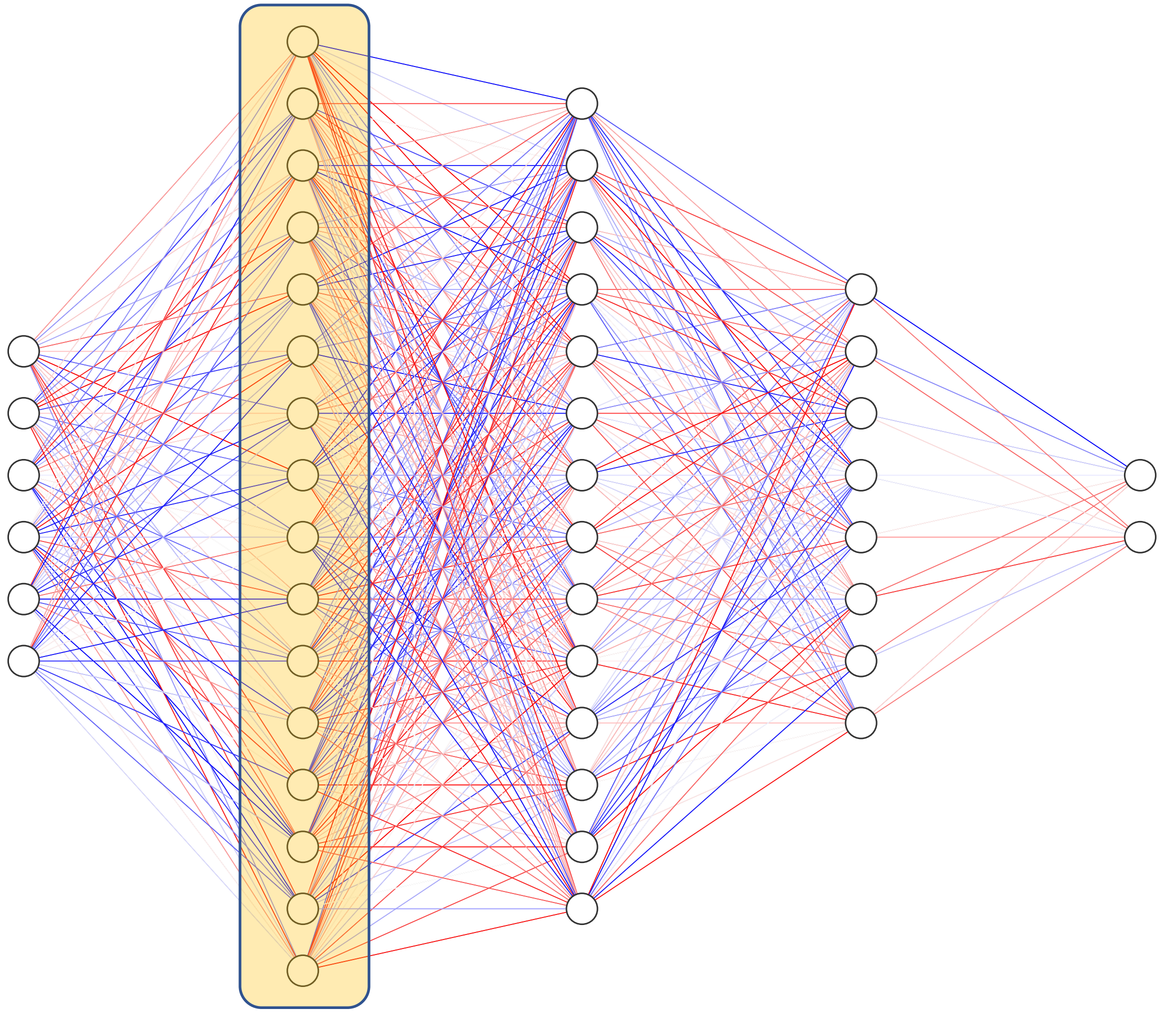
The Base Model

Example: Layer Ablation (4/6)



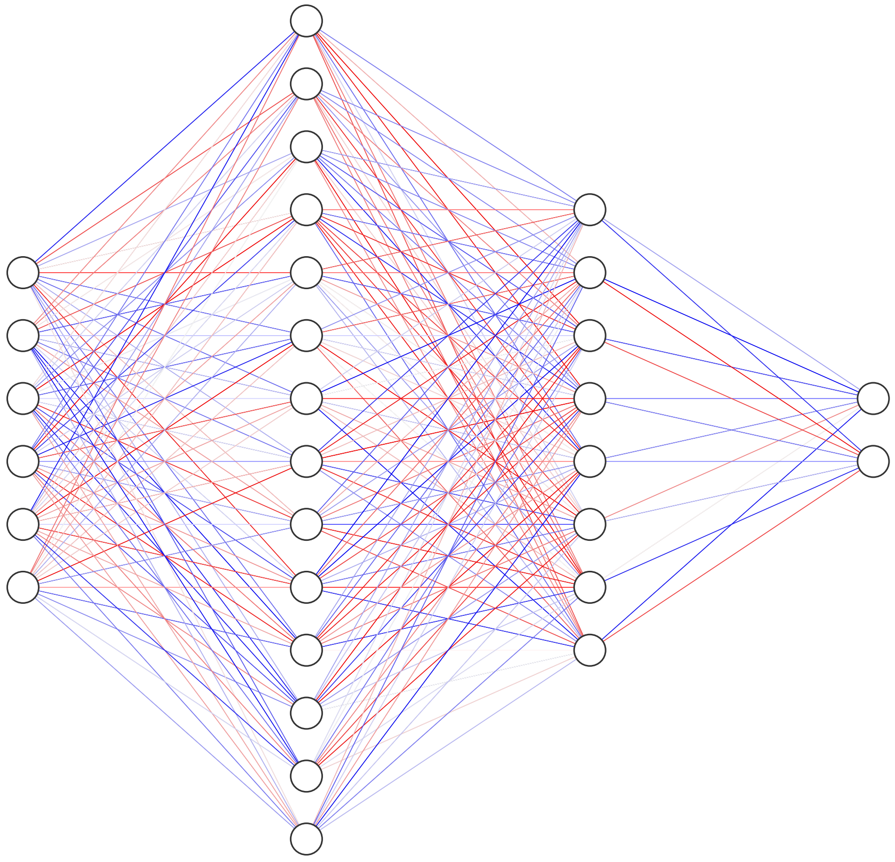
Accuracy: 67%

Example: Layer Ablation (5/6)



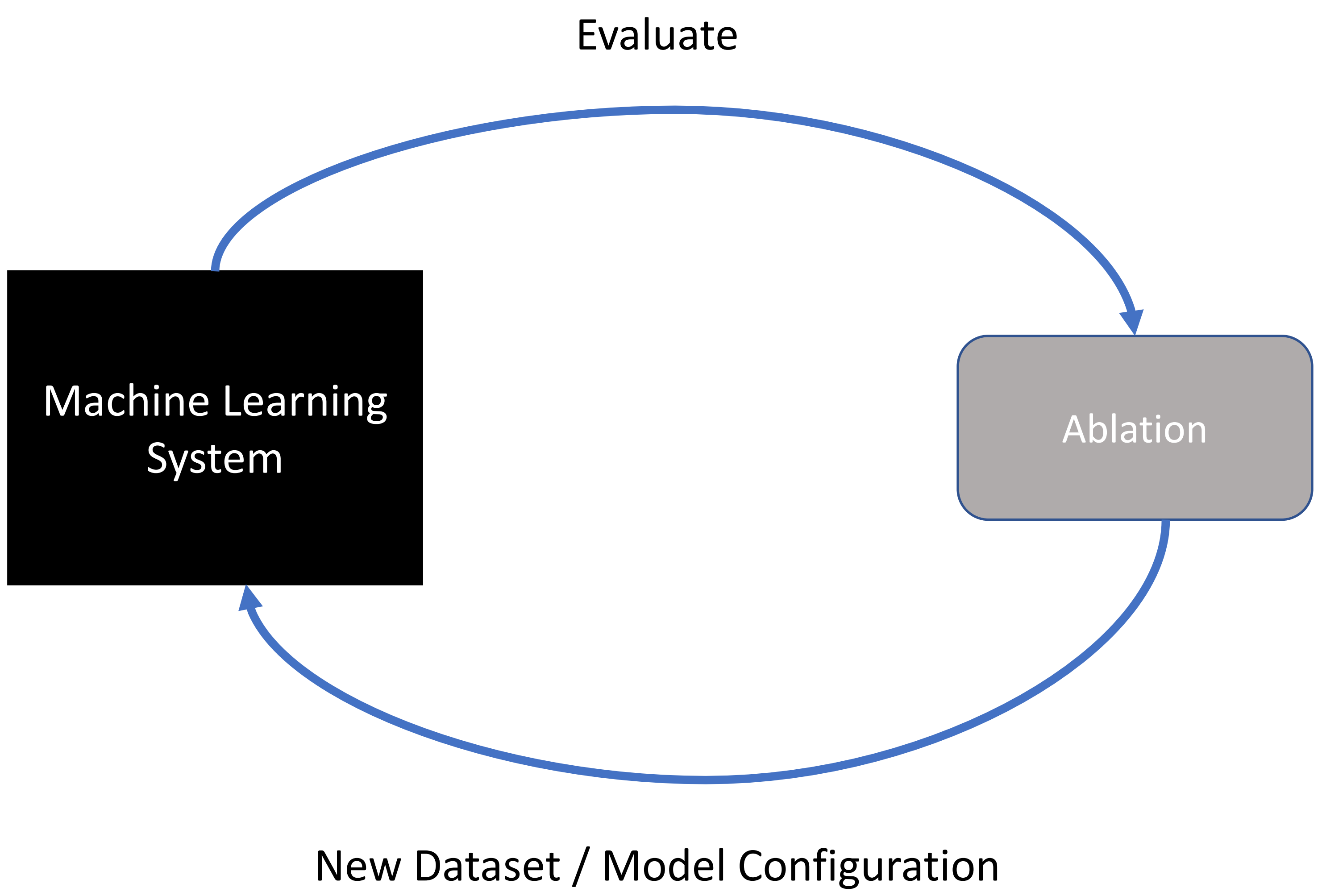
The Base Model

Example: Layer Ablation (6/6)

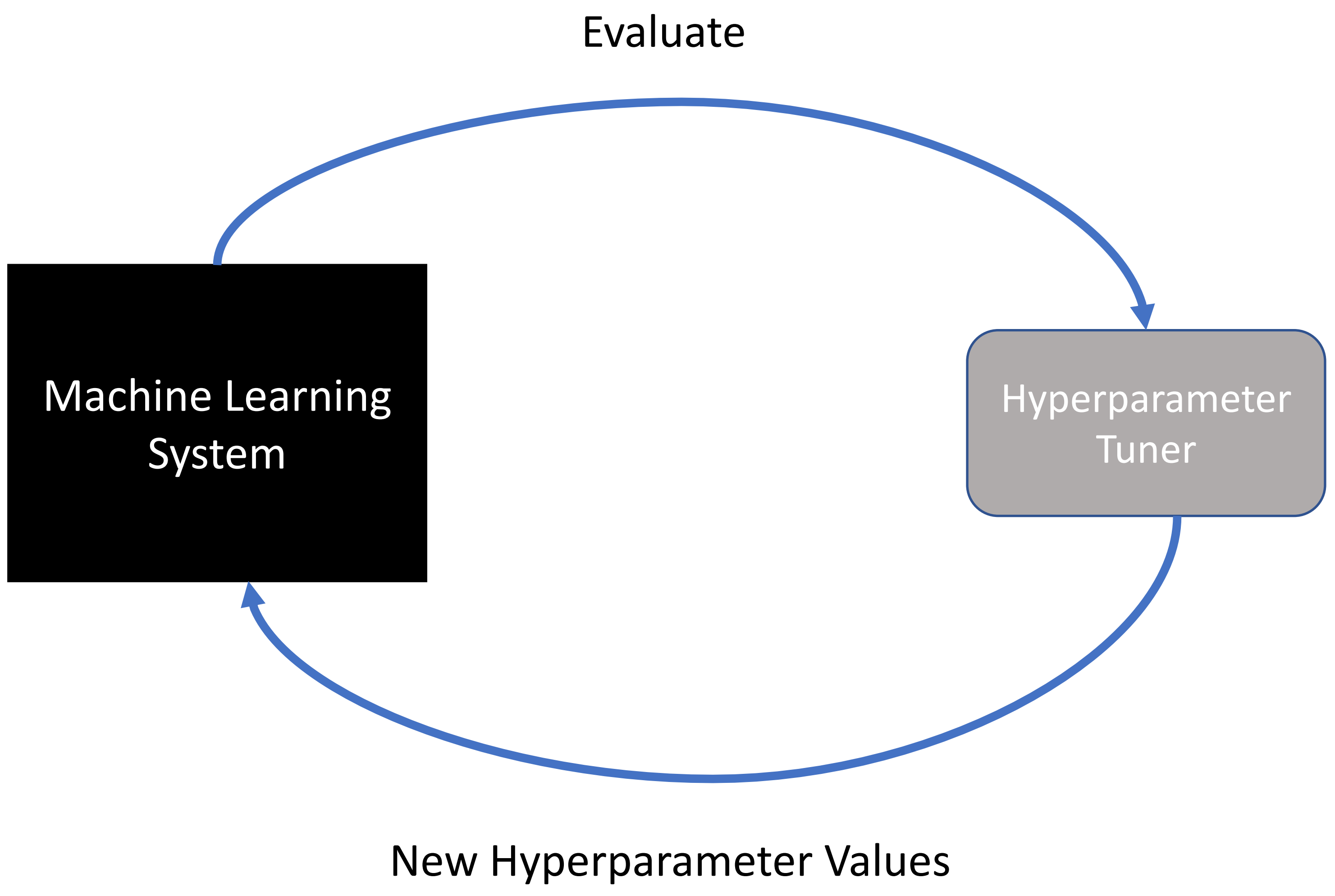


Accuracy: 63%

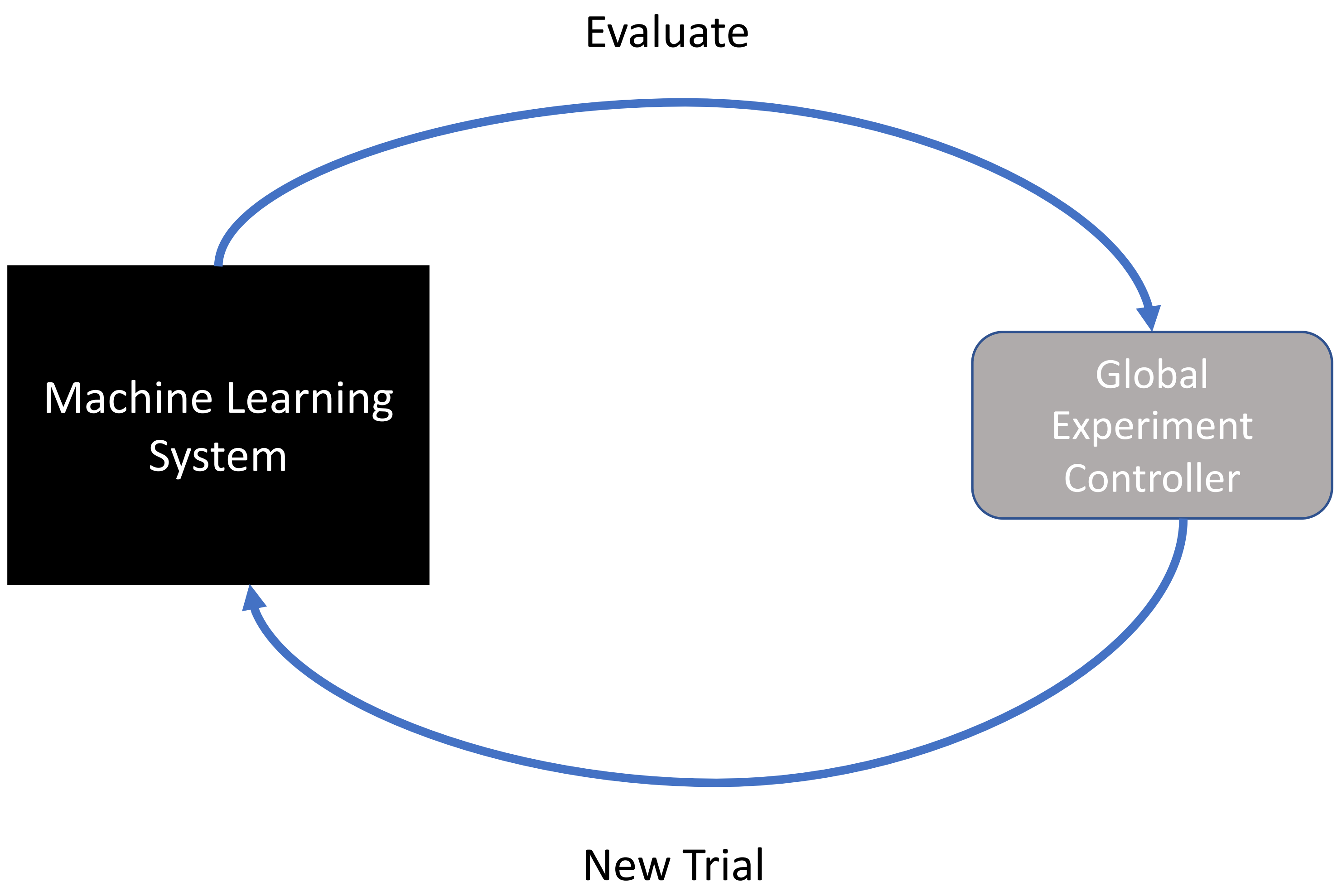
Ablation Study



Hyperparameter Tuning



System Experimentation (Search)



Better Parallel

- Ability to train better models, faster
- Ability to modify and inspect, easier

("Parallel Training" - by [Maxim Melnikov])

Parallelization in Practice

Machine Learning
Deep Learning

TensorFlow

Keras

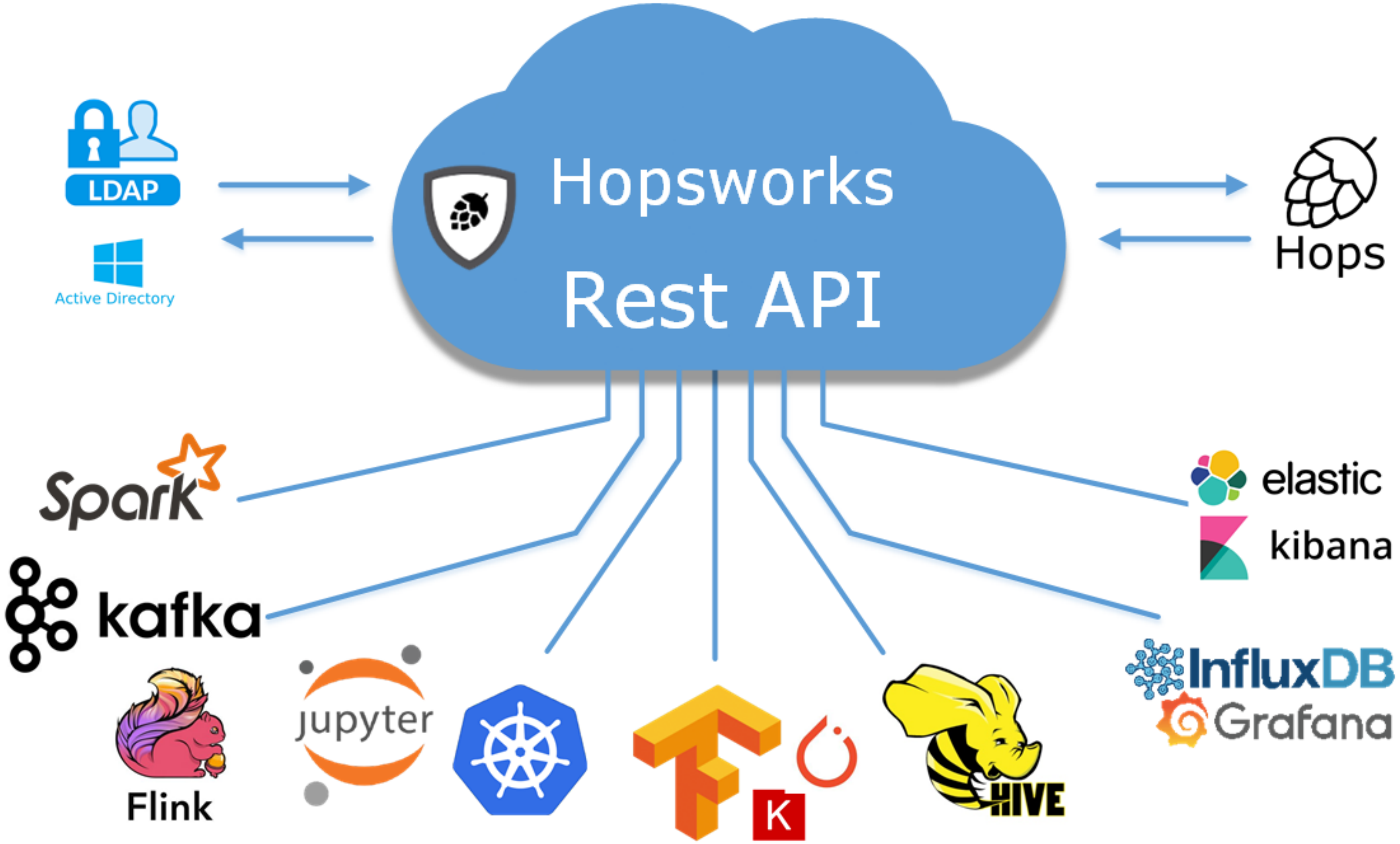
Parallel
Processing

Apache Spark™

(TensorFlow, the TensorFlow logo and any related marks are trademarks of Google Inc.)

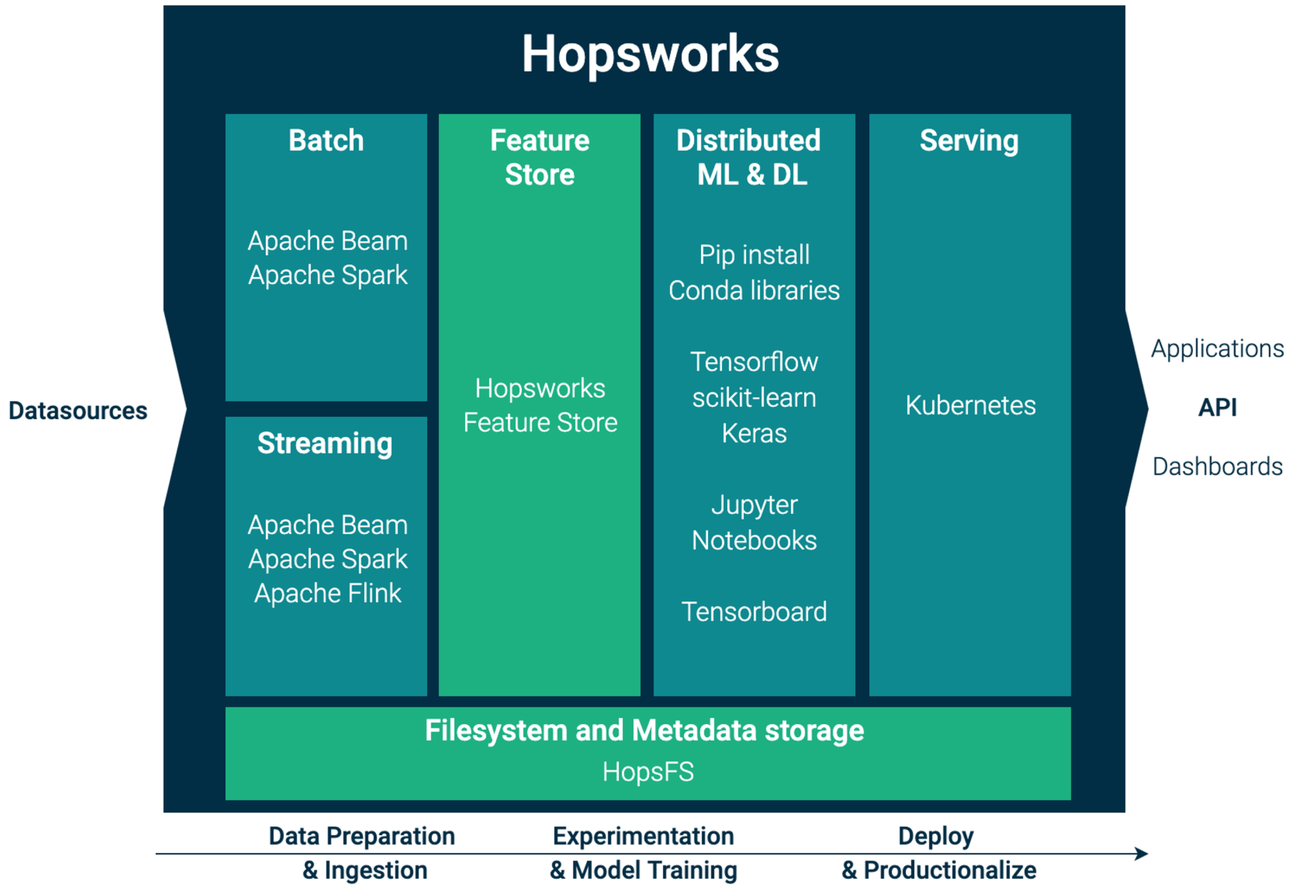
Hopsworks

Open-source Platform for Data-intensive AI



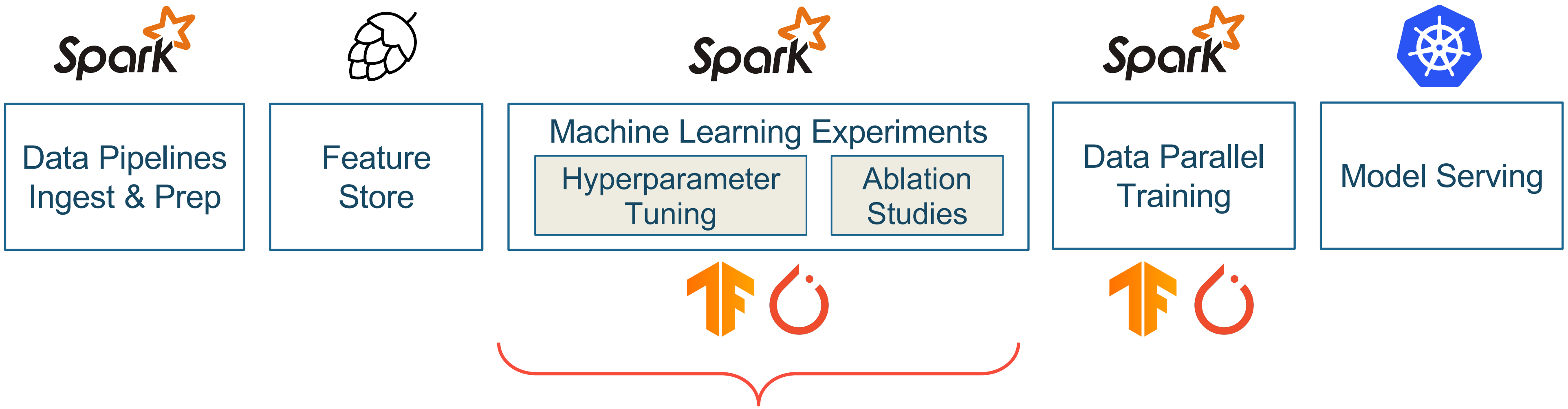
Hopsworks

Open-source Platform for Data-intensive AI



What is Hopsworks?
https://tinyurl.com/y4ze79d4

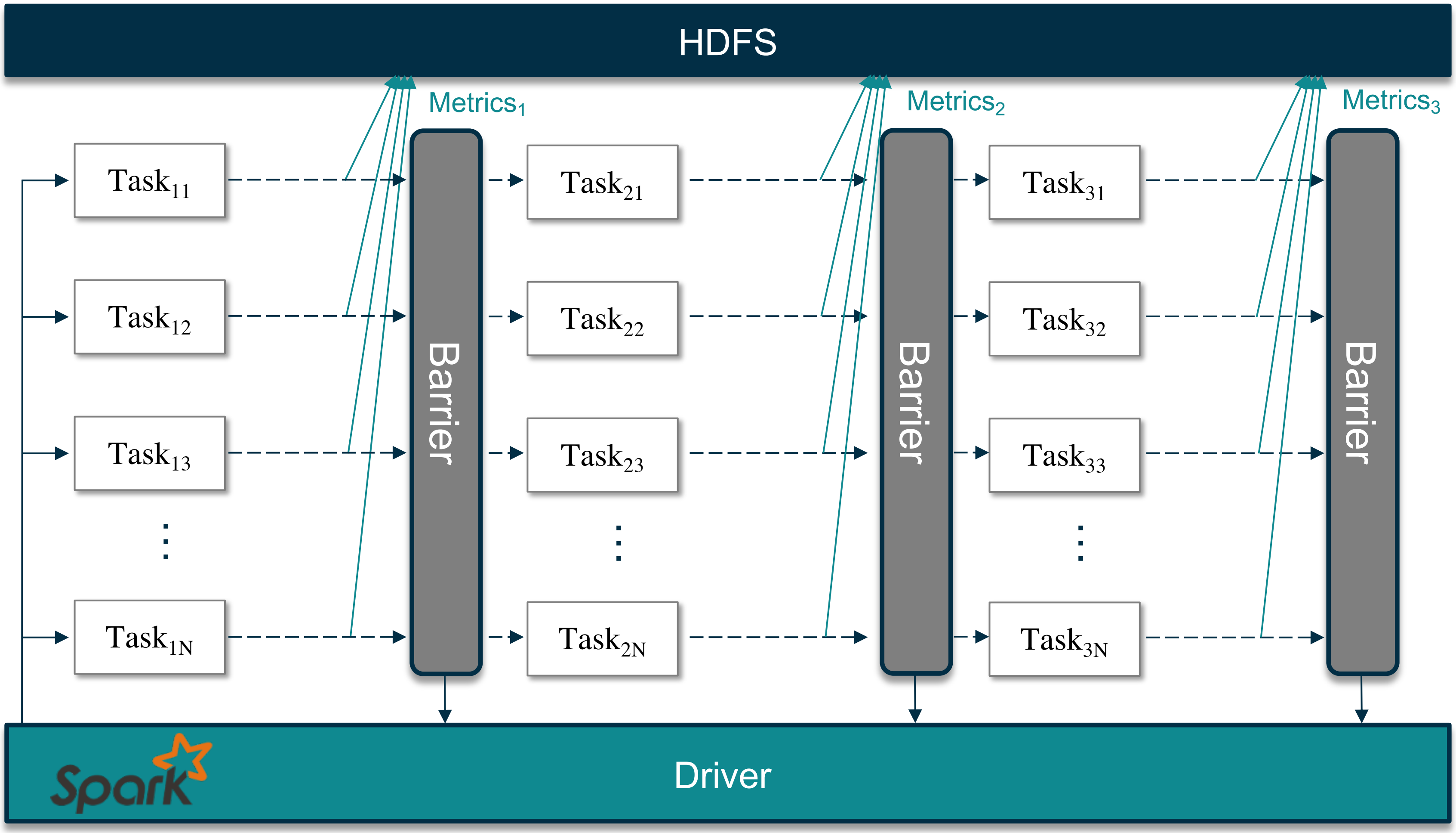
ML/DL in Hopsworks



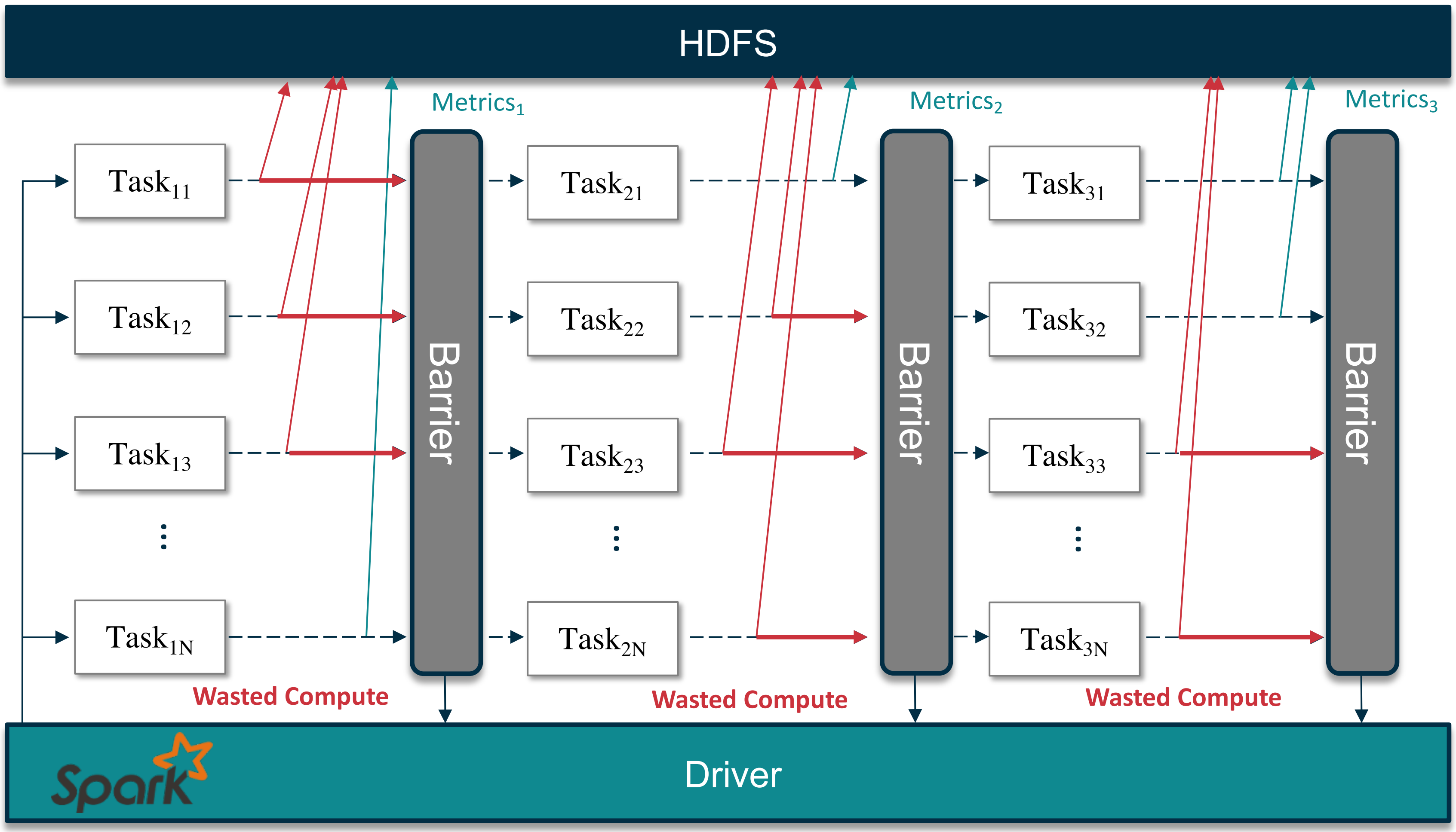
Bottleneck, due to

- iterative nature
- human interaction

Spark and Bulk Synchronous Parallel Model



Example: Synchronous Hyperparameter Search



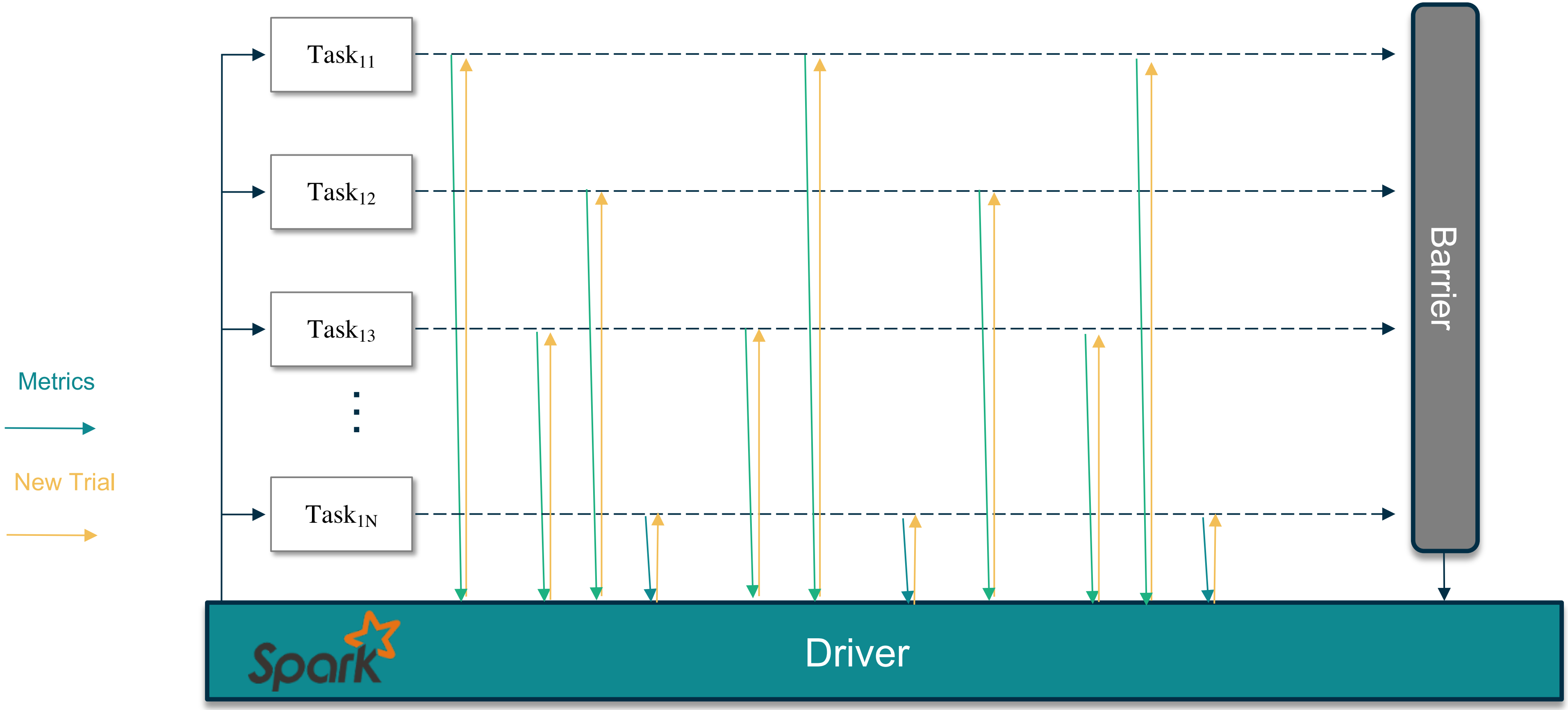
Critical Requirements

- Parallel execution of trials
- Support for early stopping of trials
- Support for global control of the experiment
- Resilience to stragglers
- Simple, “Unified” User & Developer API

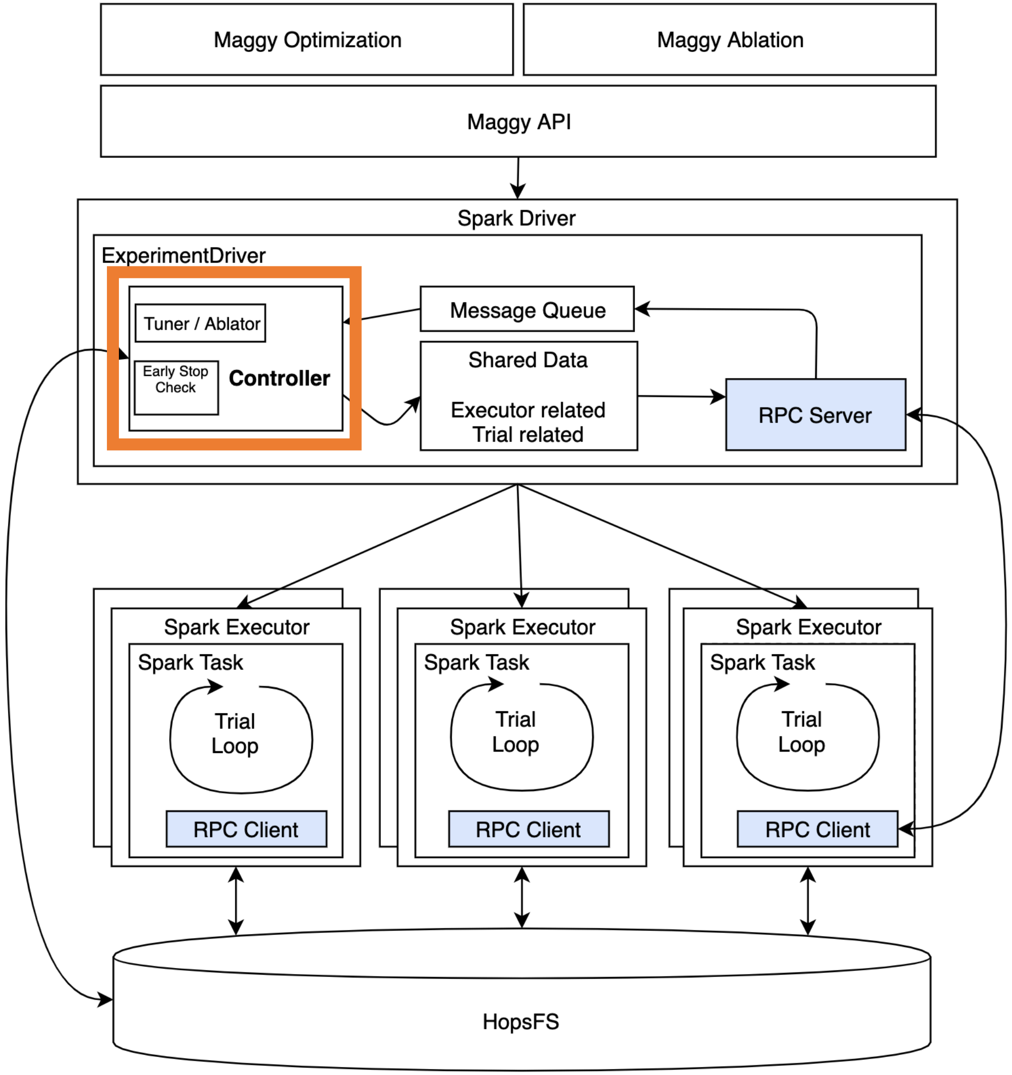
Maggy

An Open-source Framework for Asynchronous Computation on top of Apache Spark

Key Idea: Long Running Tasks



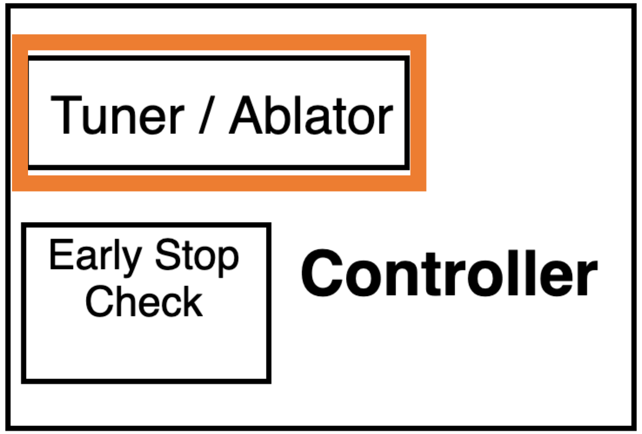
Maggy Core Architecture



Back to Ablation

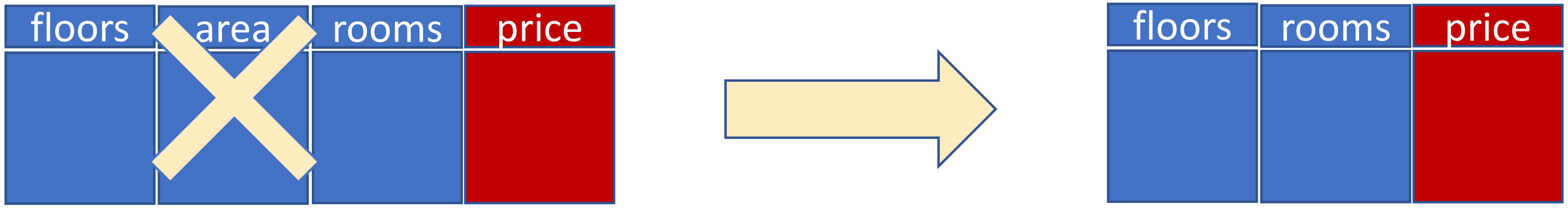
LOCO: Leave One Component Out

- A simple, “natural” ablation policy: an implementation of an ablator
- Currently supports Feature Ablation + Layer Ablation



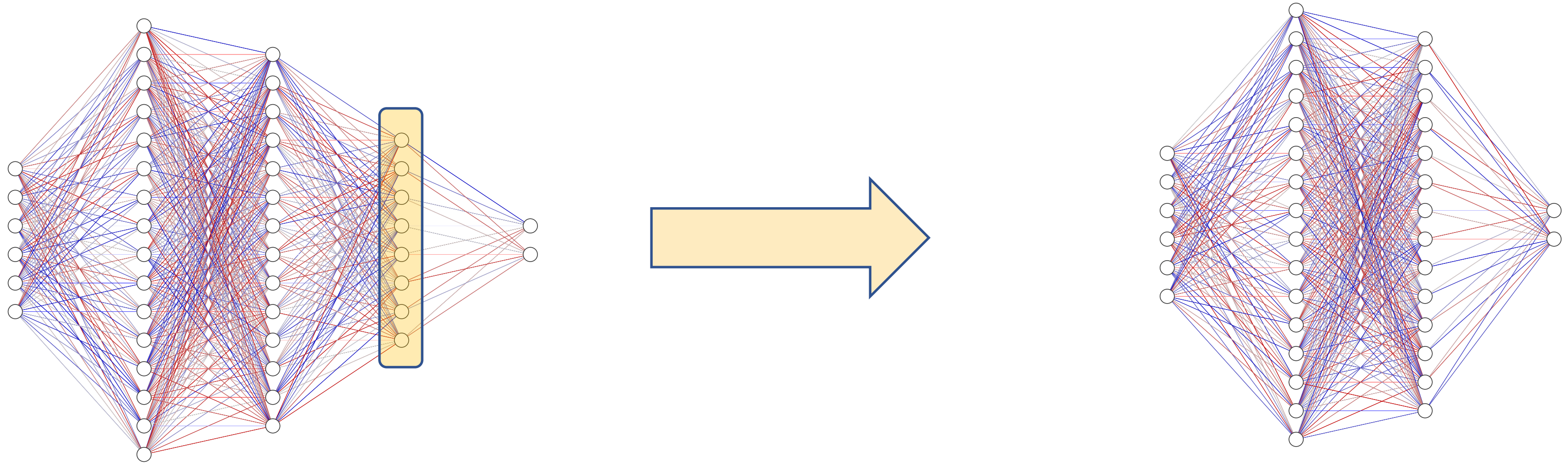
Feature Ablation

- Uses the Feature Store to access the dataset metadata
- Generates Python *callables* that once called, will return modified datasets
  - Removes one-feature-at-a-time



Layer Ablation

- Uses a base model function
- Generates Python *callables* that once called, will return modified models
  - Uses the model configuration to find and remove layer(s)
  - Removes one-layer-at-a-time (or one-layer-group-at-a-time)



(Example Notebook Available!)

Ablation User & Developer API

User API: Initialize the Study and Add Features

```python
import tensorflow as tf
import maggy
from maggy.ablation import AblationStudy

ablation_study = AblationStudy('titanic_train_dataset',
                               training_dataset_version=1,
                               label_name='survived')

ablation_study.features.include('pclass', 'fare')
```

User API: Define Base Model

```python
def base_model_generator():
    model = tf.keras.Sequential()
    model.add(tf.keras.layers.Dense(64, activation='relu'))
    model.add(tf.keras.layers.Dense(64, name='my_dense_two', activation='relu'))
    model.add(tf.keras.layers.Dense(32, name='my_dense_three', activation='relu'))
    model.add(tf.keras.layers.Dense(32, name='my_dense_four', activation='relu'))
    model.add(tf.keras.layers.Dense(2, name='my_dense_sigmoid', activation='sigmoid'))
    # output layer
    model.add(tf.keras.layers.Dense(1, activation='linear'))
    return model
```

User API: Setup Model Ablation

```python
# set base model generator
ablation_study.model.set_base_model_generator(base_model_generator)

# include layers
ablation_study.model.layers.include('my_dense_two', 'my_dense_three',
                                    'my_dense_four', 'my_dense_sigmoid')

# add a layer group using a list
ablation_study.model.layers.include_groups(['my_dense_two', 'my_dense_four'])

# add a layer group using a prefix
ablation_study.model.layers.include_groups(prefix='my_dense')
```

User API: Wrap the Training Function

```python
def training_fn(dataset_function, model_function):
    import tensorflow as tf
    epochs = 5
    batch_size = 10
    tf_dataset = dataset_function(epochs, batch_size)
    model = model_function()
    model.compile(optimizer=tf.train.AdamOptimizer(0.001),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    history = model.fit(tf_dataset, epochs=5, steps_per_epoch=30, verbose=0)
    return float(history.history['acc'][-1])
```

User API: Lagom!

```
result = experiment.lagom(map_fun=training_fn, experiment_type='ablation',
                          ablation_study=ablation_study,
                          ablator='loco',
                          name='Titanic-LOCO'
                         )
```

```
------ LOCO Results ------
BEST Config Excludes {"ablated_feature": "fare", "ablated_layer": "None"} -- metric 0.6766666730244955
WORST Config Excludes {"ablated_feature": "None", "ablated_layer": "Layers prefixed my_dense"} -- metric 0.3533333403
368791
AVERAGE metric -- 0.5800000042275146
Total Job Time 43 seconds
```

Developer API: Policy Implementation (1/2)

```python
class AbstractAblator(ABC):

    def __init__(self, ablation_study, final_store):
        self.ablation_study = ablation_study
        self.final_store = final_store
        self.trial_buffer = []

    @abstractmethod
    def get_number_of_trials(self):
        pass

    @abstractmethod
    def get_dataset_generator(self, ablated_feature=None, dataset_type='tfrecord'):
        pass

    @abstractmethod
    def get_model_generator(self, ablated_layer):
        pass
```

Developer API: Policy Implementation (2/2)

```python
@abstractmethod
def initialize(self):
    pass

@abstractmethod
def get_trial(self, ablation_trial=None):
    pass

@abstractmethod
def finalize_experiment(self, trials):
    pass
```

Hyperparameter Tuning: User API

```
from maggy import Searchspace
from maggy import experiment

# The searchspace can be instantiated with parameters
sp = Searchspace(kernel=('INTEGER', [2, 8]), pool=('INTEGER', [2, 8]))

# Or additional parameters can be added one by one
sp.add('dropout', ('DOUBLE', [0.01, 0.99]))

def train_fn(kernel, pool, dropout, reporter):
    # This is your training iteration loop
    For i in range(nr_iterations):
        ...
        # add maggy reporter to heartbeat the metric
        reporter.broadcast(metric=accuracy)
        reporter.log('Current acc: {}'.format(accuracy))
        ...
    # Return the final metric
    return accuracy

# Lagom maggy experiment
result = experiment.lagom(train_fn,
                          searchspace=sp,
                          optimizer='randomsearch',
                          num_trials=5,
                          name='demo',
                          direction='max')
```

Hyperparameter Tuning: Developer API

```python
# Developers implement abstract class
class CustomOptimizer(AbstractOptimizer):

    def __init__(self):
        super().__init__()

    def initialize(self):
        pass

    def get_suggestion(self, trial=None):
        # Return trial, return None if experiment finished
        pass

    def finalize_experiment(self, trials):
        pass



class CustomEarlyStop(AbstractEarlyStop):

    def earlystop_check(to_check, finalized_trials, direction):
        pass
```

Maggy is Open-source

- Code Repository: https://github.com/logicalclocks/maggy

- API Documentation: https://maggy.readthedocs.io/en/latest/

Next Steps

- More Ablators
- More Tuners
- Support for More Frameworks

Thank you! ☺

(Example Notebook Available!)

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Thanks to the entire Logical Clocks Team ☺

Specially:

Moritz Meister	@morimeister
Jim Dowling	@jim_dowling
Robin Andersson	@robzor92
Kim Hammar	@KimHammar1
Alex Ormenisan	@alex_ormenisan

@logicalclocks

@hopsworks

GitHub

https://github.com/hopshadoop/maggy

https://maggy.readthedocs.io/en/latest/

https://logicalclocks.com/whitepapers/