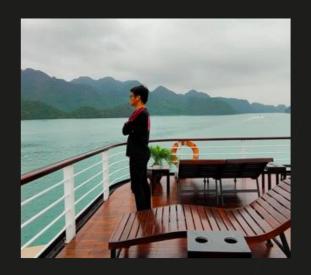
MACHINE LEARNING ENGINEERING DONE RIGHT

Designing and Building Complex Intelligent Systems and Workflows with **Python**

[CONF42]



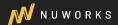


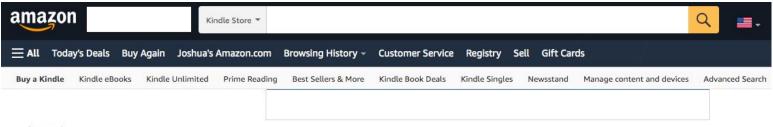




Joshua "ARVS" Lat

- ➤ Chief Technology Officer of NuWorks Interactive Labs
- ➤ AWS Machine Learning Hero
- ➤ Author of a Machine Learning Engineering Book Amazon SageMaker Cookbook (2021)]





Back to results



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MACHINE LEARNING ENGINEERING DONE RIGHT

UNDERSTANDING THE NEEDS OF THE BUSINESS AND THE CUSTOMERS

MAKING THE MOST OUT OF ML FRAMEWORKS AND ML PLATFORMS

KNOWING WHEN TO WRITE PRODUCTION-LEVEL PYTHON CODE

WORKING WITH AUTOMATED ML BIAS DETECTION AND ML EXPLAINABILITY CAPABILITIES

ENFORCING PRACTICAL PYTHON CODING GUIDELINES

REAPING THE BENEFITS OF CLOUD COMPUTING FOR AUTOMATED HYPERPARAMETER OPTIMIZATION JOBS

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UTILIZING CONTINUOUS INTEGRATION AND DEPLOYMENT PIPELINES

SECURING MACHINE LEARNING ENVIRONMENTS



UNDERSTANDING THE NEEDS OF THE BUSINESS AND THE CUSTOMERS



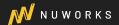
MACHINE LEARNING PREDICTION ENDPOINT

[FLASK]

VS

MACHINE LEARNING EXPERIMENT

[JUPYTER NOTEBOOK]



ENFORCING PRACTICAL PYTHON CODING GUIDELINES

20-LINE RULE

PEP-8

AVOIDANCE OF TRY-CATCH BLOCKS

WRITE TESTABLE PYTHON CODE

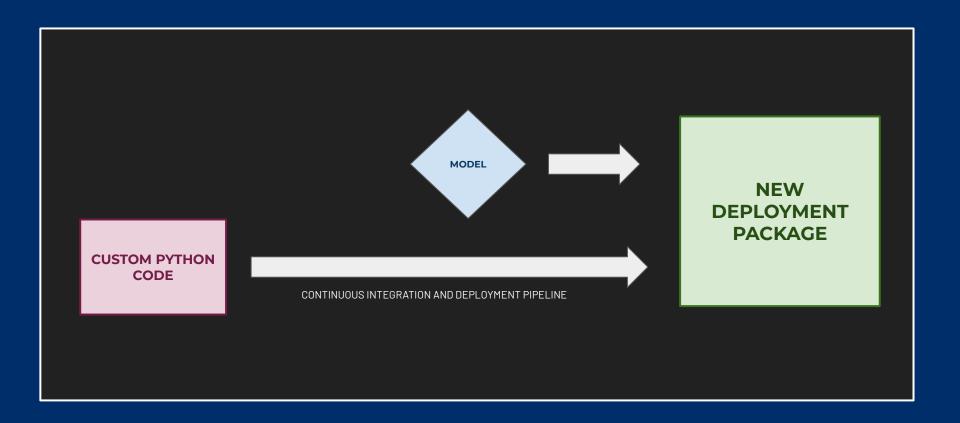


WRITE YOUR OWN CONVENIENCE LIBRARY!

(when it makes sense)



UTILIZING CONTINUOUS INTEGRATION AND DEPLOYMENT PIPELINES





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BUILD EVERYTHING FROM SCRATCH

VS

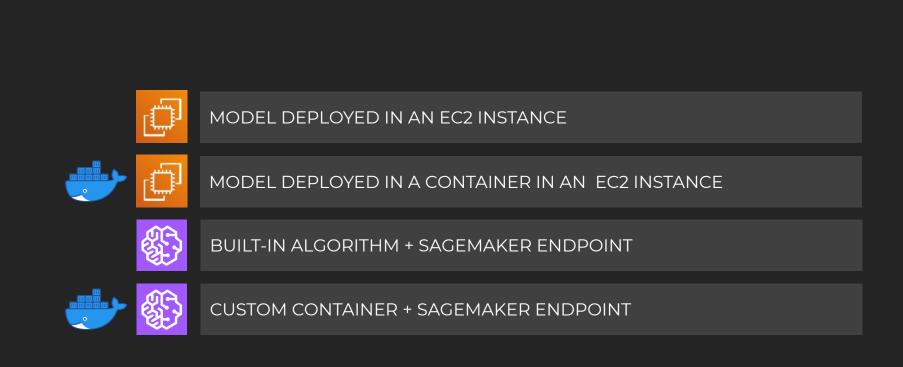


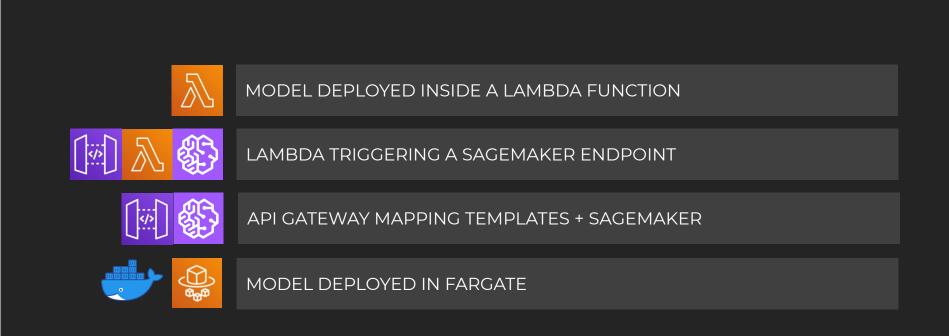




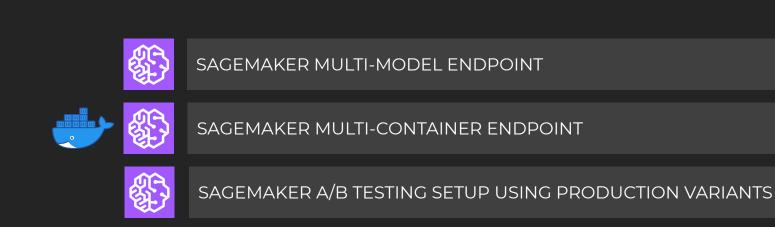


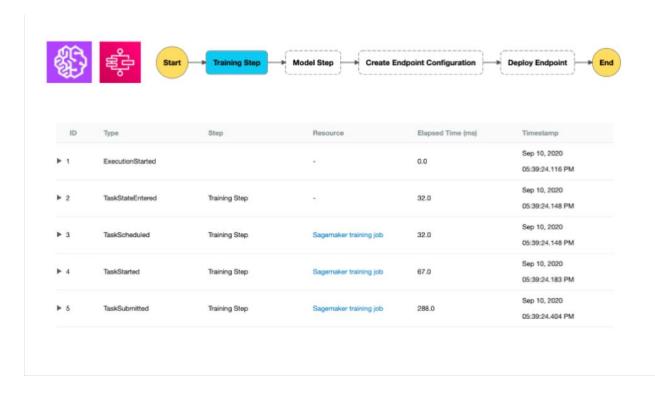




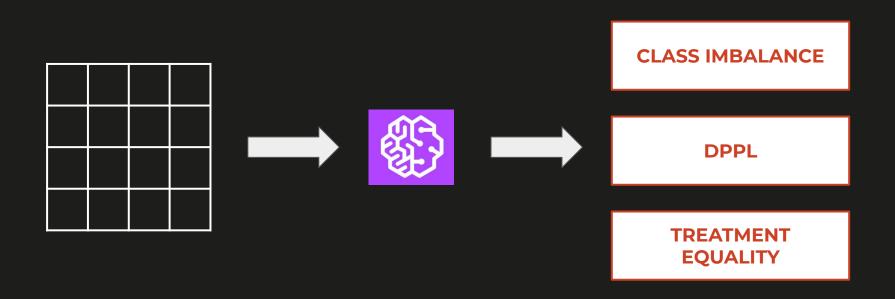


MODEL DEPLOYED INSIDE A LAMBDA FUNCTION + CONTAINER





WORKING WITH AUTOMATED ML BIAS DETECTION AND ML EXPLAINABILITY CAPABILITIES







```
from sagemaker import clarify
processor = clarify.SageMakerClarifyProcessor(
    role=role,
    instance count=1,
    instance type='ml.m5.large',
    sagemaker session=session)
data config = clarify.DataConfig(
    s3 data input path=s3 training data path,
    s3_output_path=s3_output_path,
    label='label',
    headers=training data.columns.to list(),
    dataset type='text/csv')
```

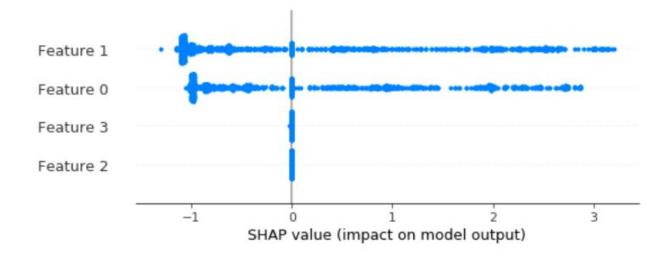


```
bias config = clarify.BiasConfig(
    label values or threshold=[1],
    facet name='a',
    facet values or threshold=[5])
processor.run pre training bias(
    data config=data config,
    data bias config=bias config,
   methods=['CI'])
processor.latest job.outputs[0].destination
```



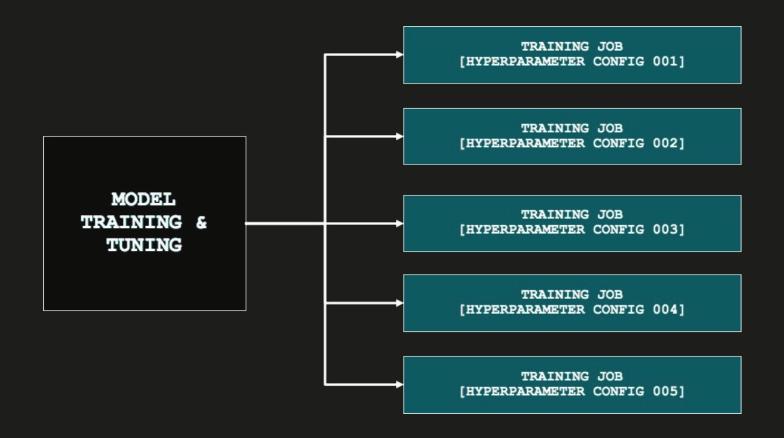
```
"version": "1.0",
"pre_training_bias_metrics": {
    "label": "label",
    "facets": {
        "a": [
                "value_or_threshold": "(5.0, 13.99152988349206]",
                "metrics": [
                        "name": "CI",
                        "description": "Class Imbalance (CI)",
                        "value": 0.95733333333333334
    },
    "label_value_or_threshold": "1"
```

WORKING WITH AUTOMATED ML BIAS DETECTION AND ML EXPLAINABILITY CAPABILITIES

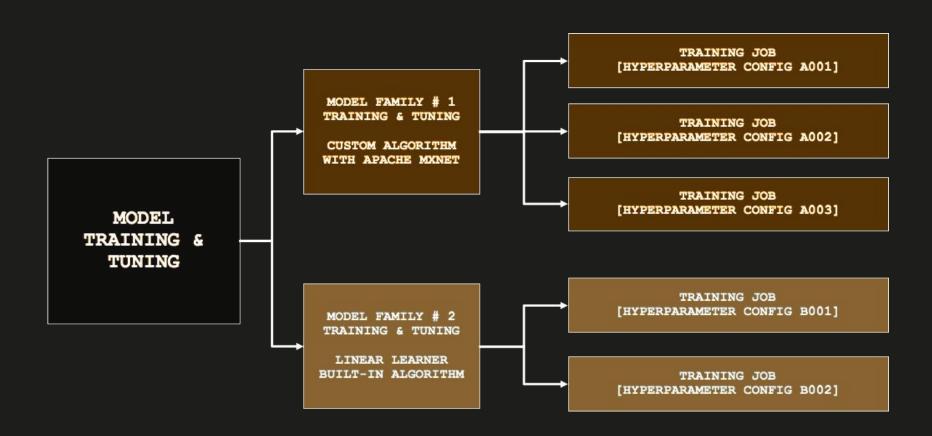




```
"version": "1.0",
"explanations": {
    "kernel_shap": {
        "label0": {
            "global_shap_values": {
                "a": 0.1173995901699019,
                "b": 0.37360024663733005,
                "c": 0.01740283967164966,
                "d": 0.015364162067494701
            },
            "expected_value": 0.34422817826271057
```

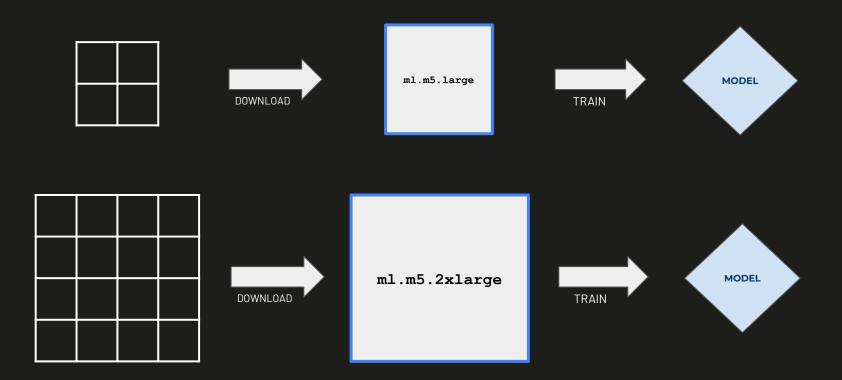








OPTIMIZING COSTS BY USING TRANSIENT ML INSTANCES FOR TRAINING MODELS





PRINCIPLE OF LEAST PRIVILEGE





Navigation

Why joblib: project goals
Installing joblib
On demand recomputing:
the *Memory* class
Embarrassingly parallel
for loops
Persistence

- · Use case
- A simple example
- · Persistence in file objects
- Compressed joblib pickles

Examples Development

joblib.Memory joblib.Parallel joblib.dump joblib.load

Persistence

Use case

joblib.dump() and joblib.load() provide a replacement for pickle to work efficiently on arbitrary Python objects containing large data, in particular large numpy arrays.

Warning:

joblib.dump() and joblib.load() are based on the Python pickle serialization model, which means that arbitrary Python code can be executed when loading a serialized object with joblib.load().

joblib.load() should therefore never be used to load objects from an untrusted source or otherwise you will introduce a security vulnerability in your program.

Note:

As of Python 3.8 and numpy 1.16, pickle protocol 5 introduced in PEP 574 supports efficient serialization and de-serialization for large data buffers natively using the standard library:

pickle.dump(large_object, fileobj, protocol=5)



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