Tutorial

This tutorial showcases how you can use MLflow end-to-end to:

- Train a linear regression model
- Package the code that trains the model in a reusable and reproducible model format
- Deploy the model into a simple HTTP server that will enable you to score predictions

This tutorial uses a dataset to predict the quality of wine based on quantitative features like the wine's "fixed acidity", "pH", "residual sugar", and so on. The dataset is from UCI's machine learning repository. [1]

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What You'll Need

To run this tutorial, you'll need to:

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- Install MLflow and scikit-learn. There are two options for installing these dependencies:
    1. Install MLflow with extra dependencies, including scikit-learn (via `pip install mlflow[extras]`)
    2. Install MLflow (via `pip install mlflow`) and install scikit-learn separately (via `pip install scikit-learn`)
- Install conda
- Clone (download) the MLflow repository via `git clone https://github.com/mlflow/mlflow`

- `cd` into the `examples` directory within your clone of MLflow - we'll use this working directory for running the tutorial. We avoid running directly from our clone of MLflow as doing so would cause the tutorial to use MLflow from source, rather than your PyPI installation of MLflow.

Training the Model

First, train a linear regression model that takes two hyperparameters: `alpha` and `l1_ratio`.

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The code is located at `examples/sklearn_elasticnet_wine/train.py` and is reproduced below.

```python
# The data set used in this example is from http://archive.ics.uci.edu/ml/datasets/Wine+Quality
# P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis.
# Modeling wine preferences by data mining from physicochemical properties. In Decision Support
Systems, Elsevier, 47(4):547-553, 2009.

import os
import warnings
import sys

import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import ElasticNet
from urllib.parse import urlparse
import mlflow
import mlflow.sklearn

import logging

logging.basicConfig(level=logging.WARN)
logger = logging.getLogger(__name__)


def eval_metrics(actual, pred):
    rmse = np.sqrt(mean_squared_error(actual, pred))
    mae = mean_absolute_error(actual, pred)
    r2 = r2_score(actual, pred)
    return rmse, mae, r2


if __name__ == "__main__":
    warnings.filterwarnings("ignore")
    np.random.seed(40)

    # Read the wine-quality csv file from the URL
    csv_url = (
        "http://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/winequality-red.csv"
    )
    try:
        data = pd.read_csv(csv_url, sep=";")
    except Exception as e:
        logger.exception(
            "Unable to download training & test CSV, check your internet connection. Error: %s", e
        )

    # Split the data into training and test sets. (0.75, 0.25) split.
    train, test = train_test_split(data)

    # The predicted column is "quality" which is a scalar from [3, 9]
    train_x = train.drop(["quality"], axis=1)
    test_x = test.drop(["quality"], axis=1)
    train_y = train[["quality"]]
    test_y = test[["quality"]]

    alpha = float(sys.argv[1]) if len(sys.argv) > 1 else 0.5
```

```python
    l1_ratio = float(sys.argv[2]) if len(sys.argv) > 2 else 0.5

    with mlflow.start_run():
        lr = ElasticNet(alpha=alpha, l1_ratio=l1_ratio, random_state=42)
        lr.fit(train_x, train_y)

        predicted_qualities = lr.predict(test_x)

        (rmse, mae, r2) = eval_metrics(test_y, predicted_qualities)

        print("Elasticnet model (alpha=%f, l1_ratio=%f):" % (alpha, l1_ratio))
        print("  RMSE: %s" % rmse)
        print("  MAE: %s" % mae)
        print("  R2: %s" % r2)

        mlflow.log_param("alpha", alpha)
        mlflow.log_param("l1_ratio", l1_ratio)
        mlflow.log_metric("rmse", rmse)
        mlflow.log_metric("r2", r2)
        mlflow.log_metric("mae", mae)

        tracking_url_type_store = urlparse(mlflow.get_tracking_uri()).scheme

        # Model registry does not work with file store
        if tracking_url_type_store != "file":

            # Register the model
            # There are other ways to use the Model Registry, which depends on the use case,
            # please refer to the doc for more information:
            # https://mlflow.org/docs/latest/model-registry.html#api-workflow
            mlflow.sklearn.log_model(lr, "model", registered_model_name="ElasticnetWineModel")
        else:
            mlflow.sklearn.log_model(lr, "model")
```

This example uses the familiar pandas, numpy, and sklearn APIs to create a simple machine learning model. The MLflow tracking APIs log information about each training run, like the hyperparameters `alpha` and `l1_ratio`, used to train the model and metrics, like the root mean square error, used to evaluate the model. The example also serializes the model in a format that MLflow knows how to deploy.

You can run the example with default hyperparameters as follows:

```
# Make sure the current working directory is 'examples'
python sklearn_elasticnet_wine/train.py
```

Try out some other values for `alpha` and `l1_ratio` by passing them as arguments to `train.py`:

```
# Make sure the current working directory is 'examples'
python sklearn_elasticnet_wine/train.py <alpha> <l1_ratio>
```

Each time you run the example, MLflow logs information about your experiment runs in the directory `mlruns`.

> Note
>
> If you would like to use the Jupyter notebook version of `train.py`, try out the tutorial notebook at `examples/sklearn_elasticnet_wine/train.ipynb`.

Comparing the Models

Next, use the MLflow UI to compare the models that you have produced. In the same current working directory as the one that contains the `mlruns` run:

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```
mlflow ui
```

and view it at http://localhost:5000.

On this page, you can see a list of experiment runs with metrics you can use to compare the models.

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					Parameters		Metrics		
	Date	User	Source	Version	alpha	l1_ratio	mae	r2	rmse
☐	2018-06-04 23:00:10	mlflow	train.py	05e956	1	1	0.649	0.04	0.862
☐	2018-06-04 23:00:10	mlflow	train.py	05e956	1	0.5	0.648	0.046	0.859
☐	2018-06-04 23:00:10	mlflow	train.py	05e956	1	0.2	0.628	0.125	0.823
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	1	0	0.619	0.176	0.799
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0.5	1	0.648	0.046	0.859
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0.5	0.5	0.628	0.127	0.822
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0.5	0.2	0.621	0.171	0.801
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0.5	0	0.615	0.199	0.787
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0	1	0.578	0.288	0.742
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0	0.5	0.578	0.288	0.742
☐	2018-06-04 23:00:09	mlflow	train.py	05e956	0	0.2	0.578	0.288	0.742
☐	2018-06-04 23:00:08	mlflow	train.py	05e956	0	0	0.578	0.288	0.742

You can use the search feature to quickly filter out many models. For example, the query `metrics.rmse < 0.8` returns all the models with root mean squared error less than 0.8. For more complex manipulations, you can download this table as a CSV and use your favorite data munging software to analyze it.

Packaging Training Code in a Conda Environment

Now that you have your training code, you can package it so that other data scientists can easily reuse the model, or so that you can run the training remotely, for example on Databricks.

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You do this by using MLflow Projects conventions to specify the dependencies and entry points to your code. The `sklearn_elasticnet_wine/MLproject` file specifies that the project has the dependencies located in a Conda environment file called `conda.yaml` and has one entry point that takes two parameters: `alpha` and `l1_ratio`.

```
name: tutorial

conda_env: conda.yaml

entry_points:
  main:
    parameters:
      alpha: {type: float, default: 0.5}
      l1_ratio: {type: float, default: 0.1}
    command: "python train.py {alpha} {l1_ratio}"
```

`sklearn_elasticnet_wine/conda.yaml` file lists the dependencies:

```
name: tutorial
channels:
  - conda-forge
dependencies:
  - python=3.7
  - pip
  - pip:
      - scikit-learn==0.23.2
      - mlflow>=1.0
      - pandas
```

To run this project, invoke `mlflow run sklearn_elasticnet_wine -P alpha=0.42`. After running this command, MLflow runs your training code in a new Conda environment with the dependencies specified in `conda.yaml`.

If the repository has an `MLproject` file in the root you can also run a project directly from GitHub. This tutorial is duplicated in the https://github.com/mlflow/mlflow-example repository which you can run with `mlflow run https://github.com/mlflow/mlflow-example.git -P alpha=5.0`.

Specifying pip requirements using `pip_requirements` and `extra_pip_requirements`

```python
"""
This example demonstrates how to specify pip requirements using `pip_requirements` and
`extra_pip_requirements` when logging a model via `mlflow.*.log_model`.
"""

import tempfile

import sklearn
from sklearn.datasets import load_iris
import xgboost as xgb
import mlflow
from mlflow.tracking import MlflowClient


def read_lines(path):
    with open(path) as f:
        return f.read().splitlines()


def get_pip_requirements(run_id, artifact_path, return_constraints=False):
    client = MlflowClient()
    req_path = client.download_artifacts(run_id, f"{artifact_path}/requirements.txt")
    reqs = read_lines(req_path)

    if return_constraints:
        con_path = client.download_artifacts(run_id, f"{artifact_path}/constraints.txt")
        cons = read_lines(con_path)
        return set(reqs), set(cons)

    return set(reqs)


def main():
    iris = load_iris()
    dtrain = xgb.DMatrix(iris.data, iris.target)
    model = xgb.train({}, dtrain)

    xgb_req = f"xgboost=={xgb.__version__}"
    sklearn_req = f"scikit-learn=={sklearn.__version__}"

    with mlflow.start_run() as run:
        run_id = run.info.run_id

        # Default (both `pip_requirements` and `extra_pip_requirements` are unspecified)
        artifact_path = "default"
        mlflow.xgboost.log_model(model, artifact_path)
        pip_reqs = get_pip_requirements(run_id, artifact_path)
        assert pip_reqs.issuperset(["mlflow", xgb_req]), pip_reqs

        # Overwrite the default set of pip requirements using `pip_requirements`
        artifact_path = "pip_requirements"
        mlflow.xgboost.log_model(model, artifact_path, pip_requirements=[sklearn_req])
        pip_reqs = get_pip_requirements(run_id, artifact_path)
        assert pip_reqs == {"mlflow", sklearn_req}, pip_reqs

        # Add extra pip requirements on top of the default set of pip requirements
```

```python
        # using `extra_pip_requirements`
        artifact_path = "extra_pip_requirements"
        mlflow.xgboost.log_model(model, artifact_path, extra_pip_requirements=[sklearn_req])
        pip_reqs = get_pip_requirements(run_id, artifact_path)
        assert pip_reqs.issuperset(["mlflow", xgb_req, sklearn_req]), pip_reqs

        # Specify pip requirements using a requirements file
        with tempfile.NamedTemporaryFile("w", suffix=".requirements.txt") as f:
            f.write(sklearn_req)
            f.flush()

            # Path to a pip requirements file
            artifact_path = "requirements_file_path"
            mlflow.xgboost.log_model(model, artifact_path, pip_requirements=f.name)
            pip_reqs = get_pip_requirements(run_id, artifact_path)
            assert pip_reqs == {"mlflow", sklearn_req}, pip_reqs

            # List of pip requirement strings
            artifact_path = "requirements_file_list"
            mlflow.xgboost.log_model(
                model, artifact_path, pip_requirements=[xgb_req, f"-r {f.name}"]
            )
            pip_reqs = get_pip_requirements(run_id, artifact_path)
            assert pip_reqs == {"mlflow", xgb_req, sklearn_req}, pip_reqs

        # Using a constraints file
        with tempfile.NamedTemporaryFile("w", suffix=".constraints.txt") as f:
            f.write(sklearn_req)
            f.flush()

            artifact_path = "constraints_file"
            mlflow.xgboost.log_model(
                model, artifact_path, pip_requirements=[xgb_req, f"-c {f.name}"]
            )
            pip_reqs, pip_cons = get_pip_requirements(
                run_id, artifact_path, return_constraints=True
            )
            assert pip_reqs == {"mlflow", xgb_req, "-c constraints.txt"}, pip_reqs
            assert pip_cons == {sklearn_req}, pip_cons


if __name__ == "__main__":
    main()
```

Serving the Model

Now that you have packaged your model using the MLproject convention and have identified the best model, it is time to deploy the model using MLflow Models. An MLflow Model is a standard format for packaging machine learning models that can be used in a variety of downstream tools — for example, real-time serving through a REST API or batch inference on Apache Spark.

In the example training code, after training the linear regression model, a function in MLflow saved the model as an artifact within the run.

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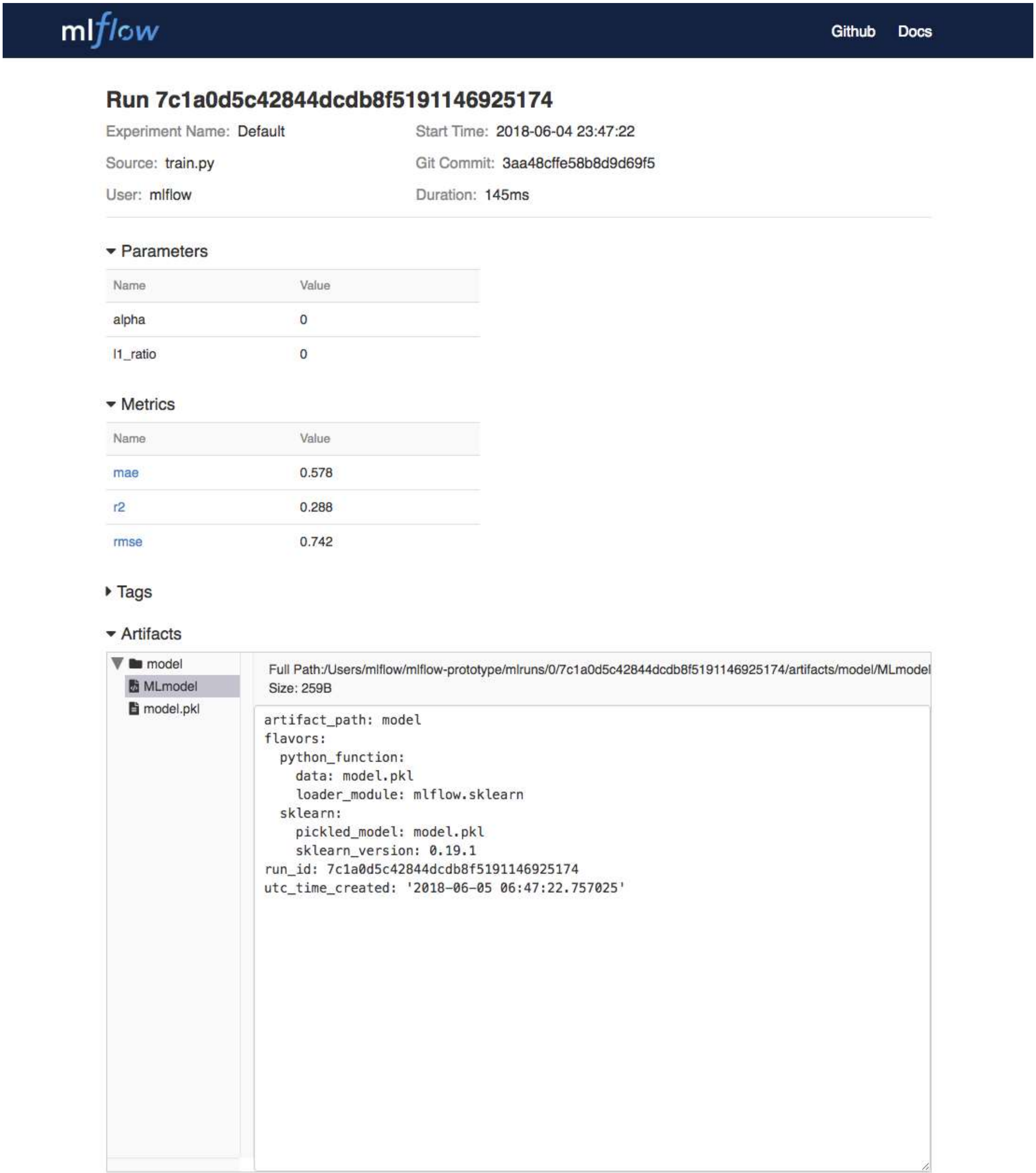
```
mlflow.sklearn.log_model(lr, "model")
```

To view this artifact, you can use the UI again. When you click a date in the list of experiment runs you'll see this page.



At the bottom, you can see that the call to `mlflow.sklearn.log_model` produced two files in `/Users/mlflow/mlflow-prototype/mlruns/0/7c1a0d5c42844dcdb8f5191146925174/artifacts/model`. The first file, `MLmodel`, is a metadata file that tells MLflow how to load the model. The second file, `model.pkl`, is a serialized version of the linear regression model that you trained.

In this example, you can use this MLmodel format with MLflow to deploy a local REST server that can serve predictions.

To deploy the server, run (replace the path with your model's actual path):

```
mlflow models serve -m /Users/mlflow/mlflow-
prototype/mlruns/0/7c1a0d5c42844dcdb8f5191146925174/artifacts/model -p 1234
```

Note

The version of Python used to create the model must be the same as the one running `mlflow models serve`. If this is not the case, you may see the error `UnicodeDecodeError: 'ascii' codec can't decode byte 0x9f in position 1: ordinal not in range(128)` or `raise ValueError, "unsupported pickle protocol: %d"`.

Once you have deployed the server, you can pass it some sample data and see the predictions. The following example uses `curl` to send a JSON-serialized pandas DataFrame with the `split` orientation to the model server. For more information about the input data formats accepted by the model server, see the MLflow deployment tools documentation.

```
# On Linux and macOS
curl -X POST -H "Content-Type:application/json; format=pandas-split" --data '{"columns":["alcohol",
"chlorides", "citric acid", "density", "fixed acidity", "free sulfur dioxide", "pH", "residual
sugar", "sulphates", "total sulfur dioxide", "volatile acidity"],"data":[[12.8, 0.029, 0.48, 0.98,
6.2, 29, 3.33, 1.2, 0.39, 75, 0.66]]}' http://127.0.0.1:1234/invocations

# On Windows
curl -X POST -H "Content-Type:application/json; format=pandas-split" --data "{\"columns\":
[\"alcohol\", \"chlorides\", \"citric acid\", \"density\", \"fixed acidity\", \"free sulfur
dioxide\", \"pH\", \"residual sugar\", \"sulphates\", \"total sulfur dioxide\", \"volatile
acidity\"],\"data\":[[12.8, 0.029, 0.48, 0.98, 6.2, 29, 3.33, 1.2, 0.39, 75, 0.66]]}"
http://127.0.0.1:1234/invocations
```

the server should respond with output similar to:

```
[6.379428821398614]
```

Deploy the Model to Seldon Core or KServe (experimental)

After training and testing our model, we are now ready to deploy it to production. MLflow allows you to serve your model using MLServer, which is already used as the core Python inference server in Kubernetes-native frameworks including Seldon Core and KServe (formerly known as KFServing). Therefore, we can leverage this support to build a Docker image compatible with these frameworks.

Note

Note that this an **optional step**, which is currently only available for Python models. Besides this, it's also worth noting that:

- This feature is **experimental** and is subject to change.
- MLServer requires **Python 3.7** or above.
- This step requires some basic Kubernetes knowledge, including familiarity with `kubectl`.

To build a Docker image containing our model, we can use the `mlflow models build-docker` subcommand, alongside the `--enable-mlserver` flag. For example, to build a image named `my-docker-image`, we could do:

```
mlflow models build-docker \
  -m /Users/mlflow/mlflow-prototype/mlruns/0/7c1a0d5c42844dcdb8f5191146925174/artifacts/model \
  -n my-docker-image \
  --enable-mlserver
```

Once we have our image built, the next step will be to deploy it to our cluster. One way to do this is by applying the respective Kubernetes manifests through the `kubectl` CLI:

```
kubectl apply -f my-manifest.yaml
```

Seldon-core   Kserve

This step assumes that you've got `kubectl` access to a Kubernetes cluster already setup with Seldon Core. To read more on how to set this up, you can refer to the Seldon Core quickstart guide.

```yaml
apiVersion: machinelearning.seldon.io/v1
kind: SeldonDeployment
metadata:
  name: mlflow-model
spec:
  predictors:
    - name: default
      annotations:
        seldon.io/no-engine: "true"
      graph:
        name: mlflow-model
        type: MODEL
      componentSpecs:
        - spec:
            containers:
              - name: mlflow-model
                image: my-docker-image
                imagePullPolicy: IfNotPresent
                securityContext:
                  runAsUser: 0
                ports:
                  - containerPort: 8080
                    name: http
                    protocol: TCP
                  - containerPort: 8081
                    name: grpc
                    protocol: TCP
```

More Resources

Congratulations on finishing the tutorial! For more reading, see MLflow Tracking, MLflow Projects, MLflow Models, and more.

1

P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis. Modeling wine preferences by data mining from physicochemical properties. In Decision Support Systems, Elsevier, 47(4):547-553, 2009.