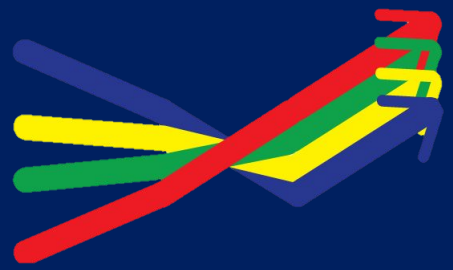
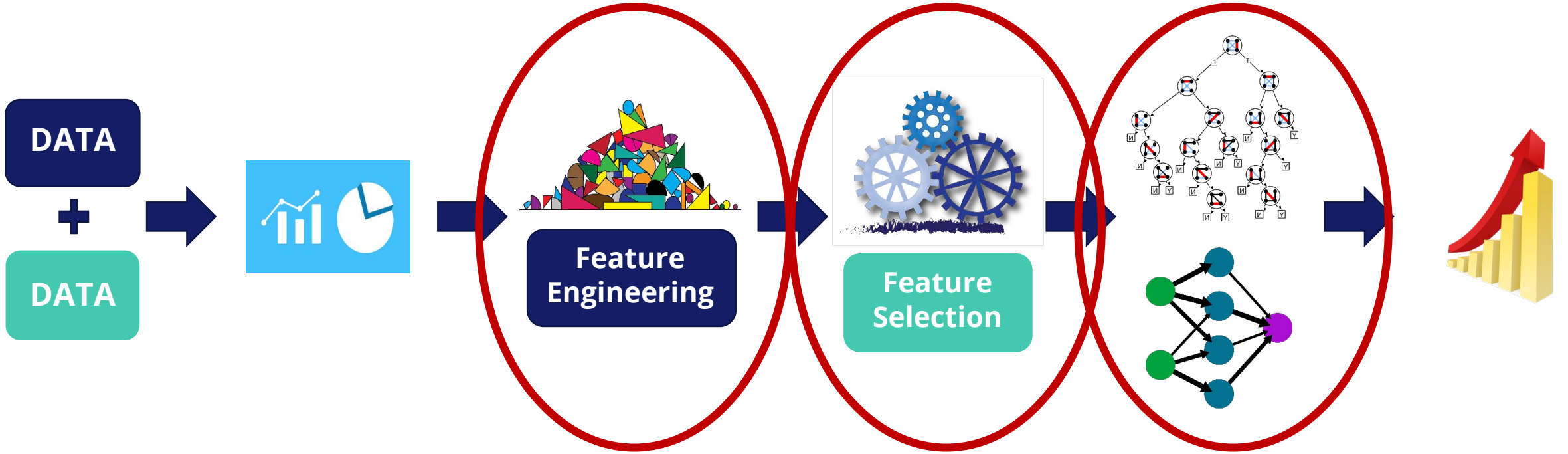
Writing Production Code for Machine Learning Deployment

Overview



Machine Learning Pipeline: Production



Gathering Data Sources

Data Analysis

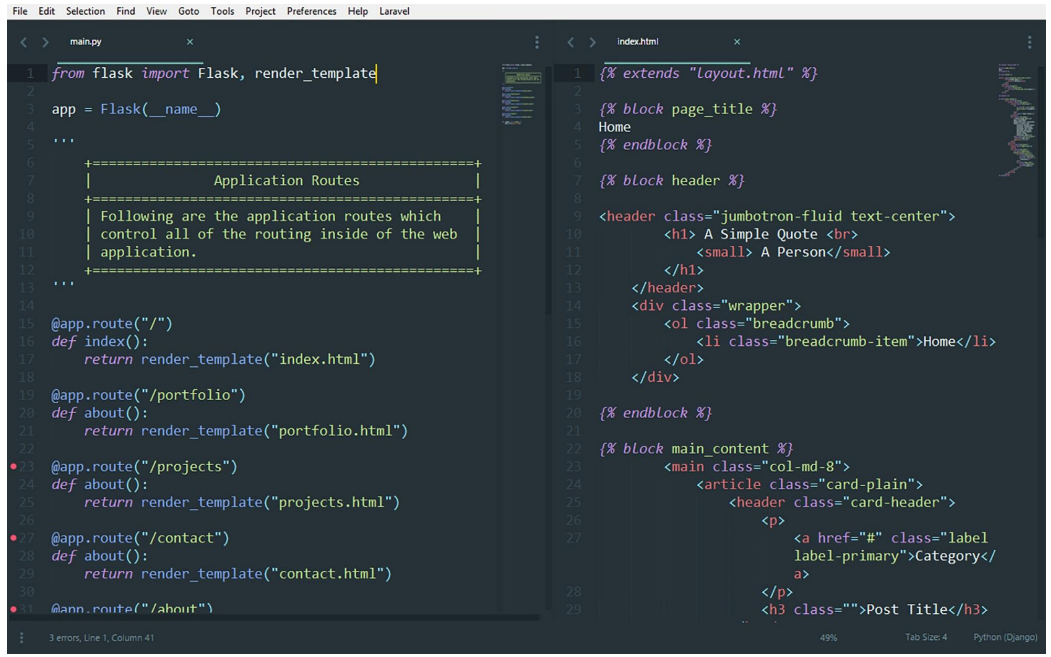
Data Pre-processing

Variable selection

Machine Learning Model building

Model building Business uplift evaluation

Towards deployment code



Code to:

- Create and Transform features
- Incorporate the feature selection
- Build Machine Learning Models
- Score new data

How to write deployment code for ML

- Procedural Programming
- Custom Pipeline Code
- Third Party Pipeline Code

Procedural Programming

Procedural Programming

In procedural programming, procedures, also known as routines, subroutines or functions, are carried out as a series of computational steps.

For us, it refers to writing the series of feature creation, feature transformation, model training and data scoring steps, as functions, that then we can call and run one after the other.

Procedural Programming: the functions

```python
# ==== EXAMPLE OF PROCEDURAL PROGRAMMING SCRIPT ===

import pandas as pd
import numpy as np

# to divide train and test set
from sklearn.model_selection import train_test_split

# feature scaling
from sklearn.preprocessing import StandardScaler

# to build the models
from sklearn.linear_model import LinearRegression, Lasso

# to evaluate the models
from sklearn.metrics import mean_squared_error


# Functional programming, getting all parameters from yaml file

def load_data(df_path):
    return pd.read_csv(df_path)


def divide_train_test(df, target):
    X_train, X_test, y_train, y_test = train_test_split(df, df[target],
                                                        test_size=0.2,
                                                        random_state=0)
    return X_train, X_test, y_train, y_test


def remove_numerical_na(df, var, mean_val):
    return df[var].fillna(mean_val)


def remove_categorical_na(df, var):
    return df[var].fillna('Missing')


def cap_outliers(df, var, cap, bigger_than=False):
    if bigger_than:
        capped_var = np.where(df[var]>cap, cap, df[var])
    else:
        capped_var = np.where(df[var]<cap, cap, df[var])

    return capped_var
```

```python
def remove_numerical_na(df, var, mean_val):
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    else:
        capped_var = np.where(df[var]<cap, cap, df[var])

    return capped_var


def transform_skewed_variables(df, var):
    return np.log(df[var])


def remove_rare_labels(df, var, frequent_labels):
    return np.where(df[var].isin(frequent_labels, df[var], 'Rare'))


def train_scaler(df, output_path):
    scaler = StandardScaler()
    scaler.fit(df)
    joblib.save(scaler, output_path)
    return scaler

def scale_features(df, scaler):
    scaler = load(scaler) # with joblib probably
    return scaler.transform(df)


def train_model(df, target, features, scaler, output_path):
    lin_model = Lasso(random_state=2909)
    lin_model.fit(scaler.transform(df[features]), target)
    joblib.save(lin_model, output_path)
    return lin_model

def predict(df, model, features, scaler):
    return model.predict_proba(scaler.transform(df[features]))
```

The functions or procedures to create and transform features, and to train and save the models and make the predictions

Procedural Programming: train script

```
#========== training pipeline ======

df = load(yaml_path_to_file)
train, test, y_train, y_test = divide_train_test(df, yaml_target_name)

# remove NA numerical
train[var1] = remove_numerical_na(train, var1, mean_val1_in_yaml)
train[var2] = remove_numerical_na(train, var2, mean_val2_in_yaml)

train[var3] = remove_categorical_na(train[var3])
train[var4] = remove_categorical_na(train[var4])

train[var5] = cap_outliers(train, var5, cap_value_in_yaml, bigger_than=False)
train[var6] = cap_outliers(train, var6, cap_value_in_yaml, bigger_than=False)

train[var7] = transform_skewed_variables(train, var7)

train[var8] = remove_rare_labels(train, var8, frequent_labels_in_yaml)

scaler = train_scaler(train, output_path_in_yaml)

lin_model = train_model(train, y_train, feature_list_in_yaml, scaler, output_path_in_yaml)

#== END
```

Calls the previous functions in order, to train and save the models

Procedural Programming: score script

```
# ============ scoring pipeline =========

data = 'load it from somewhere'

# remove NA numerical
data[var1] = remove_numerical_na(data, var1, mean_val1_in_yaml)
data[var2] = remove_numerical_na(data, var2, mean_val2_in_yaml)

data[var3] = remove_categorical_na(data[var3])
data[var4] = remove_categorical_na(data[var4])

data[var5] = cap_outliers(data, var5, cap_value_in_yaml, bigger_than=False)
data[var6] = cap_outliers(data, var6, cap_value_in_yaml, bigger_than=False)

data[var7] = transform_skewed_variables(data, var7)

data[var8] = remove_rare_labels(data, var8, frequent_labels_in_yaml)

scaler = joblib.load((output_path_in_yaml_to_scaler)
lin_model = joblib.load(output_path_in_yaml_to_model)

score = predict(data, lin_model, feature_list_in_yaml, scaler)

# ===== END
```

Calls the previous functions in order, to score new data

Procedural Programming: yaml file

```
### example of yaml ####

#paths
path_to_dataset = "path_to_my_dataset"
output_scaler_path = 'path_to_store_scaler'
output_model_path = 'path_to_store_model'

# preproc
var1_mean_val = 1
var2_mean_val = 2

var4_cap_value = 1000
var5_cap_value = 5000

var8_frequent_labels = ['frequent1', 'frequent2', 'frequent3']

# features
features = ['var1', 'var2', 'var3', 'var4', 'etc']


#====== END =======
```

Hard coded variables to engineer, and values to use to transform features.

Hardcoded paths to retrieve and store data

By changing these values, we can re-adjust our models

Procedural Programming: Overview

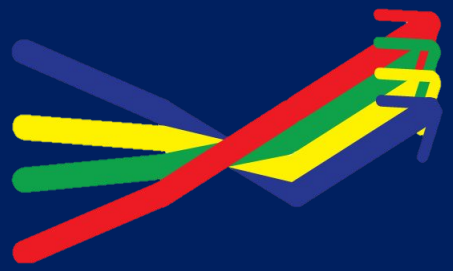
Advantages

- Straightforward from jupyter notebook
- No software development skills required
- Easy to manually check if it reproduces the original model

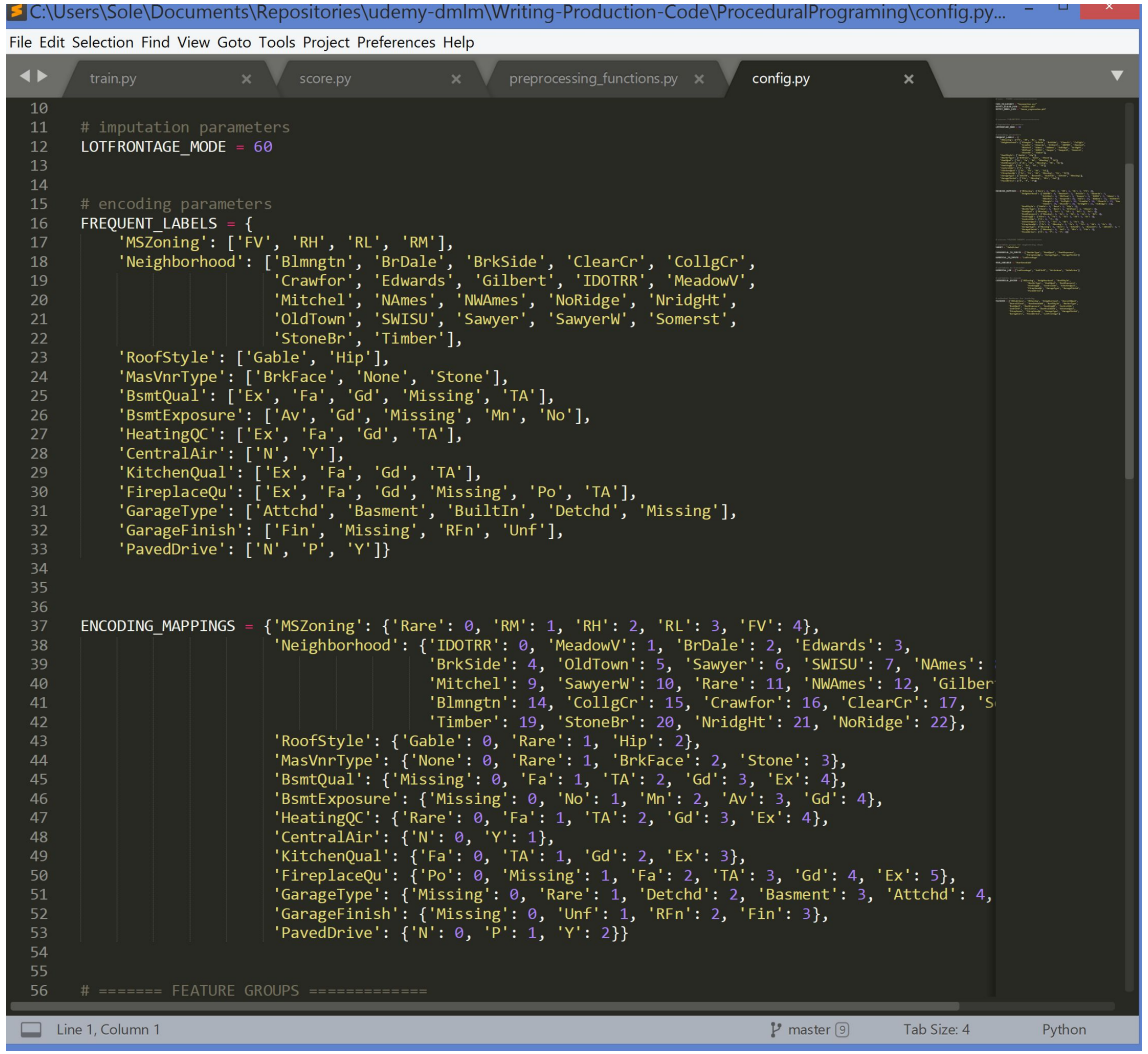
Disadvantages

- Can get buggy
- Difficult to test
- Difficult to build software on top of it
- Need to save a lot of intermediate files to store the transformation parameters

Custom Machine Learning Pipeline



Procedural Programming: hard-coded values



- Straightforward
- Hard-code parameters
- Save multiple objects or data structures

```
# ====   PATHS ====================

PATH_TO_DATASET = "houseprice.csv"
OUTPUT_SCALER_PATH = 'scaler.pkl'
OUTPUT_MODEL_PATH = 'lasso_regression.pkl'
```

Object Oriented Programming - OOP

In **Object-oriented programming** (**OOP**) we write code in the form of “objects”.

This “objects” can store **data**, and can also store instructions or **procedures** to modify that data.

- Data ⇒ attributes
- Instructions or procedures ⇒ methods

Custom ML Pipeline: OOP

In **Object-oriented programming** (**OOP**) the “objects” can learn and store this parameters

- Parameters get automatically refreshed every time model is re-trained
- No need of manual hard-coding

    - Methods:
        - Fit: to learn parameters
            - Saves the parameter in object attribute
        - Transform: to transform data with the learnt parameters
            - Calls to the object attribute to recall the parameters

    - Attributes: store the learn parameters

Custom ML Pipeline: Pipeline

A **pipeline** is a set of data processing steps connected in series, where typically, the output of one element is the input of the next one.

The elements of a pipeline can be executed in parallel or in time-sliced fashion. This is useful when we require use of big data, or high computing power, e.g., for neural networks.

Custom ML Pipeline: Summary

A custom Machine Learning pipeline is therefore a sequence of steps, aimed at loading and transforming the data, to get it ready for training or scoring, where:

- We write the processing steps as objects (OOP)
- We write the sequence, i.e., the pipeline as objects (OOP)

We save one object, the pipeline, as a Python pickle, with all the information needed to transform the raw inputs and get the predictions

Custom Pipeline: Overview

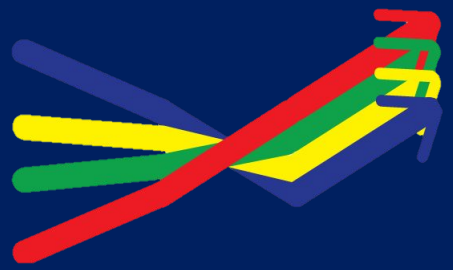
Advantages

- Can be tested, versioned, tracked and controlled
- Can build future models on top
- Good software developer practice
- Built to satisfy business needs

Disadvantages

- Requires team of software developers to build and maintain
- Overhead for DS to familiarise with code for debugging or adding on future models
- Preprocessor not reusable, need to re-write Preprocessor class for each new ML model
- Need to write new pipeline for each new ML model
- Lacks versatility, may constrain DS to what is available with the implemented pipeline

Third Party Machine Learning Pipeline: Leveraging the power of Scikit-Learn



Scikit-Learn and sklearn pipeline

Scikit-Learn is a Python library that provides a solid implementation of a range of machine learning algorithms.

Scikit-Learn provides efficient versions of a large number of common algorithms.

Scikit-Learn is characterised by a clean, uniform, and streamlined API.

Scikit-Learn is written so that most of its algorithms follow the same functionality

Once you understand the basic use and syntax of Scikit-Learn for one type of model, switching to a new model or algorithm is very straightforward

Scikit-Learn provides useful and complete online documentation that allows you to understand both what the algorithm is about and how to use it from scikit-learn

Scikit-Learn is so well established in the community, that new packages are typically designed following scikit-learn functionality to be quickly adopted by end users, e.g, Keras, MLXtend.

Scikit-Learn and sklearn pipeline

Scikit-Learn Objects

- **Transformers** - class that have fit and transform method, it transforms data
  - Scalers
  - Feature selectors
  - One hot encoders
- **Predictor** - class that has fit and predict methods, it fits and predicts.
  - Any ML algorithm like lasso, decision trees, svm, etc
- **Pipeline** - class that allows you to list an run transformers and predictors in sequence
  - All steps should be transformers except the last one
  - Last step should be a predictor

Scikit-Learn and sklearn pipeline

Here is a good example of Pipeline usage. Pipeline gives you a single interface for all 3 steps of transformation and resulting estimator. It encapsulates transformers and predictors inside, and now you can do something like:

```
vect = CountVectorizer()
tfidf = TfidfTransformer()
clf = SGDClassifier()

vX = vect.fit_transform(Xtrain)
tfidfX = tfidf.fit_transform(vX)
predicted = clf.fit_predict(tfidfX)

# Now evaluate all steps on test set
vX = vect.transform(Xtest)
tfidfX = tfidf.transform(vX)
predicted = clf.predict(tfidfX)
```

With just:

```
pipeline = Pipeline([
    ('vect', CountVectorizer()),
    ('tfidf', TfidfTransformer()),
    ('clf', SGDClassifier()),
])
predicted = pipeline.fit(Xtrain).predict(Xtrain)
# Now evaluate all steps on test set
predicted = pipeline.predict(Xtest)
```

Taken from stackoverflow

Scikit-Learn and sklearn pipeline

Feature Creation and Feature Engineering steps as Scikit-Learn Objects

- **Transformers** - class that have fit and transform method, it transforms data
- Use of scikit-learn base transformers
  - Inherit class and adjust the fit and transform methods

Scikit-Learn and sklearn pipeline

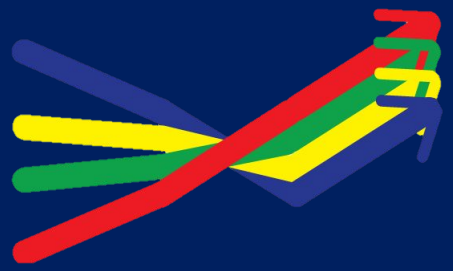
Advantages

- Can be tested, versioned, tracked and controlled
- Can build future models on top
- Good software developer practice
- Leverages the power of acknowledged API
- Data scientists familiar with Pipeline use, reduced over-head
- Engineering steps can be packaged and re-used in future ML models

Disadvantages

- Requires team of software developers to build and maintain
- Overhead for software developers to familiarise with code for sklearn API ⇒ difficulties debugging

Dive into Scikit-learn API



Scikit-Learn Objects

- Estimators
- Transformers
- Pipeline

Scikit-Learn Estimators

Estimator - A class with fit() and predict() methods.

It fits and predicts.

Any ML algorithm like Lasso, Decision trees, SVMs, are coded as estimators within Scikit-Learn.

```
class Estimator(object):

    def fit(self, X, y=None):
        """
        Fits the estimator to data.
        """
        return self

    def predict(self, X):
        """
        Compute the predictions
        """
        return predictions
```

Scikit-Learn Transformers

Transformers - class that have fit() and transform() methods.

It transforms data.

- Scalers
- Feature selectors
- One hot encoders

➢ This is the core of Feature Engine

```
class Transformer(object):

    def fit(self, X, y=None):
        """
        Learn the parameters to
        engineer the features
        """

    def transform(X):
        """
        Transforms the input data
        """
        return X_transformed
```

Scikit-Learn Pipeline

Pipeline - class that allows to run transformers and estimators in sequence.

- Most steps are Transformers
- Last step can be an Estimator

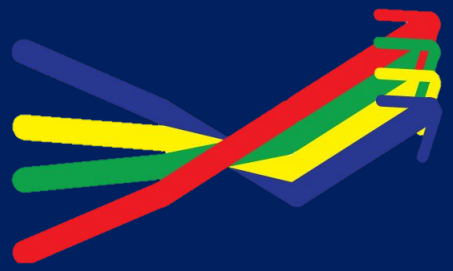
```
class Pipeline(Transformer):

    @property
    def name_steps(self):
        """Sequence of transformers
        """
        return self.steps

    @property
    def _final_estimator(self):
        """
        Estimator
        """
        return self.steps[-1]
```

Scikit-Learn API documentation

https://scikit-learn.org/stable/modules/classes.html

- base.BaseEstimator
- base.TransformerMixin

Packaging the transformers to re-use across projects



Scikit-Learn API documentation

from preprocessors import CategoricalImputer

Scikit-Learn Transformers

- Missing Data Imputation
  - SimpleImputer
  - IterativeImputer
- Categorical Variable Encoding
  - OneHotEncoder
  - OrdinalEncoder
- Discretisation
  - KBinsDiscretizer
- Variable Transformation
  - PowerTransformer
  - FunctionTransformer

Feature Engine Transformers

- Missing Data Imputation
  - MeanMedianImputer
  - RandomSampleImputer
  - EndTailImputer
  - AddNaNBinaryImputer
  - CategoricalVariableImputer
  - FrequentCategoryImputer

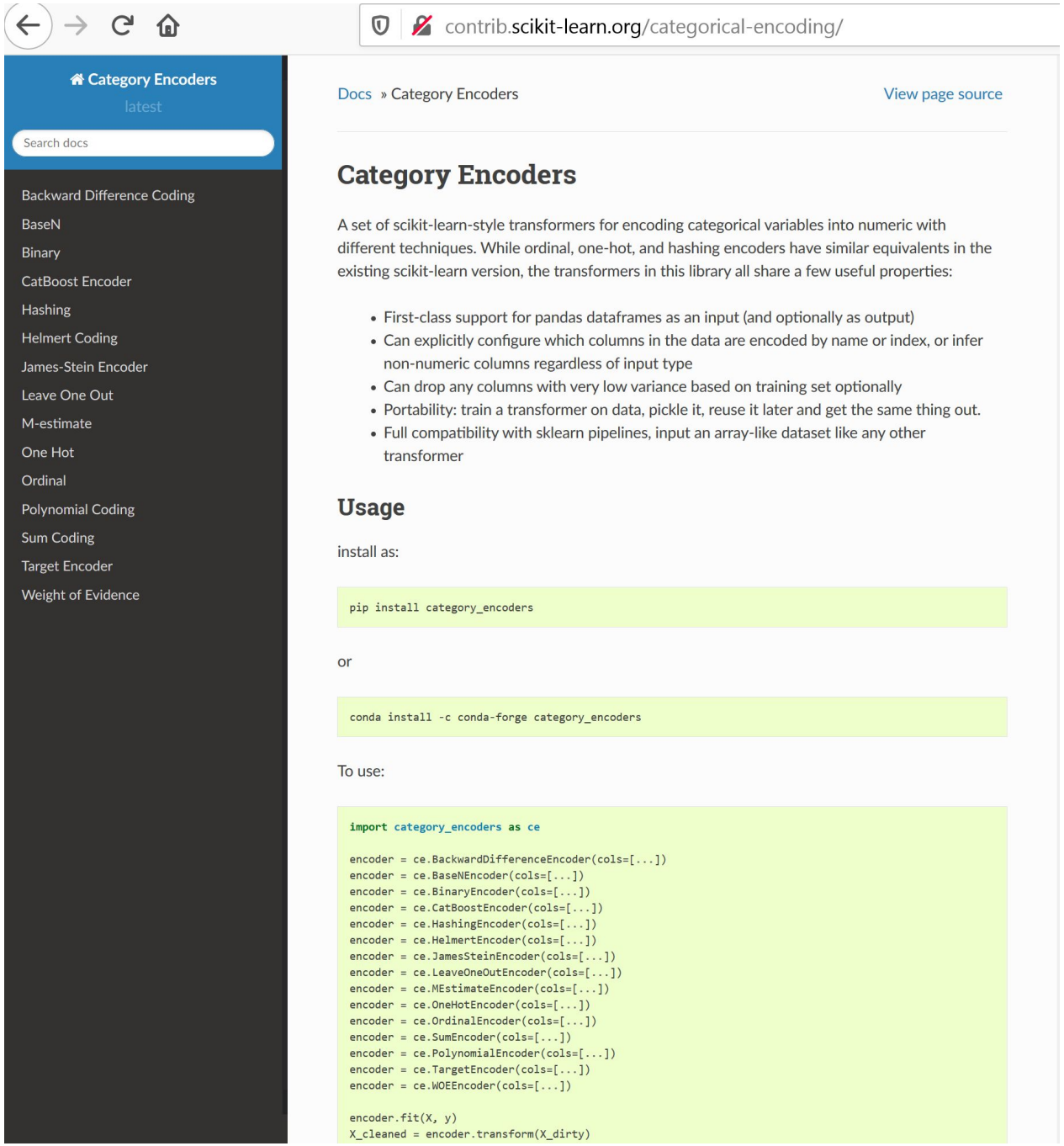
- Categorical Variable Encoding
  - CountFrequencyCategoricalEncoder
  - OrdinalCategoricalEncoder
  - MeanCategoricalEncoder
  - WoERatioCategoricalEncoder
  - OneHotCategoricalEncoder
  - RareLabelCategoricalEncoder

- Outlier Removal
  - Windsorizer
  - ArbitraryOutlierCapper

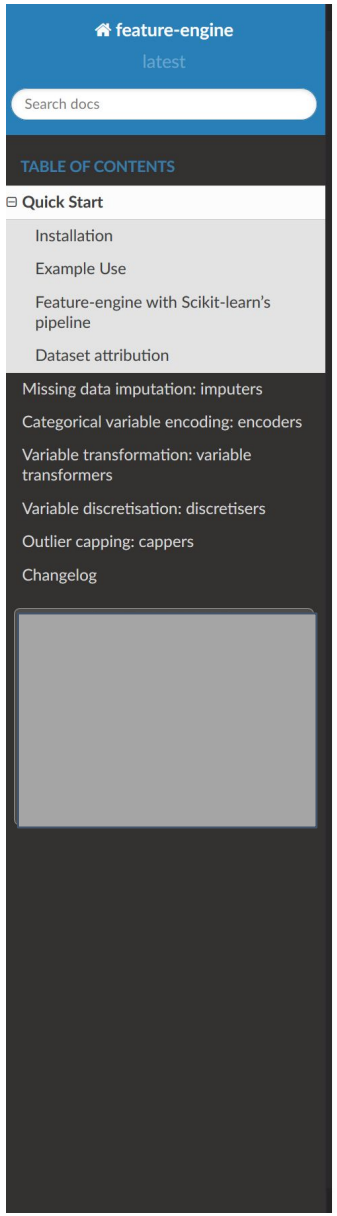
- Discretisation
  - EqualFrequencyDiscretiser
  - EqualWidthDiscretiser
  - DecisionTreeDiscretiser

- Variable Transformation
  - LogTransformer
  - ReciprocalTransformer
  - ExponentialTransformer
  - BoxCoxTransformer

Category Encoders



Pipeline with Feature-engine



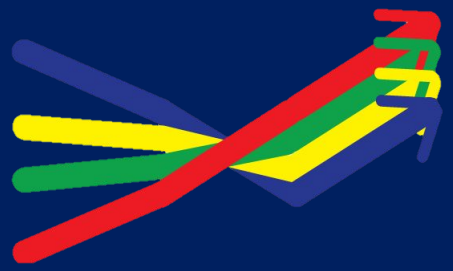

```
from math import sqrt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline as pipe
from sklearn.preprocessing import MinMaxScaler

from feature_engine import categorical_encoders as ce
from feature_engine import discretisers as dsc
from feature_engine import missing_data_imputers as mdi

# load dataset
data = pd.read_csv('houseprice.csv')

# drop some variables
data.drop(labels=['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'Id'], axis=1, inplace=True)

# categorical encoders work only with object type variables
data[discrete]= data[discrete].astype('O')

# separate into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data.drop(labels=['SalePrice'], axis=1),
                                                    data.SalePrice,
                                                    test_size=0.1,
                                                    random_state=0)

# set up the pipeline
price_pipe = pipe([
    # add a binary variable to indicate missing information for the 2 variables below
    ('continuous_var_imputer', mdi.AddNaNBinaryImputer(variables = ['LotFrontage'])),

    # replace NA by the median in the 2 variables below, they are numerical
    ('continuous_var_median_imputer', mdi.MeanMedianImputer(imputation_method='median', variables = ['Lo

    # replace NA by adding the label "Missing" in categorical variables
    ('categorical_imputer', mdi.CategoricalVariableImputer(variables = categorical)),

    # disretise numerical variables using trees
    ('numerical_tree_discretiser', dsc.DecisionTreeDiscretiser(cv = 3, scoring='neg_mean_squared_error',

    # remove rare labels in categorical and discrete variables
    ('rare_label_encoder', ce.RareLabelCategoricalEncoder(tol = 0.03, n_categories=1, variables = categ

    # encode categorical and discrete variables using the target mean
    ('categorical_encoder', ce.MeanCategoricalEncoder(variables = categorical+discrete)),

    # scale features
    ('scaler', MinMaxScaler()),

    # Lasso
    ('lasso', Lasso(random_state=2909, alpha=0.005))
     ])

# train feature engineering transformers and Lasso
price_pipe.fit(X_train, np.log(y_train))

# predict
pred_train = price_pipe.predict(X_train)
pred_test = price_pipe.predict(X_test)
```

Import predefined transformers

Accommodate transformers in the pipeline

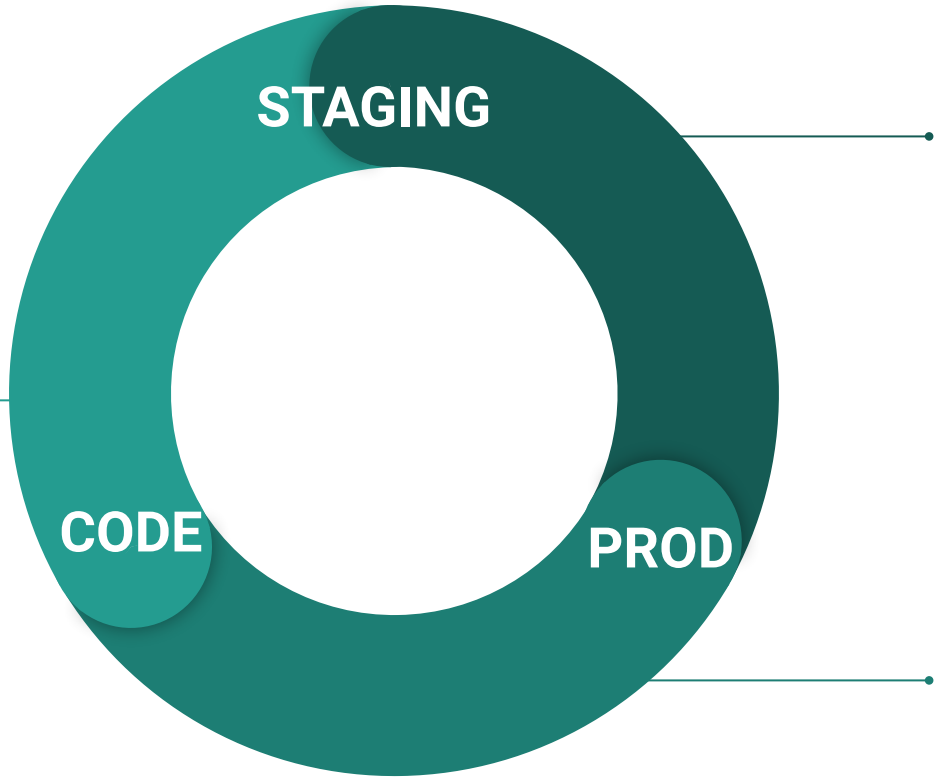
Fit the pipeline and make predictions

Should feature selection be part of the Machine Learning automated pipeline?



Feature selection in CI/CD

- New model
- Model refresh



Tests

- Model deployed
- Automatically available to other systems

Feature selection in CI/CD

Advantages

- Reduced overhead in the implementation of the new model
- The new model is almost immediately available to the business systems

Disadvantages

- Lack of data versatility
- No additional data can be fed through the pipeline, as the entire processes are based on the first dataset on which it was built

Feature selection in CI/CD

Including a feature selection algorithm as part of the pipeline,

- Ensures that from all the available features only the most useful ones are selected t train the model
- Potentially avoids overfitting
- Enhances model interpretability

However,

- We would need to deploy code to engineer all available features in the dataset, regardless of whether they will be finally used by the model
- Error handling and unit testing for all the code to engineering features

Feature selection in CI/CD

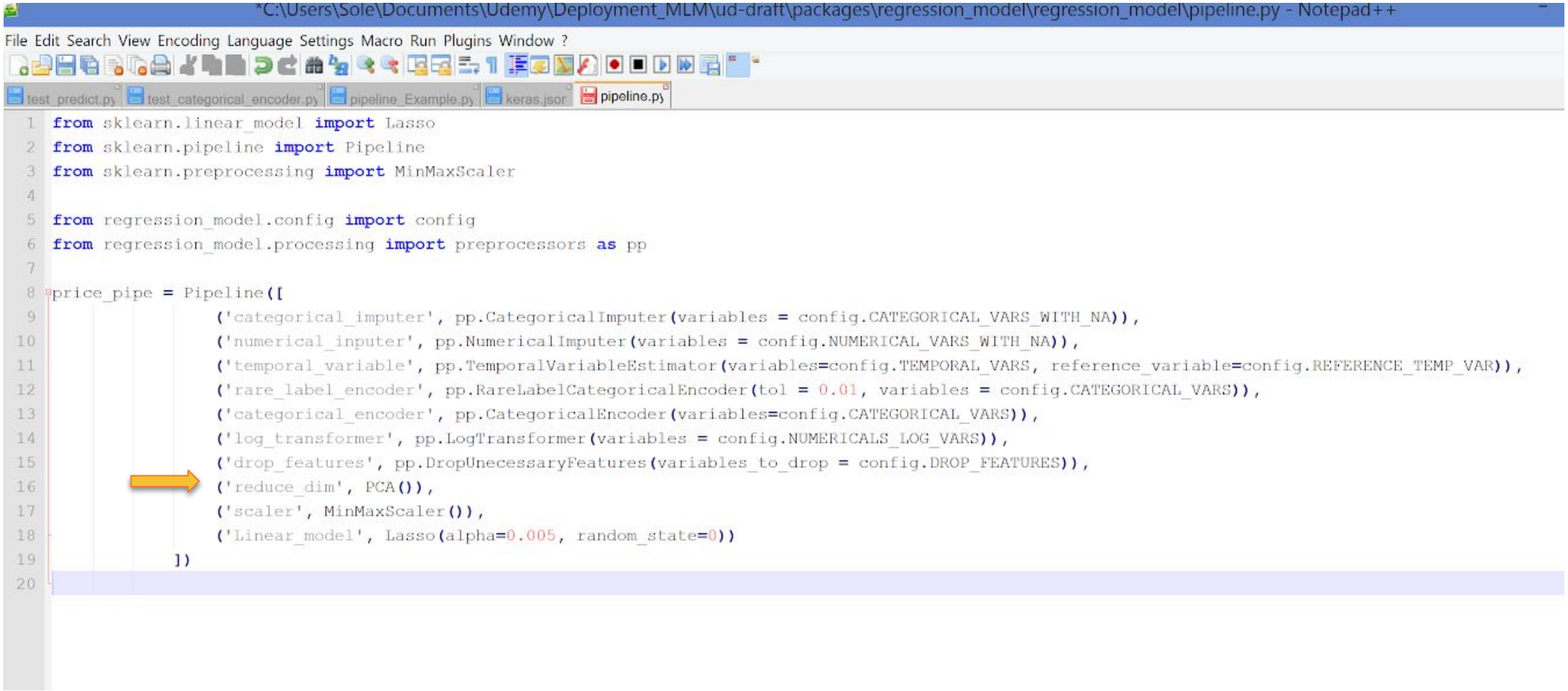
Suitable:

- Model build and refresh on same data
- Model build and refresh on smaller datasets

Not suitable,

- If model is built using datasets with a high feature space
- If model is constantly enriched with new data sources

Feature selection in the scikit-learn pipe



Feature selection transformer skeleton

```python
import numpy as np
import pandas as pd

from sklearn.base import BaseEstimator, TransformerMixin

from regression_model.processing import errors


# categorical missing value imputer
class MySpecificSelector(BaseEstimator, TransformerMixin):

    def __init__(self, some_param=None):
        self.some_param = some_param

    def fit(self, X, y=None):
        '''Code to select features. Any of your liking'''
        self.selected_features = output of the above code, the selected fetures

        return self

    def transform(self, X):
        X = X.copy()
        X = X[self.selected_features]
        return X
```