SAVE/LIKE FOR LATER

TOP 3

BAD CODING PRACTICES

DATA SCIENTISTS

should avoid

Pipeline.py

```python
from sklearn.linear_model import Lasso

class Pipeline:
    def __init__(self):
        pass

    def run(self, x, y):
        model = Lasso(alpha=0.1)
        x_train, y_train = x[:100], y[:100]
        model.fit(x_train, y_train)
        return model
```

Hardcoded parameters inside the method

TIMUR BIKMUKHAMETOV

SAVE/LIKE FOR LATER

1. Hardcoding ML pipeline and model configuration parameters

Pipeline.py

```python
from sklearn.linear_model import Lasso

class Pipeline:
    def __init__(self):
        pass

    def run(self, x, y):
        model = Lasso(alpha=0.1)
        x_train, y_train = x[:100], y[:100]
        model.fit(x_train, y_train)
        return model
```

Hardcoded parameters inside the method

Why is it bad?

SAVE/LIKE FOR LATER

Pipeline.py

```python
from sklearn.linear_model import Lasso

class Pipeline:
    def __init__(self):
        pass

    def run(self, x, y):
        model = Lasso(alpha=0.1)
        x_train, y_train = x[:100], y[:100]
        model.fit(x_train, y_train)
        return model
```

Hardcoding leads to:

- Difficulty in making changes if the codebase is big
- Difficulty in adapting parameters for similar modeled objects without lengthy "if-else" statements.
- Need for re-deployment if the parameters need to be changed.

Instead ...

SAVE/LIKE FOR LATER

1. Create a config file (.yaml should do)

2. Initialize config as a class attribute

Pipeline.py

```python
from sklearn.linear_model import Lasso

class Pipeline:
    def __init__(self, config):
        self.config = config

    def run(self, x, y):
        model = Lasso(alpha=self.config['alpha'])
        x_train = x[:self.config['train_size']]
        y_train = y[:self.config['train_size']]
        model.fit(x_train, y_train)
        return model
```

3. Get values from the attribute

Config allows:

- Easy finding and changing parameters in one place
- Avoiding re-deployment of an ML application, parameters can be changed on the fly
- Flexible selection of these parameters in the code, e.g. hyperparameters tuning.

Next!

SAVE/LIKE FOR LATER

2. Ignoring Modularization

Pipeline.py

```python
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


class Pipeline:
    def __init__(self, config):
        self.config = config

    def run(self, df):
        x_train, x_test, y_train, y_test = train_test_split(
            df.drop('target', axis=1),
            df['target'],
            test_size=self.config['test_size'])
        scaler_x = StandardScaler()
        scaler_y = StandardScaler()
        x_train_sc = scaler_x.fit_transform(x_train)
        y_train_sc = scaler_y.fit_transform(y_train)
        model = Lasso(alpha=self.config['alpha'])
        model.fit(x_train_sc, y_train_sc)
        return model
```

Splitting, scaling, and fitting are done in one function

Why is it bad?

SAVE/LIKE FOR LATER

Pipeline.py

```python
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


class Pipeline:
    def __init__(self, config):
        self.config = config

    def run(self, df):
        x_train, x_test, y_train, y_test = train_test_split(
            df.drop('target', axis=1),
            df['target'],
            test_size=self.config['test_size'])
        scaler_x = StandardScaler()
        scaler_y = StandardScaler()
        x_train_sc = scaler_x.fit_transform(x_train)
        y_train_sc = scaler_y.fit_transform(y_train)
        model = Lasso(alpha=self.config['alpha'])
        model.fit(x_train_sc, y_train_sc)
        return model
```

Ignoring modularization leads to:

- **Poor code readability and difficulty in following data transformation**
- **Difficult maintenance and testing**
- **Code repetition and limited reusability**

Instead ...

SAVE/LIKE FOR LATER

Split the code into functions (class methods)

Pipeline.py

```python
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

class Pipeline:
    def __init__(self, config):
        self.config = config

    def get_train_test_data(self, df):
        x_train, x_test, y_train, y_test = train_test_split(
            df.drop('target', axis=1),
            df['target'],
            test_size=self.config['test_size'])
        return x_train, x_test, y_train, y_test

    @staticmethod
    def scale_data(x, y):
        scaler_x = StandardScaler()
        scaler_y = StandardScaler()
        x_sc = scaler_x.fit_transform(x)
        y_sc = scaler_y.fit_transform(y)
        return x_sc, y_sc

    def fit_model(self, x, y):
        model = Lasso(alpha=self.config['alpha'])
        model.fit(x, y)
        return model

    def run(self, df):
        x_train, x_test, y_train, y_test = self.get_train_test_data(df)
        x_train_sc, y_train_sc = self.scale_data(x_train, y_train)
        model = self.fit_model(x_train_sc, y_train_sc)
        return model
```

Ideally, one function should perform one task

Good practice for "run" method is only to call other methods

Next!

SAVE/LIKE FOR LATER

3. Avoiding type annotations and documenting the code

Pipeline.py

```python
from sklearn.preprocessing import StandardScaler

def scale_data(x, y):
    scaler_x = StandardScaler()
    scaler_y = StandardScaler()
    x_sc = scaler_x.fit_transform(x)
    y_sc = scaler_y.fit_transform(y)
    return x_sc, y_sc
```

No annotation and docstring

Why is it bad?

SAVE/LIKE FOR LATER

Pipeline.py

```python
from sklearn.preprocessing import StandardScaler

def scale_data(x, y):
    scaler_x = StandardScaler()
    scaler_y = StandardScaler()
    x_sc = scaler_x.fit_transform(x)
    y_sc = scaler_y.fit_transform(y)
    return x_sc, y_sc
```

No annotation and docstring

This leads to:

- **Poor code readability, especially for other developers**
- **Inability to check type-related issues for linters**
- **Poor maintainability, especially in big codebases**
- **Inability to produce high-quality code documentation**

Instead ...

SAVE/LIKE FOR LATER

Add typing annotations and docstrings

Pipeline.py

```python
def scale_data(x: pd.DataFrame, y: pd.Series) -> Tuple[np.ndarray, np.ndarray]:
    """
    Scales the input features and target column using StandardScaler.

    Parameters:
    x: The input features as a pandas DataFrame.
    y: The target column as a pandas Series.

    Returns:
    x_sc, y_sc: a tuple containing the scaled features and scaled target as numpy arrays.
    """
    scaler_x = StandardScaler()
    scaler_y = StandardScaler()
    x_sc = scaler_x.fit_transform(x)
    y_sc = scaler_y.fit_transform(y)
    return x_sc, y_sc
```

Even in this simple case, we can see that we change the data type from a dataframe to NumPy arrays

Let's see tips altogether!

SAVE/LIKE FOR LATER

Bad practices code

Pipeline.py

```python
class Pipeline:
    def __init__(self):
        pass

    def run(self, df):
        x_train, x_test, y_train, y_test = train_test_split(
            df.drop('target', axis=1),
            df['target'],
            test_size=0.2)
        scaler_x = StandardScaler()
        scaler_y = StandardScaler()
        x_train_sc = scaler_x.fit_transform(x_train)
        y_train_sc = scaler_y.fit_transform(y_train)
        model = Lasso(alpha=0.1)
        model.fit(x_train_sc, y_train_sc)
        return model
```

- Hardcoded
- Monolithic
- Hard to test
- Hard to understand if the code growths

Instead ...

SAVE/LIKE FOR LATER

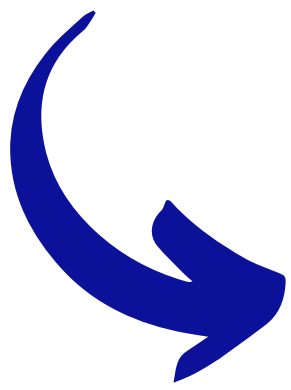
Best practices code

Pipeline.py

```python
class Pipeline:
    def __init__(self, config: Dict[Any, Any]):
        """
        Initializes the Pipeline with the given configuration file.
        """
        self.config = config

    def get_train_test_data(self, df: pd.DataFrame) -> Tuple[pd.DataFrame, pd.DataFrame, pd.Series, pd.Series]:
        """
        Splits the DataFrame into training and testing sets.

        Parameters:
        df: The input DataFrame containing features and target.

        Returns:
        x_train, x_test, y_train, y_test: The training and testing sets for features and target.
        """
        x_train, x_test, y_train, y_test = train_test_split(
            df.drop('target', axis=1),
            df['target'],
            test_size=self.config['test_size'])
        return x_train, x_test, y_train, y_test

    @staticmethod
    def scale_data(x: pd.DataFrame, y: pd.Series) -> Tuple[np.ndarray, np.ndarray]:
        """
        Scales the features and target using StandardScaler.

        Parameters:
        x (pd.DataFrame): The input features as a pandas DataFrame.
        y (pd.Series): The target column as a pandas Series.

        Returns:
        x_sc, y_sc: The scaled features and target as numpy arrays.
        """
        scaler_x = StandardScaler()
        scaler_y = StandardScaler()
        x_sc = scaler_x.fit_transform(x)
        y_sc = scaler_y.fit_transform(y.values.reshape(-1, 1)).flatten()
        return x_sc, y_sc

    def fit_model(self, x: np.ndarray, y: np.ndarray) -> BaseEstimator:
        """
        Fits a Lasso model to the scaled training data.

        Parameters:
        x (np.ndarray): The scaled training features.
        y (np.ndarray): The scaled training target.

        Returns:
        model: The trained Lasso model.
        """
        model = Lasso(alpha=self.config['alpha'])
        model.fit(x, y)
        return model

    def run(self, df: pd.DataFrame) -> BaseEstimator:
        """
        Runs the complete pipeline: data splitting, scaling, and model fitting.

        Parameters:
        df (pd.DataFrame): The input DataFrame containing features and target.

        Returns:
        model: The trained Lasso model.
        """
        x_train, x_test, y_train, y_test = self.get_train_test_data(df)
        x_train_sc, y_train_sc = self.scale_data(x_train, y_train)
        model = self.fit_model(x_train_sc, y_train_sc)
        return model
```

- Configurable
- Less error-prone
- Easy to read
- Easy to maintain
- Easy to test

You may think it is too much...



SAVE/LIKE FOR LATER

Short answer - No!

Long answer:

- This code is scalable to more complex pipelines and multiple ML model cases
- In a growing codebase, it will be more maintainable
- It is easy to collaborate with colleagues and future yourself

Finally...

Want to see more tips like this?

Like post

Follow Follow me

so I know that the content resonates!

TIMUR BIKMUKHAMETOV