**Code Explaination**

1. **Target and Type of regression**

The dataset file path and metadata such as the target variable and prediction type are extracted from  **algoparams\_from\_ui.json** file.

* **df** holds the full dataset.
* **target\_variable** defines the column to be predicted.
* **prediction\_type** specifies whether the task is **regression** or **classification**.

1. **Custom Custom\_Feature\_Handling**

I built a **custom transformer** called Custom\_Feature\_Handling to clean and prepare both **numerical** and **text** features — all based on instructions from a JSON configuration.

**Handling Numerical Features**

For each numerical column in the dataset, we check:

* **Is the column selected for modelling ?**
* **Are there missing values?** If yes, we fill them using:
  + The **average (mean)** of the column, or
  + A **custom value** defined in the config file.

This makes sure that model doesn’t break because of missing values and keeps things consistent.

### Handling Text Features

Text columns are handled slightly different:

* If there's any **missing text**, fill it with "missing\_text" to avoid errors.
* If the configuration says to use "Tokenize and hash":
  + We apply a **hashing trick** to turn the text into a fixed number of numerical columns.

This step ensures that text data can be used in the model, without adding unnecessary complexity.

1. **Custom Custom\_Feature\_Reduction**

We created a custom class called Custom\_Feature\_Reduction that reduces dataset's size by keeping only the most relevant columns.

And the best part?

It adapts its strategy based on what’s defined in the configuration JSON.

### Modes Strategies

Depending on what’s set in the config, the transformer can use **one of four strategies**:

#### **1. Correlation with Target**

* Measures how strongly each feature relates to the target variable.
* Keeps the **top K** features that show the strongest correlation.

#### **2. Tree-Based Importance**

* Trains a **Random Forest** to find which features are most important in making predictions.
* Ranks features by their importance scores from the forest.
* Selects the **top K** features that contribute most to accuracy.

#### **3. Principal Component Analysis (PCA)**

* PCA compresses many correlated features into a few **uncorrelated components**.
* It’s like blending information from several features into fewer new ones.
* Keeps only the top **N components** that explain the most variance.

#### **4. No Reduction**

* If the config says "No Reduction", the transformer **keeps all columns** (or a fixed number of them).

1. **Hyper parameter tuning i.e., use GridSearchCV**

Most important step is **choosing the best model** to make predictions. But different models have different strengths — and they need the **right hyperparameters** to perform well.

**Selects, tunes, and evaluates models using GridSearchCV**

### Step 1: MODEL\_tune() Mapping of models to hyperparameters

If I want to use model X, then these are the hyperparameters I should try tuning and here's how to extract those tuning ranges from the config data.

**MODEL\_tune** **declares what to tune** and **how to fetch the range definition** from the input config.

The following regression and classification models are tuned:

* **Regression**:
  + LinearRegression, Ridge, Lasso, ElasticNet
  + RandomForestRegressor, DecisionTreeRegressor
  + GradientBoostingRegressor, ExtraTreesRegressor, XGBRegressor
  + MLPRegressor (neural network)
* **Classification**:
  + LogisticRegression, RandomForestClassifier, DecisionTreeClassifier
  + GradientBoostingClassifier, ExtraTreesClassifier, XGBClassifier
  + SVM, KNeighborsClassifier, MLPClassifier, SGDClassifier

### Step 2: build\_pmt\_grid() Creates the actual parameter grid

This function **interprets the hyperparameter definitions** from MODEL\_tune and **builds the final parameter grid** that will be passed to GridSearchCV.

build\_pmt\_grid **converts abstract definitions into real values** to form a concrete pmt\_grid

**Step 3 :**  Custom **ModelSelectionWithGridSearch**

This project automates that process through a custom scikit-learn-compatible class called ModelSelectionWithGridSearch.

It is designed to **choose, configure, and fine-tune** machine learning models using parameters provided in a JSON configuration file.

### What This Component Does

The ModelSelectionWithGridSearch class acts as the **final estimator** in the pipeline. It performs the following steps programmatically:

1. **Parses the JSON configuration** to determine:
   * Whether the task is **regression** or **classification**
   * Which models are selected ("is\_selected": true)
   * What parameter ranges should be explored during hyperparameter tuning
2. **Builds model instances** using scikit-learn classes like RandomForestRegressor, LogisticRegression, SVC, MLPClassifier, etc., depending on the type of task.
3. **Creates parameter grids** from the JSON file using keys like range(min,max) or range\_float(min,max,step) that are parsed into actual hyperparameter value ranges.
4. **Runs GridSearchCV** on each selected model:
   * Uses **5-fold cross-validation** (KFold) to evaluate each hyperparameter combination
   * Identifies the best-performing combination for each model
   * Stores the model and its best parameters for later use
5. **Returns a list of best estimators**, one for each selected model, sorted by their validation performance.

Each of these models can be **turned on/off** and **customized** just by changing values in the JSON file — making the system highly modular and reusable.

1. **Execute the pipeline**

### Building the Pipeline

The pipeline is constructed with three core components:

Custom\_Feature\_Handling

Custom\_Feature\_Reduction

ModelSelectionWithGridSearch

**Output**

At the end of this step:

* We get the **best version of each selected model**, tuned and validated.
* These models are stored in self.selected\_models\_ as a list of tuples: (model\_name, best\_estimator\_).

This design makes it **extremely reusable and configurable**. Just change the JSON file, and you can handle a completely new dataset, apply different reduction strategies, or try different model/hyperparameter combinations — **without changing the code**.