## **Cheat Sheet: Building Supervised Learning Models**

## **Common supervised learning models**

<b>Process Name</b>	Brief Description	Code Syntax
One vs One classifier (using logistic regression)	Process: This method trains one classifier for each pair of classes.  Key hyperparameters: - `estimator`: Base classifier (e.g., logistic regression)  Pros: Can work well for small datasets.  Cons: Computationally expensive for large datasets.  Common applications: Multiclass classification problems where the number of classes is relatively small.	<pre>1. from sklearn.multiclass import     OneVsOneClassifier 2. from sklearn.linear_model import     LogisticRegression 3. model =     OneVsOneClassifier(LogisticRegression())</pre>

<b>Process Name</b>	Brief Description	Code Syntax
One vs All classifier (using logistic regression)	Process: Trains one classifier per class, where each classifier distinguishes between one class and the rest.  Key hyperparameters: - `estimator`: Base classifier (e.g., Logistic Regression) - `multi_class`: Strategy to handle multiclass classification (`ovr`)  Pros: Simpler and more scalable than One vs One.  Cons: Less accurate for highly imbalanced classes.  Common applications: Common in multiclass classification problems such as image classification.	<pre>1. from sklearn.multiclass import     OneVsRestClassifier 2. from sklearn.linear_model import     LogisticRegression 3. model =     OneVsRestClassifier(LogisticRegression()) or  1. from sklearn.linear_model import     LogisticRegression 2. model_ova =     LogisticRegression(multi_class='ovr')</pre>

Process Name	Brief Description	Code Syntax
Decision tree classifier	Process: A tree-based classifier that splits data into smaller subsets based on feature values.  Key hyperparameters: - `max_depth`: Maximum depth of the tree Pros: Easy to interpret and visualize.  Cons: Prone to overfitting if not pruned properly.  Common applications: Classification tasks, such as credit risk assessment.	<pre>1. from sklearn.tree import     DecisionTreeClassifier 2. model = DecisionTreeClassifier(max_depth=5)</pre>
Decision tree regressor	Process: Similar to the decision tree classifier, but used for regression tasks to predict continuous values.  Key hyperparameters: - `max_depth`: Maximum depth of the tree  Pros: Easy to interpret, handles nonlinear data.  Cons: Can overfit and perform poorly on noisy data.  Common applications: Regression tasks, such as predicting housing prices.	<pre>1. from sklearn.tree import     DecisionTreeRegressor 2. model = DecisionTreeRegressor(max_depth=5)</pre>

Process Name	Brief Description	Code Syntax
Linear SVM classifier	Process: A linear classifier that finds the optimal hyperplane separating classes with a maximum margin.  Key hyperparameters: - `C`: Regularization parameter - `kernel`: Type of kernel function (`linear`, `poly`, `rbf`, etc.) - `gamma`: Kernel coefficient (only for `rbf`, `poly`, etc.)  Pros: Effective for high-dimensional spaces.  Cons: Not ideal for nonlinear problems without kernel tricks.  Common applications: Text classification and image recognition.	<pre>1. from sklearn.svm import SVC 2. model = SVC(kernel='linear', C=1.0)</pre>

Process Name	Brief Description	Code Syntax
K-nearest neighbors classifier	Process: Classifies data based on the majority class of its nearest neighbors.  Key hyperparameters:  '`n_neighbors`: Number of neighbors to use  '`weights`: Weight function used in prediction (`uniform` or `distance`)  '`algorithm`: Algorithm used to compute the nearest neighbors (`auto`, `ball_tree`, `kd_tree`, `brute`)  Pros: Simple and effective for small datasets.  Cons: Computationally expensive as the dataset grows.  Common applications: Recommendation systems, image recognition.	<ol> <li>from sklearn.neighbors import         KNeighborsClassifier</li> <li>model = KNeighborsClassifier(n_neighbors=5,         weights='uniform')</li> </ol>

Process Name	<b>Brief Description</b>	Code Syntax
Random Forest regressor	Process: An ensemble method using multiple decision trees to improve accuracy and reduce overfitting.  Key hyperparameters: - `n_estimators`: Number of trees in the forest - `max_depth`: Maximum depth of each tree  Pros: Less prone to overfitting than individual decision trees.  Cons: Model complexity increases with the number of trees.  Common applications: Regression tasks such as predicting sales or stock prices.	<pre>1. from sklearn.ensemble import   RandomForestRegressor 2. model =   RandomForestRegressor(n_estimators=100,   max_depth=5)</pre>

Process Name	<b>Brief Description</b>	Code Syntax
XGBoost regressor	Process: A gradient boosting method that builds trees sequentially to correct errors from previous trees.  Key hyperparameters: - `n_estimators`: Number of boosting rounds - `learning_rate`: Step size to improve accuracy - `max_depth`: Maximum depth of each tree  Pros: High accuracy and works well with large datasets.  Cons: Computationally intensive, complex to tune.  Common applications: Predictive modeling, especially in Kaggle competitions.	<pre>1. import xgboost as xgb 2. model = xgb.XGBRegressor(n_estimators=100,     learning_rate=0.1, max_depth=5)</pre>

## **Associated functions used**

Method Name	Brief Description	Code Syntax
OneHotEncoder	Transforms categorical features into a one-hot encoded matrix.	<ol> <li>from sklearn.preprocessing import OneHotEncoder</li> <li>encoder = OneHotEncoder(sparse=False)</li> <li>encoded_data = encoder.fit_transform(categorical_data)</li> </ol>
accuracy_score	Computes the accuracy of a classifier by comparing predicted and true labels.	<ol> <li>from sklearn.metrics import accuracy_score</li> <li>accuracy = accuracy_score(y_true, y_pred)</li> </ol>
LabelEncoder	Encodes labels (target variable) into numeric format.	<ol> <li>from sklearn.preprocessing import LabelEncoder</li> <li>encoder = LabelEncoder()</li> <li>encoded_labels = encoder.fit_transform(labels)</li> </ol>
plot_tree	Plots a decision tree model for visualization.	<ol> <li>from sklearn.tree import plot_tree</li> <li>plot_tree(model, max_depth=3, filled=True)</li> </ol>
normalize	Scales each feature to have zero mean and unit variance (standardization).	<ol> <li>from sklearn.preprocessing import normalize</li> <li>normalized_data = normalize(data, norm='12')</li> </ol>

Method Name	Brief Description	Code Syntax
compute_sample_weight	Computes sample weights for imbalanced datasets.	<ol> <li>from sklearn.utils.class_weight import         compute_sample_weight</li> <li>weights =         compute_sample_weight(class_weight='balanced',         y=y)</li> </ol>
roc_auc_score	Computes the Area Under the Receiver Operating Characteristic Curve (AUC- ROC) for binary classification models.	<ol> <li>from sklearn.metrics import roc_auc_score</li> <li>auc = roc_auc_score(y_true, y_score)</li> </ol>