Cheat Sheet: Building Supervised Learning Models

Common supervised learning models

Process Name	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.
		`from sklearn.multiclass import OneVsOneClassifier`
		`from sklearn.linear_model import LogisticRegression`
		`model = OneVsOneClassifier(LogisticRegression())`

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.
		`from sklearn.multiclass import OneVsRestClassifier`
		`from sklearn.linear_model import LogisticRegression`
		`model = OneVsRestClassifier(LogisticRegression())`
		or
		`from sklearn.linear_model import LogisticRegression`
		`model_ova = LogisticRegression(multi_class='ovr')`

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.	`from sklearn.tree import DecisionTreeClassifier` `model = DecisionTreeClassifier(max_depth=5)`
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.	`from sklearn.tree import DecisionTreeRegressor` `model = DecisionTreeRegressor(max_depth=5)`
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.	`from sklearn.svm import SVC` `model = SVC(kernel='linear', C=1.0)`

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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.	`from sklearn.neighbors import KNeighborsClassifier` `model = KNeighborsClassifier(n_neighbors=5, weights='uniform')`
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.	`from sklearn.ensemble import RandomForestRegressor` `model = RandomForestRegressor(n_estimators=100, max_depth=5)`
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.	`import xgboost as xgb` `model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1, max_depth=5)`

Associated functions used

Method Name	Brief Description	Code Syntax

OneHotEncoder	Transforms categorical features into a one-hot encoded matrix.	`from sklearn.preprocessing import OneHotEncoder`
		`encoder = OneHotEncoder(sparse=False)`
		`encoded_data = encoder.fit_transform(categorical_data)`

accuracy_score	Computes the accuracy of a classifier by comparing predicted and true labels.	`from sklearn.metrics import accuracy_score` `accuracy = accuracy_score(y_true, y_pred)`

LabelEncoder	Encodes labels (target variable) into numeric format.	`from sklearn.preprocessing import LabelEncoder`
		`encoder = LabelEncoder()`
		`encoded_labels = encoder.fit_transform(labels)`

Method Name	Brief Description	Code Syntax
plot_tree	Plots a decision tree model for visualization.	`from sklearn.tree import plot_tree` `plot_tree(model, max_depth=3, filled=True)`
normalize	Scales each feature to have zero mean and unit variance (standardization).	`from sklearn.preprocessing import normalize` `normalized_data = normalize(data, norm='l2')`
compute_sample_weight	Computes sample weights for imbalanced datasets.	`from sklearn.utils.class_weight import compute_sample_weight` `weights = compute_sample_weight(class_weight='balanced', y=y)`
roc_auc_score	Computes the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) for binary classification models.	`from sklearn.metrics import roc_auc_score` `auc = roc_auc_score(y_true, y_score)`

Author

Jeff Grossman
Abhishek Gagneja

Skills Network