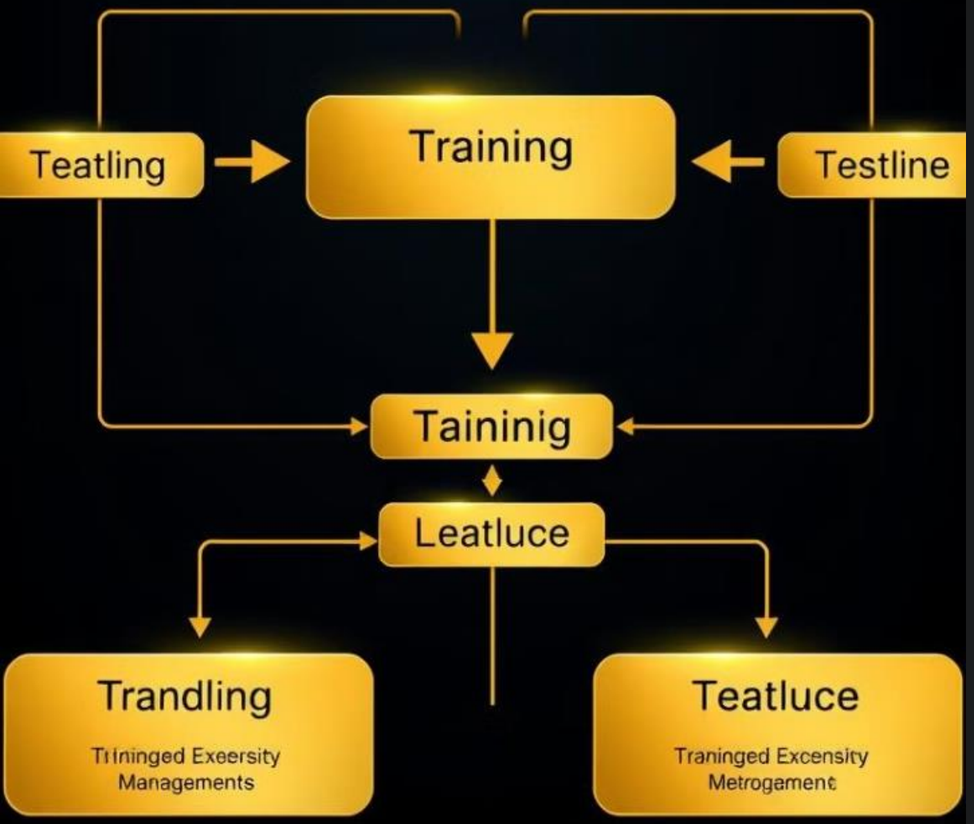


Cross-Validation and Model Evaluation Techniques

This presentation will cover cross-validation and model evaluation techniques, essential aspects of machine learning. We'll delve into various methods like train-test split, K-fold cross-validation, and leave-one-out cross-validation. We will also explore the bias-variance tradeoff and important metrics like accuracy, precision, recall, and F1-score.

By Nisha A K

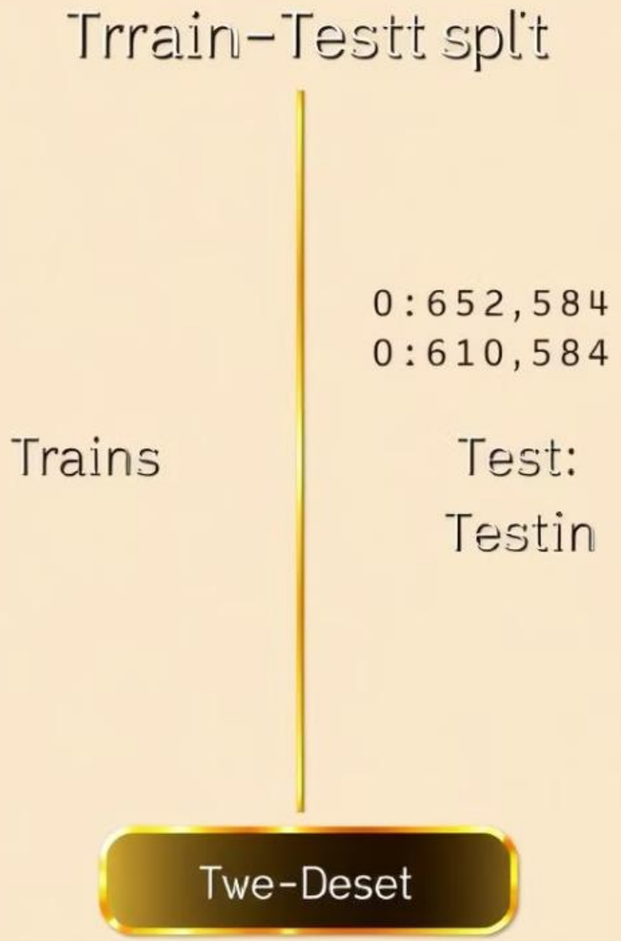
The Importance of Model Evaluation

Unbiased assessment

Model evaluation helps us understand how well a model performs on unseen data, providing an unbiased assessment of its accuracy and reliability.

Model comparison

Comparing different models using various metrics allows us to choose the best model for our specific task and dataset.



Train-Test Split

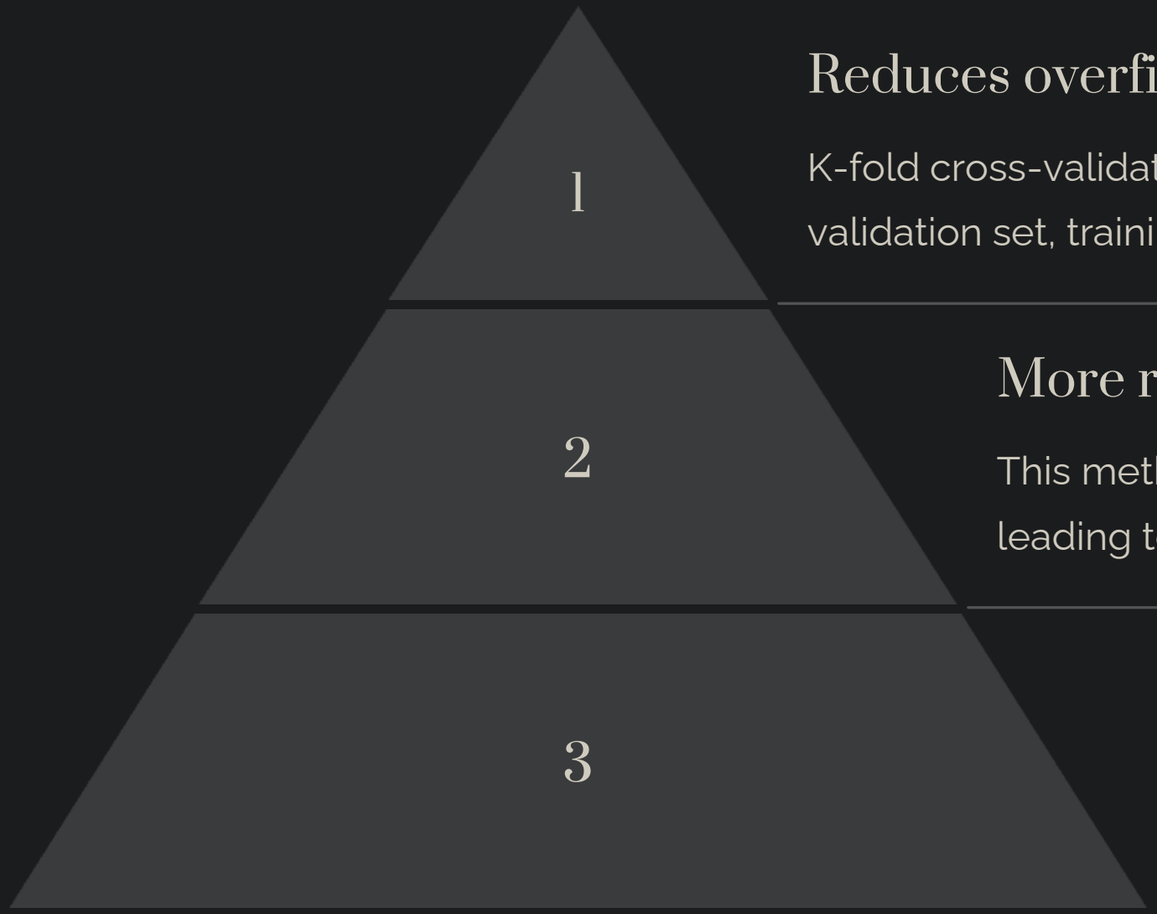
Simple and efficient

The train-test split divides a dataset into two parts: training and testing. The training set is used to train the model, while the testing set is used to evaluate its performance.

Limited data

This method works well with large datasets, but it may not be ideal for smaller datasets because it can result in a limited number of samples for evaluation.

K-Fold Cross-Validation



Reduces overfitting

K-fold cross-validation divides the data into K folds and uses each fold as a validation set, training the model on the remaining folds.

More robust

This method is more robust and reliable than a single train-test split, leading to a more accurate estimate of the model's performance.

Computational cost

K-fold cross-validation is computationally more expensive than a single train-test split.

Leave-One-Out Cross-Validation

1

High variance

Leave-one-out cross-validation (LOOCV) uses each data point as a validation set, training the model on the remaining data.

2

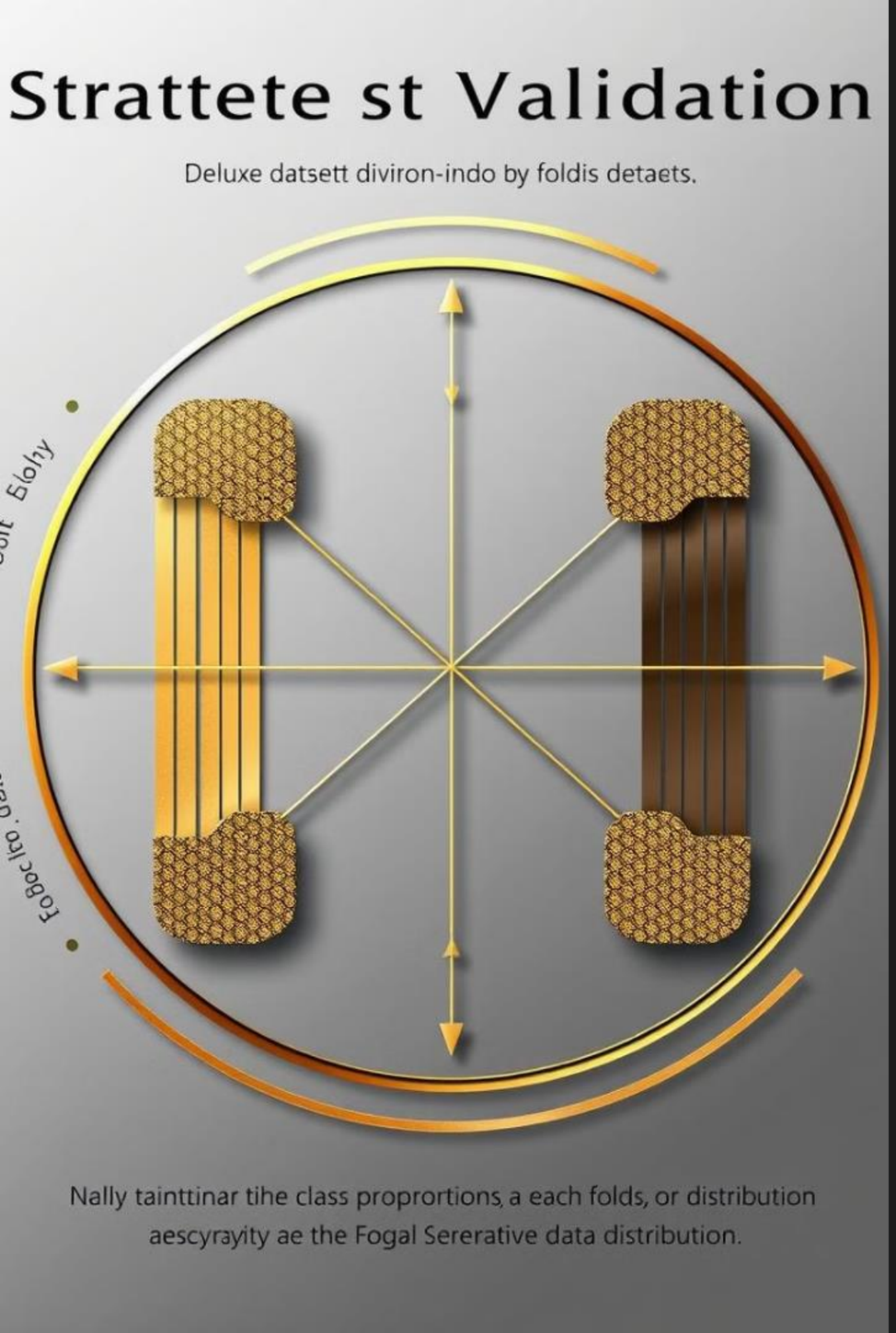
Very computationally expensive

LOOCV is highly accurate but computationally expensive, especially with large datasets.

3

Used for small datasets

LOOCV is typically used for smaller datasets because it can be highly time-consuming with larger datasets.



Stratified Cross-Validation

Class balance

Stratified cross-validation ensures that the class distribution in each fold reflects the original dataset's proportions, preserving the balance.

More accurate evaluation

This method is particularly useful when dealing with imbalanced datasets, leading to a more accurate evaluation.

Bias-Variance Tradeoff

1

Bias

Bias refers to the error introduced by a model's assumptions.

2

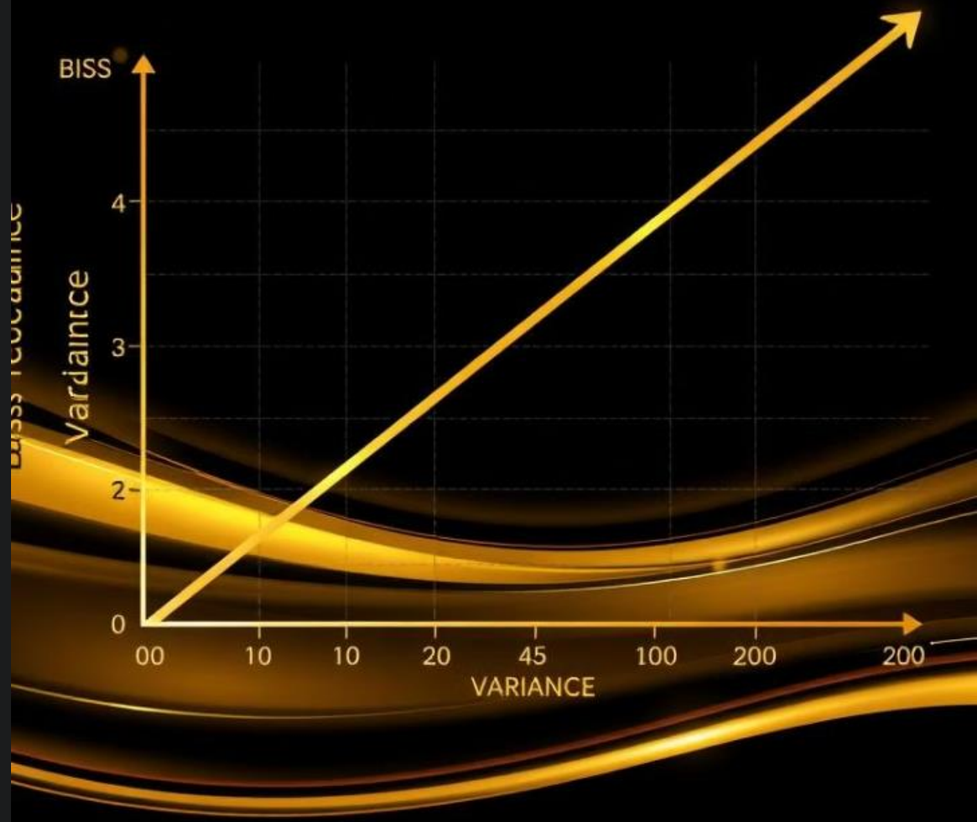
Variance

Variance represents the model's sensitivity to the specific training data.

3

Balance

The goal is to find a balance between bias and variance to achieve optimal model performance.



Evaluation Metrics

Accuracy

Accuracy represents the overall proportion of correctly classified instances.

Precision

Precision measures the proportion of correctly predicted positive instances out of all predicted positive instances.

Recall

Recall measures the proportion of correctly predicted positive instances out of all actual positive instances.

F1-score

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance.

Hyperparameter Tuning and Cross-Validation

1

Hyperparameters

Hyperparameters are parameters that control the learning process of a model.

2

Cross-validation

Hyperparameter tuning is often performed using cross-validation to find the best hyperparameters for the model.

Overfitting and Underfitting