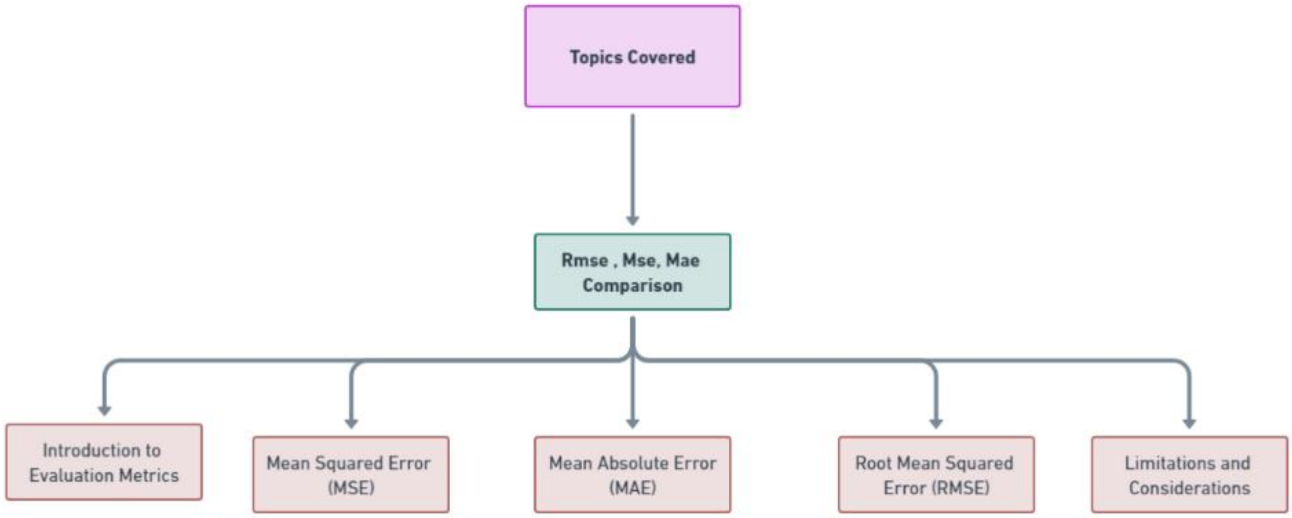
Lesson Plan

Advanced Constraints

Topic's Covered

- Introduction to Evaluation Metrics
- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Limitations and Considerations



Introduction to Evaluation Metrics

- Machine learning models are designed to make predictions or classifications based on patterns learned from data. However, building a model is not enough; we need a systematic way to assess its performance.
- Evaluation metrics play a crucial role in quantifying how well a model is performing, helping us understand its strengths and weaknesses. Without proper evaluation, it's challenging to gauge the effectiveness of a model and make informed decisions about its deployment.
- Selecting the right evaluation metrics is essential because different problems require different measures of success.
- For example, in a regression problem, we might be interested in how close our predictions are to the actual values, while in a classification problem, we might be more concerned with the accuracy of predicting classes.
- Choosing appropriate metrics ensures that the evaluation aligns with the specific goals and characteristics of the problem at hand, providing meaningful insights for model improvement.

Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- MSE calculates the squared difference between each prediction and the actual value, emphasizing larger errors due to squaring. This has the effect of penalizing larger errors more heavily than smaller ones.
- Squaring the differences also ensures that negative and positive errors don't cancel each other out, providing a clear measure of overall model accuracy.
- The use of squared differences in MSE serves several purposes:
  - Emphasis on Larger Errors: Squaring amplifies the impact of larger errors, making the model more sensitive to significant deviations.
  - Mathematical Convenience: Squaring eliminates the need to consider the direction of errors (overestimation or underestimation), simplifying mathematical computations.
  - Continuous and Differentiable: Squaring maintains the continuity and differentiability of the error function, which is crucial for optimization algorithms used in model training.
- **Code Implementation:**

```
# Import necessary libraries
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,
mean_absolute_error
import numpy as np

# Load the Diabetes dataset
data = load_diabetes()
X = data.data
y = data.target

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Initialize the linear regression model
model = LinearRegression()

# Train the model on the training set
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)

# Print the MSE score
print(f'Mean Squared Error (MSE): {mse}')
```

Output:

Mean Squared Error (MSE): 2900.193628493482

Mean Absolute Error (MAE)

- Mean Absolute Error (MAE) is a metric used to measure the average absolute difference between the actual and predicted values in a set of data points. It is a popular evaluation metric in regression problems.
- The formula for MAE is given by:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- MAE measures the average absolute difference between the actual and predicted values.
- Unlike Mean Squared Error (MSE), MAE does not square the differences, making it less sensitive to outliers. Each absolute difference contributes equally to the overall error, providing a straightforward interpretation of the model's performance.
- Comparison with MSE, Highlighting the Differences:
  - **Sensitivity to Outliers:** MAE is less sensitive to outliers than MSE since it doesn't magnify the impact of large errors. This makes MAE a more robust metric when dealing with datasets containing extreme values.
  - **Interpretability:** MAE represents the average absolute error, and its values are in the same unit as the original data, making it more interpretable compared to MSE, where errors are squared.
- **Code:**

```
# we will use same dataset used for MSE
# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_pred)

print(f'Mean Absolute Error (MAE): {mae}')
```

Output:

Mean Absolute Error (MAE): 42.79409467959994

Root Mean Squared Error (RMSE)

- Root Mean Squared Error (RMSE) is a modified version of MSE and is often used as an evaluation metric in regression problems.
- It is the square root of the average of the squared differences between actual and predicted values.
- The formula for RMSE is derived from MSE and is given by:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

- Root Mean Squared Error (RMSE) is a modified version of MSE and is often used as an evaluation metric in regRMSE is derived from MSE by taking the square root of the average squared differences. This modification is done to ensure that the metric is in the same unit as the original data, making it more interpretable.ession problems.
- It is the square root of the average of the squared differences between actual and predicted values.
- The formula for RMSE is derived from MSE and is given by:

- **Benefits of Taking the Square Root:** The square root operation in RMSE mitigates the issue of the squared units in MSE, providing a measure of error that is on the same scale as the original data. This enhances the interpretability of the metric.
- **Impact on Sensitivity to Outliers:** Similar to MSE, RMSE is sensitive to large errors due to the squaring operation. However, the square root somewhat mitigates this sensitivity compared to MSE.
- **Code:**

```
# Optionally, you can print the Root Mean Squared Error (RMSE)
for a more interpretable metric
# Implementing code on the Same dataset
rmse = np.sqrt(mse)
print(f'Root Mean Squared Error (RMSE): {rmse}')
```

Output:

Root Mean Squared Error (RMSE): 53.85344583676593

Limitations and Considerations

- **Mean Squared Error (MSE):**
  - Sensitive to Outliers: MSE gives higher weight to large errors due to squaring, making it sensitive to outliers.
  - Lack of Intuitive Interpretation: The squared error units may not be easily interpretable in the context of the original data.

- **Mean Absolute Error (MAE):**
  - Insensitivity to Outliers: MAE is less sensitive to outliers than MSE, but extreme values still contribute equally to the error.
  - Lack of Squaring: By not squaring errors, MAE may not penalize large errors enough in some applications.

- **Root Mean Squared Error (RMSE):**
  - Magnifies Large Errors: Similar to MSE, RMSE is sensitive to large errors due to the squaring operation.
  - Complexity in Interpretation: While RMSE is an improvement over MSE, interpreting its value might still be less intuitive compared to MAE.