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Assignment Report of Week 5

1. Evaluation Metrics for Regression Algorithms

Regression algorithms predict continuous values. Evaluating their performance requires specialized metrics that measure the accuracy of these predictions. Below are key metrics used for regression evaluation:

a) Mean Absolute Error (MAE)

- **Description:** MAE calculates the average absolute difference between actual and predicted values.
- **Formula:**

$$MAE = \frac{1}{n}\sum|y - \hat{y}|$$

- **When to Use:** Suitable for scenarios where you want to understand the average size of the errors, such as predicting house prices.
- **Example:** If a model predicts temperature and the actual temperature is 30°C while the prediction is 27°C, the error is 3°C.

b) Mean Squared Error (MSE)

- **Description:** MSE calculates the average of squared differences between actual and predicted values.
- **Formula:**

$$MSE = \frac{1}{n}\sum(y - \hat{y})^2$$

- **When to Use:** Preferred when larger errors need to be penalized more, such as in energy consumption predictions.
- **Example:** Useful when predicting stock market trends where large deviations are costly.

c) Root Mean Squared Error (RMSE)

- **Description:** RMSE is the square root of the MSE, providing an error metric in the same unit as the target variable.
- **Formula:**

$$RMSE = \sqrt{\frac{1}{n}\sum(y - \hat{y})^2}$$

- **When to Use:** Ideal for real-world interpretability where errors in the original unit are important, like weather forecasts.

d) R-Squared (R^2) Score

- **Description:** R^2 measures how well the model fits the data. It ranges from 0 to 1, where 1 indicates perfect prediction.
- **Formula:**

  $$R^2 = 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2}$$

  When to Use: Use when you need to understand the proportion of variance explained by the model, such as sales forecasting.

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2. Understanding the Confusion Matrix

A confusion matrix evaluates classification models by comparing actual and predicted outputs. It includes:

	Predicted Positive (1)	**Predicted Negative (0)**
Actual Positive (1)	True Positive (TP)	False Negative (FN)
Actual Negative (0)	False Positive (FP)	True Negative (TN)

Why is it Useful?

- Provides a comprehensive view of model performance.
- Helps to calculate key metrics like precision, recall, and F1 score.

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3. Example AI Model and Results

Scenario: An AI model is used by a robot to identify human faces in images. If the model detects a human, it outputs 1; otherwise, it outputs 0.

Input #	Actual	Predicted
1	0	0
2	0	1
3	1	1
4	0	1

Input #	Actual	Predicted
5	1	0
...	...	...
10	1	1

From the provided data, we calculate the confusion matrix:

	Predicted Human (1)	Predicted Not Human (0)
Actual Human (1)	2 (TP)	1 (FN)
Actual Not Human (0)	2 (FP)	1 (TN)

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4. Performance Metrics Calculation

1. **Precision**: Measures the proportion of true positive predictions among all positive predictions.

   $$Precision = \frac{TP}{TP+FP} = \frac{2}{2+2} = 0.5$$

2. **Recall (Sensitivity)**: Measures the proportion of actual positives correctly identified. $\frac{TP}{TP+FN} = \frac{2}{2+1} = 0.6667$

3. **F1 Score**: Harmonic mean of precision and recall.
   $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{0.5 \times 0.6667}{0.5 + 0.6667} = 0.571$

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5. Meaning of the Results

- **Precision (0.5):** For every positive prediction, 50% are correct. This indicates the model has moderate accuracy in identifying humans.
- **Recall (0.6667):** The model identifies 66.67% of actual humans correctly, meaning it misses about 33.33%.
- **F1 Score (0.571):** This balanced metric suggests moderate performance. There is room for improvement in both precision and recall.

Conclusion: This analysis shows how various metrics evaluate a model’s performance and emphasizes the importance of using the right metric based on the model's objective. Future improvements might involve fine-tuning the model to reduce false positives and false negatives.