Logistic Regression - Student Learning Guide

Feature Importance: Understanding What Drives Your Model

Feature importance tells us which variables have the most influence on a machine learning model's predictions.

Understanding feature importance helps with model interpretability and decision-making.

1. Why Visualize Feature Importance?

Why Visualize Feature Importance?

- Identify which inputs drive predictions
- Simplify models by removing unimportant features
- Build trust and explainability in sensitive domains (e.g., healthcare)

2. Methods to Calculate Feature Importance

Common Ways to Calculate Feature Importance:

- 1. Coefficients in Linear Models (e.g., Logistic Regression)
- 2. Gini Importance (used in Tree-based models like Random Forest, XGBoost)
- 3. Permutation Importance (measuring drop in accuracy when shuffling a feature)
- 4. SHAP Values (advanced method to explain individual predictions)

3. Coefficients in Logistic Regression

Logistic Regression Coefficients:

- Each feature gets a coefficient (beta value).
- Positive beta -> increases probability of class 1 (e.g., ASD)
- Negative beta -> decreases probability of class 1
- Larger absolute beta = more impact on prediction

Tip: Always scale features before interpreting coefficients!

4. Feature Importance in Tree Models

Tree-Based Model Importances:

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- Feature importance is based on how often and how well a feature splits the data.
- Higher importance = more splits or higher information gain
- Easily visualized using bar plots

5. How to Visualize Feature Importance

Visualizing Feature Importance:

- Use bar plots to rank feature influence
- For logistic regression, sort and plot the absolute values of coefficients
- For XGBoost or Random Forest, use model.feature_importances_ directly
- Visual tools help you explain the model to non-technical audiences

6. Caution When Interpreting

Caution:

- Coefficients assume linear relationships
- Feature importance is model-specific (don't compare across model types)
- High correlation between features can distort interpretation