Model Diagnostics, Selection, and Evaluation in Regression and Classification

A Comprehensive Approach for Robust Models

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Boston Housing Dataset

- Objective: Predict median house prices in Boston suburbs.
- Features (13 predictors):
 - CRIM: Per capita crime rate.
 - ZN: Proportion of residential land zoned for large lots.
 - RM: Average number of rooms per dwelling.
 - ► LSTAT: Percentage of lower status population.
 - PTRATIO: Pupil-teacher ratio, etc.
- Target Variable:
 - ► MEDV: Median value of owner-occupied homes (\$1000s).
- Applications:
 - Housing market analysis.
 - Urban planning and development.

Iris Dataset

- Objective: Classify iris flowers into species based on physical measurements.
- **Features** (4 predictors):
 - Sepal length and width.
 - Petal length and width.
- Target Variable:
 - Species: Setosa, Versicolor, Virginica.
- Applications:
 - ▶ Pattern recognition and classification.
 - Benchmarking classification algorithms.

Diagnostics for Regression Models

- ► Multicollinearity:
 - ▶ Definition: Occurs when predictors are highly correlated, making coefficient estimation unreliable.
 - ► **Test**: Variance Inflation Factor (VIF). A VIF greater than 5 indicates significant multicollinearity.
 - ▶ **Solution**: Remove correlated predictors or use regularization methods (Ridge/Lasso).

Residual Analysis:

- ► Tests:
 - Normality: Q-Q plots and histograms.
 - ► Heteroscedasticity: Scatterplot of residuals vs. predictions.
- Interpretation:
 - Normal residuals ensure unbiased predictions.
 - Random variance indicates consistent estimates.
- Outlier Detection:
 - ► **Tests**: Cook's Distance and Leverage Statistics.
 - Interpretation: High values suggest data points influencing model parameters.

https://github.com/martinpius/PG training

- Metrics for Selection:
 - AIC (Akaike Information Criterion):
 - Penalizes model complexity.
 - Lower values indicate better models.
 - BIC (Bayesian Information Criterion):
 - Stronger penalty for complexity than AIC.
 - Lower values preferred for simpler models.
- R-squared and RMSE:
 - ▶ R-squared: Measures variance explained by the model.
 - RMSE: Root mean square error to assess prediction error.

Example:

Linear vs Polynomial Regression: Use AIC, BIC, and Cross-Validation RMSE to select the best fit.

Model Selection: Classification

Metrics for Evaluation:

Precision: Fraction of correctly predicted positives.

$$\mathsf{Precision} = \frac{\mathsf{TP}}{\mathsf{TP} + \mathsf{FP}}$$

Recall: Fraction of actual positives correctly identified.

$$Recall = \frac{TP}{TP + FN}$$

► **F1-Score**: Harmonic mean of precision and recall.

$$F1-Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

ROC Curve and AUC:

- ROC Curve visualizes the trade-off between sensitivity and specificity.
- ► Higher AUC indicates better performanee. বিচাৰ চিক্তি ভাৰত বি

Cross-Validation

Definition: Resampling technique for robust model evaluation.

▶ Benefits:

- Reduces overfitting.
- Provides reliable performance estimates.

Types:

- ightharpoonup K-Folds Cross-Validation: Split data into K folds; train on K-1, test on the remaining fold.
- LOOCV (Leave-One-Out Cross-Validation): Use one data point as a test set in each iteration.
- Split data into K folds.
- ▶ Train on K-1, test on the remaining fold.
- Average performance across folds.

Summary

- Diagnostics ensure model reliability:
 - Multicollinearity: Address with VIF or dimensionality reduction.
 - Residual Analysis: Check for normality and constant variance.
 - Outliers: Investigate influential data points.
- Model Selection:
 - Regression: Use AIC/BIC for simplicity and accuracy.
 - Classification: Use Precision, Recall, F1-Score, and AUC.
- Cross-Validation improves model robustness and generalization.

Thank You for Listening

Questions?

https://github.com/martinpius/PG_training