

Data 572: Project working title

Avalvir Kaur Sekhon, Zihuan Liu & Jordan Kaseram

February 6, 2026

Abstract

Introduction

hello

Methodology

Titanic Data Set

The Titanic dataset consists of passenger-level information from the sinking of the RMS *Titanic*. Each observation corresponds to an individual passenger, with the response variable indicating survival status (1 = survived, 0 = did not survive). The dataset contains a mixture of demographic, socioeconomic, and voyage-related features, including age, sex, passenger class, fare paid, family composition, and cabin information.

In total, the dataset contains 891 observations with a diverse set of categorical and numerical variables. As is typical of real-world data, the raw dataset presents several challenges, including missing values, highly sparse columns, and correlated features derived from similar underlying information.

These characteristics make the Titanic dataset well suited for evaluating classification methods while also requiring careful preprocessing and feature selection prior to model fitting.

Data Preprocessing

Data preprocessing was performed using Python and the pandas library, which provides flexible and efficient tools for data cleaning, transformation, and preparation prior to machine learning analysis. Identifier variables such as passenger identifiers, ticket numbers, and booking references were removed, as they do not contain predictive information and may introduce unnecessary noise into the models.

Missing data were handled using simple, distribution-preserving imputation techniques. Missing values in passenger age, a numerical variable, were imputed using the median age within each passenger class. This approach allows age estimates to reflect socioeconomic differences across classes while remaining robust to outliers. Missing values in the port of embarkation, a categorical variable, were imputed using the mode, preserving the empirical distribution of this feature.

Categorical predictors were converted into numerical form using one-hot encoding creating dummy variables. To reduce redundancy and limit multicollinearity, several highly correlated or derived features were evaluated and pruned. For example, the variables `SibSp`, `Parch`, and `is_alone` were replaced by a single variable `family_size`.

The resulting feature set provides a stable and interpretable foundation for training supervised machine learning models for binary classification.

Resampling and Validation Strategy

To ensure reliable model evaluation and reduce overfitting, the dataset was partitioned into training (75%) and testing (25%) sets using a stratified split to preserve the original survival class proportions. Stratification is particularly important for the Titanic dataset due to its class imbalance between survivors and non-survivors.

All model training, hyperparameter tuning, and feature selection were performed exclusively on the training set using stratified k -fold cross-validation with $k = 5$. This resampling strategy maintains class balance within each fold and provides stable performance estimates while preventing information leakage.

Final model performance was evaluated on the held-out test set, which remained untouched during model selection. This approach yields an unbiased estimate of generalization performance and ensures fair comparison across all classification methods.

Model Selection

Three classification methods were selected to evaluate the predictive performance of the features present in the Titanic data set. These methods include: Logistic Regression, Linear Discriminant Analysis (LDA) and K-Nearest Neighbours (KNN). Logistic Regression and LDA were considered for their interpretability due to linearity [2]. Moreover, the Titanic prediction task is a binary response with a mix of numeric and categorical variables which these models perform well on [1].

These parametric tests assume a structured relationship between the predictors and the response, enabling stable parameter estimation and favourable bias-variance trade-offs. In contrast, KNN was included as a non-parametric test to capture potential non-linear patterns without assuming strong distribution assumptions. KNN provides a useful comparison model by classifying passengers based on identifying the observations that are nearest it rather than a global decision boundary [1].

Hyperparameter Tuning Strategy

Hyperparameter tuning was conducted using grid search, which is a simple memoryless method that can be used to explore predefined hyperparameter values [3]. This was combined with stratified cross-validation to identify the optimal model configuration.

For Linear Discriminant Analysis, hyperparameter tuning focused on the choice of solver (`svd` versus `lsqr`) and the use of covariance shrinkage, as shrinkage regularization is known to stabilize covariance estimation in the presence of correlated predictors and limited sample sizes [2, 3].

For Logistic Regression, tuning was performed over the regularization strength parameter C and the choice of ℓ_1 and ℓ_2 penalties, allowing control over model complexity and coefficient sparsity, which directly affects bias-variance trade-offs and interpretability in high-dimensional settings [1, 4].

For K-Nearest Neighbours, hyperparameters including the number of neighbours, distance metric, and weighting scheme were tuned to balance local versus global decision behavior and to regulate model sensitivity to noise and class overlap [1, 4].

Experiment

Experimental Design

The experimental design focused on comparing the predictive performance and interpretability of multiple classification models under a controlled and consistent evaluation framework. All models were trained using the same feature set and evaluated using identical performance metrics to isolate the effect of model choice and tuning decisions.

Each classification method was first evaluated in a baseline configuration to establish a reference point for performance. These baseline results were used to assess how well each model captured the underlying structure of the data without additional complexity. The next set of experiments introduced hyperparameter tuning and feature selection to evaluate whether these refinements led to meaningful improvements in generalization performance.

Comparisons were conducted across models using cross-validated accuracy estimates on the training data, followed by final evaluation on a held-out test set. This design enabled direct comparison between linear and non-linear approaches, as well as between parametric and non-parametric models, while controlling for differences in data preprocessing and evaluation procedures.

In addition to predictive performance, model interpretability was examined through feature importance analyses. This allowed assessment of whether performance gains were accompanied by stable and meaningful explanations of survival outcomes.

Results and Analysis

The performance of the three classification models was first evaluated using baseline configurations and subsequently compared against tuned versions obtained through cross-validated grid search. Model performance was assessed using cross-validation accuracy, test-set accuracy, mean squared error, and class-specific precision.

Baseline Model Performance Among the baseline models, Linear Discriminant Analysis (LDA) achieved the strongest overall performance, with a mean cross-validation accuracy of 0.8249 and a test accuracy of 0.8386. Logistic Regression followed closely with a test accuracy of 0.8251, while K-Nearest Neighbours (KNN) exhibited lower predictive performance, achieving a test accuracy of 0.8027. Confusion matrices reveal that both LDA and Logistic Regression maintained a balanced trade-off between precision and recall across survival classes, whereas KNN showed reduced recall for the survivor class, indicating greater sensitivity to class overlap.

Table 1: Performance of baseline classification models on the Titanic dataset.

Baseline Model	CV Accuracy (Mean)	CV Accuracy (Std)	Test Accuracy	Test MSE
LDA	0.8249	0.0439	0.8386	0.1614
Logistic Regression	0.8368	0.0452	0.8251	0.1749
KNN	0.8139	0.0483	0.8027	0.1973

Feature importance analysis for the linear models revealed consistent patterns. Variables related to passenger title, sex, passenger class, age, and family size contributed most strongly to model decisions. This aligns with that passengers on the Titanic adopted the ‘*women and children*’ first policy which influenced survival. In contrast, KNN relied more heavily on proximity-based features such as family size and ticket group size, reflecting its local decision-making nature.

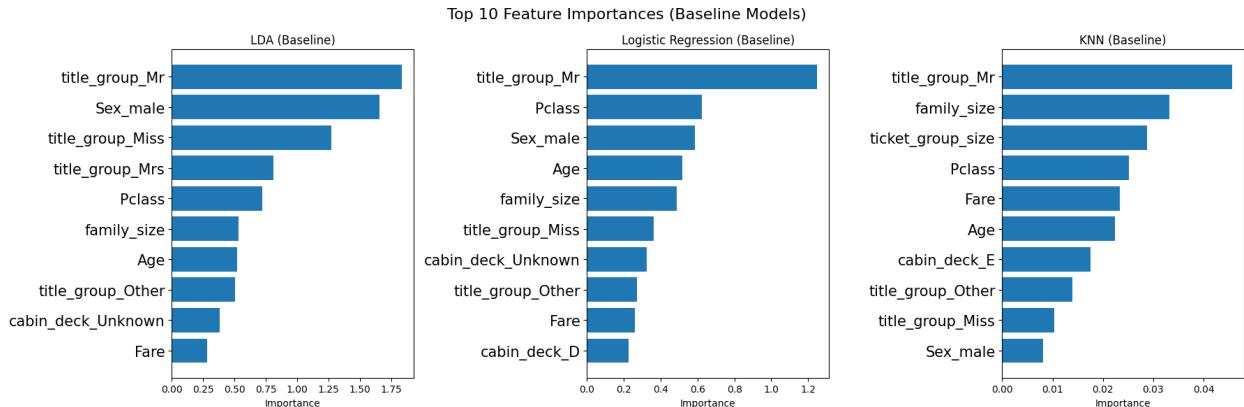


Figure 1: Top 10 Features from the Baseline model for LDA, Logistic regression and KNN

Effect of Hyperparameter Tuning After hyperparameter tuning, Logistic Regression exhibited a modest improvement in cross-validation accuracy, increasing from 0.8368 to 0.8408, while maintaining the same test accuracy of 0.8251. This suggests that regularization tuning improved model stability without substantially altering generalization performance. LDA, however, experienced a slight decrease in test accuracy after tuning, from 0.8386 to 0.8117, likely due to shrinkage regularization introducing additional bias in an already well-conditioned covariance structure.

Table 2: Performance of tuned classification models on the Titanic dataset.

Tuned Model	CV Accuracy (Mean)	CV Accuracy (Std)	Test Accuracy	Test MSE
LDA	0.8269	0.0477	0.8117	0.1883
Logistic Regression	0.8408	0.0441	0.8251	0.1749
KNN	0.8249	0.0479	0.7713	0.2287

KNN performance declined following tuning, with test accuracy dropping from 0.8027 to 0.7713. This degradation highlights the sensitivity of KNN to hyperparameter choices and confirms that increasing model flexibility does not necessarily lead to improved generalization, particularly in datasets with moderate sample sizes and overlapping class distributions.

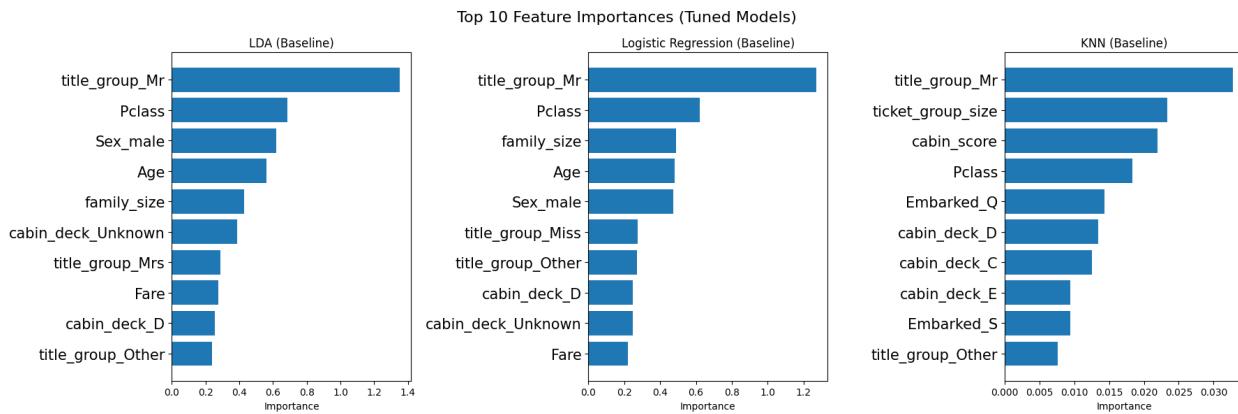


Figure 2: Top 10 Features from the Tuned model for LDA, Logistic regression and KNN

Discussion

Conclusion

References

- [1] James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). An introduction to statistical learning: Python edition.
- [2] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning.
- [3] Franceschi, L., Donini, M., Perrone, V., Klein, A., Archambeau, C., Seeger, M., ... & Frasconi, P. (2025). Hyperparameter optimization in machine learning. Foundations and Trends® in Machine Learning, 18(6), 975-1109.
- [4] Kuhn, M., & Johnson, K. (2013). Applied predictive modeling (Vol. 26, p. 13). New York: Springer.