

Applied Statistics for Data Scientists with R

Class 19: GLM and Logistic Regression

What is GLM?



- GLM (**Generalized Linear Model**) is a flexible generalization of ordinary linear regression that allows for response variables to have error distributions other than a normal distribution.
- If the residuals (resulting from the response variable) do not follow normal distribution, then such method helps.

Odds



$$Odds = \frac{Probability \ of \ Success}{Probability \ of \ Failure} = \frac{P(Success)}{1 - P(Success)}$$

- So, if a student has 0.75 probability of passing an exam, then the probability of failure is 0.25
- Hence, $odds = \frac{0.75}{0.25} = 3$.
- It means the student is three times more likely to pass than fail.

Logistic Regression



$$\log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

$$\log\left(rac{P(Survived)}{1-P(Survived)}
ight) = eta_0 + eta_1Pclass + eta_2Sex + eta_3Age + eta_4Fare$$

Example: Predicting Chance of Survival



- Pclass (-1.27): Higher-class passengers had better survival odds. Each increase in class (from 1st to 2nd or 2nd to 3rd) decreases the log-odds of survival by 1.27 (lower class = lower survival chance).
- SexFemale (2.52): Being female significantly increases survival odds. The log-odds increase by 2.52 if the passenger is female compared to a male. This means women were much more likely to survive.
- Age (-0.037): Older passengers had a lower survival probability. A 1-year increase in age decreases log-odds by 0.037, meaning younger people had slightly better survival odds.
- Fare (0.00054): Fare has a very small positive effect on survival, but it's not statistically significant (p = 0.805), meaning we can't conclude that fare significantly impacted survival.

Performance Evaluation



	Reference		
Predicted	Event	No Event	
Event	A	В	
No Event	С	D	

The formulas used here are:

$$Sensitivity = \frac{A}{A+C}$$

$$Specificity = \frac{D}{B+D}$$

$$Prevalence = \frac{A+C}{A+B+C+D}$$

$$PPV = \frac{sensitivity \times prevalence}{((sensitivity \times prevalence) + ((1-specificity) \times (1-prevalence))}$$

$$NPV = \frac{specificity \times (1-prevalence)}{((1-sensitivity) \times prevalence) + ((specificity) \times (1-prevalence))}$$

$$Detection Rate = \frac{A}{A+B+C+D}$$

$$Detection Prevalence = \frac{A+B}{A+B+C+D}$$

$$Balanced Accuracy = (sensitivity + specificity)/2$$

$$Precision = \frac{A}{A+B}$$

$$Recall = \frac{A}{A+C}$$

$$F1 = \frac{(1+\beta^2) \times precision \times recall}{(\beta^2 \times precision) + recall}$$

From caret package: https://topepo.github.io/caret/measuring-performance.html

Confusion Matrix & Related KPIs



Reference Prediction 0 1 0 357 81 1 67 209

	Actual Not Survived	Actual Survived	Total
Predicted Not Survived	TN = 357	FN = 81	424
Predicted Survived	FP = 67	TP = 209	290
Total	438	276	714

- True Negatives (TN = 357): Model correctly predicted non-survivors.
- False Positives (FP = 81): Model incorrectly predicted some non-survivors as survivors.
- False Negatives (FN = 67): Model missed predicting some actual survivors.
- True Positives (TP = 209): Model correctly predicted survivors.

Confusion Matrix & Related KPIs



	Actual Not Survived	Actual Survived	Total
Predicted Not Survived	TN = 357	FN = 81	438
Predicted Survived	FP = 67	TP = 209	276
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$$Accuracy = \frac{TP + TN}{Total}$$

• model correctly classifies survival status about 79% of the time.

$$NIR = \frac{max(Class Counts)}{Total}$$

 $NIR = \frac{max(Class\ Counts)}{Total}$ • If we blindly guessed the majority class (non-survivors), we'd be right 59.38% of the time.

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

 $Sensitivity = \frac{TP}{TP + FN} \quad \bullet \quad \text{The model correctly identifies 84.2\% of actual survivors. Also called recall.}$

Specificity =
$$\frac{TN}{TN + FP}$$

 $Specificity = \frac{TN}{TN + FP} \quad \bullet \quad \text{The model correctly identifies 72.07\% of non-survivors.}$

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

 $Precision = \frac{TP}{TP + FP} \quad \bullet \quad 81.51\% \text{ of passengers predicted as "Survived" actually survived.}$

Confusion Matrix & Related KPIs



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McNemar's Test (p = 0.2853)

- Tests if false positives and false negatives occur at the same rate.
- p > 0.05: No significant difference between misclassifications.

$$Balanced\ Accuracy = \frac{Sensitivity + Specificity}{2}$$

 Average of Sensitivity (detecting survivors) and Specificity (detecting non-survivors).

$$F1 = 2 imes rac{ ext{Precision} imes ext{Recall}}{ ext{Precision} + ext{Recall}}$$

- F1 = 82.83%: A harmonic mean of precision and recall.
- Balances both False Positives & False Negatives.

$$\begin{aligned} \text{Prevalence} &= \frac{\text{Total Positive Cases}}{\text{Total Samples}} \end{aligned}$$

59.38% of passengers did NOT survive

Kappa Statistic



- The Kappa statistic measures how well a classification model performs beyond random chance. Unlike accuracy, which can be misleading when classes are imbalanced, Kappa accounts for chance agreement.
- Ranges from -1 to +1
 - 1: Perfect agreement
 - $> 0.7 \rightarrow$ Good agreement.
 - $0.5 0.6 \rightarrow Moderate agreement.$
 - 0: No better than chance
 - Negative: Worse than random guessing