

Logistic Regression

Friday, 23 December 2022

12:22 AM

Regression



Continuous Columns

Classification



Categorical Columns

Mathematical Intuition

$$\hat{y} = \beta + \beta_1 x_1$$

\downarrow
 $-\infty \text{ to } \infty$

\rightarrow $-\infty \text{ to } \infty$

But for Logistic Regression

$$\hat{y} \neq \beta + \beta_1 x_1$$

\downarrow
This comes as Probability
 $0 \text{ to } 1$

To overcome this

$$P = \beta + \beta_1 x_1$$
$$\frac{P}{1-P} \neq \beta + \beta_1 x_1$$

\uparrow
 $0 \text{ to } \infty$

\downarrow
Odds: Probability of getting something upon Probability of not Finding something

To overcome this

$$\log \frac{P}{1-P} = \beta + \beta_1 x_1$$

\uparrow
 $-\infty \text{ to } \infty$



Solving this

$$\log \frac{P}{1-P} = \beta + \beta_1 x_1$$
$$\frac{P}{1-P} = e^{\beta + \beta_1 x_1}$$
$$P = \frac{e^{\beta + \beta_1 x_1}}{1 + e^{\beta + \beta_1 x_1}}$$

→ $-\infty$ to ∞

;

$$= \beta + \beta x$$

$$+ \beta x$$

$$- P * e^{\beta + \beta x}$$

$$) = e^{\beta + \beta x}$$

Stats Model

Linear Regression

Logistic Regression

Interpretation is possible because stats model can give you sum

$$P = \frac{e^{\beta + \beta x}}{1 + e^{\beta + \beta x}}$$



We always get Probability values, after this we classify using a **P threshold**

Classification

Binary Classification

Multiclass Classification

Binary Classification: We have only 2 sub categories in dependent column

Multiclass Classification: We have more than 2 subcategories in dependent column

Model Performance Methods

- Performance can be calculated by comparing 2 models

Maximum Log Likelihood

$$LL = \sum_{i=1}^N y \log P(y) + (1 - y) \log(1 - P(y))$$

- Gives Performance of model
- Higher is better
- It is boundless
- Value always in negative

Deviance

$$Deviance = -2 * LL$$

- Lower is better

Two Types of Deviance:

Null Deviance: When not a single in

on

mary

assify it into a category

ification

ndependent

- value always in negative

Log Loss Function

$$\text{Log Loss} = \frac{-1}{n} * LL$$

- Always in positive
- Lower is better

Bayesian Information Criteria

$$BIC = -2LL + k \log n$$

- K is total no features
- N is total no rows
- It accounts both rows and features to calculate model performance

Feature is considered while calculating

Residual Deviance: When all independent variables are considered while calculating LL

Akaike Information Criteria/AIC

$$AIC = -2LL + 2k$$

- K is total no of features
- It accounts features in calculating model performance
- Lower is better

Model Evaluation

Confusion Matrix

| | | Predicted | |
|--------|-------|-----------|-----------|
| | | False | True |
| Actual | False | TN | FP |
| | True | FN | TP |

Confusion Matrix Transposed

| | | Actual | |
|-----------|-------|-----------|-----------|
| | | False | True |
| Predicted | False | TN | FN |
| | True | FP | TP |

Given Errors:

| Category | Actual | Predicted |
|----------|--------|-----------|
| Accepted | 450 | 600 |
| Rejected | 550 | 400 |

Confusion Matrix ?

Predicted

Confusion Matrix Transposed

| | | Actual | |
|-----------|----------|-------------|-------------|
| | | Rejected | Accepted |
| Predicted | Rejected | T400 | F0 |
| | Accepted | F0 | T450 |

ating LL

endent features

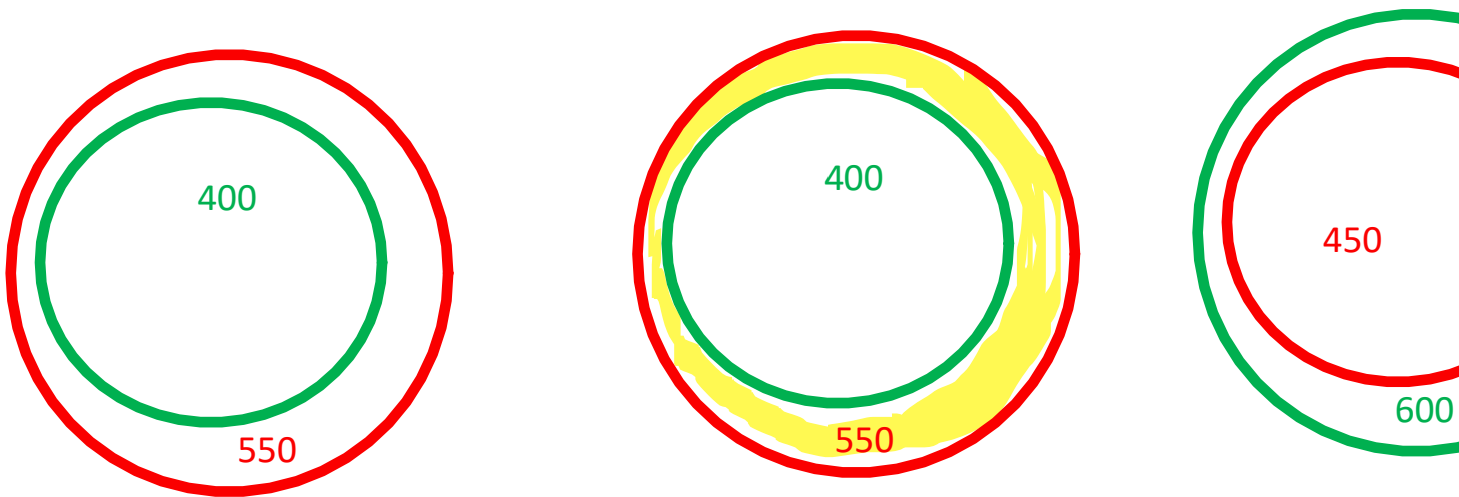
ating model

Transposed

| |
|-----------|
| True |
| FN |
| TP |

posed

| |
|-------------|
| cccepted |
| F150 |
| T450 |



Accuracy

$$Accuracy = \frac{\text{Total True Prediction}}{\text{Total Values}} = \frac{TP + TN}{TP + FN + FP + TN}$$

- Higher is better
- In percentage
- Chances are that model identifies TP but not TN, in such case

Precision

$$Precision = \frac{\text{True Positive}}{\text{Total Predicted Positive Values}} = \frac{TP}{TP + FP}$$

F1 SCORE

$$F1 = \frac{-2PR}{P + R}$$

Recall

$$Recall = \frac{\text{True Positive}}{\text{Total Actual Values}} = \frac{TP}{TP + FN}$$

- It is the harmonic
- Higher is better

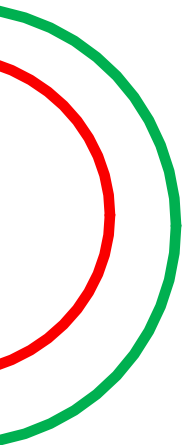
Probability Threshold

The value used to determine which class observed value should be classified as, Changing can render all above calculation as useless, To over come this

True Prediction Rate/TPR

True Postive Prediction

TP



c mean of precision & recall

this threshold



TPR

$$TPR = \frac{\text{True Positive Prediction}}{\text{Total Actual Positive}} = \frac{TP}{TP + FN}$$

FPR



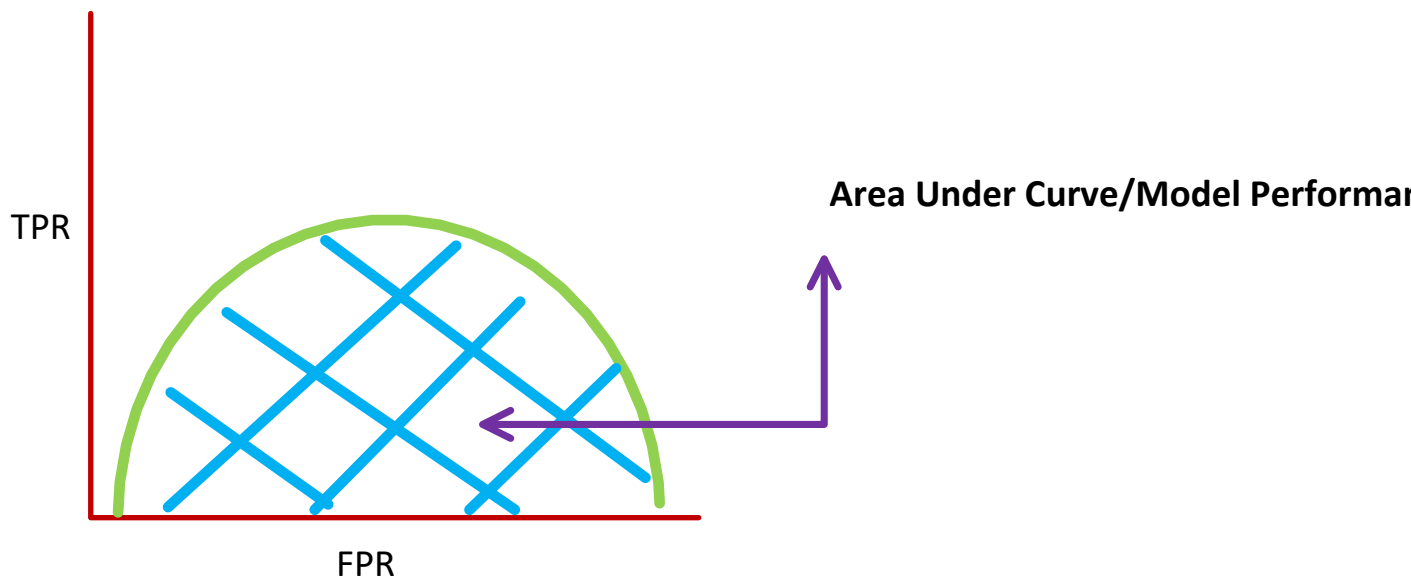
False Prediction Rate

$$FPR = \frac{\text{False Positive Prediction}}{\text{Total Actual Negative Values}} = \frac{FP}{FP + TN}$$

Our main objective is to decrease FPR, Increase TPR

Receiver Operating Characteristics/Area under Curve

- When TPR plotted on y and FPR on x, Area formed under curve will evaluate model independent of threshold
- It can also be used to figure the best Probability Threshold for model



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performance

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