

Classification

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Topics covered so far

1. Intro: Classification
2. Gaussian Models
3. Logistic Regression
4. Performance Assessments
5. K-Nearest Neighbors

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Discussion questions

1. Why do we use logistic regression?
2. What is a confusion matrix and how can you interpret it?
3. Why is accuracy not always a good performance measure?
4. How to choose the threshold using the Precision-Recall curve?
5. Is there a performance measure that can cover both Precision and Recall?
6. How does the K-NN algorithm work? How to identify K in this algorithm?

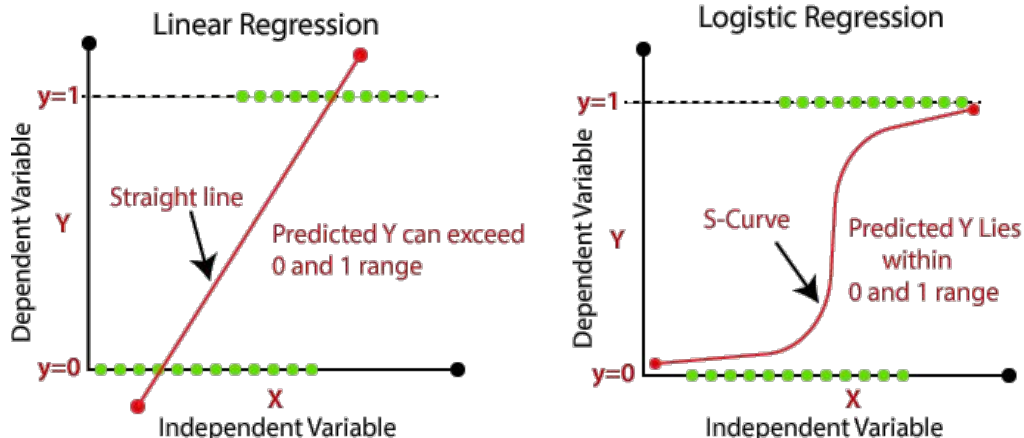
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Why do we use logistic regression?

- Logistic Regression is a supervised learning algorithm that is used for classification problems, i.e., where the dependent variable is categorical.
- In logistic regression, we use the Sigmoid function to calculate the probability of the dependent variable.
- The real-life applications of logistic regression are churn prediction, spam detection, etc.
- The below image shows how logistic regression is different from linear regression in fitting the model.



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Confusion matrix

It is used to measure the performance of a classification algorithm. It can be used to calculate the following metrics:

1. **Accuracy:** Proportion of correctly predicted results among the total number of observations

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN)$$

2. **Precision:** Proportion of true positives to all the predicted positives, i.e., how valid the predictions are

$$\text{Precision} = (TP)/(TP+FP)$$

3. **Recall:** Proportion of true positives to all the actual positives, i.e., how complete the predictions are

$$\text{Recall} = (TP)/(TP+FN)$$

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

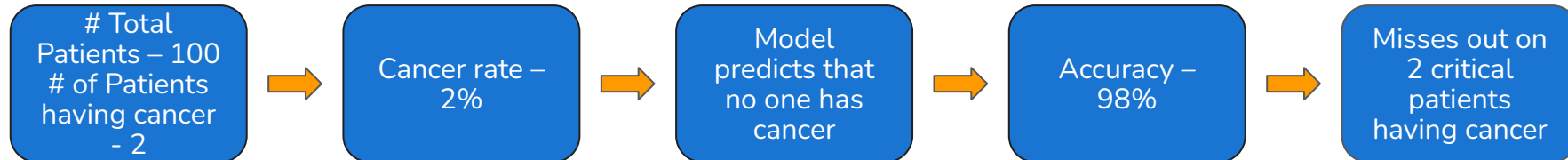
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Why accuracy is not always a good performance measure

Accuracy is simply the overall % of correct predictions and can be high even for very useless models.



- Here, accuracy will be 98%, even if we simply predict that every patient does not have cancer.
- In this case, Recall should be used as a measure of model performance; high recall imply fewer false negatives.
- Fewer false negatives implies a lower chance of 'missing' a cancer patient, i.e., predicting a cancer patient as one not having cancer.
- This is where we need other metrics to evaluate model performance.

- The other important metrics are Recall and Precision:
 - Recall - What % of actuals 1s did the model capture in prediction?
 - Precision - What % of predicted 1s are actual 1s?
- There is a tradeoff - as you try to increase the Recall, the Precision will reduce and vice versa.
- This tradeoff can be used to figure out the right threshold to use for the model.

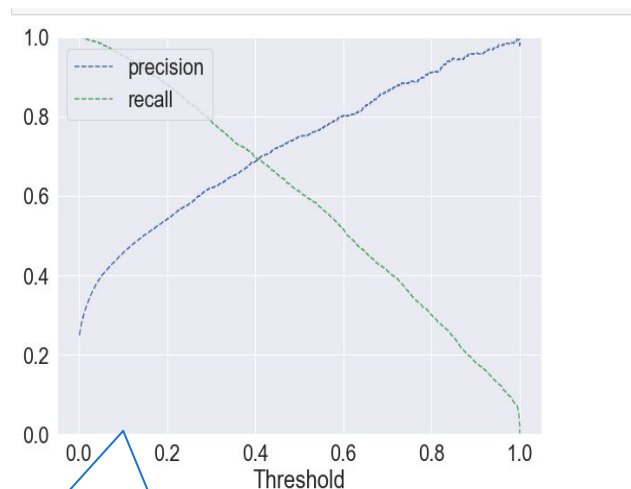
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How to choose thresholds using the Precision-Recall curve?

- The Precision-Recall curve is a useful measure of the success of prediction when the classes are imbalanced.
- The curve shows the tradeoff between the precision and the recall for different thresholds.
- It can be used to select an optimal threshold as required to improve the model performance.
- Here, as we can see, the precision and the recall are almost equal when the threshold is around 0.4.
- If we want a higher precision, we can increase the threshold.
- If we want a higher recall, we can decrease the threshold.



*Choosing different thresholds can completely change the model's performance.
It is important to think about what constitutes the 'sweet spot'.*

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Is there a performance measure that can cover both Precision and Recall?

- F1 Score is a measure that takes into account both Precision and Recall.
- The F1 Score is the harmonic mean of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

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

- The highest possible value of the F1 score is 1, indicating perfect precision and recall, and the lowest possible value is 0.

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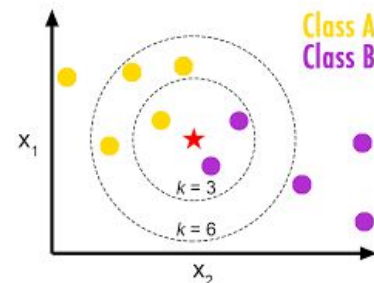
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K-Nearest Neighbours (K-NN) algorithm

This algorithm uses features from the training data to predict the values of new data points, which means the new data point will be assigned a value based on how similar it is to the data points in the training set. We can define its working in the following steps:

- Step 1: We need to choose the value of K, i.e., the number of nearest data points to consider. K can be any positive integer.
- Step 2: For each point in the test data do the following:
 - Calculate the distance between the test point and each training point with the help of any of the distance methods, namely: Euclidean, Manhattan, etc. The most commonly used method to calculate the distance is the Euclidean method.
 - Now, based on the distance value, sort them in ascending order.
 - Next, choose the top K rows from the sorted array.
 - Now, assign a class to the test point based on the most frequent class.
- Step 3: Repeat this process until all the test points are classified in a particular class.

We try different values of K and plot them against the test error. The lower the value of the test error, the better the value of K.



Case Study

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Appendix

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LDA vs QDA

Linear Discriminant Analysis	Quadratic Discriminant Analysis
It is a linear classifier but much less flexible than QDA	It is a non-linear classifier but more flexible than LDA
It assumes a common covariance matrix for all the classes	It assumes that each class has its covariance matrix
It is preferred when the training set only has a few observations	It is preferred when the training set is very large
It can be used as a dimensionality reduction technique	It cannot be used as a dimensionality reduction technique

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