Output for logistic regression:

Opening file Titanic.csv.
Theta is -0.636037
Time taken by function: 149825000 nanoseconds
Accuracy: 0.785425
Specificity: 0.765101
Sensitivity: 0.695652

Process finished with exit code 0

Output for naive bayes:

Opening file Titanic.csv.
The coefficients are: 0.61,0.39,1.2784,2.60768,1.05736,
Time taken by function: 5423100 nanoseconds
Accuracy: 0.785425
Sensitivity: 0.695652
Specificity: 0.863636

Process finished with exit code 0

I received the same accuracy and sensitivity for both algorithms but received a different specificity for them. This means that the bayes algorithm is better at identifying negative cases than the logistic regression. This was most likely because of the additional features that the bayes theorem used to predict which made it better distinguish the characteristics of the males who survived and females that did not. However, the logistic model only predicted based on sex and still received the same accuracy as the naive bayes model, showing that sex was a strong predictor of who survived on the ship or not.

Generative and discriminative classifiers are two types of machine learning algorithms used for classification tasks. Generative classifiers model the probability distribution of input data for each category and use Bayes' theorem to calculate the probability of each category given the input data. Discriminative classifiers, on the other hand, directly model the decision boundary between the categories without explicitly modeling the

underlying probability distribution. They learn the conditional probability of the labels given the input features and focus on maximizing the margin between the different categories. Generative classifiers are good at generating new data points that are similar to the training data, while discriminative classifiers are more flexible and powerful in modeling complex decision boundaries and can achieve higher accuracy on some tasks.
Choosing between generative and discriminative classifiers depends on the specific task and the trade-offs between accuracy, interpretability, and other factors. Generative models are better suited for tasks where generating new data points is important, such as image or text generation. Discriminative models are better suited for tasks where decision boundaries are complex and the margin between categories is small, such as image classification.

https://sebastianraschka.com/faq/docs/generative_vs_discriminative.html
https://www.oreilly.com/content/generative-and-discriminative-models-overview-and-applications/

Reproducible research in machine learning is the practice of making research findings, methods, and code openly accessible in order to enable the independent reproduction of the results. Reproducibility is important in machine learning research because it enables independent verification of research findings and provides a means for researchers to build upon the work of others. This is especially important in the context of deep learning, where large and complex models can be difficult to reproduce without access to the original code and data.
Implementing reproducible research involves several best practices, such as using open-source software, sharing data and code, and documenting the computational environment. By sharing code and data, other researchers can verify the results and build upon them. By using open-source software, researchers can ensure that others can easily access and use their tools. By documenting the computational environment, researchers can provide a clear record of the methods and tools used in the research. Reproducible research is essential for advancing the field of machine learning and ensuring that research findings can be applied in real-world settings. Researchers can implement reproducibility by adopting best practices such as sharing data and code, documenting the computational environment, and using open-source software.

Arisoy, E., Chen, D. L., & Garcia-Gathright, J. I. (2019). Reproducibility in machine learning for health research: Still a ways to go. Digital Medicine, 2(1), 1-7.

https://www.jmlr.org/reproducibility/

https://towardsdatascience.com/reproducible-machine-learning-7a64c399f12