CS 760: Machine Learning Spring 2024

Homework 4: Decision Trees

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Problem 4.1

Passenger Class: First class is 1 and other classes are 0. I figured there are marginal benefits after 1st class.
Sex: I left sex alone, since it was already binary.
Age: I split age based on if you were a minor or not (i.e. age < 18yo).
Siblings/Spouse: I chose 1 for no siblings/spouses and 0 for any number of them. My thought that is that any number of children, be it one or many, has a similar affect
Parents/Children: Similarly, I chose 1 for no parents/children and 0 for any
Fare: I split fare based on the median, if you are above, you get 1, otherwise 0.

Problem 4.2

See *decision_trees.ipynb* under section 4.2 for code

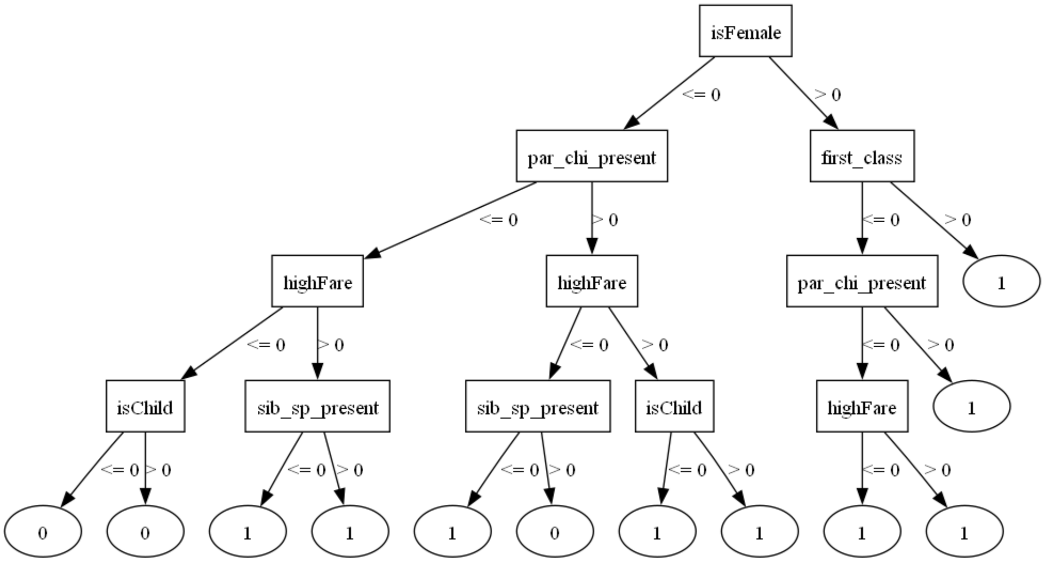
Mutual Information of Features x1-x6 (rounded 5 digits):
x1: 0.05727
x2: 0.21685
x3: 0.00669
x4: 0.00924
x5: 0.01504
x6: 0.05510

Problem 4.3

See *decision_trees.ipynb* under section 4.3 for code

Two variables, *max_depth* and *min_samples_split*, are defined as my stopping conditions. If a node exceeds the max depth, then stop. Otherwise, if a node is about to be split more times than our minimum sample split, then it will stop as well. This prevents the tree from getting too deep or wide.

Problem 4.4



Problem 4.5

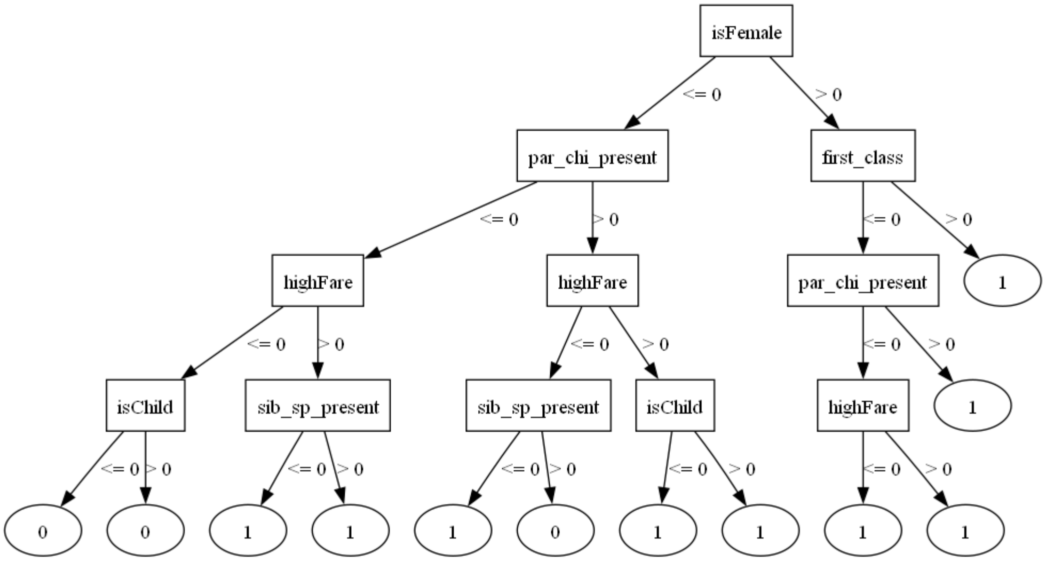
After running CV, I come up with an accuracy of around 89%

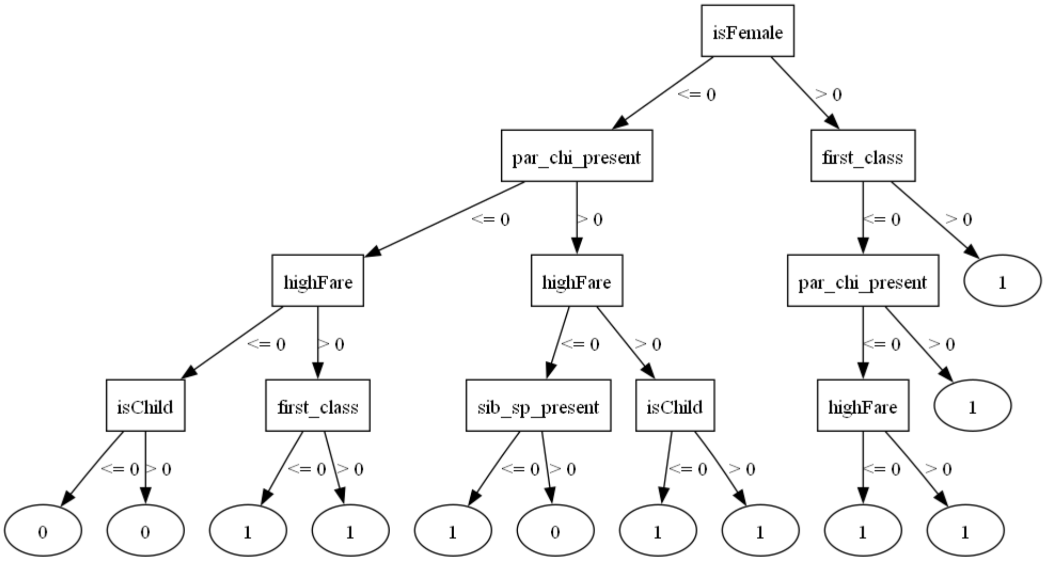
Problem 4.6

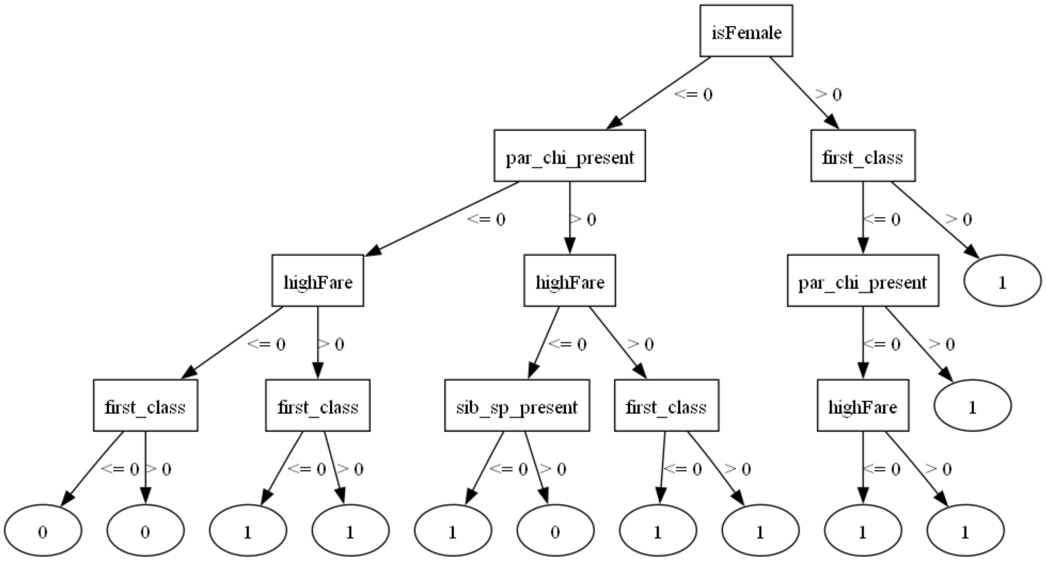
For a man paying a low fare with no children, siblings and parents on board, I would not have survived the titanic.

Problem 4.7

(a) Notably, no matter how I sampled the 80% of my data, all the subsets produced similar trees.



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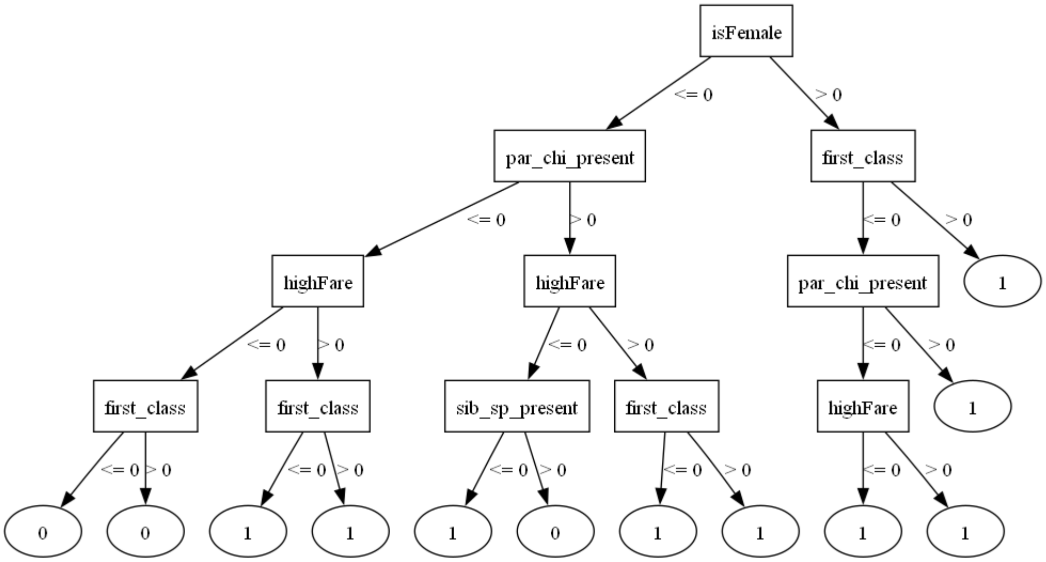
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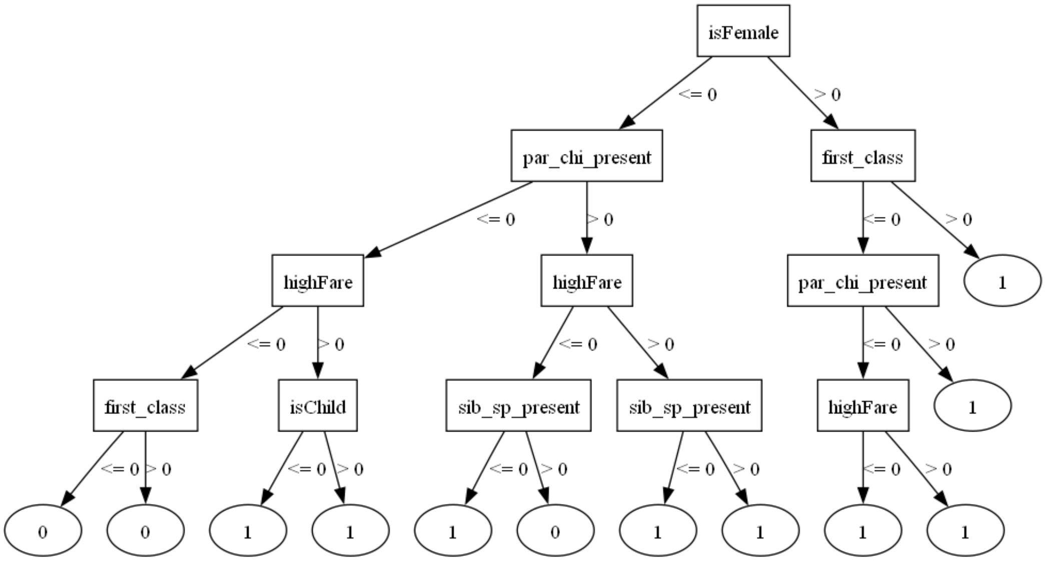
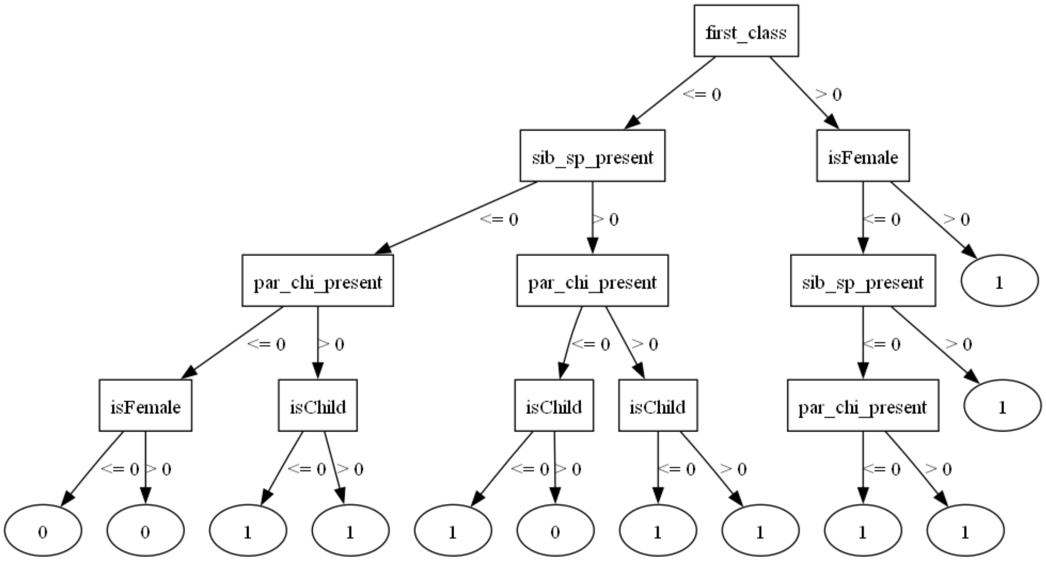


(b) Using 10-fold cross validation, I get an accuracy of 89%.

(c) Using the same feature from before, I get the same results and do not survive, unfortunately.

Problem 4.8

(a)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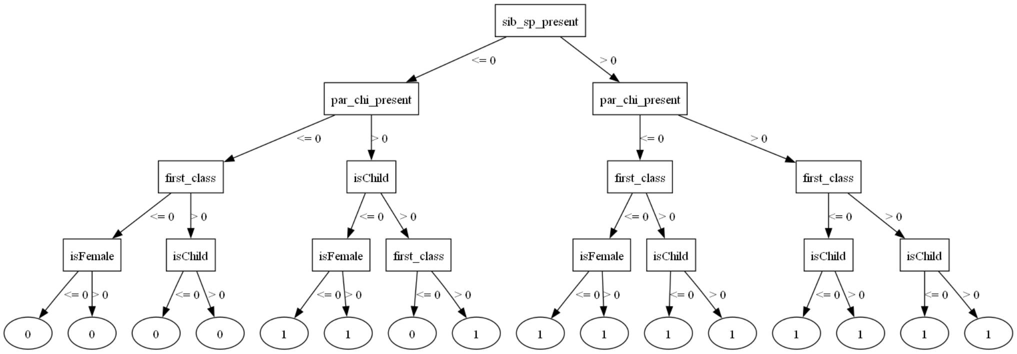
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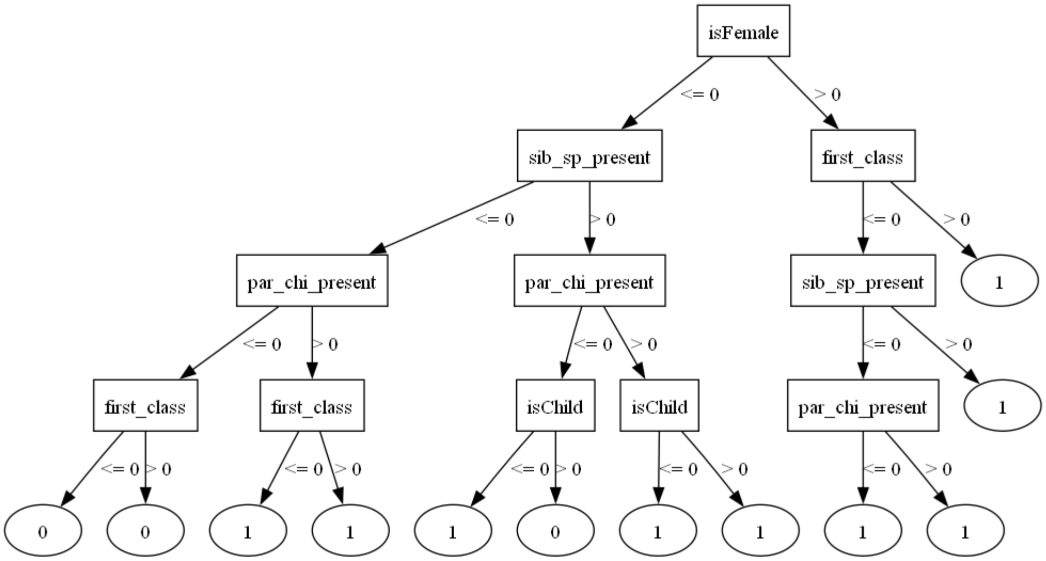
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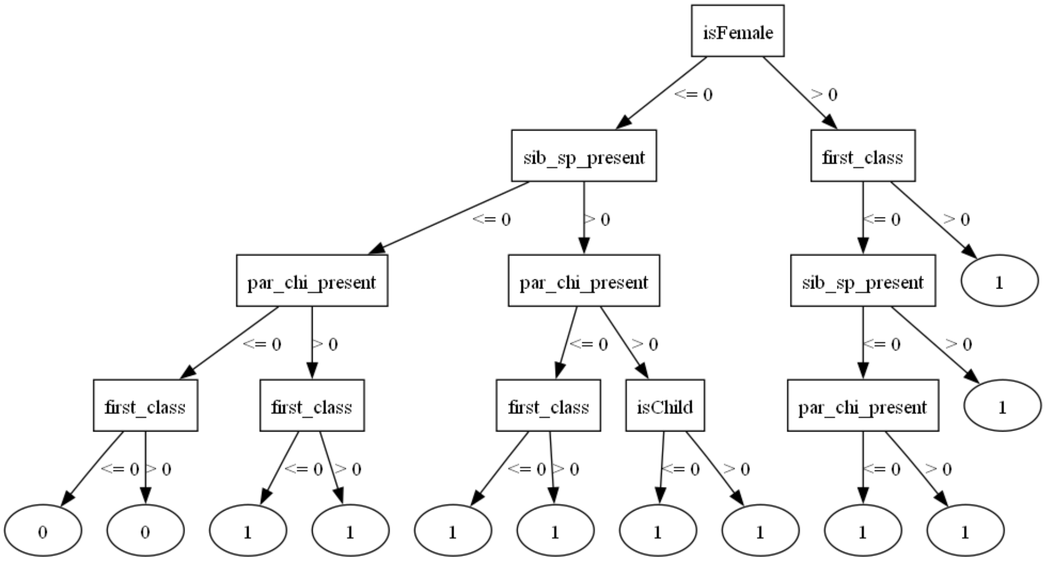
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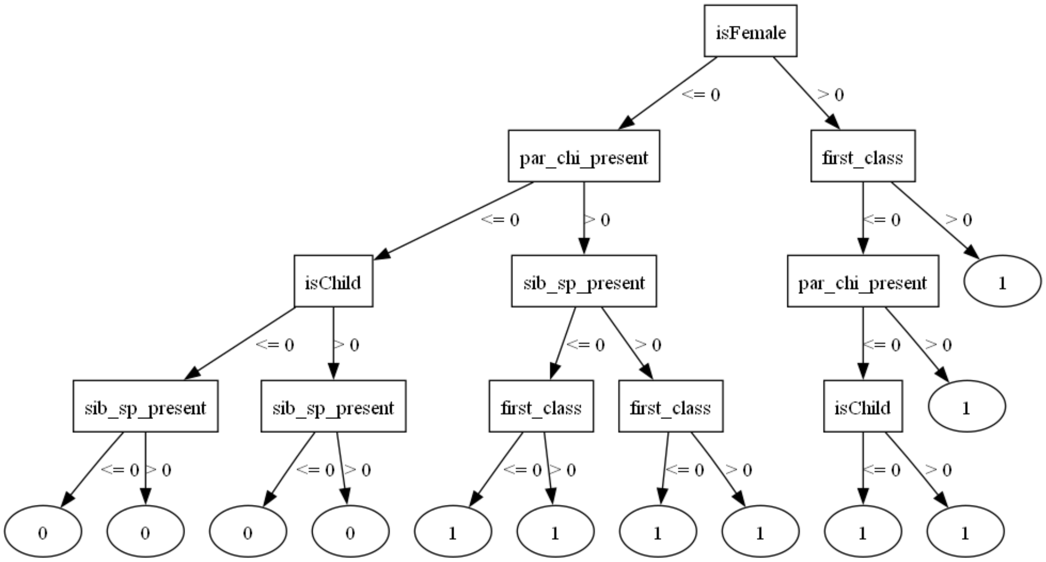
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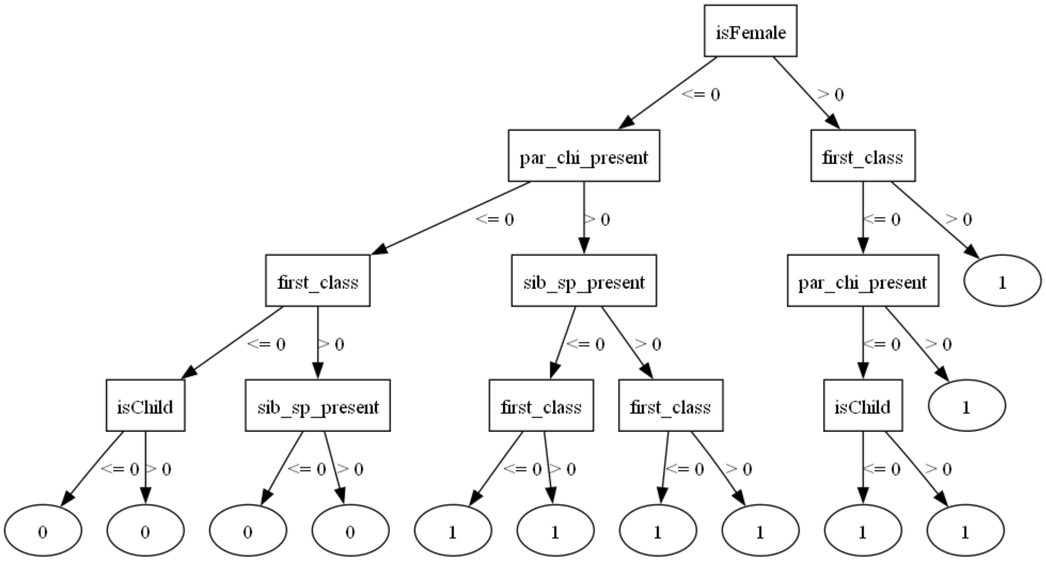

(b) My accuracy reduced, but not by a lot. It went down to 86%.

(c) No, I would not have survived. This is using the same feature as the previous two.

Problem 4.9

My decision tree predictions agree, but those disagree with my logistic regression predictions. My assumption as to why is because I'm binarizing my data here and I potentially lose information in the process. I would prefer to use logistic regression, in no small part because I find it far simpler to implement and understand.

Problem 4.10

From the definition of mutual information, we know that:

$$I(x;y) = H(x) - H(x|y)$$

So, to prove that $I(x;y) = I(y;x)$, we need to show:

$$H(x) - H(x|y) = H(y) - H(y|x)$$

Conditional entropy is defined as:

$$H(x|y) = H(x,y) - H(y) \text{ and, conversely } H(y|x) = H(y,x) - H(x)$$

Substituting these equations into the above, we get:

$$H(x) - (H(x,y) - H(y)) = H(y) - (H(y,x) - H(x))$$

After rearranging, we get:

$$H(x) + H(y) - H(x,y) = H(x) + H(y) - H(y,x)$$

To clean up, we subtract $H(y)$ and $H(x)$ from both sides, multiply by -1, and get:

$$H(x,y) = H(y,x)$$

This still necessitates that we show that joint entropy is symmetric, so we define joint entropy as:

$$H(X,Y) = -\sum_{x \in X} \sum_{y \in Y} \mathbb{P}(x,y) log_2[\mathbb{P}(x,y)]$$

$$H(Y,X) = -\sum_{y \in Y} \sum_{x \in X} \mathbb{P}(y,x) log_2[\mathbb{P}(y,x)]$$

Since the order of summation doesn't affect the result and we know that joint probability is symmetric, we can say prove that $H(x,y) = H(y,x)$