# Titanic Machine Learning from Disaster: Classification model investigation

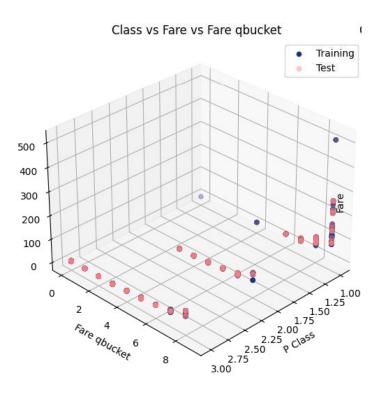
## Objective and dataset

#### **Objectives**

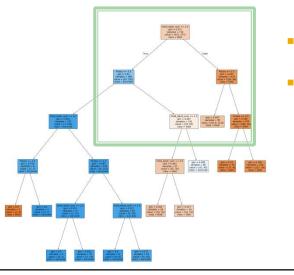
- Fit Logistic Regression model to Titanic Machine Learning from Disaster Kaggle competition data and measure accuracy.
- Compare performance of different classifier, not focussed on optimising for accuracy due to time limits

#### **Data Preparation**

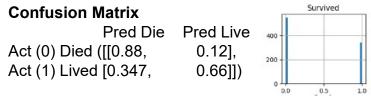
- Cabin data had too many null values and ticket too many unique values to be useful - not used
  - Likely to vary between datasets which may be issue for model reuse, test transformation
- Sex was label encoded to binary (male = 1, female = 0)
- Embarked null values filled with "S" (most frequent) and label encoded to 0-2
- Age data investigation Women and children first
  - Lot of null age data
  - generated new feature Child/Adult by decomposing Name and looking at Parent child (Parch) relationship and label encoded
    - child female o, child male 1, adult female 2, adult male 3
  - Age null filled with median and alternate using child/adult data to assign more appropriate age
    - Minimal difference due to small population of children
- Fare had some null data but also some zero values
  - Zero values Traced back to 15 men with no apparent link, set to null
  - median Fare assigned to all nulls
  - Quartile bucket of Fare data (refer to image)
- Reference Will Cukierski. Titanic Machine Learning from Disaster. https://kaggle.com/competitions/titanic, 2012. Kaggle.



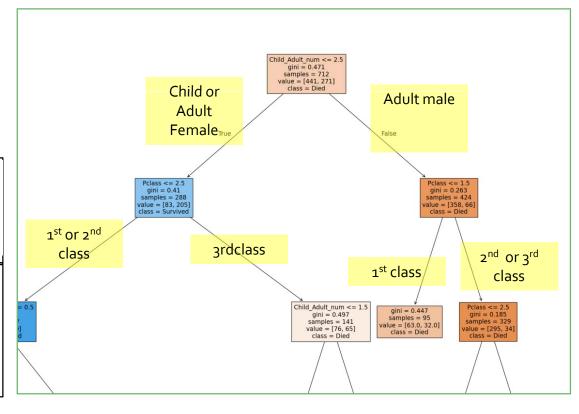
#### Decision Tree - Data Visualisation 1



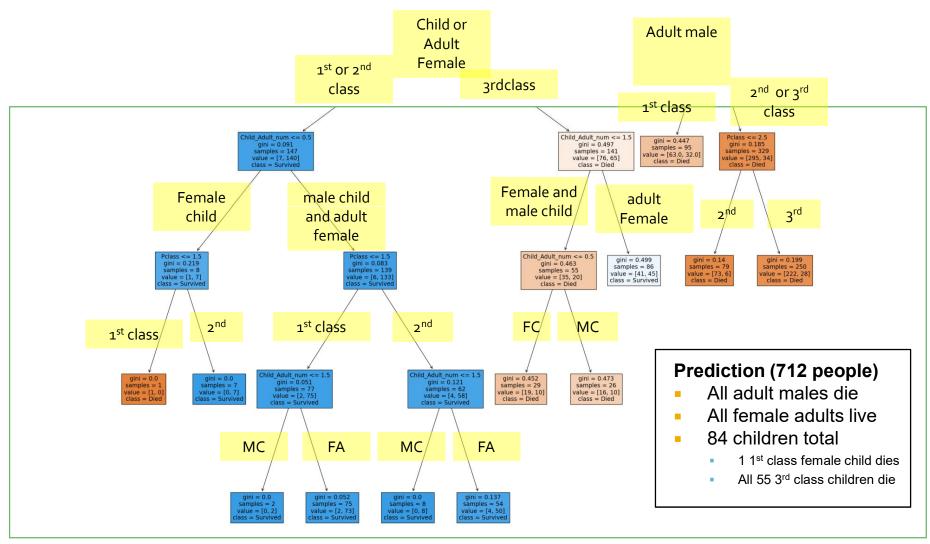
- Class and Child/Adult new feature only
  - not scaled, training data 80/20 test split
- Gini default model accuracy 79%



- 88% of the time will predict person died correctly
- 34.7~% of the time will predict person died when they survived
- 12% of time will predict someone lived when they died
- 66.5% of the time will predict person survived correctly



#### Decision Tree - Data Visualisation 2

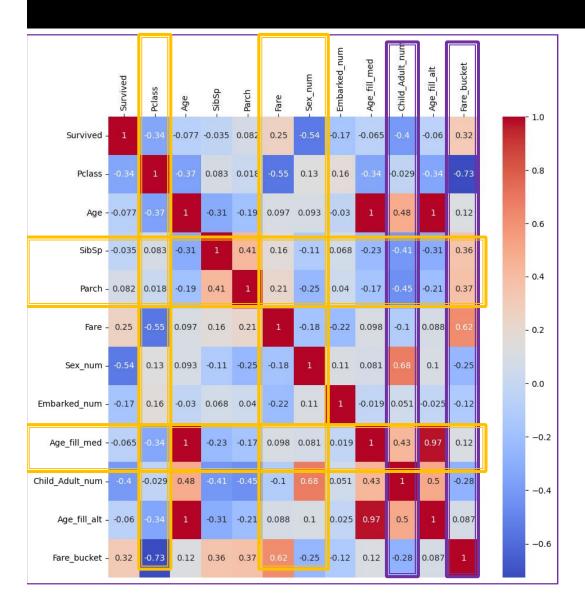


# Classifier Models compared

- All 8o/20 test split of training data
- Comparable confusion matrix for most except Sigmoid and Bernoulli NB
  - K = 3 KNN model gives better prediction of survivors
- Due to imbalanced dataset models not as good at predicting those that survived
  - 60 % accuracy BeronulliNB couldn't predict anyone living

Model	Logistic regression	KI	IN	SVM			Decision Tree			Naive Bayes			
Features	Class, Child/Adult, Fare bucket								Class, Child/Adult	Class, Child/Adult, Fare bucket			
Scaling	Robust								none				
Other conditions		k = 3, error ~0.197	k = 9, error ~0.18	linear	sigmoid	rbf	gini/ entropy	gini with max depth	gini/ entropy /g	Gaussian	Multinomial	Bernoulli	
Accuracy %	77	82	82	82	51	80		81	79	73	69	60	
predict person died correctly (pink add to 100) %	88	87	94	91	61	91	94	90	88	83	77	100	
predict person died when they survived (blue add to 100) %	39	27	35	31	64	37	35	32	34	42	45	100	
predict someone lived when they died (pink add to 100) %	12	13	6	9	39	g	6	10	12	17	22	0	
predict person survived correctly (blue add to 100) %	61	73	65	69	35	63	65	67	66	58	55	0	
					Proxy for neural					Bernouilli for binary data, Multinomial for discrete counts s (doesn't like negative values of scaled data), Gaussian assumes			
Comments					networks				*gini presented	norm dist *tried text data but errored			

### **Feature Correlation**



- Fare qbucket and Child/Adult encoded (new features purple), used instead of Fare and Sex encoded (original orange):
  - Have a stronger correlation than original variable with sibling/spouse, parent/child relationships and age
- Haven't incorporated the port that passengers embarked from but only weak correlations to everything

## Conclusion

- A simple unoptimised decision Tree predicts that all adult males die, all adult females live, all 3<sup>rd</sup> class children die
- Models 80+/-3% accuracy with comparable confusion matrix except:
  - SVM sigmoid
  - Naive Bayes, particularly Bernouli
- As per competition 100% accuracy possible if model all training data and fit test data (not used in modelling)
  - Further refinement of models and features