# Lesson #10
# Kaggle Fundamentals

notas

Getting Started with Kaggle

Kaggle Workflow

- Load Libraries
- Get data, including EDA
- Clean, prepare and manipulate Data (feature engineering)
- Modeling (train and test)
- Algorithm Tuning
- Finalizing the Model (submission)

notas

kaggle

What is Kaggle?
Why I Participate?
What is the Impact?

- Competitions
- Datasets
- Notebooks
- Discussion
- Courses
- Jobs
- Social Network
- ...

Getting Started Prediction Competition

# Titanic: Machine Learning from Disaster

Start here! Predict survival on the Titanic and get familiar with ML basics

Kaggle · 11,209 teams · Ongoing



Overview



## 👋 🚢 Ahoy, welcome to Kaggle! You're in the right place.

This is the legendary Titanic ML competition – the best, first challenge for you to dive into ML competitions and familiarize yourself with how the Kaggle platform works.

The competition is simple: use machine learning to create a model that predicts which passengers survived the Titanic shipwreck.

Read on or watch the video below to explore more details. Once you're ready to start competing, click on the "Join Competition button to create an account and gain access to the competition data. Then check out Alexis Cook's Titanic Tutorial that walks you through step by step how to make your first submission!

Getting Started Prediction Competition

# Titanic: Machine Learning from Disaster

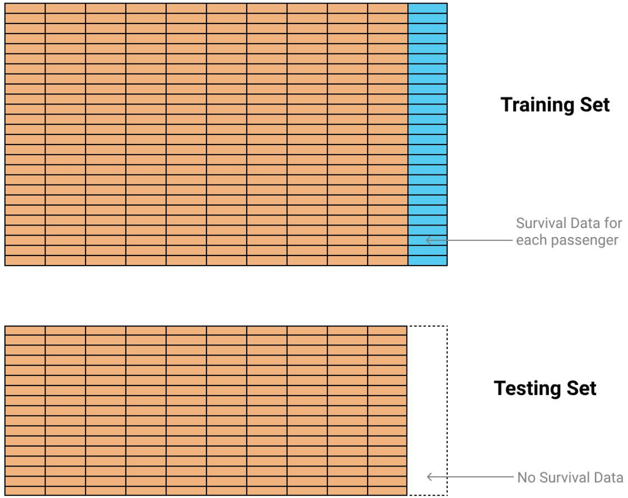
Start here! Predict survival on the Titanic and get familiar with ML basics

Kaggle · 11,209 teams · Ongoing

Overview | Data | Notebooks | Discussion | Leaderboard | Rules | Team | My Submissions | Submit Predictions

## Data Sources

| | |
|---|---|
| gender_submission.csv | 418 x 2 |
| test.csv | 418 x 11 |
| train.csv | 891 x 12 |



Overview Data Notebooks Discussion Leaderboard Rules Team My Submissions **Submit Predictions**

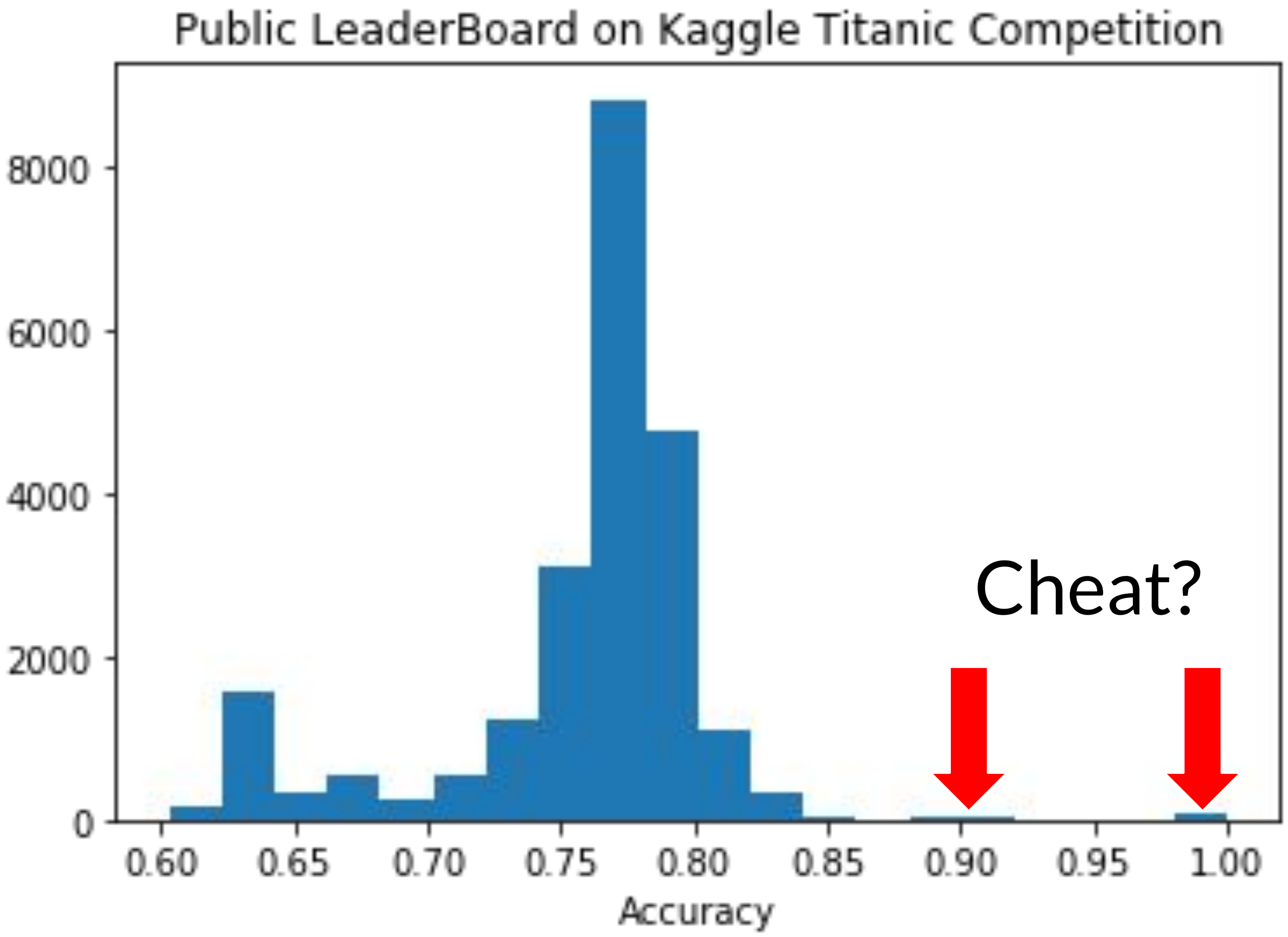
Public Leaderboard | Private Leaderboard

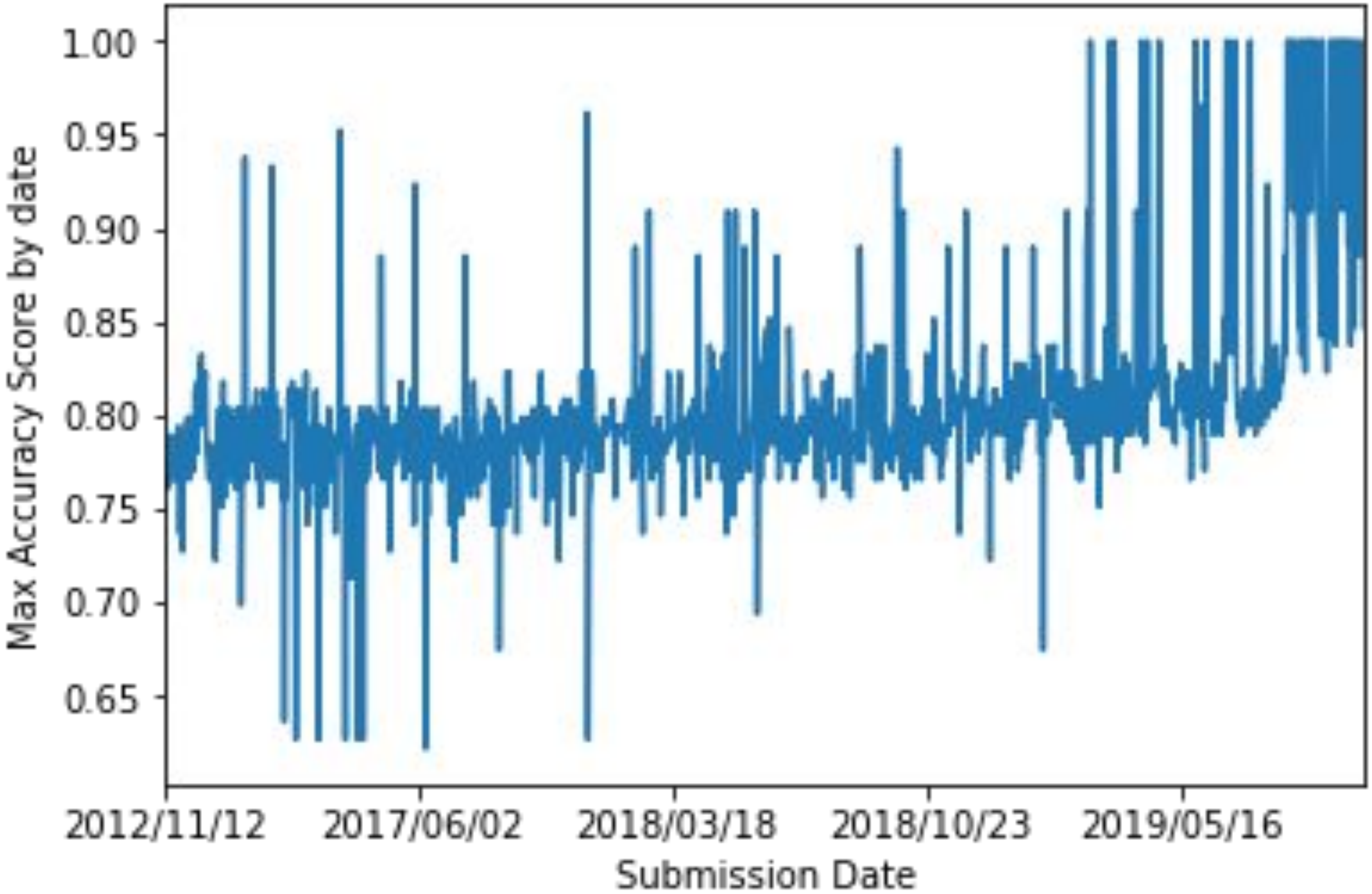
This leaderboard is calculated with approximately 50% of the test data.

The final results will be based on the other 50%, so the final standings may be different.

Raw Data Refresh

| # | Team Name | Notebook | Team Members | Score | Entries | Last |
|---|---|---|---|---|---|---|
| 1 | **Reza R Pratama** | | | 1.00000 | 1 | 2mo |
| 2 | **Matheus Silva** | | | 1.00000 | 1 | 2mo |
| 3 | **Batsy** | | | 1.00000 | 1 | 2mo |
| 4 | **Patrick Bruecker** | | | 1.00000 | 1 | 2mo |
| 5 | **SoiSoCiu** | | | 1.00000 | 25 | 2mo |
| 6 | **ambition12** | | | 1.00000 | 2 | 2mo |
| 7 | **harshitsheoran** | | | 1.00000 | 1 | 2mo |
| 8 | **James Strong** | | | 1.00000 | 1 | 2mo |
| 9 | **chauncey** | | | 1.00000 | 14 | 1mo |

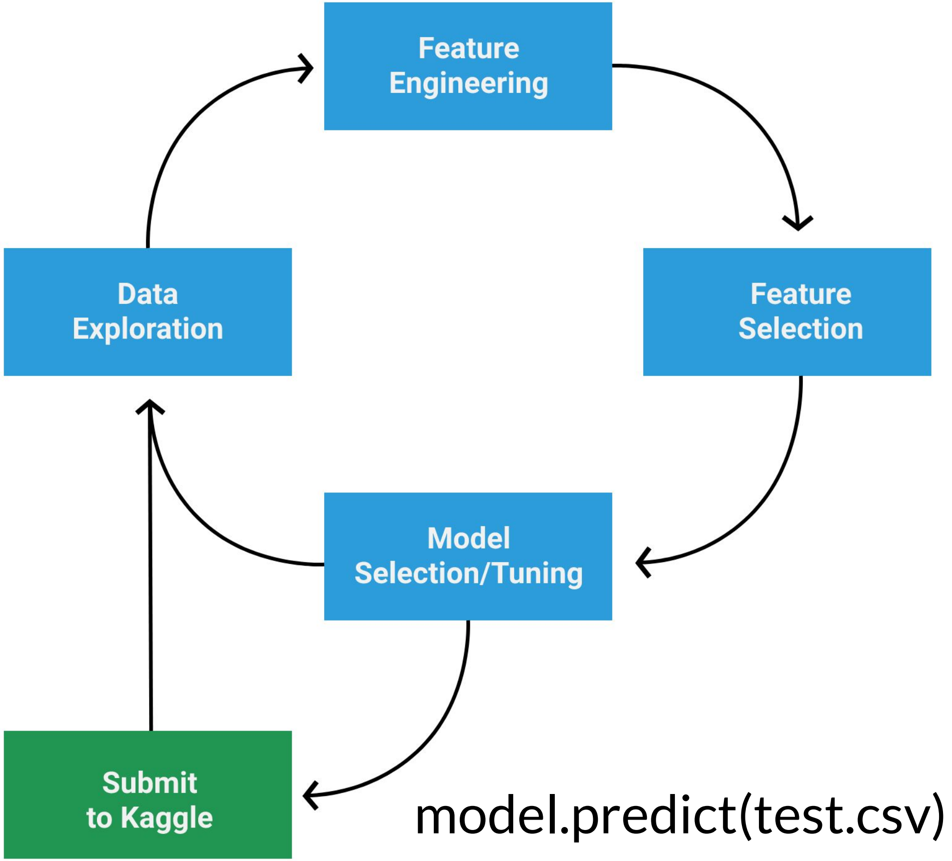

Public LeaderBoard on Kaggle Titanic Competition
8000
6000
4000
2000
0
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
Accuracy
Cheat?



Max Accuracy Score by date
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
2012/11/12
2017/06/02
2018/03/18
2018/10/23
2019/05/16
Submission Date

train.csv

Problem

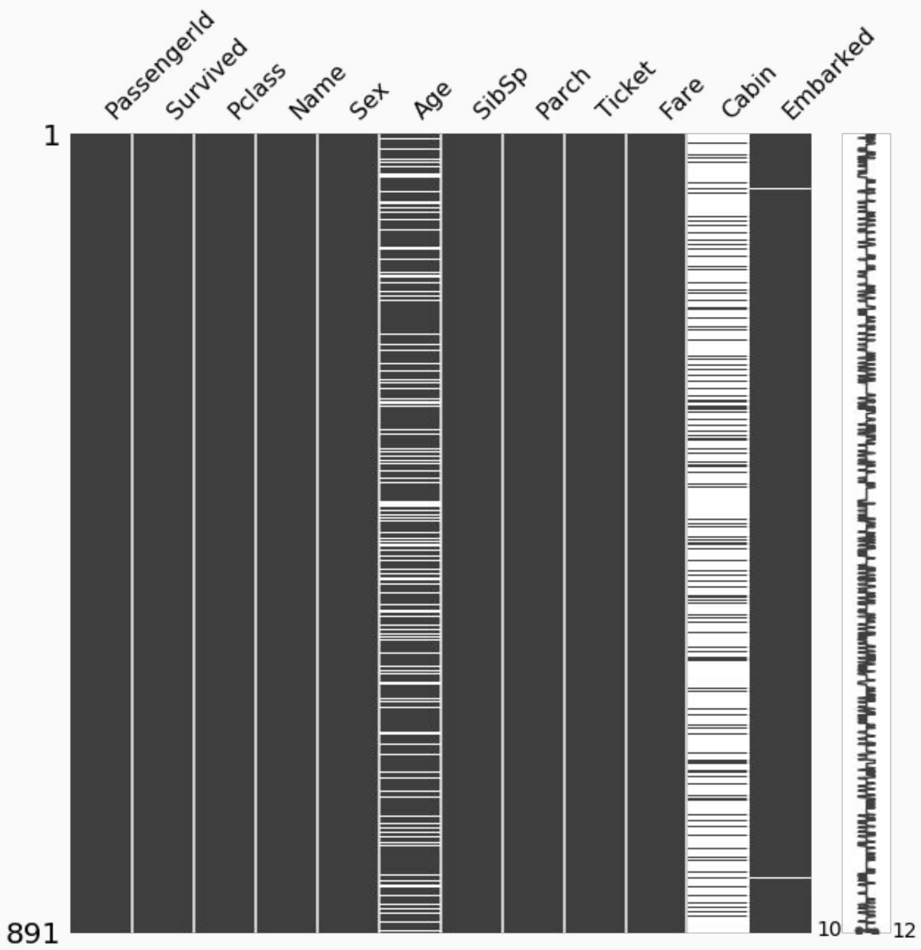



1. Load Libraries
2. Get data, including EDA
3. Clean, prepare and manipulate Data (feature engineering)
4. Modeling (train and test)
5. Algorithm Tuning
6. Creating a submission file

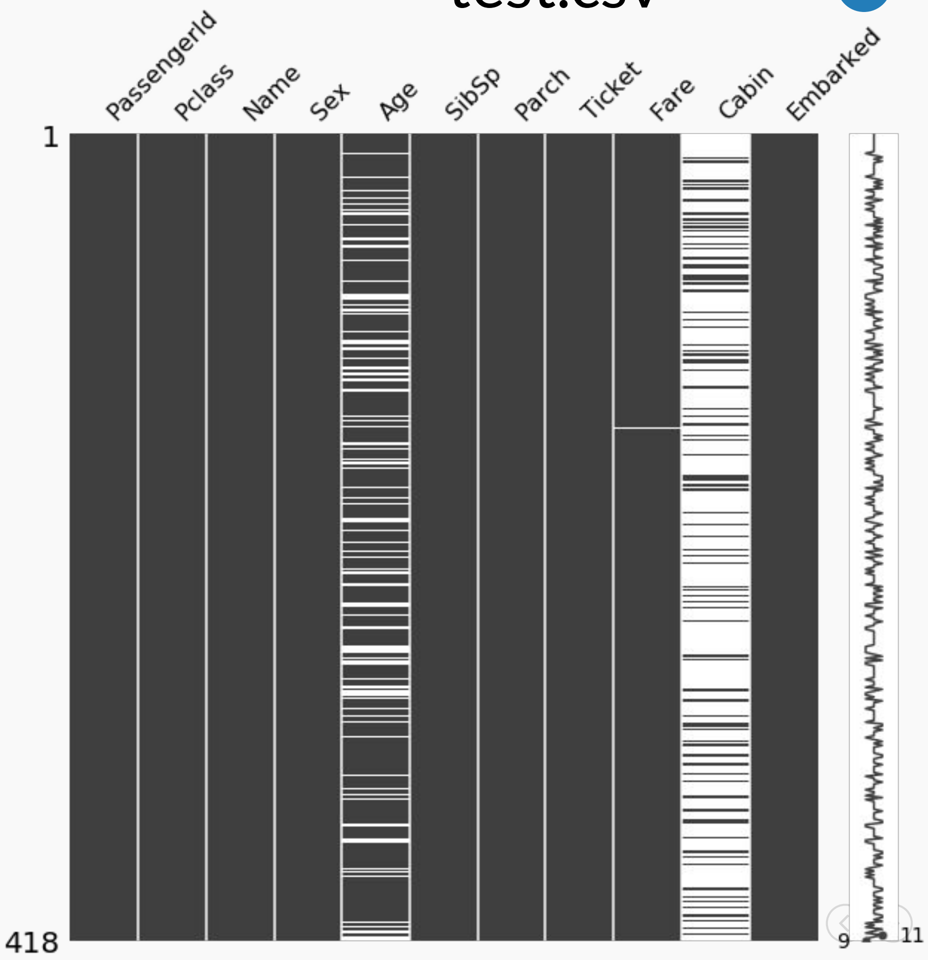
# Data Exploration (EDA)

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| **2** | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| **3** | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| **4** | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S |

# train.csv




# test.csv

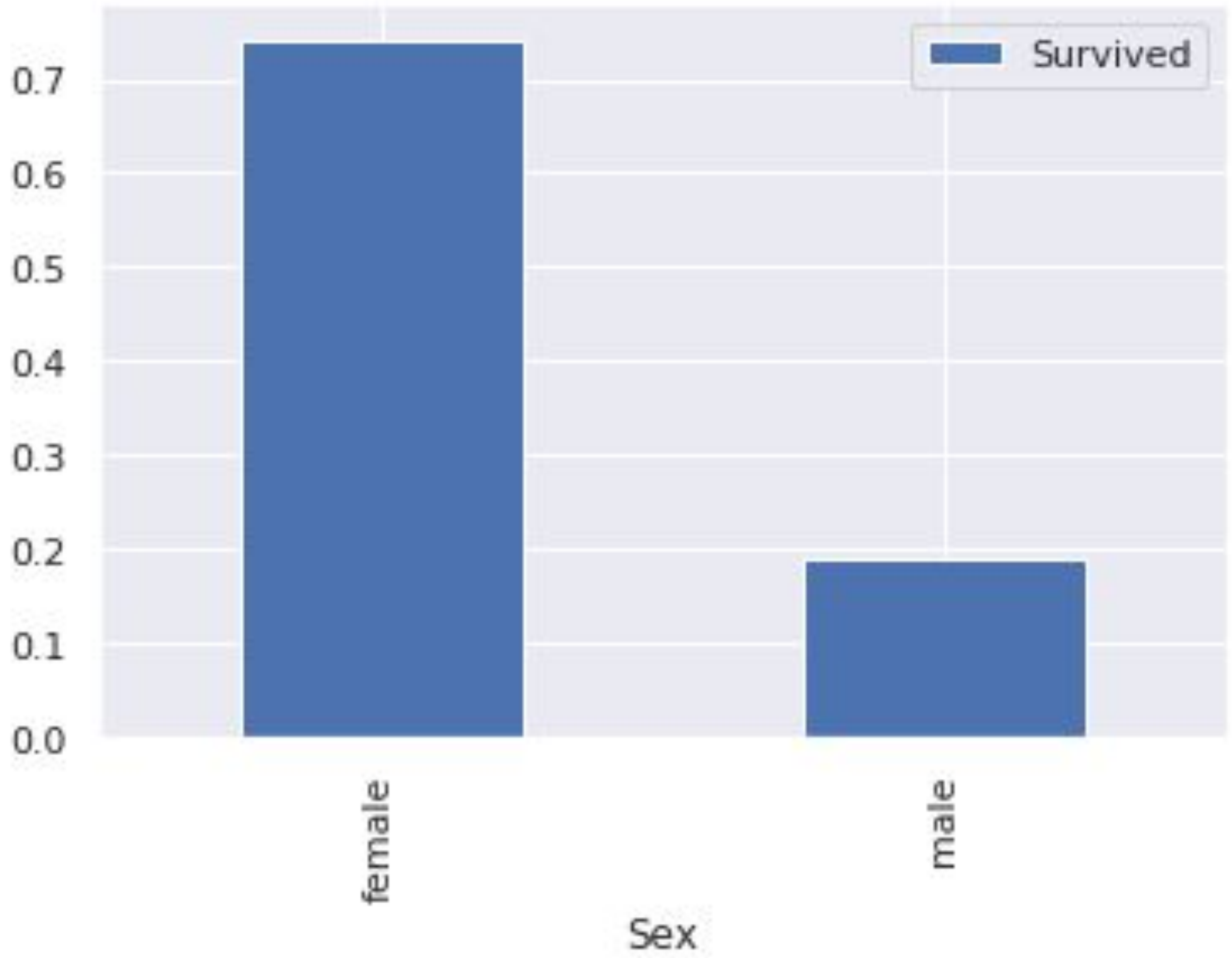


```
train.Survived.value_counts()
```

```
0      549
1      342
```

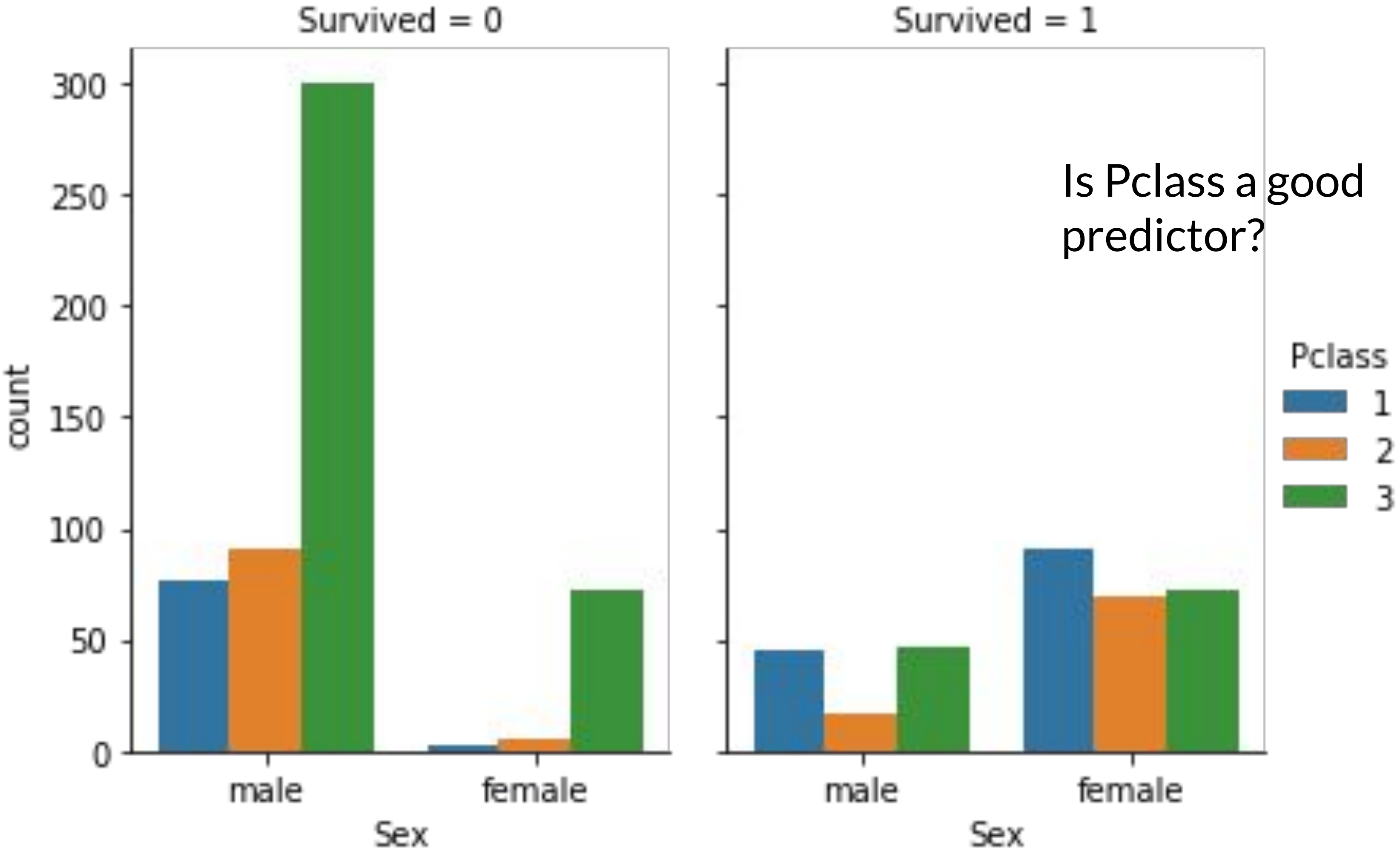
## Hypothesis #01 (naive)

The simplest strategy of guessing that all died since the majority died

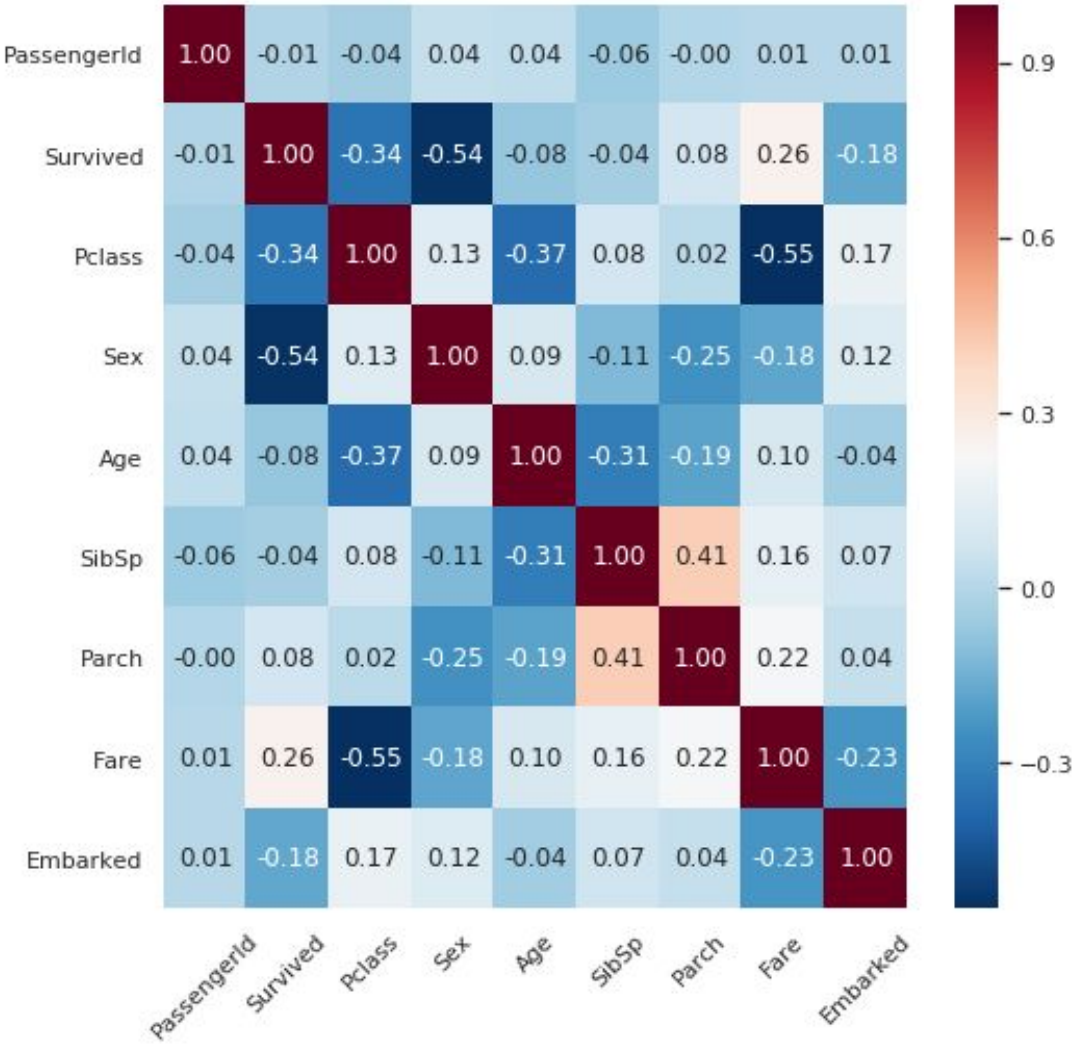

Survived
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
female
male
Sex

# Hypothesis #02

Since roughly 75% of females survived and roughly only 20% of males survived, what's the score when you guess all females survived and all males perished?




Is Pclass a good predictor?

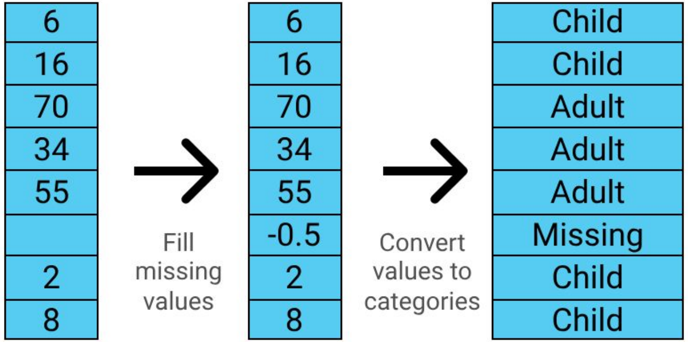


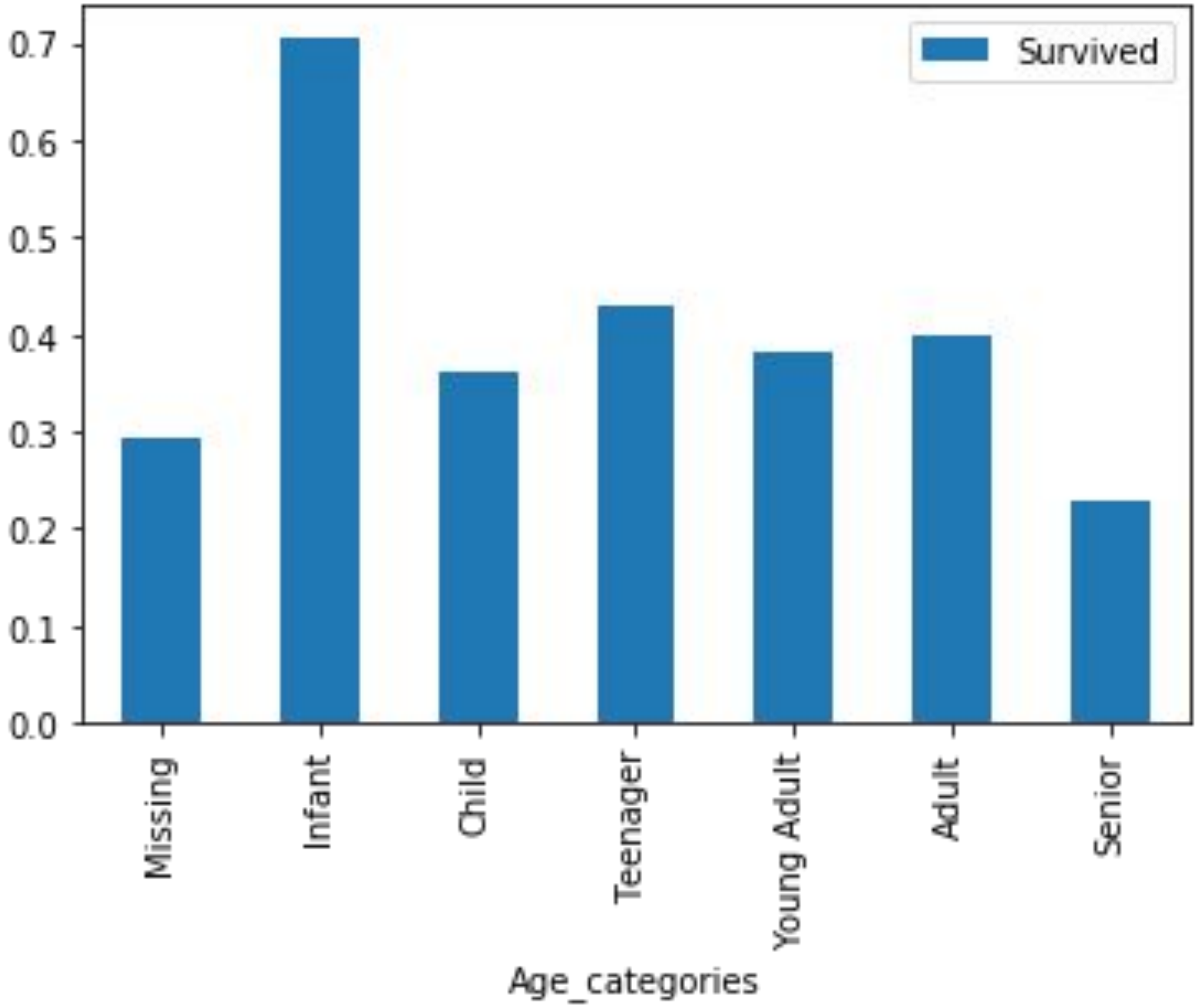

- A correlation of -0.54 shows Sex carries a lot of information about Survived.
- We see then Pclass (-0.34) and Fare (0.26) are the next features that correlate with Survived
- However, Fare and Pclass are very much correlated at (0.55) as we may expect

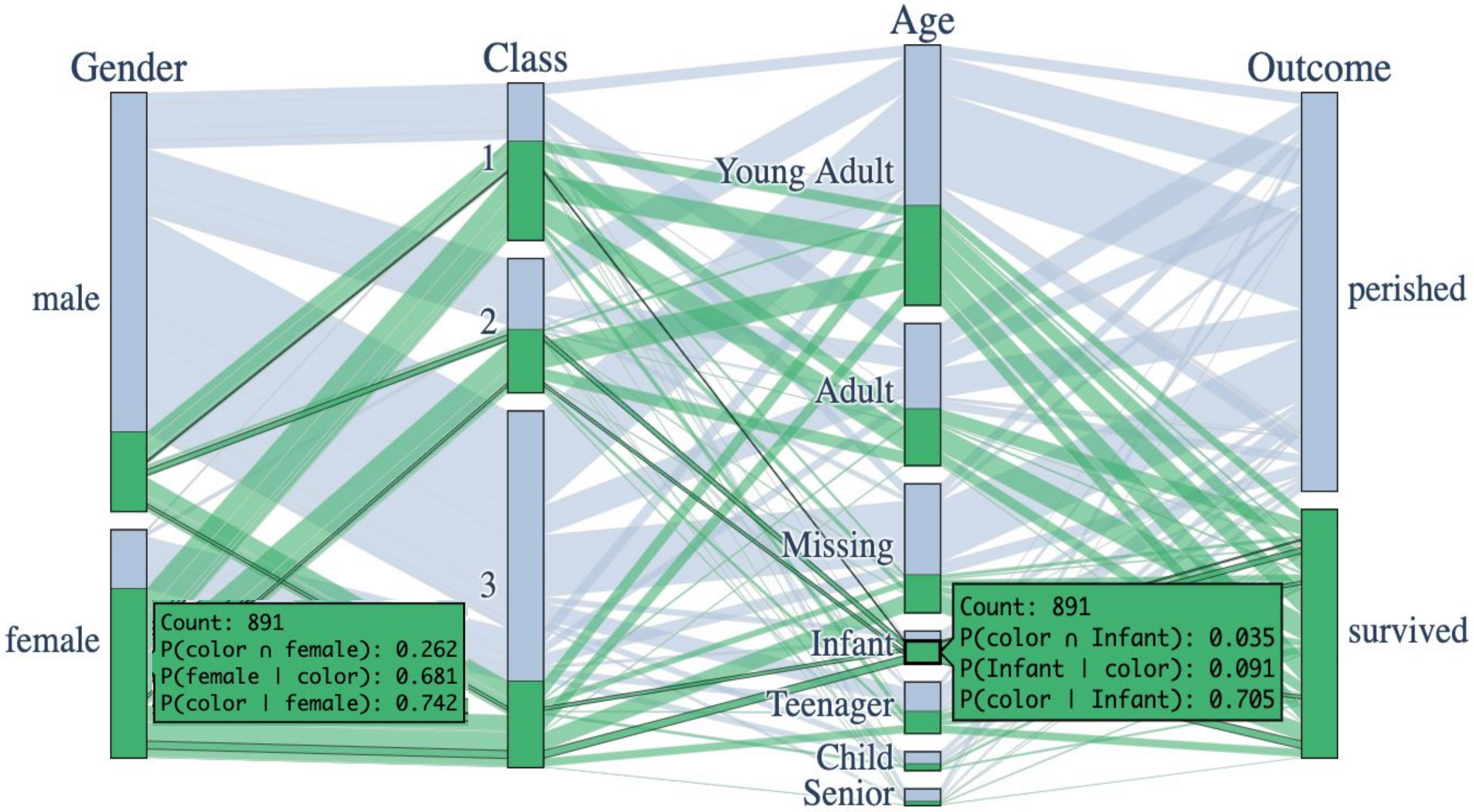

# "Women and Children First"

# Clean, Preparing and Manipulate Data

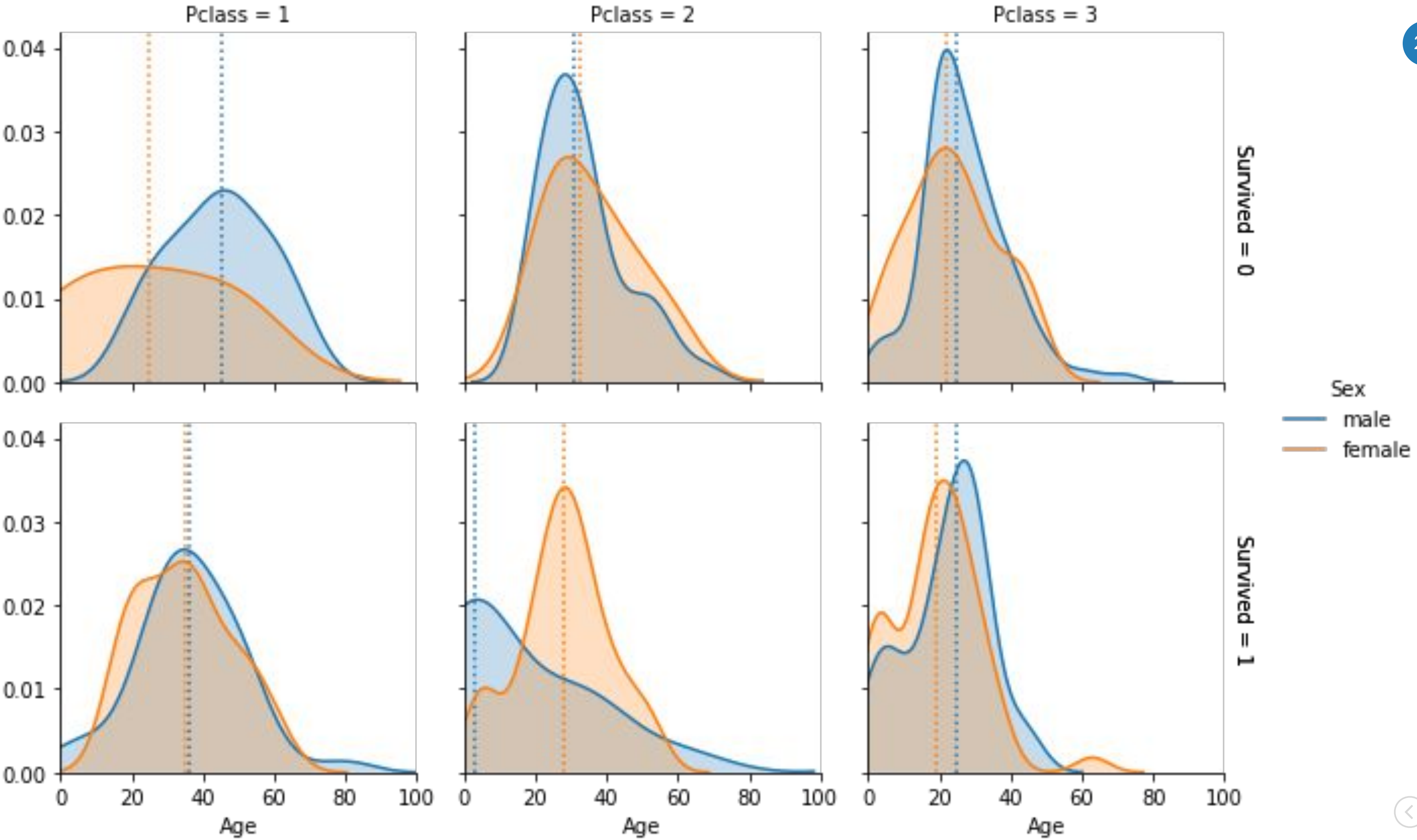
```
# fill missing values with -0.5
train["Age"] = train["Age"].fillna(-0.5)

# divide age column into a range of values
cut_points = [-1,0,5,12,18,35,60,100]
label_names = ["Missing","Infant","Child",
               "Teenager","Young Adult","Adult","Senior"]
train["Age_categories"] = pd.cut(train["Age"],
                                 cut_points,
                                 labels=label_names)
```




Survived
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Missing
Infant
Child
Teenager
Young Adult
Adult
Senior
Age_categories



Gender
Class
Age
Outcome
male
female
1
2
3
Young Adult
Adult
Missing
Infant
Teenager
Child
Senior
perished
survived
Count: 891
P(color ∩ female): 0.262
P(female | color): 0.681
P(color | female): 0.742
Count: 891
P(color ∩ Infant): 0.035
P(Infant | color): 0.091
P(color | Infant): 0.705



Pclass = 1
Pclass = 2
Pclass = 3
Survived = 0
Survived = 1
Sex
male
female
Age
0.00
0.01
0.02
0.03
0.04
0
20
40
60
80
100

# Preparing our Data for Machine Learning

- Sex
- Pclass
- Age_categories

- Before we build our model, we need to prepare these columns for machine learning.
- Most machine learning algorithms can't understand text labels, so we have to convert our values into numbers.

# Preparing our Data for Machine Learning

| Pclass |
|---|
| 3 |
| 1 |
| 3 |
| 1 |
| 3 |
| 3 |
| 1 |
| 3 |
| 3 |
| 2 |

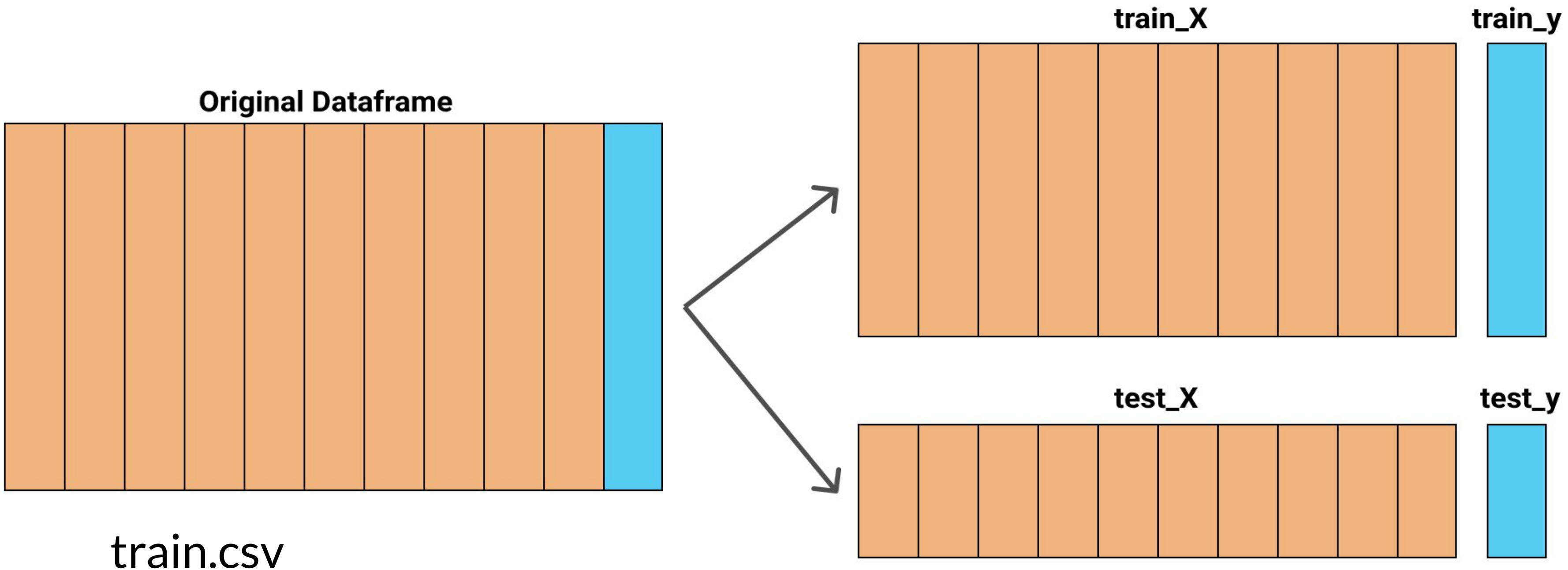
| Pclass_1 | Pclass_2 | Pclass_3 |
|---|---|---|
| 0 | 0 | 1 |
| 1 | 0 | 0 |
| 0 | 0 | 1 |
| 1 | 0 | 0 |
| 0 | 0 | 1 |
| 0 | 0 | 1 |
| 1 | 0 | 0 |
| 0 | 0 | 1 |
| 0 | 0 | 1 |
| 0 | 1 | 0 |

```
def create_dummies(df,column_name):
    # drop_first = True to avoid colinearity
    dummies = pd.get_dummies(df[column_name],
                             prefix=column_name,
                             drop_first=True)
    df = pd.concat([df,dummies],axis=1)
    return df

train = create_dummies(train,"Pclass")
train = create_dummies(train,"Age_categories")
train = create_dummies(train,"Sex")
```

- Model [0]
  - Sex column (categorized), Pclass (raw)
- Model [1]
  - Sex column (get_dummies(drop_first=True)), Pclass (raw)
- Model [2]
  - Sex column (get_dummies(drop_first=True)), Pclass (get_dummies(drop_first=False))
- Model [3]
  - Sex column (get_dummies(drop_first=True)), Pclass (raw), Age (get_dummies(drop_first=False))

# Everything ends in **Pipelines**

# Creating our First Machine Learning Model




train.csv

# Creating a Submission File

| PassengerId | Survived |
|---|---|
| 892 | 0 |
| 893 | 1 |
| 894 | 0 |

```
predict_final = best_model.best_estimator_.predict(test)

holdout_ids = test["PassengerId"]
submission_df = {"PassengerId": holdout_ids,
                 "Survived": predict_final}
submission = pd.DataFrame(submission_df)

submission.to_csv("submission.csv",index=False)
```

| | | | | |
|---|---|---|---|---|
| 9042 | Nikita Nazarov | 0.75598 | 1 | 17h |
| 9043 | tani0 | 0.75598 | 2 | 11h |
| 9044 | OTHELLO31 | 0.75598 | 2 | 6h |
| 9045 | CHIAKI3 | 0.75598 | 6 | 3h |
| 9046 | pallavisonagote | 0.75598 | 5 | 3h |
| 9047 | IvanovitchSilva | 0.75598 | 6 | 4m |

**Your Best Entry ↑**

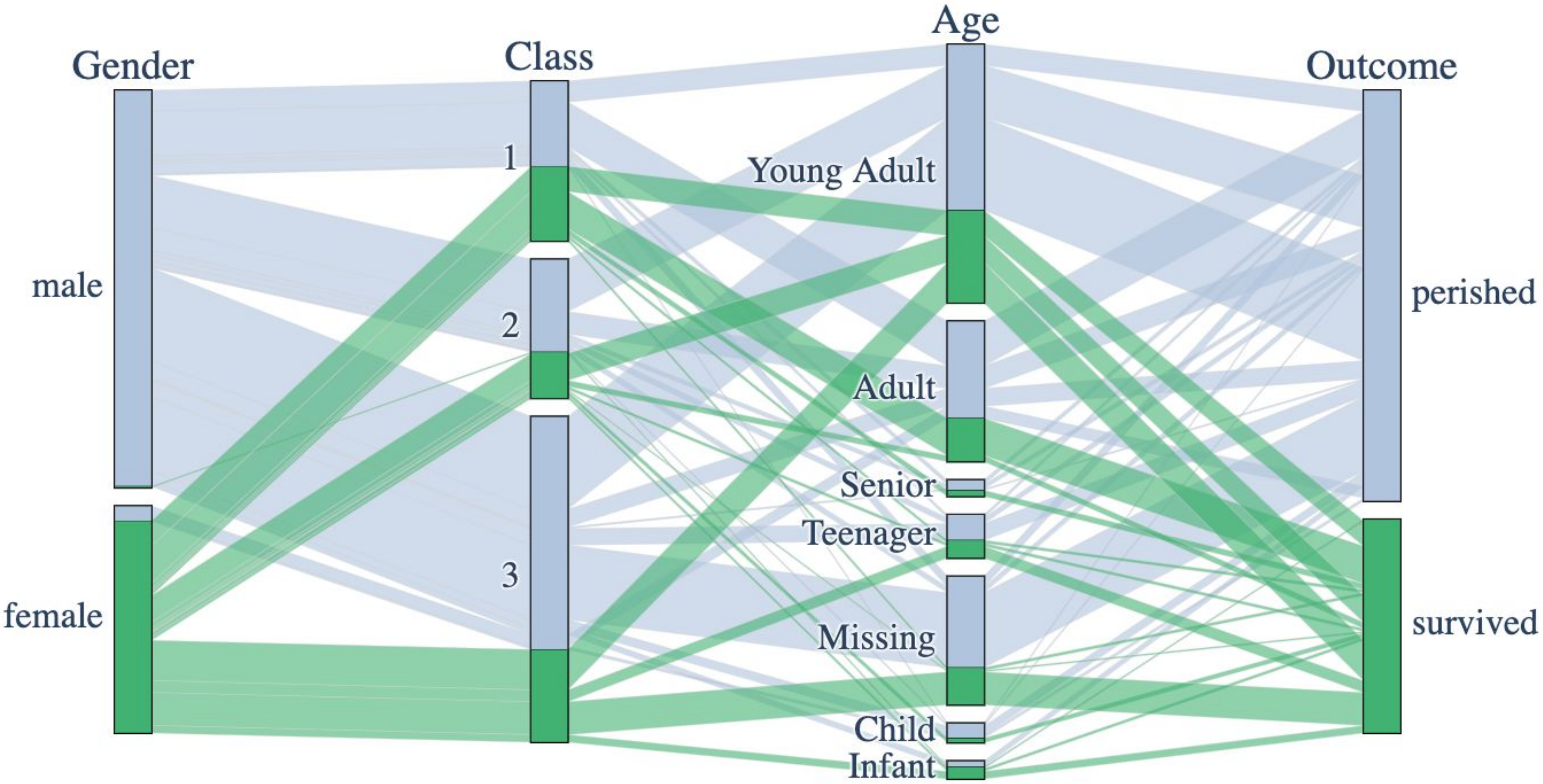
Your submission scored 0.75119, which is not an improvement of your best score. Keep trying!

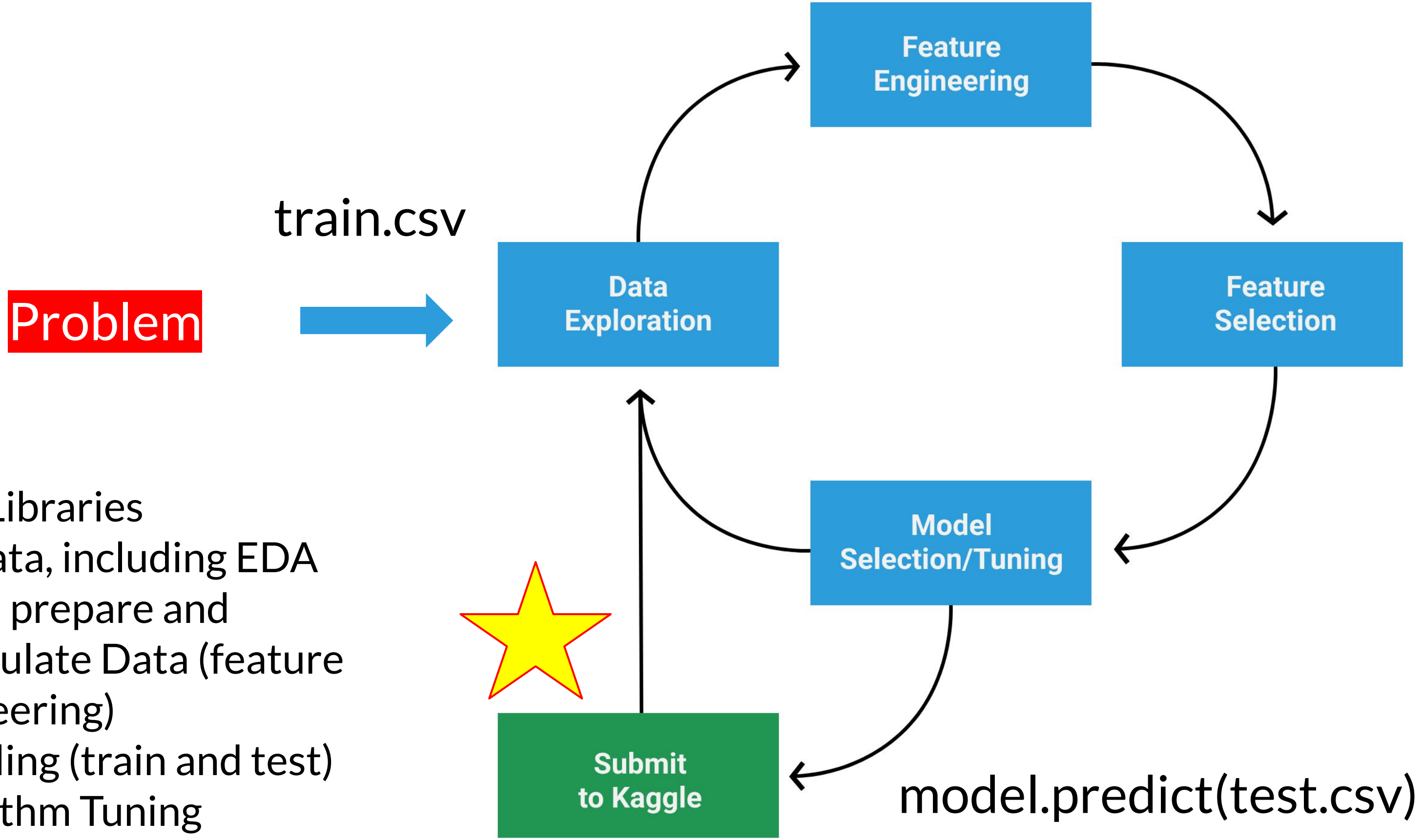
| | | | | |
|---|---|---|---|---|
| 9048 | ctron | 0.75119 | 1 | 2mo |
| 9049 | RyoNamiki | 0.75119 | 1 | 2mo |
| 9050 | nan7674 | 0.75119 | 1 | 2mo |
| 9051 | Madhan Varadhodiyil | 0.75119 | 2 | 2mo |
| 9052 | fanxiaohong | 0.75119 | 2 | 2mo |
| 9053 | Kristof Nachtergaele | 0.75119 | 3 | 2mo |
| 9054 | Saurabh_Dalakoti | 0.75119 | 1 | 2mo |
| 9055 | NP_29 | 0.75119 | 1 | 2mo |

| Model | Features | Parameters | Score | Ratio |
|---|---|---|---|---|
| All-Dead | - | All zeros | 0.62679 | - |
| [0] RandomForest | Sex (categorized)<br>Pclass (raw) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [1] RandomForest | Sex (dummies(T))<br>Pclass (raw) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [2] RandomForest | Sex (dummies(T))<br>Pclass (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [3] XGBClassifier | Sex (dummies(T))<br>Pclass (raw)<br>Age (dummies(F)) | learning_rate: 0.001<br>max_depth: 4<br>n_estimators: 50 | 0.75119 | 19.84% |
| All-Females Survived<br>All-Males Perished | - | if Sex == "female"<br>Survived = 1<br>else Survived== 0 | 0.76555 | 22.13% |

# Model #3 - Analyzing the predictions





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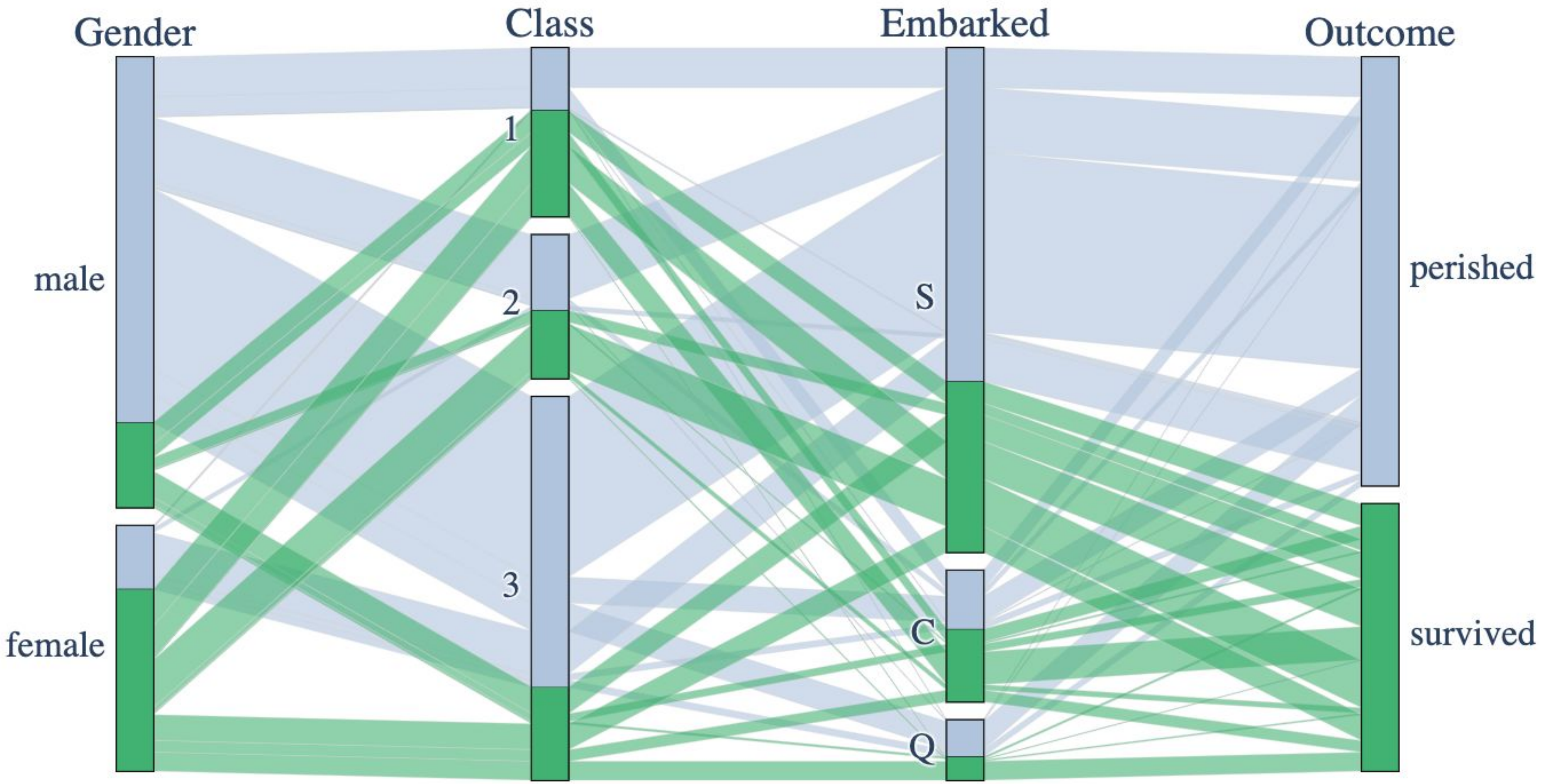
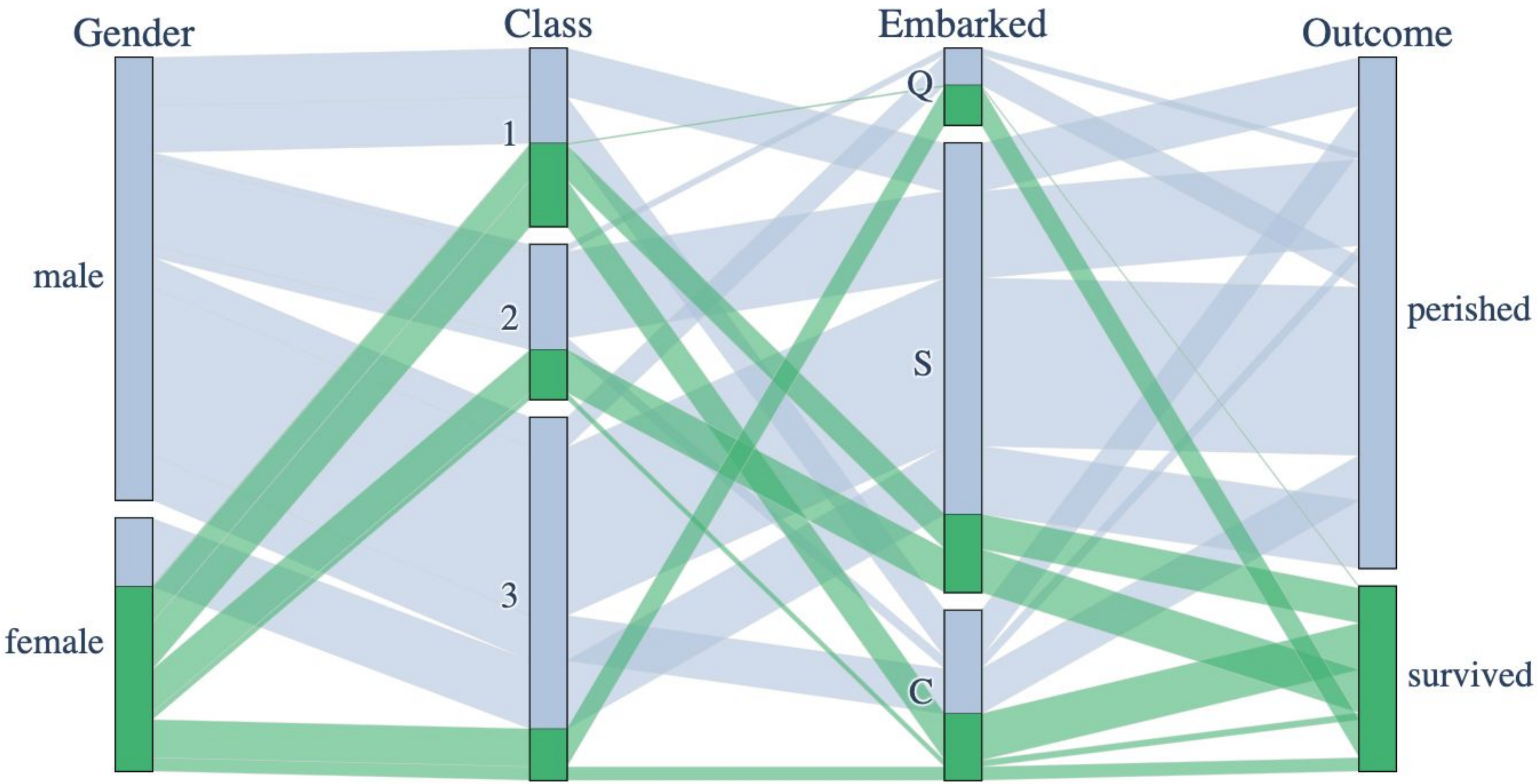
# What about adding Embarked on top?



- Model [4]
  - Sex column (get_dummies(drop_first=True)), Pclass (raw), Embarked (categorized)
- Model [5]
  - Sex column (get_dummies(drop_first=True)), Pclass (raw), Embarked (get_dummies(drop_first=False))

# Models #4 #5 - Analyzing the predictions



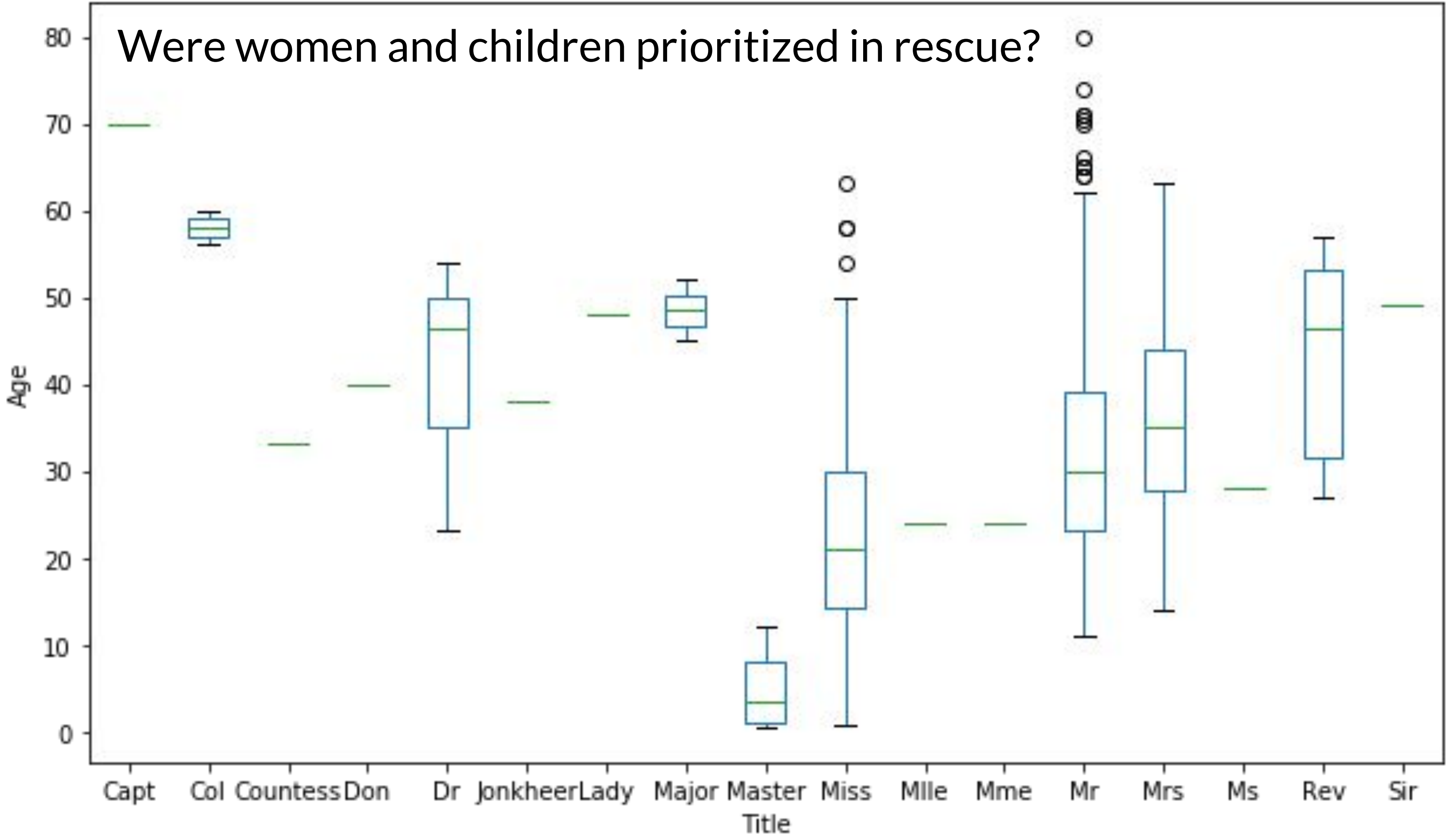


| Model | Features | Parameters | Score | Ratio |
|---|---|---|---|---|
| All-Dead | - | All zeros | 0.62679 | - |
| [0] RandomForest | Sex (categorized)<br>Pclass (raw) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [1] RandomForest | Sex (dummies(T))<br>Pclass (raw) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [2] RandomForest | Sex (dummies(T))<br>Pclass (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.74641 | 19.08% |
| [3] XGBClassifier | Sex (dummies(T))<br>Pclass (raw)<br>Age (dummies(F)) | learning_rate: 0.001<br>max_depth: 4<br>n_estimators: 50 | 0.75119 | 19.84% |
| All-Females Survived<br>All-Males Perished | - | if Sex == "female"<br>Survived = 1<br>else Survived== 0 | 0.76555 | 22.13% |
| [4] RandomForest | Sex (dummies(T))<br>Pclass (raw)<br>Embarked (Categorized) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.77990 | 24.42% |
| [5] RandomForest | Sex (dummies(T))<br>Pclass (raw)<br>Embarked (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.77990 | 24.42% |

# The Title feature is a good predictor?

'Mr', 'Mrs', 'Miss', 'Master', 'Don', 'Rev', 'Dr', 'Mme', 'Ms', 'Major', 'Lady', 'Sir', 'Mlle', 'Col', 'Capt', 'Countess', 'Jonkheer', 'Dona'

# Were women and children prioritized in rescue?



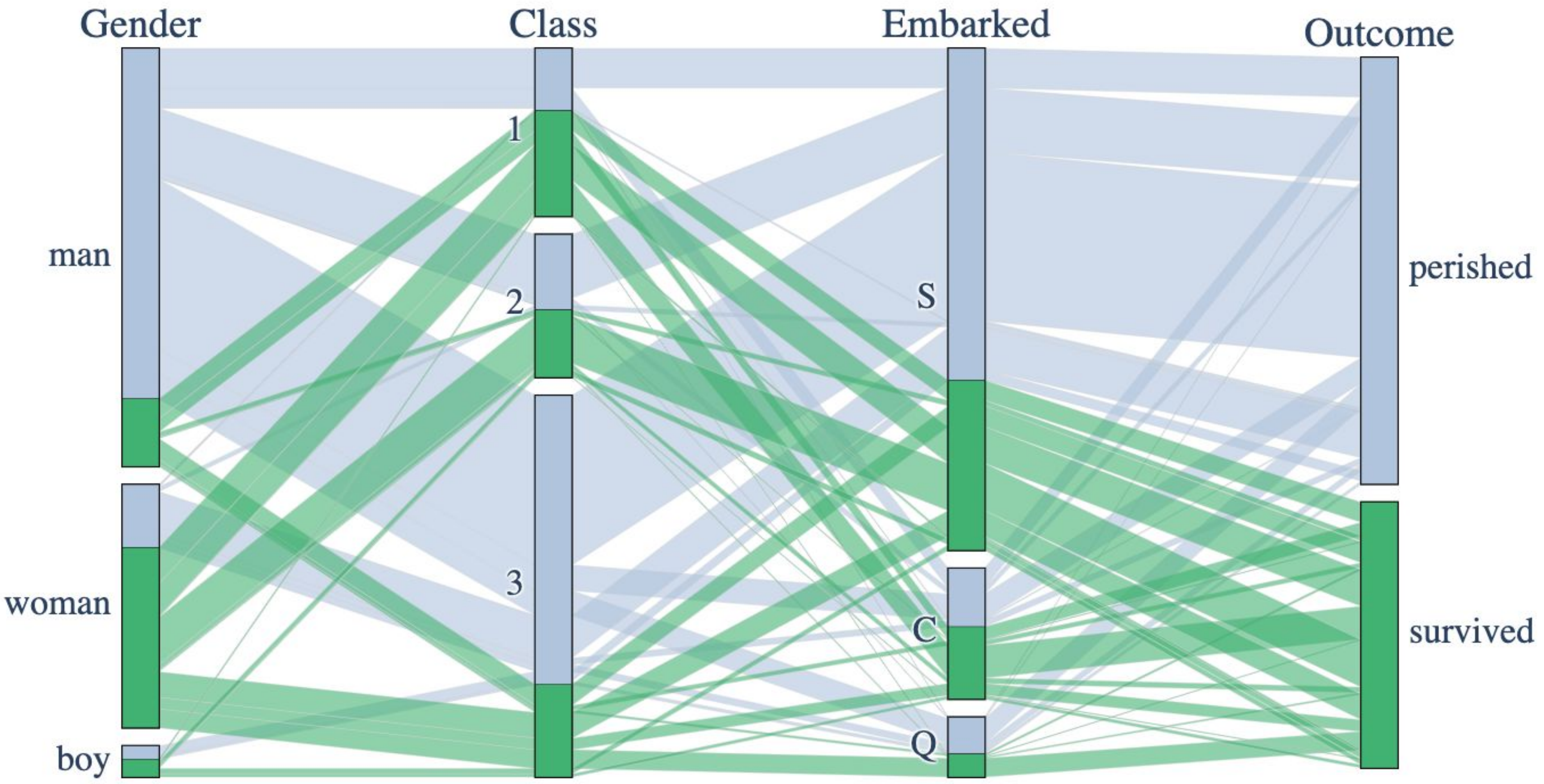
```python
df["Title"] = df["Name"].str.extract(' ([A-Za-z]+)\.',expand=False)
titles = {
    "Mr" :          "man",
    "Mme":          "woman",
    "Ms":           "woman",
    "Mrs" :         "woman",
    "Master" :      "boy",
    "Mlle":         "woman",
    "Miss" :        "woman",
    "Capt":         "man",
    "Col":          "man",
    "Major":        "man",
    "Dr":           "man",
    "Rev":          "man",
    "Jonkheer":     "man",
    "Don":          "man",
    "Sir" :         "man",
    "Countess":     "woman",
    "Dona":         "woman",
    "Lady" :        "woman"
}
```

# New Sex Column

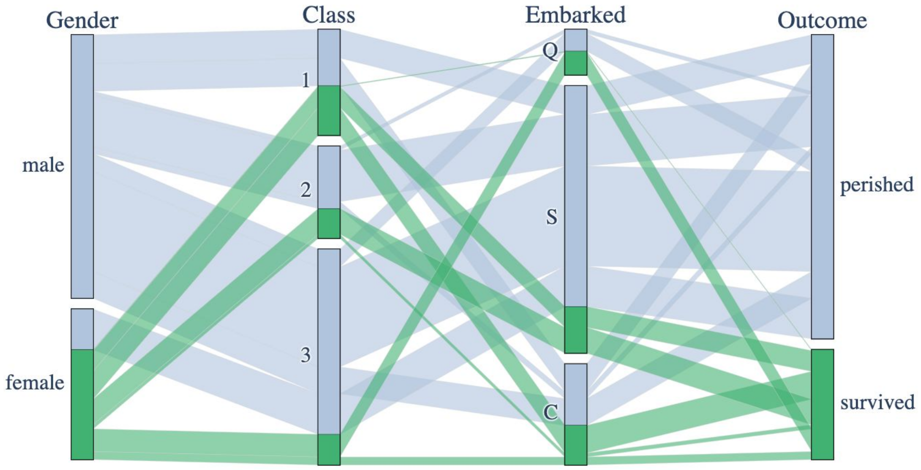
- sex+age+name

```python
df["Sex"] = df["Title"].map(titles)
```

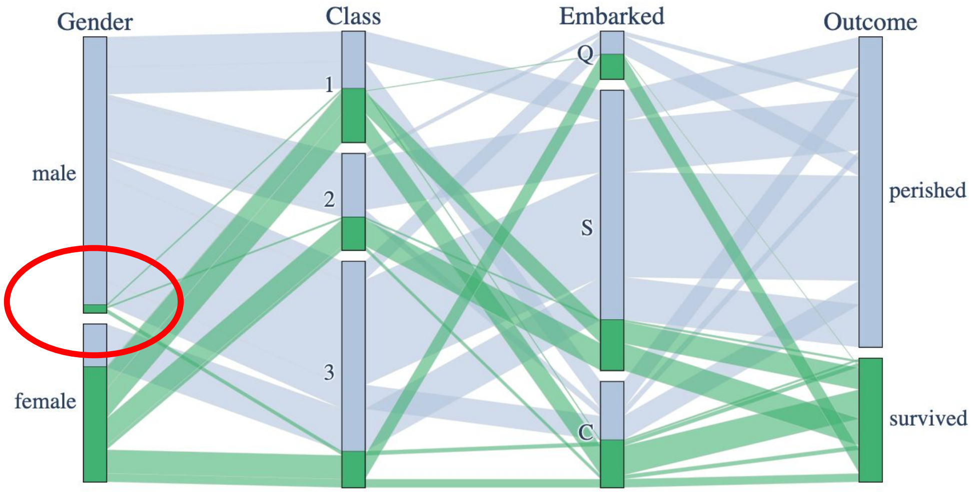
# Models #6 #7  Gender = name+age



# Models #4 and #5




# Models #6 and #7



| Model | Features | Parameters | Score | Ratio |
|---|---|---|---|---|
| All-Dead | - | All zeros | 0.62679 | - |
| All-Females Survived<br>All-Males Perished | - | if Sex == "female"<br>Survived = 1<br>else Survived== 0 | 0.76555 | 22.13% |
| [4] RandomForest | Sex (dummies(T))<br>Pclass (raw)<br>Embarked (Categorized) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.77990 | 24.42% |
| [5] RandomForest | Sex (dummies(T))<br>Pclass (raw)<br>Embarked (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.77990 | 24.42% |
| [6] RandomForest | Sex (name+age)<br>Pclass (raw)<br>Embarked (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.78947 | 25.95% |
| [7] RandomForest | Sex dummies(name+age,T)<br>Pclass (raw)<br>Embarked (dummies(F)) | criterion: entropy<br>n_estimators:100<br>max_leaf_nodes: 64 | 0.78947 | 25.95% |

# Next Steps

- **Improving the features:**
  - Feature Engineering: Create new features from the existing data (family_size, ticket, cabin, fare, etc)
  - Feature Selection: Select the most relevant features to reduce noise and overfitting.
- **Improving the model:**
  - Model Selection: Try a variety of models to improve performance.
  - Hyperparameter Optimization: Optimize the settings within each particular machine learning model.

# Getting Started with Kaggle.ipynb

https://www.kaggle.com/pliptor/how-am-i-doing-with-my-score/report