# titanic_notebook

May 4, 2018

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from IPython.display import display, HTML
```

## 1 UMBC CS 471 Project 3: Titanic Survivors with Random Forests

Using a Jupyter notebook like a boss. Already imported pandas and numpy, will import sklearn later. Also the display function for Jupyter notebooks.

### 1.1 Preprocessing

First thing I had to do was to actually load the data into a dataframe. It's a good thing Pandas has a function just for this. Then just display the head in order to make sure it read in everything.

```
In [2]: # Data file is in the same file as the rest.
        file_name = "./train.csv"
        df = pd.read_csv(file_name)

        # Display the head.
        display(df.head())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
```

```
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

Nice so it looks like things loaded in correctly. I looked at an old project I did with the same data set to get what each value meant:

- **Survived:** Outcome of survival (0 = No; 1 = Yes)
- **Pclass:** Socio-economic class (1 = Upper class; 2 = Middle class; 3 = Lower class)
- **Name:** Name of passenger
- **Sex:** Sex of the passenger
- **Age:** Age of the passenger (Some entries contain NaN)
- **SibSp:** Number of siblings and spouses of the passenger aboard
- **Parch:** Number of parents and children of the passenger aboard
- **Ticket:** Ticket number of the passenger
- **Fare:** Fare paid by the passenger
- **Cabin:** Cabin number of the passenger (Some entries contain NaN)
- **Embarked:** Port of embarkation of the passenger (C = Cherbourg; Q = Queenstown; S = Southampton)

Since the **Survived** column is a boolean, lets tell pandas to treat it like one and take a look at the new data frame

```
In [3]: df = df.astype({'Survived': bool})
        display(df.head())
```

```
   PassengerId  Survived  Pclass  \
0            1     False       3
1            2      True       1
2            3      True       3
3            4      True       1
4            5     False       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

Nice! That worked exactly how I wanted it to!

To get a better idea of what the data looks like, lets describe each column's data. That should tell us about any NaN's and whatnot. There are 891 datapoints, so any columns with < 891 data points have missing data. I'm going to both `count()` the values in each column and use `describe()` on all the ones not having `NaN` as the **Age**, since from previous looks, **Age** is the only continuous one with missing data.

```
In [4]: df.loc[df["Age"].isnull() == False].describe()
```

```
Out[4]:        PassengerId      Pclass         Age       SibSp       Parch        Fare
        count   714.000000  714.000000  714.000000  714.000000  714.000000  714.000000
        mean    448.582633    2.236695   29.699118    0.512605    0.431373   34.694514
        std     259.119524    0.838250   14.526497    0.929783    0.853289   52.918930
        min       1.000000    1.000000    0.420000    0.000000    0.000000    0.000000
        25%     222.250000    1.000000   20.125000    0.000000    0.000000    8.050000
        50%     445.000000    2.000000   28.000000    0.000000    0.000000   15.741700
        75%     677.750000    3.000000   38.000000    1.000000    1.000000   33.375000
        max     891.000000    3.000000   80.000000    5.000000    6.000000  512.329200
```

```
In [5]: df.count()
```

```
Out[5]: PassengerId    891
        Survived       891
        Pclass         891
        Name           891
        Sex            891
        Age            714
        SibSp          891
        Parch          891
        Ticket         891
        Fare           891
        Cabin          204
        Embarked       889
        dtype: int64
```

Nice, so the only ones with missing data are **Age**, **Cabin** and **Embarked**. That's pretty good. I do find it kind of weird that the minimum age is a float, especially one that isn't a divisor of 12. Kind of weird but whatever.

For convenience sake, I want to create a nice little function though that will tell me how many are missing though, so I can use it again. (Got this idea from here).

Then I'm going to use it on each column (via apply) and print the results, to get a baseline value. Future iterations can just call `print_missing` with the frame in order to check missing values in each column.

```
In [6]: def num_missing(x) -> int:
            return sum(x.isnull())

        def print_missing(frame):
            print(frame.apply(num_missing, axis=0))
```

```
        print_missing(df)
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Nice, that confirms what I already thought about the missing data based on the earlier count.

### 1.1.1 Embarked

But I am curious as to why only two embarked values are missing. I'm going to use `loc[]` to see what's special about them.

```
In [7]: df.loc[df["Embarked"].isnull()]
```

```
Out[7]:      PassengerId  Survived  Pclass                                       Name  \
        61            62      True       1                        Icard, Miss. Amelie
        829          830      True       1  Stone, Mrs. George Nelson (Martha Evelyn)

                Sex   Age  SibSp  Parch  Ticket  Fare Cabin Embarked
        61   female  38.0      0      0  113572  80.0   B28      NaN
        829  female  62.0      0      0  113572  80.0   B28      NaN
```

Okay that's weird. They were both in the same cabin and ticket. If we were making a really long decision tree, Embarked would almost certainly be a split, but would probably overfit.

In order to prevent errors later on with `NaN`, I'm just going to set the point of embarktation for those two as `U` for Unknown.

```
In [8]: df = df.fillna({"Embarked": "U"})
        print_missing(df)
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
```

```
SibSp           0
Parch           0
Ticket          0
Fare            0
Cabin         687
Embarked        0
dtype: int64
```

Nice! No more missing values in **Embarked**! I believe it's safe to insert dummy values for Embarked, because it's already a category as is. **Age** might be harder since it's a continuous variable, but first I want to look at **Cabin**, which are missing *a lot* but probably have a lot of juicy info. (In fact I don't think I will do anything for age, as it's potentially valuable to know that someone has no age on record.

### 1.1.2 Cabin

The first few **Cabin** values all start with a letter, but I don't want to take that for granted, others might have different values. I'm going to do some weird trickery here in order to analyze this. First I want to get a pandas Series containing only non-NaN cabin values.

```
In [9]: non_nan_cabins = df.loc[df["Cabin"].isnull() == False]["Cabin"]
        non_nan_cabins.count()
```

```
Out[9]: 204
```

Nice! That matches what we know should be there. Our earlier count of the non-null values of **Cabin** returned 204, so that's what we were hoping for! Now lets see what all that data looks like. Thankfully, pandas provides a nice vectorized function that should let me run a regex over each part of the series. I can then describe that data, or even make a nice histogram!

There's a couple things I want to test from a brief look at the CSV in Excel: * Most Cabins seem to be in the format with a letter and then one or more numbers, so I'll start by counting the number of cabin numbers matching that format in each row. * I'll check ones that are letters only. * I'll check ones that are numbers only. * I also want to check which ones have lower case letters (if any at all).

```
In [10]: # First lets import python's regex module.
         import re

         # Standard regex format (letter + numbers)
         std_format_regex = re.compile(r'([A-Z]+)([0-9]+)')
         std_format_count = non_nan_cabins.str.count(std_format_regex)
         display(std_format_count.describe())

         # Letters but no numbers.
         no_num_regex = re.compile(r'\b([A-Z]+)(?![A-Z]*[0-9]+)')
         no_num_count = non_nan_cabins.str.count(no_num_regex)
         display(no_num_count.describe())
```

```
# Numbers but no letters
no_let_regex = re.compile(r'\b([0-9]+)(?![0-9]*[A-Z]+)')
no_let_count = non_nan_cabins.str.count(no_let_regex)
display(no_let_count.describe())
```

```
count    204.000000
mean       1.127451
std        0.519028
min        0.000000
25%        1.000000
50%        1.000000
75%        1.000000
max        4.000000
Name: Cabin, dtype: float64
```

```
count    204.000000
mean       0.039216
std        0.194585
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
Name: Cabin, dtype: float64
```

```
count    204.0
mean       0.0
std        0.0
min        0.0
25%        0.0
50%        0.0
75%        0.0
max        0.0
Name: Cabin, dtype: float64
```

The `describe()` function wasn't exactly as helpful as I would've liked, so lets try a different thing using `count()` and `loc()`. I'm not particularly interested in the means and what not, I more so just want to make sure everything is accounted for. Which means removing non-zeros. Though since the third regex looks like it was unneccessary, we can omit that for future tests!

```
In [11]: # Lets get a chunk of the nonzero entries.
         std_non_zero = std_format_count.nonzero()
         nn_non_zero = no_num_count.nonzero()

         # Check to see how many got triggered on each
         print(len(std_non_zero[0]))
         print(len(nn_non_zero[0]))
```

```
200
8
```

That's unexpected... those shouldn't have totaled to more than 204. Looks like the regex isn't perfect, or the data is werider than I thought. Lets turn those into sets and take the union.

```
In [12]: snz_set = set(std_non_zero[0])
         nnnz_set = set(nn_non_zero[0])

         print("Std non zero set len:", len(snz_set))
         print("No number non zero set len:", len(nnnz_set))

         common = snz_set & nnnz_set
         print(common)
```

```
Std non zero set len: 200
No number non zero set len: 8
{25, 163, 156, 15}
```

So the `nonzero` function would have returned the index of the values, so we can just look at those rows of `non_nan_cabins` indivually to see what's special about them.

```
In [13]: display(non_nan_cabins.iloc[list(common)])
```

```
128    F E69
715    F G73
699    F G63
75     F G73
Name: Cabin, dtype: object
```

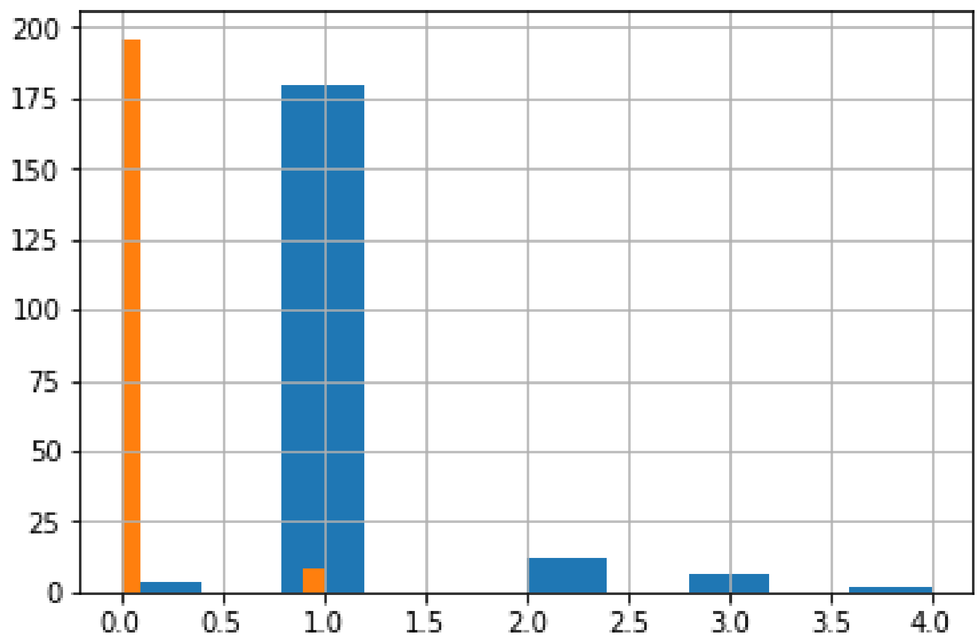
Oh. So it just had both letter only and standard format cabins. I'm not sure if the `F` is part of the cabin description, but that may not matter. I'm going to create a histogram of each of the counts, as well as print out all the columns with lone letters, to help give me a better idea of what to do with them.

```
In [14]: std_format_count.hist()
         no_num_count.hist()

         display(non_nan_cabins.iloc[list(nnnz_set)])
```

```
715    F G73
327        D
473        D
339        T
75     F G73
128    F E69
```

```
292           D
699     F G63
Name: Cabin, dtype: object
```




Nice, that gives me a better idea of what I'm working with. From looking at the sole letters, I'm not sure what to make of what those mean, but I do think I know how I want to categorize the data. (I'll add a few more columns to the table with categories of number of cabins, cabin letter and single letter cabins. We can do more pandas stuff after that.

```
In [15]: df["num_std_cabins"] = std_format_count
         df["num_let_cabins"] = no_num_count

         df = df.fillna({"num_std_cabins": -1, "num_let_cabins": -1})

         df["num_std_cabins"] = df["num_std_cabins"].astype(int)
         df["num_let_cabins"] = df["num_let_cabins"].astype(int)

         display(df.head())

         display(df.loc[df['num_std_cabins'] > 1])
```

```
   PassengerId  Survived  Pclass  \
0            1     False       3
1            2      True       1
2            3      True       3
3            4      True       1
```

```
4             5     False       3

                                              Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked  num_std_cabins  \
0      0         A/5 21171   7.2500   NaN        S              -1
1      0          PC 17599  71.2833   C85        C               1
2      0  STON/O2. 3101282   7.9250   NaN        S              -1
3      0            113803  53.1000  C123        S               1
4      0            373450   8.0500   NaN        S              -1

   num_let_cabins
0              -1
1               0
2              -1
3               0
4              -1


     PassengerId  Survived  Pclass  \
27            28     False       1
88            89      True       1
97            98      True       1
118          119     False       1
297          298     False       1
299          300      True       1
305          306      True       1
311          312      True       1
341          342      True       1
390          391      True       1
435          436      True       1
438          439     False       1
498          499     False       1
679          680      True       1
700          701      True       1
742          743      True       1
763          764      True       1
789          790     False       1
802          803      True       1
872          873     False       1

                                                Name     Sex    Age  SibSp  \
27                        Fortune, Mr. Charles Alexander    male  19.00      3
```

| | | | | |
|---|---|---|---|---|
| 88 | Fortune, Miss. Mabel Helen | female | 23.00 | 3 |
| 97 | Greenfield, Mr. William Bertram | male | 23.00 | 0 |
| 118 | Baxter, Mr. Quigg Edmond | male | 24.00 | 0 |
| 297 | Allison, Miss. Helen Loraine | female | 2.00 | 1 |
| 299 | Baxter, Mrs. James (Helene DeLaudeniere Chaput) | female | 50.00 | 0 |
| 305 | Allison, Master. Hudson Trevor | male | 0.92 | 1 |
| 311 | Ryerson, Miss. Emily Borie | female | 18.00 | 2 |
| 341 | Fortune, Miss. Alice Elizabeth | female | 24.00 | 3 |
| 390 | Carter, Mr. William Ernest | male | 36.00 | 1 |
| 435 | Carter, Miss. Lucile Polk | female | 14.00 | 1 |
| 438 | Fortune, Mr. Mark | male | 64.00 | 1 |
| 498 | Allison, Mrs. Hudson J C (Bessie Waldo Daniels) | female | 25.00 | 1 |
| 679 | Cardeza, Mr. Thomas Drake Martinez | male | 36.00 | 0 |
| 700 | Astor, Mrs. John Jacob (Madeleine Talmadge Force) | female | 18.00 | 1 |
| 742 | Ryerson, Miss. Susan Parker "Suzette" | female | 21.00 | 2 |
| 763 | Carter, Mrs. William Ernest (Lucile Polk) | female | 36.00 | 1 |
| 789 | Guggenheim, Mr. Benjamin | male | 46.00 | 0 |
| 802 | Carter, Master. William Thornton II | male | 11.00 | 1 |
| 872 | Carlsson, Mr. Frans Olof | male | 33.00 | 0 |

| | Parch | Ticket | Fare | Cabin | Embarked | num_std_cabins \ |
|---|---|---|---|---|---|---|
| 27 | 2 | 19950 | 263.0000 | C23 C25 C27 | S | 3 |
| 88 | 2 | 19950 | 263.0000 | C23 C25 C27 | S | 3 |
| 97 | 1 | PC 17759 | 63.3583 | D10 D12 | C | 2 |
| 118 | 1 | PC 17558 | 247.5208 | B58 B60 | C | 2 |
| 297 | 2 | 113781 | 151.5500 | C22 C26 | S | 2 |
| 299 | 1 | PC 17558 | 247.5208 | B58 B60 | C | 2 |
| 305 | 2 | 113781 | 151.5500 | C22 C26 | S | 2 |
| 311 | 2 | PC 17608 | 262.3750 | B57 B59 B63 B66 | C | 4 |
| 341 | 2 | 19950 | 263.0000 | C23 C25 C27 | S | 3 |
| 390 | 2 | 113760 | 120.0000 | B96 B98 | S | 2 |
| 435 | 2 | 113760 | 120.0000 | B96 B98 | S | 2 |
| 438 | 4 | 19950 | 263.0000 | C23 C25 C27 | S | 3 |
| 498 | 2 | 113781 | 151.5500 | C22 C26 | S | 2 |
| 679 | 1 | PC 17755 | 512.3292 | B51 B53 B55 | C | 3 |
| 700 | 0 | PC 17757 | 227.5250 | C62 C64 | C | 2 |
| 742 | 2 | PC 17608 | 262.3750 | B57 B59 B63 B66 | C | 4 |
| 763 | 2 | 113760 | 120.0000 | B96 B98 | S | 2 |
| 789 | 0 | PC 17593 | 79.2000 | B82 B84 | C | 2 |
| 802 | 2 | 113760 | 120.0000 | B96 B98 | S | 2 |
| 872 | 0 | 695 | 5.0000 | B51 B53 B55 | S | 3 |

| | num_let_cabins |
|---|---|
| 27 | 0 |
| 88 | 0 |
| 97 | 0 |
| 118 | 0 |
| 297 | 0 |

```
299                 0
305                 0
311                 0
341                 0
390                 0
435                 0
438                 0
498                 0
679                 0
700                 0
742                 0
763                 0
789                 0
802                 0
872                 0
```

Well here's some good news! It looks like non of the people with duplicate cabins have different letters. So I should be safe to just separate out the cabins as I planned. I'm going to create a separate column now, one to store what standard cabin letter they were in and one to store what letter only cabin they were in.

I'm going to want to make this a function in order to use it again for testing data, and I'll use the same regex's I had before.

```
In [16]: def get_std_cabin_letter(row):
             match = std_format_regex.match(str(row["Cabin"]))
             if match:
                 return match.group(1)
             else:
                 return "NA"

         def get_no_num_cabin_letter(row):
             match = no_num_regex.match(str(row["Cabin"]))
             if match:
                 return match.group(1)
             else:
                 return "NA"

         df["std_cabin_letter"] = df.apply(lambda row: get_std_cabin_letter(row), axis=1)
         df["no_num_letter"] = df.apply(lambda row: get_no_num_cabin_letter(row), axis=1)
         display(df.head())
```

```
   PassengerId  Survived  Pclass  \
0            1     False       3
1            2      True       1
2            3      True       3
3            4      True       1
4            5     False       3
```

```
                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked  num_std_cabins  \
0      0         A/5 21171   7.2500   NaN        S              -1
1      0          PC 17599  71.2833   C85        C               1
2      0  STON/O2. 3101282   7.9250   NaN        S              -1
3      0            113803  53.1000  C123        S               1
4      0            373450   8.0500   NaN        S              -1

   num_let_cabins std_cabin_letter no_num_letter
0              -1               NA            NA
1               0                C            NA
2              -1               NA            NA
3               0                C            NA
4              -1               NA            NA
```

Alright, I think I'm done with preprocessing mostly. The only thing I want to do is to one-hot encode the category values, to make random forests do their things better. I'm also going to normalize the fare prices using sklearn's `MinMaxScaler`. I'm not going to do that with the ages though because their values are in a relatively sane area already and they contain NaN, which doesn't work with sklearn's preprocessor. I'm going to one-hot encode **Pclass** as well, but I don't know if that will be useful or not.

***fuck, you can't have NaN in it.***

fine i'll just fill it with zero and then normalize.

Finally I want to split the **Survived** category into a separate date frame since it is going to be our desired label.

```
In [17]: from sklearn.preprocessing import MinMaxScaler

         df_final = df
         # Initialize a scaler, then apply it to the features
         scaler = MinMaxScaler() # default=(0, 1)
         df_final['Age'] = df['Age'].fillna(0)
         numerical = ['Age', 'Fare']

         df_final[numerical] = scaler.fit_transform(df[numerical])

         df_final = pd.get_dummies(df, columns=['Pclass', 'Sex', 'Embarked', 'std_cabin_letter',

         outcome = df_final['Survived']
         df_final = df_final.drop('Survived', axis=1)
```

```
display(df_final.head())
print(df_final.columns)
```

```
   PassengerId                                               Name     Age  \
0            1                            Braund, Mr. Owen Harris  0.2750
1            2  Cumings, Mrs. John Bradley (Florence Briggs Th...  0.4750
2            3                             Heikkinen, Miss. Laina  0.3250
3            4       Futrelle, Mrs. Jacques Heath (Lily May Peel)  0.4375
4            5                           Allen, Mr. William Henry  0.4375

   SibSp  Parch            Ticket      Fare Cabin  num_std_cabins  \
0      1      0         A/5 21171  0.014151   NaN              -1
1      1      0          PC 17599  0.139136   C85               1
2      0      0  STON/O2. 3101282  0.015469   NaN              -1
3      1      0            113803  0.103644  C123               1
4      0      0            373450  0.015713   NaN              -1

   num_let_cabins       ...         std_cabin_letter_C  std_cabin_letter_D  \
0             -1       ...                          0                   0
1              0       ...                          1                   0
2             -1       ...                          0                   0
3              0       ...                          1                   0
4             -1       ...                          0                   0

   std_cabin_letter_E  std_cabin_letter_F  std_cabin_letter_G  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   std_cabin_letter_NA  no_num_letter_D  no_num_letter_F  no_num_letter_NA  \
0                    1                0                0                 1
1                    0                0                0                 1
2                    1                0                0                 1
3                    0                0                0                 1
4                    1                0                0                 1

   no_num_letter_T
0                0
1                0
2                0
3                0
4                0

[5 rows x 31 columns]
```

```
Index(['PassengerId', 'Name', 'Age', 'SibSp', 'Parch', 'Ticket', 'Fare',
       'Cabin', 'num_std_cabins', 'num_let_cabins', 'Pclass_1', 'Pclass_2',
       'Pclass_3', 'Sex_female', 'Sex_male', 'Embarked_C', 'Embarked_Q',
       'Embarked_S', 'Embarked_U', 'std_cabin_letter_A', 'std_cabin_letter_B',
       'std_cabin_letter_C', 'std_cabin_letter_D', 'std_cabin_letter_E',
       'std_cabin_letter_F', 'std_cabin_letter_G', 'std_cabin_letter_NA',
       'no_num_letter_D', 'no_num_letter_F', 'no_num_letter_NA',
       'no_num_letter_T'],
      dtype='object')
```

### 1.2 Parameters

Alright, time for the next step of the project! I'm going to throw out the columns **PassengerId**, **Name** and **Ticket** right away because there's not really any information to be gained from them since they are just artificial values, or (in the case of Ticket) something I can't really make any sense of.

I'm also going to throw out the Cabin column since I've already gotten everything I needed out of that.

In [18]:
```
to_drop = ['PassengerId', 'Name', 'Ticket', 'Cabin']
df_final = df_final.drop(to_drop, axis=1)

display(df_final.head())
print(df_final.columns)
```

```
      Age  SibSp  Parch      Fare  num_std_cabins  num_let_cabins  Pclass_1  \
0  0.2750      1      0  0.014151              -1              -1         0
1  0.4750      1      0  0.139136               1               0         1
2  0.3250      0      0  0.015469              -1              -1         0
3  0.4375      1      0  0.103644               1               0         1
4  0.4375      0      0  0.015713              -1              -1         0

   Pclass_2  Pclass_3  Sex_female        ...          std_cabin_letter_C  \
0         0         1           0        ...                           0
1         0         0           1        ...                           1
2         0         1           1        ...                           0
3         0         0           1        ...                           1
4         0         1           0        ...                           0

   std_cabin_letter_D  std_cabin_letter_E  std_cabin_letter_F  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0
```

```
   std_cabin_letter_G  std_cabin_letter_NA  no_num_letter_D  no_num_letter_F  \
0                   0                    1                0                0
1                   0                    0                0                0
2                   0                    1                0                0
3                   0                    0                0                0
4                   0                    1                0                0

   no_num_letter_NA  no_num_letter_T
0                 1                0
1                 1                0
2                 1                0
3                 1                0
4                 1                0

[5 rows x 27 columns]
```

```
Index(['Age', 'SibSp', 'Parch', 'Fare', 'num_std_cabins', 'num_let_cabins',
       'Pclass_1', 'Pclass_2', 'Pclass_3', 'Sex_female', 'Sex_male',
       'Embarked_C', 'Embarked_Q', 'Embarked_S', 'Embarked_U',
       'std_cabin_letter_A', 'std_cabin_letter_B', 'std_cabin_letter_C',
       'std_cabin_letter_D', 'std_cabin_letter_E', 'std_cabin_letter_F',
       'std_cabin_letter_G', 'std_cabin_letter_NA', 'no_num_letter_D',
       'no_num_letter_F', 'no_num_letter_NA', 'no_num_letter_T'],
      dtype='object')
```

### 1.2.1 Cross Validation

Alright, time to set up cross validation. I'm going to use ten-fold cross validation because there isn't much data to work with. I'm going to have sklearn shuffle it first though, because I don't know who entered the CSV originally so there may be some meaning to it. I am going to set a random state at the beginning though so I can be consistent and compare my results as I tweak parameters.

In [19]:
```
from sklearn.model_selection import KFold
from collections import namedtuple

K_Split = namedtuple('K_Split', ['X_test', 'X_train', 'y_test', 'y_train'])

RANDOM_STATE = 1337

kf = KFold(n_splits=10, shuffle=True, random_state=RANDOM_STATE)

X = df_final
y = outcome
```

### 1.2.2 Accuracy

So in order to calculate the accuracy, I'm going to use the `accuracy_score` from `sklearn` because that's what I've used before when working with data like this. Since it doesn't really matter whether I correctly predict someone living or dying, the accuracy should be fine.

In order to have a good baseline, I'm going to use the actual percentage of who survived the Titanic, which is easy enough. However, I can't use everything being categorized as correct for this, because then the accuracy and fbeta will just be 1! So instead I'm going to make the naive model kill everyone, since most people on the titanic died.

The Positive will be someone surviving and the negative will be someone not surviving in the real life scenario, but since I can't do that with precision scores,

Then I'm going to have to calculate the first accuracy and fbeta scores myself since sklearn can't do that.

```
In [21]: naive_TP = 0
         naive_FP = 0

         naive_TN = outcome.count() - np.sum(outcome)
         naive_FN = np.sum(outcome)

         naive_accuracy = (naive_TP + naive_TN) / (naive_TP + naive_FP + naive_TN + naive_FN)
         lazy_max_accuracy = .70

         # Print the results
         print("Naive Predictor: [Accuracy score: {:.4f}]".format(naive_accuracy))
```

```
Naive Predictor: [Accuracy score: 0.6162]
```

That's some neat accuracy, espectally since the accuracy you put in the project description was just 70%.

So time to do some stuff. I want to make a generic function that I can use to train any model and any split. So lets make that.

```
In [22]: from sklearn.metrics import accuracy_score

         # Returns the accuracy score.
         def train_test_single_split(learner, X_train, X_test, y_train, y_test):
             learner = learner.fit(X_train, y_train)
             predictions = learner.predict(X_test)
             return accuracy_score(y_test, predictions)

         def train_test_kfold(learner, X, y, kf):
             scores = []
             for train_index, test_index in kf.split(X):
                 X_train, y_train = X.iloc[train_index], y.iloc[train_index]
                 X_test, y_test = X.iloc[test_index], y.iloc[test_index]
                 single_score = train_test_single_split(learner, X_train, X_test, y_train, y_tes
                 scores += [single_score]
             return sum(scores) / len(scores)
```

Okay lets actually do the stuff now. I'm running out of time :(

I'm going to use some of sklearn's fancy libraries to do the work for me.

This is basically me. Minus the google part, rip host matching. oh and minus the not sklearn thing, that too. but same deal.

Okay I hope my laptop doesn't catch on fire here.

In [27]:
```
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer
```

In [28]:
```
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer

clf = RandomForestClassifier(random_state=RANDOM_STATE)

# tbh i'd rather use fbeta but w/e
scorer = make_scorer(accuracy_score)

parameters = {
    'n_estimators': [5, 10, 15, 25],
    'criterion': ['gini', 'entropy'],
    'max_features': ['auto', 'sqrt', 'log2', None],
    'max_depth': [None, 2, 4, 8]
}

print("did the easy shit")



# yeah idk if anything else should be added, knock yourself out.

# tfw you forget the random state the first time
# tfw gridsearch doesn't actually take a random state
grid = GridSearchCV(clf, param_grid=parameters, scoring=scorer, cv=kf)

print("made the intense thing")

grid.fit(X, y)

print("finished the intense thing")

# nearly named this the "chad_clf"
best_clf = grid.best_estimator_

# Don't need to do this beacuse the gridsearch keeps track of the best estimator result
```

```
#best_accuracy = train_test_kfold(best_clf, X, y, kf)

#print("Best accuracy:", best_accuracy)
```

```
did the easy shit
made the intense thing
finished the intense thing
```

yeah okay that's good enough for tonight. confusion matricies are overrated, idk even know how to do that for kfold.

oh yeah my computer is not on fire but it is certainly not happy, i've been waiting like 10 minutes now or something idk.

yeah i can get the best parameters too if this **ever finishes running**

holy fuck it just finished with a FUCKING ERROR

okay so apparently grid search doesn't take a random_state that is... annoying.

any way, i reduced the number of possible parameters so hopefully it will actually finish this time.

```
In [29]: best_params = grid.best_params_
         best_score = grid.best_score_

         print("The GridSearchCV found the best number of estimators to be: {}, the best criteri
         print("The final GridSearch RandomForest accuracy was: {:.4f}".format(best_score))
```

```
The GridSearchCV found the best number of estimators to be: 25, the best criterion to be: entrop
The final GridSearch RandomForest accuracy was: 0.8272
```

### 1.3 Final Result

It finally fucking finished. I had reduced a bunch of the possible parameters so that may have been it. The ones I found with the random state of 1337 decided that a Random Forest with the following parameters was best.

- **n_estimators**: 25
- wow, how surprising, it's the maximum amount /s
- **criterion**: entropy
- this was actually kind of surprising since sklearn's default is gini. but i guess we learned this in class.
- **max_features**: None
- how surprising, it wants more of my cpu /s
- **max_depth**: 8
- This is actually surprising since 8 is **not** the maximum depth it could choose, that would be None. But it is the max among the numbers I provided.

I've tried to find a way to create a confusion matrix or some graphs for this, but I don't think it's feasible to do while using grid search. especially since I still want to run the entire notebook kernel fresh. Plus I think it's going to rain soon so i g2g. enjoy.