MACHINE LEARNING Project Presentation DS105

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<u>Dataset</u>

This dataset is on the unsinkable ship, RMS Titanic.

Size of dataset: 12 columns, 891 entries

Some of the features:

- Survived, Passenger Class, Sex, Age

Source:

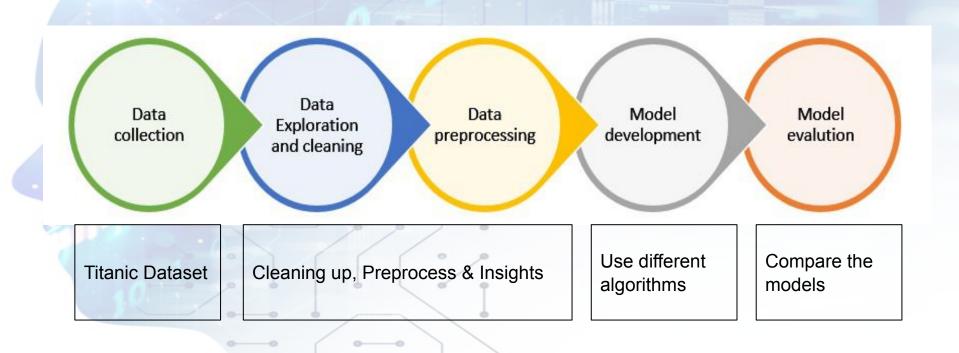
https://www.kaggle.com/competitions/titanic

Goal

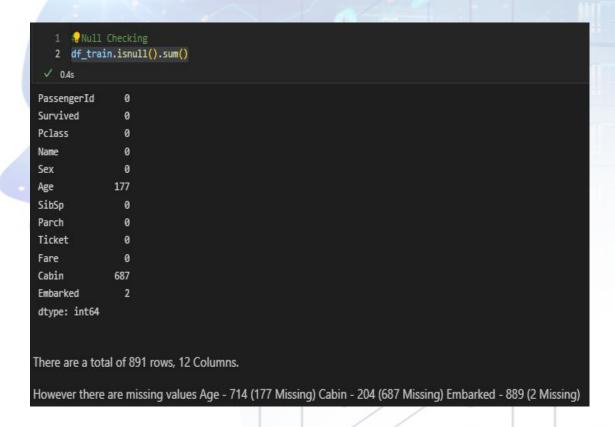
To predict the survivability of a person on the ship using ML models and to see which would be the best model to use.

Passenger Id [™]	Survived T	Pclass [™]	Name 7	Sex ▼	Age [⊤]	Sib Sp ₹	Parch T	Ticket T	Fare 7	Cabin T	Embarked T
1	0	3	Braund, Mr. Owe	male	22	1	0	A/5 21171	7.25		S
2			Cumings, Mrs. Jo	female	38	1		PC 17599	71.28	C85	С
3	1		Heikkinen, Miss.	female	26	0	0	STON/O2. 31012	7.93		S
4			Futrelle, Mrs. Jac	female	35	1		113803	53.1	C123	S
5	0		Allen, Mr. Willian	male	35	0		373450	8.05		S
6	0		Moran, Mr. Jame	male		0		330877	8.46		Q
7	0		McCarthy, Mr. Ti	male	54	0	0	17463	51.86	E46	S
8	0		Palsson, Master.	male		3		349909	21.08		S
9	1		Johnson, Mrs. Os	female	27	0		347742	11.13		S
10			Nasser, Mrs. Nich	female	14	1		237736	30.07		С
11	1		Sandstrom, Miss.	female	4	1		PP 9549	16.7	G6	S
12			Bonnell, Miss. Eli	female	58	0		113783	26.55	C103	S
13	0		Saundercock, Mr	male	20	0	0	A/5. 2151	8.05		S
14	0		Andersson, Mr. A	male	39	1		347082	31.28		S
15	0		Vestrom, Miss. H	female	14	0	0	350406	7.85		S
16			Hewlett, Mrs. (M	female	55	0		248706	16		S
17	0		Rice, Master. Eug	male		4		382652	29.13		Q
18			Williams, Mr. Cha	male		0		244373			S
19	0		Vander Planke, M	female	31	1		345763	18		S
20			Masselmani, Mrs	female		0		2649	7.23		С
21	0		Fynney, Mr. Jose	male	35	Ö		239865	26		S
22			Beesley, Mr. Law	male	34	0		248698		D56	S
23	1		McGowan, Miss.	female	15	0		330923	8.03		Q
24			Sloper, Mr. Willia	male	28	0		113788	35.5	A6	S
25	0		Palsson, Miss. To	female	8	3		349909	21.08		S
26			Asplund, Mrs. Ca	female	38			347077	31.39		S
27	0		Emir, Mr. Farred	male		0		2631	7.23		С
28			Fortune, Mr. Cha	male				19950	263	C23 C25 C27	S
29	1		O'Dwyer, Miss. E	female		0	0	330959	7.88		Q
30	0		Todoroff, Mr. Lali	male		0		349216	7.9		S
31	0		Uruchurtu, Don.	male	40	0		PC 17601	27.72		С
32			Spencer, Mrs. Wi	female		1		PC 17569	146.52	B78	С
33			Glynn, Miss. Mar	female		0	0	335677	7.75		Q
34			Wheadon, Mr. Ed	male	66	0		C.A. 24579	10.5		S
35	0		Meyer, Mr. Edga	male	28	1	0	PC 17604	82.17		С
36			Holverson, Mr. A	male	42			113789			S
37			Mamee, Mr. Han	male		0		2677	7.23		С
38			Cann, Mr. Ernest	male		0		A./5. 2152	8.05		S
39	0		Vander Planke, N	female	18	2		345764	18		S
40			Nicola-Yarred, M	female	14			2651	11.24		С
41	0	3	Ahlin, Mrs. Johan	female	40	1	0	7546	9.48		S
42			Turpin, Mrs. Willi	female	27			11668			S

General Workflow



Preprocessing & Cleaning



Missing/NaN Values

3 features with null values.

Age ~20%

Cabin ~77%

Embarked ~0%

What I did

Age - Imputed median

Cabin - Totally dropped

Embarked - Input the most used value, 'S'

Preprocessing & Cleaning

```
# Combine Sibsp & ParCh together as Companions, since these are there together as a group

df_train['Companion'] = df_train['SibSp'] + df_train['Parch']

03s

# Drop the SibSp and Parch columns

cols = ['SibSp', 'Parch']

df_train = df_train.drop(cols, axis=1)

03s
```

Combined similar features

'SibSp' & 'Parch'

Combined into Companion

```
1 cols = ['Name', 'Ticket', 'Cabin']
2 drain = df_train.drop(cols, axis=1)

✓ 0.4s
```

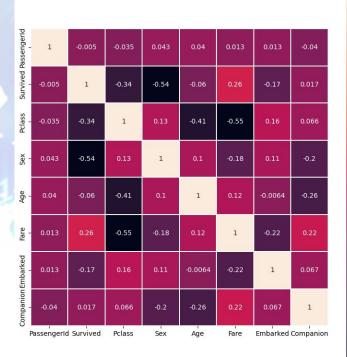
<u>Dropped unhelpful features</u>

Cabin

Name

Ticket

Analysis & Insights



Correlationship Heatmap

The darker the color, the worse the relationship

-Age & Pclass,

- 0.8

- 0.6

- 0.4

- 0.2

0.0

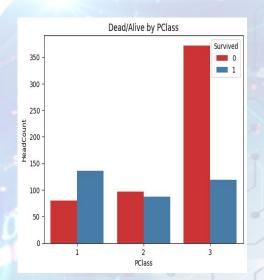
- -0.2

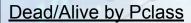
- -0.4

- -Fare & PClass,
- -Pclass & Survived
- -Sex & Survived,

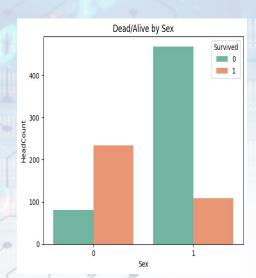
Have terrible relations.

Analysis & Insights





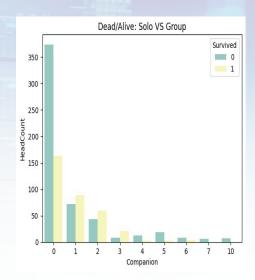
1st class has the highest probability of surviving



Dead/Alive by Sex

Females are more likely to survive

0



Dead/Alive wrt Companion

Solo passengers are much more likely to die

Groups between 1-3 have better chances of surviving

Machine Learning Models

Model		
Score	re	Sc
92.14 Random Forest	14	9
80.25 Logistic Regression	25	8
79.35 Naive Bayes	35	7
78.34 Support Vector Machines	34	7
73.51 KNN	51	7.

Machine Learning Models (RandomForest)

```
# Random Forest
      random forest = RandomForestClassifier(criterion='gini'.
          n estimators=700.
          min_samples_split=10,
          min_samples_leaf=1,
          max features='auto',
          oob score=True,
          random state=1.
          n jobs=-1)
   12 random_forest.fit(X_train, Y_train)
   14 Y pred = random_forest.predict(X test)
   16 acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
   17 acc_random_forest
c:\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\ensemble\_forest.py:425: Fut
be removed in 1.3. To keep the past behaviour, explicitly set `max features='sgrt'` or remove
RandomForestClassifiers and ExtraTreesClassifiers.
  warn(
92.14
   1 rf = RandomForestClassifier(n_estimators=700)
   2 scores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
   3 print("Scores:", scores)
   4 print("Mean:", scores.mean())
   5 print("Standard Deviation:", scores.std())
Scores: [0.77777778 0.78651685 0.75280899 0.79775281 0.88764045 0.85393258
0.85393258 0.80898876 0.82022472 0.82022472]
Mean: 0.8159800249687889
Standard Deviation: 0.03840732207728619
   2 9X-Validation shows that it has an accuracy of 81.5% with deviation of 3.8%
```

Referenced a tuned RandomForest code of a user

Simpler Randomforest code gave a much higher score

Model ran a score of 92.14

Cross-Validation gave accuracy of 81.5%, deviation of 3.8%

Machine Learning Models (Log Regression)

```
# Log Regression
                           (variable) Y train: Series
      logreg = LogisticReg (variable) Y_train: Any
      logreg.fit(X train, Y train)
      Y_pred = logreg.predict(X_test)
     acc_log = round(logreg.score(X train, Y train) * 100, 2)
     acc log
 ✓ 0.6s
c:\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\linear_model\_logis
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
   https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
   https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
 n_iter_i = _check_optimize_result(
80.25
  1 rf = LogisticRegression()
     scores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
      print("Scores:", scores)
     print("Mean:", scores.mean())
     print("Standard Deviation:", scores.std())

√ 0.2s

Scores: [0.78888889 0.80898876 0.76404494 0.84269663 0.80898876 0.7752809
0.80898876 0.79775281 0.83146067 0.79775281]
Mean: 0.8024843945068664
Standard Deviation: 0.02242945427644189
```

Model ran a score of 80.25

Cross-Validation gave accuracy of 80.24%, deviation of 2.24%

However, would require more iterations as per the advice.

Could potentially be a good model to use

Machine Learning Models (Naive Bayes)

```
1 # Naive Bayes
   3 gaussian = GaussianNB()
      gaussian.fit(X train, Y train)
      Y_pred = gaussian.predict(X_test)
   8 acc_gaussian = round(gaussian.score(X_train, Y_train) * 100, 2)
   9 acc gaussian
 √ 0.1s
79.35
   1 rf = GaussianNB()
   2  Pores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
   3 print("Scores:", scores)
   4 print("Mean:", scores.mean())
   5 print("Standard Deviation:", scores.std())

√ 0.1s

Scores: [0.71111111 0.76404494 0.7752809 0.79775281 0.79775281 0.7752809
 0.82022472 0.83146067 0.7752809 0.82022472]
Mean: 0.7868414481897628
Standard Deviation: 0.0333370363637702
   2 - X-Validation shows that it has an accuracy of 78.7% with deviation of 3.33%
```

Model ran a score of 79.35

Cross-Validation gave accuracy of 78.7%, deviation of 3.33%

Not bad, but not the best

Machine Learning Models (SVM)

```
linear_svc.fit(X_train, Y_train)
      Y pred = linear svc.predict(X test)
   8 acc_linear_svc = round(linear_svc.score(X_train, Y_train) * 100, 2)
 :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to converge,
 warnings.warn(
78.34
      scores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
      print("Scores:", scores)
   4 print("Mean:", scores.mean())
   5 print("Standard Deviation:", scores.std())
 :\Users\user\anaconda3\envs\name-pv10\lib\site-packages\sklearn\sym\ base.pv:1244: ConvergenceWarning: Liblinear failed to converge.
 terations
 :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\ base.py:1244: ConvergenceWarning: Liblinear failed to converge,
iterations.
 :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\ base.py:1244: ConvergenceWarning: Liblinear failed to converge,
iterations
 warnings.warn(
  :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to converge,
 :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to converge,
 :\Users\user\anaconda3\envs\name-pv10\lib\site-packages\sklearn\sym\ base.pv:1244: ConvergenceWarning: Liblinear failed to converge.
 terations.
 :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to converge,
 terations.
  :\Users\user\anaconda3\envs\name-py10\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to converge
 iterations
 warnings.warn(
Scores: [0.71111111 0.80898876 0.65168539 0.84269663 0.7752809 0.60674157
 0.80898876 0.78651685 0.70786517 0.797752811
```

Model ran a score of 78.34

Cross-Validation gave accuracy of 75%, deviation of 7.3%

Repeated warnings of 'LibLinear failed to converge'

Current parameters are not good enough, hence predictions from this model might be useless

Machine Learning Models (KNN)

```
1 # KNN
      knn = KNeighborsClass (variable) X_test: DataFrame
      knn.fit(X_train, Y_tr
                             (variable) X test: Any
      Y pred = knn.predict(X test)
      acc knn = round(knn.score(X train, Y train) * 100, 2)
      acc_knn
 √ 0.8s
73.51
   1 rf = KNeighborsClassifier(n_neighbors = 6)
      $\oldsymbol{Q}\text{ores} = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
      print("Scores:", scores)
      print("Mean:", scores.mean())
      print("Standard Deviation:", scores.std())

√ 0.1s

Scores: [0.48888889 0.62921348 0.49438202 0.46067416 0.4494382 0.52808989
0.50561798 0.50561798 0.68539326 0.65168539]
Mean: 0.5399001248439451
Standard Deviation: 0.07953945202686367
      2X-Validation shows that it has an accuracy of 54% with deviation of 8%
                                                                                         0
```

Model ran a score of 73.51

Cross-Validation gave accuracy of 54%, deviation of 8%

Not a good predictive model

