# OUTPUTS FOR TASK\_5

## **OUTPUTS FOR .SHAPE()**

5	Shape: (891, 12)											
:	Passengerld	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

## OUTPUT FOR .DESCRIBE()

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

#### **OUTPUT FOR .INFO()**

<class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns): Non-Null Count Column Dtype 0 PassengerId 891 non-null int64 1 Survived 891 non-null int64 2 Pclass 891 non-null int64 3 Name 891 non-null object 4 object Sex 891 non-null 714 non-null 5 Age float64 6 SibSp 891 non-null int64 7 Parch 891 non-null int64 object Ticket 8 891 non-null 9 Fare 891 non-null float64 204 non-null object 10 Cabin object 11 Embarked 889 non-null

dtypes: float64(2), int64(5), object(5)

memory usage: 83.7+ KB

#### OUTPUT FOR VALUE\_COUNT()

	Id Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarke
d 2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38.0	1	0	PC 17599	71.2833	C85	С
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S
1 12 1	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	C103	S
 872	1	1	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	1	1	11751	52.5542	D35	S
873	0	1	Carlsson, Mr. Frans Olof	male	33.0	0	0	695	5.0000	B51 B53 B55	S
880	1	1	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	0	1	11767	83.1583	C50	С
888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
1 890 1	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	С
Name: cou	nt, Length: :	L83, dtyp	pe: int64								

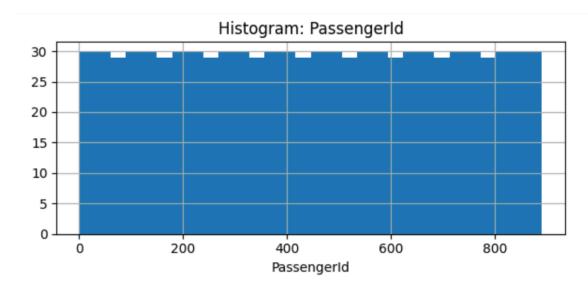
### **OUTPUT FOR MISSING VALUES**

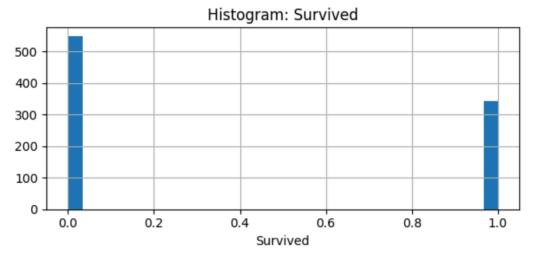
	missing_count	missing_pct
Cabin	687	77.104377
Age	177	19.865320
Embarked	2	0.224467
PassengerId	0	0.000000
Name	0	0.000000
Pclass	0	0.000000
Survived	0	0.000000
Sex	0	0.000000
Parch	0	0.000000
SibSp	0	0.000000
Fare	0	0.000000
Ticket	0	0.000000

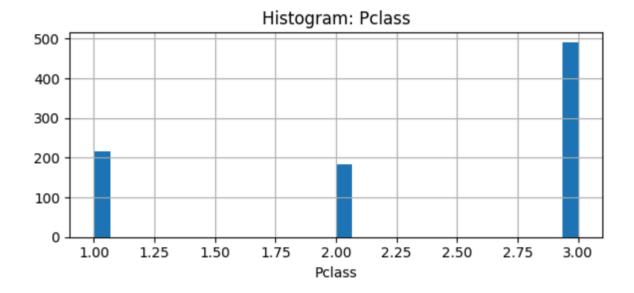
### **OUTPUT FOR CLEANING THE DATA**

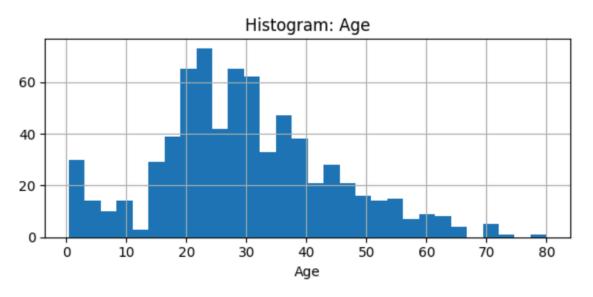
]:		Age	${\bf Age\_median\_fill}$	Cabin	HasCabin
	0	22.0	22.0	NaN	0
	1	38.0	38.0	C85	1
	2	26.0	26.0	NaN	0
	3	35.0	35.0	C123	1
	4	35.0	35.0	NaN	0

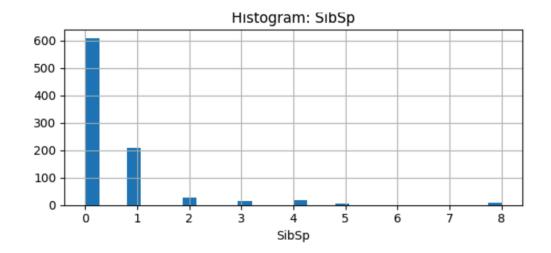
## **OUTPUTS FOR VISUALIZATION**

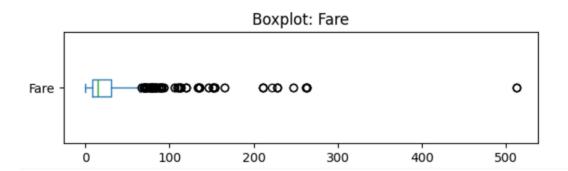


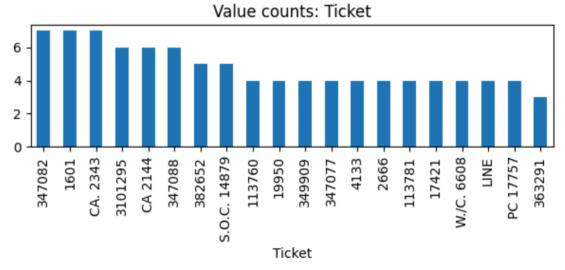




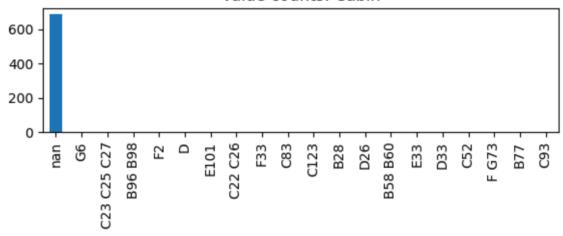


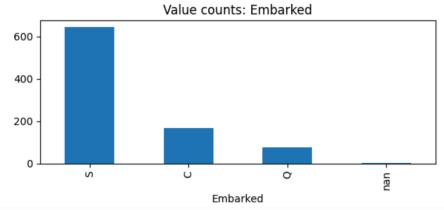


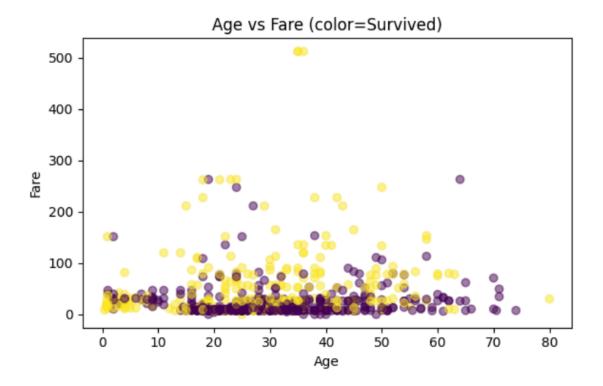


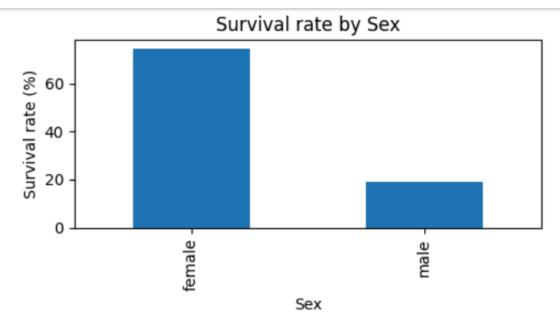


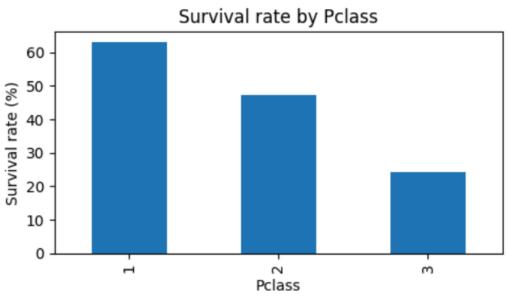












#### CONCLUSION

To explore the dataset, I started by importing a few essential Python libraries — pandas to load and manipulate the data, numpy for quick numerical calculations, and matplotlib.pyplot to create visualizations. I loaded the dataset using pd.read\_csv('/mnt/data/train.csv'), which stored everything in a DataFrame called df. To get a quick overview of what I was working with, I ran df.info(), which showed me how many rows and columns the dataset has, along with the data types of each column. This also helped me spot missing values and understand which features were numeric vs. categorical. I used df. shape to confirm the dataset size and df.columns.tolist() to list out all the column names. After that, I separated numeric and categorical columns using select\_dtypes. To check data quality, I calculated how many values were missing in each column with df.isnull().sum() and also computed their percentages using df.isnull().mean()\*100. This made it obvious that features like Age and Cabin had a lot of missing entries. Next. I ran df[numeric\_cols].describe() to get summary statistics such as mean, median, standard deviation, and quartile ranges, which helped me understand how values were distributed. For visualization, I plotted histograms (df[col].plot(kind='hist')) to see how features like Age and Fare were spread out, and created boxplots (df[col].plot(kind='box')) to detect any extreme outliers. To check relationships between variables, I generated a correlation heatmap using plt.imshow(df.corr()), which showed patterns like higher fares being associated with passengers from better classes. I also created a scatter matrix to visually compare multiple numeric features against each other. Finally, to get real-world insights, I calculated survival rates across different groups using value\_counts(normalize=True), which clearly showed that women and first-class passengers had much higher chances of survival. All the plots were saved into a folder for easy access, and everything was organized into a Jupyter Notebook for reporting.