Data Pre-Processing

In this document, we will try to adapt the data we have to the machine learning model by using various data sets.

In [3]:
```
import pandas as pd
import seaborn as sns

pd.set_option('display.max_columns', None)
pd.set_option('display.width', 500)
df = sns.load_dataset("titanic")
df.head()
```

Out[3]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	dec
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN

Overview of the Titanic Dataset

In [4]:
```
from EDA import check_df

check_df(df)
```

```
##################### Shape #####################
(891, 15)
##################### Types #####################
survived          int64
pclass            int64
sex              object
age             float64
sibsp             int64
parch             int64
fare            float64
embarked         object
class          category
who              object
adult_male         bool
deck           category
embark_town      object
alive            object
alone              bool
dtype: object
##################### Head #####################
##################### Tail #####################
```

```
     survived  pclass     sex   age  sibsp  parch   fare embarked   class    who  ad
ult_male deck  embark_town alive  alone
886         0       2    male  27.0      0      0  13.00        S  Second    man
True  NaN  Southampton    no   True
887         1       1  female  19.0      0      0  30.00        S   First  woman
False    B  Southampton   yes   True
888         0       3  female   NaN      1      2  23.45        S   Third  woman
False  NaN  Southampton    no  False
889         1       1    male  26.0      0      0  30.00        C   First    man
True    C    Cherbourg   yes   True
890         0       3    male  32.0      0      0   7.75        Q   Third    man
True  NaN   Queenstown    no   True
###################### NA ######################
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
###################### Quantiles ######################
          count       mean        std   min    0%     5%      50%        95%
99%      100%       max
survived  891.0   0.383838   0.486592  0.00  0.00  0.000   0.0000    1.00000    1.00
000    1.0000    1.0000
pclass    891.0   2.308642   0.836071  1.00  1.00  1.000   3.0000    3.00000    3.00
000    3.0000    3.0000
age       714.0  29.699118  14.526497  0.42  0.42  4.000  28.0000   56.00000   65.87
000   80.0000   80.0000
sibsp     891.0   0.523008   1.102743  0.00  0.00  0.000   0.0000    3.00000    5.00
000    8.0000    8.0000
parch     891.0   0.381594   0.806057  0.00  0.00  0.000   0.0000    2.00000    4.00
000    6.0000    6.0000
fare      891.0  32.204208  49.693429  0.00  0.00  7.225  14.4542  112.07915  249.00
622  512.3292  512.3292
```

Analysis of Categorical Variables

In [5]:
```
df["survived"].value_counts()
```

Out[5]:
```
0    549
1    342
Name: survived, dtype: int64
```

In [6]:
```
df["sex"].unique()
```

Out[6]:
```
array(['male', 'female'], dtype=object)
```

In [7]:
```
df["class"].nunique()
```

Out[7]:
```
3
```

In [8]:
```
from EDA import *
cat_summary(df,'sex')
```

```
        sex      Ratio
male    577  64.758698
female  314  35.241302
##########################################
```

Let's find out what are categorical variables

In [9]:
```
cat_cols, num_cols, cat_but_car = grab_col_names(df)
cat_cols
```

Out[9]:
```
Observations: 891
Variables: 15
cat_cols: 9
num_cols: 2
cat_but_car: 0
num_but_cat: 0
['sex',
 'embarked',
 'class',
 'who',
 'adult_male',
 'deck',
 'embark_town',
 'alive',
 'alone']
```

In [10]:
```
# Numerical columns

num_cols
```

Out[10]:
```
['age', 'fare']
```

In [11]:
```
# Categorical but High cardinality columns

cat_but_car
```

Out[11]:
```
[]
```

In [12]:
```
# Summary for categorical variables
from EDA import cat_summary

for col in cat_cols:
    cat_summary(df, col)
```

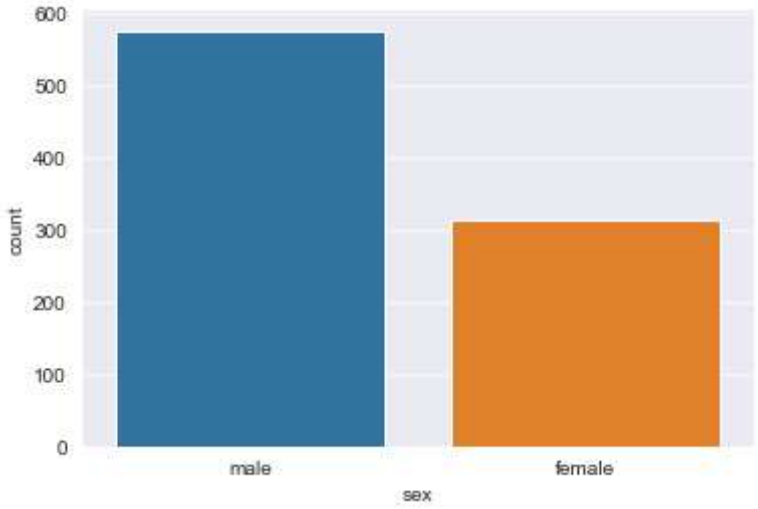
```
        sex      Ratio
```

```
male    577  64.758698
female  314  35.241302
##########################################
   embarked      Ratio
S       644  72.278339
C       168  18.855219
Q        77   8.641975
##########################################
        class      Ratio
Third     491  55.106622
First     216  24.242424
Second    184  20.650954
##########################################
       who      Ratio
man    537  60.269360
woman  271  30.415264
child   83   9.315376
##########################################
   adult_male     Ratio
1         537  60.26936
0         354  39.73064
##########################################
   deck     Ratio
C    59  6.621773
B    47  5.274972
D    33  3.703704
E    32  3.591470
A    15  1.683502
F    13  1.459035
G     4  0.448934
##########################################
             embark_town      Ratio
Southampton          644  72.278339
Cherbourg            168  18.855219
Queenstown            77   8.641975
##########################################
     alive      Ratio
no     549  61.616162
yes    342  38.383838
##########################################
   alone     Ratio
1    537  60.26936
0    354  39.73064
##########################################
```

In [13]:

```
cat_summary(df, "sex", plot=True)
```

```
        sex      Ratio
male    577  64.758698
female  314  35.241302
##########################################
```



Analysis of Numerical Variables

In [15]:
```
num_summary(df, "age")
```

```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
5%         4.000000
10%       14.000000
20%       19.000000
30%       22.000000
40%       25.000000
50%       28.000000
60%       31.800000
70%       36.000000
80%       41.000000
90%       50.000000
95%       56.000000
99%       65.870000
max       80.000000
Name: age, dtype: float64
```

Summary information for all numeric variables

In [16]:
```
for col in num_cols:
    num_summary(df, col)
```

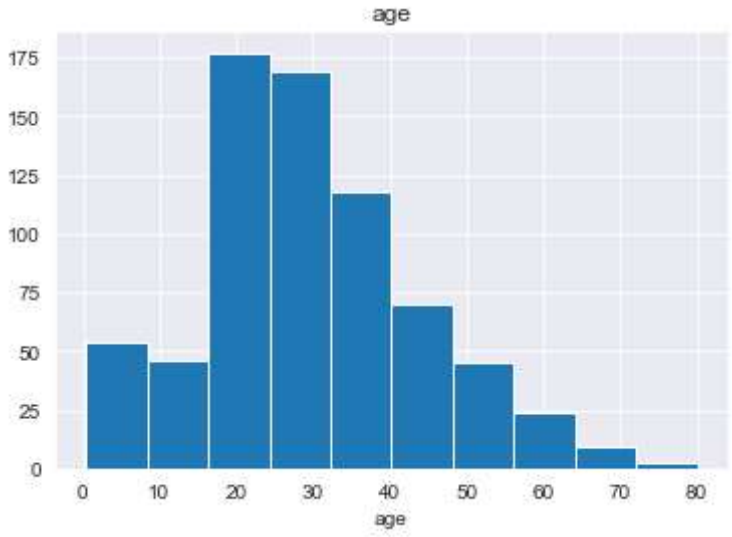
```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
5%         4.000000
10%       14.000000
20%       19.000000
30%       22.000000
40%       25.000000
50%       28.000000
60%       31.800000
```

```
70%       36.000000
80%       41.000000
90%       50.000000
95%       56.000000
99%       65.870000
max       80.000000
Name: age, dtype: float64
count    891.000000
mean      32.204208
std       49.693429
min        0.000000
5%         7.225000
10%        7.550000
20%        7.854200
30%        8.050000
40%       10.500000
50%       14.454200
60%       21.679200
70%       27.000000
80%       39.687500
90%       77.958300
95%      112.079150
99%      249.006220
max      512.329200
Name: fare, dtype: float64
```

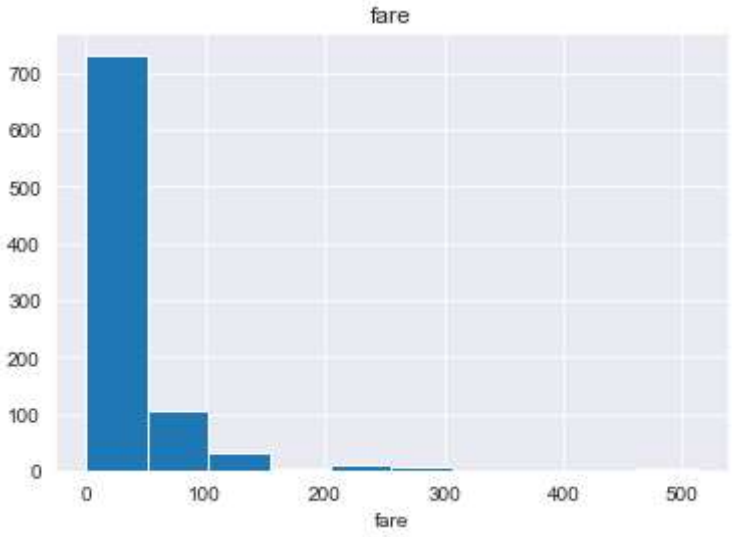
In [17]:

```
for col in num_cols:
    num_summary(df, col, plot=True)
```

```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
5%         4.000000
10%       14.000000
20%       19.000000
30%       22.000000
40%       25.000000
50%       28.000000
60%       31.800000
70%       36.000000
80%       41.000000
90%       50.000000
95%       56.000000
99%       65.870000
max       80.000000
Name: age, dtype: float64
```




```
count    891.000000
mean      32.204208
std       49.693429
min        0.000000
5%         7.225000
10%        7.550000
20%        7.854200
30%        8.050000
40%       10.500000
50%       14.454200
60%       21.679200
70%       27.000000
80%       39.687500
90%       77.958300
95%      112.079150
99%      249.006220
max      512.329200
Name: fare, dtype: float64
```



Analysis of Target Variable

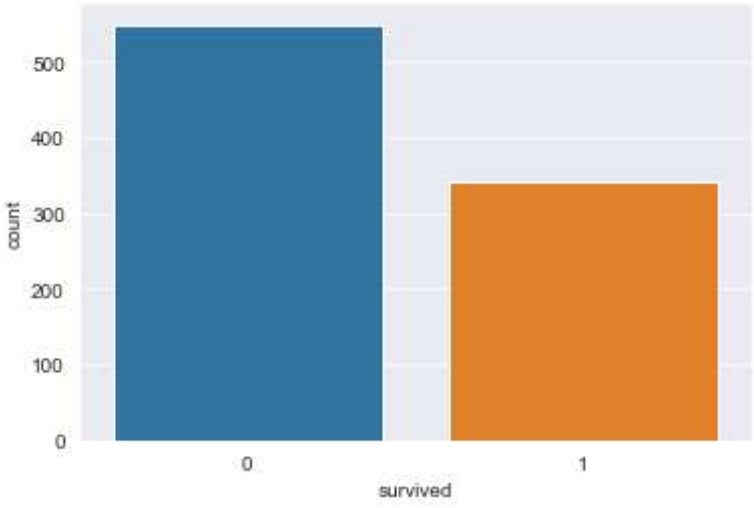
In [18]:

```
df["survived"].value_counts()
```

Out[18]:
```
0    549
1    342
Name: survived, dtype: int64
```

In [19]:
```
cat_summary(df, "survived", plot=True)
```

```
   survived      Ratio
0       549  61.616162
1       342  38.383838
##########################################
```



Analysis of the Target Variable with Categorical Variables

In [20]:
```
from EDA import target_summary_with_cat

target_summary_with_cat(df, "survived", "pclass")
```

```
        TARGET_MEAN
pclass
1          0.629630
2          0.472826
3          0.242363
```

In [21]:
```
for col in cat_cols:
    target_summary_with_cat(df, "survived", col)
```

```
        TARGET_MEAN
sex
female     0.742038
male       0.188908


          TARGET_MEAN
embarked
C            0.553571
Q            0.389610
```

```
S            0.336957
```

```
        TARGET_MEAN
class
First      0.629630
Second     0.472826
Third      0.242363
```

```
       TARGET_MEAN
who
child     0.590361
man       0.163873
woman     0.756458
```

```
             TARGET_MEAN
adult_male
0               0.717514
1               0.163873
```

```
      TARGET_MEAN
deck
A        0.466667
B        0.744681
C        0.593220
D        0.757576
E        0.750000
F        0.615385
G        0.500000
```

```
              TARGET_MEAN
embark_town
Cherbourg       0.553571
Queenstown      0.389610
Southampton     0.336957
```

```
       TARGET_MEAN
alive
no             0.0
yes            1.0
```

```
       TARGET_MEAN
alone
0         0.505650
1         0.303538
```

Analysis of Target Variable with Numerical Variables

In [22]:
```
from EDA import target_summary_with_num

for col in num_cols:
    target_summary_with_num(df, "survived", col)
```

```
                age
survived
0         30.626179
1         28.343690


               fare
survived
0         22.117887
1         48.395408
```

Analysis of Correlation

In [23]:
```
from EDA import high_corr_cols

df = pd.read_csv("breast_cancer.csv")
df = df.iloc[:, 1:-1]
df.head()
```

Out[23]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactr
0	M	17.99	10.38	122.80	1001.0	0.11840	
1	M	20.57	17.77	132.90	1326.0	0.08474	
2	M	19.69	21.25	130.00	1203.0	0.10960	
3	M	11.42	20.38	77.58	386.1	0.14250	
4	M	20.29	14.34	135.10	1297.0	0.10030	

In [24]:
```
cat_cols, num_cols, cat_but_car = grab_col_names(df)
```

```
Observations: 569
Variables: 31
cat_cols: 1
num_cols: 30
cat_but_car: 0
num_but_cat: 0
```

In [25]:
```
corr = df[num_cols].corr()
corr
```

Out[25]:

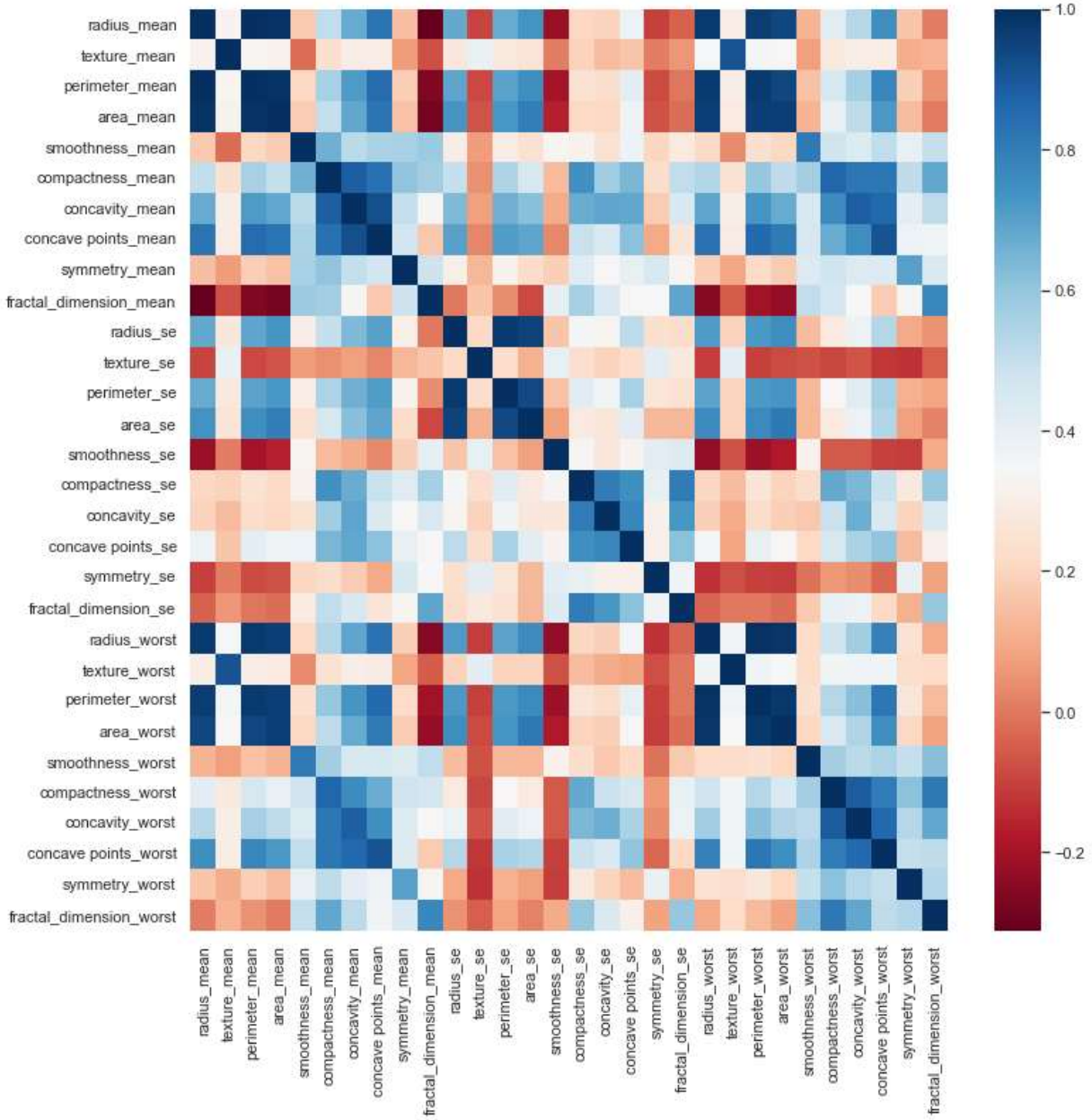
	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean
radius_mean	1.000000	0.323782	0.997855	0.987357	0.170581
texture_mean	0.323782	1.000000	0.329533	0.321086	-0.023389
perimeter_mean	0.997855	0.329533	1.000000	0.986507	0.207278
area_mean	0.987357	0.321086	0.986507	1.000000	0.177028
smoothness_mean	0.170581	-0.023389	0.207278	0.177028	1.000000
compactness_mean	0.506124	0.236702	0.556936	0.498502	0.659123
concavity_mean	0.676764	0.302418	0.716136	0.685983	0.521984
concave points_mean	0.822529	0.293464	0.850977	0.823269	0.553695
symmetry_mean	0.147741	0.071401	0.183027	0.151293	0.557775
fractal_dimension_mean	-0.311631	-0.076437	-0.261477	-0.283110	0.584792
radius_se	0.679090	0.275869	0.691765	0.732562	0.301467
texture_se	-0.097317	0.386358	-0.086761	-0.066280	0.068406
perimeter_se	0.674172	0.281673	0.693135	0.726628	0.296092
area_se	0.735864	0.259845	0.744983	0.800086	0.246552
smoothness_se	-0.222600	0.006614	-0.202694	-0.166777	0.332375
compactness_se	0.206000	0.191975	0.250744	0.212583	0.318943
concavity_se	0.194204	0.143293	0.228082	0.207660	0.248396
concave points_se	0.376169	0.163851	0.407217	0.372320	0.380676
symmetry_se	-0.104321	0.009127	-0.081629	-0.072497	0.200774
fractal_dimension_se	-0.042641	0.054458	-0.005523	-0.019887	0.283607
radius_worst	0.969539	0.352573	0.969476	0.962746	0.213120
texture_worst	0.297008	0.912045	0.303038	0.287489	0.036072
perimeter_worst	0.965137	0.358040	0.970387	0.959120	0.238853
area_worst	0.941082	0.343546	0.941550	0.959213	0.206718
smoothness_worst	0.119616	0.077503	0.150549	0.123523	0.805324
compactness_worst	0.413463	0.277830	0.455774	0.390410	0.472468
concavity_worst	0.526911	0.301025	0.563879	0.512606	0.434926
concave points_worst	0.744214	0.295316	0.771241	0.722017	0.503053
symmetry_worst	0.163953	0.105008	0.189115	0.143570	0.394309
fractal_dimension_worst	0.007066	0.119205	0.051019	0.003738	0.499316

In [26]:

```
sns.set(rc={'figure.figsize': (12, 12)})
sns.heatmap(corr, cmap="RdBu")
```

```
plt.show()
```

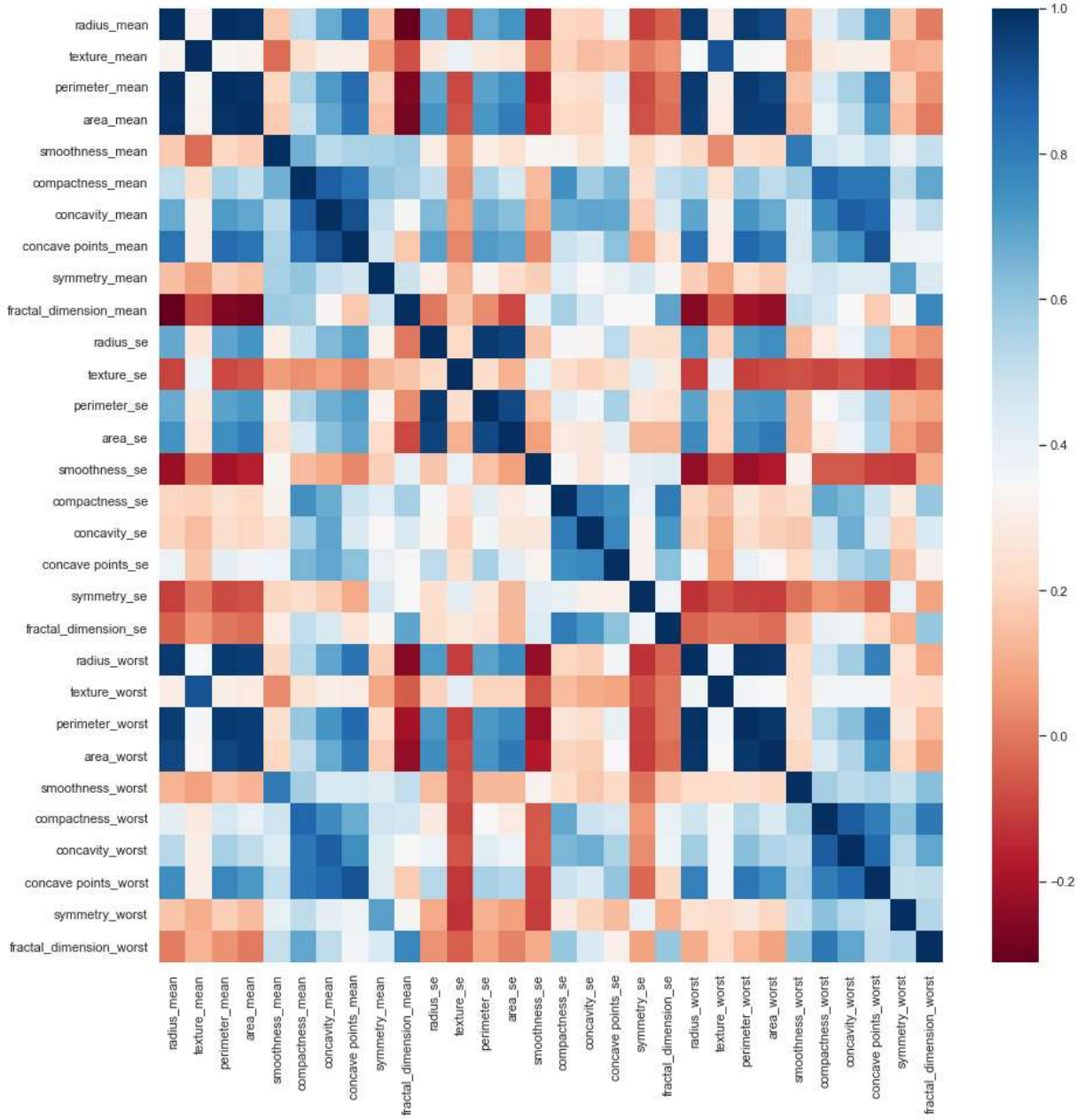


Deleting Highly Correlation Variables

In [28]:
```
high_corr_cols(df)
```

Out[28]:
```
['perimeter_mean',
 'area_mean',
 'concave points_mean',
 'perimeter_se',
 'area_se',
 'radius_worst',
 'texture_worst',
 'perimeter_worst',
 'area_worst',
 'concave points_worst']
```

In [29]:
```
drop_list = high_corr_cols(df, plot=True)
```



In [30]:
```
df.drop(drop_list, axis=1)
```

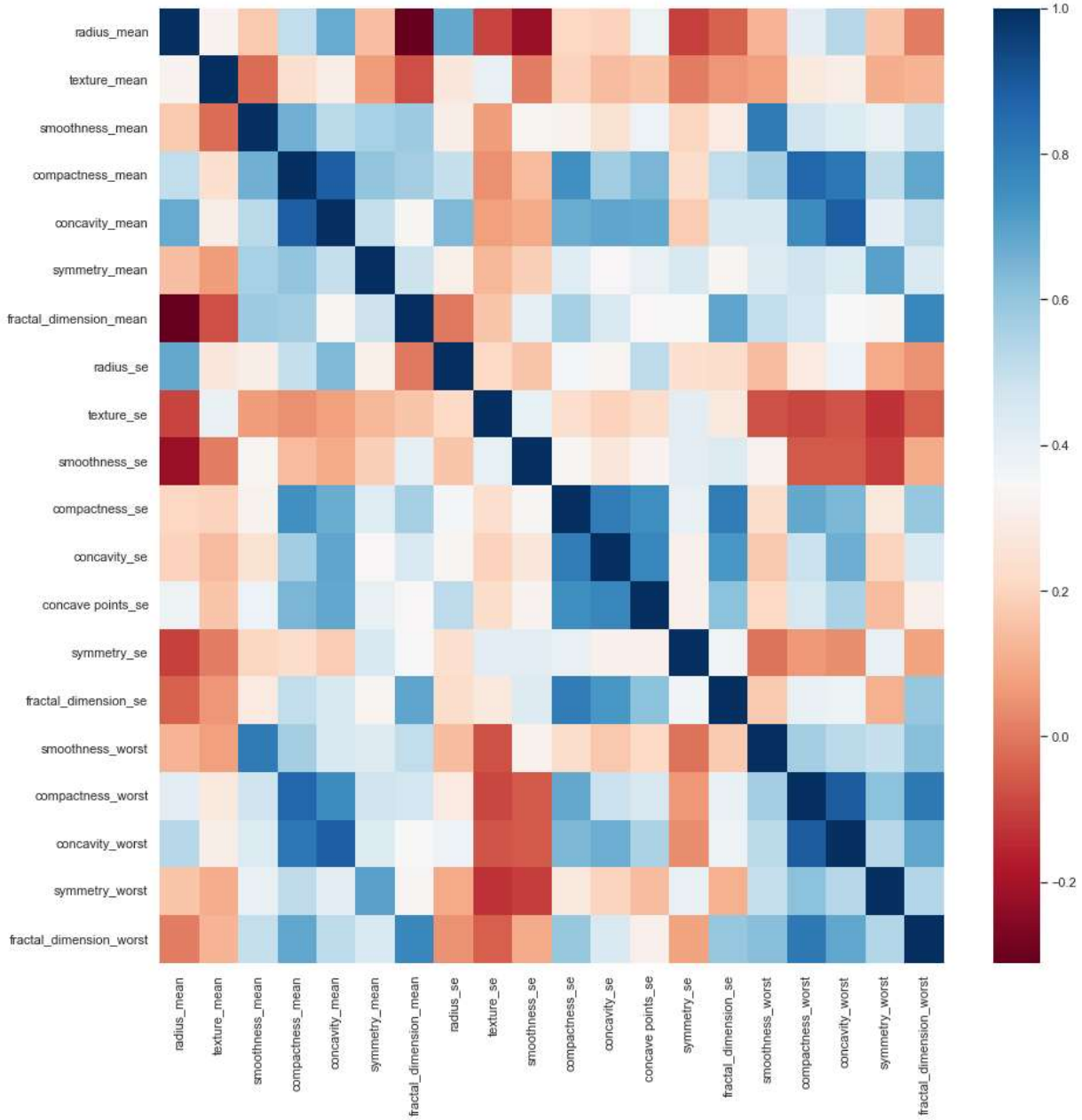
Out[30]:

	diagnosis	radius_mean	texture_mean	smoothness_mean	compactness_mean	concavity_mean
0	M	17.99	10.38	0.11840	0.27760	0.30010
1	M	20.57	17.77	0.08474	0.07864	0.08690
2	M	19.69	21.25	0.10960	0.15990	0.19740
3	M	11.42	20.38	0.14250	0.28390	0.24140
4	M	20.29	14.34	0.10030	0.13280	0.19800
...	...	...	...	...	...	...
564	M	21.56	22.39	0.11100	0.11590	0.24390

	diagnosis	radius_mean	texture_mean	smoothness_mean	compactness_mean	concavity_mean
565	M	20.13	28.25	0.09780	0.10340	0.14400
566	M	16.60	28.08	0.08455	0.10230	0.09251
567	M	20.60	29.33	0.11780	0.27700	0.35140
568	B	7.76	24.54	0.05263	0.04362	0.00000

569 rows × 21 columns

In [31]:
```
high_corr_cols(df.drop(drop_list, axis=1), plot=True)
```



Out[31]:
```
[]
```

How to Catch Outliers?

In [32]:
```
from PreProcessing import outlier_thresholds

df = sns.load_dataset('titanic')
```

In [33]:
```
outlier_thresholds(df, "age")
```

Out[33]:
```
(-6.6875, 64.8125)
```

In [34]:
```
outlier_thresholds(df, "fare")
```

Out[34]:
```
(-26.724, 65.6344)
```

In [35]:
```
low, up = outlier_thresholds(df, "fare")
low, up
```

Out[35]:
```
(-26.724, 65.6344)
```

Is there any outlier value?

In [37]:
```
from PreProcessing import check_outlier

check_outlier(df, "age")
```

Out[37]:
```
True
```

In [38]:
```
check_outlier(df, "fare")
```

Out[38]:
```
True
```

In [39]:
```
df = pd.read_csv('application_train.csv')

cat_cols, num_cols, cat_but_car = grab_col_names(df)
```

```
Observations: 307511
Variables: 122
cat_cols: 19
num_cols: 61
cat_but_car: 1
num_but_cat: 4
```

In [40]:
```
num_cols = [col for col in num_cols if col not in "SK_ID_CURR"]
num_cols
```

Out[40]:
```
['AMT_INCOME_TOTAL',
```

```
'AMT_CREDIT',
'AMT_ANNUITY',
'AMT_GOODS_PRICE',
'REGION_POPULATION_RELATIVE',
'DAYS_REGISTRATION',
'OWN_CAR_AGE',
'CNT_FAM_MEMBERS',
'EXT_SOURCE_1',
'EXT_SOURCE_2',
'EXT_SOURCE_3',
'APARTMENTS_AVG',
'BASEMENTAREA_AVG',
'YEARS_BEGINEXPLUATATION_AVG',
'YEARS_BUILD_AVG',
'COMMONAREA_AVG',
'ELEVATORS_AVG',
'ENTRANCES_AVG',
'FLOORSMAX_AVG',
'FLOORSMIN_AVG',
'LANDAREA_AVG',
'LIVINGAPARTMENTS_AVG',
'LIVINGAREA_AVG',
'NONLIVINGAPARTMENTS_AVG',
'NONLIVINGAREA_AVG',
'APARTMENTS_MODE',
'BASEMENTAREA_MODE',
'YEARS_BEGINEXPLUATATION_MODE',
'YEARS_BUILD_MODE',
'COMMONAREA_MODE',
'ELEVATORS_MODE',
'ENTRANCES_MODE',
'FLOORSMAX_MODE',
'FLOORSMIN_MODE',
'LANDAREA_MODE',
'LIVINGAPARTMENTS_MODE',
'LIVINGAREA_MODE',
'NONLIVINGAPARTMENTS_MODE',
'NONLIVINGAREA_MODE',
'APARTMENTS_MEDI',
'BASEMENTAREA_MEDI',
'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BUILD_MEDI',
'COMMONAREA_MEDI',
'ELEVATORS_MEDI',
'ENTRANCES_MEDI',
'FLOORSMAX_MEDI',
'FLOORSMIN_MEDI',
'LANDAREA_MEDI',
'LIVINGAPARTMENTS_MEDI',
'LIVINGAREA_MEDI',
'NONLIVINGAPARTMENTS_MEDI',
'NONLIVINGAREA_MEDI',
'TOTALAREA_MODE',
'OBS_30_CNT_SOCIAL_CIRCLE',
'DEF_30_CNT_SOCIAL_CIRCLE',
'OBS_60_CNT_SOCIAL_CIRCLE',
'DAYS_LAST_PHONE_CHANGE',
'AMT_REQ_CREDIT_BUREAU_MON',
'AMT_REQ_CREDIT_BUREAU_QRT',
'AMT_REQ_CREDIT_BUREAU_YEAR']
```

In [41]:

```
for col in num_cols:
    print(col, check_outlier(df, col))
```

```
AMT_INCOME_TOTAL True
AMT_CREDIT True
AMT_ANNUITY True
AMT_GOODS_PRICE True
REGION_POPULATION_RELATIVE True
DAYS_REGISTRATION True
OWN_CAR_AGE True
CNT_FAM_MEMBERS True
EXT_SOURCE_1 False
EXT_SOURCE_2 False
EXT_SOURCE_3 False
APARTMENTS_AVG True
BASEMENTAREA_AVG True
YEARS_BEGINEXPLUATATION_AVG True
YEARS_BUILD_AVG True
COMMONAREA_AVG True
ELEVATORS_AVG True
ENTRANCES_AVG True
FLOORSMAX_AVG True
FLOORSMIN_AVG True
LANDAREA_AVG True
LIVINGAPARTMENTS_AVG True
LIVINGAREA_AVG True
NONLIVINGAPARTMENTS_AVG True
NONLIVINGAREA_AVG True
APARTMENTS_MODE True
BASEMENTAREA_MODE True
YEARS_BEGINEXPLUATATION_MODE True
YEARS_BUILD_MODE True
COMMONAREA_MODE True
ELEVATORS_MODE True
ENTRANCES_MODE True
FLOORSMAX_MODE True
FLOORSMIN_MODE True
LANDAREA_MODE True
LIVINGAPARTMENTS_MODE True
LIVINGAREA_MODE True
NONLIVINGAPARTMENTS_MODE True
NONLIVINGAREA_MODE True
APARTMENTS_MEDI True
BASEMENTAREA_MEDI True
YEARS_BEGINEXPLUATATION_MEDI True
YEARS_BUILD_MEDI True
COMMONAREA_MEDI True
ELEVATORS_MEDI True
ENTRANCES_MEDI True
FLOORSMAX_MEDI True
FLOORSMIN_MEDI True
LANDAREA_MEDI True
LIVINGAPARTMENTS_MEDI True
LIVINGAREA_MEDI True
NONLIVINGAPARTMENTS_MEDI True
NONLIVINGAREA_MEDI True
TOTALAREA_MODE True
OBS_30_CNT_SOCIAL_CIRCLE True
```

```
DEF_30_CNT_SOCIAL_CIRCLE True
OBS_60_CNT_SOCIAL_CIRCLE True
DAYS_LAST_PHONE_CHANGE True
AMT_REQ_CREDIT_BUREAU_MON True
AMT_REQ_CREDIT_BUREAU_QRT True
AMT_REQ_CREDIT_BUREAU_YEAR True
```

Accessing Outliers

In [42]:
```
from PreProcessing import grab_outliers

df = sns.load_dataset('titanic')
grab_outliers(df,'age')
```

```
     survived  pclass   sex   age  sibsp  parch     fare embarked   class  who  adul
t_male deck  embark_town alive  alone
33          0       2  male  66.0      0      0  10.5000        S  Second  man
True  NaN  Southampton    no   True
54          0       1  male  65.0      0      1  61.9792        C   First  man
True    B    Cherbourg    no  False
96          0       1  male  71.0      0      0  34.6542        C   First  man
True    A    Cherbourg    no   True
116         0       3  male  70.5      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
280         0       3  male  65.0      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
```

In [43]:
```
grab_outliers(df, "age", True)
```

```
     survived  pclass   sex   age  sibsp  parch     fare embarked   class  who  adul
t_male deck  embark_town alive  alone
33          0       2  male  66.0      0      0  10.5000        S  Second  man
True  NaN  Southampton    no   True
54          0       1  male  65.0      0      1  61.9792        C   First  man
True    B    Cherbourg    no  False
96          0       1  male  71.0      0      0  34.6542        C   First  man
True    A    Cherbourg    no   True
116         0       3  male  70.5      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
280         0       3  male  65.0      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
```

Out[43]:
```
Int64Index([33, 54, 96, 116, 280, 456, 493, 630, 672, 745, 851], dtype='int64')
```

In [44]:
```
age_index = grab_outliers(df, "age", True)
```

```
     survived  pclass   sex   age  sibsp  parch     fare embarked   class  who  adul
t_male deck  embark_town alive  alone
33          0       2  male  66.0      0      0  10.5000        S  Second  man
True  NaN  Southampton    no   True
54          0       1  male  65.0      0      1  61.9792        C   First  man
True    B    Cherbourg    no  False
96          0       1  male  71.0      0      0  34.6542        C   First  man
True    A    Cherbourg    no   True
116         0       3  male  70.5      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
```

```
280         0       3  male  65.0      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
```

In [45]:
```
outlier_thresholds(df, "age")
```

Out[45]:
```
(-6.6875, 64.8125)
```

In [47]:
```
check_outlier(df, "age")
```

Out[47]:
```
True
```

In [48]:
```
grab_outliers(df, "age", True)
```

Out[48]:
```
     survived  pclass   sex   age  sibsp  parch     fare embarked   class  who  adul
t_male deck  embark_town alive  alone
33          0       2  male  66.0      0      0  10.5000        S  Second  man
True  NaN  Southampton    no   True
54          0       1  male  65.0      0      1  61.9792        C   First  man
True    B    Cherbourg    no  False
96          0       1  male  71.0      0      0  34.6542        C   First  man
True    A    Cherbourg    no   True
116         0       3  male  70.5      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
280         0       3  male  65.0      0      0   7.7500        Q   Third  man
True  NaN   Queenstown    no   True
Int64Index([33, 54, 96, 116, 280, 456, 493, 630, 672, 745, 851], dtype='int64')
```

Solving the Outlier Problem

1) Deletion

In [49]:
```
cat_cols, num_cols, cat_but_car = grab_col_names(df)
```

```
Observations: 891
Variables: 15
cat_cols: 9
num_cols: 2
cat_but_car: 0
num_but_cat: 0
```

In [50]:
```
num_cols = [col for col in num_cols if col not in "PassengerId"]
```

In [51]:
```
df.shape
```

Out[51]:
```
(891, 15)
```

In [52]:
```
from PreProcessing import remove_outlier
```

```
for col in num_cols:
    new_df = remove_outlier(df, col)
```

In [53]:
```
df.shape[0] - new_df.shape[0]
```

Out[53]:
```
116
```

2) re-assignment with thresholds

In [54]:
```
low, up = outlier_thresholds(df, "fare")
low, up
```

Out[54]:
```
(-26.724, 65.6344)
```

In [55]:
```
df = sns.load_dataset('titanic')
df.shape
```

Out[55]:
```
(891, 15)
```

In [56]:
```
cat_cols, num_cols, cat_but_car = grab_col_names(df)
```

```
Observations: 891
Variables: 15
cat_cols: 9
num_cols: 2
cat_but_car: 0
num_but_cat: 0
```

In [57]:
```
num_cols = [col for col in num_cols if col not in "PassengerId"]
```

In [60]:
```
from PreProcessing import replace_with_thresholds

for col in num_cols:
    print(col, check_outlier(df, col))
```

```
age True
fare True
```

In [61]:
```
for col in num_cols:
    replace_with_thresholds(df, col)
```

In [62]:
```
for col in num_cols:
    print(col, check_outlier(df, col))
```

```
age False
fare False
```

Solving the Missing Value Problem

In [63]:
```
df = sns.load_dataset('titanic')
df.shape
```

Out[63]:
```
(891, 15)
```

1) Deletion

In [64]:
```
df.dropna().shape
```

Out[64]:
```
(182, 15)
```

2) Filling with Simple Assignment Methods

In [65]:
```
df = sns.load_dataset('titanic')
df.isnull().sum()
```

Out[65]:
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [67]:
```
df['age'] = df["age"].fillna(df["age"].mean())
df.isnull().sum()
```

Out[67]:
```
survived         0
pclass           0
sex              0
age              0
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [68]:

```
df = sns.load_dataset('titanic')
df.isnull().sum()
```

Out[68]:
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [69]:
```
df["age"].fillna(df["age"].median())
```

Out[69]:
```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888    28.0
889    26.0
890    32.0
Name: age, Length: 891, dtype: float64
```

In [70]:
```
df = sns.load_dataset('titanic')

cat_cols, num_cols, cat_but_car = grab_col_names(df)
num_cols = [col for col in num_cols if col not in "PassengerId"]
```

```
Observations: 891
Variables: 15
cat_cols: 9
num_cols: 2
cat_but_car: 0
num_but_cat: 0
```

In [71]:
```
df.isnull().sum()
```

Out[71]:
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
```

```
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [72]:
```
df.loc[:, num_cols] = df[num_cols].apply(lambda x: x.fillna(x.mean()), axis=0)
df.isnull().sum()
```

Out[72]:
```
survived         0
pclass           0
sex              0
age              0
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [73]:
```
df["embarked"].isnull().sum()
```

Out[73]:
```
2
```

In [74]:
```
df['embarked'] = df["embarked"].fillna(df["embarked"].mode()[0])
```

In [75]:
```
df["embarked"].isnull().sum()
```

Out[75]:
```
0
```

Examining the Relationship of Missing Values with the Dependent Variable

In [76]:
```
from PreProcessing import missing_values_table

df = sns.load_dataset('titanic')

missing_values_table(df, True)
```

```
             n_miss  ratio
deck            688  77.22
age             177  19.87
```

```
embarked          2   0.22
embark_town       2   0.22
```

Out[76]:
```
['age', 'embarked', 'deck', 'embark_town']
```

In [77]:
```
na_cols = missing_values_table(df, True)
```

```
             n_miss  ratio
deck            688  77.22
age             177  19.87
embarked          2   0.22
embark_town       2   0.22
```

In [78]:
```
from PreProcessing import missing_vs_target

missing_vs_target(df, "survived", na_cols)
```

```
             TARGET_MEAN  Count
age_NA_FLAG
0               0.406162    714
1               0.293785    177


                  TARGET_MEAN  Count
embarked_NA_FLAG
0                    0.382452    889
1                    1.000000      2


               TARGET_MEAN  Count
deck_NA_FLAG
0                 0.669951    203
1                 0.299419    688


                     TARGET_MEAN  Count
embark_town_NA_FLAG
0                       0.382452    889
1                       1.000000      2
```

Label Encoding & Binary Encoding

In [79]:
```
df = sns.load_dataset('titanic')

df["sex"].head()
```

Out[79]:
```
0      male
1    female
2    female
3    female
4      male
Name: sex, dtype: object
```

In [80]:

```
from PreProcessing import label_encoder

binary_cols = [col for col in df.columns if df[col].dtype not in [int, float]
               and df[col].nunique() == 2]

for col in binary_cols:
    label_encoder(df, col)

df.sex.head()
```

Out[80]:
```
0    1
1    0
2    0
3    0
4    1
Name: sex, dtype: int32
```

One-Hot Encoding

In [81]:
```
from PreProcessing import one_hot_encoder

df = sns.load_dataset('titanic')
df["embarked"].value_counts()
```

Out[81]:
```
S    644
C    168
Q     77
Name: embarked, dtype: int64
```

In [82]:
```
ohe_cols = [col for col in df.columns if 10 >= df[col].nunique() > 2]
ohe_cols
```

Out[82]:
```
['pclass', 'sibsp', 'parch', 'embarked', 'class', 'who', 'deck', 'embark_town']
```

In [83]:
```
one_hot_encoder(df, ohe_cols).head()
```

Out[83]:

	survived	sex	age	fare	adult_male	alive	alone	pclass_2	pclass_3	sibsp_1	sibsp_2	si
0	0	male	22.0	7.2500	True	no	False	0	1	1	0	
1	1	female	38.0	71.2833	False	yes	False	0	0	1	0	
2	1	female	26.0	7.9250	False	yes	True	0	1	0	0	
3	1	female	35.0	53.1000	False	yes	False	0	0	1	0	
4	0	male	35.0	8.0500	True	no	True	0	1	0	0	

Rare Encoding

In [84]:
```
from PreProcessing import rare_encoder,rare_analyser
```

```
df = pd.read_csv('application_train.csv')
df["NAME_EDUCATION_TYPE"].value_counts()
```

Out[84]:
```
Secondary / secondary special    218391
Higher education                  74863
Incomplete higher                 10277
Lower secondary                    3816
Academic degree                     164
Name: NAME_EDUCATION_TYPE, dtype: int64
```

In [85]:
```
cat_cols, num_cols, cat_but_car = grab_col_names(df)
```

```
Observations: 307511
Variables: 122
cat_cols: 19
num_cols: 61
cat_but_car: 1
num_but_cat: 4
```

In [86]:
```
for col in cat_cols:
    cat_summary(df, col)
```

```
                 NAME_CONTRACT_TYPE      Ratio
Cash loans                   278232  90.478715
Revolving loans               29279   9.521285
##########################################
     CODE_GENDER      Ratio
F         202448  65.834393
M         105059  34.164306
XNA            4   0.001301
##########################################
   FLAG_OWN_CAR      Ratio
N        202924  65.989184
Y        104587  34.010816
##########################################
   FLAG_OWN_REALTY      Ratio
Y           213312  69.367275
N            94199  30.632725
##########################################
                 NAME_TYPE_SUITE      Ratio
Unaccompanied             248526  80.818572
Family                     40149  13.056118
Spouse, partner            11370   3.697429
Children                    3267   1.062401
Other_B                     1770   0.575589
Other_A                      866   0.281616
Group of people              271   0.088127
##########################################
                      NAME_INCOME_TYPE      Ratio
Working                         158774  51.631974
Commercial associate             71617  23.289248
Pensioner                        55362  18.003258
State servant                    21703   7.057634
Unemployed                          22   0.007154
Student                             18   0.005853
Businessman                         10   0.003252
Maternity leave                      5   0.001626
```

```
########################################
                          NAME_EDUCATION_TYPE      Ratio
Secondary / secondary special               218391  71.018923
Higher education                             74863  24.344820
Incomplete higher                            10277   3.341994
Lower secondary                               3816   1.240931
Academic degree                                164   0.053331
########################################
                     NAME_FAMILY_STATUS      Ratio
Married                             196432  63.878040
Single / not married                 45444  14.778008
Civil marriage                       29775   9.682580
Separated                            19770   6.429038
Widow                                16088   5.231683
Unknown                                  2   0.000650
########################################
                    NAME_HOUSING_TYPE      Ratio
House / apartment               272868  88.734387
With parents                     14840   4.825844
Municipal apartment              11183   3.636618
Rented apartment                  4881   1.587260
Office apartment                  2617   0.851026
Co-op apartment                   1122   0.364865
########################################
                     OCCUPATION_TYPE      Ratio
Laborers                         55186  17.946025
Sales staff                      32102  10.439301
Core staff                       27570   8.965533
Managers                         21371   6.949670
Drivers                          18603   6.049540
High skill tech staff            11380   3.700681
Accountants                       9813   3.191105
Medicine staff                    8537   2.776161
Security staff                    6721   2.185613
Cooking staff                     5946   1.933589
Cleaning staff                    4653   1.513117
Private service staff             2652   0.862408
Low-skill Laborers                2093   0.680626
Waiters/barmen staff              1348   0.438358
Secretaries                       1305   0.424375
Realty agents                      751   0.244219
HR staff                           563   0.183083
IT staff                           526   0.171051
########################################
          WEEKDAY_APPR_PROCESS_START      Ratio
TUESDAY                          53901  17.528153
WEDNESDAY                        51934  16.888502
MONDAY                           50714  16.491768
THURSDAY                         50591  16.451769
FRIDAY                           50338  16.369496
SATURDAY                         33852  11.008387
SUNDAY                           16181   5.261926
########################################
                     FONDKAPREMONT_MODE      Ratio
reg oper account                    73830  24.008897
reg oper spec account               12080   3.928315
not specified                        5687   1.849365
org spec account                     5619   1.827252
########################################
                 HOUSETYPE_MODE      Ratio
```

```
block of flats            150503  48.942314
specific housing            1499   0.487462
terraced house              1212   0.394132
##########################################
             WALLSMATERIAL_MODE      Ratio
Panel                        66040  21.475655
Stone, brick                 64815  21.077295
Block                         9253   3.008998
Wooden                        5362   1.743677
Mixed                         2296   0.746640
Monolithic                    1779   0.578516
Others                        1625   0.528436
##########################################
     EMERGENCYSTATE_MODE      Ratio
No                159428  51.844649
Yes                 2328   0.757046
##########################################
      DEF_60_CNT_SOCIAL_CIRCLE      Ratio
0.0                      280721  91.288117
1.0                       21841   7.102510
2.0                        3170   1.030857
3.0                         598   0.194465
4.0                         135   0.043901
5.0                          20   0.006504
6.0                           3   0.000976
7.0                           1   0.000325
24.0                          1   0.000325
##########################################
     AMT_REQ_CREDIT_BUREAU_HOUR      Ratio
0.0                      264366  85.969608
1.0                        1560   0.507299
2.0                          56   0.018211
3.0                           9   0.002927
4.0                           1   0.000325
##########################################
     AMT_REQ_CREDIT_BUREAU_DAY      Ratio
0.0                      264503  86.014159
1.0                        1292   0.420148
2.0                         106   0.034470
3.0                          45   0.014634
4.0                          26   0.008455
5.0                           9   0.002927
6.0                           8   0.002602
9.0                           2   0.000650
8.0                           1   0.000325
##########################################
     AMT_REQ_CREDIT_BUREAU_WEEK      Ratio
0.0                      257456  83.722534
1.0                        8208   2.669173
2.0                         199   0.064713
3.0                          58   0.018861
4.0                          34   0.011057
6.0                          20   0.006504
5.0                          10   0.003252
8.0                           5   0.001626
7.0                           2   0.000650
##########################################
```

In [87]:

```
df["NAME_INCOME_TYPE"].value_counts()
```

Out[87]:
```
Working                 158774
Commercial associate     71617
Pensioner                55362
State servant            21703
Unemployed                  22
Student                     18
Businessman                 10
Maternity leave              5
Name: NAME_INCOME_TYPE, dtype: int64
```

In [88]:
```
df.groupby("NAME_INCOME_TYPE")["TARGET"].mean()
```

Out[88]:
```
NAME_INCOME_TYPE
Businessman             0.000000
Commercial associate    0.074843
Maternity leave         0.400000
Pensioner               0.053864
State servant           0.057550
Student                 0.000000
Unemployed              0.363636
Working                 0.095885
Name: TARGET, dtype: float64
```

In [89]:
```
rare_analyser(df, "TARGET", cat_cols)
```

```
NAME_CONTRACT_TYPE : 2
                  COUNT     RATIO  TARGET_MEAN
Cash loans       278232  0.904787     0.083459
Revolving loans   29279  0.095213     0.054783


CODE_GENDER : 3
      COUNT     RATIO  TARGET_MEAN
F    202448  0.658344     0.069993
M    105059  0.341643     0.101419
XNA       4  0.000013     0.000000


FLAG_OWN_CAR : 2
    COUNT     RATIO  TARGET_MEAN
N  202924  0.659892     0.085002
Y  104587  0.340108     0.072437


FLAG_OWN_REALTY : 2
    COUNT     RATIO  TARGET_MEAN
N   94199  0.306327     0.083249
Y  213312  0.693673     0.079616


NAME_TYPE_SUITE : 7
                  COUNT     RATIO  TARGET_MEAN
Children           3267  0.010624     0.073768
Family            40149  0.130561     0.074946
Group of people     271  0.000881     0.084871
Other_A             866  0.002816     0.087760
Other_B            1770  0.005756     0.098305
Spouse, partner   11370  0.036974     0.078716
```

```
Unaccompanied    248526  0.808186     0.081830


NAME_INCOME_TYPE : 8
                      COUNT     RATIO  TARGET_MEAN
Businessman              10  0.000033     0.000000
Commercial associate   71617  0.232892     0.074843
Maternity leave            5  0.000016     0.400000
Pensioner              55362  0.180033     0.053864
State servant          21703  0.070576     0.057550
Student                   18  0.000059     0.000000
Unemployed                22  0.000072     0.363636
Working               158774  0.516320     0.095885


NAME_EDUCATION_TYPE : 5
                               COUNT     RATIO  TARGET_MEAN
Academic degree                  164  0.000533     0.018293
Higher education               74863  0.243448     0.053551
Incomplete higher              10277  0.033420     0.084850
Lower secondary                 3816  0.012409     0.109277
Secondary / secondary special  218391  0.710189     0.089399


NAME_FAMILY_STATUS : 6
                       COUNT     RATIO  TARGET_MEAN
Civil marriage         29775  0.096826     0.099446
Married               196432  0.638780     0.075599
Separated              19770  0.064290     0.081942
Single / not married   45444  0.147780     0.098077
Unknown                    2  0.000007     0.000000
Widow                  16088  0.052317     0.058242


NAME_HOUSING_TYPE : 6
                     COUNT     RATIO  TARGET_MEAN
Co-op apartment       1122  0.003649     0.079323
House / apartment   272868  0.887344     0.077957
Municipal apartment  11183  0.036366     0.085397
Office apartment      2617  0.008510     0.065724
Rented apartment      4881  0.015873     0.123131
With parents         14840  0.048258     0.116981


OCCUPATION_TYPE : 18
                       COUNT     RATIO  TARGET_MEAN
Accountants             9813  0.031911     0.048303
Cleaning staff          4653  0.015131     0.096067
Cooking staff           5946  0.019336     0.104440
Core staff             27570  0.089655     0.063040
Drivers                18603  0.060495     0.113261
HR staff                 563  0.001831     0.063943
High skill tech staff  11380  0.037007     0.061599
IT staff                 526  0.001711     0.064639
Laborers               55186  0.179460     0.105788
Low-skill Laborers      2093  0.006806     0.171524
Managers               21371  0.069497     0.062140
Medicine staff          8537  0.027762     0.067002
Private service staff   2652  0.008624     0.065988
Realty agents            751  0.002442     0.078562
```

```
Sales staff            32102  0.104393     0.096318
Secretaries             1305  0.004244     0.070498
Security staff          6721  0.021856     0.107424
Waiters/barmen staff    1348  0.004384     0.112760


WEEKDAY_APPR_PROCESS_START : 7
           COUNT     RATIO  TARGET_MEAN
FRIDAY     50338  0.163695     0.081469
MONDAY     50714  0.164918     0.077572
SATURDAY   33852  0.110084     0.078873
SUNDAY     16181  0.052619     0.079291
THURSDAY   50591  0.164518     0.081003
TUESDAY    53901  0.175282     0.083505
WEDNESDAY  51934  0.168885     0.081604


FONDKAPREMONT_MODE : 4
                      COUNT     RATIO  TARGET_MEAN
not specified          5687  0.018494     0.075435
org spec account       5619  0.018273     0.058195
reg oper account      73830  0.240089     0.069782
reg oper spec account 12080  0.039283     0.065563


HOUSETYPE_MODE : 3
                   COUNT     RATIO  TARGET_MEAN
block of flats    150503  0.489423     0.069434
specific housing    1499  0.004875     0.101401
terraced house      1212  0.003941     0.084983


WALLSMATERIAL_MODE : 7
              COUNT     RATIO  TARGET_MEAN
Block          9253  0.030090     0.070247
Mixed          2296  0.007466     0.075348
Monolithic     1779  0.005785     0.047218
Others         1625  0.005284     0.083077
Panel         66040  0.214757     0.063477
Stone, brick  64815  0.210773     0.074057
Wooden         5362  0.017437     0.096979


EMERGENCYSTATE_MODE : 2
      COUNT     RATIO  TARGET_MEAN
No   159428  0.518446     0.069649
Yes    2328  0.007570     0.095790


DEF_60_CNT_SOCIAL_CIRCLE : 9
       COUNT     RATIO  TARGET_MEAN
0.0   280721  0.912881     0.078348
1.0    21841  0.071025     0.105169
2.0     3170  0.010309     0.121451
3.0      598  0.001945     0.158863
4.0      135  0.000439     0.111111
5.0       20  0.000065     0.150000
6.0        3  0.000010     0.000000
7.0        1  0.000003     0.000000
24.0       1  0.000003     0.000000
```

```
AMT_REQ_CREDIT_BUREAU_HOUR : 5
      COUNT     RATIO  TARGET_MEAN
0.0  264366  0.859696     0.077173
1.0    1560  0.005073     0.080128
2.0      56  0.000182     0.107143
3.0       9  0.000029     0.000000
4.0       1  0.000003     0.000000


AMT_REQ_CREDIT_BUREAU_DAY : 9
      COUNT     RATIO  TARGET_MEAN
0.0  264503  0.860142     0.077096
1.0    1292  0.004201     0.096749
2.0     106  0.000345     0.103774
3.0      45  0.000146     0.044444
4.0      26  0.000085     0.115385
5.0       9  0.000029     0.000000
6.0       8  0.000026     0.000000
8.0       1  0.000003     0.000000
9.0       2  0.000007     0.000000


AMT_REQ_CREDIT_BUREAU_WEEK : 9
      COUNT     RATIO  TARGET_MEAN
0.0  257456  0.837225     0.077159
1.0    8208  0.026692     0.077729
2.0     199  0.000647     0.100503
3.0      58  0.000189     0.068966
4.0      34  0.000111     0.117647
5.0      10  0.000033     0.100000
6.0      20  0.000065     0.050000
7.0       2  0.000007     0.000000
8.0       5  0.000016     0.000000
```

In [90]:
```
new_df = rare_encoder(df, 0.01)
```

In [91]:
```
rare_analyser(new_df, "TARGET", cat_cols )
```

```
NAME_CONTRACT_TYPE : 2
                  COUNT     RATIO  TARGET_MEAN
Cash loans       278232  0.904787     0.083459
Revolving loans   29279  0.095213     0.054783


CODE_GENDER : 3
       COUNT     RATIO  TARGET_MEAN
F     202448  0.658344     0.069993
M     105059  0.341643     0.101419
Rare       4  0.000013     0.000000


FLAG_OWN_CAR : 2
    COUNT     RATIO  TARGET_MEAN
N  202924  0.659892     0.085002
```

```
Y  104587  0.340108     0.072437


FLAG_OWN_REALTY : 2
    COUNT     RATIO  TARGET_MEAN
N   94199  0.306327     0.083249
Y  213312  0.693673     0.079616


NAME_TYPE_SUITE : 5
                 COUNT     RATIO  TARGET_MEAN
Children          3267  0.010624     0.073768
Family           40149  0.130561     0.074946
Rare              2907  0.009453     0.093911
Spouse, partner  11370  0.036974     0.078716
Unaccompanied   248526  0.808186     0.081830


NAME_INCOME_TYPE : 5
                      COUNT     RATIO  TARGET_MEAN
Commercial associate  71617  0.232892     0.074843
Pensioner             55362  0.180033     0.053864
Rare                     55  0.000179     0.181818
State servant         21703  0.070576     0.057550
Working              158774  0.516320     0.095885


NAME_EDUCATION_TYPE : 5
                               COUNT     RATIO  TARGET_MEAN
Higher education               74863  0.243448     0.053551
Incomplete higher              10277  0.033420     0.084850
Lower secondary                 3816  0.012409     0.109277
Rare                             164  0.000533     0.018293
Secondary / secondary special  218391  0.710189     0.089399


NAME_FAMILY_STATUS : 6
                       COUNT     RATIO  TARGET_MEAN
Civil marriage         29775  0.096826     0.099446
Married               196432  0.638780     0.075599
Rare                       2  0.000007     0.000000
Separated              19770  0.064290     0.081942
Single / not married   45444  0.147780     0.098077
Widow                  16088  0.052317     0.058242


NAME_HOUSING_TYPE : 5
                     COUNT     RATIO  TARGET_MEAN
House / apartment   272868  0.887344     0.077957
Municipal apartment  11183  0.036366     0.085397
Rare                  3739  0.012159     0.069805
Rented apartment      4881  0.015873     0.123131
With parents         14840  0.048258     0.116981


OCCUPATION_TYPE : 12
                       COUNT     RATIO  TARGET_MEAN
Accountants             9813  0.031911     0.048303
Cleaning staff          4653  0.015131     0.096067
Cooking staff           5946  0.019336     0.104440
```

Core staff	27570	0.089655	0.063040
Drivers	18603	0.060495	0.113261
High skill tech staff	11380	0.037007	0.061599
Laborers	55186	0.179460	0.105788
Managers	21371	0.069497	0.062140
Medicine staff	8537	0.027762	0.067002
Rare	9238	0.030041	0.098181
Sales staff	32102	0.104393	0.096318
Security staff	6721	0.021856	0.107424

WEEKDAY_APPR_PROCESS_START : 7

	COUNT	RATIO	TARGET_MEAN
FRIDAY	50338	0.163695	0.081469
MONDAY	50714	0.164918	0.077572
SATURDAY	33852	0.110084	0.078873
SUNDAY	16181	0.052619	0.079291
THURSDAY	50591	0.164518	0.081003
TUESDAY	53901	0.175282	0.083505
WEDNESDAY	51934	0.168885	0.081604

FONDKAPREMONT_MODE : 4

	COUNT	RATIO	TARGET_MEAN
not specified	5687	0.018494	0.075435
org spec account	5619	0.018273	0.058195
reg oper account	73830	0.240089	0.069782
reg oper spec account	12080	0.039283	0.065563

HOUSETYPE_MODE : 2

	COUNT	RATIO	TARGET_MEAN
Rare	2711	0.008816	0.094061
block of flats	150503	0.489423	0.069434

WALLSMATERIAL_MODE : 5

	COUNT	RATIO	TARGET_MEAN
Block	9253	0.030090	0.070247
Panel	66040	0.214757	0.063477
Rare	5700	0.018536	0.068772
Stone, brick	64815	0.210773	0.074057
Wooden	5362	0.017437	0.096979

EMERGENCYSTATE_MODE : 2

	COUNT	RATIO	TARGET_MEAN
No	159428	0.518446	0.069649
Rare	2328	0.007570	0.095790

DEF_60_CNT_SOCIAL_CIRCLE : 9

	COUNT	RATIO	TARGET_MEAN
0.0	280721	0.912881	0.078348
1.0	21841	0.071025	0.105169
2.0	3170	0.010309	0.121451
3.0	598	0.001945	0.158863
4.0	135	0.000439	0.111111
5.0	20	0.000065	0.150000
6.0	3	0.000010	0.000000

```
7.0        1  0.000003     0.000000
24.0       1  0.000003     0.000000


AMT_REQ_CREDIT_BUREAU_HOUR : 5
      COUNT     RATIO  TARGET_MEAN
0.0  264366  0.859696     0.077173
1.0    1560  0.005073     0.080128
2.0      56  0.000182     0.107143
3.0       9  0.000029     0.000000
4.0       1  0.000003     0.000000


AMT_REQ_CREDIT_BUREAU_DAY : 9
      COUNT     RATIO  TARGET_MEAN
0.0  264503  0.860142     0.077096
1.0    1292  0.004201     0.096749
2.0     106  0.000345     0.103774
3.0      45  0.000146     0.044444
4.0      26  0.000085     0.115385
5.0       9  0.000029     0.000000
6.0       8  0.000026     0.000000
8.0       1  0.000003     0.000000
9.0       2  0.000007     0.000000


AMT_REQ_CREDIT_BUREAU_WEEK : 9
      COUNT     RATIO  TARGET_MEAN
0.0  257456  0.837225     0.077159
1.0    8208  0.026692     0.077729
2.0     199  0.000647     0.100503
3.0      58  0.000189     0.068966
4.0      34  0.000111     0.117647
5.0      10  0.000033     0.100000
6.0      20  0.000065     0.050000
7.0       2  0.000007     0.000000
8.0       5  0.000016     0.000000
```