

```
In [1]: # Import packages that will be used for the logistics regression analysis
import pylab
import seaborn as sb
sb.set(style="white")
sb.set(style="whitegrid", color_codes=True)
import sklearn
from sklearn.metrics import confusion_matrix
from sklearn import preprocessing
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import classification_report
from sklearn import metrics
import matplotlib.pyplot as plt
plt.rc("font", size=14)
import numpy as np
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.graphics.mosaicplot import mosaic
from statsmodels.stats.outliers_influence import variance_inflation_factor
from IPython.core.display import HTML
from IPython.display import display
import pandas as pd
from pandas.api.types import CategoricalDtype
from pandas import Series, DataFrame
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE

# Import data set that will be used for the logistics regression analysis
pd.set_option('display.max_columns', None)
df = pd.read_csv(r'C:\Users\fahim\Documents\0_WGUDocuments\d208\1medical_clean.csv')
# Check data types and number of values, as well as overall size of dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10000 entries, 0 to 9999
```

```
Data columns (total 50 columns):
```

#	Column	Non-Null	Count	Dtype
0	CaseOrder	10000	non-null	int64
1	Customer_id	10000	non-null	object
2	Interaction	10000	non-null	object
3	UID	10000	non-null	object
4	City	10000	non-null	object
5	State	10000	non-null	object
6	County	10000	non-null	object
7	Zip	10000	non-null	int64
8	Lat	10000	non-null	float64
9	Lng	10000	non-null	float64
10	Population	10000	non-null	int64
11	Area	10000	non-null	object
12	TimeZone	10000	non-null	object
13	Job	10000	non-null	object
14	Children	10000	non-null	int64
15	Age	10000	non-null	int64
16	Income	10000	non-null	float64
17	Marital	10000	non-null	object
18	Gender	10000	non-null	object
19	ReAdmis	10000	non-null	object
20	VitD_levels	10000	non-null	float64
21	Doc_visits	10000	non-null	int64
22	Full_meals_eaten	10000	non-null	int64
23	vitD_supp	10000	non-null	int64
24	Soft_drink	10000	non-null	object
25	Initial_admin	10000	non-null	object
26	HighBlood	10000	non-null	object
27	Stroke	10000	non-null	object
28	Complication_risk	10000	non-null	object
29	Overweight	10000	non-null	object
30	Arthritis	10000	non-null	object
31	Diabetes	10000	non-null	object
32	Hyperlipidemia	10000	non-null	object
33	BackPain	10000	non-null	object
34	Anxiety	10000	non-null	object
35	Allergic_rhinitis	10000	non-null	object
36	Reflux_esophagitis	10000	non-null	object
37	Asthma	10000	non-null	object
38	Services	10000	non-null	object
39	Initial_days	10000	non-null	float64

```

40 TotalCharge      10000 non-null float64
41 Additional_charges 10000 non-null float64
42 Item1            10000 non-null int64
43 Item2            10000 non-null int64
44 Item3            10000 non-null int64
45 Item4            10000 non-null int64
46 Item5            10000 non-null int64
47 Item6            10000 non-null int64
48 Item7            10000 non-null int64
49 Item8            10000 non-null int64

```

dtypes: float64(7), int64(16), object(27)

memory usage: 3.8+ MB

```

In [2]: # Visually inspect dataframe to facilitate exploration, spot problems
pd.set_option("display.max_columns", None)
df.head(5)

```

```

Out[2]:

```

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng	Popul
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	-86.72508	
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	-85.22907	
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	-96.63772	
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	-93.51479	
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	-76.88958	

```
In [3]: #check if there is any duplicate data entries present in columns
df[df.duplicated()]
```

```
Out[3]: CaseOrder  Customer_id  Interaction  UID  City  State  County  Zip  Lat  Lng  Population  Area  TimeZone  Job  Children  Age  Income  I
```

```
In [4]: # check if there are any duplicated columns in the data set - if there are none then the output should be False
df.columns.duplicated().any()
```

```
Out[4]: False
```

```
In [5]: # check if there are any duplicated rows in the data set - if there are none then the output should be False
df.duplicated().any()
```

```
Out[5]: False
```

```
In [6]: #Summary Statistics
df.Age.describe()
```

```
Out[6]: count    10000.000000
mean         53.511700
std          20.638538
min          18.000000
25%          36.000000
50%          53.000000
75%          71.000000
max          89.000000
Name: Age, dtype: float64
```

```
In [7]: df.Gender.value_counts()
```

```
Out[7]: Female      5018
Male        4768
Nonbinary     214
Name: Gender, dtype: int64
```

```
In [8]: df.VitD_levels.describe()
```

```
Out[8]: count    10000.000000  
mean         17.964262  
std          2.017231  
min          9.806483  
25%         16.626439  
50%         17.951122  
75%         19.347963  
max         26.394449  
Name: VitD_levels, dtype: float64
```

```
In [9]: df.Initial_admin.value_counts().sort_index()
```

```
Out[9]: Elective Admission    2504  
Emergency Admission    5060  
Observation Admission    2436  
Name: Initial_admin, dtype: int64
```

```
In [10]: df.HighBlood.value_counts()
```

```
Out[10]: No    5910  
Yes    4090  
Name: HighBlood, dtype: int64
```

```
In [11]: df.Complication_risk.value_counts().sort_index()
```

```
Out[11]: High    3358  
Low    2125  
Medium    4517  
Name: Complication_risk, dtype: int64
```

```
In [12]: df.Overweight.value_counts()
```

```
Out[12]: Yes    7094  
No    2906  
Name: Overweight, dtype: int64
```

```
In [13]: df.BackPain.value_counts()
```

```
Out[13]: No    5886  
Yes    4114  
Name: BackPain, dtype: int64
```

```
In [14]: df.Diabetes.value_counts()
```

```
Out[14]: No    7262  
Yes    2738  
Name: Diabetes, dtype: int64
```

```
In [15]: df.Asthma.value_counts()
```

```
Out[15]: No      7107  
Yes       2893  
Name: Asthma, dtype: int64
```

```
In [16]: df.Initial_days.describe()
```

```
Out[16]: count    10000.000000  
mean         34.455299  
std          26.309341  
min           1.001981  
25%           7.896215  
50%          35.836244  
75%          61.161020  
max          71.981490  
Name: Initial_days, dtype: float64
```

```
In [17]: df.Initial_days.nlargest(n=20)
```

```
Out[17]: 7968    71.98149  
5326    71.96869  
7479    71.96546  
6166    71.96415  
8066    71.96342  
5874    71.96164  
5829    71.96134  
9159    71.95813  
8817    71.95472  
7524    71.94732  
9074    71.94459  
7839    71.92930  
9677    71.92647  
9221    71.92413  
5162    71.92171  
9101    71.90712  
9766    71.90694  
5374    71.90056  
6601    71.89863  
7214    71.89805  
Name: Initial_days, dtype: float64
```

```
In [18]: df.Arthritis.value_counts()
```

```
Out[18]: No      6426
         Yes     3574
         Name: Arthritis, dtype: int64
```

```
In [19]: # Data Preparation for analysis
# Convert column to category from string
df["TimeZone"] = df["TimeZone"].astype("category")
# Reformat column representing currency in USD to 3 decimal places from 6
df["Income"] = df["Income"].astype(int)
# Convert column to category from string
df["Marital"] = df["Marital"].astype("category")
# Convert column to category from string
df["Gender"] = df["Gender"].astype("category")

# Convert categorical yes/no values to numeric 1/0 values
df = df.replace(to_replace = ['Yes', 'No'], value = [1,0])

# Perform one-hot encoding
# Generate columns of dummy values for dataframe's Gender column
gender_temp_df = pd.get_dummies(data=df["Gender"], drop_first=True)
# Generate columns of dummy values for dataframe's Initial_admin column
initial_admit_temp_df = pd.get_dummies(data=df["Initial_admin"], drop_first=True)
# Generate columns of dummy values for dataframe's Complication_risk column
comp_risk_temp_df = pd.get_dummies(data=df["Complication_risk"], drop_first=True)
# Create the new df with the variables used for this analysis
regress_df = df[["Age", "VitD_levels", "HighBlood", "Overweight", "Arthritis", "Diabetes", "BackPain", "Asthma", "Initi
# Generate and apply new Pythonic names for ease of use
pythonic_columns = ["age", "vit_d_level", "high_bp", "overweight", "arthritis", "diabetes", "back_pain", "asthma", "day
regress_df.set_axis(pythonic_columns, axis=1, inplace=True)
# Insert the generated dummy variables to new dataframe, placing them in the same order as the original dataframe
# Dummies for Complication Risk
regress_df.insert(4, "comp_risk_medium", comp_risk_temp_df.Medium)
regress_df.insert(4, "comp_risk_low", comp_risk_temp_df.Low)
# Dummies for Initial Admit
regress_df.insert(3, "initial_admit_emerg", initial_admit_temp_df["Emergency Admission"])
regress_df.insert(3, "initial_admit_observ", initial_admit_temp_df["Observation Admission"])
# Dummies for Gender
regress_df.insert(2, "gender_nonbinary", gender_temp_df.Nonbinary)
regress_df.insert(2, "gender_male", gender_temp_df.Male)
# Check resulting dataframe
regress_df
```

Out[19]:

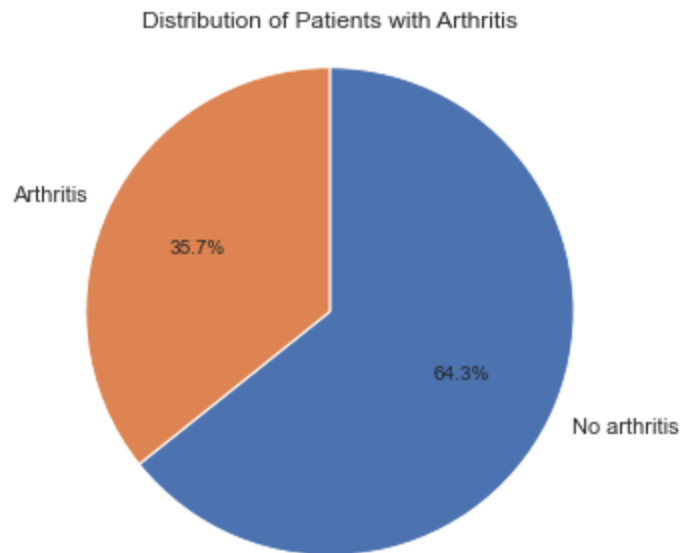
	age	vit_d_level	gender_male	gender_nonbinary	high_bp	initial_admit_observ	initial_admit_emerg	overweight	comp_risk_low	comp_
0	53	19.141466	1	0	1	0	1	0	0	
1	51	18.940352	0	0	1	0	1	1	0	
2	53	18.057507	0	0	1	0	0	1	0	
3	78	16.576858	1	0	0	0	0	0	0	
4	22	17.439069	0	0	0	0	0	0	1	
...
9995	25	16.980860	1	0	1	0	1	0	0	
9996	87	18.177020	1	0	1	0	0	1	0	
9997	45	17.129070	0	0	1	0	0	1	0	
9998	43	19.910430	1	0	0	0	1	1	0	
9999	70	18.388620	0	0	0	1	0	1	1	

10000 rows × 15 columns

```

In [20]: #Bivariate distribution of Arthritis
plt.figure(figsize = [16,5])
plt.title('Distribution of Patients with Arthritis')
arthritis_counts = regress_df.arthritis.value_counts()
arthritis_labels = ["No arthritis", "Arthritis"]
plt.pie(arthritis_counts, labels=arthritis_labels, autopct='%1.1f%%', startangle=90, counterclock=False)
plt.axis('square');

```

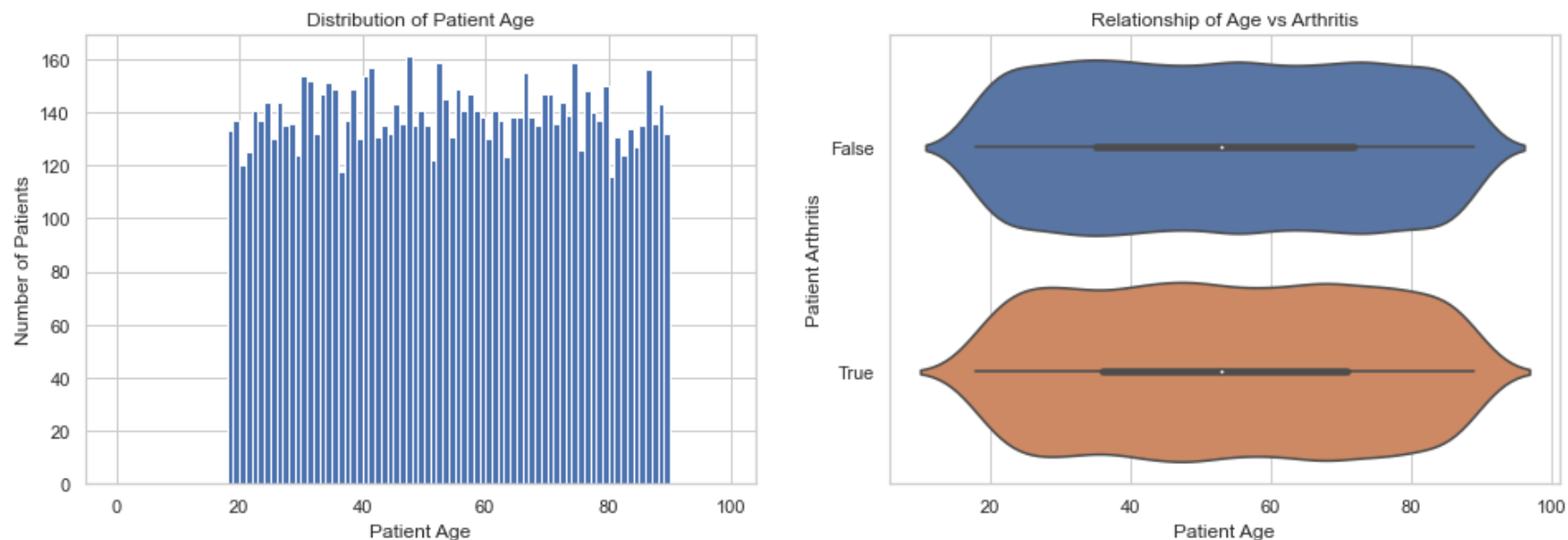



```
In [21]: #Univariate and bivariate distribution of Age
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Age")

# LEFT plot: Univariate exploration of age
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Age')
bins = np.arange(0, 100, 1)
plt.hist(data=regress_df, x="age", bins=bins)
plt.xlabel('Patient Age')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of age vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Age vs Arthritis")
sb.violinplot(data = regress_df, x="age", y="arthritis", orient='h')
plt.xlabel("Patient Age")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```

Visual exploration of Patient's Age

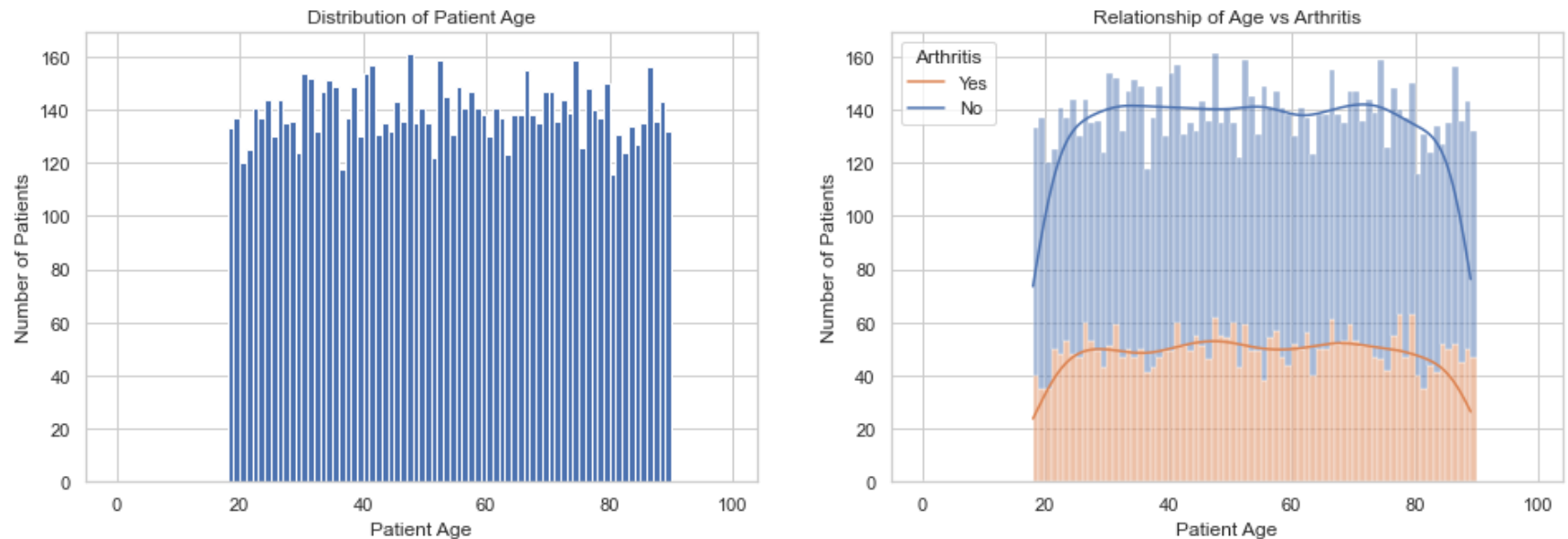


```
In [22]: plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Age")

# LEFT plot: Univariate exploration of age
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Age')
bins = np.arange(0, 100, 1)
plt.hist(data=regress_df, x="age", bins=bins)
plt.xlabel('Patient Age')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of age vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Age vs Arthritis")
sb.histplot(data = regress_df, x="age", hue="arthritis", bins=bins, kde=True, multiple="stack")
plt.legend(title="Arthritis", labels=["Yes", "No"])
plt.xlabel("Patient Age")
plt.ylabel("Number of Patients");
```

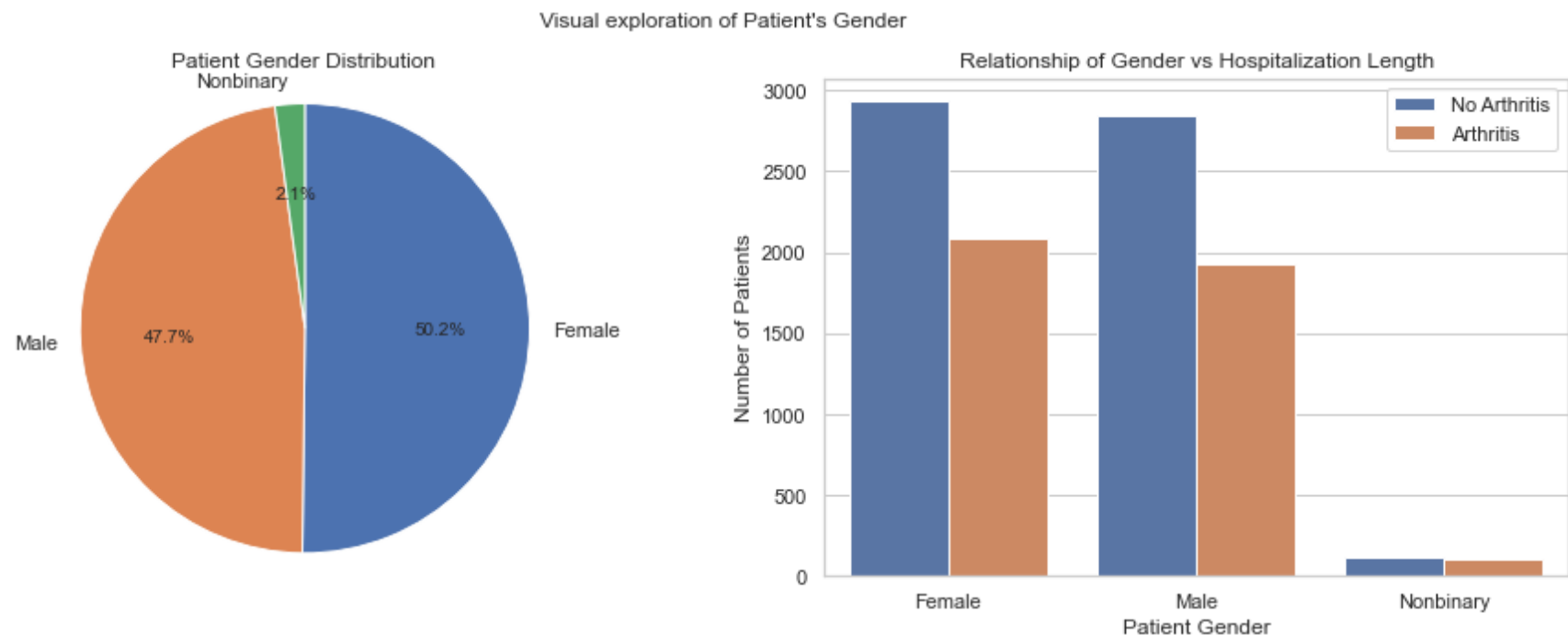
Visual exploration of Patient's Age



```
In [23]: #Univariate and bivariate distribution of Gender
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Gender")

# LEFT plot: Univariate exploration of num_children
plt.subplot(1, 2, 1)
plt.title("Patient Gender Distribution")
gender_counts = df["Gender"].value_counts()
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# RIGHT plot: Bivariate exploration of num_children vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Gender vs Hospitalization Length")
sb.countplot(data = df, x="Gender", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Gender")
plt.ylabel("Number of Patients");
```

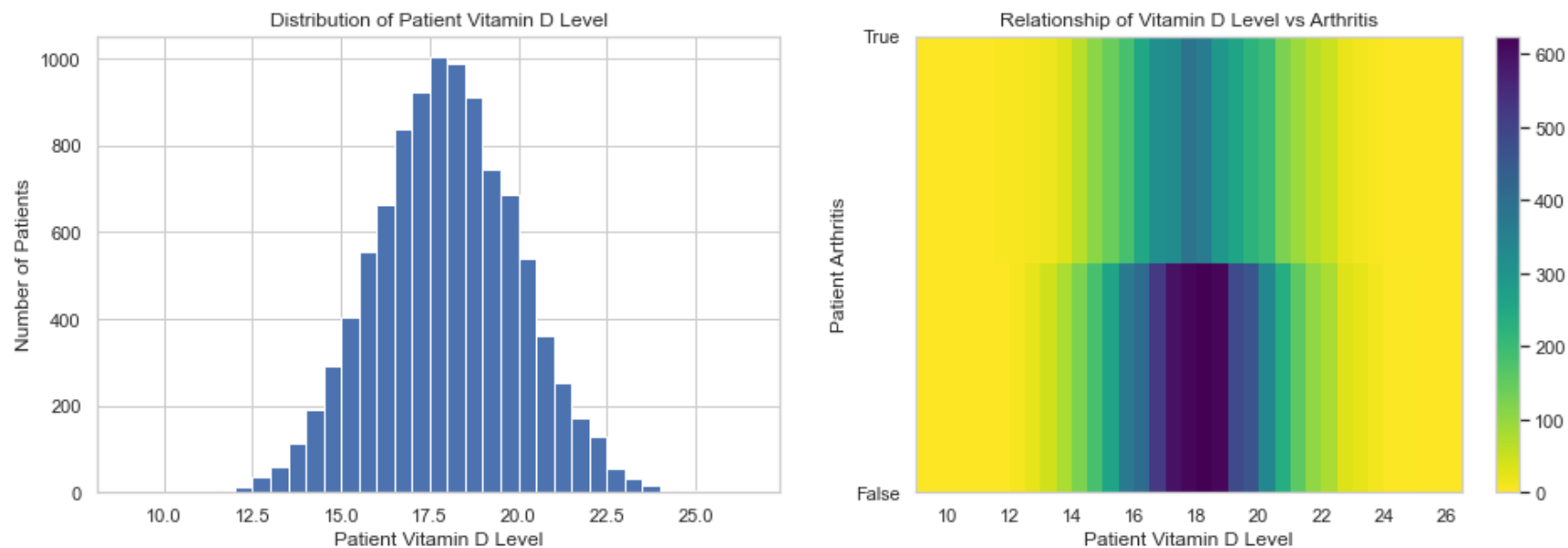


```
In [24]: #Univariate and bivariate distribution of Vitamin D Level
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Vitamin D Level")

# LEFT plot: Univariate exploration of vit_d_level
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Vitamin D Level')
bins = np.arange(9, 27, 0.5)
plt.hist(data=regress_df, x="vit_d_level", bins=bins)
plt.xlabel('Patient Vitamin D Level')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of vit_d_level vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Vitamin D Level vs Arthritis")
bins_y = np.arange(0, 1.25, 0.5)
plt.hist2d(data= regress_df, x="vit_d_level", y="arthritis", bins=[bins, bins_y], cmap= "viridis_r")
plt.colorbar()
plt.xlabel("Patient Vitamin D Level")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```

Visual exploration of Patient's Vitamin D Level

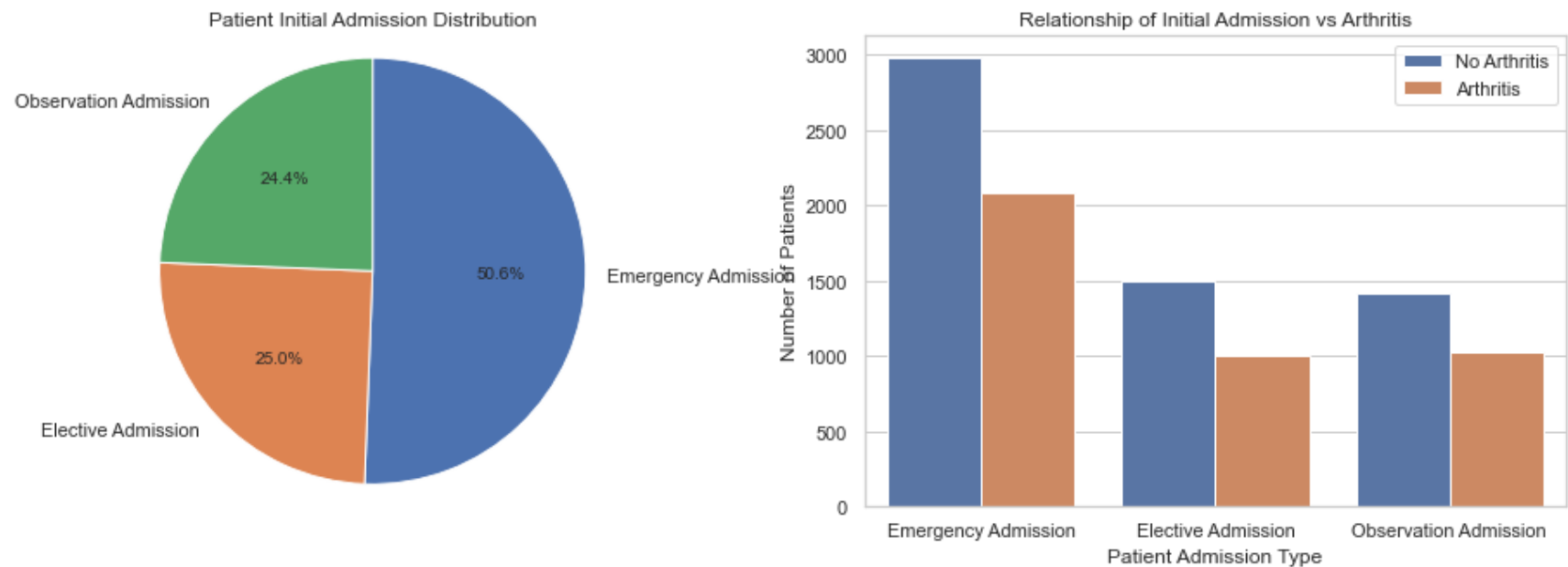


```
In [25]: #Univariate and bivariate distribution of Initial Admissions
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Initial Admissions")

# LEFT plot: Univariate exploration of initial_admin
plt.subplot(1, 2, 1)
plt.title("Patient Initial Admission Distribution")
init_admit_counts = df["Initial_admin"].value_counts()
plt.pie(init_admit_counts, labels=init_admit_counts.index, autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

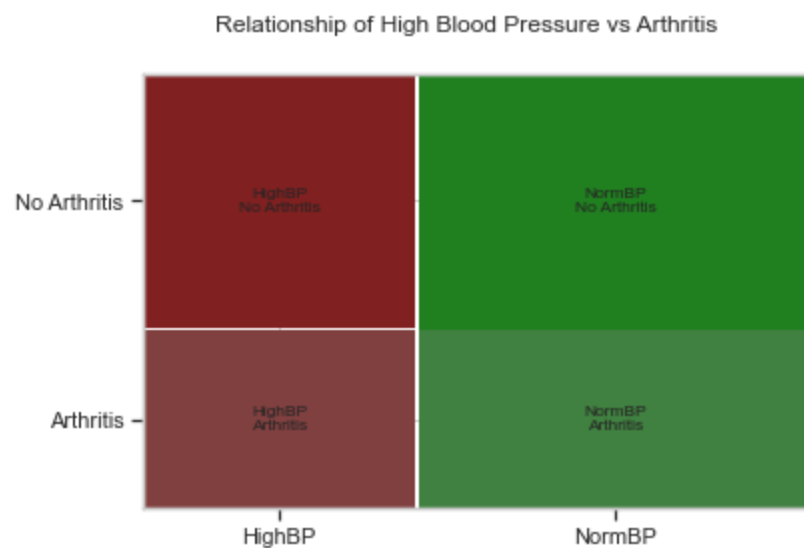
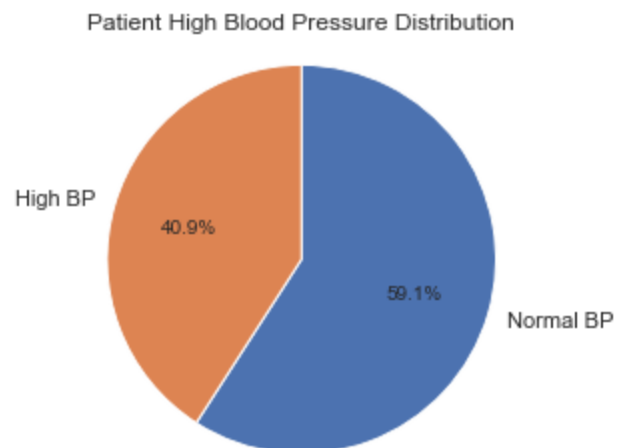
# RIGHT plot: Bivariate exploration of Initial_admin vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Initial Admission vs Arthritis")
sb.countplot(data = df, x="Initial_admin", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Admission Type")
plt.ylabel("Number of Patients");
```

Visual exploration of Patient's Initial Admissions



```
In [26]: #Univariate and bivariate distribution of High Blood pressure
# TOP plot: Univariate exploration of high bp
plt.title("Patient High Blood Pressure Distribution")
high_bp_counts = df["HighBlood"].value_counts()
plt.pie(high_bp_counts, labels=["Normal BP", "High BP"], autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

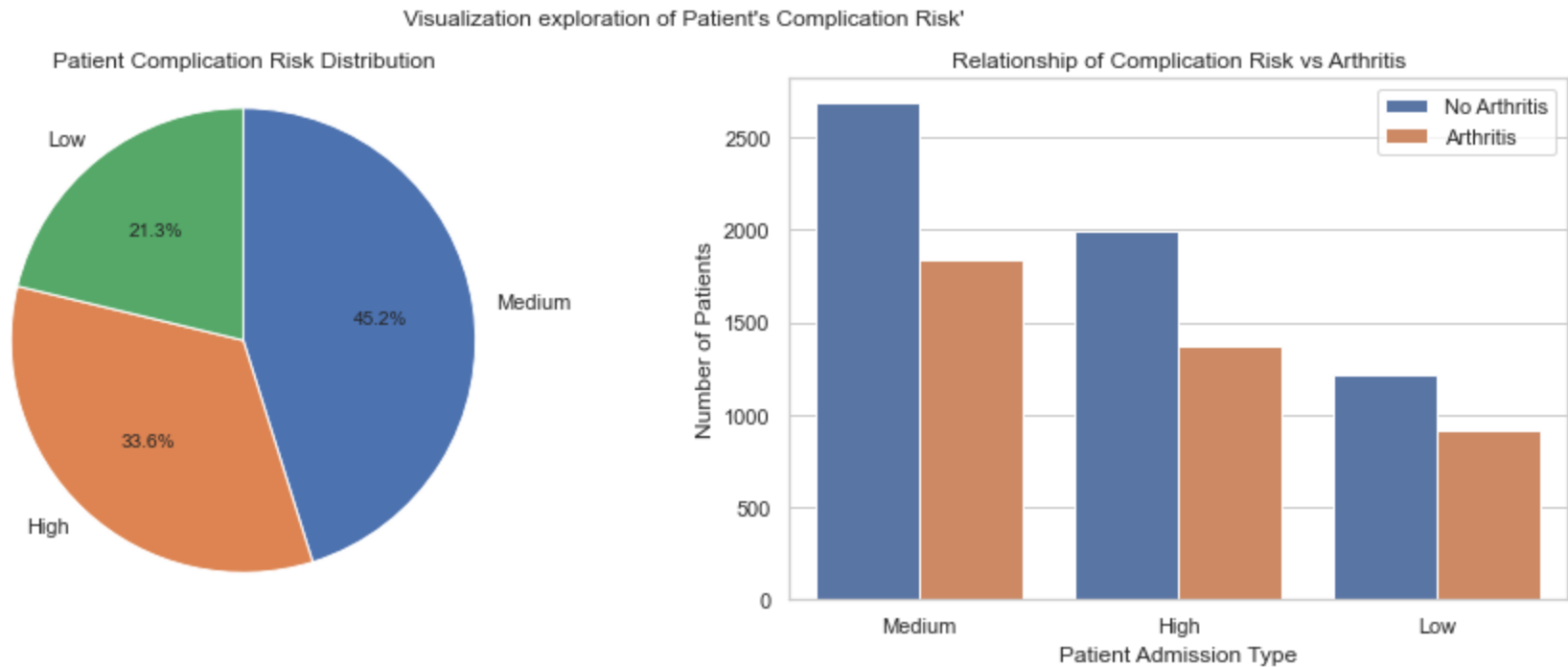
# BOTTOM plot: Bivariate exploration of high bp vs arthritis
temp_df = df[["HighBlood", "BackPain"]].copy()
high_bp_map = {1 : "HighBP", 0: "NormBP"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["HighBlood"] = temp_df["HighBlood"].map(high_bp_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["HighBlood", "BackPain"])
plt.suptitle("Relationship of High Blood Pressure vs Arthritis");
```



```
In [27]: #Univariate and bivariate distribution of Complication Risk
plt.figure(figsize = [16,5])
plt.suptitle("Visualization exploration of Patient's Complication Risk")

# LEFT plot: Univariate exploration of complication_risk
plt.subplot(1, 2, 1)
plt.title("Patient Complication Risk Distribution")
comp_risk_counts = df["Complication_risk"].value_counts()
comp_risk_labels = ["Medium", "High", "Low"]
plt.pie(comp_risk_counts, labels=comp_risk_counts.index, autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');
```

```
# RIGHT plot: Bivariate exploration of complication_risk vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Complication Risk vs Arthritis")
sb.countplot(data = df, x="Complication_risk", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Admission Type")
plt.ylabel("Number of Patients");
```

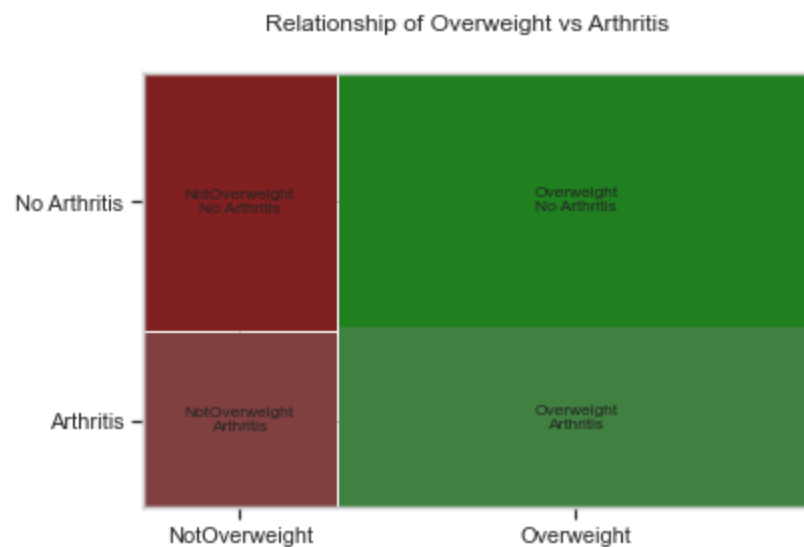
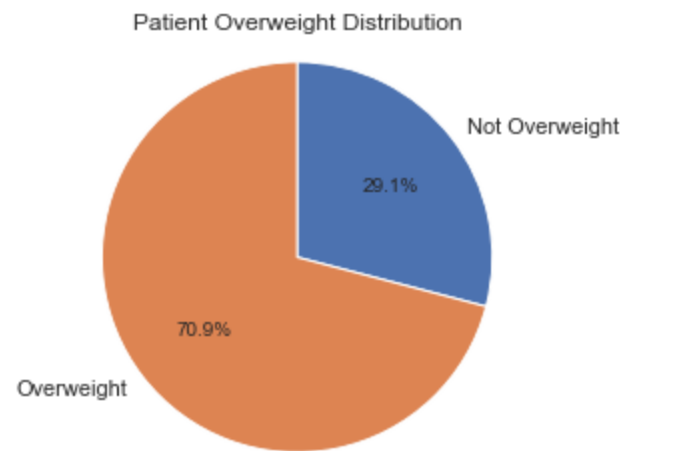


```
In [28]: #Univariate and bivariate distribution of Overweight
# TOP plot: Univariate exploration of overweight
plt.title("Patient Overweight Distribution")
overweight_counts = df["Overweight"].value_counts().sort_index()
plt.pie(overweight_counts, labels=["Not Overweight", "Overweight"], autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# BOTTOM plot: Bivariate exploration of overweight vs arthritis
temp_df = df[["Overweight", "BackPain"]].copy()
overweight_map = {1 : "Overweight", 0: "NotOverweight"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Overweight"] = temp_df["Overweight"].map(overweight_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
```



```
mosaic(temp_df, ["Overweight", "BackPain"])
plt.suptitle("Relationship of Overweight vs Arthritis");
```



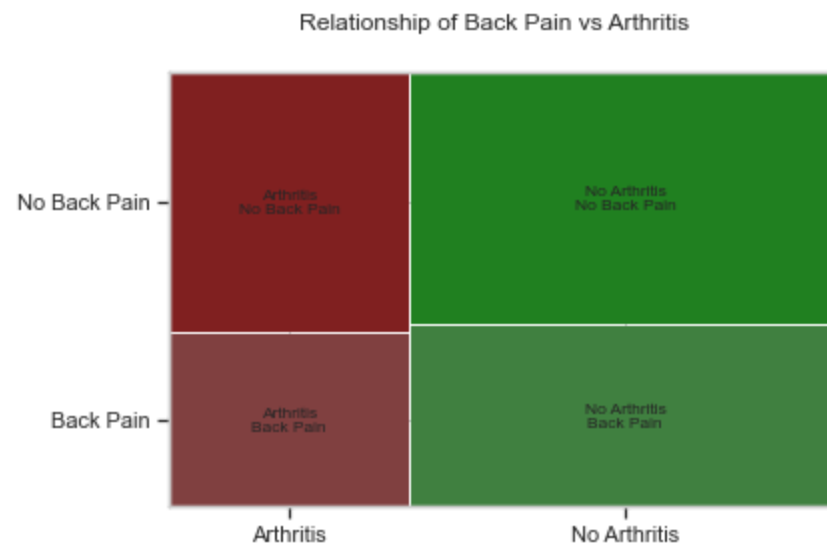
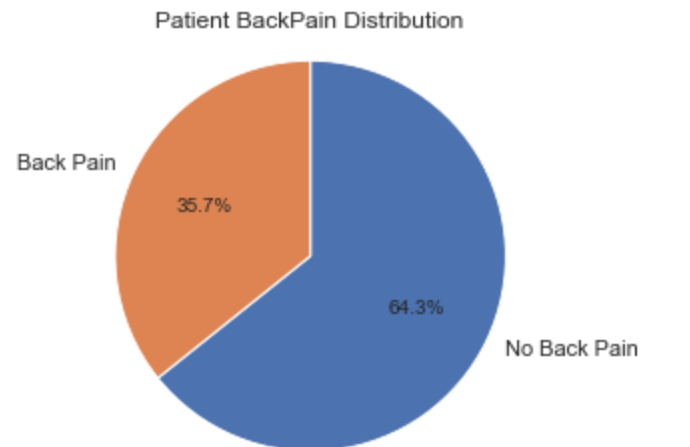
```
In [29]: #Univariate and bivariate distribution of BackPain
# TOP plot: Univariate exploration of arthritis
plt.title("Patient BackPain Distribution")
back_pain_counts = df["BackPain"].value_counts().sort_index()
plt.pie(arthritis_counts, labels=["No Back Pain", "Back Pain"], autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# BOTTOM plot: Bivariate exploration of arthritis vs back_pain
temp_df = df[["Arthritis", "BackPain"]].copy()
```

```

back_pain_map = {1 : "Back Pain", 0: "No Back Pain"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["BackPain"] = temp_df["BackPain"].map(back_pain_map)
temp_df["Arthritis"] = temp_df["Arthritis"].map(arthritis_map)
mosaic(temp_df, ["Arthritis", "BackPain"])
plt.suptitle("Relationship of Back Pain vs Arthritis");

```



```

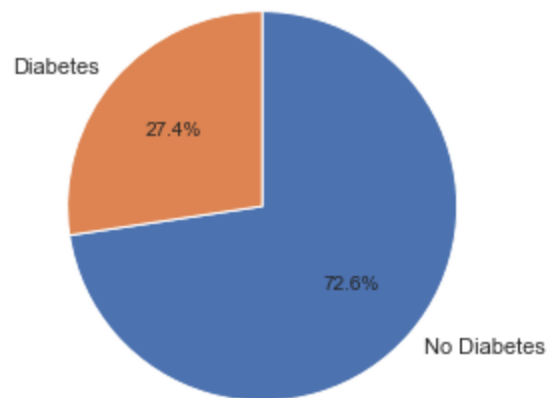
In [30]: #Univariate and bivariate distribution of Diabetes
# TOP plot: Univariate exploration of diabetes
plt.title("Patient Diabetes Distribution")
diabetes_counts = df["Diabetes"].value_counts().sort_index()
plt.pie(diabetes_counts, labels=["No Diabetes", "Diabetes"], autopct='%1.1f%%', startangle=90, counterclock = False)

```

```
plt.axis('square');

# BOTTOM plot: Bivariate exploration of diabetes vs arthritis
temp_df = df[["Diabetes", "BackPain"]].copy()
diabetes_map = {1 : "Diabetes", 0: "No Diabetes"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Diabetes"] = temp_df["Diabetes"].map(diabetes_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["Diabetes", "BackPain"])
plt.suptitle("Relationship of Diabetes vs Arthritis");
```

Patient Diabetes Distribution

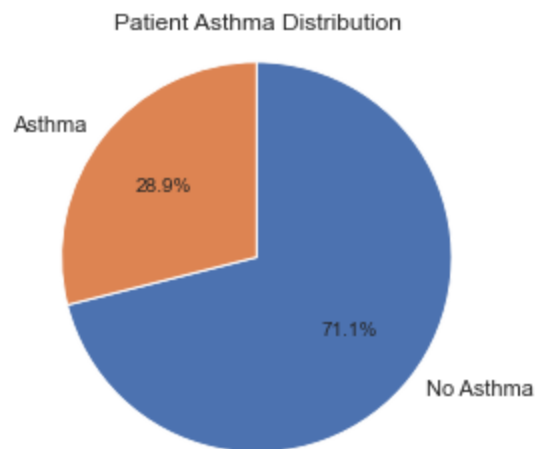


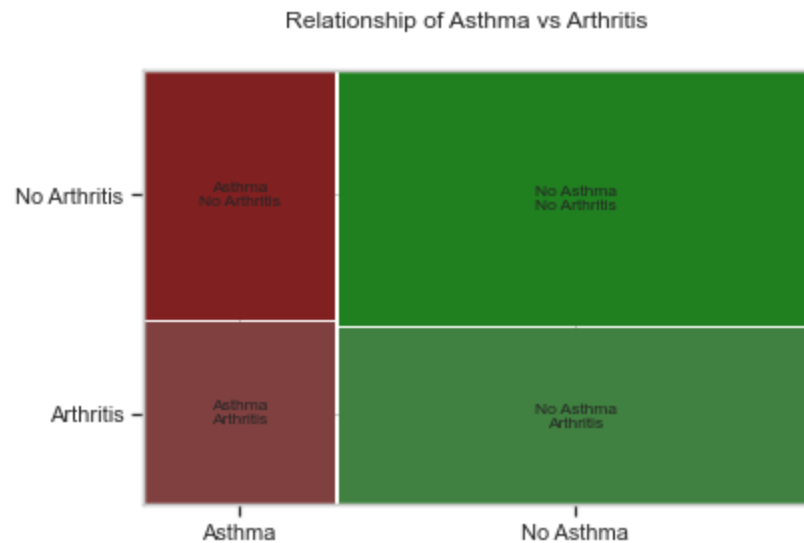
Relationship of Diabetes vs Arthritis



```
In [31]: #Univariate and bivariate distribution of Asthma
# TOP plot: Univariate exploration of asthma
plt.title("Patient Asthma Distribution")
asthma_counts = df["Asthma"].value_counts()
plt.pie(asthma_counts, labels=["No Asthma", "Asthma"], autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# BOTTOM plot: Bivariate exploration of asthma vs arthritis
temp_df = df[["Asthma", "BackPain"]].copy()
asthma_map = {1 : "Asthma", 0: "No Asthma"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Asthma"] = temp_df["Asthma"].map(asthma_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["Asthma", "BackPain"])
plt.suptitle("Relationship of Asthma vs Arthritis");
```



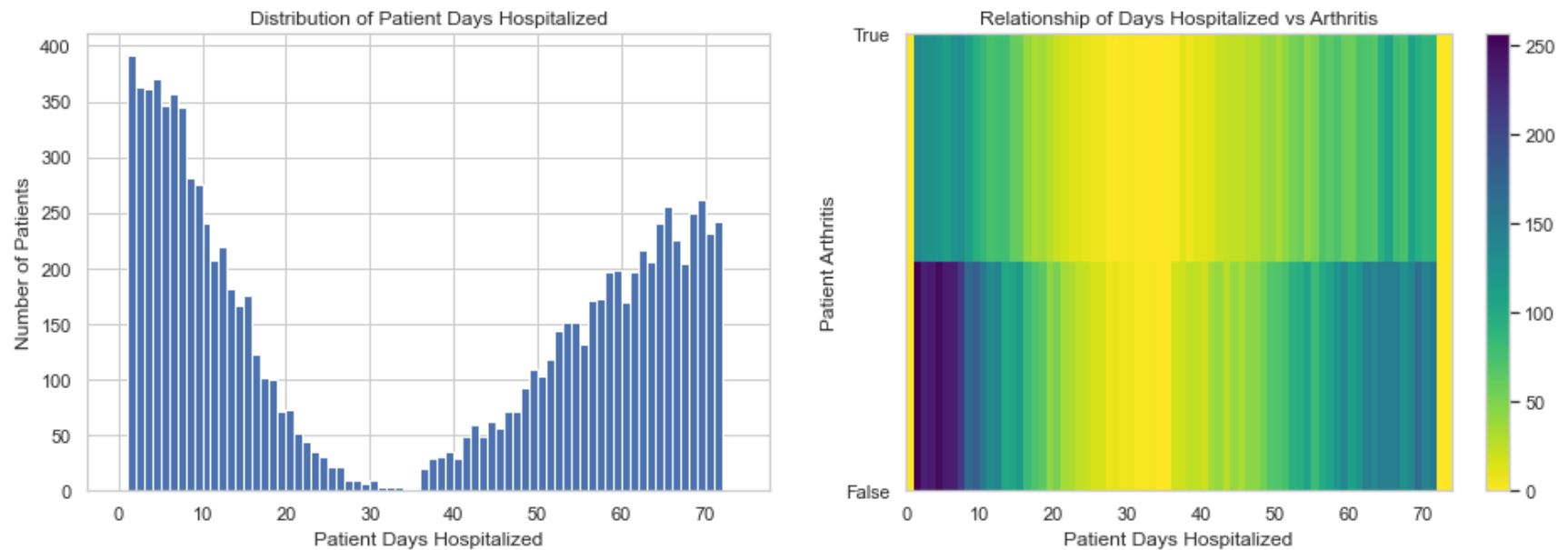


```
In [32]: #Univariate and bivariate distribution of Days Hospitalized
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Days Hospitalized")

# LEFT plot: Univariate exploration of days_hospitalized
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Days Hospitalized')
bins = np.arange(0, 75, 1)
plt.hist(data=regress_df, x="days_hospitalized", bins=bins)
plt.xlabel('Patient Days Hospitalized')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of days_hospitalized vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Days Hospitalized vs Arthritis")
bins_y = np.arange(0, 1.25, 0.5)
plt.hist2d(data= regress_df, x="days_hospitalized", y="arthritis", bins=[bins, bins_y], cmap= "viridis_r")
plt.colorbar()
plt.xlabel("Patient Days Hospitalized")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```

Visual exploration of Patient's Days Hospitalized



```
In [33]: # Save dataframe to CSV
df.to_csv('d208task2_full_clean.csv', index=False)

# Save dataframe to CSV
regress_df.to_csv('d208task2_red_clean.csv', index=False)
```

```
In [34]: # Check for VIF to determine if variables should be eliminated due to high multicollinearity
# Selecting the features for VIF calculation
X = regress_df[["age", "gender_male", "gender_nonbinary", "vit_d_level", "initial_admit_observ", "initial_admit_emerg"],

# Calculating VIF for each feature
vif_df = pd.DataFrame()
vif_df["feature"] = X.columns
vif_df["vif"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

print(vif_df)
```

	feature	vif
0	age	7.241869
1	gender_male	1.925995
2	gender_nonbinary	1.043023
3	vit_d_level	16.271274
4	initial_admit_observ	1.937244
5	initial_admit_emerg	2.958304
6	high_bp	1.686147
7	comp_risk_low	1.616292
8	comp_risk_medium	2.314051
9	overweight	3.371494
10	back_pain	1.691642
11	diabetes	1.368503
12	asthma	1.404802
13	days_hospitalized	2.671751

```
In [35]: #Create the Initial Logistic Regression model
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "vit_d_level", "initial_admit_observ", "initial_admit_emerg",
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651068

Iterations 4

Logit Regression Results

Dep. Variable:	arthritis	No. Observations:	10000
Model:	Logit	Df Residuals:	9985
Method:	MLE	Df Model:	14
Date:	Sun, 22 Oct 2023	Pseudo R-squ.:	0.001288
Time:	19:14:59	Log-Likelihood:	-6510.7
converged:	True	LL-Null:	-6519.1
Covariance Type:	nonrobust	LLR p-value:	0.2675

	coef	std err	z	P> z	[0.025	0.975]
age	0.0008	0.001	0.747	0.455	-0.001	0.003
gender_male	0.0396	0.042	0.936	0.349	-0.043	0.122
gender_nonbinary	0.1982	0.143	1.386	0.166	-0.082	0.478
vit_d_level	-2.453e-05	0.010	-0.002	0.998	-0.020	0.020
initial_admit_observ	-0.0007	0.059	-0.012	0.991	-0.117	0.116
initial_admit_emerg	-0.0005	0.051	-0.010	0.992	-0.101	0.100
high_bp	0.0307	0.042	0.723	0.470	-0.053	0.114
comp_risk_low	0.0752	0.058	1.295	0.195	-0.039	0.189
comp_risk_medium	0.1020	0.048	2.137	0.033	0.008	0.196
overweight	0.0186	0.046	0.404	0.686	-0.072	0.109
back_pain	-0.0822	0.043	-1.931	0.053	-0.166	0.001
diabetes	0.0422	0.047	0.902	0.367	-0.049	0.134
asthma	-0.0301	0.046	-0.652	0.515	-0.121	0.060
days_hospitalized	0.0015	0.001	1.899	0.058	-4.82e-05	0.003
const	-0.7592	0.208	-3.659	0.000	-1.166	-0.353

```
In [36]: # Check for VIF to see if variables should be eliminated due to high multicollinearity
X = regress_df[["age", "gender_male", "gender_nonbinary", "vit_d_level", "initial_admit_observ", "initial_admit_emerg"],

vif_df = pd.DataFrame()
vif_df["feature"] = X.columns

vif_df["VIF"] = [variance_inflation_factor(X.values, i)
for i in range(len(X.columns))]

print(vif_df)
```


	feature	VIF
0	age	7.241869
1	gender_male	1.925995
2	gender_nonbinary	1.043023
3	vit_d_level	16.271274
4	initial_admit_observ	1.937244
5	initial_admit_emerg	2.958304
6	high_bp	1.686147
7	comp_risk_low	1.616292
8	comp_risk_medium	2.314051
9	overweight	3.371494
10	back_pain	1.691642
11	diabetes	1.368503
12	asthma	1.404802
13	days_hospitalized	2.671751

```
In [37]: # Eliminated vit_d_level (VIF = 16.271274), rerunning analysis to see if any VIF still above 10
X = regress_df[["age", "gender_male", "gender_nonbinary", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low", "comp_risk_medium", "overweight", "back_pain", "diabetes", "asthma", "days_hospitalized"]]

vif_df = pd.DataFrame()
vif_df["feature"] = X.columns

vif_df["VIF"] = [variance_inflation_factor(X.values, i)
for i in range(len(X.columns))]

print(vif_df)
```

	feature	VIF
0	age	5.106574
1	gender_male	1.841550
2	gender_nonbinary	1.039726
3	initial_admit_observ	1.777416
4	initial_admit_emerg	2.587708
5	high_bp	1.644376
6	comp_risk_low	1.548105
7	comp_risk_medium	2.162291
8	overweight	3.028072
9	back_pain	1.658025
10	diabetes	1.350051
11	asthma	1.385518
12	days_hospitalized	2.493187

```
In [38]: # BACKWARD ELIMINATION # 1: Seek highest p-value above 0.10
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low", "comp_risk_medium", "overweight", "back_pain", "diabetes", "asthma", "days_hospitalized"]]
```

```
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651068

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit      Df Residuals:              9986
Method:                 MLE       Df Model:                  13
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.001288
Time:                  19:14:59    Log-Likelihood:         -6510.7
converged:              True      LL-Null:                -6519.1
Covariance Type:        nonrobust    LLR p-value:            0.2091
=====
```

	coef	std err	z	P> z	[0.025	0.975]
age	0.0008	0.001	0.747	0.455	-0.001	0.003
gender_male	0.0396	0.042	0.936	0.349	-0.043	0.122
gender_nonbinary	0.1982	0.143	1.386	0.166	-0.082	0.478
initial_admit_observ	-0.0007	0.059	-0.012	0.991	-0.117	0.116
initial_admit_emerg	-0.0005	0.051	-0.010	0.992	-0.101	0.100
high_bp	0.0307	0.042	0.723	0.470	-0.053	0.114
comp_risk_low	0.0752	0.058	1.295	0.195	-0.039	0.189
comp_risk_medium	0.1020	0.048	2.137	0.033	0.008	0.196
overweight	0.0186	0.046	0.404	0.686	-0.072	0.109
back_pain	-0.0822	0.043	-1.931	0.053	-0.166	0.001
diabetes	0.0422	0.047	0.903	0.367	-0.049	0.134
asthma	-0.0301	0.046	-0.652	0.515	-0.121	0.060
days_hospitalized	0.0015	0.001	1.899	0.058	-4.82e-05	0.003
const	-0.7597	0.094	-8.119	0.000	-0.943	-0.576

```
In [39]: # BACKWARD ELIMINATION # 2: Seek highest p-value above 0.10 (eliminated initial_admit_emerg, p-value of 0.992)
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "initial_admit_observ", "high_bp", "comp_risk_low", "comp_ris
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651068

Iterations 4

Logit Regression Results

Dep. Variable:	arthritis	No. Observations:	10000
Model:	Logit	Df Residuals:	9987
Method:	MLE	Df Model:	12
Date:	Sun, 22 Oct 2023	Pseudo R-squ.:	0.001288
Time:	19:14:59	Log-Likelihood:	-6510.7
converged:	True	LL-Null:	-6519.1
Covariance Type:	nonrobust	LLR p-value:	0.1577

	coef	std err	z	P> z	[0.025	0.975]
age	0.0008	0.001	0.747	0.455	-0.001	0.003
gender_male	0.0396	0.042	0.936	0.349	-0.043	0.122
gender_nonbinary	0.1982	0.143	1.386	0.166	-0.082	0.478
initial_admit_observ	-0.0004	0.049	-0.008	0.994	-0.096	0.095
high_bp	0.0307	0.042	0.723	0.470	-0.053	0.114
comp_risk_low	0.0752	0.058	1.295	0.195	-0.039	0.189
comp_risk_medium	0.1020	0.048	2.137	0.033	0.008	0.196
overweight	0.0186	0.046	0.404	0.686	-0.072	0.109
back_pain	-0.0822	0.043	-1.931	0.053	-0.166	0.001
diabetes	0.0422	0.047	0.903	0.367	-0.049	0.134
asthma	-0.0301	0.046	-0.652	0.515	-0.121	0.060
days_hospitalized	0.0015	0.001	1.900	0.057	-4.8e-05	0.003
const	-0.7600	0.087	-8.776	0.000	-0.930	-0.590

```
In [40]: # BACKWARD ELIMINATION # 3: Seek highest p-value above 0.10 (eliminated initial_admit_observ, p-value of 0.994)
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "high_bp", "comp_risk_low", "comp_risk_medium", "overweight",
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651068

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9988
Method:                 MLE         Df Model:                  11
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.001288
Time:                  19:14:59          Log-Likelihood:         -6510.7
converged:              True           LL-Null:                 -6519.1
Covariance Type:        nonrobust        LLR p-value:            0.1142
=====
```

	coef	std err	z	P> z	[0.025	0.975]
age	0.0008	0.001	0.747	0.455	-0.001	0.003
gender_male	0.0396	0.042	0.937	0.349	-0.043	0.122
gender_nonbinary	0.1982	0.143	1.386	0.166	-0.082	0.478
high_bp	0.0307	0.042	0.723	0.470	-0.053	0.114
comp_risk_low	0.0752	0.058	1.295	0.195	-0.039	0.189
comp_risk_medium	0.1020	0.048	2.138	0.033	0.008	0.196
overweight	0.0186	0.046	0.404	0.686	-0.072	0.109
back_pain	-0.0822	0.043	-1.931	0.053	-0.166	0.001
diabetes	0.0422	0.047	0.903	0.367	-0.049	0.134
asthma	-0.0301	0.046	-0.652	0.515	-0.121	0.060
days_hospitalized	0.0015	0.001	1.900	0.057	-4.8e-05	0.003
const	-0.7601	0.086	-8.853	0.000	-0.928	-0.592

```
=====
```

```
In [41]: # BACKWARD ELIMINATION # 4: Seek highest p-value above 0.10 (eliminated overweight, p-value of 0.686)
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain",
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651076

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis  No. Observations:          10000
Model:                  Logit      Df Residuals:              9989
Method:                 MLE        Df Model:                  10
Date:                   Sun, 22 Oct 2023  Pseudo R-squ.:          0.001275
Time:                   19:15:00      Log-Likelihood:          -6510.8
converged:              True         LL-Null:                -6519.1
Covariance Type:        nonrobust     LLR p-value:             0.08303
=====
```

	coef	std err	z	P> z	[0.025	0.975]
age	0.0008	0.001	0.743	0.457	-0.001	0.003
gender_male	0.0395	0.042	0.936	0.349	-0.043	0.122
gender_nonbinary	0.1984	0.143	1.388	0.165	-0.082	0.479
high_bp	0.0312	0.042	0.734	0.463	-0.052	0.114
comp_risk_low	0.0752	0.058	1.294	0.196	-0.039	0.189
comp_risk_medium	0.1023	0.048	2.144	0.032	0.009	0.196
back_pain	-0.0821	0.043	-1.927	0.054	-0.165	0.001
diabetes	0.0420	0.047	0.900	0.368	-0.050	0.134
asthma	-0.0298	0.046	-0.647	0.518	-0.120	0.061
days_hospitalized	0.0015	0.001	1.895	0.058	-5.13e-05	0.003
const	-0.7470	0.079	-9.401	0.000	-0.903	-0.591

```
=====
```

```
In [42]: # BACKWARD ELIMINATION # 5: Seek highest p-value above 0.10 (eliminated asthma, p-value of 0.518)
y = regress_df.arthritis
X = regress_df[["age", "gender_male", "gender_nonbinary", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain",
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651097

Iterations 4

Logit Regression Results

Dep. Variable:	arthritis	No. Observations:	10000
Model:	Logit	Df Residuals:	9990
Method:	MLE	Df Model:	9
Date:	Sun, 22 Oct 2023	Pseudo R-squ.:	0.001243
Time:	19:15:00	Log-Likelihood:	-6511.0
converged:	True	LL-Null:	-6519.1
Covariance Type:	nonrobust	LLR p-value:	0.06265

	coef	std err	z	P> z	[0.025	0.975]
age	0.0007	0.001	0.737	0.461	-0.001	0.003
gender_male	0.0394	0.042	0.932	0.351	-0.043	0.122
gender_nonbinary	0.1980	0.143	1.385	0.166	-0.082	0.478
high_bp	0.0310	0.042	0.729	0.466	-0.052	0.114
comp_risk_low	0.0749	0.058	1.289	0.197	-0.039	0.189
comp_risk_medium	0.1020	0.048	2.138	0.033	0.008	0.196
back_pain	-0.0824	0.043	-1.937	0.053	-0.166	0.001
diabetes	0.0415	0.047	0.889	0.374	-0.050	0.133
days_hospitalized	0.0015	0.001	1.905	0.057	-4.39e-05	0.003
const	-0.7549	0.079	-9.613	0.000	-0.909	-0.601

```
In [43]: # BACKWARD ELIMINATION # 6: Seek highest p-value above 0.10 (eliminated age, p-value of 0.461)
y = regress_df.arthritis
X = regress_df[["gender_male", "gender_nonbinary", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hospitalized"]]
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651124

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis  No. Observations:          10000
Model:                  Logit      Df Residuals:              9991
Method:                  MLE       Df Model:                  8
Date:                    Sun, 22 Oct 2023  Pseudo R-squ.:          0.001201
Time:                    19:15:00    Log-Likelihood:          -6511.2
converged:                True      LL-Null:                  -6519.1
Covariance Type:          nonrobust  LLR p-value:              0.04744
=====
```

	coef	std err	z	P> z	[0.025	0.975]
gender_male	0.0389	0.042	0.921	0.357	-0.044	0.122
gender_nonbinary	0.1980	0.143	1.386	0.166	-0.082	0.478
high_bp	0.0312	0.042	0.735	0.462	-0.052	0.114
comp_risk_low	0.0747	0.058	1.287	0.198	-0.039	0.189
comp_risk_medium	0.1018	0.048	2.133	0.033	0.008	0.195
back_pain	-0.0818	0.043	-1.922	0.055	-0.165	0.002
diabetes	0.0416	0.047	0.892	0.373	-0.050	0.133
days_hospitalized	0.0015	0.001	1.917	0.055	-3.45e-05	0.003
const	-0.7152	0.057	-12.509	0.000	-0.827	-0.603

```
=====
```

```
In [44]: # BACKWARD ELIMINATION # 7: Seek highest p-value above 0.10 (eliminated gender_male, p-value of 0.357)
y = regress_df.arthritis
X = regress_df[["gender_nonbinary", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hosp"]
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651167

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9992
Method:                 MLE         Df Model:                  7
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.001136
Time:                  19:15:00          Log-Likelihood:         -6511.7
converged:              True           LL-Null:                -6519.1
Covariance Type:        nonrobust        LLR p-value:            0.03842
=====
```

	coef	std err	z	P> z	[0.025	0.975]
gender_nonbinary	0.1790	0.141	1.266	0.206	-0.098	0.456
high_bp	0.0315	0.042	0.741	0.459	-0.052	0.115
comp_risk_low	0.0746	0.058	1.285	0.199	-0.039	0.188
comp_risk_medium	0.1021	0.048	2.139	0.032	0.009	0.196
back_pain	-0.0823	0.043	-1.934	0.053	-0.166	0.001
diabetes	0.0416	0.047	0.890	0.374	-0.050	0.133
days_hospitalized	0.0015	0.001	1.924	0.054	-2.86e-05	0.003
const	-0.6964	0.053	-13.050	0.000	-0.801	-0.592

```
=====
```

```
In [45]: # BACKWARD ELIMINATION # 8: Seek highest p-value above 0.10 (eliminated high_bp, p-value of 0.459)
y = regress_df.arthritis
X = regress_df[["gender_nonbinary", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hospitalized"]]
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```


Optimization terminated successfully.

Current function value: 0.651194

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9993
Method:                 MLE         Df Model:                  6
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.001094
Time:                  19:15:00          Log-Likelihood:         -6511.9
converged:              True           LL-Null:                -6519.1
Covariance Type:       nonrobust        LLR p-value:            0.02678
=====
```

	coef	std err	z	P> z	[0.025	0.975]
gender_nonbinary	0.1806	0.141	1.277	0.202	-0.097	0.458
comp_risk_low	0.0736	0.058	1.268	0.205	-0.040	0.187
comp_risk_medium	0.1021	0.048	2.140	0.032	0.009	0.196
back_pain	-0.0822	0.043	-1.931	0.053	-0.166	0.001
diabetes	0.0414	0.047	0.886	0.376	-0.050	0.133
days_hospitalized	0.0015	0.001	1.919	0.055	-3.21e-05	0.003
const	-0.6832	0.050	-13.585	0.000	-0.782	-0.585

```
=====
```

```
In [46]: # BACKWARD ELIMINATION # 9: Seek highest p-value above 0.10 (eliminated diabetes, p-value of 0.376)
y = regress_df.arthritis
X = regress_df[["gender_nonbinary", "comp_risk_low", "comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651233

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9994
Method:                  MLE        Df Model:                  5
Date:                   Sun, 22 Oct 2023    Pseudo R-squ.:          0.001034
Time:                   19:15:01    Log-Likelihood:         -6512.3
converged:              True        LL-Null:                -6519.1
Covariance Type:        nonrobust    LLR p-value:            0.01923
=====
```

	coef	std err	z	P> z	[0.025	0.975]
gender_nonbinary	0.1803	0.141	1.275	0.202	-0.097	0.457
comp_risk_low	0.0739	0.058	1.274	0.203	-0.040	0.188
comp_risk_medium	0.1022	0.048	2.142	0.032	0.009	0.196
back_pain	-0.0827	0.043	-1.943	0.052	-0.166	0.001
days_hospitalized	0.0015	0.001	1.917	0.055	-3.39e-05	0.003
const	-0.6716	0.049	-13.833	0.000	-0.767	-0.576

```
=====
```

```
In [47]: # BACKWARD ELIMINATION # 10: Seek highest p-value above 0.10 (eliminated comp_risk_low, p-value of 0.203)
y = regress_df.arthritis
X = regress_df[["gender_nonbinary", "comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651314

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9995
Method:                 MLE         Df Model:                  4
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.0009100
Time:                  19:15:01          Log-Likelihood:         -6513.1
converged:              True           LL-Null:                -6519.1
Covariance Type:        nonrobust        LLR p-value:            0.01839
=====
```

	coef	std err	z	P> z	[0.025	0.975]
gender_nonbinary	0.1784	0.141	1.262	0.207	-0.099	0.456
comp_risk_medium	0.0734	0.042	1.750	0.080	-0.009	0.156
back_pain	-0.0817	0.043	-1.922	0.055	-0.165	0.002
days_hospitalized	0.0015	0.001	1.937	0.053	-1.8e-05	0.003
const	-0.6437	0.043	-14.890	0.000	-0.728	-0.559

```
=====
```

```
In [48]: # BACKWARD ELIMINATION # 11: Seek highest p-value above 0.10 (eliminated gender_nonbinary, p-value of 0.207)
y = regress_df.arthritis
X = regress_df[["comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651393

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit        Df Residuals:              9996
Method:                  MLE          Df Model:                  3
Date:                   Sun, 22 Oct 2023    Pseudo R-squ.:          0.0007894
Time:                   19:15:01          Log-Likelihood:         -6513.9
converged:              True            LL-Null:                -6519.1
Covariance Type:        nonrobust        LLR p-value:            0.01624
=====
```

	coef	std err	z	P> z	[0.025	0.975]
comp_risk_medium	0.0732	0.042	1.747	0.081	-0.009	0.155
back_pain	-0.0807	0.043	-1.897	0.058	-0.164	0.003
days_hospitalized	0.0015	0.001	1.942	0.052	-1.44e-05	0.003
const	-0.6403	0.043	-14.843	0.000	-0.725	-0.556

```
=====
```

```
In [49]: # All p-values for independent variables are < 0.10, this is the final reduced model
y = regress_df.arthritis
X = regress_df[["comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.651393

Iterations 4

Logit Regression Results

```
=====
Dep. Variable:          arthritis    No. Observations:          10000
Model:                  Logit       Df Residuals:              9996
Method:                 MLE         Df Model:                  3
Date:                  Sun, 22 Oct 2023    Pseudo R-squ.:          0.0007894
Time:                  19:15:01          Log-Likelihood:         -6513.9
converged:              True           LL-Null:                 -6519.1
Covariance Type:        nonrobust        LLR p-value:            0.01624
=====
```

	coef	std err	z	P> z	[0.025	0.975]
comp_risk_medium	0.0732	0.042	1.747	0.081	-0.009	0.155
back_pain	-0.0807	0.043	-1.897	0.058	-0.164	0.003
days_hospitalized	0.0015	0.001	1.942	0.052	-1.44e-05	0.003
const	-0.6403	0.043	-14.843	0.000	-0.725	-0.556

```
=====
```

```
In [55]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg.score(X_test, y_test)))
final_matrix = confusion_matrix(y_test, y_pred)
print(final_matrix)
```

Accuracy of logistic regression classifier on test set: 0.66

```
[[1319  0]
 [ 681  0]]
```

```
In [51]: result.params
```

```
Out[51]: comp_risk_medium    0.073224
back_pain                 -0.080667
days_hospitalized        0.001541
const                     -0.640284
dtype: float64
```

```
In [52]: # Calculate odds ratios for each coefficient
print(f"The odds ratio for comp_risk_medium is {round(np.exp(0.073224), 3)}. Given this, the change in odds for arthritis is {round(np.exp(0.073224), 3)}")
print(f"The odds ratio for back_pain is {round(np.exp(-0.080667), 3)}. Given this, the change in odds for arthritis is {round(np.exp(-0.080667), 3)}")
print(f"The odds ratio for days_hospitalized is {round(np.exp(0.001541), 3)}. Given this, the change in odds for arthritis is {round(np.exp(0.001541), 3)}")
```

The odds ratio for comp_risk_medium is 1.076. Given this, the change in odds for arthritis is 7.597
The odds ratio for back_pain is 1.084. Given this, the change in odds for arthritis is 8.401
The odds ratio for days_hospitalized is 1.002. Given this, the change in odds for arthritis is 0.154

In []: