Health Data Exploration

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Pleminary Wrangling

This document explores a data set containing 10000 Patients with 15 variables on each patient's health, such as Blood Type, Medical Condition, Date of Admission and many others. The goal of this project is to gain insight into our data in order to carry out informed decision making. Alongside, various models will be tested, with their accuracies compared in order to be able to predict a patient's test result based on parameters like Age, Gender, Blood Type, Medical Condition, Billing Amount, Admission Type. Such a model will enable quicker decision making in hospitals and allow for time and cost management

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Data Gathering

In [230]:
```
# import all packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

## %matplotlib inline
```

In [231]:
```
# load in the dataset into a pandas dataframe, print statistics
Health = pd.read_csv('healthcare_dataset.csv')
```

Data Assessment

a) Visual Assessment

In [232]:
```
# high-level overview of data shape and composition
print(Health.shape)
print(Health.dtypes)
```

```
(10000, 15)
Name                   object
Age                     int64
Gender                 object
Blood Type             object
Medical Condition      object
Date of Admission      object
Doctor                 object
Hospital               object
Insurance Provider     object
Billing Amount        float64
Room Number             int64
Admission Type         object
Discharge Date         object
Medication             object
Test Results           object
dtype: object
```

In [233]:
```
Health.head(10)
```

Out[233]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	Roon Numbe
0	Tiffany Ramirez	81	Female	O-	Diabetes	2022-11-17	Patrick Parker	Wallace-Hamilton	Medicare	37490.983364	14
1	Ruben Burns	35	Male	O+	Asthma	2023-06-01	Diane Jackson	Burke, Griffin and Cooper	UnitedHealthcare	47304.064845	40
2	Chad Byrd	61	Male	B-	Obesity	2019-01-09	Paul Baker	Walton LLC	Medicare	36874.896997	29
3	Antonio Frederick	49	Male	B-	Asthma	2020-05-02	Brian Chandler	Garcia Ltd	Medicare	23303.322092	48
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis	2021-07-09	Dustin Griffin	Jones, Brown and Murray	UnitedHealthcare	18086.344184	47
5	Patrick Parker	41	Male	AB+	Arthritis	2020-08-20	Robin Green	Boyd PLC	Aetna	22522.363385	18
6	Charles Horton	82	Male	AB+	Hypertension	2021-03-22	Patricia Bishop	Wheeler, Bryant and Johns	Cigna	39593.435761	16
7	Patty Norman	55	Female	O-	Arthritis	2019-05-16	Brian Kennedy	Brown Inc	Blue Cross	13546.817249	38
8	Ryan Hayes	33	Male	A+	Diabetes	2020-12-17	Kristin Dunn	Smith, Edwards and Obrien	Aetna	24903.037270	21
9	Sharon Perez	39	Female	O-	Asthma	2022-12-15	Jessica Bailey	Brown-Golden	Blue Cross	22788.236026	31

Tidiness issues

We begin by addressing tidiness issues. These issues pertain to the structure of data. These structural problems generally prevent easy analysis. Upon visual assessment of our data we could observe it is tidy enough for further analysis and following the norms of tidiness, that is:

- Each variable is a column; each column is a variable.
- Each observation is a row; each row is an observation.
- Each value is a cell; each cell is a single value.

b) Programmatic Assessment

- Crosschecking for incorrect/inconsistent data types/formats

In [234]:
```
Health.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Name                10000 non-null  object 
 1   Age                 10000 non-null  int64  
 2   Gender              10000 non-null  object 
 3   Blood Type          10000 non-null  object 
 4   Medical Condition   10000 non-null  object 
 5   Date of Admission   10000 non-null  object 
 6   Doctor              10000 non-null  object 
 7   Hospital            10000 non-null  object 
 8   Insurance Provider  10000 non-null  object 
 9   Billing Amount      10000 non-null  float64
 10  Room Number         10000 non-null  int64  
 11  Admission Type      10000 non-null  object 
 12  Discharge Date      10000 non-null  object 
 13  Medication          10000 non-null  object 
 14  Test Results        10000 non-null  object 
dtypes: float64(1), int64(2), object(12)
memory usage: 1.1+ MB
```

Upon marching each variable to its content/datatype stored, we can observe that the Discharge and Admission Date variables have incorrect datatype and will require cleaning

- Crosschecking for duplicate enteries/records

In [235]:
```
Health.duplicated()
```

Out[235]:
```
0       False
1       False
2       False
3       False
4       False
        ...  
9995    False
9996    False
9997    False
9998    False
9999    False
Length: 10000, dtype: bool
```

In [236]:
```
sum(Health.duplicated())
```

Out[236]:
```
0
```

No duplicate enteries as well....our data is free of duplicate records for a paticular patient

- crosschecking for null values/enteries

From our result after running Health.info(), we can also observe the absence of null enteries

In [237]:
```
#crosschecking statistical information related to our data for data inconsistency and inaccuracy
Health.describe()
```

Out[237]:

	Age	Billing Amount	Room Number
count	10000.000000	10000.000000	10000.000000
mean	51.452200	25516.806778	300.082000
std	19.588974	14067.292709	115.806027
min	18.000000	1000.180837	101.000000
25%	35.000000	13506.523967	199.000000
50%	52.000000	25258.112566	299.000000
75%	68.000000	37733.913727	400.000000
max	85.000000	49995.902283	500.000000

No abnormalities observed as pertaining to the data

Addressing Quality Issues

In this phase, we proceed to address data quality issues. Essentially, data quality relates to its accuracy, completeness, consistency, and validity. In our analysis, we aim to address issues such as : Duplicate data, Inaccurate data, Inconsistent formats, Incomplete data, Hidden data, Data downtime, Human error, Irrelevant data, Outdated data, Missing values, Unstructured data, Poor data accessibility

Upon carrying out our programmatic analysis, we observed the date fields to not have a correct data type. Saving a date related column with an object data type rather than a datetime datatype will not permit calculations relating to time on that column so we have to address that issue

Data Cleaning

To clean this issue we will use the Define-Code-Test methodology

Define

Incorrect data types for two columns : Date of admission and Discharge Date

Code

In [238]:
```
# convert the two 'Date' columns to datetime format
Health['Date of Admission']= pd.to_datetime(Health['Date of Admission'])
Health['Discharge Date']= pd.to_datetime(Health['Discharge Date'])
```

Test

In [239]:
```
# Check the format of 'Date' column
Health.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype         
---  ------              --------------  -----         
 0   Name                10000 non-null  object        
 1   Age                 10000 non-null  int64         
 2   Gender              10000 non-null  object        
 3   Blood Type          10000 non-null  object        
 4   Medical Condition   10000 non-null  object        
 5   Date of Admission   10000 non-null  datetime64[ns]
 6   Doctor              10000 non-null  object        
 7   Hospital            10000 non-null  object        
 8   Insurance Provider  10000 non-null  object        
 9   Billing Amount      10000 non-null  float64       
 10  Room Number         10000 non-null  int64         
 11  Admission Type      10000 non-null  object        
 12  Discharge Date      10000 non-null  datetime64[ns]
 13  Medication          10000 non-null  object        
 14  Test Results        10000 non-null  object        
dtypes: datetime64[ns](2), float64(1), int64(2), object(10)
memory usage: 1.1+ MB
```

As observed, we can see our datatypes have been readjusted

Exploratory Data Analysis and visualisation

In [240]:
```
#reloading our data for easy access
Health.sample(10)
```

Out[240]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	R Nur
1719	Marissa Schultz	78	Female	B-	Cancer	2020-04-07	Laurie Bryan	Moss, Davidson and Ball	Cigna	39106.761780	
9378	Dawn Harrison	66	Female	O+	Cancer	2021-06-04	Tammy Martinez	Davis LLC	Cigna	15032.487348	
2747	Lisa Beck	54	Female	AB-	Obesity	2022-08-31	Patrick Davis	Miller-Riggs	Cigna	20841.542773	
2540	Andrea Poole	85	Male	AB+	Hypertension	2019-06-29	Erik Allen	Allen, Collins and Morris	Medicare	44225.219870	
7568	Eric Miles	82	Female	A+	Cancer	2019-07-09	Eric Heath	Morgan-Lopez	UnitedHealthcare	20042.115211	
6016	Margaret Brown	59	Male	B-	Obesity	2019-07-23	Sarah Hodges	Oneal Inc	Medicare	46805.421013	
2789	Zachary Turner	38	Female	AB-	Diabetes	2019-05-03	Wendy Romero	Shepherd and Sons	Cigna	26019.286316	
5179	Jessica Schultz	80	Female	AB+	Obesity	2022-01-31	James Henry	Moore Group	UnitedHealthcare	4355.584888	
4440	Anna Glass	29	Male	B-	Arthritis	2018-12-04	Bryan Ford	Olson, Reed and Wood	Cigna	19142.010715	
3773	Thomas Jacobs	73	Male	A+	Asthma	2019-09-08	Tanya Jennings	Johnson-Norris	UnitedHealthcare	31484.254283	

In this phase we proceed to manipulating our data for inference and discovering patterns to answer likewise uncover some relevant questions. Some of the questions our study aim to answer include:

1. Which admission type is most encountered

In [241]:
```
Health['Admission Type'].value_counts()
```

Out[241]:
```
Urgent       3391
Emergency    3367
Elective     3242
Name: Admission Type, dtype: int64
```

2. Most Visited Hospitals

In [242]:
```
#first we begin by retrieving the different number of hospitals
len(Health['Hospital'].unique())
```

Out[242]:
```
8639
```

There are 8639 hospitals involved in our study

In [243]:
```
Hospital_con = Health['Hospital'].value_counts() > 10
```

In [244]:
```
Top_Hospital = Health[Health['Hospital'].isin(Hospital_con[Hospital_con].index)]
```

In [245]:
```
print(Top_Hospital.Hospital.value_counts())
```

```
Smith PLC         19
Smith and Sons    17
Smith Inc         14
Smith Ltd         14
Johnson PLC       13
Williams LLC      12
Smith Group       12
Williams Inc      12
Thomas Group      11
Johnson Ltd       11
Johnson Group     11
Name: Hospital, dtype: int64
```

Above, we can observe the most visited hospitals, with hospitals being owned by Smiths groups being among the most visited. This could be an indicator of high performance or accessibility as people will mostly prefer visiting hospitals that are easily accessible, affordable or have well qualified practitioners

3. Most Trusted Insurance Provider

In [246]:
```
#first we begin by retrieving the different number of hospitals
print(len(Health['Hospital'].unique()))

#next we retrieve the top insurance companies
Insurance_con = Health['Insurance Provider'].value_counts() > 10
Top_Ins = Health[Health['Insurance Provider'].isin(Insurance_con[Insurance_con].index)]
print(Top_Ins['Insurance Provider'].value_counts())
```

```
8639
Cigna               2040
Blue Cross          2032
Aetna               2025
UnitedHealthcare    1978
Medicare            1925
Name: Insurance Provider, dtype: int64
```

We can observe the top 5 insurance companies taken by patients

4. How long is the average recovery period for patients

In [247]:
```
from datetime import datetime

# Calculate the number of days between the two dates
Health['num_days'] = (Health['Discharge Date'] - Health['Date of Admission']).dt.days
```

In [248]:
```
Health.head(10)
```

Out[248]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	Room Numbe
0	Tiffany Ramirez	81	Female	O-	Diabetes	2022-11-17	Patrick Parker	Wallace-Hamilton	Medicare	37490.983364	146
1	Ruben Burns	35	Male	O+	Asthma	2023-06-01	Diane Jackson	Burke, Griffin and Cooper	UnitedHealthcare	47304.064845	404
2	Chad Byrd	61	Male	B-	Obesity	2019-01-09	Paul Baker	Walton LLC	Medicare	36874.896997	292
3	Antonio Frederick	49	Male	B-	Asthma	2020-05-02	Brian Chandler	Garcia Ltd	Medicare	23303.322092	480
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis	2021-07-09	Dustin Griffin	Jones, Brown and Murray	UnitedHealthcare	18086.344184	477
5	Patrick Parker	41	Male	AB+	Arthritis	2020-08-20	Robin Green	Boyd PLC	Aetna	22522.363385	180
6	Charles Horton	82	Male	AB+	Hypertension	2021-03-22	Patricia Bishop	Wheeler, Bryant and Johns	Cigna	39593.435761	161
7	Patty Norman	55	Female	O-	Arthritis	2019-05-16	Brian Kennedy	Brown Inc	Blue Cross	13546.817249	384
8	Ryan Hayes	33	Male	A+	Diabetes	2020-12-17	Kristin Dunn	Smith, Edwards and Obrien	Aetna	24903.037270	215
9	Sharon Perez	39	Female	O-	Asthma	2022-12-15	Jessica Bailey	Brown-Golden	Blue Cross	22788.236026	310

In [249]:
```
Health.describe()
```

Out[249]:

	Age	Billing Amount	Room Number	num_days
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	51.452200	25516.806778	300.082000	15.561800
std	19.588974	14067.292709	115.806027	8.612038
min	18.000000	1000.180837	101.000000	1.000000
25%	35.000000	13506.523967	199.000000	8.000000
50%	52.000000	25258.112566	299.000000	16.000000
75%	68.000000	37733.913727	400.000000	23.000000
max	85.000000	49995.902283	500.000000	30.000000

The average recovery period is 15 days.

In [250]:
```
Health.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Name                10000 non-null  object
 1   Age                 10000 non-null  int64
 2   Gender              10000 non-null  object
 3   Blood Type          10000 non-null  object
 4   Medical Condition   10000 non-null  object
 5   Date of Admission   10000 non-null  datetime64[ns]
 6   Doctor              10000 non-null  object
 7   Hospital            10000 non-null  object
 8   Insurance Provider  10000 non-null  object
 9   Billing Amount      10000 non-null  float64
 10  Room Number         10000 non-null  int64
 11  Admission Type      10000 non-null  object
 12  Discharge Date      10000 non-null  datetime64[ns]
 13  Medication          10000 non-null  object
 14  Test Results        10000 non-null  object
 15  num_days            10000 non-null  int64
dtypes: datetime64[ns](2), float64(1), int64(3), object(10)
memory usage: 1.2+ MB
```

5. Among the best hospitals, which hospital has the best recovery period?

In [251]:
```
Hospital_con = Health['Hospital'].value_counts() > 10
```

In [252]:
```
Top_Hospital = Health[Health['Hospital'].isin(Hospital_con[Hospital_con].index)]
```

In [253]:
```
Top_Hospital
```

Out[253]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	R Nu
47	Jasmine Singleton	37	Male	AB-	Obesity	2019-06-26	Larry Guzman	Thomas Group	Blue Cross	34132.623000	
266	Jamie Kelley	48	Male	O-	Asthma	2022-07-10	Samuel Lowe	Williams LLC	Aetna	42621.449647	
298	Cody Gonzales	30	Male	B-	Obesity	2020-03-06	Rachel Roberts	Smith Group	Blue Cross	16592.012153	
303	Cynthia Patterson	42	Female	B-	Cancer	2020-01-02	Dr. Sean Russell	Johnson Ltd	Medicare	26419.324813	
318	Daniel Alexander	70	Male	AB-	Hypertension	2020-03-19	Jill Hughes	Smith Inc	Aetna	36496.775644	
...	...	...	...	...	...	...	...	...	...	...	
9497	Glen Rowe	55	Male	A-	Cancer	2022-09-12	Ashley Gross	Smith Group	Blue Cross	12988.802893	
9514	Rhonda Allen	56	Female	B-	Diabetes	2019-05-14	Diane Houston	Johnson PLC	UnitedHealthcare	15054.431375	
9536	Charles Hernandez	78	Male	O-	Hypertension	2019-12-04	Cynthia Malone	Thomas Group	Blue Cross	49409.780541	
9659	Alison Cline	55	Female	AB+	Hypertension	2019-04-11	Jacob Griffin	Smith PLC	Medicare	46941.697956	
9763	Jasmine Brooks	27	Male	AB+	Arthritis	2022-04-20	Michael Morrow	Smith PLC	Cigna	18469.360164	

146 rows × 16 columns

In [254]:
```
top_days = Top_Hospital.sort_values('num_days')
top_days[['Hospital','num_days']]
```

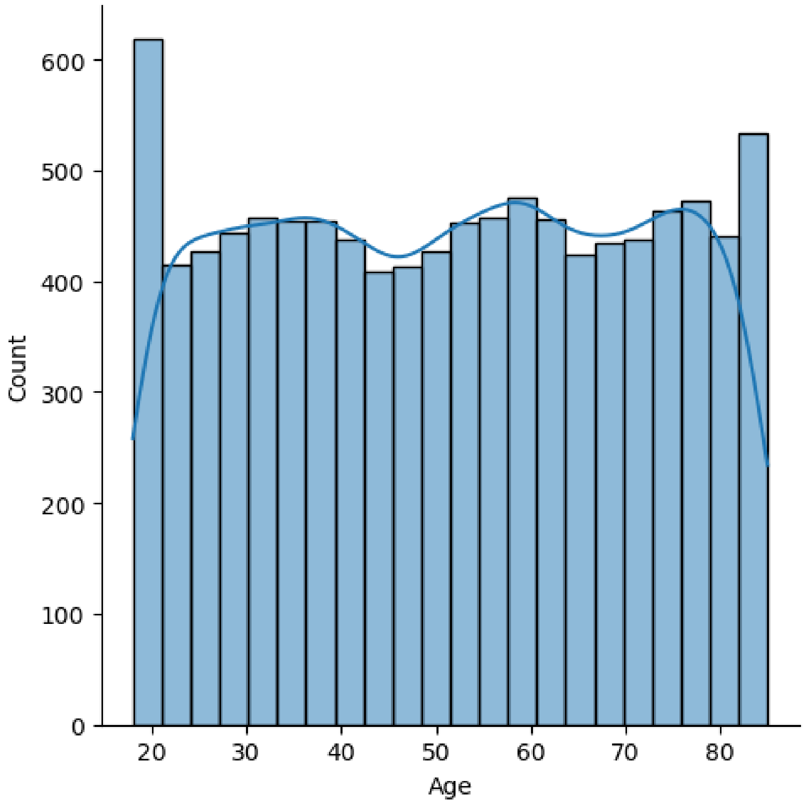
Out[254]:

	Hospital	num_days
3896	Johnson Ltd	1
2597	Smith Inc	1
5157	Smith PLC	1
3012	Johnson Ltd	1
1560	Williams LLC	2
...	...	...
1563	Smith PLC	29
6987	Thomas Group	29
7854	Smith PLC	30
4050	Smith and Sons	30
8996	Smith Inc	30

146 rows × 2 columns

6. What is the age distribution in hospitals?

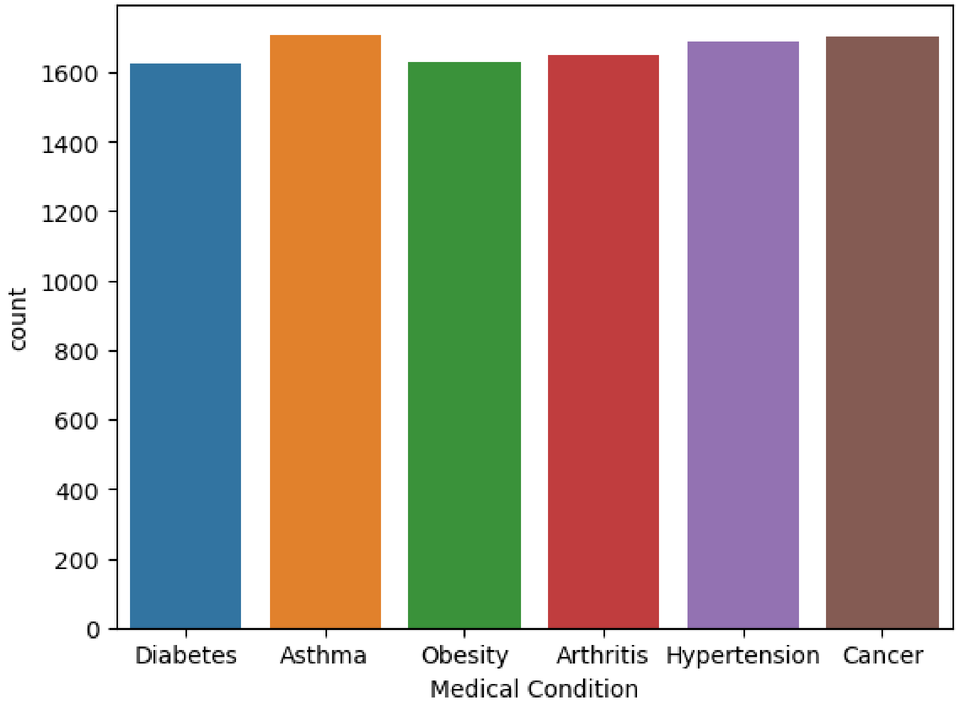
In [229]:
```
import seaborn as sb
sb.displot(Health['Age'], kde='True', bins='auto')
plt.show()
```



From the histogram, we can see patients aged around 20 and over 80 have highest count.

7. How does the distribution of illnesses look like?

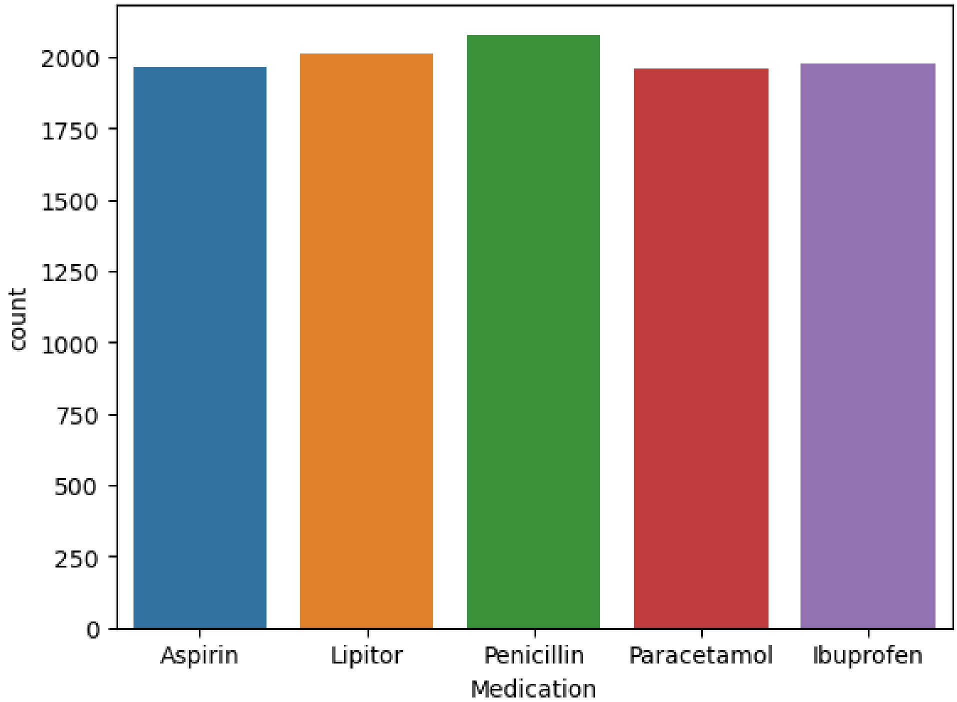
In [227]:
```
sb.countplot(x='Medical Condition',data=Health)
plt.show()
```



Although medical condition counts are pretty similar, asthma and cancer occupy the highest two places.

8. What was the most prescribed medication?

In [228]:
```
sb.countplot(x='Medication', data=Health)
plt.show()
```



In [ ]:

Model Predictions and Accuracy Evaluation

Feature extraction

In [255]:
```
#creatin a copy of our cleaned data to work on
df = Health.copy()
```

In [256]:
```
#verifyin if copyin was successful
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Name                10000 non-null  object
 1   Age                 10000 non-null  int64
 2   Gender              10000 non-null  object
 3   Blood Type          10000 non-null  object
 4   Medical Condition   10000 non-null  object
 5   Date of Admission   10000 non-null  datetime64[ns]
 6   Doctor              10000 non-null  object
 7   Hospital            10000 non-null  object
 8   Insurance Provider  10000 non-null  object
 9   Billing Amount      10000 non-null  float64
 10  Room Number         10000 non-null  int64
 11  Admission Type      10000 non-null  object
 12  Discharge Date      10000 non-null  datetime64[ns]
 13  Medication          10000 non-null  object
 14  Test Results        10000 non-null  object
 15  num_days            10000 non-null  int64
dtypes: datetime64[ns](2), float64(1), int64(3), object(10)
memory usage: 1.2+ MB
```

In [257]:
```
#droppin columns unnecessary for our prediction
df.drop('Date of Admission', axis=1, inplace=True)
df.drop('Discharge Date', axis=1, inplace=True)
df.drop('Doctor', axis=1, inplace=True)
df.drop('Hospital', axis=1, inplace=True)
df.drop('Room Number', axis=1, inplace=True)
df.drop('Name', axis=1, inplace=True)
```

In [258]:
```
df.drop('Insurance Provider', axis=1, inplace=True)
```

In [259]:
```
#verifyin if deletion was successful
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Age                10000 non-null  int64
 1   Gender             10000 non-null  object
 2   Blood Type         10000 non-null  object
 3   Medical Condition  10000 non-null  object
 4   Billing Amount     10000 non-null  float64
 5   Admission Type     10000 non-null  object
 6   Medication         10000 non-null  object
 7   Test Results       10000 non-null  object
 8   num_days           10000 non-null  int64
dtypes: float64(1), int64(2), object(6)
memory usage: 703.2+ KB
```

Label Encoding

In [260]:
```
#encoding text fields

from sklearn.preprocessing import LabelEncoder
lc=LabelEncoder()
cols=['Gender', 'Blood Type', 'Medical Condition','Admission Type', 'Medication','Test Results'
for i in cols:
  df[i]=lc.fit_transform(df[i])
```

In [261]:
```
df
```

Out[261]:

	Age	Gender	Blood Type	Medical Condition	Billing Amount	Admission Type	Medication	Test Results	num_days
0	81	0	7	3	37490.983364	0	0	1	14
1	35	1	6	1	47304.064845	1	2	2	14
2	61	1	5	5	36874.896997	1	2	2	30
3	49	1	5	1	23303.322092	2	4	0	1
4	51	1	7	0	18086.344184	2	3	2	24
...	...	...	...	...	...	...	...	...	...
9995	83	1	0	5	39606.840083	0	1	0	4
9996	47	0	2	0	5995.717488	1	1	2	23
9997	54	1	5	0	49559.202905	0	1	2	14
9998	84	1	0	0	25236.344761	2	4	2	20
9999	20	1	5	0	37223.965865	1	4	0	24

10000 rows × 9 columns

In [262]:
```
#separating data into features(x) and target (y)

X=df.drop(['Test Results'],axis=1)
y=df['Test Results']

#seperating our data into test and train

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import scale

#model importation
from sklearn import neighbors, metrics
from sklearn import svm
from sklearn import linear_model
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
#from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 26)
```

XGB Classifier

model1= XGBClassifier() model1.fit(X_train, y_train)

y_pred = model1.predict(X_test) print("---") print(f"The accuraccy score is: ------>> {accuracy_score(y_test,y_pred)}") print("---") print(f"The Confusion Matrix is: ------>> \n{confusion_matrix(y_test,y_pred)}") print("---") print(f"The Classification Report is: ---->> {classification_report(y_test,y_pred)}")

xgb_classifier = xgb.XGBClassifier() xgb_accuracy = cross_val_score(xgb_classifier, X_test, y_test, cv=8).mean() print("cross validation score: ", xgb_accuracy)

Support Vector Machine

In [263]:

```
svm_classifier = svm.SVC()
svm_classifier.fit(X_train, y_train)
from sklearn.model_selection import cross_val_score
svm_accuracy = cross_val_score(svm_classifier, X_test, y_test, cv=8).mean()

print("cross validation score: ", svm_accuracy)
```

```
cross validation score:  0.3485
```

In [264]:

```
y_pred = svm_classifier.predict(X_test)
print("-----------------------------------------------------------------------")
print(f"The accuraccy score is: ------>>  {accuracy_score(y_test,y_pred)}")
print("-----------------------------------------------------------------------")
print(f"The Confusion Matrix is: ------>> \n{confusion_matrix(y_test,y_pred)}")
print("-----------------------------------------------------------------------")
#print(f"The Classification Report is: ---->> {classification_report(y_test,y_pred)}")
```

```
-----------------------------------------------------------------------
The accuraccy score is: ------>>  0.3435
-----------------------------------------------------------------------
The Confusion Matrix is: ------>>
[[687   0   0]
 [682   0   0]
 [631   0   0]]
-----------------------------------------------------------------------
```

Logistic Regression

In [221]:

```
model3 = linear_model.LinearRegression()
model3.fit(X_train,y_train)
```

Out[221]:

```
LinearRegression()
```

In [ ]:

```
y_pred = model3.predict(X_test)
print("-----------------------------------------------------------------------")
print(f"The accuraccy score is: ------>>  {accuracy_score(y_test,y_pred)}")
print("-----------------------------------------------------------------------")
print(f"The Confusion Matrix is: ------>> \n{confusion_matrix(y_test,y_pred)}")
print("-----------------------------------------------------------------------")
print(f"The Classification Report is: ---->> {classification_report(y_test,y_pred)}")
```

Random Forest

In [265]:

```
model4 = RandomForestClassifier()
model4.fit(X_train,y_train)
```

Out[265]:

```
RandomForestClassifier()
```

In [266]:
```
y_pred = model4.predict(X_test)
print("--------------------------------------------------------------------------")
print(f"The accuraccy score is: ------>>  {accuracy_score(y_test,y_pred)}")
print("--------------------------------------------------------------------------")
print(f"The Confusion Matrix is: ------>> \n{confusion_matrix(y_test,y_pred)}")
print("--------------------------------------------------------------------------")
print(f"The Classification Report is: ---->> {classification_report(y_test,y_pred)}")
```

```
-------------------------------------------------------------------------
The accuraccy score is: ------>>  0.3275
-------------------------------------------------------------------------
The Confusion Matrix is: ------>>
[[277 200 210]
 [291 187 204]
 [247 193 191]]
-------------------------------------------------------------------------
The Classification Report is: ---->>               precision    recall  f1-score   support

           0       0.34      0.40      0.37       687
           1       0.32      0.27      0.30       682
           2       0.32      0.30      0.31       631

    accuracy                           0.33      2000
   macro avg       0.33      0.33      0.32      2000
weighted avg       0.33      0.33      0.33      2000
```

Decision Tree

In [267]:
```
model5 = DecisionTreeClassifier()
model5.fit(X_train,y_train)
```

Out[267]:
```
DecisionTreeClassifier()
```

In [268]:
```
y_pred = model5.predict(X_test)
print("--------------------------------------------------------------------------")
print(f"The accuraccy score is: ------>>  {accuracy_score(y_test,y_pred)}")
print("--------------------------------------------------------------------------")
print(f"The Confusion Matrix is: ------>> \n{confusion_matrix(y_test,y_pred)}")
print("--------------------------------------------------------------------------")
print(f"The Classification Report is: ---->> {classification_report(y_test,y_pred)}")
```

```
-------------------------------------------------------------------------
The accuraccy score is: ------>>  0.3245
-------------------------------------------------------------------------
The Confusion Matrix is: ------>>
[[233 225 229]
 [230 213 239]
 [223 205 203]]
-------------------------------------------------------------------------
The Classification Report is: ---->>               precision    recall  f1-score   support

           0       0.34      0.34      0.34       687
           1       0.33      0.31      0.32       682
           2       0.30      0.32      0.31       631

    accuracy                           0.32      2000
   macro avg       0.32      0.32      0.32      2000
weighted avg       0.33      0.32      0.32      2000
```

Summarily, the following models produced the following accuracies :

DecisionTree - 0.3175

Logistic Regression - Classification metrics can't handle a mix of multiclass and continuous targets

Random Forest - 0.326

Support vector Machine - 0.3435/0.3485

XGBClassifier - Still to be tested

Therefore, for our dataset, the most accurate model with respect to this study is the Support Vector Machine model