1. Collate the 2 excel files to have all the information at one place. Check for missing values and duplicates before joining the 2 datasets.

```
!pip install xgboost
```

```
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: xgboost in c:\users\naven\appdata\
roaming\python\python312\site-packages (2.1.4)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\
site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\
site-packages (from xgboost) (1.13.1)
```

```
import xgboost as xgb
print(xgb.__version__)
```

```
2.1.4
```

```
# All libraries/functions required

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OrdinalEncoder
import plotly.express as px
from statsmodels.formula.api import ols
import statsmodels.api  as sm
import scipy.stats as stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from sklearn.linear_model import SGDRegressor, Ridge
from sklearn.model_selection import KFold, StratifiedKFold,
RandomizedSearchCV, train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as mse, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.pipeline import Pipeline
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
```

```
address = ''
```

```
hosp = pd.read_csv(r'I:\December 2024\PGC DS Capstone\Project\
Datasets_updated\Capstone _1\Hospitalisation details.csv')
medic = pd.read_csv(r'I:\December 2024\PGC DS Capstone\Project\
Datasets_updated\Capstone _1\Medical Examinations.csv')
```

```python
names = pd.read_excel(r'I:\December 2024\PGC DS Capstone\Project\
Datasets_updated\Capstone _1\Names.xlsx')

# hosp = pd.read_excel('/content/drive/MyDrive/Colab
Notebooks/Hospitalisation details.xlsx')
# medic = pd.read_excel('/content/drive/MyDrive/Colab
Notebooks/Medical Examinations.xlsx')
```

Data inspection using .info()

```python
hosp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2343 entries, 0 to 2342
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Customer ID    2343 non-null   object 
 1   year           2343 non-null   object 
 2   month          2343 non-null   object 
 3   date           2343 non-null   int64  
 4   children       2343 non-null   int64  
 5   charges        2343 non-null   float64
 6   Hospital tier  2343 non-null   object 
 7   City tier      2343 non-null   object 
 8   State ID       2343 non-null   object 
dtypes: float64(1), int64(2), object(6)
memory usage: 164.9+ KB
```

```python
medic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2335 entries, 0 to 2334
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Customer ID             2335 non-null   object 
 1   BMI                     2335 non-null   float64
 2   HBA1C                   2335 non-null   float64
 3   Heart Issues            2335 non-null   object 
 4   Any Transplants         2335 non-null   object 
 5   Cancer history          2335 non-null   object 
 6   NumberOfMajorSurgeries  2335 non-null   object 
 7   smoker                  2335 non-null   object 
dtypes: float64(2), object(6)
memory usage: 146.1+ KB
```

```python
names.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2335 entries, 0 to 2334
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Customer ID  2335 non-null   object
 1   name         2335 non-null   object
dtypes: object(2)
memory usage: 36.6+ KB
```

```
master_data = pd.merge(hosp, medic, how = 'inner', on = 'Customer ID')
```

```
master_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2335 entries, 0 to 2334
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Customer ID             2335 non-null   object 
 1   year                    2335 non-null   object 
 2   month                   2335 non-null   object 
 3   date                    2335 non-null   int64  
 4   children                2335 non-null   int64  
 5   charges                 2335 non-null   float64
 6   Hospital tier           2335 non-null   object 
 7   City tier               2335 non-null   object 
 8   State ID                2335 non-null   object 
 9   BMI                     2335 non-null   float64
 10  HBA1C                   2335 non-null   float64
 11  Heart Issues            2335 non-null   object 
 12  Any Transplants         2335 non-null   object 
 13  Cancer history          2335 non-null   object 
 14  NumberOfMajorSurgeries  2335 non-null   object 
 15  smoker                  2335 non-null   object 
dtypes: float64(3), int64(2), object(11)
memory usage: 292.0+ KB
```

```
master_data = master_data.merge(names,on='Customer ID')
```

```
master_data.head(2)
```

```
  Customer ID  year month  date  children  charges Hospital tier City 
tier  \
0      Id2335  1992   Jul     9         0   563.84      tier - 2  tier 
- 3   
1      Id2334  1992   Nov    30         0   570.62      tier - 2  tier 
- 1   

  State ID    BMI  HBA1C Heart Issues Any Transplants Cancer 
history  \
```

```
0    R1013  17.58   4.51           No               No              No

1    R1013  17.60   4.39           No               No              No


  NumberOfMajorSurgeries smoker                        name
0                      1     No    German, Mr.  Aaron K
1                      1     No  Rosendahl, Mr.   Evan P
```

```
master_data["Customer ID"].head()
```

```
0    Id2335
1    Id2334
2    Id2333
3    Id2332
4    Id2331
Name: Customer ID, dtype: object
```

```
master_data.columns = master_data.columns.str.lower()
master_data.columns = master_data.columns.str.replace(' ', '_')
master_data.columns
```

```
Index(['customer_id', 'year', 'month', 'date', 'children', 'charges',
       'hospital_tier', 'city_tier', 'state_id', 'bmi', 'hba1c',
       'heart_issues', 'any_transplants', 'cancer_history',
       'numberofmajorsurgeries', 'smoker', 'name'],
      dtype='object')
```

```
master_data.customer_id
```

```
0       Id2335
1       Id2334
2       Id2333
3       Id2332
4       Id2331
         ...
2330       Id5
2331       Id4
2332       Id3
2333       Id2
2334       Id1
Name: customer_id, Length: 2335, dtype: object
```

2. The data seems to have trivial values in a few variables. These are "?". Find the percentage of rows which have such value ("?") in any column. Delete such rows in case you don't lose significant information.

```
(master_data == '?').sum()
```

```
customer_id                  0
year                         2
month                        3
date                         0
children                     0
charges                      0
hospital_tier                1
city_tier                    1
state_id                     2
bmi                          0
hba1c                        0
heart_issues                 0
any_transplants              0
cancer_history               0
numberofmajorsurgeries       0
smoker                       2
name                         0
dtype: int64
```

```
# replacing '?' with np.NA for easy access and removal

miss_perc = (master_data == '?').sum(axis = 1)/master_data.shape[1] *
100
miss_perc[miss_perc > 0]
```

```
11       5.882353
13       5.882353
17      11.764706
542      5.882353
1046     5.882353
1049     5.882353
1700     5.882353
1775     5.882353
2165     5.882353
2332     5.882353
dtype: float64
```

```
miss_perc[miss_perc>0].index
```

```
Index([11, 13, 17, 542, 1046, 1049, 1700, 1775, 2165, 2332],
dtype='int64')
```

```
miss_perc_col = (master_data == '?').sum(axis =
0)/master_data.shape[0] * 100
miss_perc_col.sort_values(ascending= False)
```

```
month                        0.128480
state_id                     0.085653
smoker                       0.085653
year                         0.085653
hospital_tier                0.042827
```

```
city_tier                  0.042827
heart_issues               0.000000
numberofmajorsurgeries     0.000000
cancer_history             0.000000
any_transplants            0.000000
customer_id                0.000000
hba1c                      0.000000
bmi                        0.000000
charges                    0.000000
children                   0.000000
date                       0.000000
name                       0.000000
dtype: float64
```

```
master_noq = master_data.drop(index = miss_perc[miss_perc>0].index)
master_noq.shape
```

```
(2325, 17)
```

```
master_noq.isna().sum()
```

```
customer_id                0
year                       0
month                      0
date                       0
children                   0
charges                    0
hospital_tier              0
city_tier                  0
state_id                   0
bmi                        0
hba1c                      0
heart_issues               0
any_transplants            0
cancer_history             0
numberofmajorsurgeries     0
smoker                     0
name                       0
dtype: int64
```

3. The data has nominal and ordinal categorical variables. How are you going to incorporate these variables in the next steps of modelling. Use necessary transformation methods to deal with nominal and ordinal types of data.

```
master_noq[['city_tier', 'hospital_tier']]
```

```
     city_tier hospital_tier
0     tier - 3      tier - 2
```

```
1     tier - 1      tier - 2
2     tier - 1      tier - 2
3     tier - 3      tier - 3
4     tier - 3      tier - 3
...        ...           ...
2329  tier - 3      tier - 1
2330  tier - 2      tier - 1
2331  tier - 3      tier - 1
2333  tier - 3      tier - 2
2334  tier - 3      tier - 1

[2325 rows x 2 columns]
```

```
master_noq.state_id.value_counts()
```

```
state_id
R1013    609
R1011    574
R1012    572
R1024    159
R1026     84
R1021     70
R1016     64
R1025     40
R1023     38
R1017     36
R1019     26
R1022     14
R1014     13
R1015     11
R1018      9
R1020      6
Name: count, dtype: int64
```

```
master_noq.state_id.head()
```

```
0    R1013
1    R1013
2    R1013
3    R1013
4    R1013
Name: state_id, dtype: object
```

```
master_noq.state_id.nunique()
```

```
16
```

```
# Using ordinalencoder to deal with ordinal categorical variables - 
city tier and hospital tier

ordinal = OrdinalEncoder(categories= [['tier - 3', 'tier - 2', 'tier - 
```

```
1'],['tier - 3', 'tier - 2', 'tier - 1']])
master_noq[['city_tier_ord','hospital_tier_ord']] =
ordinal.fit_transform(master_noq[['city_tier', 'hospital_tier']])

pd.crosstab(master_noq['city_tier_ord'],master_noq['city_tier'])

city_tier      tier - 1  tier - 2  tier - 3
city_tier_ord
0.0                   0         0       789
1.0                   0       807         0
2.0                 729         0         0

pd.crosstab(master_noq['hospital_tier_ord'],master_noq['hospital_tier'
])

hospital_tier      tier - 1  tier - 2  tier - 3
hospital_tier_ord
0.0                       0         0       691
1.0                       0      1334         0
2.0                     300         0         0

master_noq.head(3)

  customer_id  year month  date  children  charges hospital_tier
city_tier  \
0      Id2335  1992   Jul     9         0   563.84      tier - 2  tier
- 3
1      Id2334  1992   Nov    30         0   570.62      tier - 2  tier
- 1
2      Id2333  1993   Jun    30         0   600.00      tier - 2  tier
- 1

  state_id    bmi  hba1c heart_issues any_transplants
cancer_history  \
0    R1013  17.58   4.51           No              No              No

1    R1013  17.60   4.39           No              No              No

2    R1013  16.47   6.35           No              No             Yes


  numberofmajorsurgeries smoker                    name  city_tier_ord
\
0                      1     No    German, Mr.  Aaron K            0.0

1                      1     No  Rosendahl, Mr.  Evan P            2.0

2                      1     No      Albano, Ms.  Julie            2.0


   hospital_tier_ord
```

```
0                 1.0
1                 1.0
2                 1.0
```

4. State ID has around 16 states. The data does not have proportional representation of all the states. Also creating dummy variables corresponding to all the regions may lead to too many insignificant predictors. Nevertheless, only R1011, R1012 and R1013 are important to look deeper into. Keeping these ideas in mind, come up with a suitable strategy here.

```
vc = master_noq.state_id.value_counts()   # frequency of each category
vc

state_id
R1013    609
R1011    574
R1012    572
R1024    159
R1026     84
R1021     70
R1016     64
R1025     40
R1023     38
R1017     36
R1019     26
R1022     14
R1014     13
R1015     11
R1018      9
R1020      6
Name: count, dtype: int64

vc[:3].index                              # picking top 3 most 
frequent categories

Index(['R1013', 'R1011', 'R1012'], dtype='object', name='state_id')

for i in vc[:3].index:
    var_name = 'state_id_' +i   # create name for the dummy varible
    print(var_name)
    master_noq[var_name] = 0    # giving a dummy value 0 to dummy 
variable
    master_noq.loc[master_noq.state_id == i,var_name] = 1  # replacing 
0 by 1 where state id is equal to category of the dummy variable
```

```
state_id_R1013
state_id_R1011
state_id_R1012
```

```
master_noq.state_id.value_counts()
```

```
state_id
R1013    609
R1011    574
R1012    572
R1024    159
R1026     84
R1021     70
R1016     64
R1025     40
R1023     38
R1017     36
R1019     26
R1022     14
R1014     13
R1015     11
R1018      9
R1020      6
Name: count, dtype: int64
```

```
# checking the no of records corresponding to R1013

master_noq['state_id_R1013'].value_counts()
```

```
state_id_R1013
0    1716
1     609
Name: count, dtype: int64
```

```
master_noq['state_id_R1012'].value_counts()
```

```
state_id_R1012
0    1753
1     572
Name: count, dtype: int64
```

5. Variable ‘NumberOfMajorSurvalue_counts seems to have string values as well. You may want to clean this variable.

```
master_noq.numberofmajorsurgeries.unique()
```

```
array(['1', 'No major surgery', '2', '3'], dtype=object)
```

```
master_noq.loc[master_noq.numberofmajorsurgeries == 'No major
surgery','numberofmajorsurgeries' ] = 0
```

```
master_noq.numberofmajorsurgeries =
master_noq.numberofmajorsurgeries.astype(int)

master_noq.numberofmajorsurgeries.unique()

array([1, 0, 2, 3])
```

6. Age seems to an important factor for this analysis. Based on date of birth information, calculate the age of the patients.

```
master_noq.year = master_noq.year.astype(int)

master_noq['age'] = 2025 - master_noq.year

master_noq.head(2)

  customer_id  year month  date  children  charges hospital_tier
city_tier  \
0      Id2335  1992   Jul     9         0   563.84      tier - 2  tier
- 3
1      Id2334  1992   Nov    30         0   570.62      tier - 2  tier
- 1

  state_id    bmi  ...  cancer_history numberofmajorsurgeries
smoker  \
0    R1013  17.58  ...              No                      1     No

1    R1013  17.60  ...              No                      1     No


                     name  city_tier_ord hospital_tier_ord
state_id_R1013  \
0    German, Mr.  Aaron K            0.0               1.0
1
1  Rosendahl, Mr.  Evan P            2.0               1.0
1

   state_id_R1011  state_id_R1012  age
0               0               0   33
1               0               0   33

[2 rows x 23 columns]
```

7. Gender of the patient may be an important factor to decide the hospitalization cost. Salutation provided in the name of the beneficiary can be used to determine the gender. Create a new field for the gender of beneficiary.

```
master_noq.name
```

```
0                      German, Mr.  Aaron K
1                    Rosendahl, Mr.  Evan P
2                        Albano, Ms.  Julie
3       Riveros Gonzalez, Mr.  Juan D. Sr.
4                     Brietzke, Mr.  Jordan
                          ...
2329                 Baker, Mr.  Russell B.
2330                   Kadala, Ms.  Kristyn
2331                   Osborne, Ms.  Kelsey
2333                 Lehner, Mr.  Matthew D
2334                      Hawks, Ms.  Kelly
Name: name, Length: 2325, dtype: object
```

```
master_noq['title'] =
master_noq.name.str.split('[,.]').str[1].str.strip()
```

```
master_noq.title.value_counts()
```

```
title
Mr     1160
Ms     1023
Mrs     142
Name: count, dtype: int64
```

```
master_noq.shape
```

```
(2325, 24)
```

```
1160+1023+142
```

```
2325
```

```
master_noq['gender'] = 'female'
master_noq.loc[master_noq.title == 'Mr', 'gender'] = 'male'
```

```
master_noq.loc[master_noq.title == 'Mrs']
```

```
     customer_id  year month  date  children   charges
hospital_tier  \
24        Id2311  2001   Aug    19         0    964.71       tier - 3

172       Id2163  2004   Dec    27         0   1863.45       tier - 3

197       Id2138  2004   Jun    12         0   2094.10       tier - 3

328       Id2007  1993   Sep    25         0   3162.02       tier - 2

348       Id1987  2003   Dec     5         0   3300.70       tier - 2

...          ...   ...   ...   ...       ...       ...            ...

1790       Id545  1963   Jul     4         0  18208.34       tier - 1
```

```
1808       Id527  1963   Dec      6         0  18883.33      tier - 1

1811       Id524  1963   Oct    20         0  18954.56      tier - 1

1839       Id496  1966   Aug    10         0  19995.29      tier - 1

1848       Id487  1962   Jul      2         0  20354.50      tier - 3


     city_tier state_id    bmi  ...  smoker
name  \
24    tier - 2    R1013  25.19  ...      No        Keys, Mrs.
Kathleen
172   tier - 1    R1025  27.06  ...      No    Stanislav, Mrs.  Grace
H
197   tier - 2    R1025  27.74  ...      No        Padula, Mrs.
Lauren
328   tier - 3    R1013  25.61  ...      No     Martin, Mrs.  Kristen
M
348   tier - 2    R1025  30.54  ...      No  Mendez-Karr, Mrs.
Cynthia
...        ...      ...    ...  ...     ...                         ..
.
1790  tier - 2    R1026  44.20  ...      No      Shigezumi, Mrs.
Teiko
1808  tier - 1    R1026  46.19  ...      No      Hughey, Mrs.  Ashley
E
1811  tier - 1    R1026  46.40  ...      No      Rogers, Mrs.  Anita
L.
1839  tier - 3    R1026  51.74  ...      No       Oehlke, Mrs.
Jessica
1848  tier - 2    R1026  49.77  ...      No        Argall, Mrs.  Tara
R

     city_tier_ord hospital_tier_ord  state_id_R1013 state_id_R1011  \
24             1.0               0.0               1              0
172            2.0               0.0               0              0
197            1.0               0.0               0              0
328            0.0               1.0               1              0
348            1.0               1.0               0              0
...            ...               ...             ...            ...
1790           1.0               2.0               0              0
1808           2.0               2.0               0              0
1811           2.0               2.0               0              0
1839           0.0               2.0               0              0
1848           1.0               0.0               0              0

     state_id_R1012  age  title  gender
24                0   24    Mrs  female
```

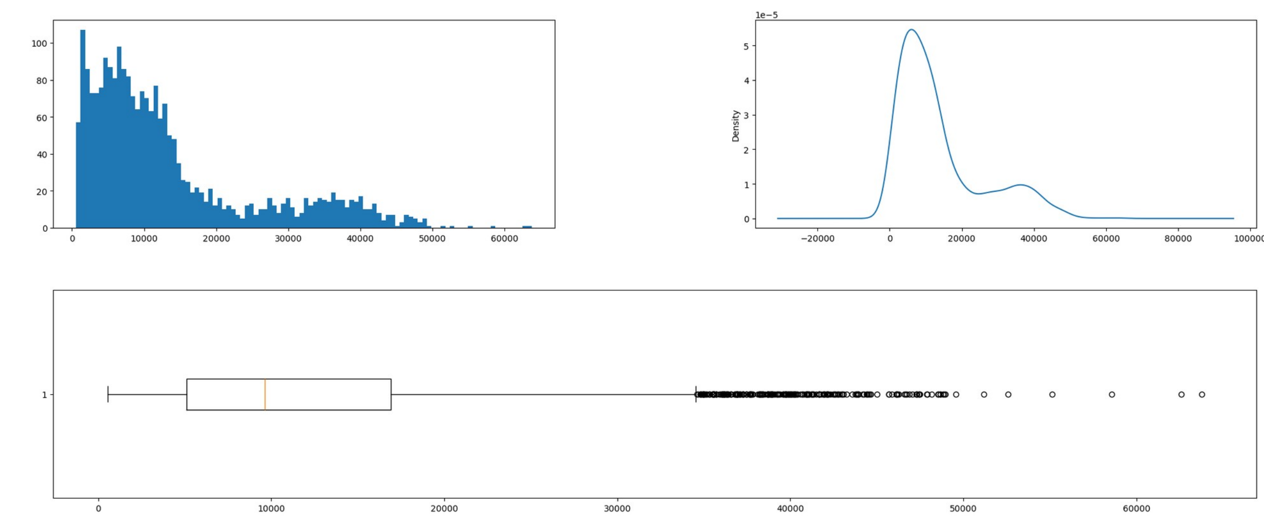
```
172                0   21    Mrs  female
197                0   21    Mrs  female
328                0   32    Mrs  female
348                0   22    Mrs  female
...              ...  ...    ...     ...
1790               0   62    Mrs  female
1808               0   62    Mrs  female
1811               0   62    Mrs  female
1839               0   59    Mrs  female
1848               0   63    Mrs  female

[142 rows x 25 columns]
```

```
master_noq['gender']
```

```
0         male
1         male
2       female
3         male
4         male
         ...
2329      male
2330    female
2331    female
2333      male
2334    female
Name: gender, Length: 2325, dtype: object
```

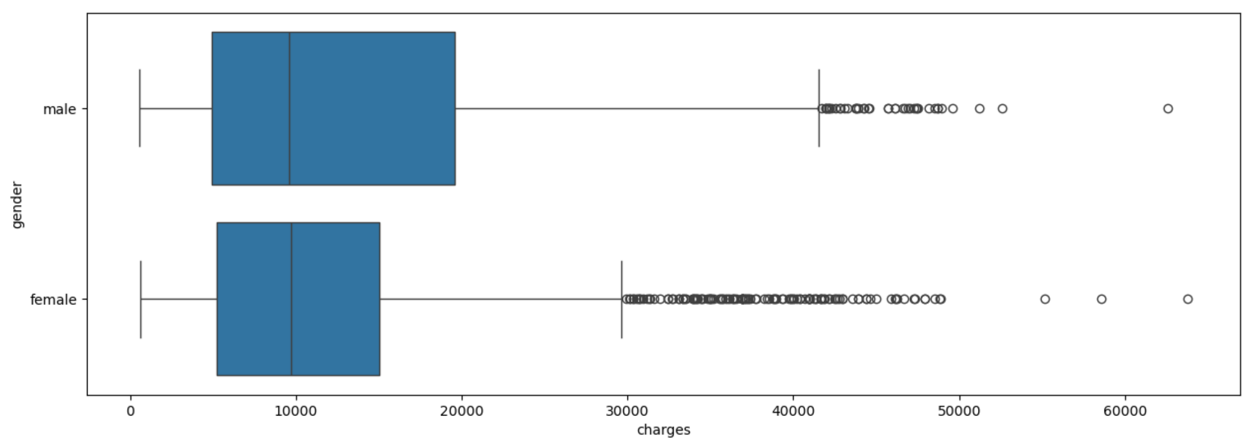
8. Visualize the distribution of cost using histogram, box and whisker and swarm plot. How the distribution is different across gender and different tiers of hospitals. Share your observation.

```
plt.figure(figsize = (25,10))
grid = plt.GridSpec(2, 2, wspace=0.4, hspace=0.3)
plt.subplot(grid[0, 0])
plt.hist(master_noq.charges, bins = 100)
plt.subplot(grid[0, 1])
master_noq.charges.plot.kde()
plt.subplot(grid[1, :])
plt.boxplot(master_noq.charges, vert = False)
plt.show()
```



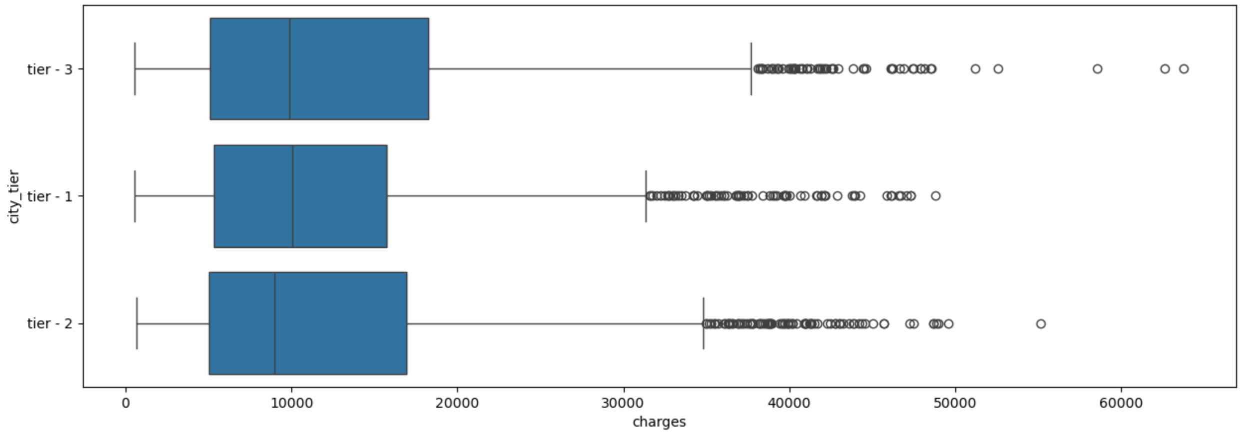
WRT gender

```
plt.figure(figsize = (15,5))
sns.boxplot(x = "charges",y = "gender", data = master_noq)
plt.show()
```



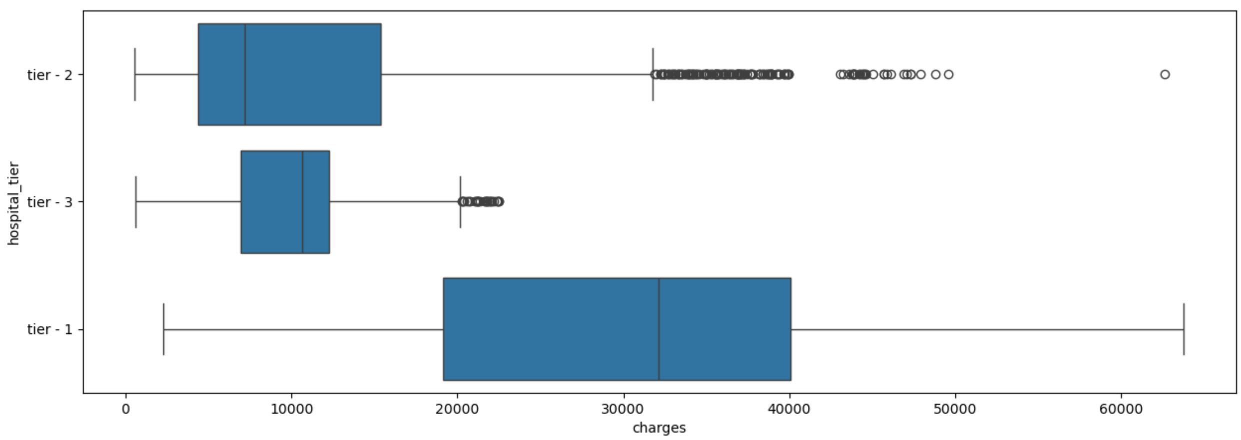
WRT city tier

```
plt.figure(figsize = (15,5))
sns.boxplot(x = "charges",y = "city_tier", data = master_noq)
plt.show()
```



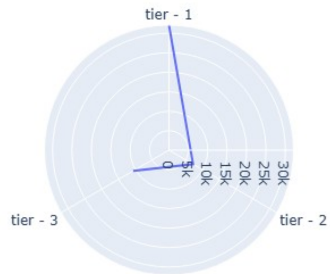
WRT Hospital tier

```
plt.figure(figsize = (15,5))
sns.boxplot(x = "charges",y = "hospital_tier", data = master_noq)
plt.show()
```



9. Create a radar chart to showcase the median hospitalization cost across different tiers of hospitals.

```
median = master_noq.groupby('hospital_tier')
[['charges']].median().reset_index()

fig = px.line_polar(median, r='charges', theta='hospital_tier') #,
line_close=True
fig.show()
```

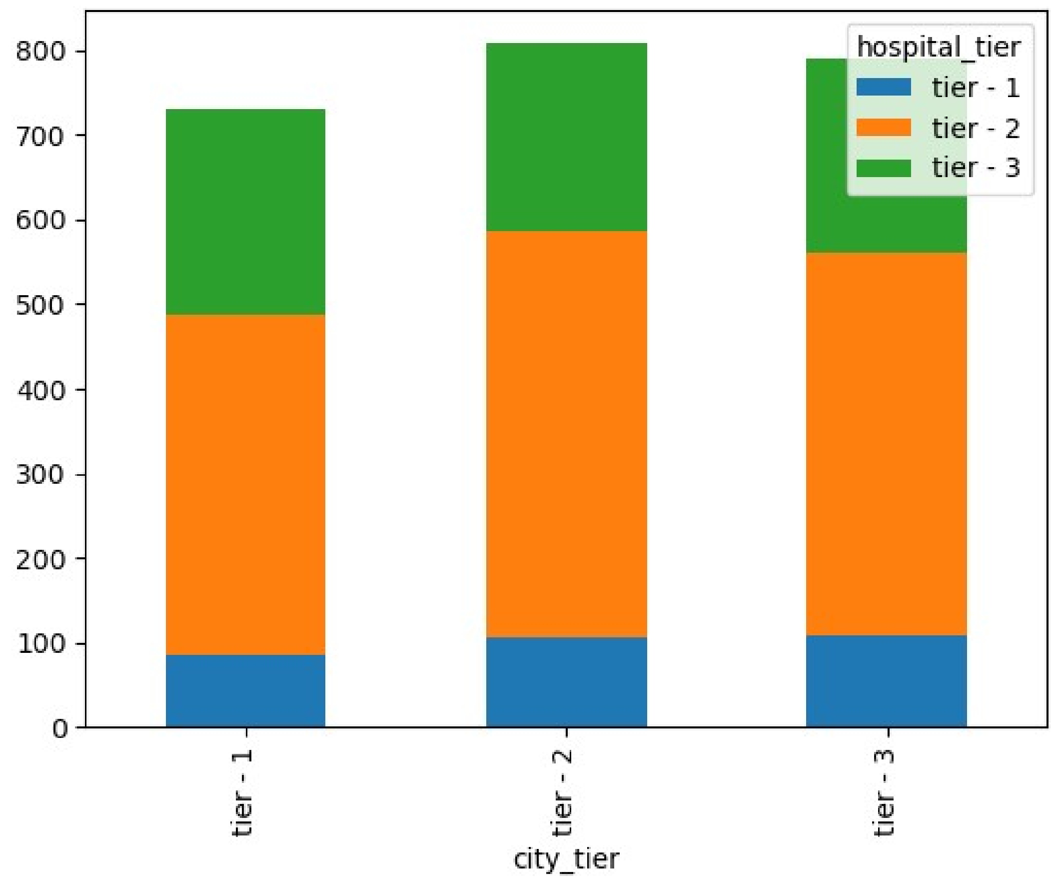


10. Create a frequency table and hence a stacked bar-chart to visualize the count of people in different tiers of cities and hospitals.

```
pd.crosstab(master_noq.city_tier, master_noq.hospital_tier)
```

hospital_tier	tier - 1	tier - 2	tier - 3
city_tier			
tier - 1	85	403	241
tier - 2	106	479	222
tier - 3	109	452	228

```
pd.crosstab(master_noq.city_tier,
master_noq.hospital_tier).plot.bar(stacked = True)
plt.show()
```



11. Test the following null hypotheses:

```
- Average hospitalization cost across the 3 types of hospitals is not
significantly different
- Average hospitalization cost across the 3 types of cities is not
significantly different
- Average hospitalization cost for smokers is not significantly
different than non-smokers
- Smoking and Hearth issues are independent
```

H0 : Average hospitalization cost across the 3 types of hospitals is not significantly different

```
mod = ols('charges ~ hospital_tier', data = master_noq).fit()
res = sm.stats.anova_lm(mod)
res
```

```
                   df        sum_sq       mean_sq           F
PR(>F)
hospital_tier     2.0  9.763011e+10  4.881505e+10  493.989566
1.773822e-179
Residual       2322.0  2.294554e+11  9.881799e+07         NaN
NaN
```

H0 = Average hospitalization cost across the 3 types of cities is not significantly different

```
mod = ols('charges ~ city_tier', data = master_noq).fit()
res = sm.stats.anova_lm(mod)
res
```

	df	sum_sq	mean_sq	F	PR(>F)
city_tier	2.0	4.092192e+08	2.046096e+08	1.454356	0.233763
Residual	2322.0	3.266763e+11	1.406874e+08	NaN	NaN

H0: Average hospitalization cost for smokers is not significantly different than non-smokers

```
sample1 = master_noq.loc[master_noq.smoker == 'yes', 'charges']
sample2 = master_noq.loc[master_noq.smoker != 'yes', 'charges']
stats.ttest_ind(sample1, sample2)
```

```
TtestResult(statistic=74.15560699695726, pvalue=0.0, df=2323.0)
```

H0 : Smoking and Heart issues are independent4

```
observed_table = pd.crosstab(master_noq.smoker,
master_data.heart_issues)

observed_table
```

heart_issues	No	yes
smoker		
No	1108	731
yes	297	189

```
chi, p, df, expected = stats.chi2_contingency(observed_table)

chi, p, df, expected
```

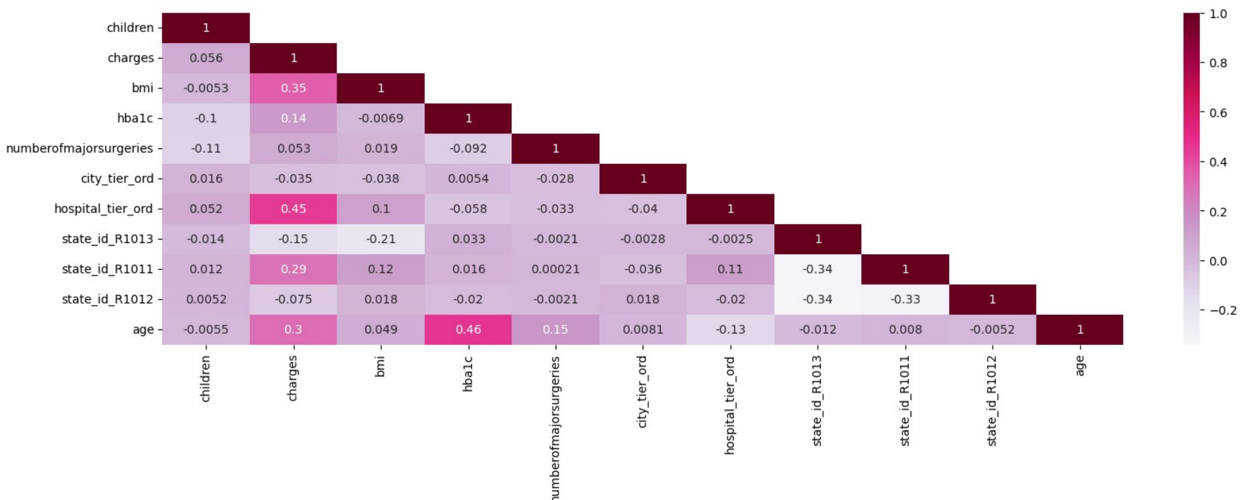
```
(0.08588150449910657,
 0.7694797581780767,
 1,
 array([[1111.30967742,  727.69032258],
        [ 293.69032258,  192.30967742]]))
```

12. Check the correlation between predictors to identify highly correlated predictors. Visualize using a heatmap.

```
master_noq.columns
```

```
Index(['customer_id', 'year', 'month', 'date', 'children', 'charges',
       'hospital_tier', 'city_tier', 'state_id', 'bmi', 'hba1c',
       'heart_issues', 'any_transplants', 'cancer_history',
       'numberofmajorsurgeries', 'smoker', 'name', 'city_tier_ord',
```

```
       'hospital_tier_ord', 'state_id_R1013', 'state_id_R1011',
       'state_id_R1012', 'age', 'title', 'gender'],
      dtype='object')

data = master_noq.drop(columns = ['customer_id','name', 'year',
'month', 'date','hospital_tier',
       'city_tier', 'state_id' , 'title'])

corr_plot = data.select_dtypes(exclude='object').corr()
ma = np.ones_like(corr_plot)
ma[np.tril_indices_from(ma)] = 0

plt.figure(figsize = (18,5))
sns.heatmap(corr_plot, annot= True , mask = ma, cmap='PuRd')
plt.show()
```



13. Final Model Development and Evaluation :

Perform stratified 5-fold cross validation technique for final prediction and validation. Make sure to use standardization, hyperparameter tuning effectively. There must be effective use of sklearn-pipelines.

a. Create 5 fold in the data. You may want to create a variable to identify the folds.

```
data_2 = pd.get_dummies(data, drop_first=True)
data_2.reset_index(drop=True, inplace = True)

data_2.head()

   children  charges    bmi  hba1c  numberofmajorsurgeries
city_tier_ord  \
0         0   563.84  17.58   4.51                       1
0.0
1         0   570.62  17.60   4.39                       1
2.0
```

```
2          0   600.00  16.47   6.35                         1
2.0
3          0   604.54  17.70   6.28                         1
0.0
4          0   637.26  22.34   5.57                         1
0.0

   hospital_tier_ord  state_id_R1013  state_id_R1011  state_id_R1012
age  \
0                1.0               1               0               0
33
1                1.0               1               0               0
33
2                1.0               1               0               0
32
3                0.0               1               0               0
33
4                0.0               1               0               0
27

   heart_issues_yes  any_transplants_yes  cancer_history_Yes
smoker_yes  \
0             False                False               False
False
1             False                False               False
False
2             False                False                True
False
3             False                False               False
False
4             False                False               False
False

   gender_male
0         True
1         True
2        False
3         True
4         True

# rearrange data to put 'charges' as first column or last
model_data = data_2.drop(columns = 'charges')
model_data.head()
model_data['charges'] = data_2.charges
model_data.head()

   children    bmi  hba1c  numberofmajorsurgeries  city_tier_ord  \
0         0  17.58   4.51                       1            0.0
1         0  17.60   4.39                       1            2.0
2         0  16.47   6.35                       1            2.0
```

```
3         0  17.70   6.28                      1            0.0
4         0  22.34   5.57                      1            0.0

   hospital_tier_ord  state_id_R1013  state_id_R1011  state_id_R1012
age  \
0                1.0               1               0               0
33
1                1.0               1               0               0
33
2                1.0               1               0               0
32
3                0.0               1               0               0
33
4                0.0               1               0               0
27

   heart_issues_yes  any_transplants_yes  cancer_history_Yes
smoker_yes  \
0             False                False               False
False
1             False                False               False
False
2             False                False                True
False
3             False                False               False
False
4             False                False               False
False

   gender_male  charges
0         True   563.84
1         True   570.62
2        False   600.00
3         True   604.54
4         True   637.26
```

```
model_data.columns = model_data.columns.str.lower()

model_data.columns
```

```
Index(['children', 'bmi', 'hba1c', 'numberofmajorsurgeries',
'city_tier_ord',
       'hospital_tier_ord', 'state_id_r1013', 'state_id_r1011',
       'state_id_r1012', 'age', 'heart_issues_yes',
'any_transplants_yes',
       'cancer_history_yes', 'smoker_yes', 'gender_male', 'charges'],
      dtype='object')
```

```
# converting y to categorical for stratified k fold
y = model_data['charges']
X = model_data.drop(columns = 'charges')

X.head()
```

```
   children    bmi  hba1c  numberofmajorsurgeries  city_tier_ord  \
0         0  17.58   4.51                       1            0.0
1         0  17.60   4.39                       1            2.0
2         0  16.47   6.35                       1            2.0
3         0  17.70   6.28                       1            0.0
4         0  22.34   5.57                       1            0.0

   hospital_tier_ord  state_id_r1013  state_id_r1011  state_id_r1012
age  \
0                1.0               1               0               0
33
1                1.0               1               0               0
33
2                1.0               1               0               0
32
3                0.0               1               0               0
33
4                0.0               1               0               0
27

   heart_issues_yes  any_transplants_yes  cancer_history_yes
smoker_yes  \
0             False                False               False
False
1             False                False               False
False
2             False                False                True
False
3             False                False               False
False
4             False                False               False
False

   gender_male
0         True
1         True
2        False
3         True
4         True
```

```
#scoring='neg_root_mean_squared_error'
```

```python
#Setting up a pipeline
pipeline = Pipeline(steps=[('scaler', StandardScaler()), ('regressor',
Ridge())])

# Defining the parameters for hyperparameter tuning
parameters = {'regressor__alpha': [0.001, 0.01, 0.1, 1, 10, 100]}

# Creating the KFold object
kfold = KFold(n_splits=5, shuffle=True, random_state=42)

# Creating the grid search object
model_ridge = GridSearchCV(pipeline, parameters, cv=kfold,
scoring='neg_mean_squared_error')

model_ridge.fit(X, y)

GridSearchCV(cv=KFold(n_splits=5, random_state=42, shuffle=True),
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('regressor', Ridge())]),
             param_grid={'regressor__alpha': [0.001, 0.01, 0.1, 1, 10,
100]},
             scoring='neg_mean_squared_error')

# Getting the best parameters and the best model
model_ridge.best_params_

{'regressor__alpha': 10}

model_ridge.best_estimator_

Pipeline(steps=[('scaler', StandardScaler()), ('regressor',
Ridge(alpha=10))])
```

Gradient Boosting Algorithm

```python
from sklearn.ensemble import GradientBoostingRegressor

# Assuming df is your DataFrame
# Use df appropriately to prepare X (input) and y (output)

# Split the data into training and testing sets
# (Make sure to replace X and y with your data appropriately)
X_train,X_test,y_train,y_test = train_test_split(X,y)
# Train the XGBoost model
model = GradientBoostingRegressor()
model.fit(X_train, y_train)


# You can print the feature importances if needed
print(model.feature_importances_)

# Identify redundant variables based on the importance scores
```

```
[3.43110020e-03 1.09566693e-01 4.62959352e-03 2.44790703e-05
 0.00000000e+00 2.59776218e-02 5.73988790e-03 6.66669833e-03
 2.42889525e-04 9.32630891e-02 1.53224388e-04 1.73460830e-05
 3.26352026e-04 7.49727697e-01 2.33328128e-04]
```

Variable Importance

```
pd.DataFrame({'Features':model.feature_names_in_,'Importance':model.feature_importances_}).sort_values("Importance",ascending=False)
```

	Features	Importance
13	smoker_yes	0.749728
1	bmi	0.109567
9	age	0.093263
5	hospital_tier_ord	0.025978
7	state_id_r1011	0.006667
6	state_id_r1013	0.005740
2	hba1c	0.004630
0	children	0.003431
12	cancer_history_yes	0.000326
8	state_id_r1012	0.000243
14	gender_male	0.000233
10	heart_issues_yes	0.000153
3	numberofmajorsurgeries	0.000024
11	any_transplants_yes	0.000017
4	city_tier_ord	0.000000

```
# train score
model.score(X_train,y_train)
```

```
0.9380089945557816
```

```
# test score
model.score(X_test,y_test)
```

```
0.9017407518696134
```

15. Predict the hospitalization cost for Christopher, Ms. Jayna (Date of birth – 12/28/1988, height 170 cm and weight 85 kgs). She resides in a tier1 city (state : stateid = R1011) with husband and 2 of her kids. She is tested non-diabetic (hbA1c = 5.8). She smokes but otherwise she is healthy, no transplants and no major surgeries so far. Her father had lung cancer and that was the reason of his early demise. Hospitalization cost to predicted considering tier1 hospitals.

Find predicted hospitalization cost based on all the 5 models. The predicted value should be mean of all the 5 predicted values from the 5 models.

```
model_data.columns

Index(['children', 'bmi', 'hba1c', 'numberofmajorsurgeries',
'city_tier_ord',
       'hospital_tier_ord', 'state_id_r1013', 'state_id_r1011',
       'state_id_r1012', 'age', 'heart_issues_yes',
'any_transplants_yes',
       'cancer_history_yes', 'smoker_yes', 'gender_male', 'charges'],
      dtype='object')

pred_data = pd.DataFrame({'Name' : ['Christopher, Ms. Jayna'],
                      'DOB' : ['12/28/1988'],
                      'city_tier' : ['tier - 1'], 'children' :[ 2],
                       'HbA1c' : [5.8],
                       'smoker_yes' : [1],
                       'heart_issues_yes' : [0],
                       'any_transplants_yes' : [0],
                       'numberofmajorsurgeries' :[ 0],
                       'cancer_history_yes' : [1],
                       'hospital_tier' : ['tier - 1'],
                       'bmi' : [85/(1.70 **2)],
                       'state_id_R1011' : [1]
                      })

pred_data

                     Name         DOB city_tier  children  HbA1c
smoker_yes  \
0  Christopher, Ms. Jayna  12/28/1988  tier - 1         2    5.8
1

   heart_issues_yes  any_transplants_yes  numberofmajorsurgeries  \
```

```
0                  0                     0                        0

   cancer_history_yes hospital_tier        bmi  state_id_R1011
0                   1      tier - 1  29.411765               1

pred_data.columns = pred_data.columns.str.lower()


# we will create columns according to the final model data already
created

pred_data['gender_male']  = 0
pred_data.loc[pred_data.name.str.split('[,.]').str[1] == 'Mr',
'gender_male'] = 1
pred_data.drop(columns = 'name', inplace = True)

pred_data

          dob city_tier  children  hba1c  smoker_yes  heart_issues_yes
\
0  12/28/1988  tier - 1         2    5.8           1                 0


   any_transplants_yes  numberofmajorsurgeries  cancer_history_yes  \
0                    0                       0                   1

  hospital_tier        bmi  state_id_r1011  gender_male
0      tier - 1  29.411765               1            0

#pred_data['age'] =2023 - pred_data.dob.astype(np.datetime64).dt.year

pred_data.drop(columns = 'dob', inplace = True)

pred_data[['city_tier_ord', 'hospital_tier_ord']] =
ordinal.transform(pred_data[['city_tier', 'hospital_tier']])

pred_data.drop(columns =['city_tier', 'hospital_tier'], inplace = True
)

# initializing the missing columns with 0 and not include charges

for col in model_data.columns:
    if col not in pred_data.columns and col != 'charges':
        pred_data[col] = 0

pred_data

   children  hba1c  smoker_yes  heart_issues_yes  any_transplants_yes
\
0         2    5.8           1                 0                    0


   numberofmajorsurgeries  cancer_history_yes        bmi
```

```
state_id_r1011  \
0                       0                   1  29.411765
1

   gender_male  city_tier_ord  hospital_tier_ord  state_id_r1013  \
0            0            2.0                2.0               0

   state_id_r1012  age
0               0    0

### Apply Gradient BOOST model for predi
model_data.columns

Index(['children', 'bmi', 'hba1c', 'numberofmajorsurgeries',
'city_tier_ord',
       'hospital_tier_ord', 'state_id_r1013', 'state_id_r1011',
       'state_id_r1012', 'age', 'heart_issues_yes',
'any_transplants_yes',
       'cancer_history_yes', 'smoker_yes', 'gender_male', 'charges'],
      dtype='object')

pred_data.columns

Index(['children', 'hba1c', 'smoker_yes', 'heart_issues_yes',
       'any_transplants_yes', 'numberofmajorsurgeries',
'cancer_history_yes',
       'bmi', 'state_id_r1011', 'gender_male', 'city_tier_ord',
       'hospital_tier_ord', 'state_id_r1013', 'state_id_r1012',
'age'],
      dtype='object')

pred_data=pred_data[model_data.drop(columns='charges').columns]

model.predict(pred_data)

array([22677.0047916])

test =
pd.read_html("https://en.wikipedia.org/wiki/List_of_the_busiest_airpor
ts_in_the_United_States")

len(test)

10

test[4]

  Rank                                       Airport name  \
  Rank                                       Airport name
0    1                      Memphis International Airport
1    2          Ted Stevens Anchorage International Airport
2    3        Louisville Muhammad Ali International Airport
```

```
3    4                           O'Hare International Airport
4    5                            Miami International Airport
5    6                      Los Angeles International Airport
6    7  Cincinnati/Northern Kentucky International Air...
7    8                    Indianapolis International Airport
8    9               Dallas/Fort Worth International Airport
9   10                          Ontario International Airport

                   Location IATA code        Cargo
                   Location IATA code         lbs. % chg. 2017/16
0       Memphis, Tennessee       MEM  23949525780          00.35%
1        Anchorage, Alaska       ANC  17337337377          02.79%
2     Louisville, Kentucky       SDF  13403682652          04.68%
3        Chicago, Illinois       ORD  10373559593         010.84%
4           Miami, Florida       MIA   7963988407          00.82%
5  Los Angeles, California       LAX   7197930264          03.85%
6         Hebron, Kentucky       CVG   5700282994         033.32%
7    Indianapolis, Indiana       IND   5138500318         0-3.58%
8            Irving, Texas       DFW   4155362297          07.65%
9      Ontario, California       ONT   3522510318         015.81%
```