Bussiness Context:

In [5]:

df.describe()

Apollo Hospitals was established in 1983, renowned as the architect of modern healthcare in India. As the nation's first corporate hospital, Apollo Hospitals is acclaimed for pioneering the private healthcare revolution in the country.

As a data scientist working at Apollo 24/7, the ultimate goal is to tease out meaningful and actionable insights from Patient-level collected data.

You can help Apollo hospitals to be more efficient, to influence diagnostic and treatment processes, to map the spread of a pandemic.

One of the best examples of data scientists making a meaningful difference at a global level is in the response to the COVID-19 pandemic, where they have improved information collection, provided ongoing and accurate estimates of infection spread and health system demand, and assessed the effectiveness of government policies.

```
In [1]:
#importing libraries
import numpy as np
import pandas as pd
import seaborn as sns
import datetime
from scipy import stats
import statsmodels.api as sm
from scipy.stats import chi2 contingency
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
In [2]:
df=pd.read csv('Apollo.csv')
In [3]:
df.shape
Out[3]:
(1338, 7)
In [4]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
                              Non-Null Count Dtype
   Column
   age
                              1338 non-null int64
 0
                              1338 non-null object
   sex
 1
                              1338 non-null object
   smoker
 3
    region
                              1338 non-null
                                             object
    viral load
                             1338 non-null
                                             float64
 5
    severity level
                             1338 non-null
                                              int64
    hospitalization charges 1338 non-null
                                              int64
dtypes: float64(1), int64(3), object(3)
memory usage: 73.3+ KB
```

```
Out[5]:
                     viral load severity level hospitalization charges
              age
count 1338.000000 1338.000000
                               1338.000000
                                                    1338.000000
                     10.221233
                                                   33176.058296
         39.207025
                                  1.094918
mean
  std
         14.049960
                     2.032796
                                  1.205493
                                                   30275.029296
         18.000000
                     5.320000
                                  0.000000
                                                    2805.000000
  min
 25%
         27.000000
                     8.762500
                                  0.000000
                                                   11851.000000
         39.000000
                     10.130000
                                  1.000000
                                                   23455.000000
 50%
 75%
         51.000000
                     11.567500
                                  2.000000
                                                   41599.500000
         64.000000
                     17.710000
                                  5.000000
                                                  159426.000000
  max
In [6]:
df.describe(include = 'object')
Out[6]:
         sex smoker
                        region
 count 1338
                          1338
                1338
unique
           2
                  2
                            4
   top male
                 no southeast
         676
                1064
                          364
  freq
In [7]:
#Checking Null Values
df.isna().sum()
Out[7]:
                                 0
age
sex
                                 0
smoker
region
viral load
                                 0
severity level
                                 0
hospitalization charges
                                 0
dtype: int64
In [8]:
#Checking Duplicates
df.duplicated().sum()
Out[8]:
1
In [9]:
#Getting duplicate row
df[df.duplicated()]
```

In [10]:

0

4099

region viral load severity level hospitalization charges

10.2

Out[9]:

581

sex smoker

19 male

no northwest

```
#removing auplicate row
df.drop(581,axis=0,inplace=True)
```

-----UNI-VARIATE ANALYSIS------

4

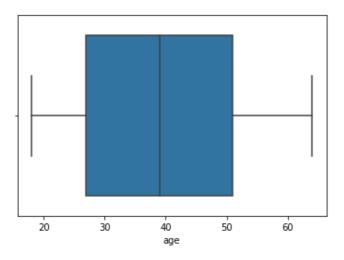
18 **▶** 1

In [11]:

```
#checking if we have any outliers in age
sns.boxplot(df['age'])
```

Out[11]:

<AxesSubplot:xlabel='age'>

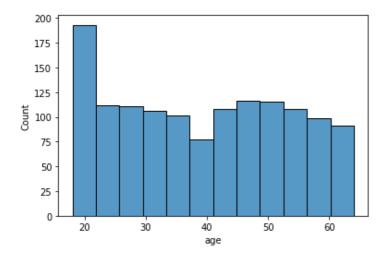


In [12]:

```
sns.histplot(df['age'])
```

Out[12]:

<AxesSubplot:xlabel='age', ylabel='Count'>

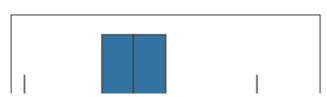


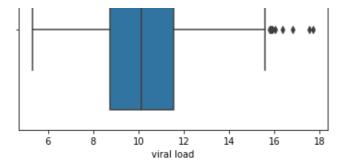
In [13]:

#checking if we have any outliers in viral load
sns.boxplot(df['viral load'])

Out[13]:

<AxesSubplot:xlabel='viral load'>



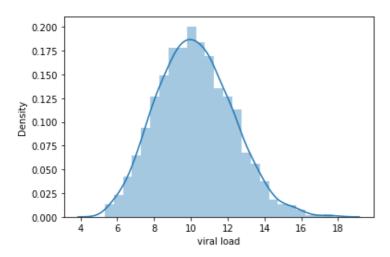


In [14]:

```
sns.distplot(df['viral load'])
```

Out[14]:

<AxesSubplot:xlabel='viral load', ylabel='Density'>



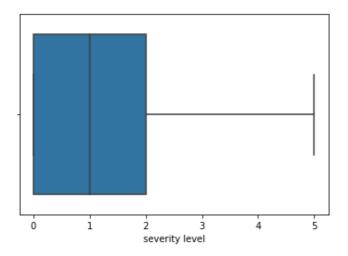
viral load column follows normal distribution

In [15]:

```
#checking if we have any outliers in severity level
sns.boxplot(df['severity level'])
```

Out[15]:

<AxesSubplot:xlabel='severity level'>



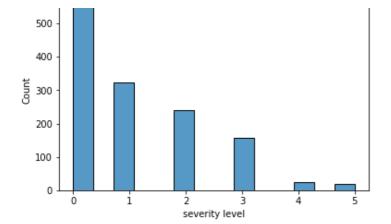
In [16]:

```
sns.histplot(df['severity level'])
```

Out[16]:

<AxesSubplot:xlabel='severity level', ylabel='Count'>

600

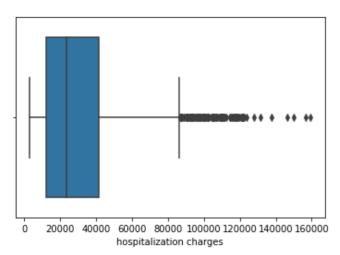


In [17]:

```
sns.boxplot(df['hospitalization charges'])
```

Out[17]:

<AxesSubplot:xlabel='hospitalization charges'>

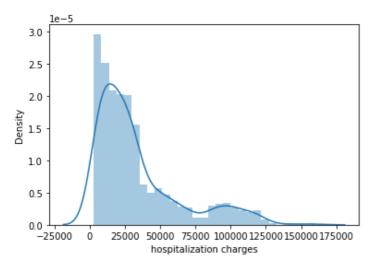


In [18]:

```
sns.distplot(df['hospitalization charges'])
```

Out[18]:

<AxesSubplot:xlabel='hospitalization charges', ylabel='Density'>



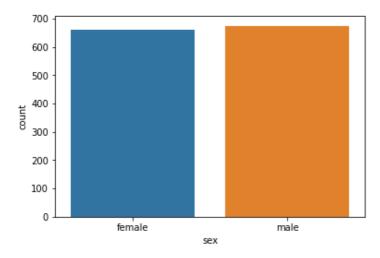
Hospitalization charges is extremely right skewed distribution.

```
In [19]:
```

```
sns.countplot(df['sex'])
```

Out[19]:

<AxesSubplot:xlabel='sex', ylabel='count'>



In [20]:

```
df['sex'].value counts(normalize=True)
```

Out[20]:

male 0.504862 female 0.495138

Name: sex, dtype: float64

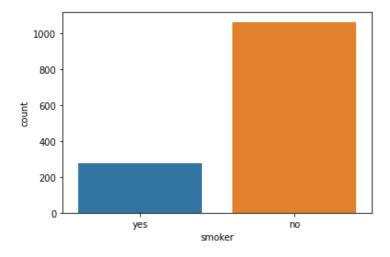
There are almost equal amount of male and female patients and there is a just mere difference of 0.05 % between male and female count

In [21]:

```
sns.countplot(df['smoker'])
```

Out[21]:

<AxesSubplot:xlabel='smoker', ylabel='count'>



In [22]:

```
df['smoker'].value counts(normalize=True)
```

Out[22]:

no 0.795064 yes 0.204936

Name: smoker, dtype: float64

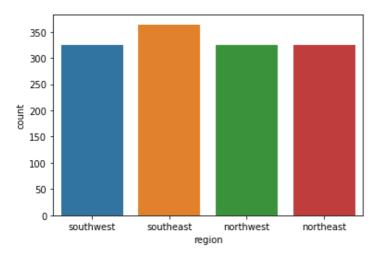
Almost 80 percent of the patients are non smokers, onlu 20 percent of the patients are smokers

In [23]:

```
sns.countplot(df['region'])
```

Out[23]:

<AxesSubplot:xlabel='region', ylabel='count'>



In [24]:

```
df['region'].value_counts(normalize=True)
```

Out[24]:

 southeast
 0.272251

 southwest
 0.243082

 northwest
 0.242334

 northeast
 0.242334

Name: region, dtype: float64

all the regions have almost same proportion of patients except south east region. South East has 0.03% larger number of patients compared to other regions

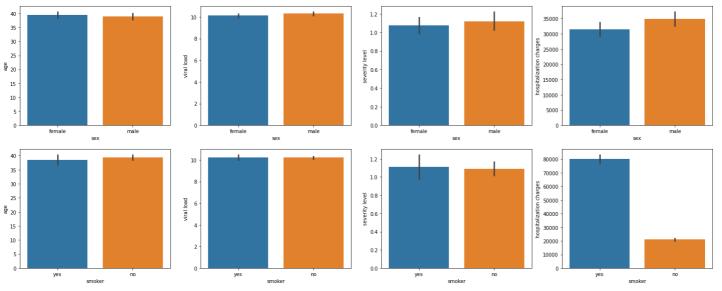
---- BI-VARIATE ANALYSIS -----

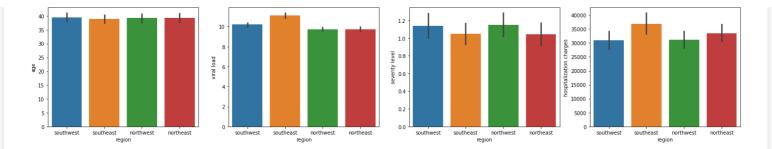
In [25]:

Þ

```
#Relation Between numerical and categorical variables
num_col=['age','viral load','severity level','hospitalization charges']
cat_col=['sex','smoker','region']

fig, axes = plt.subplots(3, 4, figsize=(25, 15))
for i in range(len(cat_col)):
    for j in range(len(num_col)):
        sns.barplot(df[cat_col[i]],df[num_col[j]],ax=axes[i, j])
```





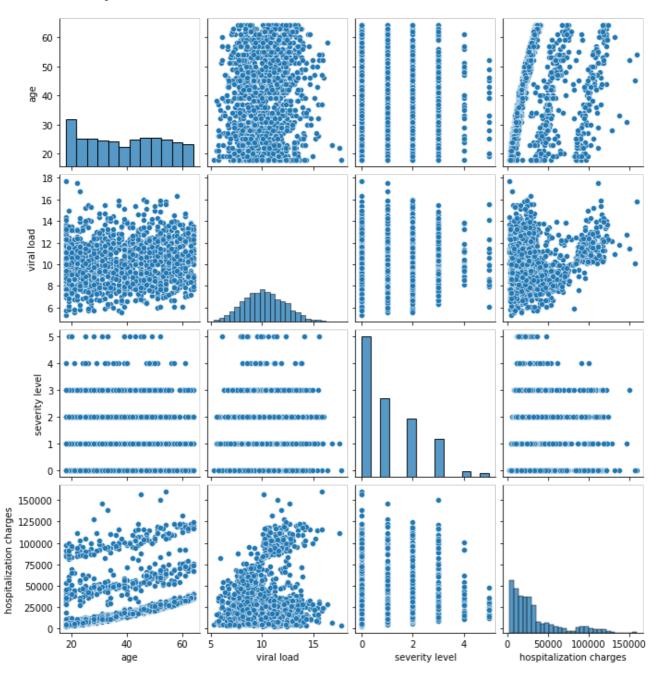
- Proportion of male and female are same across all the regions except in south east. In South east Male population is graeter than female
- Hospitalisation charges for female patients is lower compared to male patients
- All the regions have same age groups
- Southeast region have high viral load and pay high amount of hospitalisation charges compared to other regions

In [26]:

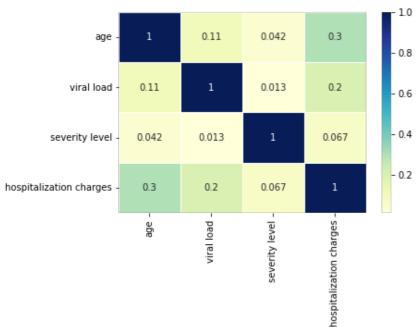
#Relation Between numerical variables
sns.pairplot(df)

Out[26]:

<seaborn.axisgrid.PairGrid at 0x1b8e04d32e0>



```
نا لا الما الما
sns.heatmap(df.corr(), cmap ="YlGnBu", annot=True, linewidths = 0.5)
Out [27]:
<AxesSubplot:>
                                                            1.0
                              0.11
                                       0.042
                                                 0.3
              age
                                                            0.8
```



- None of the numerical columns are either highly positively or negitively correalted
- Age and Viral load columns are slightly positively correlated to hospilization charges
- Age and Viral load columns are slightly positively correlated

In [28]:

```
#relation between categorical variables
fig, axes = plt.subplots(1,6, figsize=(30,5))
count=0
for i in range(len(cat col)):
    for j in range(len(cat col)):
        if i!=j:
             sns.histplot(x=cat_col[i], hue=cat_col[j], data=df, stat="count", multiple="
stack", ax=axes[count])
             count+=1
            yes no
                                                                  25
                 300
                                 400
                                                  400
 200
                 200
```

MULTI-VARIATE ANALYSIS-

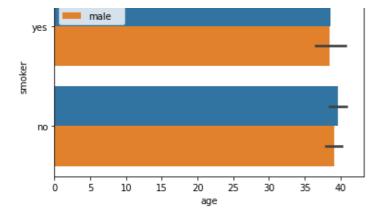
```
In [30]:
```

```
sns.barplot(df['age'], df["smoker"], hue=df['sex'])
```

Out[30]:

<AxesSubplot:xlabel='age', ylabel='smoker'>

```
sex
female
```

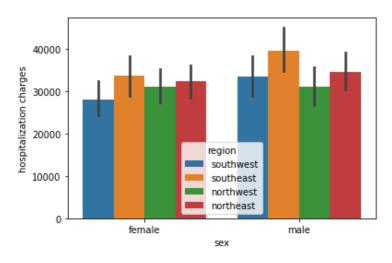


In [31]:

```
sns.barplot(df['sex'],df['hospitalization charges'],hue=df['region'])
```

Out[31]:

<AxesSubplot:xlabel='sex', ylabel='hospitalization charges'>



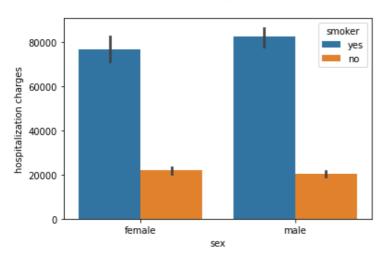
- All the regions have male patients greater than female patients except in NorthWest. in NorthWest female patients are sligtly larger compared to male
- Lowest number of female patient count was recorded in South West
- . Southeast records largest number of male and female patients compared to all other regions

In [32]:

```
sns.barplot(df['sex'],df['hospitalization charges'],hue=df['smoker'])
```

Out[32]

<AxesSubplot:xlabel='sex', ylabel='hospitalization charges'>



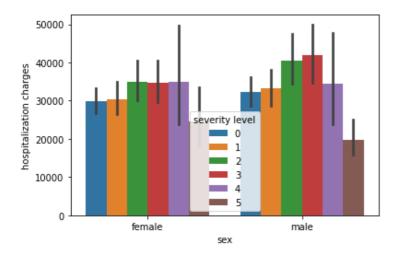
 Hospitalisation charges for people who smoke is way larger than hospitalisation of charges who doesnt smoke

In [33]:

```
sns.barplot(df['sex'],df['hospitalization charges'],hue=df['severity level'])
```

Out[33]:

<AxesSubplot:xlabel='sex', ylabel='hospitalization charges'>



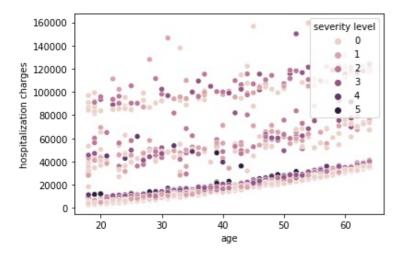
- Patients who have severity level 5 has less hospitalization charges compared to other severity levels
- Female patients of severity level 0 are higher compared to male patients of severity level 0
- Female patients of severity level 1,2,3,4 have less hospitalization charges compared to male patients of severity level 1,2,3,4

In [34]:

```
sns.scatterplot(df['age'],df['hospitalization charges'],hue=df['severity level'])
```

Out[34]:

<AxesSubplot:xlabel='age', ylabel='hospitalization charges'>

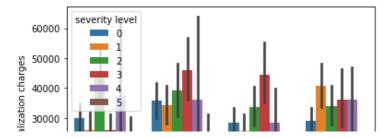


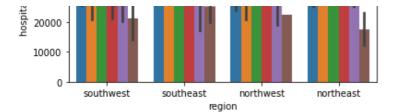
In [35]:

```
sns.barplot(df['region'], df['hospitalization charges'], hue=df['severity level'])
```

Out[35]:

<AxesSubplot:xlabel='region', ylabel='hospitalization charges'>





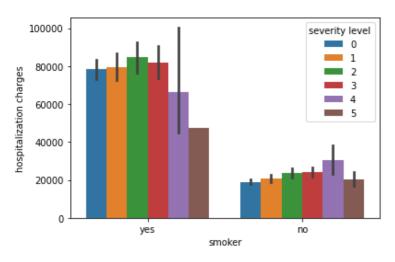
- Southwest region has higher cases of severity 2 level
- Southeast and north west region has higher cases of severity 3 level
- Northeast has higher cases of severity 1 level

In [36]:

sns.barplot(df['smoker'], df['hospitalization charges'], hue=df['severity level'])

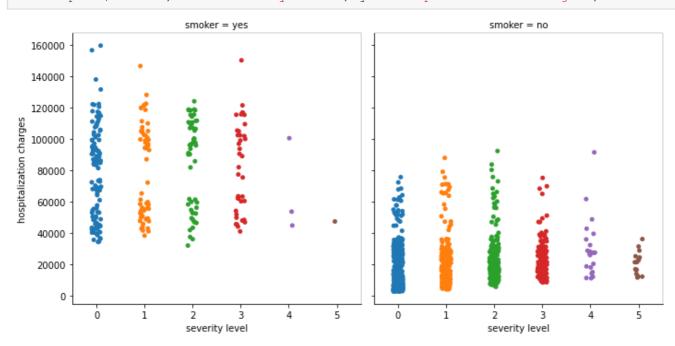
Out[36]:

<AxesSubplot:xlabel='smoker', ylabel='hospitalization charges'>



In [37]:

sns.catplot(data=df, x = 'severity level', y = 'hospitalization charges', col='smoker');



Hypothesis Testing

greater than those who don't? (T-test Right tailed)

T-TEST:

A t-test can only be used when comparing the means of two groups (a.k.a. pairwise comparison). If you want to compare more than two groups, or if you want to do multiple pairwise comparisons, use an ANOVA test or a post-hoc test.

The t-test is a parametric test of difference, meaning that it makes the same assumptions about your data as other parametric tests. The t-test assumes your data:

- are independent
- are (approximately) normally distributed.
- have a similar amount of variance within each group being compared (a.k.a. homogeneity of variance)

Checking Assumptions For T-Test

```
In [38]:

df['smoker'].value_counts()

Out[38]:

no    1063
yes    274
Name: smoker, dtype: int64
```

Sample indedependence exists since we are randomly selecting 274 values for smoker and non smoker.

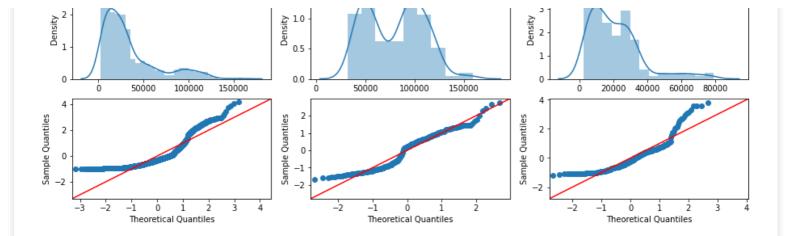
```
In [39]:
smoker=df[df['smoker']=='yes'].sample(274)
non_smoker=df[df['smoker']=='no'].sample(274)
```

Normality Test

```
In [40]:
```

```
col=[df, smoker, non_smoker]
name=['given data (df)', 'smoker', 'non_smoker']
fig, axes = plt.subplots(2, 3, figsize=(15, 5))
for i in range(len(col)):
    sns.distplot(ax=axes[0, i], x=col[i]['hospitalization charges'])
    sm.qqplot(col[i]['hospitalization charges'], line='45', fit=True, dist=stats.norm, ax=ax
es[1, i])
    p=stats.normaltest(col[i]['hospitalization charges']).pvalue
    if p<0.05:
        print('hospitalization charges of '+name[i]+' doesnt follow normal distribution
p_val:'+str(p))
    else:
        print('hospitalization charges of '+name[i]+' follow normal distribution p_val:'
+str(p))</pre>
```

```
hospitalization charges of given data (df) doesnt follow normal distribution p_val:8.7616 68448064204e-74 hospitalization charges of smoker doesnt follow normal distribution p_val:5.5604327030590 49e-14 hospitalization charges of non_smoker doesnt follow normal distribution p_val:5.189683606 987243e-19
```



Levene test to check equality of variances

```
In [41]:
```

```
import scipy.stats as st

stat,p_val=st.levene(smoker['hospitalization charges'],non_smoker['hospitalization charges'],center='median')

if p_val<0.05:
    print('smoker and non smoker groups doesnot have similar amount of variance')

else:
    print('smoker and non smoker groups have similar amount of variance')</pre>
```

smoker and non smoker groups doesnot have similar amount of variance

Right tailed T-Test to prove hospitalization charges of people who do smoking are greater than those who don't

Hypothesis:

```
H_0: \mu_{non-smoker} \ <= \mu_{smoker} \ H_1: \mu_{non-smoker} \ > \mu_{smoker} \ <lpha = 0.05
```

where, μ is the sample mean of hospitalization charges of people smoke and doesn't smoke

```
In [42]:
```

```
p=stats.ttest_ind(smoker['hospitalization charges'], non_smoker['hospitalization charges']
,equal_var=False,alternative='greater').pvalue
```

```
In [43]:
```

```
if p<0.05:
    print('Alternate Hypothesis is accepted - Hospitalization charges of people who do sm
oking are greater than those who donot smoke')
else:
    print('Null Hypothesis is accepted - Hospitalization charges of people who do smoking
are less than or equal to those who donot smoke')</pre>
```

Alternate Hypothesis is accepted - Hospitalization charges of people who do smoking are g reater than those who do not smoke

Prove (or disprove) with statistical evidence that the viral load of females is different from that of males

```
In [44]:

df['sex'].value_counts()

Out[44]:

male    675
female    662
Name: sex, dtype: int64
```

Checking Assumptions For T-Test

Sample indedependence exists since we are randomly selecting 500 values for male and female.

```
In [45]:
```

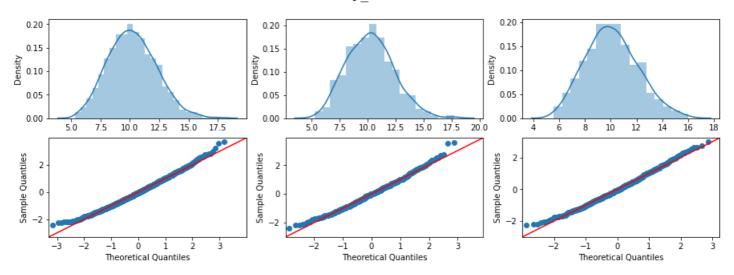
```
male=df[df['sex']=='male'].sample(500)
female=df[df['sex']=='female'].sample(500)
```

Normality Test

```
In [46]:
```

```
col=[df,male, female]
name=['given data (df)', 'male', 'female']
fig, axes = plt.subplots(2, 3, figsize=(15, 5))
for i in range(len(col)):
    sns.distplot(ax=axes[0, i], x=col[i]['viral load'])
    sm.qqplot(col[i]['viral load'], line='45', fit=True, dist=stats.norm, ax=axes[1, i])
    p=stats.normaltest(col[i]['viral load']).pvalue
    if p<0.05:
        print('->'+name[i]+' doesnt follow normal distribution p_val:'+str(p))
    else:
        print('-->'+name[i]+' follow normal distribution p_val:'+str(p))
```

- ->given data (df) doesnt follow normal distribution p val:0.00015815069842074636
- ->male doesnt follow normal distribution p val:0.012121224057439324
- ->female doesnt follow normal distribution p val:0.026229419355718542



Levene test to check equality of variances

```
In [47]:
```

```
stat,p_val=st.levene(male['viral load'],female['viral load'],center='mean')
if p_val<0.05:
    print('smoker and non smoker groups doesnot have similar amount of variance')</pre>
```

```
else:
   print('smoker and non smoker groups have similar amount of variance')
```

smoker and non smoker groups have similar amount of variance

T-Test to prove Viral load of females is different from that of males

Hypothesis:

```
H_0: \mu_{Female} \ = \mu_{Male} \ H_1: \mu_{Female} \ 
eq \mu_{Male} \ 
eq \alpha = 0.05
```

where, μ_{Female} and μ_{Male} are the sample mean of viral load of female and male

```
In [48]:
```

```
p=stats.ttest_ind(male['viral load'], female['viral load'], alternative='two-sided').pvalu
e
p
Out[48]:
0.1656281004679383

In [49]:

if p<0.05:
    print('Alternate Hypothesis is accepted-Viral load of females is different from that of males')
else:</pre>
```

print('Null Hypothesis is accepted-Viral load of females is similar to that of males'

Null Hypothesis is accepted-Viral load of females is similar to that of males

Is the proportion of smoking significantly different across different regions?

Chi-square test:

A chi-square (χ 2) statistic is a test that measures how a model compares to actual observed data.

Assumptions:

- 1. Both variables are categorical.
- 2. All observations are independent.
- 3. Cells in the contingency table are mutually exclusive.
- 4. Expected value of cells should be 5 or greater in at least 80% of cells.

Checking Assumptions

```
In [50]:
ctab=pd.crosstab(df['smoker'],df['region'])
ctab
```

```
Out[50]:
```

region northeast northwest southeast southwest

smoker

no	257	266	273	267
yes	67	58	91	58

- Variables(Smoker and region) are categorical and independent
- Cells in the contingency table are mutually exclusive.both the variables are very different from each other
- Expected value of cells should be 5 or greater in at least 80% of cells.

Chi Square test to prove of proportion of smoking significantly different across different regions

Hypothesis:

Null Hypothesis: Proportion of smoking is same across different regions

Alternate Hypothesis: Proportion of smoking is not same across different regions

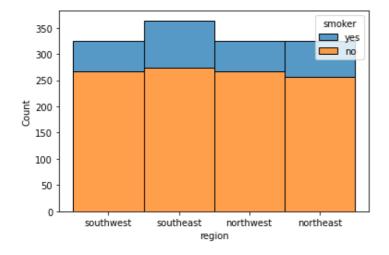
 $\alpha = 0.05$

In [51]:

sns.histplot(binwidth=0.5, x="region", hue="smoker", data=df, stat="count", multiple="state")

Out[51]:

<AxesSubplot:xlabel='region', ylabel='Count'>



In [52]:

```
stat, p, dof, expected = chi2 contingency(ctab)
```

In [53]:

```
print(dof, stat, p)
```

3 7.277902541321909 0.06354826573182332

In [54]:

```
if p<0.05:
    print('Alternate Hypothesis is accepted - Proportion of smoking is not same across di
fferent regions')
else:
    print('Null Hypothesis is accepted - Proportion of smoking is same across different r
egions')</pre>
```

Null Hypothesis is accepted - Proportion of smoking is same across different regions

Prove the mean viral load of women with 0 Severity level, 1 Severity level, and 2 Severity level the same?

ANNOVA:

ANOVA, which stands for Analysis of Variance, is a statistical test used to analyze the difference between the means of more than two groups.

we use a one-way ANOVA when you have collected data about one categorical independent variable and one quantitative dependent variable. The independent variable should have at least three levels

Assumptions:

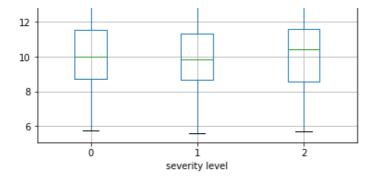
In [55]:

14

The results of a one-way ANOVA can be considered reliable as long as the following assumptions are met:

- 1. Response variable residuals are normally distributed (or approximately normally distributed).
- 2. Variances of populations are equal.
- 3. Responses for a given group are independent and identically distributed normal random variables (not a simple random sample (SRS)).

```
df['severity level'].value counts(normalize=True)
Out [55]:
0
     0.428571
1
     0.242334
2
     0.179506
3
     0.117427
4
     0.018699
5
     0.013463
Name: severity level, dtype: float64
In [56]:
#taking sample of female patients with severity level 0,1,2
sample=df[(df['severity level']!=4) & (df['severity level']!=5) & (df['severity level']!
=3) & (df['sex'] == 'female')]
In [57]:
sample['severity level'].value counts()
Out[57]:
0
     289
     158
1
     119
Name: severity level, dtype: int64
In [58]:
sample.boxplot('viral load',by='severity level')
Out[58]:
<AxesSubplot:title={'center':'viral load'}, xlabel='severity level'>
            Boxplot grouped by severity level
16
          Ó
```



Checking Assumptions

Sample indedependence exists since we are randomly selecting 100 values for all the three samples.

```
In [59]:
```

```
sample1=sample[sample['severity level']==0].sample(100)
sample2=sample[sample['severity level']==1].sample(100)
sample3=sample[sample['severity level']==2].sample(100)
```

Normality Test

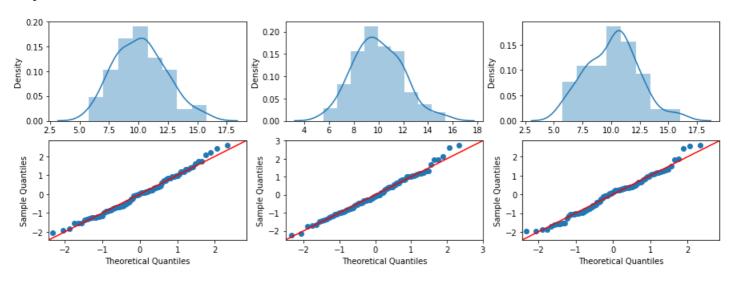
```
In [60]:
```

```
col=[sample1, sample2, sample3]
```

```
In [61]:
```

```
fig, axes = plt.subplots(2, 3, figsize=(15, 5))
for i in range(len(col)):
    sns.distplot(ax=axes[0, i], x=col[i]['viral load'])
    sm.qqplot(col[i]['viral load'], line='45', fit=True, dist=stats.norm, ax=axes[1, i])
    p=stats.normaltest(col[i]['viral load']).pvalue
    if p<0.05:
        print('sample'+str(i+1)+' doesnt follow normal distribution')
    else:
        print('sample'+str(i+1)+' follow normal distribution')</pre>
```

```
sample1 follow normal distribution
sample2 follow normal distribution
sample3 follow normal distribution
```



Levene test to check equality of variances

```
stat,p_val=st.levene(sample1['viral load'],sample2['viral load'],sample3['viral load'],c
enter='mean')
```

In [63]:

```
if p_val<0.05:
    print('Variance of all the three samples are equal')
else:
    print('Variance of all the three samples are not equal')</pre>
```

Variance of all the three samples are not equal

Anova to check if mean viral load of women with Severity levels 0,1,2 are the same

```
In [64]:
```

```
import pingouin as pg
aov = pg.anova(data=sample, dv='viral load', between='severity level', detailed=True)
print(aov)
           Source
                            SS
                                 DF
                                           MS
                                                       F
                                                             p-unc
                                                                        np2
                      2.741077
                                 2
                                     1.370538
                                                0.335506
                                                          0.715119
                                                                    0.00119
  severity level
1
           Within 2299.847921
                                563 4.084987
                                                                        NaN
                                                     NaN
                                                               NaN
```

In [65]:

```
if p<0.05:
    print('Alternate Hypothesis is accepted-mean viral load of women with 0 Severity leve
1 , 1 Severity level, and 2 Severity level not the same')
else:
    print('Null Hypothesis is accepted-mean viral load of women with 0 Severity level , 1
Severity level, and 2 Severity level the same')</pre>
```

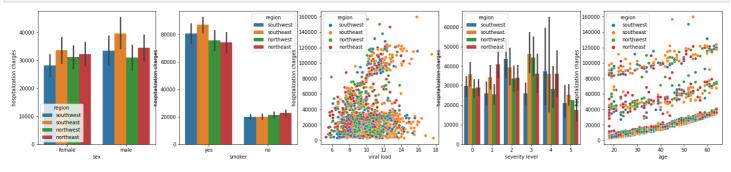
Null Hypothesis is accepted-mean viral load of women with 0 Severity level , 1 Severity level, and 2 Severity level the same

Which variables are significant in predicting the reason for hospitalization for different regions

```
In [66]:
```

```
col=['sex','smoker','viral load','severity level','age']
fig, axes = plt.subplots(1, 5, figsize=(25, 5))
c=0
for i in col:

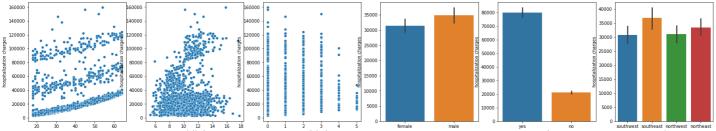
if i=='age' or i=='viral load':
    sns.scatterplot(df[i],df['hospitalization charges'],hue=df['region'],ax=axes[c])
else:
    sns.barplot(df[i],df['hospitalization charges'],hue=df['region'],ax=axes[c])
c+=1
```



In [69]:

```
col=['age', 'viral load', 'severity level','sex', 'smoker', 'region']
```

```
fig, axes = plt.subplots(1, 6, figsize=(28, 5))
c=0
for i in col:
    if i in ['sex', 'smoker', 'region']:
        sns.barplot(df[i],df['hospitalization charges'],ax=axes[c])
    else:
        sns.scatterplot(df[i],df['hospitalization charges'],ax=axes[c])
    c+=1
```



 Smoker column is more significant and age and viral load are less significant in predicting the reason for hospitalization for different regions

```
In [ ]:
```