Import libraries

In [83]:
```python
import pandas as pd # Data manipulation
import numpy as np # Linear algebra
import warnings # Ignore warnings
import seaborn as sns #plots
import matplotlib.pyplot as plt # plots
```

In [84]:
```python
warnings.filterwarnings("ignore")
```

Load Data

In [85]:
```python
df=pd.read_csv("/content/drive/MyDrive/Datasets/insurance.csv")
```

In [86]:
```python
df.head()
```

Out[86]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

Data Visualization

Unique Values

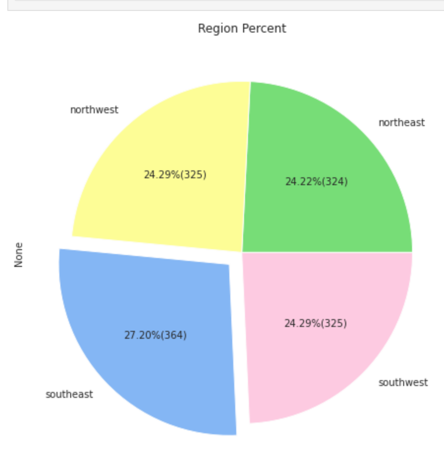
In [87]:
```python
{col:list(df[col].unique()) for col in df.select_dtypes("object")}
```

Out[87]:
```
{'region': ['southwest', 'southeast', 'northwest', 'northeast'],
 'sex': ['female', 'male'],
 'smoker': ['yes', 'no']}
```

In [88]:
```python
class Pie_plot():

  def __init__(self,serie,title,colors,explode):

    self.serie=serie
    self.title=title
    self.colors=colors
    self.explode=explode

  def pie(self):


    self.serie.plot(kind='pie',title=self.title, figsize=[20,8],
                    colors=self.colors,explode=self.explode,
          autopct=lambda p: '{:.2f}%({:.0f})'.format(p,(p/100)*self.serie.sum()))


class Pie_Option(Pie_plot):

  def option_plot(self,option):

    if option== "region":


      super().pie()


    elif option == "smoker":

      super().pie()


    elif option == "sex":

      super().pie()

    elif option == "children":

      super().pie()
```

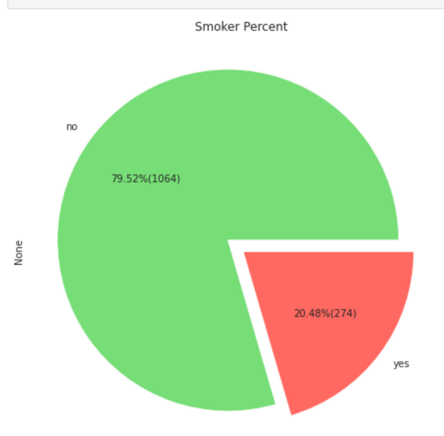
In [89]:
```python
region_serie=df.groupby('region').size()
title="Region Percent"
colors=['#77dd77','#fdfd96','#84b6f4','#fdcae1']
explode= [0,0,0.1,0]
```

In [90]:
```python
region_pie=Pie_Option(region_serie,title,colors,explode)
region_pie.option_plot("region")
```



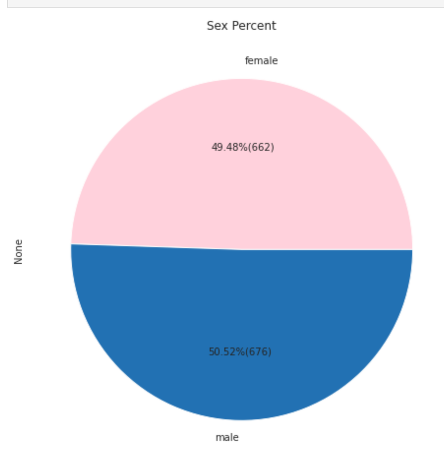
In [91]:
```python
smoker_serie=df.groupby('smoker').size()
title="Smoker Percent"
colors=['#77dd77','#ff6961']
explode=[0.1,0.01]
```

In [92]:
```python
smoker_pie=Pie_Option(smoker_serie,title,colors,explode)
smoker_pie.option_plot("smoker")
```



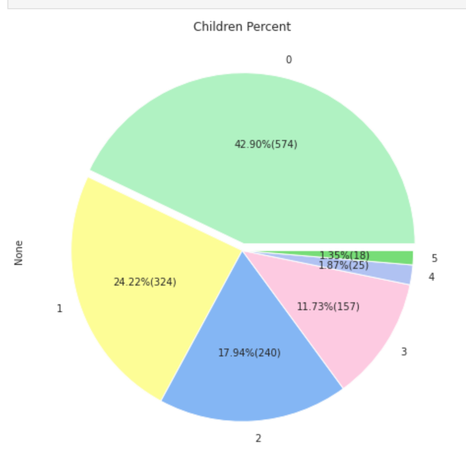
In [93]:
```python
sex_serie=df.groupby('sex').size()
title="Sex Percent"
colors=['#FFD1DC','#2271b3']
explode=[0,0]
```

In [94]:
```python
smoker_pie=Pie_Option(sex_serie,title,colors,explode)
smoker_pie.option_plot("sex")
```



In [95]:
```python
children_serie=df.groupby('children').size()
title='Children Percent'
colors=['#b0f2c2','#fdfd96','#84b6f4','#fdcae1','#b0c2f2','#77dd77']
explode=[0.04,0,0,0,0,0]
```

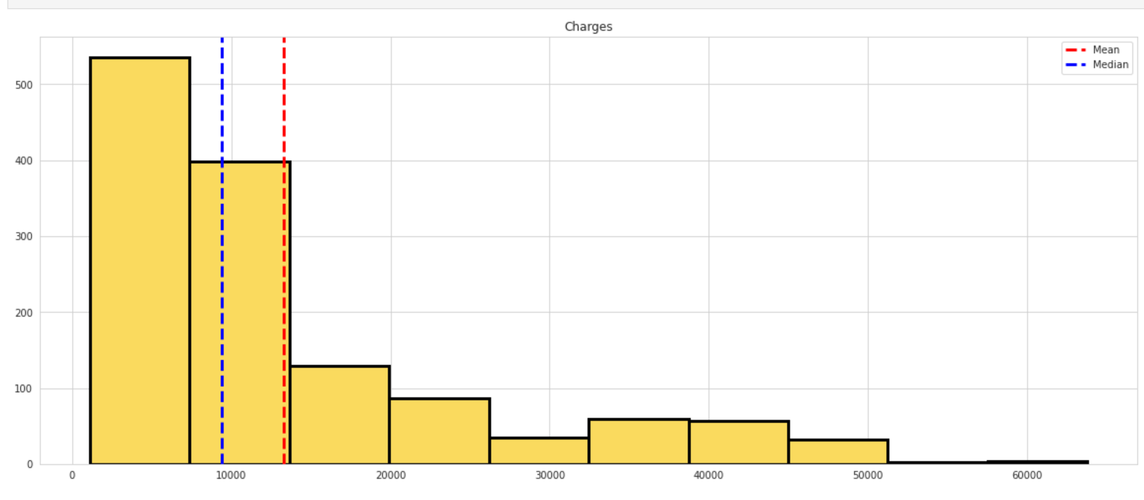
In [96]:
```python
children_pie=Pie_Option(children_serie,title,colors,explode)
children_pie.option_plot("children")
```



In [97]:
```python
sns.set_style(style="whitegrid")
```

In [98]:
```python
def histogram(feature,title):


  fig,ax=plt.subplots(1,1,figsize=(20,8))

  ax.set_title(title)
  ax.hist(df[feature],ec="k",color="#FADA5E",lw=3)


  ax.axvline(df[feature].mean(),
          color="red",
          linestyle="--",
          lw=3,label="Mean")


  ax.axvline(df[feature].median(),
          color="blue",
          linestyle="--",
          lw=3,label="Median")

  ax.legend()

  plt.show()
```

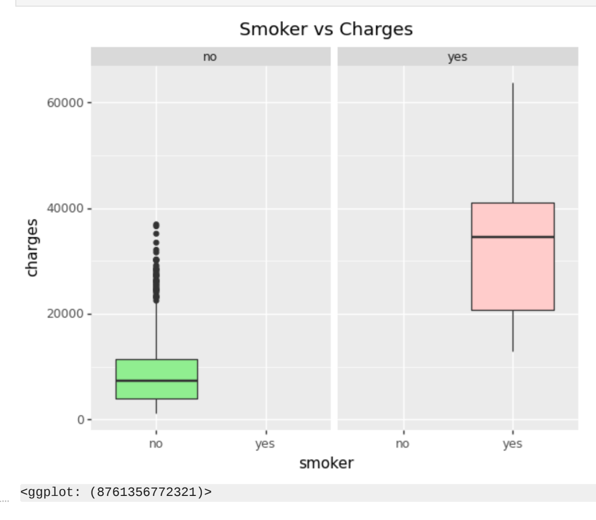
In [99]:
```python
histogram("charges","Charges")
```



In [100]:
```python
from plotnine import ggplot, aes, geom_point,geom_boxplot,labs,facet_wrap,scale_fill_manual,theme
```

The price of insurance is higher for people who smoke?

In [101]:
```python
(

    ggplot(df)
    + aes(x="smoker",y="charges",fill="smoker")
    + geom_boxplot() + labs(title="Smoker vs Charges")
    + facet_wrap("smoker")
    + theme(legend_position="none")
    +  scale_fill_manual(values=["#90ee90","#ffcccb"])



)
```



Out[101]:
```
<ggplot: (8761356772321)>
```

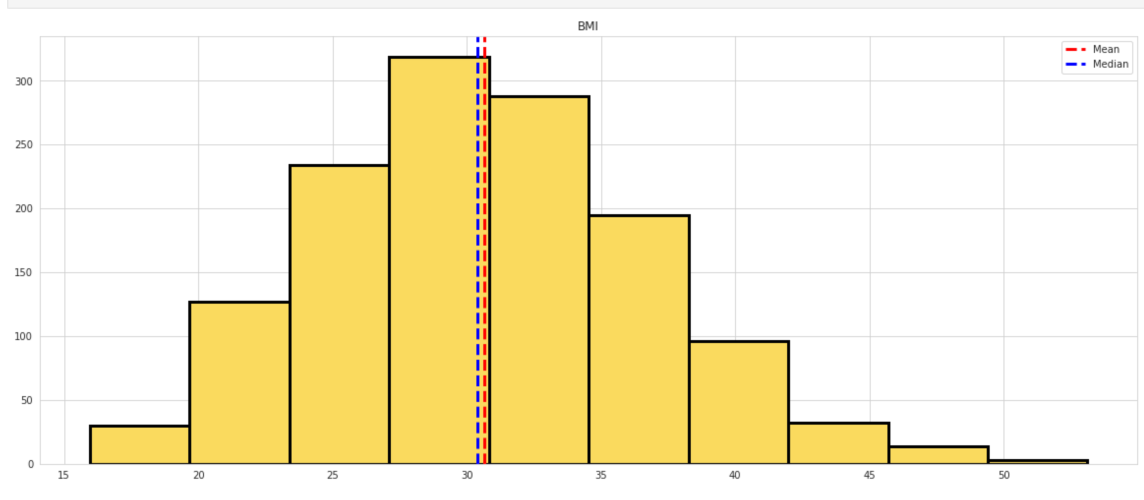
We observe a strong presence of outliers, for the category of non-smokers.

In [102]:
```python
df.groupby("smoker")["charges"].mean()
```

Out[102]:
```
smoker
no      8434.268298
yes    32050.231832
Name: charges, dtype: float64
```

The average price of smokers is considerably much higher than non-smokers. Since smokers generally have a worse state of health and as a consequence the medical charge will be higher.

In [103]:
```python
histogram("bmi","BMI")
```

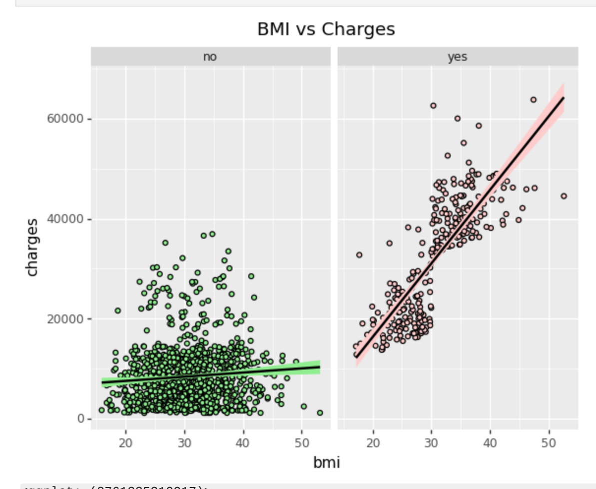


Most of the BMI data is within a normal distribution. But even so, it is possible to appreciate outlier values in the upper range.

In [104]:
```python
from plotnine.facets import facet_grid

from plotnine.geoms import geom_smooth

def scatter_plots(feature,title):

  return((ggplot(df)
    + aes(x=feature,y="charges",fill="smoker",alpha=0.1)
    + geom_point() + labs(title=title,x=feature)
    + facet_wrap("smoker")
    + theme(legend_position="none")
    +  scale_fill_manual(values=["#90ee90","#ffcccb"])
    + geom_smooth(method="lm")))
```

People with a high BMI the insurance charge is higher?

In [105]:
```python
scatter_plots("bmi","BMI vs Charges")
```

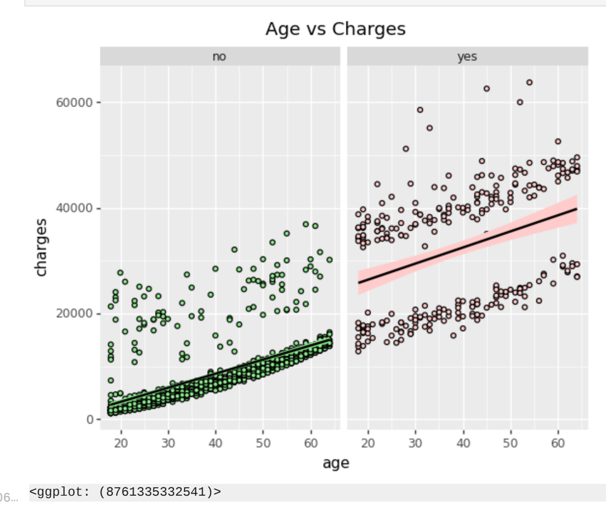


Out[105]:
```
<ggplot: (8761335210917)>
```

- For non-smokers, the data trend remains constant.
- While for smokers the trend line is linear, that is, one value increases proportionally with another.

Does age influence the price of insurance?

In [106]:
```python
scatter_plots("age","Age vs Charges")
```



Out[106]:
```
<ggplot: (8761335332541)>
```

We observe 4 "clusters"

1. The first is for healthy people who do not smoke are healthy, as a consequence they do not have severe medical problems.
2. People who do not smoke but have significant health problems.
3. People who smoke but have a good health condition.
4. Users who smoke and have serious medical problems.

We could create an additional feature, to be able to classify users based on the degree of health of the user. Since, as we can see in the graph, the quality of health influences the medical position.

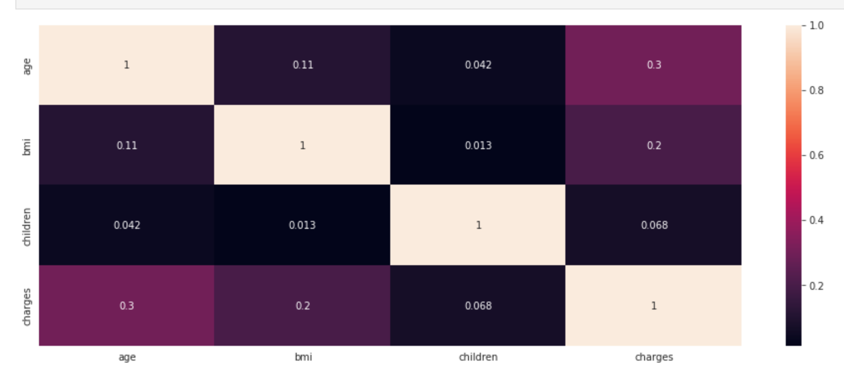
In [107]:
```python
corr_pearson=df.corr(method="pearson")
corr_spearman=df.corr(method="spearman")

def correlation_matrix(corr_matrix):

  plt.figure(figsize=(16, 6))
  sns.heatmap(corr_matrix,annot=True)

  plt.show()
```

Correlation Matrix

It is used to establish possible relationships between variables

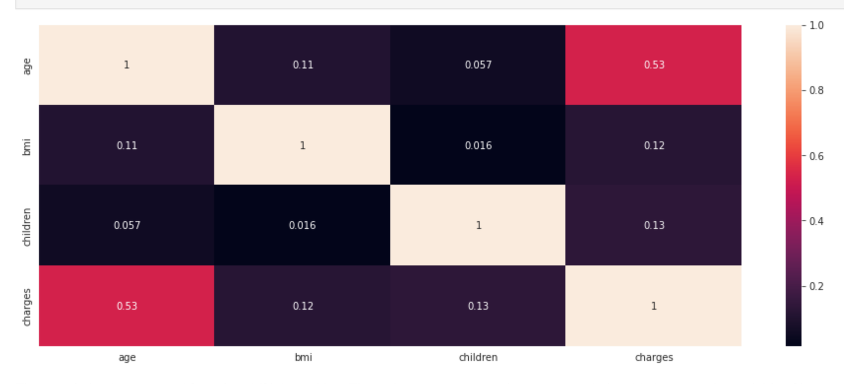
Pearson

In [108]:
```python
correlation_matrix(corr_pearson)
```



Spearman

In [109]:
```python
correlation_matrix(corr_spearman)
```



The correlation is measured from 0 to 1 if it is positive. There does not appear to be a strong relationship between the variable of interest. It is still too early to start ruling out variables, since these variables can complement the predictions.

Conclusion

- The variables that refer to describe some habits and characteristics of users influence the insurance charge.
- We discovered a new hidden characteristic in the dataset when comparing age with the price of insurance based on whether the user smokes or not, we could add another new variable to the problem that refers to the degree of the health problem.