```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

pd.plotting.register_matplotlib_converters()
%matplotlib inline
plt.style.use('seaborn-whitegrid')
pd.set_option('display.max_columns', 500)
warnings.filterwarnings("ignore")

from google.colab import files
uploaded = files.upload()

Choose Files insurance.csv
```

• **insurance.csv**(application/vnd.ms-excel) - 55628 bytes, last modified: 1/18/2022 - 100% done Saving insurance.csv to insurance.csv

```
data = pd.read_csv('insurance.csv')
data.head()
```

	age	sex	bmi	children	smoker	region	charges	7
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	

```
print(f'Shape of the data: {data.shape}')
print(f'There are {data.shape[0]} rows in the data.')
```

Shape of the data: (1338, 7) There are 1338 rows in the data.

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):

#	Column	Non-Null Count	Dtype
0	age	1338 non-null	int64
1	sex	1338 non-null	object
2	bmi	1338 non-null	float64
3	children	1338 non-null	int64
4	smoker	1338 non-null	object
5	region	1338 non-null	object

```
charges 1338 non-null
                                    float64
      6
     dtypes: float64(2), int64(2), object(3)
     memory usage: 73.3+ KB
# What are the different datatypes present in the data?
data.dtypes.unique()
     array([dtype('int64'), dtype('0'), dtype('float64')], dtype=object)
# Let's check out individual columns:
data.columns
     Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object
# Transform the Index object to a series, and grouping by data types:
g = data.columns.to_series().groupby(data.dtypes).groups
g
     {int64: ['age', 'children'], float64: ['bmi', 'charges'], object: ['sex', 'smoker',
# let's create a dictionary containing various datatypes (Integer, Float and object) and t
dt = {k.name: v for k, v in g.items()}
# Display the columns by different datatypes:
attributes_by_datatype = pd.DataFrame(list(dt.values()), index = dt.keys(), columns = ['At
attributes_by_datatype
              Attr 1 Attr 2 Attr 3
       int64
                 age children
                                None
      float64
                     charges
                                None
                 bmi
      object
                               region
                 sex
                      smoker
# Unique values for 'children':
sorted(data['children'].unique())
     [0, 1, 2, 3, 4, 5]
#Let's check if the DataFrame contains any missing or null values.:
data.isnull().any()
                 False
     age
                 False
     sex
                 False
     bmi
     children
                 False
```

False

False

False

smoker region

charges

dtype: bool

#Summary:

data.describe().transpose()

	count	mean	std	min	25%	50%	:
age	1338.0	39.207025	14.049960	18.0000	27.00000	39.000	51.0000
bmi	1338.0	30.663397	6.098187	15.9600	26.29625	30.400	34.6937
children	1338.0	1.094918	1.205493	0.0000	0.00000	1.000	2.0000
charges	1338.0	13270.422265	12110.011237	1121.8739	4740.28715	9382.033	16639.912

```
# Let's construct a function that shows the summary and density distribution of a numerica
def summary(x):
    x_min = data[x].min()
    x_{max} = data[x].max()
    Q1 = data[x].quantile(0.25)
    Q2 = data[x].quantile(0.50)
    Q3 = data[x].quantile(0.75)
    print(f'5 Point Summary of {x.capitalize()} Attribute:\n'
          f'{x.capitalize()}(min) : {x_min}\n'
          f'Q1
                                  : {Q1}\n'
          f'Q2(Median)
                                  : {Q2}\n'
          f'Q3
                                  : {Q3}\n'
          f'{x.capitalize()}(max) : {x_max}')
    fig = plt.figure(figsize=(16, 10))
    plt.subplots_adjust(hspace = 0.6)
    sns.set_palette('pastel')
    plt.subplot(221)
    ax1 = sns.distplot(data[x], color = 'r')
    plt.title(f'{x.capitalize()} Density Distribution')
    plt.subplot(222)
    ax2 = sns.violinplot(x = data[x], palette = 'Accent', split = True)
    plt.title(f'{x.capitalize()} Violinplot')
    plt.subplot(223)
    ax2 = sns.boxplot(x=data[x], palette = 'cool', width=0.7, linewidth=0.6)
    plt.title(f'{x.capitalize()} Boxplot')
    plt.subplot(224)
    ax3 = sns.kdeplot(data[x], cumulative=True)
    plt.title(f'{x.capitalize()} Cumulative Density Distribution')
    plt.show()
# Let's take a closer look at the Boxplot, and calculate the measure of skewness and total
def box_plot(x = 'bmi'):
```

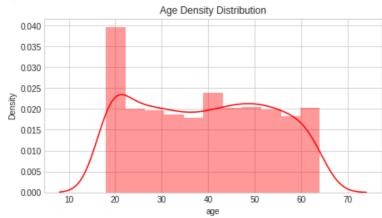
```
def add values(bp, ax):
        """ This actually adds the numbers to the various points of the boxplots"""
        for element in ['whiskers', 'medians', 'caps']:
            for line in bp[element]:
                # Get the position of the element. y is the label you want
                (x_1, y), (x_r, _) = line.get_xydata()
                # Make sure datapoints exist
                # (I've been working with intervals, should not be problem for this case)
                if not np.isnan(y):
                    x_{line\_center} = x_1 + (x_r - x_1)/2
                    y_line_center = y # Since it's a line and it's horisontal
                    # overlay the value: on the line, from center to right
                    ax.text(x_line_center, y_line_center, # Position
                            '%.2f' % y, # Value (3f = 3 decimal float)
                            verticalalignment='center', # Centered vertically with line
                            fontsize=12, backgroundcolor="white")
   fig, axes = plt.subplots(1, figsize=(4, 8))
   red_diamond = dict(markerfacecolor='r', marker='D')
   bp_dict = data.boxplot(column = x,
                             grid=True,
                             figsize=(4, 8),
                             ax=axes,
                             vert = True,
                             notch=False,
                             widths = 0.7,
                             showmeans = True,
                             whis = 1.5,
                             flierprops = red_diamond,
                             boxprops= dict(linewidth=3.0, color='black'),
                             whiskerprops=dict(linewidth=3.0, color='black'),
                             return_type = 'dict')
   add_values(bp_dict, axes)
   plt.title(f'{x.capitalize()} Boxplot', fontsize=16)
   plt.ylabel(f'{x.capitalize()}', fontsize=14)
   plt.show()
   skew = data[x].skew()
   Q1 = data[x].quantile(0.25)
   Q3 = data[x].quantile(0.75)
   IQR = Q3 - Q1
   total_outlier_num = ((data[x] < (Q1 - 1.5 * IQR)) | (data[x] > (Q3 + 1.5 * IQR))).sum(
   print(f'Mean {x.capitalize()} = {data[x].mean()}')
   print(f'Median {x.capitalize()} = {data[x].median()}')
   print(f'Skewness of {x}: {skew}.')
   print(f'Total number of outliers in {x} distribution: {total_outlier_num}.')
#Age Distribution:
summary('age')
```

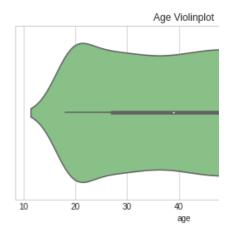
5 Point Summary of Age Attribute:

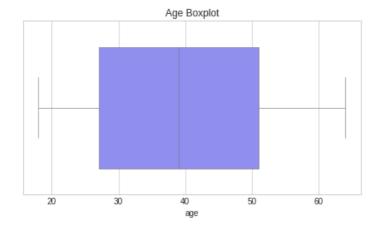
Age(min) : 18

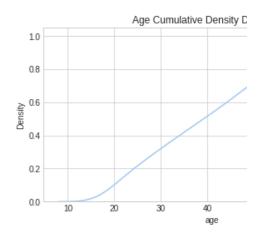
Q1 : 27.0 Q2(Median) : 39.0 Q3 : 51.0

Age(max): 64

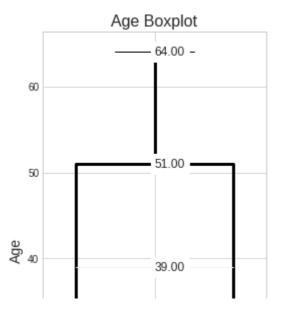








box_plot('age')



```
# How many of the insured have the age of 64?
df = data[data['age'] == data['age'].max()]
print(df.head())
print()
print(f'Total number of insured people with the age of 64: {len(df)}.')
```

	age	sex	bmi	children	smoker	region	charges
62	64	male	24.70	1	no	northwest	30166.61817
94	64	female	31.30	2	yes	southwest	47291.05500
199	64	female	39.33	0	no	northeast	14901.51670
328	64	female	33.80	1	yes	southwest	47928.03000
335	64	male	34.50	0	no	southwest	13822.80300

Total number of insured people with the age of 64: 22.

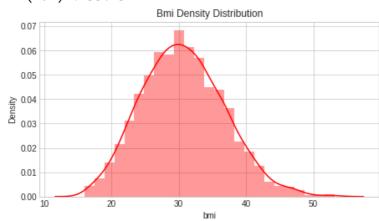
#BMI Distribution:
summary('bmi')

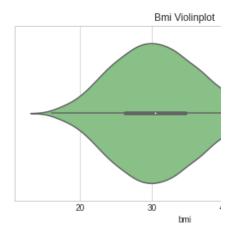
5 Point Summary of Bmi Attribute:

Bmi(min): 15.96

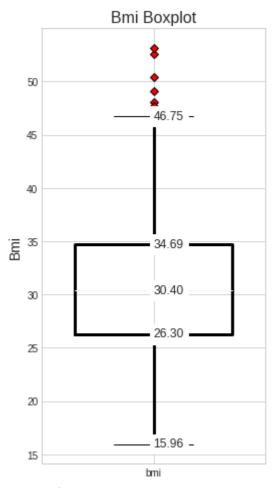
Q1 : 26.29625 Q2(Median) : 30.4 Q3 : 34.69375

Bmi(max) : 53.13





box_plot('bmi')



Mean Bmi = 30.663396860986538

Median Bmi = 30.4

Skewness of bmi: 0.2840471105987448.

Total number of outliers in bmi distribution: 9.

Who is the insured with the highest BMI, and how does his charges compare to the rest?
data[data['bmi'] == data['bmi'].max()]

age sex bmi children smoker region charges

data['charges'].mean(), data['charges'].median()

(13270.422265141257, 9382.033)

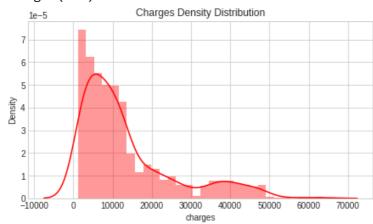
#Charges Distribution: summary('charges')

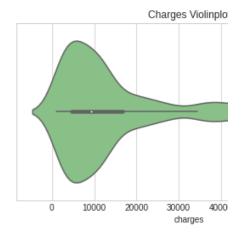
5 Point Summary of Charges Attribute:

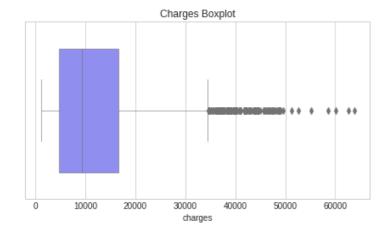
Charges(min) : 1121.8739

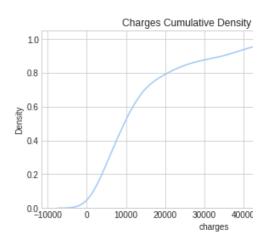
Q1 : 4740.28715 Q2(Median) : 9382.033 Q3 : 16639.912515

Charges(max): 63770.42801

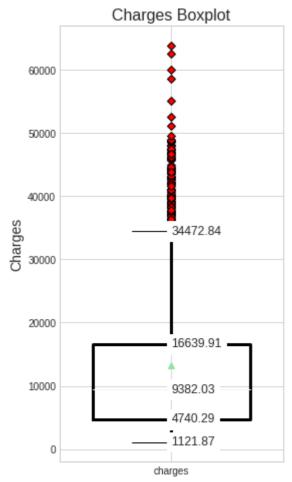








box_plot('charges')



Mean Charges = 13270.422265141257

Who is paying the highest charges?
data[data['charges'] == data['charges'].max()]

		age	sex	bmi	children	smoker	region	charges	1
Ę	543	54	female	47.41	0	yes	southeast	63770.42801	

Who is the insured with the highest BMI, and how does his charges compare to the rest?
data[data['bmi'] == data['bmi'].max()]

	age	sex	bmi	children	smoker	region	charges	1
1317	18	male	53.13	0	no	southeast	1163.4627	

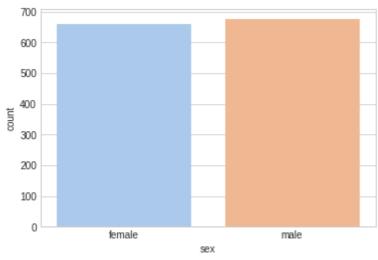
#Summary and Distribution of categorical attributes:
Create a function that returns a Pie chart for categorical variable:
def pie_chart(x = 'smoker'):

Function creates a Pie chart for categorical variables.

fig, ax = plt.subplots(figsize=(8, 6), subplot_kw=dict(aspect="equal"))

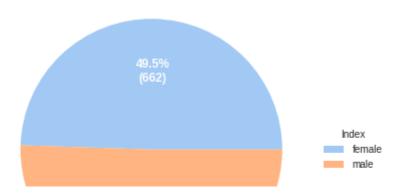
#Sex: sns.countplot(x = 'sex', data = data)

<matplotlib.axes._subplots.AxesSubplot at 0x7f4015cf40d0>



```
pie_chart('sex')
```

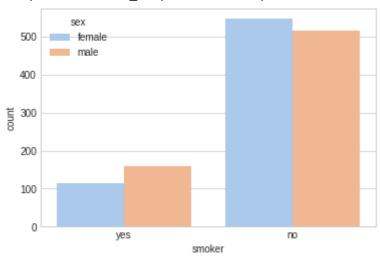
Sex Piechart



#Smoker:

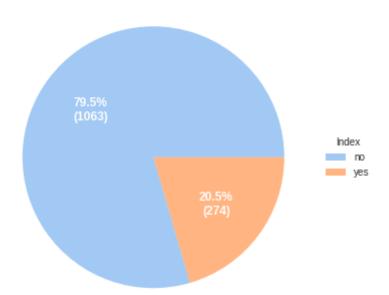
sns.countplot(x = 'smoker', hue = 'sex', data = data)

<matplotlib.axes._subplots.AxesSubplot at 0x7f4015deaed0>



pie_chart('smoker')

Smoker Piechart



Are average premium charges for smokers significantly higher than non-smokers? data['charges'].groupby(data['smoker']).mean()

smoker

no 8434.268298 yes 32050.231832

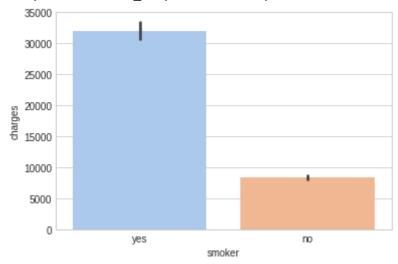
Name: charges, dtype: float64

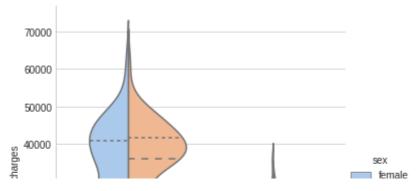
data.groupby(['smoker', 'sex']).agg('count')

		age	bmi	children	region	charges	1
smoker	sex						
no	female	547	547	547	547	547	
	male	517	517	517	517	517	
yes	female	115	115	115	115	115	
	male	159	159	159	159	159	

yes, average premium charges for smokers are indeed significantly higher than non-smoker sns.barplot(x = "smoker", y = "charges", data = data)

<matplotlib.axes._subplots.AxesSubplot at 0x7f4015d20990>





data.groupby(['smoker', 'sex']).agg('count')['age']

smoker sex

no female 547

male 517

yes female 115

male 159

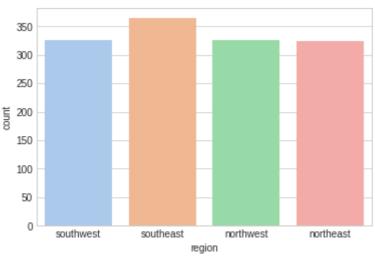
Name: age, dtype: int64

SHIONG

#Regions:

sns.countplot(x = 'region', data = data)

<matplotlib.axes._subplots.AxesSubplot at 0x7f4019088f50>

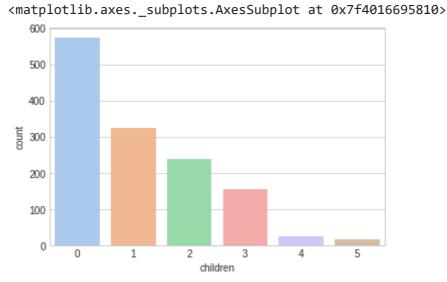


pie_chart('region')

Region Piechart

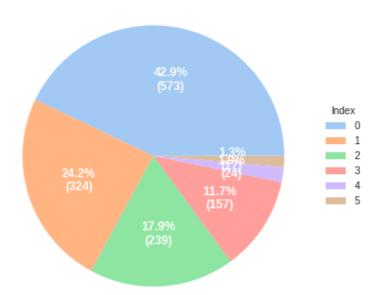


#Number of Children:
sns.countplot(x = 'children', data = data)



pie_chart('children')

Children Piechart



data.groupby(['children']).agg('count')['age']

children

- 0 574
- 1 324
- 2 240
- 3 157
- 4 25

```
5 18
```

Name: age, dtype: int64

```
#Pairplot:
```

```
for x in ['sex', 'children', 'smoker', 'region']:
    data[x] = data[x].astype('category')
```

data.dtypes

age int64
sex category
bmi float64
children category
smoker category
region category
charges float64

type(data.dtypes)

dtype: object

pandas.core.series.Series

Next, we select all columns of the dataFrame with datatype = category:
cat_columns = data.select_dtypes(['category']).columns
cat_columns

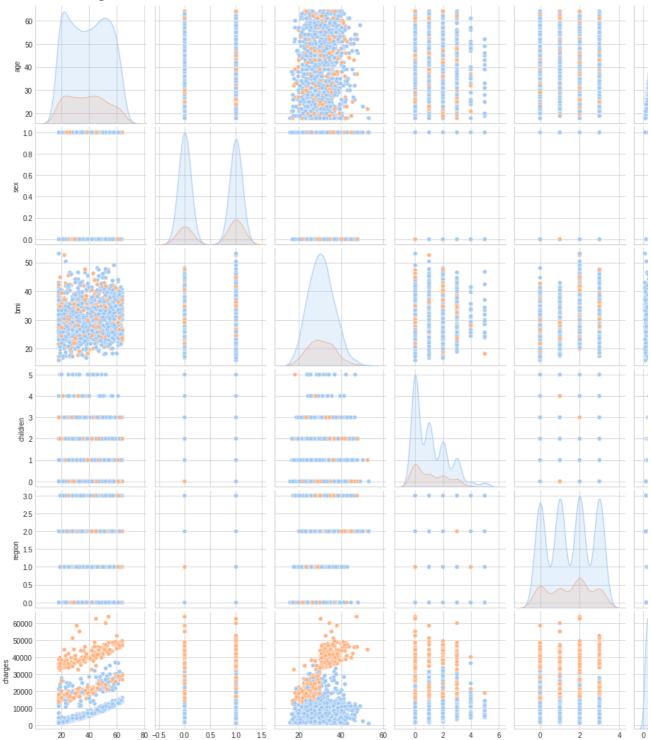
```
Index(['sex', 'children', 'smoker', 'region'], dtype='object')
```

Finally, we transform the original columns by replacing the elements with their category
data[cat_columns] = data[cat_columns].apply(lambda x: x.cat.codes)
data.head()

	age	sex	bmi	children	smoker	region	charges	1
0	19	0	27.900	0	1	3	16884.92400	
1	18	1	33.770	1	0	2	1725.55230	
2	28	1	33.000	3	0	2	4449.46200	
3	33	1	22.705	0	0	1	21984.47061	
4	32	1	28.880	0	0	1	3866.85520	

Now we can plot all columns of our dataset in a pairplot!
sns.pairplot(data, hue = 'smoker')

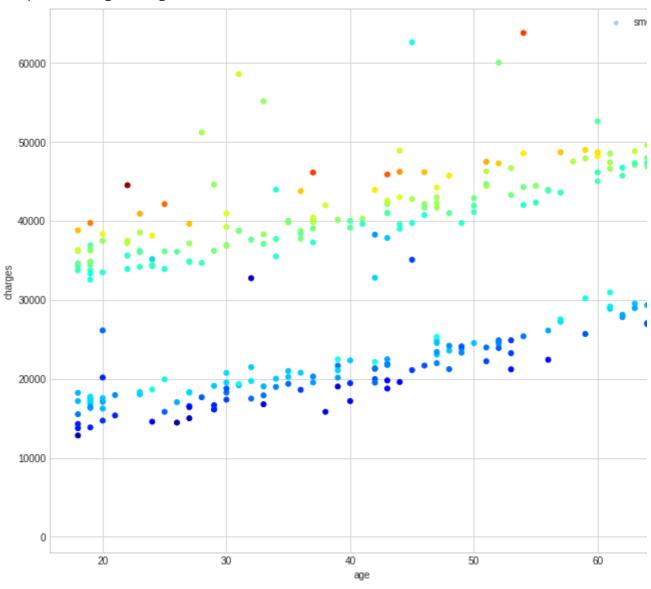
<seaborn.axisgrid.PairGrid at 0x7f401672ebd0>



age

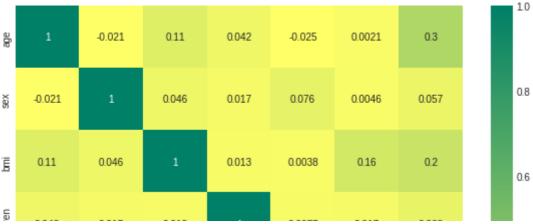
```
c='bmi', cmap=plt.get_cmap("jet"), colorbar=True,
    sharex=False)
plt.legend()
```

<matplotlib.legend.Legend at 0x7f401672ef50>



```
#Correlation:
corr = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap = 'summer_r')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f400b1263d0>



```
#Hypothesis Testing:
# Step 1: State the null and alternative hypothesis
#H0: \mu s = \mu n
#HA: \mu s != \mu n
#Where:
\#\mu s = Mean Charge of all smokers in our data
#μn = Mean Charge of all non - smokers in our data
# Step 2: Select an appropriate statistical test and the corresponding test statistic
#We select a 2-sample t-test as our statistical test and the corresponding t statistic as
#Step 3: Choose level of significance \alpha
#We select \alpha = 0.05
#Step 4: Collect data and calculate the value of test statistic:
smokers = data[data['smoker'] == 0]
nonsmokers = data[data['smoker'] == 1]
charge_smokers = smokers['charges']
charge_nonsmokers = nonsmokers['charges']
print(f'Number of smokers: {smokers.shape[0]}')
print(f'Variance in charges of smokers: {np.var(charge smokers)}')
print(f'Number of non - smokers: {nonsmokers.shape[0]}')
print(f'Variance in charges of non - smokers: {np.var(charge_nonsmokers)}')
     Number of smokers: 1064
     Variance in charges of smokers: 35891656.00316425
     Number of non - smokers: 274
     Variance in charges of non - smokers: 132721153.13625304
from scipy.stats import ttest ind
t statistic, p value = ttest ind(charge smokers, charge nonsmokers, equal var=False)
print(f't_statistic: {t_statistic}\np_value: {p_value}')
     t_statistic: -32.751887766341824
```

#Step 5: Determine the probability associated with the test statistic under the null hypot print ("two-sample t-test p-value=". p value)

p_value: 5.88946444671698e-103

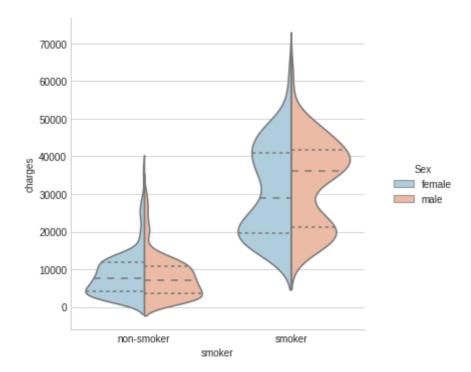
```
SWAYAM PRAVA RATH insurance.ipynb - Colaboratory
     two-sample t-test p-value= 5.88946444671698e-103
#Step 6: Compare the probability associated with the test statistic with level of signific
#At 5% significance level, \alpha = 0.05
p value > 0.05
     False
#Do charges of people who smoke differ significantly from the people who don't?
# Step 1: State the null and alternative hypothesis
#H0: \mu s = \mu n
#HA: μs != μn
#Where:
\mus = Mean Charge of all smokers in our data
#μn = Mean Charge of all non - smokers in our data
# Step 2: Select an appropriate statistical test and the corresponding test statistic
#We select a 2-sample t-test as our statistical test and the corresponding t statistic as
# Step 3: Choose level of significance \alpha
#We select \alpha = 0.05
 #Step 4: Collect data and calculate the value of test statistic
smokers = data[data['smoker'] == 0]
nonsmokers = data[data['smoker'] == 1]
charge_smokers = smokers['charges']
charge_nonsmokers = nonsmokers['charges']
print(f'Number of smokers: {smokers.shape[0]}')
print(f'Variance in charges of smokers: {np.var(charge smokers)}')
print(f'Number of non - smokers: {nonsmokers.shape[0]}')
print(f'Variance in charges of non - smokers: {np.var(charge nonsmokers)}')
     Number of smokers: 1064
     Variance in charges of smokers: 35891656.00316425
     Number of non - smokers: 274
     Variance in charges of non - smokers: 132721153.13625304
#Visualizing the collected data:
g = sns.catplot(x="smoker", y="charges", hue="sex",
            kind="violin", inner="quartiles", split=True,
            palette="RdBu_r", data=data, legend_out = True);
xlabels = ['non-smoker', 'smoker']
```

g.set_xticklabels(xlabels)

g._legend.set_title(new_title)

new_title = 'Sex'

```
g._legend.set_bbox_to_anchor([1.1, 0.5])
# replace labels
new_labels = ['female', 'male']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)
```



from scipy.stats import ttest_ind

```
t_statistic, p_value = ttest_ind(charge_smokers, charge_nonsmokers, equal_var=False)
print(f't_statistic: {t_statistic}\np_value: {p_value}')
```

t_statistic: -32.751887766341824 p_value: 5.88946444671698e-103

#Step 5: Determine the probability associated with the test statistic under the null hypot
print ("two-sample t-test p-value=", p_value)

two-sample t-test p-value= 5.88946444671698e-103

#Step 6: Compare the probability associated with the test statistic with level of signific #At 5% significance level, α = 0.05 p_value > 0.05

False

```
#Does BMI of males differ significantly from that of females?  
# Step 1: State the null and alternative hypothesis  
#H0: \mum = \muf  
#HA: \mum != \muf  
#Where:  
#\mum = Mean BMI of all male insured in our data  
#\muf = Mean BMI of all female insured in our data  
#\muf = Step 2: Select an appropriate statistical test and the corresponding test statistic
```

replace labels

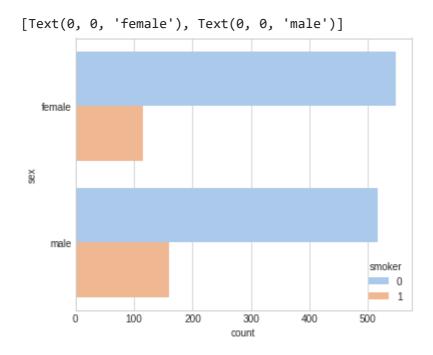
new labels = ['non-smoker', 'smoker']

for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

```
#We select a 2-sample t-test as our statistical test and the corresponding t statistic as
# Step 3: Choose level of significance \alpha
#We select \alpha = 0.05
# Step 4: Collect data and calculate the value of test statistic
males = data[data['sex'] == 1]
females = data[data['sex'] == 0]
bmi_males = males['bmi']
bmi_females = females['bmi']
print(f'Number of males: {males.shape[0]}')
print(f'Variance in BMI of males: {np.var(bmi_males)}')
print(f'Number of females: {females.shape[0]}')
print(f'Variance in BMI of females: {np.var(bmi_females)}')
     Number of males: 676
     Variance in BMI of males: 37.6491607363954
     Number of females: 662
     Variance in BMI of females: 36.49917703379856
#Visualizing the collected data:
g = sns.catplot(x="sex", y="bmi", hue="smoker",
            kind="violin", inner="quartiles", split=True,
            palette="pastel", data=data, legend_out = True);
xlabels = ['female', 'male']
g.set_xticklabels(xlabels)
new_title = 'Smoker'
g. legend.set title(new title)
g._legend.set_bbox_to_anchor([1.1, 0.5])
```

```
from scipy.stats import ttest_ind
t_statistic, p_value = ttest_ind(bmi_males, bmi_females, equal_var=False)
print(f't_statistic: {t_statistic}\np_value: {p_value}')
     t_statistic: 1.697027933124022
     p_value: 0.08992430667834876
                               [ - - - -
        30
#Step 5: Determine the probability associated with the test statistic under the null hypot
print ("two-sample t-test p-value=", p_value)
     two-sample t-test p-value= 0.08992430667834876
# Step 6: Compare the probability associated with the test statistic with level of signifi
#At 5% significance level, \alpha = 0.05
p_value > 0.05
     True
#Is the proportion of smokers significantly different in different genders?
#'sex' and 'smoker' are two categorical variables.
#We want to see if the proportion of smokers in the female population is significantly les
# Step 1: State the null and alternative hypothesis
#H0 : pm = pf
#HA: pm != pf
#Where:
#pm = Male Smokers / Total Male insured
#pf = Female Smokers / Total Female insured
# Step 2: Select an appropriate statistical test and the corresponding test statistic
#We select a proportion Z - test as our statistical test and the corresponding Z statistic
\# Step 3: Choose level of significance \alpha
#We select \alpha = 0.05
# Step 4: Collect data and calculate the value of test statistic
n_females = data['sex'].value_counts()[0] # number of females in the data
n_males = data['sex'].value_counts()[1] # number of females in the data
female smokers = data[data['sex'] == 0].smoker.value counts()[1] # number of female smoker
male_smokers = data[data['sex'] == 1].smoker.value_counts()[1] # number of male smokers
print([female_smokers, male_smokers] , [n_females, n_males])
print(f' Proportion of smokers in females, males = {round(115/662,4)*100}%, {round(159/676
     [115, 159] [662, 676]
      Proportion of smokers in females, males = 17.37%, 23.52% respectively.
```

```
# Visualization of the collected data:
plt.figure(figsize=(6,5))
chart = sns.countplot(y = 'sex', hue = 'smoker', data = data)
chart.set_yticklabels(['female', 'male'])
```



The proportions are different, but are they statistically significant? from statsmodels.stats.proportion import proportions_ztest

stat, pval = proportions_ztest([female_smokers, male_smokers] , [n_females, n_males])
print(f'Statistic: {stat}\np_value: {pval}')

Statistic: -2.7867402154855503 p_value: 0.005324114164320532

Step 5: Determine the probability associated with the test statistic under the null hypo

if pval < 0.05:

 $print(f'With a p-value of \{pval\}\ the difference is significant. We reject the Null Hypelse:$

print(f'With a p-value of {pval} the difference is not significant. We fail to reject

With a p-value of 0.005324114164320532 the difference is significant. We reject the N



Is the distribution of bmi across women with no children, one child and two children, the same? Analysis of variance (ANOVA) ANOVA is a hypothesis testing technique tests the equality of two or more population means by examining the variances of samples that are taken.

ANOVA tests the general rather than specific differences among means.

Assumptions of ANOVA All populations involved follow a normal distribution All populations have the same variance The samples are randomly selected and independent of one another

Step 1: State the null and alternative hypothesis H0 : μ 0 = μ 1 = μ 2 HA : Atleast one of the means are different. Where:

μi = Population mean of BMI of women having 0, 1 and 2 children.

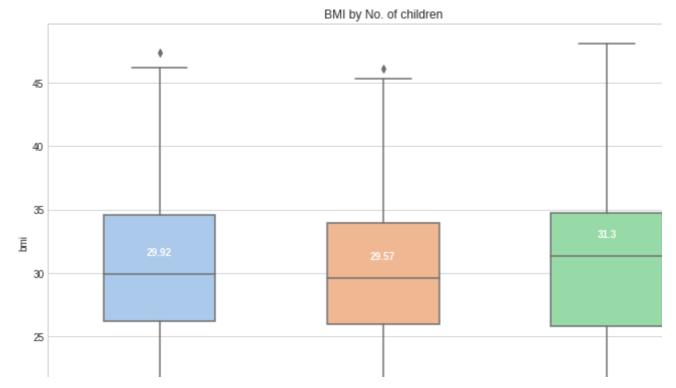
Step 2: Select an appropriate statistical test and the corresponding test statistic We select one way ANOVA as our test and mean BMI of the different groups as our test statistic.

Step 3: Choose level of significance α We select α = 0.05

Step 4: Collect data and calculate the value of test statistic Here we have 3 groups. Analysis of variance can determine whether the means of three or more groups are different. ANOVA uses F-tests to statistically test the equality of means.

```
df = data[data['children'] <= 2]
female = df[df['sex'] == 0]
female.head()</pre>
```

	age	sex	bmi	children	smoker	region	charges	1
0	19	0	27.90	0	1	3	16884.92400	
5	31	0	25.74	0	0	2	3756.62160	
6	46	0	33.44	1	0	2	8240.58960	
9	60	0	25.84	0	0	1	28923.13692	
11	62	0	26.29	0	1	2	27808.72510	



Step 5: Calculate p value using ANOVA table statsmodels.formula.api.ols creates a model from a formula and dataframe statsmodels.api.sm.stats.anova_lm gives an Anova table for one or more fitted linear models.

Step 6: Conclusion: We Fail to Reject the null hypothesis that for BMI for 3 groups of women having no, one or two children respectively, mean BMI of all groups are equal. Hence, the distribution of BMI across women with no children, one child and two children are the same. Determine which mean(s) is / are different An ANOVA test will test that at least one mean is different. We have falied to reject the null hypothesis but do not know which mean(s) is / are different. We use Tukey-krammer HSD test to detect which mean(s) is / are different.

0 2 0.2883 0.8942 -1.2636 1.8402 False 1 2 0.5971 0.6797 -1.1323 2.3265 False

✓ 0s completed at 11:39 AM

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