Medical Cost Personal Datasets

Insurance Forecast by using Linear Regression

OUTLINE:

```
1. Download the dataset
2. Explore and Analyze the data
3. Prepare the dataset for ML training
4. Train the model
5. Make prediction
6. Documentation
```

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error
import seaborn as sns
```

Analyze the dataset

Read data from csv

In [2]:
```
data = pd.read_csv("insurance.csv")
```

In [3]:
```
print (data.shape)
```

```
(1338, 7)
```

In [4]:
```
print (data.columns)
```

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

Data has 1338 entries and 7 columns : age, sex, bmi, children, smoker, region, charges

In [5]:
```
data.describe()
```

Out[5]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

In [6]:
```
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 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

The count of each column is same thus there are No Null entries in the dataset. The dataset has no unique identifying column thus we are using external indexing Columns and the their Data Types: Age : Integer Sex : String BMI : Float Children : Integer Smoker : String Region : String Charges : Float

In [7]:
```
data.head()
```

Out[7]:

	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

In [19]:
```
data.isna().sum()
```

Out[19]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

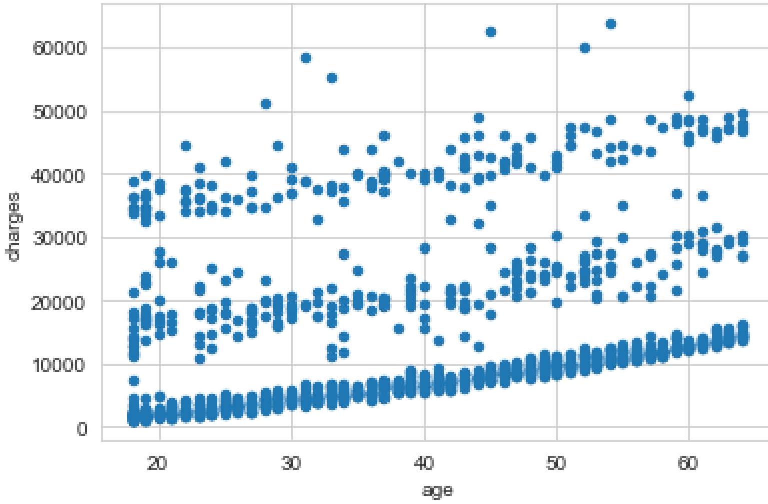
No NAN values

EDA

In [20]:
```
data.columns
```

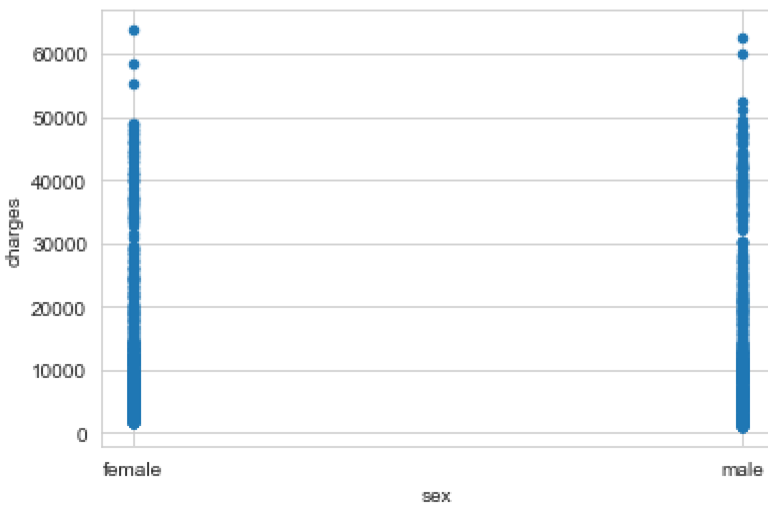
Out[20]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype
='object')
```

In [21]:
```
data.plot(kind='scatter', x='age',y='charges') ;
plt.show()
```

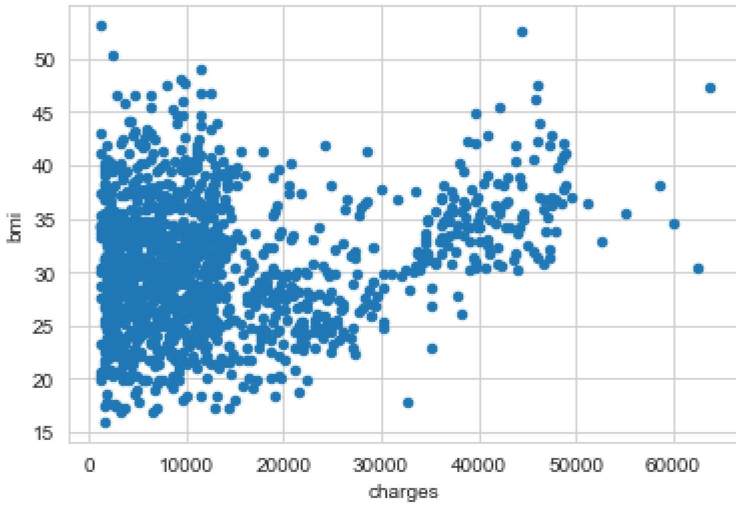


We can observe that the charges increase with age.

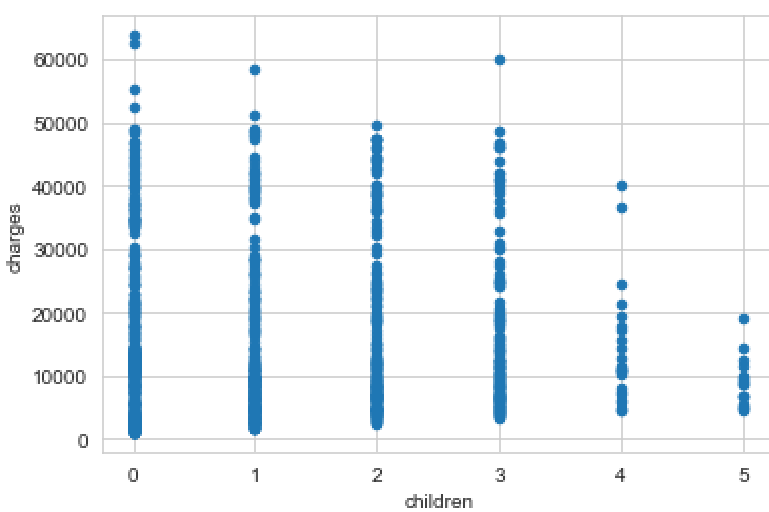
In [22]:
```
data.plot(kind='scatter', y='charges', x='sex') ;
plt.show()
```



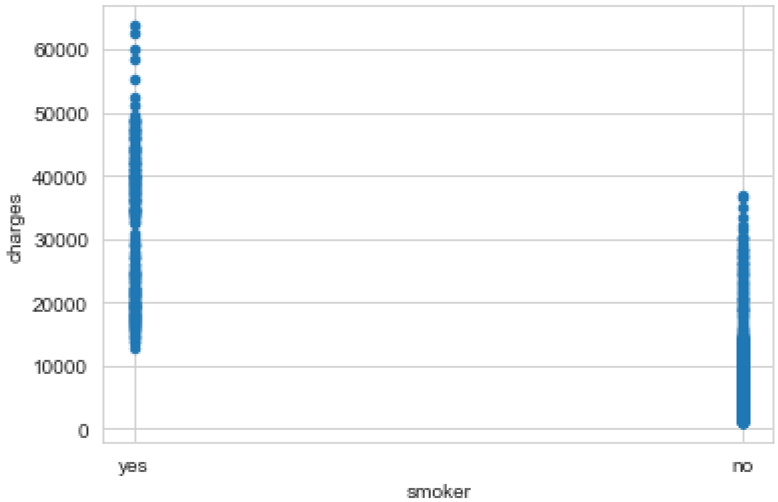
In [23]:
```
data.plot(kind='scatter', x='charges', y='bmi') ;
plt.show()
```



In [24]:
```
data.plot(kind='scatter', y='charges', x='children') ;
plt.show()
```

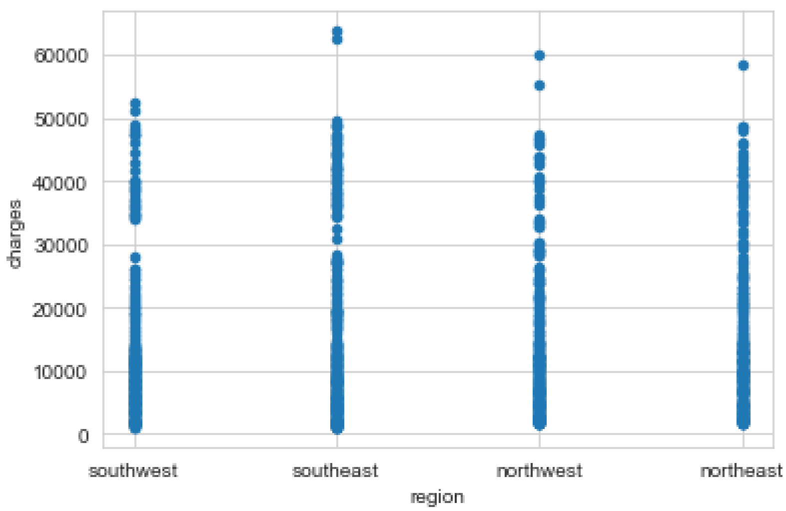


In [25]:
```
data.plot(kind='scatter', y='charges', x='smoker') ;
plt.show()
```



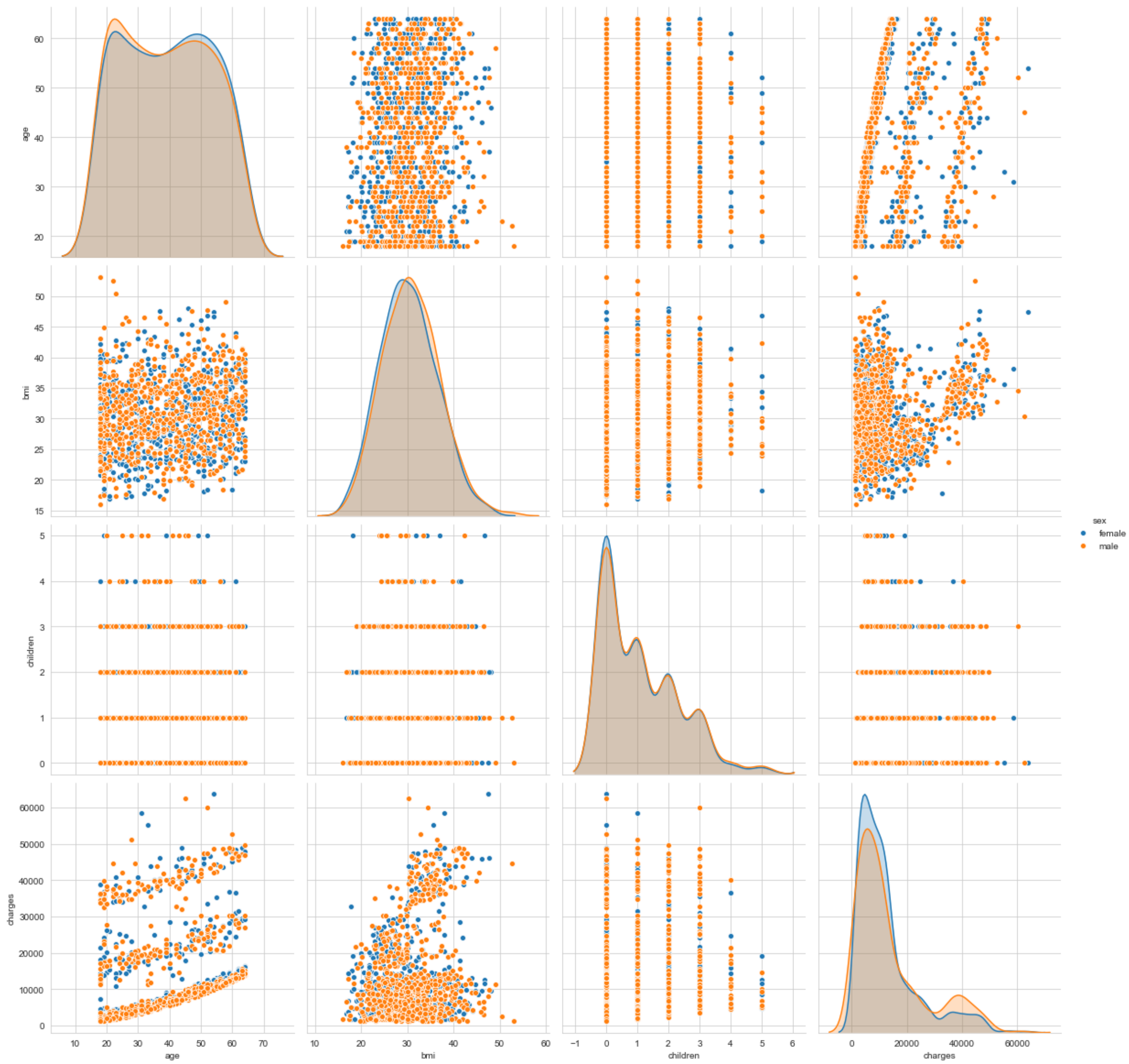
The minimum of charges for smoker are more than then non-smokers. As we can see non-smoker charges start from 0 and smoker charges start from 12000

In [26]:
```
data.plot(kind='scatter', y='charges', x='region') ;
plt.show()
```

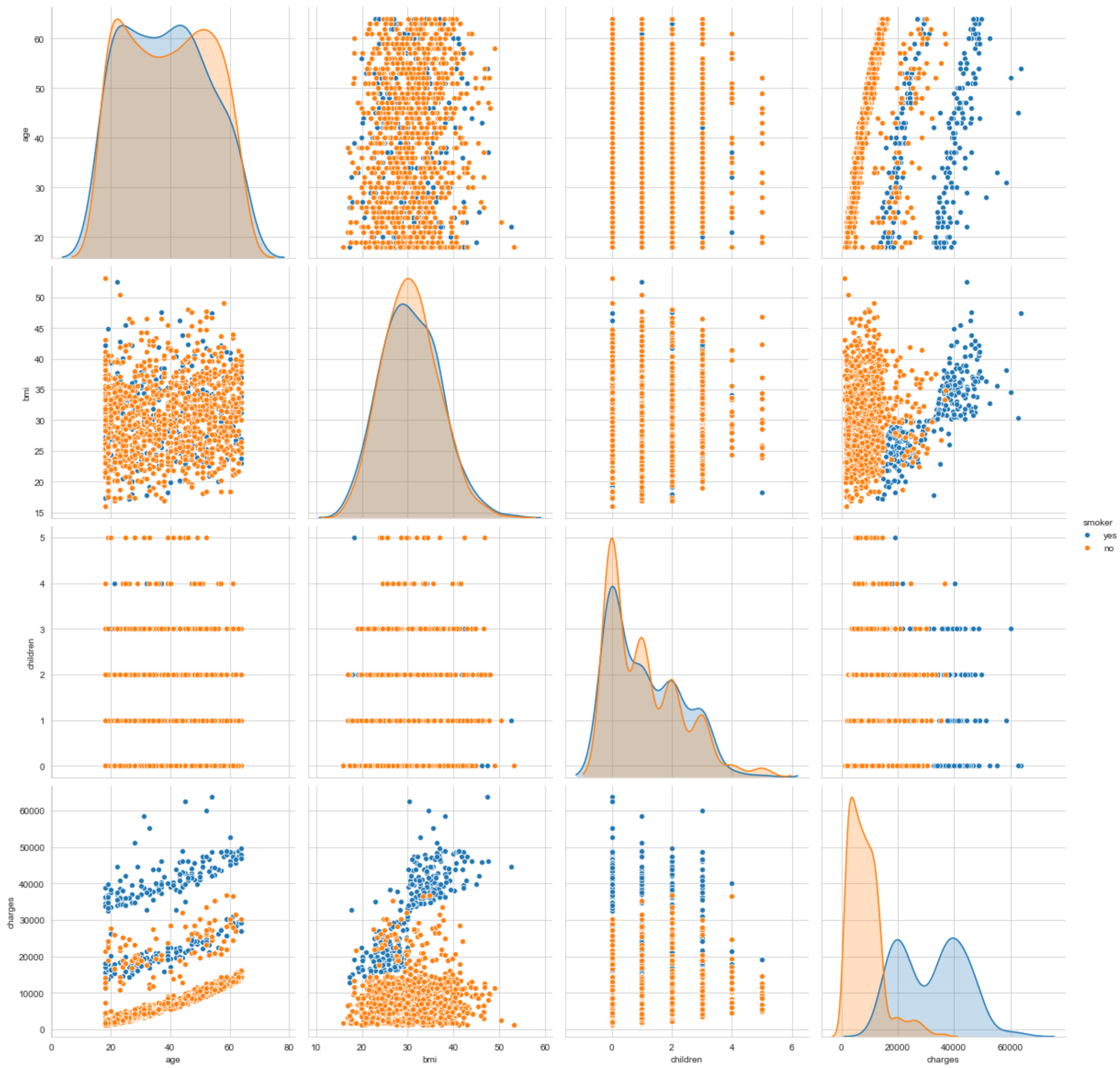


The region doesnt affect the charges

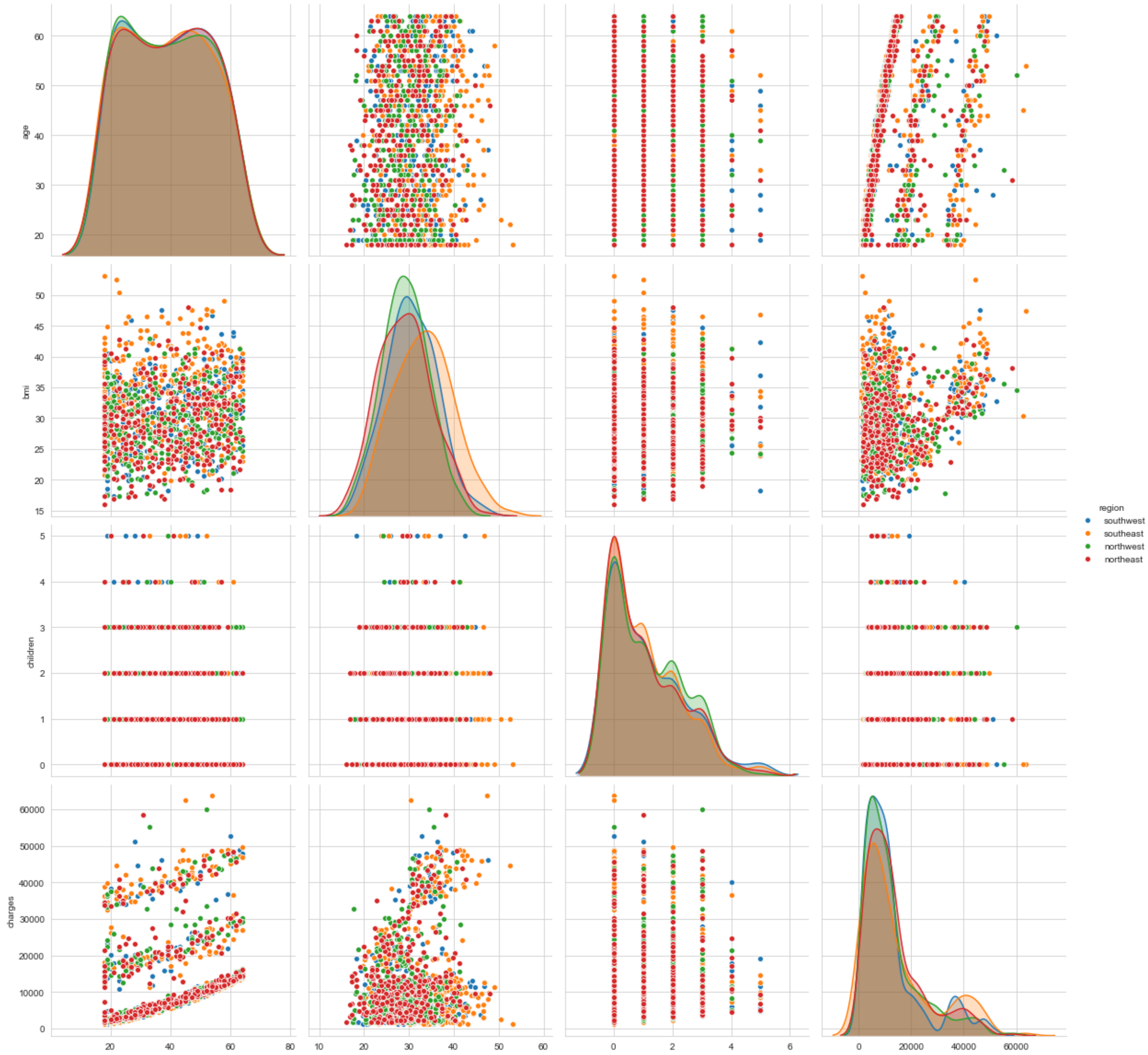
In [27]:
```
plt.close();
sns.set_style("whitegrid");
sns.pairplot(data, height=4,diag_kind="kde",hue ='sex');
plt.show()
```



In [28]:
```
plt.close();
sns.set_style("whitegrid");
sns.pairplot(data, height=4,diag_kind="kde",hue ='smoker');
plt.show()
```

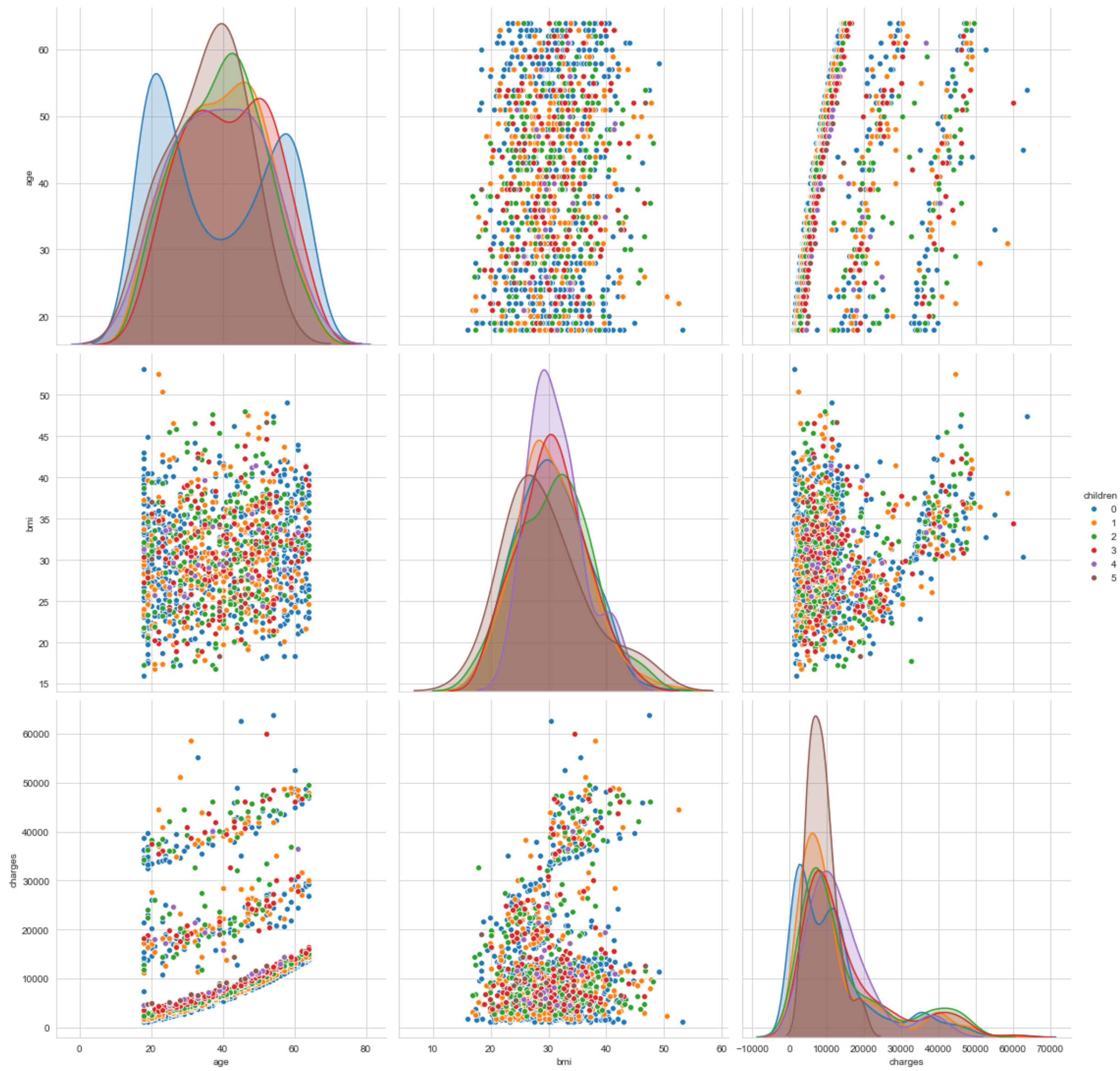


In [29]:
```
plt.close();
sns.set_style("whitegrid");
sns.pairplot(data, height=4,diag_kind="kde",hue ='region');
plt.show()
```



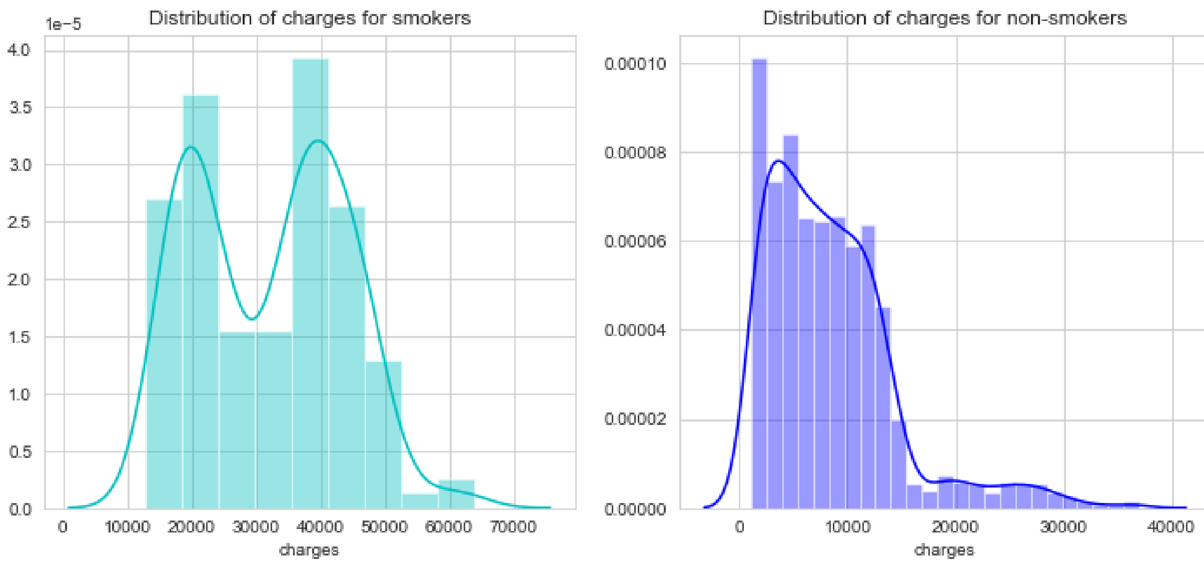
Region is not affecting the charges

In [30]:
```
plt.close();
sns.set_style("whitegrid");
sns.pairplot(data, height=5,hue ='children');
plt.show()
```



In [31]:
```
f= plt.figure(figsize=(12,5))

ax=f.add_subplot(121)
sns.distplot(data[(data.smoker == 'yes')]["charges"],color='c',ax=ax)
ax.set_title('Distribution of charges for smokers')

ax=f.add_subplot(122)
sns.distplot(data[(data.smoker == 'no')]['charges'],color='b',ax=ax)
ax.set_title('Distribution of charges for non-smokers')
```

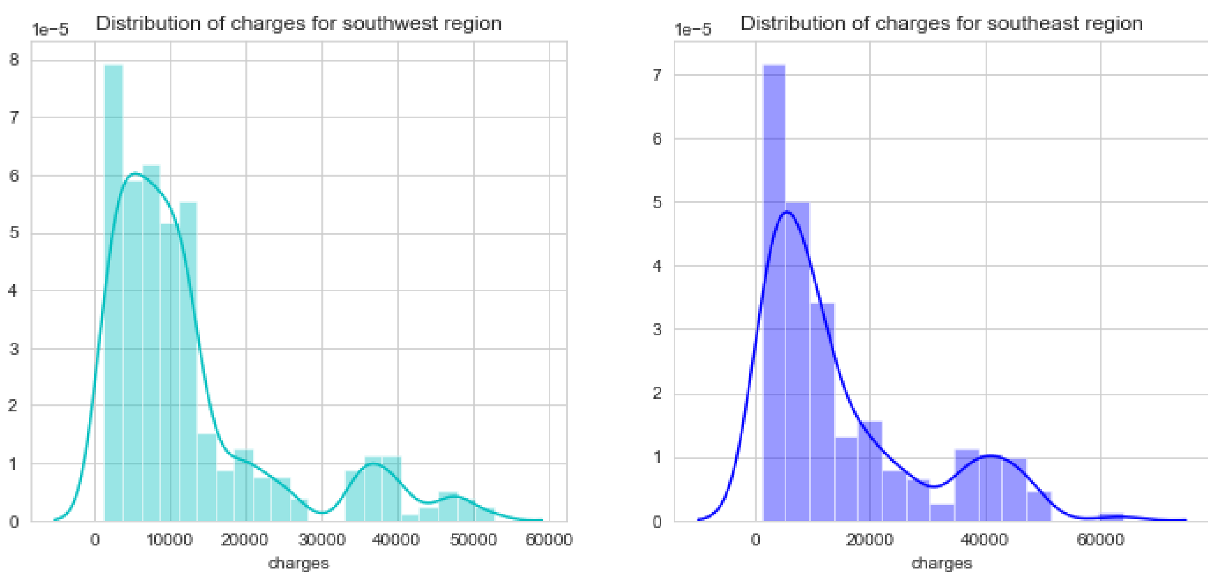
Out[31]:
```
Text(0.5, 1.0, 'Distribution of charges for non-smokers')
```

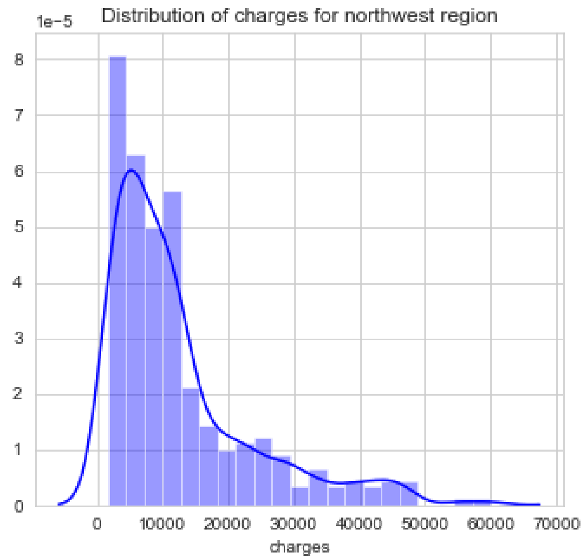


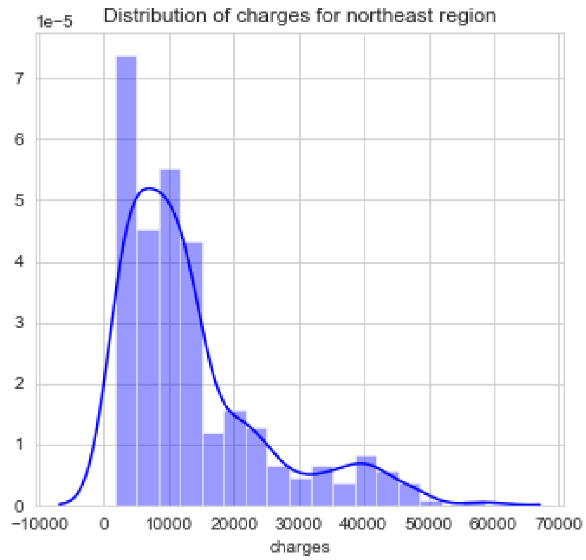
We can observe that smoker population distribution is high and across the charges range. Whereas, the non-smoker population distribution of charges is on the lower end of the graph.

In [32]:
```
f= plt.figure(figsize=(12,5))

ax=f.add_subplot(121)
sns.distplot(data[(data.region == 'southwest')]["charges"],color='c',ax=ax)
ax.set_title('Distribution of charges for southwest region')

ax=f.add_subplot(122)
sns.distplot(data[(data.region == 'southeast')]['charges'],color='b',ax=ax)
ax.set_title('Distribution of charges for southeast region')

f= plt.figure(figsize=(12,5))

ax=f.add_subplot(121)
sns.distplot(data[(data.region == 'northwest')]['charges'],color='b',ax=ax)
ax.set_title('Distribution of charges for northwest region')

ax=f.add_subplot(122)
sns.distplot(data[(data.region == 'northeast')]['charges'],color='b',ax=ax)
ax.set_title('Distribution of charges for northeast region')
```

Out[32]:
```
Text(0.5, 1.0, 'Distribution of charges for northeast region')
```







Split the columns to get numerical data for sex, region, smoker and children

In [33]:
```
data1=pd.get_dummies(data, columns=['sex','smoker'])
```

In [34]:
```
data1.head()
```

Out[34]:

	age	bmi	children	region	charges	sex_female	sex_male	smoker_no	smoker_yes
0	19	27.900	0	southwest	16884.92400	1	0	0	1
1	18	33.770	1	southeast	1725.55230	0	1	1	0
2	28	33.000	3	southeast	4449.46200	0	1	1	0
3	33	22.705	0	northwest	21984.47061	0	1	1	0
4	32	28.880	0	northwest	3866.85520	0	1	1	0

Prepare x and y where x has independent variable and y has dependent variables

In [35]:
```
x = data1.copy()
x=x.drop(['charges','region','children'],1)
y = data1[['charges']]
```

So from the analysis we come to know that Region and children is not affecting the charges. So we drop these columns from the training dataset.

In [36]:
```
x.head() #Independent
```

Out[36]:

	age	bmi	sex_female	sex_male	smoker_no	smoker_yes
0	19	27.900	1	0	0	1
1	18	33.770	0	1	1	0
2	28	33.000	0	1	1	0
3	33	22.705	0	1	1	0
4	32	28.880	0	1	1	0

In [37]:
```
y.head() #dependent
```

Out[37]:

	charges
0	16884.92400
1	1725.55230
2	4449.46200
3	21984.47061
4	3866.85520

Split data into training set and testing set for X and Y where test set is 20% of the complete dataset and training set is 80%. Random state is 25 to fetch random data from dataset

In [38]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y, test_size=0.2, random_state
```

In [39]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[39]: ((1070, 6), (268, 6), (1070, 1), (268, 1))

In [40]:
```
y_test.head()
```

Out[40]:

	charges
748	8556.90700
633	7173.35995
651	10579.71100
411	19594.80965
502	22218.11490

In [41]:
```
y_train.head()
```

Out[41]:

	charges
629	42983.458500
556	8334.589600
427	7323.734819
1047	44501.398200
98	22412.648500

Creating model and fit training dataset into the model

In [42]:
```
model = LinearRegression()
model.fit(x_train,y_train)
predict_data=model.predict(x_test)
```

In [43]:
```
Result=x_test.copy()
Result['Actual'] = y_test
Result['Predicted'] = predict_data
Result=Result.drop(['age','bmi','sex_female','sex_male','smoker_no','smoker_yes']
```

In [44]:
```
Result.head(10)
```

Out[44]:

	Actual	Predicted
748	8556.90700	12253.263475
633	7173.35995	6146.390480
651	10579.71100	14975.798300
411	19594.80965	30554.711152
502	22218.11490	33336.587291
471	2203.47185	2805.142236
595	8823.98575	11259.726071
425	9788.86590	7965.620049
1103	11363.28320	15143.808461
1312	4536.25900	11091.976946

Analysis of the predicted data

In [45]:
```
model.coef_
```

Out[45]:
```
array([[ 2.60401201e+02,  3.22257671e+02, -1.75578444e-01,
         1.75578444e-01, -1.20815217e+04,  1.20815217e+04]])
```

In [46]:
```
model.intercept_
```

Out[46]:
```
array([494.82814909])
```

Score

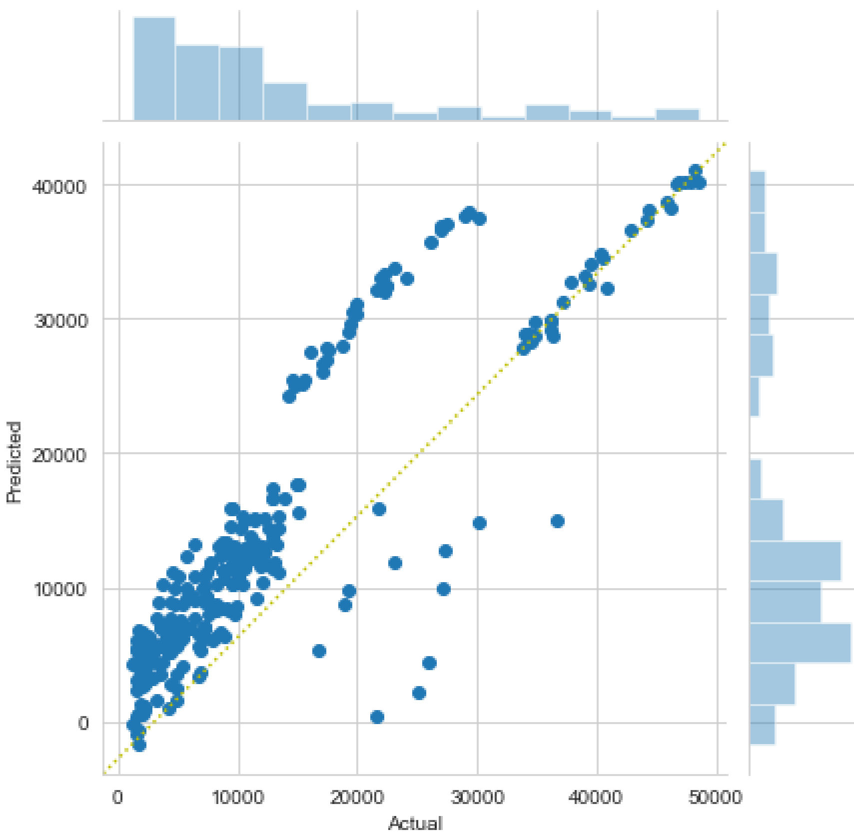
In [101]:
```
r2_score(y_test,predict_data)
```

Out[101]:
```
0.7617522336482346
```

In [102]:
```
model.score(x_test, y_test)
```

Out[102]:
```
0.7617522336482346
```

In [47]:
```
g = sns.jointplot(data=Result, x='Actual', y='Predicted')
g.ax_joint.plot([0,1], [0,1], ':y', transform=g.ax_joint.transAxes)
plt.show()
```



In [50]:
```
score = r2_score(y_test , predict_data)
print("R2 Score              : {}".format(score))
print("Accuracy of the Model : {}%".format(score * 100))
```

```
R2 Score              : 0.7617522336482346
Accuracy of the Model : 76.17522336482347%
```

In [ ]:

In [ ]: