Medical Cost Personal Insurance Project

In [2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```python
df= pd.read_csv('medical_cost_insurance.csv')
df.head()
```

Out[3]:

	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 [4]:
```python
df.tail()
```

Out[4]:

	age	sex	bmi	children	smoker	region	charges
1333	50	male	30.97	3	no	northwest	10600.5483
1334	18	female	31.92	0	no	northeast	2205.9808
1335	18	female	36.85	0	no	southeast	1629.8335
1336	21	female	25.80	0	no	southwest	2007.9450
1337	61	female	29.07	0	yes	northwest	29141.3603

In [5]:
```python
df.shape
```

Out[5]:
```
(1338, 7)
```

In [6]:
```python
df.describe()
```

Out[6]:

	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 [7]:
```python
df.dtypes
```

Out[7]:
```
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

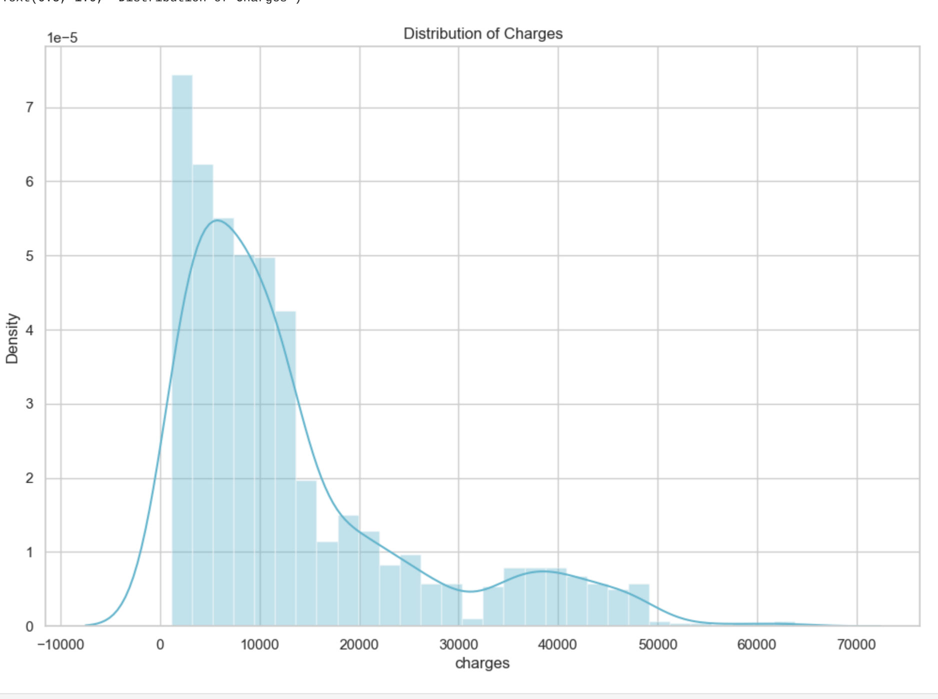
In [8]:
```python
df.isnull().sum()
```

Out[8]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

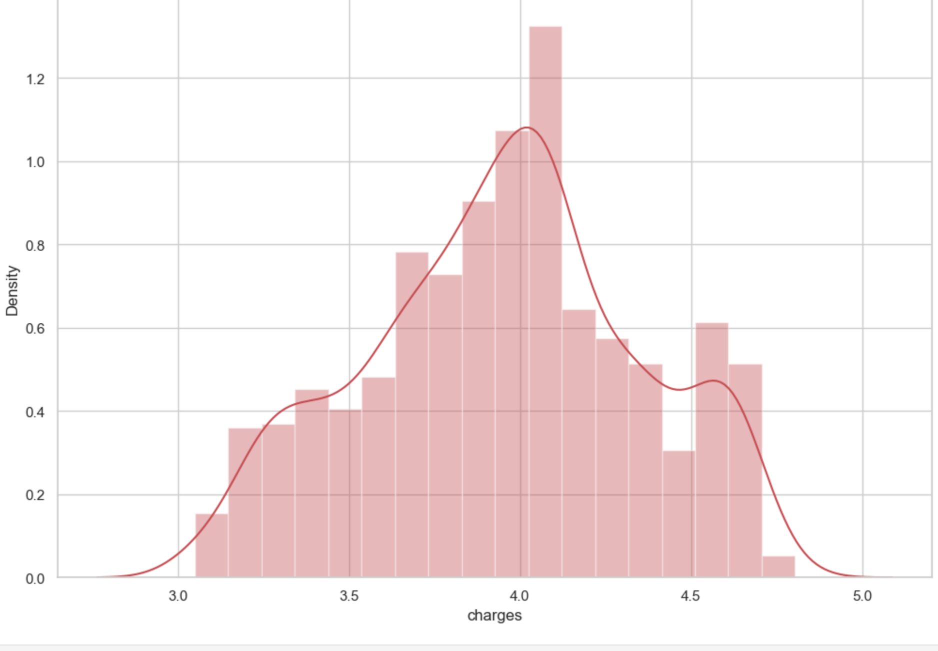
EDA and Visualizations

In [9]:
```python
sns.set(style='whitegrid')
f, ax = plt.subplots(1,1, figsize=(12, 8))
ax = sns.distplot(df['charges'], kde = True, color = 'c')
plt.title('Distribution of Charges')
```

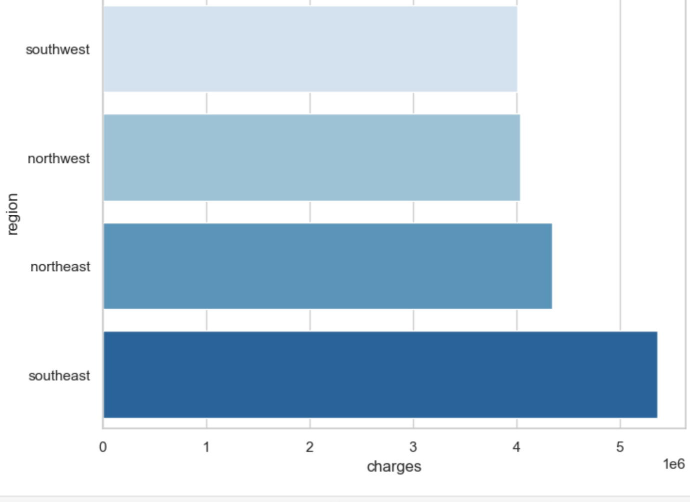
Out[9]:
```
Text(0.5, 1.0, 'Distribution of Charges')
```



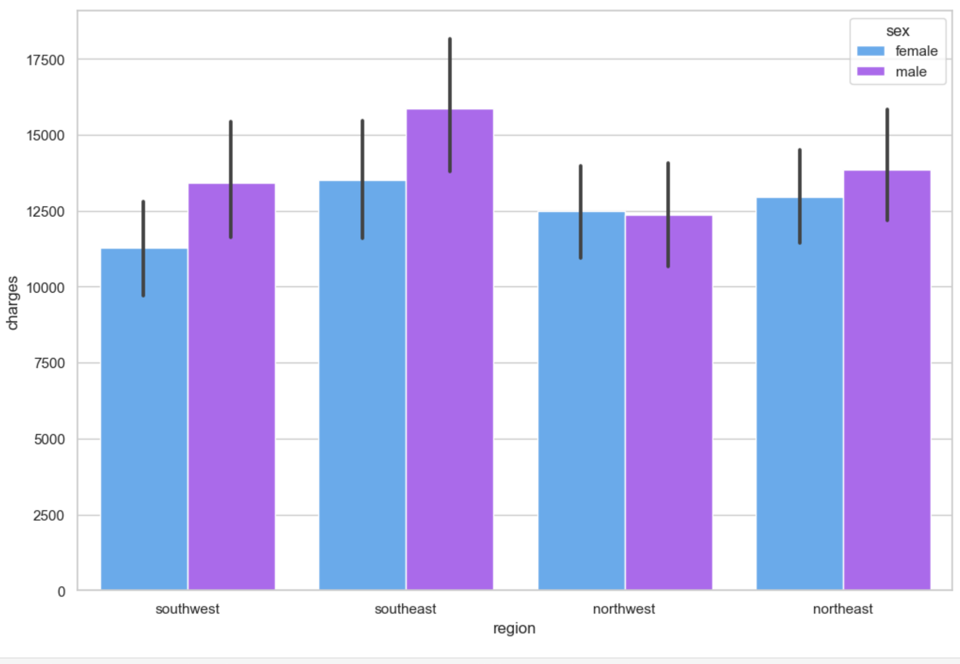
In [10]:
```python
f, ax = plt.subplots(1, 1, figsize=(12, 8))
ax = sns.distplot(np.log10(df['charges']), kde = True, color = 'r' )
```



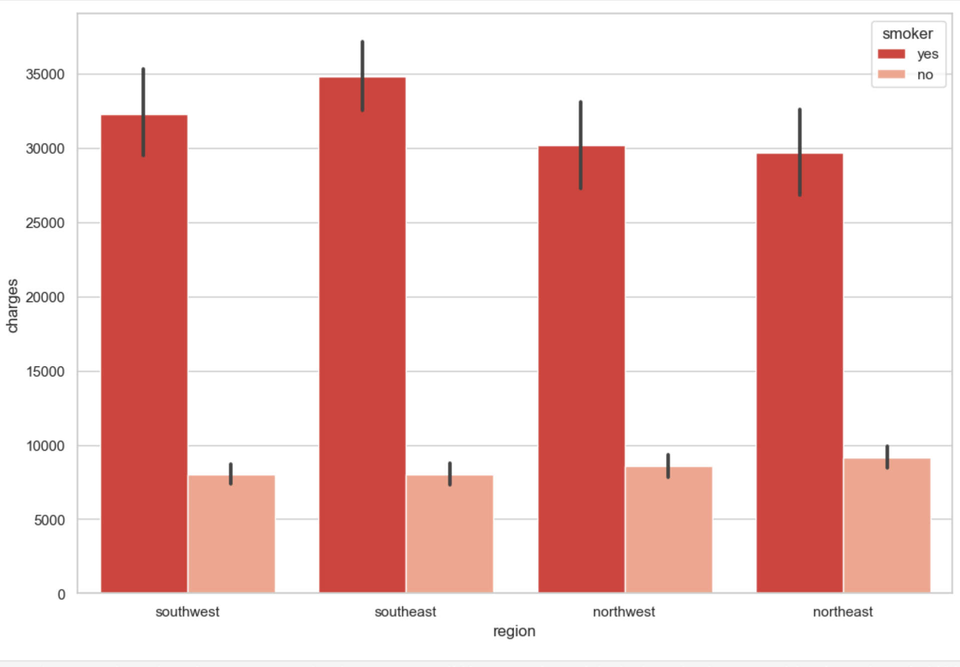
In [11]:
```python
#Now we are calculating total charges by region column
#sorting it by ascending value and  creating a bar plot to visualize the top few regions with the lowest charges
charges = df['charges'].groupby(df.region).sum().sort_values(ascending =True)
f, ax = plt.subplots(1, 1, figsize=(8,6))
ax = sns.barplot(x=charges.head(), y=charges.head().index, palette= 'Blues')
```



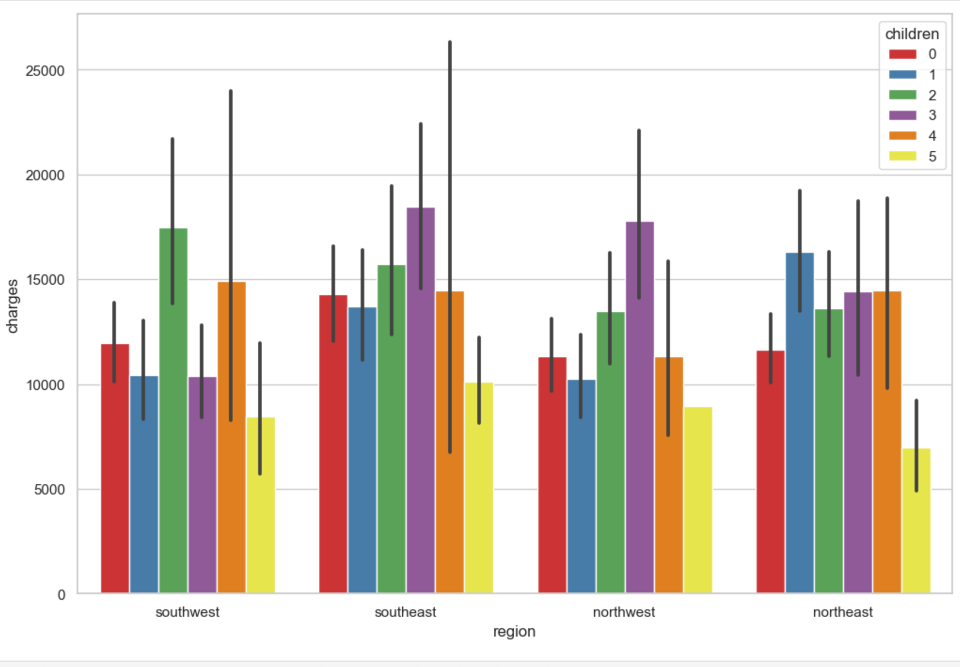
In [12]:
```python
#Now I want to compare the charges across different regions with the bars further grouped by sex using hue parameter
f, ax = plt.subplots(1, 1, figsize=(12, 8))
ax = sns.barplot(x='region', y='charges', hue='sex', data=df, palette='cool')
```



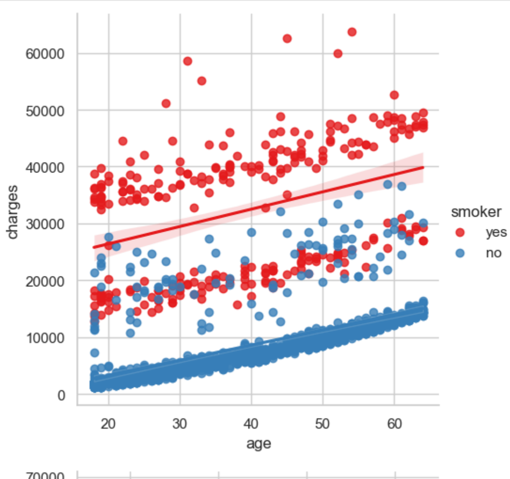
In [13]:
```python
# Now i want to create a bar plot to compare the charges across different regions with the bars grouped by smoker using the hue parameter
f, ax = plt.subplots(1, 1, figsize=(12,8))
ax = sns.barplot(x = 'region', y ='charges', hue='smoker', data=df, palette='Reds_r')
```

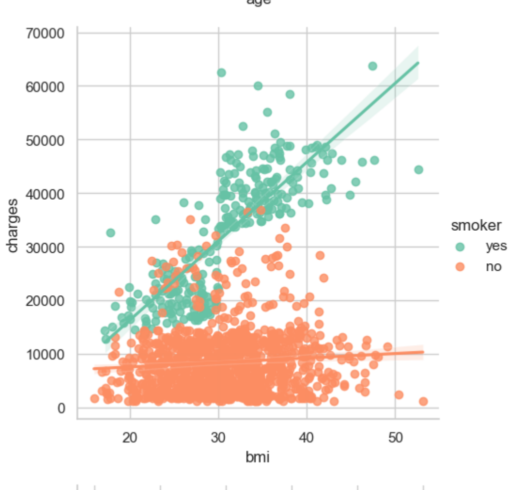


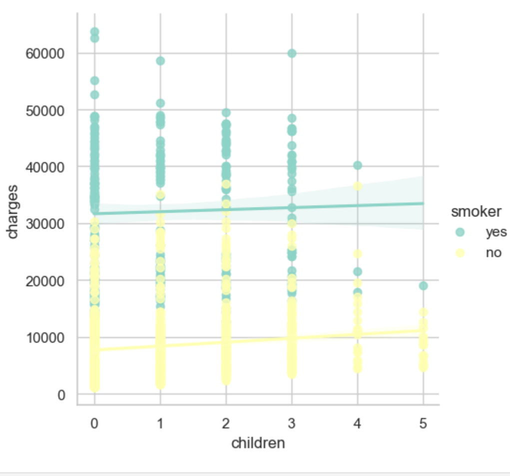
In [14]:
```python
#Now i am creating a bar plot to compare the charges across different regions with the bars further grouped by the number of children using the hue

f, ax = plt.subplots(1, 1, figsize=(12, 8))
ax = sns.barplot(x='region', y='charges', hue='children', data=df, palette='Set1')
```



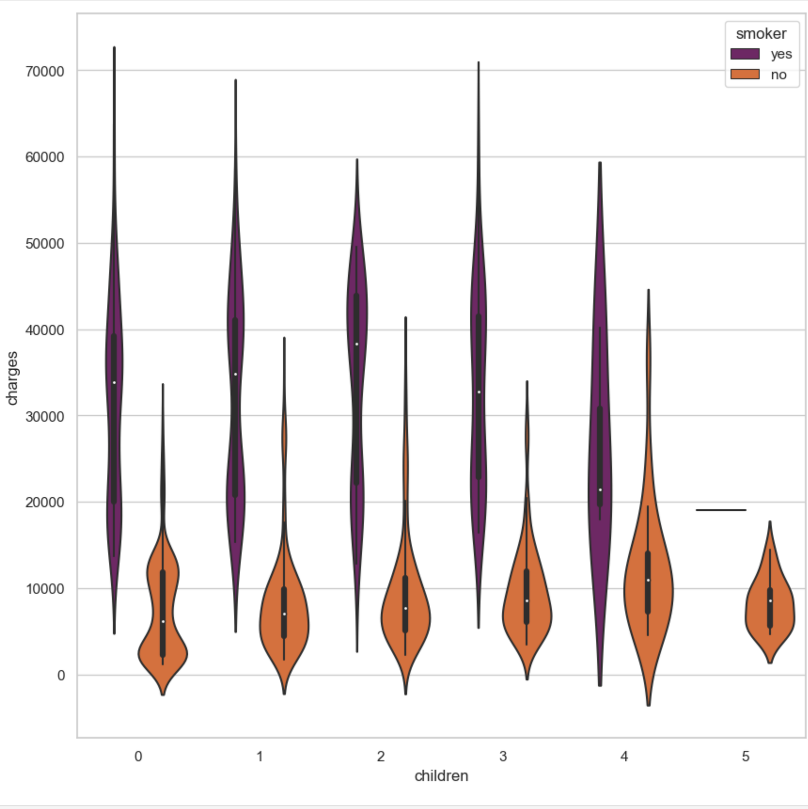
In [15]:
```python
#Now i am creating three separate scatter plots to visualize the relationship between age bmi children with charges
ax = sns.lmplot(x = 'age', y = 'charges', data=df, hue='smoker', palette= 'Set1')
ax = sns.lmplot(x = 'bmi', y = 'charges', data=df, hue='smoker', palette=  'Set2')
ax = sns.lmplot(x = 'children', y = 'charges', data=df, hue='smoker', palette= 'Set3')
```







In [16]:
```python
#Now I am using violiplot to visualize the distribution of charges on the number of children
f, ax = plt.subplots(1,1, figsize=(10, 10))
ax = sns.violinplot(x = 'children', y = 'charges', data=df, orient= 'v', hue='smoker', palette= 'inferno')
```



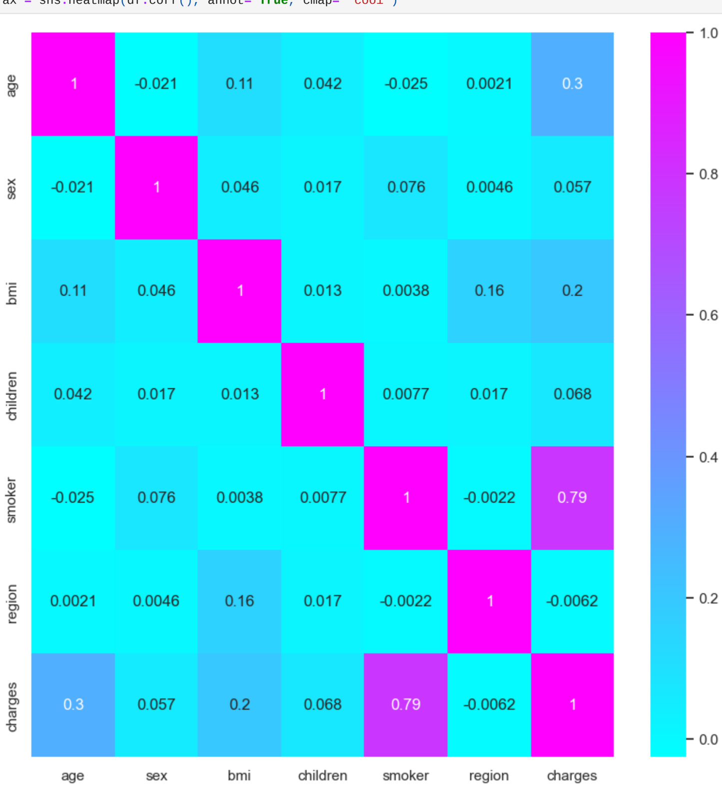
In [17]:
```python
#Converting objects labels into categorical
df[['sex', 'smoker', 'region']] = df[['sex', 'smoker', 'region']].astype('category')
df.dtypes
```

Out[17]:
```
age            int64
sex         category
bmi          float64
children       int64
smoker      category
region      category
charges      float64
dtype: object
```

In [18]:
```python
##Converting category labels into numerical using LabelEncoder

from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()
label.fit(df.sex.drop_duplicates())
df.sex = label.transform(df.sex)
label.fit(df.smoker.drop_duplicates())
df.smoker = label.transform(df.smoker)
label.fit(df.region.drop_duplicates())
df.region =label.transform(df.region)
df.dtypes
```

Out[18]:
```
age           int64
sex           int32
bmi         float64
children      int64
smoker        int32
region        int32
charges     float64
dtype: object
```

In [19]:
```python
f, ax = plt.subplots(1, 1, figsize=(10, 10))
ax = sns.heatmap(df.corr(), annot= True, cmap= 'cool')
```



Training model

Linear Regression

In [20]:
```python
# Importing the necessary libraries
from sklearn.model_selection import train_test_split as holdout
from sklearn.linear_model import LinearRegression
from sklearn import metrics

#Load the dataset
x = df.drop(['charges'],axis=1)
y = df['charges']

#Split the dataset inot training anf testing Datasets
x_train,x_test,y_train,y_test = holdout(x,y, test_size=0.2, random_state=0)

#create a Linear Regression model
Lin_reg = LinearRegression()
Lin_reg.fit(x_train, y_train)

#Print the Intercept,Coefficent ,and score of the model
print(Lin_reg.intercept_)
print(Lin_reg.coef_)
print(Lin_reg.score(x_test, y_test))
```

```
-11661.983908824424
[  253.99185244   -24.32455098   328.40261701   443.72929547
 23568.87948381  -288.50857254]
0.7998747145449959
```

Ridge Regression

In [21]:
```python
#Importing the required library
from sklearn.linear_model import Ridge

#Creating the Ridge Regression Model
Ridge = Ridge(alpha=0.5)

#Train the ridge Regression Model
Ridge.fit(x_train, y_train)

#Print the intercept,coeff,and score of the model
print(Ridge.intercept_)
print(Ridge.coef_)
print(Ridge.score(x_test, y_test))
```

```
-11643.440927495836
[ 2.53893751e+02 -2.15112284e+01  3.28339566e+02  4.44238477e+02
  2.35009674e+04 -2.89027871e+02]
0.7996989632063141
```

Lasso Regression

In [22]:
```python
#Importing the library
from sklearn.linear_model import Lasso

#Create the lasso Regression Model
Lasso = Lasso(alpha=0.2, fit_intercept=True, precompute=False,max_iter=1000,
              tol=0.0001, warm_start=False, positive=False, random_state=None, selection='cyclic')

#Train the Lasso regression model
Lasso.fit(x_train, y_train)

#print the interncept,coed,socre of the model
print(Lasso.intercept_)
print(Lasso.coef_)
print(Lasso.score(x_test, y_test))
```

```
-11661.838929039533
[ 2.53991436e+02 -2.34569821e+01  3.28389438e+02  4.43587436e+02
  2.35676136e+04 -2.88340296e+02]
0.7998690236224706
```

Random Forest Regressor

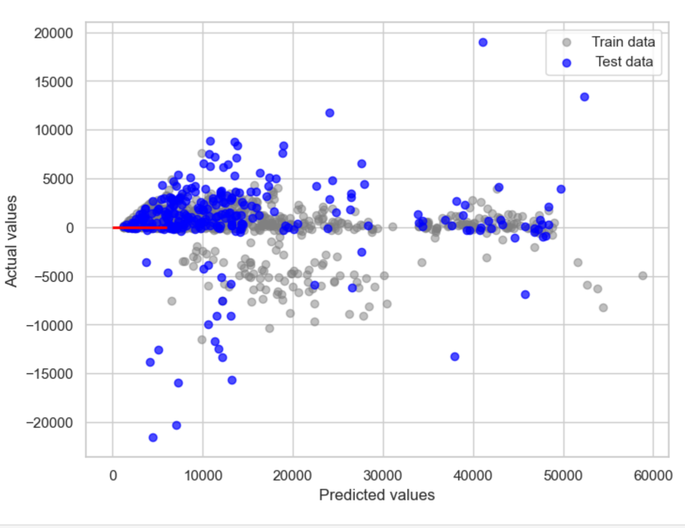
In [23]:
```python
#Importing the libraryt
from sklearn.ensemble import RandomForestRegressor as rfr

#load the dataset
x= df.drop(['charges'],axis = 1)
y= df.charges

#Create a Random Forest Regression
Rfr = rfr(n_estimators = 100, criterion ='squared_error',
                              random_state=1,
                                n_jobs = -1)
#Train the Random Forest Model
Rfr.fit(x_train,y_train)

#Make predictions of the model
x_train_pred= Rfr.predict(x_train)
x_test_pred= Rfr.predict(x_test)

#print the mean square of the model
print('MSE train data: %.3f, MSE test data: %.3f' %
      (metrics.mean_squared_error(x_train_pred, y_train),
       metrics.mean_squared_error(x_test_pred,  y_test)))
```

```
MSE train data: 3628893.887, MSE test data: 19730453.910
```

Results and Analysis

In [24]:
```python
plt.figure(figsize=(8,6))

plt.scatter(x_train_pred, x_train_pred - y_train,
          c ='gray', marker = 'o', s=35, alpha =0.5,
           label = 'Train data')
plt.scatter(x_test_pred, x_test_pred -y_test,
          c ='blue', marker ='o', s=35, alpha = 0.7,
           label = ' Test data')

plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.legend(loc = 'upper right')
plt.hlines(y= 0, xmin =0 , xmax =6000, lw =2, color = 'red')
```

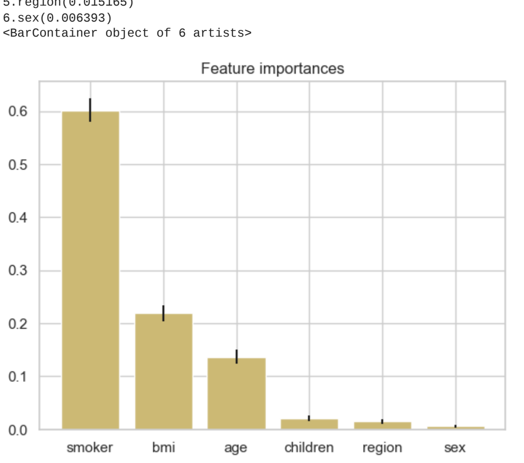
Out[24]:
```
<matplotlib.collections.LineCollection at 0x240e4574a60>
```



In [33]:
```python
print('Feature importance ranking\n\n')
importances = Rfr.feature_importances_
std = np.std([tree.feature_importances_ for tree in Rfr.estimators_],axis =0)
indices = np.argsort(importances)[::-1]
variables =['age','sex', 'bmi','children','smoker', 'region']
importance_list =[]
for f in range(x.shape[1]):
    variable = variables[indices[f]]
    importance_list.append(variable)
    print("%d.%s(%f)"% (f + 1, variable, importances[indices[f]]))

#Plot the feature importance of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(importance_list, importances[indices],
        color="y", yerr=std[indices], align="center")
```

```
Feature importance ranking


1.smoker(0.601678)
2.bmi(0.218831)
3.age(0.136943)
4.children(0.020990)
5.region(0.015165)
6.sex(0.006393)
```

Out[33]:
```
<BarContainer object of 6 artists>
```



Polynomial Regression

In [36]:
```python
#Importing the library
from sklearn.preprocessing import PolynomialFeatures

#Load the Data set
x = df.drop(['charges','sex','region'],axis =1)
y = df.charges

#Create polynomial features
pol = PolynomialFeatures (degree = 2)
x_pol = pol.fit_transform(x)

#Split the dataset into training and testing
x_train, x_test, y_train, y_test = holdout(x_pol, y, test_size=0.2, random_state=0)

#Create the polynomial regression model
Pol_reg = LinearRegression()
Pol_reg.fit(x_train, y_train)

#make predictions of the model
y_train_pred = Pol_reg.predict(x_train)
y_test_pred  = Pol_reg.predict(x_test)

#print the intercept,coeff,and score of the model
print(Pol_reg.intercept_)
print(Pol_reg.coef_)
print(Pol_reg.score(x_test, y_test))
```

```
-5325.881705252405
[ 0.00000000e+00 -4.01606591e+01  5.23702019e+02  8.52025026e+02
 -9.52698471e+03  3.04430186e+00  1.84508369e+00  6.01720286e+00
  4.20849790e+00 -9.38983382e+00  3.81612289e+00  1.40840670e+03
 -1.45982790e+02 -4.46151855e+02 -9.52698471e+03]
0.8812595703345228
```

In [37]:
```python
#Evaluating the performance of the algorithm
print('Mean Absolute Error :', metrics.mean_absolute_error(y_test, y_test_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_test_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
```

```
Mean Absolute Error : 2824.4950454776426
Mean Squared Error: 18895160.09878039
Root Mean Squared Error: 4346.856346692445
```

In [39]:
```python
#Predicting the charges
y_test_pred = Pol_reg.predict(x_test)
#Comparing the actual output values with the predicted values
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_test_pred})
df
```

Out[39]:

	Actual	Predicted
578	9724.53000	12101.156323
610	8547.69130	10440.782266
569	45702.02235	48541.022951
1034	12950.07120	14140.067522
198	9644.25250	8636.235727
...	...	...
1084	15019.76005	16712.196281
726	6664.68595	8654.565461
1132	20709.02034	12372.050609
725	40932.42950	41465.617268
963	9500.57305	10941.780705

268 rows × 2 columns

In [ ]: