1) Importing modules & dataframe

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import linear_regression as lr
import utils
```

In [2]:
```
df = pd.read_csv('./insurance.csv')
```

2) Preprocessing

2.1) Checking out our data

In [3]:
```
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

age, sex, children, smoker, region are categorical columns and bmi, charges are continuous columns.

We have to predict charges given the rest of the features. And because charges is a continuous variable, this is a regression problem.

In [4]:
```
df.describe()
```

Out[4]:

	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

2.2) Dealing with missing values

In [5]:
```
df.isna().sum()
```

Out[5]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [6]:
```
(df == "?").sum()
```

Out[6]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

We don't have any missing values. So we are good to go!

2.3) Dealing with categorical and non-numeric data

We have three categorical and non-numeric columns here - sex, smoker & region. We will do one-hot encoding for them.

In [7]:
```
column_names_to_one_hot = ['sex', 'smoker', 'region']
df = pd.get_dummies(df, columns=column_names_to_one_hot, drop_first=True)
```

drop_first is set to True in pd.get_dummies() to avoid 'Dummy Variable Trap'. Read more about it here: https://www.learndatasci.com/glossary/dummy-variable-trap/

In [8]:
```
df.head()
```

Out[8]:

	age	bmi	children	charges	sex_male	smoker_yes	region_northwest	region_southeast	region_sout
0	19	27.900	0	16884.92400	0	1	0	0	
1	18	33.770	1	1725.55230	1	0	0	1	
2	28	33.000	3	4449.46200	1	0	0	1	
3	33	22.705	0	21984.47061	1	0	1	0	
4	32	28.880	0	3866.85520	1	0	1	0	

2.4) Dropping duplicate rows

In [9]:
```
# Checking for duplicate rows
df.duplicated().sum()
```

Out[9]:
```
1
```

We have just one duplicate row. Let's drop that row.

In [10]:
```
df.drop(axis='rows', labels=df.index[df.duplicated()], inplace=True)
df.reset_index(inplace=True, drop=True)
```

In [11]:
```
df.duplicated().sum()
```

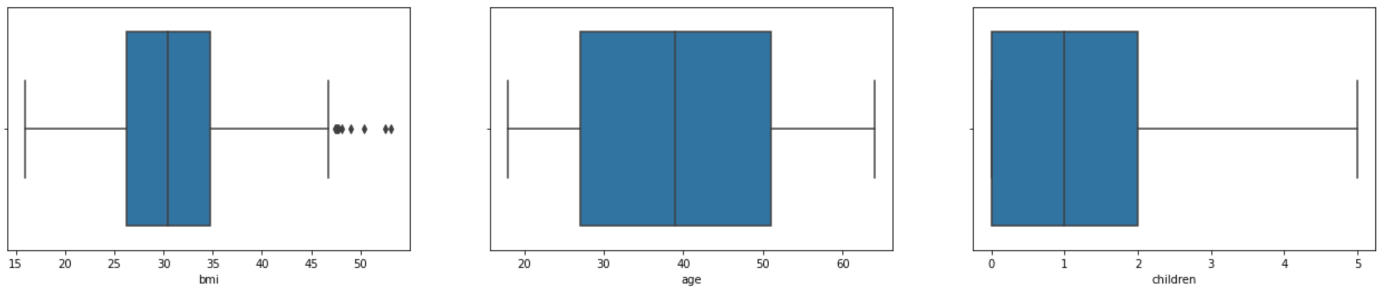
Out[11]: 0

We have no duplicate rows now!

3) EDA

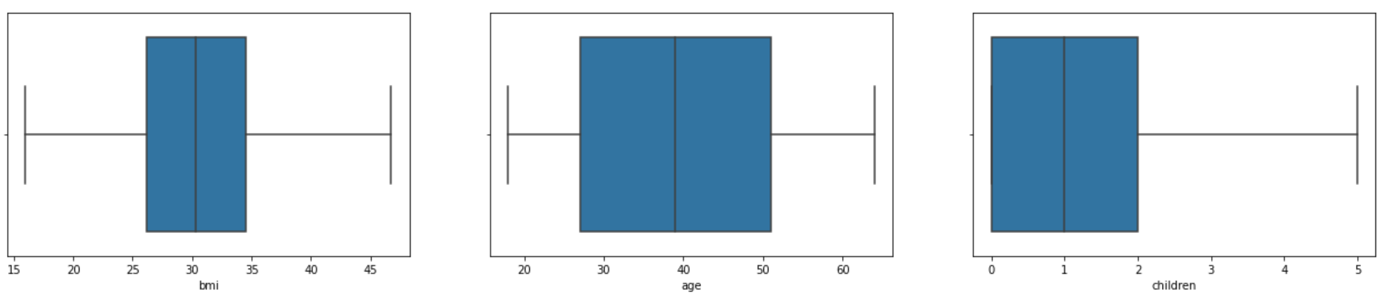
3.1) Outlier detection and removal

In [12]:
```
# Detecting outliers in bmi, age and children columns
fig, ax = plt.subplots(1, 3, figsize=(22, 4))
sns.boxplot(ax=ax[0], x=df['bmi'])
sns.boxplot(ax=ax[1], x=df['age'])
sns.boxplot(ax=ax[2], x=df['children'])
plt.show()
```



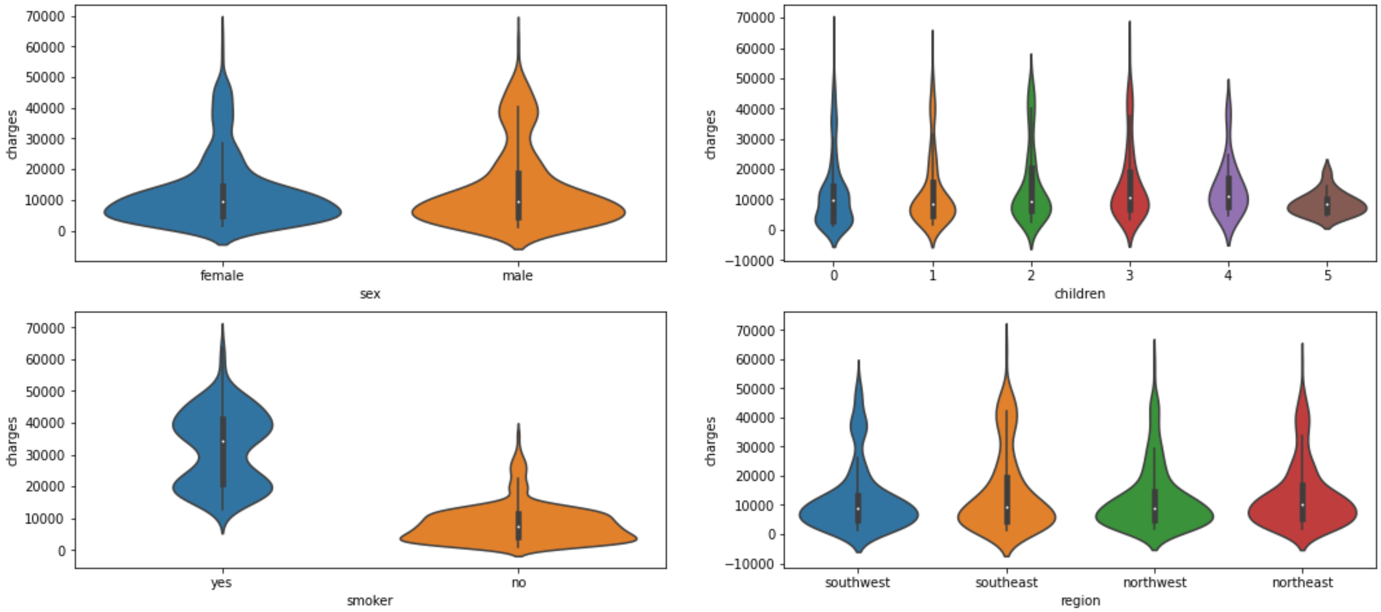
In [13]:
```
# Removing outliers from bmi
utils.remove_outlier(df, 'bmi')
```

In [14]:
```
fig, ax = plt.subplots(1, 3, figsize=(22, 4))
sns.boxplot(ax=ax[0], x=df['bmi'])
sns.boxplot(ax=ax[1], x=df['age'])
sns.boxplot(ax=ax[2], x=df['children'])
plt.show()
```

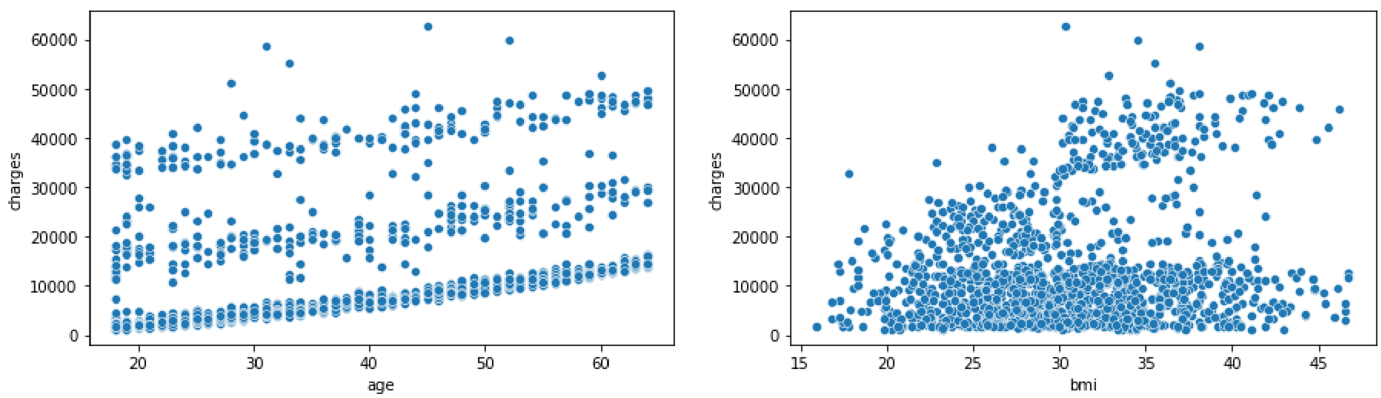


3.2) Correlation

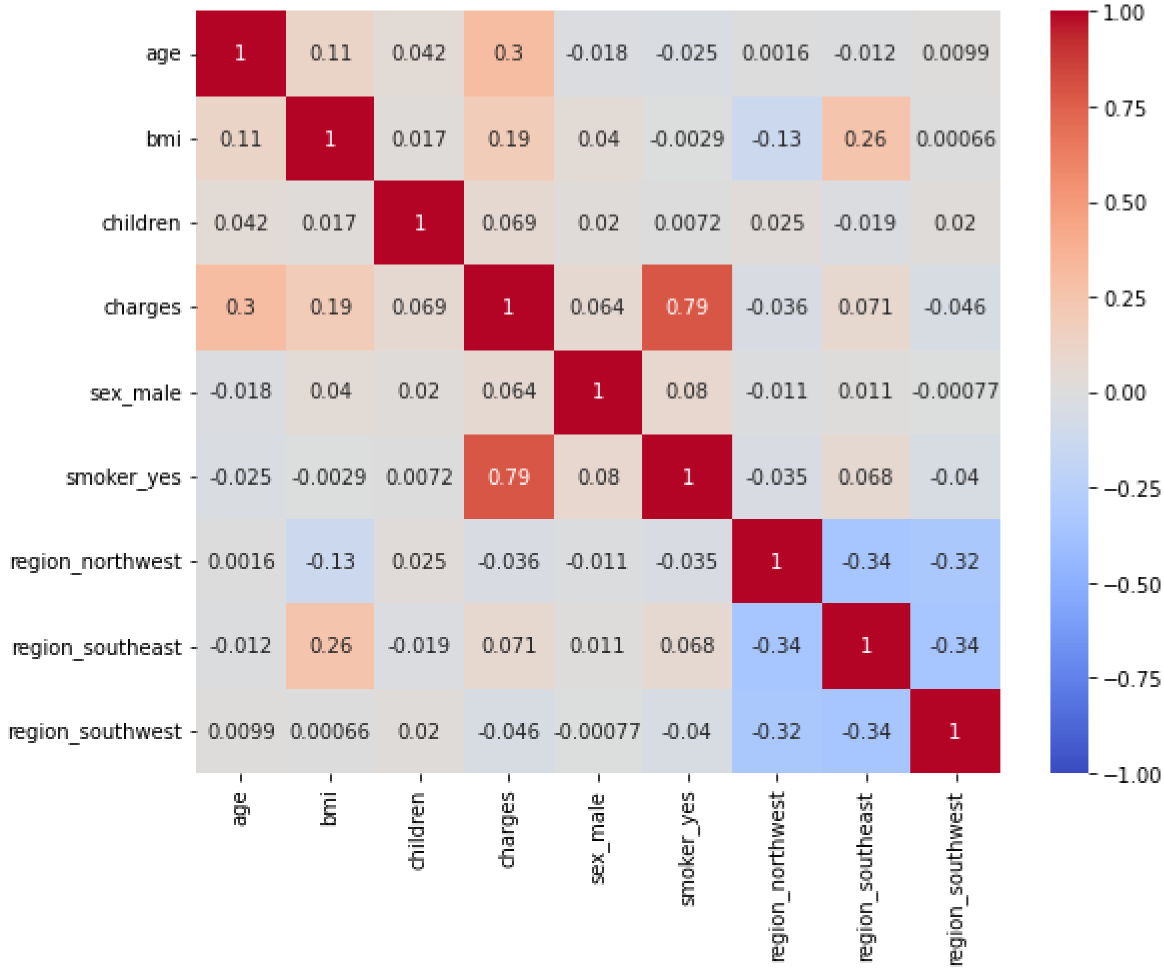
In [15]:
```
main_df = pd.read_csv('./insurance.csv')

fig, ax = plt.subplots(2, 2, figsize=(18, 8))
sns.violinplot(ax=ax[0,0], x="sex", y="charges", data=main_df)
sns.violinplot(ax=ax[0,1], x="children", y="charges", data=main_df)
sns.violinplot(ax=ax[1,0], x="smoker", y="charges", data=main_df)
sns.violinplot(ax=ax[1,1], x="region", y="charges", data=main_df)
plt.show()
```



In [16]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 4))
sns.scatterplot(ax=ax[0], x="age", y="charges", data=df)
sns.scatterplot(ax=ax[1], x="bmi", y="charges", data=df)
plt.show()
```



In [17]:
```
plt.figure(figsize=(9,7))
sns.heatmap(df.corr(), vmin=-1, cmap="coolwarm", annot=True)
plt.show()
```



We can see that children, sex and region columns have very less correlation with charges (the output). So, we can drop them.

In [18]:
```
df.drop(['children', 'sex_male', 'region_northwest', 'region_southeast', 'region_southwe
```

3.3) Normalization and standardization

In [19]:
```
df['bmi'] = utils.normalize(df['bmi'])
df['age'] = utils.normalize(df['age'])
```

In [20]:
```
# Scaling the output variable (charges) by a factor of 1000
df['charges'] = df['charges']/1000
```

4) Multivariate Linear Regression

4.1) Feature-target split

In [21]:
```
X = df.drop(axis='columns', labels='charges').to_numpy().astype(np.float64)

# Adding a column of ones to the data matrix
n = X.shape[0]
X =  np.c_[ np.ones(n), X]

y = df['charges'].to_numpy().astype(np.float64)
```

4.2) Train-test split

In [22]:
```python
X_train, X_test, y_train, y_test = utils.train_test_split(X, y, train_size=0.75)
```

4.3) Closed Form

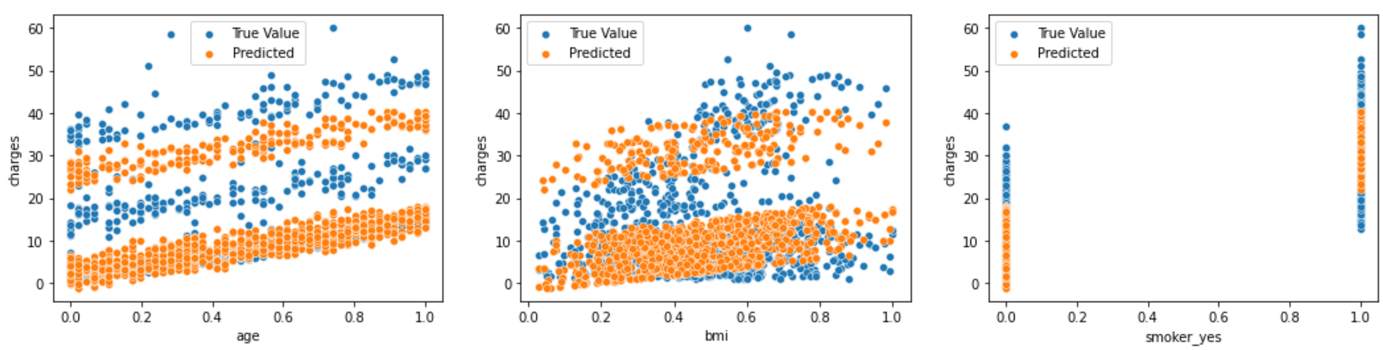
4.3.1) Training

In [23]:
```python
w = lr.closed_form(X_train, y_train)
```

In [24]:
```python
yhat_train = lr.predict(X_train, w)
print('Metrics for the training data:')
print('MSE', utils.mean_squared_error(y_train, yhat_train))
print('MAE', utils.mean_absolute_error(y_train, yhat_train))
```

```
Metrics for the training data:
MSE 34.27654428672158
MAE 4.093436671285072
```

In [25]:
```python
# Plot the results
features = ['age', 'bmi', 'smoker_yes']
fig, ax = plt.subplots(1, 3, figsize=(18, 4))
for i in range(1,4):
  sns.scatterplot(ax=ax[i-1], x=X_train[:,i], y=y_train, label = 'True Value')
  sns.scatterplot(ax=ax[i-1], x=X_train[:,i], y=yhat_train, label = 'Predicted')
  ax[i-1].set_xlabel(features[i-1])
  ax[i-1].set_ylabel('charges')
plt.legend()
plt.show()
```

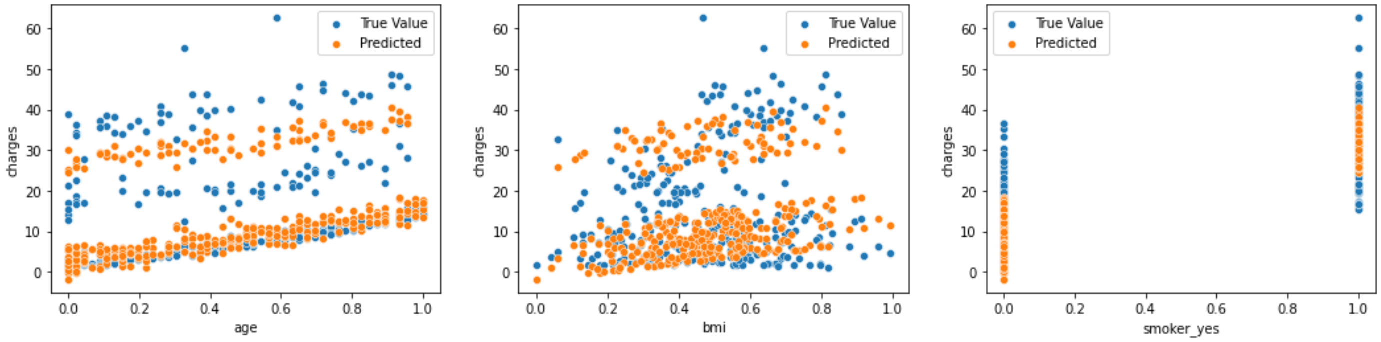


4.3.2) Testing

In [26]:
```python
yhat_test = lr.predict(X_test, w)
print('Metrics for test data:')
print('MSE', utils.mean_squared_error(y_test, yhat_test))
print('MAE', utils.mean_absolute_error(y_test, yhat_test))
```

```
Metrics for test data:
MSE 43.19853329289433
MAE 4.443096903456985
```

In [27]:
```python
# Plot the results
features = ['age', 'bmi', 'smoker_yes']
fig, ax = plt.subplots(1, 3, figsize=(18, 4))
for i in range(1,4):
  sns.scatterplot(ax=ax[i-1], x=X_test[:,i], y=y_test, label = 'True Value')
  sns.scatterplot(ax=ax[i-1], x=X_test[:,i], y=yhat_test, label = 'Predicted')
  ax[i-1].set_xlabel(features[i-1])
  ax[i-1].set_ylabel('charges')
plt.legend()
plt.show()
```



4.4) Gradient Descent

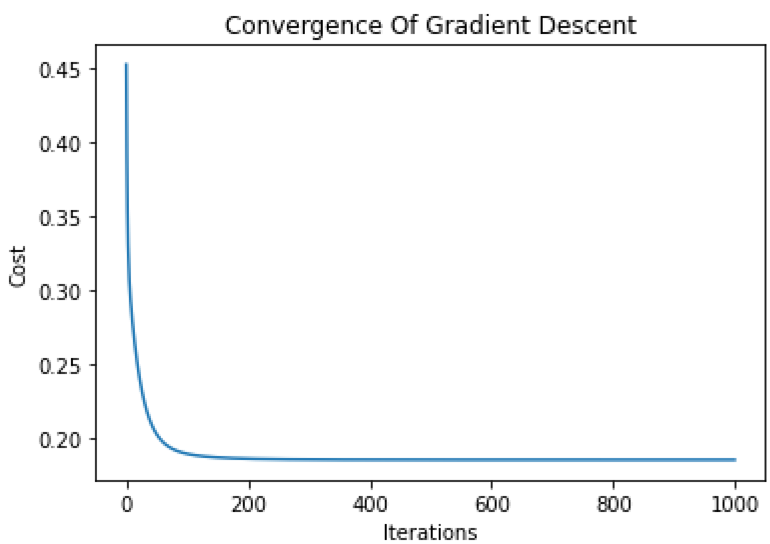
4.4.1) Training

In [28]:
```
iters = 1000
w, cost = lr.fit(X_train, y_train, 0.1, iters)
```

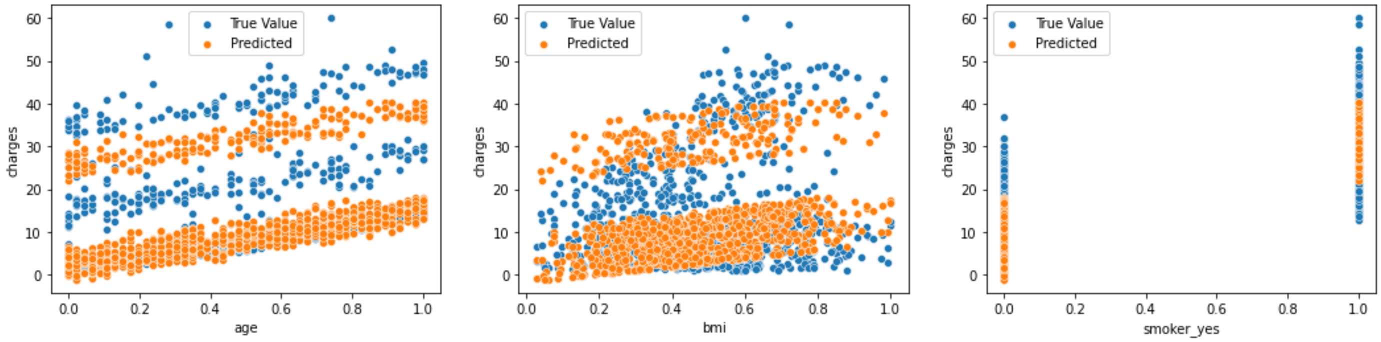
In [29]:
```
yhat_train = lr.predict(X_train, w)
print('Metrics for the training data:')
print('MSE', utils.mean_squared_error(y_train, yhat_train))
print('MAE', utils.mean_absolute_error(y_train, yhat_train))
```

```
Metrics for the training data:
MSE 34.27655679747978
MAE 4.092583452025161
```

In [30]:
```
# Convergence of gradient descent
plt.title('Convergence Of Gradient Descent')
plt.ylabel('Cost')
plt.xlabel('Iterations')
plt.plot(range(iters), cost)
plt.show()
```



In [31]:
```
# Plot the results
features = ['age', 'bmi', 'smoker_yes']
fig, ax = plt.subplots(1, 3, figsize=(18, 4))
for i in range(1,4):
  sns.scatterplot(ax=ax[i-1], x=X_train[:,i], y=y_train, label = 'True Value')
  sns.scatterplot(ax=ax[i-1], x=X_train[:,i], y=yhat_train, label = 'Predicted')
  ax[i-1].set_xlabel(features[i-1])
  ax[i-1].set_ylabel('charges')
plt.legend()
plt.show()
```

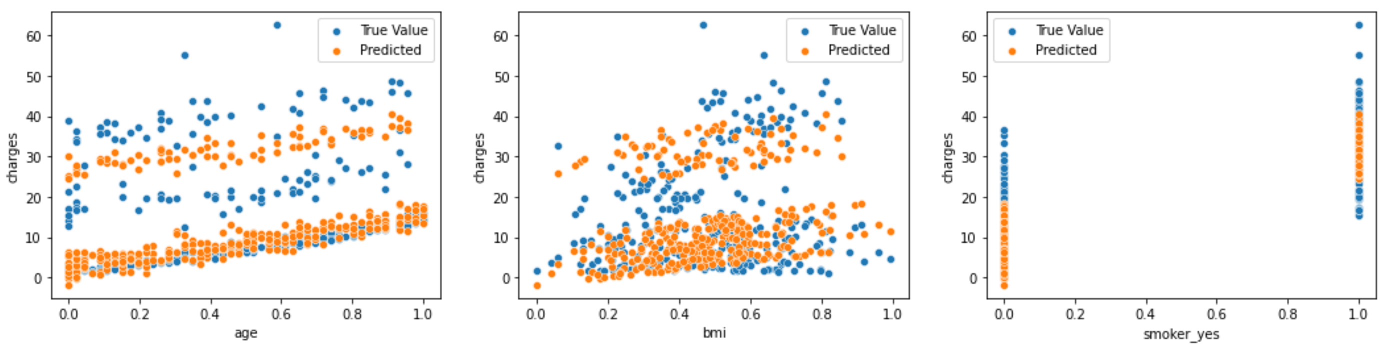


4.4.1) Testing

In [32]:
```
yhat_test = lr.predict(X_test, w)
print('Metrics for test data:')
print('MSE', utils.mean_squared_error(y_test, yhat_test))
print('MAE', utils.mean_absolute_error(y_test, yhat_test))
```

```
Metrics for test data:
MSE 43.19954714763513
MAE 4.4424370353870675
```

In [33]:
```
# Plot the results
features = ['age', 'bmi', 'smoker_yes']
fig, ax = plt.subplots(1, 3, figsize=(18, 4))
for i in range(1,4):
  sns.scatterplot(ax=ax[i-1], x=X_test[:,i], y=y_test, label = 'True Value')
  sns.scatterplot(ax=ax[i-1], x=X_test[:,i], y=yhat_test, label = 'Predicted')
  ax[i-1].set_xlabel(features[i-1])
  ax[i-1].set_ylabel('charges')
plt.legend()
plt.show()
```



5) Univariate Linear Regression

We'll use age as our input feature and charges as our target variable.

5.1) Feature-target split

In [34]:
```
X = df['age'].to_numpy().astype(np.float64).reshape(-1,1)

# Adding a column of ones to the data matrix
n = X.shape[0]
X =  np.c_[ np.ones(n), X]

y = df['charges'].to_numpy().astype(np.float64)
```

5.2) Train-test split

In [35]:
```
X_train, X_test, y_train, y_test = utils.train_test_split(X, y, train_size=0.75)
```

5.3) Closed Form

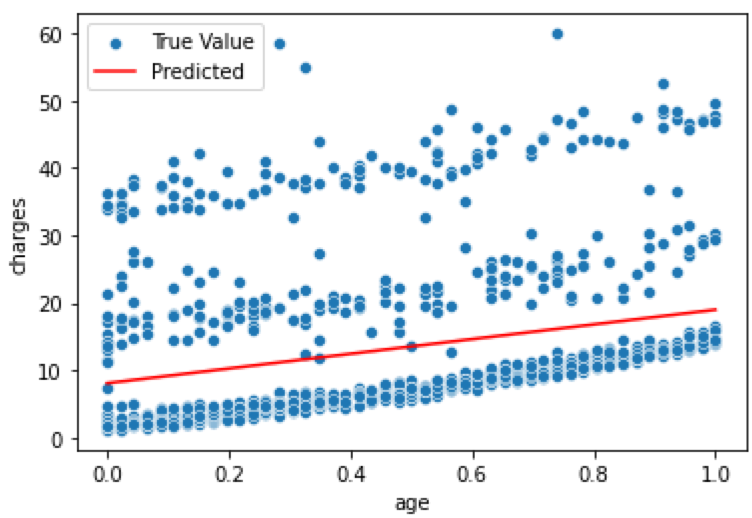
5.3.1) Training

In [36]:
```
w = lr.closed_form(X_train, y_train)
```

In [37]:
```
yhat_train = lr.predict(X_train, w)
print('Metrics for the training data:')
print('MSE', utils.mean_squared_error(y_train, yhat_train))
print('MAE', utils.mean_absolute_error(y_train, yhat_train))
```

```
Metrics for the training data:
MSE 127.7258718002987
MAE 8.869895866118968
```

In [38]:
```
# Plot the results
sns.scatterplot(x=X_train[:,1], y=y_train, label = 'True Value')
sns.lineplot(x=X_train[:,1], y=yhat_train, label = 'Predicted', color='red')
plt.xlabel('age')
plt.ylabel('charges')
plt.legend()
plt.show()
```

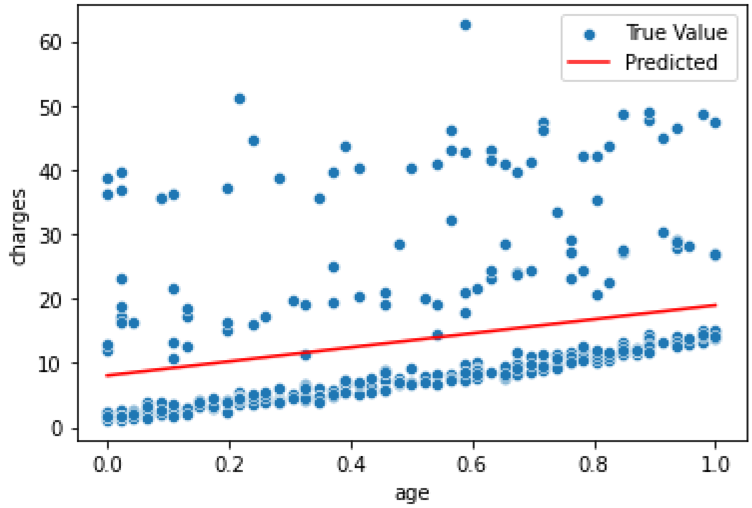


5.3.2) Testing

In [39]:
```
yhat_test = lr.predict(X_test, w)
print('Metrics for test data:')
print('MSE', utils.mean_squared_error(y_test, yhat_test))
print('MAE', utils.mean_absolute_error(y_test, yhat_test))
```

```
Metrics for test data:
MSE 140.27309565146032
MAE 9.080383025558111
```

In [40]:
```
# Plot the results
sns.scatterplot(x=X_test[:,1], y=y_test, label = 'True Value')
sns.lineplot(x=X_test[:,1], y=yhat_test, label = 'Predicted', color='red')
plt.xlabel('age')
plt.ylabel('charges')
plt.legend()
plt.show()
```



5.4) Gradient Descent

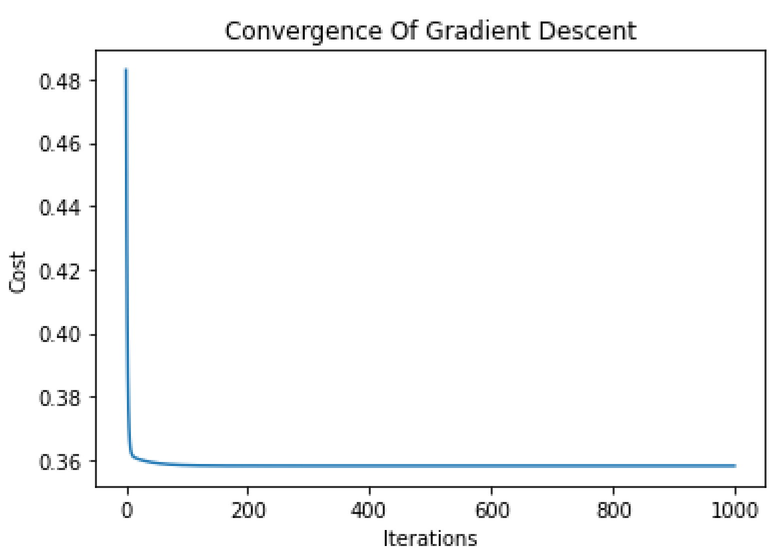
5.4.1) Training

In [41]:
```
iters = 1000
w, cost = lr.fit(X_train, y_train, 0.1, iters)
```

In [42]:
```
yhat_train = lr.predict(X_train, w)
print('Metrics for the training data:')
print('MSE', utils.mean_squared_error(y_train, yhat_train))
print('MAE', utils.mean_absolute_error(y_train, yhat_train))
```

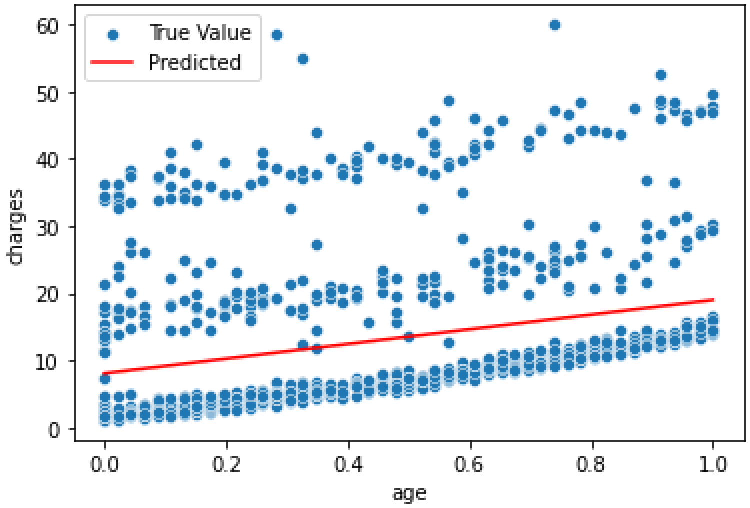
```
Metrics for the training data:
MSE 127.7258718002989
MAE 8.869895872811778
```

In [43]:
```
# Convergence of gradient descent
plt.title('Convergence Of Gradient Descent')
plt.ylabel('Cost')
plt.xlabel('Iterations')
plt.plot(range(iters), cost)
plt.show()
```



In [44]:
```
# Plot the results
sns.scatterplot(x=X_train[:,1], y=y_train, label = 'True Value')
sns.lineplot(x=X_train[:,1], y=yhat_train, label = 'Predicted', color='red')
plt.xlabel('age')
plt.ylabel('charges')
```

```
plt.legend()
plt.show()
```



5.4.2) Testing

In [45]:
```
yhat_test = lr.predict(X_test, w)
print('Metrics for test data:')
print('MSE', utils.mean_squared_error(y_test, yhat_test))
print('MAE', utils.mean_absolute_error(y_test, yhat_test))
```

```
Metrics for test data:
MSE 140.2730965539362
MAE 9.080383055192343
```

In [47]:
```
# Plot the results
sns.scatterplot(x=X_test[:,1], y=y_test, label = 'True Value')
sns.lineplot(x=X_test[:,1], y=yhat_test, label = 'Predicted', color='red')
plt.xlabel('age')
plt.ylabel('charges')
plt.legend()
plt.show()
```