Medical Insurance Costs Prediction

Predict medical insurance costs based on patient demographics (age, sex, bmi), number of dependents or children, region within the United States using predictive machine learning modeling.

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

Data

Data is from https://github.com/stedy/Machine-Learning-with-R-datasets/blob/master/insurance.csv

Data consists of

- age: age of patient
- sex: gender, female, male
- bmi: Body mass index
- children: number of children/dependents
- smoker: yes or no
- region: reside in the northeast, southeast, southwest, northwest of USA
- charges: medical costs billed by health insurance

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

Out[2]:

	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 [3]:
```
print('Number of patients: ', df.shape[0])
print('Number of columns: ', df.shape[1])
```

```
Number of patients:  1338
Number of columns:  7
```

Information on data.

In [4]:
```
df.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
```

Summary statistics of data.

Wide range in age, bmi, children and charges.

In [5]:
```
df.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

Cleaning data by removing duplicates.

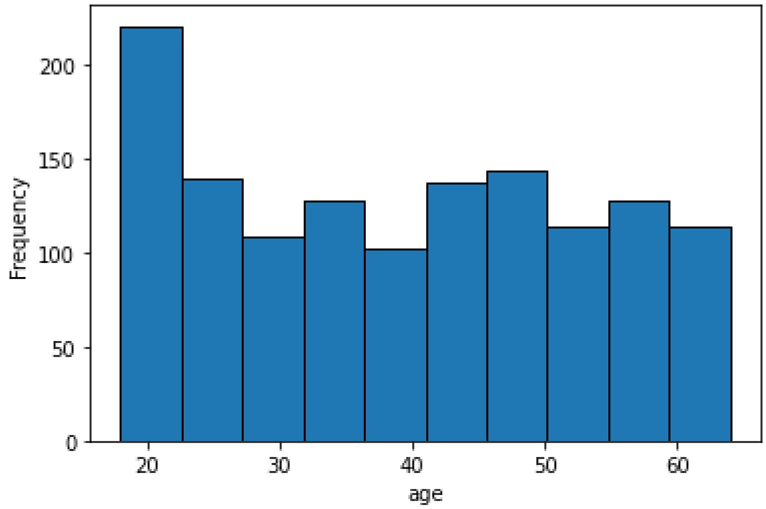
In [6]:
```
print('Duplicated observation ', df[df.duplicated()])
df = df.drop_duplicates()
print('New number of patients: ', df.shape[0])
```

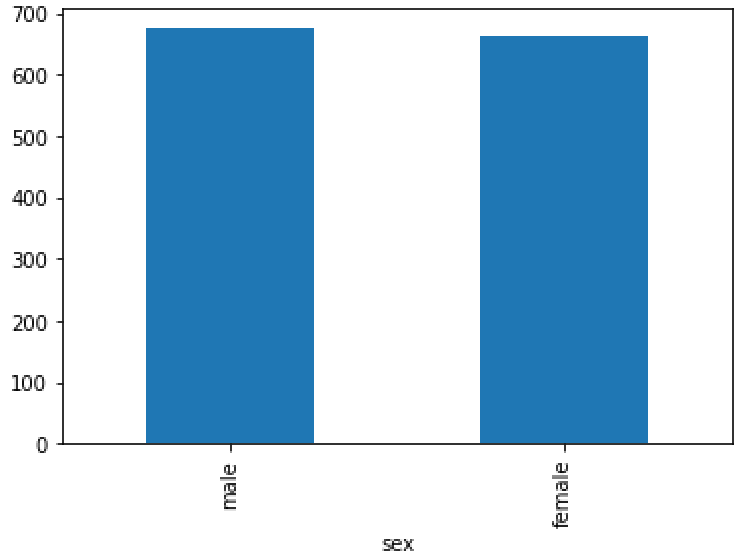
```
Duplicated observation       age   sex    bmi  children smoker     region    charges
581   19  male  30.59         0     no  northwest  1639.5631
New number of patients:  1337
```

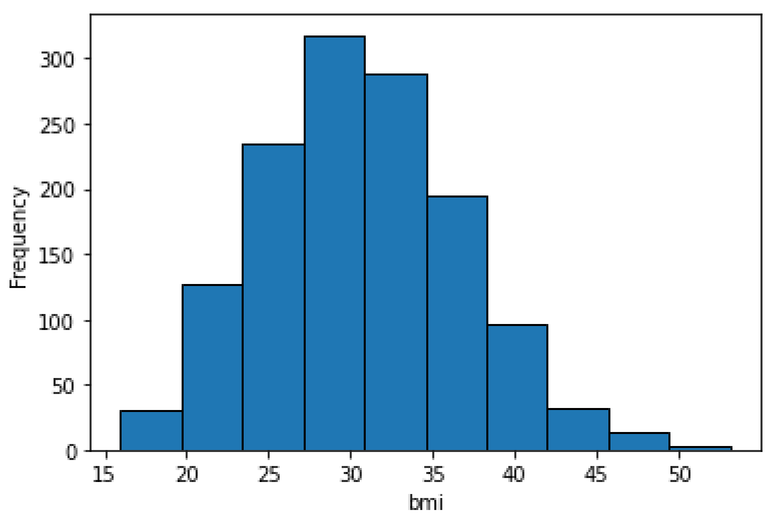
Distribution of data.

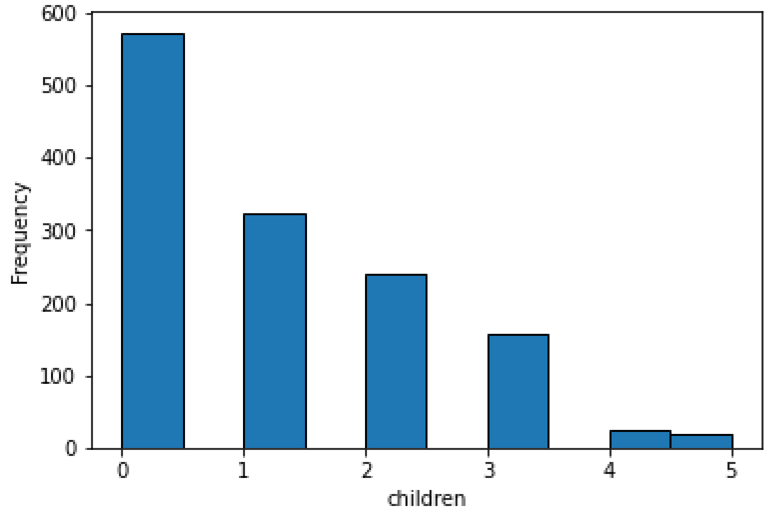
In [7]:
```
for column in df.columns:
    if df[column].dtypes != 'object':
        plt.figure()
        df[column].plot.hist(edgecolor = "black");
        plt.xlabel(column)
    else:
        plt.figure()
```

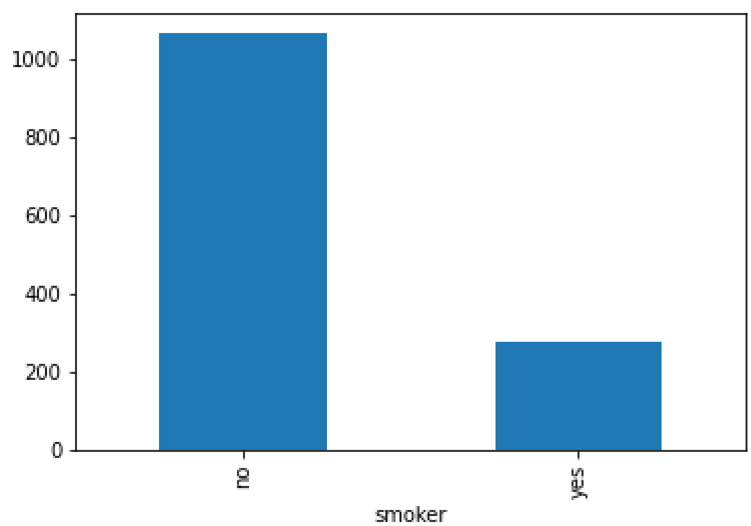
```
        df[column].value_counts().plot(kind='bar')
        plt.xlabel(column)
```

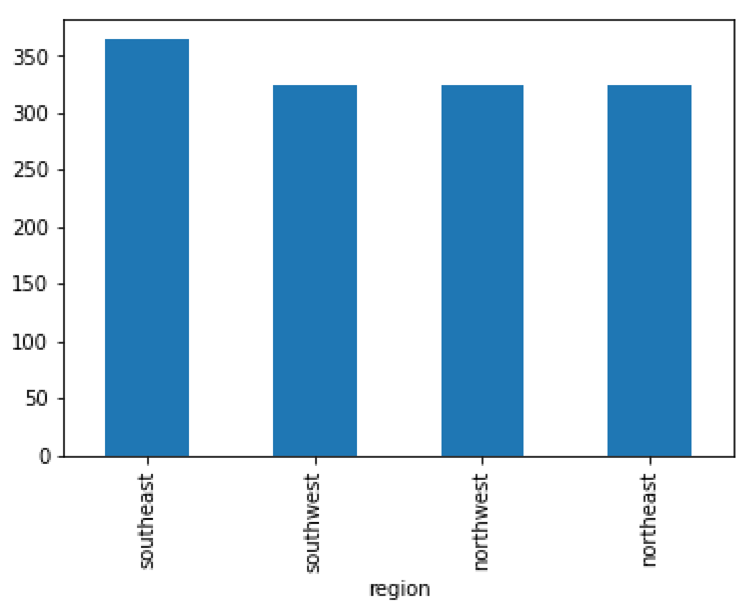


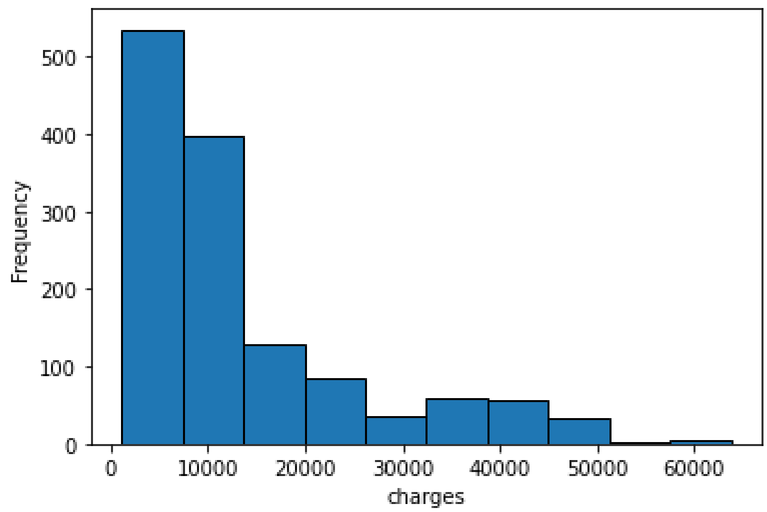





600
500
400
300
200
100
0
Frequency
0
1
2
3
4
5
children

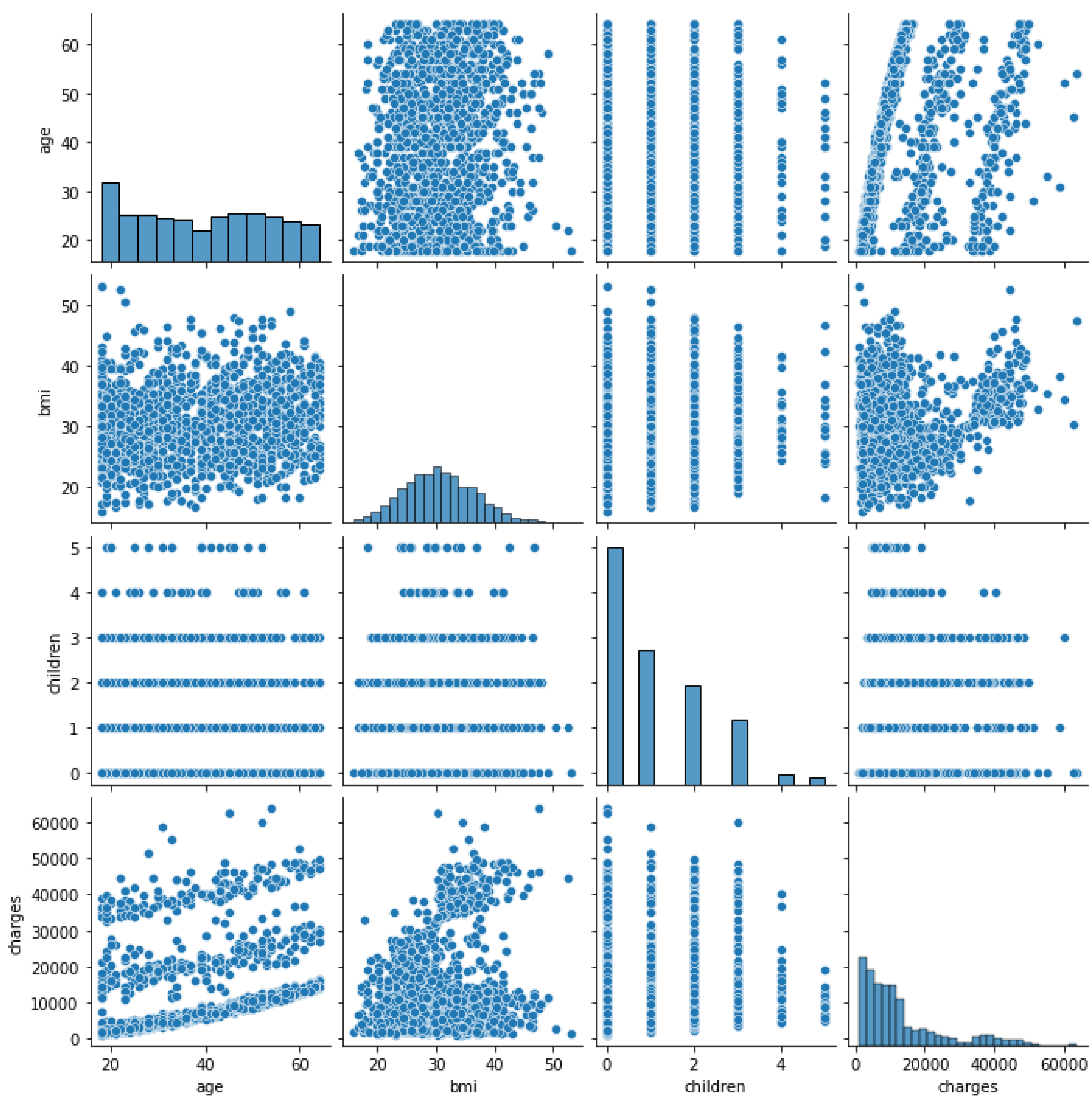

1000
800
600
400
200
0
no
yes
smoker


350
300
250
200
150
100
50
0
southeast
southwest
northwest
northeast
region



Visualize correlations between numerical data.

In [8]:
```
sns.pairplot(df);
```

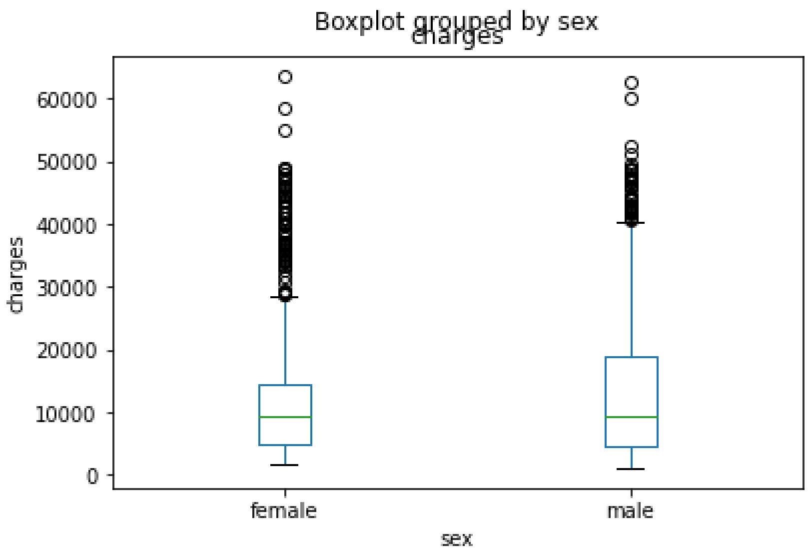


Charges by sex

Similar charges for female and male.

In [9]:
```
plt.figure();
df.boxplot(by='sex', column=['charges'], grid=False);
plt.ylabel('charges');
```

```
<Figure size 432x288 with 0 Axes>
```

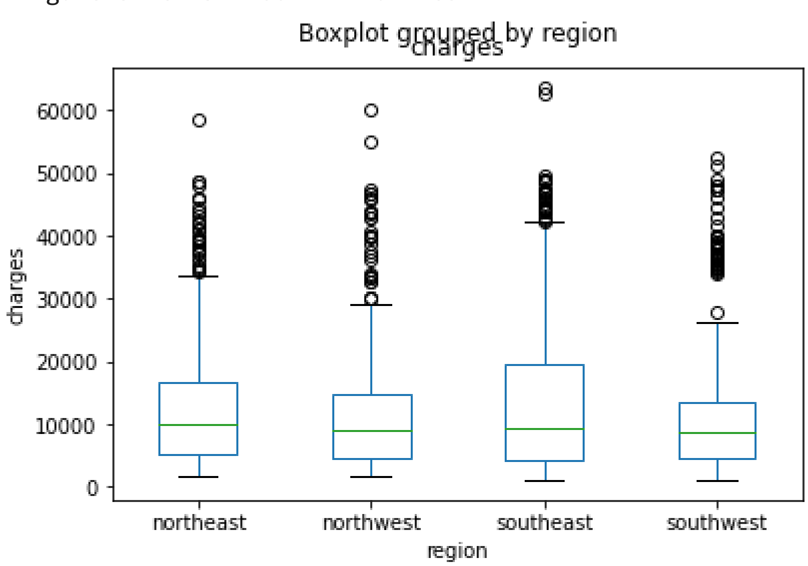


Charges by region

Similar charges by region.

In [10]:
```
plt.figure();
df.boxplot(by='region', column=['charges'], grid=False);
plt.ylabel('charges');
```

```
<Figure size 432x288 with 0 Axes>
```

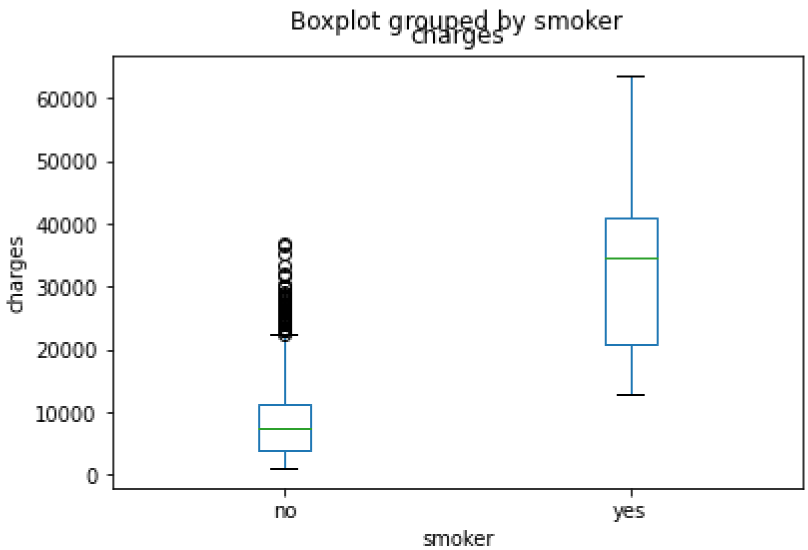


Charges by smoker

Much higher charges for smoker than non-smoker.

In [11]:
```
plt.figure();
df.boxplot(by='smoker', column=['charges'], grid=False);
plt.ylabel('charges');
```

```
<Figure size 432x288 with 0 Axes>
```



Feature engineering.

Convert categorical features (sex, region, smoker) to nominal.

Male = 1, Female = 0

Smoker = 1, Non-smoker = 0

Represent region = 1, Do not represent region = 0

In [12]:
```
df_sex_smoker = pd.get_dummies(df[['sex', 'smoker']], drop_first=True)
df_sex_smoker.columns = ['gender', 'is_smoker']

df_region = pd.get_dummies(df[['region']], drop_first=False)

df_featured = pd.concat([df, df_sex_smoker, df_region], axis=1)
df_featured = df_featured.drop(['sex', 'smoker', 'region'], axis=1, errors='ignore')
```

Prediction machine learning modeling using regression.

3 models used,

1. Linear Regression
2. Ridge Regression
3. Lasso Regression

StandardScaler is used to normalized features.

PolynomialFeatures is used to create new polynomial combinations of features.

GridSearchCV is used for hyperparameter tunning of each of the 3 models.

In [13]:
```
import numpy as np
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
```

Metric for evaluation is root mean square error.

In [14]:
```
def rmse(ytrue, ypredicted):
    return np.sqrt(mean_squared_error(ytrue, ypredicted))
```

Separate data into features and target

In [15]:
```
X = df_featured.drop('charges', axis=1)
y = df_featured['charges']
```

Split dataset into training and testing

In [16]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size= 0.2, random_state=
```

Instantiate KFold with 5 folds.

In [17]:
```
kf = KFold(shuffle=True, random_state=12345, n_splits=5)
```

Create Pipeline and GridSearchCV and params range for Linear Regression model

In [18]:
```
estimator_lr = Pipeline([("scaler", StandardScaler()),
                        ("polynomial_features", PolynomialFeatures()),
                        ("linear_regression", LinearRegression())])

params = {
    'polynomial_features__degree': [1, 2, 3]
}
grid_lr = GridSearchCV(estimator_lr, params, cv=kf)
```

Create Pipeline and GridSearchCV and params range for Ridge Regression model

In [19]:
```
estimator_ridge = Pipeline([("scaler", StandardScaler()),
                        ("polynomial_features", PolynomialFeatures()),
                        ("ridge_regression", Ridge())])

params = {
    'polynomial_features__degree': [1, 2, 3],
    'ridge_regression__alpha': np.geomspace(1, 80, 50)
}
grid_ridge = GridSearchCV(estimator_ridge, params, cv=kf)
```

Create Pipeline and GridSearchCV and params range for Lasso Regression model

In [20]:
```
estimator_lasso = Pipeline([("scaler", StandardScaler()),
                        ("polynomial_features", PolynomialFeatures()),
                        ("lasso_regression", Lasso())])

params = {
    'polynomial_features__degree': [1, 2, 3],
    'lasso_regression__alpha': np.geomspace(10, 500, 25),
    'lasso_regression__max_iter': [100000]
}
grid_lasso = GridSearchCV(estimator_lasso, params, cv=kf)
```

Run computation over all models and get RMSE for each

In [21]:
```
grid_list = [grid_lr, grid_ridge, grid_lasso]
model_list = ['Linear regression', 'Ridge regression', 'Lasso regression']

for model, grid in zip(model_list, grid_list):
    print(model)
    grid.fit(X_train, y_train)
    print('Best score: ', grid.best_score_)
    print('Best parameters: ', grid.best_params_)
    print('R2: ', r2_score(y_test, grid.predict(X_test)))
    print('\n')
```

```
Linear regression
Best score:  0.8313270429058314
Best parameters:  {'polynomial_features__degree': 2}
R2:  0.8560216170784641


Ridge regression
Best score:  0.8317353210701258
Best parameters:  {'polynomial_features__degree': 2, 'ridge_regression__alpha': 19.12
8144696681773}
R2:  0.857609253693778


Lasso regression
Best score:  0.8348821824168651
Best parameters:  {'lasso_regression__alpha': 135.7208808297453, 'lasso_regression__m
ax_iter': 100000, 'polynomial_features__degree': 2}
R2:  0.8605858244876337
```

Best model

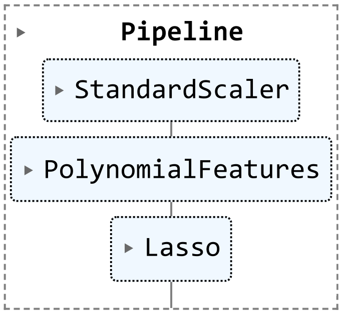
Lasso with largest R2, indicating best predictor for charges.

Polynomial features degree = 2 Lasso regression alpha = 135.72

Create best pipeline/model using tunned hyperparameters.

In [22]:
```
best_estimator_lasso = Pipeline([("scaler", StandardScaler()),
                        ("polynomial_features", PolynomialFeatures(degree=grid_lasso.b
                        ("lasso_regression", Lasso(alpha=grid_lasso.best_params_['lass
best_estimator_lasso.fit(X_train, y_train)
```

Out[22]:



In [23]:
```
print('Magnitude of Lasso coefficients:', abs(best_estimator_lasso.named_steps["lasso_
print('Total number of coeffients for Lasso:', (best_estimator_lasso.named_steps["lass
print('Number of coeffients not equal to 0 for Lasso:', (best_estimator_lasso.named_st
```

```
Magnitude of Lasso coefficients: 17758.892156014354
Total number of coeffients for Lasso: 55
Number of coeffients not equal to 0 for Lasso: 20
```

Rank magnitude of coefficients of Lasso regression.

In [24]:
```
df_importances = pd.DataFrame(zip(best_estimator_lasso.named_steps["polynomial_feature
                 best_estimator_lasso.named_steps["lasso_regression"].coef_))
df_importances.sort_values(by=1)
```

Out[24]:

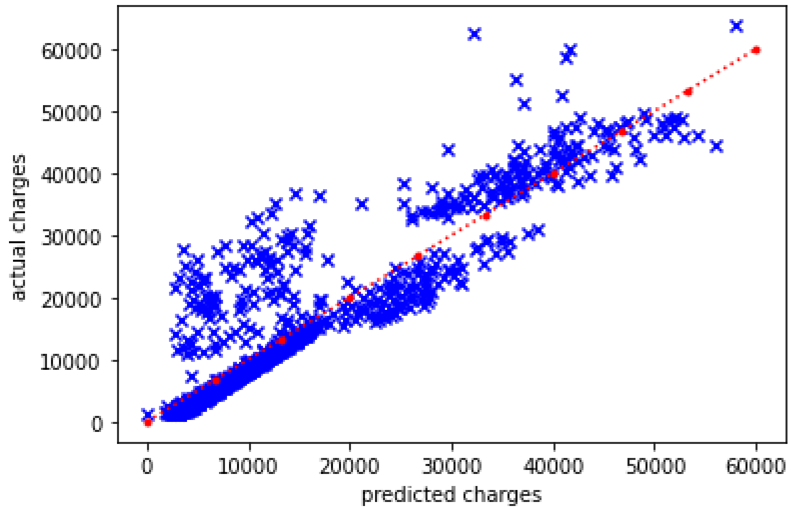
	0	1
19	x1^2	-217.010161
4	x3	-112.878686
15	x0 x5	-83.915542
29	x2 x4	-61.167928
33	x2 x8	-42.371547
25	x1 x7	-27.833712
54	x8^2	-14.789512
36	x3 x5	-8.217561
28	x2 x3	-0.000000
30	x2 x5	0.000000
32	x2 x7	-0.000000
34	x3^2	0.000000
35	x3 x4	0.000000
37	x3 x6	0.000000
38	x3 x7	0.000000
41	x4 x5	-0.000000
42	x4 x6	-0.000000
43	x4 x7	-0.000000
46	x5 x6	-0.000000
47	x5 x7	-0.000000
48	x5 x8	0.000000
49	x6^2	0.000000
50	x6 x7	-0.000000
51	x6 x8	0.000000
52	x7^2	-0.000000
39	x3 x8	-0.000000
53	x7 x8	0.000000
0	1	0.000000
24	x1 x6	0.000000
5	x4	0.000000
6	x5	0.000000
7	x6	0.000000
8	x7	-0.000000

	0	1
9	x8	-0.000000
26	x1 x8	-0.000000
12	x0 x2	-0.000000
13	x0 x3	0.000000
11	x0 x1	-0.000000
16	x0 x6	-0.000000
14	x0 x4	-0.000000
20	x1 x2	-0.000000
27	x2^2	-0.000000
18	x0 x8	0.000000
21	x1 x3	8.411023
31	x2 x6	65.004672
44	x4 x8	70.933694
17	x0 x7	73.882792
23	x1 x5	134.359783
45	x5^2	234.869822
10	x0^2	576.760147
3	x2	644.728176
2	x1	1896.754861
22	x1 x4	3475.232360
1	x0	3585.916873
40	x4^2	6423.853303

Compare prediction of charges with actual

In [25]:
```
y_predict = best_estimator_lasso.predict(X)

max_charge = round(max(y_predict),-4)
plt.scatter(y_predict, y, marker='x', color='blue');
plt.plot(np.linspace(0, max_charge, 10), np.linspace(0, max_charge, 10), color= "red",
plt.xlabel('predicted charges');
plt.ylabel('actual charges');
```



Flaws and improvements

Medical costs is complicated with a lot of factors accounting for it beyond age, gender, bmi, number of dependents, smoking and region. From the exploratory analyses, smoking appears to be a strong indicator for higher costs. But there are also other more apparent factors like occupation, pre-existing conditions, genetic predispositions, etc., which should be included to improve the prediction accuracies.

Further improvements can be with the use other regression models like Decision Trees, Random Forest Regressor, Gradient Boosted Regressor.

In [ ]: