In [1]:
```
cd C:/Users/anshu/Desktop/kaggle/boston_housePrice_Pridiction
```

```
C:\Users\anshu\Desktop\kaggle\boston_housePrice_Pridiction
```

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics
%matplotlib inline
```

In [3]:
```
#if you dont have column name in your csv, add names tag and enter column name and put header = None and DONE
data = pd.read_csv("housing.csv", names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO','B', 'LSTAT','PRICE'], header = None)
data.head()
```

Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

In [4]:
```
# data.drop(['PRICE'], axis = 1, inplace = True) #without inplace=True it will not give desired output
# data.head()
```

In [5]:
```
data.shape #no brackets
```

Out[5]:
```
(506, 14)
```

In [6]:
```
data.columns #no brackets with s in colmun
```

Out[6]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'PRICE'],
      dtype='object')
```

In [7]:
```
data.dtypes #with a s
```

Out[7]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD          int64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
PRICE      float64
dtype: object
```

In [8]:
```
data.nunique() #identify unique number of values in column
```

Out[8]:
```
CRIM       452
ZN          27
INDUS       77
CHAS        16
NOX        132
RM         437
AGE        399
DIS        361
RAD         10
TAX         67
PTRATIO     85
B          374
LSTAT      445
PRICE      210
dtype: int64
```

In [9]:
```
data.isnull().sum() #brackets in both
```

Out[9]:
```
CRIM        0
ZN          0
INDUS       0
CHAS        0
NOX         0
RM          0
AGE         0
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT       0
PRICE      54
dtype: int64
```

In [10]:
```
data = data.dropna()
```

In [11]:
```
#see rows with missing values
data[data.isnull().any(axis=1)].head() #prices has 54 null value and we need to impute the data
```

Out[11]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE

In [12]:
```
data.describe()
```

Out[12]:

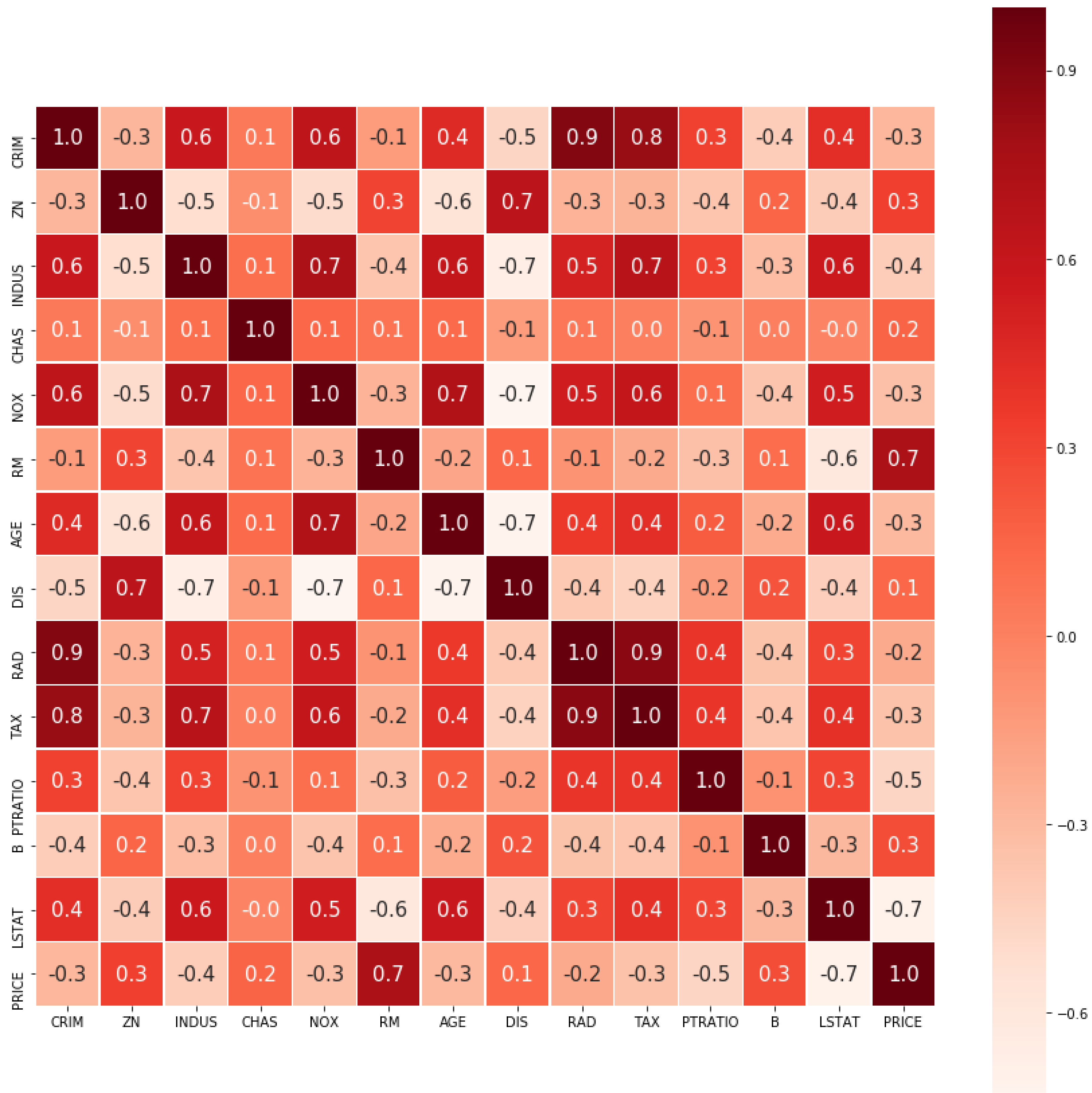
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
count	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000	452.000000
mean	1.420825	12.721239	10.304889	0.077434	0.540816	6.343538	65.557965	4.043570	7.823009	377.442478	18.247124	369.826504	11.441881	23.750442
std	2.495894	24.326032	6.797103	0.267574	0.113816	0.666808	28.127025	2.090492	7.543494	151.327573	2.200064	68.554439	6.156437	8.808602
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	6.300000
25%	0.069875	0.000000	4.930000	0.000000	0.447000	5.926750	40.950000	2.354750	4.000000	276.750000	16.800000	377.717500	6.587500	18.500000
50%	0.191030	0.000000	8.140000	0.000000	0.519000	6.229000	71.800000	3.550400	5.000000	307.000000	18.600000	392.080000	10.250000	21.950000
75%	1.211460	20.000000	18.100000	0.000000	0.605000	6.635000	91.625000	5.401100	7.000000	411.000000	20.200000	396.157500	15.105000	26.600000
max	9.966540	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	34.410000	50.000000

In [13]:
```
#find out correlation between the features
corr = data.corr()
corr.shape
```

Out[13]:
```
(14, 14)
```

```
In [14]: # visualizing correlation on a heat map
         plt.figure(figsize=(15,15)) #decides the size of the image
         sns.heatmap(corr, cbar=True, square= True, fmt='.1f', annot=True, annot_kws={'size':15}, cmap='Reds', linewidth = 0.5)

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaed8dd9b0>
```



In [15]:
```
#splitting target variable and independent variable
X = data.drop(['PRICE'], axis = 1)
Y = data['PRICE']
```

In [16]:
```
#splitting them to training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.3, random_state = 4)
```

LINEAR REGRESSION

training the model

In [17]:
```
#importing library
from sklearn.linear_model import LinearRegression

#creating linear regressor
lr = LinearRegression()

#train the model using training set
lr.fit(X_train, Y_train) #drop nan otherwise throw error
```

Out[17]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [18]:
```
lr.intercept_ #value of y intercept
```

Out[18]:
```
21.550127507326124
```

Model Evaluation

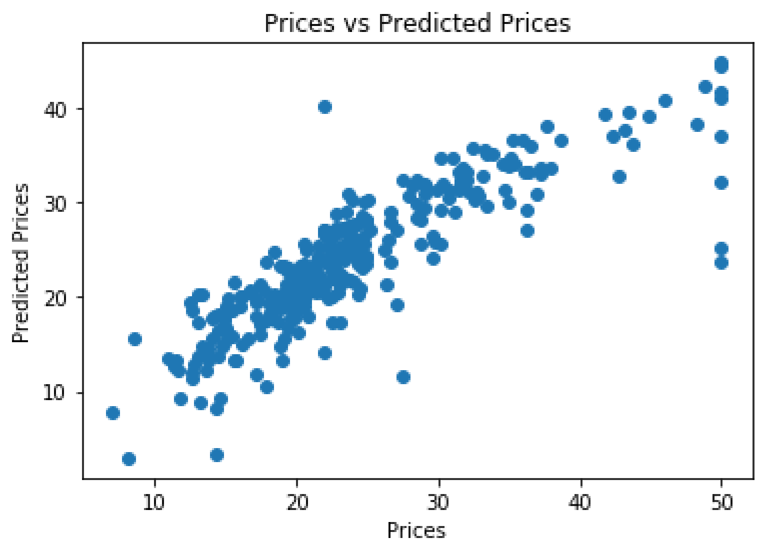
In [19]:
```
y_pred = lr.predict(X_train)
```

In [20]:
```
#Evaluating model
print('R^2: ', metrics.r2_score(Y_train,y_pred))
# print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
print('MAE: ', metrics.mean_absolute_error(Y_train,y_pred))
print('MSE: ', metrics.mean_squared_error(Y_train, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(Y_train,y_pred)))
```

```
R^2:  0.7403225970999185
MAE:  2.86611343196035
MSE:  18.24409071946878
RMSE: 4.271310187690514
```

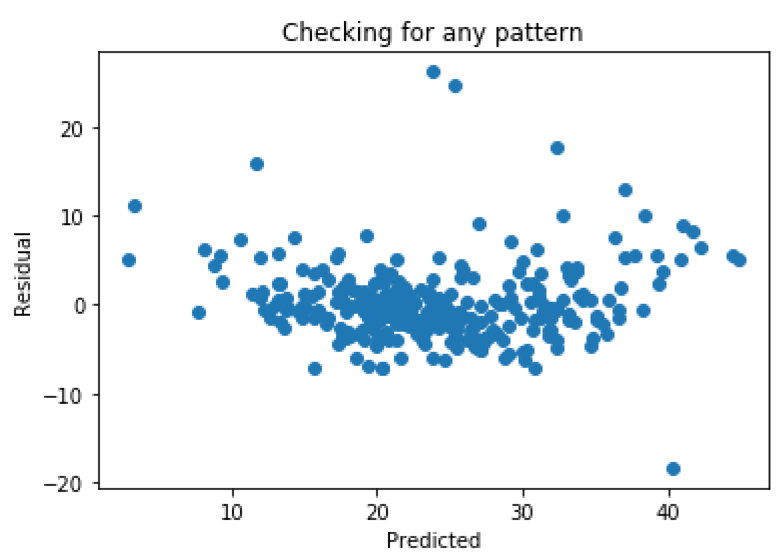
In [21]:
```
#visualizing the actual price and the predicted prices

plt.scatter(Y_train,y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted Prices")
plt.title("Prices vs Predicted Prices")
plt.show()
```



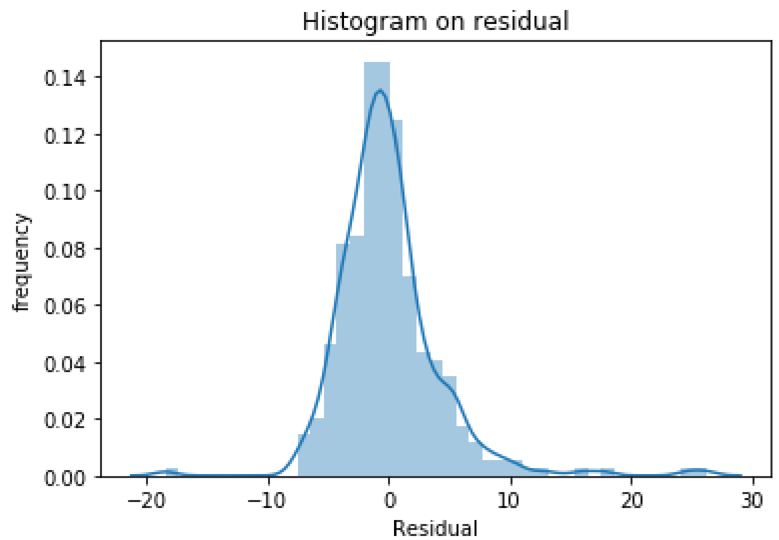
In [22]:
```
#Checking residual plot
plt.scatter(y_pred, Y_train-y_pred)
plt.xlabel("Predicted")
plt.ylabel("Residual")
plt.title("Checking for any pattern")
plt.show()

#There is no pattern visible in this plot and values are distributed equally around zero.
#So Linearity assumption is satisfied
```



In [23]:
```
sns.distplot(Y_train-y_pred)
plt.title("Histogram on residual")
plt.xlabel("Residual")
plt.ylabel("frequency")
plt.show()

#Here the residuals are normally distributed. So normality assumption is satisfied
```



predicting test data

In [24]:
```
y_test_pred = lr.predict(X_test)
```

In [25]:
```
#model evaluation
acc_linreg = metrics.r2_score(Y_test, y_test_pred)
print("R^2: ", acc_linreg)
print("MAE: ", metrics.mean_absolute_error(Y_test, y_test_pred))
print("MSE: ", metrics.mean_squared_error(Y_test, y_test_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(Y_test, y_test_pred)))

#Here the model evaluations scores are almost matching with that of train data. So the model is not overfitting.
```

```
R^2:  0.732036504130758
MAE:  3.4301016596809273
MSE:  25.180362809153582
RMSE:  5.018003866992689
```

RANDOM FOREST REGRESSOR

Train the model

In [26]:
```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor()

reg.fit(X_train, Y_train)
```

```
C:\Users\anshu\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:246: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[26]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
```

Model predcition on train Data

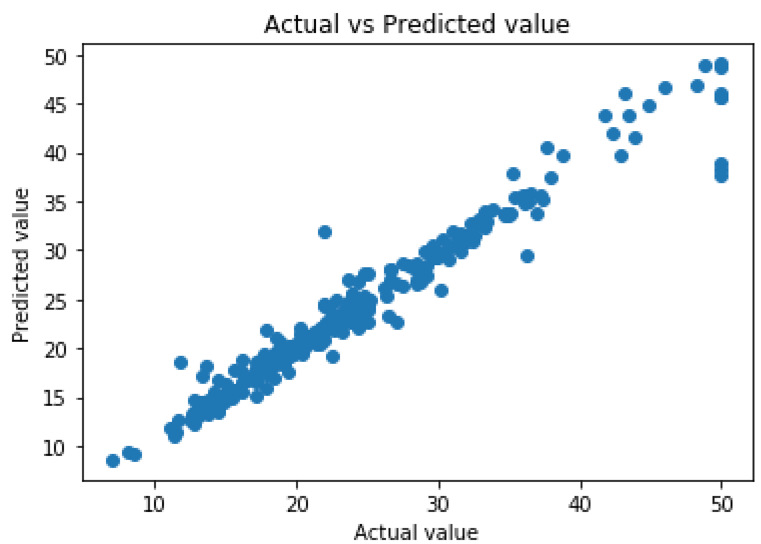
In [27]:
```
y_pred = reg.predict(X_train)
```

Model Evaluation

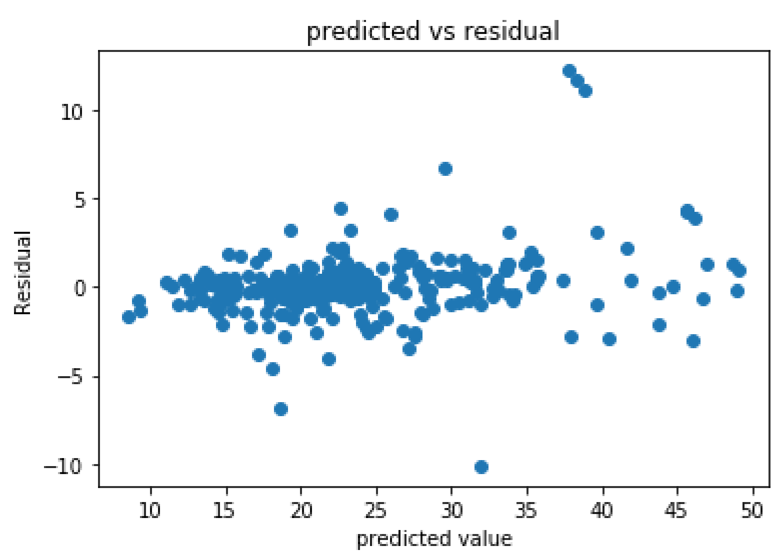
In [28]:
```
print("R^2: ", metrics.r2_score(Y_train, y_pred))
print("MAE: ", metrics.mean_absolute_error(Y_train, y_pred))
print("MSE: ", metrics.mean_squared_error(Y_train, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(Y_train, y_pred)))
```

```
R^2:  0.9512933335585091
MAE:  1.0096835443037977
MSE:  3.4219721518987334
RMSE:  1.8498573328499508
```

In [29]:
```
#Visualizing the differences between actual prices and the predicted prices
plt.scatter(Y_train, y_pred)
plt.xlabel("Actual value")
plt.ylabel("Predicted value")
plt.title("Actual vs Predicted value")
plt.show()
```



In [30]:
```
#Checking on the residual
plt.scatter(y_pred, Y_train-y_pred)
plt.xlabel("predicted value")
plt.ylabel("Residual")
plt.title("predicted vs residual")
plt.show()
```



predicting the test data

In [31]:
```
y_test_pred = reg.predict(X_test)
```

Model Evaluation

In [32]:
```
acc_random = metrics.r2_score(Y_test, y_test_pred)
print("R^2 : ", acc_random)
print("MAE: ", metrics.mean_absolute_error(Y_test, y_test_pred))
print("MSE: ", metrics.mean_squared_error(Y_test, y_test_pred))
print("RMSE : ", np.sqrt(metrics.mean_squared_error(Y_test, y_test_pred)))
```

```
R^2 :  0.8615991865862214
MAE:  2.4008823529411765
MSE:  13.005438235294116
RMSE :  3.6063053441568305
```

XGBoost Regressor

In [33]:
```
from xgboost import XGBRegressor

xgb = XGBRegressor()

xgb.fit(X_train, Y_train)
```

```
[23:07:30] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.

C:\Users\anshu\Anaconda3\lib\site-packages\xgboost\core.py:587: FutureWarning: Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
```

Out[33]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=1, gamma=0,
       importance_type='gain', learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1)
```

max_depth (int) – Maximum tree depth for base learners.

learning_rate (float) – Boosting learning rate (xgb's "eta")

n_estimators (int) – Number of boosted trees to fit.

gamma (float) – Minimum loss reduction required to make a further partition on a leaf node of the tree.

min_child_weight (int) – Minimum sum of instance weight(hessian) needed in a child.

subsample (float) – Subsample ratio of the training instance.

colsample_bytree (float) – Subsample ratio of columns when constructing each tree.

objective (string or callable) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below).

nthread (int) – Number of parallel threads used to run xgboost. (Deprecated, please use n_jobs)

scale_pos_weight (float) – Balancing of positive and negative weights.

Model Evaluator

In [34]:
```
y_pred = xgb.predict(X_train)
```

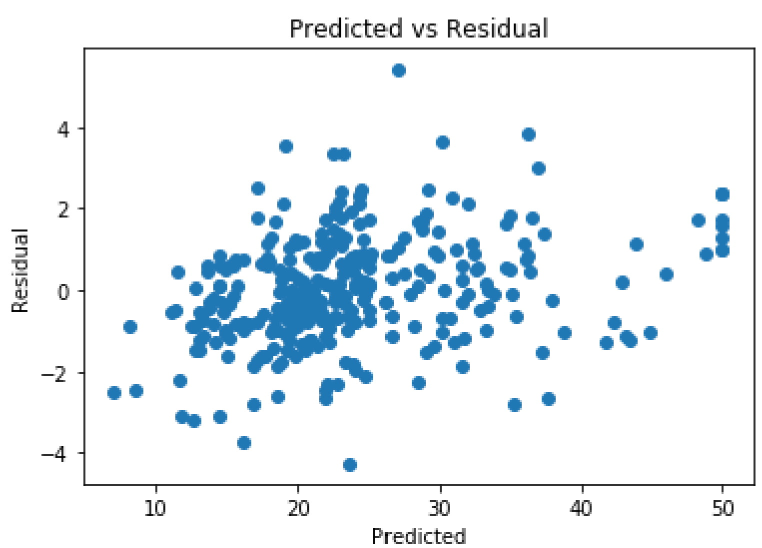
Model Evaluation

In [35]:
```
print('R^2:',metrics.r2_score(Y_train, y_pred))
#print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(Y_train, y_pred))
print('MSE:',metrics.mean_squared_error(Y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(Y_train, y_pred)))
```

```
R^2: 0.9748394089729945
MAE: 1.0260493260395678
MSE: 1.7677013868964468
RMSE: 1.3295493172110793
```

In [36]:
```
plt.scatter(Y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```

In [37]:
```
#residual
plt.scatter(Y_train, Y_train-y_pred)
plt.xlabel("Predicted")
plt.ylabel("Residual")
plt.title("Predicted vs Residual")
plt.show()
```



Predicting test data

In [38]:
```
y_test_pred = reg.predict(X_test)
```

In [39]:
```
acc_xgb = metrics.r2_score(Y_test, y_test_pred)
print('R^2:',acc_xgb)
#print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(Y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(Y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(Y_test, y_test_pred)))
```

```
R^2: 0.8615991865862214
MAE: 2.4008823529411765
MSE: 13.005438235294116
RMSE: 3.6063053441568305
```

SVM Regressor

In [40]:
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
C:\Users\anshu\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645: DataConversionWarning: Data with input dtype int64, float64 were all converted to float64 by StandardScal
er.
  return self.partial_fit(X, y)
C:\Users\anshu\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversionWarning: Data with input dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\anshu\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataConversionWarning: Data with input dtype int64, float64 were all converted to float64 by StandardScaler.
```

train the model

In [41]:
```
from sklearn import svm

svm_reg = svm.SVR()
```

In [42]:
```
svm_reg.fit(X_train, Y_train)
```

Out[42]:
```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
  gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
  tol=0.001, verbose=False)
```

C : float, optional (default=1.0): The penalty parameter of the error term. It controls the trade off between smooth decision boundary and classifying the training points correctly.

kernel : string, optional (default='rbf'): kernel parameters selects the type of hyperplane used to separate the data. It must be one of 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or a callable.

degree : int, optional (default=3): Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.

gamma : float, optional (default='auto'): It is for non linear hyperplanes. The higher the gamma value it tries to exactly fit the training data set. Current default is 'auto' which uses 1 / n_features.

coef0 : float, optional (default=0.0): Independent term in kernel function. It is only significant in 'poly' and 'sigmoid'.

Model Evaluation

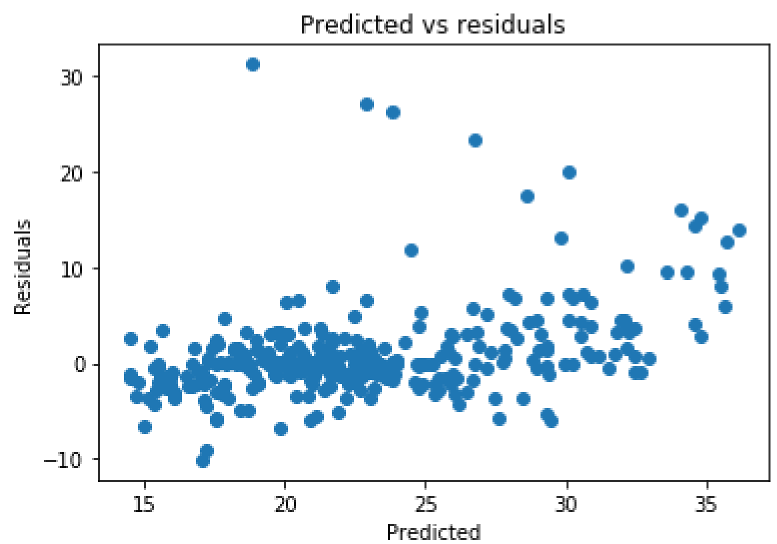
In [43]:
```
y_pred = svm_reg.predict(X_train)
```

In [44]:
```
print('R^2:',metrics.r2_score(Y_train, y_pred))
#print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train, y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(Y_train, y_pred))
print('MSE:',metrics.mean_squared_error(Y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(Y_train, y_pred)))
```

```
R^2: 0.6510940793642486
MAE: 2.841175439488562
MSE: 24.512996500845805
RMSE: 4.951060139085952
```

In [45]:
```
plt.scatter(Y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```

In [46]:
```
plt.scatter(y_pred,Y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



for Test data set

In [47]:
```
y_test_pred = svm_reg.predict(X_test)
```

Model Evaluate

In [48]:
```
acc_svm = metrics.r2_score(Y_test, y_test_pred)
print('R^2:', acc_svm)
#print('Adjusted R^2:',1 - (1-metrics.r2_score(y_test, y_test_pred))*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(Y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(Y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(Y_test, y_test_pred)))
```

```
R^2: 0.5425335609760945
MAE: 3.7719750353519044
MSE: 42.98783634788254
RMSE: 6.556510988924105
```

Evaluation and Comparison of all the models

In [49]:
```python
models = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'XGBoost', 'Support Vector Machines'],
    'R-squared Score': [acc_linreg*100, acc_random*100, acc_xgb*100, acc_svm*100]})
models.sort_values(by='R-squared Score', ascending=False)
```

Out[49]:

	Model	R-squared Score
1	Random Forest	86.159919
2	XGBoost	86.159919
0	Linear Regression	73.203650
3	Support Vector Machines	54.253356

In [50]:
```python
# Since R-square is best for Random Forest, according to me we should go for Random Forest
# to predcit the house price in Boston.
```