In [59]:

```
# Importing the libraries
import pandas as pd
import numpy as np
```

In [60]:

```
data_url = "http://lib.stat.cmu.edu/datasets/boston"
raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
target = raw_df.values[1::2, 2]
```

In [61]:

```
# Initializing the dataframe
data = pd.DataFrame(boston.data)
```

In [62]:

```
# See head of the dataset
data.head()
```

Out[62]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [63]:

```
#Adding the feature names to the dataframe
data.columns = boston.feature_names
data.head()
```

Out[63]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	I
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	

In [64]:

```
#Adding target variable to dataframe
data['PRICE'] = boston.target
# Median value of owner-occupied homes in $1000s
```

In [65]:

```
#Check the shape of dataframe
data.shape
```

Out[65]:

```
(506, 14)
```

In [66]:

```
data.columns
```

Out[66]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'LSTAT', 'PRICE'],
      dtype='object')
```

In [67]:

```
data.dtypes
```

Out[67]:

```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
PRICE      float64
dtype: object
```

In [68]:

```
# Identifying the unique number of values in the dataset
data.nunique()
```

Out[68]:

```
CRIM       504
ZN          26
INDUS       76
CHAS         2
NOX         81
RM         446
AGE        356
DIS        412
RAD          9
TAX         66
PTRATIO     46
B          357
LSTAT      455
PRICE      229
dtype: int64
```

In [69]:

```
# Check for missing values
data.isnull().sum()
```

Out[69]:

```
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      0
dtype: int64
```

In [70]:

```
# See rows with missing values
data[data.isnull().any(axis=1)]
```

Out[70]:

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

In [71]:

```
# Viewing the data statistics
data.describe()
```

Out[71]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

In [72]:

```
# Finding out the correlation between the features
corr = data.corr()
corr.shape
```

Out[72]:

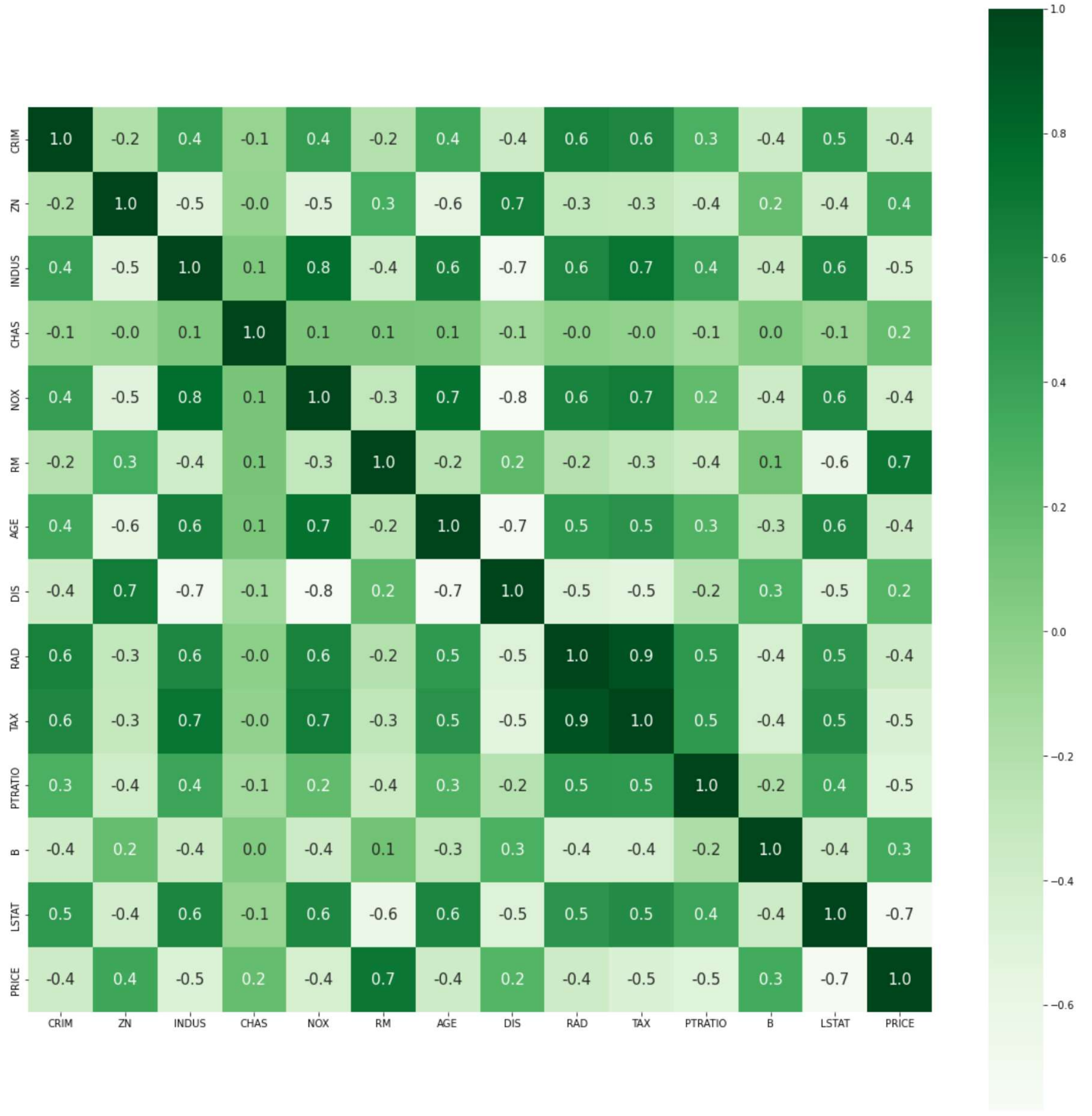
```
(14, 14)
```

In [73]:

```
# Plotting the heatmap of correlation between features
plt.figure(figsize=(20,20))
sns.heatmap(corr, cbar=True, square= True, fmt='.1f', annot=True, annot_kws={'size':15},
```

Out[73]:

```
<AxesSubplot:>
```



In [74]:

```
# Spliting target variable and independent variables
X = data.drop(['PRICE'], axis = 1)
y = data['PRICE']
```

In [75]:

```
# Splitting to training and testing data

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 =
```

In [76]:

```
# Import library for Linear Regression
from sklearn.linear_model import LinearRegression

# Create a Linear regressor
lm = LinearRegression()

# Train the model using the training sets
lm.fit(X_train, y_train)
```

Out[76]:

```
LinearRegression()
```

In [77]:

```
# Value of y intercept
lm.intercept_
```

Out[77]:

```
36.35704137659466
```

In [78]:

```
#Converting the coefficient values to a dataframe
coeffcients = pd.DataFrame([X_train.columns,lm.coef_]).T
coeffcients = coeffcients.rename(columns={0: 'Attribute', 1: 'Coefficients'})
coeffcients
```

Out[78]:

	Attribute	Coefficients
0	CRIM	-0.12257
1	ZN	0.055678
2	INDUS	-0.008834
3	CHAS	4.693448
4	NOX	-14.435783
5	RM	3.28008
6	AGE	-0.003448
7	DIS	-1.552144
8	RAD	0.32625
9	TAX	-0.014067
10	PTRATIO	-0.803275
11	B	0.009354
12	LSTAT	-0.523478

In [79]:

```
# Model prediction on train data
y_pred = lm.predict(X_train)
```

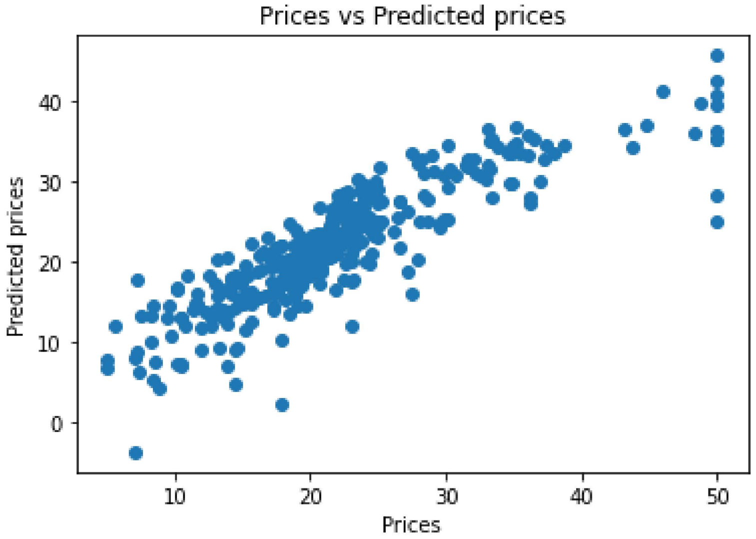
In [80]:

```
# Model Evaluation
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_
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: 0.7465991966746854
Adjusted R^2: 0.736910342429894
MAE: 3.08986109497113
MSE: 19.07368870346903
RMSE: 4.367343437774162
```

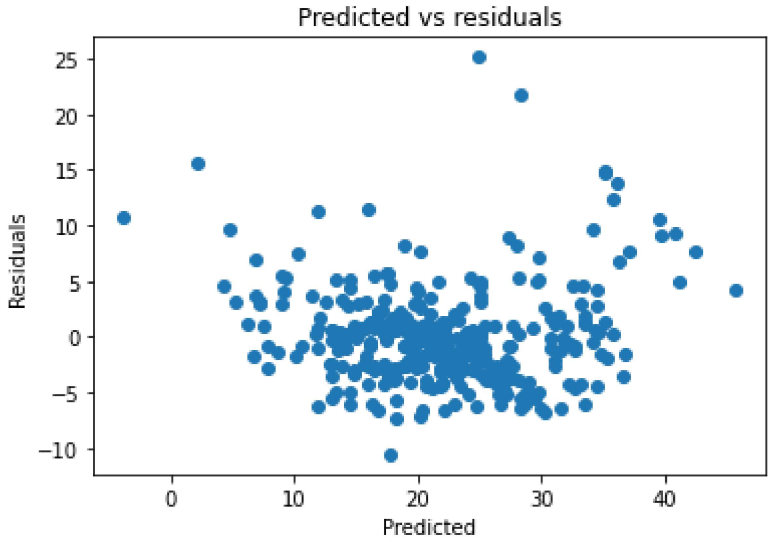
In [81]:

```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```



In [82]:

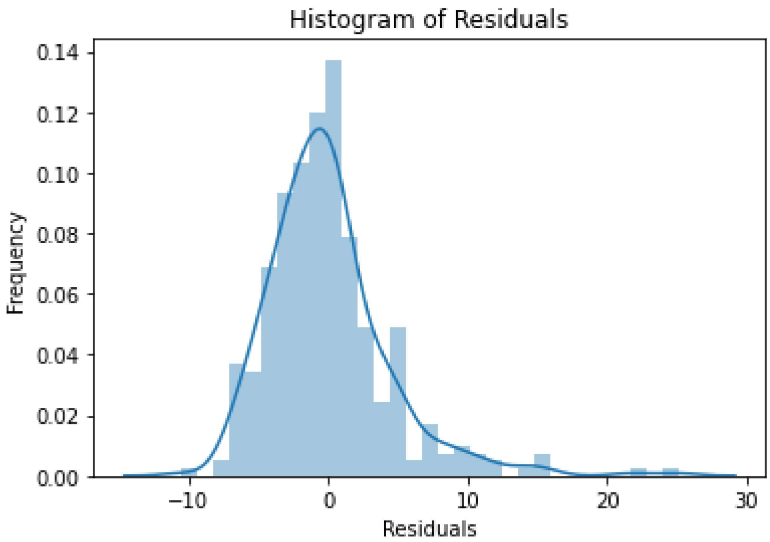
```
# Checking residuals
plt.scatter(y_pred,y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



In [83]:

```
# Checking Normality of errors
sns.distplot(y_train-y_pred)
plt.title("Histogram of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.show()
```

```
C:\Users\rachi\AppData\Local\Programs\Python\Python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [84]:

```
# Predicting Test data with the model
y_test_pred = lm.predict(X_test)
```

In [85]:

```
# Model Evaluation
acc_linreg = metrics.r2_score(y_test, y_test_pred)
print('R^2:', acc_linreg)
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_test, y_test_pred))*(len(y_test)-1)/(len
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: 0.7121818377409181
Adjusted R^2: 0.6850685326005699
MAE: 3.859005592370746
MSE: 30.053993307124284
RMSE: 5.482152251362988
```

In [86]:

```
# Import Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

# Create a Random Forest Regressor
reg = RandomForestRegressor()

# Train the model using the training sets
reg.fit(X_train, y_train)
```

Out[86]:

```
RandomForestRegressor()
```

In [87]:

```
# Model prediction on train data
y_pred = reg.predict(X_train)
```

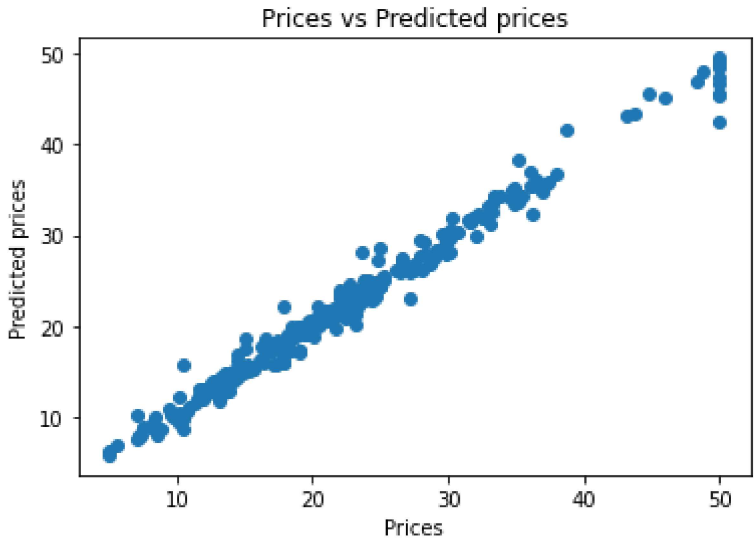
In [88]:

```
# Model Evaluation
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_
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: 0.9798924504026062
Adjusted R^2: 0.9791236323297646
MAE: 0.8283022598870055
MSE: 1.5135119406779671
RMSE: 1.2302487312238803
```

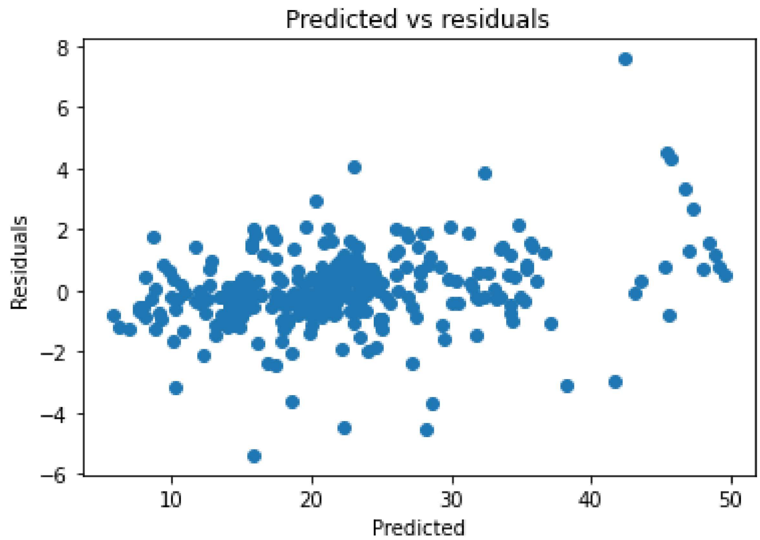
In [89]:

```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```



In [90]:

```
# Checking residuals
plt.scatter(y_pred,y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



In [91]:

```
# Predicting Test data with the model
y_test_pred = reg.predict(X_test)
```

In [92]:

```
# Model Evaluation
acc_rf = metrics.r2_score(y_test, y_test_pred)
print('R^2:', acc_rf)
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_test, y_test_pred))*(len(y_test)-1)/(len
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: 0.8254540421090988
Adjusted R^2: 0.8090113069454632
MAE: 2.5385131578947364
MSE: 18.226101539473685
RMSE: 4.269203853117544
```

In [93]:

```
# Import XGBoost Regressor
from xgboost import XGBRegressor

#Create a XGBoost Regressor
reg = XGBRegressor()

# Train the model using the training sets
reg.fit(X_train, y_train)
```

Out[93]:

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=Non
e,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=No
ne,
             interaction_constraints=None, learning_rate=None, max_bin=Non
e,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=Non
e,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
```

In [94]:

```
# Model prediction on train data
y_pred = reg.predict(X_train)
```

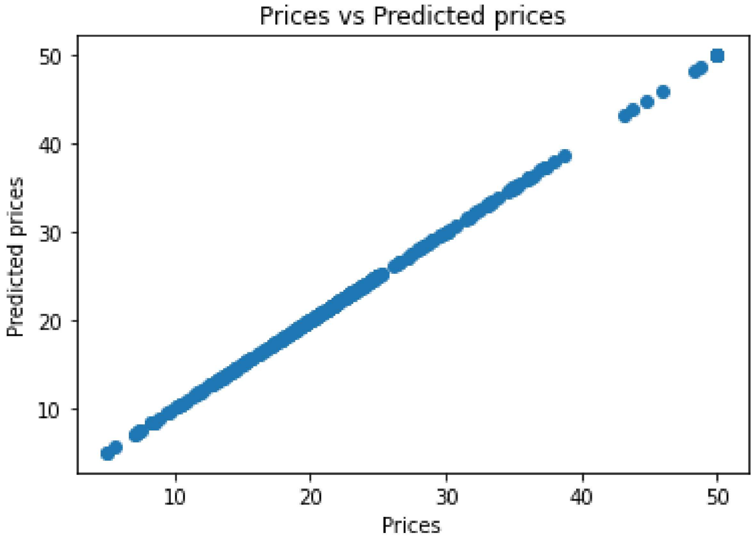
In [95]:

```
# Model Evaluation
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_
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: 0.9999980912185324
Adjusted R^2: 0.9999980182357117
MAE: 0.008653184923075066
MSE: 0.00014367556470779537
RMSE: 0.011986474240067234
```

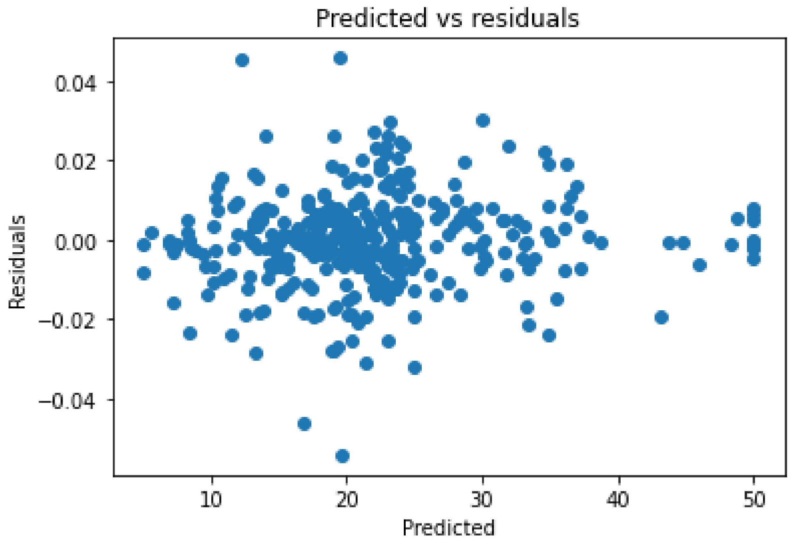
In [96]:

```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```



In [97]:

```
# Checking residuals
plt.scatter(y_pred,y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



In [98]:

```
#Predicting Test data with the model
y_test_pred = reg.predict(X_test)
```

In [99]:

```
# Model Evaluation
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_test, y_test_pred))*(len(y_test)-1)/(len
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: 0.8579951986672496
Adjusted R^2: 0.8446179347735847
MAE: 2.5309582503218397
MSE: 14.828151619536392
RMSE: 3.850733906612659
```

In [100]:

```
# Creating scaled set to be used in model to improve our results
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [101]:

```
# Import SVM Regressor
from sklearn import svm

# Create a SVM Regressor
reg = svm.SVR()
```

In [102]:

```
# Train the model using the training sets
reg.fit(X_train, y_train)
```

Out[102]:

```
SVR()
```

In [103]:

```
# Model prediction on train data
y_pred = reg.predict(X_train)
```

In [104]:

```
# Model Evaluation
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_
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)))
```

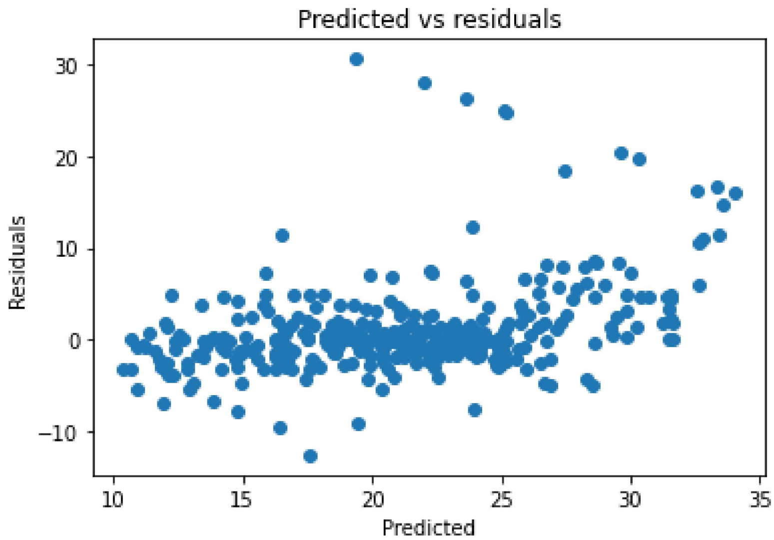
```
R^2: 0.6419097248941195
Adjusted R^2: 0.628218037904777
MAE: 2.9361501059460293
MSE: 26.953752101332935
RMSE: 5.191700309275655
```

In [105]:

```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```

In [106]:

```
# Checking residuals
plt.scatter(y_pred,y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



In [107]:

```
# Predicting Test data with the model
y_test_pred = reg.predict(X_test)
```

In [108]:

```
# Model Evaluation
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
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: 0.5900158460478174
Adjusted R^2: 0.5513941503856553
MAE: 3.7561453553021686
MSE: 42.81057499010247
RMSE: 6.542979060802691
```

In [109]:

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

Out[109]:

	Model	R-squared Score
2	XGBoost	85.799520
1	Random Forest	82.545404
0	Linear Regression	71.218184
3	Support Vector Machines	59.001585