# Practical No 04

**Create a Linear Regression Model using Python/R to predict home prices using Boston Housing Dataset (https://www.kaggle.com/c/boston-housing). The Boston Housing dataset contains information about various houses in Boston through different parameters. There are 506 samples and 14 feature variables in this dataset. The objective is to predict the value of prices of the house using the given features.**

## Dataset Information

Boston House Prices Dataset was collected in 1978 and has 506 entries with 14 attributes or features for homes from various suburbs in Boston.

```
Boston Housing Dataset Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's
```

## Import modules

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

## Loading the dataset

In [2]:
```
df = pd.read_csv("Boston Dataset.csv")
df.drop(columns=['Unnamed: 0'], axis=0, inplace=True)
df.head()
```

Out [2]:

| | crim | zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | black | lstat | medv |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 | 4.98 | 24.0 |
| **1** | 0.02731 | 0.0 | 7.07 | 0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.14 | 21.6 |
| **2** | 0.02729 | 0.0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.03 | 34.7 |
| **3** | 0.03237 | 0.0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.94 | 33.4 |
| **4** | 0.06905 | 0.0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | 5.33 | 36.2 |

In [3]:
```
# statistical info
df.describe()
```

Out [3]:

| | crim | zn | indus | chas | nox | rm | age | dis | rad | |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 50 |
| **mean** | 3.613524 | 11.363636 | 11.136779 | 0.069170 | 0.554695 | 6.284634 | 68.574901 | 3.795043 | 9.549407 | 40 |
| **std** | 8.601545 | 23.322453 | 6.860353 | 0.253994 | 0.115878 | 0.702617 | 28.148861 | 2.105710 | 8.707259 | 16 |
| **min** | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 | 1.129600 | 1.000000 | 18 |
| **25%** | 0.082045 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.025000 | 2.100175 | 4.000000 | 27 |
| **50%** | 0.256510 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 77.500000 | 3.207450 | 5.000000 | 33 |

| | crim | zn | indus | chas | nox | rm | age | dis | rad | |
|---|---|---|---|---|---|---|---|---|---|---|
| **75%** | 3.677083 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 94.075000 | 5.188425 | 24.000000 | 66 |
| **max** | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 | 12.126500 | 24.000000 | 71 |

In [4]:
```
# datatype info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   crim     506 non-null    float64
 1   zn       506 non-null    float64
 2   indus    506 non-null    float64
 3   chas     506 non-null    int64  
 4   nox      506 non-null    float64
 5   rm       506 non-null    float64
 6   age      506 non-null    float64
 7   dis      506 non-null    float64
 8   rad      506 non-null    int64  
 9   tax      506 non-null    int64  
 10  ptratio  506 non-null    float64
 11  black    506 non-null    float64
 12  lstat    506 non-null    float64
 13  medv     506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

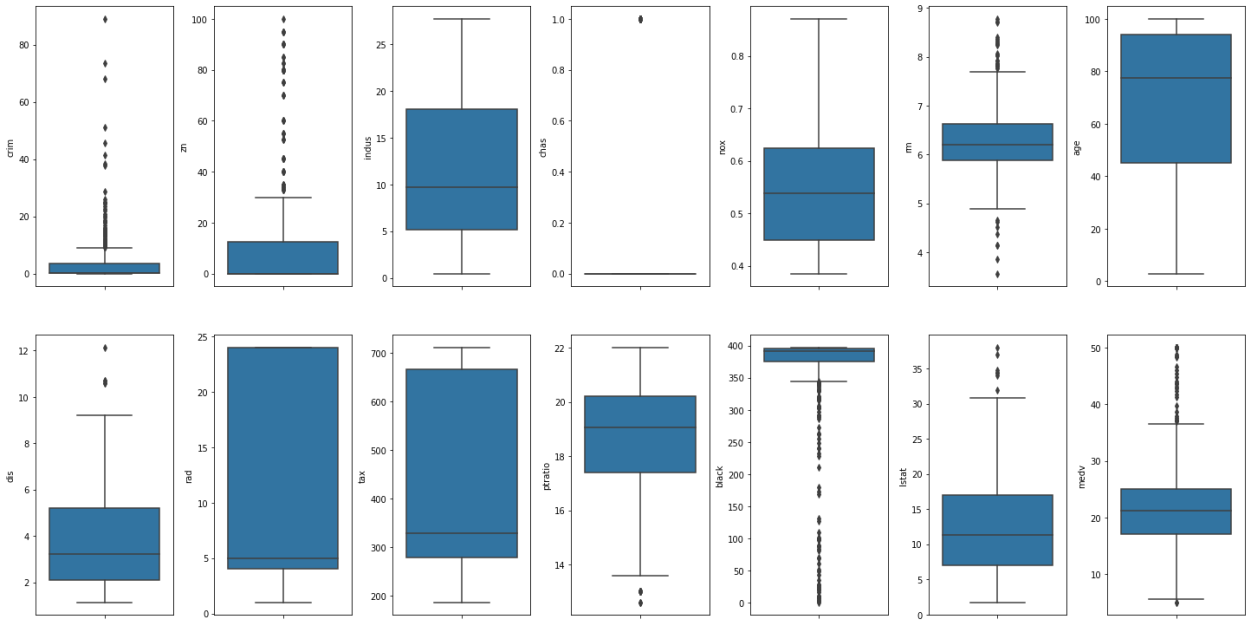
## Preprocessing the dataset

In [5]:
```
# check for null values
df.isnull().sum()
```

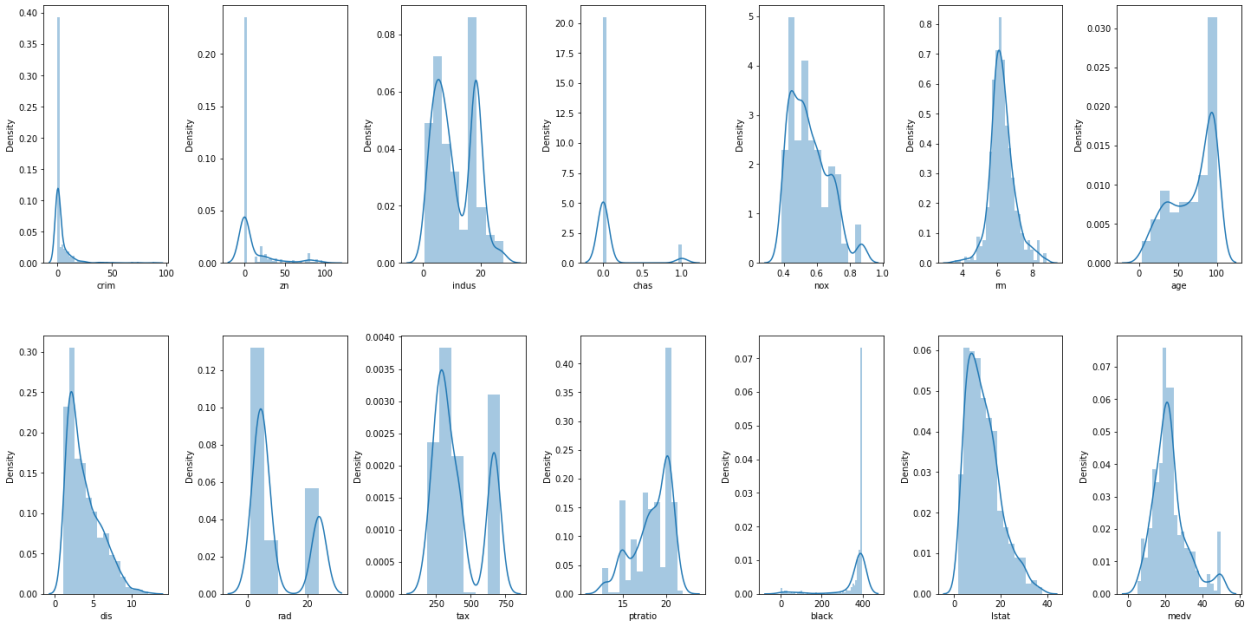
Out [5]:
```
crim       0
zn         0
indus      0
chas       0
nox        0
rm         0
age        0
dis        0
rad        0
tax        0
ptratio    0
black      0
lstat      0
medv       0
dtype: int64
```

## Exploratory Data Analysis

In [6]:
```
# create box plots
fig, ax = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
ax = ax.flatten()

for col, value in df.items():
    sns.boxplot(y=col, data=df, ax=ax[index])
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```




In [7]:
```
# create dist plot
fig, ax = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
ax = ax.flatten()

for col, value in df.items():
    sns.distplot(value, ax=ax[index])
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```

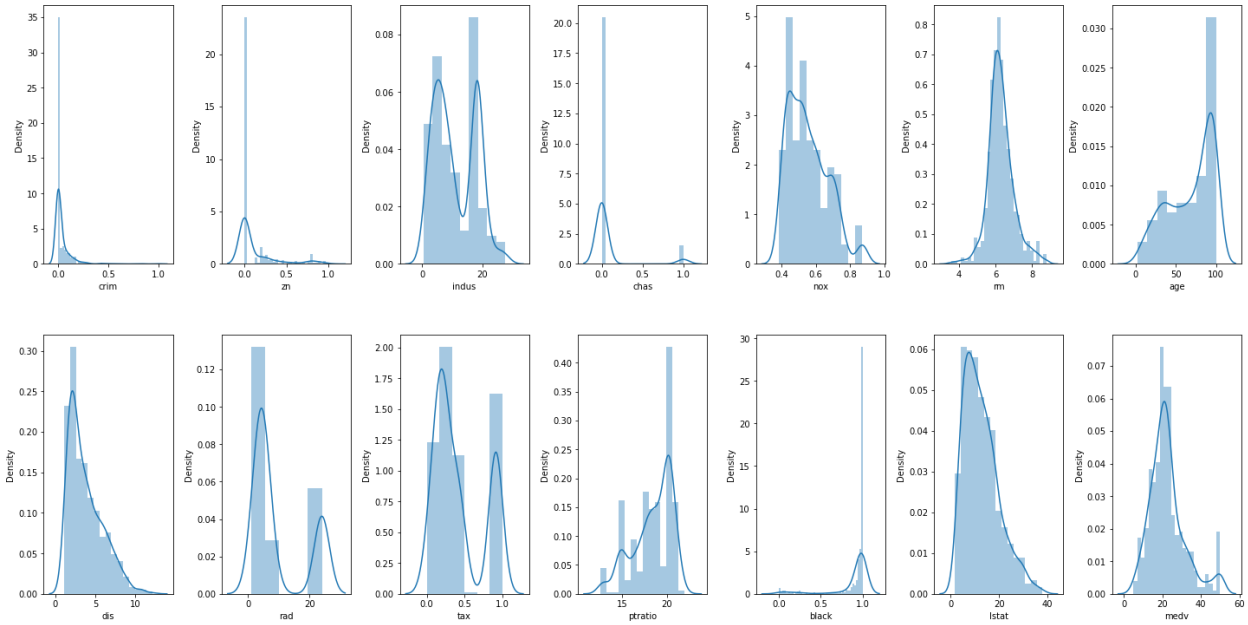



## Min-Max Normalization

In [8]:
```
cols = ['crim', 'zn', 'tax', 'black']
for col in cols:
    # find minimum and maximum of that column
    minimum = min(df[col])
    maximum = max(df[col])
    df[col] = (df[col] - minimum) / (maximum - minimum)
```

In [9]:
```
fig, ax = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
ax = ax.flatten()
```

```
for col, value in df.items():
    sns.distplot(value, ax=ax[index])
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



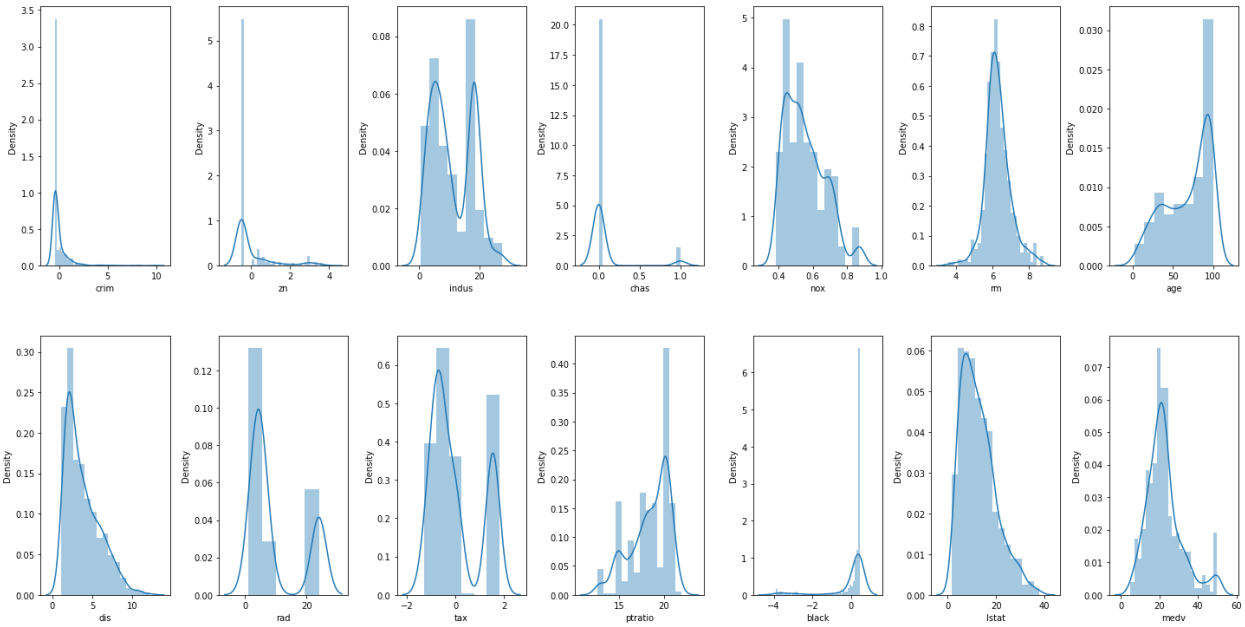

In [10]:
```
# standardization
from sklearn import preprocessing
scalar = preprocessing.StandardScaler()

# fit our data
scaled_cols = scalar.fit_transform(df[cols])
scaled_cols = pd.DataFrame(scaled_cols, columns=cols)
scaled_cols.head()
```

Out [10]:

| | crim | zn | tax | black |
|---|---|---|---|---|
| **0** | -0.419782 | 0.284830 | -0.666608 | 0.441052 |
| **1** | -0.417339 | -0.487722 | -0.987329 | 0.441052 |
| **2** | -0.417342 | -0.487722 | -0.987329 | 0.396427 |
| **3** | -0.416750 | -0.487722 | -1.106115 | 0.416163 |
| **4** | -0.412482 | -0.487722 | -1.106115 | 0.441052 |

In [11]:
```
for col in cols:
    df[col] = scaled_cols[col]
```

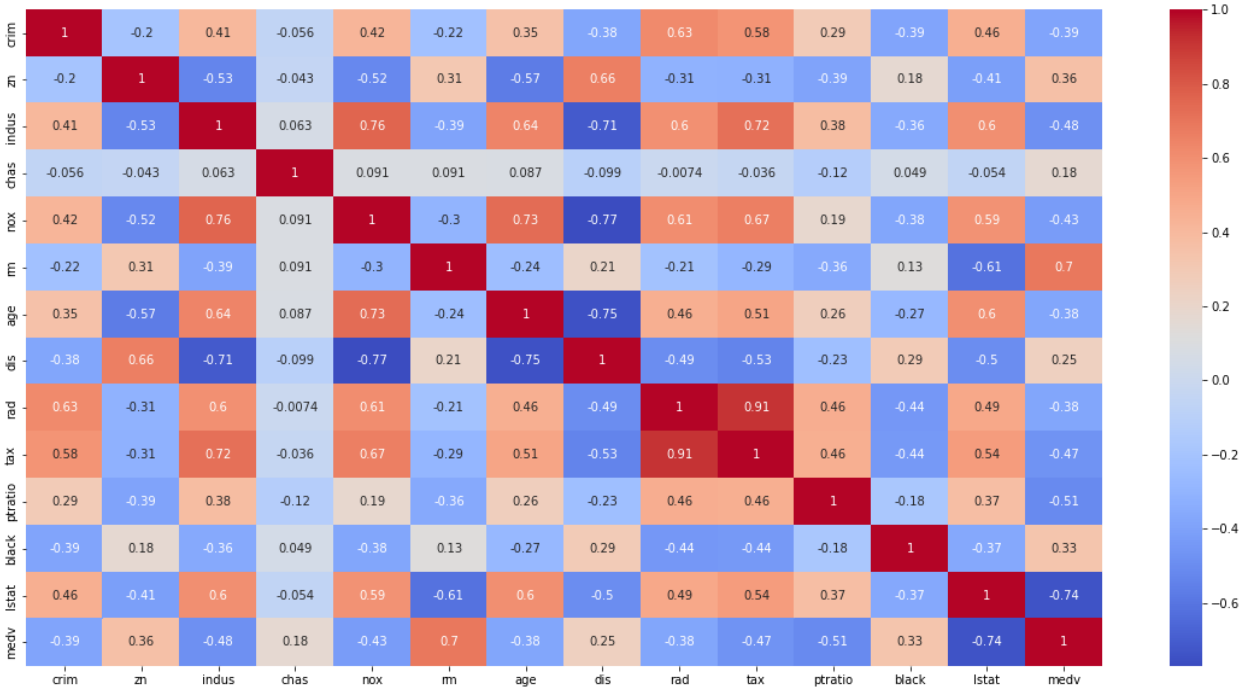
In [12]:
```
fig, ax = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
ax = ax.flatten()

for col, value in df.items():
    sns.distplot(value, ax=ax[index])
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```




## Coorelation Matrix

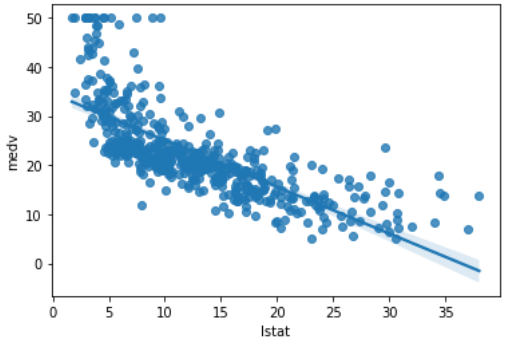
In [13]:
```
corr = df.corr()
plt.figure(figsize=(20,10))
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

Out [13]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3db6fb20>



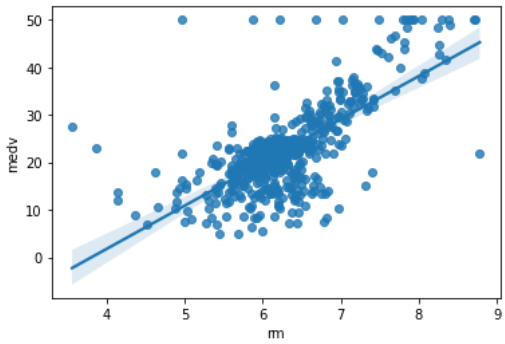

In [14]:
```
sns.regplot(y=df['medv'], x=df['lstat'])
```

Out [14]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3a672160>



In [15]:
```
sns.regplot(y=df['medv'], x=df['rm'])
```

Out [15]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa38815af0>




## Input Split

In [16]:
```
X = df.drop(columns=['medv', 'rad'], axis=1)
y = df['medv']
```

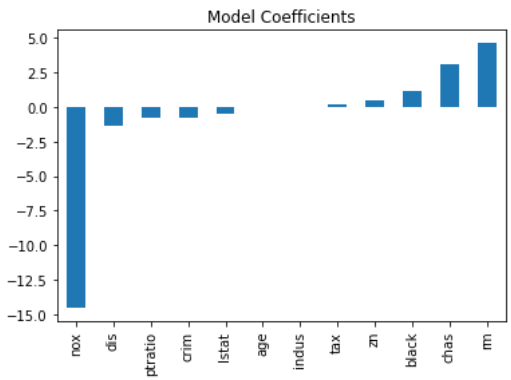
## Model Training

In [17]:
```
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
def train(model, X, y):
    # train the model
    x_train, x_test, y_train, y_test = train_test_split(X, y, random_state=42)
    model.fit(x_train, y_train)

    # predict the training set
    pred = model.predict(x_test)

    # perform cross-validation
    cv_score = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=5)
    cv_score = np.abs(np.mean(cv_score))

    print("Model Report")
    print("MSE:",mean_squared_error(y_test, pred))
    print('CV Score:', cv_score)
```

In [18]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression(normalize=True)
train(model, X, y)
coef = pd.Series(model.coef_, X.columns).sort_values()
coef.plot(kind='bar', title='Model Coefficients')
```

```
Model Report
MSE: 23.8710050673649
CV Score: 35.581366210769204
```

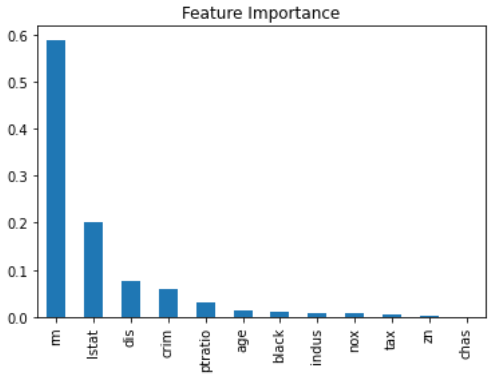
Out [18]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3cb1ac10>



In [19]:
```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title='Feature Importance')
```

```
Model Report
MSE: 10.865118110236219
CV Score: 44.27399242865463
```

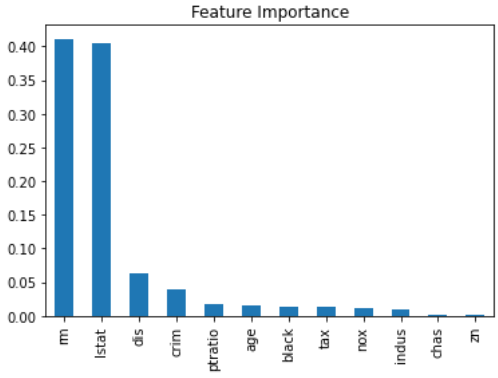
Out [19]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3cdd7d00>




In [20]:
```
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title='Feature Importance')
```

```
Model Report
MSE: 9.302050535433075
CV Score: 21.95170135701804
```

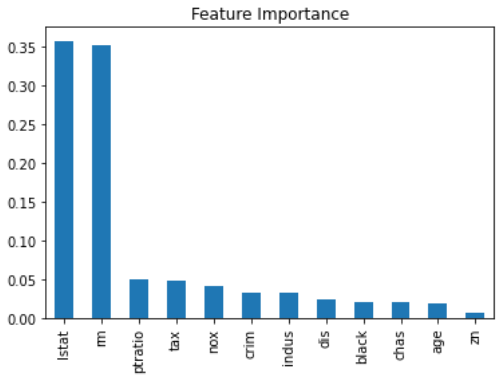
Out [20]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3a382730>




In [21]:
```
from sklearn.ensemble import ExtraTreesRegressor
model = ExtraTreesRegressor()
train(model, X, y)
coef = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
coef.plot(kind='bar', title='Feature Importance')
```

```
Model Report
MSE: 11.587783771653548
CV Score: 19.738606818210037
```

Out [21]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa3a39ebe0>




In [22]:
```
pred = model.predict(x_test)
```

```
---------------------------------------------------------------------------NameError                                 Traceback
----> 1 pred = model.predict(x_test)
NameError: name 'x_test' is not defined
```

In [ ]:
```
pred
```

In [ ]:
```
```