Алёшин Александр Денисович ИУ5-63Б. РК1. Технологии разведочного анализа и обработки данных.

In [55]:
```
import numpy as np
import matplotlib.pyplot as plt

import pandas as pd
import seaborn as sns

%matplotlib inline
```

In [27]:
```
from sklearn.datasets import load_boston
boston_dataset = load_boston()
#boston_dataset = pd.read_csv('housing_data1.txt', sep="\s+|\t+|\s+\t+|\t+\s+", engine = 'python')
```

In [29]:
```
print(boston_dataset.keys())
```

```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [30]:
```
boston_dataset.DESCR
```

Out[30]:
```
".. _boston_dataset:\n\nBoston house prices dataset\n---------------------------\n\n**Data Set Characteristics:**  \n\n    :Number of Instances: 506 \n\n    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually the target.\n\n    :Attribute Information (in order):\n        - CRIM     per capita crime rate by town\n        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.\n        - INDUS    proportion of non-retail business acres per town\n        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nitric oxides concentration (parts per 10 million)\n        - RM       average number of rooms per dwelling\n        - AGE      proportion of owner-occupied units built prior to 1940\n        - DIS      weighted distances to five Boston employment centres\n        - RAD      index of accessibility to radial highways\n        - TAX      full-value property-tax rate per $10,000\n        - PTRATIO  pupil-teacher ratio by town\n        - B        1000(Bk - 0.63)^2 where Bk is the proportion of black people by town\n        - LSTAT    % lower status of the population\n        - MEDV     Median value of owner-occupied homes in $1000's\n\n    :Missing Attribute Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-databases/housing/\n\n\nThis dataset was taken from the StatLib library which is maintained at Carnegie Mellon University.\n\nThe Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\nprices and the demand for clean air', J. Environ. Economics & Management,\nvol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 1980.  N.B. Various transformations are used in the table on\npages 244-261 of the latter.\n\nThe Boston house-price data has been used in many machine learning papers that address regression\nproblems.   \n\n    \n\n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.\n"
```

In [31]:
```
boston = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)
boston.head()
```

Out[31]:

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

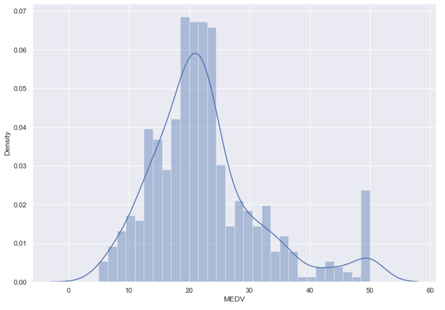
In [32]:
```
boston['MEDV'] = boston_dataset.target
```

In [33]:
```
boston.isnull().sum()
```

Out[33]:
```
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
MEDV       0
dtype: int64
```

In [34]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.distplot(boston['MEDV'], bins=30)
plt.show()
```

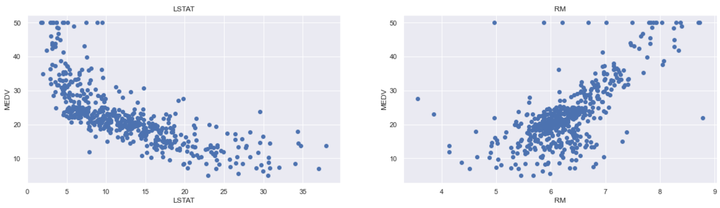
```
C:\Users\79772\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [35]:
```
correlation_matrix = boston.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```

Out[35]:
```
<AxesSubplot:>
```

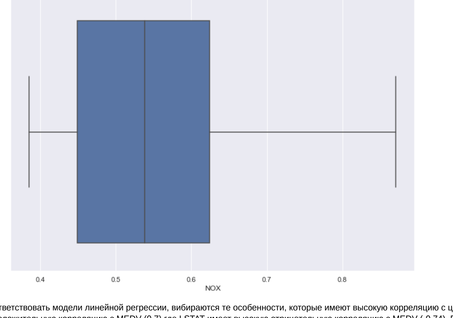
In [36]:
```
plt.figure(figsize=(20, 5))

features = ['LSTAT', 'RM']
target = boston['MEDV']

for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = boston[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('MEDV')
```



Цены растут по мере линейного увеличения стоимости RM. Существуют выбросы. Данные ограничены 50. Цены имеют тенденцию к снижению с ростом LSTAT.

In [51]:
```
sns.boxplot(x=boston['NOX'])
#boston_dataset.feature_names[0]
```

Out[51]:
```
<AxesSubplot:xlabel='NOX'>
```



Чтобы соответствовать модели линейной регрессии, вибираются те особенности, которые имеют высокую корреляцию с целевой переменной MEDV. Глядя на матрицу корреляции видно, что RM имеет сильную положительную корреляцию с MEDV (0,7) где LSTAT имеет высокую отрицательную корреляцию с MEDV (-0,74). RAD,TAX имеют соотношение 0,91. Эти пары признаков сильно связаны друг с другом. Мы не должны выбирать обе эти функции вместе для обучения модели. То же самое касается признаков DIS а также AGE которые имеют корреляцию -0,75.