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Кафедра «Системы обработки информации и управления»

Лабораторная работа №1
по дисциплине
«Технологии машинного обучения»
на тему
«Разведочный анализ данных. Исследование и визуализация данных»

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0.0.1. Задание

- Выбрать набор данных (датасет). Вы можете найти список свободно распространяемых датасетов здесь.
- Для первой лабораторной работы рекомендуется использовать датасет без пропусков в данных, например из Scikit-learn.
- Пример преобразования датасетов Scikit-learn в Pandas Dataframe можно посмотреть здесь. Для лабораторных работ не рекомендуется выбирать датасеты большого размера.
- Создать ноутбук, который содержит следующие разделы:
    1. Текстовое описание выбранного Вами набора данных.
    2. Основные характеристики датасета.
    3. Визуальное исследование датасета.
    4. Информация о корреляции признаков.
- Сформировать отчет и разместить его в своем репозитории на github.

1. Дома в Бостоне

[25]:
```
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
%matplotlib inline
```

[26]:
```
from sklearn.datasets import load_boston
```

[27]:
```
data = load_boston()
```

[5]:
```
for x in data:
    print(x)
```

```
data
target
feature_names
DESCR
filename
```

[6]:
```
X, y = data['data'], data['target']
```

[7]:
```
print(data['DESCR'])
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------
```

```
**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(attribute 14) is usually the target.

    :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

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at␣
 ↪Carnegie
Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
…', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that
address regression
problems.

.. topic:: References
```

```
   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - 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.


     -
     -                                              25 000   .     .
     - INDUS       ,                          ,
     -             CHAS Charles River (= 1,                    ; 0           )
     -                 NOX (       10       )
     -
     -            ,             ,          1940  .
     - DIS
     -
     -                                      10 000         .
     -                    PTRATIO
     - B 1000 (Bk - 0,63) ^ 2,    Bk -
     - LSTAT%
     - MEDV                       1000
```

Предсказываем среднюю стоимость частных домов в тысячах долларов.

[9]:
```
data.feature_names
```

[9]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

[10]:
```
X_df = pd.DataFrame(data = X, columns=data.feature_names)
y_df = pd.Series(y)
```

[31]:
```
data = X_df.merge(y_df.rename('MEDV'), left_index=True, right_index=True)
```

[32]:
```
data.head()
```

[32]:

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

	PTRATIO	B	LSTAT	MEDV
0	15.3	396.90	4.98	24.0
1	17.8	396.90	9.14	21.6
2	17.8	392.83	4.03	34.7
3	18.7	394.63	2.94	33.4
4	18.7	396.90	5.33	36.2

[33]:
```
data.shape
```

[33]:
```
(506, 14)
```

[34]:
```
data.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    float64
 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    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(14)
memory usage: 55.5 KB
```

Все столбцы ненулевые.

[35]:
```
data.describe()
```

[35]:

	CRIM	ZN	INDUS	CHAS	NOX	RM
count	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
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

	AGE	DIS	RAD	TAX	PTRATIO	B
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032
std	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864
min	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000
25%	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500
50%	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000

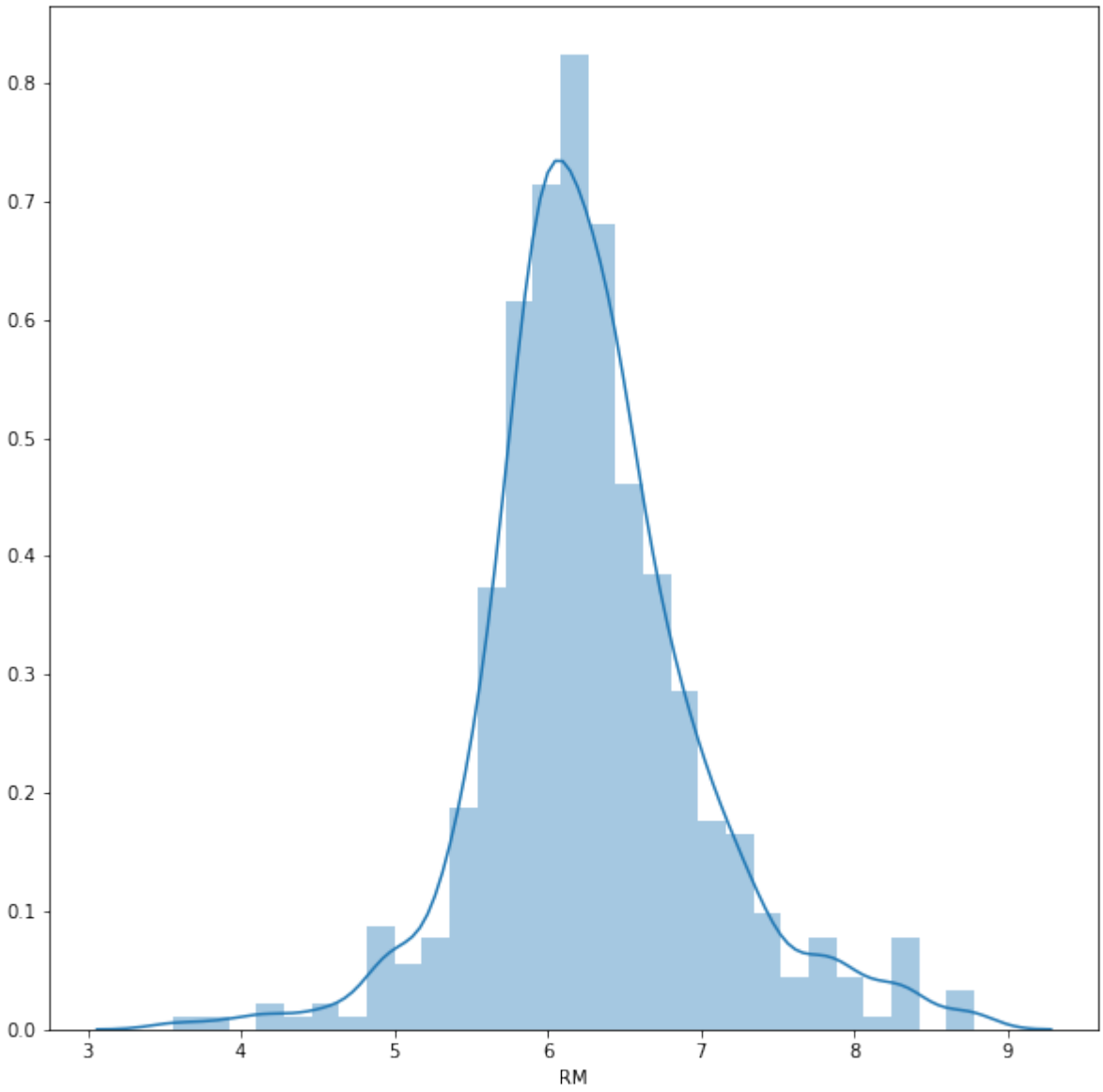
```
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

             LSTAT        MEDV
count   506.000000  506.000000
mean     12.653063   22.532806
std       7.141062    9.197104
min       1.730000    5.000000
25%       6.950000   17.025000
50%      11.360000   21.200000
75%      16.955000   25.000000
max      37.970000   50.000000
```

2. Визуальное исследование датасета

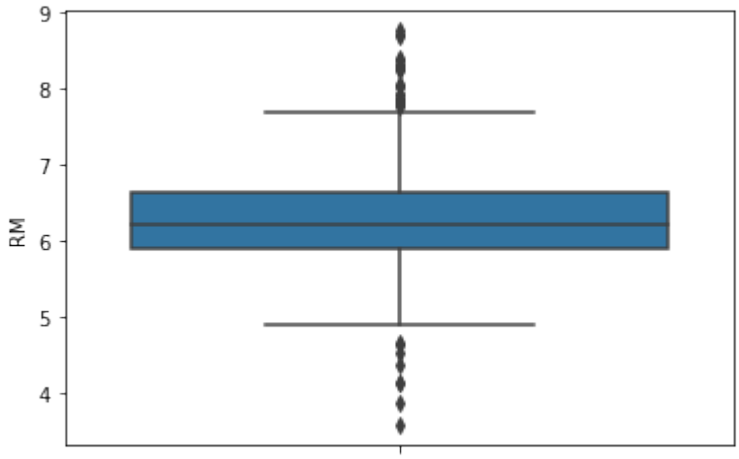
[46]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['RM'])
```

[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5730d15b0>
```



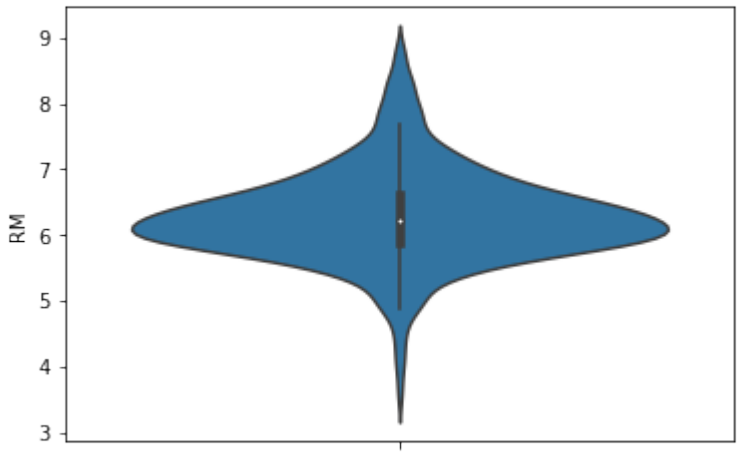
[47]:
```
sns.boxplot(y=data['RM'])
```

[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5726400d0>
```



[48]:
```
sns.violinplot(y=data['RM'])
```

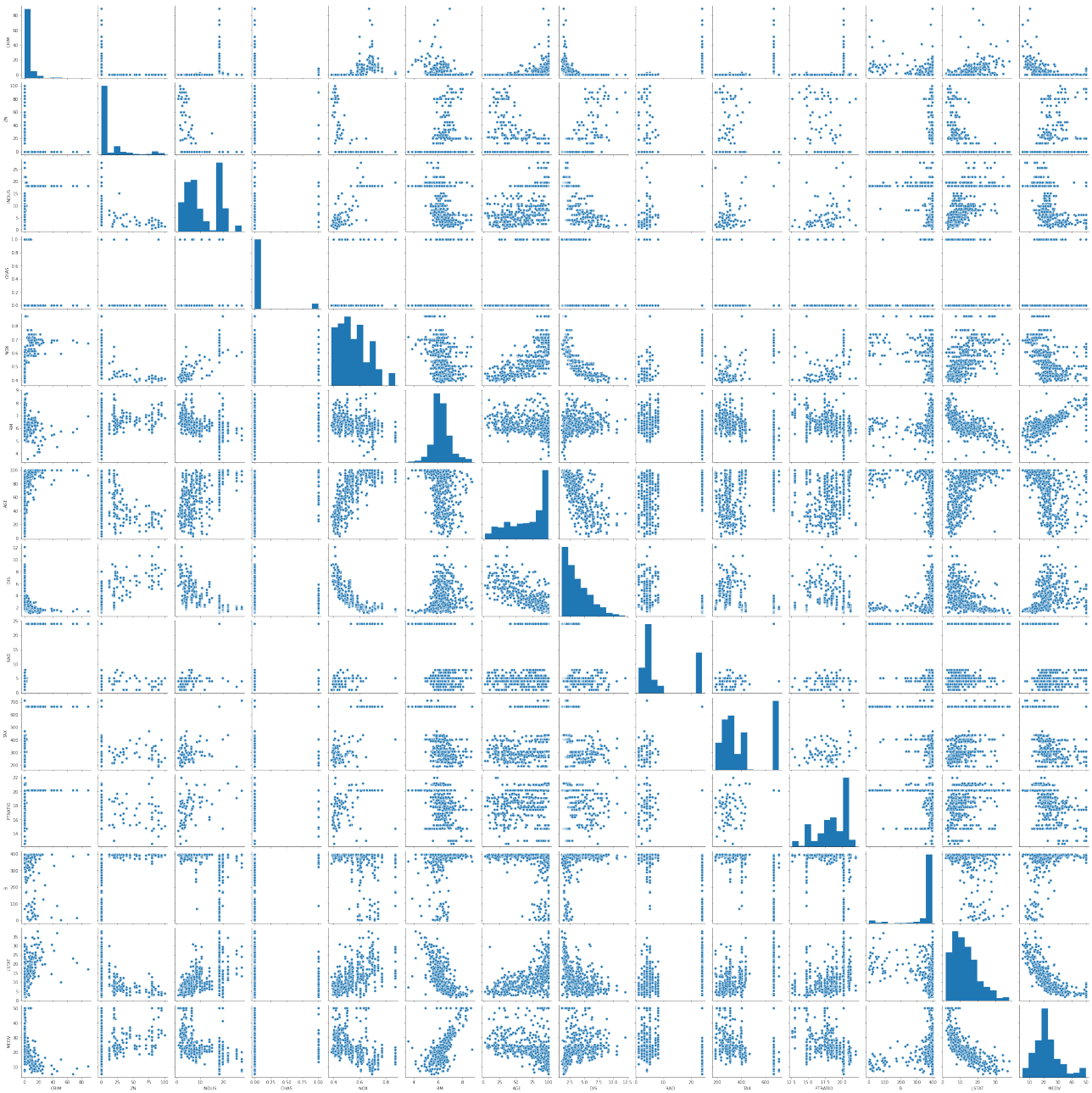
[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5727529d0>
```



Количество комнат в домах в Бостоне распределено нормально, в среднем комнат 6

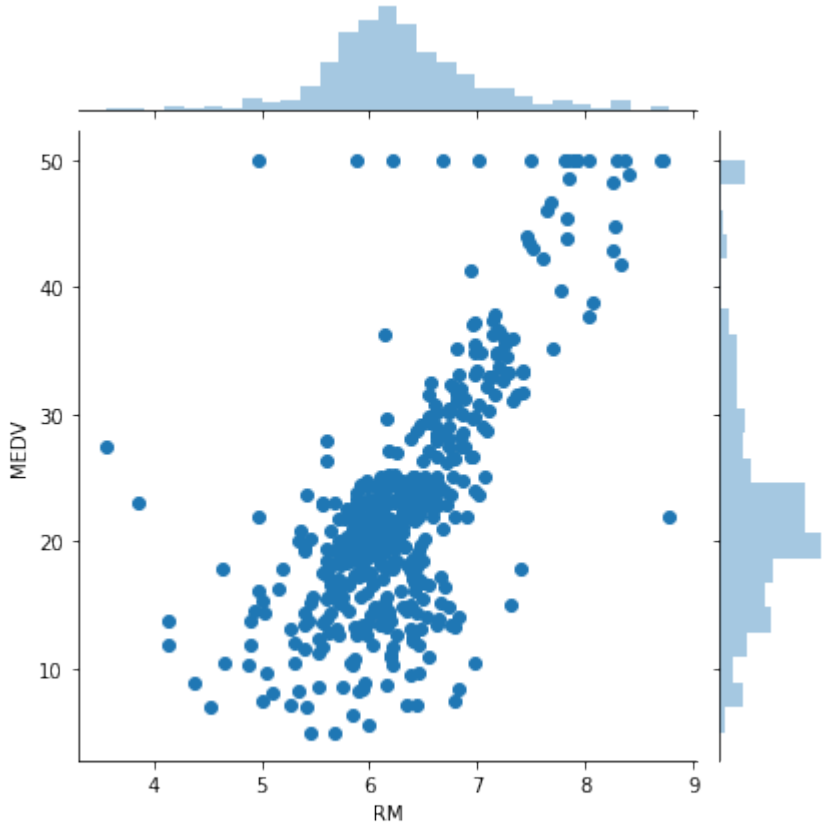
[39]:
```
sns.pairplot(data)
```

[39]:
```
<seaborn.axisgrid.PairGrid at 0x7ff582c10250>
```



[50]:
```
sns.jointplot(x='RM', y='MEDV', data=data)
```

[50]:
```
<seaborn.axisgrid.JointGrid at 0x7ff573b0ef40>
```



Прослеживается линейная зависимость между количеством комнат в доме и его ценой

3. Информация о корреляции признаков

[22]:
```
data.corr()
```

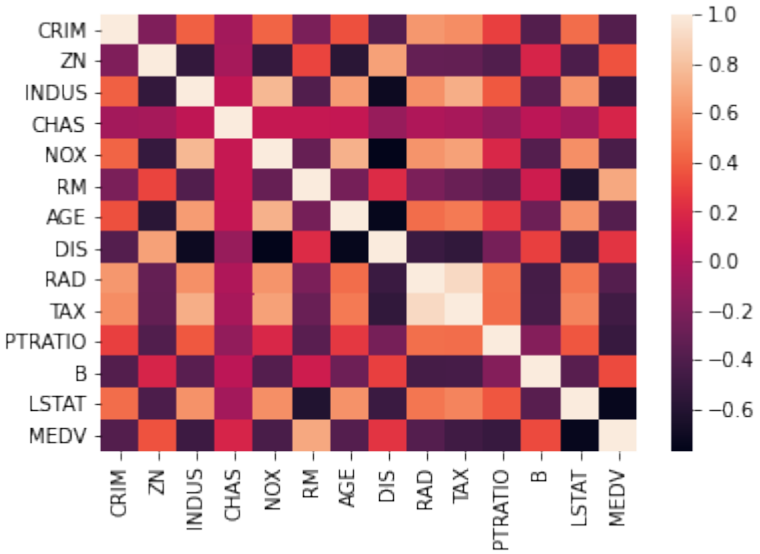
[22]:
```
                CRIM        ZN     INDUS      CHAS       NOX        RM  ␣
↪AGE  \
CRIM     1.000000 -0.200469  0.406583 -0.055892  0.420972 -0.219247  0.352734
ZN      -0.200469  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.406583 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055892 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.420972 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219247  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.352734 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.379670  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.625505 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.582764 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.289946 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
B       -0.385064  0.175520 -0.356977  0.048788 -0.380051  0.128069 -0.273534
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339
MEDV    -0.388305  0.360445 -0.483725  0.175260 -0.427321  0.695360 -0.376955

                DIS       RAD       TAX   PTRATIO         B     LSTAT      MEDV
```

```
CRIM    -0.379670  0.625505  0.582764  0.289946 -0.385064  0.455621 -0.388305
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995  0.360445
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800 -0.483725
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929  0.175260
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879 -0.427321
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808  0.695360
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339 -0.376955
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996  0.249929
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676 -0.381626
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993 -0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044 -0.507787
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087  0.333461
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000 -0.737663
MEDV     0.249929 -0.381626 -0.468536 -0.507787  0.333461 -0.737663  1.000000
```

[23]:
```
sns.heatmap(data.corr())
```

[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5999d38b0>
```



- Лучше всего цена дома коррелирует со статусом населения LSTAT (-0.737), количеством комнат RM (0.695) и соотношением учеников и учителей PTRATIO (0.508)
- Меньше всего на цену дома влияет наличие водоёмов CHAS (0,175) и растояние до бостонских центров занятости DIS (0,249). Эти признаки лучше исключить.

[ ]: