In [1]: import pandas as pd import numpy as np import matplotlib.pyplot as plt %matplotlib inline In [2]: housing = pd.read\_csv('C:\\Users\91820\\Downloads\\original.CSV') housing In [3]: Out[3]: dist4 teache price dist1 dist2 dist3 crime\_rate resid\_area air\_qual room\_num age 0.00632 32.31 0.538 4.01 0 24.0 6.575 65.2 4.35 3.81 4.18 24 37.07 6 421 78.9 4.99 5.06 22 1 21.6 0.02731 0.469 4.70 5.12 61.1 34.7 0.02729 37.07 0.469 5.03 4.86 5.01 4.97 22 7.185 3 33.4 0.03237 45.8 5.93 21 32.18 0.458 6.998 6.21 6.16 5.96 36.2 0.06905 32.18 0.458 7.147 54.2 6.16 5.86 6.37 5.86 21 501 22.4 0.06263 41.93 0.573 6.593 69.1 2.64 2.45 2.76 2.06 19 41.93 502 20.6 0.04527 0.573 6.120 76.7 2.44 2.11 2.46 2.14 19 0.573 503 23.9 0.06076 41.93 6.976 91.0 2.34 2.06 2.29 1.98 19 504 22.0 41.93 2.31 19 0.10959 0.573 6.794 89.3 2.54 2.40 2.31 6.030 505 19.0 0.04741 41.93 0.573 80.8 2.72 2.24 2.64 2.42 19 506 rows × 19 columns housing.describe() In [4]: Out[4]: resid\_area room\_num price crime\_rate air\_qual age dist1 506.000000 50 **count** 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 22.528854 3.613524 41.136779 0.554695 6.284634 68.574901 3.971996 mean std 9.182176 8.601545 6.860353 0.115878 0.702617 28.148861 2.108532 min 5.000000 0.006320 30.460000 0.385000 3.561000 2.900000 1.130000 25% 17.025000 0.449000 2.270000 0.082045 35.190000 5.885500 45.025000 50% 21.200000 0.256510 39.690000 0.538000 6.208500 77.500000 3.385000 75% 25.000000 3.677082 48.100000 0.624000 6.623500 94.075000 5.367500 max 50.000000 88.976200 57.740000 0.871000 8.780000 100.000000 12.320000 1 In [5]: # observation: missing values in "n\_hos\_beds" plt.scatter(x='n\_hot\_rooms',y='price',data=housing) In [6]: <matplotlib.collections.PathCollection at 0x1535c943048> 50 40 30 20 10 60 40 20 80 100 # observation: two outliers In [7]: plt.scatter(x='rainfall', y='price', data=housing) In [8]: Out[8]: <matplotlib.collections.PathCollection at 0x1535cd33848> 50 40 30 20 10 10 # observation: single outlier In [9]: In [10]: housing.head() Out[10]: dist2 dist3 dist4 teachers price crime\_rate resid\_area air\_qual room\_num age dist1 24.0 0.00632 32.31 0.538 6.575 65.2 4.35 3.81 4.01 24.7 4.18 21.6 37.07 22.2 1 0.02731 0.469 6.421 78.9 4.99 4.70 5.12 5.06 34.7 0.02729 37.07 0.469 7.185 61.1 5.03 4.86 5.01 4.97 22.2 33.4 0.03237 32.18 6.998 45.8 6.21 5.93 6.16 5.96 21.3 0.458 36.2 0.06905 32.18 0.458 54.2 6.16 5.86 6.37 5.86 21.3 In [11]: import seaborn as sns sns.countplot(x='airport', data=housing) In [12]: Out[12]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1535ed7d048> 250 200 150 100 50 YES NO airport sns.countplot(x='waterbody', data=housing) In [13]: Out[13]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1535edef488> 175 150 125 100 75 50 25 0 River Lake None Lake and River waterbody sns.countplot(x='bus\_ter', data=housing) In [14]: Out[14]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1535ee53148> 500 400 300 200 100 0 YES bus\_ter In [15]: # observation: all values are "yes", the data is not going to effect predictions. In [16]: housing.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 506 entries, 0 to 505 Data columns (total 19 columns): # Column Non-Null Count Dtype 0 price 506 non-null float64 1 crime\_rate 506 non-null float64 2 resid\_area 506 non-null float64 3 float64 air\_qual 506 non-null 4 room\_num 506 non-null float64 5 506 non-null float64 age 6 dist1 506 non-null float64 7 dist2 float64 506 non-null 8 dist3 506 non-null float64 9 dist4 506 non-null float64 10 float64 teachers 506 non-null 11 506 non-null float64 poor\_prop 12 airport 506 non-null object 13 n\_hos\_beds 498 non-null float64 14 n\_hot\_rooms 506 non-null float64 15 object waterbody 506 non-null 16 rainfall 506 non-null int64 17 bus\_ter 506 non-null object 18 506 non-null float64 parks dtypes: float64(15), int64(1), object(3) memory usage: 75.2+ KB ul = np.percentile(housing.n\_hot\_rooms,[99])[0] In [17]: In [18]: ul Out[18]: 15.399519999999999 housing[(housing.n\_hot\_rooms>ul)] In [19]: Out[19]: resid\_area air\_qual room\_num dist1 dist2 dist3 dist4 teache price crime rate age 22 2 34.7 0.02729 37.07 0.4690 7.185 61.1 5.03 4.86 5.01 4.97 2.01019 49.58 0.6050 166 50.0 7.929 96.2 2.11 1.91 2.31 1.86 25 204 50.0 0.02009 32.68 0.4161 8.034 31.9 5.41 4.80 5.28 4.99 25 267 50.0 0.57834 33.97 0.5750 8.297 67.0 2.60 2.13 2.43 2.52 27 50.0 5.66998 48.10 6.683 19 369 0.6310 96.8 1.55 1.28 1.65 0.94 7.05042 423 13.4 48.10 0.6140 6.103 85.1 2.08 1.80 2.34 1.87 19 In [20]: | housing.n\_hot\_rooms[(housing.n\_hot\_rooms>3\*ul)] = 3\*ul C:\Users\91820\anaconda3\envs\tensorflow\lib\site-packages\ipykernel\_l auncher.py:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame See the caveats in the documentation: https://pandas.pydata.org/pandas -docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy """Entry point for launching an IPython kernel. In [21]: uv = np.percentile(housing.rainfall,[1])[0] In [22]: uv Out[22]: 20.0 housing[(housing.rainfall<uv)]</pre> In [23]: Out[23]: resid\_area air\_qual room\_num dist1 dist2 dist3 dist4 teache price crime rate age 6.375 213 28.1 0.14052 40.59 0.489 32.3 4.11 3.92 4.18 3.57 21 In [24]: housing.rainfall[(housing.rainfall<uv)]=0.3\*uv C:\Users\91820\anaconda3\envs\tensorflow\lib\site-packages\ipykernel\_l auncher.py:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame See the caveats in the documentation: https://pandas.pydata.org/pandas -docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy """Entry point for launching an IPython kernel. housing[(housing.rainfall<uv)] In [25]: Out[25]: crime\_rate resid\_area air\_qual room\_num dist1 dist2 dist3 dist4 teache price age 6.375 213 28.1 0.14052 40.59 0.489 32.3 4.11 3.92 4.18 3.57 21 In [26]: housing.n\_hos\_beds=housing.n\_hos\_beds.fillna(housing.n\_hos\_beds.mean ()) In [27]: housing.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 506 entries, 0 to 505 Data columns (total 19 columns): Column Non-Null Count Dtype float64 0 price 506 non-null float64 1 crime\_rate 506 non-null resid\_area float64 2 506 non-null air\_qual float64 3 506 non-null 4 room\_num 506 non-null float64 float64 5 506 non-null age 6 dist1 506 non-null float64 float64 7 dist2 506 non-null 8 dist3 506 non-null float64 9 dist4 506 non-null float64 float64 teachers 10 506 non-null poor\_prop 11 506 non-null float64 506 non-null 12 airport object float64 506 non-null 13 n\_hos\_beds n\_hot\_rooms 506 non-null float64 14 waterbody 506 non-null 15 object 16 rainfall 506 non-null int64 17 bus\_ter object 506 non-null 506 non-null float64 18 parks dtypes: float64(15), int64(1), object(3)memory usage: 75.2+ KB In [28]: # fixed missing values In [29]: plt.scatter(x='crime\_rate',y='price',data=housing) # it apparently has outliers but it's not linear so will be treated di fferently Out[29]: <matplotlib.collections.PathCollection at 0x1535ef06248> 50 40 30 20 10 20 80 In [30]: housing.crime\_rate = np.log(1+housing.crime\_rate) In [31]: plt.scatter(x='crime\_rate',y='price',data=housing) Out[31]: <matplotlib.collections.PathCollection at 0x1535ef5bc88> 50 40 30 20 10 housing['avg\_dist']= (housing.dist1+housing.dist2+housing.dist3+housin In [32]: g.dist4)/4In [33]: del housing['dist1'] In [34]: del housing['dist2'] In [35]: del housing['dist3'] In [36]: del housing['dist4'] In [37]: housing.describe() Out[37]: resid\_area teachers price crime\_rate air\_qual room\_num age pc 506.000000 count 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 50 mean 22.528854 0.813418 41.136779 0.554695 6.284634 68.574901 21.544466 1 9.182176 1.022731 6.860353 0.115878 0.702617 28.148861 2.164946 std 5.000000 0.006300 30.460000 0.385000 3.561000 2.900000 18.000000 min 25% 17.025000 0.078853 35.190000 0.449000 5.885500 45.025000 19.800000 21.200000 0.228336 39.690000 0.538000 6.208500 77.500000 20.950000 50% 25.000000 1.542674 48.100000 0.624000 6.623500 94.075000 22.600000 **75%** 1 50.000000 4.499545 57.740000 0.871000 8.780000 100.000000 27.400000 max #all locations have bus terminal no effect on prediction so In [38]: In [39]: del housing['bus\_ter'] In [40]: housing.head() Out[40]: resid\_area teachers airport price crime rate air\_qual room\_num age poor\_prop n ho 0 24.0 0.006300 32.31 0.538 6.575 65.2 24.7 4.98 YES 0.026944 1 21.6 37.07 0.469 6.421 78.9 22.2 9.14 NO 34.7 0.026924 37.07 0.469 7.185 61.1 22.2 4.03 NO 33.4 0.031857 32.18 0.458 6.998 45.8 21.3 2.94 YES 3 36.2 0.066770 32.18 0.458 7.147 54.2 21.3 5.33 NO In [41]: housing = pd.get\_dummies(housing) In [42]: housing.head() Out[42]: poor\_prop n\_hos\_beds price crime rate resid\_area air\_qual room\_num age teachers 0.006300 0 24.0 32.31 0.538 6.575 65.2 24.7 4.98 5.480 1 21.6 0.026944 37.07 0.469 6.421 78.9 22.2 9.14 7.332 34.7 0.026924 37.07 0.469 7.185 61.1 22.2 4.03 7.394 33.4 0.031857 32.18 0.458 6.998 45.8 21.3 2.94 9.268 36.2 0.066770 32.18 0.458 54.2 5.33 8.824 7.147 21.3 del housing['airport\_NO'] [43] del housing['waterbody\_None'] In [44]: In [45]: # dealing with categorical data housing.corr() In [46]: Out[46]: price crime\_rate resid\_area air\_qual room\_num age teachers 0.505655 1.000000 -0.466527 -0.484754 -0.429300 0.696304 -0.377999 price -0.466527 1.000000 0.660283 0.707587 -0.288784 0.559591 -0.390052 crime\_rate 1.000000 resid area -0.484754 0.660283 0.763651 -0.391676 0.644779 -0.383248 air\_qual -0.429300 0.707587 0.763651 1.000000 -0.302188 0.731470 -0.188933 -0.240265 0.355501 0.696304 -0.288784 -0.391676 -0.302188 1.000000 room\_num -0.377999 0.559591 0.644779 0.731470 -0.240265 1.000000 -0.261515 age 1.000000 teachers 0.505655 -0.390052 -0.383248 -0.188933 0.355501 -0.261515 -0.740836 0.608970 0.603800 0.590879 -0.613808 0.602339 -0.374044 poor\_prop -0.049553 n\_hos\_beds 0.108880 -0.004089 0.005799 0.032009 -0.021012 -0.008056 n\_hot\_rooms 0.017007 0.056570 -0.003761 0.007238 0.014583 0.013918 -0.037007 rainfall -0.047200 0.082151 0.055845 0.091956 -0.064718 0.074684 -0.045928 -0.391574 0.638951 0.707635 0.915544 -0.282817 0.673850 -0.187004 parks avg\_dist -0.708022 0.205241 -0.747906 0.232452 0.249289 -0.586371 -0.769247 airport\_YES 0.182867 -0.134486 -0.115401 -0.073903 0.163774 0.005101 0.069437 waterbody\_Lake 0.036233 -0.025390 -0.026590 -0.046393 -0.0041950.003452 0.048717 waterbody\_Lake -0.037497 0.009076 0.051649 0.013849 0.010554 -0.004354 -0.046981 and River 0.071751 -0.060099 -0.098976 -0.037772 0.046251 -0.088609 0.094256 waterbody\_River del housing['parks'] In [47]: In [50]: from sklearn.linear\_model import LinearRegression In [51]: y = housing['price'] In [52]: X = housing[['room\_num']] In [53]: lm = LinearRegression() In [54]: lm.fit(X,y)Out[54]: LinearRegression(copy\_X=True, fit\_intercept=True, n\_jobs=None, normali ze=False) In [55]: print(lm.intercept\_,lm.coef\_) -34.65924312309721 [9.09966966] In [56]: lm.predict(X) Out[56]: array([25.17108491, 23.76973578, 30.72188341, 29.02024518, 30.3760959 23.85163281, 20.04797089, 21.50391804, 16.58099675, 19.9751735 3, 23.36935032, 20.02067188, 18.92871152, 19.4746917 , 20.8123431 4, 18.42822969, 19.34729633, 19.84777816, 14.98855456, 17.4545650 16.0259169 , 19.62028642, 21.23092795, 18.23713663, 19.2471999 6, 16.28980732, 18.23713663, 20.36645933, 24.44311134, 26.0719522 1, 17.32716966, 20.59395107, 19.48379137, 17.21797363, 20.8123431 4, 19.32909699, 18.49192738, 18.57382441, 19.62938609, 25.3530783 29.25683659, 26.9455205 , 21.47661903, 21.85880515, 20.5666520 6, 17.0450799 , 17.99144555, 20.21176495, 14.46987339, 16.3171063 3, 19.60208708, 20.98523687, 24.58870605, 19.92057552, 18.9196118 5, 31.30426226, 23.42394834, 27.3641053 , 21.25822696, 19.2744989 7, 17.58196041, 19.62938609, 24.08822422, 26.87272314, 29.9848101 6, 22.57767906, 18.00054522, 18.82861516, 16.24430897, 18.8923128 4, 23.7333371 , 19.58388774, 20.53025338, 22.16819392, 22.4229846 7, 22.54128038, 22.47758269, 21.21272861, 22.04989822, 18.7922164 8, 26.5542347 , 25.57147038, 22.68687509, 21.45841969, 23.4785463 5, 25.67156674, 20.0752699 , 21.03983488, 29.10214221, 29.7573184 2, 23.7333371 , 23.62414107, 23.96082885, 21.85880515, 22.2045926 25.62606839, 21.42202101, 38.76599139, 36.50017364, 32.8239071 26.5542347 , 27.04561686, 23.62414107, 21.1854296 , 21.4584196 9, 18.58292408, 18.44642903, 21.0944329 , 24.25201828, 22.0225992 1, 21.71321044, 26.44503866, 19.14710359, 20.77594446, 22.2500909 5, 19.28359864, 21.54031672, 20.12986792, 18.77401714, 17.4909637 2, 18.7558178 , 19.97517353, 19.58388774, 18.62842242, 18.8377148 3, 19.81137948, 16.4172027 , 17.14517627, 23.86073248, 16.6355947 7, 24.10642356, 22.90526717, 23.32385197, 18.31903366, 17.7275551 3, 22.98716419, 19.41099401, 24.07002488, 18.63752209, 21.3128249 7, 21.52211738, 11.01199892, 14.50627207, 15.09775059, 9.9564372 3, 21.12173191, 16.55369774, 10.16572964, 12.53164375, 16.2716079 8, 21.04893455, 14.51537174, 10.94830123, 17.29077098, 21.1126322 4, 21.32192464, 13.31421534, 28.51976335, 20.53935305, 24.5796063 8, 22.21369227, 33.48818298, 36.33637959, 41.55049031, 18.6102230 8, 20.85784149, 37.49203764, 18.81951549, 22.84156948, 23.5968420 6, 18.80131615, 18.8468145 , 16.04411624, 23.72423744, 18.6557214 3, 24.90719449, 20.12076825, 22.8051708 , 27.76449077, 28.8564511 3, 35.99969181, 21.24912729, 30.44889332, 25.06188888, 16.3353056 7, 21.33102431, 36.60027001, 27.05471653, 24.99819119, 30.7218834 1, 28.5925607 , 26.66343074, 30.65818572, 27.21851059, 25.4349753 3, 37.00065547, 31.65004971, 30.01210917, 31.53175401, 28.8109527 8, 30.26689992, 21.41292134, 34.58924301, 36.80046274, 38.4475029 5, 18.94691086, 22.90526717, 17.96414654, 20.52115371, 13.9693915 6, 19.57478807, 14.51537174, 18.18253861, 23.35115098, 14.5881690 9, 21.59491473, 18.91961185, 25.78076278, 19.49289104, 23.3329516 4, 28.5925607 , 21.43112068, 27.93738449, 25.56237071, 40.5586263 1, 44.73537469, 38.50210097, 30.52169067, 35.28081791, 24.9617925 1, 19.76588113, 32.78750842, 41.20470286, 40.38573259, 26.5451350 3, 20.72134645, 25.68066641, 32.29612626, 24.31571596, 25.4531746 7, 28.10117854, 20.80324347, 23.19645659, 23.51494503, 16.2352093 16.34440534, 20.92153918, 21.9953002 , 23.87893182, 26.4723376 7, 24.37031398, 23.92443017, 28.64715872, 40.49492862, 20.9215391 8, 18.81041582, 33.16969455, 44.54428162, 32.06863452, 27.6006967 1, 30.88567746, 33.77027274, 41.75978271, 32.0140365 , 30.9129764 7, 15.9349202 , 29.16583989, 40.84071607, 33.31528926, 19.2108012 8, 18.62842242, 22.12269557, 24.83439713, 35.32631626, 26.8363244 6, 27.70989275, 31.46805632, 27.455102 , 24.32481563, 27.3277066 2, 36.50017364, 28.74725509, 34.90773145, 37.43743962, 29.8392154 5, 24.06092521, 22.03169888, 21.84060581, 22.8051708 , 25.0800882 1, 27.77359044, 30.38519563, 25.67156674, 21.0944329 , 20.0206718 8, 26.10835089, 24.9344935 , 18.02784423, 23.07816089, 29.4115309 7, 27.86458713, 25.30757996, 24.44311134, 28.87465046, 31.1859665 6, 25.54417137, 32.86030578, 27.6643944 , 25.71706509, 19.6839841 10.59341411, 21.04893455, 20.14806726, 22.35928699, 25.0982875 5, 17.2543723 , 19.15620326, 17.95504687, 23.41484867, 20.9670375 3, 23.81523413, 23.36025065, 20.31186131, 17.28167131, 23.7151377 7, 23.86073248, 22.77787179, 20.69404744, 18.73761846, 22.9689648 5, 21.24912729, 17.26347197, 20.22086461, 22.81427047, 22.7596724 5, 20.27546263, 18.74671813, 18.98330954, 20.47565537, 19.8022798 1, 19.64758543, 31.23146491, 24.85259647, 26.27214494, 27.8918861 4, 20.06617023, 19.01060855, 24.6342044 , 25.71706509, 28.4833646 7, 24.39761299, 25.20748359, 18.88321317, 26.56333437, 16.8721861 8, 19.356396 , 21.86790482, 23.53314437, 21.0944329 , 20.9579378 6, 23.56044338, 22.22279194, 14.13318561, 18.14613993, 45.2358565 -2.25531945, 10.50241741, 0.49278079, 10.5661151 , 26.1538492 4, 29.18403923, 21.9043035 , 18.80131615, 9.98373624, 4, 31.88664112, 25.84446047, 27.16391257, 23.39664933, 21.9680011 9, 28.74725509, 24.89809482, 15.71652813, 15.57093342, 5.0881139 7, 13.35971369, 7.67242015, 10.83910519, 9.74714483, 14.3879763 6, 17.32716966, 20.40285801, 11.1666933 , 21.6950111 , 18.9105121 8, 24.22471927, 23.62414107, 17.63655843, 14.96125555, 18.5920237 5, 19.82047915, 23.05996155, 23.6150414 , 14.0148899 , 15.6710297 8, 17.05417957, 2.99518994, 16.37170435, 16.45360137, 27.6916934 1, 17.72755513, 25.91725782, 7.45402808, 12.24955399, 6.4621640 8, 23.88803149, 27.05471653, 13.60540477, 19.54748906, 27.4369026 6, 23.67873909, 19.99337287, 16.73569113, 20.87604083, 15.9804185 5, 18.99240921, 18.4555287 , 21.77690813, 21.6950111 , 23.3966493 3, 23.1054599 , 27.51879968, 23.80613446, 23.90623083, 21.8315061 5, 25.66246707, 24.13372257, 21.32192464, 19.34729633, 16.5445980 7, 18.28263498, 23.63324074, 21.93160251, 24.35211464, 18.6102230 8, 24.11552323, 23.04176221, 22.22279194, 21.62221374, 23.7333371 26.75442743, 25.89905848, 22.64137675, 32.6146147 , 26.5633343 7, 24.71610143, 19.72038278, 19.356396 , 22.67777542, 20.6758481 26.31764329, 23.36025065, 22.82337014, 24.60690539, 21.8406058 1, 17.74575447, 19.50199071, 19.96607386, 19.2653993 , 17.3271696 6, 21.45841969, 22.02259921, 23.9153305 , 28.85645113, 14.7246641 4, 21.41292134, 24.34301497, 13.60540477, 21.62221374, 22.0225992 1, 22.14089491, 26.7635271 , 29.59352437, 17.77305348, 18.7649174 7, 22.77787179, 20.9761372 , 19.07430624, 14.97035522, 14.6063684 3, 11.68537447, 19.78408047, 19.78408047, 17.27257164, 19.2653993 16.93588387, 14.38797636, 18.0642429 , 20.11166858, 16.0168172 3, 20.18446594, 25.33487897, 21.03073521, 28.82005245, 27.1639125 7, 20.21176495]) In [58]: sns.jointplot(x= housing['room\_num'], y=housing['price'], data = housi ng, kind='reg') Out[58]: <seaborn.axisgrid.JointGrid at 0x1535eec1a08> 50 40 30 20 10 0 room\_num In [ ]: