ex3\_sol

May 9, 2018

# 1 Exercise 3 - Input Scaling and Regularization

Part of this exercise is taken from http://scikit-learn.org/stable/auto\_examples/preprocessing/plot\_all\_scaling.

## 2 Table of Contents

- Section 3
- Section ??
- Section 5
- Section 6

# 3 Loading the dataset

- 3.0.1 Task 1: For this exercise we want to use the california housing dataset from scikit learn. Prepare the dataset in the following way:
  - Load the dataset (fetch\_california\_housing), inspect it and create a pandas DataFrame.
  - What kind of problem is this?
  - How many example and how many features do we have? What are the features? What is the target?
  - How does the target look like?
  - Make 2D scatter plots of all input features, where the z-axis shows the target dependence.
  - What do you observe?

The original database is available from Stattit

http://lib.stat.cmu.edu/datasets/

The data contains 20,640 observations on 9 variables.

This dataset contains the average house value as target variable and the following input variables (features): average income, housing average age, average rooms, average bedrooms, population, average occupation, latitude, and longitude in that order.

#### References

-----

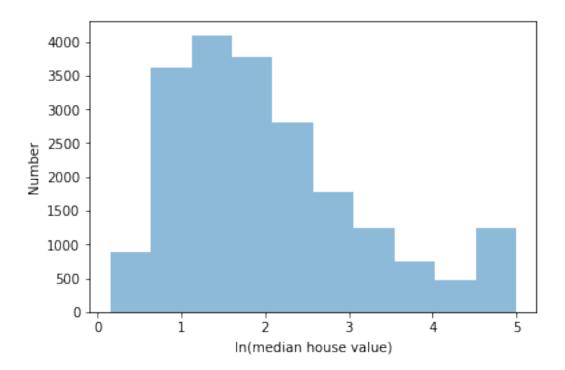
Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions, Statistics and Probability Letters, 33 (1997) 291-297.

```
In [2]: import pandas as pd
       df = pd.DataFrame(housing.data, columns=housing.feature_names)
       df.head(10)
Out[2]:
          MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude \
       0 8.3252
                                                     322.0
                                                                         37.88
                      41.0 6.984127
                                       1.023810
                                                            2.555556
       1 8.3014
                                      0.971880
                                                                         37.86
                      21.0 6.238137
                                                    2401.0 2.109842
       2 7.2574
                      52.0 8.288136
                                       1.073446
                                                     496.0 2.802260
                                                                         37.85
       3 5.6431
                      52.0 5.817352
                                       1.073059
                                                     558.0 2.547945
                                                                         37.85
       4 3.8462
                      52.0 6.281853
                                      1.081081
                                                     565.0 2.181467
                                                                         37.85
       5 4.0368
                      52.0 4.761658
                                      1.103627
                                                     413.0 2.139896
                                                                         37.85
       6 3.6591
                      52.0 4.931907
                                      0.951362
                                                    1094.0 2.128405
                                                                         37.84
       7 3.1200
                      52.0 4.797527
                                       1.061824
                                                    1157.0 1.788253
                                                                         37.84
       8 2.0804
                      42.0 4.294118
                                                    1206.0 2.026891
                                                                         37.84
                                       1.117647
       9 3.6912
                      52.0 4.970588
                                                                         37.84
                                       0.990196
                                                    1551.0 2.172269
          Longitude
       0
            -122.23
       1
            -122.22
       2
            -122.24
       3
            -122.25
       4
            -122.25
       5
            -122.25
            -122.25
       6
       7
            -122.25
       8
            -122.26
            -122.25
In [3]: %matplotlib inline
```

import matplotlib.pyplot as plt
plt.hist(housing.target, alpha=0.5)
plt.xlabel('ln(median house value)')

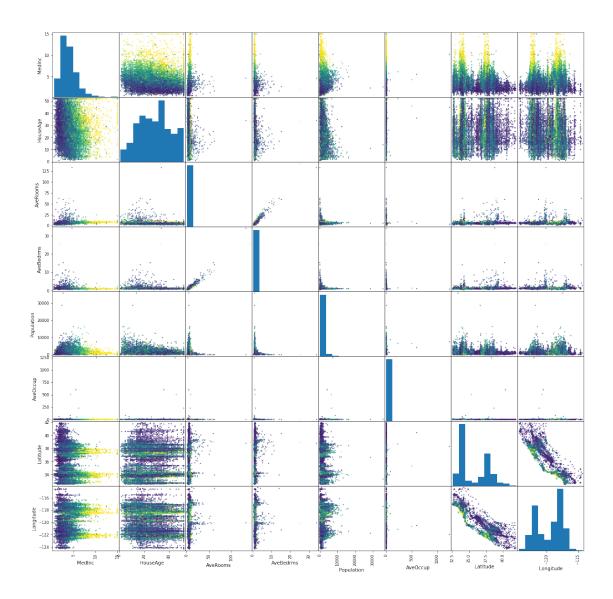
plt.ylabel('Number')

Out[3]: Text(0,0.5,u'Number')

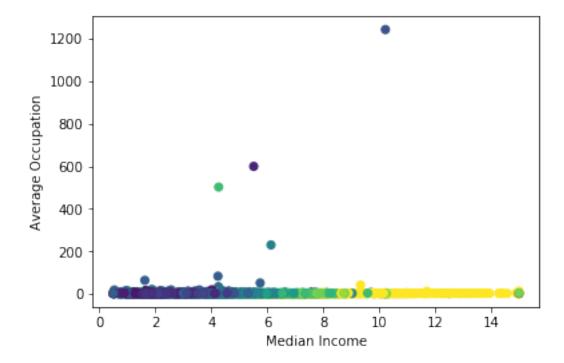


In [4]: df.shape

Out[4]: (20640, 8)



# 4 Comparison of different input scaling



Feature 0 (median income in a block) and feature 5 (number of households) of the California housing dataset have very different scales and contain some very large outliers. These two characteristics lead to difficulties to visualize the data and, more importantly, they can degrade the predictive performance of many machine learning algorithms. Unscaled data can also slow down or even prevent the convergence of many gradient-based estimators.

Indeed many estimators are designed with the assumption that each feature takes values close to zero or more importantly that all features vary on comparable scales. In particular, metric-based and gradient-based estimators often assume approximately standardized data (centered features with unit variances). A notable exception are decision tree-based estimators that are robust to arbitrary scaling of the data.

This example uses different scalers, transformers, and normalizers to bring the data within a pre-defined range.

Scalers are linear (or more precisely affine) transformers and differ from each other in the way to estimate the parameters used to shift and scale each feature.

QuantileTransformer provides a non-linear transformation in which distances between marginal outliers and inliers are shrunk.

Unlike the previous transformations, normalization refers to a per sample transformation instead of a per feature transformation.

## 4.1 Scaling the target

```
In [7]: housing.target
Out[7]: array([ 4.526,  3.585,  3.521, ...,  0.923,  0.847,  0.894]
```

It often makes sense to scale the target of a regression to something between 0 and 1, because that way you can use activation functions in the output layer which map to that range. If you use functions like sigmoid in the output layer, this keeps the backpropagated error within limits, unlike the case of unbounded linear activation functions. You could even scale to ranges like [0.3, 0.7] in order to focus on the almost linear-part of the sigmoid function. In the following we will scale the target between 0 and 1 also for plotting reasons. We will use the minmax\_scale for that

### 4.2 Scaling the input

We will focus in the following on the median income [0] and number of households [5] scatter plot and how different scalings impact their range.

```
In [9]: X = housing.data[:, [0, 5]]
```

In the following, I have taken the scaling and plotting code from http://scikit-learn.org/stable/auto\_examples/preprocessing/plot\_all\_scaling.html#results.

You don't need to understand how the scaling and plotting is done for now, but the purpose is mainly to demonstrate how different scalers impact your input

```
In [10]: # Author: Raghav RV <ruraghav93@gmail.com>
                  Guillaume Lemaitre <q.lemaitre58@qmail.com>
                    Thomas Unterthiner
         # License: BSD 3 clause
         import numpy as np
         import matplotlib as mpl
         from matplotlib import pyplot as plt
         from matplotlib import cm
         from sklearn.preprocessing import MinMaxScaler
         from sklearn.preprocessing import MaxAbsScaler
         from sklearn.preprocessing import StandardScaler
         from sklearn.preprocessing import RobustScaler
         from sklearn.preprocessing import Normalizer
         from sklearn.preprocessing.data import QuantileTransformer
         distributions = \Gamma
             ('Unscaled data', X),
             ('Data after standard scaling',
                 StandardScaler().fit_transform(X)),
```

```
('Data after min-max scaling',
                 MinMaxScaler().fit_transform(X)),
             ('Data after max-abs scaling',
                 MaxAbsScaler().fit_transform(X)),
             ('Data after robust scaling',
                 RobustScaler(quantile_range=(25, 75)).fit_transform(X)),
             ('Data after quantile transformation (uniform pdf)',
                 QuantileTransformer(output_distribution='uniform')
                 .fit_transform(X)),
             ('Data after quantile transformation (gaussian pdf)',
                 QuantileTransformer(output_distribution='normal')
                 .fit_transform(X)),
             ('Data after sample-wise L2 normalizing',
                 Normalizer().fit_transform(X))
         ]
In [11]: def create_axes(title, figsize=(16, 6)):
             fig = plt.figure(figsize=figsize)
             fig.suptitle(title)
             # define the axis for the first plot
             left, width = 0.1, 0.22
             bottom, height = 0.1, 0.7
             bottom_h = height + 0.15
             left_h = left + width + 0.02
             rect_scatter = [left, bottom, width, height]
             rect_histx = [left, bottom_h, width, 0.1]
             rect_histy = [left_h, bottom, 0.05, height]
             ax_scatter = plt.axes(rect_scatter)
             ax_histx = plt.axes(rect_histx)
             ax_histy = plt.axes(rect_histy)
             # define the axis for the zoomed-in plot
             left = width + left + 0.2
             left_h = left + width + 0.02
             rect_scatter = [left, bottom, width, height]
             rect_histx = [left, bottom_h, width, 0.1]
             rect_histy = [left_h, bottom, 0.05, height]
             ax_scatter_zoom = plt.axes(rect_scatter)
             ax_histx_zoom = plt.axes(rect_histx)
             ax_histy_zoom = plt.axes(rect_histy)
             # define the axis for the colorbar
             left, width = width + left + 0.13, 0.01
```

```
rect_colorbar = [left, bottom, width, height]
    ax_colorbar = plt.axes(rect_colorbar)
   return ((ax_scatter, ax_histy, ax_histx),
            (ax_scatter_zoom, ax_histy_zoom, ax_histx_zoom),
            ax_colorbar)
def plot_distribution(axes, X, y, hist_nbins=50, title="",
                      x0_label="", x1_label=""):
    ax, hist_X1, hist_X0 = axes
    ax.set_title(title)
    ax.set_xlabel(x0_label)
    ax.set_ylabel(x1_label)
    # The scatter plot
    colors = cm.plasma_r(y)
    ax.scatter(X[:, 0], X[:, 1], alpha=0.5, marker='o', s=5, lw=0, c=colors)
    # Removing the top and the right spine for aesthetics
    # make nice axis layout
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.get_xaxis().tick_bottom()
    ax.get_yaxis().tick_left()
    ax.spines['left'].set_position(('outward', 10))
    ax.spines['bottom'].set_position(('outward', 10))
    # Histogram for axis X1 (feature 5)
    hist_X1.set_ylim(ax.get_ylim())
    hist_X1.hist(X[:, 1], bins=hist_nbins, orientation='horizontal',
                 color='grey', ec='grey')
   hist_X1.axis('off')
    # Histogram for axis XO (feature 0)
   hist_X0.set_xlim(ax.get_xlim())
   hist_X0.hist(X[:, 0], bins=hist_nbins, orientation='vertical',
                 color='grey', ec='grey')
   hist_X0.axis('off')
```

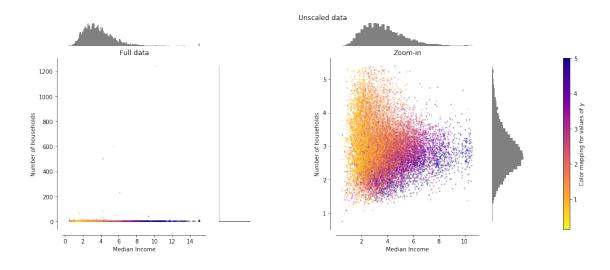
Two plots will be shown for each scaler/normalizer/transformer. The left figure will show a scatter plot of the full data set while the right figure will exclude the extreme values considering only 99 % of the data set, excluding marginal outliers. In addition, the marginal distributions for each feature will be shown on the side of the scatter plot.

```
ax_zoom_out, ax_zoom_in, ax_colorbar = create_axes(title)
axarr = (ax_zoom_out, ax_zoom_in)
plot_distribution(axarr[0], X, y, hist_nbins=200,
                  x0_label="Median Income",
                  x1_label="Number of households",
                  title="Full data")
# zoom-in
zoom_in_percentile_range = (0, 99)
cutoffs_X0 = np.percentile(X[:, 0], zoom_in_percentile_range)
cutoffs_X1 = np.percentile(X[:, 1], zoom_in_percentile_range)
non_outliers_mask = (
    np.all(X > [cutoffs_X0[0], cutoffs_X1[0]], axis=1) &
    np.all(X < [cutoffs_X0[1], cutoffs_X1[1]], axis=1))</pre>
plot_distribution(axarr[1], X[non_outliers_mask], y[non_outliers_mask],
                  hist_nbins=50,
                  x0_label="Median Income",
                  x1_label="Number of households",
                  title="Zoom-in")
norm = mpl.colors.Normalize(y_full.min(), y_full.max())
mpl.colorbar.ColorbarBase(ax_colorbar, cmap=cm.plasma_r,
                          norm=norm, orientation='vertical',
                          label='Color mapping for values of y')
```

# 4.3 Original data

Each transformation is plotted showing two transformed features, with the left plot showing the entire dataset, and the right zoomed-in to show the dataset without the marginal outliers. A large majority of the samples are compacted to a specific range, [0, 10] for the median income and [0, 6] for the number of households. Note that there are some marginal outliers (some blocks have more than 1200 households). Therefore, a specific pre-processing can be very beneficial depending of the application. In the following, we present some insights and behaviors of those pre-processing methods in the presence of marginal outliers.

```
In [13]: make_plot(0)
```

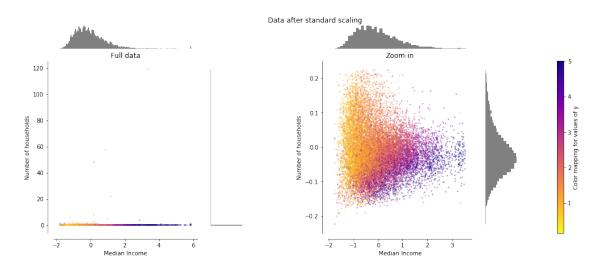


### 4.4 StandardScaler

StandardScaler removes the mean (0) and scales the data to unit variance (1). However, the outliers have an influence when computing the empirical mean and standard deviation which shrink the range of the feature values as shown in the left figure below. Note in particular that because the outliers on each feature have different magnitudes, the spread of the transformed data on each feature is very different: most of the data lie in the [-2, 4] range for the transformed median income feature while the same data is squeezed in the smaller [-0.2, 0.2] range for the transformed number of households.

StandardScaler therefore cannot guarantee balanced feature scales in the presence of outliers.

In [14]: make\_plot(1)

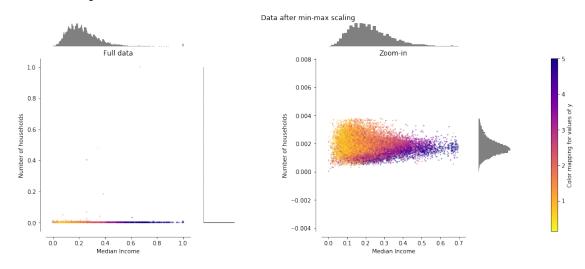


### 4.5 MinMaxScaler

MinMaxScaler rescales the data set such that all feature values are in the range [0, 1] as shown in the right panel below. However, this scaling compress all inliers in the narrow range [0, 0.005] for the transformed number of households.

As StandardScaler, MinMaxScaler is very sensitive to the presence of outliers.

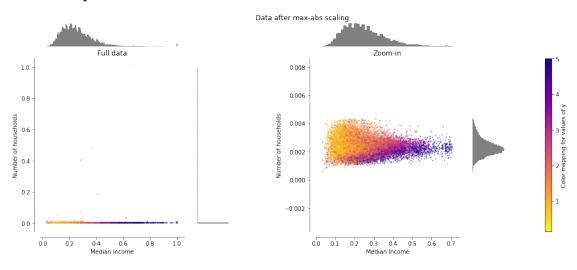
In [15]: make\_plot(2)



#### 4.6 MaxAbsScaler

MaxAbsScaler differs from the previous scaler such that the absolute values are mapped in the range [0, 1]. On positive only data, this scaler behaves similarly to MinMaxScaler and therefore also suffers from the presence of large outliers.

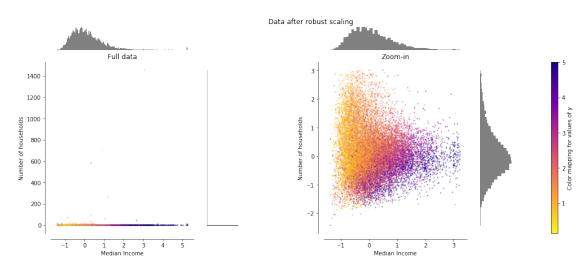
In [16]: make\_plot(3)



#### 4.7 RobustScaler

Unlike the previous scalers, the centering and scaling statistics of this scaler are based on percentiles and are therefore not influenced by a few number of very large marginal outliers. Consequently, the resulting range of the transformed feature values is larger than for the previous scalers and, more importantly, are approximately similar: for both features most of the transformed values lie in a [-2, 3] range as seen in the zoomed-in figure. Note that the outliers themselves are still present in the transformed data. If a separate outlier clipping is desirable, a non-linear transformation is required (see below).

In [17]: make\_plot(4)

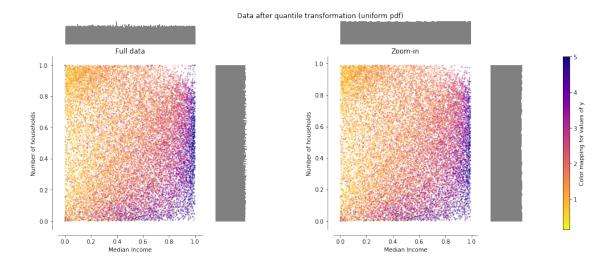


### 4.8 QuantileTransformer (uniform output)

QuantileTransformer applies a non-linear transformation such that the probability density function of each feature will be mapped to a uniform distribution. In this case, all the data will be mapped in the range [0, 1], even the outliers which cannot be distinguished anymore from the inliers.

As RobustScaler, QuantileTransformer is robust to outliers in the sense that adding or removing outliers in the training set will yield approximately the same transformation on held out data. But contrary to RobustScaler, QuantileTransformer will also automatically collapse any outlier by setting them to the a priori defined range boundaries (0 and 1).

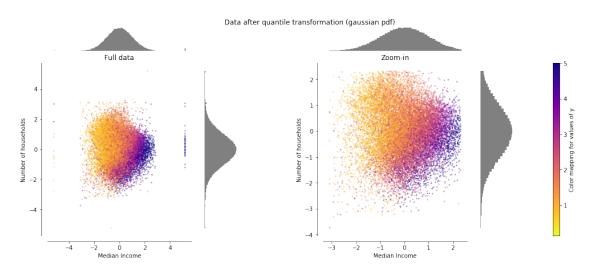
In [18]: make\_plot(5)



# 4.9 QuantileTransformer (Gaussian output)

QuantileTransformer has an additional output\_distribution parameter allowing to match a Gaussian distribution instead of a uniform distribution. Note that this non-parameteric transformer introduces saturation artifacts for extreme values.

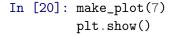
In [19]: make\_plot(6)

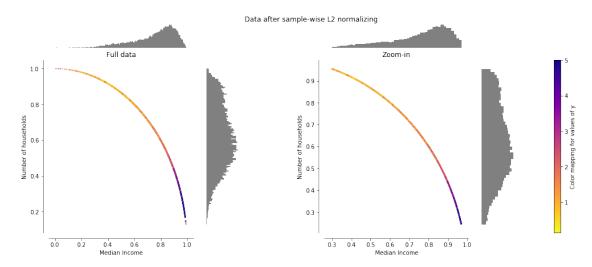


#### 4.10 Normalizer

The Normalizer rescales the vector for each sample to have unit norm, independently of the distribution of the samples. It can be seen on both figures below where all samples are mapped onto the unit circle. In our example the two selected features have only positive values; therefore the

transformed data only lie in the positive quadrant. This would not be the case if some original features had a mix of positive and negative values.





#### 4.11 Which scaler should we use?

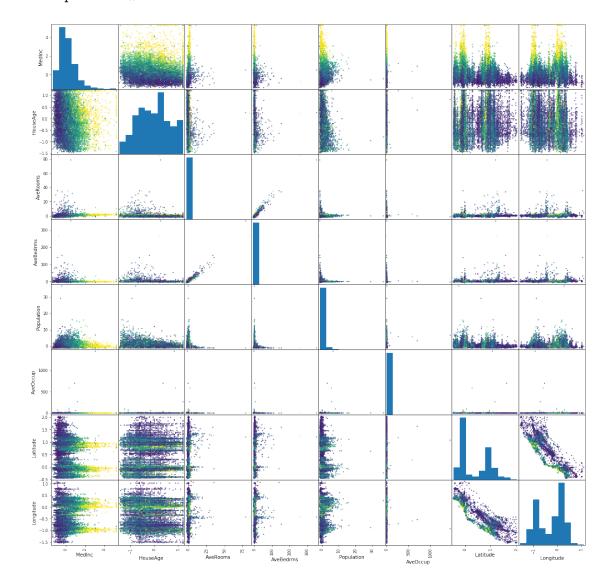
Let's have a closer look at the robust scaler on our entire dataset:

```
Out [21]:
              MedInc
                      HouseAge
                                AveRooms
                                           AveBedrms
                                                      Population AveOccup
                                                                             Latitude
            2.197582
                      0.631579
                                 1.088935
                                           -0.267221
                                                        -0.899787 -0.307981
                                                                             0.957672
         1
            2.186664 -0.421053
                                 0.626066
                                           -0.822926
                                                         1.316631 -0.830800
                                                                             0.952381
         2
            1.707732
                      1.210526
                                            0.263955
                                                        -0.714286 -0.018599
                                                                             0.949735
                                 1.898042
            0.967177
         3
                      1.210526
                                 0.364978
                                            0.259814
                                                        -0.648188 -0.316908
                                                                             0.949735
         4
            0.142854
                      1.210526
                                 0.653191
                                            0.345657
                                                        -0.640725 -0.746784
                                                                             0.949735
         5
            0.230291
                      1.210526 -0.290055
                                            0.586926
                                                        -0.802772 -0.795547
                                                                             0.949735
            0.057022
                      1.210526 -0.184419
         6
                                           -1.042501
                                                        -0.076759 -0.809026
                                                                             0.947090
         7 -0.190288
                      1.210526 -0.267799
                                            0.139580
                                                        -0.009595 -1.208021
                                                                             0.947090
         8 -0.667202
                      0.684211 -0.580152
                                            0.736958
                                                         0.042644 -0.928102
                                                                             0.947090
           0.071748
                      1.210526 -0.160418
                                                         0.410448 -0.757574
                                           -0.626926
                                                                             0.947090
```

Longitude

- 0 -0.986807
- 1 -0.984169
- 2 -0.989446
- 3 -0.992084
- 4 -0.992084

- 5 -0.992084
- 6 -0.992084
- 7 -0.992084
- 8 -0.994723
- 9 -0.992084



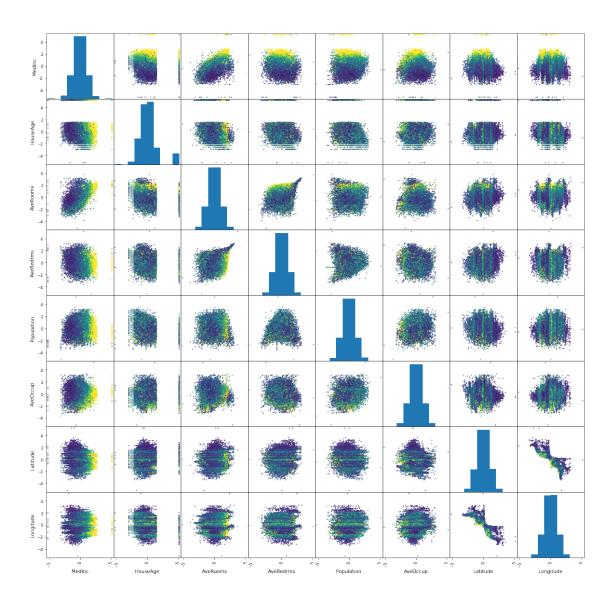
Out[24]: MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude \
0 1.919185 0.912774 1.294622 -0.388543 -1.697037 -0.450080 0.901416

```
1 1.914418 -0.479432 0.822470
                               -1.197835
                                            1.191955 -1.229273 0.886449
2 1.630171 5.199338 1.933184
                                0.352143
                                           -1.315958 -0.028306 0.879040
3 1.083447
                                0.346959
            5.199338 0.495717
                                           -1.174755 -0.465169 0.879040
4 0.193151
            5.199338 0.852294
                                0.452858
                                           -1.164444 -1.109257
                                                               0.879040
5 0.298746
            5.199338 -0.399051
                                0.720089
                                           -1.492879 -1.181873 0.879040
6 0.084155
            5.199338 -0.255539
                               -1.487964
                                           -0.111890 -1.200185 0.871679
7 -0.270671
            5.199338 -0.367135
                                0.197601
                                           -0.015055 -1.812916 0.871679
8 -1.103892 0.975466 -0.813664
                                0.861849
                                            0.060256 -1.361386
                                                               0.871679
9 0.107135 5.199338 -0.220709 -0.923979
                                            0.493081 -1.126478 0.871679
```

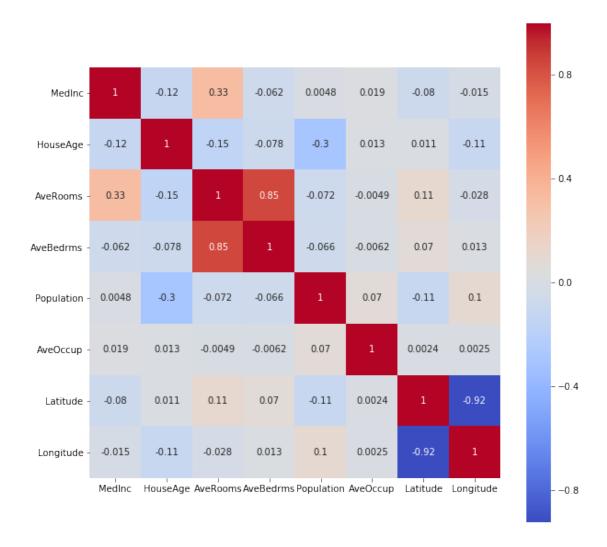
#### Longitude

- 0 -1.152175
- 1 -1.137677
- 2 -1.169401
- 3 -1.189522
- 4 -1.189522
- 5 -1.189522
- 6 -1.189522
- 7 -1.189522
- 0 4 005040
- 8 -1.225943
- 9 -1.189522

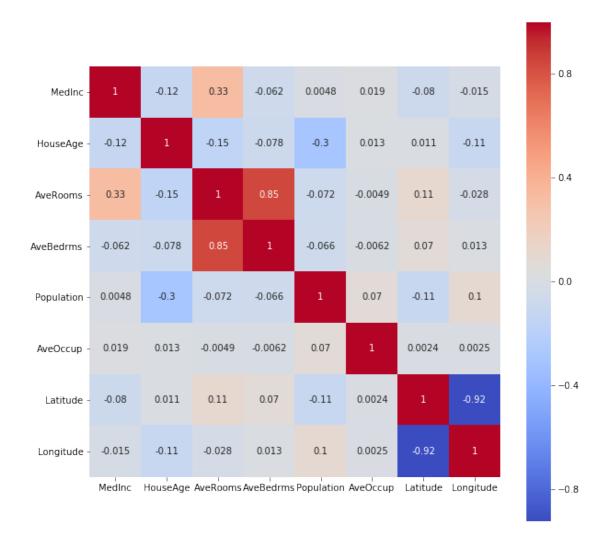
What about the non-linear gaussian transformation, if gaussian distributed shapes are ideal for most machine learning algorithms



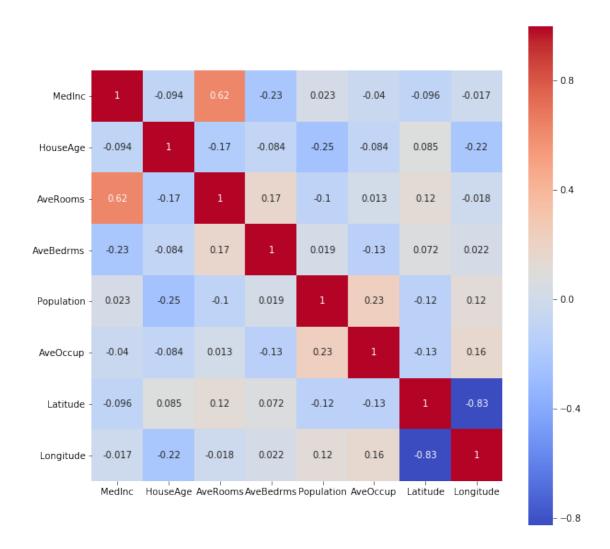
# 4.12 Impact on the correlations



Out[28]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fa742593a10>



Out[29]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fa741bbdd90>



Non-linear transformations smooth out distributions and are less influenced by outliers. However, they distort correlations and distances within and across features. There is no general answer, which scaler will work best for the problem. Like many things in machine learning, this is simply something one need to test/study.

# 5 A DNN for regression

#### 5.0.1 Task 2: Design a DNN for this regression problem

- Prepare the data by creating a robust scaled design matrix and a minmax scaled target vector and split into training (70%) and test sample.
- Design a simple fully-connected DNN for regression with 4 hidden layers. Use 30% of the training data for validation. Use adam as optimizer and set the batch size to 256.
- What is a good activation function for the output node? What is a good loss function?
- Train the DNN over 300 epochs and plot the loss function and one additional metric for linear regression as a function of epochs.

- Evaluate the obtained model on the testing data, compare the prediction to the true value.
- Use scikit-learn metrics for regression to evaluate the model
- Which feature has the highest linear correlation to the prediction? Plot the true value and the prediction dependent on this feature.

```
In [30]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(df.as_matrix(), housing.target, tes
In [31]: y_train
Out[31]: array([ 1.938, 1.697, 2.598, ..., 2.221, 2.835, 3.25 ])
In [32]: scaler = RobustScaler(quantile_range=(25, 75))
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
         scaler_y = MinMaxScaler()
         y_train = scaler_y.fit_transform(y_train.reshape(-1, 1)).reshape(-1)
         y_test = scaler_y.transform(y_test.reshape(-1, 1)).reshape(-1)
         y_train
Out[32]: array([ 0.36866034,  0.31896982,  0.50474225, ...,  0.42701061,
                 0.55360803, 0.63917468])
In [33]: from keras.models import Sequential
         from keras.layers import Dense
         model = Sequential()
         model.add(Dense(units=128, activation='relu', input_dim=8))
         model.add(Dense(units=64, activation='relu'))
         model.add(Dense(units=32, activation='relu'))
         model.add(Dense(units=8 , activation='relu'))
         model.add(Dense(units=1, activation='sigmoid'))
         model.compile(loss='mse', optimizer='adam', metrics=['mae'])
Using TensorFlow backend.
```

\_\_\_\_\_

RuntimeError Traceback (most recent call last)

RuntimeError: module compiled against API version 0xc but this version of numpy is 0xb

\_\_\_\_\_

RuntimeError Traceback (most recent call last)

RuntimeError: module compiled against API version Oxc but this version of numpy is Oxb

In [34]: model.summary()

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 128)	1152
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 8)	264
dense_5 (Dense)	(None, 1)	9
Total params: 11,761 Trainable params: 11,761		

Trainable params: 11,761 Non-trainable params: 0

#### 5.0.2 Training

Epoch 6/300

```
In [35]: # fix random seed for reproducibility
         seed = 42
         np.random.seed(seed)
```

history = model.fit(X\_train, y\_train, validation\_split=0.3, epochs=300, batch\_size=256)

Train on 10113 samples, validate on 4335 samples Epoch 1/300 Epoch 2/300 Epoch 3/300 Epoch 4/300 Epoch 5/300 

Epoch 7/300 Epoch 8/300

Epoch 9/300

T 1 40/000
Epoch 10/300
10113/10113 [===================================
Epoch 11/300
10113/10113 [===================================
Epoch 12/300
10113/10113 [===================================
Epoch 13/300
10113/10113 [===================================
Epoch 14/300
10113/10113 [===================================
Epoch 15/300
10113/10113 [===================================
Epoch 16/300
10113/10113 [===================================
Epoch 17/300
10113/10113 [===================================
Epoch 18/300
10113/10113 [===================================
Epoch 19/300
10113/10113 [===================================
Epoch 20/300
10113/10113 [===================================
Epoch 21/300
10113/10113 [===================================
Epoch 22/300
10113/10113 [===================================
Epoch 23/300
Epoch 24/300
Epoch 25/300
10113/10113 [===================================
Epoch 26/300
Epoch 27/300
10113/10113 [===================================
Epoch 28/300
10113/10113 [===================================
10113/10113 [===================================
Epoch 29/300
Epoch 29/300 10113/10113 [===================================
Epoch 29/300  10113/10113 [===================================
Epoch 29/300 10113/10113 [===================================
Epoch 29/300 10113/10113 [===================================
Epoch 29/300 10113/10113 [===================================

Epoch 34/300
10113/10113 [===================================
Epoch 35/300
10113/10113 [===================================
Epoch 36/300
10113/10113 [===================================
Epoch 37/300
10113/10113 [===================================
Epoch 38/300
10113/10113 [===================================
Epoch 39/300
10113/10113 [===================================
Epoch 40/300
10113/10113 [===================================
Epoch 41/300
10113/10113 [===================================
Epoch 42/300
10113/10113 [===================================
Epoch 43/300
10113/10113 [===================================
Epoch 44/300
10113/10113 [===================================
Epoch 45/300 10113/10113 [===================================
Epoch 46/300
10113/10113 [===================================
Epoch 47/300
10113/10113 [===================================
Epoch 48/300
10113/10113 [===================================
Epoch 49/300
10113/10113 [===================================
Epoch 50/300
10113/10113 [===================================
Epoch 51/300
10113/10113 [===================================
Epoch 52/300
10113/10113 [===================================
Epoch 53/300 10113/10113 [===================================
Epoch 54/300
10113/10113 [===================================
Epoch 55/300
10113/10113 [===================================
Epoch 56/300
10113/10113 [===================================
Epoch 57/300
10113/10113 [===================================

Epoch 58/300	
10113/10113 [===================================	ute error
Epoch 59/300	200_01101
10113/10113 [===================================	ute error
Epoch 60/300	100_01101
10113/10113 [===================================	ute error
Epoch 61/300	100_01101
10113/10113 [===================================	ute error
Epoch 62/300	
10113/10113 [===================================	ute_error
Epoch 63/300	
10113/10113 [===================================	ute_error
Epoch 64/300	
10113/10113 [===================================	ute_error
Epoch 65/300	
10113/10113 [===================================	ute_error
Epoch 66/300	
10113/10113 [===================================	ute_error
Epoch 67/300	
10113/10113 [===================================	ute_error
Epoch 68/300	
10113/10113 [===================================	ute_error
Epoch 69/300	
10113/10113 [===================================	ute_error
Epoch 70/300	
10113/10113 [===================================	ute_error
Epoch 71/300	
10113/10113 [===================================	ute_error
Epoch 72/300	
10113/10113 [===================================	ute_error
Epoch 73/300	
10113/10113 [===================================	ute_error
Epoch 74/300	
10113/10113 [===================================	ite_error
Epoch 75/300 10113/10113 [===================================	uto orror
Epoch 76/300	Tre_ellor
10113/10113 [===================================	uto error
Epoch 77/300	Tre_ellol
10113/10113 [===================================	ute error
Epoch 78/300	100_01101
10113/10113 [===================================	ute error
Epoch 79/300	
10113/10113 [===================================	ute error
Epoch 80/300	021 01
10113/10113 [===================================	ute_error
Epoch 81/300	
10113/10113 [===================================	ute_error
•	

Epoch 82/300		_	
	-	0s	11us/step - loss: 0.0095 - mean_absolute_error
Epoch 83/300		_	
	-	0s	11us/step - loss: 0.0092 - mean_absolute_error
Epoch 84/300			
	-	0s	11us/step - loss: 0.0093 - mean_absolute_error
Epoch 85/300			
	-	0s	11us/step - loss: 0.0091 - mean_absolute_error
Epoch 86/300			
10113/10113 [===================================	-	0s	11us/step - loss: 0.0091 - mean_absolute_error
Epoch 87/300			
10113/10113 [===================================	-	0s	11us/step - loss: 0.0091 - mean_absolute_error
Epoch 88/300			
10113/10113 [===================================	-	0s	10us/step - loss: 0.0090 - mean_absolute_error
Epoch 89/300			
10113/10113 [===================================	-	0s	10us/step - loss: 0.0090 - mean_absolute_error
Epoch 90/300			
10113/10113 [===================================	-	0s	11us/step - loss: 0.0090 - mean_absolute_error
Epoch 91/300			
10113/10113 [===================================	_	0s	11us/step - loss: 0.0090 - mean_absolute_error
Epoch 92/300			
10113/10113 [===================================	_	0s	10us/step - loss: 0.0091 - mean_absolute_error
Epoch 93/300			•
10113/10113 [===================================	_	0s	13us/step - loss: 0.0088 - mean_absolute_error
Epoch 94/300			•
10113/10113 [===================================	_	0s	12us/step - loss: 0.0087 - mean_absolute_error
Epoch 95/300			
-	_	0s	9us/step - loss: 0.0088 - mean_absolute_error:
Epoch 96/300			· ·
•	_	0s	9us/step - loss: 0.0087 - mean_absolute_error:
Epoch 97/300			· · ·
•	_	0s	10us/step - loss: 0.0089 - mean_absolute_error
Epoch 98/300			
<del>-</del>	_	0s	10us/step - loss: 0.0092 - mean_absolute_error
Epoch 99/300			
-	_	0s	9us/step - loss: 0.0090 - mean_absolute_error:
Epoch 100/300		0.0	cub, book loss. c.cocc mean_usscruos_circi.
•	_	0s	10us/step - loss: 0.0090 - mean_absolute_error
Epoch 101/300		Ü	Toub, book Tobb. 0.0000 mean_abbotase_offor
	_	۸q	12us/step - loss: 0.0096 - mean_absolute_error
Epoch 102/300		OB	12us/step - 10ss. 0.0000 - mean_absolute_effor
•		Λa	11us/step - loss: 0.0091 - mean_absolute_error
Epoch 103/300	_	US	ilus/step - loss. 0.0091 - mean_absolute_ellol
-		٥٥	11ug/gton logg: 0.0007 moon shaelute error
Epoch 104/300	-	υs	11us/step - loss: 0.0087 - mean_absolute_error
		0~	11us/step - loss: 0.0086 - mean_absolute_error
	-	US	ilus/step - 10ss. U.0000 - mean_absolute_error
Epoch 105/300		0~	11us/step - loss: 0.0087 - mean_absolute_error
10113/10113 []	-	US	rius/step - ross. 0.000/ - mean_absorute_error

Epoch 106/300	
10113/10113 [===================================	rror
Epoch 107/300	0 .
10113/10113 [===================================	rror
Epoch 108/300	.101
10113/10113 [===================================	rror
Epoch 109/300	101
10113/10113 [===================================	rror
Epoch 110/300	.101
10113/10113 [===================================	rror
Epoch 111/300	101
10113/10113 [===================================	rror
Epoch 112/300	101
10113/10113 [===================================	rror
Epoch 113/300	101
10113/10113 [===================================	rror
Epoch 114/300	.101
10113/10113 [===================================	rror
Epoch 115/300	.101
10113/10113 [===================================	rror
Epoch 116/300	.101
10113/10113 [===================================	rror
Epoch 117/300	.101
10113/10113 [===================================	rror
Epoch 118/300	.101
10113/10113 [===================================	rror
Epoch 119/300	.101
10113/10113 [===================================	rror
Epoch 120/300	0 .
10113/10113 [===================================	rror
Epoch 121/300	0 _
10113/10113 [===================================	rror
Epoch 122/300	0 _
10113/10113 [===================================	rror
Epoch 123/300	0 _
10113/10113 [===================================	rror
Epoch 124/300	
10113/10113 [===================================	rror
Epoch 125/300	
10113/10113 [===================================	rror
Epoch 126/300	
10113/10113 [===================================	rror
Epoch 127/300	
10113/10113 [===================================	rror
Epoch 128/300	
10113/10113 [===================================	rror
Epoch 129/300	
10113/10113 [===================================	rror
-	

Epoch 130/300									
10113/10113 [===================================	٥q	11119/sten	_	1099.	0 0083	_	mean :	ahsolute	error
Epoch 131/300	OD	rrab, boop		TODD.	0.0000		moun_	10001400	_01101
10113/10113 [===================================	٥q	11119/sten	_	1099.	0 0079	_	mean :	ahsolute	error
Epoch 132/300	OB	iiub/bucp		TOBB.	0.0013		mcan_c	10001400	_01101
10113/10113 [===================================	Λe	1111g/gten		loggi	0 0075		moan :	heolute	orror
Epoch 133/300	US	Trus/scep	_	1055.	0.0075	-	mean_	insoince	_61101
10113/10113 [===================================	Λα	11ug/gton		loggi	0 0076		moon	haoluta	orror
Epoch 134/300	US	Trus/scep		TOSS.	0.0070		mean_c	DSOTUCE	_61101
10113/10113 [===================================	Λe	1111g/gten		loggi	0 0075		moan 1	heolute	error
Epoch 135/300	US	Trus/scep		TOSS.	0.0075		mean_c	DSOTUCE	_61101
10113/10113 [===================================	Λe	1111g/gten		loggi	0 0076		moan 1	heolute	error
Epoch 136/300	US	Trus/scep		TOSS.	0.0070		mean_c	DSOTUCE	_61101
10113/10113 [===================================	Λe	1111g/gten		loggi	0 0075		moan 1	heolute	error
Epoch 137/300	US	Trus/scep		TOSS.	0.0075		mean_c	DSOTUCE	_61101
10113/10113 [===================================	Λe	1111g/gten		loggi	0 0076		moan 1	heolute	error
Epoch 138/300	OB	iius/scep		1055.	0.0070	_	mean_e	IDSOIUCE	_61101
10113/10113 [===================================	٥q	11119/sten	_	1099.	0 0074	_	mean :	ahsolut <i>e</i>	error
Epoch 139/300	OB	iiub/bucp		TOBB.	0.0071		mcan_c	10001400	_01101
10113/10113 [===================================	٥q	11119/sten	_	1099.	0 0075	_	mean :	ahsolute	error
Epoch 140/300	OD	rrab, boop		TODD.	0.0010		moun_	10001400	_01101
10113/10113 [===================================	0s	11us/step	_	loss:	0.0075	_	mean a	absolute	error
Epoch 141/300	Ů.	11ab, 200p		TODD.	0.00.0		moun_	20001400	_01101
10113/10113 [===================================	0s	11us/step	_	loss:	0.0075	_	mean a	absolute	error
Epoch 142/300	••								
10113/10113 [===================================	0s	11us/step	_	loss:	0.0076	_	mean a	absolute	error
Epoch 143/300	• •								
10113/10113 [===================================	0s	10us/step	_	loss:	0.0074	_	mean a	absolute	error
Epoch 144/300							_		
10113/10113 [===================================	0s	10us/step	_	loss:	0.0071	_	mean_a	absolute	error
Epoch 145/300							_		_
10113/10113 [===================================	0s	11us/step	_	loss:	0.0072	_	mean_a	absolute	_error
Epoch 146/300									_
10113/10113 [===================================	0s	11us/step	_	loss:	0.0076	_	mean_a	absolute	_error
Epoch 147/300		-							
10113/10113 [===================================	0s	11us/step	_	loss:	0.0073	_	mean_a	absolute	_error
Epoch 148/300		_							
10113/10113 [===================================	0s	11us/step	_	loss:	0.0072	_	mean_a	absolute	_error
Epoch 149/300									
10113/10113 [===========	0s	12us/step	-	loss:	0.0071	-	mean_a	absolute	_error
Epoch 150/300									
10113/10113 [===========	0s	11us/step	-	loss:	0.0073	-	mean_a	absolute	_error
Epoch 151/300									
10113/10113 [===========	0s	11us/step	-	loss:	0.0074	-	mean_a	absolute	_error
Epoch 152/300									
10113/10113 [===================================	0s	11us/step	-	loss:	0.0074	-	mean_a	absolute	_error
Epoch 153/300									
10113/10113 [=======] -	0s	11us/step	-	loss:	0.0072	-	mean_a	absolute	_error

Epoch 154/300										
10113/10113 [===================================	_	۸q	11119/sten	_	1088.	0 0073	_	mean :	ahsolute	error
Epoch 155/300		Ü	rius, sucp		TODD.	0.0010		moun_	10001400	_01101
10113/10113 [===================================	_	۸q	11119/sten	_	1088.	0 0071	_	mean :	ahsolute	error
Epoch 156/300		OB	rius, scep		TOBB.	0.0071		mcan_	10001400	_01101
10113/10113 [===================================		۸۵	11ug/gton		loggi	0 0074		moan	heolute	orror
Epoch 157/300	_	OS	Trus/scep	_	1055.	0.0074	-	mean_	insoince	_61101
10113/10113 [===================================		Λa	11ug/gton		loggi	0 0060		moon	haoluto	orror
Epoch 158/300	_	OS	ilus/scep	Ī	TOSS.	0.0003	_	mean_	DSOIUCE	_61101
10113/10113 [===================================		۸۵	1111g/gton		loggi	0 0071		moan	heolute	error
Epoch 159/300	_	OS	ilus/scep	Ī	TOSS.	0.0071	_	mean_	DSOIUCE	_61101
10113/10113 [===================================		۸۵	1111g/gton		loggi	0 0070		moan	heolute	error
Epoch 160/300	_	OS	Trus/scep	_	1055.	0.0070	-	mean_	insoince	_61101
10113/10113 [===================================		۸۵	1111g/gton		loggi	0 0069		moan	heolute	error
Epoch 161/300	_	OS	ilus/scep	_	TOSS.	0.0003	_	mean_	DSOIUCE	_61101
10113/10113 [===================================		۸۵	1111g/gton		loggi	0 0071		moan	heolute	error
Epoch 162/300	_	OS	iius/scep	_	TOSS.	0.0071	_	mean_	DSOTUCE	_61101
10113/10113 [===================================	_	۸q	11119/9ten	_	1088.	0 0071	_	mean :	ahsolute	error
Epoch 163/300		OB	ттав, всер		TOBB.	0.0071		mcan_	10001400	_01101
10113/10113 [===================================	_	۸q	19119/sten	_	1088.	0 0070	_	mean :	ahsolute	error
Epoch 164/300		Ü	12db/ boop		TODD.	0.0010		moun_	10001400	_01101
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0069	_	mean a	absolute	error
Epoch 165/300		Ü	rrab, btop		TODD.	0.000		moun_	10001400	_01101
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0072	_	mean a	absolute	error
Epoch 166/300		Ů.	rrab, btop		1000.	0.0012		mour_	20001400	_01101
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0070	_	mean a	absolute	error
Epoch 167/300		•								
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0068	_	mean a	absolute	error
Epoch 168/300			, <sub>F</sub>					_		
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0068	_	mean_a	absolute	error
Epoch 169/300			. 1					_		_
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0068	_	mean_a	absolute	_error
Epoch 170/300										_
10113/10113 [===================================	_	0s	10us/step	_	loss:	0.0071	_	mean_a	absolute	_error
Epoch 171/300			•							
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0071	_	mean_a	absolute	_error
Epoch 172/300			•							
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0066	-	mean_a	absolute	_error
Epoch 173/300										
10113/10113 [=======]	-	0s	11us/step	_	loss:	0.0069	-	mean_a	absolute	_error
Epoch 174/300										
10113/10113 [===================================	-	0s	13us/step	-	loss:	0.0067	-	mean_a	absolute	_error
Epoch 175/300										
10113/10113 [==========]	-	0s	11us/step	-	loss:	0.0065	-	mean_a	absolute	_error
Epoch 176/300										
10113/10113 []	-	0s	11us/step	-	loss:	0.0065	-	mean_a	absolute	_error
Epoch 177/300										
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0065	-	mean_a	absolute	_error

Epoch 178/300
10113/10113 [===================================
Epoch 179/300
10113/10113 [===================================
Epoch 180/300
10113/10113 [===================================
Epoch 181/300
10113/10113 [===================================
Epoch 182/300
10113/10113 [===================================
Epoch 183/300
10113/10113 [===================================
Epoch 184/300
10113/10113 [===================================
Epoch 185/300
10113/10113 [===================================
Epoch 186/300
10113/10113 [===================================
Epoch 187/300
10113/10113 [===================================
Epoch 188/300
10113/10113 [===================================
Epoch 189/300
10113/10113 [===================================
Epoch 190/300
10113/10113 [===================================
Epoch 191/300
10113/10113 [===================================
Epoch 192/300
10113/10113 [===================================
Epoch 193/300
10113/10113 [===================================
Epoch 194/300
10113/10113 [===================================
Epoch 195/300
10113/10113 [===================================
Epoch 196/300
10113/10113 [===================================
Epoch 197/300
10113/10113 [===================================
Epoch 198/300
10113/10113 [===================================
Epoch 199/300
10113/10113 [===================================
Epoch 200/300
10113/10113 [===================================
Epoch 201/300
10113/10113 [===================================
<del>-</del>

Epoch 202/300
10113/10113 [===================================
Epoch 203/300
10113/10113 [===================================
Epoch 204/300
10113/10113 [===================================
Epoch 205/300
10113/10113 [===================================
Epoch 206/300
10113/10113 [===================================
Epoch 207/300
10113/10113 [===================================
Epoch 208/300
10113/10113 [===================================
Epoch 209/300
10113/10113 [===================================
Epoch 210/300
10113/10113 [===================================
Epoch 211/300
10113/10113 [===================================
Epoch 212/300
10113/10113 [===================================
Epoch 213/300
10113/10113 [===================================
Epoch 214/300
10113/10113 [===================================
Epoch 215/300
10113/10113 [===================================
Epoch 216/300
10113/10113 [===================================
Epoch 217/300 10113/10113 [===================================
Epoch 218/300
10113/10113 [===================================
Epoch 219/300
10113/10113 [===================================
Epoch 220/300
10113/10113 [===================================
Epoch 221/300
10113/10113 [===================================
Epoch 222/300
10113/10113 [===================================
Epoch 223/300
10113/10113 [===================================
Epoch 224/300
10113/10113 [===================================
Epoch 225/300
10113/10113 [===================================

Epoch 226/300	
10113/10113 [===================================	an absolute error
Epoch 227/300	an_anso_anso_or
10113/10113 [===================================	an absolute error
Epoch 228/300	an_anso_ans_
10113/10113 [===================================	an absolute error
Epoch 229/300	
10113/10113 [===================================	an_absolute_error
Epoch 230/300	
10113/10113 [===================================	an_absolute_error
Epoch 231/300	
10113/10113 [===================================	an_absolute_error
Epoch 232/300	
10113/10113 [===================================	an_absolute_error
Epoch 233/300	
10113/10113 [===================================	an_absolute_error
Epoch 234/300	
10113/10113 [===================================	an_absolute_error
Epoch 235/300	
10113/10113 [===================================	an_absolute_error
Epoch 236/300	
10113/10113 [===================================	an_absolute_error
Epoch 237/300	
10113/10113 [===================================	an_absolute_error
Epoch 238/300	
10113/10113 [===================================	an_absolute_error
Epoch 239/300	blut
10113/10113 [===================================	an_absolute_error
10113/10113 [===================================	an absolute error
Epoch 241/300	an_absolute_ellor
10113/10113 [===================================	an absolute error
Epoch 242/300	dil_dbbolute_cllor
10113/10113 [===================================	an absolute error
Epoch 243/300	an_assorass_orror
10113/10113 [===================================	an_absolute_error
Epoch 244/300	
10113/10113 [===================================	an_absolute_error
Epoch 245/300	
10113/10113 [===================================	an_absolute_error
Epoch 246/300	
10113/10113 [===================================	an_absolute_error
Epoch 247/300	
10113/10113 [===================================	an_absolute_error
Epoch 248/300	
10113/10113 [===================================	an_absolute_error
Epoch 249/300	
10113/10113 [===================================	an_absolute_error

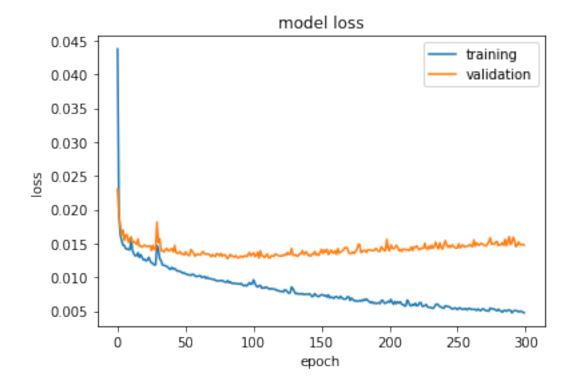
Epoch 250/300								
10113/10113 [===================================	_	0s	13us/step	_	loss:	0.0054	_	mean absolute error
Epoch 251/300			. 1					
10113/10113 [===================================	_	0s	15us/step	_	loss:	0.0052	_	mean_absolute_error
Epoch 252/300			1					
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0054	_	mean_absolute_error
Epoch 253/300			•					
10113/10113 [===================================	-	0s	13us/step	-	loss:	0.0055	-	mean_absolute_error
Epoch 254/300								
10113/10113 [==========]	-	0s	12us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 255/300								
10113/10113 [=======]	-	0s	12us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 256/300								
10113/10113 [=======]	-	0s	11us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 257/300								
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0054	-	mean_absolute_error
Epoch 258/300		^	44 / 1		-	0 0050		1 1 .
10113/10113 [===================================	-	US	llus/step	-	loss:	0.0052	-	mean_absolute_error
Epoch 259/300 10113/10113 [===================================		٥٥	11ug/g+on		1000.	0 0052		maan ahaaluta arran
Epoch 260/300	_	US	rius/scep	-	TOSS.	0.0055	-	mean_absolute_ellor
10113/10113 [===================================	_	0s	11us/sten	_	loss	0 0054	_	mean absolute error
Epoch 261/300		OB	ттав, всер		TOBB.	0.0001		mcdii_dbboiutc_ciioi
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0052	_	mean absolute error
Epoch 262/300			, <sub>F</sub>					
10113/10113 [===================================	_	0s	12us/step	_	loss:	0.0052	_	mean_absolute_error
Epoch 263/300			_					
10113/10113 [===========]	-	0s	13us/step	-	loss:	0.0052	-	mean_absolute_error
Epoch 264/300								
10113/10113 [=======]	-	0s	11us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 265/300								
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0051	-	mean_absolute_error
Epoch 266/300		^	44 / .		-	0 0050		
10113/10113 [===================================	-	US	llus/step	-	loss:	0.0053	-	mean_absolute_error
10113/10113 [===================================		Λa	11ug/gton		loggi	0 0052		moon obsolute error
Epoch 268/300	_	OS	iius/scep	_	TOSS.	0.0052	_	mean_absolute_ellor
10113/10113 [===================================	_	0s	12us/step	_	loss:	0.0050	_	mean absolute error
Epoch 269/300		•						
10113/10113 [===================================	_	0s	11us/step	_	loss:	0.0053	_	mean_absolute_error
Epoch 270/300			•					
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 271/300			_					
10113/10113 [=======]	-	0s	12us/step	-	loss:	0.0052	-	mean_absolute_error
Epoch 272/300								
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0050	-	mean_absolute_error
Epoch 273/300		•			7	0.0055		, ,
10113/10113 [===================================	-	US	11us/step	-	TOSS:	0.0050	-	mean_absolute_error

E 1 074/000								
Epoch 274/300		^	44 / 1		,	0 0050		1 7 .
10113/10113 [===================================	-	US	llus/step	-	loss:	0.0050	-	mean_absolute_error
Epoch 275/300		_			_			
10113/10113 [===================================	-	Us	llus/step	-	loss:	0.0054	-	mean_absolute_error
Epoch 276/300		_			_			
10113/10113 [===================================	-	0s	12us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 277/300								
10113/10113 [===================================	-	0s	11us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 278/300								
10113/10113 [=======]	-	0s	12us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 279/300								
10113/10113 [=======]	-	0s	12us/step	-	loss:	0.0052	-	mean_absolute_error
Epoch 280/300								
10113/10113 [=======]	-	0s	13us/step	-	loss:	0.0050	-	mean_absolute_error
Epoch 281/300								
10113/10113 [==========]	-	0s	12us/step	-	loss:	0.0053	-	mean_absolute_error
Epoch 282/300								
10113/10113 [===================================	-	0s	13us/step	-	loss:	0.0051	-	mean_absolute_error
Epoch 283/300								
10113/10113 [===================================	-	0s	12us/step	_	loss:	0.0050	-	mean_absolute_error
Epoch 284/300								
10113/10113 [===================================	-	0s	13us/step	_	loss:	0.0048	-	mean_absolute_error
Epoch 285/300								
10113/10113 [===================================	-	0s	13us/step	_	loss:	0.0051	-	mean_absolute_error
Epoch 286/300			_					
10113/10113 [===================================	_	0s	12us/step	_	loss:	0.0051	_	mean_absolute_error
Epoch 287/300			-					
10113/10113 [===================================	_	0s	13us/step	_	loss:	0.0049	_	mean_absolute_error
Epoch 288/300			-					
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0051	_	mean_absolute_error
Epoch 289/300			-					
10113/10113 [===================================	_	0s	13us/step	_	loss:	0.0051	_	mean_absolute_error
Epoch 290/300			-					
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0051	_	mean_absolute_error
Epoch 291/300			-					
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0047	_	mean_absolute_error
Epoch 292/300			•					
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0050	_	mean_absolute_error
Epoch 293/300			. 1					_
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0051	_	mean absolute error
Epoch 294/300								
10113/10113 [===================================	_	0s	14us/step	_	loss:	0.0051	_	mean absolute error
Epoch 295/300			-142, 200p			0.0002		
10113/10113 [===================================	_	0,5	13us/sten	_	loss:	0.0050	_	mean absolute error
Epoch 296/300		2.5	, 500p					
10113/10113 [===================================	_	()s	13us/sten	_	loss	0.0049	_	mean absolute error
Epoch 297/300		25	_сал, воср		1000.	0.0010		
10113/10113 [===================================	_	0.5	13us/sten	_	10881	0.0050	_	mean absolute error
10110/ 10110 [	_	JB	1045/ 50ep		1000.	0.0000		mean_apporate_error

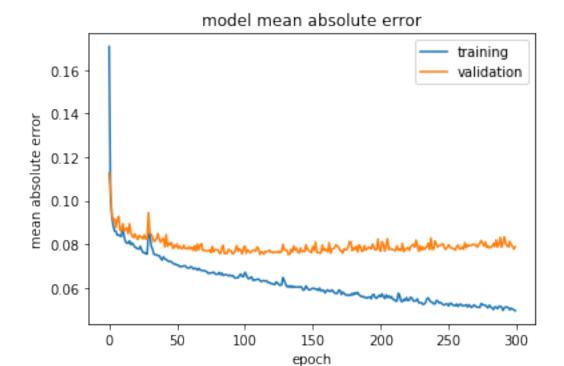
During the training process we have saved the loss and the defined metrics of the training and validation data:

```
In [36]: print(history.history.keys())
['val_mean_absolute_error', 'loss', 'mean_absolute_error', 'val_loss']
```

We can now plot the loss evolution over the training epochs for the training and validation dataset:



Similarly, we can plot the mean absolute error

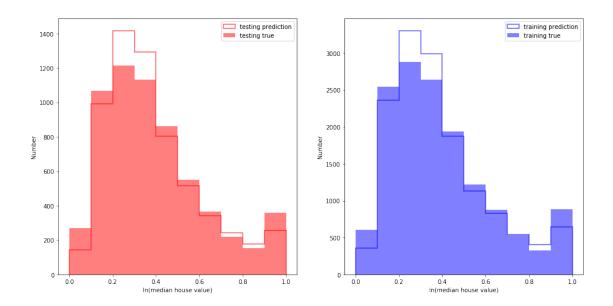


### 5.0.3 Evaluation

Let's evaluate the loss and mean absolute error on our test data:

Let's make the prediction for our test data:

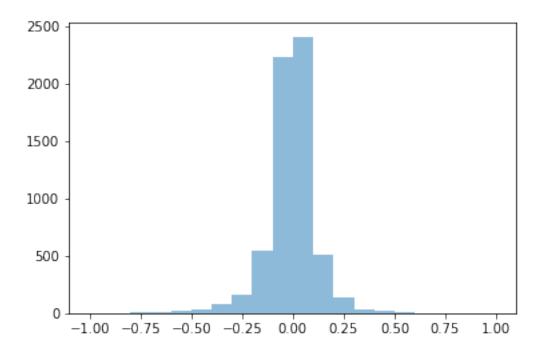
```
In [40]: print 'Testing...'
        y_pred = model.predict(X_test, verbose = True, batch_size=256)
Testing...
6192/6192 [========= ] - Os 7us/step
In [41]: # predictions
        y_pred.reshape(-1)
Out[41]: array([ 0.04962008,  0.24929287,  0.99948633, ...,  0.27626351,
                0.26855168, 0.34332156], dtype=float32)
  In order to compare the test prediction with the training prediction, we will also obtain a
training prediction:
In [42]: y_train_pred = model.predict(X_train, verbose = True, batch_size=256)
        y_train_pred = y_train_pred.reshape(-1)
In [43]: plt.figure(figsize=(16,8))
        plt.subplot(121)
        plt.hist(y_test, alpha=0.5, color='red', range=[0, 1], bins=10)
        plt.hist(y_pred, alpha=0.5, color='red', range=[0, 1], bins=10, histtype='step', linewi
        plt.xlabel('ln(median house value)')
        plt.ylabel('Number')
        plt.legend(['testing prediction', 'testing true'], loc='upper right')
        plt.subplot(122)
        plt.hist(y_train, alpha=0.5, color='blue', range=[0, 1], bins=10)
        plt.hist(y_train_pred, alpha=0.5, color='blue', range=[0, 1], bins=10, histtype='step',
        plt.xlabel('ln(median house value)')
        plt.ylabel('Number')
        plt.legend(['training prediction', 'training true'], loc='upper right')
Out[43]: <matplotlib.legend.Legend at 0x7fa728125f10>
```



How well do the histograms agree? We can use the Kolmogorov-Smirnov statistic to quantify that:

Alternatively, we could also look at the difference between the true and prediction values in order to see the spread on example basis:

```
In [45]: plt.hist(y_pred.reshape(-1)-y_test, alpha=0.5, range=[-1, 1], bins=20)
Out[45]: (array([ 1.00000000e+00,
                                    1.0000000e+00,
                                                      4.0000000e+00,
                  9.00000000e+00,
                                    1.60000000e+01,
                                                      3.4000000e+01,
                  8.20000000e+01,
                                    1.60000000e+02,
                                                      5.39000000e+02,
                  2.22900000e+03,
                                    2.40900000e+03,
                                                      5.07000000e+02,
                   1.36000000e+02,
                                    3.50000000e+01,
                                                      1.7000000e+01,
                  8.0000000e+00,
                                    3.0000000e+00,
                                                      1.0000000e+00,
                   1.0000000e+00,
                                    0.00000000e+00]),
         array([-1., -0.9, -0.8, -0.7, -0.6, -0.5, -0.4, -0.3, -0.2, -0.1, 0.,
                                   0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.
                 0.1, 0.2, 0.3,
          <a list of 20 Patch objects>)
```



### 5.0.4 Use the scikit learn metrics to evaluate the model

```
In [46]: from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error

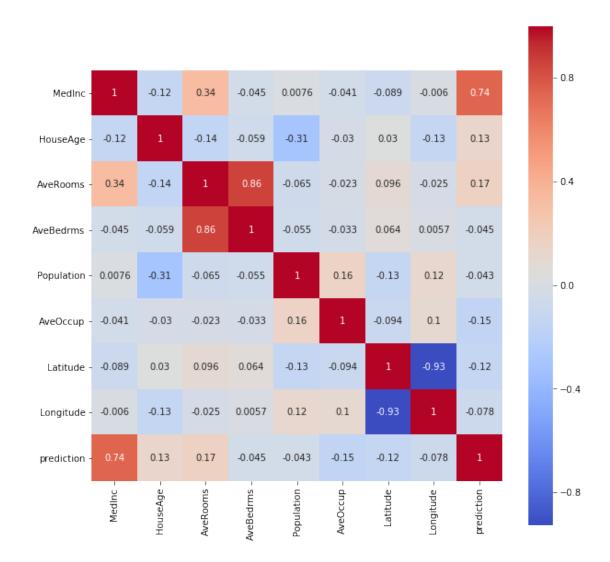
# Explained variance score: 1 is perfect prediction
print('Coefficient of determination: %.2f' % r2_score(y_test, y_pred))
# The mean squared error
print("Mean squared error: %.2f" % mean_squared_error(y_test, y_pred))
# The mean squared error
print("Mean absolute error: %.2f" % mean_absolute_error(y_test, y_pred))
```

Coefficient of determination: 0.74

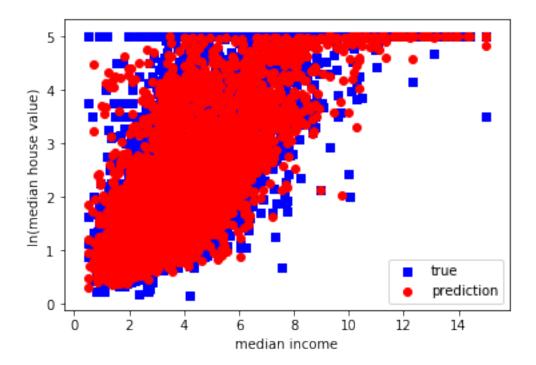
Mean squared error: 0.01 Mean absolute error: 0.08

### 5.0.5 Plot the correlations of the input features to the predictions

```
3 \quad 1.003492 \quad -0.631579 \quad 0.577761 \quad -0.313113 \quad 0.573718 \quad 0.739080 \quad 0.002646
          4 \quad 0.084853 \quad 0.263158 \quad 0.161667 \quad -0.229352 \quad -0.112179 \quad -0.392931 \quad 0.621693
             Longitude
          0 -0.131926
          1 -0.250660
          2 -1.036939
          3 -0.055409
          4 -0.902375
In [49]: df_out = df_out.assign(prediction=y_pred)
          df_out.head()
               MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude \
Out [49]:
          0 -0.848027 -0.210526 -0.645394 -0.290855
                                                              0.239316 1.249230 0.473545
          1 -0.460004 0.052632 -0.119769
                                               1.539384
                                                              0.424145 -0.161828 0.230159
          2 - 0.026930 \quad 1.210526 \quad -0.778816 \quad 1.457971 \quad 0.151709 \quad -1.716414 \quad 0.933862
          3 \quad 1.003492 \quad -0.631579 \quad 0.577761 \quad -0.313113 \qquad 0.573718 \quad 0.739080 \quad 0.002646
          4 \quad 0.084853 \quad 0.263158 \quad 0.161667 \quad -0.229352 \quad -0.112179 \quad -0.392931 \quad 0.621693
             Longitude prediction
          0 -0.131926
                         0.049620
          1 -0.250660
                            0.249293
          2 -1.036939 0.999486
          3 -0.055409
                         0.577571
          4 -0.902375 0.642027
In [50]: plt.figure(figsize=(10,10))
          sns.heatmap(df_out.corr(), annot=True, square=True, cmap='coolwarm')
Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa710786310>
```



### 5.0.6 Plot the most important input feature dependent on the true value and the prediction



# 6 Regularization

The training and validation loss function diverge during the training resulting in a considerably higher validation loss than the data. Can we use regularizer in order to control that?

## 6.1 L1/L2 Regularizer

### 6.1.1 Task 3: Train and evaluate the same DNN with an L2 Regularizer

- The regularizer can be simply set by importing from keras.regularizers import 12 and adding kernel\_regularizer=12(12\_lambda) as option to the Dense layer
- Choose l2\_lambda=0.0001
- Perform the same scaling of the inputs
- How does the loss function evaluation change?
- How does the performance and the prediction change?

```
In [52]: from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(df.as_matrix(), housing.target, test
    scaler = RobustScaler(quantile_range=(25, 75))
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

scaler_y = MinMaxScaler(feature_range=(0, 1))
```

```
model = Sequential()
     12 \ lambda = 0.0001
     model.add(Dense(units=128, activation='relu', kernel_regularizer=12(12_lambda), input_d
     model.add(Dense(units=64, activation='relu', kernel_regularizer=12(12_lambda)))
     model.add(Dense(units=32, activation='relu', kernel_regularizer=12(12_lambda)))
     model.add(Dense(units=8 , activation='relu', kernel_regularizer=12(12_lambda)))
     model.add(Dense(units=1, activation='sigmoid'))
     model.compile(loss='mse', optimizer='adam', metrics=['mae'])
     model.summary()
Layer (type)
        Output Shape
                         Param #
______
dense_6 (Dense)
                (None, 128)
_____
                (None, 64)
dense_7 (Dense)
                               8256
______
                (None, 32)
dense_8 (Dense)
                               2080
-----
dense_9 (Dense)
                (None, 8)
                               264
dense_10 (Dense)
               (None, 1)
______
Total params: 11,761
Trainable params: 11,761
Non-trainable params: 0
           _____
In [54]: history = model.fit(X_train, y_train, validation_split=0.3, epochs=300, batch_size=256)
Train on 10113 samples, validate on 4335 samples
Epoch 1/300
Epoch 2/300
Epoch 3/300
Epoch 4/300
Epoch 5/300
```

y\_train = scaler\_y.fit\_transform(y\_train.reshape(-1, 1)).reshape(-1)

y\_test = scaler\_y.transform(y\_test.reshape(-1, 1)).reshape(-1)

Out[52]: array([ 0.36866034, 0.31896982, 0.50474225, ..., 0.42701061,

0.55360803, 0.63917468])

In [53]: from keras.regularizers import 12

y\_train

```
Epoch 6/300
Epoch 7/300
Epoch 8/300
Epoch 9/300
Epoch 10/300
Epoch 11/300
Epoch 12/300
Epoch 13/300
Epoch 14/300
Epoch 15/300
Epoch 16/300
Epoch 17/300
Epoch 18/300
Epoch 19/300
Epoch 20/300
Epoch 21/300
Epoch 22/300
Epoch 23/300
Epoch 24/300
Epoch 25/300
Epoch 26/300
Epoch 27/300
Epoch 28/300
Epoch 29/300
```

```
Epoch 30/300
Epoch 31/300
Epoch 32/300
Epoch 33/300
Epoch 34/300
Epoch 35/300
Epoch 36/300
Epoch 37/300
Epoch 38/300
Epoch 39/300
Epoch 40/300
Epoch 41/300
Epoch 42/300
Epoch 43/300
Epoch 44/300
Epoch 45/300
Epoch 46/300
Epoch 47/300
Epoch 48/300
Epoch 49/300
Epoch 50/300
Epoch 51/300
Epoch 52/300
Epoch 53/300
```

```
Epoch 54/300
Epoch 55/300
Epoch 56/300
Epoch 57/300
Epoch 58/300
Epoch 59/300
Epoch 60/300
Epoch 61/300
Epoch 62/300
Epoch 63/300
Epoch 64/300
Epoch 65/300
Epoch 66/300
Epoch 67/300
Epoch 68/300
Epoch 69/300
Epoch 70/300
Epoch 71/300
Epoch 72/300
Epoch 73/300
Epoch 74/300
Epoch 75/300
Epoch 76/300
Epoch 77/300
```

```
Epoch 78/300
Epoch 79/300
Epoch 80/300
Epoch 81/300
Epoch 82/300
Epoch 83/300
Epoch 84/300
Epoch 85/300
Epoch 86/300
Epoch 87/300
Epoch 88/300
Epoch 89/300
Epoch 90/300
Epoch 91/300
Epoch 92/300
Epoch 93/300
Epoch 94/300
Epoch 95/300
Epoch 96/300
Epoch 97/300
Epoch 98/300
Epoch 99/300
Epoch 100/300
Epoch 101/300
```

```
Epoch 102/300
Epoch 103/300
Epoch 104/300
Epoch 105/300
Epoch 106/300
Epoch 107/300
Epoch 108/300
Epoch 109/300
Epoch 110/300
Epoch 111/300
Epoch 112/300
Epoch 113/300
Epoch 114/300
Epoch 115/300
Epoch 116/300
Epoch 117/300
Epoch 118/300
Epoch 119/300
Epoch 120/300
Epoch 121/300
Epoch 122/300
Epoch 123/300
Epoch 124/300
Epoch 125/300
```

```
Epoch 126/300
Epoch 127/300
Epoch 128/300
Epoch 129/300
Epoch 130/300
Epoch 131/300
Epoch 132/300
Epoch 133/300
Epoch 134/300
Epoch 135/300
Epoch 136/300
Epoch 137/300
Epoch 138/300
Epoch 139/300
Epoch 140/300
Epoch 141/300
Epoch 142/300
Epoch 143/300
Epoch 144/300
Epoch 145/300
Epoch 146/300
Epoch 147/300
Epoch 148/300
Epoch 149/300
```

```
Epoch 150/300
Epoch 151/300
Epoch 152/300
Epoch 153/300
Epoch 154/300
Epoch 155/300
Epoch 156/300
Epoch 157/300
Epoch 158/300
Epoch 159/300
Epoch 160/300
Epoch 161/300
Epoch 162/300
Epoch 163/300
Epoch 164/300
Epoch 165/300
Epoch 166/300
Epoch 167/300
Epoch 168/300
Epoch 169/300
Epoch 170/300
Epoch 171/300
Epoch 172/300
Epoch 173/300
```

```
Epoch 174/300
Epoch 175/300
Epoch 176/300
Epoch 177/300
Epoch 178/300
Epoch 179/300
Epoch 180/300
Epoch 181/300
Epoch 182/300
Epoch 183/300
Epoch 184/300
Epoch 185/300
Epoch 186/300
Epoch 187/300
Epoch 188/300
Epoch 189/300
Epoch 190/300
Epoch 191/300
Epoch 192/300
Epoch 193/300
Epoch 194/300
Epoch 195/300
Epoch 196/300
Epoch 197/300
```

```
Epoch 198/300
Epoch 199/300
Epoch 200/300
Epoch 201/300
Epoch 202/300
Epoch 203/300
Epoch 204/300
Epoch 205/300
Epoch 206/300
Epoch 207/300
Epoch 208/300
Epoch 209/300
Epoch 210/300
Epoch 211/300
Epoch 212/300
Epoch 213/300
Epoch 214/300
Epoch 215/300
Epoch 216/300
Epoch 217/300
Epoch 218/300
Epoch 219/300
Epoch 220/300
Epoch 221/300
```

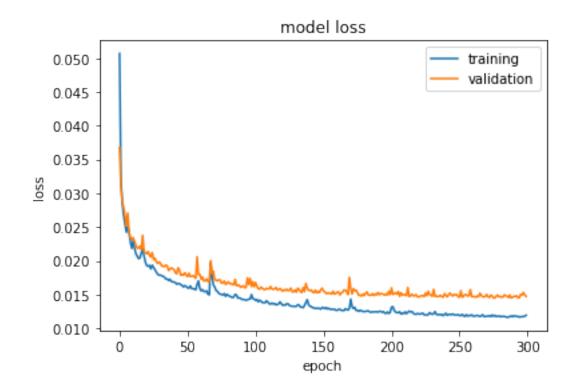
```
Epoch 222/300
Epoch 223/300
Epoch 224/300
Epoch 225/300
Epoch 226/300
Epoch 227/300
Epoch 228/300
Epoch 229/300
Epoch 230/300
Epoch 231/300
Epoch 232/300
Epoch 233/300
Epoch 234/300
Epoch 235/300
Epoch 236/300
Epoch 237/300
Epoch 238/300
Epoch 239/300
Epoch 240/300
Epoch 241/300
Epoch 242/300
Epoch 243/300
Epoch 244/300
Epoch 245/300
```

```
Epoch 246/300
Epoch 247/300
Epoch 248/300
Epoch 249/300
Epoch 250/300
Epoch 251/300
Epoch 252/300
Epoch 253/300
Epoch 254/300
Epoch 255/300
Epoch 256/300
Epoch 257/300
Epoch 258/300
Epoch 259/300
Epoch 260/300
Epoch 261/300
Epoch 262/300
Epoch 263/300
Epoch 264/300
Epoch 265/300
Epoch 266/300
Epoch 267/300
Epoch 268/300
Epoch 269/300
```

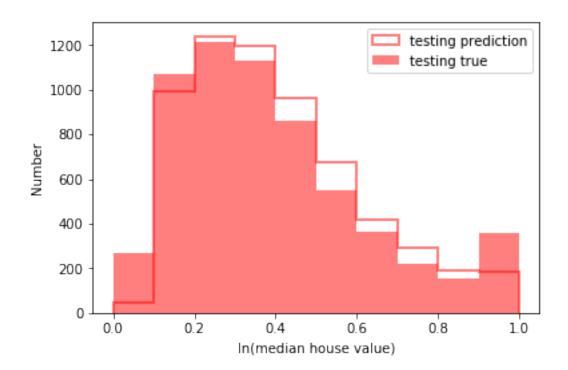
```
Epoch 270/300
Epoch 271/300
Epoch 272/300
Epoch 273/300
Epoch 274/300
Epoch 275/300
Epoch 276/300
Epoch 277/300
Epoch 278/300
Epoch 279/300
Epoch 280/300
Epoch 281/300
Epoch 282/300
Epoch 283/300
Epoch 284/300
Epoch 285/300
Epoch 286/300
Epoch 287/300
Epoch 288/300
Epoch 289/300
Epoch 290/300
Epoch 291/300
Epoch 292/300
Epoch 293/300
```

```
Epoch 294/300
Epoch 295/300
10113/10113 [====
           =========] - 0s 16us/step - loss: 0.0117 - mean_absolute_error
Epoch 296/300
10113/10113 [=
                ==] - Os 15us/step - loss: 0.0117 - mean_absolute_error
Epoch 297/300
10113/10113 [==
             =======] - Os 15us/step - loss: 0.0117 - mean_absolute_error
Epoch 298/300
Epoch 299/300
Epoch 300/300
```

# In [55]: # summarize history for loss plt.plot(history.history['loss']) plt.plot(history.history['val\_loss']) plt.title('model loss') plt.ylabel('loss') plt.xlabel('epoch') plt.legend(['training', 'validation'], loc='upper right') plt.show()



```
In [56]: loss_and_metrics = model.evaluate(X_test, y_test, batch_size=256)
        print loss_and_metrics
        y_pred = model.predict(X_test, verbose = True, batch_size=256)
6192/6192 [========== ] - Os 6us/step
[0.01388180063609082, 0.074833445847804533]
6192/6192 [=========== ] - Os 12us/step
In [57]: # Explained variance score: 1 is perfect prediction
        print('Coefficient of determination: %.2f' % r2_score(y_test, y_pred))
        # The mean squared error
        print("Mean squared error: %.2f" % mean_squared_error(y_test, y_pred))
        # The mean squared error
        print("Mean absolute error: %.2f" % mean_absolute_error(y_test, y_pred))
Coefficient of determination: 0.79
Mean squared error: 0.01
Mean absolute error: 0.07
In [58]: # predictions
        y_pred.reshape(-1)
        plt.hist(y_test, alpha=0.5, color='red', range=[0, 1], bins=10)
        plt.hist(y_pred, alpha=0.5, color='red', range=[0, 1], bins=10, histtype='step', linewi
        plt.xlabel('ln(median house value)')
        plt.ylabel('Number')
        plt.legend(['testing prediction', 'testing true'], loc='upper right')
Out[58]: <matplotlib.legend.Legend at 0x7fa6d355d990>
```



## 6.2 Dropout

```
In [59]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(df.as_matrix(), housing.target, tes
         scaler = RobustScaler(quantile_range=(25, 75))
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
         scaler_y = MinMaxScaler()
         y_train = scaler_y.fit_transform(y_train.reshape(-1, 1)).reshape(-1)
         y_test = scaler_y.transform(y_test.reshape(-1, 1)).reshape(-1)
         y_train
Out[59]: array([ 0.36866034, 0.31896982, 0.50474225, ..., 0.42701061,
                 0.55360803, 0.63917468])
In [60]: from keras.layers import Dropout
         model = Sequential()
         dropout=0.2
         model.add(Dense(units=128, activation='relu', input_dim=8))
         model.add(Dropout(dropout))
         model.add(Dense(units=64, activation='relu'))
         model.add(Dropout(dropout))
         model.add(Dense(units=32, activation='relu'))
```

```
model.add(Dropout(dropout))
     model.add(Dense(units=8 , activation='relu'))
     model.add(Dropout(dropout))
     model.add(Dense(units=1, activation='sigmoid'))
     model.compile(loss='mse', optimizer='adam', metrics=['mae'])
     model.summary()
Layer (type)
                Output Shape
dense_11 (Dense)
                 (None, 128)
_____
dropout_1 (Dropout)
                 (None, 128)
                                  8256
dense_12 (Dense)
                 (None, 64)
.....
              (None, 64)
dropout_2 (Dropout)
    ._____
dense_13 (Dense)
                 (None, 32)
dropout_3 (Dropout)
                 (None, 32)
_____
dense_14 (Dense)
                 (None, 8)
______
              (None, 8)
dropout_4 (Dropout)
_____
dense_15 (Dense) (None, 1)
______
Total params: 11,761
Trainable params: 11,761
Non-trainable params: 0
In [61]: history = model.fit(X_train, y_train, validation_split=0.3, epochs=300, batch_size=256)
```

```
Epoch 7/300
Epoch 8/300
Epoch 9/300
Epoch 10/300
Epoch 11/300
Epoch 12/300
Epoch 13/300
Epoch 14/300
Epoch 15/300
Epoch 16/300
Epoch 17/300
Epoch 18/300
Epoch 19/300
Epoch 20/300
Epoch 21/300
Epoch 22/300
Epoch 23/300
Epoch 24/300
Epoch 25/300
Epoch 26/300
Epoch 27/300
Epoch 28/300
Epoch 29/300
Epoch 30/300
```

```
Epoch 31/300
Epoch 32/300
Epoch 33/300
Epoch 34/300
Epoch 35/300
Epoch 36/300
Epoch 37/300
Epoch 38/300
Epoch 39/300
Epoch 40/300
Epoch 41/300
Epoch 42/300
Epoch 43/300
Epoch 44/300
Epoch 45/300
Epoch 46/300
Epoch 47/300
Epoch 48/300
Epoch 49/300
Epoch 50/300
Epoch 51/300
Epoch 52/300
Epoch 53/300
Epoch 54/300
```

```
Epoch 55/300
Epoch 56/300
Epoch 57/300
Epoch 58/300
Epoch 59/300
Epoch 60/300
Epoch 61/300
Epoch 62/300
Epoch 63/300
Epoch 64/300
Epoch 65/300
Epoch 66/300
Epoch 67/300
Epoch 68/300
Epoch 69/300
Epoch 70/300
Epoch 71/300
Epoch 72/300
Epoch 73/300
Epoch 74/300
Epoch 75/300
Epoch 76/300
Epoch 77/300
Epoch 78/300
```

```
Epoch 79/300
Epoch 80/300
Epoch 81/300
Epoch 82/300
Epoch 83/300
Epoch 84/300
Epoch 85/300
Epoch 86/300
Epoch 87/300
Epoch 88/300
Epoch 89/300
Epoch 90/300
Epoch 91/300
Epoch 92/300
Epoch 93/300
Epoch 94/300
Epoch 95/300
Epoch 96/300
Epoch 97/300
Epoch 98/300
Epoch 99/300
Epoch 100/300
Epoch 101/300
Epoch 102/300
```

```
Epoch 103/300
Epoch 104/300
Epoch 105/300
Epoch 106/300
Epoch 107/300
Epoch 108/300
Epoch 109/300
Epoch 110/300
Epoch 111/300
Epoch 112/300
Epoch 113/300
Epoch 114/300
Epoch 115/300
Epoch 116/300
Epoch 117/300
Epoch 118/300
Epoch 119/300
Epoch 120/300
Epoch 121/300
Epoch 122/300
Epoch 123/300
Epoch 124/300
Epoch 125/300
Epoch 126/300
```

```
Epoch 127/300
Epoch 128/300
Epoch 129/300
Epoch 130/300
Epoch 131/300
Epoch 132/300
Epoch 133/300
Epoch 134/300
Epoch 135/300
Epoch 136/300
Epoch 137/300
Epoch 138/300
Epoch 139/300
Epoch 140/300
Epoch 141/300
Epoch 142/300
Epoch 143/300
Epoch 144/300
Epoch 145/300
Epoch 146/300
Epoch 147/300
Epoch 148/300
Epoch 149/300
Epoch 150/300
```

```
Epoch 151/300
Epoch 152/300
Epoch 153/300
Epoch 154/300
Epoch 155/300
Epoch 156/300
Epoch 157/300
Epoch 158/300
Epoch 159/300
Epoch 160/300
Epoch 161/300
Epoch 162/300
Epoch 163/300
Epoch 164/300
Epoch 165/300
Epoch 166/300
Epoch 167/300
Epoch 168/300
Epoch 169/300
Epoch 170/300
Epoch 171/300
Epoch 172/300
Epoch 173/300
Epoch 174/300
```

```
Epoch 175/300
Epoch 176/300
Epoch 177/300
Epoch 178/300
Epoch 179/300
Epoch 180/300
Epoch 181/300
Epoch 182/300
Epoch 183/300
Epoch 184/300
Epoch 185/300
Epoch 186/300
Epoch 187/300
Epoch 188/300
Epoch 189/300
Epoch 190/300
Epoch 191/300
Epoch 192/300
Epoch 193/300
Epoch 194/300
Epoch 195/300
Epoch 196/300
Epoch 197/300
Epoch 198/300
```

```
Epoch 199/300
Epoch 200/300
Epoch 201/300
Epoch 202/300
Epoch 203/300
Epoch 204/300
Epoch 205/300
Epoch 206/300
Epoch 207/300
Epoch 208/300
Epoch 209/300
Epoch 210/300
Epoch 211/300
Epoch 212/300
Epoch 213/300
Epoch 214/300
Epoch 215/300
Epoch 216/300
Epoch 217/300
Epoch 218/300
Epoch 219/300
Epoch 220/300
Epoch 221/300
Epoch 222/300
```

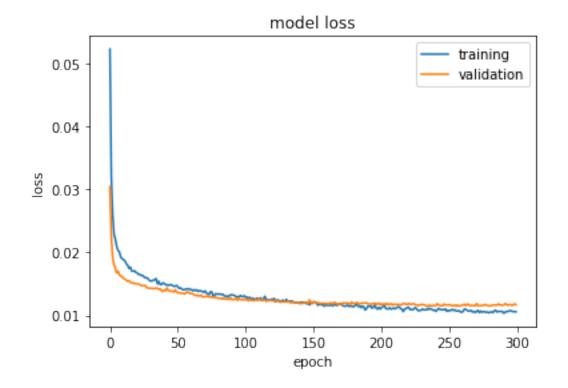
```
Epoch 223/300
Epoch 224/300
Epoch 225/300
Epoch 226/300
Epoch 227/300
Epoch 228/300
Epoch 229/300
Epoch 230/300
Epoch 231/300
Epoch 232/300
Epoch 233/300
Epoch 234/300
Epoch 235/300
Epoch 236/300
Epoch 237/300
Epoch 238/300
Epoch 239/300
Epoch 240/300
Epoch 241/300
Epoch 242/300
Epoch 243/300
Epoch 244/300
Epoch 245/300
Epoch 246/300
```

```
Epoch 247/300
Epoch 248/300
Epoch 249/300
Epoch 250/300
Epoch 251/300
Epoch 252/300
Epoch 253/300
Epoch 254/300
Epoch 255/300
Epoch 256/300
Epoch 257/300
Epoch 258/300
Epoch 259/300
Epoch 260/300
Epoch 261/300
Epoch 262/300
Epoch 263/300
Epoch 264/300
Epoch 265/300
Epoch 266/300
Epoch 267/300
Epoch 268/300
Epoch 269/300
Epoch 270/300
```

```
Epoch 271/300
Epoch 272/300
Epoch 273/300
Epoch 274/300
Epoch 275/300
Epoch 276/300
Epoch 277/300
Epoch 278/300
Epoch 279/300
Epoch 280/300
Epoch 281/300
Epoch 282/300
Epoch 283/300
Epoch 284/300
Epoch 285/300
Epoch 286/300
Epoch 287/300
Epoch 288/300
Epoch 289/300
Epoch 290/300
Epoch 291/300
Epoch 292/300
Epoch 293/300
Epoch 294/300
```

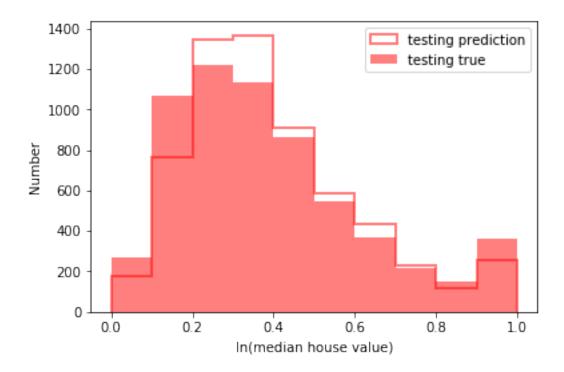
```
Epoch 295/300
Epoch 296/300
             ========] - Os 23us/step - loss: 0.0108 - mean_absolute_error
10113/10113 [====
Epoch 297/300
10113/10113 [=
                  ==] - Os 22us/step - loss: 0.0107 - mean_absolute_error
Epoch 298/300
10113/10113 [==
               =======] - Os 20us/step - loss: 0.0106 - mean_absolute_error
Epoch 299/300
Epoch 300/300
```

# In [62]: # summarize history for loss plt.plot(history.history['loss']) plt.plot(history.history['val\_loss']) plt.title('model loss') plt.ylabel('loss') plt.xlabel('epoch') plt.legend(['training', 'validation'], loc='upper right') plt.show()



You have to treat this result with care: The training loss is evaluated after each batch, where nodes are dropped, while the validation loss is calculated after one epoch, where all nodes are included.

```
In [63]: loss_and_metrics = model.evaluate(X_test, y_test, batch_size=256)
        print loss_and_metrics
        y_pred = model.predict(X_test, verbose = True, batch_size=256)
6192/6192 [========== ] - Os 5us/step
[0.01133931456109658, 0.070766112678118762]
6192/6192 [=========== ] - Os 20us/step
In [64]: # Explained variance score: 1 is perfect prediction
        print('Coefficient of determination: %.2f' % r2_score(y_test, y_pred))
        # The mean squared error
        print("Mean squared error: %.2f" % mean_squared_error(y_test, y_pred))
        # The mean squared error
        print("Mean absolute error: %.2f" % mean_absolute_error(y_test, y_pred))
Coefficient of determination: 0.80
Mean squared error: 0.01
Mean absolute error: 0.07
In [65]: # predictions
        y_pred.reshape(-1)
        plt.hist(y_test, alpha=0.5, color='red', range=[0, 1], bins=10)
        plt.hist(y_pred, alpha=0.5, color='red', range=[0, 1], bins=10, histtype='step', linewi
        plt.xlabel('ln(median house value)')
        plt.ylabel('Number')
        plt.legend(['testing prediction', 'testing true'], loc='upper right')
Out[65]: <matplotlib.legend.Legend at 0x7fa6d2d09790>
```



# 6.3 Task 4 (Bonus) - Playtime

- What do you need to change in the DNN if you don't scale the target vector?
- How does the result change if you use a quantile transformer with uniform output?
- How does the L1 regularizer perform?
- What happens if you change the L2 regularizer strength?
- What happens if you change the drop out percentage?
- How does the result change if you use only the 3 most important features?