18.337 - HW #3

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In this exercise, you are going to preprocess the Boston Housing Dataset, and then use it to train a linear regression model. Please submit your solution as a IJulia notebook.

The housing dataset has housing related information for 506 neighborhoods in Boston from 1978. Each neighborhood is represented using 13 attributes such as crime rate or distance to employment centers. The goal is to predict the median value of the houses given in \$1000's.

EXERCISE 0

In order to use some necessary functions, we need to import some modules. Just insert the following line as first line or cell,

using DelimitedFiles, Statistics, Random

Statistics contains statistical procedures like mean and std, DelimitedFiles contains our data read procedure functions (readdlm) and Random is for random numbers (rand, Random.seed! etc.).

EXERCISE 1

First download, and then read the data file. Here's the <u>link</u> to the dataset. You need to download the data within your IJulia notebook (please have a look at the readdlm, download functions of Julia). If you look at the data, you see that each house is represented with 13 attributes separated by whitespaces and there are 506 lines in total.

506×14 Ar	ray{Fl	oat64,2	}:								
0.00632	18.0	2.31	0.0	0.538	6.575		296.0	15.3	396.9	4.98	24.0
0.02731	0.0	7.07	0.0	0.469	6.421		242.0	17.8	396.9	9.14	21.6
0.02729	0.0	7.07	0.0	0.469	7.185		242.0	17.8	392.83	4.03	34.7
0.03237	0.0	2.18	0.0	0.458	6.998		222.0	18.7	394.63	2.94	33.4
0.06905	0.0	2.18	0.0	0.458	7.147		222.0	18.7	396.9	5.33	36.2
0.02985	0.0	2.18	0.0	0.458	6.43		222.0	18.7	394.12	5.21	28.7
0.08829	12.5	7.87	0.0	0.524	6.012		311.0	15.2	395.6	12.43	22.9
0.14455	12.5	7.87	0.0	0.524	6.172		311.0	15.2	396.9	19.15	27.1
0.21124	12.5	7.87	0.0	0.524	5.631		311.0	15.2	386.63	29.93	16.5
0.17004	12.5	7.87	0.0	0.524	6.004		311.0	15.2	386.71	17.1	18.9
0.22489	12.5	7.87	0.0	0.524	6.377		311.0	15.2	392.52	20.45	15.0
0.11747	12.5	7.87	0.0	0.524	6.009		311.0	15.2	396.9	13.27	18.9
0.09378	12.5	7.87	0.0	0.524	5.889		311.0	15.2	390.5	15.71	21.7
1					:	23	·.	:			
0.27957	0.0	9.69	0.0	0.585	5.926		391.0	19.2	396.9	13.59	24.5
0.17899	0.0	9.69	0.0	0.585	5.67		391.0	19.2	393.29	17.6	23.1
0.2896	0.0	9.69	0.0	0.585	5.39		391.0	19.2	396.9	21.14	19.7
0.26838	0.0	9.69	0.0	0.585	5.794		391.0	19.2	396.9	14.1	18.3
0.23912	0.0	9.69	0.0	0.585	6.019		391.0	19.2	396.9	12.92	21.2
0.17783	0.0	9.69	0.0	0.585	5.569		391.0	19.2	395.77	15.1	17.5
0.22438	0.0	9.69	0.0	0.585	6.027		391.0	19.2	396.9	14.33	16.8
0.06263	0.0	11.93	0.0	0.573	6.593		273.0	21.0	391.99	9.67	22.4
0.04527	0.0	11.93	0.0	0.573	6.12		273.0	21.0	396.9	9.08	20.6
0.06076	0.0	11.93	0.0	0.573	6.976		273.0	21.0	396.9	5.64	23.9
0.10959	0.0	11.93	0.0	0.573	6.794		273.0	21.0	393.45	6.48	22.0
0.04741	0.0	11.93	0.0	0.573	6.03		273.0	21.0	396.9	7.88	11.9

EXERCISE 2

The resulting data matrix should have 506 rows representing neighborhoods and 14 columns representing the attributes. The last attribute is the median house price to be predicted, so let's separate it. Also, take transpose of this data matrix so instances/samples are in columns. We will use Julia's array indexing operation to split the data array into input x and output y. (Hint: you may want to reshape y array into a matrix with size 1x506, use reshape procedure for this purpose)

13×506 Array{Float64,2}:

0.00632	0.02731	0.02729	 0.06076	0.10959	0.04741
18.0	0.0	0.0	0.0	0.0	0.0
2.31	7.07	7.07	11.93	11.93	11.93
0.0	0.0	0.0	0.0	0.0	0.0
0.538	0.469	0.469	0.573	0.573	0.573
6.575	6.421	7.185	 6.976	6.794	6.03
65.2	78.9	61.1	91.0	89.3	80.8
4.09	4.9671	4.9671	2.1675	2.3889	2.505
1.0	2.0	2.0	1.0	1.0	1.0
296.0	242.0	242.0	273.0	273.0	273.0
15.3	17.8	17.8	 21.0	21.0	21.0
396.9	396.9	392.83	396.9	393.45	396.9
4.98	9.14	4.03	5.64	6.48	7.88

EXERCISE 3

As you can see, input attributes have different ranges. We need to normalize attributes by subtracting their mean and then dividing by their standard deviation (hint: take means and standard deviations of row vectors). The mean and std functions calculate mean and standard deviation values of x. Calculate mean and standard deviation on input data.

```
13×506 Array{Float64,2}:
```

-0.419367	-0.416927	-0.416929	 -0.413038	-0.407361	-0.41459
0.284548	-0.48724	-0.48724	-0.48724	-0.48724	-0.48724
-1.28664	-0.592794	-0.592794	0.115624	0.115624	0.115624
-0.272329	-0.272329	-0.272329	-0.272329	-0.272329	-0.272329
-0.144075	-0.73953	-0.73953	0.157968	0.157968	0.157968
0.413263	0.194082	1.28145	 0.983986	0.724955	-0.362408
-0.119895	0.366803	-0.265549	0.796661	0.736268	0.434302
0.140075	0.556609	0.556609	-0.772919	-0.667776	-0.61264
-0.981871	-0.867024	-0.867024	-0.981871	-0.981871	-0.981871
-0.665949	-0.986353	-0.986353	-0.802418	-0.802418	-0.802418
-1.45756	-0.302794	-0.302794	 1.1753	1.1753	1.1753
0.440616	0.440616	0.396035	0.440616	0.402826	0.440616
-1.0745	-0.491953	-1.20753	-0.982076	-0.864446	-0.668397

Important Note on Random Number Generation

Before generating random numbers, strings etc., you need to set a seed, because Julia uses a pseudo random number generator. In pseudo random number generators you set a seed and you obtain some certain random number generation order based on that seed. If you don't set a seed, the results you obtain in the next exercises will be different. When you fail in some part, run the cells again starting from the cell or line you set random seed.

EXERCISE 4

It is necessary to split our dataset into training and test subsets so we can estimate how good our model will perform on unseen data. There are 506 instances in our dataset. Let's take 400 of them randomly, use them as training data. Let the rest be test data. In the end, you will have 4 different arrays: xtrn, ytrn, xtst and ytst.

Use randperm function to split our dataset into train and test sets. Note that, results will differ since usage of randperm function introduces randomness. If you want to produce reproducible results, set a seed by using Random.seed! function. In this exercise, please set seed as 1 just before randperm call and you will get exactly the same results as below. Use @doc macro to see documentation about randperm and Random.seed! (e.g. type @doc randperm to Julia REPL or notebook).

You can see the results of the split operation below.

xtrn

13×400 Arra	y{Float64,2}:				
-0.410443	-0.113706	-0.414262	 -0.41168	-0.405218	-0.408378
-0.48724	-0.48724	1.01346	2.08539	-0.48724	-0.48724
-1.26477	-0.180279	-0.740017	-1.37701	-0.375604	-0.164245
-0.272329	-0.272329	-0.272329	-0.272329	-0.272329	-0.272329
-0.575564	-0.0922961	-1.00792	-1.24006	-0.299411	-0.0664067
-0.968713	-1.86678	-0.823542	 -0.570203	0.269515	0.612518
0.75403	-1.09329	-1.42723	-1.77893	1.01337	0.462722
-0.383311	-0.605802	1.3514	3.28405	-0.64688	-0.53072
-0.752178	-0.637331	-0.981871	-0.637331	-0.522484	-0.407638
-1.27709	-0.618482	-0.618482	0.0163931	-0.143809	0.140995
-0.302794	-0.0256513	-0.718509	 -0.0718418	1.12911	-0.302794
0.37599	-0.068175	0.40907	0.390558	0.422433	0.426267
0.185818	-0.00182931	-0.0312367	-0.681	-0.0536423	-0.349117

ytrn

1×400 Array{Float64,2}: 26.4 16.1 17.1 19.0 21.7 17.4 ... 23.9 18.3 8.8 18.6 19.8 22.8 xtst

13×106 Arra	y{Float64,2	}:			
-0.411772	1.25847	-0.41599	 0.241611	-0.403706	-0.405478
-0.48724	-0.48724	0.970582	-0.48724	-0.48724	1.44223
2.11552	1.01499	-0.735644	1.01499	0.405697	-1.12192
-0.272329	-0.272329	-0.272329	-0.272329	-0.272329	-0.272329
0.227006	0.365083	-1.0502	0.244266	-1.01568	-1.01568
-0.399413	0.807503	0.434612	 -0.242855	-0.703988	0.386221
0.551536	1.11639	-1.00093	0.398776	-0.375678	-1.40236
-0.758719	-1.1063	0.805741	-0.118318	1.1991	0.366459
-0.867024	1.6596	-0.292791	1.6596	-0.637331	-0.522484
-1.30676	1.52941	-0.470147	1.52941	-0.707483	-0.0607412
0.297683	0.805778	-1.08803	 0.805778	-1.13422	-1.50375
0.22998	-1.94221	0.428019	0.394392	0.440616	0.286609
0.226428	0.998022	-0.44154	0.325853	0.446283	-1.13331

ytst

1×106 Array{Float64,2}: 20.3 27.5 22.0 30.7 19.4 24.5 ... 24.8 42.3 16.3 19.1 20.3 29.8

EXERCISE 5

Our data is ready to be used. First, let's look at how good a randomly initialized linear regression model performs on our processed data.

Basically, we need to use some weights with whom we're going to multiply the attributes of houses and add a bias so that we can predict the price of that house. Neighborhoods are represented with 13 attributes and we need to predict the prices which is a single number. We need to have a weight matrix with size 1x13. We also use a bias value which is 0.

To create weight matrix, we will sample from normal distribution with zero mean and a small standard deviation. In this tutorial, our standard deviation value is equal to 0.1. Use randn function to create a random weight matrix whose values are sampled from a unit normal distribution (mean=0, standard deviation=1). Multiply our weight matrix by 0.1 which is our desired standard deviation. Set the bias to 0. w - weights and bias

([0.0426637 0.0378471 ... -0.066244 -0.0257344], [0.0])

EXERCISE 6

Now, we have input and weights. Let's write a function to predict price. Implement a function takes the weight matrix and neighborhood attributes as input and outputs a single value, house price prediction. Simply perform a matrix multiplication inside this function add the bias and return the output vector. We call this function the **predict** function.

Call the predict function and store the output as ypred.

ypred

```
1×400 Array{Float64,2}:
0.227025 -0.0623266 -0.0604358 ... 0.207288 0.0592333 -0.0221864
```

ypred is an 1x400 dimensional array. Each value in this array is the model's price prediction for an average house in corresponding neighborhood.

EXERCISE 7

Let's implement a loss function called the Mean Squared Error (MSE),

$$J = \frac{1}{2N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

In this function we calculate J, our loss value, half the average of squared difference between real price values and predicted price values.

Implement MSE loss function which takes the model parameters, input matrix (xtrn or xtst) and ground truth prices (ytrn or ytst). Helpful functions: sum, mean, size, abs2, .* You don't have to use all of them. Use the dot notation

for broadcasting e.g. abs2.(x). Calculate the loss value for both train and test splits by using your MSE loss function.

(train loss/test loss): (297.3036503276774,299.0172855668773)

EXERCISE 8

Let's find in how many of the neighborhoods, the randomly initialized model predicts the price with an error less than the average error. Measure the absolute difference between the predicted price and correct price for each neighborhood and compare those differences with the square root of the loss value calculated in previous exercise. Use sqrt function (with dot syntax, e.g. sqrt.(x)) to take square roots. Perform this step for only training set. The result should be 108.

EXERCISE 9

Write an SGD training loop using AutoGrad utilities. Train your model. Start with a learning rate of 0.1 and optimize it for fast convergence (note that SGD may diverge if you set the learning rate too high). You should be able to get a test loss less than 8.5 within 50 epochs. Here is a summary of AutoGrad usage (see `@doc AutoGrad` for more details):

```
x = Param([1,2,3])  # user declares parameters
x => P([1,2,3])  # they are wrapped in a struct
value(x) => [1,2,3]  # we can get the original value
sum(abs2,x) => 14  # they act like regular values outside of diff
y = @diff sum(abs2,x)  # if you want the gradients
y => T(14)  # you get another struct
value(y) => 14  # which represents the same value
grad(y,x) => [2,4,6]  # but also contains gradients for all Params
Sample run:
epoch=0 trnloss=297.3036503276774 tstloss=299.0172855668773
epoch=1 trnloss=151.46737772662826 tstloss=140.62408482836196
epoch=2 trnloss=81.33677873335634 tstloss=82.63525728938849
. . .
epoch=49 trnloss=11.72306660031736 tstloss=8.428948061703453
epoch=50 trnloss=11.720071050577763 tstloss=8.42861947294791
```