BITS F464 Machine Learning
Multi-Layer Perceptron

1. Introduction:

In this report, we try to analyse the performance (accuracy, fscore, recall and precision) of a neural network that we built using NumPy. The implementation of this network is similar to that of Keras and the whole code has been written in a completely modularized fashion.

2. Data Preprocessing:

The dataset *housepricesdata.csv* contained 1460 data points, each containing 10 input features (representing house features) and one binary target variable (representing if the house price is above or below the median price). In the preprocessing stage, all features were standardized and randomly split into *train_set* and *test_set* (80-20 split ratio).

3. Activation functions:

- linear: $y = x$
- tanh: $y = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
- sigmoid: $y = \frac{1}{1+e^{-x}}$
- ReLU: $y = max(0, x)$

4. Loss function:

- $L_n = -t_n log(y_n) - (1 - t_n) log(1 - y_n)$

5. Network Architecture:

5.1 Two-Layer NN

The first model we built was a 2-layer neural network (i.e. with one hidden layer). We experimented with activations like linear, ReLU and tanh for the hidden layer. The input layer had 10 neuron units with a ReLU activation (for best results. A slight drop in accuracy was observed when linear activation was used for the input layer). The final layer had an activation of sigmoid for binary classification. Output value greater than or equal to 0.5 was taken to represent positive classes and less than 0.5 to represent negative classes. `np.random.random()` and `np.random.randn()` methods were used to randomly initialize weights and biases associated network to initialize the weights according to a Uniform or Guassian distribution respectively. Best results were obtained using uniformly distributed weights/biases with a seed=5 and 4 hidden neurons with ReLU and learning_rate=0.001 with 20000 training epochs. The loss was observed to have more fluctuations using this configuration after 40000 epochs and thus lowering the accuracy. The avg. loss using this configuration was observed to be 0.7 (per data point). The highest accuracy achieved by this model using this configuration was 87.67% and the lowest accuracy was 80% with an average accuracy of 84%.

5.2 Three-Layer NN

The second model we built and experimented with was a three layer neural network. The accuracy of the three layer neural network was found to be better than that of the two layer network. Both the hidden layers had 5 neurons with ReLU activation for optimal results. Training the network, in this case, required more iterations as there were more number of parameter to be tuned than the two layer network. The optimal number of neurons for both hidden layers were chosen accordingly as suggested in research article *Review on Methods to Fix Number of Hidden Neurons in Neural Networks* by Gnana Sheela et al. Once again, best results were obtained using uniform distribution of weights with learning_rate=0.01 and 40000 iterations. The following combination yielded the highest accuracy of 91.43% with a minimum accuracy of 80% and an average accuracy of 86%.

6. Conclusion:

- In general, a three layer network performs better than a two layer network. Adding more layers/more neurons to the hidden layers provides more trainable parameters which help the network to fit the model in a better way. But the drawback of adding multiple layers/mulitple neurons is that, the model requires more iterations to train. In this case, there is a higher chance that the model might overfit the data, and hence giving a low testing accuracy.
- A lower learning rate requires more iterations to converge, but conversely, using a higher learning rate might lead to fluctuation in the loss/exploding gradient.
- Different initialization of weights leads to convergence of the model at different local minima (initializations mentioned above).
- Different activation functions for the hidden layers provides drastically varying results. We have used ReLU (Rectified Linear) which is by and the far, the de-facto standard activation used for hidden layers. Other activations like tanh or sigmoid gave very low accuracy as compared to that of ReLU. ReLU suffers from the *dying neuron problem*, in which the output of a neuron might be 0 for most of the training (i.e. that neuron is not contributing to the network), and hence we tried using leaky-ReLU, but the accuracy was found to more or less the same.

[results on next page]

7. Additional Work:

- SGD Momentum and Decay
  $M_t = \beta M_{t-1} + (1-\beta)\nabla E$
  $W = W - \eta M_t$
- RMSprop
  $V_t = \beta V_{t-1} + (1-\beta)(\nabla E)^2$
  $W = W - \eta \frac{\nabla E}{\sqrt{V_t + \epsilon}}$
- Adam
  $M_t = \beta M_{t-1} + (1-\beta_1)\nabla E$
  $V_t = \beta V_{t-1} + (1-\beta_2)(\nabla E)^2$
  $\hat{M}_t = \frac{M_t}{1-\beta_1^t}$; $\hat{V}_t = \frac{V_t}{1-\beta_2^t}$
  $W = W - \eta \frac{\hat{M}_t}{\sqrt{\hat{V}_t + \epsilon}}$

8. Results:

```
training metrics:
tp = 508, tn = 479, fp = 111, fn = 70
final accuracy: 84.50342465753424
final recall: 87.88927335640139
final precision: 82.06785137318255
final fscore: 84.87886382623225

testing metrics:
tp = 133, tn = 123, fp = 19, fn = 17
final accuracy: 87.67123287671232
final recall: 88.66666666666667
final precision: 87.5
final fscore: 88.0794701986755
```

```
training metrics:
tp = 544, tn = 402, fp = 188, fn = 34
final accuracy: 80.9931506849315
final recall: 94.11764705882352
final precision: 74.31693989071039
final fscore: 83.05343511450381

testing metrics:
tp = 144, tn = 107, fp = 35, fn = 6
final accuracy: 85.95890410958904
final recall: 96.0
final precision: 80.44692737430168
final fscore: 87.53799392097265
```

2-Layer NN using uniform distribution

```
training metrics:
tp = 552, tn = 453, fp = 137, fn = 26
final accuracy: 86.0445205479452
final recall: 95.50173010380622
final precision: 80.11611030478954
final fscore: 87.13496448303077

testing metrics:
tp = 143, tn = 111, fp = 31, fn = 7
final accuracy: 86.98630136986301
final recall: 95.33333333333334
final precision: 82.18390804597702
final fscore: 88.27160493827162
```

```
training metrics:
tp = 521, tn = 495, fp = 95, fn = 57
final accuracy: 86.98630136986301
final recall: 90.13840830449827
final precision: 84.57792207792207
final fscore: 87.26968174204356

testing metrics:
tp = 141, tn = 126, fp = 16, fn = 9
final accuracy: 91.43835616438356
final recall: 94.0
final precision: 89.80891719745223
final fscore: 91.85667752442997
```

3-Layer NN using uniform distirbution

```
training metrics:
tp = 393, tn = 432, fp = 158, fn = 185
final accuracy: 70.63356164383562
final recall: 67.99307958477509
final precision: 71.32486388384754
final fscore: 69.6191319751993

testing metrics:
tp = 117, tn = 101, fp = 41, fn = 33
final accuracy: 74.65753424657534
final recall: 78.0
final precision: 74.0506329113924
final fscore: 75.97402597402596
```

```
training metrics:
tp = 489, tn = 480, fp = 110, fn = 89
final accuracy: 82.96232876712328
final recall: 84.60207612456747
final precision: 81.63606010016694
final fscore: 83.09260832625318

testing metrics:
tp = 130, tn = 115, fp = 27, fn = 20
final accuracy: 83.9041095890411
final recall: 86.66666666666667
final precision: 82.80254777070064
final fscore: 84.69055374592834
```

2-Layer NN using normal distirbution

```
training metrics:
tp = 479, tn = 460, fp = 130, fn = 99
final accuracy: 80.39383561643835
final recall: 82.8719723183391
final precision: 78.65353037766832
final fscore: 80.70766638584666

testing metrics:
tp = 131, tn = 112, fp = 30, fn = 19
final accuracy: 83.21917808219177
final recall: 87.33333333333333
final precision: 81.36645962732919
final fscore: 84.2443729903537
```

```
training metrics:
tp = 468, tn = 470, fp = 120, fn = 110
final accuracy: 80.3082191780822
final recall: 80.96885813148789
final precision: 79.59183673469387
final fscore: 80.27444253859348

testing metrics:
tp = 128, tn = 113, fp = 29, fn = 22
final accuracy: 82.53424657534246
final recall: 85.33333333333334
final precision: 81.52866242038218
final fscore: 83.38762214983714
```

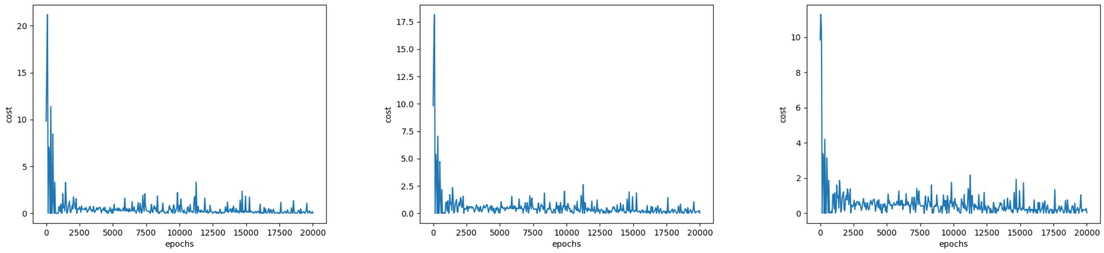
3-Layer NN using normal distirbution

```
training metrics:
tp = 519, tn = 492, fp = 98, fn = 59
final accuracy: 86.5582191780822
final recall: 89.79238754325259
final precision: 84.11669367909238
final fscore: 86.86192468619247

testing metrics:
tp = 141, tn = 126, fp = 16, fn = 9
final accuracy: 91.43835616438356
final recall: 94.0
final precision: 89.80891719745223
final fscore: 91.85667752442997
```

```
training metrics:
tp = 505, tn = 504, fp = 86, fn = 73
final accuracy: 86.38698630136986
final recall: 87.37024221453287
final precision: 85.44839255499154
final fscore: 86.39863130881095

testing metrics:
tp = 138, tn = 127, fp = 15, fn = 12
final accuracy: 90.75342465753424
final recall: 92.0
final precision: 90.19607843137256
final fscore: 91.0891089108911
```

3-Layer NN using uniform distirbution with momentum and decay

9. Additional Results:



Loss vs Epochs for Adam, RMSprop and Momentum respectively

```
100%|
training metrics:
tp = 504, tn = 511, fp = 79, fn = 74
final accuracy: 86.90068493150685
final recall: 87.19723183391004
final precision: 86.44939965694682
final fscore: 86.82170542635659

testing metrics:
tp = 139, tn = 130, fp = 12, fn = 11
final accuracy: 92.12328767123287
final recall: 92.66666666666666
final precision: 92.05298013245033
final fscore: 92.35880398671097
```

```
100%|
training metrics:
tp = 506, tn = 505, fp = 85, fn = 72
final accuracy: 86.5582191780822
final recall: 87.5432525951557
final precision: 85.6175972927242
final fscore: 86.56971770744225

testing metrics:
tp = 137, tn = 126, fp = 16, fn = 13
final accuracy: 90.06849315068493
final recall: 91.33333333333333
final precision: 89.54248366013073
final fscore: 90.42904290429043
```

```
100%|
training metrics:
tp = 501, tn = 512, fp = 78, fn = 77
final accuracy: 86.72945205479452
final recall: 86.67820069204151
final precision: 86.52849740932642
final fscore: 86.60328435609334

testing metrics:
tp = 135, tn = 126, fp = 16, fn = 15
final accuracy: 89.38356164383562
final recall: 90.0
final precision: 89.40397350993378
final fscore: 89.70099667774085
```

3-Layer NN with Adam, RMSprop and Momentum respectively for 3750 epochs