

# Machine Learning HW2 Report

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## 1. Logistic regression function

### 1) Function Set & Cross Entropy (code, where np = numpy)

```
Y = 1.0/(1.0+np.exp(-np.dot(X,W)))  
Loss = np.mean(-(Y_*np.log(Y+e)+(1-Y_)*np.log(1-Y+e))) (e is 1e-20)
```

### 2) Gradient

```
Grad = -np.dot(X.T,(Y_-Y))/len(X)
```

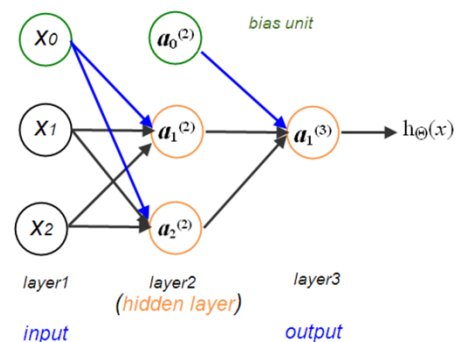
### 3) Optimizer: AdamOptimizer (Wil explain below)

Best Kaggle Accuracy: 0.92667

## 2. Describe your another method, and which one is best.

I use [Neural Network](#) for my another method, the model is like the figure below.

The only [one](#) hidden layer neurons are 40, and I combine the bias unit in it, so there are [41 hidden neurons](#), the input layer neurons are [58](#), which are the 57 input features and one bias unit, and the output layer is a neuron used to predict two classes, all the activation function I used are [sigmoid](#).



The optimizer I used was [AdamOptimizer](#), because the downtrend of the loss when I used Gradient Descent is sluggish. Therefore, the loss would drop steadily. The parameters and the algorithm are as below.

[learning\\_rate=0.001](#), [beta1=0.9](#), [beta2=0.999](#), [epsilon=1e-08](#), [g = Gradient](#)

```
m_0 <- 0 (Initialize initial 1st moment vector)  
v_0 <- 0 (Initialize initial 2nd moment vector)  
t <- 0 (Initialize timestep)
```

```
t <- t + 1  
lr_t <- learning_rate * sqrt(1 - beta2^t) / (1 - beta1^t)
```

```
m_t <- beta1 * m_{t-1} + (1 - beta1) * g  
v_t <- beta2 * v_{t-1} + (1 - beta2) * g * g  
variable <- variable - lr_t * m_t / (sqrt(v_t) + epsilon)
```


Best Kaggle Accuracy: 0.9600, which is much better than logistic regression.

### 3. How did I choose the nn model ?

First, I try to use the **regularization** to avoid overfitting, so it just need to add a  $\lambda W$  to the gradient. Therefore, I use **3601 training data & 400 validation data** to choose my model. After I choose the  $\lambda$ , I try to base on the  $\lambda$  and then choose the **number of hidden neurons**.

The **stop condition** when I use training data to train and use validation data to test is that when the output of the network would not change too much( less than 0.004), I would stop the training and start to use validation data to test.

The graph below is the model I chose.

$\lambda = 0.01$ (neuron=32)	Validation ACC = 0.9649		$\lambda = 0.01$ , 16 neurons	Validation ACC = 0.9525
$\lambda = 0.1$ (neuron=32)	Validation ACC = 0.9549		$\lambda = 0.01$ , 32 neurons	Validation ACC = 0.9649
$\lambda = 10$ (neuron=32)	Validation ACC = 0.9525		$\lambda = 0.01$ , 40 neurons	Validation ACC = 0.9675
$\lambda = 100$ (neuron=32)	Validation ACC = 0.9605		$\lambda = 0.01$ , 64 neurons	Validation ACC = 0.9649

Result1: fix  $\lambda = 0.01$  , start to tune the hidden neurons,

Result2: the final model:  $\lambda = 0.01$  40 neurons (hidden layer)