NOTES

Machine Learning.

Different training models.

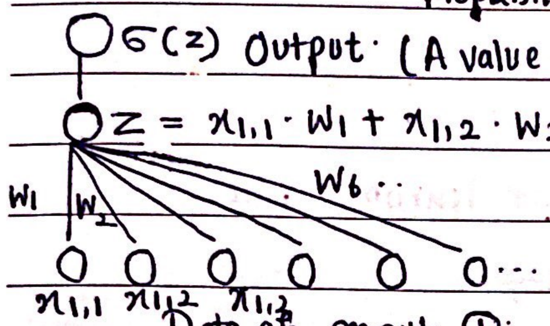
Logistic regression.

Probability.

$\sigma(z)$ Output (A value between 0, 1)

$z = x_{1,1} \cdot W_1 + x_{1,2} \cdot W_2 + \cdots + b_0$

base.



Data of input ①

Simple model.

$z = x_1 \odot W + b_0$

Inner product.

Only ① filter (W)

Used for linearly seperable data.

There can be several different inputs (Ex:- MNSET 0,1,2.. 9) for each of them the filter sets are different. bias values are different.

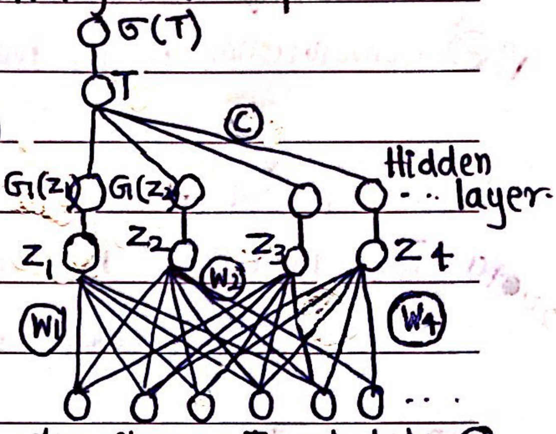
Then

$T_1 = C \odot G(W \odot x_1 + b) + t_1$

$\therefore$ Input to 2^{nd} layer z_1 is send through another fcng G (Softmax,)

(A neural network)

Multilayer Perceptron.



Input data ①

Complex model.

Multiple filters.

$W_1, W_2, W_3, \cdots \quad C.$

~~Used for non linear seperable~~ data.

$z_1 = x_{1,1} \cdot W_{1,1} + x_{1,2} \cdot W_{1,2} + \cdots + b_1$

$z_1 = x_1 \odot W_1 + b_1$

$z_2 = x_1 \odot W_2 + b_2$

Input to the 2^{nd} layer isn't this z value.

$\because$ If we do that

$T = (C \odot z + t)$

$z = W \odot x_1 + b \; (b_1, b_2, ..)$

$(z_1, z_2 \cdots) \; (W_1, W_2, \cdots)$

$= (C \odot (W \odot x_1 + b) + t)$

$= F \odot x_1 + f$

This is same as LR

There are different models that we can use in ML.

Ex:- Logistic regression, MLP, CNN, ...

Overfitting:- Using complex models can perform well on training data and not so well in real (Not generalized model). When we increase the depth of our model → increase the parameters of the model → increase error rate.

Complex relationships may be too complex for reality.

How to choose a suitable model?

Trying the model in real word by getting new real word data set

X Costly.

∴ Split our training data for 3 groups.

Training - Train the model.

Validation.- Compare each approach. Use repeatedly to select best performance

Testing - Evaluate performance of our model by running the test set.

Equal to running new data (real world data)

Should only be used once. If not lead to bias.

Training set ← redefine the model

↓

learn parameters → estimate models preformance. on validation set

↓ If the performance good

Test set.

NOTES

How to choose (best) ~~optimized~~ parameters?

The values of parameters when the loss function is minimum. - Gradiant desent.

$L(x_i, L_i)$ - The distance between the true label and the predicted label by the model for i^{th} input.

We need to take the average loss value.

$$AVGL = \frac{1}{N} \sum_{i=1}^{N} \underbrace{L(x_i, L_i)}_{\text{Normaly}}$$

N - All the input

$= -\log P(L_i | \sigma(z_i))$

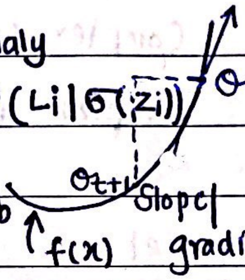
$\sigma(z_i)$ - Predicted output value prob

Mostly used cross entropy $= -\sigma(z_i) \log(L_i)$

We take θ value when loss function is at it's local minimum.

In ML θ is the parameters that we have to learn.

Gradiant desenent



Take the gradiant of the loss func in an arbitary point. Then (update) move the arbitary point in direction the gradiant descent (ශ්‍රේණිය)

$$\theta_{t+1} = \theta_t - \overset{\text{step size}}{\alpha} \underbrace{\nabla f(\theta_t)}_{\text{gradiant at point } \theta_t}$$

We keep updating the parameters until loss func is minimum. And the gradient $(\nabla_\theta f)$ is taken w.r.t. parameters we have to learn.

For large data set calculating gradiant descent this way ~~was~~ required looking at every input data point ($\because$ $\nabla AVGL = \nabla \frac{1}{N} \sum_{i=1}^{N} L(x_i, L_i) = \frac{1}{N} \sum_{i=1}^{N} \nabla L(x_i, L_i)$ have to calculate gradient of each data point and sum them)

Approximation - Randomly chosen subset of N or a points (J) gradiant (Estimated grad) is approximately equal to $\nabla AVGL$

$$\nabla L(x_j, L_j) = \nabla AVGL \text{ or } \nabla \frac{1}{\underbrace{|S_t|}_{\text{size of the subset}}} \sum_{i \in S_t} L(x_i, L_i)$$

This is known as Stochastic gradient descent.

Not accurate as gradient descent

But fast. Does more updates within a single time.

May go in both gradient ascending and descending directions. But avg at descending way.

In SGD point update $\theta^{t+1} = \theta^{t} - \alpha \underbrace{\nabla f(\theta i)}_{\text{Estimated gradient}}$

$= \nabla \hat{f}(\alpha t)$

Early stopping.

Optimization goal - Do as well as possible in training set

Validation / Generalization goal - Maximize performance in real world.

Combine optimization with validation process.

Run training data set (with every iteration avg loss ↓)

~~While running training data we will run validation set also~~ once in a while. Not for parameter optimization. To estimate real world performance.

With every iteration compute avg loss. Before we choose optimized parameters when avg loss converge to 0. But now we will stop optimization when validation avg loss stops improving.

Advantage - Save computational cost.

Perform better in real world.