

MIDS W207

Applied Machine Learning

Spring 2023

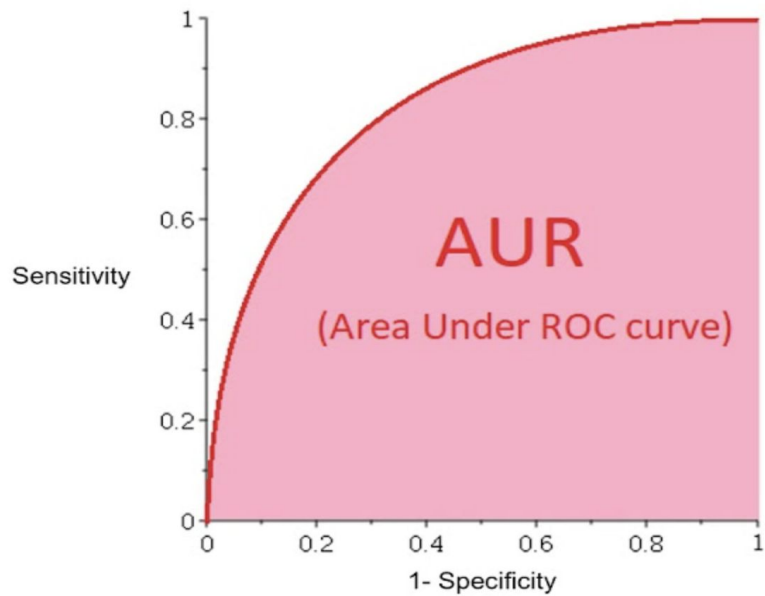
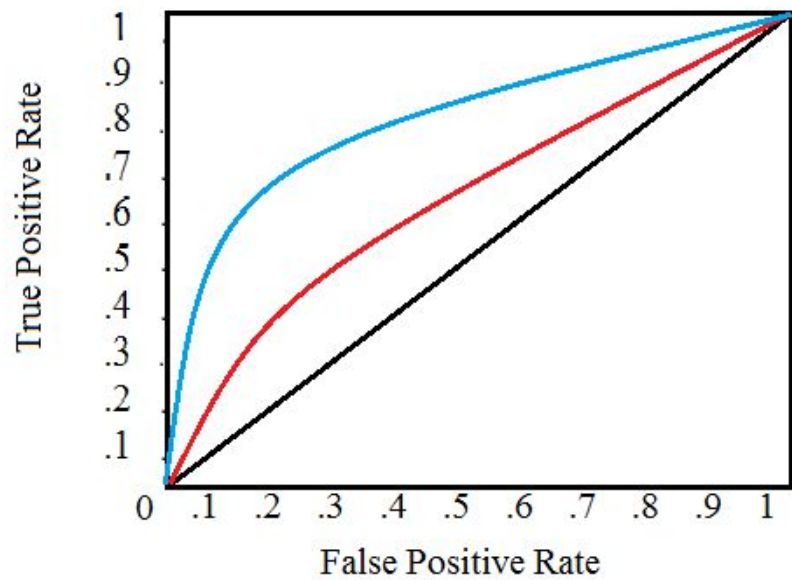
Week 5

Classification Metrics

Confusion Matrix			
		Actual Value	
		Yes (1)	No (0)
Predicted Value	Yes (1)	TP	FP
	No (0)	FN	TN

TP= True Positive
FP= False Positive
FN= False Negative
TN= True Negative

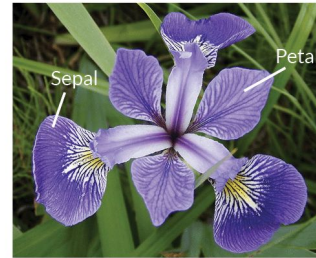
- If you have supervised data, you will want to maximize an objective function.
 - **Precision:** $TP \div (TP + FP)$ % positives correctly identified
 - **Recall:** $TP \div (TP + FN)$ % existing positives identified
 - **Optimal point** on ROC (precision/recall) curve
 - **Accuracy:** $(TP + TN) \div (TP + TN + FP + FN)$
 - **F-test:** $2 \cdot (P \cdot R) \div (P + R)$



Multiclass Classification

SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
6.8	3.2	5.9	2.3	Iris-virginica
6.9	3.1	5.1	2.3	Iris-virginica
4.9	3.0	1.4	0.2	Iris-setosa
5.6	3.0	4.5	1.5	Iris-versicolor
4.8	3.1	1.6	0.2	Iris-setosa
5.8	2.8	5.1	2.4	Iris-virginica
7.2	3.6	6.1	2.5	Iris-virginica
5.1	3.5	1.4	0.3	Iris-setosa
4.7	3.2	1.6	0.2	Iris-setosa
6.6	3.0	4.4	1.4	Iris-versicolor

Fig.1: Iris dataset having three categories



Iris Versicolor

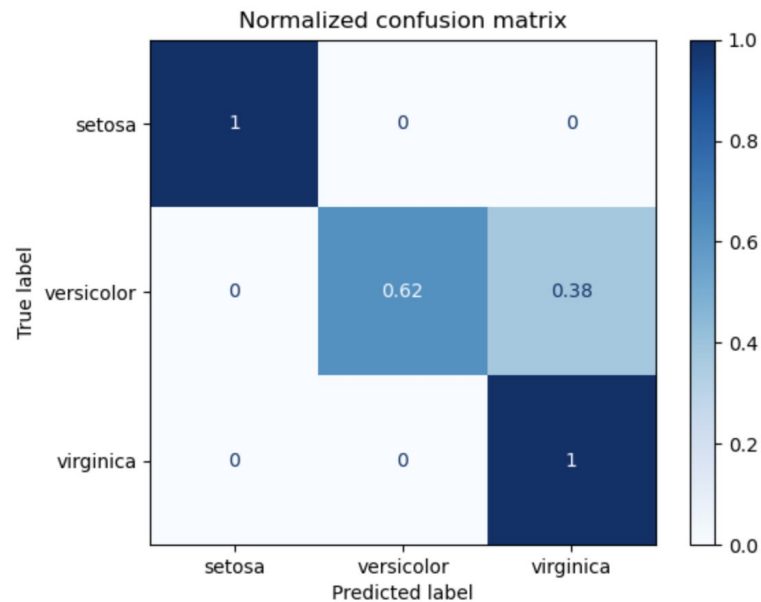
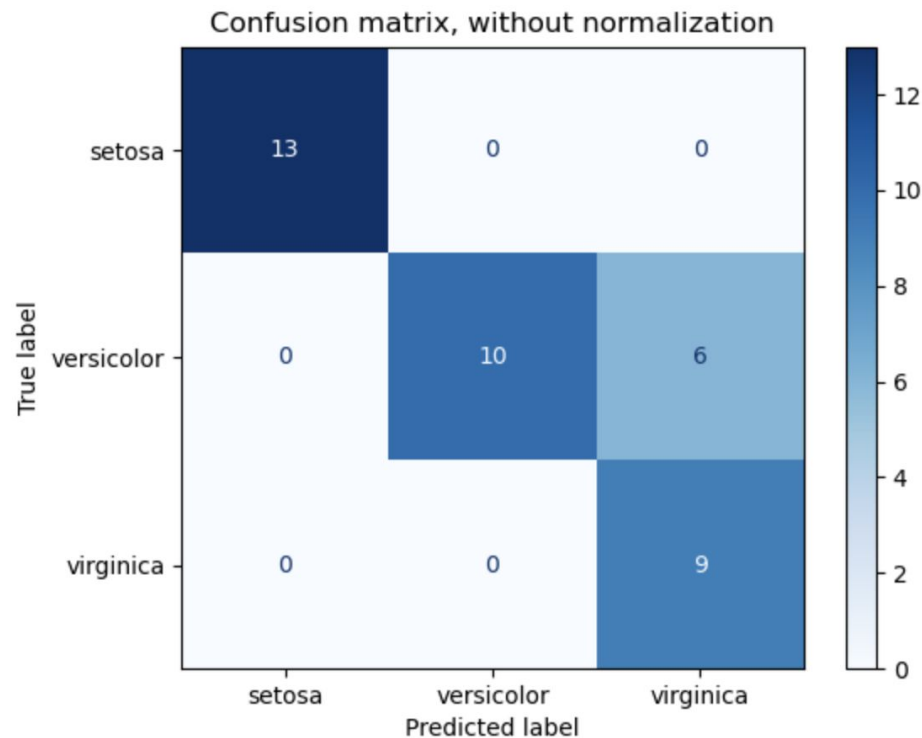


Iris Setosa

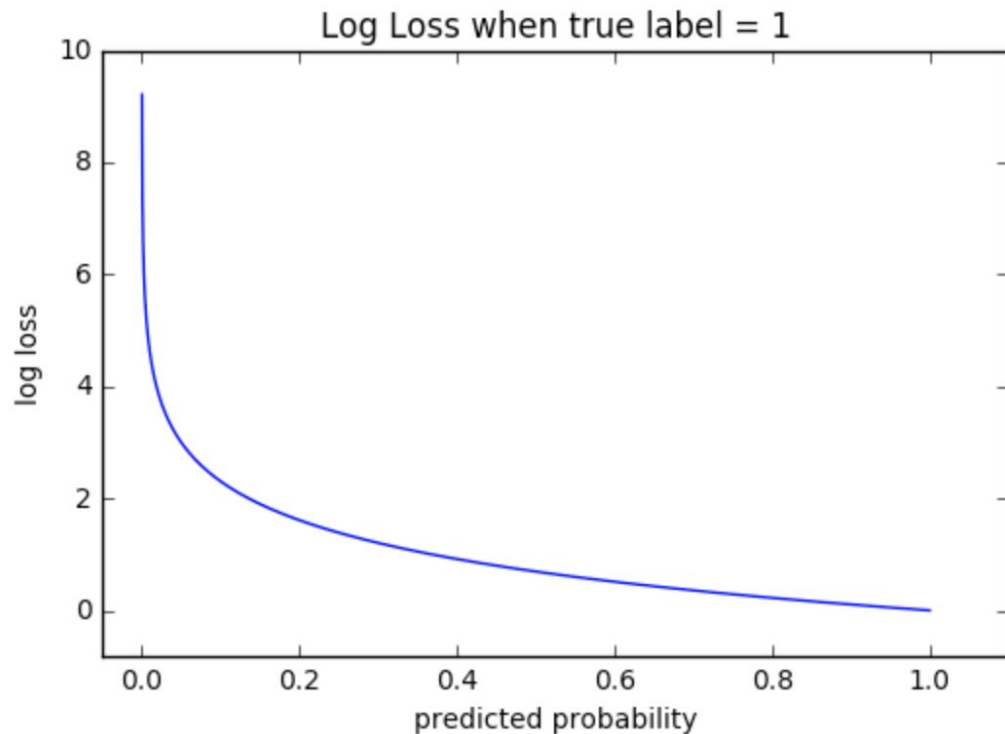


Iris Virginica

Multiclass Classification Confusion Matrix



Cross Entropy



$$-(y \log(p) + (1 - y) \log(1 - p))$$

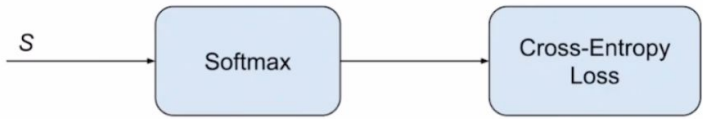
$$-\sum_{c=1}^M y_{o,c} \log(p_{o,c})$$

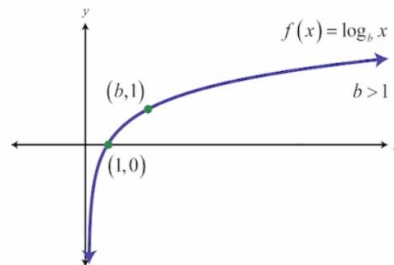
Categorical Cross Entropy Loss (Softmax Loss)

- It is a Softmax activation plus a cross-entropy loss

$$CE = -\log \left(\frac{e^{s_p}}{\sum_j^C e^{s_j}} \right) =$$

Sp is the positive class


$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \quad CE = -\sum_i^C t_i \log(f(s)_i)$$



- Example:

True Label: Rabbit

Prediction: Dog = 1, Cat = 4, Rabbit = 8, Squirrel = 2

Softmax : D = e^1/SUM , C = e^4/SUM , R = e^8/SUM , S = e^2/SUM

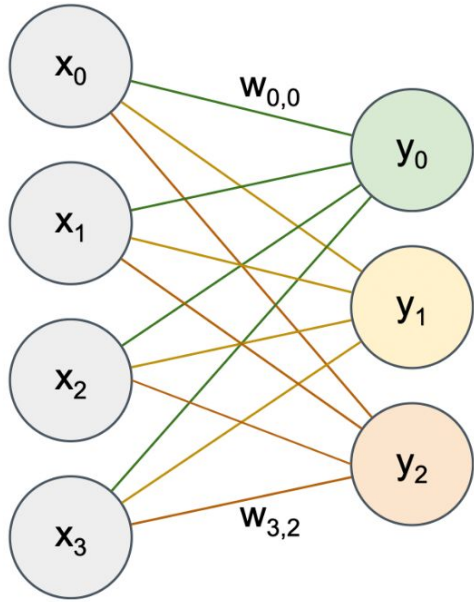
$$\begin{aligned} \text{CE Loss} &= - (0 * \ln(D) + 0 * \ln(C) + 1 * \ln(R) + 0 * \ln(S)) \\ &= - (0 + 0 + (-?) + 0) \\ &= + ? \end{aligned}$$

Only the positive class contributes to the CE loss!

Logistic Regression Network Graph

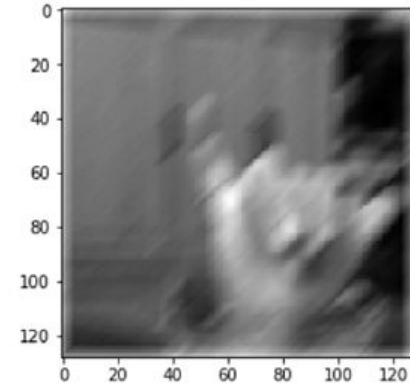
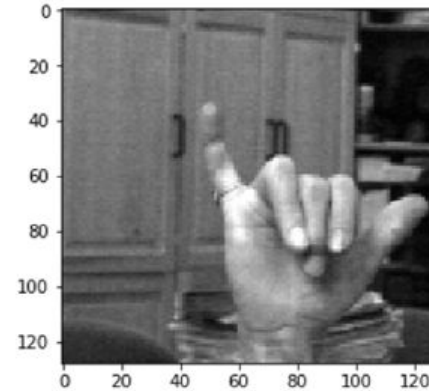
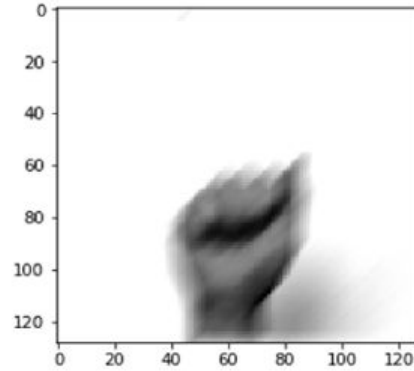
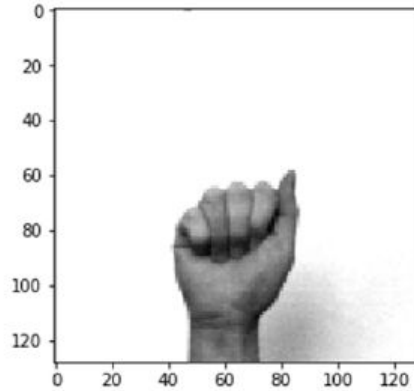
Input Layer

Output Layer



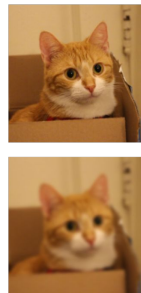
$$\begin{pmatrix} x_{0,0} & x_{0,1} & x_{0,2} & x_{0,3} \\ x_{1,0} & x_{1,1} & x_{1,2} & x_{1,3} \end{pmatrix} \begin{pmatrix} w_{0,0} & w_{0,1} & w_{0,2} \\ w_{1,0} & w_{1,1} & w_{1,2} \\ w_{2,0} & w_{2,1} & w_{2,2} \\ w_{3,0} & w_{3,1} & w_{3,2} \end{pmatrix} \xrightarrow{\sigma} \begin{pmatrix} y_{0,0} & y_{0,1} & y_{0,2} \\ y_{1,0} & y_{1,1} & y_{1,2} \end{pmatrix}$$

Linear Model Limitations

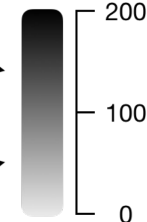


- 1000 clear images
- 1000 blurry images

85% accuracy



Score



200

100

0

Clear

Blurry

Convolution Operation



Input

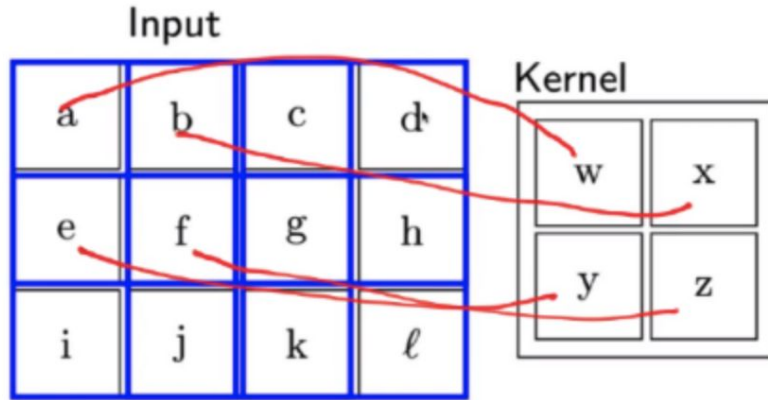
a	b	c	d
e	f	g	h
i	j	k	ℓ

Kernel

w	x
y	z

$$S_{ij} = (I * K)_{ij} = \sum_{a=0}^{m-1} \sum_{b=0}^{n-1} I_{i+a, j+b} K_{a,b}$$

Convolution Operation

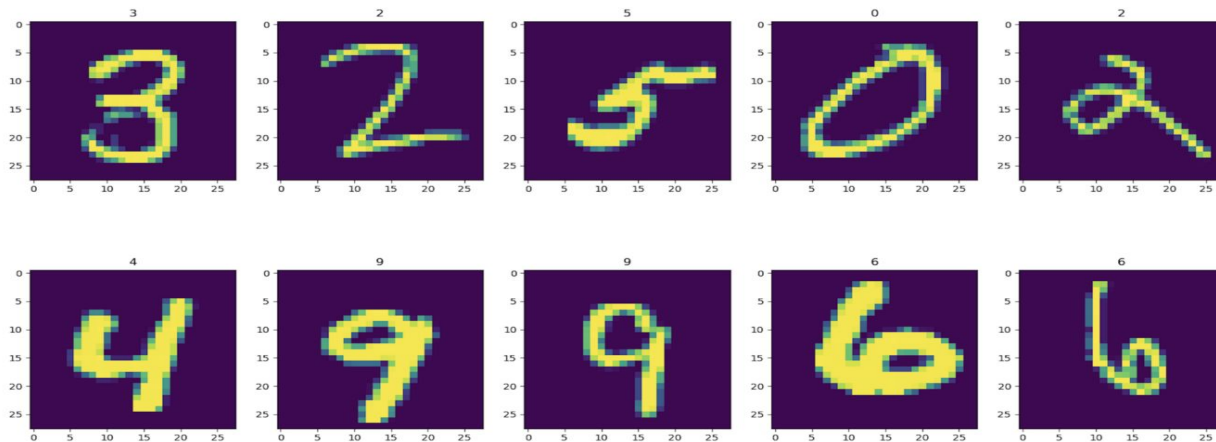


$$aw+bx+ey+fz$$

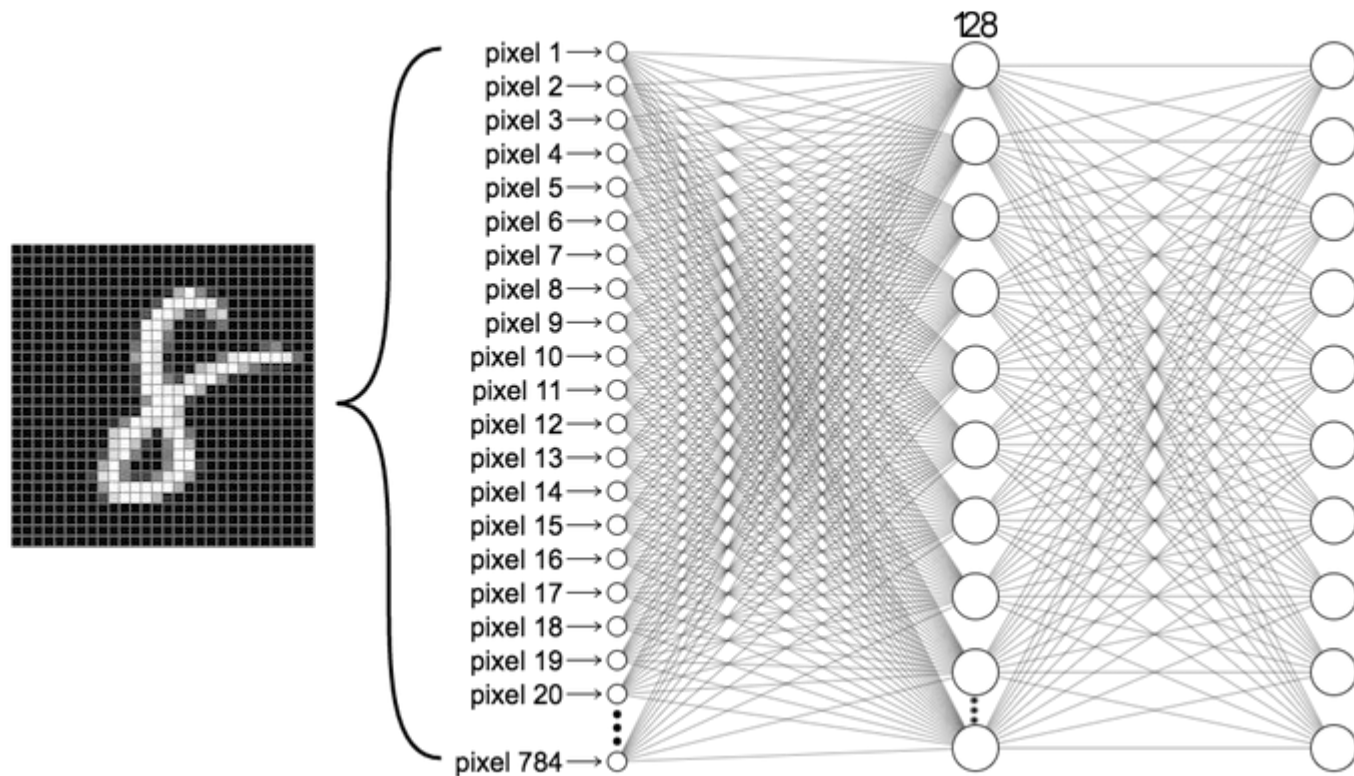
$$bw+cx+fy+gz$$

$$cw+dx+gy+hz$$

Digit Classification Problem



Digit Classification Problem



Code Review