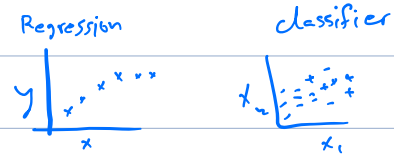


Linear classifier \Rightarrow Linear decision boundary

may use features expansion for complicated distribution



* Perceptron:-

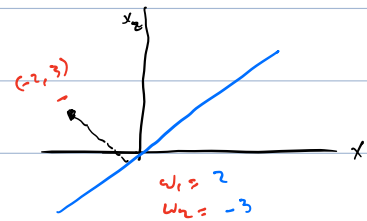
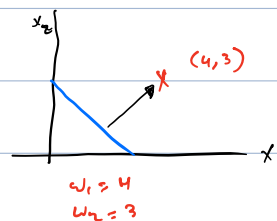
$$x_1 w_1 + x_2 w_2 + b = 0$$

↓
shifter

Assumption \Rightarrow there is exist linear classifier
if not \Rightarrow infinite loop

it provides a random separator

the best line to classify
when it's \perp to the sample



relative
(two classes)

+ve Sample $\Rightarrow w = w + x$

-ve Sample $\Rightarrow w = w - x$

b will be including in w and x will be 1

\Rightarrow Start with $w_1 = w_2 = 0$

$y(x_1 w_1 + x_2 w_2) > 0 \Rightarrow$ correct classify

if $y(x_1 w_1 + x_2 w_2) \leq 0$

if y is +ve:-

$$w_1 = w_1 + x_1$$

$$w_2 = w_2 + x_2$$

elseif y is -ve:-

$$w_1 = w_1 - x_1$$

$$w_2 = w_2 - x_2$$

if $y^i(\sum w_j x_j) > 0$

\Leftrightarrow

elseif $y^i(\sum w_j x_j) \leq 0$

$$\vec{w} \leftarrow \vec{w} + y^{(i)} \vec{x}^{(i)}$$

$$b \leftarrow b + y^{(i)} \quad \text{red arrow} \quad -1 \text{ or } 1$$

\Rightarrow repeat until all samples correctly classified

classification Rule = $y_i = \text{sign}(\sum w x)$

* of iteration that will take until find a solution = $\left(\frac{R}{\gamma}\right)^2$

longest
↑
↓
closest

* the solution of Linear classifier depending on the order of samples

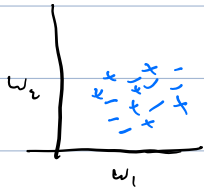
base % = 50% (random)
goal % = human %

- It will give us the result with a confidence rate (how much we are sure that our answer is correct)
- It will solve the problem of running into an infinity loop when we don't have a linear line that separates the data.

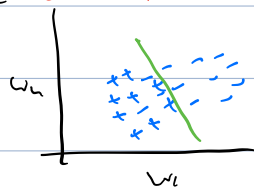
affected by imbalance data

LOGISTIC REGRESSION \Rightarrow It is ^{linear} classifier

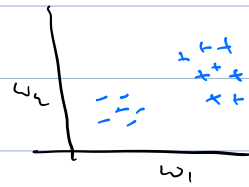
hyper parameters:- learning-rate (if you Regularize)
step-size (doesn't affect accuracy)



there is problem with w



not sure with class but it's good for some fields



linear classifier

farther from decision boundary \Rightarrow more confidence that right class

logistic function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$\sum w_i x_i + b$

0 \rightarrow 0.5
+ve \rightarrow > 0.5
+ ∞ \rightarrow 1
-ve \rightarrow < 0.5
- ∞ \rightarrow 0

from positive side

testing

Training θ :-

$$\prod_i PC y_i = +1/-1 \mid w, x, b$$

should be maximize to get good classifier

$$-\sum_i \log P(y^i = +1/-1 | w, x, b)$$

$$\hat{y} = \sigma(wx+b)$$

Loss and total cost:-

$$L(y, \hat{y}) = -y \log \hat{y} - (1-y) \log (1-\hat{y})$$

Cross-entropy

$$J = \frac{1}{n} \sum -y \log \hat{y} - (1-y) \log (1-\hat{y})$$

* there is no closed-form solution because there is no inverse of the sum.

* gradient descent:- (Same as linear regression but with new dw and db)

$$1 \rightarrow w, b = 0$$

$$\frac{\partial L}{\partial w} = (\hat{y} - y) x$$

$$2 \rightarrow J$$

$$\frac{\partial L}{\partial b} = (\hat{y} - y)$$

$$3 \rightarrow \frac{\partial J}{\partial w}, \frac{\partial J}{\partial b}$$

$$4 \rightarrow w_j \leftarrow w_j - \frac{\partial J}{\partial w} \rightarrow \frac{1}{n} \sum (\hat{y} - y) x_j$$

$$b \leftarrow b - \frac{\partial J}{\partial b} \rightarrow \frac{1}{n} \sum (\hat{y} - y)$$

5 \rightarrow repeat 2-4 until convergence

$$J^{KH} - J^K \leq (10^{-6})$$

* Regularization is very important for Logistic Regression

① Ridge

② Lasso

③ Early stopping

* We deal with overfitting and underfitting like linear regression

□ Perform training and check the error:

□ If error is high: (underfitting)

➢ Add more features

➢ More complex model by polynomial

□ If overfitting:

➢ Add more data

➢ Perform regularization

~~XX~~ Sentiment analysis

Example of Logistics Regression \Rightarrow

BOV \rightarrow bag of words

we lost the sequence of words

We can solve it by taking n-gram

the size of each sample is big

Pre processing:-

1- punctuation removal

2- stop word removal

3- case normalization

4- remove root word

the length of sample will be same for all samples, and it will be vector of what word is there or not

* margin :-

In the binary classification problem, if we want to use linear regression, we will give a threshold value and the probability that higher than this will be positive, otherwise negative. Normally, it is 50%:

if $y \geq 0.5$:

$y = +ve$

else:

$y = -ve$

margin = 0.3

if $y \geq 0.8$:

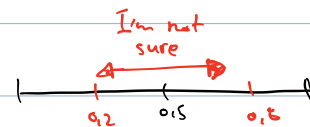
$y = +ve$

else $y \leq 0.2$:

$y = -ve$

else:

I'm not sure



* having margin = 0.45, it doesn't mean you are 95% confident

* to get the most positive and most negative words:-

sort the w vector. then take the highest and lowest words

because word with most positive has most magnitude of w

XX Multiclass

logistic regression for every class

* SoftMax $\frac{e^{z_i}}{\sum_j e^{z_j}}$ $\rightarrow z_i = w \cdot x + b$
do one vs All classification \Rightarrow if you have 5 classes, you will get 5 classifiers

XX Imbalance data sets:-

accuracy is not a good indicator for it
when a class has much more data than another

* normally:- the class with fewer data is considered +ve

XX Recall and Precision

		Actual	
		+ve	-ve
Predict	+ve	TP	FP
	-ve	FN	TN

Recall is indicated by a green circle around TP and FN. Precision is indicated by an orange circle around TP and FP.

accuracy = $\frac{TP + TN}{all}$

precision = $\frac{TP}{TP + FP}$ recall = $\frac{TP}{TP + FN}$

for regression: MSE, ASE

Precision goes opposite recall

XX F-B score \rightarrow combine P and R

$F_B = (1 + B^2) \frac{P \times R}{B^2 P + R}$ $\rightarrow [0, 1]$

calculate the mean with different weights

without
Preferring
anyone

$$F_1 = 2 \frac{P \times R}{P + R}$$

$\beta = [0, 1) \Rightarrow$ Prefer Recall

$\beta = 1 \Rightarrow$ without Preferring

$\beta = (1, 2] \Rightarrow$ Prefer Precision

✗ P and R for multiclass

using confusion matrix

		Actual		
		A	B	C
Prediction	A	10	2	1
	B	1	7	2
	C	3	2	15

TP

$$P_B = \frac{7}{7+2+1}$$

$$P_C = \frac{15}{15+2+3}$$

$$R_B = \frac{7}{7+2+2}$$

$$R_C = \frac{15}{15+2+1}$$

✗ How to deal with Imbalance Data

* of samples		
class A	class B	
180	20	

① Data Level \rightarrow on train data

① under sampling \rightarrow select ²⁰ random samples from class A

② over sampling \rightarrow ① make copies of class B to get 180 sample

③ hybrid ① and ② with \rightarrow ① SMOTE \Rightarrow create new samples between samples

	sleep	study	grade
	6	6	pass
	5	6	pass
new sample \rightarrow	5.5	6	pass

④ change the weight of class in cost function

$$J = \frac{1}{n} \sum -\log(\log \hat{y}) - (1-y) \log(1-\hat{y})$$

~~XX~~ How to deal with categorical features:-

One-hot encoding → + avoid weighted features

- adding more features

- will not work if you have 2 animals in one image

Embedding

* Zip-code should be categorical to avoid weight