

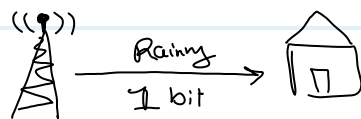
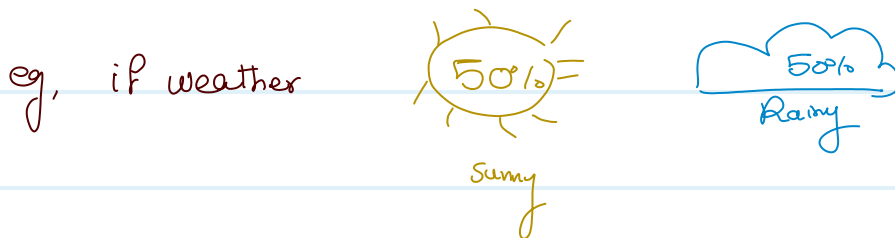
in Machine learning  $\Rightarrow$

Cross-Entropy mostly used as cost function  
in training the classifier

Come From Information theory (Claude Shannon) :

in theorem :

to transfer 1 bit of information = Uncertainty divide by 2



if send 1 bit it divide uncertainty by 2

$\therefore$  there's two options, now there's just one

$\therefore$  mean: it send you in 1 bit of useful info even if it send 8 bits

eg, what if there's 8 states of weather equally likely  
(Sunny, Cloudy, Rainy, ...) )

when station send you information  $\Rightarrow$  it divide your uncertainty  
by factor of  $8=2^3$



meaning ③ bits are the actual useful information

it's easy to calculate  $\# \text{ useful bits} = \log_2 \left( \text{uncertainty Reduction Factor} \right)$

$$= \log_2 (8)$$

eg, what if probability not equally likely





if   $\xrightarrow{\text{Raining}}$    $\Rightarrow$  this mean your uncertainty drop By factor of  $\underline{4} = 2^2$

Notes:  $\text{uncertainty Reduction} = \text{inverse of probability of event}$

$$= \frac{1}{p}$$

so  $\# \text{ useful bits} = \log_2 \left( \text{uncertainty Reduction} \right) = \log_2 \left( \frac{1}{p} \right) = -\log_2 (p)$

if   $\xrightarrow{\text{Sunny}}$    $\Rightarrow$   $\text{uncertainty Reduction} = \frac{1}{0.75} = 1.33$   
 $\# \text{ useful bits} = -\log_2 (0.75) = 0.41$

Not so much useful  $\approx$  as I am already 75%.

sure that's sunny  
Before you tell me

$\Rightarrow$  Note /  $\# \text{ useful bits}$  / can be translated also as /  $\# \text{ useful info.}$  /

What the average of useful information?

↳ as there's 75% it's sunny & it'll send (0.41) useful info  
 ↳ also there's 25% it's Rainy & it'll send (2) useful info.

$$\begin{aligned} \text{so \# avg info} &= 0.75 (0.41) + 0.25 (2) = 0.81 \text{ bits} \\ &= -P_S \log(P_S) - P_R \log(P_R) \end{aligned}$$

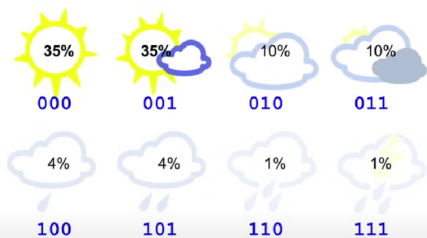
= Entropy  $\Rightarrow$  nice Measure of Uncertain  
Events are

Entropy =  $H(\vec{P}) = -\sum p_i \log(p_i)$  = how much on avg information you get  $\rightarrow$  when you sample event from distrib.  $\vec{P}$

= how unpredictable the probability distribution

Cross Entropy = avg message length (that actually sent)

(1)



**Entropy**  
 $= 0.35 \log_2(0.35) + \dots + 0.01 \log_2(0.01)$   
 $= 2.23 \text{ bits}$



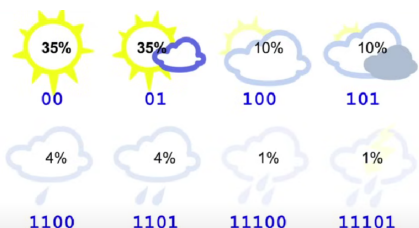
$$\begin{aligned} \text{Cross Entropy} &= 0.35 * 3 + 0.35 * 3 + 0.1 * 3 + \dots \\ &= 3 \text{ bits} \end{aligned}$$

Other words: We sent 3 bits on avg

But also 2.23 on avg are useful

②

4

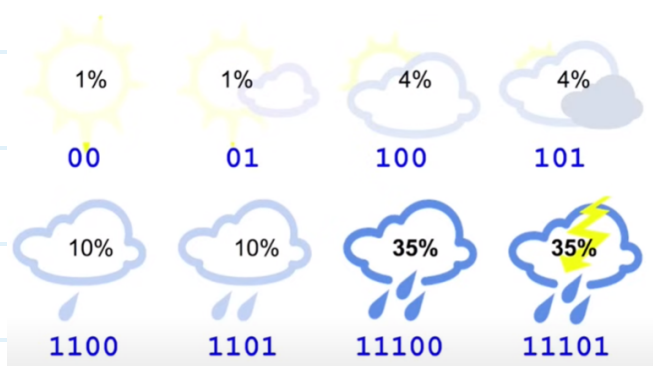


$$35\% \times 2 + 35\% \times 2 + 10\% \times 3 + 10\% \times 3 + 4\% \times 4 + 4\% \times 4 + 1\% \times 5 + 1\% \times 5 = 2.42 \text{ bits}$$

↑  
Cross-Entropy

⇒ We can do Better By changing Encoding

③ What if we use Encoding in different location with different distrib.



$$\text{Cross-Entropy} = \underline{\underline{4.58}} \text{ bits}$$

Why? as we send ② bits for Sunny weather  $\approx$  we predicted that uncertainty Reduc. knowing it's Sunny = 4

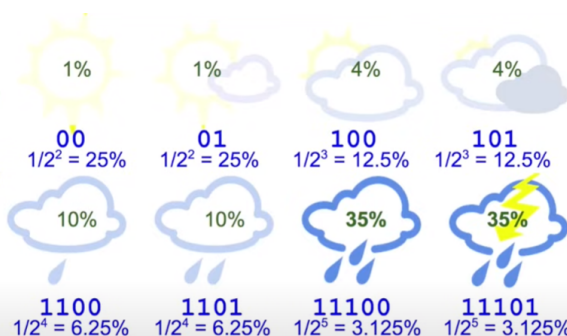
$\approx$  meaning we predicted 25% Sunny

Very Wrong assumption/predication

So our predicated probability =  $\frac{1}{\text{uncertainty Red.}} = \frac{1}{2^{\# \text{bits}}} = 2$

p = true distribution

q = predicted distribution



$$\text{Cross Entropy} = H(\vec{p}; \vec{q})$$

$$= -\sum_{i=1}^I p_i \log_2(q_i)$$

Notes : - if Cross Entropy = Entropy  $\Rightarrow$  very efficient

- if Cross Entropy  $\gg$  Entropy  $\Rightarrow$  Make very wrong Assumption

$$\begin{aligned} \text{"Cross Entropy"} - \text{"Entropy"} &= \text{Relative Entropy} \\ &= \text{Kullback-Leibler Divergence} \\ &= \text{KL Divergence} \end{aligned}$$

OR Better :

$$\text{Cross Entropy} = \text{Entropy} + \text{KL Divergence}$$

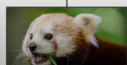
OR :

$$D_{KL}(P \parallel Q) = H(P, Q) - H(P)$$

Cross Entropy as Cost Function :

True distribution:	0%	0%	0%	0%	100%	0%	0%
	Cat	Dog	Fox	Cow	Red Panda	Bear	Dolphin
Predicted distribution:	2%	30%	45%	0%	25%	5%	0%

Classifier



**Cross-Entropy Loss:**

$$H(p, q) = -\sum_i p_i \log(q_i)$$

$$= -\log(0.25) = 1.386$$

Since it's One hot Encoding

then 'Cross Entropy loss' =  $-\log(0.25)$

if it predicted "1"  $\Rightarrow$  loss = 0

if it predicted "0"  $\Rightarrow$  Loss = 1

