

We want to find the joint probability distribution of x, t

finding $p(x, t)$ is very difficult to find, since we have limited data points

The moment we figure out $p(z)$, where z is your data we can predict anything

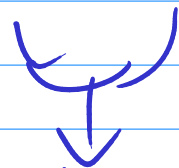
Now if we, while finding $p(z)$, we find $q(z)$
How different is $q(z)$ from $p(z)$

We assumed initially that $t \sim N(y(x), \sigma^2)$
 $p(x, t)$ could be assumed that way

- * When x takes a very likely value, it won't have much info
- * But if it contains a value unlikely to happen

$$① \leftarrow h(x=x) \propto \frac{1}{p(x=x)}$$

$$② \leftarrow h(x=x \wedge x=y) = h(x=x) + h(x=y)$$



independent events

$$③ \leftarrow p(x=x \wedge x=y) = p(x=x) p(x=y)$$

$$h(x) = -(\log(p(x)))$$

$$h(x, y) = -(\log(p(x)p(y)))$$

$$= -(\log(p(x)) - \log(p(y)))$$

$$= h(x) + h(y) \rightarrow \textcircled{3} \text{ satisfied}$$

$$h(x) \propto \frac{1}{p(x)} \text{ isn't completely satisfied but kinda}$$

$$h(x) = -(\log(p(x)))$$

$$\log\left(\frac{1}{p(x)}\right)$$

	Uniform	
x	1	0
p(x)	0.52	0.48

	non-uniform	
x	1	0
p(x)	0.1	0.9

$$x = 1, 2, 3, \dots, 100$$

we need

this to understand Decision Tree

Our average information is

$$E(\text{Info}(x)) = -\sum p_i \log p_i$$

which is Entropy