

N / A / N / O / D / E / G / R / E / E

지도학습 알고리즘

07. Information Theory

Logistic regression

- ✓ Negative logarithm of the likelihood, which gives the cross-entropy error function

$$\underline{E(\mathbf{w})} = -\log p(\mathbf{t} | \mathbf{w}) = -\sum_{n=1}^N \{ \underline{t_n \log y_n} + \underline{(1 - t_n) \log(1 - y_n)} \}$$

m'm.

P.f.
예를. $y_n = P(C_1 | \mathbf{x}_n) \leftarrow$
 $1 - y_n = P(C_2 | \mathbf{x}_n) \leftarrow$
 $\rightarrow \underline{t_n} = C_1 \text{ 이면 } +1, C_2 \text{ 이면 } 0.$
 $\rightarrow 1 - t_n = C_1 \text{ 이면 } 0, C_2 \text{ 이면 } +1.$

- ✓ Taking the gradient of the error function, we obtain

$$\nabla E(\mathbf{w}) = \sum_{n=1}^N (y_n - t_n) \mathbf{x}_n$$

참 확률변수

\downarrow
 $\left\{ \begin{array}{l} \underline{t_n = 1} \text{ 인 경우} \\ \underline{t_n = 0} \end{array} \right. \leftarrow \left\{ \begin{array}{l} \underline{P(C_1 | \mathbf{x}_n) = 1} \\ \underline{P(C_1 | \mathbf{x}_n) = 0} \end{array} \right.$

예를.
확률변수

\downarrow

Entropy

- ✓ Discrete random variable

X

- ✓ Probability mass function

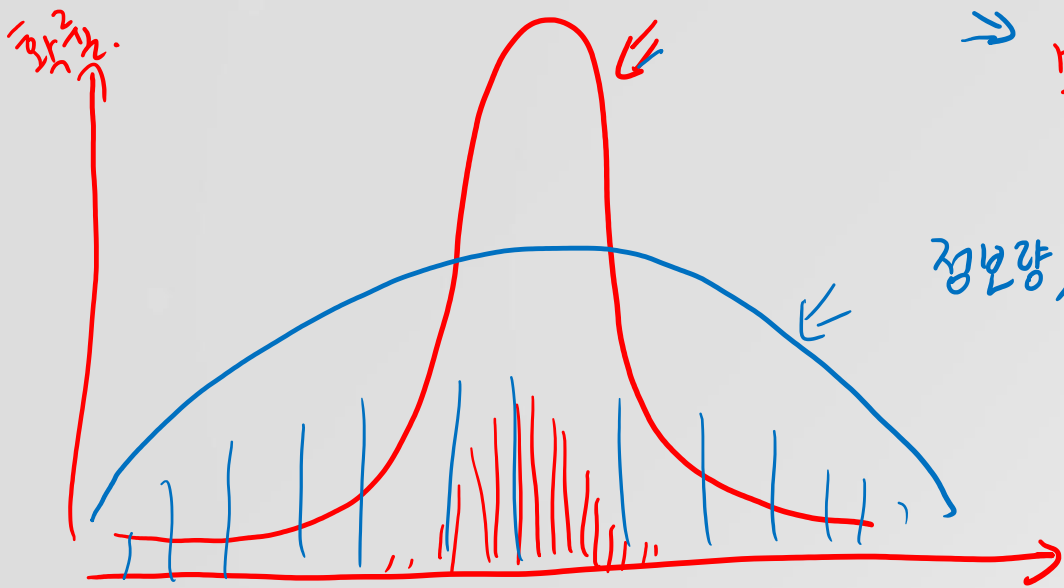
$p(x)$

- ✓ Entropy = 평균 정보량 *평균 무질서도.*

$$H(p) = \underbrace{\mathbb{E}}_{\text{평균}}[\underbrace{-\log p}] = \boxed{-\sum p(x) \log p(x)}$$

Entropy와 불확실성, 그리고 정보량

Entropy = 무질서도, 얼마나 무작위하냐.



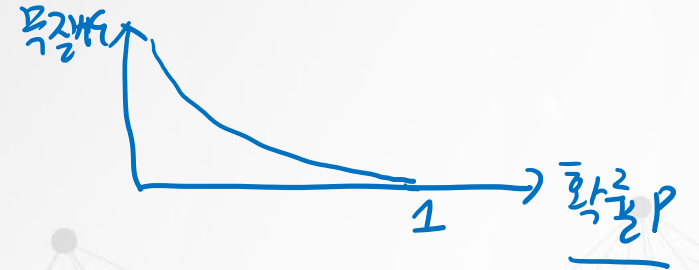
→ Entropy. 무질서도.

정반량, 무질서도.

비발간색 분포

$$\underline{-\log P}$$

< 파란색 분포.



Entropy. 평균 무질서도.

$$E[-\log P] = \sum_x \underline{-p(x) \log p(x)}$$

$$X \sim p(x)$$

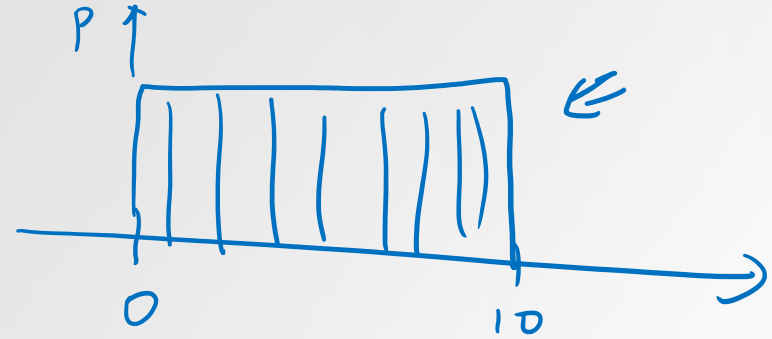
기대값.

$$E[x] = \sum x p(x)$$

Entropy와 불확실성, 그리고 정보량

✓ Entropy가 최대인 확률 분포

- Discrete: uniform distribution
- Continuous: Gaussian distribution



신경망 → cross-entropy
softmax → 확률값 ↗

expectation-maximization
variational approximation ← relative entropy

효율적 추론 ← efficient estimator
Cramer-Rao lower bound

Cross-entropy and relative entropy

- ✓ Cross-entropy

$$H(p, q) = -\mathbb{E}_p[\log q]$$

Entropy $E[-\log p(x)] = -\sum p(x) \log p(x)$

cross-entropy. $H(p, q) = -\mathbb{E}_p[\log q]$

$$= -\sum p(x) \log q(x)$$

- ✓ Relative entropy

, KL divergence.

$$\mathcal{D}_{\text{KL}}(p||q) = \mathbb{E}_p \left[\log \frac{p}{q} \right] = \sum p(x) \log \frac{p(x)}{q(x)} \quad \boxed{\geq 0}$$

- ✓ 두 분포가 같을 때, relative entropy = 0

$$\mathcal{D}_{\text{KL}}(p||q) = 0 \iff p(x) = q(x)$$

두 확률 분포의 Similarity 각을 수직
비슷한 값

p, q_1, q_2 $\mathcal{D}_{\text{KL}}(q_1||p)$
 $\mathcal{D}_{\text{KL}}(q_2||p)$

Cross-entropy and relative entropy

Entropy, cross-entropy and relative entropy

$$\underbrace{H(p, q)}_{\text{cross } p, q \text{ entropy}} = \underbrace{H(p)}_{\text{p의 Entropy}} + \underbrace{D_{\text{KL}}(p||q)}_{\substack{\text{q에 대한} \\ \text{p의 relative-entropy}}} \geq 0.$$

$\text{⊖} \quad p=q \text{ 동일할때.}$

$$\min H(p, q) \implies \min D_{\text{KL}}(p||q)$$

\implies 우리가 원하는 $p=q$ 같게,
가능한 유사하게.