Inductive biases - Rob Romijnders - 23.09.2019
github.com/RobRomijnders/overview

$$p(x|y_c, \theta) = \prod_{d=1}^{D} p(x_d|y_c, \theta_{cd})$$

Naive Bayes Classifier

Maximal conditional independence

Minimum cross validation error

Cross validation!

$$\mathcal{D}_1', \mathcal{D}_2', \ldots, \mathcal{D}_M' \sim \mathcal{D}$$
$$p(y^*|x^*, \mathcal{D}) = \frac{1}{M} \sum_m p(y^*|x^*, \mathcal{D}_m')$$

Bootstrap

Resamples

Models

h1 h2 h3 h4

h

$$p(y^*|x^*, D) = \frac{\sum_{(x,y) \in D} y \times k(x, x^*)}{\sum_{(x,y) \in D} k(x, x^*)}$$

Nearest Neighbor classification

Follow the neighbors

Inductive biases

$$x_{\text{real}} \sim P$$
$$c \sim q(c)$$
$$z \sim q(z)$$
$$x_{\text{fake}} = G(c, z)$$
$$y \sim Ber(0.5)$$
$$x = \begin{cases} x_{\text{real}} & \text{if } y = 1 \\ x_{\text{fake}} & \text{if } y = -1 \end{cases}$$

GAN

Minimize $I(X, Y)$

Mutual information

$$-J(q(z)) = H[q(z)] + E_q[\log p(z, \mathcal{D})]$$

Maximum evidence

Minimum description length / free energy

Representation learning

Maximize $I(X, Z)$

$$I(X, Y) = H[Y] - H[Y|X]$$

$$p(\mathcal{D}|H) = \int_\theta p(\mathcal{D}|\theta, H) p(\theta|H) d\theta$$

$$J(q(z)) = E_q[-\log p(\mathcal{D}|z)] + D_{KL}(q(z)||p(z))$$

Z hidden/latent variable

X Observed variable