

NB: this is not a comprehensive list of formulae used in the course.

- Euclidean distance:

$$r_2(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\| = \sqrt{\sum_{i=1}^D (x_i - y_i)^2}$$

cf. $\text{sim}(\mathbf{x}, \mathbf{y}) = \frac{1}{1+r_2(\mathbf{x}, \mathbf{y})}$ as a similarity measure

- Pearson correlation coefficient:

$$\rho(x, y) = \frac{1}{N-1} \sum_{n=1}^N \frac{(x_n - \mu_x)}{\sigma_x} \frac{(y_n - \mu_y)}{\sigma_y}$$

- Bayes Theorem

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$
$$P(C_k|\mathbf{x}) = \frac{p(\mathbf{x}|C_k)P(C_k)}{p(\mathbf{x})} = \frac{p(\mathbf{x}|C_k)P(C_k)}{\sum_{k=1}^K p(\mathbf{x}|C_k)P(C_k)}$$

- Bayes decision rule (cf. MAP decision rule)

$$k^* = \arg \max_k P(C_k | \mathbf{x}) = \arg \max_k P(\mathbf{x}|C_k)P(C_k)$$

- Naive Bayes for document classification

(vocabulary: $V = \{w_1, \dots, w_{|V|}\}$, test document: $D = (o_1, \dots, o_L)$)

– Likelihood by Bernoulli document model

$$P(\mathbf{b}|C_k) = \prod_{t=1}^{|V|} [b_t P(w_t | C_k) + (1-b_t)(1-P(w_t | C_k))]$$

– Likelihood by Multinomial document model

$$p(\mathbf{x}|C_k) \propto \prod_{t=1}^{|V|} P(w_t|C_k)^{x_t} = \prod_{i=1}^L P(o_i|C_k)$$

- Univariate Gaussian pdf:

$$p(x | \mu, \sigma^2) = N(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(x - \mu)^2}{2\sigma^2}\right)$$

- Multivariate Gaussian pdf:

$$p(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2} |\boldsymbol{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)$$

Parameter estimation from samples:

$$\hat{\boldsymbol{\mu}} = \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n, \quad \hat{\boldsymbol{\Sigma}} = \frac{1}{N-1} \sum_{n=1}^N (\mathbf{x}_n - \hat{\boldsymbol{\mu}})(\mathbf{x}_n - \hat{\boldsymbol{\mu}})^T$$

NB: N in case of MLE

- Correlation coefficient:

$$\rho(x_i, x_j) = \rho_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}}, \quad \boldsymbol{\Sigma} = (\sigma_{ij})$$

- Logistic sigmoid function:

$$y = g(a) = \frac{1}{1 + \exp(-a)}$$

$$g'(a) = g(a)(1 - g(a))$$

- Softmax activation function (for multiple output nodes):

$$y_k = \frac{\exp(a_k)}{\sum_{\ell=1}^K \exp(a_\ell)}$$