

# Formula Sheet

## Chapter 10: Generalization and Bias-Variance

- Bias-Variance Decomposition:

$$\mathbb{E}[(f_{\mathcal{D}}(X) - f^*(X))^2] = \mathbb{E}_X [(\mathbb{E}_{\mathcal{D}}[f_{\mathcal{D}}(X)] - f^*(X))^2 + \text{Var}_{\mathcal{D}}[f_{\mathcal{D}}(X)]] \quad (1)$$

- Double Descent Phenomenon: Occurs in overparameterized regimes where test error decreases as model capacity increases beyond interpolation threshold.

## Chapter 11: Mixture Models

- Mixture Model Density:

$$p(\mathbf{x}|\boldsymbol{\theta}) = \sum_{k=1}^m w_k p(\mathbf{x}|\boldsymbol{\theta}_k) \quad (2)$$

- EM Algorithm:

$$\text{E-step: } p_t[i, k] = \frac{w_k^{(t)} p(\mathbf{x}_i|\boldsymbol{\theta}_k^{(t)})}{\sum_{j=1}^m w_j^{(t)} p(\mathbf{x}_i|\boldsymbol{\theta}_j^{(t)})} \quad (3)$$

$$\text{M-step: } w_k^{(t+1)} = \frac{1}{n} \sum_{i=1}^n p_t[i, k], \quad \boldsymbol{\theta}_k^{(t+1)} = \text{argmax}_{\boldsymbol{\theta}_k} \sum_{i=1}^n p_t[i, k] \ln p(\mathbf{x}_i|\boldsymbol{\theta}_k) \quad (4)$$

- Gaussian Mixture Updates:

$$\boldsymbol{\mu}_k = \frac{\sum_{i=1}^n p_t[i, k] \mathbf{x}_i}{\sum_{i=1}^n p_t[i, k]}, \quad \boldsymbol{\Sigma}_k = \frac{\sum_{i=1}^n p_t[i, k] (\mathbf{x}_i - \boldsymbol{\mu}_k)(\mathbf{x}_i - \boldsymbol{\mu}_k)^\top}{\sum_{i=1}^n p_t[i, k]} \quad (5)$$

## Chapter 12: Variational Autoencoders (VAEs)

- Evidence Lower Bound (ELBO):

$$\text{ELBO} = \mathbb{E}_{\mathbf{h} \sim q} [\ln p(\mathbf{x}|\mathbf{h}, \mathbf{W})] - D_{\text{KL}}(q(\mathbf{h}|\mathbf{x}) \| p(\mathbf{h})) \quad (6)$$

- Reparameterization Trick:

$$\mathbf{h} = \boldsymbol{\mu}(\mathbf{x}) + \boldsymbol{\sigma}(\mathbf{x}) \odot \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \quad (7)$$

- KL Divergence for Gaussian Encoder:

$$D_{\text{KL}}(q(\mathbf{h}|\mathbf{x}) \| \mathcal{N}(\mathbf{0}, \mathbf{I})) = \frac{1}{2} \sum_{j=1}^d (\sigma_j^2 + \mu_j^2 - 1 - \ln \sigma_j^2) \quad (8)$$

- Conditional VAE ELBO:

$$\text{ELBO}_{\text{cond}} = \mathbb{E}_{\mathbf{h} \sim q} [\ln p(\mathbf{x}|\mathbf{h}, \mathbf{y}, \mathbf{W})] - D_{\text{KL}}(q(\mathbf{h}|\mathbf{x}, \mathbf{y}) \| \mathcal{N}(\mathbf{0}, \mathbf{I})) \quad (9)$$

## Chapter 13: Evaluating Generative Models

- Test Log-Likelihood:

$$\text{Perf}(\theta) = \frac{1}{m} \sum_{\mathbf{x} \in \mathcal{D}_{\text{test}}} \ln p(\mathbf{x}|\theta) \quad (10)$$

- Importance Sampling for VAE Likelihood:

$$p(\mathbf{x}|\mathbf{W}) \approx \frac{1}{m} \sum_{k=1}^m \frac{p(\mathbf{h}_k)}{q(\mathbf{h}_k|\mathbf{x})} p(\mathbf{x}|\mathbf{h}_k, \mathbf{W}), \quad \mathbf{h}_k \sim q(\mathbf{h}|\mathbf{x}) \quad (11)$$

## Chapter 14: Missing Data

- Matrix Completion Objective:

$$\min_{\mathbf{H}, \mathbf{D}} \sum_{i=1}^n \sum_{j \in \mathcal{A}_i} (x_{ij} - \mathbf{h}_i \mathbf{D}_{:,j})^2 \quad (12)$$

- Autoencoder Imputation Loss:

$$\min_{\mathbf{W}, \mathbf{x}, \mathcal{M}_i} \sum_{i=1}^n \|\mathbf{x}_i - f_{\mathbf{W}}(\mathbf{x}_i)\|_2^2 \quad (13)$$

## Chapter 15: Bayesian Methods

- Bayesian Linear Regression Posterior (Multivariate):

$$\boldsymbol{\mu}_n = \boldsymbol{\Lambda}_n^{-1} \mathbf{X}^\top \mathbf{y}, \quad \boldsymbol{\Sigma}_n = \sigma_y^2 \boldsymbol{\Lambda}_n^{-1}, \quad \boldsymbol{\Lambda}_n = \mathbf{X}^\top \mathbf{X} + \lambda \mathbf{I} \quad (14)$$

- Gaussian Process Regression:

$$\mathbb{E}[f(\mathbf{x})] = \mathbf{k}(\mathbf{x}, \mathbf{X})(\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{y} \quad (15)$$

$$\text{Var}[f(\mathbf{x})] = k(\mathbf{x}, \mathbf{x}) - \mathbf{k}(\mathbf{x}, \mathbf{X})(\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{k}(\mathbf{x}, \mathbf{X})^\top \quad (16)$$

- Normal-Inverse-Gamma (NIG) Posterior Updates:

$$\boldsymbol{\Lambda}_n = \mathbf{X}^\top \mathbf{X} + \boldsymbol{\Lambda}_0, \quad \boldsymbol{\mu}_n = \boldsymbol{\Lambda}_n^{-1} (\mathbf{X}^\top \mathbf{y} + \boldsymbol{\Lambda}_0 \boldsymbol{\mu}_0) \quad (17)$$

$$a_n = a_0 + \frac{n}{2}, \quad b_n = b_0 + \frac{1}{2} (\mathbf{y}^\top \mathbf{y} + \boldsymbol{\mu}_0^\top \boldsymbol{\Lambda}_0 \boldsymbol{\mu}_0 - \boldsymbol{\mu}_n^\top \boldsymbol{\Lambda}_n \boldsymbol{\mu}_n) \quad (18)$$