Advanced Machine Learning

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github.com/silvasta/summary-aml

Sigm. $\sigma(x) = \frac{1}{1+e^{-x}}$, $\sigma'(x) = \sigma(x)(1-\sigma(x))$
Variance $\mathbb{E}[(\hat{y} - \mathbb{E}[\hat{y}])^2]$
Logistic $\ell(y,p) = -y \log p - (1-y)\log(1-p)$
Cross-Entropy loss $\mathcal{L} = -\sum_i y_i \log(\hat{y}_i)$
Sherman-Morrison: $(A+UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1}+VA^{-1}U)^{-1}VA^{-1}$
Ridge SVD: $X\beta^r = UD(D^2+\lambda I)^{-1}DU^TY$. $||\beta^r||^2 = \sum \frac{\gamma_i v_i^2}{(\gamma_i+\lambda)^2}$
GDA to Logistic: $w = \Sigma^{-1}(\mu_+ - \mu_-)$, $w_0 = \frac{1}{2}\mu_-^T\Sigma^{-1}\mu_- - \frac{1}{2}\mu_+^T\Sigma^{-1}\mu_+$
Bootstrap: Prob not picked $\approx$ 0.368. $Err^{.632} = 0.368 \cdot Err_{boot} + 0.632 \cdot Err^{(1)}$
Robbins-Monro: $\sum \alpha_n = \infty, \sum \alpha_n^2 < \infty$.
BIC: $p(X) \approx p(X|\theta_{ML})n^{-k/2}$. $BIC = -\ln p(X|\theta_{ML}) + \frac{k}{2}\ln n$

1 Representations

1.1 Empirical Risk Minimization (ERM)

$R(f) = \mathbb{E}_{(x,y)\sim\mathcal{D}}[\ell(f(x),y)]$ $\mathcal{D}$ data distrib.
Empirical Risk: $\hat{R}(f) = \frac{1}{n}\sum_{i=1}^n \ell(f(x_i),y_i)$
CRLB Lower bound on variance of unbiased estimators $\hat{\theta}$ of param θ.
Trick CRLB achieved iff estimator is efficient, Multivariate: Use inverse Fisher matrix.
Hint for exams Always check unbiasedness first; compute via Hessian or score function.

1.2 Formulas: Fisher Information

$\mathbb{E}\left[\left(\frac{\partial}{\partial\theta}\log p(X|\theta)\right)^2\right] = -\mathbb{E}\left[\frac{\partial^2}{\partial\theta^2}\log p(X|\theta)\right]$
Multivariate ($\theta \in \mathbb{R}^k$): Matrix form
$[I(\theta)]_{ij} = \mathbb{E}\left[\frac{\partial \log p}{\partial\theta_i}\frac{\partial \log p}{\partial\theta_j}\right] = -\mathbb{E}\left[\frac{\partial^2 \log p}{\partial\theta_i\partial\theta_j}\right]$
Trick: For iid $X_1,..,X_n$, $I_n(\theta) = nI(\theta)$
Example: Gaussian $\mathcal{N}(\mu,\sigma^2=1)$
Score: $\frac{\partial \log p}{\partial\mu} = x-\mu$. Fisher: $I(\mu)=1$.

1.3 Rao-Cramér Lower Bound (CRLB)

For unbiased $\hat{\theta}(X)$: Var$(\hat{\theta}) \geq \frac{1}{I(\theta)}$ (scalar)
Multiv. Var$(g(\hat{\theta})) \geq \left(\frac{\partial g}{\partial\theta}\right)^T I(\theta)^{-1}\left(\frac{\partial g}{\partial\theta}\right)$
General CRLB: Cov$(\hat{\theta}) \succeq I(\theta)^{-1}$
Equality if $\hat{\theta} = a(\theta)\cdot s(X) + b(\theta)$, $s(X)$ is suff. stat. (Gauss. sample mean givs CRLB)

1.4 Calculus Recipes & Derivations

- Compute $I(\theta)$: (1) Write $\log L(\theta|X) = \sum \log p(x_i|\theta)$. (2) Take 2nd deriv or score sq. (3) Expectation over $p(X|\theta)$.
- For representations: Info in feature space: $I_\phi(\theta) = \mathbb{E}[\phi(X)^T\phi(X)]^{-1}$
- Exam hint: CRLB bounds learning rates (e.g., variance in param est. for neural nets).

2 Gaussian Processes (GPs)

Distribution over functions $f(\mathbf{x})$, defined by mean function $m(\mathbf{x}) = 0$ (zero-mean prior) and covariance (kernel) function $k(\mathbf{x},\mathbf{x}')$.
For any finite set of inputs $\mathbf{X} = [\mathbf{x}_1,\ldots,\mathbf{x}_n]$, $\mathbf{f} = [f(\mathbf{x}_1),\ldots,f(\mathbf{x}_n)]^T \sim \mathcal{N}(\mathbf{0},\mathbf{K})$, where $\mathbf{K}_{ij} = k(\mathbf{x}_i,\mathbf{x}_j)$.
Prior: Multivariate Gaussian $\mathcal{N}(\boldsymbol{\mu},\boldsymbol{\Sigma})$ with $\boldsymbol{\mu} = \mathbf{0}$, $\boldsymbol{\Sigma} = \mathbf{K} + \sigma_n^2\mathbf{I}$ (noisy)
Posterior: $\mathbf{y} = \mathbf{f} + \boldsymbol{\epsilon}$, $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0},\sigma_n^2\mathbf{I})$.
Joint: $\begin{bmatrix}\mathbf{y}\\ f_*\end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix}\mathbf{K}+\sigma_n^2\mathbf{I} & \mathbf{k}_*\\ \mathbf{k}_*^T & k(\mathbf{x}_*,\mathbf{x}_*)\end{bmatrix}\right)$
$f_*|\mathbf{X},\mathbf{y},\mathbf{x}_* \sim \mathcal{N}(\mu_*,\sigma_*^2)$, $\mu_* = \mathbf{k}_*^T(\mathbf{K}+\sigma_n^2\mathbf{I})^{-1}\mathbf{y}$, $\sigma_*^2 = k(\mathbf{x}_*,\mathbf{x}_*) - \mathbf{k}_*^T(\mathbf{K}+\sigma_n^2\mathbf{I})^{-1}\mathbf{k}_*$

3 Ensemble Methods

3.1 Bagging (Bootstrap Aggregating)

Average B models: $\hat{f}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^B \hat{f}_b(\mathbf{x})$
Reduction: Var$(\hat{f}) \approx \frac{1}{B}$ Var if uncorrelated
Random Forest: Bagging + random feature
Importance $I(f) = \sum_{\text{nodes}} \Delta\text{impurity}\cdot p(\text{node})$

3.2 Boosting

Sequential, weight misclassified points.
Final: $H(\mathbf{x}) = \text{sign}\left(\sum_m \alpha_m h_m(\mathbf{x})\right)$, $\alpha_m = \frac{1}{2}\log\frac{1-\epsilon_m}{\epsilon_m}$. Reduces bias.
AdaBoost
Weights $w_i^{(t+1)} = w_i^{(t)}\exp(-\alpha_t y_i h_t(\mathbf{x}_i))$, normalized. $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$, where ϵ_t = weighted error.
Error bound: $\epsilon \leq 2^M\prod_m\sqrt{\epsilon_m(1-\epsilon_m)}$.
Gradient Boosting min $L = \sum_i l(y_i,F(\mathbf{x}_i))$, update $F_m = F_{m-1} + \nu h_m$, where h_m fits pseudo-residuals $r_{im} = -\frac{\partial l}{\partial F_{m-1}(\mathbf{x}_i)}$.

4 Support Vector Machines (SVMs)

Primal: min $\frac{1}{2}\|\mathbf{w}\|^2$ s.t. $y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1\ \forall i$
Dual: max $\sum_i\alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j \mathbf{x}_i^T\mathbf{x}_j$ s.t. $\alpha_i \geq 0$, $\sum_i \alpha_i y_i = 0$ Margin: $\gamma = \frac{2}{\|\mathbf{w}\|}$
Decision: $f(\mathbf{x}) = \text{sign}\left(\sum_i \alpha_i y_i \mathbf{x}_i^T\mathbf{x} + b\right)$
Support vectors: Points w. $\alpha_i > 0$ (on margin)

4.1 Soft-Margin SVM

Primal: min $\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i\xi_i$
s.t. $y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0$
Hinge loss: $\ell(y,\hat{y}) = \max(0, 1-y\hat{y})$.
Dual: Same as hard-margin but $0 \leq \alpha_i \leq C$.
C trades bias/var. large $C \to$ hard-margin
Kernel Trick Replace $\mathbf{x}_i^T\mathbf{x}_j$ with $k(\mathbf{x}_i,\mathbf{x}_j)$

- Polynomial: $k(\mathbf{x},\mathbf{z}) = (\mathbf{x}^T\mathbf{z}+c)^d$
- RBF: $k(\mathbf{x},\mathbf{z}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{z}\|^2}{2\sigma^2}\right)$
- Matérn: $k(r) = \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}r}{\ell}\right)^\nu K_\nu\left(\frac{\sqrt{2\nu}r}{\ell}\right)$ ($\nu = 3/2$ or $5/2$ for smoothness).

Mercer's condition Kernel matrix ≥ 0 (PSD)

5 Neural Networks: Basics

5.1 Propagation

Forward: $z^l = W^la^{l-1} + b^l$, $a^l = \sigma(z^l)$
Backward: $\delta^L = \nabla_a L \odot \sigma'(z^L)$, $\delta^l = (W^{l+1})^T\delta^{l+1} \odot \sigma'(z^l)$
Weight update: $\frac{\partial L}{\partial W^l} = \delta^l(a^{l-1})^T$

6 Attention Mechanisms

Attention$(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$
Q/K/V: Linear projections of input. Scaled for stability (prevents large dot-products).

6.1 Multi-Head Attention

Concat(head$_1$, .., head$_h$)W^O, head$_i$ = Attention(QW_i^Q, KW_i^K, VW_i^V) - h heads project to subspaces (e.g., h=8). - Advantage: Captures multiple dependency types.

7 Transformers

Architecture: Encoder (self-attn + FFN) stack; Decoder (masked self-attn + enc-dec attn + FFN) stack. - FFN: Two linear layers with ReLU: FFN$(\mathbf{x}) = \max(0, \mathbf{x}\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2$. - Residual: $\mathbf{x} \leftarrow \mathbf{x} + \text{Sublayer}(\mathbf{x})$. LayerNorm after.
Positional Encoding Add to input embeddings.
$\text{PE}_{(pos,2i|+1)} = \sin | \cos \left(\frac{pos}{10000^{2i/d}}\right)$
Allows order awareness; fixed or learned.

8 Computer Vision

8.1 Convolutional Neural Networks (CNNs)

Discrete Convolution (2D)
Input I: (H,W,C), Kernel K: $(k_h \times k_w \times C)$
$O[i,j] = \sum_{m=0}^{k_h-1}\sum_{n=0}^{k_w-1}\sum_{c=1}^{C} I[i+m,j+n,c]\cdot K[m,n,c] + b$, p = padding, s = stride:
Output size: $\lfloor(H-k_h+2p)/s\rfloor + 1$,
Pooling (Max/Avg): Reduces dims, e.g., max-pool: $O[i,j] = \max_{m,n} I[i\cdot s+m, j\cdot s+n]$.
Backpropagation in CNNs: Gradients via chain rule. For conv layer: - Weight grad: $\frac{\partial\mathcal{L}}{\partial K[m,n,c]} = \sum_{i,j}\frac{\partial\mathcal{L}}{\partial O[i,j]}\cdot I[i+m,j+n,c]$.
- Input grad: Rotate kernel 180° and convolve with output grad.

9 Graph Neural Networks (GNNs)

9.1 Basics & Notation

Graph $G = (V,E)$, $|V| = n$ nodes, adjacency matrix $\mathbf{A} \in \{0,1\}^{n\times n}$ (symmetric for undirected). Feature matrix $\mathbf{X} \in \mathbb{R}^{n\times d}$ (node features). Degree matrix $\mathbf{D}$ = diad$(\sum_j A_{ij})$.
Normalized adjacency: $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ (self-loops), $\hat{\mathbf{A}} = \mathbf{D}^{-1/2}\tilde{\mathbf{A}}\mathbf{D}^{-1/2}$ (symmetric normalization).
Message passing: Update node v as $h_v^{(l+1)} = \sigma\left(\sum_{u\in\mathcal{N}(v)} m_{u\to v}^{(l)}\right)$, where m aggregates

neighbor info.

9.2 Graph Convolutional Network (GCN)

Layer: $\mathbf{H}^{(l+1)} = \sigma(\hat{\mathbf{A}}\mathbf{H}^{(l)}\mathbf{W}^{(l)})$, with $\mathbf{H}^{(0)} = \mathbf{X}$.

Spectral view: Approximation of graph Laplacian $\mathbf{L} = \mathbf{D} - \mathbf{A}$, normalized $\hat{\mathbf{L}} = \mathbf{I} - \hat{\mathbf{A}}$.

9.3 Graph Attention Network (GAT)

Attention: $\alpha_{ij} = \text{softmax}_j\left(\text{LeakyReLU}\left(\mathbf{a}^\top[\mathbf{W}h_i \| \mathbf{W}h_j]\right)\right)$

Update: $h_i^{(l+1)} = \sigma\left(\sum_{j\in\mathcal{N}(i)\cup i} \alpha_{ij}\mathbf{W}h_j^{(l)}\right)$.

Multi-head: Concat or average heads.

10 Information Theory

Entropy: $H(X) = -\mathbb{E}_{p(x)}[\log p(x)]$

Joint entropy: $H(X,Y) = -\mathbb{E}[\log p(x,y)]$.

Conditional: $H(Y|X) = H(X,Y) - H(X)$.

Mutual information: $I(X;Y) = H(X) + H(Y) - H(X,Y) = H(X) - H(X|Y) = \text{KL}(p(x,y)\|p(x)p(y)) \geq 0$. Cross-entropy: $H(p,q) = -\mathbb{E}_p[\log q] = H(p) + \text{KL}(p\|q)$.

KL divergence $\text{KL}(p\|q) = \mathbb{E}_p[\log(p/q)] \geq 0$

Tricks: Jensen-Shannon divergence for stability: $\text{JSD}(p\|q) = \frac{1}{2}\text{KL}(p\|m) + \frac{1}{2}\text{KL}(q\|m)$, $m = (p+q)/2$.

11 Anomaly Detection

11.1 Statistical Methods

Z-Score: Score $z_i = \frac{x_i - \mu}{\sigma}$. Anomaly if $|z_i| > \theta$

Mahalanobis Distance Accounts for cov. $D_M(\mathbf{x}) = \sqrt{(\mathbf{x}-\boldsymbol{\mu})^T\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu})}$
Anomaly if $D_M > \theta$ (e.g., from χ^2 dist.).

11.2 Proximity-Based Methods

11.3 Isolation Forest

Randomly partition until isolation. **Anomaly Score**: $s(\mathbf{x}, n) = 2^{-\frac{E(h(\mathbf{x}))}{c(n)}}$, where $h(\mathbf{x})$ = path length, $E(\cdot)$ = avg over trees, $c(n) = 2H(n-1) - \frac{2(n-1)}{n}$ (H = harmonic number). Anomaly if $s \approx 0.5$ (normal) or $s \to 1$ (anomaly). Works well in high dims.

11.4 One-Class SVM

Hyperplane maximizing margin from origin $\min_{\mathbf{w},\xi_i,\rho} \frac{1}{2}\|\mathbf{w}\|^2 + \frac{1}{\nu n}\sum_i \xi_i - \rho$
s.t. $\mathbf{w}^T\phi(\mathbf{x}_i) \geq \rho - \xi_i$

Decision: $f(\mathbf{x}) = \text{sign}(\mathbf{w}^T\phi(\mathbf{x}) - \rho)$. $\nu \in (0,1]$

12 RL & Active Learning

12.1 Markov Decision Processes (MDPs)

$V^\pi(s) = \mathbb{E}_\pi\left[\sum_{t=0}^\infty \gamma^t R(s_t,a_t) \mid s_0 = s\right]$

Action-value $Q^\pi(s,a) = \mathbb{E}_\pi\left[\sum_{t=0}^\infty \gamma^t R(s_t,a_t) \mid s_0 = s, a_0 = a\right]$

Advantage $A^\pi(s,a) = Q^\pi(s,a) - V^\pi(s)$.

Bellman Optimality: $V^*(s) = \max_a \sum_{s',r} P(s',r|s,a)[r + \gamma V^*(s')]$

Discounted Return: $G_t = \sum_{k=t}^\infty \gamma^{k-t}R_{k+1}$.

Exploration ϵ-greedy (random w.p. ϵ), UCB ($a = \arg\max[Q(s,a) + c\sqrt{\frac{\ln t}{N(s,a)}}]$)

Policy Gradient Thm: $\nabla_\theta J(\theta) = \mathbb{E}_\pi[\nabla_\theta \log \pi_\theta(a|s) Q^\pi(s,a)]$

REINFORCE: $\hat{\nabla} J = \sum_t \nabla_\theta \log \pi(a_t|s_t) G_t$. Var. reduct. Subtract baseline $b(s_t) \approx V(s_t)$

Actor-Critic: $A = r + \gamma V(s') - V(s)$.

13 Reproducing Kernel Hilbert Spaces (RKHS)

A Reproducing Kernel Hilbert Space (RKHS) is a Hilbert space $\mathcal{H}$ of functions $f : \mathcal{X} \to \mathbb{R}$ with a kernel $k : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ such that:

- k is positive semi-definite (PSD): For any x_i, the Gram matrix $K_{ij} = k(x_i, x_j) \succeq 0$.
- Reproducing $\langle f, k(x,\cdot)\rangle_\mathcal{H} = f(x)\, \forall f \in \mathcal{H}$.

Counterfactual invariance In causal ML, models invariant under interventions (e.g., do-calculus). For a structural causal model (SCM) $Y = f(X,U)$, counterfactuals ask "What if?" (e.g., $Y_{x'}$ where x' is intervened). Invariance ensures predictions stable across envs.

Moore-Aronszajn Every PSD kernel k defines a unique RKHS where $\text{span}\{k(x,\cdot)\}$ is dense.

Mercer for continuous PSD kernels on compact $\mathcal{X}$, $k(x,x') = \sum_{i=1}^\infty \lambda_i\phi_i(x)\phi_i(x')$, with $\lambda_i \geq 0$, enabling eigen-decomposition.

SVMs K decision $f(x) = \sum \alpha_i y_i k(x_i, x) + b$
GP Prior $f \sim \mathcal{GP}(m,k)$ in RKHS, posterior mean $\bar{f}(x_*) = k_*^\top(K + \sigma^2 I)^{-1}y$

Counterfactuals in ML: Use invariant risk minimization (IRM) to minimize risk invariant to spurious correlations (e.g., Arjovsky et al.).

Solve Use reproducing property for f evaluation: $f(x) = \langle f, k(x,\cdot)\rangle$ Show PSD via Mercer.

Counterfactual Trick: For invariance, compute $P(Y|do(X = x'))$ using causal graphs; compare to observational $P(Y|X)$.

14 Variational Autoencoders (VAEs)

14.1 Evidence Lower Bound (ELBO)

$\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - \text{KL}(q_\phi(z|x)\|p(z))$

15 Non-Parametric Bayesian Methods

15.1 Dirichlet Processes & Non-Param. Bayes

$\sum_{k=1}^\infty \pi_k\delta_{\theta_k}$, $\pi_k = \beta_k\prod_{j=1}^{k-1}(1-\beta_j)$

16 PAC Learning

- **Realizable** $\exists h^* \in \mathcal{H}$ with true risk $L(h^*) = 0$.
- **PAC Learnable**: $\exists$ learner s.t. $\forall$ distributions $\mathcal{D}, \forall\epsilon,\delta > 0$, with prob. $\geq 1-\delta$, outputs h with $L(h) \leq \epsilon$ using $m = m(\epsilon,\delta)$ samples.
- **Agnostic PAC**: No assumption on h^*; minimize excess risk over $\mathcal{H}$.
- **True Risk**: $L(h) = \mathbb{E}_{(x,y)\sim\mathcal{D}}[\ell(h(x),y)]$ (e.g., 0-1 loss: $\ell = \mathbf{1}_{h(x)\neq y}$).
- **Empirical Risk**: $\hat{L}(h) = \frac{1}{m}\sum_{i=1}^m \ell(h(x_i), y_i)$

16.1 VC Dimension & Shattering

- **Shattering**: $\mathcal{H}$ shatters set $S \subseteq \mathcal{X}$ if $|\{\mathbf{y} \in \{0,1\}^{|S|} : \exists h \in \mathcal{H}$ realizes $\mathbf{y}$ on $S\}| = 2^{|S|}$.
- **Growth Function**: $\Pi_\mathcal{H}(m) = \max_{S:|S|=m} |\{h|_S : h \in \mathcal{H}\}| \leq \left(\frac{em}{d}\right)^d$ (Sauer-Shelah, if VC-dim $d < \infty$).
- **VC Dimension** $d = \text{VC}(\mathcal{H})$: Largest $|S|$ s.t. $\mathcal{H}$ shatters S (infinite if no such max).
- **Trick for VC Calc**: Find largest shatterable set (e.g., for half-planes: 3 points not collinear shatter, 4 do not).

Fundamental Thm of PAC (Realizable, Finite $\mathcal{H}$): $m \geq \frac{1}{\epsilon}(\ln|\mathcal{H}| + \ln(1/\delta))$ samples suffice for $L(h) \leq \epsilon$ w.p. $\geq 1-\delta$ via ERM.

Infinite $\mathcal{H}$ (VC-based): For VC-dim d, $m \geq C\frac{d + \ln(1/\delta)}{\epsilon}$ (lower bound); upper: $m = O\left(\frac{d\ln(1/\epsilon) + \ln(1/\delta)}{\epsilon}\right)$.

Agnostic PAC (Uniform Convergence): w.p. $\geq 1-\delta$, $|L(h) - \hat{L}(h)| \leq \sqrt{\frac{2d\ln(em/d) + \ln(2/\delta)}{m}}$

Sample Complexity (Agnostic): $m = O\left(\frac{d\ln(1/\epsilon) + \ln(1/\delta)}{\epsilon^2}\right)$ for excess risk $\leq \epsilon$.

Tricks:

- Use Hoeffding for finite $|\mathcal{H}|$: $\Pr(|L - \hat{L}| > \epsilon) \leq 2|\mathcal{H}|e^{-2m\epsilon^2}$.
- For VC, bound $\Pi_\mathcal{H}(m) \leq \sum_{i=0}^d \binom{m}{i} \leq (em/d)^d$.
- ERM is PAC if $\mathcal{H}$ has finite VC-dim.

Question For a finite hypothesis class $\mathcal{H}$, how many samples n are needed to ensure that with probability $1-\delta$, an ERM hypothesis with zero training error has true risk $R(h) \leq \epsilon$?

Solution We need $P(\exists h \in \mathcal{H}_{bad}$ s.t. $\hat{R}(h) = 0) \leq \delta$. Using Union Bound: $|\mathcal{H}_{bad}|(1-\epsilon)^n \leq |\mathcal{H}|e^{-n\epsilon} \leq \delta$. Take logs: $\ln|\mathcal{H}| - n\epsilon \leq \ln\delta \implies n\epsilon \geq \ln|\mathcal{H}| + \ln(1/\delta)$. Result: $n \geq \frac{1}{\epsilon}(\ln|\mathcal{H}| + \ln(1/\delta))$.

Question Show that $\ln p(x) = ELBO(q) + KL(q(z|x)||p(z|x))$.

Solution $\ln p(x) = \int q(z|x)\ln p(x)dz = \int q(z|x)\ln\frac{p(x,z)}{p(z|x)}dz = \int q(z|x)\ln\frac{p(x,z)q(z|x)}{q(z|x)p(z|x)}dz = \int q(z|x)\ln\frac{p(x,z)}{q(z|x)}dz + \int q(z|x)\ln\frac{q(z|x)}{p(z|x)}dz = ELBO + KL$.

Question Assume $P(Y=1) = P(Y=0) = 0.5$. $X|Y = k \sim \mathcal{N}(\mu_k, \sigma^2 I)$. Show that $P(Y=1|X=x) = \sigma(w^Tx + w_0)$.

Solution Use Bayes: $P(Y=1|x) = \frac{p(x|1)0.5}{p(x|1)0.5 + p(x|0)0.5} = \frac{1}{1+\exp(-\ln\frac{p(x|1)}{p(x|0)})}$. Let $a = \ln\frac{p(x|1)}{p(x|0)} = \ln\frac{\exp(-\frac{1}{2\sigma^2}||x-\mu_1||^2)}{\exp(-\frac{1}{2\sigma^2}||x-\mu_0||^2)} = -\frac{1}{2\sigma^2}[||x-\mu_1||^2 - ||x-\mu_0||^2]$. Expanding terms: $a = \frac{1}{\sigma^2}(\mu_1-\mu_0)^Tx + \frac{1}{2\sigma^2}(\mu_0^T\mu_0 - \mu_1^T\mu_1)$. Thus $w = \frac{\mu_1-\mu_0}{\sigma^2}$ and $w_0 = \frac{||\mu_0||^2 - ||\mu_1||^2}{2\sigma^2}$.