Model Error

Empirical Risk $\hat{R}_D(f) = \frac{1}{n}\sum \ell(y, f(x))$

Population Risk $R(f) = \mathbb{E}_{x,y\sim p}[\ell(y, f(x))]$

It holds that $\mathbb{E}_D[\hat{R}_D(\hat{f})] \leq R(\hat{f})$. We call $R(\hat{f})$ the generalization error.

Bias Variance Tradeoff:
Pred. error = Bias^2 + Variance + Noise

$$\mathbb{E}_D[R(\hat{f})] = \mathbb{E}_x[f^*(x) - \mathbb{E}_D[\hat{f}_D(x)]]^2 + \mathbb{E}_x[\mathbb{E}_D[(\hat{f}_D(x) - \mathbb{E}_D[\hat{f}_D(x)])^2]] + \sigma$$

Bias: how close $\hat{f}$ can get to f^*

Variance: how much $\hat{f}$ changes with D

Regression

Squared loss (convex)

$$\frac{1}{n}\sum(y_i - f(x_i))^2 = \frac{1}{n}||y - Xw||_2^2$$
$$\nabla_w L(w) = 2X^\top(Xw - y)$$

Solution: $\hat{w} = (X^\top X)^{-1}X^\top y$

Regularization

Lasso Regression (sparse)

$$\underset{w\in\mathbb{R}^d}{\text{argmin}} ||y - \Phi w||_2^2 + \lambda ||w||_1$$

Ridge Regression

$$\underset{w\in\mathbb{R}^d}{\text{argmin}} ||y - \Phi w||_2^2 + \lambda ||w||_2^2$$
$$\nabla_w L(w) = 2X^\top(Xw - y) + 2\lambda w$$

Solution: $\hat{w} = (X^\top X + \lambda I)^{-1}X^\top y$

large $\lambda \Rightarrow$ larger bias but smaller variance

Cross-Validation

- For all folds $i = 1, \dots, k$:
  - Train $\hat{f}_i$ on $D' - D'_i$
  - Val. error $R_i = \frac{1}{|D'_i|}\sum \ell(\hat{f}_i(x), y)$
- Compute CV error $\frac{1}{k}\sum_{i=1}^k R_i$
- Pick model with lowest CV error

Gradient Descent

Converges only for convex case.

$$w^{t+1} = w^t - \eta_t \cdot \nabla\ell(w^t)$$

For linear regression:

$$||w^t - w^*||_2 \leq ||I - \eta X^\top X||_{op}^t ||w^0 - w^*||_2$$

$\rho = ||I - \eta X^\top X||_{op}^t$ conv. speed for const. η.

Opt. fixed $\eta = \frac{2}{\lambda_{\min} + \lambda_{\max}}$ and max. $\eta \leq \frac{2}{\lambda_{\max}}$.

Momentum: $w^{t+1} = w^t + \gamma\Delta w^{t-1} - \eta_t \nabla\ell(w^t)$

Learning rate η_t guarantees convergence if $\sum_t \eta_t = \infty$ and $\sum_t \eta_t^2 < \infty$

Classification

Zero-One loss not convex or continuous

$$\ell_{0-1}(\hat{f}(x), y) = \mathbb{I}_{y \neq \text{sgn}\hat{f}(x)}$$

Logistic loss $\log(1 + e^{-y\hat{f}(x)})$

$$\nabla\ell(\hat{f}(x), y) = \frac{-y_i x_i}{1 + e^{y_i \hat{f}(x)}}$$

Hinge loss $\max(0, 1 - y\hat{f}(x))$

Softmax $p(1|x) = \frac{1}{1+e^{-\hat{f}(x)}}$, $p(-1|x) = \frac{1}{1+e^{\hat{f}(x)}}$

Multi-Class $\hat{p}_k = e^{\hat{f}_k(x)} / \sum_{i=1}^K e^{\hat{f}_j(x)}$

Linear Classifiers

$f(x) = w^\top x$, the decision boundary $f(x) = 0$.

If data is lin. sep., grad. desc. converges to

Maximum-Margin Solution:

$$w_{MM} = \text{argmax margin}(w) \text{ with } ||w||_2 = 1$$

Where $\text{margin}(w) = \min_i y_i w^\top x_i$.

Support Vector Machines

Hard SVM

$$\hat{w} = \min_w ||w||_2 \text{ s.t. } \forall i\ y_i w^\top x_i \geq 1$$

Soft SVM allow "slack" in the constraints

$$\hat{w} = \min_{w,\xi} \frac{1}{2}||w||_2^2 + \lambda \sum_{i=1}^n \underbrace{\max(0, 1 - y_i w^\top x_i)}_{\text{hinge loss}}$$

Metrics

Choose $+1$ as the more important class.

	True Class $y=+1$	True Class $y=-1$
Prediction $f(x)=+1$	TP	FP
Prediction $f(x)=-1$	FN	TN

error$_1$/FPR : $\frac{\text{FP}}{\text{TN + FP}}$

error$_2$/FNR : $\frac{\text{FN}}{\text{TP + FN}}$

Precision : $\frac{\text{TP}}{\text{TP + FP}}$

TPR / Recall : $\frac{\text{TP}}{\text{TP + FN}}$

AUROC: Plot TPR vs. FPR and compare different ROC's with area under the curve.

F1-Score: $\frac{2\text{TP}}{2\text{TP + FP + FN}}$, Accuracy : $\frac{\text{TP + TN}}{\text{P + N}}$

Goal: large recall and small FPR.

Kernels

Parameterize: $w = \Phi^\top\alpha$, $K = \Phi\Phi^\top$

A kernel is **valid** if K is sym.: $k(x,z) = k(z,x)$ and psd: $z^\top Kz \geq 0$

lin.: $k(x,z) = x^\top z$, **poly.**: $k(x,z) = (x^\top z + 1)^m$

rbf: $k(x,z) = \exp(-\frac{||x-z||_\alpha}{\tau})$

$\alpha = 1 \Rightarrow$ laplacian kernel

$\alpha = 2 \Rightarrow$ gaussian kernel

Kernel composition rules

$k = k_1 + k_2$, $k = k_1 \cdot k_2$ $\forall c > 0.\ k = c \cdot k_1$, $\forall f$ convex. $k = f(k_1)$, holds for polynoms with pos. coefficients or exp function.

$\forall f.\ k(x,y) = f(x)k_1(x,y)f(y)$

Mercers Theorem: Valid kernels can be decomposed into a lin. comb. of inner products.

Kern. Ridge Reg. $\frac{1}{n}||y - K\alpha||_2^2 + \lambda\alpha^\top K\alpha$

KNN Classification

- Pick k and distance metric d
- For given x, find among $x_1, \dots, x_n \in D$ the k closest to $x \rightarrow x_{i_1}, \dots, x_{i_k}$
- Output the majority vote of labels

Neural Networks

w are the weights and $\varphi : \mathbb{R} \mapsto \mathbb{R}$ is a nonlinear **activation function**: $\phi(x,w) = \varphi(w^\top x)$

ReLU: $\max(0,z)$, **Tanh:** $\frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)}$

Sigmoid: $\frac{1}{1+\exp(-z)}$

Universal Approximation Theorem: We can approximate any arbitrary smooth target function, with 1+ layer with sufficient width.

Forward Propagation

Input: $v^{(0)} = [x; 1]$ Output: $f = W^{(L)}v^{(L-1)}$

Hidden: $z^{(l)} = W^{(l)}v^{(l-1)}$, $v^{(l)} = [\varphi(z^{(l)}); 1]$

Backpropagation

Non-convex optimization problem:

$$(\nabla_{W^{(L)}}\ell)^T = \frac{\partial\ell}{\partial W^{(L)}} = \frac{\partial\ell}{\partial f}\frac{\partial f}{\partial W^{(L)}}$$
$$(\nabla_{W^{(L-1)}}\ell)^T = \frac{\partial\ell}{\partial W^{(L-1)}} = \frac{\partial\ell}{\partial f}\frac{\partial f}{\partial z^{(L-1)}}\frac{\partial z^{(L-1)}}{\partial W^{(L-1)}}$$
$$(\nabla_{W^{(L-2)}}\ell)^T = \frac{\partial\ell}{\partial W^{(L-2)}} = \frac{\partial\ell}{\partial f}\frac{\partial f}{\partial z^{(L-1)}}\frac{\partial z^{(L-1)}}{\partial z^{(L-2)}}\frac{\partial z^{(L-2)}}{\partial W^{(L-2)}}$$

Only compute **the gradient**. Rand. init. weights by distr. assumption for φ. ($2/n_{in}$ for ReLu and $1/n_{in}$ or $1/(n_{in} + n_{out})$ for Tanh)

Overfitting

Regularization; **Early Stopping**; **Dropout**: ignore hidden units with prob. p, after training use all units and scale weights by p;

Batch Normalization: normalize the input data (mean 0, variance 1) in each layer

CNN

$\varphi(W * v^{(l)})$

For each channel there is a separate filter.

Convolution

$C = channel$ $F = filterSize$ $inputSize = I$ $padding = P$ $stride = S$

$$\text{Output size l} = \frac{I + 2P - K}{S} + 1$$
$$\text{Output dimension} = l \times l \times m$$
$$\text{Inputs} = W * H * D * C * N$$
$$\text{Trainable parameters} = F * F * C * \#filters$$

Unsupervised Learning

k-Means Clustering

Optimization Goal (non-convex):

$$\hat{R}(\mu) = \sum_{i=1}^n \min_{j\in\{1,\dots,k\}} ||x_i - \mu_j||_2^2$$

Lloyd's heuristics: Init.cluster centers $\mu^{(0)}$:

- Assign points to closest center
- Update μ_i as mean of assigned points

Converges in exponential time.

Initialize with **k-Means++**:

- Random data point $\mu_1 = x_i$
- Add seq $\mu_2, \dots, \mu_k$ rand., with prob: given $\mu_{1:j}$ pick $\mu_{j+1} = x_i$ where $p(i) = \frac{1}{z}\min_{l\in\{1,\dots,j\}} ||x_i - \mu_l||_2^2$

Converges expectation $\mathcal{O}(\log k) *$ opt.solution.

Find k by negligible loss decrease or reg.

Principal Component Analysis

Optimization goal: $\underset{||w||_2=1,z}{\text{argmin}} \sum_{i=1}^n ||x_i - z_i w||_2^2$

The optimal solution is given by $z_i = w^\top x_i$. Substituting gives us:

$$\hat{w} = \text{argmax}_{||w||_2=1}\ w^\top\Sigma w$$

Where $\Sigma = \frac{1}{n}\sum_{i=1}^n x_i x_i^\top$ is the empirical covariance. Closed form solution given by the principal eigenvector of Σ, i.e. $w = v_1$ for $\lambda_1 \geq \dots \geq \lambda_d \geq 0$: $\Sigma = \sum_{i=1}^d \lambda_i v_i v_i^\top$

For $k > 1$ we have to change the normalization to $W^\top W = I$ then we just take the first k principal eigenvectors so that $W = [v_1, \dots, v_k]$.

PCA through SVD

- The first k col of V where $X = USV^\top$.
- linear dimension reduction method
- first principal component eigenvector of data covariance matrix with largest eigenvalue
- covariance matrix is symmetric $\rightarrow$ all principal components are mutually orthogonal

Kernel PCA

$\Sigma = \frac{1}{n}\sum_{i=1}^n x_i x_i^\top = X^\top X \Rightarrow$ kernel trick:

$$\hat{\alpha} = \text{argmax}_\alpha \frac{\alpha^\top K^\top K\alpha}{\alpha^\top K\ \alpha}$$

Closed form solution:

$$\alpha^{(i)} = \frac{1}{\sqrt{\lambda_i}}v_i \quad K = \sum_{i=1}^n \lambda_i v_i v_i^\top, \lambda_1 \geq \dots \geq 0$$

A point x is projected as: $z_i = \sum_{j=1}^n \alpha_j^{(i)} k(x_j, x)$

Autoencoders

We want to minimize $\frac{1}{n}\sum_{i=1}^n ||x_i - \hat{x}_i||_2^2$.

$$\hat{x} = f_{dec}(f_{enc}(x, \theta_{enc}); \theta_{dec})$$

Lin.activation func. & square loss => PCA

Statistical Perspective

Assume that data is generated iid. by some $p(x,y)$. We want to find $f : X \mapsto Y$ that minimizes the **population risk**.

Opt. Predictor for the Squared Loss

f minimizing the population risk:

$$f^*(x) = \mathbb{E}[y \mid X = x] = \int y \cdot p(y \mid x)dy$$

Estimate $\hat{p}(y \mid x)$ with MLE:

$$\theta^* = \underset{\theta}{\text{argmax}}\ \hat{p}(y_1, \dots, y_n \mid x_1, \dots, x_n, \theta)$$
$$= \underset{\theta}{\text{argmin}} - \sum_{i=1}^n \log p(y_i \mid x, \theta)$$

The MLE for linear regression is unbiased and has minimum variance among all unbiased estimators. However, it can overfit.

Ex. Conditional Linear Gaussian

Assume Gaussian noise $y = f(x) + \varepsilon$ with $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ and $f(x) = w^\top x$:

$$\hat{p}(y \mid x, \theta) = \mathcal{N}(y; w^\top x, \sigma^2)$$

The optimal $\hat{w}$ can be found using MLE:

$$\hat{w} = \underset{w}{\text{argmax}}\ p(y|\ x, \theta) = \underset{w}{\text{argmin}} \sum(y_i - w^\top x_i)^2$$

Maximum a Posteriori Estimate

Introduce bias to reduce variance. The small weight assumption is a Gaussian prior $w_i \sim \mathcal{N}(0,\beta^2)$. The posterior distribution of w is given by: $p(w \mid x,y) = \frac{p(w)\cdot p(y \mid x,w)}{p(y \mid x)}$

Now we want to find the MAP for w:

$$\begin{aligned}\hat{w} &= \operatorname{argmax}_w \; p(w \mid \bar{x},\bar{y}) \\ &= \operatorname{argmin}_w -\log \frac{p(w)\cdot p(y \mid x,w)}{p(y \mid x)} \\ &= \operatorname{argmin}_w \frac{\sigma^2}{\beta^2}||w||_2^2 + \sum_{i=1}^n (y_i - w^\top x_i)^2\end{aligned}$$

Regularization can be understood as MAP inference, with different priors (= regularizers) and likelihoods (= loss functions).

Statistical Models for Classification

f minimizing the population risk:

$$f^*(x) = \operatorname{argmax}_{\hat{y}} \; p(\hat{y} \mid x)$$

This is called the Bayes' optimal predictor for the 0-1 loss. Assuming iid. Bernoulli noise, the conditional probability is:

$$p(y \mid x,w) \sim \operatorname{Ber}(y;\sigma(w^\top x))$$

Where $\sigma(z) = \frac{1}{1+\exp(-z)}$ is the sigmoid function. Using MLE we get:

$$\hat{w} = \operatorname*{argmin}_w \sum_{i=1}^n \log(1+\exp(-y_i w^\top x_i))$$

Which is the logistic loss. Instead of MLE we can estimate MAP, e.g. with a Gaussian prior:

$$\hat{w} = \operatorname*{argmin}_w \lambda ||w||_2^2 + \sum_{i=1}^n \log(1+e^{-y_i w^\top x_i})$$

Bayesian Decision Theory

Given $p(y \mid x)$, a set of actions A and a cost $C: Y \times A \mapsto \mathbb{R}$, pick the action with the maximum expected utility.

$$a^* = \operatorname{argmin}_{a \in A} \mathbb{E}_y[C(y,a) \mid x]$$

Can be used for asymetric costs or abstention.

Generative Modeling

Aim to estimate $p(x,y)$ for complex situations using Bayes' rule: $p(x,y) = p(x|y)\cdot p(y)$

Naive Bayes Model

GM for classification tasks. Assuming for a class label, each feature is independent. This helps estimating $p(x \mid y) = \prod_{i=1}^d p(x_i \mid y_i)$.

Gaussian Naive Bayes Classifier

Naive Bayes Model with Gaussian's features. Estimate the parameters via MLE:

MLE for class prior: $p(y) = \hat{p}_y = \frac{\text{Count}(Y=y)}{n}$

MLE for feature distribution:

$$P(x_i|y) = \frac{Count(X_i = x_i, Y = y)}{Count(Y = y)}$$

Predictions are made by:

$$y = \operatorname*{argmax}_{\hat{y}} p(\hat{y} \mid x) = \operatorname*{argmax}_{\hat{y}} p(\hat{y}) \cdot \prod_{i=1}^d p(x_i \mid \hat{y})$$

Equivalent to decision rule for bin. class.:

$$y = \operatorname{sgn}\left(\log \frac{p(Y=+1 \mid x)}{p(Y=-1 \mid x)}\right)$$

Where $f(x)$ is called the discriminant function. If the conditional independence assumption is violated, the classifier can be overconfident.

Gaussian Bayes Classifier

No independence assumption, model the features with a multivariant Gaussian $\mathcal{N}(x;\mu_y,\Sigma_y)$:

$$\mu_y = \frac{1}{\text{Count}(Y=y)} \sum_{j \mid y_j = y} x_j$$

$$\Sigma_y = \frac{1}{\text{Count}(Y=y)} \sum_{j \mid y_j = y} (x_j - \hat{\mu}_y)(x_j - \hat{\mu}_y)^\top$$

This is also called the **quadratic discriminant analysis** (QDA). LDA: $\Sigma_+ = \Sigma_-$, Fisher LDA: $p(y) = \frac{1}{2}$, Outlier detection: $p(x) \leq \tau$.

Avoiding Overfitting

MLE is prone to overfitting. Avoid this by restricting model class (fewer parameters, e.g. GNB) or using priors (restrict param. values).

Generative vs. Discriminative

Discriminative models:
$p(y|x)$, can't detect outliers, more robust

Generative models:
$p(x,y)$, can be more powerful (dectect outliers, missing values) if assumptions are met, are typically less robust against outliers

Gaussian Mixture Model

Assume that data is generated from a convex-combination of Gaussian distributions:
$p(x|\theta) = p(x|\mu,\Sigma,w) = \sum_{j=1}^k w_j \mathcal{N}(x;\mu_j,\Sigma_j)$

We don't have labels and want to cluster this data. The problem is to estimate the param. for the Gaussian distributions.

$$\operatorname{argmin}_\theta \; -\sum_{i=1}^n \log \sum_{j=1}^k w_j \cdot \mathcal{N}(x_i \mid \mu_j,\Sigma_j)$$

This is a non-convex objective. Similar to training a GBC without labels. Start with guess for our parameters, predict the unknown labels and then impute the missing data. Now we can get a closed form update.

Hard-EM Algorithm

E-Step: predict the most likely class for each data point:

$$\begin{aligned}z_i^{(t)} &= \operatorname*{argmax}_z p(z \mid x_i, \theta^{(t-1)}) \\ &= \operatorname*{argmax}_z p(z \mid \theta^{(t-1)}) \cdot p(x_i \mid z, \theta^{(t-1)})\end{aligned}$$

M-Step: compute MLE of $\theta^{(t)}$ as for GBC.

Problems: labels if the model is uncertain, tries to extract too much inf. Works poorly if clusters are overlapping. With uniform weights and spherical covariances is equivalent to k-Means with Lloyd's heuristics.

Soft-EM Algorithm

E-Step: calculate the cluster membership weights for each point ($w_j = \pi_j = p(Z=j)$):

$$\gamma_j^{(t)}(x_i) = p(Z=j \mid D) = \frac{w_j \cdot p(x_i;\theta_j^{(t-1)})}{\sum_k w_k \cdot p(x_i;\theta_k^{(t-1)})}$$

M-Step: compute MLE with closed form:

$$w_j^{(t)} = \frac{1}{n}\sum_{i=1}^n \gamma_j^{(t)}(x_i) \qquad \mu_j^{(t)} = \frac{\sum_{i=1}^n x_i \cdot \gamma_j^{(t)}(x_i)}{\sum_{i=1}^n \gamma_j^{(t)}(x_i)}$$

$$\Sigma_j^{(t)} = \frac{\sum_{i=1}^n \gamma_j^{(t)}(x_i)(x_i - \mu_j^{(t)})(x_i - \mu_j^{(t)})^\top}{\sum_{i=1}^n \gamma_j^{(t)}(x_i)}$$

Init. the weights as uniformly distributed, rand. or with k-Means++ and for variances use spherical init. or empirical covariance of the data. Select k using cross-validation.

Degeneracy of GMMs

GMMs can overfit with limited data. Avoid this by add $v^2 I$ to variance, so it does not collapse (equiv. to a Wishart prior on the covariance matrix). Choose v by cross-validation.

Gaussian-Mixture Bayes Classifiers

Assume that $p(x \mid y)$ for each class can be modelled by a GMM.

$$p(x \mid y) = \sum_{j=1}^{k_y} w_j^{(y)} \mathcal{N}(x;\mu_j^{(y)},\Sigma_j^{(y)})$$

Giving highly complex decision boundaries:

$$p(y \mid x) = \frac{1}{z} p(y) \sum_{j=1}^{k_y} w_j^{(y)} \mathcal{N}(x;\mu_j^{(y)},\Sigma_j^{(y)})$$

GMMs for Density Estimation

Can be used for anomaly detection or data imputation. Detect outliers, by comparing the estimated density against τ. Allows to control the FP rate. Use ROC curve as evaluation criterion and optimize using CV to find τ.

General EM Algorithm

E-Step: Take the expected value over latent variables z to generate likelihood function Q:

$$\begin{aligned}Q(\theta;\theta^{(t-1)}) &= \mathbb{E}_Z[\log p(X,Z \mid \theta) \mid X, \theta^{(t-1)}] \\ &= \sum_{i=1}^n \sum_{z_i=1}^k \gamma_{z_i}(x_i) \log p(x_i, z_i \mid \theta)\end{aligned}$$

with $\gamma_z(x) = p(z \mid x, \theta^{(t-1)})$

M-Step: Compute MLE / Maximize:

$$\theta^{(t)} = \operatorname*{argmax}_\theta Q(\theta;\theta^{(t-1)})$$

We have monotonic convergence, each EM-iteration increases the data likelihood.

GANs

Learn f: "simple" distr. $\mapsto$ non linear distr. Computing likelihood of the data becomes hard, therefore we need a different loss.

$$\min_{w_G} \max_{w_D} \mathbb{E}_{x \sim p_{\text{data}}}[\log D(x,w_D)] + \mathbb{E}_{z \sim p_z}[\log(1 - D(G(z,w_G),w_D))]$$

Training requires finding a saddle point, always converges to saddle point with if G, D have enough capacity. For a fixed G, the optimal discriminator is:

$$D_G(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_G(x)}$$

The prob. of being fake is $1 - D_G$. Too powerful discriminator could lead to memorization of finite data. Other issues are oscillations/divergence or mode collapse.

One possible performance metric:

$$DG = \max_{w_D'} M(w_G, w_D') - \min_{w_G'} M(w_G', w_D)$$

Where $M(w_G, w_D)$ is the training objective.

Various

Derivatives:

$$\nabla_x x^\top A = A \quad \nabla_x a^\top x = \nabla_x x^\top a = a$$
$$\nabla_x b^\top A x = A^\top b \quad \nabla_x x^\top x = 2x \quad \nabla_x x^\top A x = 2Ax$$
$$\nabla_w ||y - Xw||_2^2 = 2X^\top(Xw - y)$$

Bayes Theorem:

$$p(y \mid x) = \frac{1}{p(x)} \underbrace{p(y) \cdot p(x \mid y)}_{p(x,y)}$$

Normal Distribution:

$$\mathcal{N}(x;\mu,\Sigma) = \frac{1}{\sqrt{(2\pi)^d \det(\Sigma)}} \exp\left(-\frac{(x-\mu)^\top \Sigma^{-1}(x-\mu)}{2}\right)$$

Other Facts

$\operatorname{Tr}(AB) = \operatorname{Tr}(BA)$, $\operatorname{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2$, $X \in \mathbb{R}^{n \times d}: \; X^{-1} \to \mathcal{O}(d^3) \; X^\top X \to \mathcal{O}(nd^2)$, $\binom{n}{k} = \frac{n!}{(n-k)!k!}$, $||w^\top w||_2 = \sqrt{w^\top w}$

$\operatorname{Cov}[X] = \mathbb{E}[(X - \mathbb{E}[X])(X - \mathbb{E}[X])^\top] = E[XX^\top] - E[X]E[X]^\top$

$p(z|x,\theta) = \frac{p(x,z|\theta)}{p(x|\theta)}$

$E[s \cdot s^\top] = \mu \cdot \mu^\top + \Sigma = \Sigma$ where s follows a multivariate normal distribution with mean μ and covariance matrix Σ

Convexity

0: $L(\lambda w + (1-\lambda)v) \leq \lambda L(w) + (1-\lambda)L(v)$

1: $L(w) + \nabla L(w)^\top (v - w) \leq L(v)$

2: Hessian $\nabla^2 L(w) \succcurlyeq 0$ (psd)

- $\alpha f + \beta g$, $\alpha, \beta \geq 0$, convex if f, g convex
- $f \circ g$, convex if f convex and g affine or f non-decreasing and g convex
- $\max(f,g)$, convex if f, g convex