

Basics

Fundamental Assumption

Data is iid for unknown P : $(x_i, y_i) \sim P(X, Y)$

True risk and estimated error

True risk: $R(w) = \int P(x, y)(y - w^T x)^2 \partial x \partial y = \mathbb{E}_{x, y}[(y - w^T x)^2]$

Est. error: $\hat{R}_D(w) = \frac{1}{|D|} \sum_{(x, y) \in D} (y - w^T x)^2$

Standardization

Centered data with unit variance: $\tilde{x}_i = \frac{x_i - \hat{\mu}}{\hat{\sigma}}$
 $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i, \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$

Cross-Validation

For all models m , for all $i \in \{1, \dots, k\}$ do:

- 1. Split data: $D = D_{train}^{(i)} \uplus D_{test}^{(i)}$ (Monte-Carlo or k-Fold)
 - 2. Train model: $\hat{w}_{i, m} = \operatorname{argmin}_w \hat{R}_{train}^{(i)}(w)$
 - 3. Estimate error: $\hat{R}_m^{(i)} = \hat{R}_{test}^{(i)}(\hat{w}_{i, m})$
- Select best model: $\hat{m} = \operatorname{argmin}_m \frac{1}{k} \sum_{i=1}^k \hat{R}_m^{(i)}$

Parametric vs. Nonparametric models

Parametric: have finite set of parameters. e.g. linear regression, linear perceptron

Nonparametric: grow in complexity with the size of the data, more expressive. e.g. k-NN

Gradient Descent

- 1. Pick arbitrary $w_0 \in \mathbb{R}^d$
- 2. $w_{t+1} = w_t - \eta_t \nabla \hat{R}(w_t)$

Stochastic Gradient Descent (SGD)

- 1. Pick arbitrary $w_0 \in \mathbb{R}^d$
- 2. $w_{t+1} = w_t - \eta_t \nabla_w l(w_t; x', y')$, with u.a.r. data point $(x', y') \in D$

Regression

Solve $w^* = \operatorname{argmin}_w \hat{R}(w) + \lambda C(w)$

Linear Regression

$\hat{R}(w) = \sum_{i=1}^n (y_i - w^T x_i)^2 = \|Xw - y\|_2^2$
 $\nabla_w \hat{R}(w) = -2 \sum_{i=1}^n (y_i - w^T x_i) \cdot x_i$
 $w^* = (X^T X)^{-1} X^T y$

Ridge regression

$\hat{R}(w) = \sum_{i=1}^n (y_i - w^T x_i)^2 + \lambda \|w\|_2^2$
 $\nabla_w \hat{R}(w) = -2 \sum_{i=1}^n (y_i - w^T x_i) \cdot x_i + 2\lambda w$
 $w^* = (X^T X + \lambda I)^{-1} X^T y$

L1-regularized regression (Lasso)

$\hat{R}(w) = \sum_{i=1}^n (y_i - w^T x_i)^2 + \lambda \|w\|_1$

Classification

Solve $w^* = \operatorname{argmin}_w l(w; x_i, y_i)$; loss function l

0/1 loss

$l_{0/1}(w; y_i, x_i) = 1$ if $y_i \neq \operatorname{sign}(w^T x_i)$ else 0

Perceptron algorithm

Use $l_P(w; y_i, x_i) = \max(0, -y_i w^T x_i)$ and SGD

$$\nabla_w l_P(w; y_i, x_i) = \begin{cases} 0 & \text{if } y_i w^T x_i \geq 0 \\ -y_i x_i & \text{otherwise} \end{cases}$$

Data lin. separable \Leftrightarrow obtains a lin. separator (not necessarily optimal)

Support Vector Machine (SVM)

Hinge loss: $l_H(w; x_i, y_i) = \max(0, 1 - y_i w^T x_i)$

$$\nabla_w l_H(w; y, x) = \begin{cases} 0 & \text{if } y_i w^T x_i \geq 1 \\ -y_i x_i & \text{otherwise} \end{cases}$$

$$w^* = \operatorname{argmin}_w l_H(w; x_i, y_i) + \lambda \|w\|_2^2$$

Kernels

efficient, implicit inner products

Properties of kernel

$k: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$, k must be some inner product (symmetric, positive-definite, linear) for some space \mathcal{V} . i.e. $k(\mathbf{x}, \mathbf{x}') = \langle \varphi(\mathbf{x}), \varphi(\mathbf{x}') \rangle_{\mathcal{V}} \stackrel{Eucl.}{=} \varphi(\mathbf{x})^T \varphi(\mathbf{x}')$ and $k(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}', \mathbf{x})$

Kernel matrix

$$K = \begin{bmatrix} k(x_1, x_1) & \dots & k(x_1, x_n) \\ \vdots & \ddots & \vdots \\ k(x_n, x_1) & \dots & k(x_n, x_n) \end{bmatrix}$$

Positive semi-definite matrices \Leftrightarrow kernels k

Important kernels

Linear: $k(x, y) = x^T y$
Polynomial: $k(x, y) = (x^T y + 1)^d$
Gaussian: $k(x, y) = \exp(-\|x - y\|_2^2 / (2h^2))$
Laplacian: $k(x, y) = \exp(-\|x - y\|_1 / h)$

Composition rules

Valid kernels k_1, k_2 , also valid kernels: $k_1 + k_2$; $k_1 \cdot k_2$; $c \cdot k_1$, $c > 0$; $f(k_1)$ if f polynomial with pos. coeffs. or exponential

Reformulating the perceptron

Ansatz: $w^* \in \operatorname{span}(X) \Rightarrow w = \sum_{j=1}^n \alpha_j y_j x_j$
 $\alpha^* = \operatorname{argmin}_{\alpha \in \mathbb{R}^n} \sum_{i=1}^n \max(0, -\sum_{j=1}^n \alpha_j y_i y_j x_i^T x_j)$

Kernelized perceptron and SVM

Use $\alpha^T k_i$ instead of $w^T x_i$,
use $\alpha^T D_y K D_y \alpha$ instead of $\|w\|_2^2$
 $k_i = [y_1 k(x_i, x_1), \dots, y_n k(x_i, x_n)]$, $D_y = \operatorname{diag}(y)$
Prediction: $\hat{y} = \operatorname{sign}(\sum_{i=1}^n \alpha_i y_i k(x_i, \hat{x}))$

Kernelized linear regression (KLR)

Ansatz: $w^* = \sum_{i=1}^n \alpha_i x_i$
 $\alpha^* = \operatorname{argmin}_{\alpha} \|\alpha^T K - y\|_2^2 + \lambda \alpha^T K \alpha$
 $= (K + \lambda I)^{-1} y$

Prediction: $\hat{y} = \sum_{i=1}^n \alpha_i k(x_i, \hat{x})$

k-NN

$y = \operatorname{sign}(\sum_{i=1}^n y_i [x_i \text{ among } k \text{ nearest neighbours of } x])$ – No weights \Rightarrow no training! But depends on all data : (

Imbalance

Cost Sensitive Classification

Replace loss by: $l_{CS}(w; x, y) = c_y l(w; x, y)$

Metrics

$n = n_+ + n_-$, $n_+ = TP + FN$, $n_- = TN + FP$
Accuracy: $\frac{TP + TN}{n}$, Precision: $\frac{TP}{TP + FP}$
Recall/TPR: $\frac{TP}{n_+}$, FPR: $\frac{FP}{n_-}$
F1 score: $\frac{2TP}{2TP + FP + FN}$
ROC Curve: $y = \text{TPR}, x = \text{FPR}$

Multi-class

Hinge loss

$l_{MC-H}(w^{(1)}, \dots, w^{(c)}; x, y) = \max(0, 1 + \max_{j \in \{1, \dots, y-1, y+1, \dots, c\}} w^{(j)T} x - w^{(y)T} x)$

Neural network

Parameterize feature map: $\phi(x, \theta)$ instead of $\phi(x)$, usually: $\phi(x, \theta) = \varphi(\theta^T x) = \varphi(z)$
 $\Rightarrow w^* = \operatorname{argmin}_{w, \theta} \sum_{i=1}^n l(y_i; \sum_{j=1}^m w_j \phi(x_i, \theta_j))$

Activation functions

Sigmoid: $\frac{1}{1 + \exp(-z)}$, $\varphi'(z) = (1 - \varphi(z)) \cdot \varphi(z)$
Tanh: $\varphi(z) = \tanh(z) = \frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)}$
ReLU: $\varphi(z) = \max(z, 0)$

Predict: forward propagation

$v^{(0)} = x$; for $l = 1, \dots, L-1$:
 $v^{(l)} = \varphi(z^{(l)})$, $z^{(l)} = W^{(l)} v^{(l-1)}$
 $f = W^{(L)} v^{(L-1)}$
Predict f for regression, $\operatorname{sign}(f)$ for class.

Compute gradient: backpropagation

Output layer: $\delta_j = l'_j(f_j)$, $\frac{\partial}{\partial w_{j,i}} = \delta_j v_i$
Hidden layer $l = L-1, \dots, 1$:
 $\delta_j = \varphi'(z_j) \cdot \sum_{i \in \text{Layer}_{l+1}} w_{i,j} \delta_i$, $\frac{\partial}{\partial w_{j,i}} = \delta_j v_i$

Learning with momentum

$a \leftarrow m \cdot a + \eta_t \nabla_W l(W; y, x)$; $W \leftarrow W - a$

Clustering

k-mean

$\hat{R}(\mu) = \sum_{i=1}^n \min_{j \in \{1, \dots, k\}} \|x_i - \mu_j\|_2^2$
 $\hat{\mu} = \operatorname{argmin}_{\mu} \hat{R}(\mu)$...non-convex, NP-hard

Algorithm (Lloyd's heuristic): Choose starting centers, assign points to closest center, update centers to mean of each cluster, repeat

Dimension reduction

PCA

$D = x_1, \dots, x_n \subset \mathbb{R}^d$, $\Sigma = \frac{1}{n} \sum_{i=1}^n x_i x_i^T$, $\mu = 0$
 $(W, z_1, \dots, z_n) = \operatorname{argmin} \sum_{i=1}^n \|W z_i - x_i\|_2^2$,
 $W = (v_1 | \dots | v_k) \in \mathbb{R}^{d \times k}$, orthogonal; $z_i = W^T x_i$
 v_i are the eigen vectors of Σ

Kernel PCA

Kernel PC: $\alpha^{(1)}, \dots, \alpha^{(k)} \in \mathbb{R}^n$, $\alpha^{(i)} = \frac{1}{\sqrt{\lambda_i}} v_i$,
 $K = \sum_{i=1}^n \lambda_i v_i v_i^T$, $\lambda_1 \geq \dots \geq \lambda_d \geq 0$
New point: $\hat{z} = f(\hat{x}) = \sum_{j=1}^n \alpha_j^{(i)} k(\hat{x}, x_j)$

Autoencoders

Find identity function: $x \approx f(x; \theta)$
 $f(x; \theta) = f_{\text{decode}}(f_{\text{encode}}(x; \theta_{\text{encode}}); \theta_{\text{decode}})$

Probability modeling

Find $h: X \rightarrow Y$ that min. pred. error: $R(h) = \int P(x,y)l(y;h(x))\partial y x \partial y = \mathbb{E}_{x,y}[l(y;h(x))]$

For least squares regression

Best h : $h^*(x) = \mathbb{E}[Y|X=x]$
Pred.: $\hat{y} = \hat{\mathbb{E}}[Y|X=\hat{x}] = \int \hat{P}(y|X=\hat{x})y\partial y$

Maximum Likelihood Estimation (MLE)

$\theta^* = \underset{\theta}{\operatorname{argmax}} \hat{P}(y_1,...,y_n|x_1,...,x_n,\theta)$
E.g. lin. + Gauss: $y_i = w^T x_i + \varepsilon_i, \varepsilon_i \sim \mathcal{N}(0, \sigma^2)$
i.e. $y_i \sim \mathcal{N}(w^T x_i, \sigma^2)$, With MLE (use $\operatorname{argmin} -\log$): $w^* = \underset{w}{\operatorname{argmin}} \sum (y_i - w^T x_i)^2$

Bias/Variance/Noise

Prediction error = $Bias^2 + Variance + Noise$

Maximum a posteriori estimate (MAP)

Assume bias on parameters, e.g. $w_i \in \mathcal{N}(0, \beta^2)$
Bay.: $P(w|x,y) = \frac{P(w)P(y|x,w)}{P(y|x)} = \frac{P(w)P(y|x,w)}{P(y|x)}$

Logistic regression

Link func.: $\sigma(w^T x) = \frac{1}{1+exp(-w^T x)}$ (Sigmoid)
 $P(y|x,w) = Ber(y; \sigma(w^T x)) = \frac{1}{1+exp(-yw^T x)}$
Classification: Use $P(y|x,w)$, predict most likely class label.
MLE: $\underset{w}{\operatorname{argmax}} P(y_{1:n}|w, x_{1:n})$

$\Rightarrow w^* = \underset{w}{\operatorname{argmin}} \sum_{i=1}^n \log(1+exp(-y_i w^T x_i))$
SGD update: $w = w + \eta_i y_i \hat{P}(Y = -y|w, x)$
 $\hat{P}(Y = -y|w, x) = \frac{1}{1+exp(yw^T x)}$
MAP: Gauss. prior $\Rightarrow ||w||_2^2$, Lap. p. $\Rightarrow ||w||_1$
SGD: $w = w(1 - 2\lambda \eta_t) + \eta_t y x \hat{P}(Y = -y|w, x)$

Bayesian decision theory

- Conditional distribution over labels $P(y|x)$
- Set of actions \mathcal{A}
- Cost function $C: Y \times \mathcal{A} \rightarrow \mathbb{R}$
 $a^* = \underset{a \in \mathcal{A}}{\operatorname{argmin}} \mathbb{E}[C(y,a)|x]$
Calculate \mathbb{E} via sum/integral.
Classification: $C(y,a) = [y \neq a]$; asymmetric:
$$C(y,a) = \begin{cases} c_{FP} & , \text{ if } y = -1, a = +1 \\ c_{FN} & , \text{ if } y = +1, a = -1 \\ 0 & , \text{ otherwise} \end{cases}$$

Regression: $C(y,a) = (y - a)^2$; asymmetric:

$C(y,a) = c_1 \max(y - a, 0) + c_2 \max(a - y, 0)$
E.g. $y \in \{-1, +1\}$, predict $+$ if $c_+ < c_-$,
 $c_+ = \mathbb{E}(C(y, +1)|x) = P(y = 1|x) \cdot 0 + P(y = -1|x) \cdot c_{FP}$, c_- likewise

Discriminative / generative modeling

Discr. estimate $P(y|x)$, generative $P(y,x)$
Approach (generative): $P(x,y) = P(x|y) \cdot P(y)$
- Estimate prior on labels $P(y)$
- Estimate cond. distr. $P(x|y)$ for each class y
- Pred. using Bayes: $P(y|x) = \frac{P(y)P(x|y)}{P(x)}$
 $P(x) = \sum_y P(x,y)$

Examples

MLE for $P(y) = p = \frac{n_+}{n}$
MLE for $P(x_i|y) = \mathcal{N}(x_i; \mu_{i,y}, \sigma_{i,y}^2)$:
 $\hat{\mu}_{i,y} = \frac{1}{n_y} \sum_{x \in D_{x_i|y}} x$
 $\hat{\sigma}_{i,y}^2 = \frac{1}{n_y} \sum_{x \in D_{x_i|y}} (x - \hat{\mu}_{i,y})^2$
MLE for Poi.: $\lambda = \operatorname{avg}(x_i)$
 \mathbb{R}^d : $P(X = x|Y = y) = \prod_{i=1}^d Pois(\lambda_y^{(i)}, x^{(i)})$

Deriving decision rule

$P(y|x) = \frac{1}{Z} P(y)P(x|y)$, $Z = \sum_y P(y)P(x|y)$
 $y^* = \underset{y}{\operatorname{amax}} P(y|x) = \underset{y}{\operatorname{amax}} P(y) \prod_{i=1}^d P(x_i|y)$

Gaussian Bayes Classifier

$\hat{P}(x|y) = \mathcal{N}(x; \hat{\mu}_y, \hat{\Sigma}_y)$
 $\hat{P}(Y = y) = \hat{p}_y = \frac{n_y}{n}$
 $\hat{\mu}_y = \frac{1}{n_y} \sum_{i: y_i = y} x_i \in \mathbb{R}^d$
 $\hat{\Sigma}_y = \frac{1}{n_y} \sum_{i: y_i = y} (x_i - \hat{\mu}_y)(x_i - \hat{\mu}_y)^T \in \mathbb{R}^{d \times d}$

Fisher's lin. discrim. analysis (LDA, c=2)

Assume: $p = 0.5$; $\hat{\Sigma}_- = \hat{\Sigma}_+ = \hat{\Sigma}$
discriminant function: $f(x) = \log \frac{p}{1-p} + \frac{1}{2} [\log \frac{|\hat{\Sigma}_-|}{|\hat{\Sigma}_+|} + ((x - \hat{\mu}_-)^T \hat{\Sigma}_-^{-1} (x - \hat{\mu}_-) - ((x - \hat{\mu}_+)^T \hat{\Sigma}_+^{-1} (x - \hat{\mu}_+))]$
Predict: $y = \operatorname{sign}(f(x)) = \operatorname{sign}(w^T x + w_0)$
 $w = \hat{\Sigma}^{-1} (\hat{\mu}_+ - \hat{\mu}_-)$;
 $w_0 = \frac{1}{2} (\hat{\mu}_-^T \hat{\Sigma}^{-1} \hat{\mu}_- - \hat{\mu}_+^T \hat{\Sigma}^{-1} \hat{\mu}_+)$

Outlier Detection

$P(x) \leq \tau$

Categorical Naive Bayes Classifier

MLE for feature distr.: $\hat{P}(X_i = c|Y = y) = \theta_{c|y}^{(i)}$
 $\theta_{c|y}^{(i)} = \frac{\operatorname{Count}(X_i = c, Y = y)}{\operatorname{Count}(Y = y)}$
Prediction: $y^* = \underset{y}{\operatorname{argmax}} \hat{P}(y|x)$

Missing data

Mixture modeling

Model each c. as probability distr. $P(x|\theta_j)$
 $P(D|\theta) = \prod_{i=1}^n \sum_{j=1}^k w_j P(x_i|\theta_j)$
 $L(w, \theta) = -\sum_{i=1}^n \log \sum_{j=1}^k w_j P(x_i|\theta_j)$

Gaussian-Mixture Bayes classifiers

Estimate prior $P(y)$; Est. cond. distr. for each class: $P(x|y) = \sum_{j=1}^{k_y} w_j^{(y)} \mathcal{N}(x; \mu_j^{(y)}, \Sigma_j^{(y)})$

Hard-EM algorithm

Initialize parameters $\theta^{(0)}$
E-step: Predict most likely class for each point: $z_i^{(t)} = \underset{z}{\operatorname{argmax}} P(z|x_i, \theta^{(t-1)})$
 $= \underset{z}{\operatorname{argmax}} P(z|\theta^{(t-1)}) P(x_i|z, \theta^{(t-1)})$;
M-step: Compute the MLE: $\theta^{(t)} = \underset{\theta}{\operatorname{argmax}} P(D^{(t)}|\theta)$, i.e. $\mu_j^{(t)} = \frac{1}{n_j} \sum_{i: z_i = j} x_j$

Soft-EM algorithm

E-step: Calc p for each point and cls.: $\gamma_j^{(t)}(x_i)$
M-step: Fit clusters to weighted data points:
 $w_j^{(t)} = \frac{1}{n} \sum_{i=1}^n \gamma_j^{(t)}(x_i)$; $\mu_j^{(t)} = \frac{\sum_{i=1}^n \gamma_j^{(t)}(x_i) x_i}{\sum_{i=1}^n \gamma_j^{(t)}(x_i)}$
 $\sigma_j^{(t)} = \frac{\sum_{i=1}^n \gamma_j^{(t)}(x_i) (x_i - \mu_j^{(t)})^T (x_i - \mu_j^{(t)})}{\sum_{i=1}^n \gamma_j^{(t)}(x_i)}$

Soft-EM for semi-supervised learning

labeled y_i : $\gamma_j^{(t)}(x_i) = [j = y_i]$, unlabeled:
 $\gamma_j^{(t)}(x_i) = P(Z = j|x_i, \mu^{(t-1)}, \Sigma^{(t-1)}, w^{(t-1)})$

Useful math

Probabilities

$\mathbb{E}_x[X] = \begin{cases} \int x \cdot p(x) \partial x & \text{if continuous} \\ \sum_x x \cdot p(x) & \text{otherwise} \end{cases}$
 $\operatorname{Var}[X] = \mathbb{E}[(X - \mu_X)^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$

$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$; $p(Z|X, \theta) = \frac{p(X, Z|\theta)}{p(X|\theta)}$
 $P(x,y) = P(y|x) \cdot P(x) = P(x|y) \cdot P(y)$

Bayes Rule

$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$

P-Norm

$||x||_p = (\sum_{i=1}^n |x_i|^p)^{\frac{1}{p}}$, $1 \leq p < \infty$
Some gradients
 $\nabla_x ||x||_2^2 = 2x$
 $f(x) = x^T A x$; $\nabla_x f(x) = (A + A^T)x$
E.g. $\nabla_w \log(1 + \exp(-yw^T x)) = \frac{1}{1 + \exp(-yw^T x)} \cdot \exp(-yw^T x) \cdot (-yx) = \frac{1}{1 + \exp(yw^T x)} \cdot (-yx)$

Convex / Jensen's inequality
 $g(x)$ convex $\Leftrightarrow g''(x) > 0 \Leftrightarrow x_1, x_2 \in \mathbb{R}, \lambda \in [0, 1]$:
 $g(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda g(x_1) + (1 - \lambda)g(x_2)$

Gaussian / Normal Distribution

$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(x-\mu)^2}{2\sigma^2})$
Multivariate Gaussian
 Σ = covariance matrix, μ = mean
 $f(x) = \frac{1}{2\pi\sqrt{|\Sigma|}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$
Empirical: $\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n x_i x_i^T$ (needs centered data points)

Positive semi-definite matrices
 $M \in \mathbb{R}^{n \times n}$ is psd $\Leftrightarrow \forall x \in \mathbb{R}^n : x^T M x \geq 0 \Leftrightarrow$ all eigenvalues of M are positive: $\lambda_i \geq 0$