General Remarks

$\mathrm{d}(x,y) = \|\|x-y\|\|$,	$\mathrm{dist}(x,y) = 1 - \mathrm{sim}(x,y)$
l_2-euclidean distance	$\sqrt{\sum_{i=1}^d (x_i - y_i)^2}$
l_1-manhatten distance	$\sum_{i=1}^d \|x_i - y_i\|$
l_p-distance	$(\sum_{i=1}^d \|x_i - y_i\|^p)^{1/p}$
l_∞-distance	$\max_i \|x_i - y_i\|$
Mahalanobis norm	$\|\|w\|\|_G^2 = \|\|Gw\|\|_2^2$
Cosine-Similarity	$\cos \frac{x^T y}{\|\|x\|\|_2 \|\|y\|\|_2}$
Jaccard-Distance	$1 - \mathrm{sim}(A,B) = 1 - \frac{\|A \cap B\|}{\|A \cup B\|}$

Function Properties

Concave function

$f(a+s) - f(a) \geq f(b+s) - f(b)\ \forall a \leq b, s > 0$

Convex functions A function $f : S \to \mathbb{R}$, $S \subseteq \mathbb{R}^d$, is called convex if $\forall x, x' \in S, \lambda \in [0,1]$ it holds that $\lambda f(x) + (1-\lambda) f(x') \geq f(\lambda x + (1-\lambda) x')$

H-strongly convex

$f(x') \geq f(x) + \nabla f(x)^T (x'-x) + \frac{H}{2} ||x'-x||^2, H > 0$

1-D: f is H-sc $\Leftarrow f''(x) \geq H, \forall x$.

d-D: f is H-sc $\Leftarrow \lambda_{\min}(\nabla^2 f(x)) \geq H, \forall x$.

Subgradients Given a convex not necessarily differentiable function f, a subgradient $\mathbf{g_x} \in \nabla f(x)$ is the slope of a linear lower bound of f, tight at x, that is $\forall x' \in S$: $f(x') \geq f(x) + \mathbf{g_x}^T (x' - x)$

Locality Sensitive Hashing

Near-duplicate detection

$\{(x,y) \in X \times X : x \neq y, \mathrm{d}(x,y) \leq \epsilon\}$

(r,ϵ)-neighbour search Find all points with distance $\leq r$ and no points with distance $> (1+\epsilon) r$ from query q. Pick $(r, (1+\epsilon) \cdot r, p, q)$-sensitive family and boost.

Min-hashing $h(C) = h_\pi(C) = \min_{i : C(i) = 1} \pi(i)$

$\pi(i) = h_{a,b}(i) = ((a \cdot i + b) \mod p) \mod N)$, p prime (fixed) $> N$, N number of documents $(d_1, d_2, 1 - d_1, 1 - d_2)$-sensitive with Jaccard sim.

```
for each column c do
    for each row r do
        if c has 1 in row r then
            for each hash fn h_i do
                M_{i,c} ← min{h_i(r), M_{i,c}}
```

Band-hashing Signature matrix into b bands of r hash fns, per-column into b hash tables. If any h-table has a collision, report candidate pair. s^r prob of col on band j: $P(\text{col in } \geq 1 \text{ band}) = 1 - (1 - s^r)^b$

$(d1, d2, p1, p2)$-sensitivity Assume $d_1 < d_2$, $p_1 > p_2$.

$\forall x, y \in S : d(x,y) \leq d_1 \Rightarrow Pr[h(x) = h(y)] \geq p_1$

$\forall x, y \in S : d(x,y) \geq d_2 \Rightarrow Pr[h(x) = h(y)] \leq p_2$

r-way AND $h(x) = h(y) \iff \forall i : h_i(x) = h_i(y)$

(d_1, d_2, p_1^r, p_2^r) – big r, more FN

b-way OR $h(x) = h(y) \iff \exists i : h_i(x) = h_i(y)$

$(d_1, d_2, 1 - (1-p_1)^b, 1 - (1-p_2)^b)$ – big b, more FP

AND-OR cascade $(d_1, d_2, 1 - (1 - p_1^r)^b, 1 - (1 - p_2^r)^b)$

OR-AND cascade

$(d_1, d_2, (1 - (1-p_1)^b)^r, (1 - (1-p_2)^b)^r)$

Hash Functions

Euclidean distance $h_{w,b}(x) = \lfloor (\frac{w^T x - b}{a}) \rfloor$ where $w \leftarrow \frac{w}{||w||_2}$, $w \sim \mathcal{N}(0, I)$, $w_i \sim \mathcal{N}(0,1)$, $b \sim Unif([0,a])$, yields $(a/2, 2a, 1/2, 1/3)$-sensitive

Cosine distance $\mathcal{H} = \{h(v) = \mathrm{sgn}(w^T v)\}$ where $w \sim \mathrm{Unif}\{x \in \mathbb{R}^n : ||x||_2 = 1\}$

$Pr(h_u(x) = h_v(y)) = 1 - \Theta_{x,y}/\pi$

$(\Theta_1, \Theta_2, 1 - \Theta_1/\pi, 1 - \Theta_2/\pi)$-sensitive

Support Vector Machines

SVM SVM = Max margin linear classifier

$\min_{w, \xi \geq 0} \frac{1}{2} w^T w + C \sum_{i=1}^n \xi_i$ s. t. $y_i w^T x_i \geq 1 - \xi_i\ \forall i$

Support vectors (SV) are all data points on the margin and data points with non-zero slack

Regularized hinge loss formulation $C = 1/\lambda$

$\min_w \lambda w^T w + C \sum_i \max(0, 1 - y_i w^T x_i)$

Norm-constrained hinge loss minimization

$\min_w \sum_i \max(0, 1 - y_i w^T x_i)$ s.t. $||w||_2 \leq \frac{1}{\sqrt{\lambda}}$

Strongly convex formulation

$\min_w \frac{1}{T} \sum_{t=1}^T \left(\frac{\lambda}{2} ||w||_2^2 + \max(0, 1 - y_t w^T x_t) \right)$

s.t. $||w||_2 \leq \frac{1}{\sqrt{\lambda}}$

$\mathrm{Proj}_S^{(2)}(w) = w \cdot \min\left(1, \frac{1/\sqrt{\lambda}}{||w||}\right)$

$\mathrm{Proj}_S^{(\infty)}(w) = \min\left((1/\sqrt{\lambda}, \ldots, 1/\sqrt{\lambda})^T, w\right) \cdot \mathrm{sgn}(w)$

Small C, Big λ: Greater margin, more misclassification

Kernels

Dual SVM Formulation

$\max_\alpha \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j$

s.t. $0 \leq \alpha_i \leq C$

$\Rightarrow$ optimal w: $w^* = \sum_i \alpha_i^* y_i x_i = \sum_{i \in \mathrm{SV}} \alpha_i^* y_i x_i$

Kernel trick Substitute inner product $x_i^T x_j$ in dual formulation and in classification function with $k(x_i, x_j) = \phi(x_i)^T \phi(x_j)$, where $\phi(\cdot) : \mathbb{R}^d \to \mathbb{R}^{>d}$

Kernel functions A kernel is function $k : X \times X \to \mathbb{R}$:

1. Symmetry: $\forall x, x' \in X : k(x, x') = k(x', x)$
2. PSD: $\forall n \in \mathbb{N}$, any set $S = \{x_1, .., x_n\} \subseteq X$, the Gram matrix is PSD.

Random Features (Inverse Kernel Trick)

Shift-invariant kernel $k(x,y) = k'(x-y)$. Then the kernel has Fourier transform, such that:

$$k(x-y) = \int_{\mathbb{R}^d} p(w) \cdot e^{i w^T (x-y)} dw$$

where $p(w)$ is the Fourier transformation, i.e. we map $k(s)$ to another function $p(w)$.

Random fourier features (prerequisites) Interpret kernel as expectation $k(x-y) =$

$$\int_{\mathbb{R}^d} p(w) \cdot \underbrace{e^{i w^T (x-y)}}_{g(w)} dw = \mathbb{E}_{w,b} \left[z_{w,b}(x) z_{w,b}(y) \right]$$

where $z_{w,b}(x) = \sqrt{2} \cos\left(w^T x + b\right)$, $b \sim U([0, 2\pi])$, $w \sim p(w)$

Random fourier features (kernel approximation)

1. $w_i \sim p, b_i \sim U([0, 2\pi])$ for $i = 1, \ldots, m$; iid
2. $z(x) = [z_{w_1, b_1}(x), \ldots, z_{w_m, b_m}(x)] / \sqrt{m}$
3. $z(x)^T z(y) = \frac{1}{m} \sum_{i=1}^m z_{w_i, b_i}(x) \cdot z_{w_i, b_i}(y)$
4. If $m \to \infty$, then (almost surely) $z(x)^T z(y) \to \mathbb{E}_{w,b}(z_{w,b}(x) \cdot z_{w,b}(y)) = k(x-y)$

Online Convex Programming

Regret $R_T = (\sum_{t=1}^T f_t(w_t)) - \min_{w \in S} \sum_{t=1}^T f_t(w)$

No-regret $\lim_{T \to \infty} \frac{R_T}{T} \to 0$

Online convex programming (OCP) If $y_t w_t^T x_t < 1$:

$w_{t+1} = \mathrm{Proj}_S(w_t - \eta_t \nabla f_t(w_t))$

$\mathrm{Proj}_S(w) = \arg\min_{w' \in S} ||w' - w||_2 = \min\left(w, \frac{w}{\lambda ||w||_2}\right)$

Regret for OCP

$$\frac{R_T}{T} \leq \frac{1}{\sqrt{T}} [||w_0 - w^*||_2^2 + ||\nabla f||_2^2]$$

where $||\nabla f||_2^2 = \sup_{w \in S, t \in \{1, \ldots, T\}} ||\nabla f(w)||_2^2$

Parallel stochastic gradient descent

1. Split data into k subsets, k = number of machines, want $k = O(1/\lambda)$
2. Each machine produces w_i on its subset
3. After T iterations, compute $w = \frac{1}{k} \sum_{i=1}^k w_i$

PEGASOS Online SVM: H-sc. lossfn. Minibatch + reg

Active Learning

Uncertainty sampling Repeat until all labels inferred:

1. Assign uncertainty score $U_t(x)$ to each unlabeled data point: $U_t(x) = U(x | x_{1:t-1}, y_{1:t-1})$
2. Greedily pick the most uncertain point and request label $x_t = \arg\max_x U_t(x)$ and retrain classifier

For SVM: $U_t(x) = \frac{1}{|w_{t-1}^T x|}$
Cost to pick m labels: $m \cdot n \cdot d + m \cdot C(m)$
n = number of data points, d = dimensions,
$C(m)$ = cost to train classifier

Hashing a hyperplane query Draw $u, v \sim \mathcal{N}(0, I)$.
Then resulting two-bit hash is:

$$h_{u,v}(a,b) = \left[\text{ sign } (u^T a), \text{ sign } (v^T b)\right]$$

Define the hash family:

$$h_{\mathcal{H}}(z) = \begin{cases} h_{u,v}(z,z) & \text{if } z \text{ is a database point vector} \\ h_{u,v}(z,-z) & \text{if } z \text{ is a query hyperplane vector} \end{cases}$$

Version space Set of all classifiers consistent with the data: $V(D) = \{w : \forall (x,y) \in D: \text{ sign}(w^T x) = y\}$

Relevant version space $\hat{V}(D;U)$ describes all possible labelings h of all unlabeled data U that are still possible under some model w, or,

$$\hat{V}(D;U) = \{h : U \to \{+1,-1\} : \exists w \in V(D)$$
$$\forall x \in U : \text{sign}(w^T x) = h(x)\}$$

Generalized Binary Search (GBS)

Start with $D = \emptyset$
while $|\hat{V}(D;U)| > 1$ **do**
  for each unlabeled example x in U **do**
    $v^+(x) = |\hat{V}(D \cup \{(x,+)\}; U)|$
    $v^-(x) = |\hat{V}(D \cup \{(x,-)\}; U)|$
    $\triangleright$ number of labelings left if x is $-/+$
  Pick $x^* = \arg\min_x \max(v^-(x), v^+(x))$
  $D = D \cup \{x^*\}$

Decision rules for GBS SVM, $m \sim$ margin $\sim \frac{1}{||w||}$

Max-min margin $\max_x \min\left(m^+(x), m^-(x)\right)$

Ratio margin $\max_x \min\left(\frac{m^+(x)}{m^-(x)}, \frac{m^-(x)}{m^+(x)}\right)$

Clustering

K-Means

Cost Function $L(\mu) = L(\mu_1, ..., \mu_k) =$

$$\sum_{i=1}^{N} \underbrace{\min_{j \in \{1,\dots,k\}} ||x_i - \mu_j||_2^2}_{d(\mu, x_i)}$$

Objective $\mu^* = \arg\ \min_\mu L(\mu)$

Algorithm Until convergence:

Assign each point x_i to closest center

$$z_i \leftarrow \arg \min_{j \in \{1,\dots,l\}} ||x_i - \mu_j^{(t-1)}||_2^2$$

Update center as mean of assigned data points

$$\mu_j^{(t)} \leftarrow \frac{1}{n_j} \sum_{i: z_i = j} x_i$$

Online k-means algorithm

$$\frac{\mathbf{d}d(\mu, x_t)}{\mathbf{d}\mu_j} = \begin{cases} 0 & \text{if } j \notin \arg\min_i ||\mu_i - x_t||^2 \\ 2(u_j - x_t) & \text{else} \end{cases}$$

1. Initialize centers randomly
2. For $t = 1 : N$
   - Find $c = \arg\ \min ||\mu_j - x_t||_2$
   - $\mu_c = \mu_c + \eta_t(x_t - \mu_c)$
3. For convergence: $\sum_t \eta_t = \infty$ and $\sum_t \eta_t^2 < \infty$, e.g. $\eta_t = \frac{c}{t}$.

Coresets

Idea Replace many points by one weighted point
$L_k(u; C) = \sum_{(w,x) \in C} w \cdot \min_j ||u_j - x||_2^2$

(k, ϵ)-coreset C is called a (k,ϵ)-coreset for D, if for all μ: $(1-\epsilon) L_k(\mu; D) \leq L_k(\mu; C) \leq (1+\epsilon) L_k(\mu; D)$

Operations **Merge**: union of two (k,ϵ)-csets is a (k,ϵ)-cset
Compress: (k,δ)-cset of a (k,ϵ)-cset of D is a $(k, \epsilon + \delta + \epsilon\delta)$-cset of D

Construction **D^2-sampling**: iteratively build $B = \emptyset$ by sampling $\propto \frac{d(x,B)^2}{\sum_{x' \in X} d(x',B)^2}$
Importance sampling:
$\propto \frac{\alpha d(x,B)^2}{c_\Phi} + \frac{2\alpha \sum_{x' \in B_x} d(x',B)^2}{|B_x| c_\Phi} + \frac{4|X|}{|B_x|}$ where
$c_\Phi = \frac{1}{|X|} \sum_{x \in X} d(x,B)^2$
B_x = pts in X that belong to same cluster as x

Bandits

Regret $R_T = \sum_{t=1}^T (\mu^* - \mu_{i_t})$, i_t chosen arm at time t

ϵ-greedy The algorithm goes as follows:

1. Set $\epsilon_t = \mathcal{O}(\frac{1}{t})$
2. With probability ϵ_t: explore by picking uniformly at random
3. With probability $1 - \epsilon_t$: exploit by picking arm with highest empirical mean

Regret: $R_T = \mathcal{O}(k \log(T))$

UCB1 & LinUCB

Hoeffding's inequality
$\Pr(|\mu - \frac{1}{m}\sum_{t=1}^m X_t| \geq b) \leq 2 \cdot \exp(-2b^2 m)$

Confidence bound Want: Hoeffding $\leq \delta$
$\Rightarrow b = \sqrt{\frac{1}{2m} \ln \frac{2}{\delta}}$

UCB/Mean update $UCB(i) = \hat{\mu}_i + \sqrt{\frac{2 \ln t}{\eta_i}}$
$j = \arg\max_i UCB(i)$
$\hat{\mu_j} = \hat{\mu_j} + \frac{1}{\eta_j}(y_t - \hat{u}_j)$

Contextual bandits Reward is now $y_t = f(x_t, z_t) + \epsilon_t$ with z_t user features. For us: $f(x_i, z_t) = w_{x_i}^T z_t$

LinUCB (disjoint) Ridge regression on z_t:
$\hat{w}_i = (D_i^T D_i + I)^{-1} D_i^T y_i$.
$|\hat{w}_i^T z_t - w_i^T z_t| \leq \alpha \sqrt{z_t^T (D_i^T D_i)^{-1} z_t}$ with probability $1 - \delta$ if $\alpha = 1 + \sqrt{\log(2/\delta)/2}$
$R_T / T = O(d \cdot d' \cdot \text{poly} \log T / \sqrt{T})$

Hybrid model Reward is now
$y_t = w_{x_t}^T z_t + \beta^T \phi(x_t, z_t) + \epsilon_t$

Rejection sampling First obtain data log through pure exploration, and then reiterate:

1. Get event $(x_t^{(1)}, .., x_t^{(k)}, z_t, a_t, y_t)$ from log
2. Use algorithm that is testing to pick a_t':
   - If $a_t' = a_t \Rightarrow$ Feed back reward y_t
   - Else ignore log line
3. Stop when T rewards have been fed back

Submodular Functions

Submodularity A function $F : 2^V \mapsto \mathbb{R}$ is called submodular iff for all $A \subseteq B, s \notin B$:

$$F(A \cup \{s\}) - F(A) \geq F(B \cup \{s\}) - F(B)$$

Monotonic if $S \subseteq T \Rightarrow F(S) \leq F(T)$

Union-intersection def. Same preconditions as above:

$$F(A) - F(A \cap B) \geq F(A \cup B) - F(B)$$

Closure properties F, F_i submodular on V; $S, W \subseteq V$

Linear Combinations
$F'(S) = \sum_i \lambda_i F_i(S)$, $\lambda_i \geq 0$

Restriction $F'(S) = F(S \cap W)$

Conditiong $F'(S) = F(S \cup W)$

Reflection $F'(S) = F(V \setminus S)$

Monotonic truncation F also monotonic,
$F'(S) = \min(c, F(S)), c \in \mathbb{R}$

Min/Max For $F_{1,2}(A)$, $\max\{F_1(A), F_2(A)\}$ or $\min\{F_1(A), F_2(A)\}$ **not** submodular in general.

Concavity $F(A) = g(|A|)$ where $g : \mathbb{N} \mapsto \mathbb{R}$, then F submodular iff g concave.

Lazy Greedy Optimizing submodular **monotonic** functions: $\Delta(s|A_i) \geq \Delta(s|A_{i+1})$.

1: $A_0 = \emptyset$. Keep ordered list of marginal benefits Δ_s from previous iterations $j < i$, for all $s \in \mathcal{S}$, set of articles
2: **for** $i = 1 \dots k$: **do**
3:   s is the article for which Δ_s is at the top
4:   Update: $\Delta_s = F(A_{i-1} \cup \{s\}) - F(A_{i-1})$
5:   **if** Δ_s is not top element anymore **then**
6:     re-sort the list, goto 3
7:   $A_i = A_{i-1} \cup \{s\}$