General Remarks

$d(x,y) = \|\|x-y\|\|$,	$\text{dist}(x,y) = 1 - \text{sim}(x,y)$
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	$\cos \frac{x^Ty}{\|\|x\|\|_2\|\|y\|\|_2}$
Jaccard-Distance	$1-\text{sim}(A,B) = 1-\frac{\|A\cap B\|}{\|A\cup B\|}$

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 $g_x \in \nabla f(x)$ is the slope of a linear lower bound of f, tight at x, that is $\forall x' \in S$: $f(x') \geq f(x) + g_x^T(x'-x)$

Locality Sensitive Hashing

Near-duplicate detection
$\{(x,y) \in X \times X : x \neq y, d(x,y) \leq \epsilon\}$

(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

1: **for** each column c **do**
2: **for** each row r **do**
3: **if** c has 1 in row r **then**
4: **for** each hash fn h_i **do**
5: $M_{i,c} \leftarrow \min\{h_i(r), M_{i,c}\}$

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 $h_{w,b}(x) = \lfloor(\frac{w^Tx-b}{a})\rfloor$ 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 $\mathcal{H} = \{h(v) = \text{sgn}(w^Tv)\}$ where $w \sim \text{Unif}\{x \in \mathbb{R}^n : ||x||_2 = 1\}$
$Pr(h_u(x) = h_v(y)) = 1 - \Theta_{x,y}/\pi$

Support Vector Machines

SVM SVM = Max margin linear classifier
$\min_{w,\xi\geq 0} \frac{1}{2}w^Tw + C\sum_{i=1}^n \xi_i$ s. t. $y_iw^Tx_i \geq 1-\xi_i\ \forall i$
Support vectors (SV) are all data points on the margin and data points with non-zero slack

Regularized hinge loss formulation $C = 1/\lambda$
$\min_w \lambda w^Tw + C\sum_i \max(0, 1-y_iw^Tx_i)$

Norm-constrained hinge loss minimization
$\min_w \sum_i \max(0, 1-y_iw^Tx_i)$ s.t. $||w||_2 \leq \frac{1}{\sqrt{\lambda}}$

Strongly convex formulation
$\min_w \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\lambda}{2}||w||_2^2 + \max(0, 1-y_tw^Tx_t)\right)$
s.t. $||w||_2 \leq \frac{1}{\sqrt{\lambda}}$
$\text{Proj}_S^{(2)}(w) = w \cdot \min\left(1, \frac{1/\sqrt{\lambda}}{||w||}\right)$
$\text{Proj}_S^{(\infty)}(w) = \max\left((1,\ldots,1)^T, w\right)$

Small C, Big λ: Greater margin, more misclassification

Kernels

Dual SVM Formulation
$\max_\alpha \sum_{i=1}^n \alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_jy_iy_jx_i^Tx_j$
s.t. $0 \leq \alpha_i \leq C$
$\Rightarrow$ optimal w: $w^* = \sum_i \alpha_i^* y_ix_i = \sum_{i\in\text{SV}}\alpha_i^*y_ix_i$

Kernel trick Substitute inner product $x_i^Tx_j$ 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:

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

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 $k(x-y) =$

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

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

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. $z(x)^Tz(y) = \frac{1}{m}\sum_{i=1}^m z_{w_i,b_i}(x)\cdot z_{w_i,b_i}(y)$
4. If $m \to \infty$, then (almost surely) $z(x)^Tz(y) \to \mathbb{E}_{w,b}(z_{w,b}(x)\cdot z_{w,b}(y)) = k(x-y)$

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 $y_tw_t^Tx_t < 1$:
$w_{t+1} = \text{Proj}_S(w_t - \eta_t\nabla f_t(w_t))$
$\text{Proj}_S(w) = \arg\min_{w'\in S}||w'-w||_2 = \min\left(w, \frac{w}{\lambda||w||_2}\right)$

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)

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

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

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

Objective $\mu^* = \arg\ \min_\mu L(\mu)$
Algorithm Until convergence:

1: Assign each point x_i to closest center

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

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

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

(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 $\propto \frac{\mathrm{d}(x,B)^2}{\sum_{x' \in X} \mathrm{d}(x', B)^2}$
Importance sampling:
$\propto \frac{\alpha \mathrm{d}(x,B)^2}{c_\Phi} + \frac{2\alpha \sum_{x' \in B_x} \mathrm{d}(x', B)^2}{|B_x| c_Phi} + \frac{4|X|}{|B_x|}$ where
$c_\Phi = \frac{1}{|X|} \sum_{x \in X} \mathrm{d}(x, B)^2$
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) RidgeRegression 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

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

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

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.

1: $A_0 = \emptyset$. Keep ordered list of marginal benefits Δ_i from previous iterations
2: **for** $i = 1 \ldots k$: **do**
3: $\Delta_i = F(A_{i-1} \cup \{\text{top element}\}) - F(A_{i-1})$
4: **if** i is not top element anymore **then**
5: re-sort the list
6: $A_i = A_{i-1} \cup \{\text{top element}\}$