Disclaimer
I wrote this to my best knowledge, however, no guarantees are given whatsoever.

Sources
If not noted differently, the source is the lecture slides and/or the accompanying book.

1 Approximate Retrieval

Nearest-Neighbor Find $x^* = \text{argmin}_{x\in X}\ d(x,y)$ given $S,\ y\in S,\ X\subseteq S$.

Near-Duplicate detection Find all $\boldsymbol{x},\boldsymbol{x}'\in X$ with $d(\boldsymbol{x},\boldsymbol{x}')\le\epsilon$.

1.1 k-Shingling

Documents (or videos) as set of k-shingles (a. k. a. k-grams). k-*shingle*is consecutive appearance of k chars/words.
Binary *shingle matrix* $M\in\{0,1\}^{CxN}$ where $M_{i,j}=1$ iff document j contains shingle i, N documents, C k-shingles.

1.2 Distance functions

Def. $d: S\times S\to\mathbb{R}$ is *distance function* iff pos. definite except $d(x,x)=0$ ($d(x,x')>0 \iff x\ne x'$), symmetric ($d(x,x')=d(x',x)$) and triangle inequality holds ($d(x,x'')\le d(x,x')+d(x',x'')$).

L_r-norm $d_r(x,y)=||x-y||_r=(\sum_i|x_i-y_i|^r)^{1/r}$. L_2 is *Euclidean.*

Cosine $\text{Sim}_c(A,B)=\dfrac{A\cdot B}{||A||\cdot||B||}$, $d_c(A,B)=\dfrac{\arccos(\text{Sim}_c(A,B))}{\pi}$.

Jaccard sim., d. $\text{Sim}_J(A,B)=\dfrac{|A\cap B|}{|A\cup B|}$, $d_J(A,B)=1-\text{Sim}_J(A,B)$.

1.3 LSH – local sensitive hashing

Key Idea: Similiar documents have similiar hash.
Note: Trivial for exact duplicates (hash-collision $\to$ candidate pair).

Min-hash $h_\pi(C)$ Hash is the *min (i.e. first) non-zero permutated row index*: $h_\pi(C)=\min_{i,C(i)=1}\pi(i)$, bin. vec. C, rand. perm. π.
Note: $\Pr_\pi[h_\pi(C_1)=h_\pi(C_2)]=\text{Sim}_J(C_1,C_2)$ if $\pi\in_{\text{u.a.r.}}S_{|C|}$.

Min-hash signature matrix $M_S\in[N]^{n\times C}$ with $M_S(i,c)=h_i(C_c)$ given n hash-fns h_i drawn randomly from a universal hash family.

Pseudo permutation h_π with $\pi(i)=(a\cdot i+b)\mod p\mod N$, N number of shingles, $p\ge N$ prime and $a,b\in_{\text{u.a.r.}}[p]$ with $a\ne 0$.
Use as universal hash family. Only store a and b. Much more efficient.

Compute Min-hash signature matix M_S For column $c\in[C]$, row $r\in[N]$ with $C_c(r)=1$, $M_S(i,c)\leftarrow\min\{h_i(C_c),M_S(i,c)\}$ for all h_i.

r-way AND

b-way OR

Banding as boosting Reduce FP/FN by b-way OR after r-way AND. Group signature matrix into b bands of r rows. Candidate pairs match in at least one band (check by hashing).

Tradeoff FP/FN Favor FP (work) over FN (wrong). Filter FP by checking signature matrix, shingles or even whole documents.

2 Supervised Learning

Linear classifier $y_i=\text{sgn}(\boldsymbol{w}^T\boldsymbol{x}_i)$ assuming $\boldsymbol{w}$ goes through origin.

Homogeneous transform $\tilde{\boldsymbol{x}}=[\boldsymbol{x},1];\tilde{\boldsymbol{w}}=[\boldsymbol{w},b]$, now $\boldsymbol{w}$ passes origin.

Kernels $k:\mathcal{X}\times\mathcal{X}\to\mathbb{R}$ is an inner product in high-dim. lin. space, i.e. $k(x,x')=<\phi(x),\phi(x')>$.

Convex function $f:S\to\mathbb{R}$ is convex iff $\forall x,x'\in S,\lambda\in[0,1],\lambda f(x)+(1-\lambda)f(x')\ge f(\lambda x+(1-\lambda)x')$, i. e. every segment lies above function. Equiv. bounded by linear fn. at every point.

H-strongly convex f H-strongly convex iff $f(x')\ge f(x)+\nabla f(x)^T(x'-x)+\frac{H}{2}||x'-x|_2^2$, i. e. bounded by quadratic fn (at every point).

2.1 Support vector machine (SVM)

SVM primal

Quadratic $\min_{\boldsymbol{w}}\boldsymbol{w}^T\boldsymbol{w}+C\sum_i\xi_i$, s. t. $\forall i{:}\boldsymbol{y}_i\boldsymbol{w}^Tx_i\ge 1-\xi_i$, slack C.

Hinge loss $\min_{\boldsymbol{w}}\lambda\boldsymbol{w}^T\boldsymbol{w}+\sum_i\max(0,1-y_i\boldsymbol{w}^T\boldsymbol{x}_i)$ with $\lambda=\frac{1}{C}$.

Norm-constrained $\min_{\boldsymbol{w}}\sum_i\max(0,1-y_i\boldsymbol{w}^T\boldsymbol{x}_i)$ s.t. $||\boldsymbol{w}||_2\le\frac{1}{\sqrt{\lambda}}$.

Lagrangian dual $\max_{\boldsymbol{\alpha}}\sum_i\alpha_i+\frac{1}{2}\sum_{i,j}\alpha_i\alpha_jy_iy_j\boldsymbol{x}_i^T\boldsymbol{x}_j,\ \alpha_i\in[0,C]$.
Apply kernel trick: $\max_{\boldsymbol{\alpha}}\sum_i\alpha_i+\frac{1}{2}\sum_{i,j}\alpha_i\alpha_jy_iy_jk(\boldsymbol{x}_i,\boldsymbol{x}_j)$, $\alpha_i\in[0,C]$, prediction becomes $y=\text{sgn}(\sum_{i=1}^n\alpha_iy_ik(x_i,x))$.

2.2 Convex Programming

Convex program $\min_{\boldsymbol{x}}f(\boldsymbol{x})$, s. t. $\boldsymbol{x}\in S$, f convex.

Online convex program (OCP) $\min_{\boldsymbol{w}}\sum_{t=1}^Tf_t(\boldsymbol{w})$, s. t. $\boldsymbol{w}\in S$.

General regularized form $\min_{\boldsymbol{w}}\sum_{i=1}^nl(\boldsymbol{w};\boldsymbol{x}_i,y_i)+\lambda R(\boldsymbol{w})$, where l is a (convex) loss function and R is the (convex) regularizer.

General norm-constrained form $\min_{\boldsymbol{w}}\sum_{i=1}^nl(\boldsymbol{w};\boldsymbol{x}_i,y_i)$, s. t. $\boldsymbol{w}\in S_\lambda$, l is loss and S_λ some (norm-)constraint. Note: This is an OCP.

Solving OCP *Feasible set* $S\subseteq\mathbb{R}^d$ and *start pt.* $\boldsymbol{w}_0\in S$, OCP (as above). Round $t\in[T]$: pick feasible pt. $\boldsymbol{w}_t$, get convex fn. f_t, incur $l_t=f_t(\boldsymbol{w}_t)$. Regret $R_T=(\sum_{t=1}^Tl_t)-\min_{\boldsymbol{w}\in S}\sum_{t=1}^Tf_t(\boldsymbol{w})$.

Online SVM $||\boldsymbol{w}||_2\le\frac{1}{\lambda}$ (norm-constr.). For new pt. $\boldsymbol{x}_t$ classify $y_t=\text{sgn}(\boldsymbol{w}_t^T\boldsymbol{x}_t)$, incur $l_t=\max(0,1-y_t\boldsymbol{w}_t^T\boldsymbol{x}_t)$, update $\boldsymbol{w}_t$ (see later). Best $L^*=\min_{\boldsymbol{w}}\sum_{t=1}^T\max(0,1-y_t\boldsymbol{w}^T\boldsymbol{x}_t)$, regret $R_t=\sum_{t=1}^Tl_t-L^*$.

Online proj. gradient descent (OPGD) Update for online SVM: $\boldsymbol{w}_{t+1}=\text{Proj}_S(\boldsymbol{w}_t-\eta_t\nabla f_t(\boldsymbol{w}_t))$ with $\text{Proj}_S(\boldsymbol{w})=\text{argmin}_{\boldsymbol{w}'\in S}||\boldsymbol{w}'-\boldsymbol{w}||_2$, gives regret bound $\frac{R_T}{T}\le\frac{1}{\sqrt{T}}(||\boldsymbol{w}_0-\boldsymbol{w}^*||_2^2+||\nabla f||_2^2)$.
For H-strongly convex fnset $\eta_t=\frac{1}{Ht}$ gives $R_t\le\frac{||\nabla f||^2}{2H}(1+\log T)$.

Stochastic PGD (SGD) Online-to-batch. Compute $\tilde{\boldsymbol{w}}=\frac{1}{T}\sum_{t=1}^T\boldsymbol{w}_t$. If data i. i. d.: exp. *error (risk)* $\mathbb{E}[L(\tilde{\boldsymbol{w}})]\le L(\boldsymbol{w}^*)+R_T/T$, $L(\boldsymbol{w}^*)$ is best error (risk) possible.

PEGASOS OPGD w/ mini-batches on strongly convex SVM form. $\min_w\sum_{t=1}^Tg_t(\boldsymbol{w})$, s.t. $||\boldsymbol{w}||_2\le\frac{1}{\sqrt{t}}$, $g_t(\boldsymbol{w})=\frac{\lambda}{2}||\boldsymbol{w}||_2^2+f_t(\boldsymbol{w})$.
g_t is λ-strongly convex, $\nabla g_t(\boldsymbol{w})=\lambda\boldsymbol{w}+\nabla f_t(\boldsymbol{w})$.
Performance ϵ-accurate sol. with prob. $\ge 1-\delta$ in runtime $O^*(\frac{d\cdot\log\frac{1}{\delta}}{\lambda\epsilon})$.

ADAGrad Adapt to geometry. *Mahalanobis norm* $||\boldsymbol{w}||_{\boldsymbol{G}}=||\boldsymbol{G}\boldsymbol{w}||_2$. $\boldsymbol{w}_{t+1}=\text{argmin}_{\boldsymbol{w}\in S}||\boldsymbol{w}-(\boldsymbol{w}_t-\eta\boldsymbol{G}_t^{-1}\nabla f_t(\boldsymbol{w}))||_{\boldsymbol{G}_t}$. Min. regret with $G_t=(\sum_{\tau=1}^t\nabla f_\tau(\boldsymbol{w}_\tau)\nabla f_\tau(\boldsymbol{w}_\tau)^T)^{1/2}$. Easily inv'able matrix with $G_t=\text{diag}(...)$. $R_t\in O(\frac{||\boldsymbol{w}^*||_\infty}{\sqrt{T}}\sqrt{d})$, even better for sparse data.

ADAM Add 'momentum' term: $\boldsymbol{w}_{t+1}=\boldsymbol{w}_t-\mu\bar{g}_t$, $g_t=\nabla f_t(\boldsymbol{w})$, $\bar{g}_t=(1-\beta)g_t+\beta\bar{g}_{t-1}$, $\bar{g}_0=0$. Helps for dense gradients.

Parallel SGD (PSGD) Randomly partition to k (indep.) machines. Comp. $\boldsymbol{w}=\frac{1}{k}\sum_{i=1}^k\boldsymbol{w}_i$. $\mathbb{E}[\text{err}]\in O(\epsilon(\frac{1}{k\sqrt{\lambda}}+1))$ if $T\in\Omega(\frac{\log\frac{k\lambda}{\epsilon}}{\epsilon\lambda})$. Suitable for MapReduce cluster, multi. passes possible.

Hogwild! Shared mem., no sync., sparse data. [...]

Implicit kernel trick Map $x\in\mathbb{R}^d\to\phi(x)\in\mathbb{R}^D\to z(x)\in\mathbb{R}^m$, $d\ll D,m\ll D$. Where $\phi(x)$ corresponds to a kernel $k(x,x')=\phi(x)^T\phi(x')$.

Random fourier features !TODO!

Nyström features !TODO!

3 Pool-based active Learning (semi-supervised)

Uncertainty sampl. $U_t(x)=U(x|x_{1:t-1},y_{1:t-1})$, request y_t for $x_t=\text{argmax}_xU_t(x)$. **SVM:** $x_t=\text{argmin}_{x_i}|\boldsymbol{w}^T\boldsymbol{x}_i|$, i.e. $U_t(\boldsymbol{x})=\frac{1}{|\boldsymbol{w}_t^T\boldsymbol{x}|}$.

Sub-linear time w/ LSH $|\boldsymbol{w}^T\boldsymbol{x}_i|$ small if $\angle_{\boldsymbol{w},\boldsymbol{x}_i}$ close to π.
Hash hyperplane: $h_{\boldsymbol{u},\boldsymbol{v}}(\boldsymbol{a},\boldsymbol{b})=[h_{\boldsymbol{u}}(\boldsymbol{a}),h_{\boldsymbol{v}}(\boldsymbol{b})]=[\text{sgn}(\boldsymbol{u}^T\boldsymbol{a}),\text{sgn}(\boldsymbol{v}^T\boldsymbol{b})]$. LSH hash family: $h_H(z)=h_{u,v}(\boldsymbol{z},\boldsymbol{z})$ if z datapoint, $h_H(z)=h_{u,v}(\boldsymbol{z},-\boldsymbol{z})$ if z query hyperplane. $\Pr[h_H(\boldsymbol{w})=h_H(\boldsymbol{x})]=\Pr[h_{\boldsymbol{u}}(\boldsymbol{w})=h_{\boldsymbol{u}}(\boldsymbol{x})]\Pr[h_{\boldsymbol{v}}(-\boldsymbol{w})=h_{\boldsymbol{v}}(\boldsymbol{x})]=\frac{1}{4}-\frac{1}{\pi^2}(\angle_{\boldsymbol{x},\boldsymbol{w}}-\frac{pi}{2})^2$.
Hash all unlabeled. Loop: Hash $\boldsymbol{w}$, req. labels for hash-coll., update.

Informativeness Metric of "information" gainable; $\ne$ uncertainty.

Version Space $\mathcal{V}(D)=\{\boldsymbol{w}\mid\forall(\boldsymbol{x},y)\in D\ \text{sgn}(\boldsymbol{w}^T\boldsymbol{x})=y)\}$

Relevant version space given unlabeled pool $U=\{x_1',\dots,x_n'\}$. $\tilde{\mathcal{V}}(D;U)=\{h:U\to\{\pm1\}\mid\exists\boldsymbol{w}\in\mathcal{V}(D)\ \forall x\in U\ \text{sgn}(\boldsymbol{w}^T\boldsymbol{x})=h(\boldsymbol{x})\}$.

Generalized binary search Init $D\leftarrow\{\}$. While $|\tilde{\mathcal{V}}(D;U)|>1$, comp. $v^\pm(x)=|\tilde{\mathcal{V}}(D\cup\{(x,\pm)\};U)|$, label of $\text{argmin}_x\max\{v^-(x),v^+(x)\}$.

Approx. $|\mathcal{V}|$ Margins of SVM $m^\pm(x)$ for labels $\{+,-\},\forall x$. *Max-min* $\max_x\min\{m^+(x),m^-(x))\}$ or *ratio* $\max_x\min\{\frac{m^+(x)}{m^-(x)},\frac{m^-(x)}{m^+(x)}\}$.

4 Model-based clustering – Unsupervised learning

k-means problem $\min_\mu L(\mu)$ with $L(\mu)=\sum_{i=1}^N\min_j||\boldsymbol{x}_i-\mu_j||_2^2$ and *cluster centers* $\mu=\mu_1,...,\mu_k$. Non-convex! NP-hard in general!

LLoyd's Init $\mu^{(0)}$ (somehow). *Assign* all $\boldsymbol{x}_i$ to closest center $z_i \leftarrow \text{argmin}_{j\in[k]} ||\boldsymbol{x}_i - \mu_j^{(t-1)}||_2^2$, *Update* to mean: $\mu_j^{(t)} \leftarrow \frac{1}{n_j}\sum_{i:z_i=j}\boldsymbol{x}_i$. Always converge to *local minimum*.

Online k-means Init μ somehow. For $t\in[n]$ find $z = \text{argmin}_j ||\mu_j - \boldsymbol{x}_t||_2$, set $\mu_c \leftarrow \mu_c + \eta_t(\boldsymbol{x}_t - \mu_c)$. For local optimum: $\sum_t \eta_t = \infty \wedge \sum_t \eta_t^2 < \infty$ suffices, e.g. $\eta_t = \frac{c}{t}$.

Weighted rep. C $L_k(\mu;C) = \sum_{(w,\boldsymbol{x})\in C} w \cdot \min_j ||\mu_j - \boldsymbol{x}||_2^2$.

(k,ϵ)**-coreset** iff $\forall\mu: (1-\epsilon)L_k(\mu;D) \leq L_k(\mu;C) \leq (1+\epsilon)L_k(\mu;D)$.

D^2**-sampling** Sample prob. $p(x) = \frac{d(x,B)^2}{\sum_{x'\in X} d(x',B)^2}$.

Merge coresets union of (k,ϵ)-coreset is also (k,ϵ)-coreset.

Compress a (k,δ)-coreset of a (k,ϵ)-coreset is a $(k,\epsilon+\delta+\epsilon\delta)$-coreset.

Coresets on streams Bin. tree of merge-compress. Error $\propto$ height.

Mapreduce k-means Construct (k,ϵ)-coreset C, solve k-means (w/ many restarts) on coreset. (Repeat.) Near-optimal solution.

5 Bandits

6 Submodularity