0 Essentials

Matrix/Vector

Vectors: Unit vector: $u^\top u = 1$ Orthogonal vectors: $u^\top v = 0$ **Range, Kernel, Nullity:** $range(\mathbf{A}) = \{\mathbf{z} | \exists \mathbf{x} : \mathbf{z} = \mathbf{A}\mathbf{x}\} = span(\text{columns of A})$ $rank(\mathbf{A}) = dim(range(\mathbf{A}))$ $kernel(A) = \{\mathbf{x} : \mathbf{A}\mathbf{x} = \mathbf{0}\}$ (spans nullspace) $nullity(\mathbf{A}) = dim(kernel(\mathbf{A}))$ **Ranks:** $rank(XY) \leq rank(X) \forall X \in R^{mxn}, Y \in R^{nxk}$ eq. if $Y \in R^{nxn}, rank(Y) = n$ **Rank-nullity Theorem:** $dim(kernel(\mathbf{A})) + dim(range(\mathbf{A})) = n$

Orthogonal mat. $\mathbf{A}^{-1} = \mathbf{A}^\top$, $\mathbf{A}\mathbf{A}^\top = \mathbf{A}^\top\mathbf{A} = \mathbf{I}$, $\det(\mathbf{A}) \in \{+1, -1\}$, $\det(\mathbf{A}^\top\mathbf{A}) = 1$, preserves inner product, norm, distance, angle, rank, matrix orthogonality **Outer Product:** $\mathbf{u}\mathbf{v}^\top$, $(\mathbf{u}\mathbf{v}^\top)_{i,j} = \mathbf{u}_i\mathbf{v}_j$

Inner Product: $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^\top\mathbf{y} = \sum_{i=1}^N \mathbf{x}_i\mathbf{y}_i$. $\langle \mathbf{x} \pm \mathbf{y}, \mathbf{x} \pm \mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{x} \rangle \pm 2\langle \mathbf{x}, \mathbf{y} \rangle + \langle \mathbf{y}, \mathbf{y} \rangle$ $(\mathbf{u}_i^T\mathbf{v}_j)\mathbf{v}_j = (\mathbf{v}_j\mathbf{v}_j^T)\mathbf{u}_i$ **Cross product:** $\vec{a} \times \vec{b} = (a_2b_3 - a_3b_2, a_3b_1 - a_1b_3, a_1b_2 - a_2b_1)^\top$

Trace: $trace(\mathbf{XYZ}) = trace(\mathbf{ZXY})$

Transpose: $(\mathbf{A}^\top)^{-1} = (\mathbf{A}^{-1})^\top$, $(\mathbf{AB})^\top = \mathbf{B}^\top\mathbf{A}^\top$, $(\mathbf{A}+\mathbf{B})^\top = \mathbf{A}^\top + \mathbf{B}^\top$

Cauchy-Schwarz inequality: $|\langle \mathbf{u}, \mathbf{v} \rangle| \leq \|\mathbf{u}\|\|\mathbf{v}\|$ **Jensen inequality:** for convex function f, non negative λ_i st. $\sum_{i=1}^n \lambda_i = 1$: $f(\sum_{i=1}^n \lambda_i x_i) \leq \sum_{i=1}^n \lambda_i f(x_i)$ Note: for concave, inequality sign switches **Convexity:** $f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta)f(y), \forall \theta \in [0,1]$ **Least Squares equations:** $\arg\min_{\beta \in \mathbb{R}^{p+1}} \|\mathbf{y} - \mathbf{X}\beta\|^2$, $\hat{\beta} = (X^\top X)^{-1}X^\top y$

Einstein matrix notation: $(A \cdot B)_{ij} = \sum_{k=1}^n A_{ik} \cdot B_{kj}$

Kullback-Leibler: $KL(P||Q) = \sum_{x \in X} P(x) \log \frac{P(x)}{Q(x)}$

Norms

- $\|\mathbf{x}\|_0 = |\{i | x_i \neq 0\}|$
- $\|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^N \mathbf{x}_i^2} = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}$
- $\|\mathbf{u} - \mathbf{v}\|_2 = \sqrt{(\mathbf{u}-\mathbf{v})^\top(\mathbf{u}-\mathbf{v})}$
- $\|\mathbf{x}\|_p = \left(\sum_{i=1}^N |x_i|^p\right)^{\frac{1}{p}}$; $\|\mathbf{x}\|_\infty = \max_{i=1,...,n} |x_i|$
- $\|\mathbf{M}\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n \mathbf{m}_{i,j}^2} = \sqrt{\sum_{i=1}^{\min\{m,n\}} \sigma_i^2} = \|\sigma(\mathbf{A})\|_2 = \sqrt{trace(\mathbf{M}^T\mathbf{M})}$
- $\|\mathbf{M}\|_G = \sqrt{\sum_{ij} g_{ij} x_{ij}^2}$ (weighted Frobenius)
- $\|\mathbf{M}\|_1 = \sum_{i,j} |m_{i,j}|$
- $\|\mathbf{M}\|_2 = \sigma_{\max}(\mathbf{M}) = \|\sigma((M))\|_\infty$ (spectral)
- $\|\mathbf{M}\|_p = \max_{\mathbf{v} \neq 0} \frac{\|\mathbf{M}\mathbf{v}\|_p}{\|\mathbf{v}\|_p}$
- $\|\mathbf{M}\|_\star = \sum_{i=1}^{\min(m,n)} \sigma_i = \|\sigma(\mathbf{A})\|_1$ (nuclear)

Derivatives

$\frac{\partial}{\partial \mathbf{x}}(\mathbf{b}^\top\mathbf{x}) = \frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top\mathbf{b}) = \mathbf{b}$ $\quad \frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top\mathbf{x}) = 2\mathbf{x}$
$\frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top\mathbf{A}\mathbf{x}) = (\mathbf{A}^\top + \mathbf{A})\mathbf{x}$ $\quad \frac{\partial}{\partial \mathbf{x}}(\mathbf{b}^\top\mathbf{A}\mathbf{x}) = \mathbf{A}^\top\mathbf{b}$
$\frac{\partial}{\partial \mathbf{X}}(\mathbf{c}^\top\mathbf{X}\mathbf{b}) = \mathbf{c}\mathbf{b}^\top$ $\quad \frac{\partial}{\partial \mathbf{X}}(\mathbf{c}^\top\mathbf{X}^\top\mathbf{b}) = \mathbf{b}\mathbf{c}^\top$
$\frac{\partial}{\partial \mathbf{x}}(\|\mathbf{x}-\mathbf{b}\|_2) = \frac{\mathbf{x}-\mathbf{b}}{\|\mathbf{x}-\mathbf{b}\|_2}$ $\quad \frac{\partial}{\partial \mathbf{x}}(\|\mathbf{x}\|_2^2) = \frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top\mathbf{x}) = 2\mathbf{x}$
$\frac{\partial}{\partial \mathbf{X}}(\|\mathbf{X}\|_F^2) = 2\mathbf{X}$ $\quad \frac{\partial}{\partial x}\log(x) = \frac{1}{x}$

Eigendecomposition

$\mathbf{A} \in \mathbb{R}^{N \times N}$ then $\mathbf{A} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^{-1}$ with $\mathbf{Q} \in \mathbb{R}^{N \times N}$.
if fullrank: $\mathbf{A}^{-1} = \mathbf{Q}\mathbf{\Lambda}^{-1}\mathbf{Q}^{-1}$ and $(\mathbf{\Lambda}^{-1})_{i,i} = \frac{1}{\lambda_i}$.

if $\mathbf{A}$ symmetric: $A = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^\top$ ($\mathbf{Q}$ orthogonal). Eigenvalue λ: solve $det(A - \lambda I) = 0$ Eigenvector v: solve $(A - \lambda I) * v = \vec{0}$

Probability / Statistics

- $P(x) := Pr[X = x] := \sum_{y \in Y} P(x,y)$ • $P(x|y) := Pr[X = x | Y = y] := \frac{P(x,y)}{P(y)}$, if $P(y) > 0$ • $\forall y \in Y : \sum_{x \in X} P(x|y) = 1$ (property for any fixed y) • $P(x,y) = P(x|y)P(y)$ • $\text{posterior}P(A|B) = \frac{\text{prior}P(A) \times \text{likelihood}P(B|A)}{\text{evidence}P(B)}$ (Bayes' rule) • $P(x|y) = P(x) \Leftrightarrow P(y|x) = P(y)$ (iff X, Y independent)
- $P(x_1, \ldots, x_n) = \prod_{i=1}^n P(x_i)$ (iff IID) • Variance $Var[X] := E[(X - \mu_x)^2] := \sum_{x \in X}(x - \mu_x)^2 P(x) = E(X^2) - E(X)^2$ $\text{Var}(aX) = a^2\,\text{Var}(X)$ • expectation $\mu_x := E[X] := \sum_{x \in X} xP(x)$ • $E[X+Y] = E[X] + E[Y]$ • standard deviation $\sigma_x := \sqrt{Var[X]}$

Lagrangian Multipliers

Minimize $f(\mathbf{x})$ s.t. $g_i(\mathbf{x}) \leq 0$, $i = 1,..,m$ **(inequality constr.)** and $h_i(\mathbf{x}) = \mathbf{a}_i^\top\mathbf{x} - b_i = 0$ or $h_i(\mathbf{x}) = \sum_w x_{w,i} - b_i = 0$, $i = 1,..,p$ **(equality constraint)**
$L(\mathbf{x}, \alpha, \beta) := f(\mathbf{x}) + \sum_{i=1}^m \alpha_i g_i(\mathbf{x}) + \sum_{i=1}^p \beta_i h_i(\mathbf{x})$

1 Principal Component Analysis

$\mathbf{X} \in \mathbb{R}^{D \times N}$. N observations, K rank.

1. Empirical Mean: $\overline{\mathbf{x}} = \frac{1}{N}\sum_{n=1}^N \mathbf{x}_n$.
2. Center Data: $\overline{\mathbf{X}} = \mathbf{X} - [\overline{\mathbf{x}}, \ldots, \overline{\mathbf{x}}] = \mathbf{X} - \mathbf{M}$.
3. Cov.: $\Sigma = \frac{1}{N}\sum_{n=1}^N (\mathbf{x}_n - \overline{\mathbf{x}})(\mathbf{x}_n - \overline{\mathbf{x}})^\top = \frac{1}{N}\overline{\mathbf{X}}\overline{\mathbf{X}}^\top$.
4. Eigenvalue Decomposition: $\Sigma = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^\top$.
5. Select $K < D$, only keep $\mathbf{U}_K, \lambda_K$.
6. Transform data onto new Basis: $\overline{\mathbf{Z}}_K = \mathbf{U}_K^\top\overline{\mathbf{X}}$.
7. Reconstruct to original Basis: $\tilde{\overline{\mathbf{X}}} = \mathbf{U}_k\overline{\mathbf{Z}}_K$.
8. Reverse centering: $\tilde{\mathbf{X}} = \tilde{\overline{\mathbf{X}}} + \mathbf{M}$.

For compression save $\mathbf{U}_k, \overline{\mathbf{Z}}_K, \overline{\mathbf{x}}$.
$\mathbf{U}_k \in \mathbb{R}^{D \times K}, \Sigma \in \mathbb{R}^{D \times D}, \overline{\mathbf{Z}}_K \in \mathbb{R}^{K \times N}, \overline{\mathbf{X}} \in \mathbb{R}^{D \times N}$
Calculation of: $var(X) = \frac{1}{N}\sum_{n=1}^N (X_i - \overline{X})^2$

Iterative View

Residual r_i: $x_i - \tilde{x}_i = I - uu^T x_i$
Cov of r: $\frac{1}{n}\sum_{i=1}^n (I - uu^T)x_i x_i^T (I - uu^T)^T = (I - uu^T)\Sigma(I - uu^T)^T = \Sigma - 2\Sigma uu^T + uu^T\Sigma uu^T = \Sigma - \lambda uu^T$

1. Find principal eigenvector of $(\Sigma - \lambda uu^T)$
2. which is the second eigenvector of Σ
3. iterating to get d principal eigenvector of Σ

Power Method

Power iteration: $v_{t+1} = \frac{Av_t}{||Av_t||}$, $\lim_{t \to \infty} v_t = u_1$
Assuming $\langle u_1, v_0 \rangle \neq 0$ and $|\lambda_1| > |\lambda_j| (\forall j \geq 2)$

Reconstruction Proof Sketch

Given: $\tilde{X} = U_K U_K^\top \overline{X}$ To prove: squared reconstruction error is the sum of the lowest $D - K$ eigenvalues of Σ. $err = 1/N\sum_{i=1}^N \|\tilde{x}_i - \overline{x}_i\|_2^2 = 1/N\|\tilde{X} - \overline{X}\|_F^2 = 1/N\|(U_K U_K^\top - I_d)\overline{X}\|_F^2 = 1/N * trace((U_K U_K^\top - I_d)\overline{X}\overline{X}^\top(U_K U_K^\top - I_d)^\top = 1/N * trace(([U_K; 0] - U)\Lambda([U_K; 0] - U)^\top)$

2 Singular Value Decomposition

$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^\top = \sum_{k=1}^{\text{rank}(\mathbf{A})} d_{k,k} u_k (v_k)^\top$
$\mathbf{A} \in \mathbb{R}^{N \times P}, \mathbf{U} \in \mathbb{R}^{N \times N}, \mathbf{D} \in \mathbb{R}^{N \times P}, \mathbf{V} \in \mathbb{R}^{P \times P}$
$\mathbf{U}^\top\mathbf{U} = I = \mathbf{V}^\top\mathbf{V}$ ($\mathbf{U}, \mathbf{V}$ orthonormal)
$\mathbf{U}$ columns are eigvecs of $\mathbf{A}\mathbf{A}^\top$, $\mathbf{V}$ columns are eigvecs of $\mathbf{A}^\top\mathbf{A}$, $\mathbf{D}$ diag. elements are singular values.
$(\mathbf{D}^{-1})_{i,i} = \frac{1}{\mathbf{D}_{i,i}}$ (don't forget to transpose)

1. calculate $\mathbf{A}^\top\mathbf{A}$.
2. calculate eigvals of $\mathbf{A}^\top\mathbf{A}$, the square root of them, in descending order, are the diagonal elements of $\mathbf{D}$.
3. calc. eigvecs of $\mathbf{A}^\top\mathbf{A}$ using eigvals resulting in the columns of $\mathbf{V}$.
4. calculate the missing matrix: $\mathbf{U} = \mathbf{A}\mathbf{V}\mathbf{D}^{-1}$.
5. normalize each column of $\mathbf{U}$ and $\mathbf{V}$.

Low-Rank approximation

Use only K largest eigvals (and corresp. eigvecs).
$\tilde{\mathbf{A}}_{i,j} = \sum_{k=1}^K \mathbf{U}_{i,k}\mathbf{D}_{k,k}\mathbf{V}_{j,k} = \sum_{k=1}^K \mathbf{U}_{i,k}\mathbf{D}_{k,k}(\mathbf{V}^\top)_{k,j}$.

Echart-Young Theorem

$\mathbf{A}_k = \arg\min_{rank(B)=k} \|\mathbf{A} - \mathbf{B}\|_F^2$ (not convex)
$\min_{rank(B)=K} ||A - B||_F^2 = ||A - A_k||_F^2 = \sum_{r=k+1}^{rank(A)} \sigma_r^2$
$\min_{rank(B)=K} ||A - B||_2 = ||A - A_k||_2 = \sigma_{k+1}$

3 Matrix Approximation & Reconstruction

$\min_{rank(B)=k} [\sum_{(i,j) \in I} (a_{ij} - b_{ij})^2], I = \{(i,j) : ob.\}$

Alternating Least Squares

$f(U, v_i) = \sum_{(i,j) \in I} (a_{i,j} - \langle u_j, v_i \rangle)^2$
$f(u_i, V) = \sum_{(i,j) \in I} (a_{i,j} - \langle u_j, v_i \rangle)^2$
Convex when fixed one.

Convex Optimization

Def.: $\{(x,t) | x \in dom f, f(x) \leq t\}$, $f : \mathbb{R}^D \to \mathbb{R}$ is convex, if $dom\ f$ is a convex set, and if $\forall \mathbf{x}, \mathbf{y} \in dom\ f$, and $\forall \alpha \in [0,1]$: $f(\alpha\mathbf{x} + (1-\alpha)\mathbf{y}) \leq \alpha f(\mathbf{x}) + (1-\alpha)f(\mathbf{y})$. Convex $\iff$ Hessian p.s.d $\iff$ local=global
Positive semi-definite: all principal minors (same-indexed rows and columns) ≥ 0
Positive definite: leading principal minors > 0

Convex Relaxation

Replace non-convex rank constraints by convex norm constraints (superset). Then project optimum back (hopefully still optimal).
$\min_{\mathbf{B} \in P_k} \|\mathbf{A} - \mathbf{B}\|_G^2, P_k = \{\mathbf{B} : \|\mathbf{B}\|_* \leq k\} \supseteq Q_k = \{\mathbf{B} : rank(\mathbf{B}) \leq k\}$ (in fact tightest convex lower-bound $rank(\mathbf{B}) \geq \|\mathbf{B}\|_*, for \|\mathbf{B}\|_2 \leq 1$)

SVD Thresholding

$\mathbf{B}^* = shrink_\tau(\mathbf{A}) = \arg\min_\mathbf{B} \{\|\mathbf{A} - \mathbf{B}\|_F^2 + \tau\|\mathbf{B}\|_*\}$
Then with SVD $\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}_\mathbf{T}, \mathbf{D} = diag(\sigma_i)$, holds $\mathbf{B}^* = \mathbf{U}\mathbf{D}_\tau\mathbf{V}^\mathbf{T}, \mathbf{D}_\tau = diag(\max\{0, \sigma_i - \tau\})$
Iteration: $\mathbf{B}_{t+1} = \mathbf{B}_t + \eta_t \Pi(\mathbf{A} - shrink_\tau(\mathbf{B}_t))$

4 Non-Negative Matrix Factorization

$\mathbf{X} \in \mathbb{Z}_{\geq 0}^{N \times M}$, NMF: $\mathbf{X} \approx \mathbf{U}^\top\mathbf{V}, x_{ij} = \sum_z u_{zi}v_{zj} = \langle \mathbf{u}_i \mathbf{v}_j \rangle$ Decompose object into features: topics, face parts, etc.. $\mathbf{u}$ weights on parts, $\mathbf{v}$ parts (bases). More interpretable (PCA: holistic repre.).

EM for MLE for pLSA (No global opt. guarantee)

Context Model: $p(w|d) = \sum_{z=1}^K p(w|z)p(z|d)$
Conditional independence assumption (∗):
$p(w|d) = \sum_z p(w,z|d) = \sum_z p(w|d,z)p(z|d) \overset{*}{=} \sum_z p(w|z)p(z|d)$ or $p(w|d,z) = p(w|z)$

Symmetric parameterization:
$p(w,d) = \sum_z p(z)p(w|z)p(d|z)$
Log-Likelihood: $L(\mathbf{U}, \mathbf{V}) = \sum_{i,j} x_{i,j} \log p(w_j|d_i)$
$= \sum_{(i,j) \in X} \log \sum_{z=1}^K p(w_j|z)p(z|d_i)$
$p(w_j|z) = v_{zj}$, $p(z|d_i) = u_{zi}$, $\sum_j^N v_{zj} = \sum_z^K u_{zi} = 1$
E-Step (optimal q: posterior of z over (d_i, w_j)):
$q_{zij} = \frac{p(w_j|z)p(z|d_i)}{\sum_{k=1}^K p(w_j|k)p(k|d_i)} := \frac{v_{zj}u_{zi}}{\sum_{k=1}^K v_{kj}u_{ki}}, \sum_z q_{zij} = 1$
M-Steps:
$p(z|d_i) = \frac{\sum_j x_{ij}q_{zij}}{\sum_j x_{ij}}, p(w_j|z) = \frac{\sum_i x_{ij}q_{zij}}{\sum_{i,l} x_{il}q_{zil}}$
Lower Bound of $L(\mathbf{U}, \mathbf{V})$ Jensen ineq. : $\sum_{i,j \in X} \sum_{z=1}^K q_{zij}(log(v_{zj}) + log(u_{zi}) - log(q_{zij}))$

Latent Dirichlet Allocation

To sample a new document, we need to extend X and U^T with a new row, s.t. $X = U^T V$. (While pLSA fixes both dimensions)
For each d_i sample topic weights $\mathbf{u}_i$~Dirichlet(α):
$p(u_i|\alpha) = \prod_{z=1}^K u_{zi}^{\alpha_k - 1}$, then topic z^t~Multi(u_i), word w^t~Multi(v_{z^t})
Multinom. obsv. model on wc vec: $p(\mathbf{x}|V, u) = \frac{l!}{\prod_j \mathbf{x}_j!}\prod_j \pi_j^{\mathbf{x}_j}$ where $\pi_j = \sum_z v_{zj}u_z$, $l = \sum_j x_j$
Bayesian averaging over $\mathbf{u}$: $p(\mathbf{x}|\mathbf{V}, \alpha) = \int p(\mathbf{x}|\mathbf{V}, \mathbf{u})p(\mathbf{u}|\alpha)d\mathbf{u}$

NMF Algorithm for quadratic cost function

$\min_{\mathbf{U},\mathbf{V}} J(\mathbf{U}, \mathbf{V}) = \frac{1}{2}\|\mathbf{X} - \mathbf{U}^\top\mathbf{V}\|_F^2$ (non-negativity) s.t. $\forall i, j, z : u_{zi}, v_{zj} \geq 0$
Comparison with pLSA:
1. sampling model: Gaussian vs multinomial 2. objective: quadratic vs KL divergence 3. constraints: not normalized
Alternating least squares:
1. init: $\mathbf{U}, \mathbf{V} = rand()$
2. repeat 3~4 for $maxIters$:
3. upd. $(\mathbf{V}\mathbf{V}^\top)\mathbf{U} = \mathbf{V}\mathbf{X}^\top$, proj. $u_{zi} = \max\{0, u_{zi}\}$

4. update $(\mathbf{U}\mathbf{U}^\top)\mathbf{V} = \mathbf{U}\mathbf{X}$, proj. $v_{zj} = \max\{0, v_{zj}\}$

5 Word Embeddings

Distr. Model: $p_\theta(w|w')$ = Pr[w in context of w']
Log-likelihood:
$L(\theta;\mathbf{w}) = \sum_{t=1}^T \sum_{\Delta\in I} \log p_\theta(w^{(t+\Delta)}|w^{(t)})$
Latent Vector Model: $w \to (\mathbf{x}_w, b_w) \in \mathbb{R}^{D+1}$
$p_\theta(w|w') = \frac{\exp[\langle \mathbf{x}_w,\mathbf{x}_{w'}\rangle + b_w]}{\sum_{v\in V}\exp[\langle \mathbf{x}_v,\mathbf{x}_{w'}\rangle+b_v]}$ (soft-max).
Modifications:
$\log p_\theta(w|w') = \langle y_w, x_{w'}\rangle + b_w$, word y_w, c'txt $x_{w'}$ use GloVe obj., negative sampling (logistic class.)

GloVe (Weighted Square Loss)

Co-occ.: $\mathbf{N} = (n_{ij}) \in \mathbb{R}^{|V|\times|C|} = \#w_i$ in context w_j
Objective: $H(\theta;\mathbf{N}) = \sum_{n_{ij}>0} f(n_{ij})(\log n_{ij} - \log\exp[\langle \mathbf{x}_i,\mathbf{y}_j\rangle + b_i + d_j])^2$, $f(n) = \min\{1, (\frac{n}{n_{max}})^\alpha\}$, $\alpha\in(0;1]$ $(=3/4)$ unnorm. distr. $\to$ 2-sided loss. cutoff n_{max}: limit influence of high freq. $f(n) \overset{n\to 0}{\to} 0$: as small counts very noisy
1. sample $(i,j) u.a.r, s.t. n_{ij} > 0$
2. $\mathbf{x}_i^{new} \leftarrow \mathbf{x}_i + 2\eta f(n_{ij})(\log n_{ij} - \langle \mathbf{x}_i,\mathbf{y}_j\rangle)\mathbf{y}_j$
3. $\mathbf{y}_j^{new} \leftarrow \mathbf{y}_j + 2\eta f(n_{ij})(\log n_{ij} - \langle\mathbf{x}_i,\mathbf{y}_j\rangle)\mathbf{x}_i$

embeds can model analogies and relatedness, but antonyms are usually not well captured.

6 Data Clustering & Mixture Models

K-means Target: $\min_{\mathbf{U},\mathbf{Z}} J(\mathbf{U},\mathbf{Z}) = \|\mathbf{X}-\mathbf{U}\mathbf{Z}\|_F^2 = \sum_{n=1}^N\sum_{k=1}^K \mathbf{z}_{k,n}\|\mathbf{x}_n - \mathbf{u}_k\|_2^2$
1. **Initiate:** choose K centroids $\mathbf{U} = [\mathbf{u}_1,\dots,\mathbf{u}_K]$
2. **Cluster Assign:** data points to clusters. $k^\star(\mathbf{x}_n) = \arg\min_k\{\|\mathbf{x}_n-\mathbf{u}_k\|_2\}$ returns cluster $k^\star$, whose centroid $\mathbf{u}_{k^\star}$ is closest to data point $\mathbf{x}_n$. Set $\mathbf{z}_{k^\star,n}=1$, and for $l\neq k^\star$ $\mathbf{z}_{l,n}=0$.
3. **Update centroids**: $\mathbf{u}_k = \frac{\sum_{n=1}^N z_{k,n}\mathbf{x}_n}{\sum_{n=1}^N z_{k,n}}$.
4. Repeat until $\|\mathbf{Z}-\mathbf{Z}^{\text{new}}\|_0 = \|\mathbf{Z}-\mathbf{Z}^{\text{new}}\|_F^2 = 0$.

Computational cost: $O(k\cdot n\cdot d)$ Prior: $p(z)=1/K$
K-Means++: 1. Choose centroid $\mathbf{u}_1$ randomly from datapoints S 2. For $x\in S$, calculate min. squared distance $d_m(x)$ to existing centroids $c_1,\dots,c_m$ 3. Add new centroid c_{m+1}, choosen randomly from S with prob. $p(x) = d_m(x)/\sum_{z\in S} d_m(z)$ 4. Repeat until K centroids choosen $\to$ proceed with K-means

Gaussian Mixture Models (GMM)

Gaussian $p(x) = \frac{1}{\sqrt{2\pi}\sigma}exp(-\frac{(x-\mu)^2}{2\sigma^2})$ Multivariate $p(x;\mu;\Sigma) = \frac{1}{|\Sigma|^{\frac12}(2\pi)^{\frac D2}} exp[-\frac12(x-\mu)^T\Sigma^{-1}(x-\mu)]$
For GMM let $\theta_k = (\mu_k,\Sigma_k)$; $p_{\theta_k}(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\mu_k,\Sigma_k)$
Mixture Models: $p_\theta(\mathbf{x}) = \sum_{k=1}^K \pi_k p_{\theta_k}(\mathbf{x})$
Assignment variable (generative model): $z_{ij}\in\{0,1\}$, $\sum_{j=1}^k z_{ij}=1$
Prior: $\Pr(z_k=1)=\pi_k \Leftrightarrow p(\mathbf{z}) = \prod_{k=1}^K \pi_k^{z_k}$
Complete data distribution:
$p_\theta(\mathbf{x},\mathbf{z}) = \prod_{k=1}^K (\pi_k p_{\theta_k}(\mathbf{x}))^{z_k}$
Posterior Probabilities:
$\Pr(z_k=1|\mathbf{x}) = \frac{\Pr(z_k=1)p(\mathbf{x}|z_k=1)}{\sum_{l=1}^K \Pr(z_l=1)p(\mathbf{x}|z_l=1)} = \frac{\pi_k p_{\theta_k}(\mathbf{x})}{\sum_{l=1}^K \pi_l p_{\theta_l}(\mathbf{x})}$
posterior$P(A|B) = \frac{\text{prior}P(A)\times\text{likelihood}P(B|A)}{\text{evidence}P(B)}$
Likelihood of observed data X:
$p_\theta(\mathbf{X}) = \prod_{n=1}^N p_\theta(\mathbf{x}_n) = \prod_{n=1}^N(\sum_{k=1}^K \pi_k p_{\theta_k}(\mathbf{x}_n))$
Max. Likelihood Estimation (MLE):
$\arg\max_\theta \sum_{n=1}^N \log(\sum_{k=1}^K \pi_k p_{\theta_k}(\mathbf{x}_n))$
$\geq \sum_{n=1^N}\sum_{k=1}^K q_k[\log p_{\theta_k}(\mathbf{x}_n) + \log\pi_k - \log q_k]$
with $\sum_{k=1}^K q_k = 1$ by Jensen Inequality.
Generative Model
1. sample cluster index $j\sim Categorical(\pi)$
2. given j, sample data $x\sim \text{Normal}(\mu_j,\Sigma_j)$

Expectation-Maximization (EM) for GMM
E-Step: $\Pr[z_{k,n}=1|\mathbf{x}_n] = q_{k,n} = \frac{\pi_k^{(t-1)}\mathcal{N}(\mathbf{x}_n|\mu_k^{(t-1)},\Sigma_k^{(t-1)})}{\sum_{j=1}^K \pi_j^{(t-1)}\mathcal{N}(\mathbf{x}_n|\mu_j^{(t-1)},\Sigma_j^{(t-1)})}$
M-Step: $\mu_k^{(t)} := \frac{\sum_{n=1}^N q_{k,n}\mathbf{x}_n}{\sum_{n=1}^N q_{k,n}}$, $\pi_k^{(t)} := \frac1N\sum_{n=1}^N q_{k,n}$
$\Sigma_k^{(t)} = \frac{\sum_{n=1}^N q_{k,n}(\mathbf{x}_n-\mu_k^{(t)})(\mathbf{x}_n-\mu_k^{(t)})^\top}{\sum_{n=1}^N q_{k,n}}$
K-means vs. EM hard vs soft; spherical clusters vs covariance matrix; fast and cheap vs slow and more iteration; K-means can be used as init. for EM. K-means as a special case of GMM with covariances $\Sigma_j = \sigma^2 I$. limit of $\sigma\to 0$ is K-means (hard asgmts).
Model Order Selection (AIC / BIC for GMM)
Trade-off between data fit (i.e. likelihood $p(\mathbf{X}|\theta)$) and complexity (i.e. # of free parameters $\kappa(\cdot)$). For choosing K: $\text{AIC}(\theta|\mathbf{X}) = -\log p_\theta(\mathbf{X}) + \kappa(\theta)$
$\text{BIC}(\theta|\mathbf{X}) = -\log p_\theta(\mathbf{X}) + \frac12\kappa(\theta)\log N$
# of free params, fixed covariance matrix: $\kappa(\theta) = K\cdot D + (K-1)$ (K: # clusters, D: $\dim(\text{data}) = \dim(\mu_i)$, $K-1$: π of # free clusters), full covariance matrix: $\kappa(\theta) = K(D+\frac{D(D+1)}{2}) + (K-1)$.
Compare AIC/BIC for different K – the smaller the better. BIC penalizes complexity more.

7 Sparse Coding

Orthogonal Basis

Pros: fast inverse; preserves energy. For $\mathbf{x}$ and orthog. mat. $\mathbf{U}$ compute $\mathbf{z} = \mathbf{U}^\top\mathbf{x}$. Approx $\hat{\mathbf{x}} = \mathbf{U}\hat{\mathbf{z}}$, $\hat{z}_i = z_i$ if $|z_i| > \varepsilon$ else 0. Reconstruction Error $\|\mathbf{x}-\hat{\mathbf{x}}\|^2 = \sum_{d\notin\sigma}\langle\mathbf{x},\mathbf{u}_d\rangle^2$. Choice of base depends on signal. Fourier: global support, good for sine like waves; wavelet: local support, poor for non-vanishing signal; PCA basis optimal for given Σ. Stripes & check patterns: hi-freq in Fourier. Fourier: $O(D\cdot logD)$, Wavelet: $O(D)$ or $O(D\cdot logD)$

Haar Wavelets (form orthogonal basis)

scaling fnc. $\phi(x) = [1,1,1,1]$, mother $W(x) = [1,1,-1,-1]$, dilated $W(2x) = [1,-1,0,0]$, translated $W(2x-1) = [0,0,1,-1]$ Must be normalized

Overcomplete Basis

$\mathbf{U}\in\mathbb{R}^{D\times L}$ for # atoms $= L > D = \dim(\text{data})$. Decoding involved $\to$ add constraint $\mathbf{z}^\star\in\arg\min_{\mathbf{z}}\|\mathbf{z}\|_0$ s.t. $\mathbf{x} = \mathbf{U}\mathbf{z}$. NP-hard $\to$ approximate with 1-norm (convex) or with MP.
Coherence • $m(\mathbf{U}) = \max_{i,j:i\neq j}|\mathbf{u}_i^\top\mathbf{u}_j|$ • $m(\mathbf{B}) = 0$ if $\mathbf{B}$ orthog. matrix • $m([\mathbf{B},\mathbf{u}]) \geq \frac{1}{\sqrt{D}}$ if atom $\mathbf{u}$ is added to orthog. basis $\mathbf{B}$ (o.n.b. = orthonormal base)
Matching Pursuit (MP) approximation of $\mathbf{x}$ onto $\mathbf{U}$, using K entries. Objective: $\mathbf{z}^\star\in\arg\min_{\mathbf{z}}\|\mathbf{x}-\mathbf{U}\mathbf{z}\|_2$, s.t. $\|\mathbf{z}\|_0\leq K$ 1. init: $z\leftarrow 0, r\leftarrow x$ 2. while $\|\mathbf{z}\|_0 < K$ do 3. select atom *index* with smallest angle $i^\star = \arg\max_i|\langle\mathbf{u}_i,\mathbf{r}\rangle|$ 4. update coefficients: $z_{i^\star}\leftarrow z_{i^\star} + \langle\mathbf{u}_{i^\star},\mathbf{r}\rangle$ 5. update residual: $\mathbf{r}\leftarrow\mathbf{r}-\langle\mathbf{u}_{i^\star},\mathbf{r}\rangle\mathbf{u}_{i^\star}$.
Exact recovery when: $K < 1/2(1+1/m(\mathbf{U}))$
Compressive Sensing: Compress data while gathering: • $\mathbf{x}\in\mathbb{R}^D$, K-sparse in o.n.b. $\mathbf{U}$. $\mathbf{y}\in\mathbb{R}^M$ with $y_i = \langle\mathbf{w}_i,\mathbf{x}\rangle$: M lin. combinations of signal; $\mathbf{y} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{U}\mathbf{z} = \Theta\mathbf{z}$, $\Theta\in\mathbb{R}^{M\times D}$ • Reconstruct $\mathbf{x}\in\mathbb{R}^D$ from $\mathbf{y}$; find $\mathbf{z}^\star\in\arg\min_{\mathbf{z}}\|\mathbf{z}\|_0$, s.t. $\mathbf{y} = \Theta\mathbf{z}$ (e.g. with MP, or convex it with 1-norm: can be eq.!). Given $\mathbf{z}$, reconstruct $\mathbf{x} = \mathbf{U}\mathbf{z}$
Any orthogonal $\mathbf{U}$ sufficient if: • $\mathbf{W}$ = Gaussian random projection, i.e. $w_{ij}\sim\mathcal{N}(0,\frac1D)$ • M $\geq cKlog(\frac{D}{K})$, where c is some constant

8 Dictionary Learning

Adapt dict. to signal characteristics. Obj: $(\mathbf{U}^\star,\mathbf{Z}^\star)\in\arg\min_{\mathbf{U},\mathbf{Z}}\|\mathbf{X}-\mathbf{U}\cdot\mathbf{Z}\|_F^2$ not jointly convex but convex in either. **Matrix Fact. by Iter Greedy Min.** 1. Coding step: $\mathbf{Z}^{t+1}\in\arg\min_{\mathbf{Z}}\|\mathbf{X}-\mathbf{U}^t\mathbf{Z}\|_F^2$ subject to $\mathbf{Z}$ being sparse ($\mathbf{z}_n^{t+1}\in\arg\min_{\mathbf{z}}\|\mathbf{z}\|_0$ s.t.$\|\mathbf{x}_n-\mathbf{U}^t\mathbf{z}\|_2\leq\sigma\|\mathbf{x}_n\|_2$) 2. Dict update step: $\mathbf{U}^{t+1}\in\arg\min_{\mathbf{U}}\|\mathbf{X}-\mathbf{U}\mathbf{Z}^{t+1}\|_F^2$, subj to $\forall l\in[L]$: $\|\mathbf{u}_l\|_2 = 1$. (set $\mathbf{U} = [\mathbf{u}_1^t\cdots\mathbf{u}_l\cdots\mathbf{u}_L^t]$, $\min_{\mathbf{u}_l}\|\mathbf{X}-\mathbf{U}\mathbf{Z}^{t+1}\|_F^2 = \min_{\mathbf{u}_l}\|\mathbf{R}_l^t - \mathbf{u}_l(\mathbf{z}_l^{t+1})^\top\|_F^2$ with $\mathbf{R}_l^t = \tilde{\mathbf{U}}\Sigma\tilde{\mathbf{V}}^\top$ by $\mathbf{u}_l^* = \tilde{\mathbf{u}}_1$)

9 Neural Networks

Activation: scalar, non-linear $\tanh(x) = \frac{e^x-e^{-x}}{e^x+e^{-x}}$
sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$, $\sigma'(x) = \sigma(x)(1-\sigma(x))$
Neurons: $F_\sigma(\mathbf{x};\mathbf{w}) = \sigma(w_0 + \sum_{i=1}^M x_i w_i) = \sigma(w^\top x)$
Output: linear regression $\mathbf{y} = \mathbf{W}^L\mathbf{x}^{L-1}$, binary (logistic) $y_1 = \text{P}[Y=1|\mathbf{x}] = \frac{1}{1+\exp(-\mathbf{w}^T\mathbf{x}^{L-1})}$, multiclass (soft-max) $y_k = \text{P}[Y=k|\mathbf{x}] = \frac{\exp(\mathbf{w}_k^T\mathbf{x}^{L-1})}{\sum_{m=1}^K\exp(\mathbf{w}^T\mathbf{x}^{L-1})}$. **Loss** $l(y,\hat{y})$: squared loss $\frac12(y-\hat{y})^2$, cross-entropy loss $-y\log\hat{y}-(1-y)\log(1-\hat{y})$ $0\leq\hat{y}\leq 1, y\in\{0,1\}$ or $y\in[0,1]$. **layer-wise:** $\mathbf{x}^l = \sigma^l\left(\mathbf{W}^{(l)}\mathbf{x}^{(l-1)}\right)$.

Backpropagation

Layer-to-layer Jacobian: $\mathbf{x}$ = prev. layer activation, $\mathbf{x}^+$ = next layer activation. Jacobian matrix $\mathbf{J} = J_{ij}$ of mapping $\mathbf{x}\to\mathbf{x}^+$, $\mathbf{x}_i^+ = \sigma(\mathbf{w}_i^\top\mathbf{x})$, $J_{ij} = \frac{\partial\mathbf{x}_i^+}{\partial\mathbf{x}_j} = w_{ij}\cdot\sigma'(\mathbf{w}_i^\top\mathbf{x})$. Across multiple layers: $\frac{\partial\mathbf{x}^{(l)}}{\partial\mathbf{x}^{(l-n)}} = \mathbf{J}^{(l)}\cdot\frac{\partial\mathbf{x}^{(l-1)}}{\partial\mathbf{x}^{(l-n)}} = \mathbf{J}^{(l)}\cdot\mathbf{J}^{(l-1)}\cdots\mathbf{J}^{(l-n+1)}$ and then back prop. $\nabla_{\mathbf{x}^{(l)}}^\top\ell = \nabla_{\mathbf{y}}^\top\ell\cdot\mathbf{J}^{(L)}\cdots\mathbf{J}^{(l+1)}$
Weights: $\frac{\partial l}{\partial w_{ij}^{(l)}} = \frac{\partial l}{\partial x_i^{(l)}}\frac{\partial x_i^{(l)}}{\partial w_{ij}^{(l)}}$, $\frac{\partial x_i^l}{\partial w_{ij}^l} = \sigma'([\mathbf{w}_i^{(l)}]^T\mathbf{x}^{(l-1)})\cdot x_j^{(l-1)}$ (sensitivity of down-stream unit · activation of up-stream unit)<

Gradient Descent (or Deepest Descent)

Gradient: $\nabla f(\mathbf{x}) := \left(\frac{\partial f(\mathbf{x})}{\partial x_1},\dots,\frac{\partial f(\mathbf{x})}{\partial x_D}\right)^\top$
$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \gamma\nabla f(\mathbf{x}^{(t)})$, usually $\gamma\approx\frac1t$
SGD Assume additive obj. $f(x) = \frac1N\sum_{n=1}^N f_n(x)$ sample $n\in_{u.a.r.}\{1,\dots,N\}$, then $\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} - \gamma\nabla f_n(\mathbf{x}^{(t)})$, typically $\gamma\approx\frac1t$.

Neural Networks for Images (CNN)

$F_{n,m}(\mathbf{x};\mathbf{w}) = \sigma(b + \sum_{k=-2}^2\sum_{l=-2}^2 w_{k,l}x_{n+k,m+l})$.

10 Deep Unsupervised Learning

AR: Image $p(\mathbf{x}) = \Pi_i^{n^2} p(x_i|x_1,\cdots,x_{i-1})$ **ELBO:** $\mathbb{E}_{x\sim P_{\mathbf{X}}}[\mathbb{E}_{z\sim Q}\log P_g(x|z) - D_{KL}(Q(z|x)\|P(z))]$
Q enc. posterior distr., $P(z)$ prior distr. on latent var z, P_g likelihood of dec. generated $\mathbf{x}$. Jointly trained: enc. optimize regularizer term, sample $\mathbf{z}\sim Q$, feed to dec., produce $\hat{x}$ to max. reconstruction quality. Both terms diff'able, can use SGD to train end-to-end. **Reparam. trick:** use variational distr.s s.t. $q_\phi(\mathbf{z};\mathbf{x}) = g_\phi(\zeta;\mathbf{x})$ with eg. $\zeta\sim\mathcal{N}(\mathbf{0},\mathbf{I})$ Example: $\zeta\sim\mathcal{N}(\mathbf{0},\mathbf{I})$, $\mathbf{z} = \mu + U\zeta$ then $z\sim\mathcal{N}(\mu,\mathbf{U}^\top\mathbf{U})$