

Basics

General

Cauchy-Schwartz Inequality: $|u \cdot v| \leq \|u\| \|v\|$

Probability Basics

$\Pr[a \leq X \leq b] = \int_a^b f_X(x) dx$
Cumulative distribution function: $F_X(x) = \mathbb{P}(X \leq x) = \int_{-\infty}^x f_X(t) dt$
Bayes: $p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)} = p(\text{model}|\text{data}) = \frac{p(\text{data}|\text{model})p(\text{model})}{p(\text{data})}$
Posterior probability \propto Likelihood \times Prior probability
Markov inequality $\mathbb{P}(g(X) \geq r) \leq \frac{\mathbb{E}[g(X)]}{r}$
Chebyshev inequality $\mathbb{P}(|X - \mu| \geq \epsilon) \leq \frac{\sigma^2}{\epsilon^2}$
Jensen inequality $\varphi(\mathbb{E}[X]) \leq \mathbb{E}[\varphi(X)]$ where φ is a *convex* function. E.g. $\log(x)$ if $x > 0$
Law of large numbers $\mathbb{P}(|\frac{S_n}{n} - \mu| \geq \epsilon) \leq \frac{\sigma^2}{n \cdot \epsilon^2} \rightarrow 0$ if $n \rightarrow 0$
Bound on disjunction: $\max \mathbb{P}(A_1), \dots, \mathbb{P}(A_n) \leq \mathbb{P}(E) \leq \min 1, \mathbb{P}(A_1) + \dots + \mathbb{P}(A_n)$
Glivenko-Catelli theorem: $\mathbb{P}(\sup_x |F_n(x) - F(x)| \rightarrow 0) = 1$ if $n \rightarrow 0$.

Derivatives

$\frac{\partial}{\partial \mathbf{x}}(\mathbf{b}^\top \mathbf{x}) = \frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top \mathbf{b}) = \mathbf{b}$ $\frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top \mathbf{x}) = 2\mathbf{x}$
 $\frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top \mathbf{A} \mathbf{x}) = (\mathbf{A}^\top + \mathbf{A})\mathbf{x}$ $\frac{\partial}{\partial \mathbf{x}}(\mathbf{b}^\top \mathbf{A} \mathbf{x}) = \mathbf{A}^\top \mathbf{b}$
 $\frac{\partial}{\partial \mathbf{X}}(\mathbf{c}^\top \mathbf{X} \mathbf{b}) = \mathbf{c} \mathbf{b}^\top$ $\frac{\partial}{\partial \mathbf{X}}(\mathbf{c}^\top \mathbf{X}^\top \mathbf{b}) = \mathbf{b} \mathbf{c}^\top$
 $\frac{\partial}{\partial \mathbf{x}}(\|\mathbf{x} - \mathbf{b}\|_2) = \frac{\mathbf{x} - \mathbf{b}}{\|\mathbf{x} - \mathbf{b}\|_2}$ $\frac{\partial}{\partial \mathbf{x}}(\|\mathbf{x}\|_2^2) = \frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^\top \mathbf{x}) = 2\mathbf{x}$
 $\frac{\partial}{\partial \mathbf{X}}(\|\mathbf{X}\|_F^2) = 2\mathbf{X}$ $\frac{\partial}{\partial \mathbf{X}}(\|\mathbf{X}\|_2) = \frac{\mathbf{x}}{\|\mathbf{X}\|_2}$
 $\frac{\partial}{\partial \mathbf{x}}(\|\mathbf{A} \mathbf{x} - \mathbf{b}\|_2^2) = 2(\mathbf{A}^\top \mathbf{A} \mathbf{x} - \mathbf{A}^\top \mathbf{b})$ $\frac{\partial}{\partial x} \frac{g(x)}{h(x)} = \frac{g'(x)h(x) - g(x)h'(x)}{h(x)^2}$
 $\frac{\partial}{\partial (w_i^T x)} \text{softmax}(j) = \text{softmax}(j)(\delta_{ij} - \text{softmax}(i))$

Maximization Basics

Calculus of Variations
Goal: find the maximum of a functional.
 $J(x + \delta x) - J(x) = 0$
Given: functional of form $J[f] = \int_a^b L[x, f(x), f'(x)] dx$
change $\delta J = \int_a^b \frac{\delta J}{\delta f(x)} \delta f(x) dx$
complete data likelihood: $p(x, k | \mu, \eta)$
incomplete data likelihood: $p(x | \mu, \eta)$
functional derivative: $\frac{\delta J}{\delta f(x)} = \frac{\partial L}{\partial f} - \frac{d}{dx} \frac{\partial L}{\partial f'}$
EM-Algorithm
given: $p(\mathbf{X}, \mathbf{Z} | \theta)$ with observed variables \mathbf{X} and latent variables \mathbf{Z} , parameters θ *goal:* maximize likelihood function $p(\mathbf{X} | \theta)$ wrt. θ .

- choose initial setting for θ^{old}
- E-step:** evaluate $Q_i(z^{(i)}) := p(z^{(i)} | x^{(i)}; \theta)$
- M-step:** $\theta := \text{argmax}_{\theta} \sum_i \sum_{z^{(i)}} Q_i(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \theta)}{Q_i(z^{(i)})}$
- check if converged.

Information Theory

Mutual information:
measures the amount of information that can be obtained about one random variable by observing another
 $I(X; Y) = \mathbb{E}_{X,Y}[SI(X, y)] = \sum_{x,y} p(x, y) \log \frac{p(x,y)}{p(x)p(y)}$
 $I(X; Y) = H(X) - H(X|Y)$.
 $I(X; Y) = I(Y; X) = H(X) + H(Y) - H(X, Y)$.
 $I(X, Y; Z) = I(X; Z) + I(Y; Z|X)$
chain rule for information: $I(X; Y, Z) = I(X; Z) + I(X; Y|Z)$
 $I(X; Y) = \mathbb{E}_{p(y)}[D_{\text{KL}}(p(X|Y = y) \| p(X))]$.
Information Processing Inequality: Let $X \rightarrow Y \rightarrow Z$ be a Markov Chain, then $I(x, z) \leq I(x, y)$

Kullback-Leibler divergence

- quantifies coding cost describing data with probability distribution q when true distribution is p .
- KL divergence is positive semidefinite. $D_{\text{KL}} \geq 0$. Use Jensen's inequality to prove it.

way of comparing two distributions: a "true"probability distribution $p(X)$, and an arbitrary probability distribution $q(X)$.
or: unnecessary surprise". **not** symmetric!
 $q(X)$ is the distribution underlying some data, when, in reality, $p(X)$ is the correct distribution, the Kullback–Leibler divergence is the number of average additional bits per datum necessary for compression.
 $D_{\text{KL}}(p(X) \| q(X)) = \sum_{x \in X} -p(x) \log q(x) - \sum_{x \in X} -p(x) \log p(x) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)}$

continuous case: $D_{\text{KL}}(P \| Q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} dx$

Dimensionality Reduction

Principal Component Analysis (PCA)

Idea
dimensionality reduction with orthogonal projection of D-dimensional data onto lower M-dimensional linear space (*principal subspace*). Variance is maximized.
Procedure

- calculate mean $\bar{x} = \frac{1}{N} \sum_{n=1}^N x_n$ and covariance matrix \mathbf{S} of data set
- find the M eigenvectors corresponding to the M largest eigenvalues.
- data projected on these eigenvectors have largest variance.

Probabilistic Principal Component Analysis (PP-CA)

Idea
 $\mathbf{x} = \mathbf{W} \mathbf{z} + \boldsymbol{\mu} + \boldsymbol{\epsilon}$, with $p(\mathbf{z}) = \mathcal{N}(\mathbf{z} | \mathbf{0}, \mathbf{I})$ and $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$
 $p(\mathbf{x} | \mathbf{z}) = \mathcal{N}(\mathbf{x} | \mathbf{W} \mathbf{z} + \boldsymbol{\mu}, \sigma^2 \mathbf{I})$
Procedure

- calculate mean $\bar{x} = \frac{1}{N} \sum_{n=1}^N x_n$ and covariance matrix \mathbf{S} of data set
- find the M eigenvectors corresponding to the M largest eigenvalues.
- data projected on these eigenvectors have largest variance.

Advantages

- computationally efficient \rightarrow no need to evaluate covariance matrix as intermediate step
- allows us to deal with missing data in data set

Locally Linear Embedding

N real valued vector \vec{X}_i of dimension D .
Assumption: data lies close on locally linear patch of manifold.
Construct each data point from its K nearest (e.g. euclidean distance) neighbors.
Reconstruction error: $\mathcal{E}(W) = \sum_i |\vec{X}_i - \sum_j W_{ij} \vec{X}_j|$
where W_{ij} summarize the contribution of the j th data point to the i th reconstruction.
LLE Algorithm:

- Compute the neighbors of each data point, \vec{X}_i .
- Compute the weights W_{ij} that best reconstruct each data point \vec{X}_i from its neighbors, minimizing the cost $\mathcal{E}(W)$ by constrained linear fits. We have $w_{ij} = \frac{\sum_k C_{jk}^{(-i)}}{\sum_{lk} C_{lk}^{(-i)}}$, where $C_{jk}^{(i)} = (x_i - x_j)^T (x_i - x_k)$
- Compute the vectors \vec{Y}_i best reconstructed by the weights W_{ij} , minimizing the quadratic form in $\Phi(Y) = \sum_i |\vec{X}_i - \sum_j W_{ij} \vec{Y}_j|^2$ by its bottom nonzero eigenvectors. The embedding vectors are given by the eigenvectors corresponding to the $d+1$ smallest eigenvalues of $M = (1 - W)^T (1 - W)$

Maximum Entropy Inference

Maximizing entropy yields least biased inference method \rightarrow maximally non-committal wrt. missing data.

Maximum entropy distribution

Idea
Outcomes $\omega_i \in \Omega$, determine probabilities $p_i = \mathbb{P}(\omega_i)$. Given constraints/moments $\mu_i = \mathbb{E}[r_j] = \sum_{i=1}^n r_j(\omega_i) p_i$, where $r_j : \Omega \rightarrow \mathbb{R}$ $j = 1, 2, \dots, n$ are different functions defined over Ω .
Gibbs distribution
minimal sesitivity to changes in constraint moments μ_i
 $p(x) = \frac{1}{Z} \exp(-\sum_{j=1}^m \lambda_j r_j(x))$ where m is the number of constraints.

$Z = \int_x \exp(-\sum_{j=1}^m \lambda_j r_j(x)) dx$

Gibbs Free Energy
 $G(p) = \sum_x p(x) E(x) + \frac{1}{\beta} \sum_x p(x) \log p(x) = \frac{1}{\beta} D_{KL}(p \| p_{\beta}) + F(\beta)$ Minimising $G(p)$ minimises the expected cost and maximises the entropy of $p(x)$.
Derive least sensitive distributions

- determine all r_j from constraints.

- calculate Z and $p(x)$ from Gibbs distribution
- calculate all moments and set equal to constraints.

For a general cost function:
$$\mathbf{P}(\mathbf{c}) = \frac{e^{-\beta \mathcal{R}(\mathbf{c})}}{\sum_{\mathbf{c}' \in \mathcal{C}} e^{-\beta \mathcal{R}(\mathbf{c}')}} = \frac{e^{-\beta \mathcal{R}(\mathbf{c})}}{Z} = \exp(-\beta(\mathcal{R}(\mathbf{c}) - \mathcal{F}))$$
where $\mathcal{F}(\beta) = -\frac{1}{\beta} \log(Z)$ is known as „free energy“.
Free energy for any distribution: $\mathcal{F} = -\frac{1}{\beta} S(\mathbf{P}) + \mathbb{E}_{\mathbf{P}} \mathcal{R}$

Entropy

H_X of a discrete random variable X is a measure of the amount of *uncertainty* associated with the value of X when only its distribution is known
 $H(X) = \mathbb{E}_X[I(X)] = -\sum_{x \in \mathbb{X}} p(x) \log p(x)$
 $H(Y|X) = \sum_{x,y} p(x,y) \log(p(y|x))$
Chain rule: $H(X, Y) = H(X) + H(Y|X)$

$H(X, Y|Z) = H(X|Z) + H(Y|X, Z)$

Maximum Entropy Clustering

Idea
Determine probabilistic centroids y_{α} and probabilistic assignments $P_{i\alpha}$ of i -th object to cluster α . Data \mathcal{X} and labelings c are r.v.
Procedure

- Define posterior probability distribution $P(c | \mathcal{X}, \mathcal{Y})$, $c \in \mathcal{C}$, constraint $\mathbb{E}_{P(c | \mathcal{X}, \mathcal{Y})} \mathcal{R}(c, \mathcal{X}, \mathcal{Y}) = \mu$ where μ is a constant.
- find centroid conditions and assignments $P_{i\alpha}$ by maximizing entropy wrt. $\mathcal{Y} \rightarrow \frac{\partial}{\partial \mathbf{y}_{\alpha}} H(P(c | \mathcal{X}, \mathcal{Y})) = \mathbf{0}$

Most agnostic $P(c | \mathcal{X}, \mathcal{Y})$ is Gibbs distribution.

$$P(c | \mathcal{X}, \mathcal{Y}) = \frac{\exp(-\mathcal{R}(c, \mathcal{X}, \mathcal{Y})/T)}{\sum_{c' \in \mathcal{C}} \exp(-\mathcal{R}(c', \mathcal{X}, \mathcal{Y})/T)}$$

Remark: If the cost function is linear in individual costs, posterior can be factorized!

Clustering distributional data

Idea
„Close“ objects have similar feature distributions. \rightarrow cluster via similarity.
Distributional data encoded in dyads (pair $(x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$): n different objects $\{x_i\} \in \mathcal{X}$, m possible feature values $\{y_i\} \in \mathcal{Y}$. Data is set of l observations $\mathcal{Z} = \{(x_{i(r)}, y_{j(r)})\}_{r=1}^l$.
Likelihood of data \mathcal{Z} $\mathcal{L}(\mathcal{Z}) = \prod_{i \leq n} \prod_{j \leq m} P((i, j) | c(i), Q)^{l \hat{P}(i)}$ where $l \hat{P}(i) = \#$ object i exhibits value j and $\hat{P}(i)$ = empirical probability finding object i with feature value j .

Procedure

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Parametric distributional clustering

Density estimation is assumed to be Gaussian $g_a(y)$.
 $p(y | \nu) = \sum_{a \leq s} g_a(y) p(a | \nu)$ where $p(a | \nu)$ mixture coefficients, s number of mixture components.
Remark: Often feature values are restricted to specific domains, mixture components \rightarrow rectified. Complete data likelihood is given by: $p(x, M | \theta) = \prod_{i=1}^n \sum_{r=1}^k M_{ir} p_r p(x_i | r)$, where $M_{ir} \in \{0, 1\}$ and $\sum_r M_{ir} = 1$
Assuming that the observations x_{ij} are taken from domain I , which is equipartitioned into I_p for $p = 1..m$, we have $p(x_{ij} \in i_p | \alpha) =: G_{\alpha}(p)$. Thus: $p(x, M | \theta) = \prod_{i=1}^n \prod_{r=1}^k [p_r \prod_{p=1}^m \sum_{\alpha=1}^l p(\alpha | r) G_{\alpha}(p)^{n_{ip}}]^{M_{ir}}$, where n_{ip} counts how many observations x_{ij} from object i fell into bin I_p
The connection to the Info Bottleneck idea is given by:
 X : decision to pick an object i uniformly.
 \hat{X} : encoding of object i by cluster r .
 Y : Relative frequency of observing bin p .
Seeing that $I(X, \hat{X}) = H(X \hat{X}) = -\sum_{r=1} p_r \log p_r$, i.e. $I(X, \hat{X}) = \log k$ for $p_r = \frac{1}{k}$
We also have $H(Y | \hat{X}) = -\sum_{i=1}^n \sum_{r=1}^k \sum_{p=1}^m M_{ir} \frac{n_{ip}}{n_i} \frac{1}{n} \log \sum_{\alpha} p(\alpha | r) G_{\alpha}(p)$
Putting it all together we get that $I(X, \hat{X}) - \lambda I(\hat{X}, Y) = -\sum_r (\frac{1}{n} \sum_i M_{ir}) \log p_r - \lambda \sum_{i,r} \frac{1}{n} M_{ir} \sum_p \frac{n_{ip}}{n_i} \log \sum_{\alpha} p(\alpha | r) G_{\alpha}(p) - \lambda H(Y) = -\frac{1}{n} \sum_{i,r} M_{ir} [\log p_r + \frac{\lambda}{n_i} \sum_p n_{ip} \log \sum_{\alpha} p(\alpha | r) G_{\alpha}(p)] - \lambda H(Y)$
By choosing the right constants and then dropping stuff that doesn't affect the minimum. That this is equal to the negative log likelihood.

Markov Chain Monte Carlo (MCMC)

Idea: sampling from a probability distribution by constructing a Markov chain that has the desired distribution as its equilibrium distribution.

Markov Chain

$P_N(x_1, \dots, x_N) = p_1(x_1) \prod_{t=1}^{N-1} w(x_t \rightarrow x_{t+1})$
where $\{p_1(x)\}_{x \in \mathcal{X}}$ is the initial state and $\{w(x \rightarrow y)\}_{x,y \in \mathcal{X}}$ are the transition probabilities
transition probabilities must be non-negative and normalized: $\sum_y p_{in, \mathcal{X}} w(x \rightarrow y) = 1$, for any $y \in \mathcal{X}$
Eigenvalues:
First eigenvalue is always equal to 1. The smaller λ_2 the faster the MCMC converges.
irreducible: It is possible to get to any state from any state
Detailed balance: $\pi_i P_{ij} = \pi_j P_{ji}$ or $p(x)(x \rightarrow y) = p(y)p(y \rightarrow x)$, implies stationarity!
Stationarity: $\pi \mathbf{P} = \pi$
Aperiodic: Chain should not get trapped in cycles, i.e. for all states x, y there's an integer $n(x, y)$, s.t. $\forall n > n(x, y)$, there's a path of length n between x and y

Metropolis-Hastings

Initialization: Choose an arbitrary point x_0 as first sample, choose arbitrary probability density $g(x|y)$ that suggests a candidate for the next sample value x . For Metropolis algorithm, g must be symmetric $\rightarrow g(x|y) = g(y|x)$ e.g. a Gaussian distribution centered at y , \rightarrow points closer to y more likely to be visited next \rightarrow sequence of samples \rightarrow random walk. function $g \rightarrow$ proposal density or jumping distribution.

Algorithm:

- Generate a new sample x' from the old x according to a proposal PDF: $x' \sim q(\cdot | x)$
 - Calculate acceptance probability $A(x', x)$ according to quotient $Q(x', x) = \frac{p(x')q(x|x')}{p(x)q(x'|x)}$
 $A(x', x) = \min(1, Q(x', x))$
 - Accept x' as new sample with with probability $A(x', x)$, else keep x .

Disadvantages:

- samples are correlated. For independent samples one would have to take only every n -th sample.
- initial samples may follow a very different distribution. Solution: throw away first 1000 samples.
- for high dimensions: finding the right jumping distribution can be difficult, as the different individual dimensions behave in very different ways, and the jumping width must be "just right"for all dimensions at once to avoid excessively slow mixing \rightarrow Gibbs Sampling.

Gibbs Sampling

given a multivariate distribution it is simpler to sample from a conditional distribution than to marginalize by integrating over a joint distribution.
Applicable if:

- conditional distribution of each variable is known and is easy (or at least, easier than joint distribution) to sample from
-

For Gibbs sampling in the Ising model we use the transition probability to a new state where only σ_i is flipped: $p_i(\sigma) = \exp(-\beta \max[0, \Delta E_i(\sigma)])$ simulated annealing is often used to reduce the "random walk"behavior in the early part of the sampling process

Heat-Bath Algorithm

Same as metropolis but with acceptance probability:
 $p(\sigma_{new}) = \exp(-\beta E(\sigma_{new})) / (\exp(-\beta E(\sigma_{new}) + \exp(-\beta E(\sigma_{old})))$

Simulated Annealing

- Idea**
- Markov process samples solution from solution space Ω
 - cost function $\mathcal{H} : \Omega \rightarrow \mathbb{R}$, $\omega \in \Omega$ denotes admissible solution.
 - solutions accepted/rejected according to Metropolis algorithm: decreased cost \rightarrow accepted, increased cost \rightarrow accepted with probability $\exp(-\Delta \mathcal{H}/T)$ where $\Delta \mathcal{H} = \mathcal{H}(\omega_{new}) - \mathcal{H}(\omega_{old})$. T is the computational temperature.
 - reduce gradually the temperature during search proces \rightarrow force system into solution with low costs. \rightarrow random walk in solution space.
 - annealing schedule, i.e. the β s, could be linear, quadratic or logarithmic for instance.

Markov process with converges to equilibrium:
 $\mathbf{P}^{Gb}(\omega) = \exp(-(\mathcal{H}(\omega) - \mathcal{F}(\mathcal{H}))/T)$
where $\mathcal{F}(\mathcal{H}) = -T \log \sum_{\omega' \in \Omega} \exp(-\mathcal{H}(\omega')/T)$

Remarks

- Temperature formally \approx Lagrange parameter \rightarrow constraint on expected costs. $\langle H \rangle = \sum_{\omega \in \Omega} P^{Gb}(\omega) \mathcal{H}(\omega)$

- Gibbs free energy related to expected cost via entropy $\mathcal{S}(P^{Gb}) = -\sum_{\omega \in \Omega} P^{Gb}(\omega) \log(P^{Gb}(\omega)) = \frac{1}{T} \langle H \rangle - \frac{1}{T} \mathcal{F}(\mathcal{H})$

Parallel Tempering

Two Monte Carlo simulation were to run in parallel, one at high and one at a low temperature. At certain steps we swap the configurations of the two runs. This way both runs have access to low and high temperature configuration improving convergence to a global optimum. We swap the configurations after each epoch.

Deterministic Annealing

Idea
deterministic variant of *Simulated annealing*.
The critical temperature, at which a cluster will split is: $T_c = 2\lambda_{max}$ where λ_{max} is the largest eigenvalue of $C_{x|y_0} = \sum_x p(x|y)(x - y)(x - y)^t$

Information Bottleneck Method

Idea
input signal X should be efficiently encoded by e.g. cluster variable \tilde{X} pre-serving relevant information about context variable Y as good as possible.
 $I(X; \tilde{X}) - \lambda I(\tilde{X}, Y)$

Parametric Distributional Clustering

Idea
cluster set of n objects \mathbf{o}_i in k groups. Assignments encoded in $M_{i,\nu}$, $M_{i,\nu} = 1$ if \mathbf{o}_i assigned to cluster ν . Enforce $\sum_{\nu \leq k} M_{i,\nu} = 1$.

Graph based clustering

relations among objects not necessarily metric.

Idea
 \mathcal{O} is the set of vertices \mathcal{V} , set of edges is inferred, set of (di)similarity mea-sures $\mathcal{D} = \{D_{ij}\}$ or $\mathcal{S} = \{S_{ij}\}$ are the weights.
Cluster defined as: $\mathcal{G}_\alpha \{ \mathbf{o} \in \mathcal{O} : c(\mathbf{O}) = \alpha \}$

Correlation Clustering

Idea
agreement within cluster, disagreement between clusters maximized.
Script p. 30

Pairwise Data Clustering

cost function:

$$\mathcal{R}^{pc}(c, \mathcal{D}) = \frac{1}{2} \sum_{\nu \leq k} \left(|\mathcal{G}_\nu| \sum_{(i,j)} \in \epsilon_{\nu\nu} \frac{D_{ij}}{|\epsilon_{\nu\nu}|} \right)$$

Remarks:

- dissimilarity matrix \mathcal{D}_{ij} only zero for self-dissimilarity entries, $|\mathcal{G}_\nu|, |\epsilon_{\nu\nu}|$ cardinality of cluster/edges.
- cost function invariant under symmetrization and constant/additive shifts of non-diagonal elements
- metric data can always be transformed to PC data but not always vice versa

⇒ embed given nonmetric proximity data problem in vector space without changing underlying properties. → see CSE.

Constant Shift Embedding (CSE)

Embed pairwise clustering problem into vector space.

CSE algorithm

- given dissimilarity matrix D , calculate central-ized version D^c (3.13)
 - calculate matrix $S^c = -1/2D^c$ (Lemma 3)
 - calculate eigenvalues of S^c . If S^c isn't positive semidefinite, $\tilde{S} = S^c - \lambda_n \cdot I_n$ (subtract smallest eigenvalue from diagonal elements)
 - $\tilde{D}_{ij} = \tilde{S}_{ii} + \tilde{S}_{jj} + \tilde{S}_{ij}$
 - Next steps only if you want embedding vectors
 - Get $\tilde{S}^c = \frac{1}{2} \tilde{D}^c$
 - Get eigendecomposition of $\tilde{S}^c = V \Lambda V^T$
 - The rows of $X_p = V_p(\Lambda_p)^{1/2}$ are the p-dimensional embedding vectors of the data. V_p are the first p eigenvectors.

Remarks:

- embedding validity shows equivalence to k-means clustering, ideas of centroids and cluster representatives can be used
- pairwise data can be denoised when transformed into vectorial data. (e.g. in preprocessing)
- minimization processes pairwise cost function or k-means problem is

\mathcal{NP} -hard → algorithms like deterministic annealing and mean field approximation needed. For \mathcal{R}^{km} it's exact, for \mathcal{R}^{pc} remains an approx-imation.

Reconstructing the embedded vectors

- calculate centralized dot product matrix $\tilde{S}^c = -\frac{1}{2} Q \tilde{D} Q$ from matrix of squared Euclidian di-stances \tilde{D} .
 - Express in its eigenbasis $\tilde{S}^c = V \Lambda V^T$, $V = (v_1, ..., v_n)$ contains eigenvectors v_i , $\Lambda = diag(\lambda_1, ..., \lambda_n)$ diagonal matrix of eigenvalues and $\lambda_1 \geq ... \geq p > \lambda_{p+1} = ... = \lambda_n = 0$,
 - calculate $n \times p$ map matrix $X_p = V_p(\Lambda_p)^{1/2}$ with $V = (v_1, ..., v_p)$, $\Lambda_p = diag(\lambda_1, ..., \lambda_p)$ rows of X_p contain vectors x_i in p dimension-al space, mutual distances are given my \tilde{D}

Predicting Cluster Membership of New Data

- given dissimilarity matrix D , calculate centrali-zed version D^c (3.13)
 - calculate matrix $S^c = -1/2D^c$ (Lemma 3)
 - calculate eigenvalues of S^c . If S^c isn't positive semidefinite, $\tilde{S} = S^c - \lambda_n \cdot I_n$ (subtract smallest eigenvalue from diagonal elements)
 - $\tilde{D}_{ij} = \tilde{S}_{ii} + \tilde{S}_{jj} + \tilde{S}_{ij}$
 - Next steps only if you want embedding vectors
 - Get $\tilde{S}^c = \frac{1}{2} \tilde{D}^c$
 - Get eigendecomposition of $\tilde{S}^c = V \Lambda V^T$
 - The rows of $X_p = V_p(\Lambda_p)^{1/2}$ are the p-dimensional embedding vectors of the data. V_p are the first p eigenvectors.

Cut

Partitioning a graph $G(V, E)$ with nodes V and edges E into disjoint sets $A, B \rightarrow$ removing edges connecting parts. Degree of dissimilarity is compu-ted as total weight of removed edges:
 $cut(A, B) = \sum_{u \in A, v \in B} w(u, v)$
Minimum cut: optimal bipartitioning of graph that minimizes cut value.
Note: Minimum cut favors cutting small sets of isolated nodes in graph. → use normalized cut.

Normalized Cut

$Ncut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$ where $assoc(A, V) = \sum_{u \in A, t \in V} w(u, t)$ $Ncut(A, B)$ can be seen as the disassociation between two groups.
measure for total normalized association within groups for a given partition:
 $Nassoc(A, B) = \frac{assoc(A, A)}{assoc(A, V)} + \frac{assoc(B, B)}{assoc(B, V)}$ where $assoc(A, A)$ are the total weights of edges connecting nodes within A, B respectively. Measures how tightly on average nodes are connected within group.
 $Ncut(A, B) = 2 - Nassoc(A, B)$

Computing Optimal Partition

Grouping algorithm

- Given image or image sequence, set up weighted graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$, set weight on edge connect-ing two nodes to measure of similarity
 - Solve $(\mathbf{D} - \mathbf{W})\mathbf{x} = \lambda \mathbf{D}\mathbf{x}$ for eigenvectors with smallest eigenvalues.
 - use eigenvector with second smallest eigenvalue to bipartition graph by finding splitting point s.t. $Ncut$ is minimized.
 - Decide if current partition should be subdivided by checking stability of cut, make sure $Ncut$ is below prespecified value.
 - recursively repartition if necessary.

Computational complexity

- Solving eigenvalue problem for all eigenvectors takes $\mathcal{O}(n^3)$ operati-ons
- Graphs often only locally connected, only top few eigenvectors needed, precision requirements low → $\mathcal{O}(nm) + \mathcal{O}(mM(n))$ where $M(n)$ is the cost of matrix-vector computation \mathbf{Ax} ($A = \mathbf{D}^{1/2}(\mathbf{D} - \mathbf{W})\mathbf{D}^{1/2}$).

Mean Field Approximation

Mean Field Theory

Approximate Gibbs distribution by neglecting correlations between stocha-stic variables → determine „most similar“ factorized distribution. Only con-sider factorized distributions: $q(\mathbf{Z}) = \prod_{i=1}^M q_i(\mathbf{Z}_i)$
→ no correlations between assignments of different objects. Then minimize the Kullback-Leibler divergence to obtain best factorial approximation.
Mean field $h_{u\alpha}$ is the expected cost $\mathcal{R}(c)$ that object u assigned to cluster α
Mean field upper bound: $F(\beta) \leq F_0(\beta) + \langle E \rangle_0 - \langle E_0 \rangle_0 = KL(p_0||p)/\beta + F(\beta) = \sum_{\sigma} p_0(\sigma) E(\sigma) + \frac{1}{\beta} \sum_{\sigma} p_0(\sigma) \log p_0(\sigma)$

Determine mean field

- split cost function \mathcal{R} into terms that contain the object u and other terms. Term has a form like $\mathcal{R}(c) = f(u) + \mathcal{R}(c|u)$
- take the expected value $\mathbb{E}_{\mathbf{Q}_{u \rightarrow \alpha}}$

Pseudocode:

- initialize $\forall i, q_i(1), \dots, q_i(k)$ randomly s.t. $\sum_{\nu} q_i(\nu) = 1$;
 - repeat**
 - draw** $u \in \{1, \dots, n\}$ randomly; // site selection
 - calculate** $h_{u,\alpha} = \mathbb{E}_{\mathbf{Q}_{u \rightarrow \alpha}}[\mathcal{R}(c)]$ for given $q_u(1), \dots, q_u(k)$;
 - estimate** $\forall \alpha$, $q_u(\alpha) = \frac{\exp(-\beta h_{u,\alpha})}{\sum_{\nu \leq k} \exp(-\beta h_{u,\nu})}$ given $h_{u,1}, \dots, h_{u,k}$;
 - $t \leftarrow t + 1$;
 - until** $\forall \alpha$ probabilities $q_u(\alpha)$ and meanfields $h_{u,\alpha}$ are converged
 - stop**

Approximation set coding

Find robust, informative pattern (hypothesis $c \in \mathcal{C}$ hypothesis space) in data

Approximation sets

data space \mathcal{X} , cost function $\mathcal{R}(c)$, hypothesis $c \in \mathcal{C}$
solution $c^\perp(X) = \operatorname{argmin}_{c \in \mathcal{C}} \mathcal{R}(c)$ is random since X is random.
→ if second set X' is used → $c^\perp(X) \neq c^\perp(X')$ → do not commit to a single answer, use set where each hypothesis c has weight.

Weights

weights w rank different hypothesis according to how well they solve pro-blem:
 $\forall c, c' \in \mathcal{C} \mathcal{R}(c, X) \leq \mathcal{R}(c, X') \Leftrightarrow w_\beta(c, X) \geq w_\beta(c, X')$
where approximation precision β controls resolution of solutions.
→ set of hypothesis that approximately solve the problem:
 $\mathcal{C}_\beta(X) = \{c \in \mathcal{C} : \mathcal{R}(c, X) - \mathcal{R}(c^\perp(X), X) \leq 1/\beta\}$
i.e. lead to solutions that are $1/\beta$ close to minimum.
assume every $c \in \mathcal{C}_\beta$ equally good → posterior $P_\beta(c|X) = \operatorname{unif}(\mathcal{C}_\beta(X))$
 $\beta \rightarrow 0$: every hypothesis good solution → not informative.
 $\beta \rightarrow \infty$: each set has only one element → not robust.
⇒ β controls tradeoff between informativeness and robustness/how much posterior distributions agree for different values of β .

Communication scenario

partition hypothesis space \mathcal{C} with distinguishable approximation sets and use them as symbols for communication

Codebook generation

Problem: usually only one set of observations available. → use set of trans-formation \mathbb{T} :

$$\forall t \in \mathbb{T}, \forall c \in \mathcal{C}, \forall \beta \in \mathbb{R}_+ w_\beta(t \circ c, t \circ X) = w_\beta(c, X)$$

Codebook construction: Script p.g 43

Communication Protocol

• chain rule for information

Model Selection

Minimum Description Length: $-logp(x|\theta_k) - logp(\theta_k)$

Bayesian Information Criterion: $-2log(\hat{p}|\hat{\theta}_k, \mathcal{M}_k) + klogn$, where \mathcal{M}_k is one of the possible model classes.
Gap Statistic: $gap_n(k) := E_n^*[log(W_k)] - log(W_k)$, where $W_k = \sum_{\eta} \frac{1}{2n\eta} \sum_{i,j \in \epsilon_{\eta\eta}} D_{ij}$ and $D_{ij} = ||x_i - x_j||^2$ The optimal k can then be chosen as: $k^* = \min[k|gap_n(k) \geq gap_n(k + 1) - \sigma_{k+1}]$

Gap Statistic:

- Train a predictor $\phi_{Z'}$ on the data $Z' := (X', \alpha(X'))$
 - Predict labels on X using $\phi_{Z'}$
 - Compare clustering solutions $(\phi_{Z'}(X_i))_{i \in [n]}$ and $\alpha(X)$ on X
- Choose classifier that matches chosen clustering model.

Coding Exercises

Deterministic Annealing Clustering

Deterministic Annealing Clustering is an approach to the unsupervised lear-ning problem of clustering. At its core the algorithm is about minimizing the Lagrangian:

$$F = D - TH$$

, where D is a measure of the distortion, the "distanceöf the datapoints from their respective cluster centers, H is the Shannon Entropy of the system and T is the temperature. The algorithm is grounded in both information theory and statistical physics. The core idea is that, at an initially high temperature the entropy is maximized. Then as we gradually lower the temperature T , the distortion is minimized.

The *preferred implementation* of the algorithm is as follows:

- Initialize the number of codevectors, the minimal temperature, the initial temperature, the initial number of clusters, the initial cluster center and it's probabilitiy.
- For i in [1,K]

$$y_i = \frac{\sum_x xp(x)(y_i|x)}{p(y_i)}$$

where

$$p(y_i|x) = \frac{p(y_i)e^{(x-y_i)^2/T}}{\sum_{j=1}^K p(y_i)e^{(x-y_j)^2/T}}$$

and

$$p(y_i) = \sum_x p(x)p(y_i|x)$$

- If not converged, repeat (2)
- If $T < T_{min}$, stop
- Cool down: $T = \alpha T$, $\alpha < 1$
- If $K < K_{max}$ check if any of the clusters has reached critical tem-perature. If so, add a new codevector $y_{K+1} = y_j + \delta, p(y_{K+1} = p(y_j)/2, p(y_j) = p(y_j)/2$, where j is the cluster that has reached critical temperature. Increase K by one.
- Repeat from (3)

The *critical temperature* is the temperature for which a given cluster splits into two. Assuming Euclidean distance as our measure of distortion, it can be explicitly computed as

$$T_{c,y_i} = 2\lambda_{max}$$

, where λ_{max} is the largest eigenvalue of $C_{x|y_i}$, which in turn is the Cova-riance matrix of the posterior distribution of $p(x|y)$

Histogram Clustering

MAP updates: $\hat{P}(y|c) = \sum_{x \in \hat{c}} \frac{n(x)}{\sum_{x' \in c} n(x')} \hat{P}(y|x)$ (1)

$$\hat{c}(x) = \operatorname{argmin}_a \{ -\sum_{y \in Y} \hat{P}(y|x) \log \hat{P}(y|a) \}$$

For DA clustering (1) becomes: $\hat{P}(y|c) = \sum_{x \in X} \hat{P}(x|c) \hat{P}(y|x)$ with $\hat{P}(c) = \sum_{x \in X} \hat{P}(c|x) \hat{P}(x)$
 $\hat{P}(x|c) = \frac{\hat{P}(c|x) \hat{P}(x)}{\sum_{x \in X} \hat{P}(c|x) \hat{P}(x)}$

and, with

$$\hat{P}(c|x) = \frac{\exp(-D_{KL}[\hat{P}(\cdot|x)||\hat{P}(\cdot|a)]/T)}{\sum_{b=1}^K \exp(-D_{KL}[\hat{P}(\cdot|x)||\hat{P}(\cdot|a)]/T)}$$

replacing equation (6)

DA for pairwise clustering

Given a dataset of size N and an $N \times N$ dissimilarity matrix $\mathbf{D} = (D_{ik})$, the problem of pairwise clustering tries to cluster the data into K clusters, represented by an $N \times K$ assignment matrix $\mathbf{M} = (M_{i\nu}) \in \{0, 1\}^{N \times K}$ that minimizes the cost function

$$\mathcal{H}^{pc}(\mathbf{M}) = \frac{1}{2} \sum_{i,k=1}^N \frac{\mathcal{D}_{ik}}{N} \left(\sum_{\nu=1}^K \frac{M_{i\nu} M_{k\nu}}{p_\nu} - 1 \right)$$

where $p_\nu = \frac{1}{N} \sum_{i=1}^N M_{i\nu}$ is the weight of cluster ν . Algorithm II approximates the Gibbs distribution given by \mathcal{H}^{pc} with the Gibbs distribution given by the factorial cost function $\mathcal{H}^0(\mathbf{M}, \mathcal{E}) = \sum_{i=1}^N \sum_{\nu=1}^K M_{i\nu} \mathcal{E}_{i\nu}$, parameterized by external mean fields $\mathcal{E} = (\mathcal{E}_{i\nu})$. Minimizing the Kullback-Leibler divergence $D^{KL}(\mathbf{P}^{Gb}(\mathcal{H}^0) \parallel \mathbf{P}^{Gb}(\mathcal{H}^{pc}))$, where $\mathbf{P}^{Gb}(\mathcal{H})$ is the Gibbs distribution for the cost function $\mathcal{H}(\mathbf{M})$ gives the optimal \mathcal{E} as

$$\mathcal{E}_{i\nu}^* = \left\langle \frac{1}{1 + \sum_{j \neq i} M_{j\nu}} \left[\frac{1}{2} \mathcal{D}_{ii} + \sum_{k \neq i} M_{k\nu} \left(\mathcal{D}_{ik} - \frac{1}{2} \frac{\sum_{j \neq i} M_{j\nu} \mathcal{D}_{jk}}{\sum_{j \neq i} M_{j\nu}} \right) \right] \right\rangle,$$

where $\langle \cdot \rangle$ corresponds to taking expectations with respect to $\mathbf{P}^{Gb}(\mathcal{H}^0(\mathbf{M}))$. In the limit of large N, this optimum can be approximated as

$$\mathcal{E}_{i\nu}^* = \frac{1}{1 + \sum_{j \neq i} \langle M_{j\nu} \rangle} \left[\frac{1}{2} \mathcal{D}_{ii} + \sum_{k \neq i} \langle M_{k\nu} \rangle \left(\mathcal{D}_{ik} - \frac{1}{2} \frac{\sum_{j \neq i} \langle M_{j\nu} \rangle \mathcal{D}_{jk}}{\sum_{j \neq i} \langle M_{j\nu} \rangle} \right) \right]$$

The expectations $\langle M_{j\alpha} \rangle$ under the Gibbs distribution $\mathbf{P}^{Gb}(\mathcal{H}^0(\mathbf{M}))$ with temperature T are then given by

$$\langle M_{j\alpha} \rangle = \frac{\exp(-\mathcal{E}_{i\alpha}^*/T)}{\sum_{\nu=1}^K \exp(-\mathcal{E}_{i\nu}^*/T)}$$

Algorithm II then uses deterministic annealing to approximate the Gibbs distribution for varying temperatures, by starting at high temperature, iteratively applying the two above equations for $\langle M_{j\alpha} \rangle$ and $\mathcal{E}_{i\nu}^*$ in an EM scheme for fixed T , and decreasing T exponentially until the final temperature is reached.

Algorithm III further constrains the variational distribution to be in the form of a Gibbs distribution for the k-means cost function

$$\mathcal{H}^{cc}(\mathbf{M}) = \sum_{i=1}^N \sum_{\nu=1}^K M_{i\nu} \|\mathbf{x}_i - \mathbf{y}_\nu\|^2,$$

where $(\mathbf{x}_i)_{i=1}^N$ are embeddings of the data to be determined, and $(\mathbf{y}_\nu)_{\nu=1}^K$ are centroids calculated from $(\mathbf{x}_i)_{i=1}^N$; in this case the mean fields are constrained to take the form $\mathcal{E}_{i\nu} = \|\mathbf{x}_i - \mathbf{y}_\nu\|^2$. Minimizing the KL-divergence $D^{KL}(\mathbf{P}^{Gb}(\mathcal{H}^{cc}) \parallel \mathbf{P}^{Gb}(\mathcal{H}^{pc}))$ with respect to $(\mathbf{x}_i)_{i=1}^N$ and $(\mathbf{y}_\nu)_{\nu=1}^K$ now gives

$$\mathbf{K}_i \mathbf{x}_i \approx \frac{1}{2} \sum_{\nu=1}^K \langle M_{i\nu} \rangle (\|\mathbf{y}_\nu\|^2 - \mathcal{E}_{i\nu}^*) (\mathbf{y}_\nu - \langle \mathbf{y} \rangle_i)$$

where $\langle \mathbf{y} \rangle_i = \sum_{\nu=1}^K \langle M_{i\nu} \rangle \mathbf{y}_\nu$ is the mean of \mathbf{y} under the conditional distribution $p(\nu|i) = \langle M_{i\nu} \rangle$ and $\mathbf{K}_i = \langle \mathbf{y} \mathbf{y}^\top \rangle_i - \langle \mathbf{y} \rangle_i \langle \mathbf{y} \rangle_i^\top$ the corresponding covariance matrix, and $\mathcal{E}_{i\nu}^*$ is as calculated in Algorithm II. Algorithm III again uses deterministic annealing, calculating $\langle M_{i\nu} \rangle^{(t+1)}$ in the E-step from the mean fields $\mathcal{E}_{i\nu}^{(t)} = \|\mathbf{x}_i^{(t)} - \mathbf{y}_\nu^{(t)}\|^2$, and in the M-step updating $\mathbf{x}_i^{(t+1)}$ and $\mathbf{y}_\nu^{(t+1)}$ iteratively from fixed $\langle M_{i\nu} \rangle^{(t+1)}$ until the variables converge.

MFA for Image Denoising in Ising Model

In the image denoising setting, we are looking for an image σ to minimize:

$$E(\sigma) = -\lambda \sum_{i=1}^N h_i \sigma - \sum_{i,j=1}^N J_{i,j} \sigma_i \sigma_j$$

where h_i is the value of pixel i in the noisy observation.

We thus seek to minimize $KL(p_0||p) + F(\beta)$, which is equivalent to minimizing the Gibbs free energy $G(p)$, where $F(\beta)$ is the free energy, p_0 the proposal distribution and p the true distribution.

It can be shown that:

$$\begin{aligned} G(p) = & -\lambda \sum_{i=1}^N m_i h_i - \sum_{i=1}^{N-1} \sum_{j=i+1}^N m_i J_{ij} m_j \\ & + 1/\beta \sum_{i=1}^N \left(\frac{1+m_i}{2} \log \frac{1+m_i}{2} + \frac{1-m_i}{2} \log \frac{1-m_i}{2} \right) \end{aligned}$$

where m_i is the mean field for pixel i . Deriving the stationary equations, we find that $G(p)$ is minimized by:

$$m_k = \tanh(\beta(\sum_{i \neq k} J_{ki} m_i + \lambda h_k)), k \in 1, N$$

Which we can solve by iteratively updating the m_k .

Model Validation

//Some of this stuff is in lecture notes so we might want to cut it. In order to compare the stability of cost functions $R(c, \mathbf{X}) \in \mathcal{R}$ under noise in the data $\mathbf{X} \sim \mathbb{P}(\mathbf{X})$, approximation set coding considers a communication scenario including a sender, a problem generator and a receiver. Each entity is initially given access to a sample $\mathbf{X}^{(1)} \sim \mathbb{P}(\mathbf{X})$ and an optimal solution $c^\perp(\mathbf{X}^{(1)}) \in \arg \max_{c \in \mathcal{C}} R(c, \mathbf{X}^{(1)})$. The sender then chooses a transformation $\tau_s \in \mathbb{T}$, $|\mathbb{T}| = 2^{n\rho}$ which acts on the solution space (by permuting elements of the dataset in the case of clustering) and sends it to the problem generator, which generates another sample

$\mathbf{X}^{(2)} \sim \mathbb{P}(\mathbf{X})$ and sends $\tau_s \circ \mathbf{X}^{(2)}$ to the receiver. The receiver then estimates τ_s by maximizing the posterior agreement between $\mathbb{P}(c|\beta, \mathbf{X}^{(1)}) \propto \exp(-\beta R(c, \mathbf{X}^{(1)}))$ and $\mathbb{P}(c|\beta, \tau \circ \mathbf{X}^{(2)}) \propto \exp(-\beta R(c, \tau \circ \mathbf{X}^{(2)}))$, returning $\hat{\tau} \in \arg \max_{\tau} \sum_{\mathbb{T}} \sum_{c \in \mathcal{C}} \exp(-\beta(R(c, \mathbf{X}^{(1)} + R(c, \tau \circ \mathbf{X}^{(2)})))$. Here β represents the degree to which the data is trusted; the larger the noise in the data, the lower β has to be chosen to prevent decoding errors. The decoding error $\mathbb{P}(\hat{\tau} \neq \tau_s | \tau_s)$ can be shown to vanish asymptotically if the rate of transmission ρ falls below the mutual information

$$\mathcal{I}_\beta(\tau_s, \hat{\tau}) = \frac{1}{n} \log \frac{|\{\tau_s\}| \mathcal{Z}_{12}}{\mathcal{Z}_1 \mathcal{Z}_2},$$

where $\mathcal{Z}_1 = \sum_{c \in \mathcal{C}} \exp(-\beta R(c, \mathbf{X}^{(1)}))$, $\mathcal{Z}_2 = \sum_{c \in \mathcal{C}} \exp(-\beta R(c, \mathbf{X}^{(2)}))$, $\mathcal{Z}_{12} = \sum_{c \in \mathcal{C}} \exp(-\beta(R(c, \mathbf{X}^{(1)} + R(c, \mathbf{X}^{(2)})))$ and $|\{\tau_s\}|$ is the number of possible realizations of $c^\perp(\tau_s \circ \mathbf{X}^{(2)})$.

The approximation capacity is then defined as the maximum of \mathcal{I}_β over all inverse temperatures β . Then to apply model selection on \mathcal{R} , we split a given dataset \mathbf{X} randomly into two datasets $\mathbf{X}^{(1)}$ and $\mathbf{X}^{(2)}$, compute the mutual information \mathcal{I}_β for each $R \in \mathcal{R}$, maximize it with respect to β , and choose the cost function with the largest approximation capacity.

For k-means clustering, we have $R(c, \mathbf{X}; \mathbf{Y}) = \sum_{i=1}^n \epsilon_{i,c(i)}$ where $\epsilon_{ik} = \epsilon_{ik}(\mathbf{X}, \mathbf{Y}) = \|x_i - y_k\|^2$ and \mathbf{Y} are the cluster centroids inferred by maximizing the entropy of $\mathbb{P}(c|\beta, \mathbf{X})$. For $\epsilon_{ik}^{(i)} = \epsilon_{ik}(\mathbf{X}^{(i)}, \mathbf{Y})$ the mutual information is calculated as

$$\mathcal{I}_\beta = \frac{1}{n} \log |\{\tau_s\}| + \frac{1}{n} \sum_{i=1}^n \log \frac{\sum_{k=1}^K e^{-\beta(\epsilon_{ik}^{(1)} + \epsilon_{ik}^{(2)})}}{\sum_{k=1}^K e^{-\beta \epsilon_{ik}^{(1)}} \sum_{k=1}^K e^{-\beta \epsilon_{ik}^{(2)}}}$$

where $|\{\tau_s\}|$ is the number of distinct clusterings on $\mathbf{X}^{(1)}$.

Then to evaluate the approximation capacity of the k-means cost function, we use deterministic annealing to compute the optimal centroids and costs $R(c, \mathbf{X}^{(i)})$ at different temperatures $T = \beta^{-1}$, allowing for $2K$ possible clusters to enable overfitting, and choose as stopping temperature the one with the highest mutual information, balancing informativeness and robustness.

Exercise Sheets

Optimal β for Expected Log-Posterior Agreement

We consider the Gibbs posterior over hypotheses: $p_\beta(c|X) = \frac{1}{\mathcal{Z}(\beta,X)}exp(-\beta R(c,X))$. For two data sets X', X'' , the posterior agreement is defined as: $\hat{k}_\beta(X', X'') = \sum_{c \in \mathcal{C}} p_\beta(c|X')p_\beta(c|X'')$ We want to find β^* for which the posterior agreement is maximal. Finding the right β can be seen as a trade off between stability and informativeness of the distribution. In a sense, the optimal β is supposed to give us the most robust solution.