

Unsupervised Learning Methods

Problem Set IV

t-SNE and (Geometric) Domain Adaptation

Due: 15.07.2021

Guidelines

- Answer all questions (PDF + two Jupyter notebooks).
- You must type your solution manual (handwriting is not allowed).
- Submission in pairs (use the forum if needed).
- You **may** submit the entire solution in a ipynb file (or in PDF + ipynb files).
- You **may** (and should) use the forum if you have any questions.
- Good luck!

1 t-SNE

The t-SNE objective is given by:

$$\min_{\mathbf{Z} \in \mathbb{R}^{d \times N}} \underbrace{D_{\text{KL}}(\mathbf{P} || \mathbf{Q})}_{:=f(\mathbf{Z})} = \min_{\mathbf{Z} \in \mathbb{R}^{d \times N}} \sum_{i=1}^N \sum_{j=1}^N p_{ij} \log \left(\frac{p_{ij}}{q_{ij}} \right)$$

See the definitions of \mathbf{P} and \mathbf{Q} in the lecture notes (do not get confused by the SNE definitions). The goal of this question is to compute the gradient of the objective:

$$\nabla f(\mathbf{Z}) = ?$$

Let us break this task into several **smaller** steps.

1.1

Show that $f(\mathbf{Z}) = D_{\text{KL}}(\mathbf{P} || \mathbf{Q})$ can be written as:

$$f(\mathbf{Z}) = C - \langle \mathbf{P}, \log[\mathbf{Q}] \rangle$$

where C is some constant (the entropy of \mathbf{P}).

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- Reminder:

$$Q[i, j] = \frac{1}{B} \begin{cases} 0 & i = j \\ (1 + \|\mathbf{z}_i - \mathbf{z}_j\|_2^2)^{-1} & i \neq j \end{cases}$$

- Let $\mathbf{D}_z \in \mathbb{R}^{N \times N}$ such that $\mathbf{D}_z[i, j] = \|\mathbf{z}_i - \mathbf{z}_j\|_2^2$.
- Let $\mathbf{S} = (\mathbf{1}\mathbf{1}^T + \mathbf{D}_z)^{\circ -1} \in \mathbb{R}^{N \times N}$, that is:

$$S[i, j] = (1 + D_z[i, j])^{-1}$$

1.2

Show that:

- 1.

$$B = \mathbf{1}^T (\mathbf{S} - \mathbf{I}) \mathbf{1} \in \mathbb{R}$$

- 2.

$$\mathbf{Q} = B^{-1} (\mathbf{S} - \mathbf{I}) \in \mathbb{R}^{N \times N}$$

1.3

Show that:

$$-\langle \mathbf{P}, \log [\mathbf{Q}] \rangle = \log (B) + \langle \mathbf{P}, \log [\mathbf{1}\mathbf{1}^T + \mathbf{D}_z] \rangle$$

Hints:

- $\mathbf{P}[i, i] = ?$
 - $\mathbf{1}^T \mathbf{P} \mathbf{1} = ?$
-

Let:

- $g_1(\mathbf{Z}) = \langle \mathbf{P}, \log [\mathbf{1}\mathbf{1}^T + \mathbf{D}_z] \rangle$
- $g_2(\mathbf{Z}) = \log (B)$

The following two exercises will be useful when computing the gradients of g_1 and g_2 .

1.4

- Consider some symmetric matrix $\mathbf{M} = \mathbf{M}^T \in \mathbb{R}^{N \times N}$.
- Let $g_3(\mathbf{Z}) = \langle \mathbf{M}, \mathbf{D}_z \rangle$.

1.4.1

- Assume that \mathbf{M} is a diagonal matrix (only in this section).
- Simplify $g_3(\mathbf{Z})$ and compute the gradient $\nabla g_3(\mathbf{Z})$.
(No computations are required for this)

1.4.2

- Express the directional derivative as $\nabla g_3(\mathbf{Z})[\mathbf{H}] = \langle \mathbf{G}, \mathbf{H} \rangle$,
where $\mathbf{G} \in \mathbb{R}^{N \times N}$ is a function of $\mathbf{M} \in \mathbb{R}^{N \times N}$ and $\mathbf{Z} \in \mathbb{R}^{d \times N}$.
- Make sure your result coincides with the diagonal case.

Hint: $\mathbf{D}_z = \text{diag}(\mathbf{Z}^T \mathbf{Z}) \mathbf{1}^T - 2\mathbf{Z}^T \mathbf{Z} + \mathbf{1} \text{diag}^T(\mathbf{Z}^T \mathbf{Z})$.

1.5

Compute the gradient of $g_1(\mathbf{Z}) := \langle \mathbf{P}, \log[\mathbf{1}\mathbf{1}^T + \mathbf{D}_z] \rangle$

$$\nabla g_1(\mathbf{Z}) = ?$$

Hints:

- $\langle \mathbf{P}, \mathbf{S} \circ \nabla(\mathbf{D}_z)[\mathbf{H}] \rangle = \langle \mathbf{P} \circ \mathbf{S}, \nabla(\mathbf{D}_z)[\mathbf{H}] \rangle$
 - \mathbf{P} and \mathbf{S} are symmetric (use 1.4.2).
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1.6

Compute the gradient of $g_2(\mathbf{Z}) = \log(B)$

$$\nabla g_2(\mathbf{Z}) = ?$$

Hints:

- $\nabla \mathbf{S}[\mathbf{H}] = \nabla (\mathbf{1}\mathbf{1}^T + \mathbf{D}_z)^{\circ-1}[\mathbf{H}] = -(\mathbf{1}\mathbf{1}^T + \mathbf{D}_z)^{\circ-2} \circ \nabla(\mathbf{D}_z)[\mathbf{H}] = -\mathbf{S} \circ \mathbf{S} \circ \nabla(\mathbf{D}_z)[\mathbf{H}]$
 - $\mathbf{Q} = \mathbf{B}^{-1}(\mathbf{S} - \mathbf{I})$
 - Use 1.4.1 and 1.4.2.
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1.7

- Combine all previous results and write the gradient of the objective:

$$\nabla f(\mathbf{Z}) = ?$$

- Use $\mathbf{A} := (\mathbf{P} - \mathbf{Q}) \circ \mathbf{S}$ to simplify your answer.
 - What can you say about the gradient $\nabla f(\mathbf{Z})$ when $\mathbf{P} = \mathbf{Q}$?
-

1.8 Implementation and applications



Solve this section in the attached notebook.



2 Geometric Domain Adaptation

- Let $\mathcal{M} \subset \mathbb{R}^3$ be the sphere manifold:

$$\mathcal{M} = \left\{ \mathbf{x}_i \in \mathbb{R}^3 \mid \|\mathbf{x}_i\|_2 = 1 \right\}$$

- The geodesic $\gamma_{\mathbf{x} \rightarrow \mathbf{y}}(t)$ is given by (assuming \mathbf{x} and \mathbf{y} are not antipodal):

$$\gamma_{\mathbf{x} \rightarrow \mathbf{y}}(t) = \cos(ta) \mathbf{x} + \sin(ta) \mathbf{p}, \quad t \in [0, 1]$$

where:

- $a = \arccos(\mathbf{x}^T \mathbf{y}) \in \mathbb{R}$
- $\mathbf{p} = \frac{(\mathbf{I} - \mathbf{x}\mathbf{x}^T)\mathbf{y}}{\|(\mathbf{I} - \mathbf{x}\mathbf{x}^T)\mathbf{y}\|_2} \in \mathbb{R}^3$

2.1

Show that:

1. $\gamma(0) = \mathbf{x}$
2. $\gamma(1) = \mathbf{y}$

Hints:

- $\|\mathbf{x}\| = \|\mathbf{y}\| = ?$
 - $\sin(\arccos(\alpha)) = ?$
 - $\|(\mathbf{I} - \mathbf{x}\mathbf{x}^T)\mathbf{y}\|_2 = \sqrt{1 - ?}$
-

- Consider the symmetric matrix

$$\mathbf{X} = \begin{bmatrix} x & y \\ y & z \end{bmatrix} \in \mathbb{R}^{2 \times 2}$$

2.2

Prove that:

$$\mathbf{X} \succ 0 \iff \begin{cases} x > 0 \\ z > 0 \\ xz > y^2 \end{cases}$$

Hints:

- Show both directions at once.
 - $\text{Tr}\{\mathbf{X}\} = \lambda_1 + ?$
 - $\det(\mathbf{X}) = \lambda_1 \cdot ?$
-

The (affine invariant) geodesic (squared) distance between two SPD matrices is given by:

$$d^2(\mathbf{X}, \mathbf{Y}) = \left\| \log \left(\mathbf{X}^{-\frac{1}{2}} \mathbf{Y} \mathbf{X}^{-\frac{1}{2}} \right) \right\|_F^2$$

2.3

1. Let $\mathbf{A} = \mathbf{A}^T \in \mathbb{R}^{d \times d}$, show that:

$$\|\mathbf{A}\|_F^2 = \sum_{i=1}^d \lambda_i^2(\mathbf{A})$$

2. Assume $\mathbf{A} \succ 0$ and show that:

$$\|\log(\mathbf{A})\|_F^2 = \sum_{i=1}^d \log^2(\lambda_i(\mathbf{A}))$$

(**Hint:** What can you say about the eigenvalues of $\log(\mathbf{A})$?)

3. Show that $\mathbf{X}^{-\frac{1}{2}} \mathbf{Y} \mathbf{X}^{-\frac{1}{2}}$ and $\mathbf{X}^{-1} \mathbf{Y}$ have the same set of eigenvalues.

(**Hint:** HW2)

4. Conclude that (explain both equality):

$$d^2(\mathbf{X}, \mathbf{Y}) = \sum_{i=1}^d \log^2 \left(\lambda_i \left(\mathbf{X}^{-\frac{1}{2}} \mathbf{Y} \mathbf{X}^{-\frac{1}{2}} \right) \right) = \sum_{i=1}^d \log^2 (\lambda_i(\mathbf{X}^{-1} \mathbf{Y}))$$

Remark:

Instead of finding the eigenvalues of $\mathbf{X}^{-1} \mathbf{Y}$, that is:

$$\mathbf{X}^{-1} \mathbf{Y} \mathbf{u} = \lambda \mathbf{u}$$

We solve the (equivalent) task:

$$\mathbf{Y} \mathbf{u} = \lambda \mathbf{X} \mathbf{u}$$

This is known as the generalized eigen problem (with \mathbf{Y} and \mathbf{X}), and we do not need to invert any matrix.

2.4

Prove that:

1. For any invertible $\mathbf{C} \in \text{GL}$:

$$d(\mathbf{C} \mathbf{X} \mathbf{C}^T, \mathbf{C} \mathbf{Y} \mathbf{C}^T) = d(\mathbf{X}, \mathbf{Y})$$

(**Hint:** use similarity between matrices)

- 2.

$$d(\mathbf{X}, \mathbf{Y}) = d(\mathbf{X}^{-1}, \mathbf{Y}^{-1})$$

- Let $S_1, S_2 \in \mathcal{T}_X \mathcal{P}$
- Let $P_{X \rightarrow Y}(S) = ESE^T$ be a parallel transport where $E = X^{\frac{1}{2}} \left(X^{-\frac{1}{2}} Y X^{-\frac{1}{2}} \right)^{\frac{1}{2}} X^{-\frac{1}{2}}$.


2.5

Show that:

$$\langle S_1, S_2 \rangle_X = \langle P_{X \rightarrow Y}(S_1), P_{X \rightarrow Y}(S_2) \rangle_Y$$

Hint: Show that $E^T Y^{-1} E = X^{-1}$

2.6 Implementation and applications

 Solve this section in the attached notebook. 