

統計的機械学習
第十回 レポート

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宿題 1

$q(\mathbf{u}_j)$ について次の比例式が成立する。

$$q(\mathbf{u}_j) \propto p(\mathbf{u}_j | \mathbf{\Lambda}_u) \exp \left\{ \sum_{j, i \in \mathcal{O}} \int q(\mathbf{v}_i) \log p(r_{j, i} | \mathbf{u}_j^T \mathbf{v}_i, \sigma^2) d\mathbf{v}_i \right\} \quad (1)$$

ここで, $p(\mathbf{u}_j | \mathbf{\Lambda}_u)$ について,

$$p(\mathbf{u}_j | \mathbf{\Lambda}_u) \propto \exp \left(-\frac{1}{2} \mathbf{u}_j^T \mathbf{\Lambda}_u \mathbf{u}_j \right) \quad (2)$$

が成立する。また,

$$l_{u, i, j} \equiv \int q(\mathbf{v}_i) \log p(r_{j, i} | \mathbf{u}_j^T \mathbf{v}_i, \sigma^2) d\mathbf{v}_i \quad (3)$$

$$\begin{aligned} &= -\frac{1}{2\sigma^2} \int q(\mathbf{v}_i) (r_{j, i} - \mathbf{u}_j^T \mathbf{v}_i)^2 d\mathbf{v}_i \\ &= -\frac{1}{2\sigma^2} \int q(\mathbf{v}_i) (r_{j, i}^2 - 2r_{j, i} \mathbf{u}_j^T \mathbf{v}_i + \mathbf{u}_j^T \mathbf{v}_i \mathbf{v}_i^T \mathbf{u}_j) d\mathbf{v}_i \\ &= -\frac{1}{2\sigma^2} (r_{j, i}^2 - 2r_{j, i} \mathbf{u}_j^T \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i] + \mathbf{u}_j^T \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] \mathbf{u}_j) \end{aligned} \quad (4)$$

となる。式 (1), (2), (4) から,

$$\begin{aligned} q(\mathbf{u}_j) &\propto \exp \left(-\frac{1}{2} \mathbf{u}_j^T \mathbf{\Lambda}_u \mathbf{u}_j \right) \exp \left\{ \sum_{j, i \in \mathcal{O}} l_{u, i, j} \right\} \\ &= \exp \left(-\frac{1}{2} \mathbf{u}_j^T \mathbf{\Lambda}_u \mathbf{u}_j \right) \exp \left\{ \sum_{j, i \in \mathcal{O}} -\frac{1}{2\sigma^2} (r_{j, i}^2 - 2r_{j, i} \mathbf{u}_j^T \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i] + \mathbf{u}_j^T \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] \mathbf{u}_j) \right\} \\ &= \exp \left\{ -\frac{1}{2\sigma^2} \left(-2\mathbf{u}_j \left(\sum_{j, i \in \mathcal{O}} r_{j, i} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i] \right) + \mathbf{u}_j^T \left(\sum_{j, i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] + \sigma^2 \mathbf{\Lambda}_u \right) \mathbf{u}_j \right) \right\} \end{aligned} \quad (5)$$

いま, 多次元正規分布に従う確率変数 \mathbf{x} について次が成立する。

$$q(\mathbf{x}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto \exp \left\{ -\frac{1}{2} (\mathbf{x}^T \boldsymbol{\Sigma}^{-1} \mathbf{x} - 2\mathbf{x} \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}) \right\} \quad (6)$$

これと式 (5) を比べると,

$$q(\mathbf{u}_j) = \mathcal{N}(\mathbf{u}_j | \boldsymbol{\mu}_{u, j}, \mathbf{V}_{u, j}) \quad (7)$$

$$\mathbf{V}_{u, j}^{-1} \boldsymbol{\mu}_{u, j} = \frac{1}{\sigma^2} \sum_{j, i \in \mathcal{O}} r_{j, i} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i] \quad (8)$$

$$\mathbf{V}_{u, j}^{-1} = \frac{1}{\sigma^2} \left(\sum_{j, i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] + \sigma^2 \mathbf{\Lambda}_u \right) \quad (9)$$

となることがわかる。これを整理すると,

$$q(\mathbf{u}_j) = \mathcal{N}(\mathbf{u}_j | \boldsymbol{\mu}_{u,j}, \mathbf{V}_{u,j}) \quad (10)$$

$$\boldsymbol{\mu}_{u,j} = \frac{1}{\sigma^2} \mathbf{V}_{u,j} \sum_{j,i \in \mathcal{O}} r_{j,i} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i] \quad (11)$$

$$\mathbf{V}_{u,j} = \sigma^2 \left(\sum_{j,i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] + \sigma^2 \boldsymbol{\Lambda}_u \right)^{-1} \quad (12)$$

となる。

同様に, \mathbf{v}_i について,

$$q(\mathbf{v}_i) \propto p(\mathbf{v}_i | \boldsymbol{\Lambda}_v) \exp \left\{ \sum_{j,i \in \mathcal{O}} \int q(\mathbf{u}_j) \log p(r_{j,i} | \mathbf{u}_j^T \mathbf{v}_i, \sigma^2) d\mathbf{u}_j \right\} \quad (13)$$

$$\begin{aligned} &= \exp \left(-\frac{1}{2} \mathbf{v}_i^T \boldsymbol{\Lambda}_v \mathbf{v}_i \right) \exp \left\{ \sum_{j,i \in \mathcal{O}} -\frac{1}{2\sigma^2} \left(r_{j,i}^2 - 2r_{j,i} \mathbf{v}_i^T \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] + \mathbf{v}_i^T \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] \mathbf{v}_i \right) \right\} \\ &= \exp \left\{ -\frac{1}{2\sigma^2} \left(-2\mathbf{v}_i \left(\sum_{j,i \in \mathcal{O}} r_{j,i} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] \right) + \mathbf{v}_i^T \left(\sum_{j,i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] + \sigma^2 \boldsymbol{\Lambda}_v \right) \mathbf{v}_i \right) \right\} \end{aligned} \quad (14)$$

となることから,

$$q(\mathbf{v}_i) = \mathcal{N}(\mathbf{v}_i | \boldsymbol{\mu}_{v,i}, \mathbf{V}_{v,i}) \quad (15)$$

$$\boldsymbol{\mu}_{v,i}^{-1} = \frac{1}{\sigma^2} \sum_{j,i \in \mathcal{O}} r_{j,i} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] \quad (16)$$

$$\mathbf{V}_{v,i}^{-1} = \frac{1}{\sigma^2} \left(\sum_{j,i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] + \sigma^2 \boldsymbol{\Lambda}_v \right) \quad (17)$$

を得て, 結局,

$$q(\mathbf{v}_i) = \mathcal{N}(\mathbf{v}_i | \boldsymbol{\mu}_{v,i}, \mathbf{V}_{v,i}) \quad (18)$$

$$\boldsymbol{\mu}_{v,i} = \frac{1}{\sigma^2} \mathbf{V}_{v,i} \sum_{j,i \in \mathcal{O}} r_{j,i} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] \quad (19)$$

$$\mathbf{V}_{v,i} = \sigma^2 \left(\sum_{j,i \in \mathcal{O}} \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] + \sigma^2 \boldsymbol{\Lambda}_v \right)^{-1} \quad (20)$$

を得る。

宿題 2

いま, $\boldsymbol{\mu}_{u,j}$ の期待値と分散について,

$$\boldsymbol{\mu}_{u,j} = \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] \quad (21)$$

$$\mathbf{V}_{u,j} = \mathbb{E}_{q(\mathbf{u}_j)}[(\mathbf{u}_j - \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j])(\mathbf{u}_j - \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j])^T] \quad (22)$$

$$= \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] - \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j] \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j]^T \quad (23)$$

$$= \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] - \boldsymbol{\mu}_{u,j} \boldsymbol{\mu}_{u,j}^T \quad (24)$$

が成立する。これより,

$$\mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] = \mathbf{V}_{u,j} + \boldsymbol{\mu}_{u,j} \boldsymbol{\mu}_{u,j}^T \quad (25)$$

となる。ここで,

$$\mathbf{u} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Lambda}_u) \quad (26)$$

の分散を標本 $\{\mathbf{u}_j\}_{j=1}^J$ を用いて表すことを考えると, 平均 $\mathbf{0}$ から,

$$\boldsymbol{\Lambda}_u = \mathbb{E}_{q(\mathbf{u})}[\mathbf{u} \mathbf{u}^T] \quad (27)$$

$$= \frac{1}{J} \sum_{j=1}^J \mathbb{E}_{q(\mathbf{u}_j)}[\mathbf{u}_j \mathbf{u}_j^T] \quad (28)$$

$$= \frac{1}{J} \sum_{j=1}^J (\mathbf{V}_{u,j} + \boldsymbol{\mu}_{u,j} \boldsymbol{\mu}_{u,j}^T) \quad (29)$$

$\boldsymbol{\Lambda}_u$ は対角成分しか持たないため, 結局,

$$\rho_{u,k}^2 = \frac{1}{J} \sum_{j=1}^J ([\mathbf{V}_{u,j}]_{k,k} + \mu_{u,j,k}^2) \quad (30)$$

同様に, \mathbf{v}_i の期待値と分散について次式が成立し,

$$\mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] = \mathbf{V}_{v,i} + \boldsymbol{\mu}_{v,i} \boldsymbol{\mu}_{v,i}^T \quad (31)$$

また,

$$\mathbf{v} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Lambda}_v) \quad (32)$$

から,

$$\boldsymbol{\Lambda}_v = \mathbb{E}_{q(\mathbf{v})}[\mathbf{v} \mathbf{v}^T] \quad (33)$$

$$= \frac{1}{I} \sum_{i=1}^I \mathbb{E}_{q(\mathbf{v}_i)}[\mathbf{v}_i \mathbf{v}_i^T] \quad (34)$$

$$= \frac{1}{I} \sum_{i=1}^I (\mathbf{V}_{v,i} + \boldsymbol{\mu}_{v,i} \boldsymbol{\mu}_{v,i}^T) \quad (35)$$

$\mathbf{\Lambda}_v$ は対角成分しか持たないため、結局、

$$\rho_{v, k}^2 = \frac{1}{I} \sum_{i=1}^I \left([\mathbf{V}_{v, i}]_{k, k} + \mu_{v, i, k}^2 \right) \quad (36)$$

最後に、 r について考える。

$$r \sim \mathcal{N}(\mathbf{u}^T \mathbf{v}, \sigma^2) \quad (37)$$

から、

$$\sigma^2 = \mathbb{E}_{q(\mathbf{u})q(\mathbf{v})} [(r - \mathbf{u}^T \mathbf{v})^2] \quad (38)$$

$$= \frac{1}{|\mathcal{O}|} \sum_{(j, i) \in \mathcal{O}} \mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} \left[(r_{j, i} - \mathbf{u}_j^T \mathbf{v}_i)^2 \right] \quad (39)$$

$$= \frac{1}{|\mathcal{O}|} \sum_{(j, i) \in \mathcal{O}} \mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} \left[r_{j, i}^2 - 2r_{j, i} \mathbf{u}_j^T \mathbf{v}_i + \mathbf{u}_j^T \mathbf{v}_i \mathbf{v}_i^T \mathbf{u}_j \right] \quad (40)$$

$$(41)$$

いま、

$$\mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} [r_{j, i}^2] = r_{j, i}^2 \quad (42)$$

$$\mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} [\mathbf{u}_j^T \mathbf{v}_i] = \mathbb{E}_{q(\mathbf{u}_j)} [\mathbf{u}_j^T] \mathbb{E}_{q(\mathbf{v}_i)} [\mathbf{v}_i] = \boldsymbol{\mu}_{u, i}^T \mathbf{v}_{v, i} \quad (43)$$

であり、また、

$$\mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} [\mathbf{u}_j^T \mathbf{v}_i \mathbf{v}_i^T \mathbf{u}_j] = \mathbb{E}_{q(\mathbf{u}_j)q(\mathbf{v}_i)} [\text{Tr}\{\mathbf{v}_i \mathbf{v}_i^T \mathbf{u}_j \mathbf{u}_j^T\}] \quad (44)$$

$$= \text{Tr}\left\{ \mathbb{E}_{q(\mathbf{v}_i)} [\mathbf{v}_i \mathbf{v}_i^T] \mathbb{E}_{q(\mathbf{u}_j)} [\mathbf{u}_j \mathbf{u}_j^T] \right\} \quad (45)$$

$$= \text{Tr}\left\{ \left(\mathbf{V}_{u, j} + \boldsymbol{\mu}_{u, j} \boldsymbol{\mu}_{u, j}^T \right) \left(\mathbf{V}_{v, i} + \boldsymbol{\mu}_{v, i} \boldsymbol{\mu}_{v, i}^T \right) \right\} \quad (46)$$

となることから、結局、

$$\sigma^2 = \frac{1}{|\mathcal{O}|} \sum_{(j, i) \in \mathcal{O}} \left\{ r_{j, i}^2 - 2r_{j, i} \boldsymbol{\mu}_{u, j}^T \boldsymbol{\mu}_{v, i} + \text{Tr}\left\{ \left(\mathbf{V}_{u, j} + \boldsymbol{\mu}_{u, j} \boldsymbol{\mu}_{u, j}^T \right) \left(\mathbf{V}_{v, i} + \boldsymbol{\mu}_{v, i} \boldsymbol{\mu}_{v, i}^T \right) \right\} \right\} \quad (47)$$

となる。