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Avoid embarrassment in this important, evaluative, domain.

Errors marked

If $K = \lambda\pi$ and $\lambda = 2$, then Eq.(11) is Gaussian, but if $\lambda \neq 2$, in order that the integral attains one, $K = \lambda\pi|A_i|^{\frac{\lambda-2}{2\lambda}}$ must be satisfied. Since K depends $|A_i|$ and $|A_i|$ might be different for each i, K cannot assume a single constant value for all i. Eq.(11) is a sole formula, which can derive Eq.(7) by using Bayes rule in E-step. Thus when $\lambda \neq 2$ there is no corresponding mixture density and the proposed KFCM clustering is unique and novel one. It is easy to generalize the discussion to high dimensional case.

In KFCM clustering, parameter λ can be changed freely during the iteration of the algorithm, we can gradually reduce the value like an annealing procedure to obtain better solution. $\sum_{k=1}^{n} u_{ik}$ indicates the number of data included in the ith cluster. From $J_{\lambda\tau}$, A_i becomes a fuzzy variance-covariance matrix as in Eq.(9). Let A_i has m linearly independent eigenvectors, i.e., principal component vectors $(\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p}_m)$. Then $\log|A_i| = \log\prod_{j=1}^{m}\delta_j^2 = \sum_{j=1}^{m}\log\delta_j^2$ where δ_j^2 is an eigen value of A_i. Therefore $\log|A_i|$ is equivalent to the sum of the log transformed variances of principal components. The third term of $J_{\lambda\tau}$, $\sum_{k=1}^{n} u_{ik}\log|A_i|$, represents the variation weighted by the number of data. Mahalanobis distance of Eq.(4) is defined by A_i^{-1}. If we put weight parameter φ to the third term of $J_{\lambda\tau}$, then u_{ik} contains φ but substituting λ/φ to λ, φ can be 1. Therefore we do not need to add any other weight parameter to the third term of the objective function.

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Errors detailed

to: depends on $|A_i|$
to: may vary over *i*
[may : unknown property, not future property]
[vary over: an individual ('each') is not different]
to: which can be used to derive
to: by the use of the Bayes rule
to: is a unique
to: generalize this discussion
to: to a high dimensional
or, better
to any higher dimensional
to: clustering, where the parameter
to: value in a simulated annealing
to: obtain a better

to: A_i have *m* linearly

to: eigenvalue [one word]
to: of the principal components
to: the log transformed variances weighted
['variation' unclear]

to: The Mahalanobis distance
to: we assign a weight
to: u_{ik} will contain φ, [comma missing]
to: λ / φ for λ,
or, better
λ / φ for the assigned clustering parameter λ.

Errors detailed 8 Yen per word

Errors corrected *in situ*

If K = λπ and λ = 2, then Eq. (11) is Gaussian, but if λ ≠ 2, in order that the integral attains one, [equation] must be satisfied. Since K depends on $|A_i|$ and $|A_i|$ may vary over *i*, *K* cannot assume a single constant value for all *i*. Eq (11) is a sole formula which can be used to derive Eq.(7) by the use of Bayes rule, for example in E-step. Thus when λ ≠ 2 there is no corresponding mixture density and the proposed KFCM clustering is a unique and novel one. It is easy to generalize this discussion to any higher dimensional case.

In KFCM clustering , where the parameter λ can be changed freely during the iteration of the algorithm, we can gradually reduce the value in a simulated annealing procedure to obtain a better solution. [equation] indicates the number of data included in the *i*th cluster. From [symbol], A_i becomes a fuzzy variance-covariance matrix as in Eq.(9). Let A_i have *m* linearly independent eigenvectors, i.e., principal component vectors ($\boldsymbol{p}_1$, $\boldsymbol{p}_2$, ... , $\boldsymbol{p}_m$). Then [equation] where [symbol] is an eigenvalue of A_i . Therefore log $|A_i|$ is equivalent to the sum of the log transformed variances of the principal components. The third term of [equation] represents the log transformed variances weighted by the number of data. The Mahalanobis distance of Eq.(4) is defined by [symbol]. If we assign a weight parameter φ to the third term of [symbol], then u_{ik} will contain φ, but substituting λ / φ for the assigned clustering parameter λ, φ can be 1. Therefore we do not need to add any further weight parameters to the third term of the objective function.

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