A Peer-review Look on Multi-modal Clustering: An Information Bottleneck Realization Method

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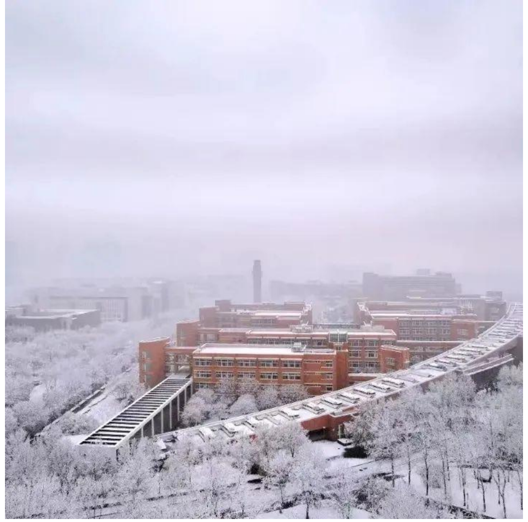

Tourist Spot

Outline

- Problem background
- Previous works
- Our proposal
- Experiments
- Conclusion

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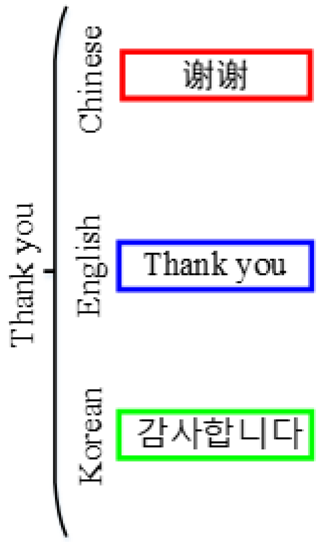
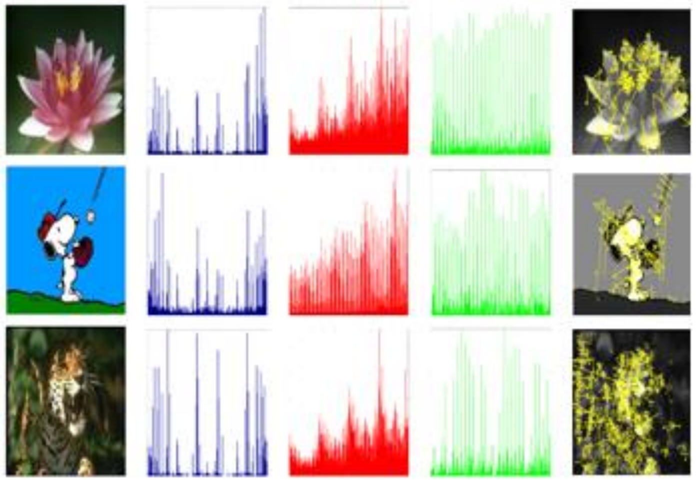
Characteristics of multi-modal datasets

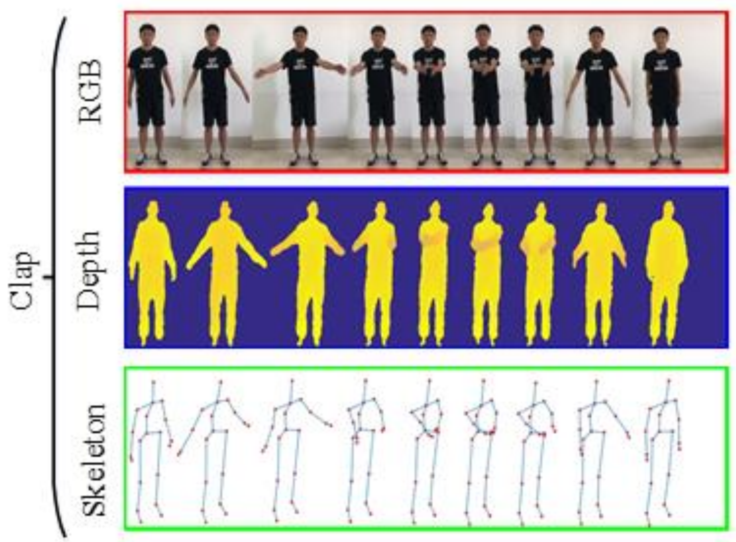
In Big Data era, many kinds of multi-modal data are emerging.



Multi-lingual Text



Multi-feature Image



Multi-modal human action video

Property: **Heterogeneous, Large-scale, Diversification, Complexity**

Limitations of supervised multi-modal classification methods

1. **Time-consuming and cost-expensive for labelling;**
2. **Over-reliance on the label information of trained data;**
3. **Ignoring the characteristics of the input data itself.**

Multi-modal Clustering

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Previous multi-modal clustering methods

- **Weighted-based methods;**
- **Shared feature learning based methods;**
- **Tensor representation learning based methods;**
- **Multi-modal consensus clustering;**
- **Multi-modal co-clustering;**
- **Multi-modal subspace clustering.**

Previous multi-modal clustering methods

- **Weighted-based methods:**
  - *discovering the complementary relationship and learning the consistent clustering structure using the learned modal weights.*

Limitations:

- *Lack of trustworthiness in learned weights.*
- *Learning weights in an isolated view.*
- *Extra weight parameters for controlling the weight distribution.*

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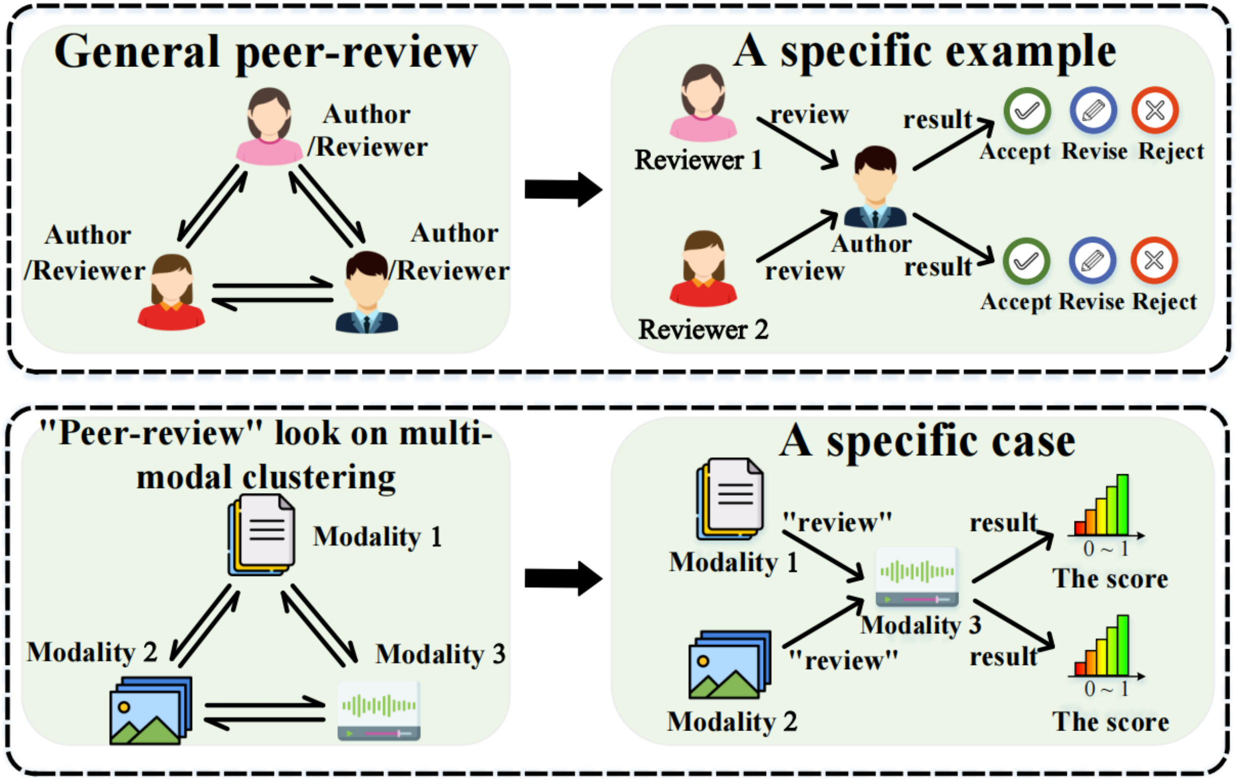
Our proposed method

- Peer-review Trustworthy Information Bottleneck (PTIB) :
  - Peer-review Score;
  - Trustworthy Score;
  - Modality Weight Learning;
  - Objective function.

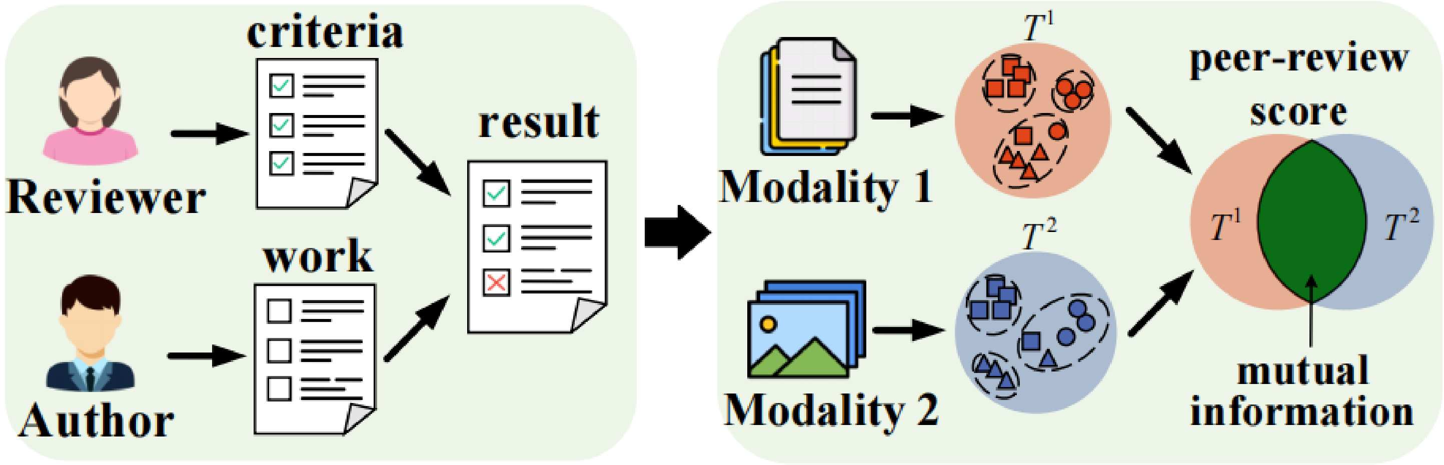
Peer-review Score

From the "peer-review" look on multi-modal clustering, one modality can either be an "author" or a "reviewer". The "reviewer" modalities review the work of the "author" modality and produces feedback review scores to evaluate the contribution.



Peer-review Score

It adopts the local clustering result of the modality as the "author" work or the "reviewer" criteria. The peer-review score depends on how similar the work is to the criteria, and the normalized mutual information is adopted to quantify this.



Peer-review Score

$$\mu_i^k = \frac{2 \times I(T^i, T^k)}{H(T^i) + H(T^k)}$$

$$\mu^k = \{\mu_1^k, \ldots, \mu_i^k, \ldots, \mu_m^k\}, i \neq k.$$

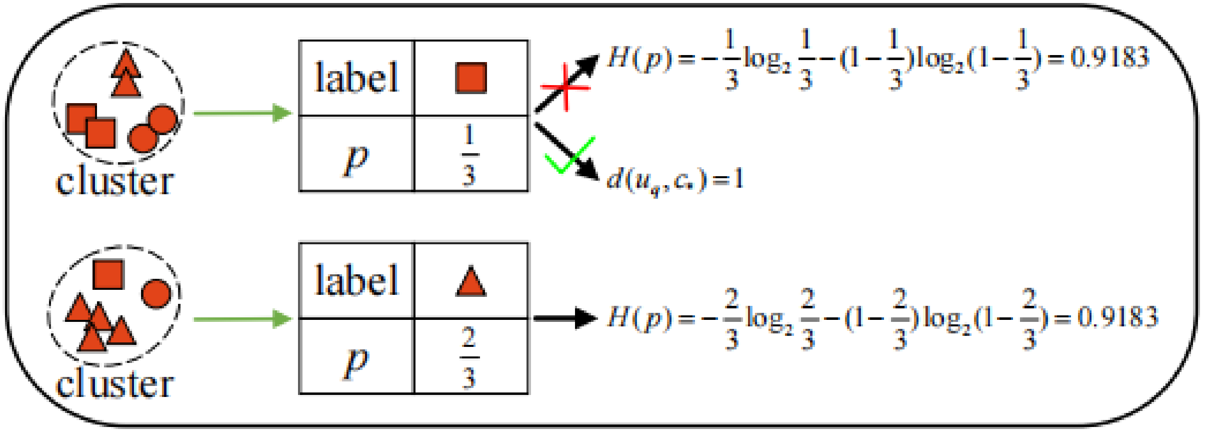
Trustworthy Score

We propose to regard the final clustering result as the "EIC / AE", which is then used to evaluate the trustworthiness of "reviewer" modalities in a self-supervision fashion.

Definition (Major/Minor Category):

Given a multi-modal dataset, if the local clustering result of modality is supervised by the final clustering result, the category of correctly assigned samples in a cluster of a specific local clustering result is called the major category, and the set of categories of incorrectly assigned samples in it is called the minor categories.

$$H(p) = -p\log_2 p - (1-p)\log_2(1-p).$$

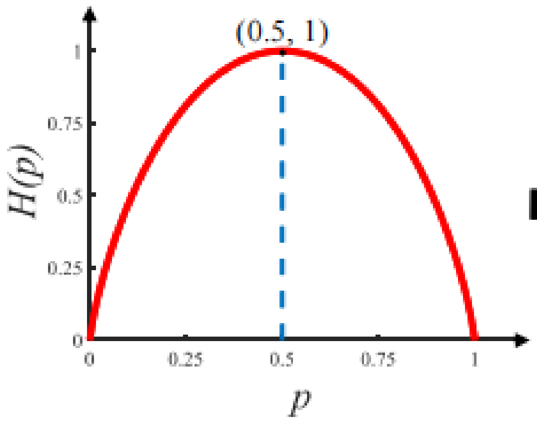


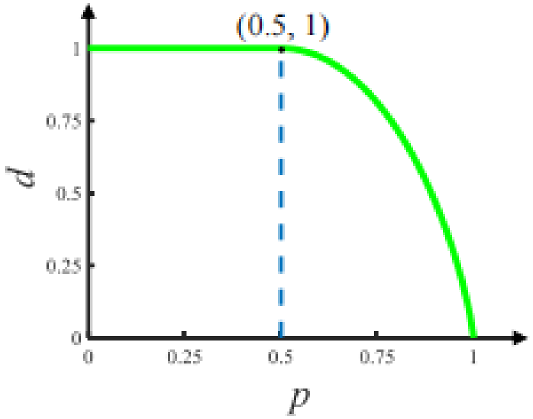
Trustworthy Score

Cluster Distortion

$$d(u_q, c_*) = \begin{cases} 1, & \text{if } 0 \le p < \frac{1}{2}, \\ H(p), & \text{if } \frac{1}{2} \le p \le 1. \end{cases}$$

$$D(U, C) = \frac{1}{|U|} \sum_{q=1}^{|U|} d(u_q, c_*).$$



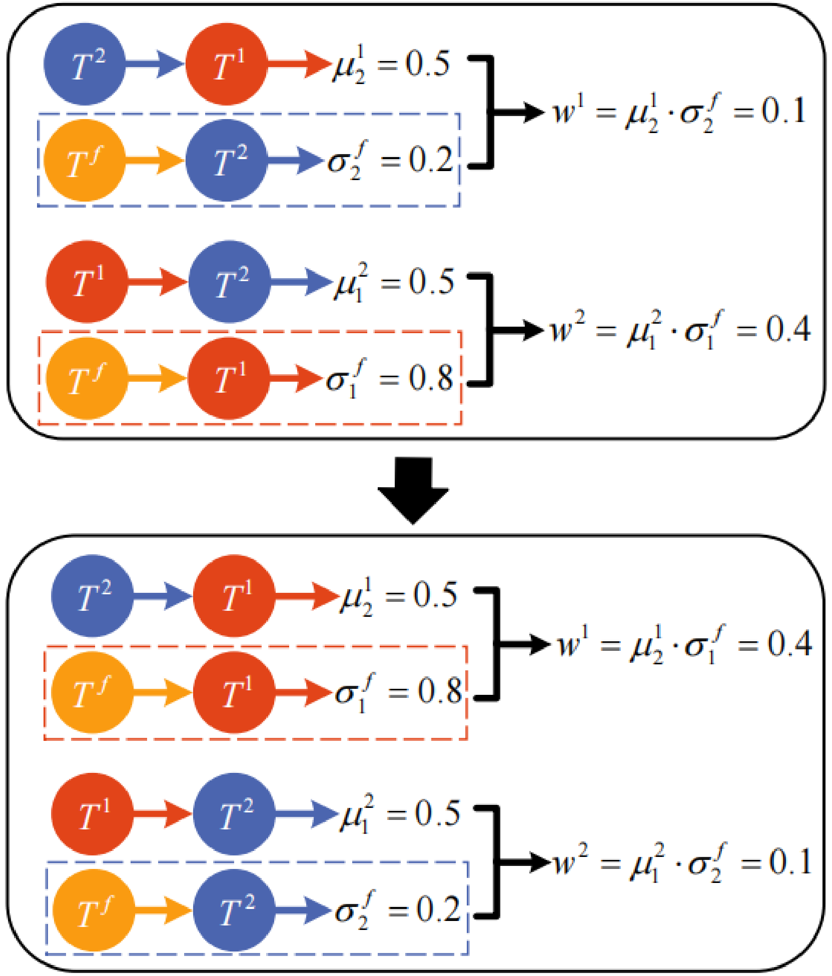


Trustworthy Score

$$\sigma_i^f = \frac{1}{D(T^i, T^f)}$$

$$\sigma^k = \{\sigma_1^f, \ldots, \sigma_i^f, \ldots, \sigma_m^f\}, i \neq k$$

Modality Weight Learning



$$w^k = \mu^k \bullet \sigma^k = \sum_{i=1, i \neq k}^{m} \mu_i^k \cdot \sigma_i^f, m > 2$$

$$w^k = \begin{cases} \sum_{i=1, i \neq k}^{m} \mu_i^k \cdot \sigma_k^f, & \text{if } m = 2, \\ \sum_{i=1, i \neq k}^{m} \mu_i^k \cdot \sigma_i^f, & \text{if } m > 2. \end{cases}$$

Objective function of PTIB

We propose a novel Peer-review Trustworthy Information Bottleneck method:

$$\mathcal{F}_{max}[p(t|x)] = \sum_{i=1}^{m} w^i \cdot [I(T;Y^i) - \beta^{-1} I(T;X)]$$

Advantages of the PTIB

- Trustworthy weight learning;
- Correlation quantization-based learning;
- Parameter-free weight learning;
- Self-supervision mechanism.

Optimization method

Algorithm 1 The Proposed PTIB

Input: m joint distributions $\{p(X, Y^i)\}_{i=1}^{m}$, the number of clusters $|T|$, the balance parameter β.
Output: Final clustering result $p(t|x)$.
Modality Weight Initialization: Compute the initial modality weights with initial peer-review and trustworthy score;
Random Clustering: $T \leftarrow$ Random partition of $\mathcal{X}$ into $|T|$ clusters;
repeat
  for all $x \in \mathcal{X}$ **do**
    Draw: Draw x from the "old" cluster t^{old} to become a separate cluster $\{x\}$;
    Merger: Select a "new" cluster t^{new} for the separate cluster $\{x\}$ to merge corresponding to the minimal merger cost in Theorem A.2;
  end for
  Update the trustworthy score using the clustering result in each iteration;
  Update the weight for each modality;
until Samples in different clusters remain unchanged or a fixed number of iterations.

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Datasets

Dataset	Type	# Modality	# Samples	# Clusters
20NG	Text	3	500	5
COIL20	Image	3	1440	20
Event	Image	3	1579	8
Soccer	Image	3	280	7
17Flowers	Image	3	1360	17
75Flowers	Image	2	5514	75
COIL100	Image	2	7200	100
MMI	Video	2	1760	22


COIL20


Soccer


17Flowers


MMI

Compared methods

1) **Single-modal Clustering**: K-Means (KM) and Ncuts.

2) **All-modal Clustering**: KM-All, Ncuts-All.

3) **Multi-modal Clustering**:
   (1) MVIB: It is the first multi-view IB method proposed to address the document clustering problems.
   (2) Co(reg): It co-regularizes the data clustering hypotheses among views to learn consistent assignments.
   (3) MfIB: It is a weighted multi-feature IB method designed for solving the unsupervised image classification.
   (4) RMSC: It solves the noisy multi-view clustering problem by designing a robust spectral method.
   (5) LMSC: It learns latent shared representations among views to make the feature subspace more robust and accurate.
   (6) MLAN: It automatically tunes the view weights without using parameters.
   (7) GMC: It is a graph-based weighted multi-view clustering method by automatically tuning the parameters.
   (8) DMIB: It jointly considers the dual correlations about the cross-feature and cross-cluster view correlations.
   (9) FPMVS-CAG: It deals the multi-view subspace clustering with the guidance of selected consensus anchors.
   (10)MCMLE: It improves the traditional Ncuts method for multi-view clustering by Laplacian embedding to learn a shared binary assignment matrix among different modalities.
   (11)TBGL: It focuses on learning tensorized bipartite graphs and considering the intra/inter-view similarities.
   (12)TIM: It works by following three principles, i.e., contained, complementary and compatible principle.
   (13)SMVAGC-SF: It adaptively fuses multiple anchor graphs with different magnitudes.

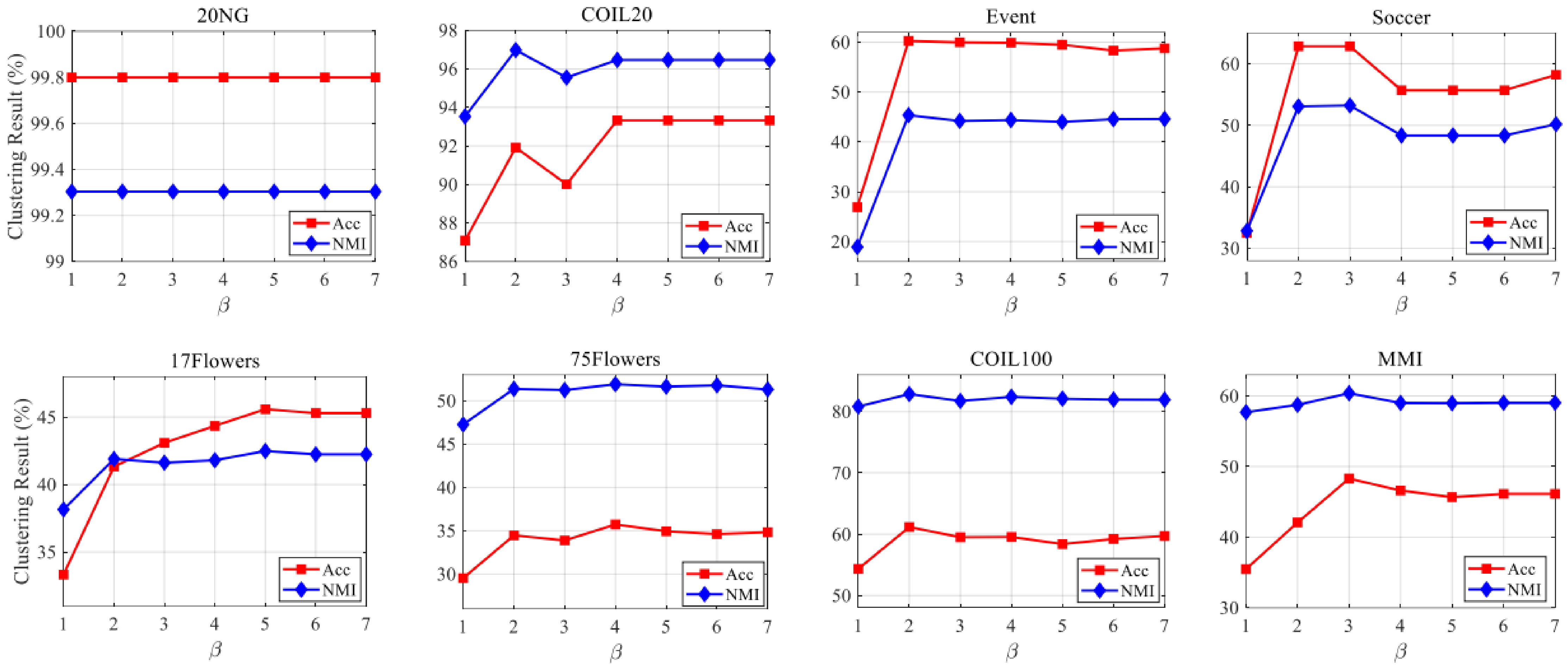
Clustering results

Method	20NG		COIL20		Event		Soccer	
	Acc	NMI	Acc	NMI	Acc	NMI	Acc	NMI
KM	22.28±1.48	4.45±2.32	53.06±3.20	65.06±2.12	33.93±4.10	19.84±2.69	25.82±5.06	18.70±7.97
Ncuts (TPAMI'00)	42.80±2.40	27.65±2.01	74.69±1.30	84.01±0.54	34.10±1.28	14.97±0.40	48.21±1.14	45.02±2.21
KM-All	21.46±0.68	1.76±0.65	46.14±6.58	60.70±4.51	28.85±2.29	11.37±2.10	22.46±3.94	8.14±3.59
Ncuts-All (TPAMI'00)	71.20±0.17	57.23±0.10	46.14±0.52	57.93±0.23	35.06±0.69	20.11±0.85	39.75±0.94	34.04±0.57
MVIB (DASFAA'07)	94.22±1.37	83.21±3.18	61.74±10.51	73.65±6.63	40.02±2.04	23.71±1.56	35.79±3.96	21.42±4.25
Co(reg) (NeurIPS'11)	20.02±0.62	3.15±0.54	64.33±1.68	83.79±0.45	38.58±0.92	24.30±0.55	24.13±0.53	11.43±0.39
MfIB (IJCAI'13)	93.76±2.89	85.11±4.54	83.81±4.29	92.39±1.97	48.58±1.50	33.41±1.35	53.64±2.76	49.74±3.44
RMSC (AAAI'14)	37.26±0.91	15.70±0.84	65.43±3.31	79.16±2.35	36.58±1.26	21.02±0.88	28.96±1.90	12.16±2.18
LMSC (CVPR'17)	96.16±0.57	88.37±1.54	71.94±2.72	82.18±2.37	43.92±2.84	27.53±2.58	31.25±6.53	15.85±8.71
MLAN (TIP'18)	96.40±0.11	89.18±0.17	87.22±2.30 ○	94.35±1.10 ○	19.90±0.72	6.66±0.80	28.21±0.01	21.27±0.17
GMC (TKDE'20)	98.20±0.00	93.92±0.00	60.90±0.00	84.67±0.00	18.11±0.00	10.74±0.00	29.29±0.00	25.82±0.00
DMIB (TCYB'22)	98.30±0.14	97.56±0.49	65.90±4.03	77.70±2.46	49.80±3.02	32.97±2.38	54.07±3.67	50.68±2.23 ○
FPMVS-CAG (TIP'22)	73.80±0.00	59.23±0.00	69.17±0.00	85.11±0.00	48.89±0.00	31.99±0.00	50.14±0.00	49.56±0.00
MCMLE (TPAMI'22)	77.40±0.00	69.96±0.00	85.83±0.00	93.48±0.00	44.46±0.00	30.24±0.00	56.07±0.00 ○	50.06±0.00
TBGL (TPAMI'23)	89.11±0.00	83.45±0.00	86.10±0.00	92.41±0.00	42.84±0.00	28.40±0.00	54.39±0.00	49.78±0.00
TIM (TIP'23)	99.40±0.00 ○	98.08±0.00 ○	56.70±4.08	71.39±0.29	54.60±2.50	36.86±1.75	48.93±0.51	41.42±4.09
SMVAGC-SF (TIP'24)	86.07±6.40	72.61±3.59	75.66±5.10	89.43±2.11	54.76±1.27○	36.97±0.65○	45.14±1.56	29.61±1.85
PTIB	**99.80±0.00** ●	**99.30±0.00** ●	**93.33±0.00** ●	**96.46±0.00** ●	**60.24±0.16** ●	**45.36±0.28** ●	**62.86±0.17** ●	**53.23±0.16** ●
Improve (● VS ○)	0.40 (↑)	1.22 (↑)	6.11 (↑)	2.11 (↑)	5.48 (↑)	8.39 (↑)	6.79 (↑)	2.55 (↑)

Clustering results

Method	17Flowers		75Flowers		COIL100		MMI	
	Acc	NMI	Acc	NMI	Acc	NMI	Acc	NMI
KM	22.41±1.67	24.31±1.14	19.48±0.85	35.21±0.75	27.96±1.78	58.13±1.52	26.89±2.95	44.15±1.60
Ncuts (TPAMI'00)	27.71±0.72	26.43±0.40	24.80±0.58	41.50±0.19	40.97±1.28	58.52±0.59	38.43±0.47	53.17±0.43
KM-All	17.63±1.27	13.55±1.86	21.13±0.88	32.57±0.71	29.25±1.57	50.55±2.15	27.11±1.81	38.76±1.59
Ncuts-All (TPAMI'00)	28.77±0.63	26.31±0.27	27.41±0.31	42.41±0.21	48.63±0.97	64.74±0.56	40.53±1.52	52.77±0.62
MVIB (DASFAA'07)	21.32±1.05	18.28±1.48	18.49±0.61	33.05±0.45	46.71±2.30	70.29±1.10	44.95±2.60 ○	54.65±1.49
Co(reg) (NeurIPS'11)	26.28±0.49	27.12±0.20	28.16±0.36	44.95±0.09	48.35±0.44	70.86±0.15	34.72±0.53	51.31±0.22
MfIB (IJCAI'13)	38.52±2.03	37.24±1.40 ○	24.57±0.32	40.79±0.37	50.52±0.08	72.81±0.46	40.14±2.09	52.50±1.69
RMSC (AAAI'14)	19.70±0.66	17.86±0.38	26.42±0.97	42.95±0.30	46.32±0.28	69.33±0.45	30.28±1.05	43.94±0.89
LMSC (CVPR'17)	33.29±2.29	31.49±1.60	24.58±0.90	42.50±0.59	48.76±1.45	66.74±0.85	40.17±1.88	51.62±1.29
MLAN (TIP'18)	24.32±1.91	22.21±1.24	25.58±0.53	34.16±1.15	45.05±0.41	59.55±0.53	38.15±0.05	52.68±0.04
GMC (TKDE'20)	6.76±0.00	4.78±0.00	18.52±0.00	30.96±0.00	38.86±0.00	67.55±0.00	35.60±0.00	55.65±0.00 ○
DMIB (TCYB'22)	35.48±6.04	32.56±5.47	26.72±1.13	43.13±0.79	50.33±1.88	72.57±0.87	41.10±2.65	52.96±2.10
FPMVS-CAG (TIP'22)	30.51±0.00	27.27±0.00	23.83±0.00	38.24±0.00	45.03±0.00	70.58±0.00	36.77±0.00	51.03±0.00
MCMLE (TPAMI'22)	32.13±0.00	32.11±0.00	28.76±0.00	47.03±0.00	50.47±0.00	74.59±0.00	42.04±0.00	52.97±0.00
TBGL (TPAMI'23)	31.07±0.00	32.46±0.00	26.52±0.00	47.09±0.00 ○	51.66±0.00	67.82±0.00	43.15±0.00	53.27±0.00
TIM (TIP'23)	32.98±3.28	29.36±3.60	21.83±0.60	26.23±1.24	51.43±1.72	74.98±0.70	28.98±1.57	39.56±2.96
SMVAGC-SF (TIP'24)	42.41±2.07○	36.40±1.43	31.92±0.63○	46.89±0.22	56.78±1.93○	76.78±0.55○	40.93±2.14	53.03±1.25
PTIB	**45.29±0.05** •	**42.49±0.08** •	**35.73±0.36** •	**51.91±0.20** •	**61.17±0.23** •	**82.86±0.19** •	**48.30±0.80** •	**60.39±0.49** •
Improve (• VS ○)	2.88 (↑)	5.25 (↑)	3.81 (↑)	4.82 (↑)	4.39 (↑)	6.08 (↑)	3.35 (↑)	4.74 (↑)

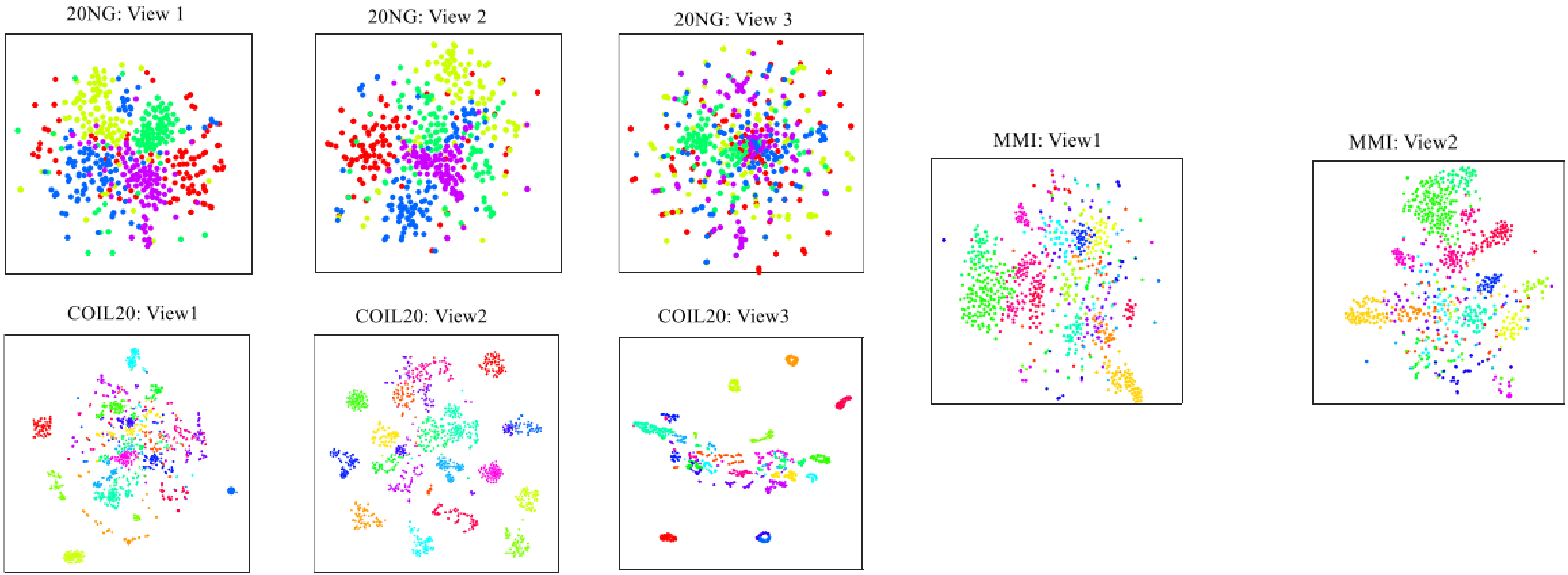
Parameter analysis of PTIB on eight datasets



Potential for Parameter-free Version

Datasets	PTIB		Parameter-free PTIB		Versus Margin	
	Acc	NMI	Acc	NMI	Acc	NMI
20NG	99.80±0.00	99.30±0.00	99.80±0.00	99.30±0.01	0.00	0.00
COIL20	93.33±0.00	96.46±0.00	86.46±0.00	93.80±0.00	-6.87	-2.66
Event	60.24±0.16	45.36±0.28	59.01±0.62	44.39±0.50	-1.23	-0.97
Soccer	62.86±0.17	53.23±0.16	59.64±0.00	51.65±0.01	-3.22	-1.58
17Flowers	45.29±0.05	42.49±0.08	42.74±1.38	40.92±0.82	-2.55	-1.57
75Flowers	35.73±0.36	51.91±0.20	34.57±0.36	51.23±0.24	-1.16	-0.68
COIL100	61.17±0.23	82.86±0.19	59.93±0.61	82.24±0.30	-1.24	-0.62
MMI	48.30±0.80	60.39±0.49	44.26±0.01	58.38±0.00	-4.04	-2.01

T-SNE visualization of Clustering results on 20NG, COIL20 and MMI datasets



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Summary

- Propose a novel peer-review trustworthy information bottleneck (PTIB) method for addressing the weighted multi-modal clustering problem.;
- Give a new peer-review look on the multi-modal clustering problem, thus designing a peer-review score for evaluating the quality of each modality. A corresponding trustworthy score is newly designed to evaluate the trustworthiness of peer-review score, ensuring the reliability of multi-modal peer-review.
- Our approach achieves state-of-the-art performance.

Thank You!

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