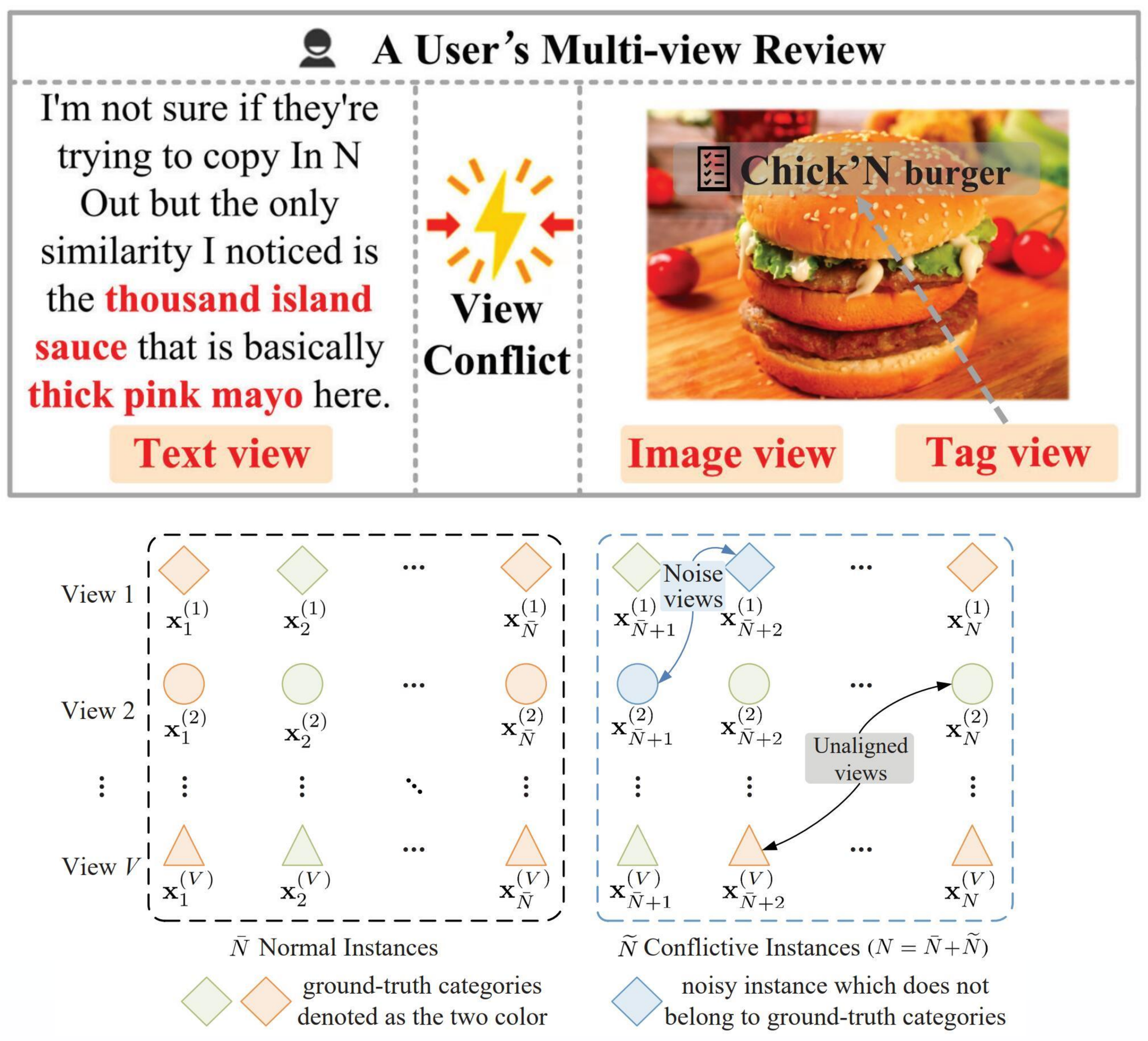
Reliable Conflictive Multi-View Learning

Cai Xu, Jiajun Si, Ziyu Guan, Wei Zhao, Yue Wu, Xiyue Gao

Background



Multi-View data obtained from multiple sources or different feature subsets.

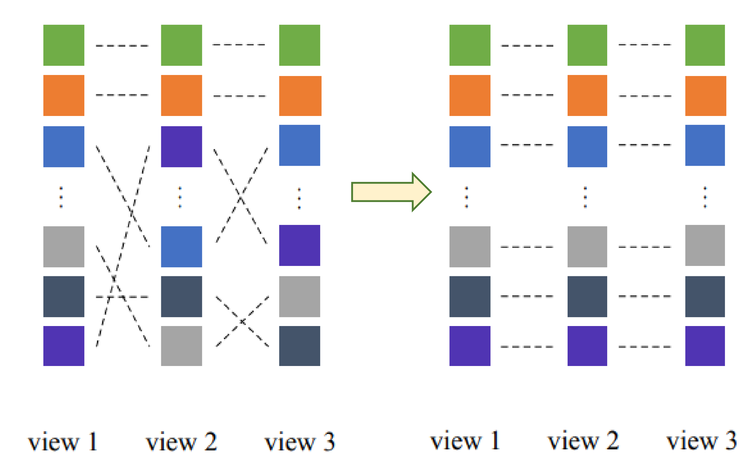
Information gathered from different sources is likely to be conflicting.

This conflictive information in different views makes most multi-view learning methods inevitably degenerate or even fail.

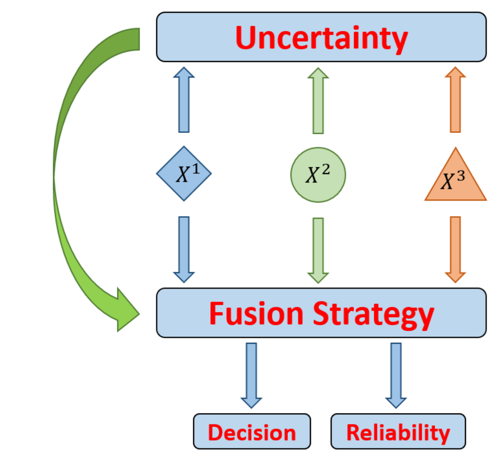
Conflictive instances contain noise and unalignment views.

Motivations

Previous methods

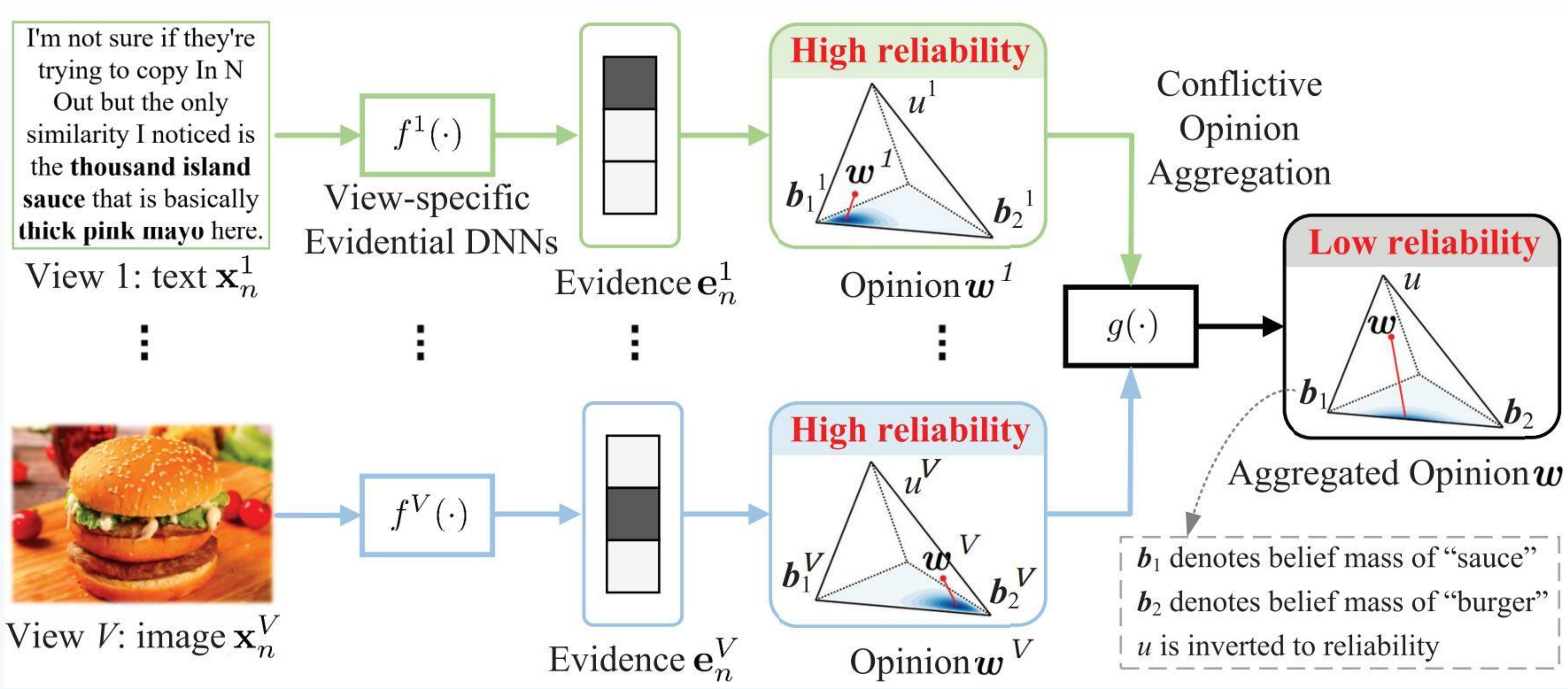


Reliable Conflictive Multi-view Learning (RCML) Problem



Previous methods aim to eliminate conflictive instances, while real-world applications usually require making decisions for them. Considering the decision of a conflictive instance might be unreliable, we need the model can answer "should the decision be reliable?".

ECML Model



Loss function of ECML:

$$L = L_{acc}(\boldsymbol{\alpha}_n) + \beta \sum_{v=1}^{V} L_{acc}(\boldsymbol{\alpha}_n^v) + \gamma L_{con}$$

$$L_{acc}(\boldsymbol{\alpha}_n) = L_{ace}(\boldsymbol{\alpha}_n) + \lambda_t L_{KL}(\boldsymbol{\alpha}_n)$$

$$L_{con} = \frac{1}{V}\sum_{p=1}^{V}\left(\sum_{q\neq p}^{V} c(\boldsymbol{w}_n^p, \boldsymbol{w}_n^q)\right)$$

$$L_{ace}(\boldsymbol{\alpha}_n) = \int \left[\sum_{j=1}^{K} -y_{nj}\log p_{nj}\right] \frac{1}{B(\boldsymbol{\alpha}_n)} \sum_{j=1}^{K} p_{nj}^{\alpha_{nj}-1}\, d\boldsymbol{p}_n = \sum_{j=1}^{K} y_{nj}(\psi(S_n) - \psi(\alpha_{nj}))$$

$$L_{KL}(\boldsymbol{\alpha}_n) = KL[D(\boldsymbol{p}_n|\tilde{\boldsymbol{\alpha}}_n)||D(\boldsymbol{p}_n|\mathbf{1})]$$

$$= \log\left(\frac{\Gamma(\sum_{k=1}^{K}\tilde{\alpha}_{nk})}{\Gamma(K)\prod_{k=1}^{K}\Gamma(\tilde{\alpha}_{nk})}\right) + \sum_{k=1}^{K}(\tilde{\alpha}_{nk}-1)[\psi(\tilde{\alpha}_{nk}) - \psi(\sum_{j=1}^{K}\tilde{\alpha}_{nj})]$$

Step 1: View-specific Evidential Deep Learning.

- obtain the view-specific evidence $\boldsymbol{e}^v$ by view-specific evidential DNNs $\{f^v(\cdot)\}_{v=1}^{V}$.
- calculate the view-specific opinion $\boldsymbol{w}^v(\boldsymbol{b}^v, u^v, \boldsymbol{a}^v)$ and the corresponding Dirichlet PDF by Subjective Logic.

Step 2: Evidential Multi-view Fusion via Conflictive Opinion Aggregation.

- get the final multi-view joint opinion $\boldsymbol{w}(\boldsymbol{b}, u, \boldsymbol{a})$, probability p_k of each class and the overall uncertainty u by conflictive opinion aggregation.

Conflictive Opinion Aggregation

$$\boldsymbol{w}^{A\underline{\diamond}B} = \boldsymbol{w}^{A}\underline{\diamond}\boldsymbol{w}^{B} = (\boldsymbol{b}^{A\underline{\diamond}B}, u^{A\underline{\diamond}B}, \boldsymbol{a}^{A\underline{\diamond}B})$$

$$b_k^{A\underline{\diamond}B} = \frac{b_k^A u^B + b_k^B u^A}{u^A + u^B},$$

$$u^{A\underline{\diamond}B} = \frac{2u^A u^B}{u^A + u^B}, \boldsymbol{a}_k^{A\underline{\diamond}B} = \frac{\boldsymbol{a}_k^A + \boldsymbol{a}_k^B}{2}$$

Step 3: Conflictive Degree.

- establish an intuitive sense of the level of conflict.
- minimizing the degree of conflict between opinions to ensure the consistency of results between different opinions during training.

$$c(\boldsymbol{w}^A, \boldsymbol{w}^B) = c_p(\boldsymbol{w}^A, \boldsymbol{w}^B) \cdot c_c(\boldsymbol{w}^A, \boldsymbol{w}^B)$$

$$c_p(\boldsymbol{w}^A, \boldsymbol{w}^B) = \frac{\sum_{k=1}^{K}|p_k^A - p_k^B|}{2}$$

$$c_c(\boldsymbol{w}^A, \boldsymbol{w}^B) = (1-u^A)(1-u^B)$$

Experiments

Dataset

Dataset	Size	Categories	Dimensionality
HandWritten	2000	10	240/76/216/47/64/6
CUB	11788	10	1024/300
HMDB	6718	51	1000/1000
Scene15	4485	15	20/59/40
Caltech101	8677	101	4096/4096
PIE	680	68	484/256/279

Baseline Methods

Baseline	Deep	Fusion strategy	Uncertainty
DCCAE	✓	feature fusion	✗
CPM-Nets	✓	feature fusion	✗
DUA-Nets	✓	feature fusion	✓
TMC	✓	decision fusion	✓
TMDL-OA	✓	decision fusion	✓
ECML	✓	decision fusion	✓

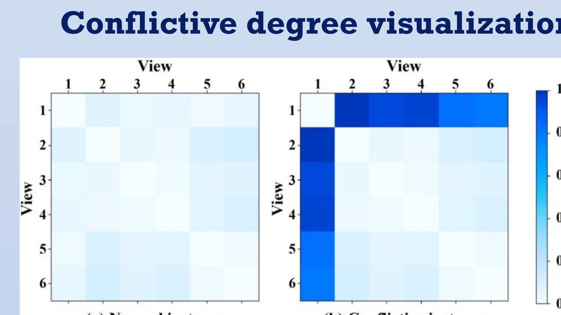
Accuracy (%) on normal test sets

Data	DCCAE	CPM-Nets	DUA-Nets	TMC	TMDL-OA	Ours	Δ%
HandWritten	95.45±0.35	94.55±1.36	98.10±0.32	98.51±0.13	99.25±0.45	**99.40±0.00**	0.15
CUB	85.39±1.36	89.32±0.38	80.13±1.67	90.57±2.96	95.43±0.20	**98.50±2.75**	3.21
HMDB	49.12±1.07	63.32±0.43	62.73±0.23	65.17±2.42	88.20±0.58	**90.84±1.86**	2.99
Scene15	55.03±0.34	67.29±1.01	68.23±0.11	67.71±0.30	75.57±0.02	**76.19±0.12**	0.82
Caltech101	89.56±0.41	90.35±2.12	93.43±0.34	92.80±0.50	94.63±0.04	**95.36±0.38**	0.77
PIE	81.96±1.04	88.53±1.23	90.56±0.47	91.85±0.23	92.33±0.36	**94.71±0.02**	2.57

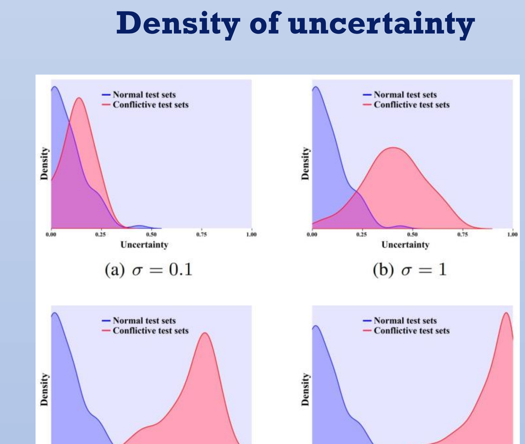
Accuracy (%) on conflictive test sets

Data	DCCAE	CPM-Nets	DUA-Nets	TMC	TMDL-OA	Ours	Δ%
HandWritten	82.85±0.38	83.34±1.07	87.16±0.34	92.76±0.15	93.05±0.05	**94.40±0.05**	1.45
CUB	63.57±1.28	68.82±0.17	60.53±1.17	73.37±2.16	74.43±0.26	**76.50±1.15**	2.78
HMDB	29.62±1.79	42.62±1.43	43.53±0.28	47.17±0.15	67.62±0.28	**70.84±1.19**	4.76
Scene15	25.97±2.86	29.63±1.12	26.18±1.31	42.27±1.61	48.42±1.02	**56.97±0.52**	17.66
Caltech101	60.90±2.32	66.54±2.89	75.19±2.34	90.16±2.50	90.63±2.05	**92.36±1.48**	1.91
PIE	26.89±1.10	53.19±1.17	56.45±1.75	61.65±1.03	68.16±0.34	**84.00±0.14**	23.24

Conflictive degree visualization



Density of uncertainty



Future Work

1、 Conflicting multi-view data is very common in the real world, but there are currently no datasets related to it, and we are working to collect data sets and share them with everyone.

2、The proposed average aggregation schema may not be the optimal solution. For example, the specific order in which fusion takes place can influence the final result.

3、 For different data sets, the results vary greatly, and we have a hypothesis that this may be related to the differences between sample categories and the number of sample views