Decouple then Classify: A Dynamic Multi-view Labeling Strategy with Shared and Specific Information

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NUDT

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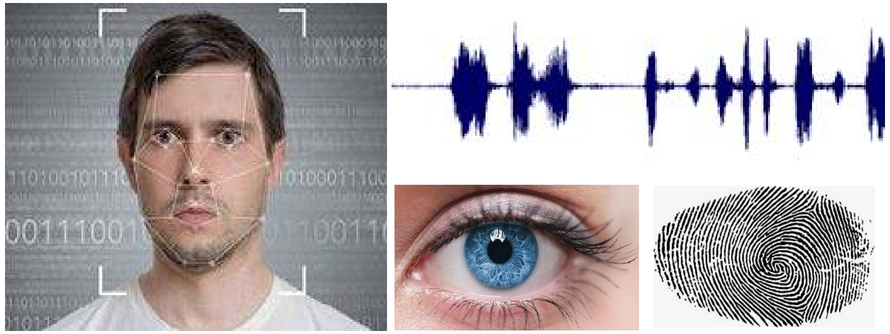
What’s Multi-view

In real applications, data frequently comes from multiple sources, and such multi-view data often contains more information



Applications

- Medical Domain: disease diagnosis
- Agricultural Domain: plant disease control
- Business Domain: recommendation system

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SSMVC

- Semi-supervised classification
  - aim to partition data into several groups with limited labeled data
  - most focus on single-view data, how to extend it to multi-view scenario
- SSMVC
  - semi-supervised multi-view classification(SSMVC), relying on multi-view fusion

Multi-view fusion

- Multi-view fusion: Fuse the multi-view information to boost the classification performance

- SSI (Shared and Specific Information): Consistent information exists among views, and specific information is kept in each view

Current Reasearch

- Existing methods
  - Graph-based(Most methods adopt GCN to conduct label propagation)
  - MF-based(matrix-factorization)
  - DR-based(to obtain discriminative representation learning)
  - Other Methods(random walk, joint SSI)
- More information can be found at

https://github.com/wanxinhang/Awesome-Semi -supervised-Multi-view-classification

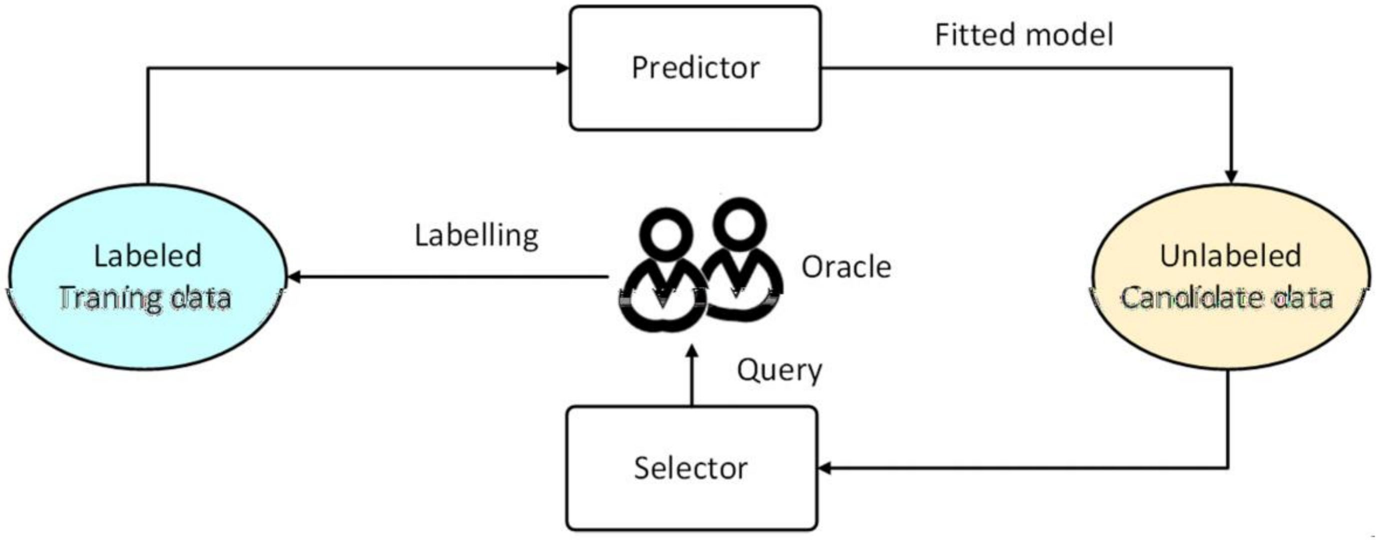
Challenges

- Drawbacks
  - Graph-based: High complexity
  - MF-based: Limited representation capability
  - DR-based: The overlook of SSI
- Common challenges
  - How to select important samples to label
  - How to adequately utilize SSI
  - How to handle large-scale data

Solution

■ How to solve sample selection

- Active learning: select valuable samples from the unlabeled dataset to label and retrain the model interactively
- Most methods annotate the most uncertain sample to clarify the decision boundary



Solution

■ **How to evaluate the uncertainty in multi-view settings**

● **Utilize SSI**: if a sample is hard to predict via both SSI, it is regarded as an uncertain sample and needs to be labeled

$$s_i = 1 - \max_{1 \le k \le K} \mathbf{p}_i^{spe} * \max_{1 \le k \le K} \mathbf{p}_i^{share}$$

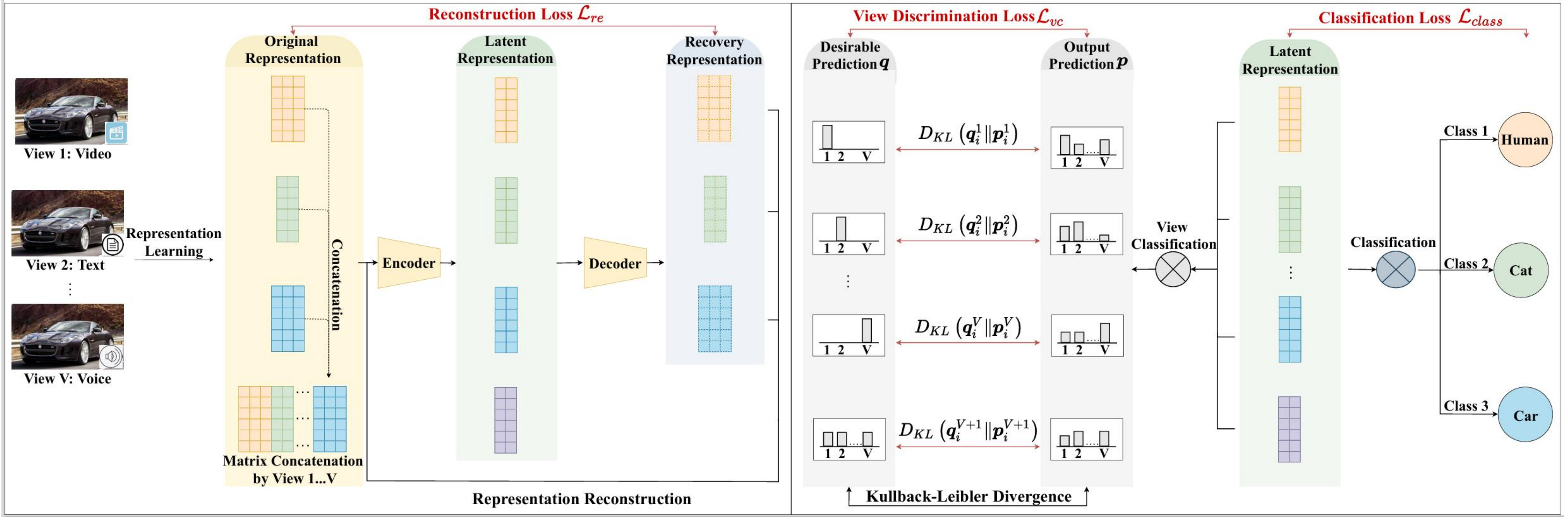
Solution

■ The design of view discriminator

- **Shared information**: shared among views
- **Specific information**: specific for each view

Solution

The Framework of the proposed DMVLS



$$\mathcal{L} = \mathcal{L}_{re} + \lambda_1 \mathcal{L}_{vc} + \lambda_2 \mathcal{L}_{class}$$

Experiments

Table 1. Datasets used in our experiments.

Dataset	Samples	Views	Categories
Handwritten	2000	2	10
BDGP	2500	3	5
Cora	2708	4	7
CiteSeer	3312	4	6
STL10	13000	4	9
YTB10	38654	4	10

Experiments

Table 2. Empirical evaluation and comparison of our method with five compared methods on six benchmark datasets in terms of ACC. Note that '-' indicates the method fails to run smoothly due to the out-of-memory error, and the best results are marked in bold.

Ratio	Methods	Handwritten	BDGP	Cora	CiteSeer	STL10	YTB10
20%	MVAR	48.14±2.06	79.41±1.93	59.92±1.15	64.22±1.15	56.88±0.66	-
	Co-GCN	87.06±3.46	74.83±0.40	50.16±1.24	60.41±0.81	29.99±1.05	99.54±1.12
	ERL-MVSC	95.48±0.77	37.24±1.78	75.59±1.98	62.57±1.69	58.23±0.64	-
	DSRL	97.06±0.49	18.77±1.48	66.53±2.12	50.44±2.66	47.99±0.22	-
	IMvGCN	93.89±0.56	71.01±0.69	77.74±0.76	71.07±0.71	**60.12±0.32**	99.61±0.44
	Ours	**98.35±0.42**	**91.38±0.19**	**82.36±0.97**	**72.99±0.99**	54.46±0.87	**100.00±0.00**
30%	MVAR	35.21±1.22	80.74±0.73	63.45±0.94	63.35±0.94	60.59±0.40	-
	Co-GCN	89.81±2.58	71.13±3.41	46.96±4.16	62.43±0.30	33.07±2.14	99.77±0.10
	ERL-MVSC	97.00±0.50	40.79±2.21	81.70±0.65	66.81±1.18	61.69±0.39	-
	DSRL	98.21±0.15	20.02±0.36	71.75±0.02	52.72±2.55	49.87±0.34	-
	IMvGCN	94.39±0.44	69.90±1.62	77.99±0.59	70.97±1.18	60.59±0.19	99.92±0.05
	Ours	**99.48±0.32**	**95.67±0.25**	**88.58±0.58**	**78.68±0.87**	**63.00±0.44**	**100.00±0.00**
40%	MVAR	71.92±1.42	82.77±0.34	67.06±1.32	62.73±1.32	61.79±0.54	-
	Co-GCN	88.86±3.80	73.23±2.80	49.19±1.39	63.05±0.42	31.42±0.74	99.84±0.01
	ERL-MVSC	97.82±0.37	44.91±3.42	83.30±0.71	70.39±0.78	63.14±0.38	-
	DSRL	98.42±0.41	20.04±0.33	70.77±2.48	54.83±2.85	51.32±0.10	-
	IMvGCN	94.10±0.63	70.19±2.18	78.17±0.53	71.69±0.87	60.55±0.14	99.72±0.50
	Ours	**99.94±0.08**	**96.88±0.19**	**92.86±1.15**	**82.51±0.35**	**70.41±0.24**	**100.00±0.00**
50%	MVAR	82.16±1.24	84.67±1.54	70.52±1.31	61.45±1.31	62.88±0.79	-
	Co-GCN	89.33±2.38	74.76±1.27	48.40±1.10	63.63±1.10	31.48±0.75	99.86±0.02
	ERL-MVSC	97.98±0.44	45.70±1.59	84.42±1.05	72.26±1.47	64.01±0.43	-
	DSRL	98.40±0.29	20.08±0.75	74.37±0.58	55.90±2.47	52.54±0.35	-
	IMvGCN	93.84±0.78	69.81±1.21	78.67±0.32	71.97±0.76	60.59±0.23	99.92±0.07
	Ours	**99.97±0.05**	**97.47±0.24**	**96.22±0.63**	**86.97±0.78**	**75.63±0.37**	**100.00±0.00**

Experiments

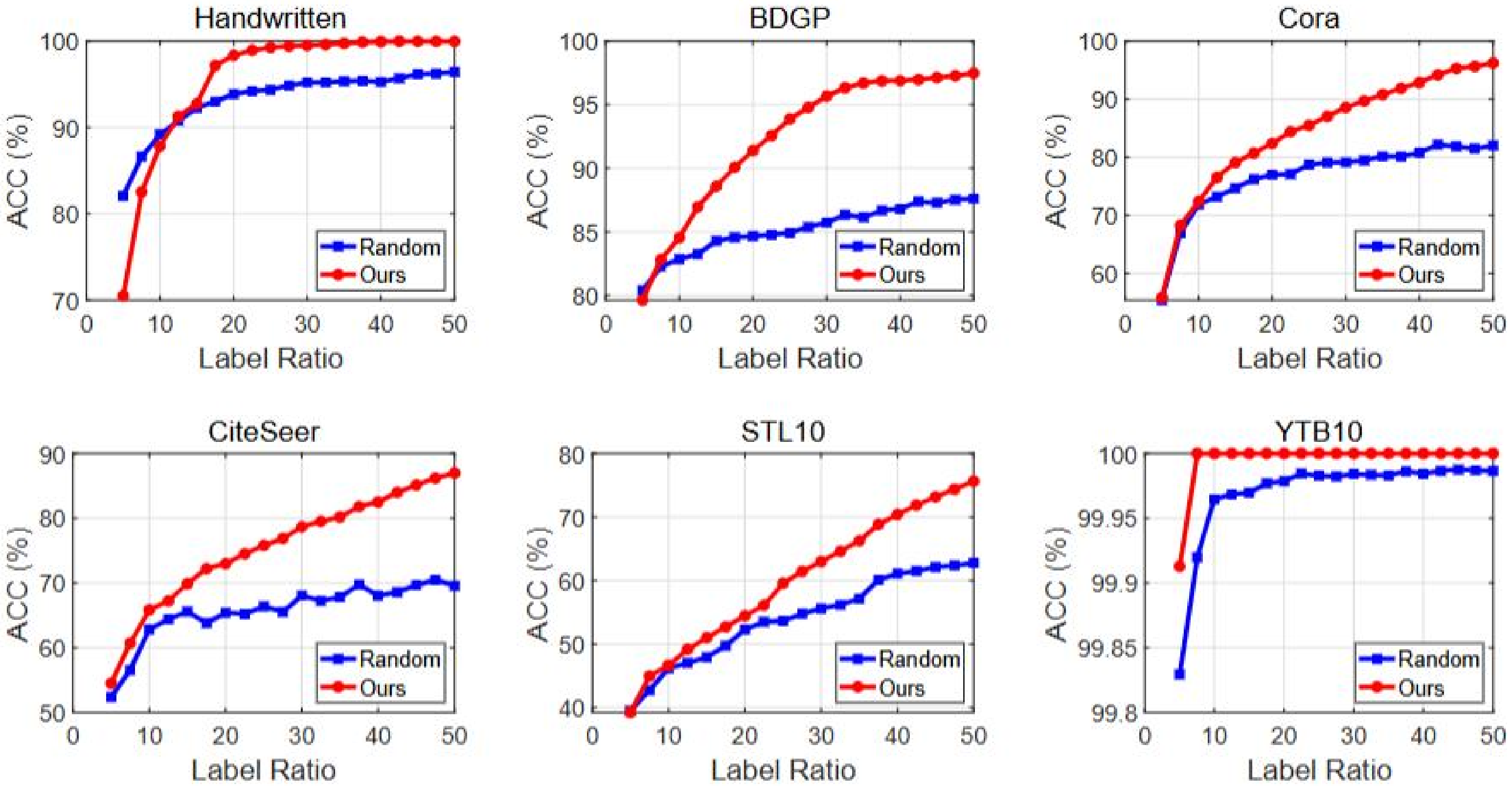


Figure 4. The classification performance varies with different label ratios on six benchmark datasets.

Experiments

Table 5. The ablation study of our method in terms of ACC. The best results are marked in bold.

Ratio	Methods	Handwritten	BDGP	Cora	CiteSeer	STL10	YTB10
20%	Remove $\mathcal{L}_{vc}$	97.83±0.11	91.08±0.32	**82.81±0.63**	70.2±0.63	54.32±2.58	100.00±0.00
	Remove $\mathcal{L}_{class1}$	95.52±4.04	91.08±0.48	80.81±2.71	58.56±11.73	51.90±5.07	100.00±0.00
	Remove $\mathcal{L}_{class2}$	92.25±9.15	90.85±1.65	81.39±1.04	71.24±0.81	44.73±6.60	100.00±0.00
	Random selection	93.87±1.18	84.65±0.53	76.98±1.44	65.39±1.13	52.31±3.56	99.98±0.01
	Ours	**98.35±0.42**	**91.38±0.19**	82.36±0.97	**72.99±0.99**	**54.46±0.87**	**100.00±0.00**
30%	Remove $\mathcal{L}_{vc}$	99.21±0.21	95.42±0.19	88.13±0.70	76.84±0.62	62.68±1.88	100.00±0.00
	Remove $\mathcal{L}_{class1}$	99.35±0.34	95.18±0.11	87.83±2.17	63.18±13.05	59.13±4.77	100.00±0.00
	Remove $\mathcal{L}_{class2}$	97.52±3.25	94.99±0.66	88.27±0.04	77.61±0.65	51.25±6.44	100.00±0.00
	Random selection	95.21±0.09	85.72±0.18	79.12±0.58	68.06±1.17	55.62±3.51	99.98±0.01
	Ours	**99.48±0.32**	**95.67±0.25**	**88.58±0.58**	**78.68±0.87**	**63.00±0.44**	**100.00±0.00**
40%	Remove $\mathcal{L}_{vc}$	99.92±0.07	96.44±0.74	92.56±0.16	81.23±1.12	70.24±1.26	100.00±0.00
	Remove $\mathcal{L}_{class1}$	99.78±0.10	95.96±0.23	92.27±1.27	68.41±13.35	67.56±2.76	100.00±0.00
	Remove $\mathcal{L}_{class2}$	99.72±0.22	96.75±0.09	92.54±0.71	82.31±0.40	57.63±7.54	100.00±0.00
	Random selection	95.26±0.41	86.79±0.18	80.76±1.11	68.05±0.72	61.10±1.00	99.98±0.01
	Ours	**99.94±0.08**	**96.88±0.19**	**92.86±1.15**	**82.51±0.35**	**70.41±0.24**	**100.00±0.00**
50%	Remove $\mathcal{L}_{vc}$	99.97±0.05	97.00±0.36	94.83±0.50	84.77±1.64	74.77±0.78	100.00±0.00
	Remove $\mathcal{L}_{class1}$	99.87±0.05	95.87±0.34	95.65±0.55	73.62±13.01	73.54±2.04	100.00±0.00
	Remove $\mathcal{L}_{class2}$	99.87±0.12	96.96±0.34	95.62±0.34	86.09±0.21	64.65±7.33	100.00±0.00
	Random selection	96.42±1.02	87.60±0.38	82.01±0.55	69.57±1.61	62.79±0.69	99.99±0.01
	Ours	**99.97±0.05**	**97.47±0.24**	**96.22±0.63**	**86.97±0.78**	**75.63±0.37**	**100.00±0.00**

Experiments

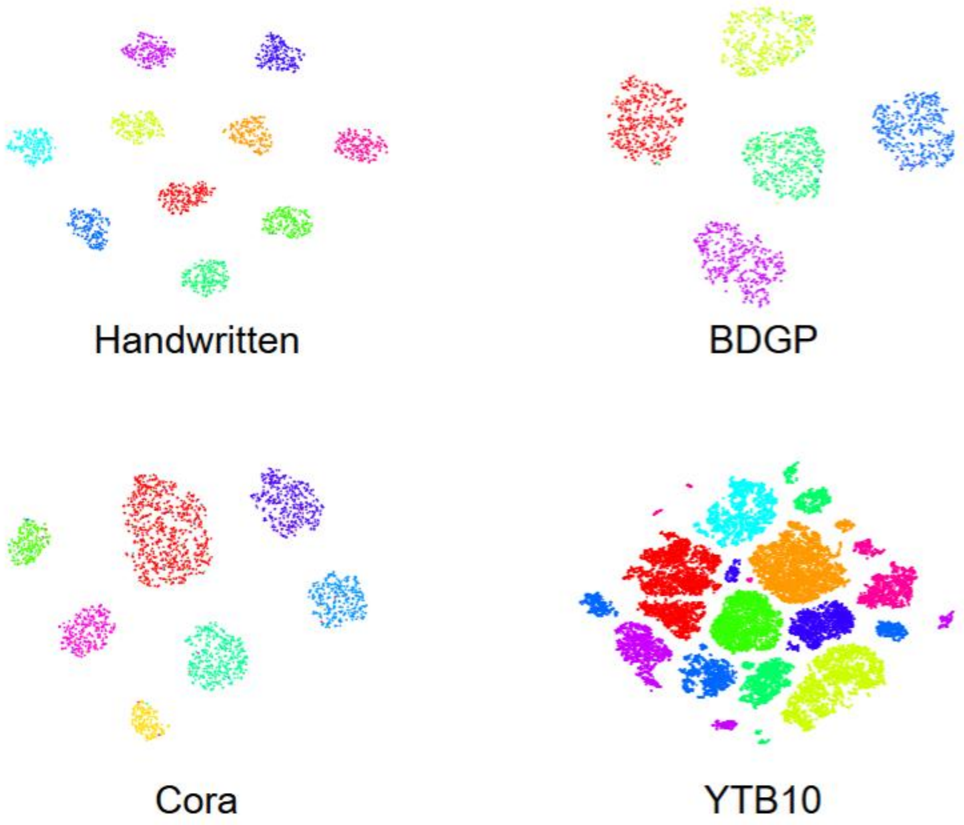


Figure 3. T-SNE visualization of our method on four datasets.

Thanks for your listening!

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