CPM-Nets: Cross Partial Multi-View Networks

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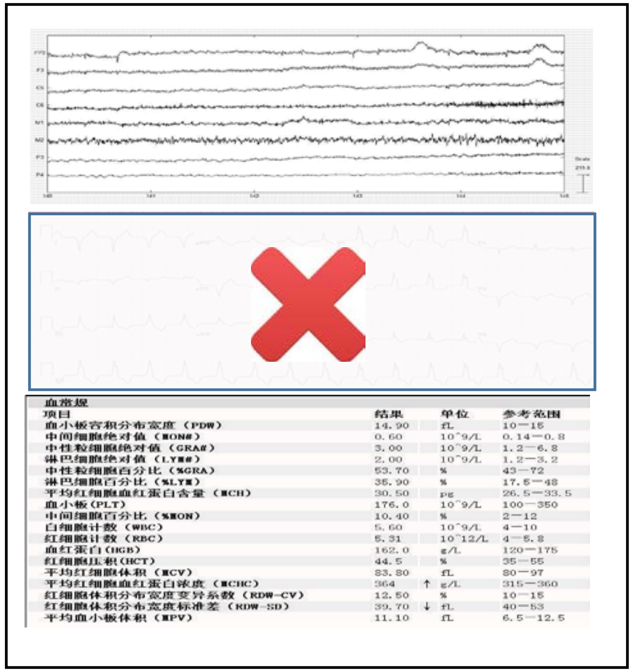
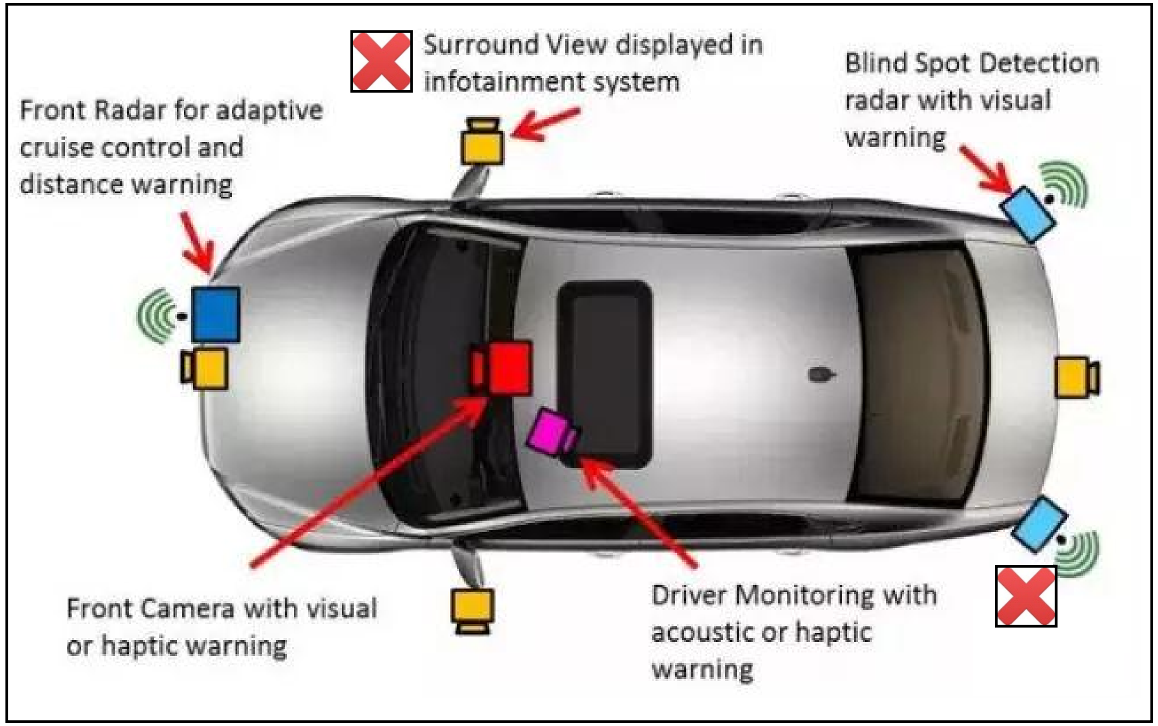
Multi-View Classification & Theory

Multi-modal medical data



Multi-sensor driving



Challenges of
Classification on Partial Multi-View Data

- For complex view-missing， how to avoid manually preprocessing (e.g., completion/discarding/grouping)?
  - Large number of views, and view-missing patterns;
  - The view-missing pattern of test sample is novel;
- How to guarantee the sufficiency in using partial multiple views?
- How to scale for large-scale & small-sample-size cases?

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Our Algorithm for Classification on Partial Multi-View Data

1. **Flexibility:** Samples with arbitrary view-missing patterns;
2. **Complete-Representation:** Compact with full information;
3. **Structured-Representation:** Simplify classifier for interpretability;

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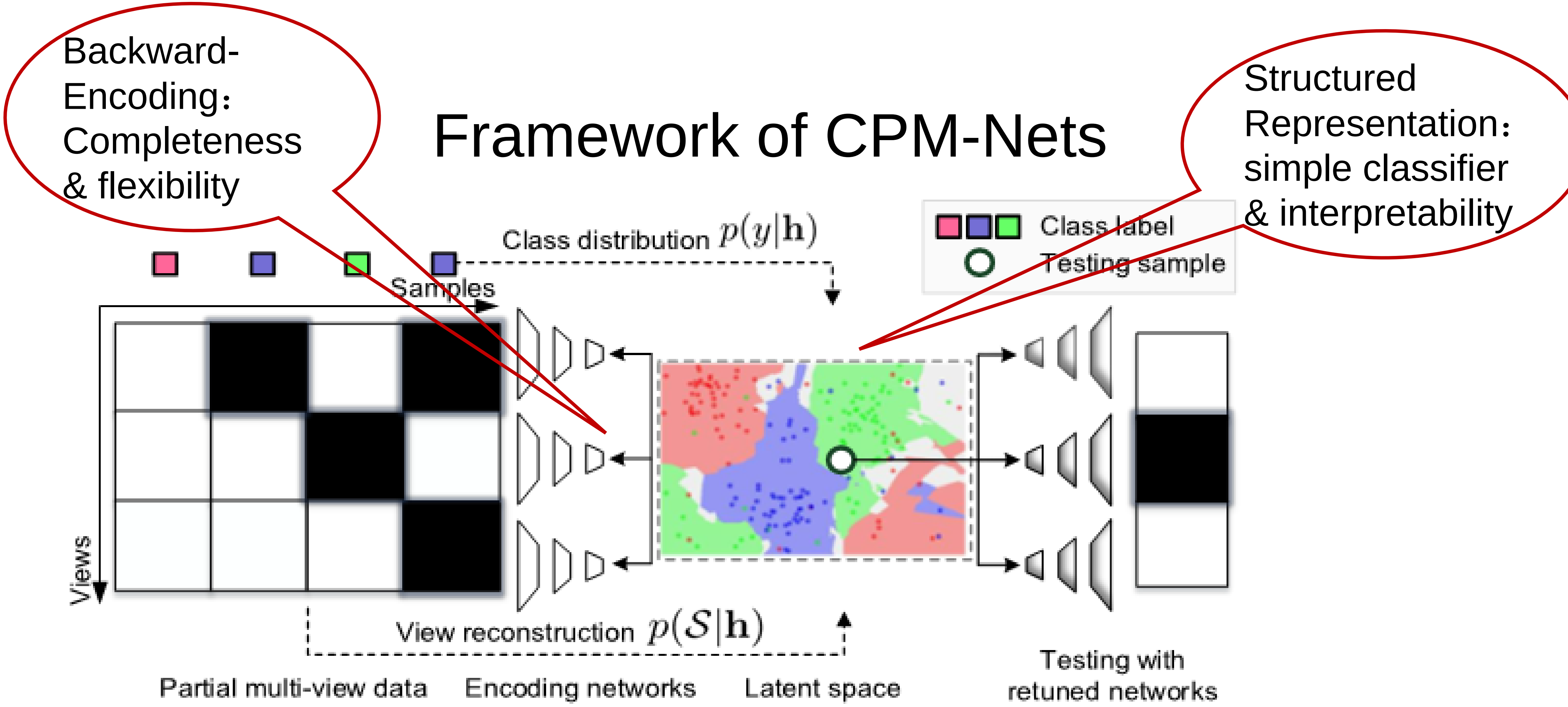
Framework of CPM-Nets



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Framework of CPM-Nets

All (partial) available views are encoded into h

Clustering-like supervised loss: structured representation + nonparametric classifier

Complete Representation

Structured Representation

$$\min_{\{\mathbf{h}_n\}_{n=1}^{N},\boldsymbol{\Theta}_r} \frac{1}{N}\sum_{n=1}^{N}\ell_r(\mathcal{S}_n,\mathbf{h}_n;\boldsymbol{\Theta}_r)+\lambda\ell_c(y_n,y,\mathbf{h}_n)$$

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Theoretical Analysis

Proposition 2.1 *(Versatility for the Multi-View Representation from Eq. (5)) There exists a solution (with respect to latent representation* $\mathbf{h}$*) to Eq. (5) which holds the versatility.*

Proof 2.1 *The proof for proposition 2.1 is as follow. Ideally, according to Eq. (5), there exists* $\mathbf{x}^{(v)} = f_v(\mathbf{h}; \mathbf{\Theta}_r^{(v)})$*, where* $f_v(\cdot)$ *is the mapping from* $\mathbf{h}$ *to* $\mathbf{x}^{(v)}$*. Hence,* $\forall\, \varphi(\cdot)$ *with* $y^{(v)} = \varphi(\mathbf{x}^{(v)})$*, there exists a mapping* $\psi(\cdot)$ *satisfying* $y^{(v)} = \psi(\mathbf{h})$ *by defining* $\psi(\cdot) = \varphi(f_v(\cdot))$*. This proves the versatility of the latent representation* $\mathbf{h}$ *based on multi-view observations* $\{\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(V)}\}$*.*

In practical case, it is usually difficult to guarantee the exact versatility for latent representation, then the goal is to minimize the error $e_y = \sum_{v=1}^{V} ||\psi(\mathbf{h}) - \varphi(\mathbf{x}^{(v)})||^2$ (i.e., $\sum_{v=1}^{V} ||\varphi(f_v(\mathbf{h}; \mathbf{\Theta}^{(v)})) - \varphi(\mathbf{x}^{(v)})||^2$*) which is inversely proportional to the degree of versatility. Fortunately, it is easy to show that* Ke_r *with* $e_r = \sum_{v=1}^{V} ||f_v(\mathbf{h}; \mathbf{\Theta}_r^{(v)}) - \mathbf{x}^{(v)}||^2$ *from Eq. (5) is the upper bound of* e_y *if* $\varphi(\cdot)$ *is Lipschitz continuous with* K *being the Lipschitz constant.* □

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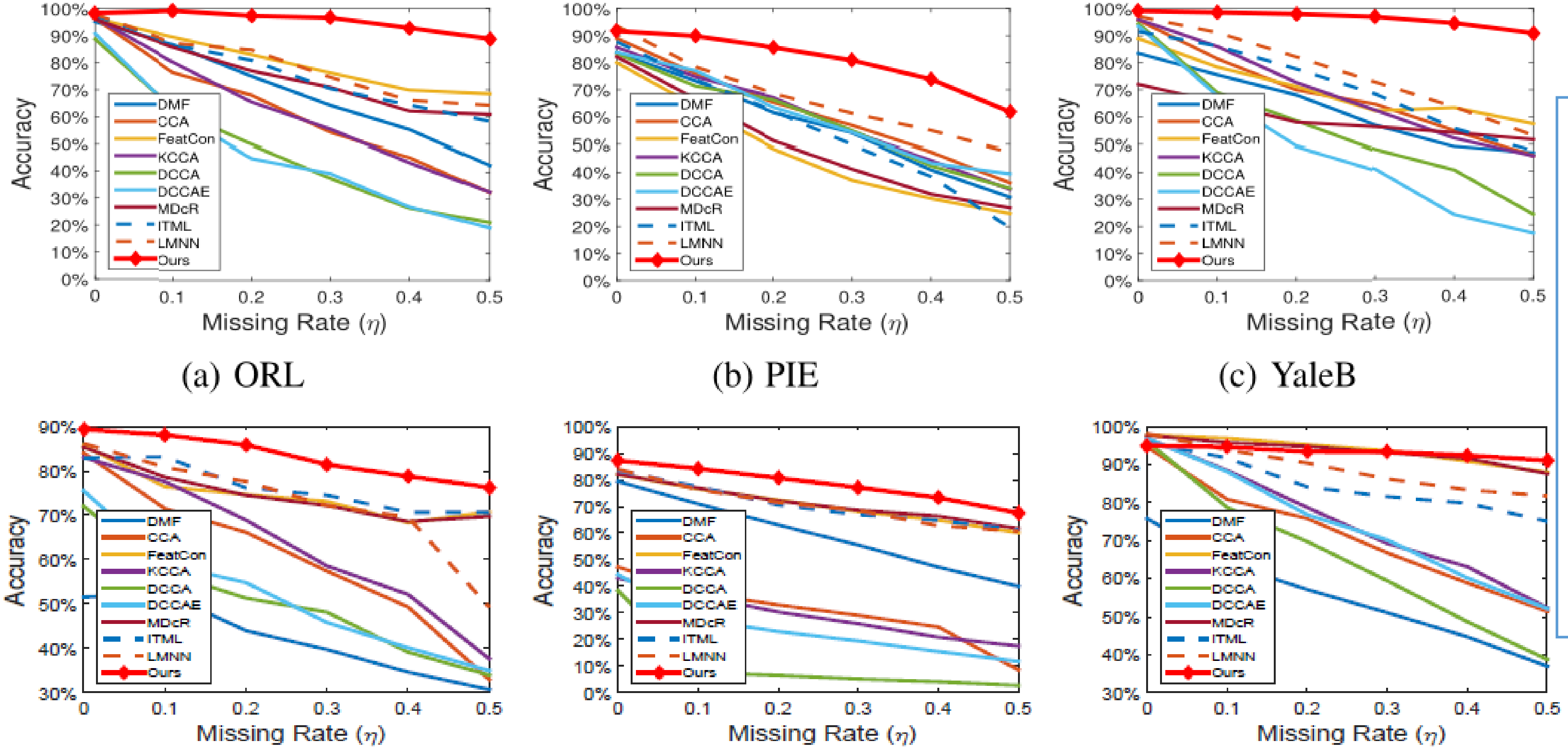
Comparison under Different Missing Rate



(a) ORL (b) PIE (c) YaleB

(d) CUB (e) Animal (f) Handwritten

- **CCA-based methods:** CCA/Kernelized CCA/Deep CCA;
- **Matrix Factorization-based method:** Deep MF;
- **Metric Learning Methods:** LMNN/ITML.

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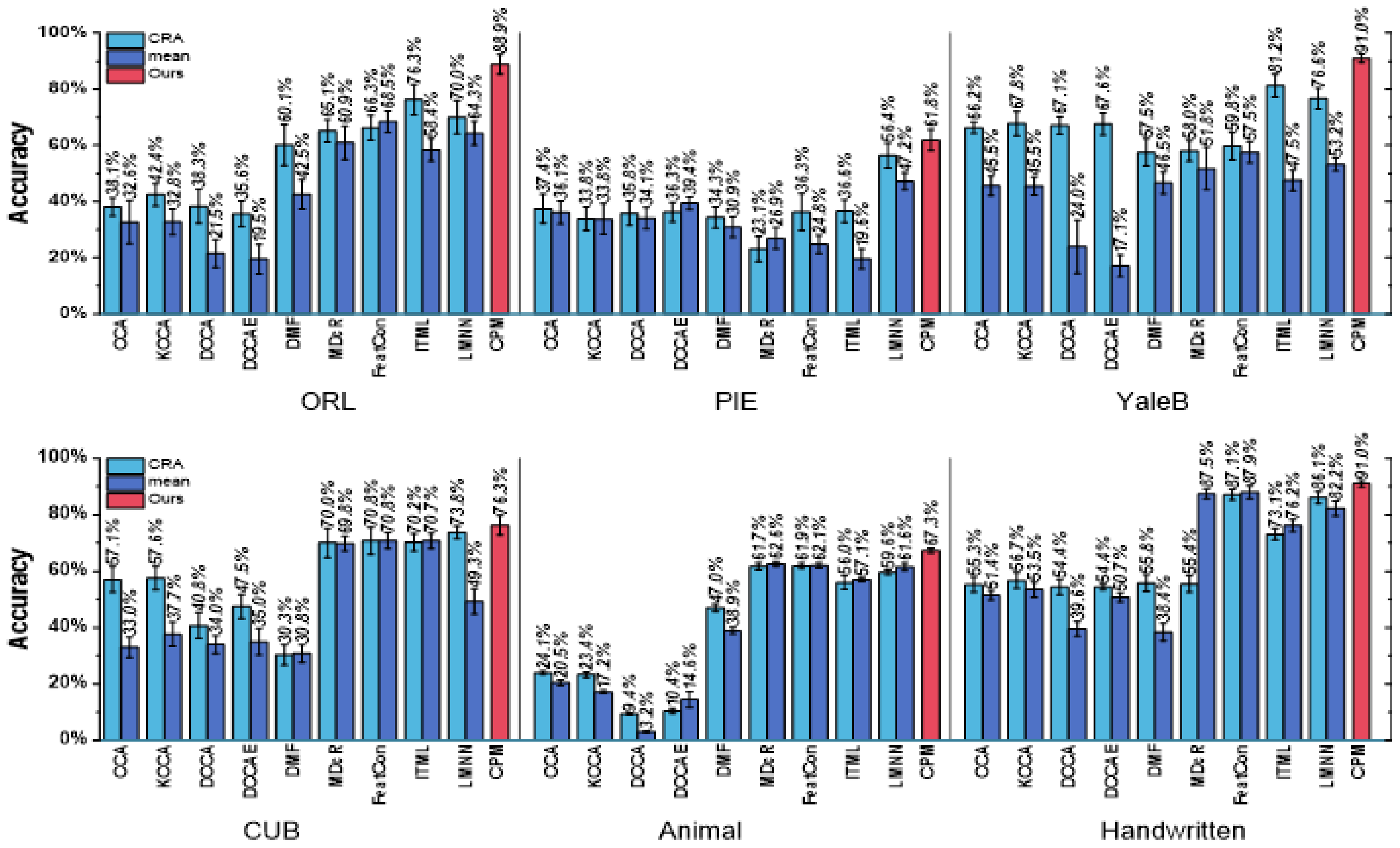
Comparison with Completion Methods



- CRA (CVPR’17) [1];
- Mean: Complete the missing values with the mean of the observed in the same class.

[1] Missing modalities imputation via cascaded residual autoencoder. CVPR, 2017.

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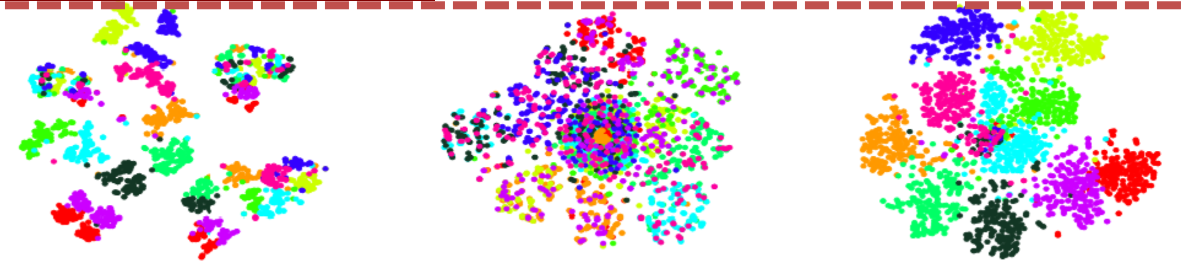
Visualization under Missing Rate: η = 0.5

Unsupervised Case



(a) FeatCon (U) (b) DCCA (U) (c) Ours (U)

Supervised Case

(d) LMNN (S) (e) ITML (S) (f) Ours (S)

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Conclusion

- **Complete Representation:** Information preservation & flexibility for arbitrary view-missing pattern;
- **Nonparametric Classifier:** Nonparametric classifier for simple structured representation;
- **Theoretical Guarantee:** Strict guarantee for idea case and bound for practical case;
- **Applicable:** Large-scale/Small-Sample-Size

Thanks!