



AE^2-Nets: Autoencoder in Autoencoder Networks for Learning Multi-view Representation

张长青

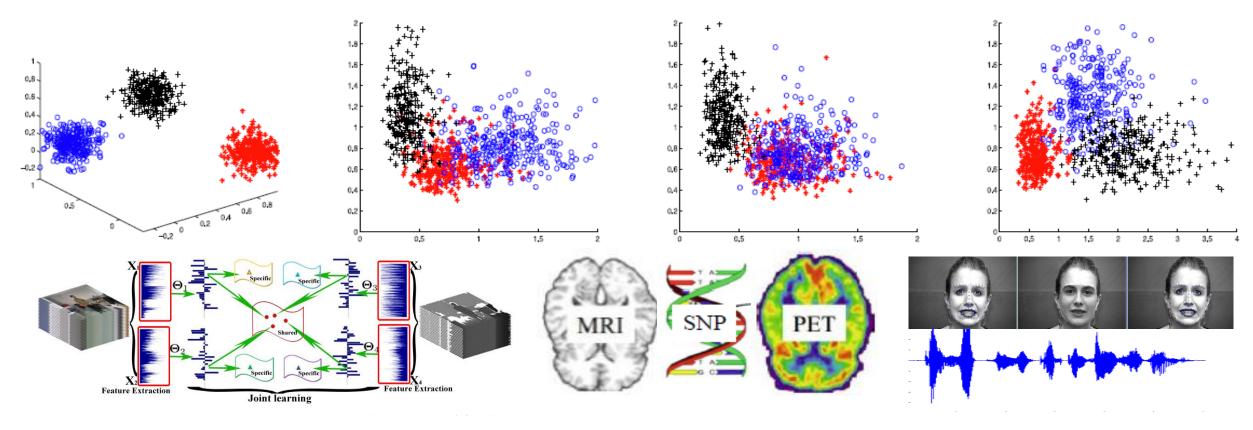
天津大学 智能与计算学部 2019-04-02

[CVPR'19] Changqing Zhang (张长青), Yeqing Liu, Huazhu Fu,

AE^2-Nets: Autoencoder in Autoencoder Networks,



为什么多视图学习重要?



天津大学智能与计算学部 COLLEGE OF INTELLIGENCE AND COMPUTING



多视图学习本质问题思考





·基本特性1:一致性(相关性),相同对象;

·基本特性2: 互补性(独立性),不同角度;

· 衍生特性: 完备性-多视图的信息是相对完备的。

• 挑战:

・高维: 维度灾难带来类可分性差、难以揭示聚类结构/过拟合;

· 度量: 预先定义的距离/相似度计算;

· 平衡: 一致性与互补性如何平衡;

・缺失: 视图残缺;

・高度异构: 如非数值属性混杂;

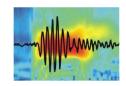
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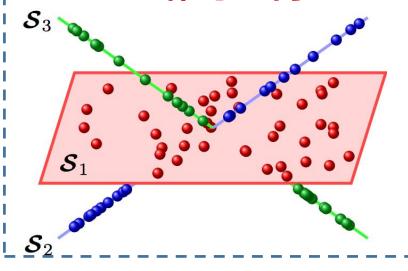
数据自表示的子空间聚类

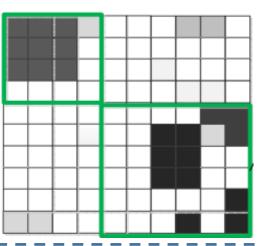
- 1. 维度灾难->维度福音 [高维]
- 2. 预先定义相似度函数->自适应学习相似度 [度量]

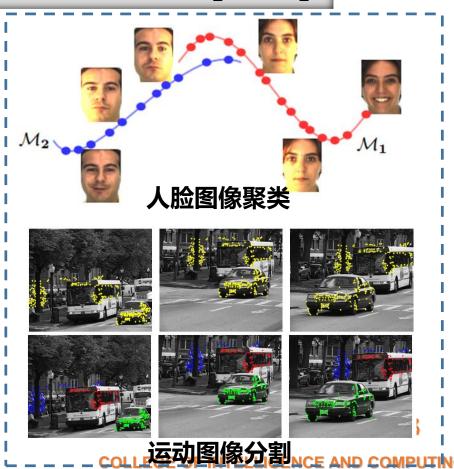
[**自表示子空间假设**]高维空间中的数据来自**多个低维子空间**,同一个子空间的数据可**由其他数据线性表示**。

线性子空间

子空间表示







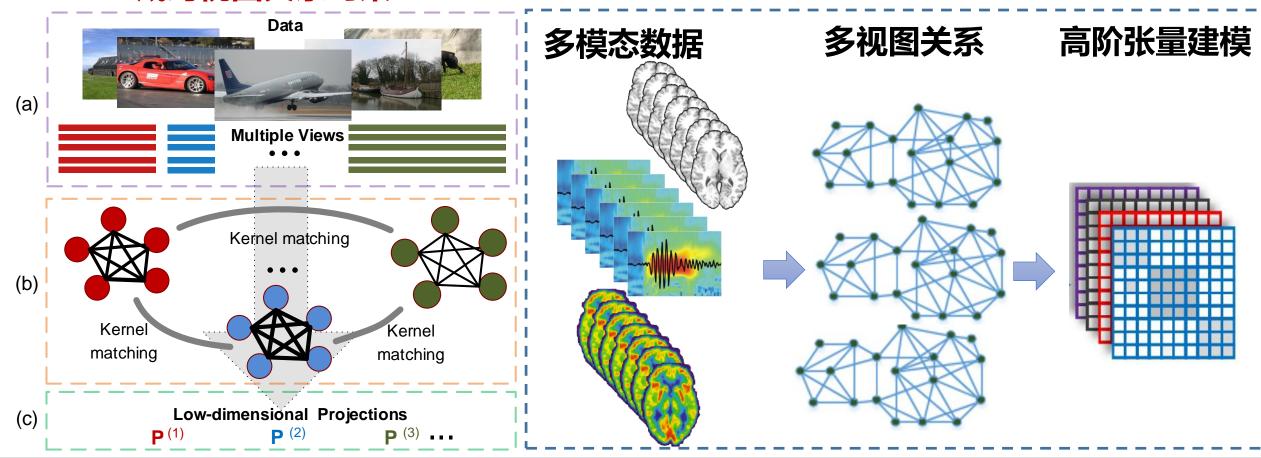


增强一致性:全局视角-高阶关联



成对视图关系约束

高阶关联



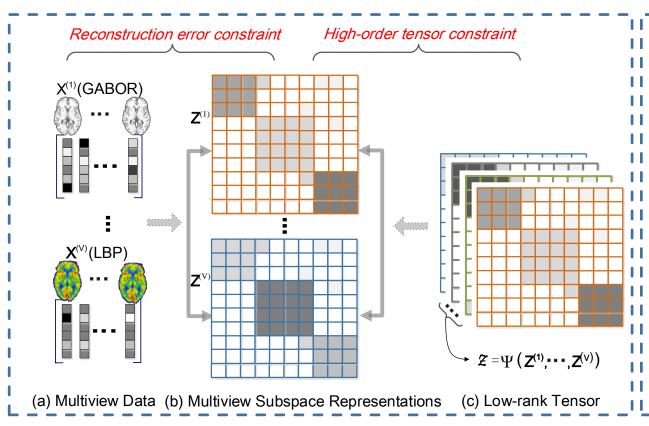
[ICCV'15] Changqing Zhang (张长青), Huazhu Fu, Si Liu, Guangcan Liu, Xiaochun Cao, Low-Rank Tensor Constrained Multiview Subspace Clustering, ICCV 2015.



增强一致性:低秩张量多视角子空间聚类



关键创新:构建相似度矩阵->学出低秩高阶张量



- 相似度矩阵自动学出,而非预先定义
- 挖掘多视图高阶关, 联而非传统成对约束
- 结构化误差, 噪声在多视图间的一致性

$$\min_{\mathbf{Z}^{(v)}, \mathbf{E}^{(v)}} ||\mathbf{Z}||_* + \lambda ||\mathbf{E}||_{2,1}$$

s.t.
$$\mathbf{X}^{(v)} = \mathbf{X}^{(v)}\mathbf{Z}^{(v)} + \mathbf{E}^{(v)}, \ v = 1, 2, ..., V,$$

$$\mathbf{\mathcal{Z}} = \Psi(\mathbf{Z}^{(1)}, \mathbf{Z}^{(2)}, ..., \mathbf{Z}^{(V)}),$$

$$\mathbf{E} = [\mathbf{E}^{(1)}; \mathbf{E}^{(2)}; ...; \mathbf{E}^{(V)}],$$

[ICCV'15] Changqing Zhang (张长青), Huazhu Fu, Si Liu, Guangcan Liu, Xiaochun Cao, Low-Rank Tensor Constrained Multiview Subspace Clustering, ICCV 2015.



增强互补性:多样性诱导的多视图聚类

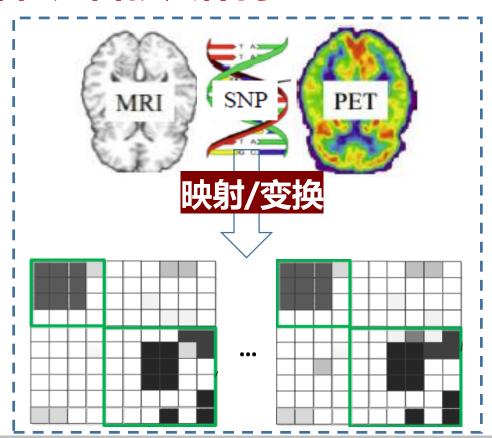


映射之后, 互补性是否依然保持?

输入多视图 具有一定互补性



输出[相似度矩阵/分 类标记/回归结果] 是否仍然具有互补性



[CVPR'15] Xiaochun Cao, <u>Changqing Zhang (张长青)*</u>, Huazhu Fu, Si Liu, Hua Zhang, Diversity-induced Multiview Subspace Clustering, <u>CVPR 2015</u>.



增强互补性:多样性诱导的多视图聚类

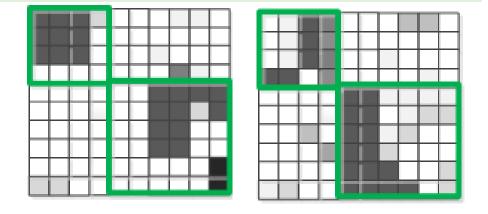


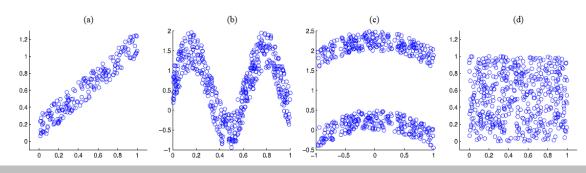
关键创新:增强多视图间的多样性(第一个多视图子空间聚类方法)

- 自适应学习相似度矩阵
- 显式增强样本自表示的多样性
- 自动加权不同视图

$$\begin{split} \mathcal{O}(\mathbf{Z}^{(1)},...,\mathbf{Z}^{(V)};\mathbf{P}^{(1)},...,\mathbf{P}^{(V)};\alpha) \\ &= \sum_{v=1}^{V} \left\{ \alpha_{v}^{r} || \mathbf{P}^{(v)} \mathbf{X}^{(v)} - \mathbf{P}^{(v)} \mathbf{X}^{(v)} \mathbf{Z}^{(v)} ||_{F}^{2} \right. \\ &+ \underbrace{\lambda_{S} tr(\mathbf{Z}^{(v)} \mathbf{L}^{(v)} \mathbf{Z}^{(v)^{T}}) + \underbrace{\lambda_{P} || \mathbf{X}^{(v)} - (\mathbf{P}^{(v)})^{T} \mathbf{P}^{(v)} \mathbf{X}^{(v)} ||_{F}^{2}}_{\text{smoothness}} \right\} \\ &+ \underbrace{\lambda_{V} \sum_{v \neq w} \text{HSIC}(\mathbf{Z}^{(v)}, \mathbf{Z}^{(w)})}_{\text{diversity}} \end{split}$$

weighted errors of different views

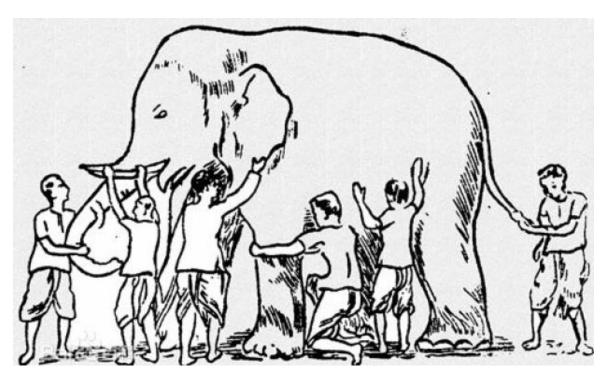




[CVPR'15] Xiaochun Cao, <u>Changqing Zhang (张长青)*</u>, Huazhu Fu, Si Liu, Hua Zhang, Diversity-induced Multiview Subspace Clustering, <u>CVPR 2015</u>.







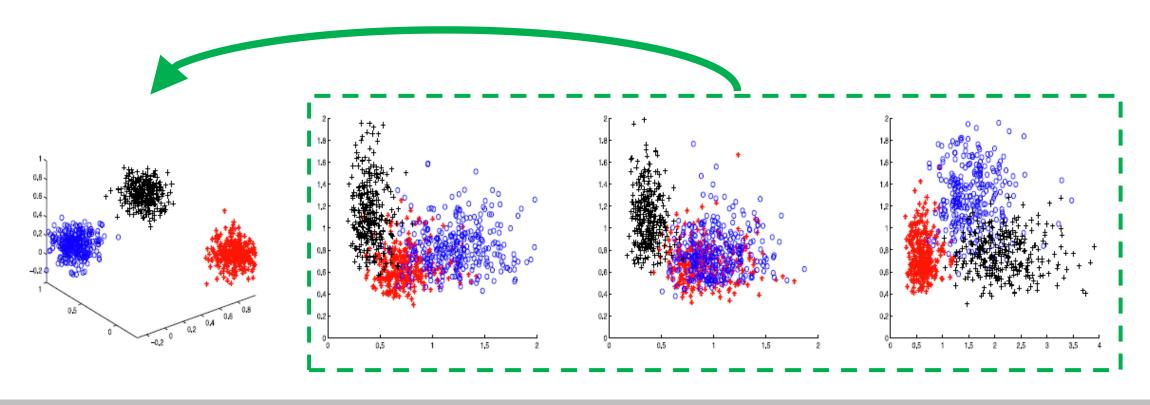
- 传统集成方式:每个视图根据各自信息决 策,然后投票决定最后结果; 【Results voting
- 新思路:面向任务、将各视图信息汇总、 提炼。 【Task-oriented representation learning \ \
- 挑战:视图之间的关联复杂,一致性(共 性) 与互补性(个性)如何共存?



增强完备性: 隐表达多视角子空间聚类



能否自适应恢复出完备的多视图表示?



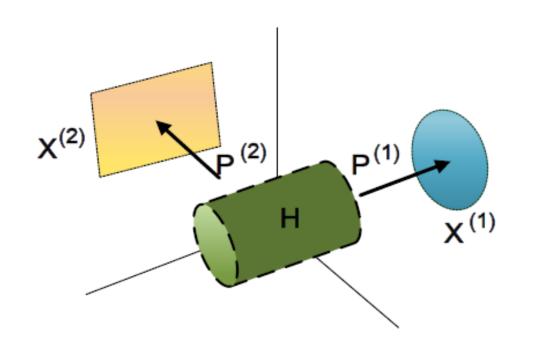
[CVPR'17] Changqing Zhang (张长青), Qinghua Hu, Huazhu Fu, Pengfei Zhu, Xiaochun Cao, Latent Multi-View Subspace Clustering, CVPR 2017 (Spotlight Paper).



增强完备性: 隐表达多视图聚类



信息融合的完备性:信息反向传输+迭代修正



- 口 传统的正向传输,难以保证完备性;
- 二 完备信息可以退化为各视角信息,模拟信息传输过程,灵活融合多源数据。

正向传输
$$\sum_{v=1}^{V} ||f(\mathbf{x}_n^{(v)}; \boldsymbol{\theta}^{(v)}) - \mathbf{h}_n||^2$$
 反向传输 $\sum_{v=1}^{V} ||f(\mathbf{h}_n; \boldsymbol{\theta}^{(v)}) - \mathbf{x}_n^{(v)}||^2$

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Motivation

- Completeness (完备性): Model multi-view integration with <u>information</u> <u>degradation mimicking data transmission</u>, which brings great flexibility for balancing the consistence and complementarity across different views.
- Robustness (鲁棒性): <u>Nested encoding</u> to integrate intrinsic information of each view from view-specific <u>autoencoder</u>.
- End-to-End (端到端): Flexible for heteronomous data by using <u>modal-specific</u> <u>convolutional neural networks</u>.

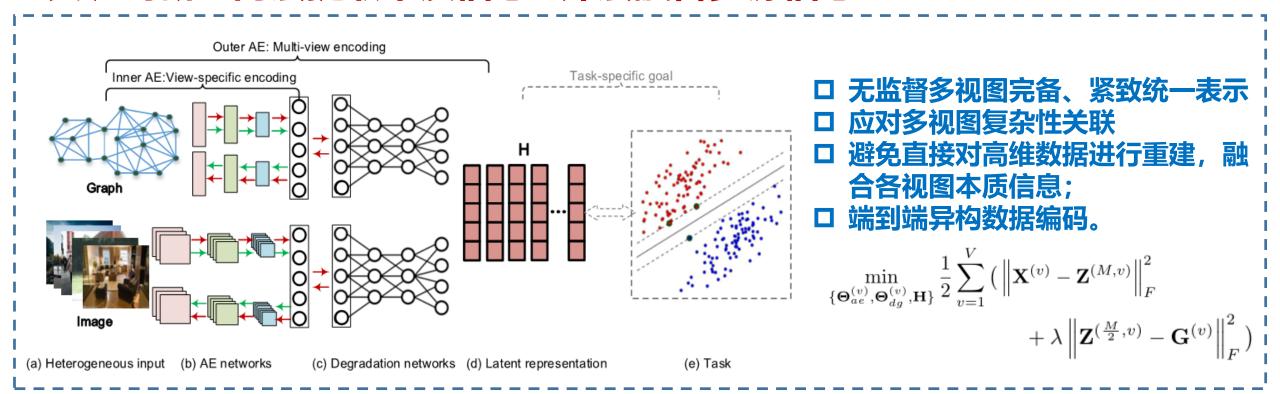
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关键创新:内层提取本质信息+外层融合多源信息



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Framework

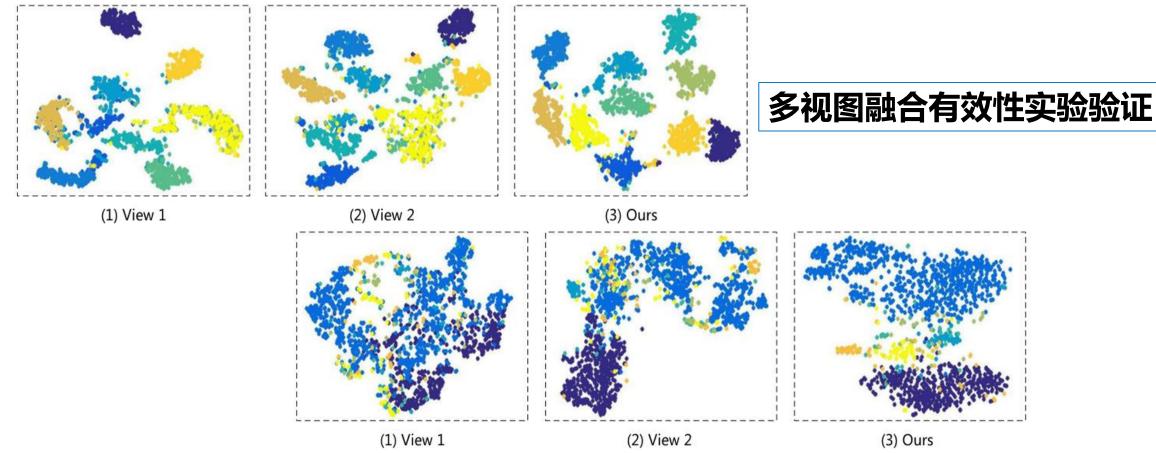
- Inner AE (内层编码器): <u>View-specific autoencoder networks</u> under the constraints of reconstructions based on the learned latent representation for better view-specific representation.
- Outer AE (外层编码器): <u>Degradation networks</u> for better latent representation to reconstruct learned view-specific representation.
- AE in AE (嵌套编码器): Integrate intrinsic information from all views into an intact latent representation.

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Table 1: Performance comparison on clustering task.

Datasets	Methods	ACC	NMI	F_score	RI
handwritten	FeatConcate	76.04 ± 2.28	75.70 ± 1.44	70.96 ± 2.05	93.93 ± 0.42
	CCA [14]	66.43 ± 7.62	69.62 ± 6.06	62.05 ± 7.70	91.83 ± 1.79
	DCCA [2]	66.26 ± 0.16	66.01 ± 0.45	59.05 ± 0.39	91.39 ± 0.06
	DCCAE [27]	69.17 ± 1.02	66.96 ± 0.91	60.50 ± 1.10	91.77 ± 0.21
	MDcR 33	76.72 ± 2.77	76.68 ± 0.93	$\textbf{71.93} \pm \textbf{2.22}$	$\textbf{94.11} \pm \textbf{0.48}$
	DMF-MVC [36]	71.86 ± 4.25	73.09 ± 3.23	66.66 ± 4.69	92.85 ± 1.13
	Ours	$\textbf{81.52} \pm \textbf{1.62}$	71.39 ± 1.50	68.57 ± 1.86	93.68 ± 0.38
Caltech101	FeatConcate	47.23 ± 0.22	57.19 ± 0.61	52.15 ± 0.28	73.45 ± 0.16
	CCA [14]	45.37 ± 0.09	50.53 ± 0.03	52.15 ± 0.19	73.27 ± 0.09
	DCCA [2]	56.71 ± 10.50	57.61 ± 6.78	62.32 ± 12.75	76.34 ± 6.86
	DCCAE [27]	62.11 ± 2.78	$\textbf{64.38} \pm \textbf{4.11}$	65.43 ± 4.24	79.31 ± 2.06
	MDcR 33	46.51 ± 0.67	56.43 ± 0.56	51.55 ± 0.56	73.27 ± 0.30
	DMF-MVC [36]	55.75 ± 5.67	45.52 ± 2.28	55.67 ± 5.50	73.43 ± 2.33
	Ours	66.46 ± 4.55	60.60 ± 1.93	$\textbf{73.42} \pm \textbf{4.91}$	$\textbf{83.14} \pm \textbf{2.33}$
ORL	FeatConcate	61.10 ± 1.51	79.28 ± 0.70	47.03 ± 2.21	97.10 ± 0.25
	CCA [14]	56.98 ± 2.06	76.03 ± 0.79	45.13 ± 1.83	97.32 ± 0.09
	DCCA [2]	59.68 ± 2.04	77.84 ± 0.83	47.72 ± 2.05	97.42 ± 0.13
	DCCAE [27]	59.40 ± 2.20	77.52 ± 0.86	46.71 ± 2.22	97.39 ± 0.14
	MDcR 33	61.70 ± 2.19	79.45 ± 1.20	48.48 ± 2.59	97.28 ± 0.22
	DMF-MVC [36]	65.38 ± 2.86	82.87 ± 1.26	52.01 ± 3.43	97.29 ± 0.30
	Ours	$\textbf{68.85} \pm \textbf{2.11}$	$\textbf{85.73} \pm \textbf{0.78}$	$\textbf{59.93} \pm \textbf{1.31}$	$\textbf{97.94} \pm \textbf{0.11}$

统一表示在分类及聚类任务上验证

Table 2: Performance comparison on classification task.

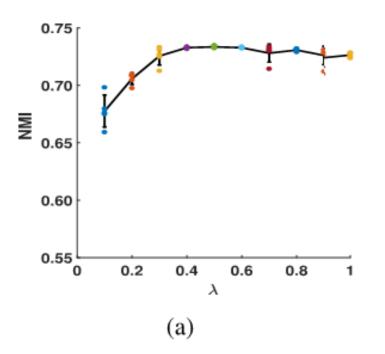
Datasets	Methods	$G_{80\%}/P_{20\%}$	$G_{70\%}/P_{30\%}$	$G_{50\%}/P_{50\%}$	$G_{20\%}/P_{80\%}$
handwritten	FeatConcate	89.60 ± 1.40	88.97 ± 0.73	88.87 ± 0.44	85.68 ± 0.53
	CCA [14]	93.78 ± 0.82	93.47 ± 0.93	93.28 ± 0.66	91.12 ± 0.74
	DCCA [2]	95.18 ± 0.55	94.62 ± 0.64	94.35 ± 0.46	92.79 ± 0.51
	DCCAE [27]	95.78 ± 0.46	95.10 ± 0.64	94.79 ± 0.58	92.63 ± 0.54
	MDcR 33	92.33 ± 0.73	91.55 ± 0.39	91.41 ± 0.68	88.11 ± 0.61
	DMF-MVC [36]	94.68 ± 0.71	93.72 ± 0.60	93.33 ± 0.46	88.23 ± 0.57
	Ours	$\textbf{96.93} \pm \textbf{0.71}$	$\textbf{96.55} \pm \textbf{0.66}$	$\textbf{95.88} \pm \textbf{0.71}$	$\textbf{93.38} \pm \textbf{0.49}$
Caltech101	FeatConcate	87.88 ± 0.67	87.47 ± 0.56	87.17 ± 0.49	87.10 ± 0.45
	CCA [14]	91.10 ± 0.96	90.07 ± 1.03	89.82 ± 0.49	89.08 ± 0.71
	DCCA [2]	92.12 ± 0.58	91.46 ± 0.70	91.30 ± 0.48	90.73 ± 0.38
	DCCAE [27]	91.58 ± 1.02	90.91 ± 0.75	90.54 ± 0.44	89.44 ± 0.43
	MDcR 33	90.14 ± 0.74	89.45 ± 0.76	88.95 ± 0.41	88.46 ± 0.35
	DMF-MVC [36]	85.51 ± 1.05	84.67 ± 0.82	81.88 ± 0.73	74.19 ± 0.99
	Ours	$\textbf{93.77} \pm \textbf{1.35}$	$\textbf{92.98} \pm \textbf{1.37}$	$\textbf{92.49} \pm \textbf{0.72}$	$\textbf{91.36} \pm \textbf{0.69}$
ORL	FeatConcate	79.13 ± 2.36	74.58 ± 1.32	68.00 ± 2.23	48.28 ± 2.27
	CCA [14]	77.13 ± 3.96	73.83 ± 4.89	67.95 ± 2.77	49.00 ± 1.84
	DCCA [2]	83.25 ± 2.71	78.92 ± 1.93	71.15 ± 1.86	51.69 ± 1.75
	DCCAE [27]	81.62 ± 2.95	80.00 ± 1.47	72.80 ± 2.04	51.25 ± 1.90
	MDcR 33	92.00 ± 1.58	90.83 ± 2.08	83.35 ± 1.08	57.38 ± 2.08
	DMF-MVC [36]	93.13 ± 1.21	91.75 ± 1.64	85.45 ± 1.85	56.44 ± 2.50
	Ours	$\textbf{97.88} \pm \textbf{1.19}$	96.00 ± 2.18	$\textbf{92.20} \pm \textbf{1.18}$	$\textbf{70.16} \pm \textbf{2.54}$

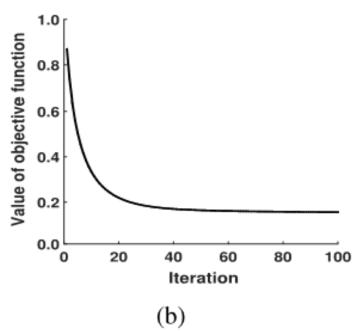
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- □ 选择相对较大的lambda值,增强 将各视图信息编码到统一表示;
- 」迭代下降,具有较好收敛特性。注: 一次iteration包含更新ae,dg和h, 其中,每个更新又分别包含多次 batch更新。

Figure 3: Parameter tuning (a) and convergence curve (b).

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谢谢大家!

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