

Seminar Paper: Group 13 Deep Clustering for Unsupervised Learning of Visual Features¹

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Mentors:

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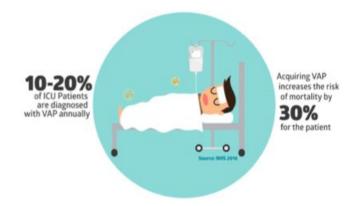
[1] Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. "Deep Clustering for Unsupervised Learning of Visual Features." arXiv:1807.05520 [cs.CV]. Proc. ECCV (2018).

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Topic: Assessing Ventilator-Associated Pneumonia (VAP) in the PICU



Chest X-Rays: empirical standard in pneumonia diagnosis

Mechanical Ventilation: critical life sustaining ICU therapy, however, with host of problems that leads to VAP

Objective: prepare automatic classifier to be used in the PICU to monitor onset of disease progression and detect VAP





Paper Summary and Background

- Methods performed by the Facebook Al Research Group, submitted to EECV (European Conference on Computer Vision) 2018
- Proposed DeepCluster, a novel clustering method
- Utilizes pre-trained Convolutional Neural Networks (CNNs) with standard clustering methods on top (k-means)
- Outperforms state-of-the-art image classification networks

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Selection Motivation

- Aims to provide **solution to internet-scale image classification** problems (*highly relevant to my project's datasets*)
- Supervised learning is **highly dependent on labeling and annotation** which is sparse in real-life problems
- Takes novel approach to network training and is considered one of the most successful approaches thus far

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Paper's Approach

- 1. Overview of Technical Methods
- 2. Implementation Details
- 3. Experiments
- 4. Results and Comparison to Prior Literature

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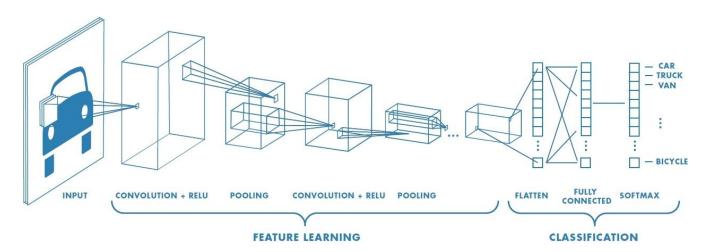
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Paper's Approach: Overview of Technical Methods

Overview of CNN Architecture



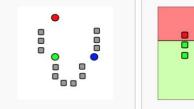
[2] Hatami, N., Gavet, Y. and Debayle, J. (2019). Classification of Time-Series Images Using Deep Convolutional Neural Networks. [online] arXiv.org. Available at: https://arxiv.org/abs/1710.00886. Accessed 20 Feb. 2019



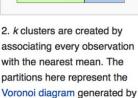
Paper's Approach: Overview of Technical Methods

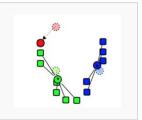
K-Means

Demonstration of the standard algorithm



1. *k* initial "means" (in this case *k*=3) are randomly generated within the data domain (shown in color).





3. The centroid of each of the *k* clusters becomes the new mean.



4. Steps 2 and 3 are repeated until convergence has been reached.

[3] Landman, Nathan, Hannah Pang, and Christopher Williams. "K-Means Clustering." Brilliant Math & Science Wiki. 2018. 20 Apr. 2019 <https://brilliant.org/wiki/k-means-clustering/>.

the means.

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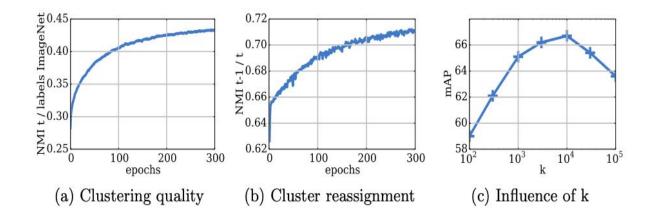
Paper's Approach: Implementation Details

- Network: utilize the pre-trained AlexNet and VGG-16 models (compare both because of trade-off in computational complexity)
- Data Acquisition: train on ImageNet (1.3M images with 1000 classes)
- CNN Parameters: dropout, L2 penalization, momentum = 0.9
- Feature regularization: PCA-reduction to 256 and whitened
- Training: over 500 epochs, update clusters after each epoch

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Paper's Approach: Experiments



NMI (Normalized Mutual Information) is the parameter that is measured above. NMI measures the information shared between two different assignments, i.e. a measure of independence

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Paper's Approach: Experiments

Method	ImageNet				Places					
	conv1	conv2	conv3	conv4	conv5	conv1	conv2	conv3	conv4	conv5
Places labels	_	_	-		-	22.1	35.1	40.2	43.3	44.6
ImageNet labels	19.3	36.3	44.2	48.3	50.5	22.7	34.8	38.4	39.4	38.7
Random	11.6	17.1	16.9	16.3	14.1	15.7	20.3	19.8	19.1	17.5
Pathak et al. [38]	14.1	20.7	21.0	19.8	15.5	18.2	23.2	23.4	21.9	18.4
Doersch et al. [25]	16.2	23.3	30.2	31.7	29.6	19.7	26.7	31.9	32.7	30.9
Zhang et al. [28]	12.5	24.5	30.4	31.5	30.3	16.0	25.7	29.6	30.3	29.7
Donahue et al. [20]	17.7	24.5	31.0	29.9	28.0	21.4	26.2	27.1	26.1	24.0
Noroozi and Favaro [26]	18.2	28.8	34.0	33.9	27.1	23.0	32.1	35.5	34.8	31.3
Noroozi et al. [45]	18.0	30.6	34.3	32.5	25.7	23.3	33.9	36.3	34.7	29.6
Zhang et al. [43]	17.7	29.3	35.4	35.2	32.8	21.3	30.7	34.0	34.1	32.5
DeepCluster	12.9	29.2	38.2	39.8	36.1	18.6	30.8	37.0	37.5	33.1

Comparison to other unsupervised learning models within the layers

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		Classif	ication	Detection		Segmentation	
Method	Training set	FC6-8	ALL	FC6-8	ALL	FC6-8	ALL
Best competitor	ImageNet	63.0	67.7	43.4^\dagger	53.2	35.8^\dagger	37.7
DeepCluster DeepCluster	ImageNet YFCC100M	$\begin{array}{c} 72.0 \\ 67.3 \end{array}$	73.7 69.3	$\begin{array}{c} 51.4 \\ 45.6 \end{array}$	$\begin{array}{c} 55.4\\ 53.0\end{array}$	$43.2 \\ 39.2$	$\begin{array}{c} 45.1\\ 42.2 \end{array}$

Comparison across performance yields that DeepCluster outperforms competitors on all tasks

Method	AlexNet	VGG-16	
ImageNet labels	56.8	67.3	
Random	47.8	39.7	
Doersch et al. [25]	51.1	61.5	
Wang and Gupta [29]	47.2	60.2	
Wang et al. [46]	-	63.2	
DeepCluster	55.4	65.9	

Comparison of VGG-16 and AlexNet shows the performance increase in using a more complex model

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Personal Critique: Areas of Improvement

• Lack of literature review into image clustering

- Paper continually references other competitors and papers in discussion of results, but does not give significance to *why DeepCluster is different*
- Would have been beneficial in understanding *why DeepCluster outperforms*

Lack of visual schematics

- Mentions the network implementation but does not give a visual representation of how weights are updated in the CNN
- Had to search for understanding on my own to supplement review material

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Personal Critique: Areas of Improvement

Sole use of hard assignments

• Would have been interesting to compare if a probabilistic (soft) clustering approach would have been more useful in updating the weights

• Resetting clusters after each epoch

- The method they chose here is very computationally intensive and perhaps inefficient given the number of epochs they train for
- Perhaps they could have computed the sample overlap between old and new clusters and assign the cluster IDs translationally *(full reset would not be necessary)*

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Personal Critique: Positives

- **Approach**: novel and fundamental to understanding of how we can combine learning methods to perform classification
- **Training and Testing**: utilized both AlexNet and VGG-16, as well as validated on image sets that were quite different in composure
- Linear Activation of Specific Layers: ability to discern where in the convolutional layers that performance starts to outperform

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Personal Takeaways

- Learned how clustering can be applied on top of a CNN's outputs to produce a more robust model for classification
- An improved understanding of the challenges associated with different image datasets and how to improve one's own model based on these parameters
- Limitations with different architectures of CNNs and how to best optimize the architecture for the task encountered

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Future Steps

- Replace hard assignments with weighted K-means or GMM-EM (Gaussian Mixture Model with Expectation Maximization) to allow more distribution in weight updating
- Test on purely unannotated and un-labeled data to see if similar performance can be achieved (pure unsupervised learning)
- Establish similar performance levels with refined networks such as ResNet and DenseNet for both improvements in efficiency and performance

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