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Improving Classification Accuracy with Graph Filtering

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ICIP Conference, Anchorage, Alaska, USA

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September 19-22, 2021

Outline

1. Deep Learning and Few-shot Learning
2. Methodology
3. Experiments
4. Conclusion and Perspectives

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Introduction

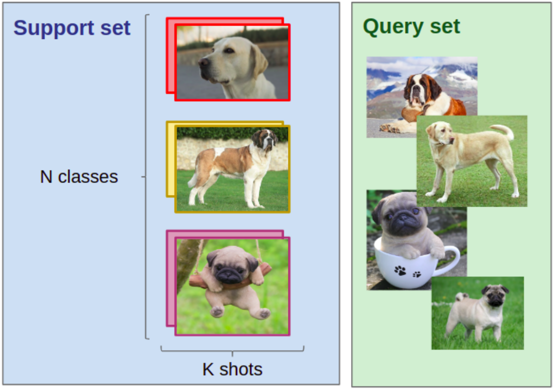
- Deep Learning is the state of the art for many machine learning problems

- Reaching peak performance typically requires large annotated datasets

- Performing predictions on batches of unlabeled inputs can boost performance: this setting is called *transductive*.

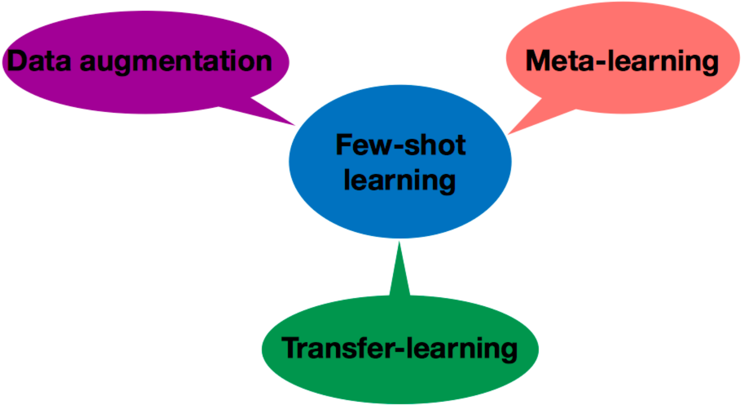
Transductive predictions are even more impactful in the case of few-shot learning

- N-way K-shot image classification



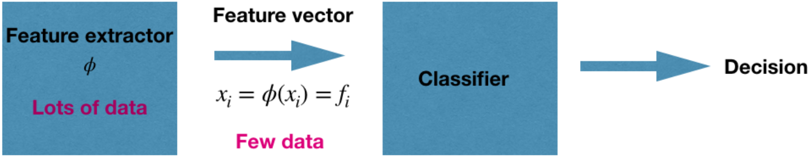
- For $K \leq 5$, classify the query images among the N classes given the $N \times K$ images in the support set

Few-shot Learning Methods



Main idea of the paper:

- Idea: Insert a denoising method after feature extraction and before classification after a model has been trained



- Goal: filter out the high frequencies within the feature representation of data to improve classification performance

- Tool: graph signal processing framework

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Graph Signal Processing (GSP)

- GSP allows to manipulate signals defined on graph structures

  - Assume $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{W})$ is connected. If not, just process each component separately

    $\mathcal{V} = \{ 1, 2, ... n \}$: finite set of n nodes or vertices
    $\mathcal{E}$: set of edges
    $\mathbf{W} : \mathcal{E} \to \mathbb{R}$: map from the set of edges to scalar values

  - Assume undirected graph with fixed graph structure

  - Vertex signal $\mathbf{f}_i : \mathcal{V} \to \mathbb{R}$

  - Graph signal $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2, ..., \mathbf{f}_n]^\top$

- Graph filters are systems that take a graph signal as an input and produce another signal indexed by the same graph as the output

Class Graphs

- Define a similarity matrix $\mathbf{W}$ between labeled samples

$$\mathbf{W}_{i,j} = w\left(\mathbf{f}_i, \mathbf{f}_j\right) \text{ if } i \neq j \text{ and } 0 \text{ otherwise,}$$

where s is a similarity measure on tensors.

- This matrix defines a graph $\mathcal{G}$

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{W})$$

with $\mathcal{V} = \{1, ..., |\mathbf{f}|\}$.

- Generate the adjacency matrix $\mathbf{W}$ of $\mathcal{G}$ for each class using k-nearest neighbors

$$\mathbf{W}_{i,j} = \begin{cases} \mathbf{W}_{i,j} & \text{if } \mathbf{W}_{i,j} \text{ is among the } k \text{ largest entries of row,} \\ 0 & \text{otherwise.} \end{cases}$$

- Normalized Laplacian matrix of $\mathcal{G}$

$$\mathbf{L} = \mathbf{I} - \mathbf{D}^{-\frac{1}{2}}\mathbf{W}\mathbf{D}^{-\frac{1}{2}},$$

where $\mathbf{D}$ is the diagonal degree matrix.

Graph Filters

- Eigenvalues $\boldsymbol{\lambda}$ of $\mathbf{L}$ are interpreted as frequencies
- A filter is usually defined by its spectral response

$$h : \lambda \mapsto h(\lambda)$$

where $\lambda \in \boldsymbol{\lambda}$.

- $\mathbf{H} = \mathrm{diag}(h(\boldsymbol{\lambda}))$, the filtered signal $\mathbf{f}^{\mathrm{filter}}$ is defined as

$$\mathbf{f}^{\mathrm{filter}} = \mathbf{U}\mathbf{H}\mathbf{U}^{\top}\mathbf{f} \ .$$

where $\mathbf{U}$ are the eigenvectors of $\mathbf{L}$.

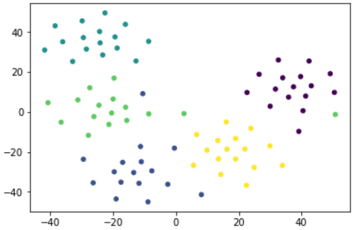
Observations

- To remove high frequencies in $\mathbf{f}$, a low-pass filter h nullifies large values of λ
- We substitute $\mathbf{f}$ with $\mathbf{f}^{\mathrm{filter}}$ as an input for the classifier

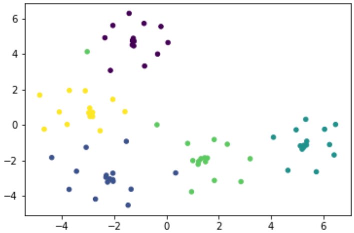
Effect of Low-pass Graph Filters on Centroids (1)

Low-pass filter: $h(\lambda) = 1$ if $\lambda \leq \lambda_m$ and $h(\lambda) = 0$ if not.

- Mini-imageNet data representation before applying any filter



- Mini-imageNet data representation after applying a graph filter



Effect of Low-pass Graph Filters on Centroids (2)

- $\mathbf{f}_i \sim \mathcal{N}(\boldsymbol{\mu}, \sigma^2\mathbf{I})$
- Centroids are computed as

$$\boldsymbol{\gamma} = \frac{1}{K}\sum_{i=1}^{K}\mathbf{f}_i \ .$$

- Filter $\mathbf{H}$ such that $h(\lambda) = 1$ if $\lambda \leq \boldsymbol{\lambda}_m$ and $h(\lambda) = 0$ otherwise ($\lambda \in \boldsymbol{\lambda}$)

Result

- We build a complete graph for each class, and let the number of labeled samples of that class $K \to \infty$, then

$$\mathbb{E}(\boldsymbol{\gamma}^{\text{filter}}) = \mathbb{E}(\boldsymbol{\gamma}) \ ,$$

$$\mathrm{Cov}(\boldsymbol{\gamma}^{\text{filter}}) = o\left(\mathrm{Cov}(\boldsymbol{\gamma})\right) \ .$$

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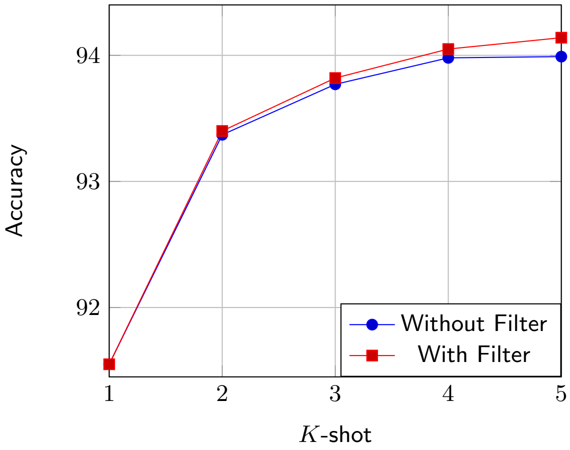
5-shot Accuracy of the Methodology Compared with State-of-the-art Method, for Various Extractors

- Runs $= 100.000$
- Number of classes $N = 5$
- Shots $K = 5$
- Queries $q = 15$

Classifier			
Dataset	Extractors	No Filter %	With Filter %
MINet	**WRN**	88.82 ± 0.013	$\mathbf{88.90 \pm 0.011}$
	DNet121	86.82 ± 0.014	$\mathbf{86.87 \pm 0.014}$
CUB	**WRN**	93.99 ± 0.011	$\mathbf{94.14 \pm 0.009}$
CIFAR	**WRN**	90.68 ± 0.015	$\mathbf{90.75 \pm 0.015}$
TINet	**DNet121**	90.44 ± 0.014	$\mathbf{90.62 \pm 0.013}$

Evolution of the Accuracy on CUB (extractor: WRN) as a Function of Shots K



Accuracy on the CIFAR-10 Dataset

	CIFAR-10		
Method	**WRN**	**ShakeNet**	**PyramidNet**
original paper	95.82 %	97.96 %	98.56 %
NCM	85.81 %	**97.97** %	98.52 %
1-NN	95.81 %	97.95 %	98.54 %
1-NN+Filter	**95.92** %	**97.97** %	**98.61** %

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Conclusion and Perspectives

- A graph-based method is proposed to improve the accuracy of classification methods
- Use of GSP to reduce the noise in the extracted feature vectors
- The effectiveness of the method was shown theoretically
- Gains are obtained in two different settings: few-shot classification and standard classification
- Explore an automatic way of choosing the best filter parameters

Thanks for Your Attention.

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