Unsupervised Learning using Pretrained CNN and Associative Memory Bank

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Introduction

- Deep learning approaches based on CNN models trained using the backpropagation algorithm require large amounts of labeled training data.
- To address the lack of large volumes of labeled training data, researchers have proposed zero-shot or one-shot approaches [6][7].
- CNN-based object recognition approaches usually do not assume any prior knowledge; unlike zero-shot or one-shot approaches, but have the advantage of allowing completely automated representation learning.
- We present a pipelined unsupervised learning framework that combines transfer learning together with an associative memory bank, and is able to provide good performance in an unseen domain without fine tuning using the backpropagation algorithm.
- Our approach is applicable to general object recognition tasks. It uses a pretrained (on a related domain) CNN model for automated feature extraction while it pipelines a Hopfield network [5] based memory bank for storing patterns for classification purposes.
Related Work

- Deep features learned from pretrained CNN models have shown competitive performances in vision related tasks. Deep learning in recognition tasks have already surpassed human-level performance [1].
- Unsupervised learning is getting more and more attention since it allows learning from unlabeled data. K-means as a popular clustering approach in unsupervised learning, also widely use in deep learning [3].
- Hopfield Associative Memory is successful in pattern recognition and robust to adversarial inputs [4].
Contributions

- We address the two main reasons for the data-hungry nature of supervised deep learning approaches based on our pipeline framework architecture. The CNN model: lack of transfer of prior knowledge to a new domain, the use of supervised learning using the backpropagation algorithm to estimate a large number of parameters (weights) based on training data.

- Our paper provides a pipelined unsupervised learning framework that combines transfer learning together with an associative memory bank, and is able to provide good performance in an unseen domain without fine tuning using the backpropagation algorithm.

- It experimentally demonstrates the effectiveness of the framework on the Caltech101, Caltech256, and CIFAR-10 benchmark datasets.
Proposed Method

Overview of Pipeline Framework
Associative Memory

- It is a single layer of fully connected recurrent neural network [5].
- It stimulates the storing and retrieving process in our human brain.
- It is energy based network and it guaranteed to converge to a local minimum.
- It has error-correcting/noise-resilience property.
Associative Memory

- Given a network with N neurons, the weighted input sum of a neuron, known as local field, can be described by the following.

\[
\xi_i = \sum_{j=1}^{N} w_{ij} x_j
\]  

(1)

- The connection weights are computed by the following.

\[
w_{ij} = \begin{cases} 
\frac{1}{N} \sum_{u=1}^{z} \varphi_{u,i} \varphi_{u,j} & i \neq j \\
0 & i = j 
\end{cases}
\]  

(2)
Associative Memory

- Then all the neurons update their state asynchronously as described by the following equation,

$$x_i(t + 1) = \text{sign} \left( \sum_{j=1}^{N} w_{ij} x_j(t) \right)$$

(3)

- Following equation (1) the energy for a neuron $i$,

$$E_i = -\frac{1}{2} \xi_i x_i$$

(4)
Associative Memory

- Then the energy for the entire network,

\[ E(v) = \sum_{i=1}^{N} E_i = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} x_i x_j \]  

(5)

- Use the following distance metric between the weight matrices as a similarity measure,

\[ Diff(T, S) = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} (W_{T_{ij}} - W_{S_{ij}})^2} \]  

(6)
Associative Memory

The stored core pattern can be retrieved based on the following equation,

$$\mathcal{R} = \text{argmin}_{\varphi_k^i \mid i \in 1..z, k \in 1..n} \text{Diff}(T, \varphi_k^i)$$  \hspace{1cm} (7)

**Algorithm 1:** Classification Algorithm

```
Input : Test pattern \( t \);
1. Stored patterns \( \varphi_k^i, i \in 1..z, k \in 1..n \).
Output: Class label \( l \) of test pattern.
2. Initialize \( \mathcal{R} \leftarrow \emptyset \);
   // Initialize \( \mathcal{R} \) to empty list
3. \( \mathcal{R} = \text{argmin}_{\varphi_k^i \mid i \in 1..z, k \in 1..n} \text{Diff}(t, \varphi_k^i) \);
   // \( \mathcal{R} \) is a list of patterns
4. if \( \text{len}(\mathcal{R}) > 1 \) then
5. \hspace{1cm} \( \varphi = \text{random_choice}(\mathcal{R}) \);
6. \hspace{1cm} return \( l = \text{label}(\varphi) \);
7. else
8. \hspace{1cm} return \( l = \text{label(first(\mathcal{R}))} \);
9. end
```
Experiment

Dataset

Caltech101 consists of 9144 images of 101 object categories. Each category has about 40 to 800 images, most categories have about 50 images.

Caltech256 contains 30607 images for 256 object categories and 1 clutter category. It has a minimum of 80 images for each category.

CIFAR-10 contains ten classes with a total of 60000 RGB images with image size 32x32 and each class has 6000 images.

Pretrained Model

ResNet-50: very deep network, 50 layers.
VGG-16: 16 weight layers.
Multiple core patterns utilized is beneficial for performance improvement.
Comparison with state-of-the-arts

Even if only one core pattern per class is used, the accuracy obtained is still competitive: 89.6% on Caltech101, 74.7% on Caltech256, and 80.5% on CIFAR-10.
Conclusion

- This paper proposed a framework that combines a pretrained CNN model for feature extraction and with a Hopfield network as an associative memory bank to provide an unsupervised learning framework that provides competitive performance on benchmark datasets.
- In future work, we will experiment with other memory frameworks such as Boltzmann machines and memory networks.
References


References


Thank You!