Visualizing and Interpreting Neural Networks

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Outlines

Introduction

Convolutional Neural Networks (CNNs)

- Powerful tools for tasks in Computer Vision [Simonyan and Zisserman, 2014] or NLP [Zhang and LeCun, 2015]
- Theory is poorly understood, and CNNs can be *stupidly* easily fooled [Nguyen et al., 2015]

Objectives

1. **Look at what the internal layers of convolutional neural networks encode by visualizing the feature maps**
2. **Try to infer how CNNs work**

Method

We use the DeconvNet model suggested by [Zeiler and Fergus, 2014]:

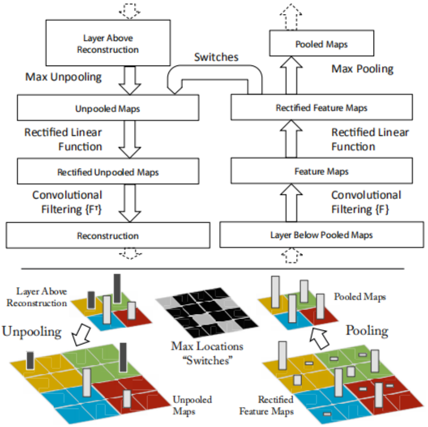


Figure 1: Idea behind DeconvNet ([Zeiler and Fergus, 2014])

Our Work

Construction and training of CNNs

We have trained our own CNNs on CIFAR-10.

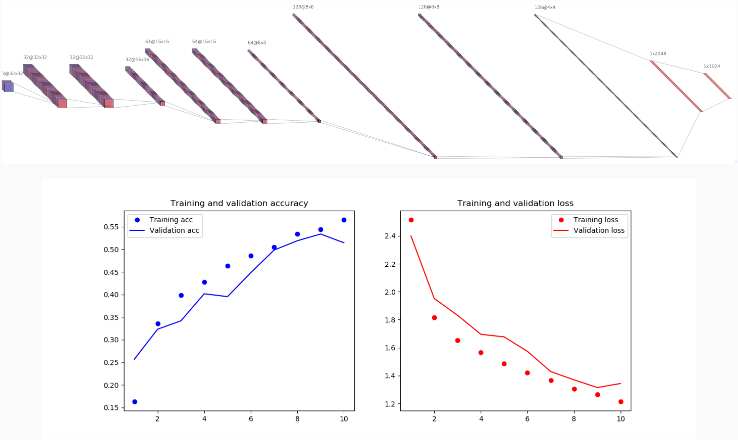


Figure 2: Architecture of [Plotka, 2017] and training loss/accuracy

#epochs=10, lr=10^{-4}, Adam optimizer, batch size = 128

Evaluation of CNNs

	Training	Validation
Accuracy	0.566	0.515
Loss	1.213	1.344

Table 1: Final training accuracy and loss on CIFAR-10 [Krizhevsky and Hinton, 2009] for [Plotka, 2017], #epochs=10, lr=10^{-4}, Adam optimizer, batch size = 128

	Training	Validation
Accuracy	0.818	0.758
Loss	0.517	0.707

Table 2: Final training accuracy and loss on CIFAR-10 [Krizhevsky and Hinton, 2009] for [Bonaccorso, 2017], #epochs=250, lr=10^{-4}, Adam optimizer, batch size = 128

Evaluation of CNNs

State-of-the-art classification accuracy on CIFAR-10:
96.53% [Graham, 2014]

These are not good results.
But model fine-tuning is not the primary goal of this project.

Visualizing outputs of layers

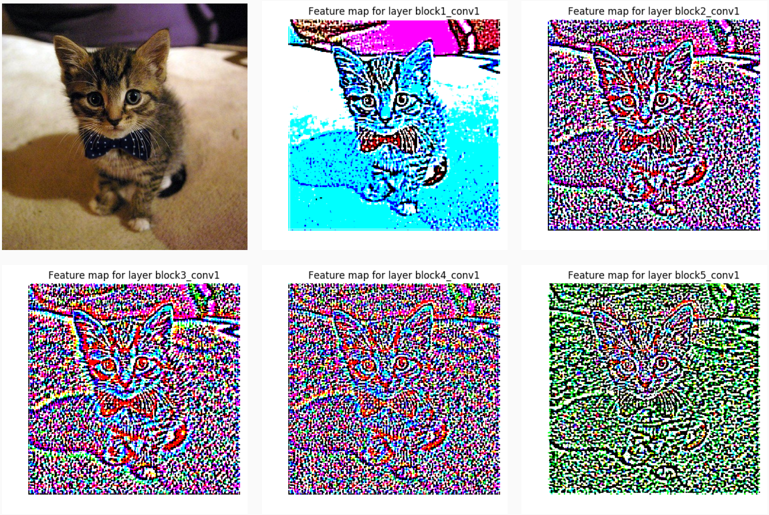


Figure 3: Input and feature map images of VGG for some convolutional layers: output of layer in initial model is deconvoluted.

Visualizing outputs of layers

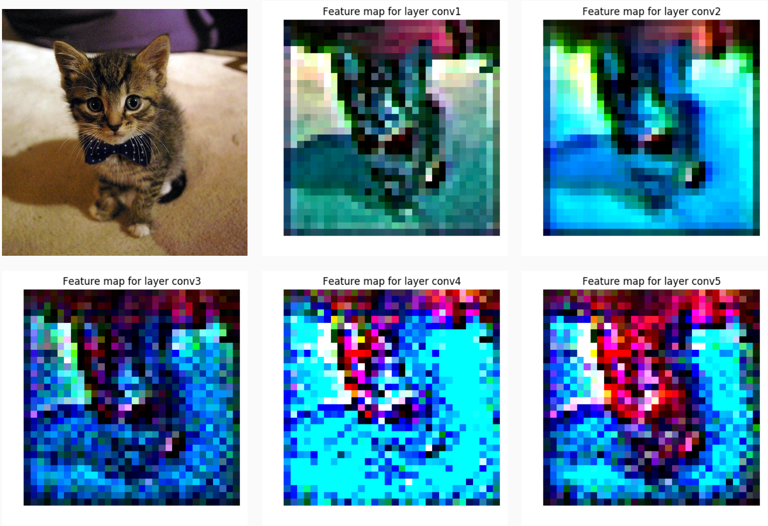


Figure 4: Input and feature map images of [Plotka, 2017] for some convolutional layers: output of layer in initial model is deconvoluted.

Reconstruction by maximizing the activation of a certain class

Algorithm 1 [Chollet, 2016]

1: Start from a random noisy image.
2: Define a loss function that seeks to maximize the activation of a certain class output of the network.
3: Use gradient descent to “twist” the image.
4: **return** the image which maximizes the activation of the *softmax* layer output associated with the considered class

Experiment

1. Gather images of one class
   here, *Siamese cat, Siamese* (284 in ImageNet).
2. Save $n = 5$ reconstructed inputs from trained model.
3. Retrain the model with the (unseen) images in the class.
4. Save $n = 5$ reconstructed inputs from model with new weights.

Reconstruction by maximizing the activation of a certain class

Let's see what the machines have learned!

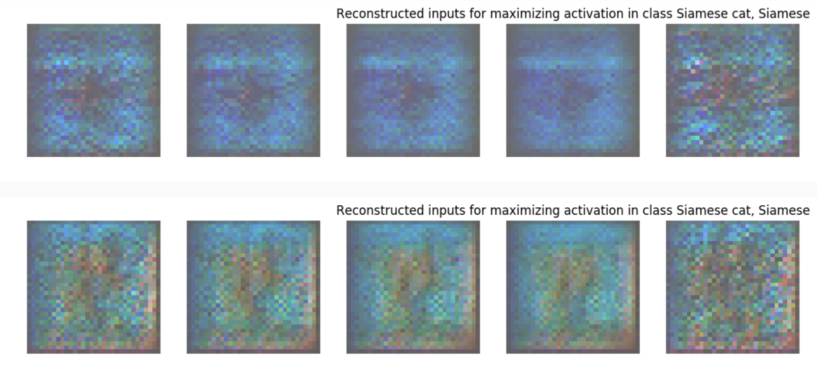


Figure 5: Feature maps before (*top line*) and after training, model [Plotka, 2017], gradient step = 10^{-4}, batch size 32, lr=10^{-3}, Adam optimizer, #epochs=10

How to quantify the results obtained above?

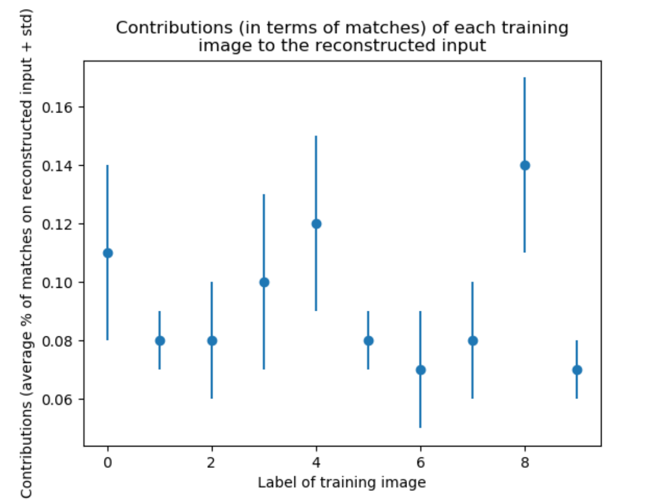
$\rightarrow$ try to describe them in terms of **descriptors**

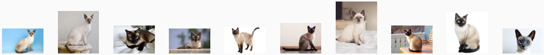
- SIFT [Lowe, 1999] (*)
- Harris corner descriptor [Harris and Stephens, 1988] (*)
- Bag-of-Words [Sivic and Zisserman, 2009] (**)

(*) **Goal**: estimate the contributions of each training image to the reconstructed input

(**) **Goal**: see if the reconstructed input gets any ”closer” to the original class after retraining

Estimate the contributions of each training image





Reconstructed input ”closer” to the original class?

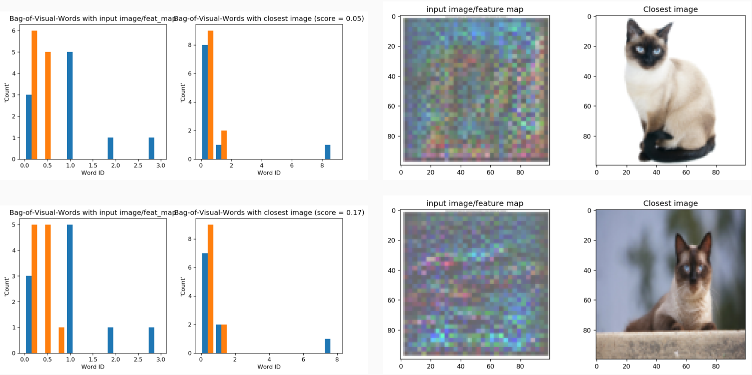


Figure 6: BoW analysis before retraining (*top*) and after retraining applied to the reconstructed inputs against the set of images of class 284 with model [Plotka, 2017].
Left: histograms associated to the reconstructed input and ”closest” image on the right-hand side.

Reconstructed input ”closer” to the original class?

The only non-random part is in the training: new weights may be different from one training session to another.

	Mean maximum score	Median maximum score
Before training	0.050	0.050
After training	0.095	0.090

Table 3: Values corresponding to the experiment described above with model [Plotka, 2017] ($n = 10$ tries).

Thus training for one class allows the NN to reconstruct slightly more resembling inputs of this class.

Conclusion

Conclusion

- We have trained 2 small CNNs using Keras.
- We have visualized the feature maps associated with an image and tried to interpret the messages that each layer encodes.
- We have reconstructed an image of a certain class from a random image by maximizing activation of the class output in the *softmax* function.
- Code is available at

  https://github.com/kuredatan/nn-visu|

Questions?

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https://gist.github.com/giuseppebonaccorso/e77e505fc7b61983f7b42dc1250f31c8.

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