

Tiny ImageNet Challenge - Scaling of Inception Layers for **Reduced Scale Classification**

1 – Problem Statement and Dataset

Tiny ImageNet Challenge

The Tiny ImageNet Challenge is a classification challenge within the CS 231N class, using the Tiny ImageNet dataset.

Tiny ImageNet Dataset

The Tiny ImageNet is a dataset used for the training and testing of neural networks for visual recognition problems comprising images of dimensions 64x64 pixels. It covers 200 different classes with:

- 100,000 labeled training images
- 10,000 labeled validation images
- 10,000 unlabeled test images

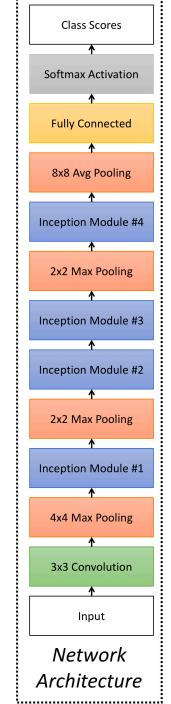
Pre-processing and Data Augmentation

The data is first normalized such that the training set has zero mean and unit variance. Data augmentation was used to increase the amount of available training data. For each image we added a second one, which was with equal probability either

- flipped in the horizontal direction,
- rotated clockwise (6, 8 or 10 degrees), or
- rotated counterclockwise (6, 8 or 10 degrees).

This yielded a training dataset of almost 200,000 labeled images.

2 – Our Convolutional Neural Network Architecture



CNN Architecture

Inspired from [1], our design is a reduced version of the original GoogleNet, which was designed for 1000 classes. We investigate how the Inception module architecture scales for a smaller classification task of 200 classes. Each convolution layer is followed by a batch normalization, a ReLU activation, and for the current architecture by a drop out layer.

Inception Modules

Inception modules are elements in CNNs that consist in parallel convolutions concatenated depthwise.

Layer			Filter size / stride		Output size		
convolution			3x3 / 1		62x62x128		
max pool			4x4	4x4 / 2		30x30x128	
in	ceptio	n #1				30x30x128	
	max p	ool	2x2	2x2 / 2		16x16x128	
in	ceptio	n #2				16x16x128	
in	ceptio	n #3				16x16x256	
max pool			2x2 / 2		8x8x258		
in	nceptio	n #4				8x8x320	
avg pool			8x8 / 1		1x1x320		
full	ly conr	nected				1x1x200	
	softm	ах				1x1x200	
#	1x1	3x3 red	3x3	5x5 red	5x5	pool	
1	32	48	64	8	16	16	
2	32	48	64	8	16	16	
3	64	96	128	16	32	32	
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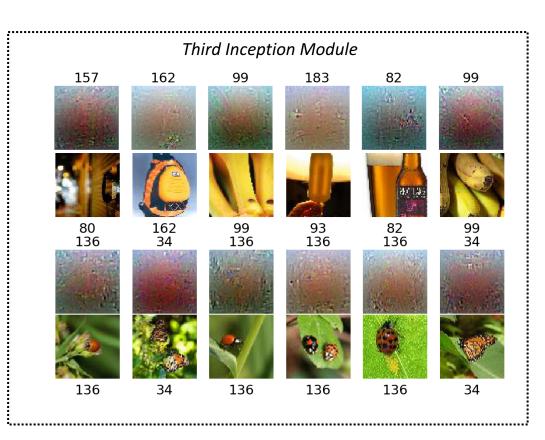
80 120 160 20

4

40 40

4 – Visualization

Visualization of activation features



CS 231N Poster Session

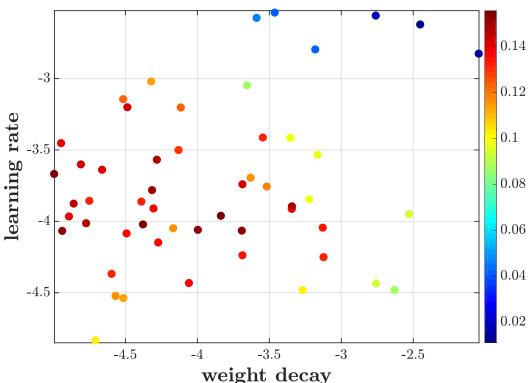
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• For each Inception module, we looked at the most 6 activated images for different neurons (bottom images with true label)[2]. We computed the gradients of the neuron with respect to the input images yielding a map of the pixels that are sensitive to the neuron (top images with predicted label) [3]

3 – Training the Network

Hyperparameter fitting

On a reduced size dataset, we compared accuracies while performing a random search over the weight decay and learning rate to get a range of reasonable values.





We tackled overfitting by introducing dropout layers and by varying the number of parameters of our architecture.

First Inception Module

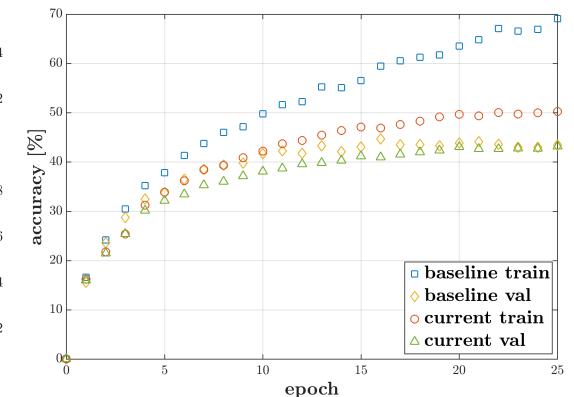
173

Last Inception Module

197

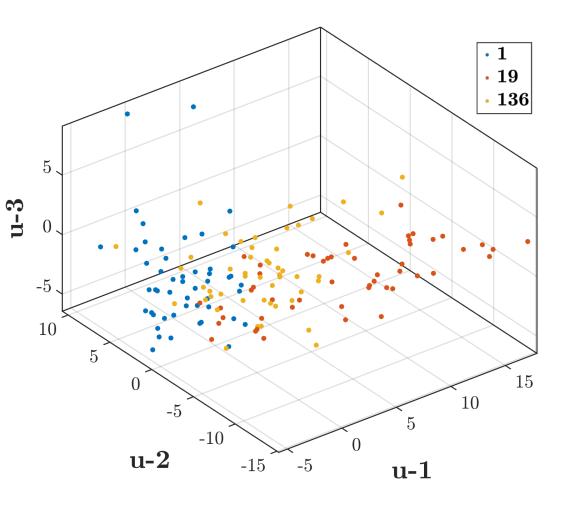
82

29



Analysis in Feature Space

- The



5 – Future Work

References

Scatter plot of the validation accuracy

Prediction accuracy learning history for baseline and current CNN



• We extracted the data entering the last layer and performed a PCA

reduced representation has 3 dimensions, accounting for 16% of the total variance. It is shown below for 3 labels.

Principal Component Analysis – Clustering of three labels

Carry on the Visualization Analysis

• Develop a Deconvolutional Network to visualize the activated pixels instead of the ones corresponding the high fluctuations [2].

• Leverage our visualization results to guide our improvement of the current architecture

[1] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. CoRR,

- abs/1409.4842, 2014.
- [2] M. D. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. CoRR, abs/1311.2901, 2013.
- [3] Erhan, D., Bengio, Y., Courville, A., and Vincent, P. Visualizing higher-layer features of a deep network. In Technical report, University of Montreal, 2009.