

A Crash Course in Computer Vision with Keras

hi, I'm Helen!

- Machine Learning Engineer
- Sidewalk Toronto Fellow
- Toronto Women's Data Group
- Mathematics, coffee, poetry





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fast.ai

Practical Deep Learning for Coders (2017 edition)

Jeremy Howard (Enlitic) & Rachel Thomas (USF)

1 year of coding + high school math

Computer vision is a subfield of deep learning which extracts understanding from digital images or video.







François Chollet ② @fchollet · Jan 31

Using Keras to automate supernovas identification, potentially cutting in half the time it would take astronomers to discover supernovas:



How 3 engineers built a record-breaking supernova identification sys... Pop into Dessa's offices and you'll soon find traces of the company's fascination with outer space. A Lego replica of Saturn V, the rocket that m... medium.com







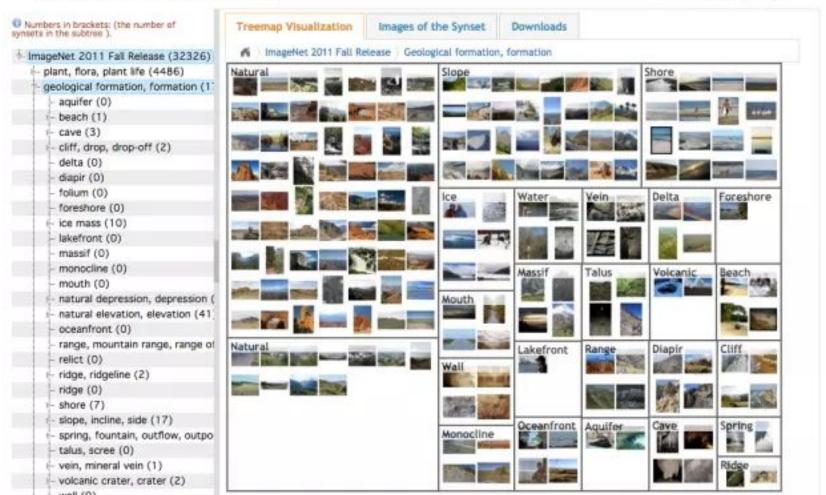
Geological formation, formation

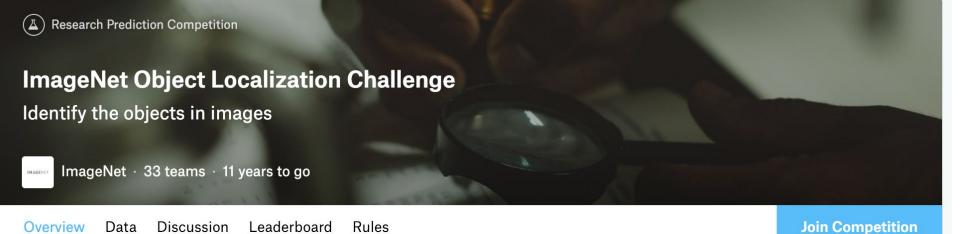
(geology) the geological features of the earth

1808 pictures

86.24% Popularity Percentile

Wordnet





Overview

Description

Evaluation

Timeline

Competition Description

While It's pretty easy for people to identify subtle differences in photos, computers still have a ways to go. Visually similar items are tough for computers to count, like this overlapping bunch of bananas



ImageNet Classification with Deep Convolutional Neural Networks

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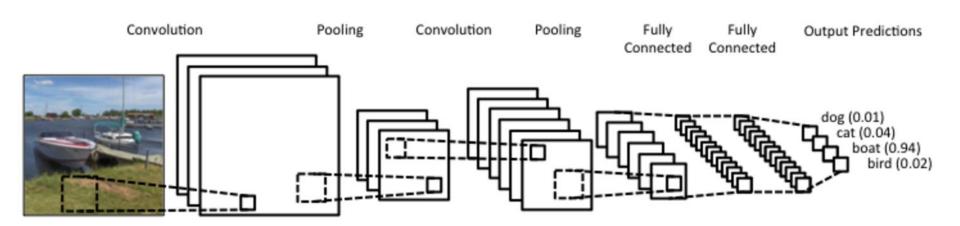
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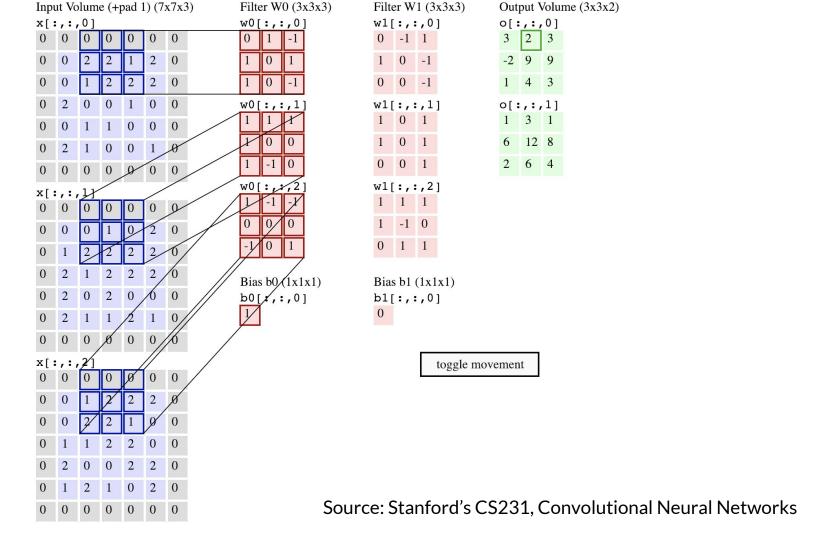
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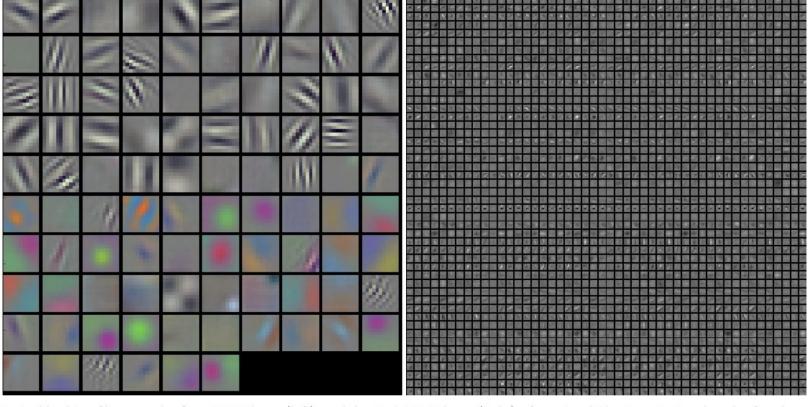
Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

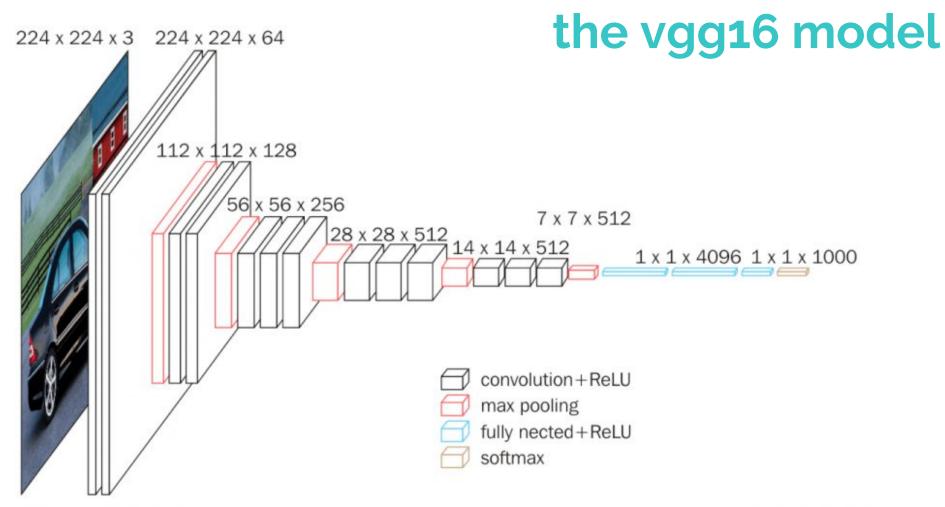
anatomy of a convnet







Typical-looking filters on the first CONV layer (left), and the 2nd CONV layer (right) of a trained AlexNet. Notice that the first-layer weights are very nice and smooth, indicating nicely converged network. The color/grayscale features are clustered because the AlexNet contains two separate streams of processing, and an apparent consequence of this architecture is that one stream develops high-frequency grayscale features and the other low-frequency color features. The 2nd CONV layer weights are not as interpretable, but it is apparent that they are still smooth, well-formed, and absent of noisy patterns.



Colaboratory by Google

- NVIDIA Tesla K80 GPUs
 - 12 GB of RAM
- 12 hours of runtime
- TPU access!

Workshop!

Open with Colaboratory:

github.com/mathemakitten/fastai-colab/blob/master/devhub_workshop.ipynb