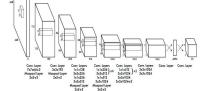






Vladimir Putin



Architectures

Corn. Layer 7x7x64+2 Maxpool Layer 2x2+2	Conv. Layer 3x3x192 Maxpool Layer 2x2+2	Conv. Layers x1x128 3x3x256 x1x256 3x3x512 Messpool Layer 2x2+2	Conv. Layers 1x1x256 3x3x512 1x1x512 1x1x512 Maxpool Layer 2x2+2	Conv. Layers 1x1x512 3x3x1024 3x3x1024 3x3x1024+2	Conv. Layers 3x3x1024 3x3x1024	Conn. Layer	Co
							S

Idea

We applied two well-known and successful algorithms, YOLO and FaceNet, in an attempt to combine the speed of YOLO with the accuracy of FaceNet on facial recognition.

In our project, we relied on Allan Zelener's Yad2k and David Sandberg's FaceNet.









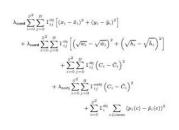








DEEP ARCHITECTURE



Loss Functions

$$\begin{split} \mathcal{L} &= \mathcal{L}_{S} + \lambda \mathcal{L}_{C} \\ &= -\sum_{i=1}^{m} \log \frac{e^{W_{y_{i}}^{T} x_{i} + b_{y_{i}}}}{\sum_{i=1}^{n} W_{i}^{T} x_{i} + b_{j}} + \frac{\lambda}{2} \sum_{i=1}^{m} \|x_{i} - c_{y_{i}}\|_{2}^{2} \end{split}$$

Accuracy Relative Image Error Size Baseline 99.2 250x250 pix 98.2 +1.0 166x166 Crop pretraining pix Crop 98.7 +0.5 166x166 (50% reduction in postpix training error disparity)

Analysis

Conclusion and Future Work

By simulating YOLO output by using random croppings on LFW images, we were able to reduce base image size by 54%. Further training on FaceNet allowed for comparable error rates.

In its original state, FaceNet relies on MTCNN, an image-pyramid based bounding box locator; far slower than YOLO. Cutting out the alignment step in favor of YOLO should allow faster pre-processing, without loss of accuracy in classification

Before the final write-up, we will run two more additional tests with a modified FaceNet, to see how speed improves with full-sized inputs of size 250 and 166, respectively. Eliminating image size normalization will give us a definitive idea of how much YOLO croppings can speed up FaceNet.

Given an additional six months, we would optimize the entire pipeline by merging the two models into a single framework, speeding it up by eliminating excess file reading.

Data

We utilized WIDER Face^[3] images and Labeled Faces in the Wild.^[4]

For each LFW image, we created 5 randomized croppings, with each dimension 3/4 that of the original. These were split into 50%/50% train/dev sets, since we were using a pretrained FaceNet model^[2] and thus needed less new data.

WIDER Face images are fed into a variant of YOLO with a single output class. These cropped images are sent to a FaceNet model pre-trained on celebrity image data. FaceNet then identifies the person selected by YOLO. Data: WIDER Face









Data: Labeled Faces in the Wild



References: [1] YOLO https://github.com/allanzelener/YAD2K, FaceNet https://github.com/davidsandberg/facenet, [3] WIDER Face http://mmlab.ie.cuhk.edu.hk/projects/WIDERFace/, [4] LFW http://vis-www.c