

Scribble-based Image Segmentation with Convexity Priors

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Objective

The objective is to design an architecture that can accurately segment an image based on user-provided scribbles, while also incorporating a convexity prior. Convexity prior refers to the assumption that objects or regions in an image are often convex in shape, meaning they have a smooth and continuous boundary without concave regions.

Overview

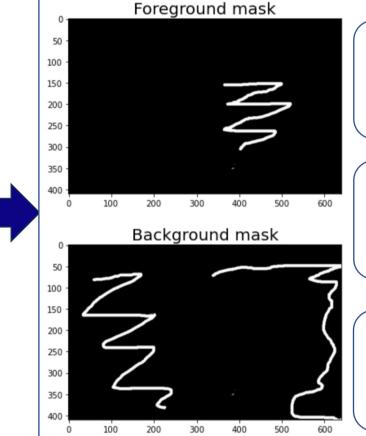
Image Segmentation for Convex objects based on Scribbled Images:

- Approach 1: Generating the convex segmented image using fully connected network and convex network architecture.
- Approach 2: : Generating the convex segmented image using segmentation network and convex network architecture.

Input

Background and foreground Scribbles are to be drawn on the

Pre-Processing and Data extraction for Deep Neural Net



- Obtain Foreground and Background masks to extract data for the fully connected network.
- Foreground: 'n' many scribbled pixels with coordinates (x, y) and colour values (r, g, b). Foreground Label: '0'
- Background: 'm' many scribbled pixels with coordinates (x, y) and colour values (r, g, b).
- Background Label: '1'

Vector of (x, y, r, g, b)

with corresponding

label (0/1). Total size of data is equal to number of scribbled pixels ('n+m').

Input Convex Network Architecture

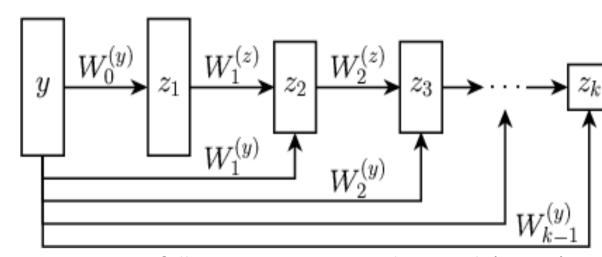


Figure: A fully input convex neural network (FICNN)

 $Z_{i+1} = g_i (W_i^{(z)} Z_i + W_i^{(y)} y + b_i), f(y;\theta) = Zk$ Where, Z_i is Layer activations (with Z_0 , $W_0^{(z)} = 0$),

 $\theta = \{w^{(y)}_{0:k-1}, W^{(z)}_{1:k-1}, b_{0:k-1}\}$ are parameters, and g_i are non-linear activation functions.

- The function f is convex in y provided that all $W^{(z)}_{1:k-1}$ are nonnegative, and all functions g_i are convex and non-decreasing.
- Source: Input Convex Neural Networks Brandon Amos¹ Lei Xu^{2*} J Zico Kolter¹

References:

- Input Convex Neural Networks Brandon Amos¹ Lei Xu^{2*} J Zico Kolter¹
- Boundary Perception Guidance: A Scribble-Supervised Semantic Segmentation Approach Bin Wang^{1,3}, Guojun Qi², Sheng Tang^{1*}, Tianzhu Zhang⁴, Yunchao Wei⁵, Linghui Li^{1,3} and Yongdong Zhang¹

Pre-Processed Data for Deep Neural Net

image which acts as

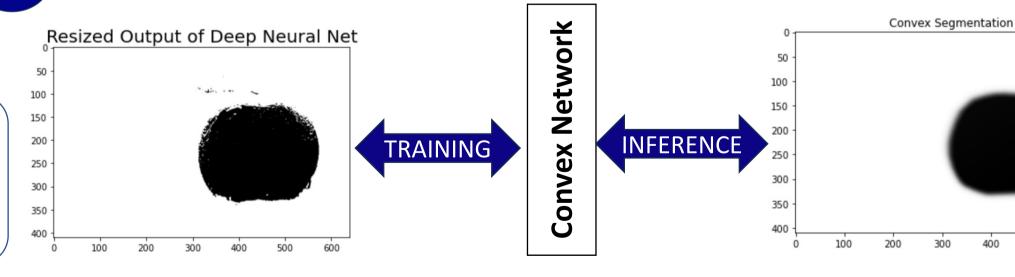
input to network.

All pixel data of Image in the form of vector (x, y, r, g, b)

Fully Connected Neural Net:

- 5 input nodes and 1 output Node. 2 Hidden layers with 256 neurons each
- ReLu activation functions
- Binary Cross Entropy with Logits Loss
- The Inference output has some wrongly segmented pixels as seen in figure.
- We send this output to convex Net to make it into a single convex region.

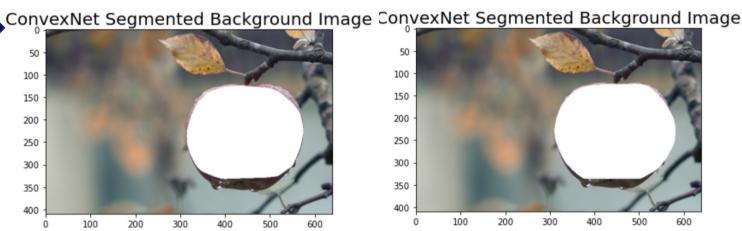
• Vector of (x,y) with corresponding label (0/1) of size (Image height x Image width) is sent to Convex Net for both training and Inference.



Approach 1 Result



ConvexNet Segmented Foreground Image ConvexNet Segmented Foreground Image



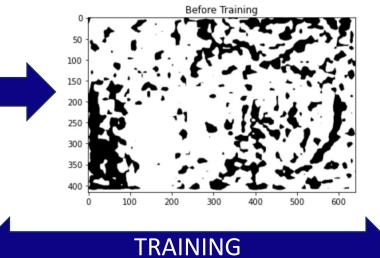
Input

Segmentation Network:

Using the segmentation models pytorch library to create a model for segmentation. It uses the ResNet34 encoder with pretrained weights from ImageNet for encoder initialization.

TRAINING

INFERENCE



- Criterion = Binary Cross Entropy with Logits Loss.
- Loss = Criterion(labels of Segmentation output pixels, labels of Scribbled pixels), for All Scribbled pixels
- Loss back propagated through all layers

INFERENCE

TRAINING

After training

Convex Segmentation **INFERENCE**