Learning Representations for Automatic Colorization

Experiment Presentation - 09/21/16
Tushar Nagarajan
Introduction

Colorization

Previous attempts: Transfer, Scribble
Idea

Predict the color histogram for each pixel
Model

Representing a pixel - Image hypercolumn
Model

Larsson et al. (2016)
Model

Image hypercolumn features: pre-trained VGG

A vector represents a histogram

Larsson et al. (2016)
Model

Image hypercolumn features: pre-trained VGG

Larsson et al. (2016)
Why just two predictions?

Lightness information already present

\[ L = \frac{R + B + G}{3} \]

\[ \tilde{H} = \frac{B - \frac{1}{2}(R + G)}{L + \epsilon} \]

\[ \tilde{S} = \frac{R - G}{L + \epsilon} \]
Results

Larsson et al. (2016)
Demo: http://colorize.ttic.edu/
Why is this important?

Larsson et al. (2016)
Experiment
Experiment - Foreground Consistency

Photo credit: Peter Zelewski
Not the best colorization we’ve seen...
Source of inconsistency?
- Averaged over 15 models
- Errors for 64 backgrounds
Background class 1
Background class 2
Qualitative Analysis
Qualitative Analysis
Qualitative Analysis
Do colorization errors in the background trickle down to the foreground?

Ans: Not too much, sorry.

$R = 0.414$
Summary

- Background coloring influences foreground coloring to some extent

- Hypercolumn features = extra background information

- Low L scenes contribute less to the top of the hypercolumn than the foreground?
Demo

http://colorize.ttic.edu/

Thank you