

Let there be Color!: Joint End-to-end Learning of Global and Local Image Priors for Automatic Image Colorization with Simultaneous Classification

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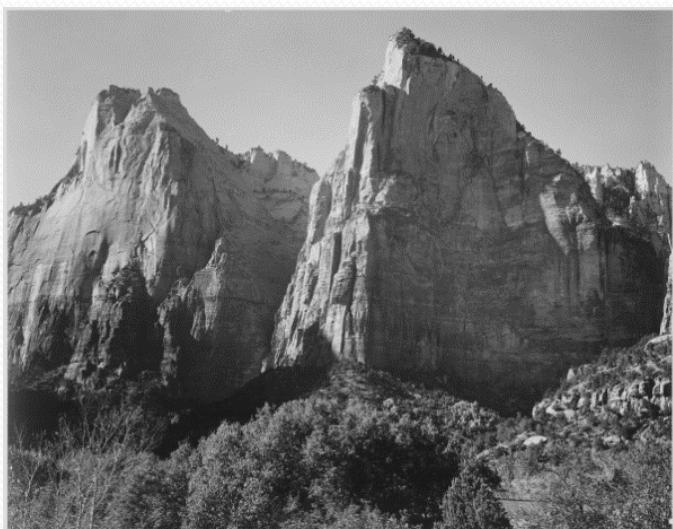
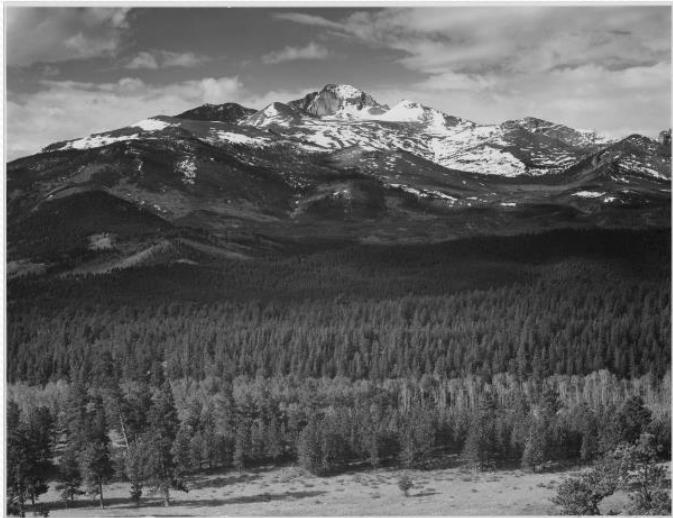
Waseda University

(*equal contribution)

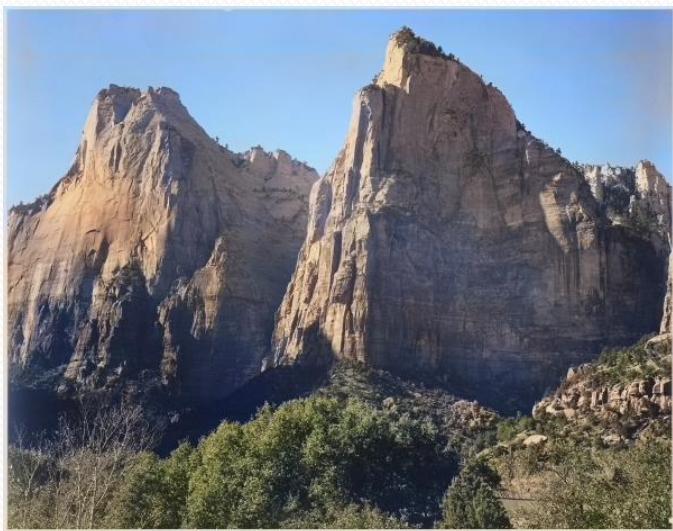


Render the Possibilities
SIGGRAPH2016

Colorization of Black-and-white Pictures



Our Goal: Fully-automatic colorization



Colorization of Old Films



Related Work

- Scribble-based [Levin+ 2004; Yatziv+ 2004; An+ 2009; Xu+ 2013; Endo+ 2016]

- Specify colors with scribbles
- **Require manual inputs**



[Levin+ 2004]

- Reference image-based [Chia+ 2011; Gupta+ 2012]

- Transfer colors of reference images
- **Require very similar images**



Input

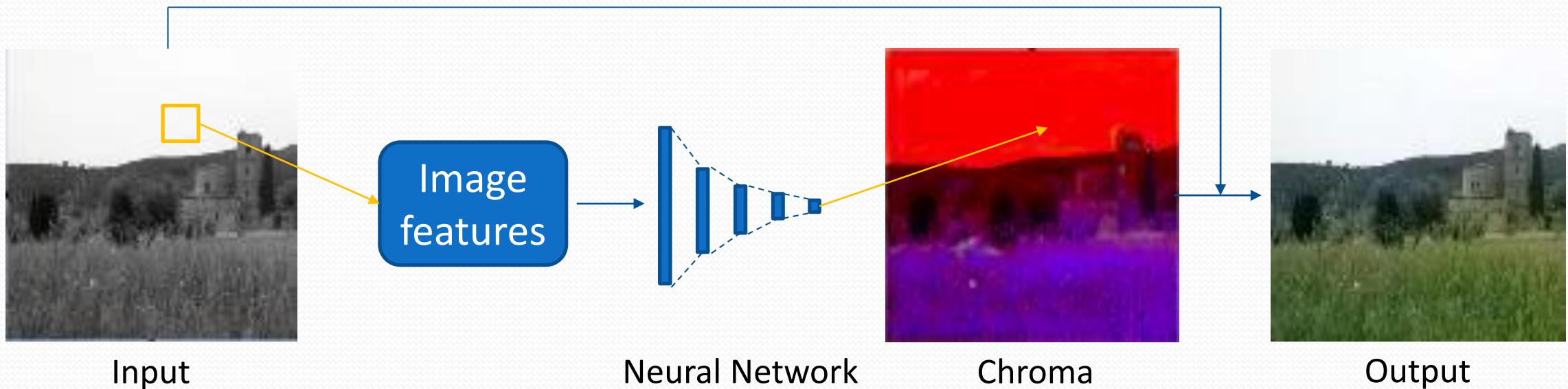
Reference

Output

[Gupta+ 2012]

Related Work

- Automatic colorization with hand-crafted features [Cheng+ 2015]
 - Uses existing multiple image features
 - Computes chrominance via a shallow neural network
 - Depends on the performance of semantic segmentation
 - Only handles simple outdoor scenes



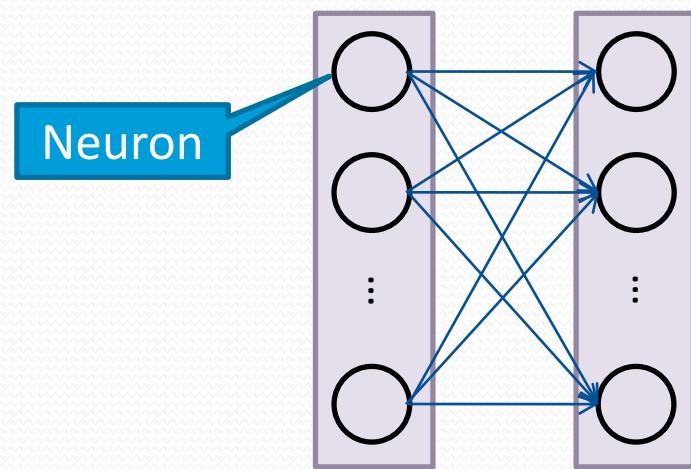
Contributions

- Novel end-to-end network that jointly learns **global and local features** for automatic image colorization
 - New fusion layer that elegantly merges the global and local features
 - Exploit classification labels for learning

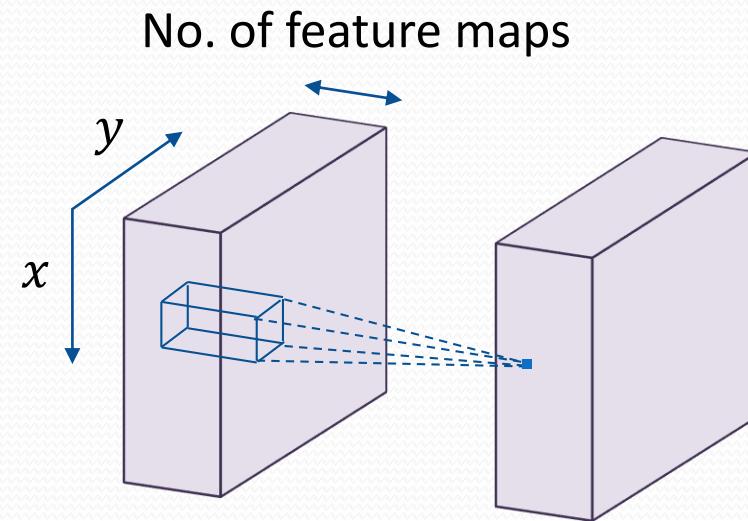


Layers of Our Model

- Fully-connected layer
 - All neurons are connected between layers
- Convolutional layer
 - Takes into account underlying spatial structure

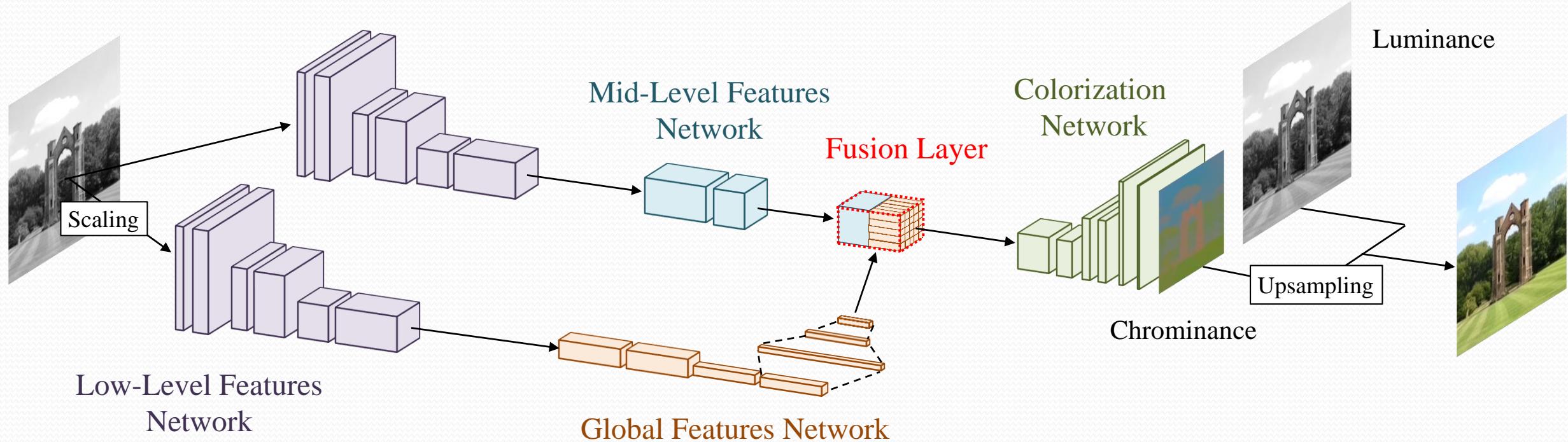


Fully-connected layer



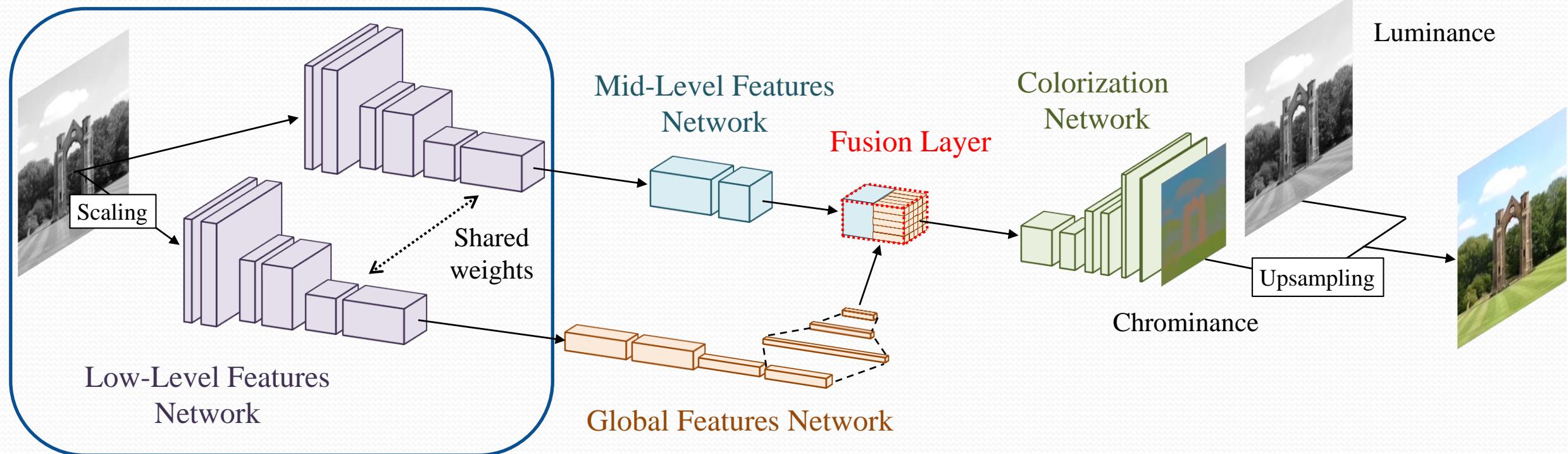
Convolutional layer

Our Model



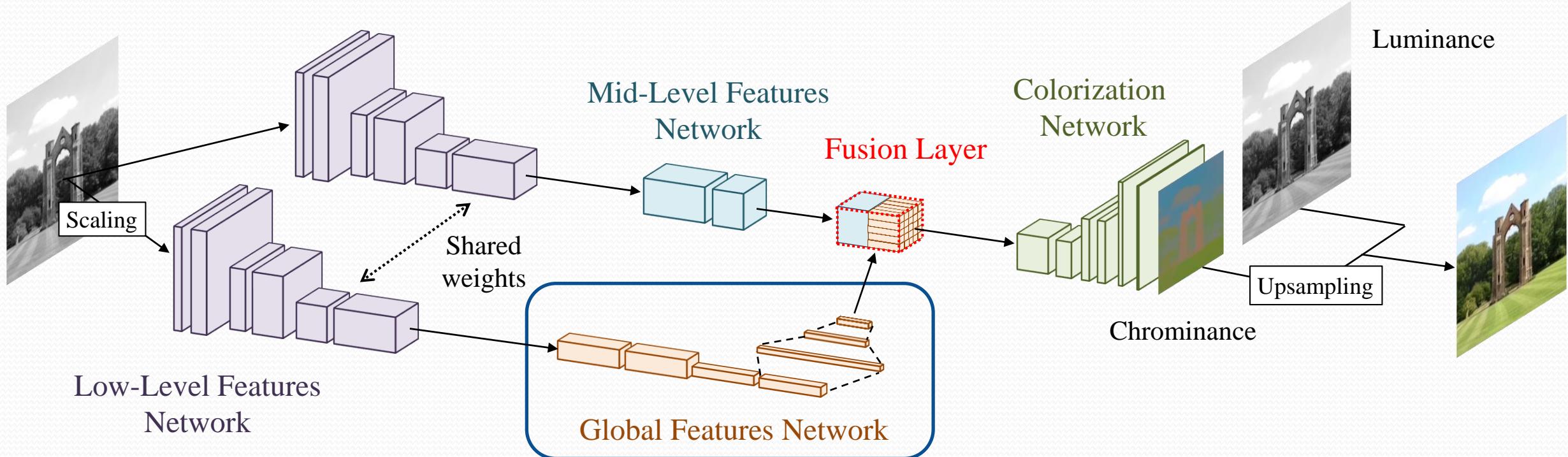
- Two branches: local features and global features
- Composed of four networks

Low-Level Features Network



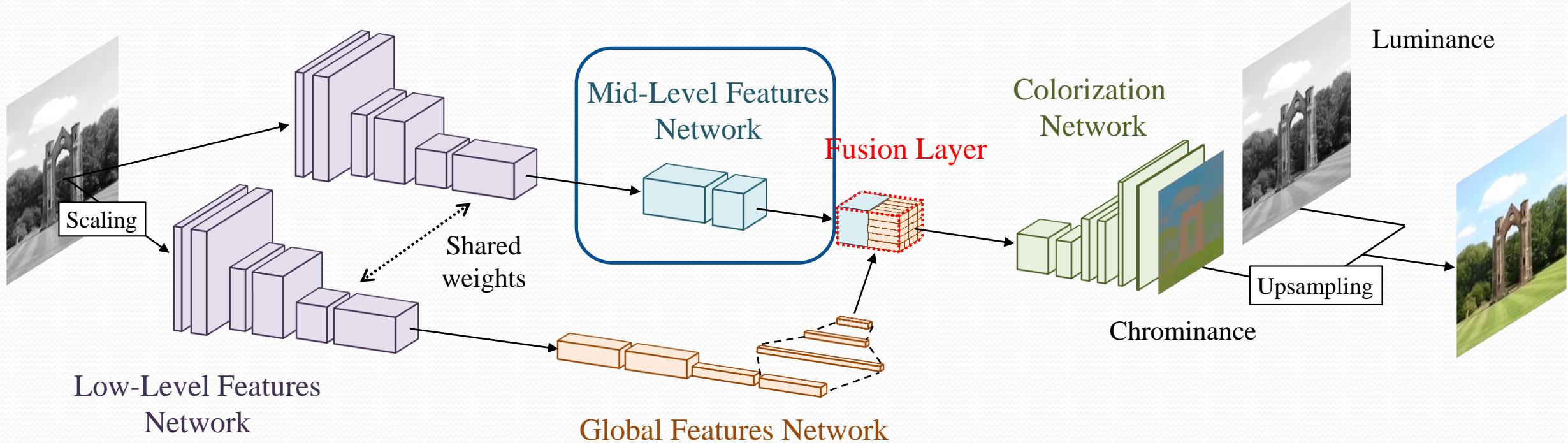
- Extract low-level features such as edges and corners
- Lower resolution for efficient processing

Global Features Network



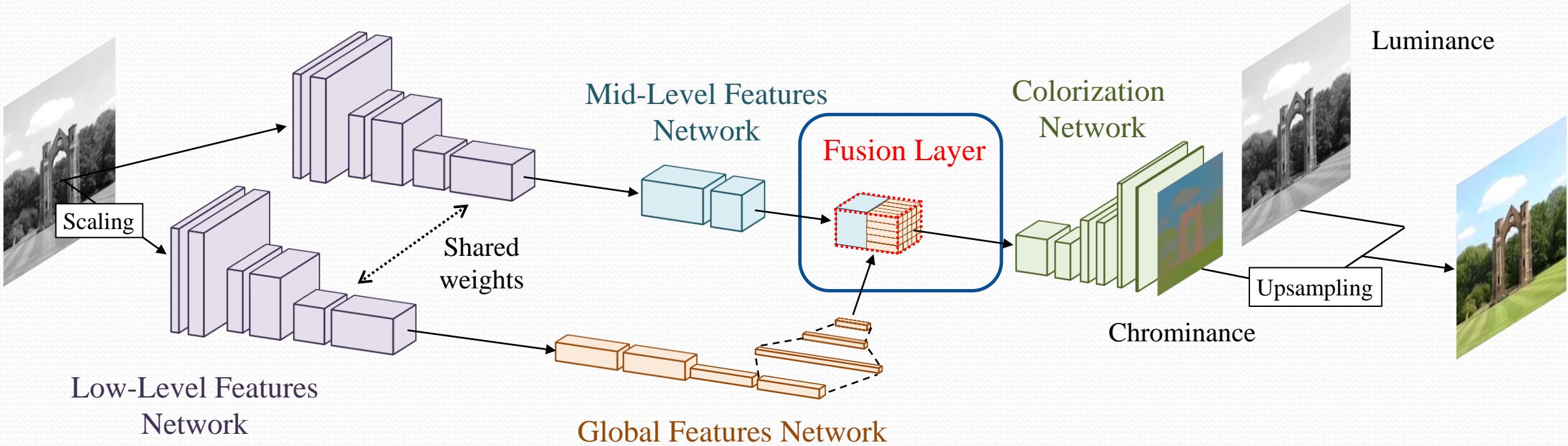
- Compute a **global** 256-dimensional vector representation of the image

Mid-Level Features Network



- Extract mid-level features such as texture

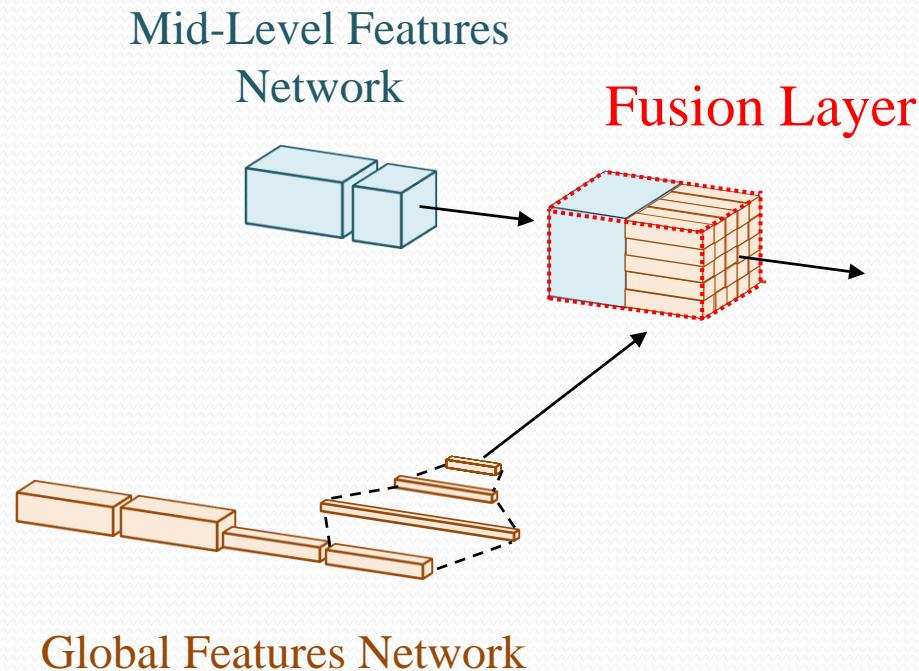
Fusion Layer



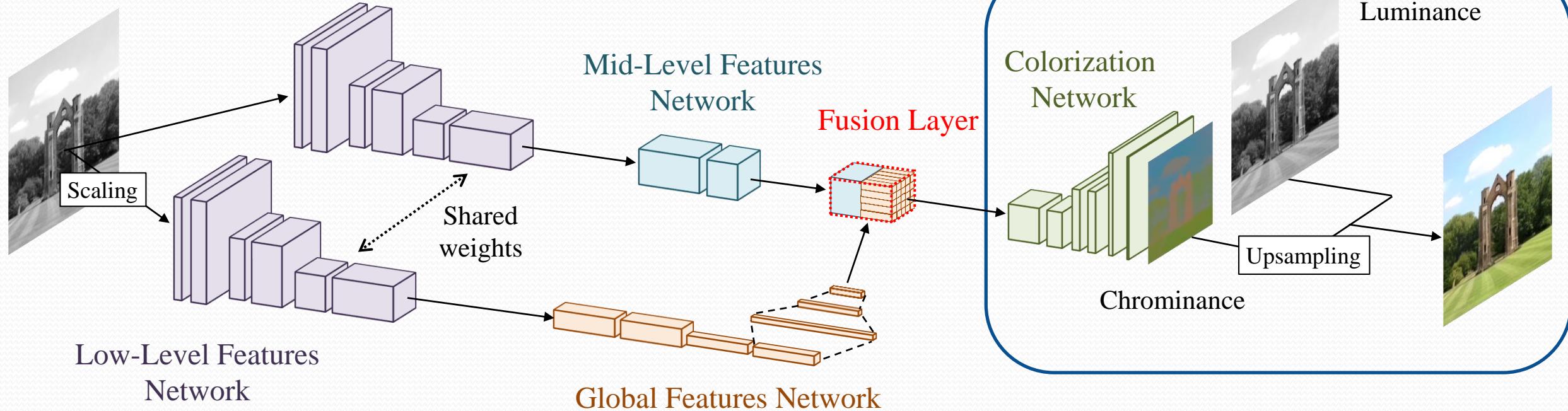
Fusion Layer

- Combine the global features with the mid-level features
- The resulting features are independent of any resolution

$$\mathbf{y}_{u,v}^{\text{fusion}} = \sigma \left(\mathbf{b} + W \begin{bmatrix} \mathbf{y}_{u,v}^{\text{global}} \\ \mathbf{y}_{u,v}^{\text{mid}} \end{bmatrix} \right)$$



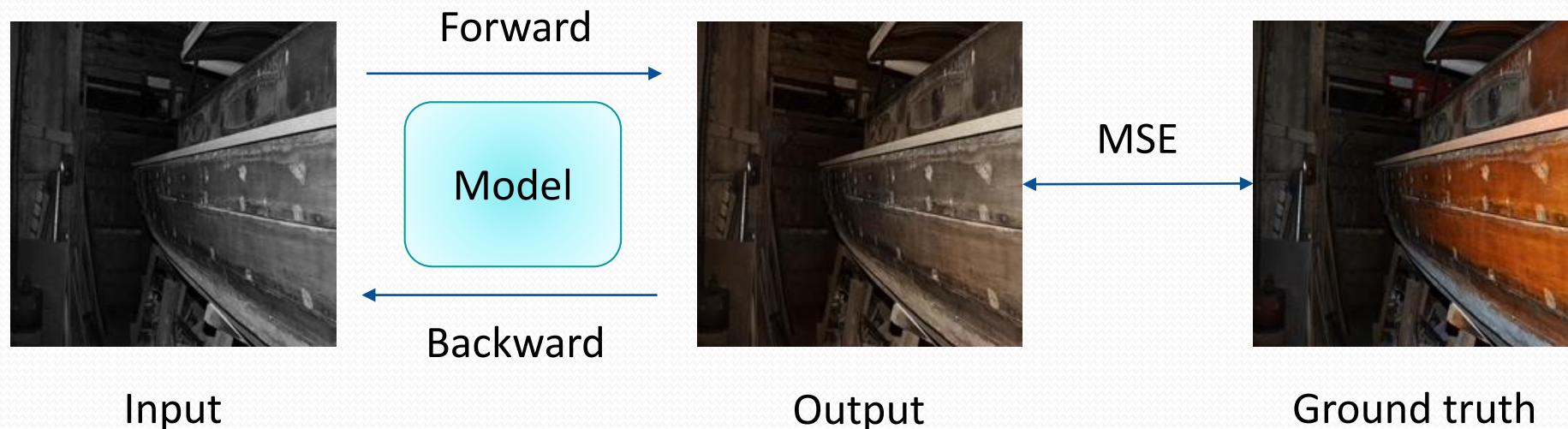
Colorization Network



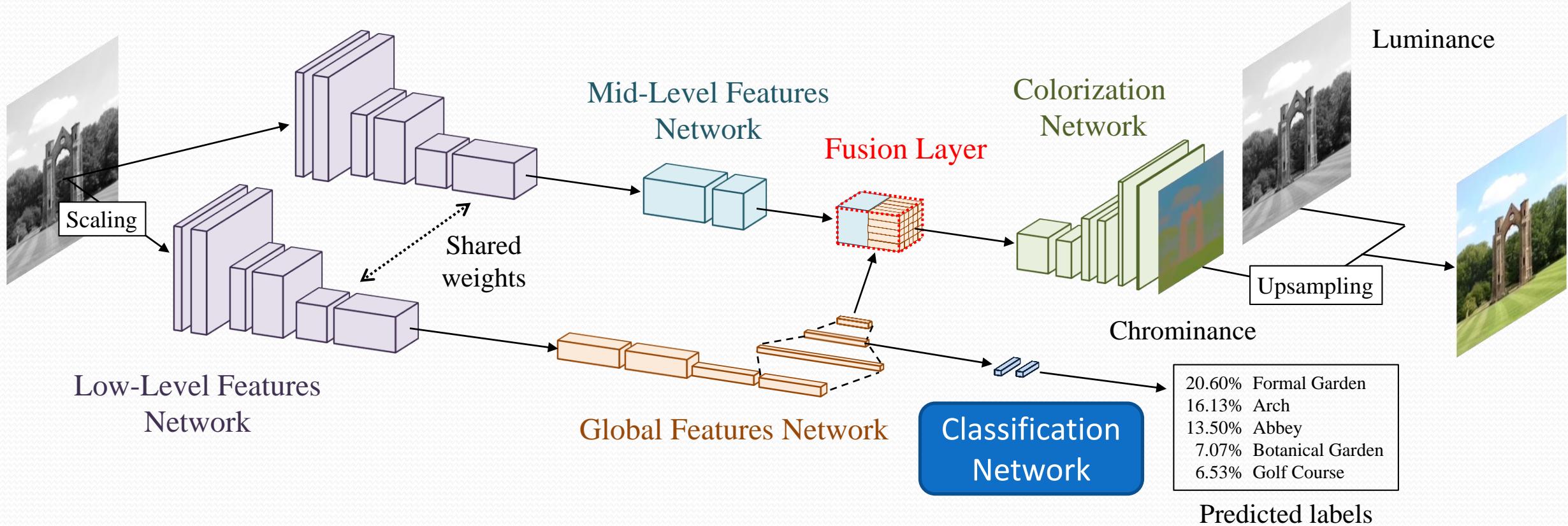
- Compute chrominance from the fused features
- Restore the image to the input resolution

Training of Colors

- Mean Squared Error (MSE) as loss function
- Optimization using ADADELTA [Zeiler 2012]
 - Adaptively sets a learning rate



Joint Training



- Training for classification jointly with the colorization
 - Classification network connected to the global features

Dataset

- MIT Places Scene Dataset [Zhou+ 2014]
- 2.3 million training images with 205 scene labels
 - 256×256 pixels



Abbey



Airport terminal



Aquarium



Baseball field

...



Dining room



Forest road



Gas station



Gift shop

...

Results

Computational Time

- Colorize within a few seconds

Image Size	Pixels	CPU (s)	GPU (s)	Speedup
224 × 224 [†]	50,176	0.399	0.080	5.0×
512 × 512	262,144	1.676	0.339	4.9×
1024 × 1024	1,048,576	5.629	1.084	5.2×
2048 × 2048	4,194,304	20.116	4.218	4.8×



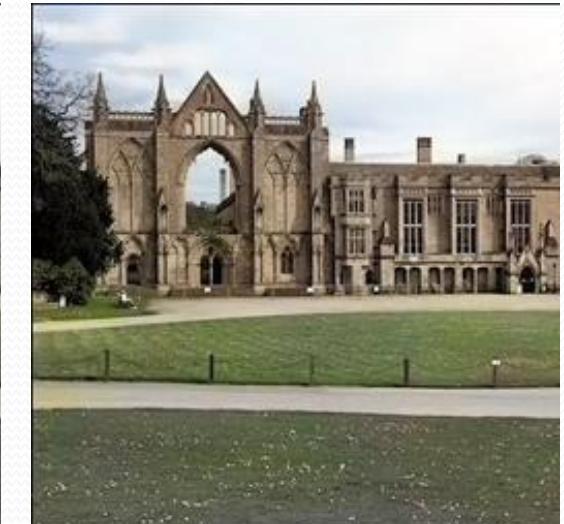
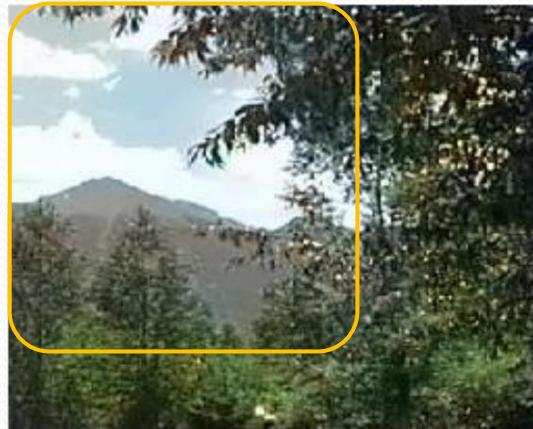
80ms
→

A large blue arrow pointing from the grayscale image to the colored image, with the text "80ms" written above it, indicating the time taken for the colorization process.

Colorization of MIT Places Dataset



Comparisons



Input

[Cheng+ 2015]

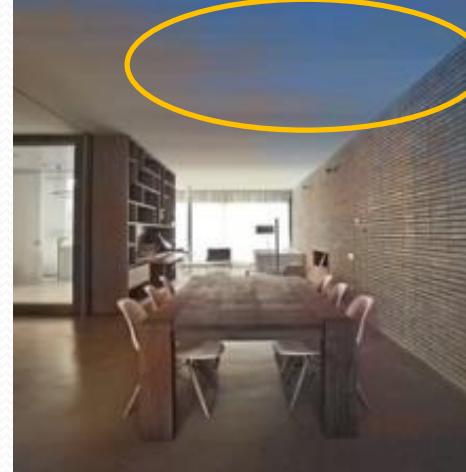
Ours
(w/o global features)

Ours
(w/ global features)

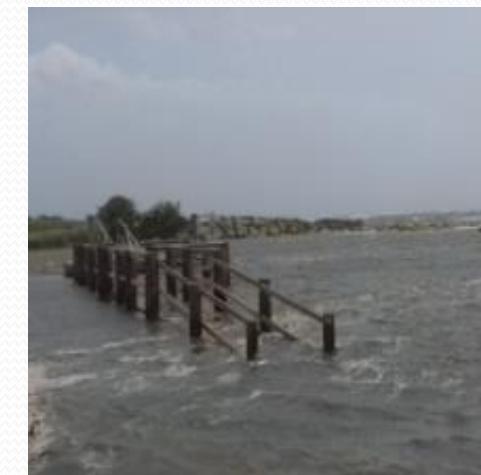
Effectiveness of Global Features



Input



w/o global features



w/ global features

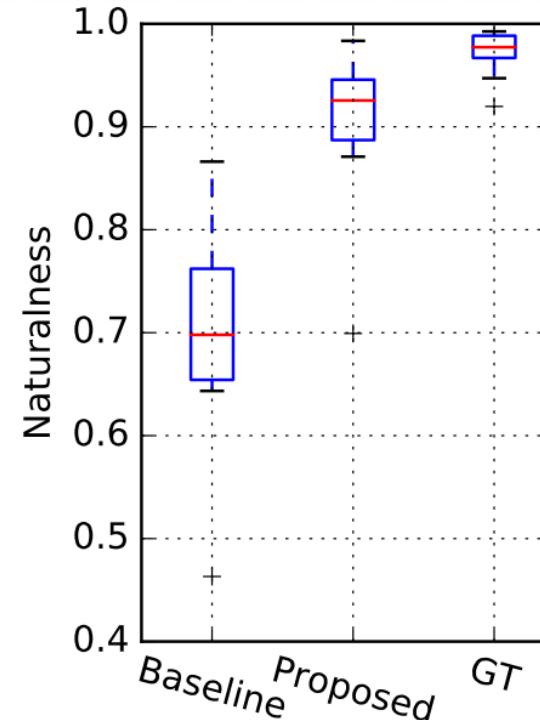
User Study

- 10 users participated
- We show 500 images of each type: total 1,500 images per user
- 90% of our results are considered “natural”



Natural

Unnatural



Approach	Naturalness (median)
Ground Truth	97.7%
Proposed	92.6%
Baseline	69.8%

Colorization of Historical Photographs



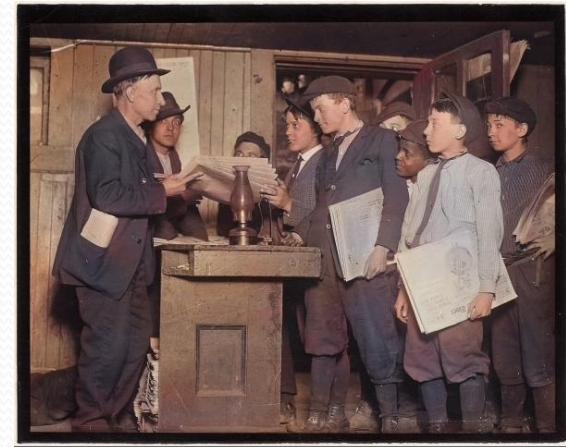
Mount Moran, 1941



Scott's Run, 1937

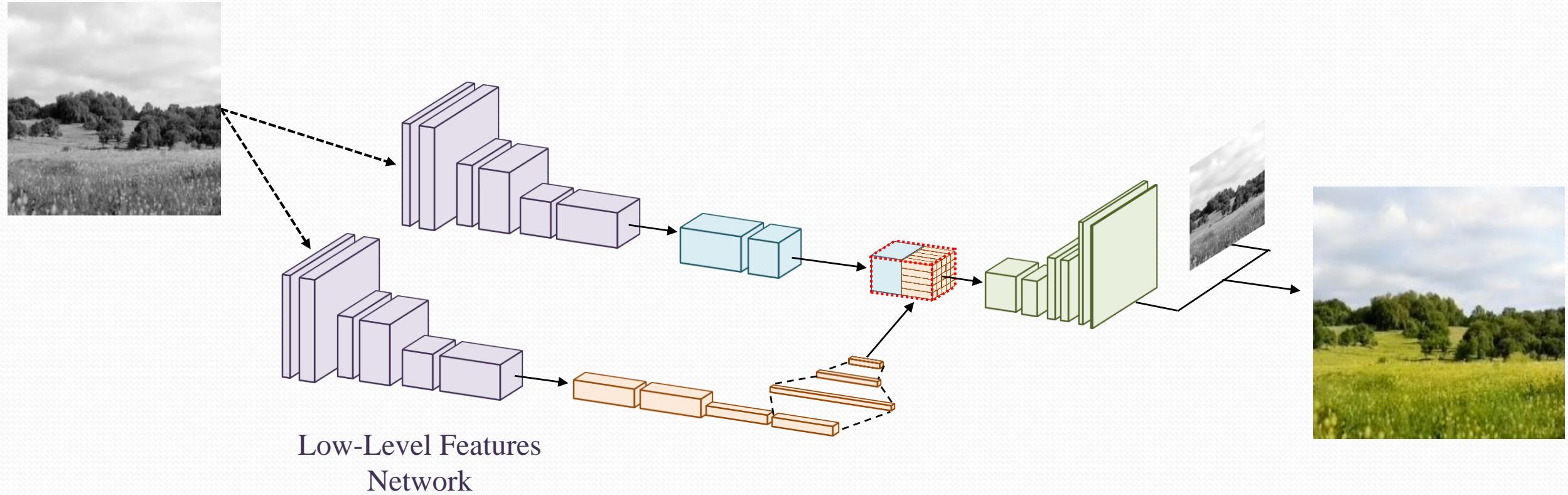


Youngsters, 1912

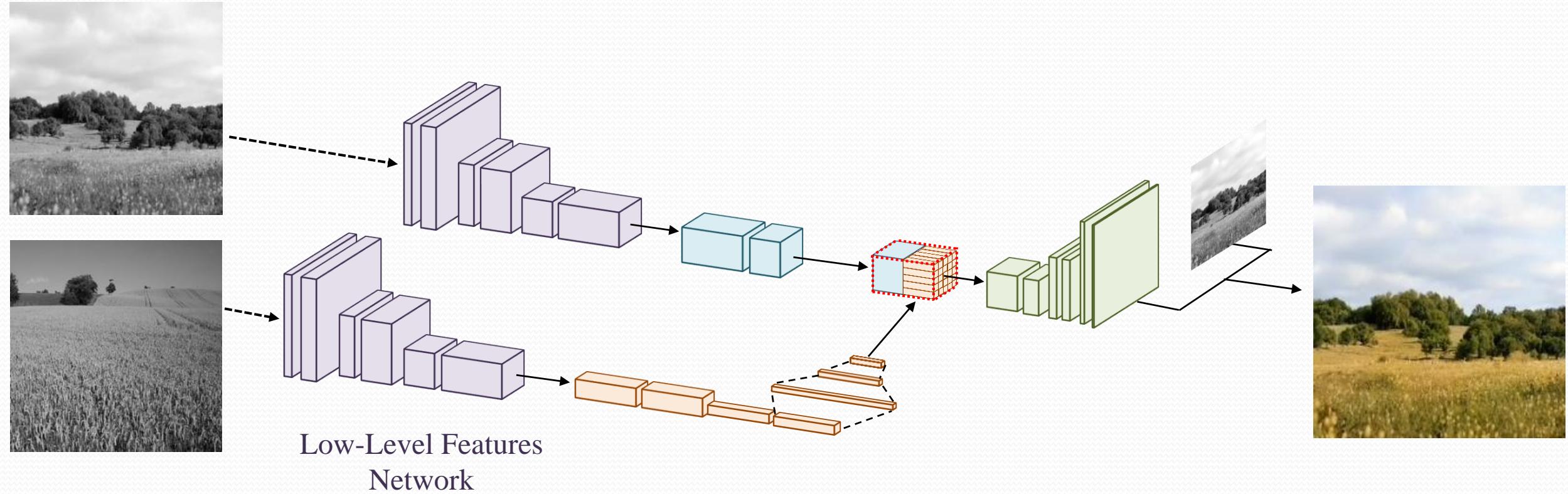


Burns Basement, 1910

Style Transfer



Style Transfer



Style Transfer

- Adapting the colorization of one image to the style of another

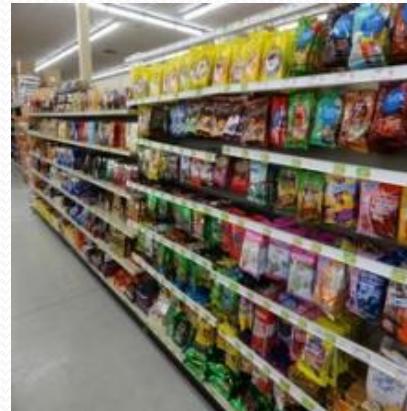


Limitations

- Difficult to output colorful images



Input



Ground truth



Output

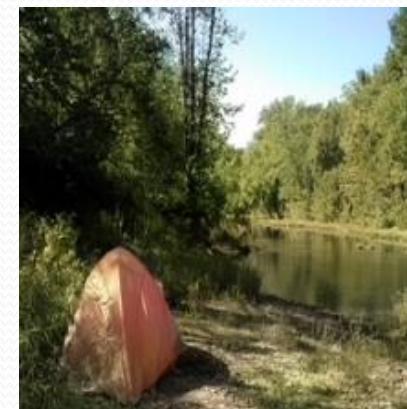
- Cannot restore exact colors



Input



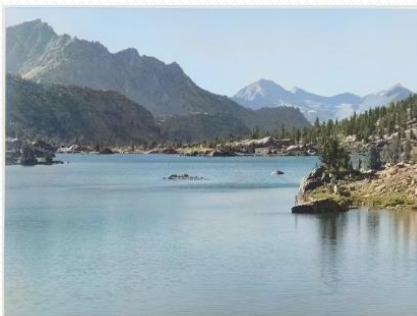
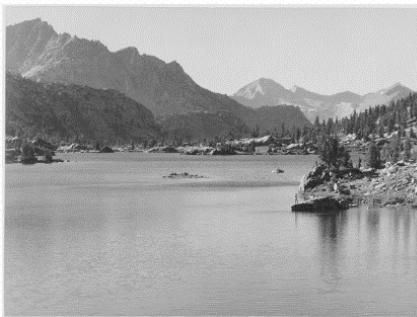
Ground truth



Output

Conclusion

- Novel approach for image colorization by fusing **global and local information**
 - Fusion layer
 - Joint training of colorization and classification
 - Style transfer



Farm Land, 1933

California National Park, 1936

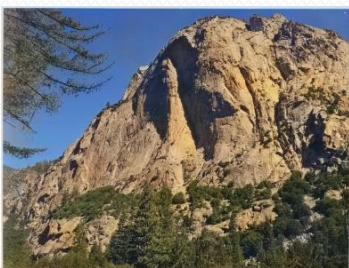
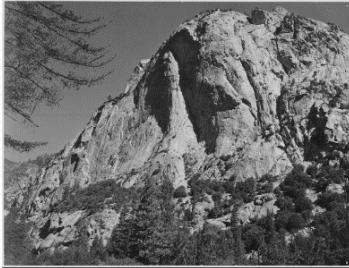
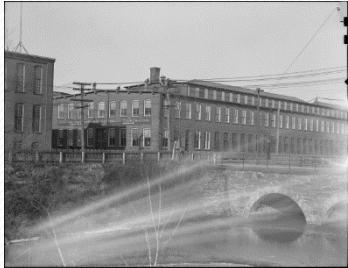
Homes, 1936

Spinners, 1910

Doffer Boys, 1909

Thank you!

- Project Page <http://hi.cs.waseda.ac.jp/~iizuka/projects/colorization>
- Code on GitHub! https://github.com/satoshiiizuka/siggraph2016_colorization



Community Center,
1936

North Dome,
1936

Norris Dam, 1933

Miner,
1937



The Lost World (1925)