



# Image Super Resolution

## Group 6

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## Overview

### Goal:

- Produce a *predicted* high resolution image based on the low-resolution input
- Balance between the running cost and predictive performance

### Outline:

- Baseline
- Advanced Algorithm (SRCNN)
- Model Evaluation



# 1. Baseline

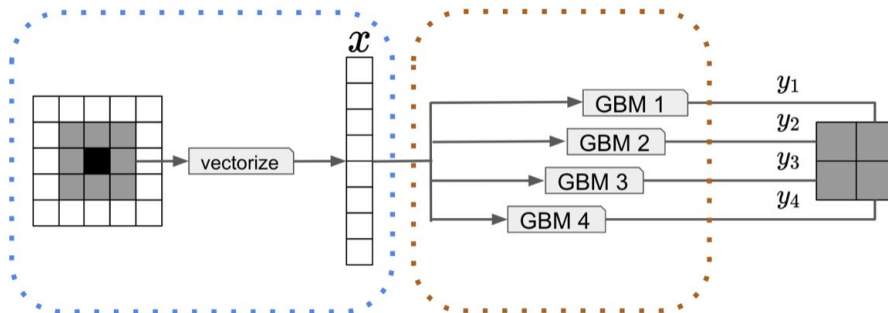
Neighboring pixels with GBM

# Feature Construction



## Baseline Algorithm

Build low/high-resolution patch pairs, and learn the best mapping between them.



## Feature Extraction

Low and High-resolution image patches ILR and IHR with sizes  $D \times D$  and  $U \times U$  ( $D=3, U=2$ )

$$x = \text{vectorize}(I_{LR}) - \text{center pixel}(I_{LR}) \in \mathbb{R}^{D^2 \times 1}$$

$$y = \text{vectorize}(I_{HR}) - \text{center pixel}(I_{LR}) \in \mathbb{R}^{U^2 \times 1}$$

# Prediction Algorithm



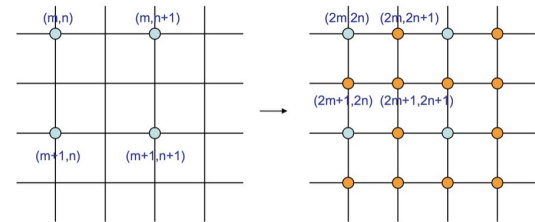
**For R/G/B channel:**

Predictor(x): First outside layer (8 pixels) of each pixel

Response(y): Corresponding 4 subpixels

**Model:**

- 3 channels \* 4 sub-pixels = 12 models
- Linear regression model
- Tune parameters by Gradient Boosting Machine(number of trees, depth, etc)



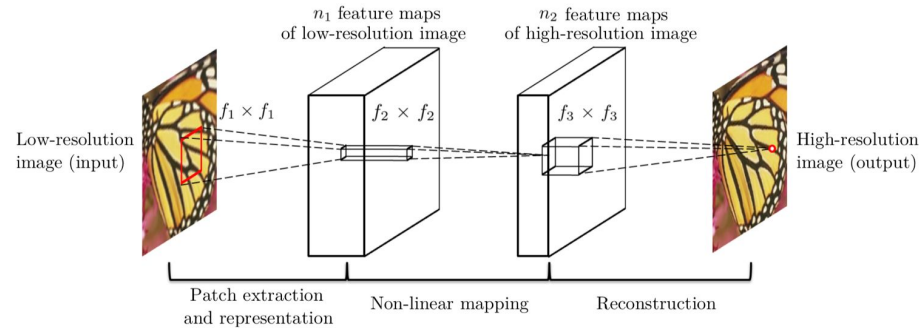


## 2. Advanced Algorithm

Super-Resolution Convolutional Neural Networks



# Architecture of Super-resolution Convolutional Neural Network



## Patch extraction and representation

Extract patches from the low-resolution image and represents each patch as a high-dimensional vector. These vectors comprise a set of feature maps.

$$F_1(\mathbf{Y}) = \max(0, W_1 * \mathbf{Y} + B_1),$$

## Non-Linear mapping

This operation nonlinearly maps each high-dimensional vector onto another high-dimensional vector. Each mapped vector is conceptually the representation of a high-resolution patch. These vectors comprise another set of feature maps.

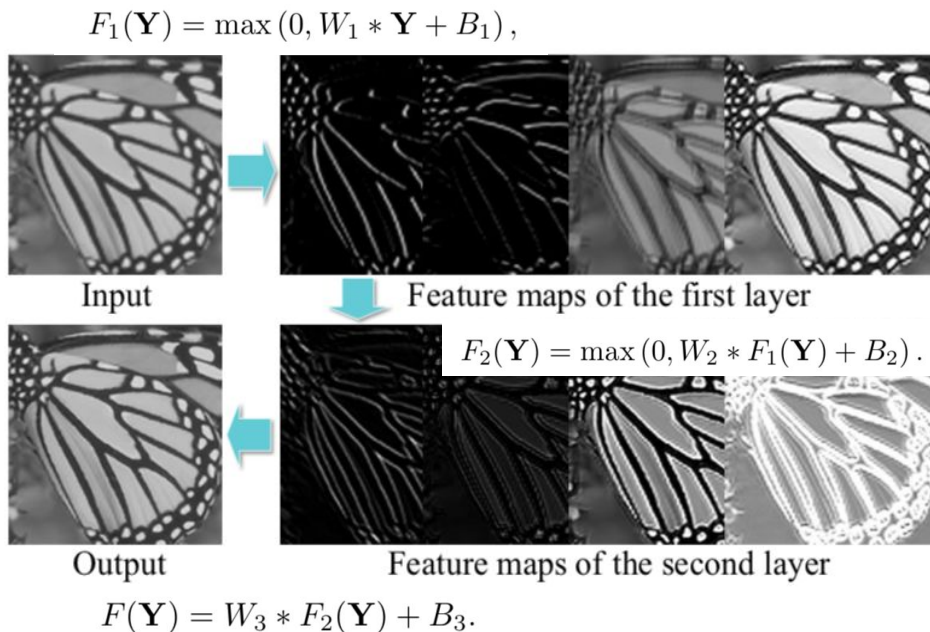
$$F_2(\mathbf{Y}) = \max(0, W_2 * F_1(\mathbf{Y}) + B_2).$$

## Reconstruction

This operation aggregates the above high-resolution patch-wise representations to generate the final high-resolution image. This image is expected to be similar to the ground truth X.

$$F(\mathbf{Y}) = W_3 * F_2(\mathbf{Y}) + B_3.$$

# Example feature maps of different layers



## Recall of Terminology

**Feature:** Piece of **information** that describes a part of image or whole image. These features could be corners, edges, lines, color, etc.

- Feature maps of the first layer: **Structures** (e.g., edges at different directions)
- Feature maps of the second layer: **Intensities**



# Model Training and Performance Trade off

**Learning algorithm:** a set of instructions that tries to model the **target function** using training dataset.

**In this case,**

Learning the end-to-end mapping function **F** requires the estimation of network parameters  $\Theta = \{W1, W2, W3, B1, B2, B3\}$ . This is achieved through minimizing the loss between the **reconstructed images**  $F(Y; \Theta)$  and the **corresponding ground truth high-resolution images X**.

Given a set of high-resolution images  $\{X_i\}$  and their corresponding low-resolution images  $\{Y_i\}$ , we use **Mean Squared Error (MSE)** as the *loss function*:

$$L(\Theta) = \frac{1}{n} \sum_{i=1}^n ||F(Y_i; \Theta) - X_i||^2,$$

Performance	Filter Numbers	Filter Size	Number of Layers
Accuracy	+	+	No apparent
Computational Efficiency	-	-	-
Setting	n1=64, n2=32	f1=9, f2=1, f3=5	3



# 3. Model Evaluation

Baseline & SRCNN

# Super Resolution by SRCNN

Original



Super Resolution



PSNR: 37.571371960526974

Original



Super Resolution



PSNR: 39.81817950331664

Original



Super Resolution



PSNR: 36.518083349668444

Original



Super Resolution



PSNR: 37.67317231587752

# Performance Improvement



	Baseline	SRCNN
Average PSNR	25.0	<b>31.2</b>
Running Time (1500 images)	20min	<b>10min</b>

# Model Comparison



Criteria	Baseline	SRCNN
Complexity	<b>Easy to implement</b>	Hard to understand
SR Speed	Time Consuming	<b>Fast</b>
Accuracy	Low Accuracy	<b>High</b>
Data Requirement	<b>Small Dataset</b>	Data hungry





# Conclusion



- SRCNN performs remarkably in the perspective of **Accuracy** and Super resolution **Speed**.
- **Computational expensive** to train.
- **Hard to comprehend** without strong theoretical foundation.





# THANKS!

- Reference

Image Super-Resolution Using Deep Convolutional Networks

<http://mmlab.ie.cuhk.edu.hk/projects/SRCNN.html>