# RAISR

Rapid and Accurate Image Super Resolution

Nearest Neighbor

Bilinear

Nearest Neighbor

Bilinear

Cubic

Lanczos4

Cubic

Lanczos4

# hqx -- Pixel Art Scaling

- Intended for simple 2D art

Nearest Neighbor

- Use patch around each pixel
- Neighbors are “close” or “distant”
- Lookup neighborhood in LUT
- Determine filter

hq3x

Not intended for photographs!

Not intended for photographs!

Nearest Neighbor

hq4x

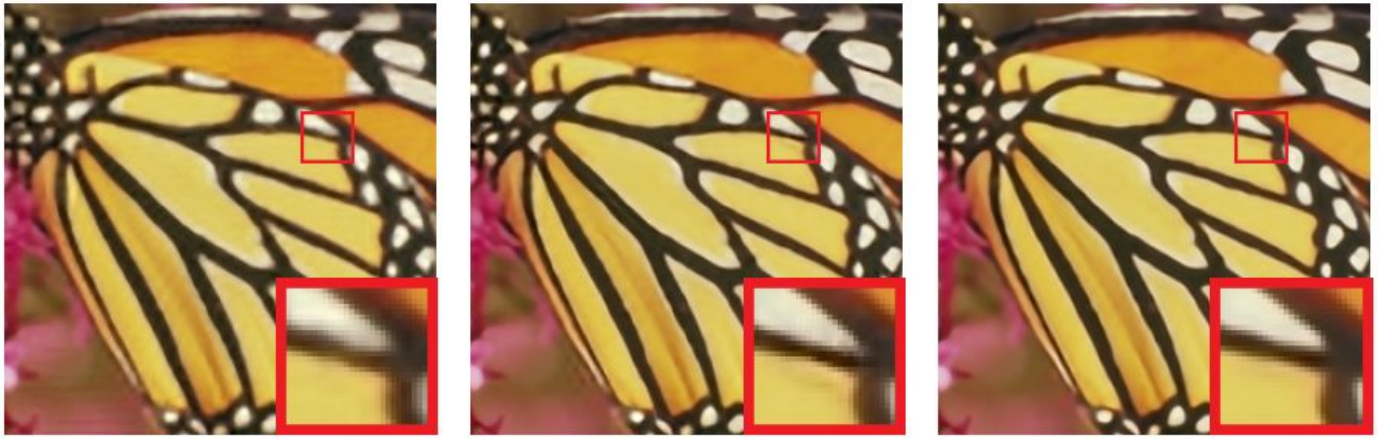
# Example-Based Approaches

- Build a dictionary from low resolution (LR) patches to high resolution (HR) patches
  - Dictionary is very large, so sparse coding is typically used
  - Usually limited to fixed upscaling factors

- Anchored Neighborhood Regression (ANR) and A+
  - Uses neighbor embedding and ridge regression
  - Somewhat fast

- SRCNN
  - End-to-end approach with a convolutional neural network (CNN)
  - Slow

(a) High-res (b) A+ (c) SRCNN



(d) JSB-NE (e) CSCN (f) DEGREE

# RAISR -- History

- Developed by Google; paper published in 2017
- Intended for mobile devices
- Lightweight, easy to parallelize, low memory requirements
- Performs roughly as well as SRCNN

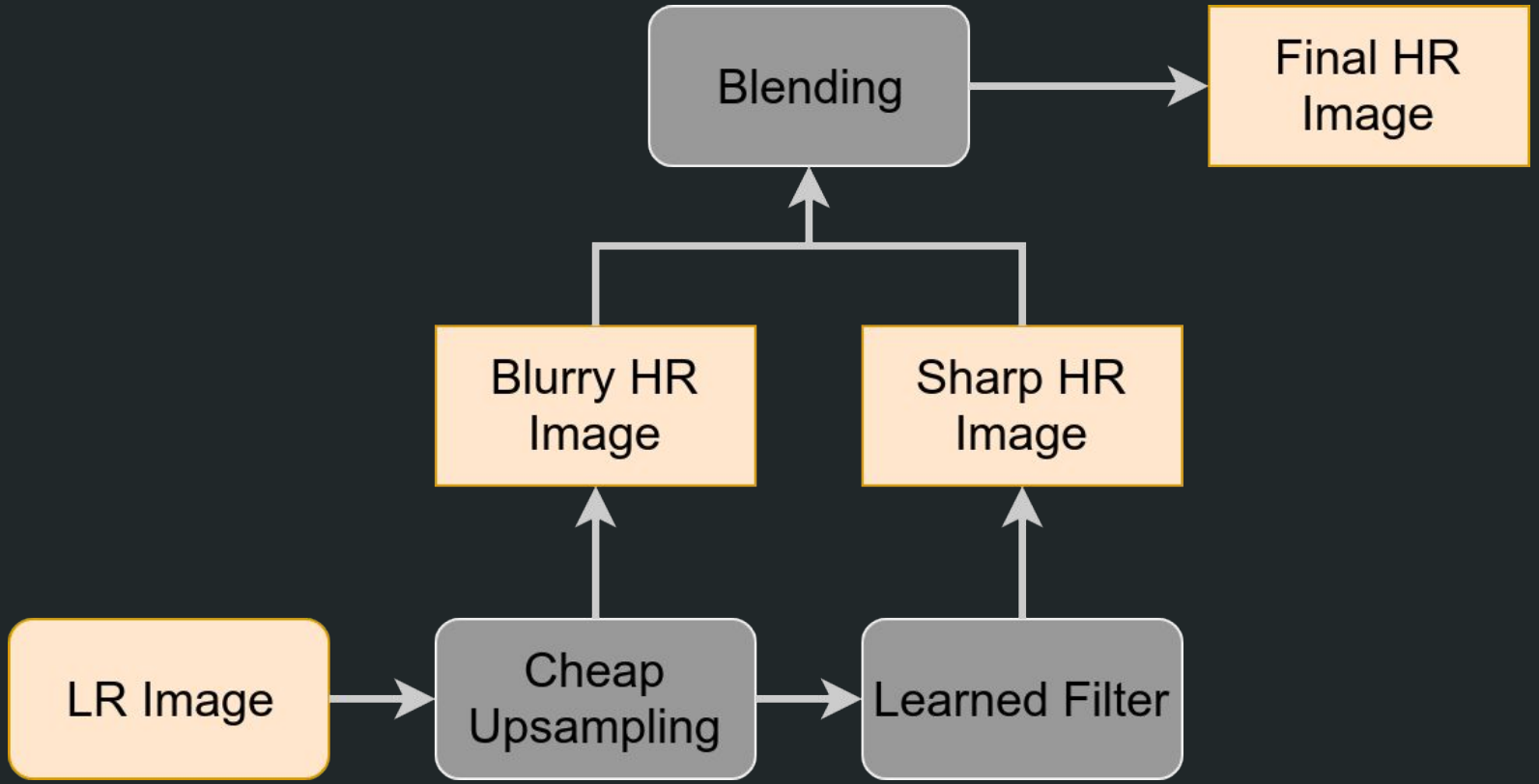
# RAISR -- Overview

- Use a cheap filter to scale the image up

- Sharpen the image using pre-learned filters
  - The filter to use depends on the neighborhood of the pixel

- Perform a blending pass to remove undesirable oversharpening effects

# RAISR -- Overview

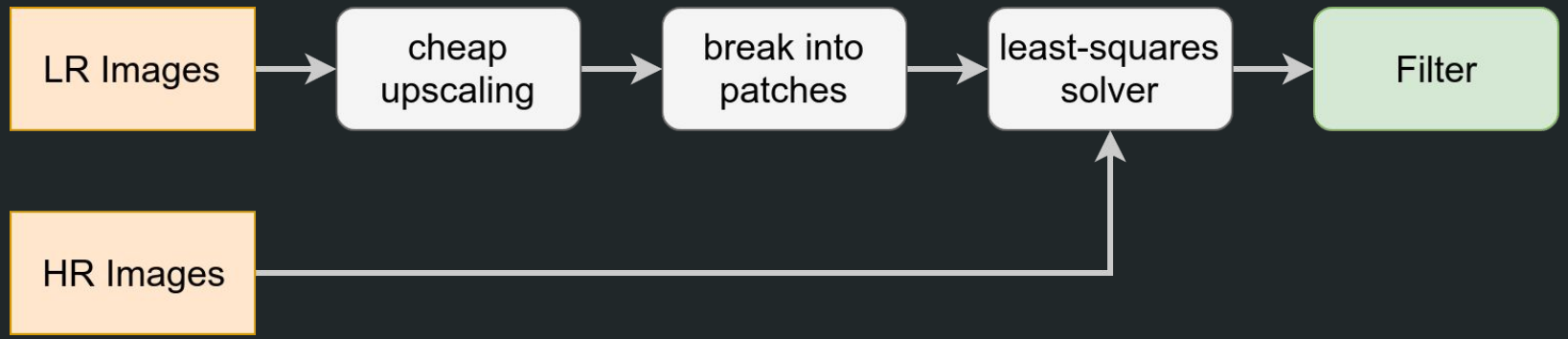


Nearest Neighbor

Bicubic Upsampling

RAISR Upsampling

# Learning Phase



# Objective Function

- Goal: A database of filters that minimizes the Euclidean distance between the **generated HR images** $x_i$ and the **training HR images** $y_i$.
- Minimize

$$\sum_{i=1}^{L} ||A_i h - b_i||_2^2$$

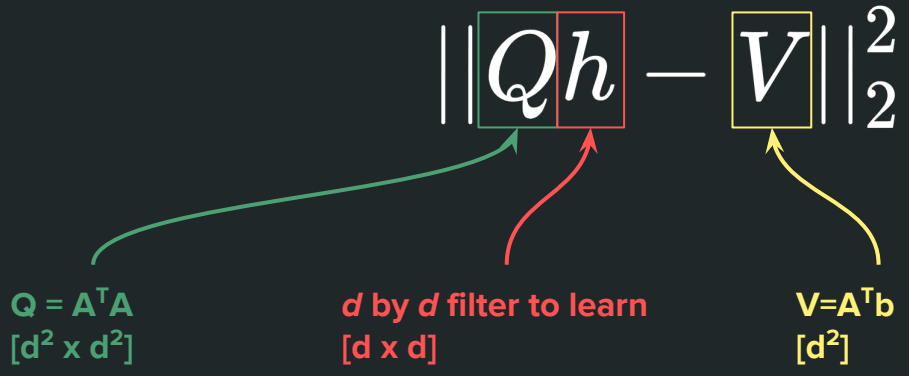
**All *d* by *d* patches in $y_i$ [M N x $d^2$]**

***d* by *d* filter to learn [d x d]**

**All pixels in $x_i$, correspond to center of $y_i$ patches [M N]**

# Actual Objective Function

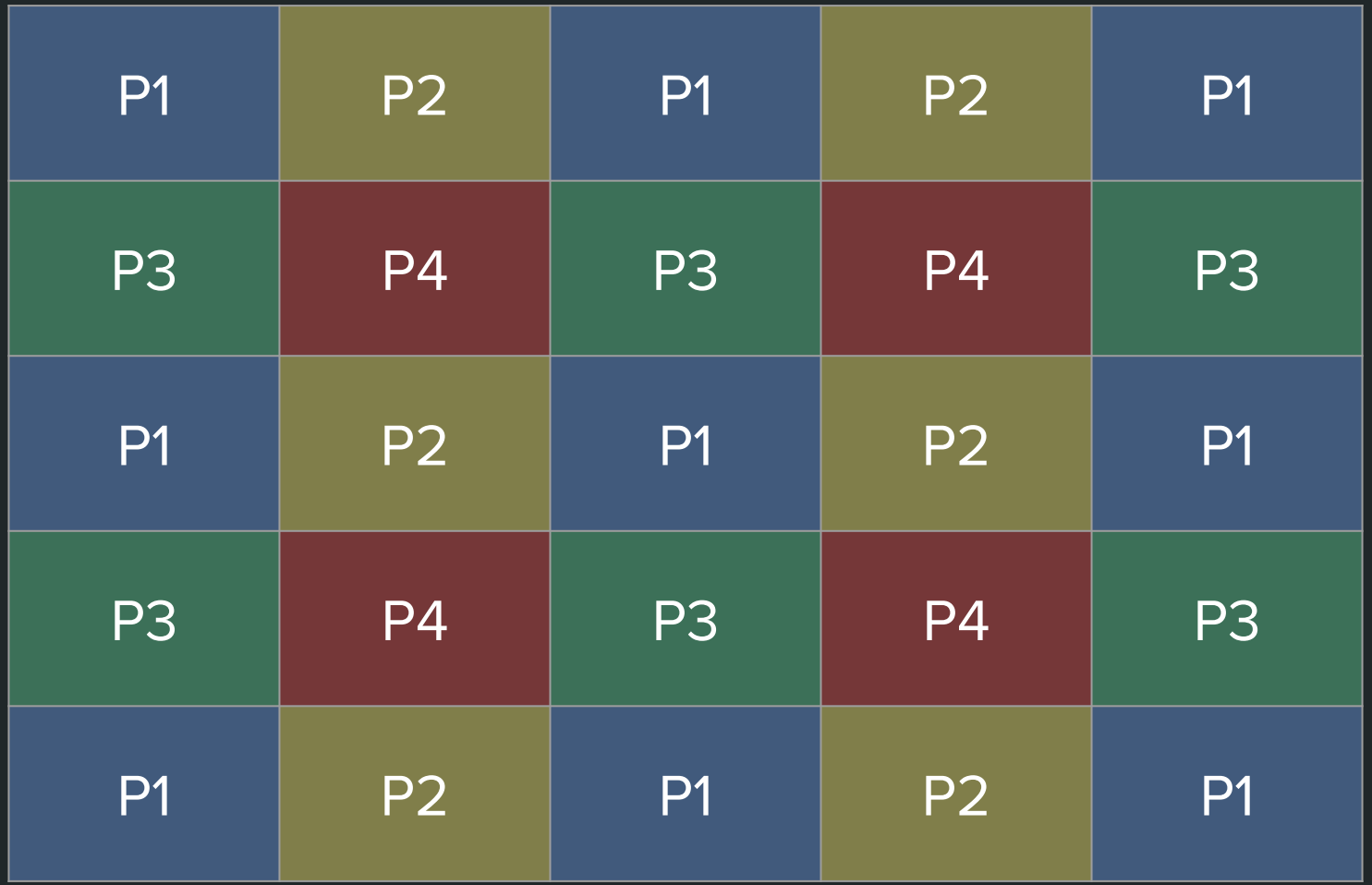
- *A* is a big matrix and we do not need all of the patches
- Much simpler computational/memory requirements in this form
- Minimize




- Q is small!
- We don’t need to keep the whole image in memory

# Shift-invariance and Aliasing

- The cheap upscaler is not shift invariant
- 2x upsample mean 4 types of pixels; 3x upsample means 9 types of pixels; etc
- Separate filter for different types of pixel


P1
P2
P1
P2
P1
P3
P4
P3
P4
P3
P1
P2
P1
P2
P1
P3
P4
P3
P4
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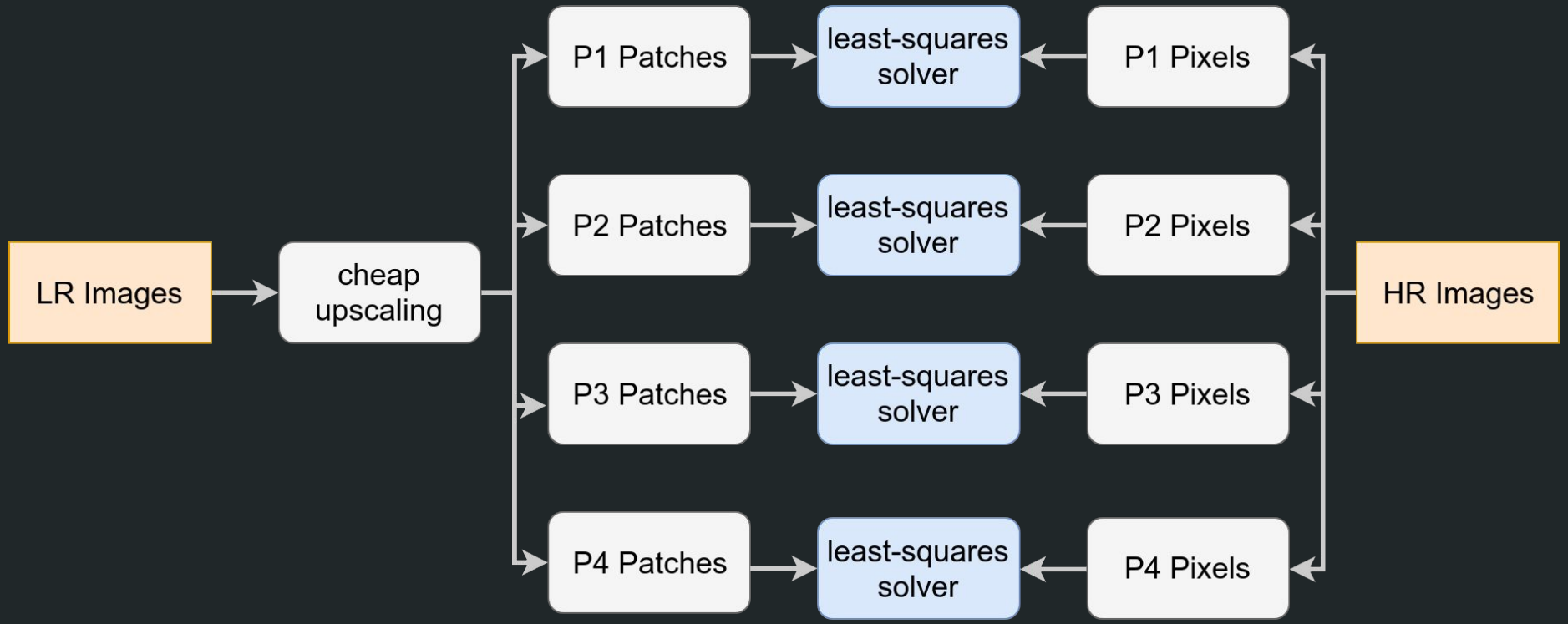
P1
P2
P1
P2
P1

# Learning Phase (with Shift Invariance)



# Hashing-Based Learning

- Global image filtering is fast, but not very accurate
- Operate on the **patch** level to improve performance
- Instead of clustering, we ***hash*** the patch to get a bucket
- Now we compute each pixel filter for each bucket

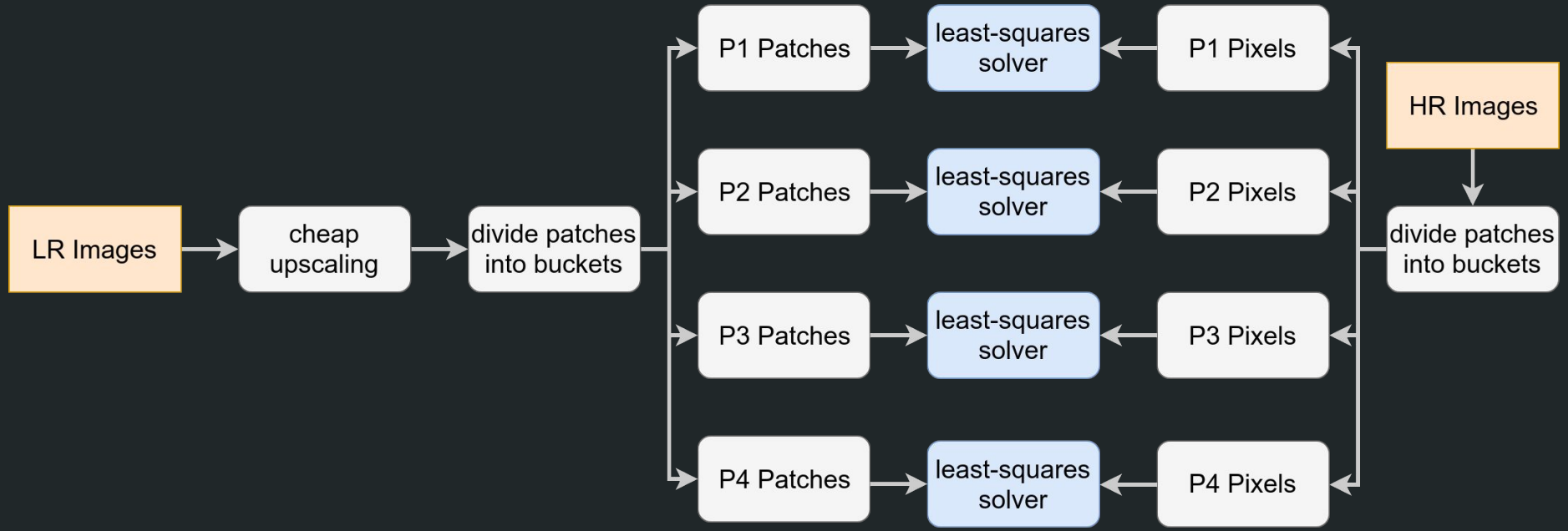
# Hashing-Based Learning

- A 9x9 neighborhood of the surrounding pixels is the hash key

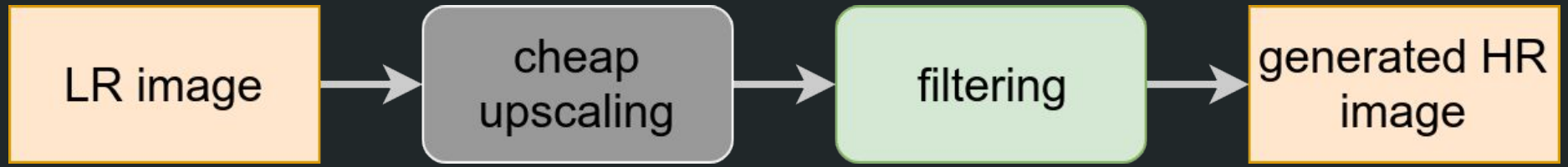
- Hash( *Neighborhood* ) = (θ, λ, μ)

- Patches are divided into buckets; solver operates on individual buckets

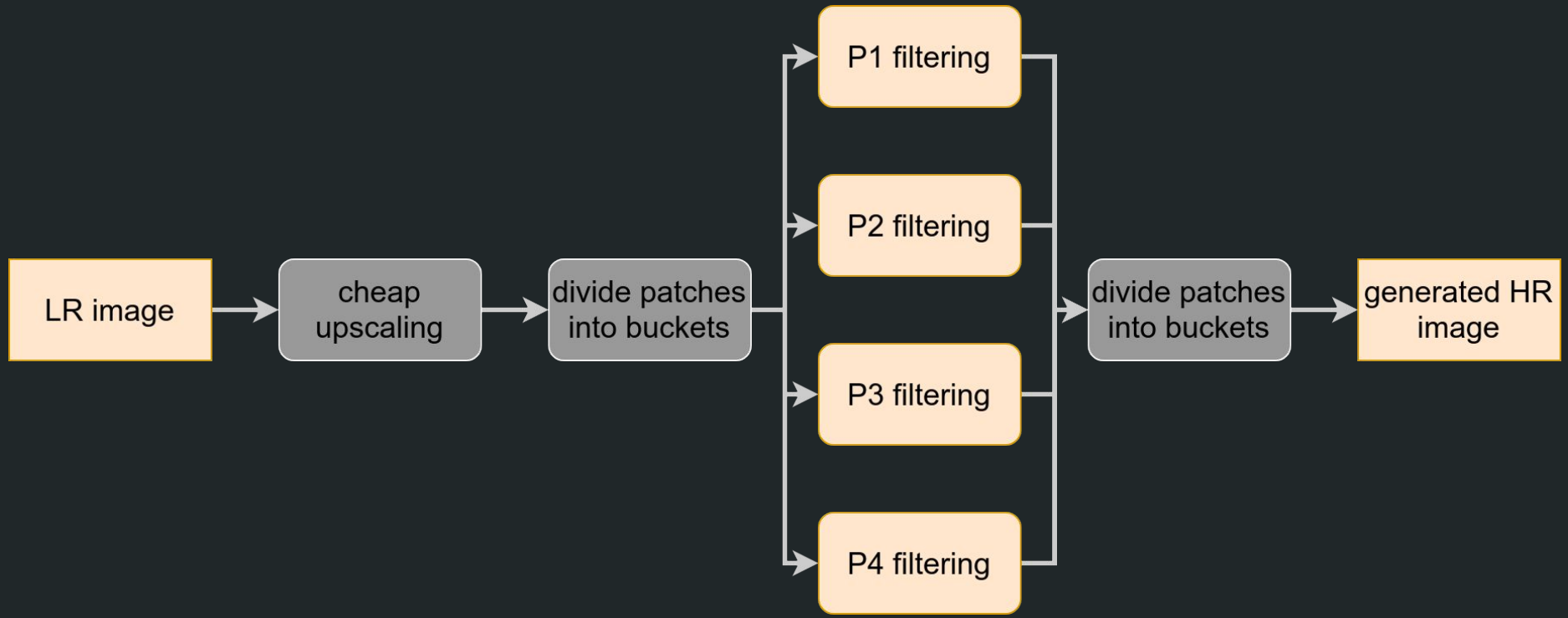
# Learning Phase (Hash-based with Shift Invariance)



# Inference Phase



# Inference Phase (Hash-based with Shift Invariance)



# Inference Phase

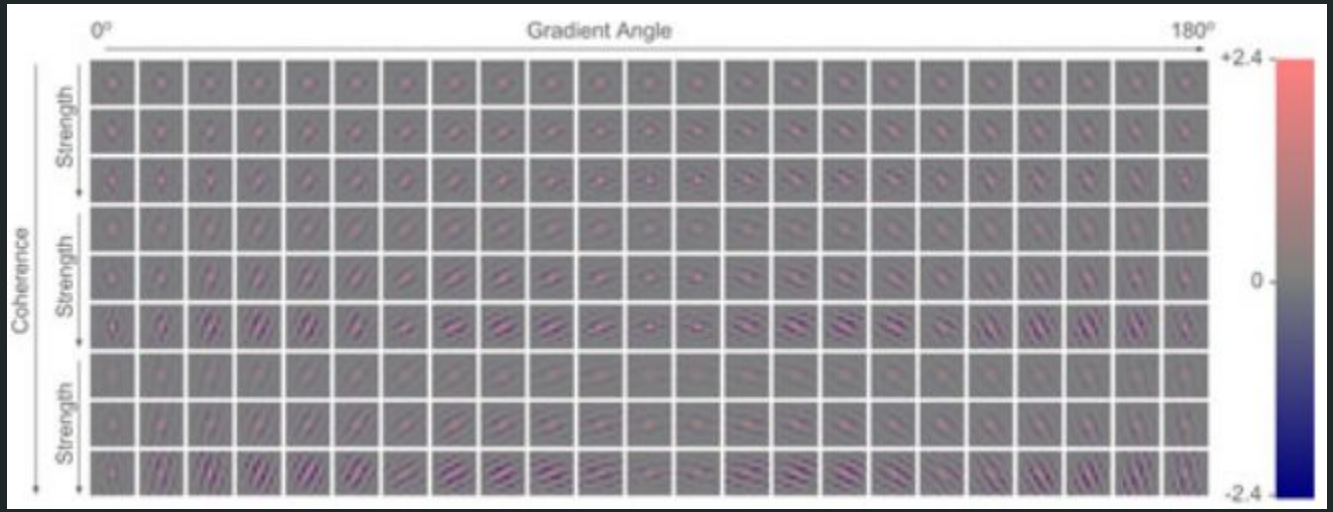
- Hash the neighborhood
- Find the bucket for that hash value
- Select the correct pixel filter from the bucket
- Apply the filter

- How does the hashing algorithm work?

# Hashing algorithm

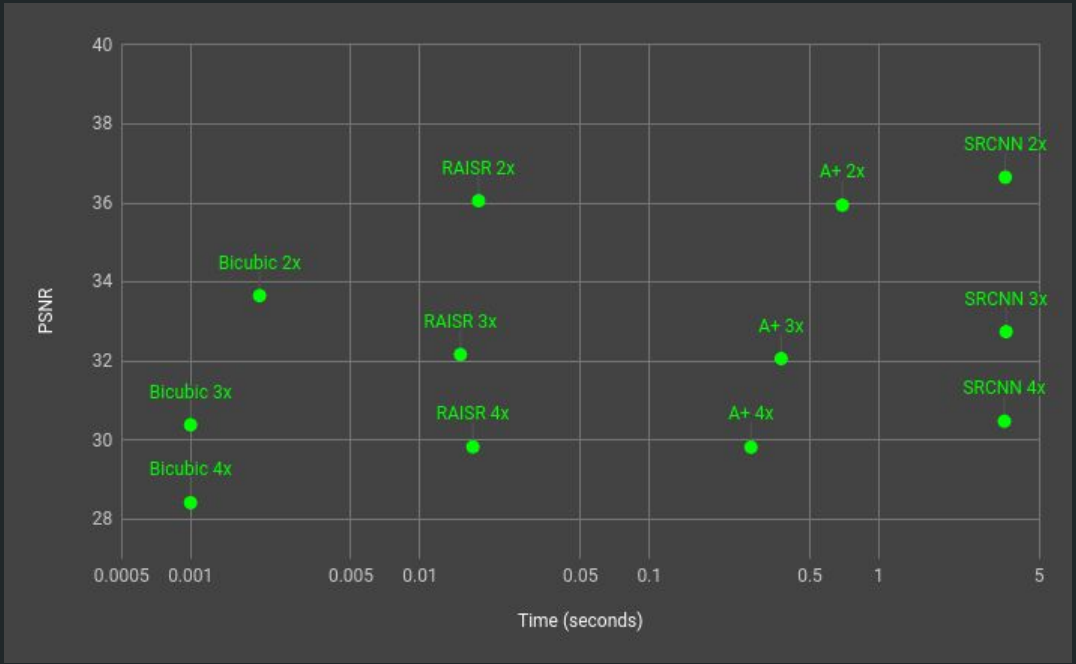
1. Collect a 9x9 neighborhood of the pixel
2. Compute the gradient of this patch
3. G is a [$n^2$ x 2] matrix where the rows are the gradients at each location
4. Compute $G^T WG$ where W is a normalized Gaussian kernel (applied separably)
    a. Note that this is a [2 x 2] matrix
5. Compute the SVD of this matrix
6. The **angle (θ)** parameter is the angle of the eigenvector corresponding to the larger singular value
7. The **strength (λ)** parameter is the square root of the larger eigenvalue.
8. The **coherence (μ)** (strength + spread) is $\frac{\sqrt{\lambda_1}-\sqrt{\lambda_2}}{\sqrt{\lambda_1}+\sqrt{\lambda_2}}$
9. Quantize gradient statistics to buckets

# Learned 2x Filters

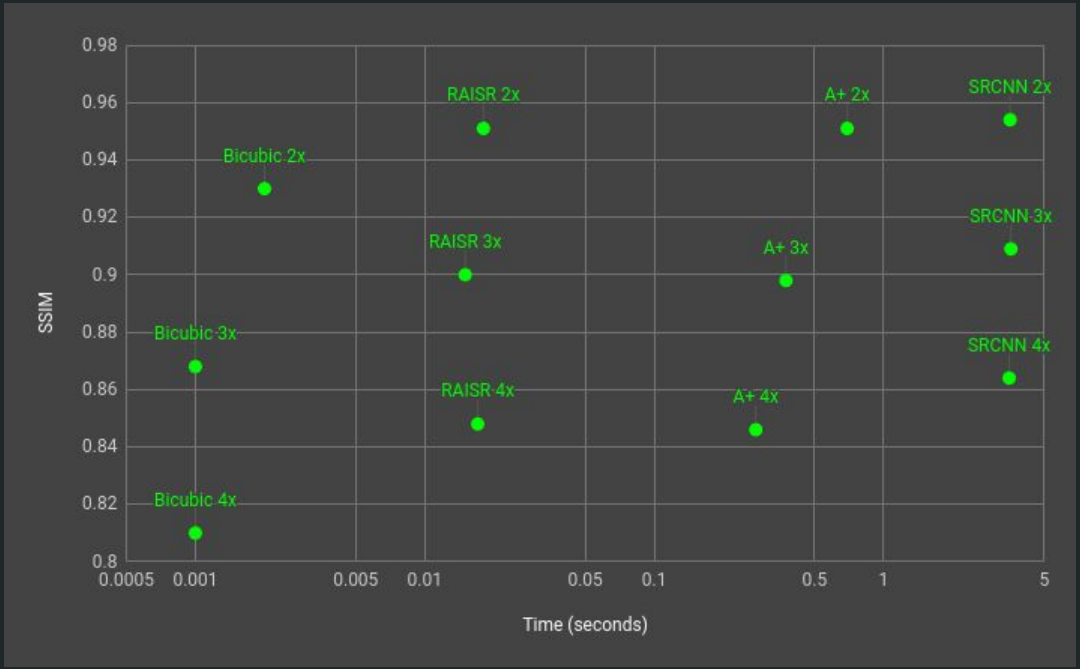


# (Almost) Final Steps

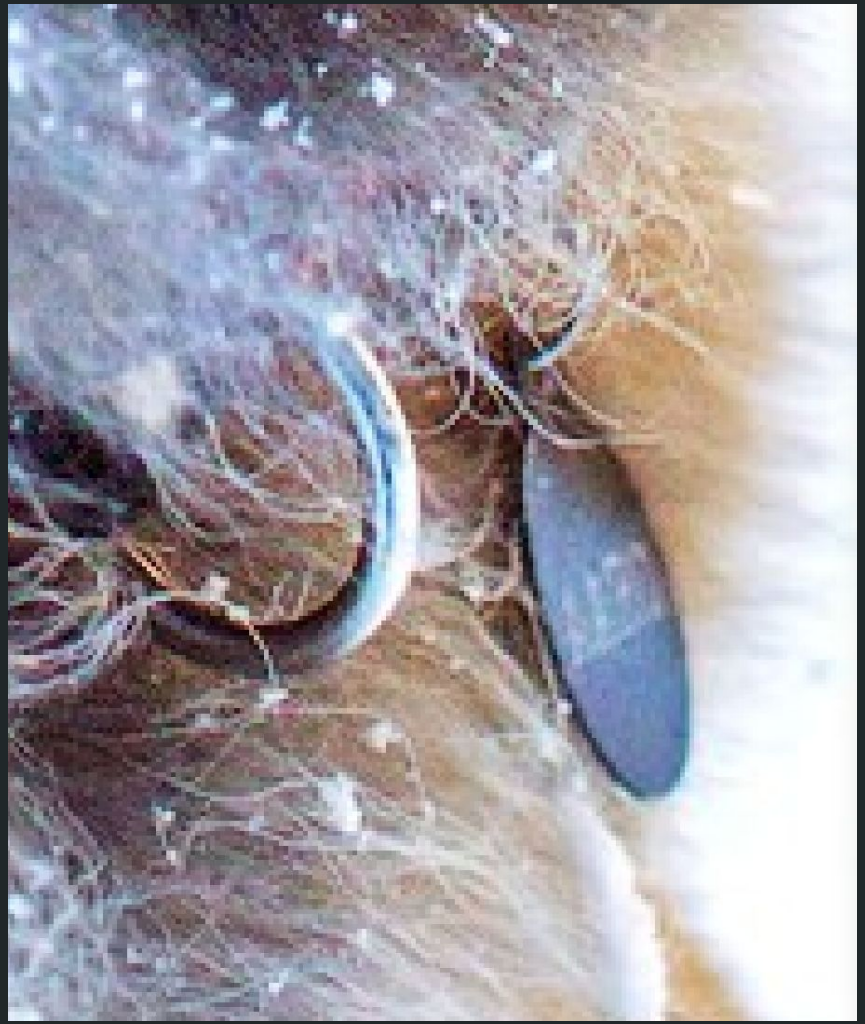
1. *FilterDatabase[θ, λ, μ, PixelType] = h*
    a. In the paper, filters were [11 x 11]
2. Apply the filter to the [11x11] neighborhood of the pixel
3. Add the (cheaply-scaled) chroma back in

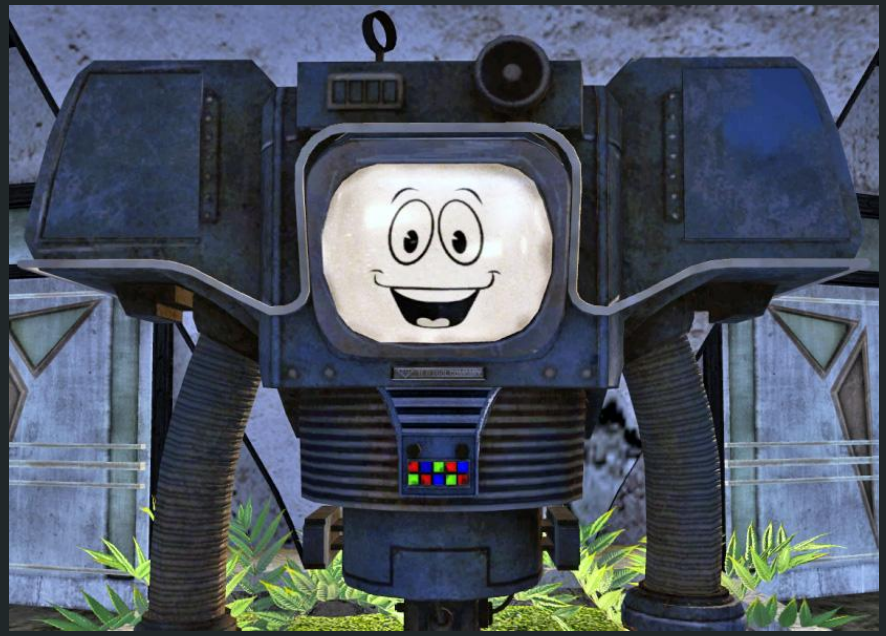


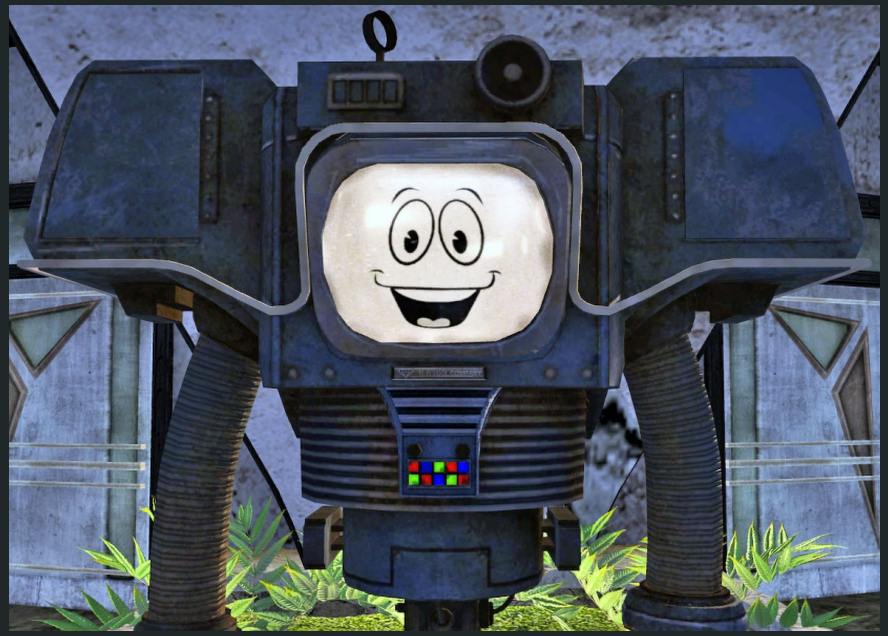

# Evaluation (PSNR) -- 3.4GHz 6-Core Xeon




# Evaluation (SSIM) -- 3.4GHz 6-Core Xeon







# Removing Artifacts

- So far RAISR worsens existing artifacts in image

- LR images are often distorted by an unknown PSF (e.g blur) or have JPEG compression artifacts

- Solution
  - To avoid oversharpening, train on LR images with ***compression artifacts*** to normal HR images
  - To avoid blurriness, train on normal LR images to ***oversharpened*** HR images.

# Removing Artifacts

Bilinear

Uncompressed LR

Compressed LR

# Avoiding Oversharpening

- Sadly this technique tends to amplify noise and create halos

- We want a cheap filter for **low**-frequency regions, learned filter for **high**-frequency regions

- Could cluster and handle areas differently, but that would be slow

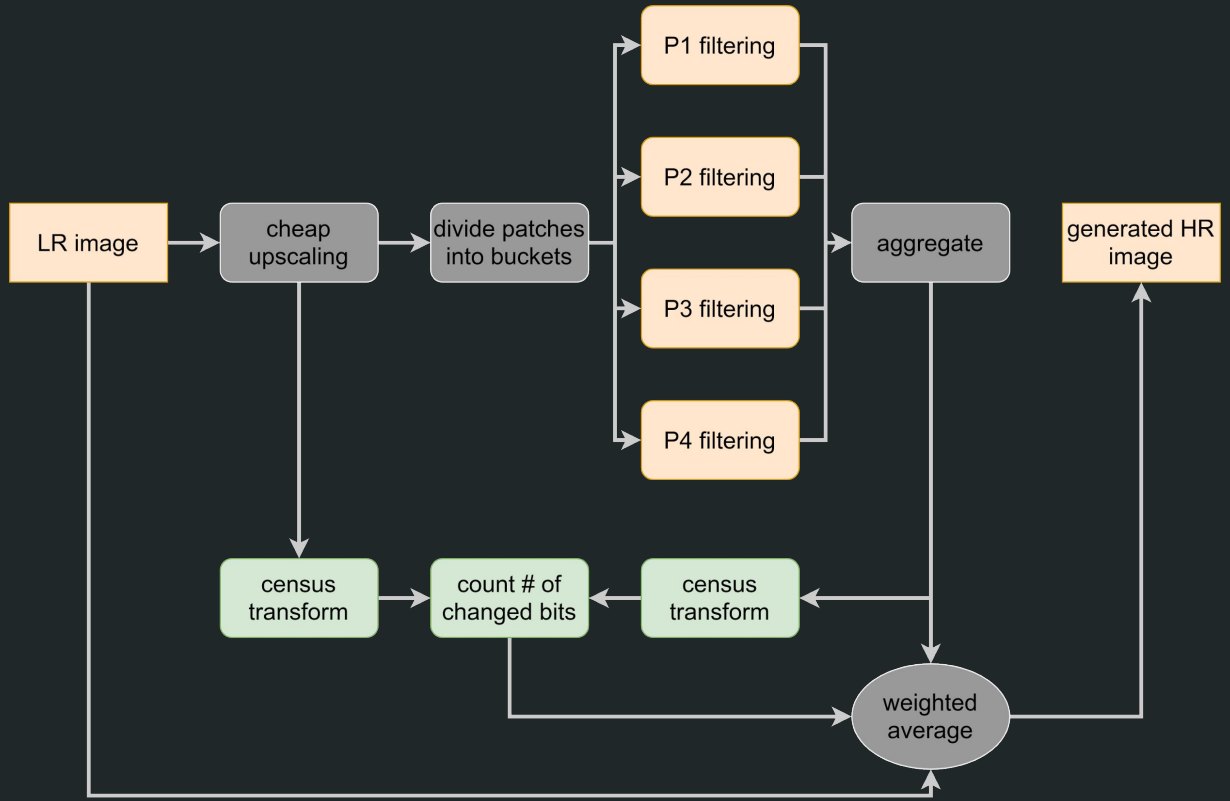
# Contrast Enhancement

- Need a measure of structure
- Least Connected Component (LCC) of the Census Transform (CT) could be used to detect high-frequency regions
- We can either selectively amplify high frequencies, or enhance a variety of frequencies

# Evaluating Local Change in Structure

- Compute the CT of the cheap upscaled image and the filtered image
- Per pixel, evaluate the Hamming distance
- Distance is proportional to the change in structure
- This weight is used for blending both images together

# Inference Phase (Everything + CE)



# Pre-processing for Contrast Enhancement

- Use a **DoG** sharpener on the HR **training** images to increase **contrast**

- Automatically enhances details (HF) and contrast (MF/LF)

Original Image (HR)

Bicubic upscaling (LR -> HR)

Filtered (**not trained** on sharpened HR)

Filtered (**trained** on sharpened HR)

Blended (with bicubic)

Original Image (once again)

# RAISR

- Lightweight
- Simpler and faster than Deep Learning techniques
- Works well for a variety of content -- games, photographs, video, etc

# Some ideas

- Applying the [11x11] filter is likely the most expensive operation (~121 MADs)
  - Why not use separable convolutions (~22 MADs)?

- 3D applications may have access to the **depth buffer**
  - Could be used in the hashing algorithm or the filter