CS448f: Image Processing For Photography and Vision

Denoising

How goes the assignment?

The course so far…

- We have a fair idea what image processing code looks like
- We know how to treat an image as a continuous function
- We know how to warp images
- What should we do next?

What are the big problems in Photography and Computer Vision, and how can Image Processing help?

Today: Denoising

How do we know a pixel is bad?

- It’s not like its neighbours
- Solution: Replace each pixel with the average of its neighbors
- I.e. Convolve by

1	1	1
1	1	1
1	1	1

3x3 Rect Filter

5x5 Rect Filter

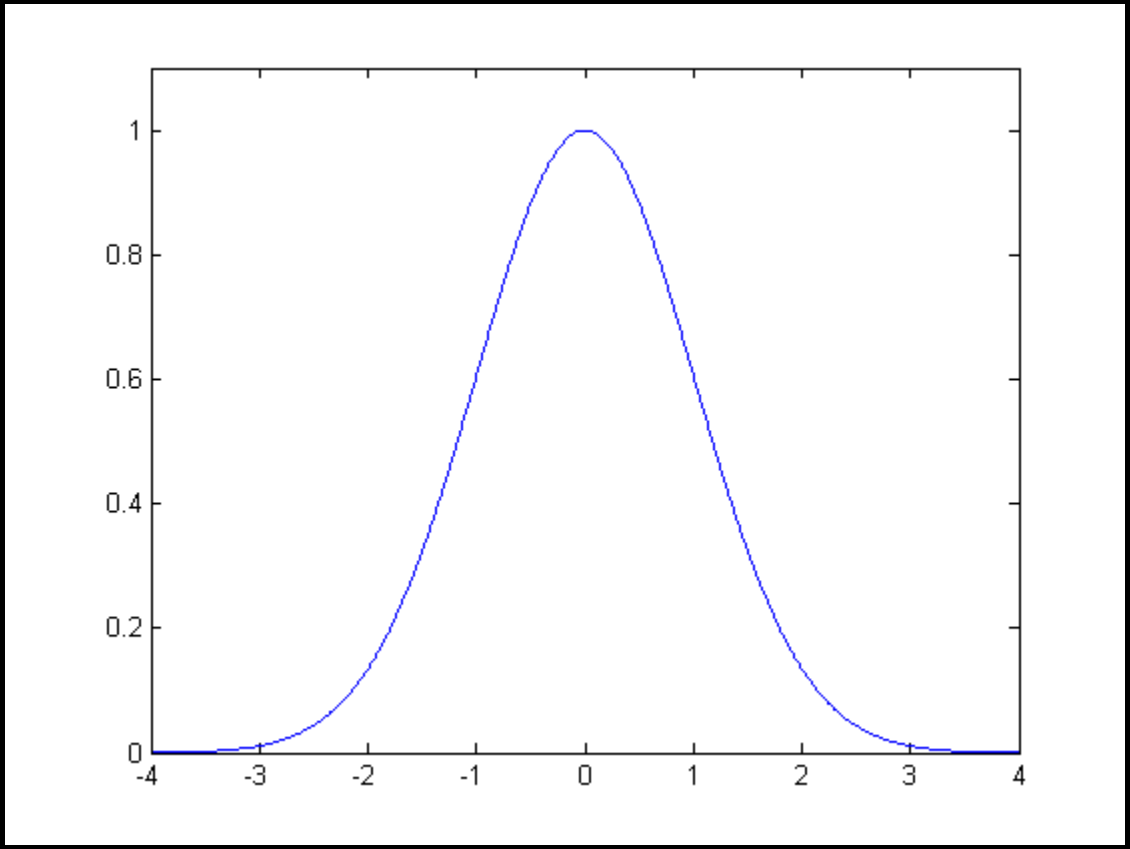
Linear Filters

- Why should a far-away pixel contribute the same amount as a nearby pixel
- Gaussian blur:

$$Out(\vec{x}) = \frac{\sum_{\vec{x}'} w(\vec{x}, \vec{x}') I(\vec{x}')}{\sum_{\vec{x}'} w(\vec{x}, \vec{x}')}$$

$$w(\vec{x}, \vec{x}') = e^{-|\vec{x}' - \vec{x}|^2 / 2\beta}$$

Gaussian Blur



beta = 2

beta = 5

Some neat properties:

- It's radially symettric and separable at the same time:

$$e^{-|\vec{x}'-\vec{x}|^2} = e^{-(x_0-x_0')^2} \cdot e^{-(x_1-x_1')^2}$$

- Its Fourier transform is also a Gaussian
- It's not very useful for denoising

Linear Filters

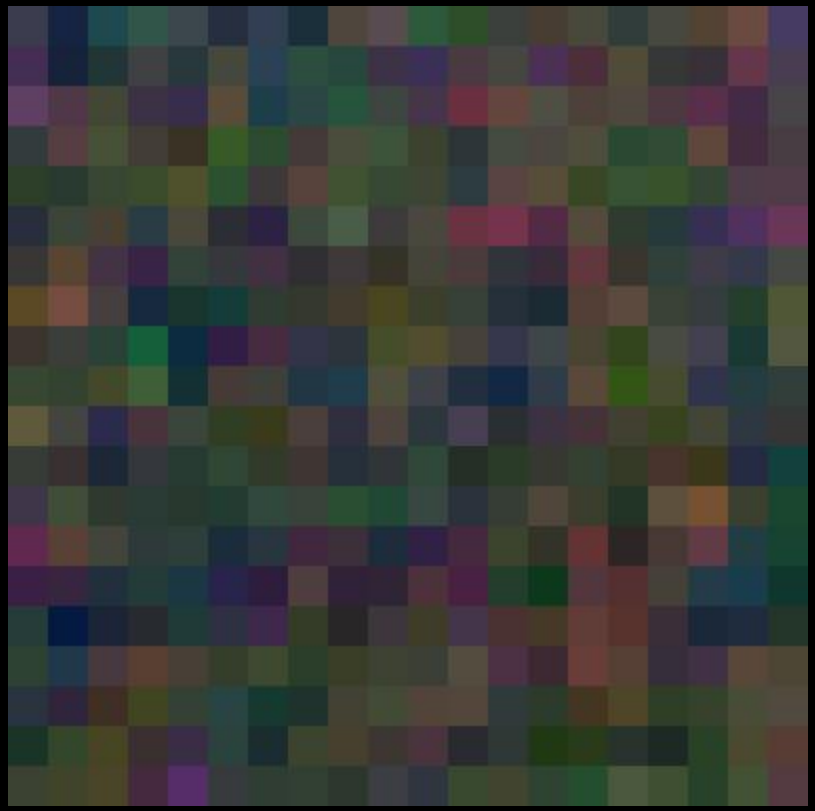
- Convolve by some kernel
- Equivalent to multiplication in Fourier domain
- Reduces high frequencies
  - But we wanted those - that's what made the image sharp!
  - You don't always need the high frequencies. The first step in many computer vision algorithms is a hefty blur.

Probabilistically...

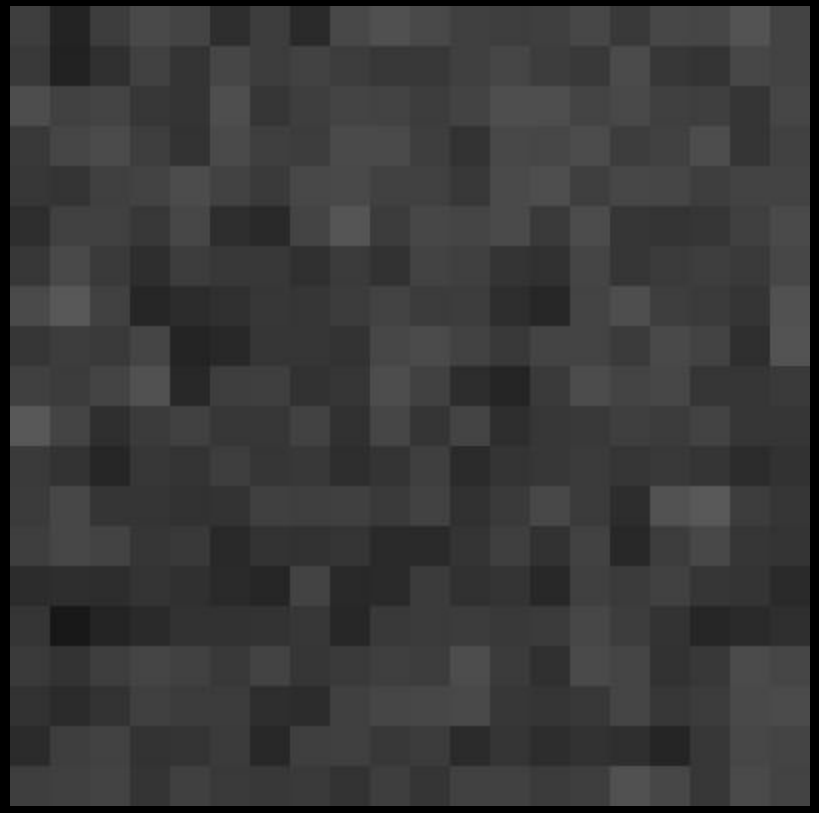
- What is the most probable value of a pixel, given its neighbors?

Probabilistically...

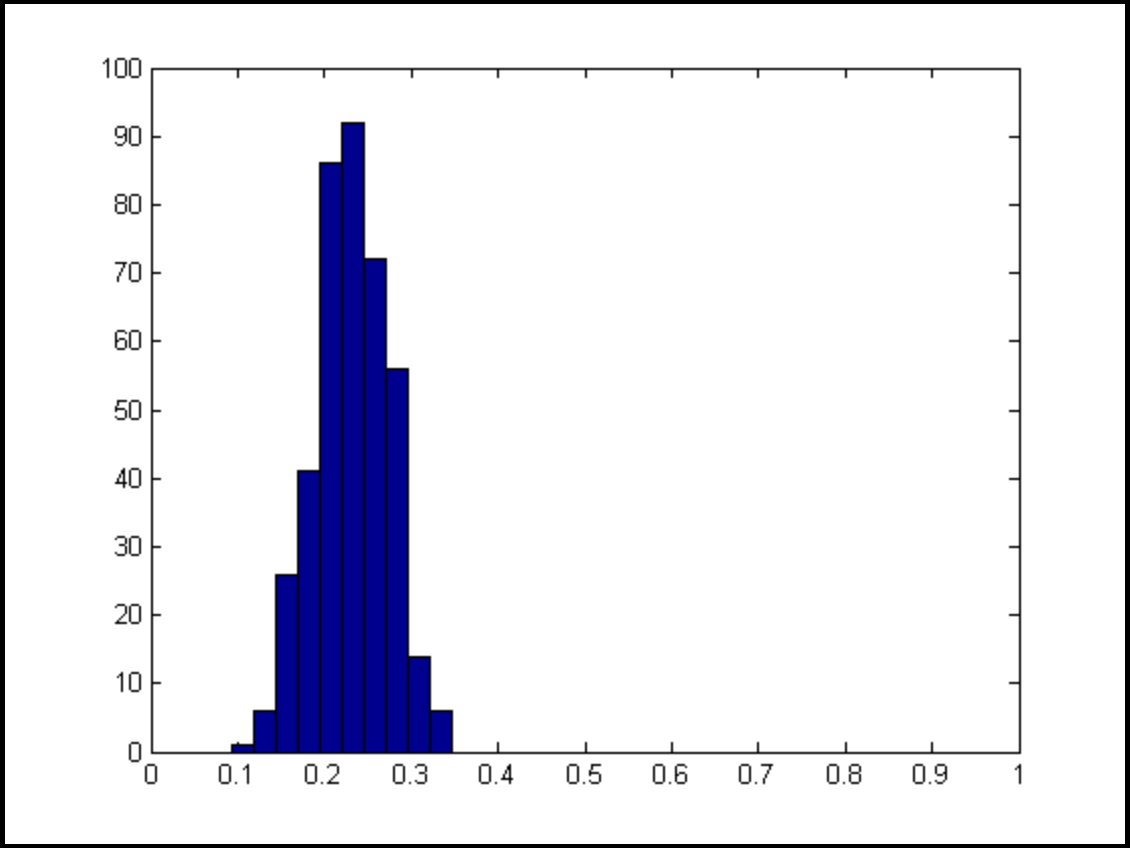
- This is supposed to be dark grey:



Let’s ignore color for now

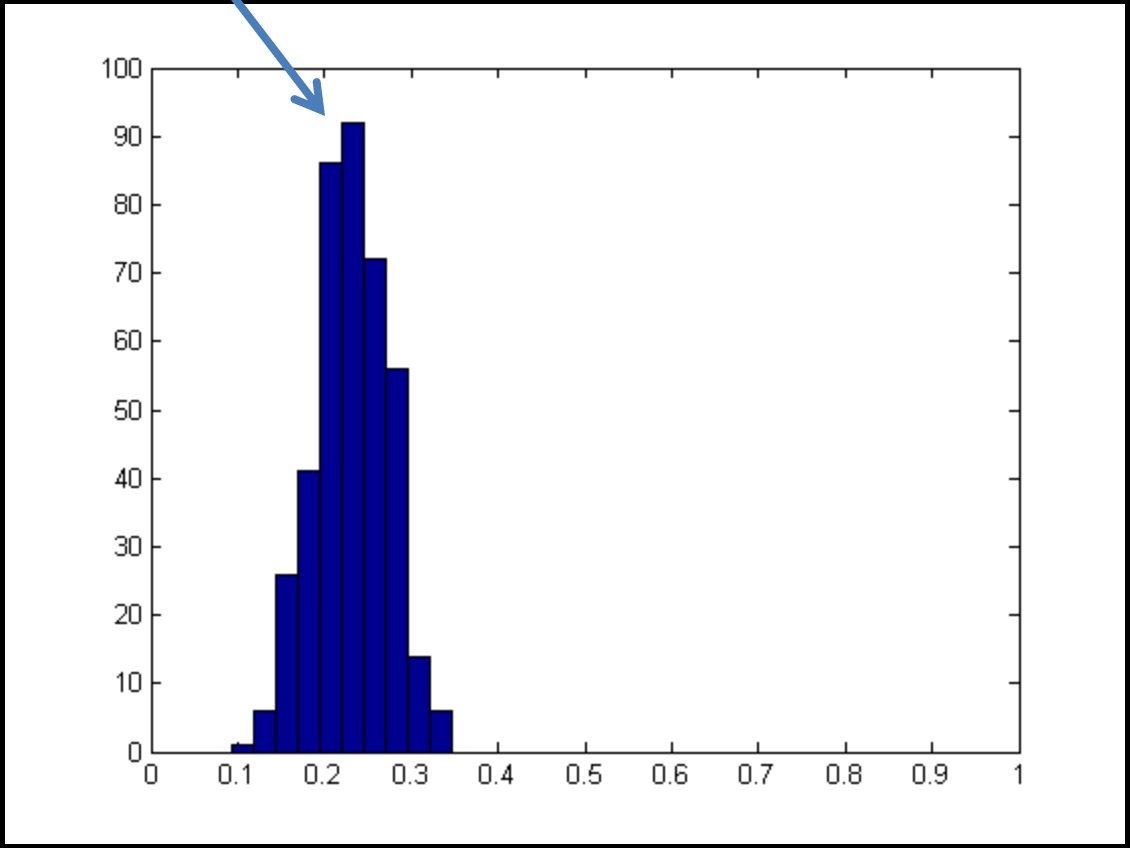


And inspect the distribution



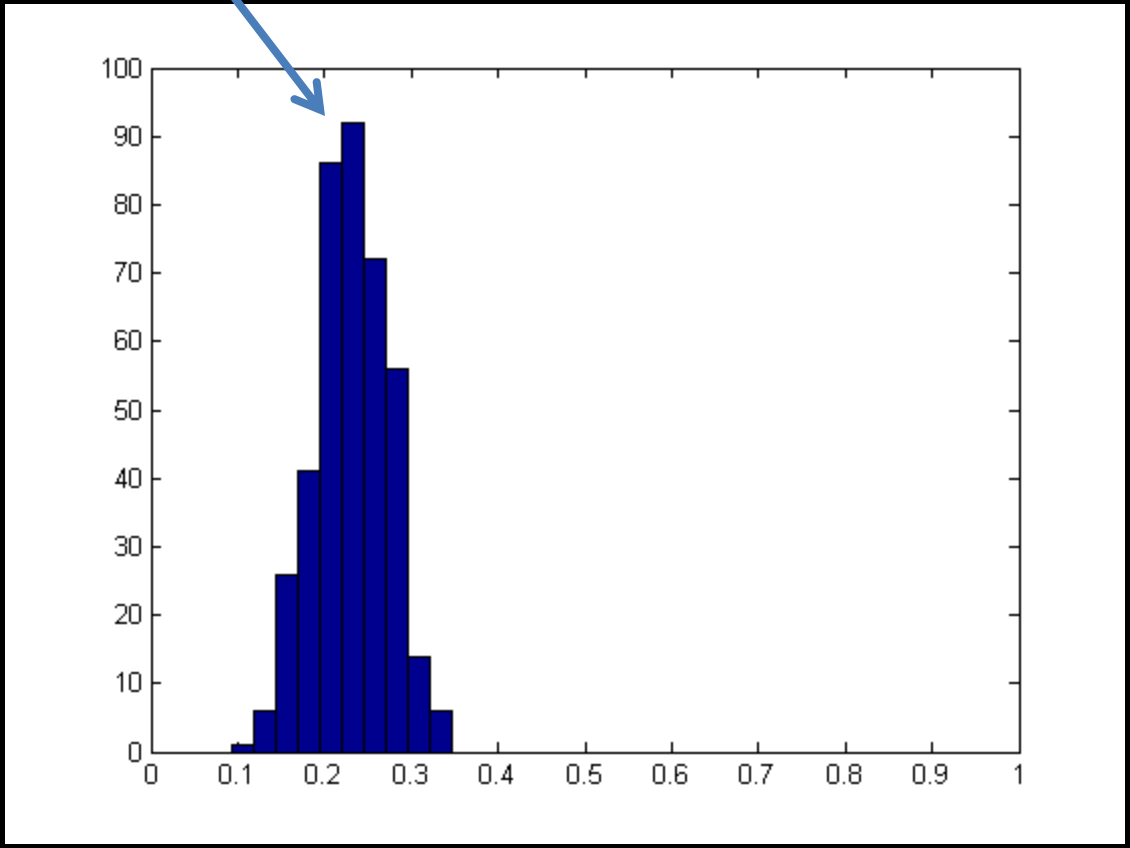
And inspect the distribution

Most probable pixel value



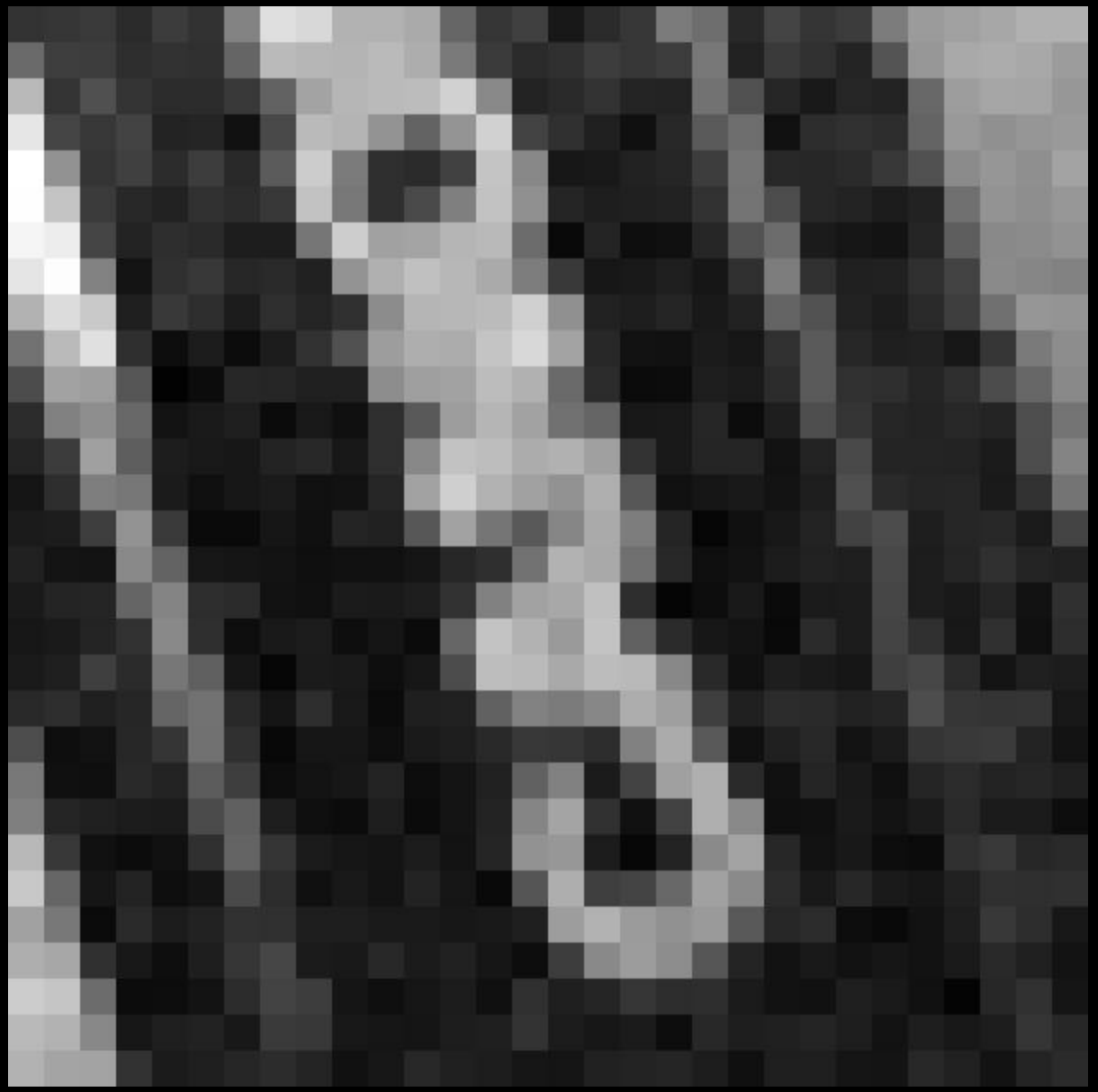
And inspect the distribution

mean = mode = median

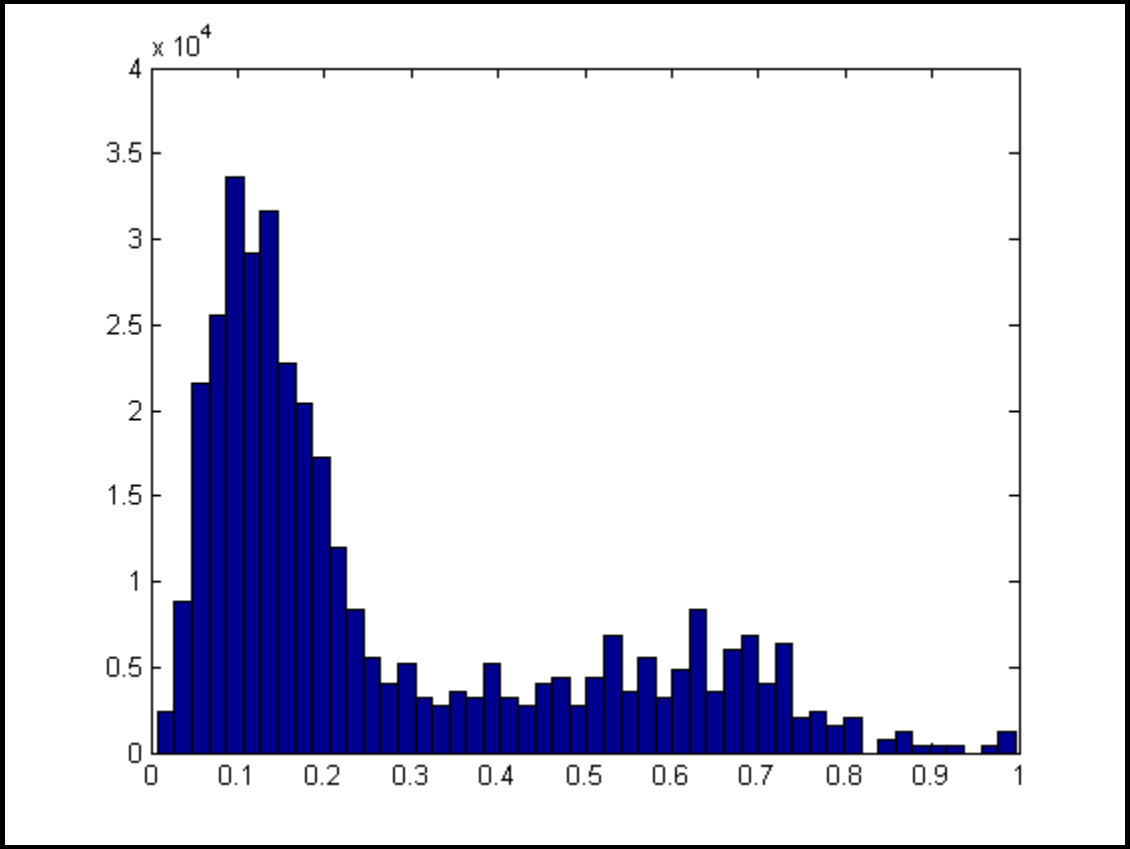


Denoising

Denoising



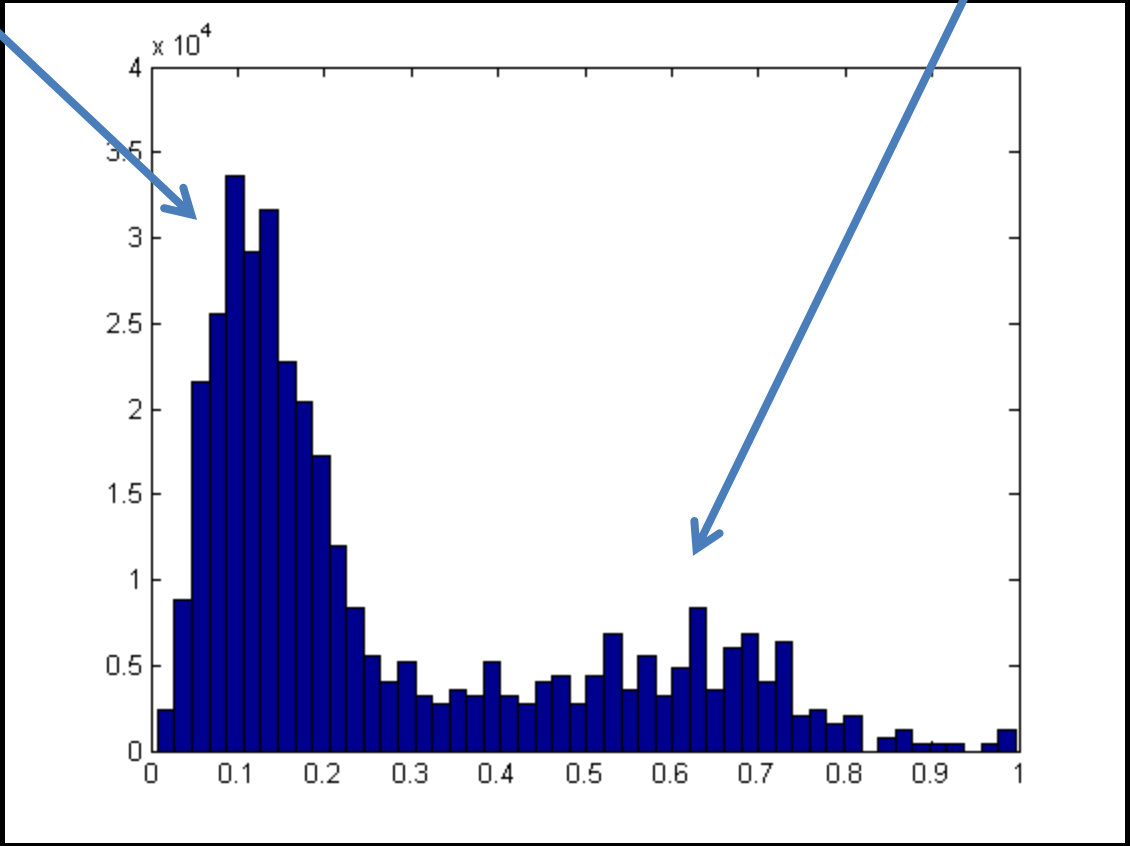
The distribution



The distribution

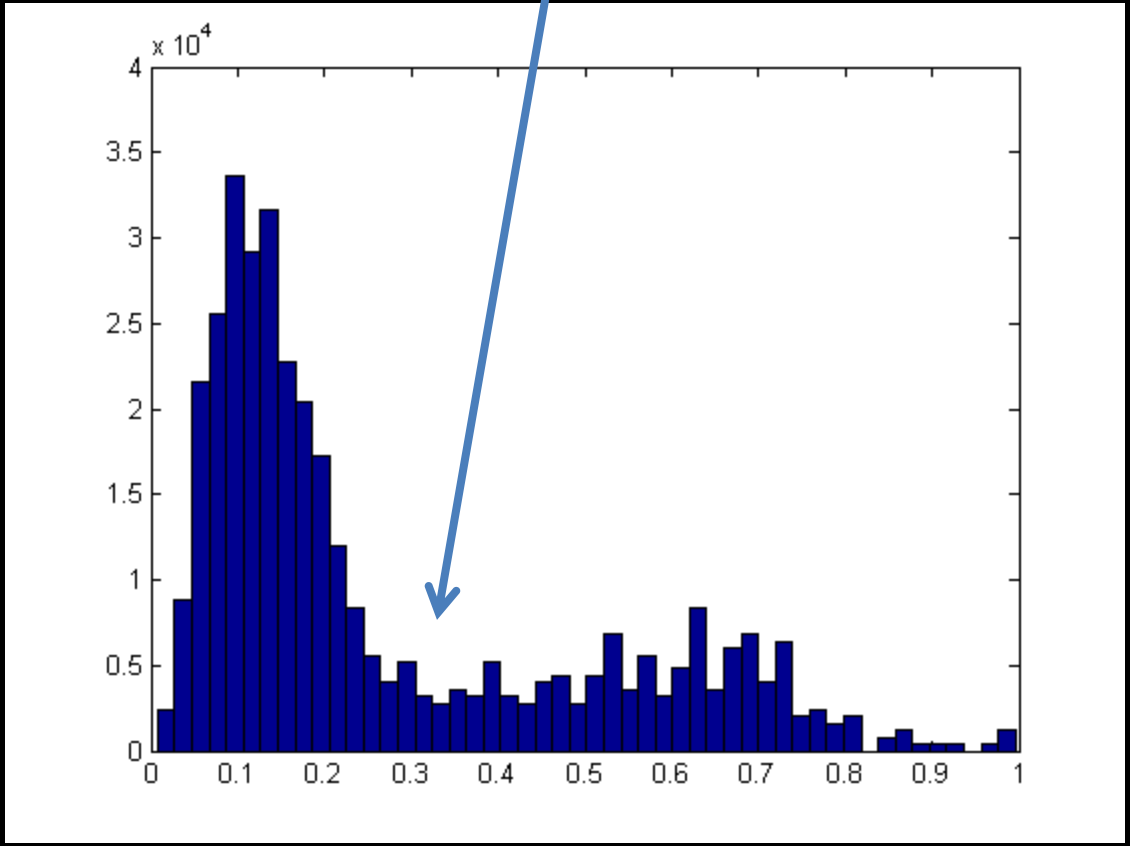
The background

The text



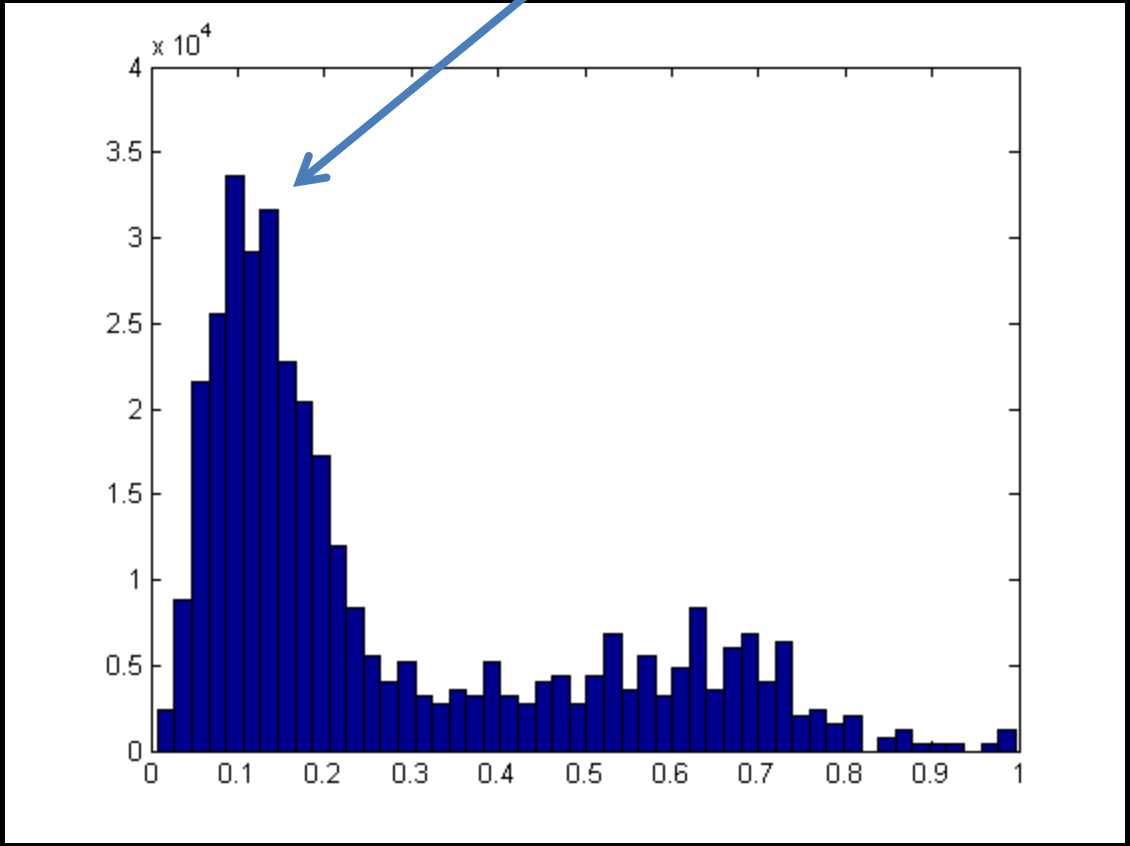
The distribution

The mean



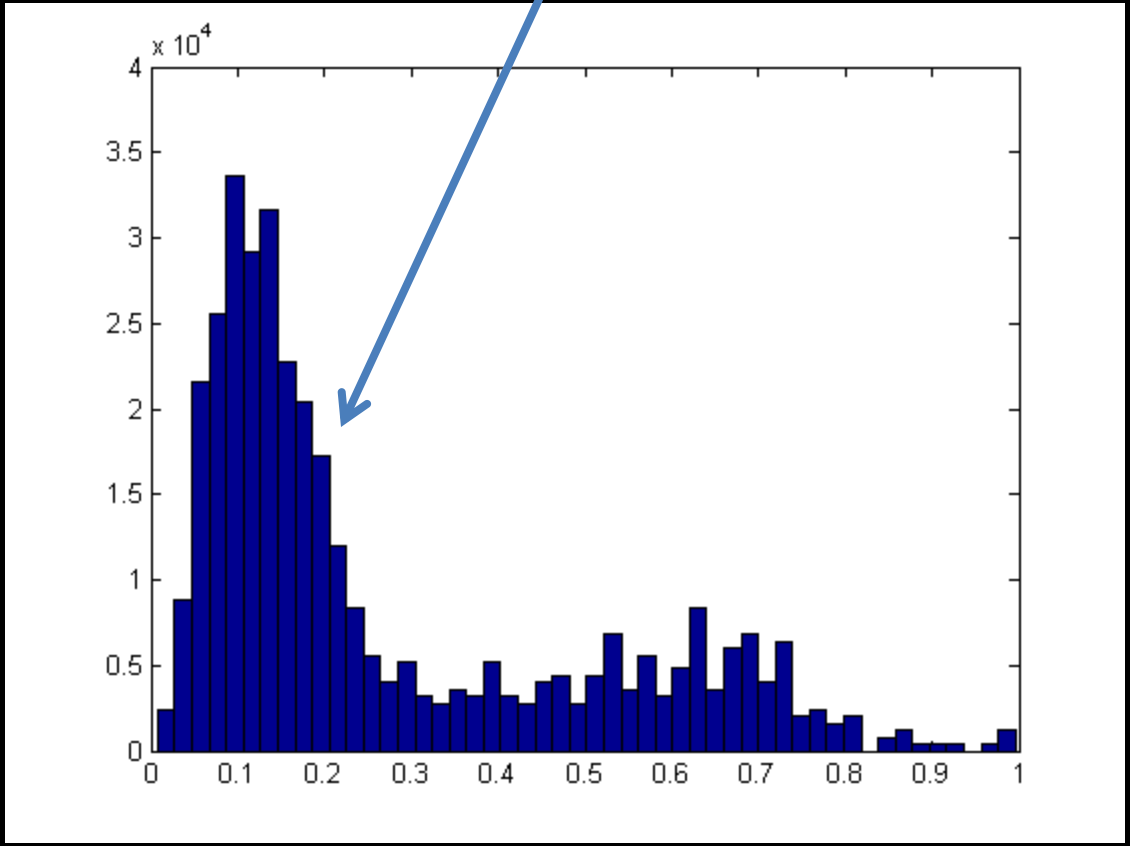
The distribution

The mode



The distribution

The median



Median Filters

- Replace each pixel with the median of its neighbours
- Great for getting rid of salt-and-pepper noise
- Removes small details

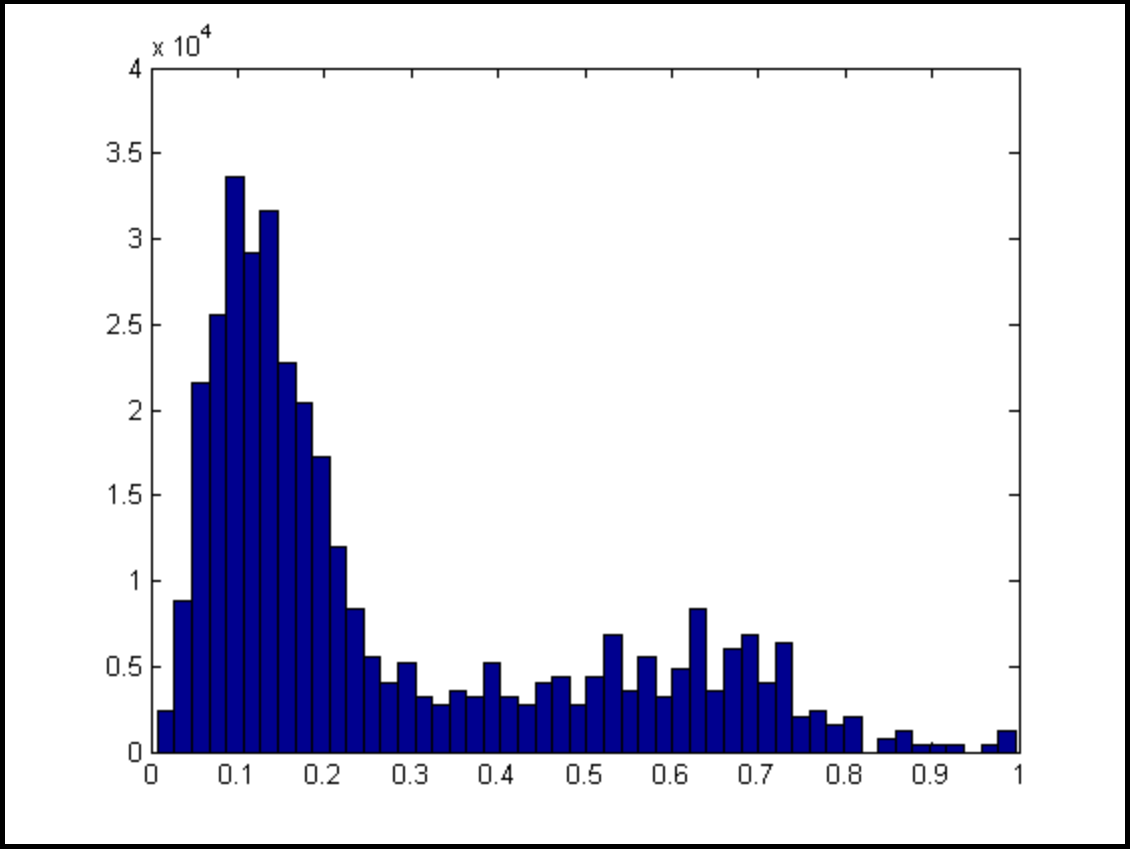
Before:

Gaussian Blur:

After Median Filter:

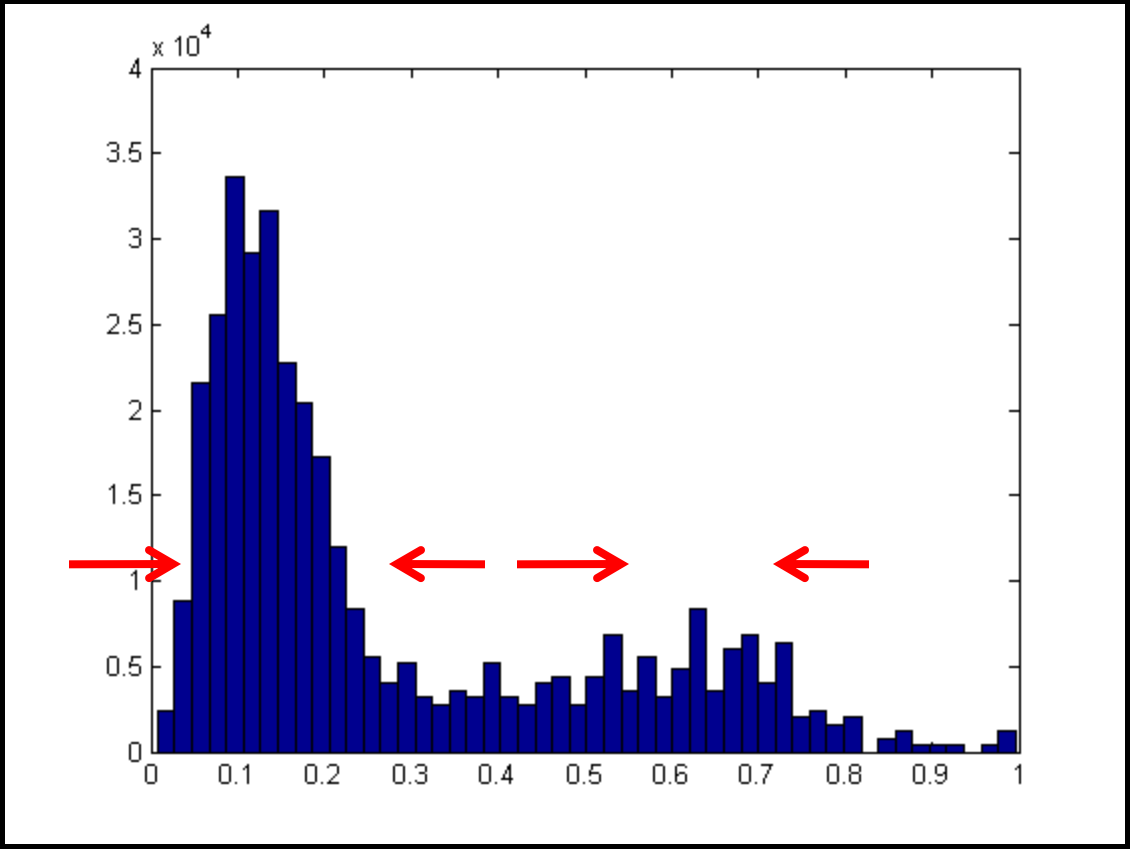
The distribution

- What is the most probable pixel value?



It depends on your current value

- The answer should vary for each pixel



An extra prior

- Method 1) Convolution
  - The pixel is probably looking at the same material as all of its neighbors, so we'll set it to the average of its neighbors.
- Method 2) Bilateral
  - The pixel is probably looking at the same material as SOME of its neighbors, so we'll set it to the average of those neighbors only.

The Bilateral Filter

- How do we select good neighbours?
- The ones with roughly similar brightnesses are probably looking at the same material.

$$Out(\vec{x}) = \frac{\sum_{\vec{x}'} w(\vec{x}, \vec{x}') I(\vec{x}')}{\sum_{\vec{x}'} w(\vec{x}, \vec{x}')}$$

$$w(\vec{x}, \vec{x}') = e^{-|I(\vec{x}')-I(\vec{x})|^2/2\alpha} \cdot e^{-|\vec{x}'-\vec{x}|^2/2\beta}$$

Before:

Gaussian Blur:

After Median Filter:

After Bilateral:

Dealing with Color

- It turns out humans are only sensitive to high frequencies in brightness
  - not in hue or saturation
- So we can blur in chrominance much more than luminance

Chroma Blurring

- 1) Convert RGB to LAB
  - L is luminance, AB are chrominance (hue and saturation)
- 2) Perform a small bilateral in L
- 3) Perform a large bilateral in AB
- 4) Convert back to RGB

Before:

After Regular Bilateral:

After Modified Bilateral:

Method Noise (Gaussian)

Method Noise (Bilateral)

Leveraging Similarity: Non-Local Means

What color should this pixel be?

What color should this pixel be?

Gaussian Blur:
A weighted average of these:

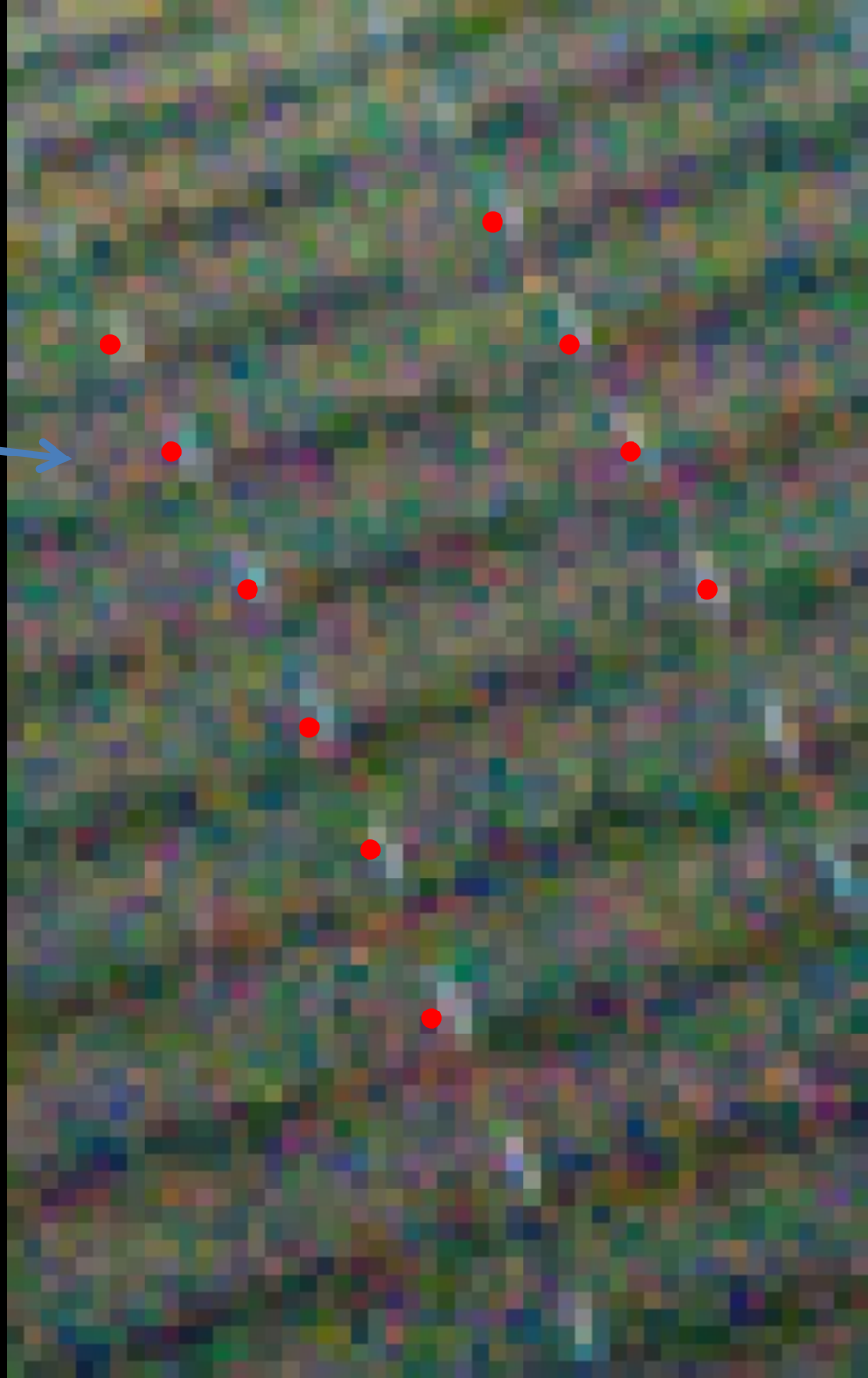
(all nearby pixels)

Bilateral filter
A weighted average of these:

(the nearby ones that have a similar color to me)

Non-Local Means
A weighted average of these:

(the ones that have similar neighbors to me)



Non-Local Means:

- For each pixel
  - Find every other (nearby) pixel that has a similar local neighborhood around it to me
  - Set my value to be the weighted average of those

$$Out(\vec{x}) = \frac{\sum_{\vec{x}'} w(\vec{x}, \vec{x}') I(\vec{x}')}{\sum_{\vec{x}'} w(\vec{x}, \vec{x}')}$$

$$w(\vec{x}, \vec{x}') = e^{-|P(\vec{x}') - P(\vec{x})|^2 / 2\alpha} \cdot e^{-|\vec{x}' - \vec{x}|^2 / 2\beta}$$

Before:

Gaussian Blur:

After Median Filter:

After Bilateral:

After Non-Local Means:

Before:

Method Noise (Gaussian)

Method Noise (Bilateral)

Method Noise (Non-Local Means)

Run-Times: Rect Filter

- For every pixel:
  - For every other nearby pixel:
    - Do a multiply and add

Run-Times: Gaussian Blur

- For every pixel:
  - For every other nearby pixel:
    - Compute a distance-based weight
      - (can be precomputed)
    - Do a multiply and add

Run-Times: Median Filter

- For every pixel:
  - For every other nearby pixel:
    - Add into a histogram
  - Compute the median of the histogram

Run-Times: Bilateral

- For every pixel:
  - For every other nearby pixel:
    - Compute a similarity weight
    - Compute a distance-based weight
      - (can be precomputed)
    - Do a multiply and add

Run-Times: Non-Local Means

- For every pixel x:
  - For every other nearby pixel y:
    - Compute a distance weight
    - Compute a similarity weight:
    - For every pixel z in a patch around y
      - Compare z to the corresponding pixel in the patch around x
      - Add to the similarity term
    - Multiply and add

These methods are all fairly useless for large filter sizes

- ... unless you can speed them up