Lecture 11: Texture

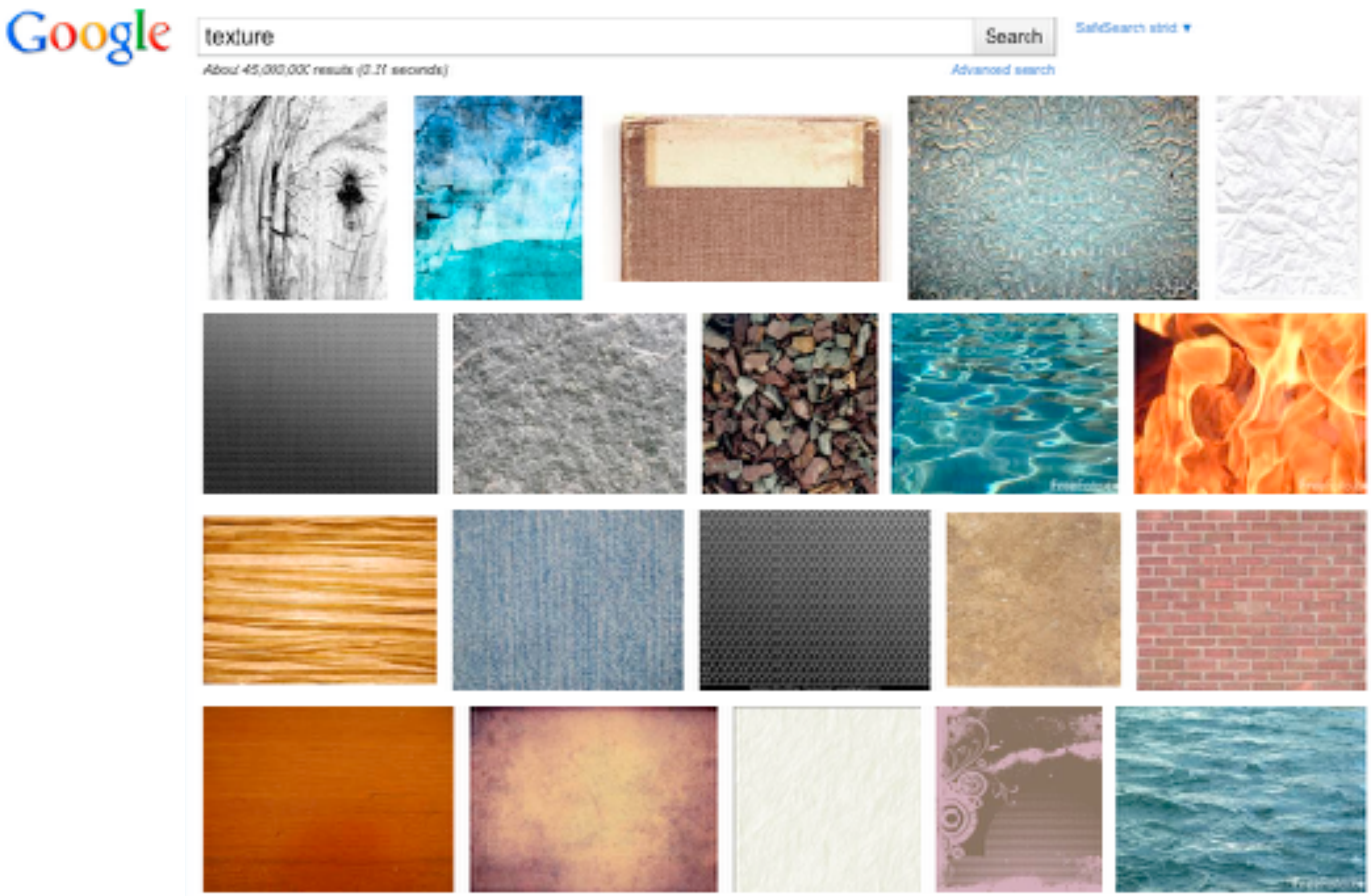
COS 429: Computer Vision

PRINCETON UNIVERSITY

Acknowledgment: slides from Antonio Torralba, Kristen Grauman, Jitendra Malik, Alyosha Efros, Tom Funkhouser, Szymon Rusinkiewicz

Texture

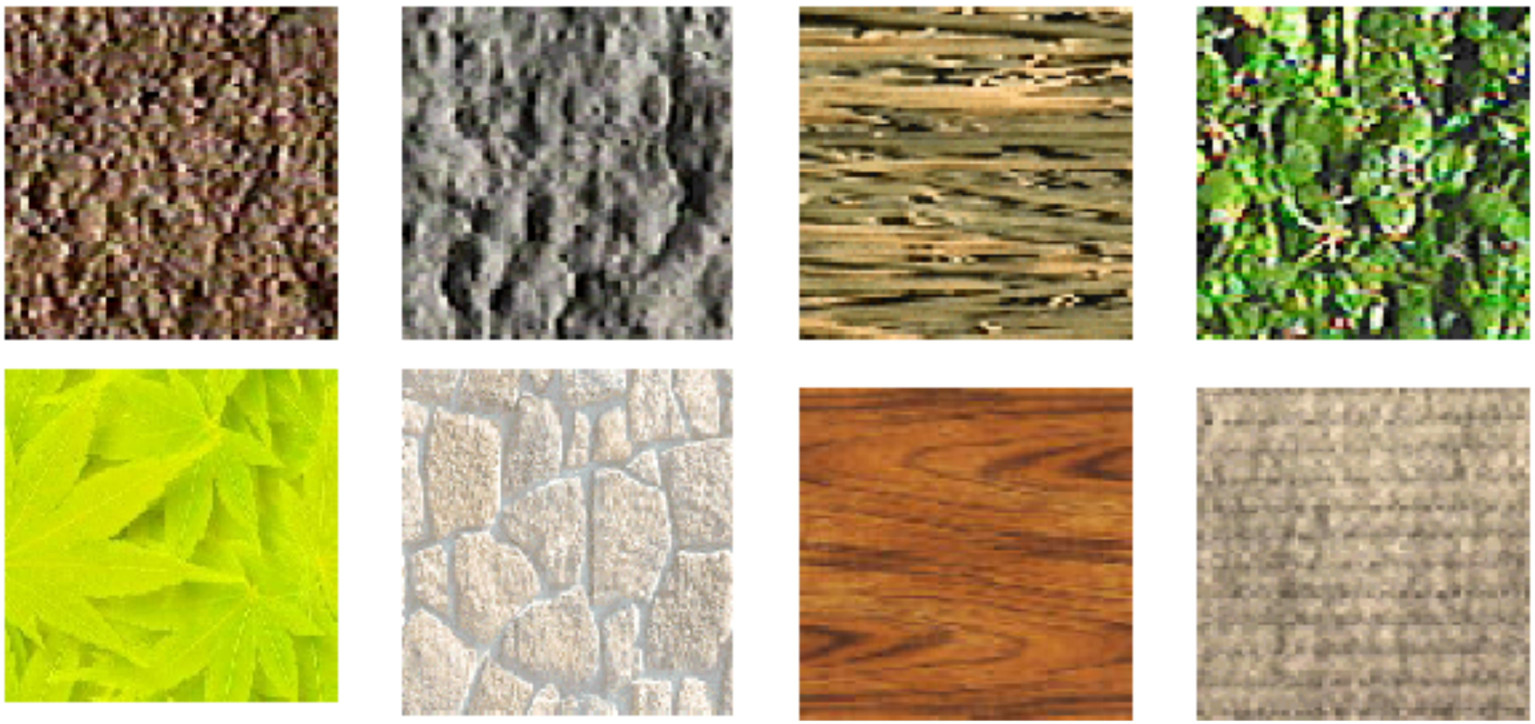
What is a texture?



Torralba

Texture

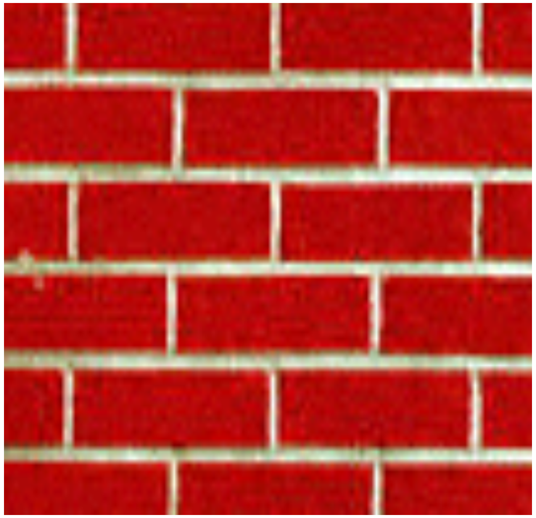
What is a texture?

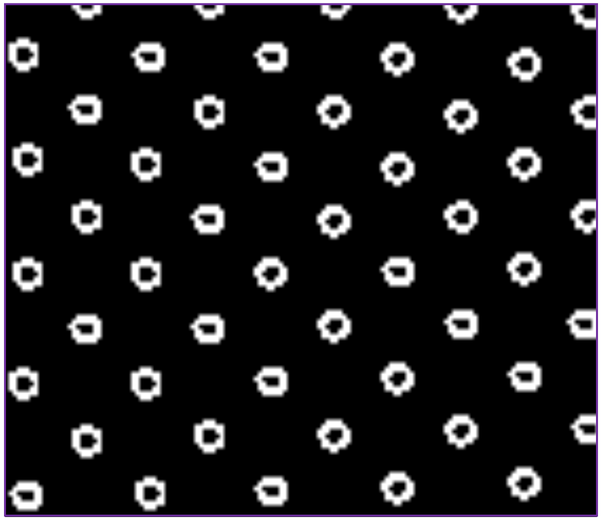


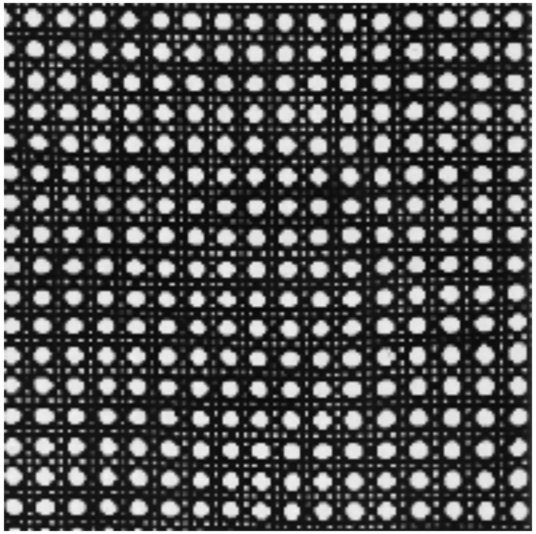
Torralba

Texture

What is a texture?

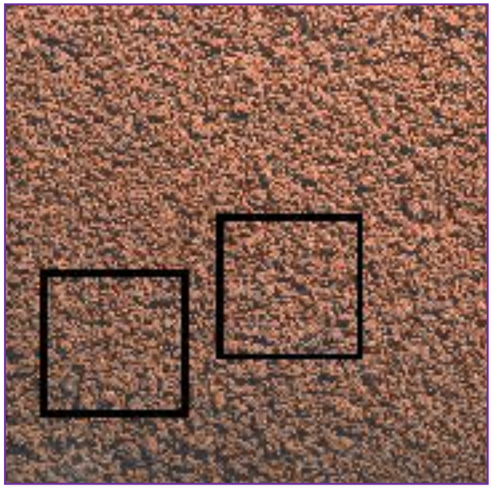






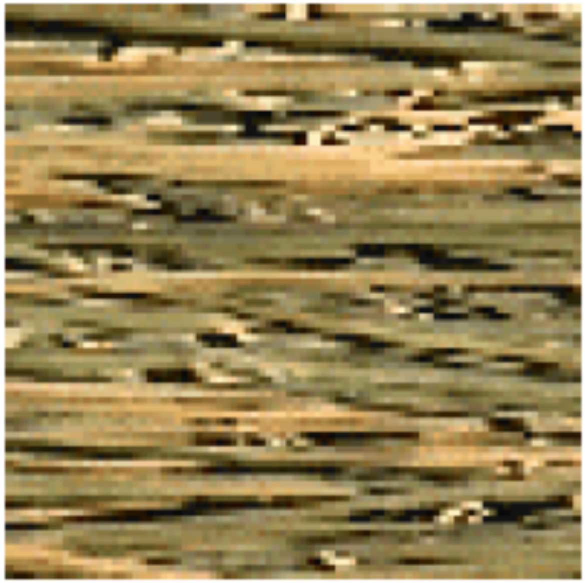
Texture

- Texture: stochastic pattern that is stationary ("looks the same" at all locations)
- May be structured or random



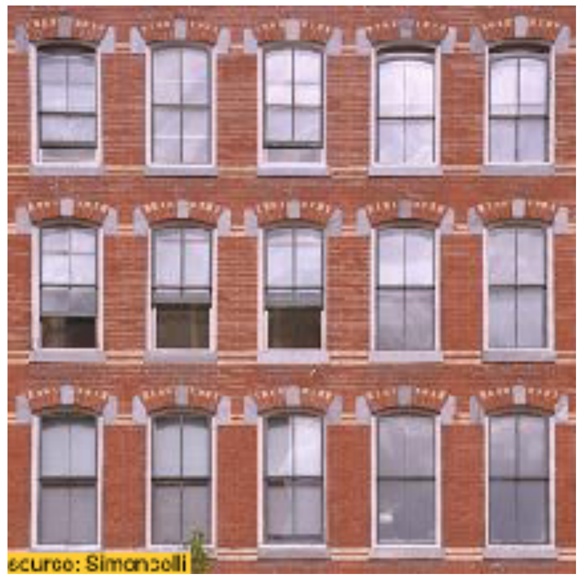
Wei & Levoy

Texture



Stochastic Stationary

Texture



Stochastic Stationary

Goal

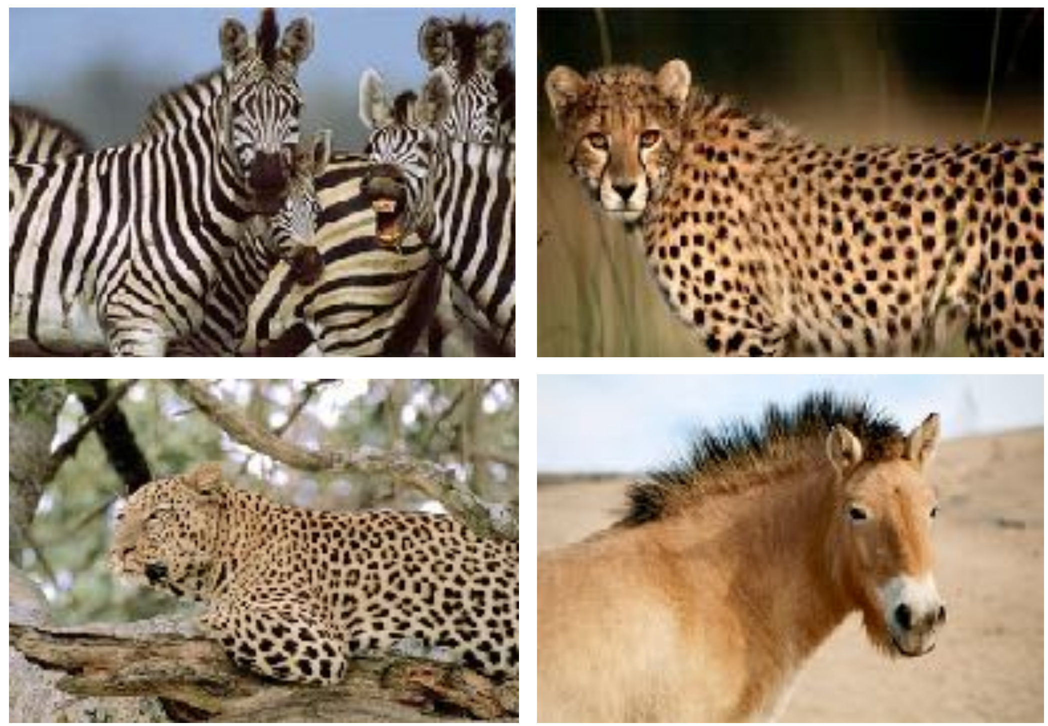
- Computational representation of texture
  - Textures generated by same stationary stochastic process have same representation
  - Perceptually similar textures have similar representations

5, 7, 34, 2, 199, 12

Hypothetical texture representation

Applications

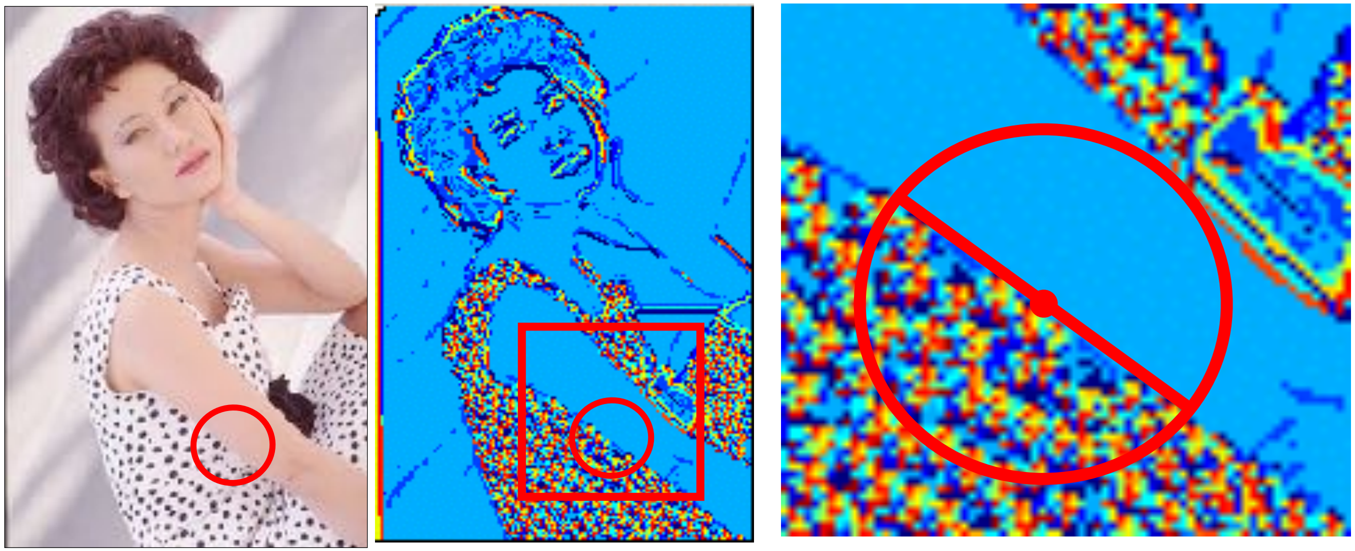
- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



http://animals.nationalgeographic.com/

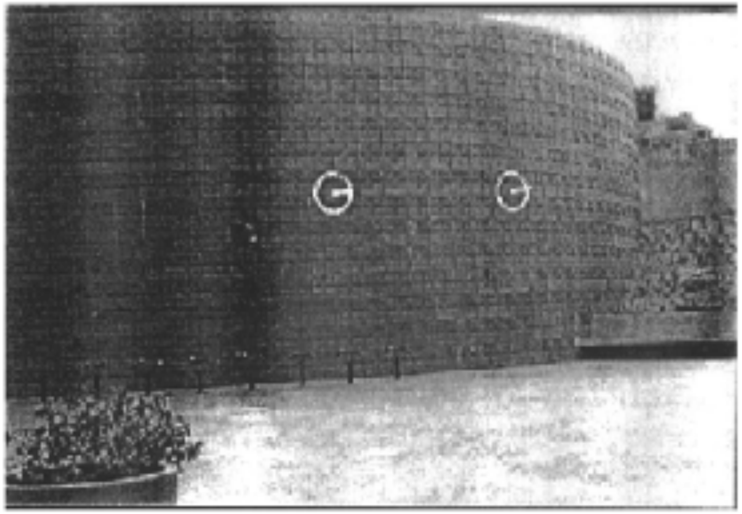
Applications

- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



Applications

- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



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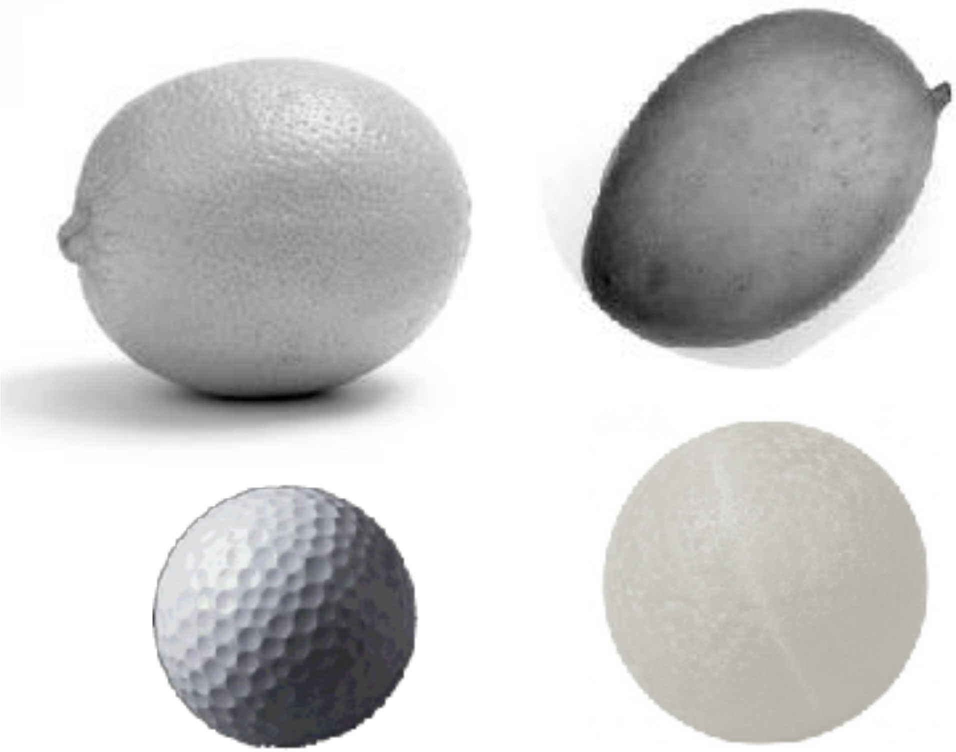
Applications

- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



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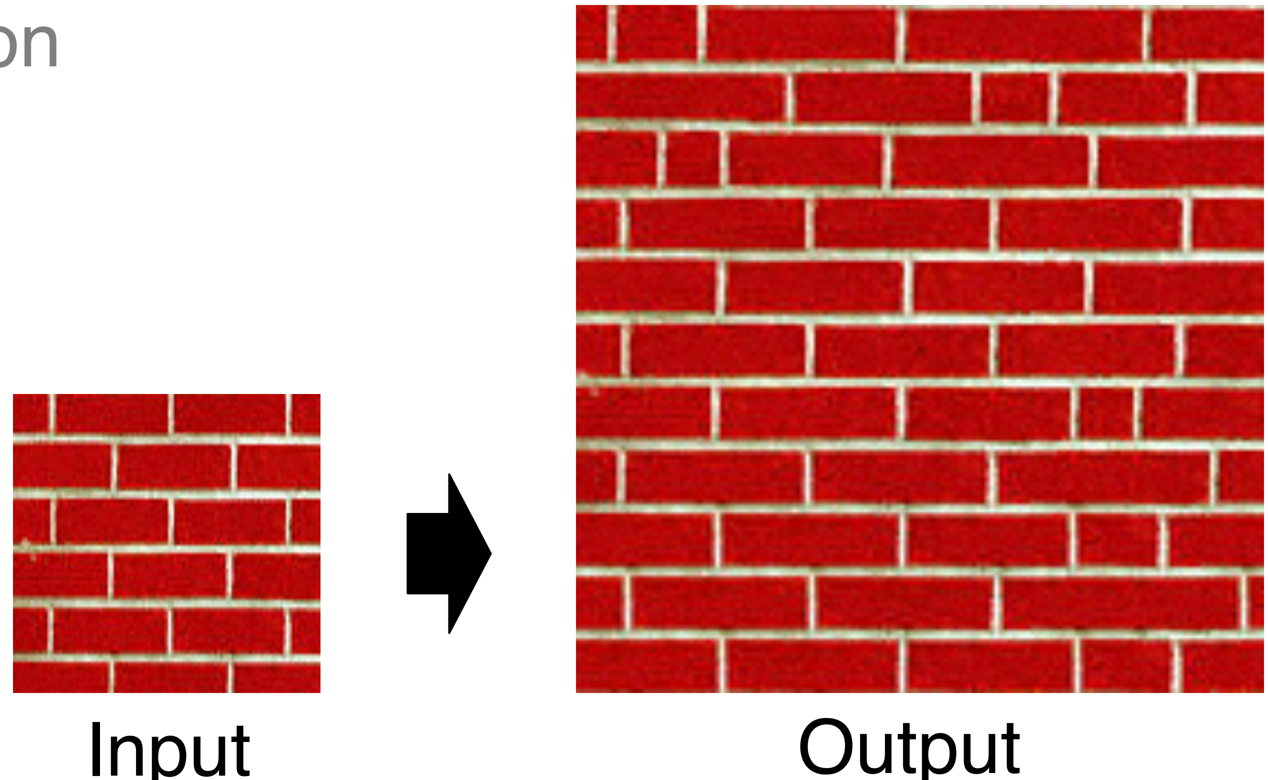
Applications

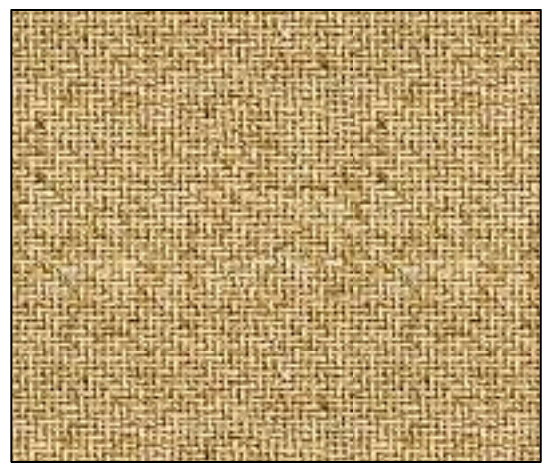
- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



Efros

Texture Representation?

- What makes a good texture representation?
  - Textures generated by same stationary stochastic process have same representation
  - Perceptually similar textures have similar representations



Statistics of filter banks

Filter-Based Texture Representation

- Research suggests that the human visual system performs local spatial frequency analysis (Gabor filters)

J. J. Kulikowski, S. Marcelja, and P. Bishop.
Theory of spatial position and spatial frequency relations in the receptive fields of simple cells in the visual cortex.
Biol. Cybern, 43:187-198, 1982.

Texture Representation

- Analyze textures based on the responses of linear filters
  - Use filters that look like patterns (spots, edges, bars, …)
  - Compute magnitudes of filter responses
- Represent textures with statistics of filter responses within local windows
  - Histogram of feature responses for all pixels in window

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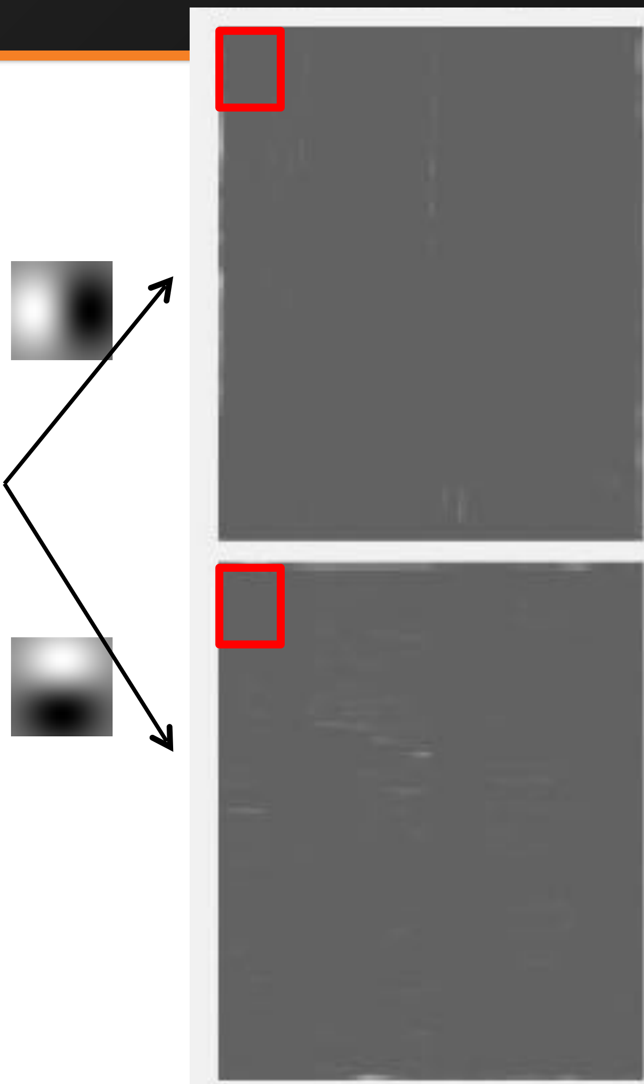
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	mean d/dy value
Win. #1	4	10

⋮

statistics to summarize patterns in small windows

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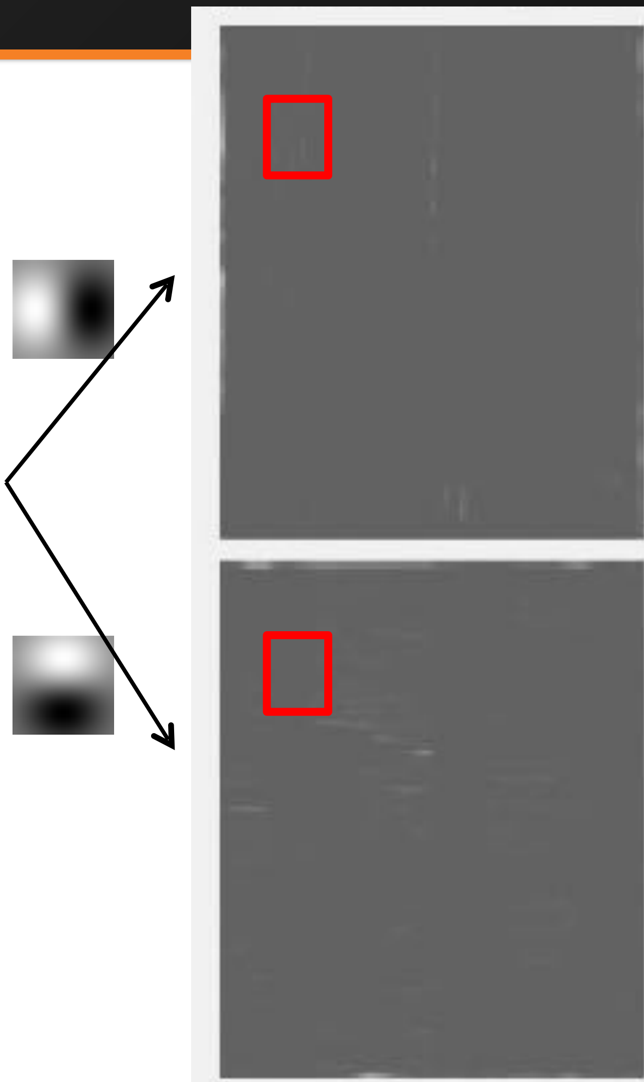
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7

⋮

statistics to summarize patterns in small windows

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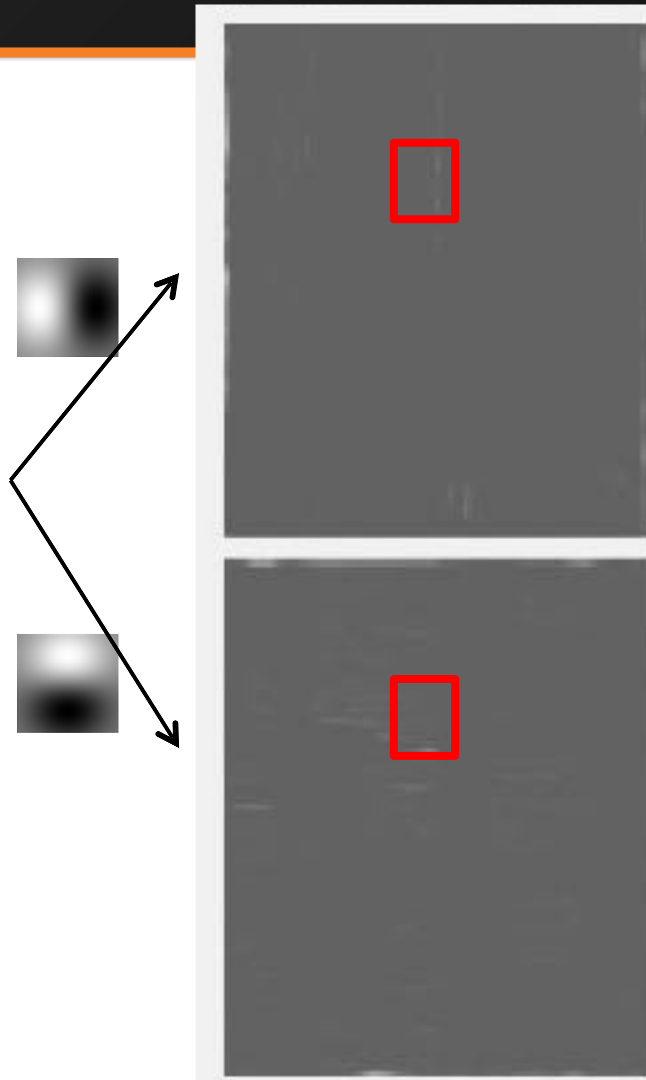
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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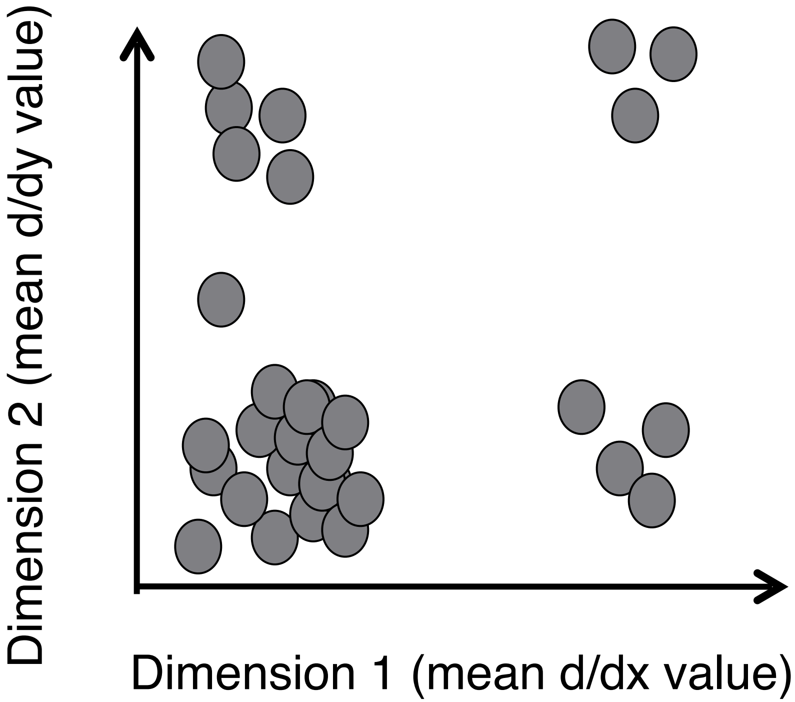
Texture Representation Example



	mean d/dx value	**mean d/dy value**
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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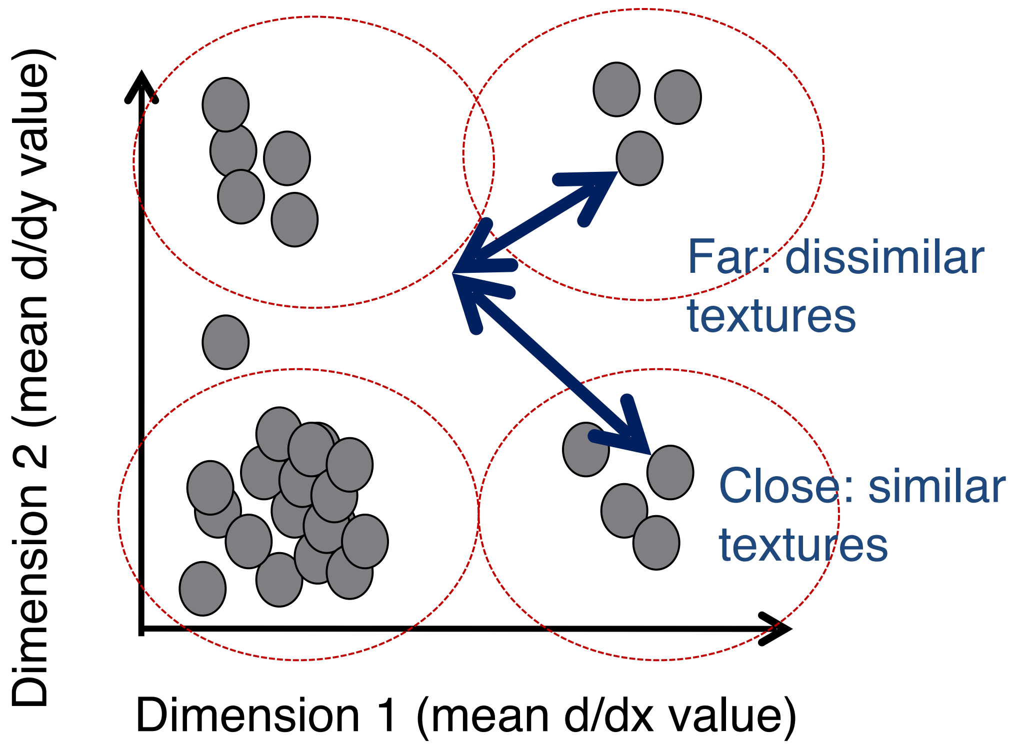
Texture Representation Example



	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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Filter Banks

- Previous example used two filters, resulting in 2-dimensional feature vector
  - x and y derivatives revealed local structure
- Filter bank: many filters
  - Higher-dimensional feature space
  - Distance still related to similarity of local structure

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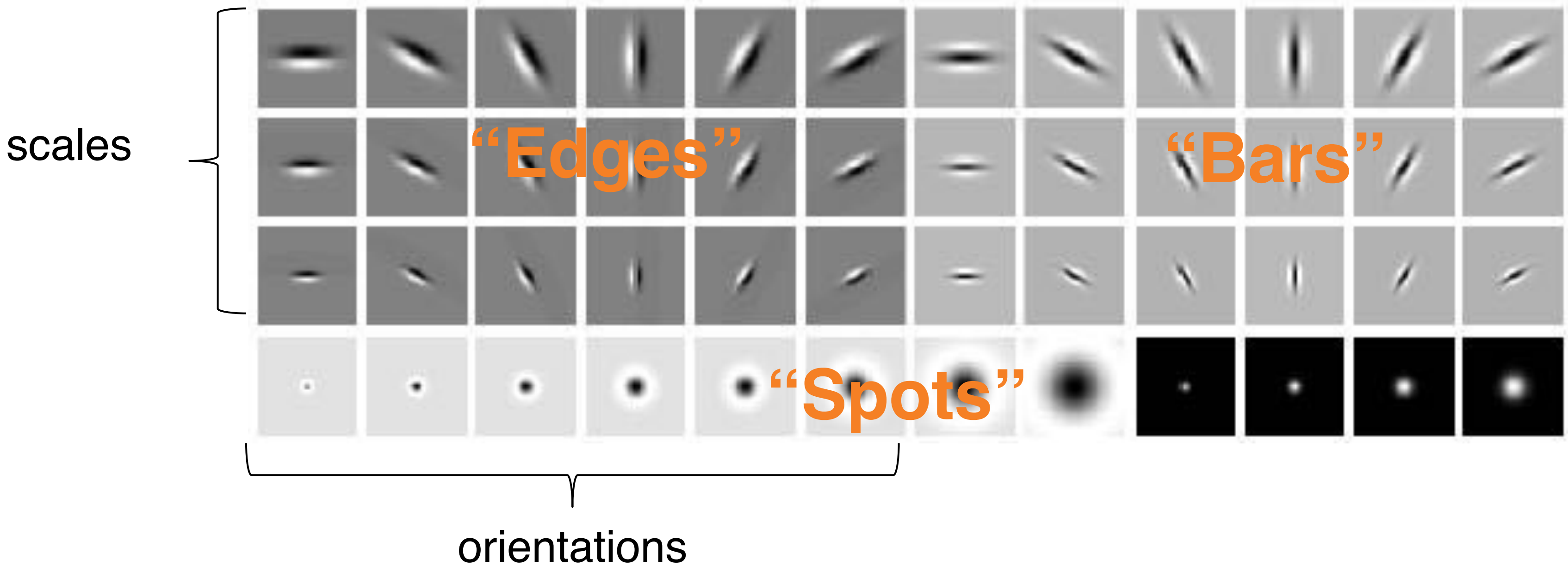
Filter banks



- What filters to put in the bank?
  - Combination of different scales, orientations, patterns

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Image from http://www.texasexplorer.com/austincap2.jpg

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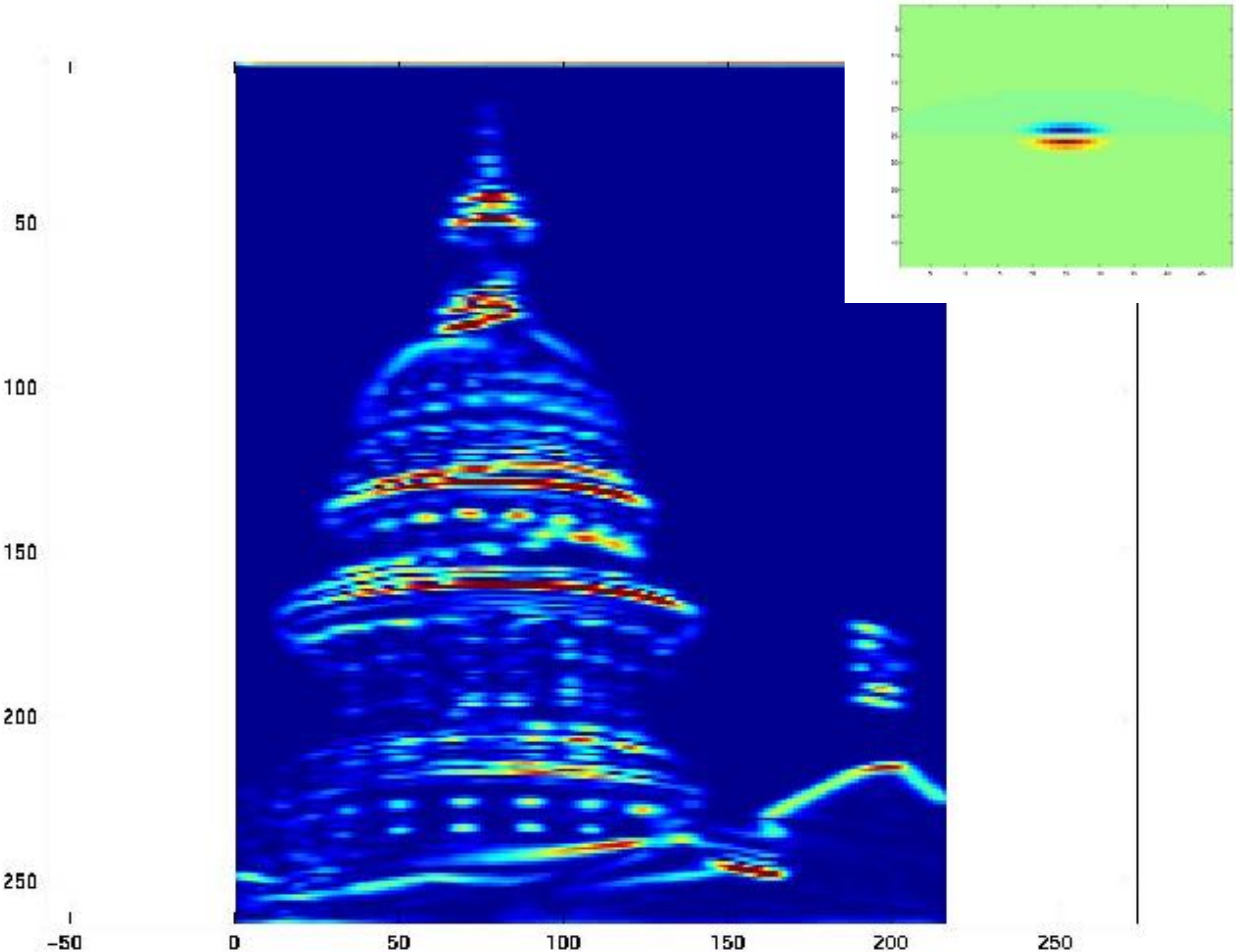

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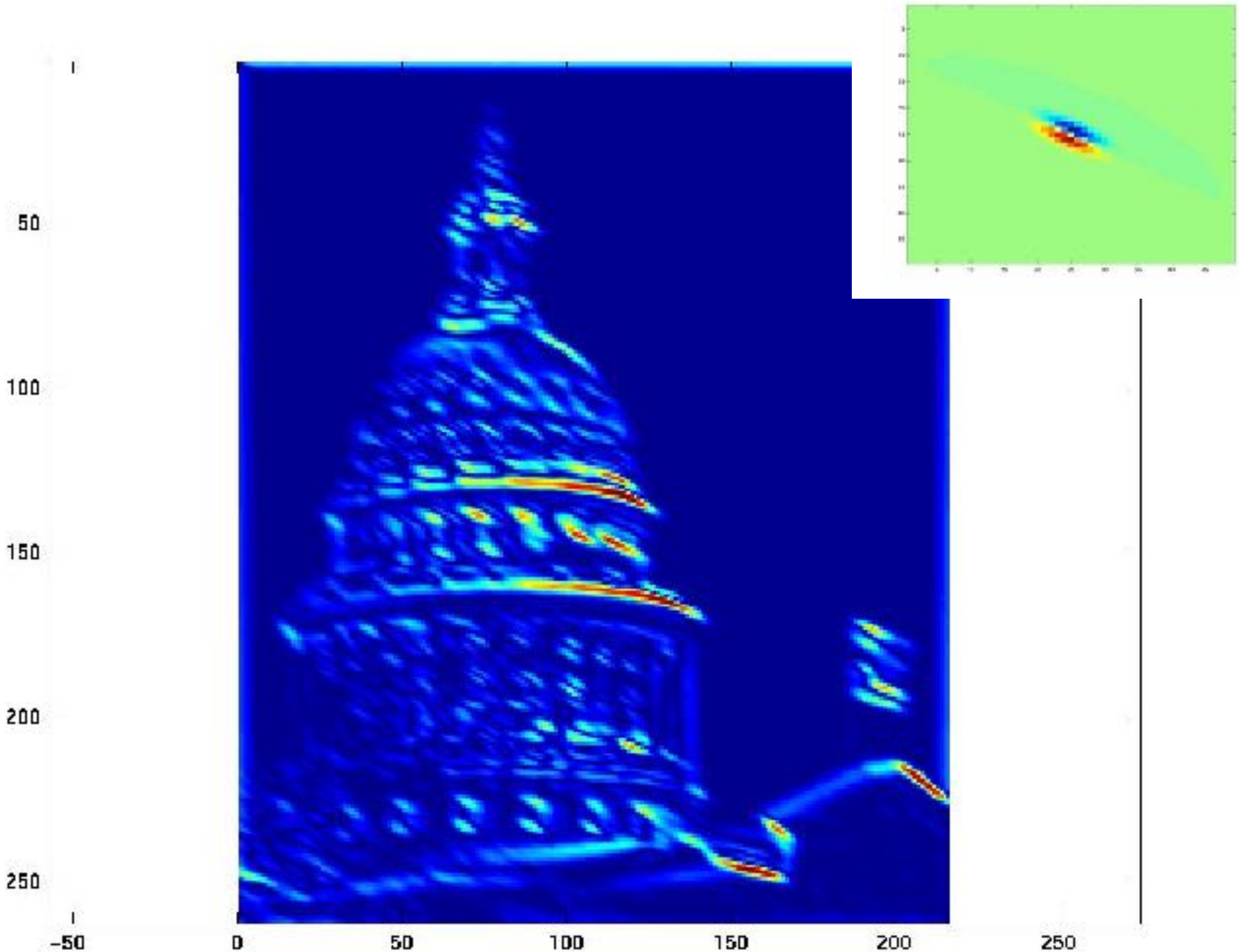

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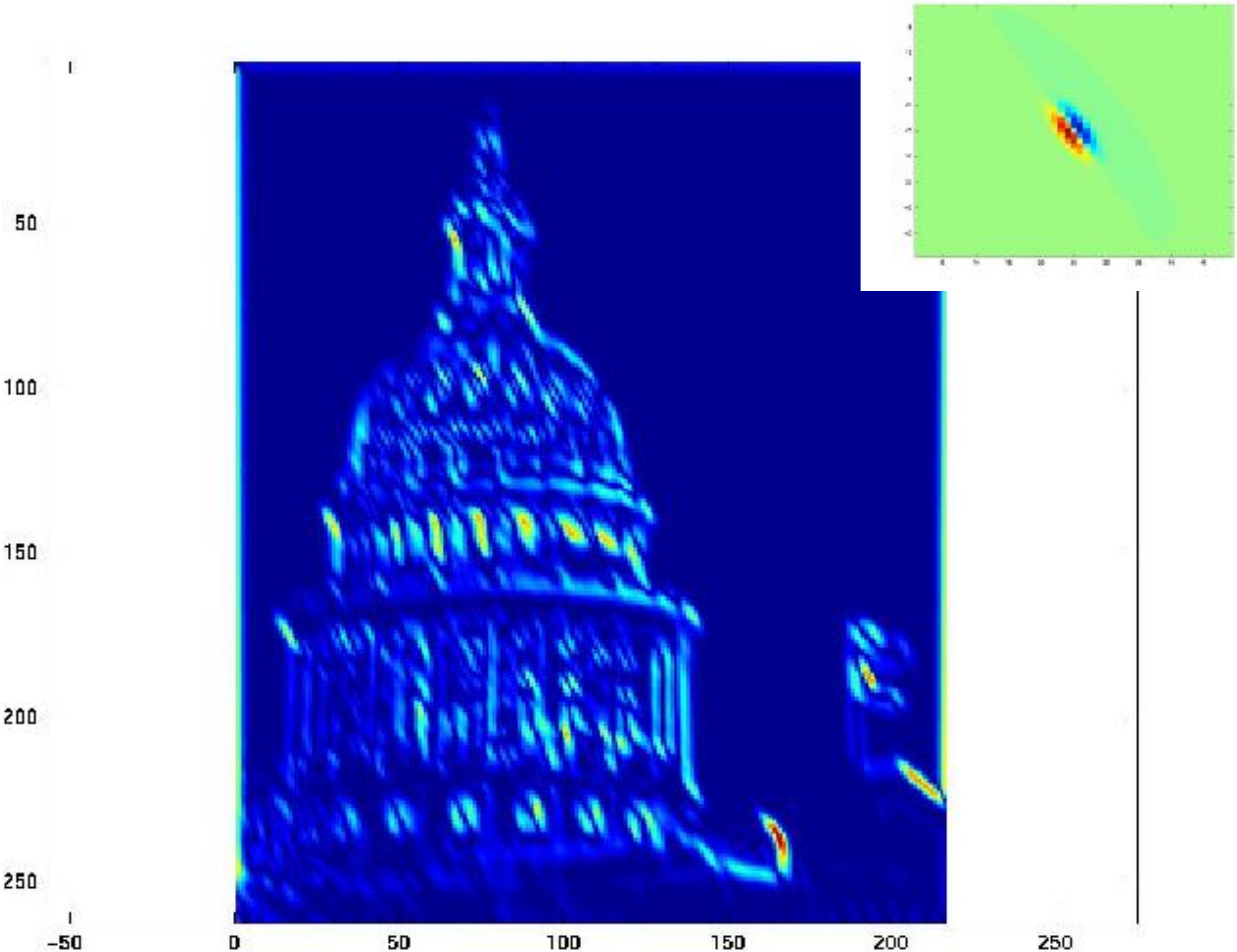

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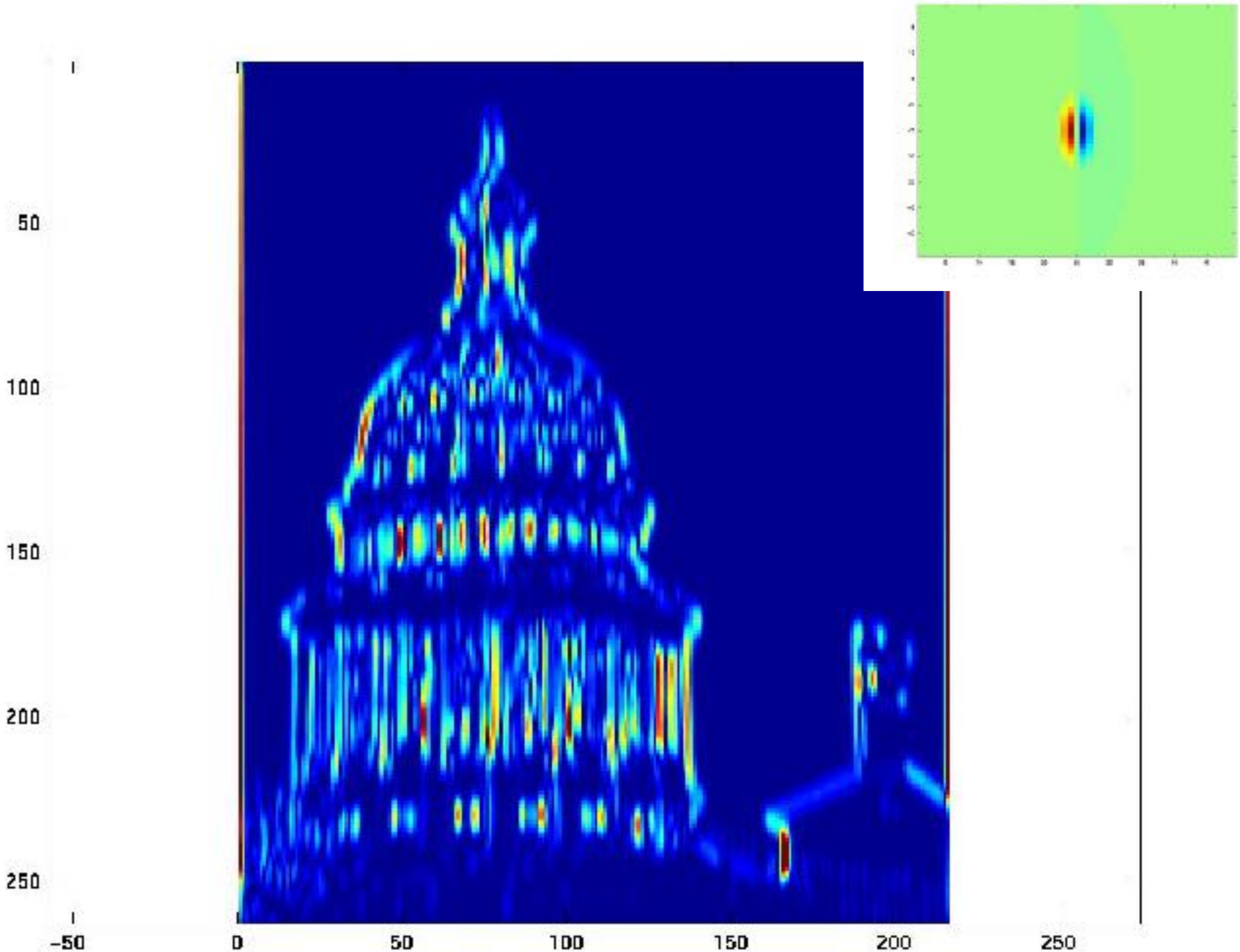

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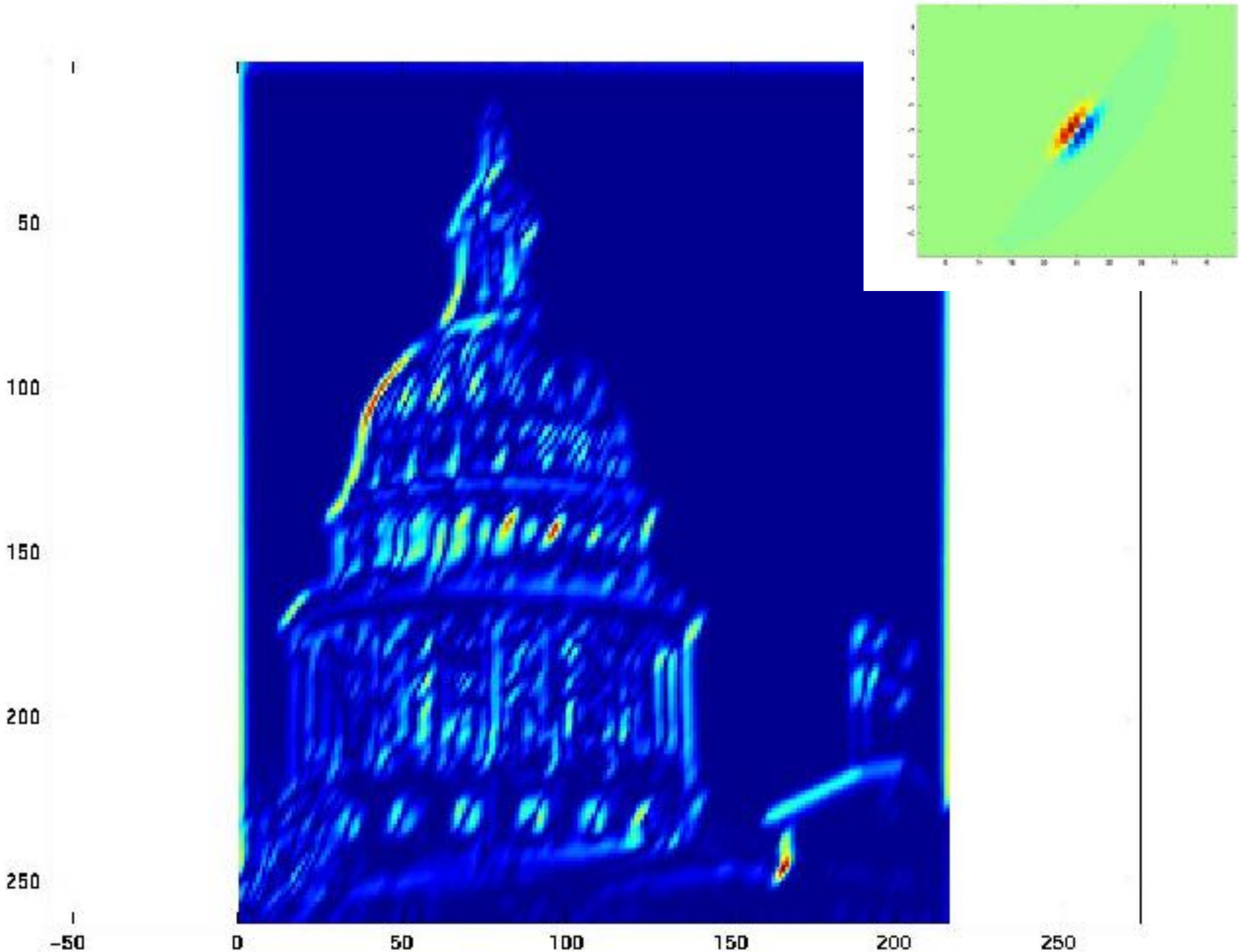

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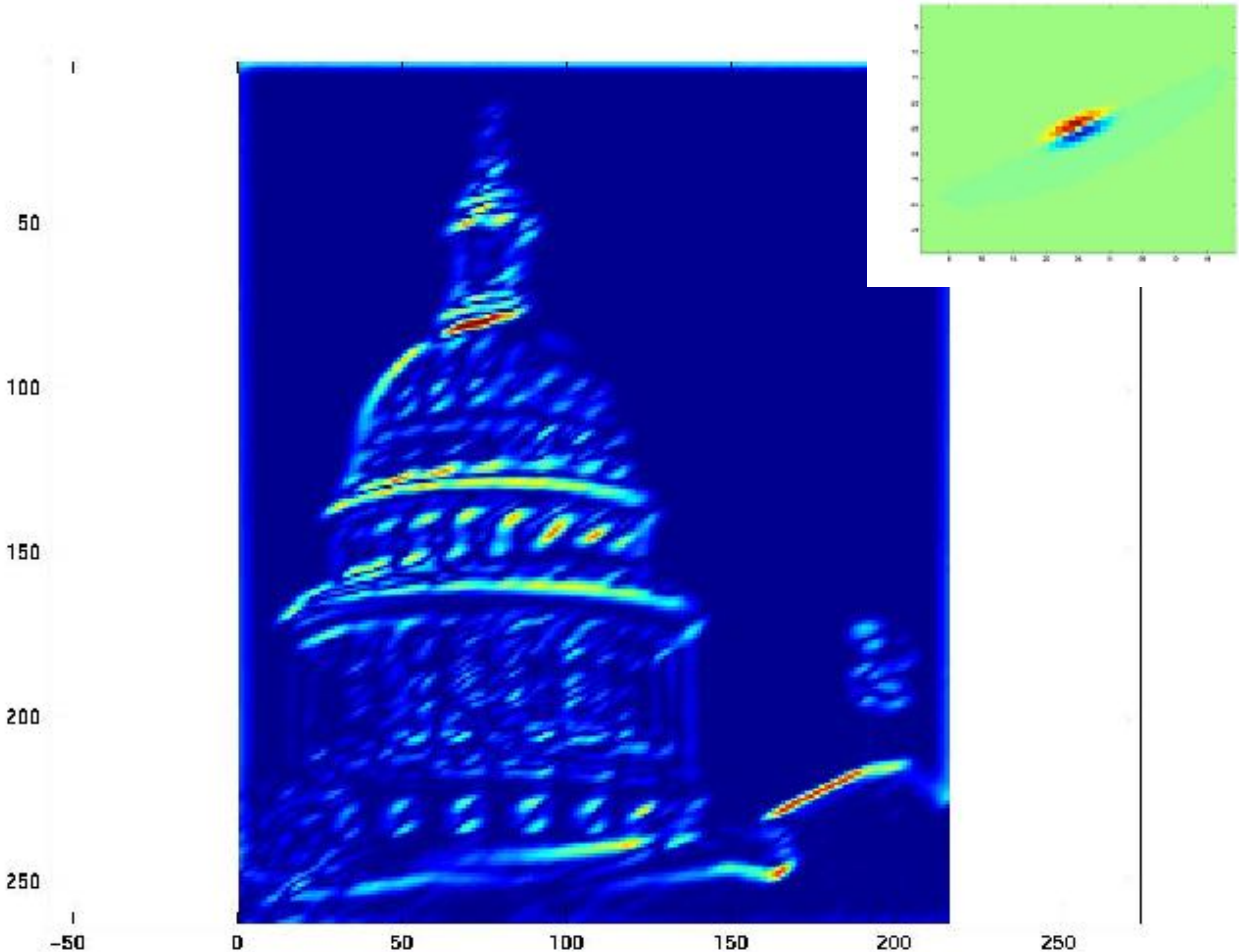

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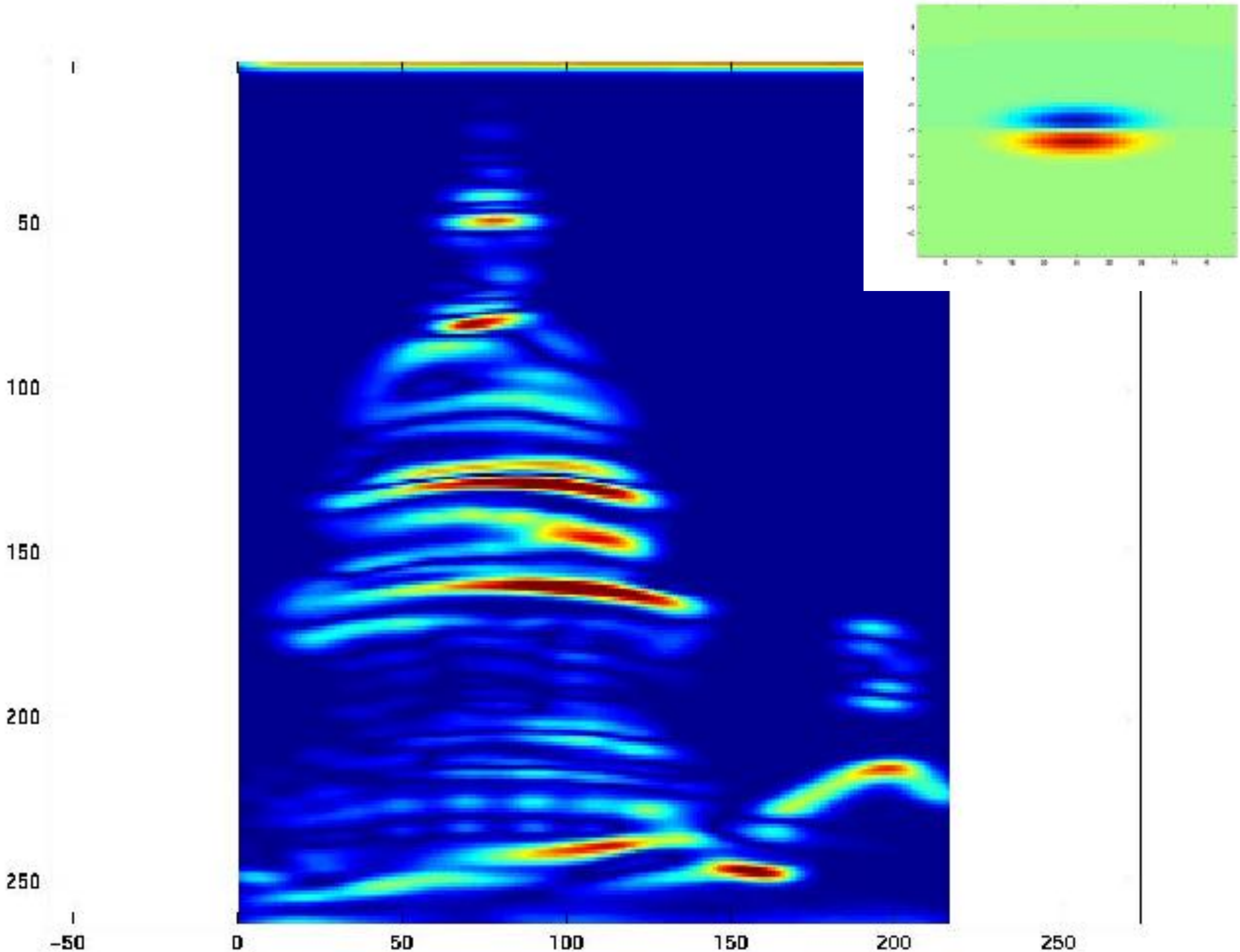

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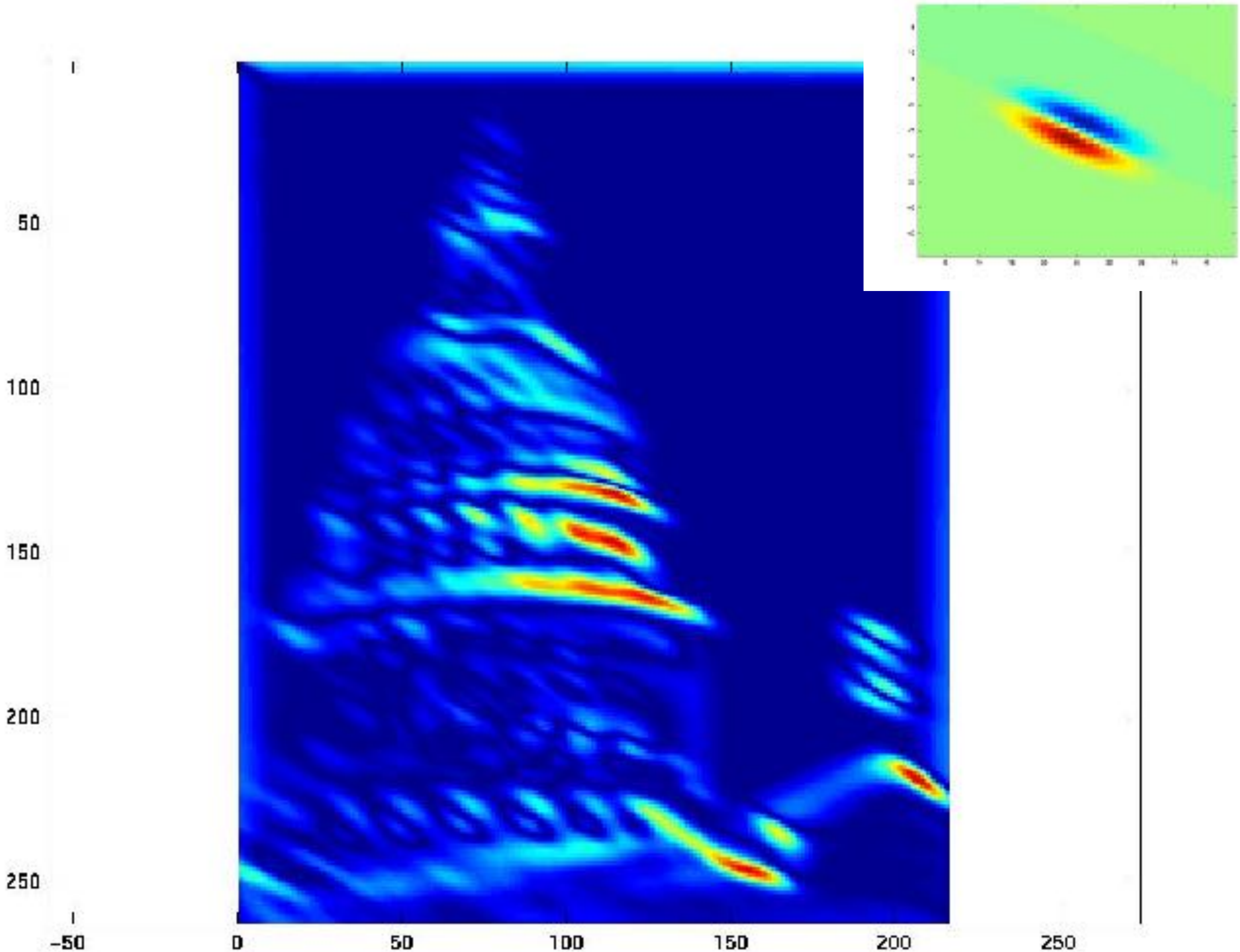

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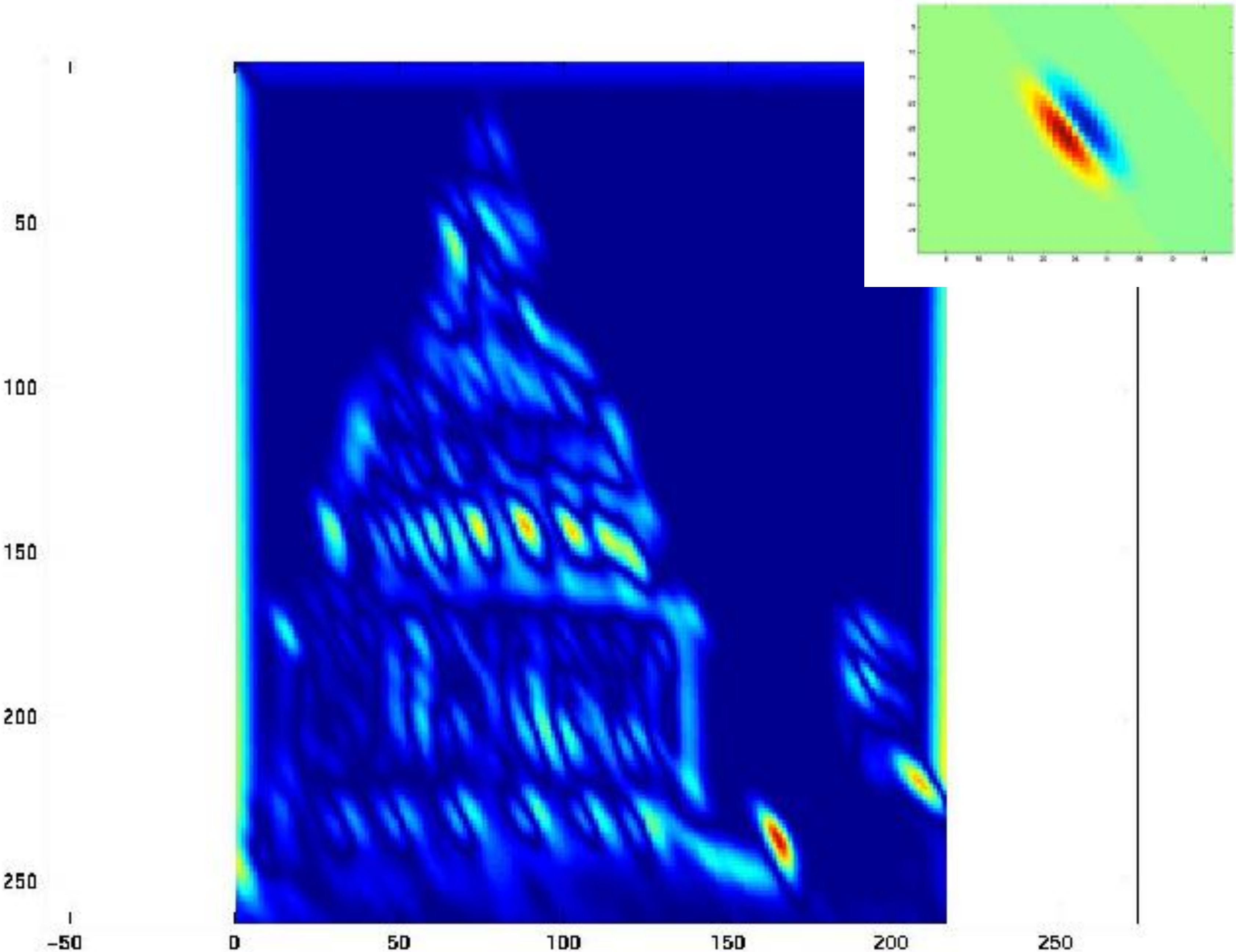

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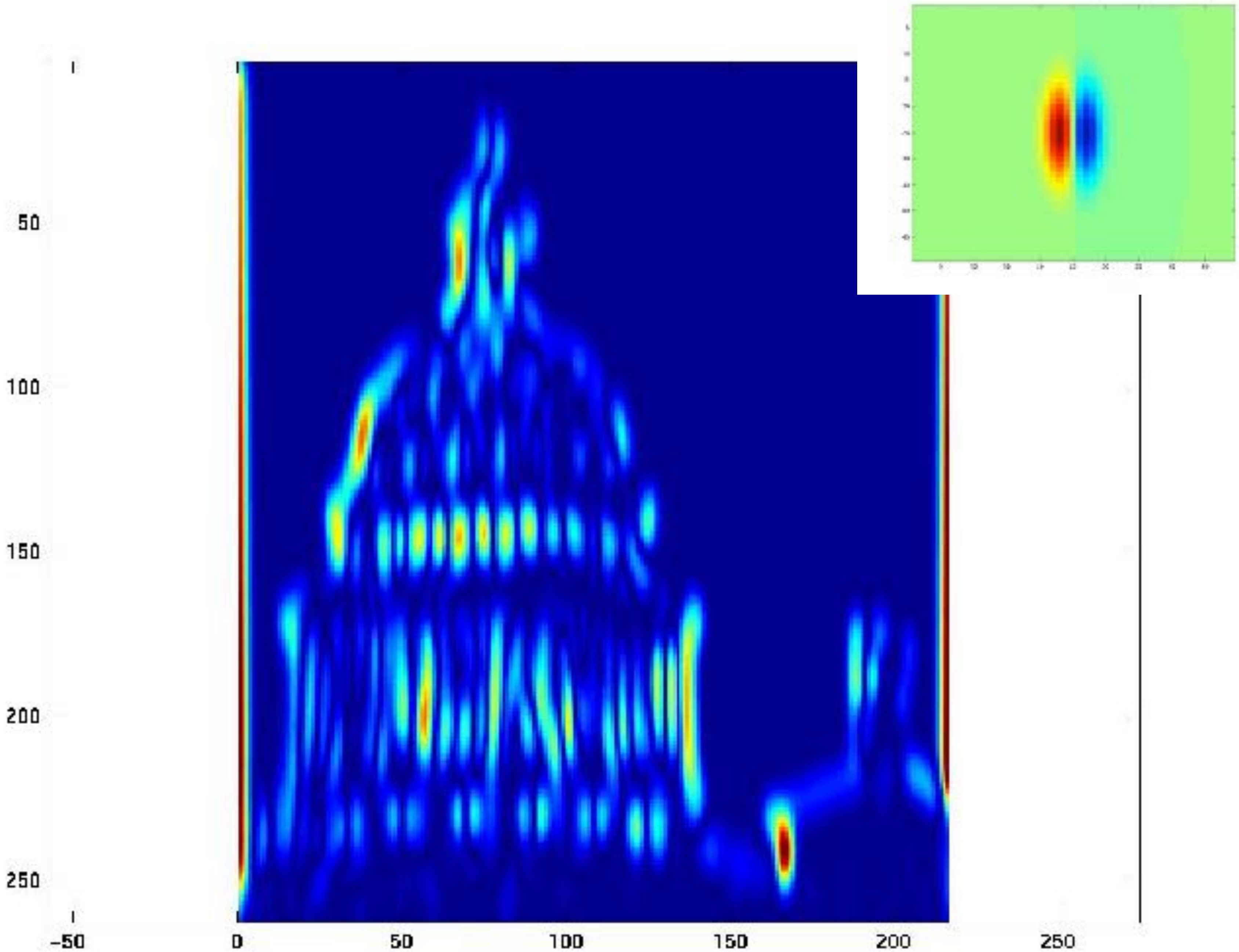

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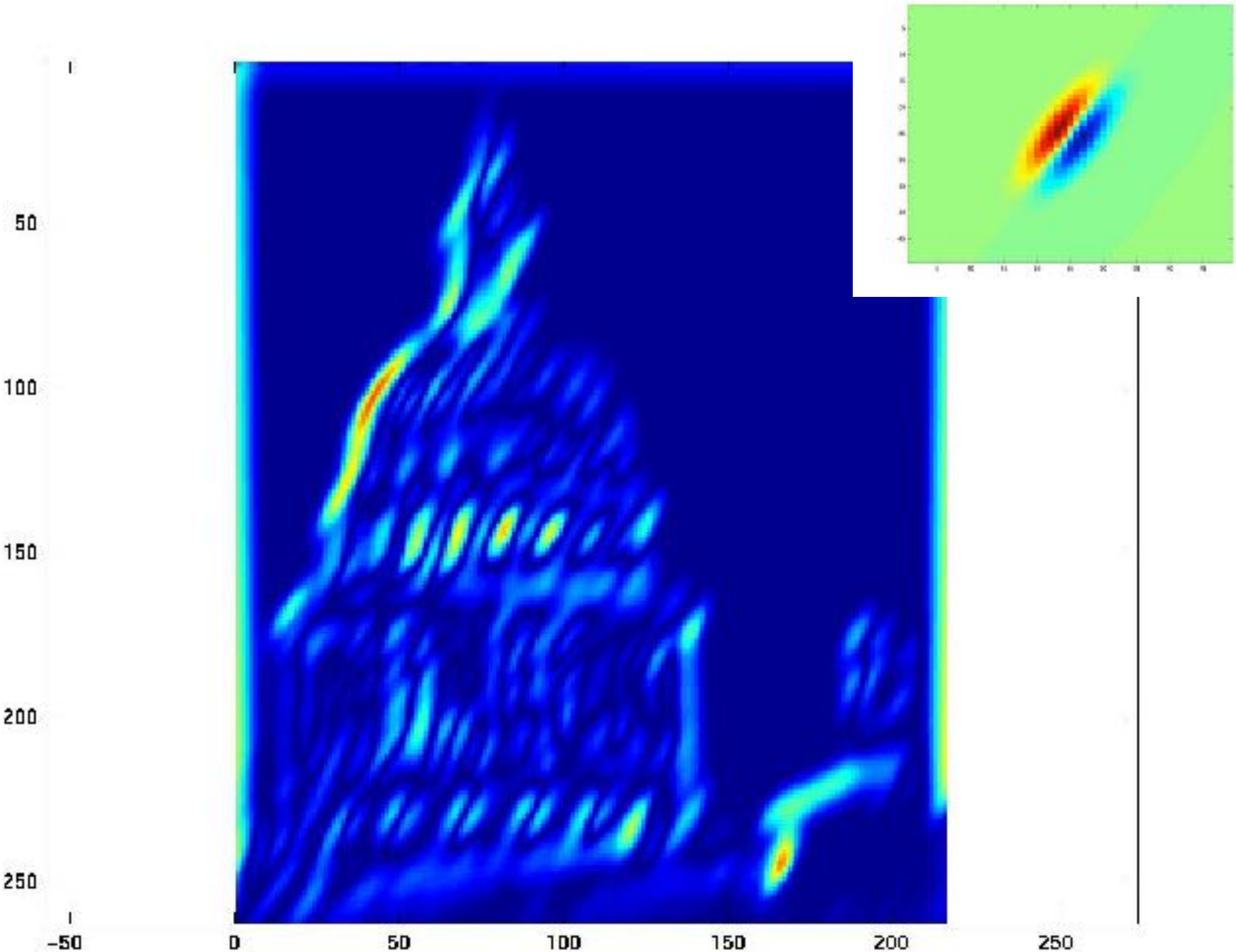

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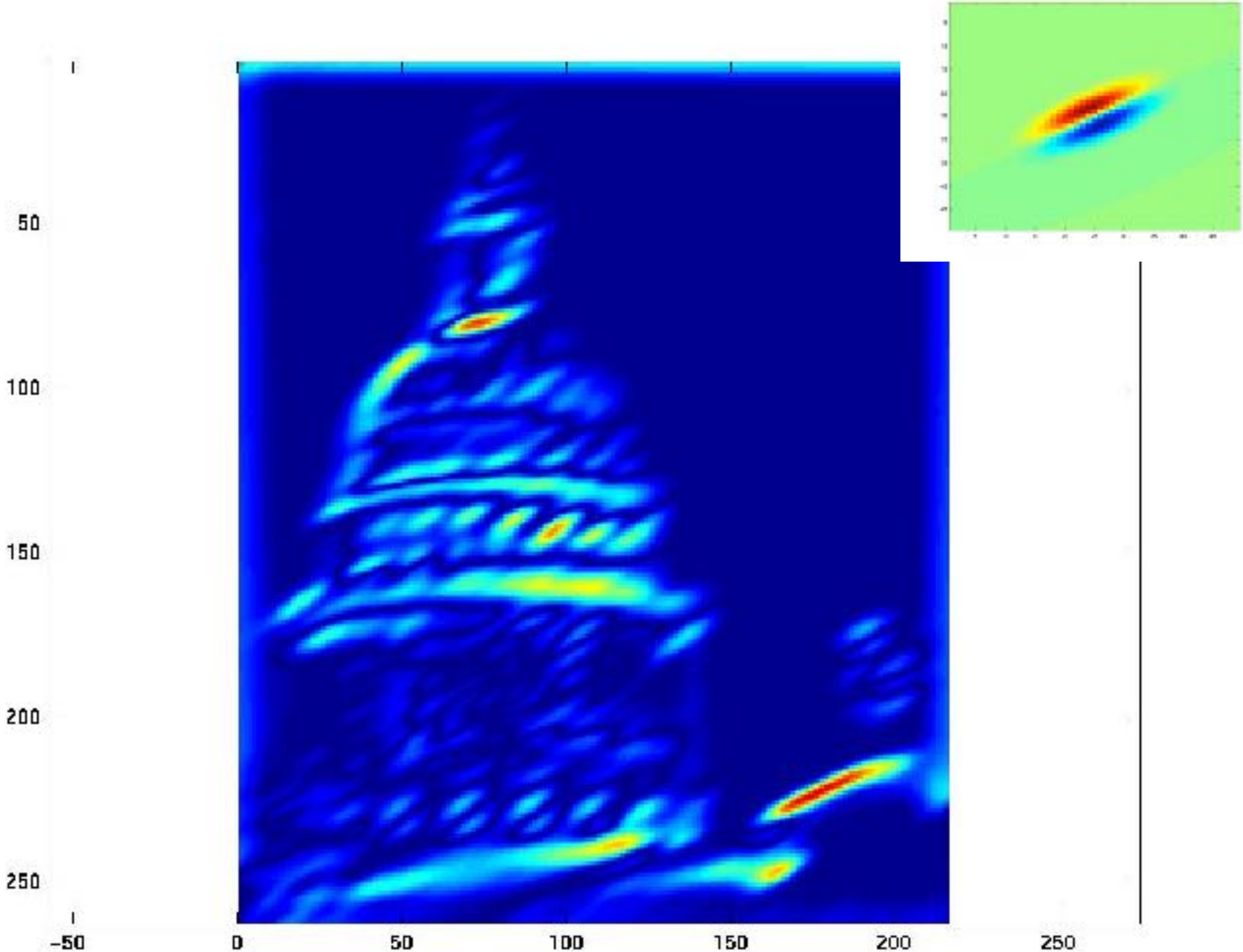

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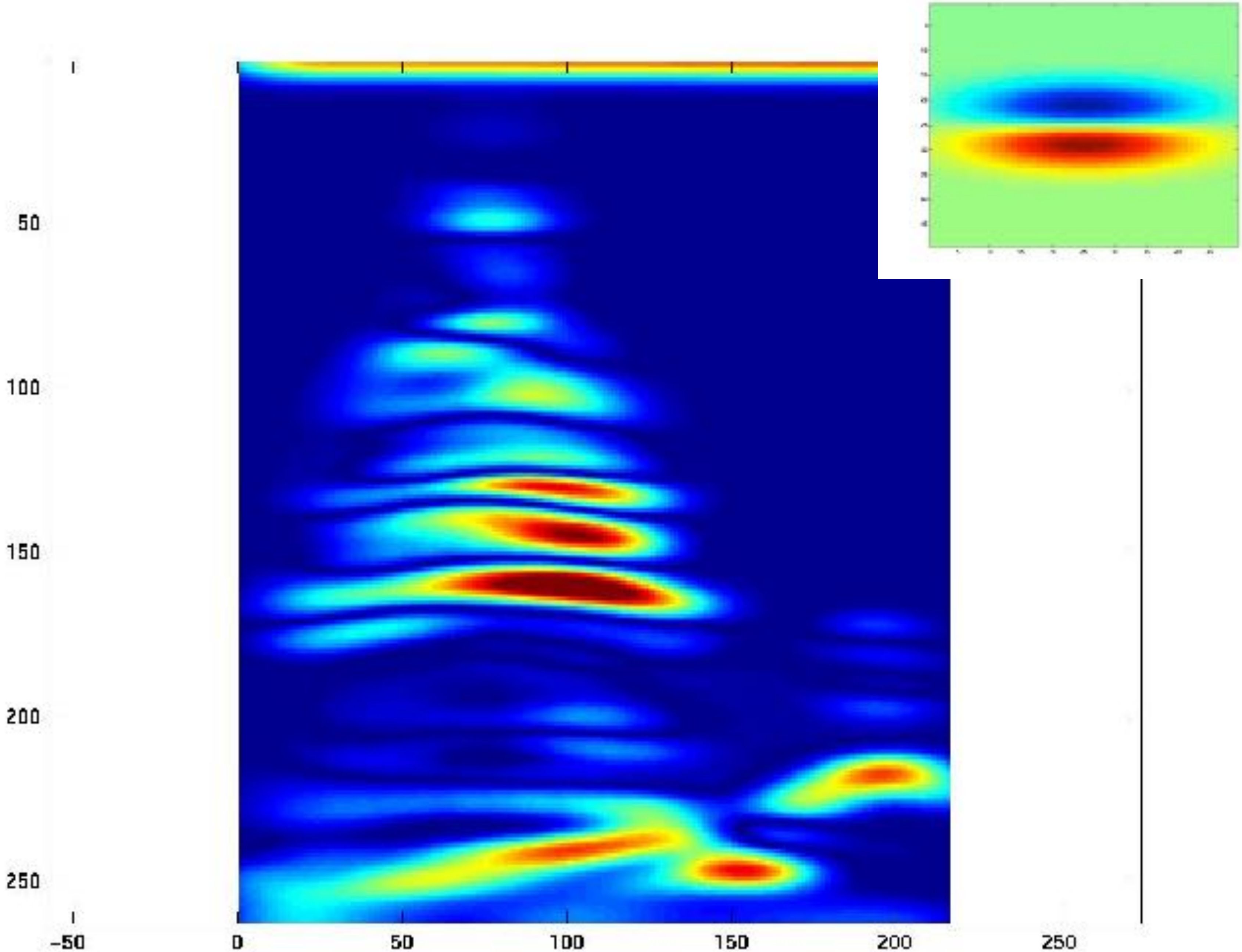

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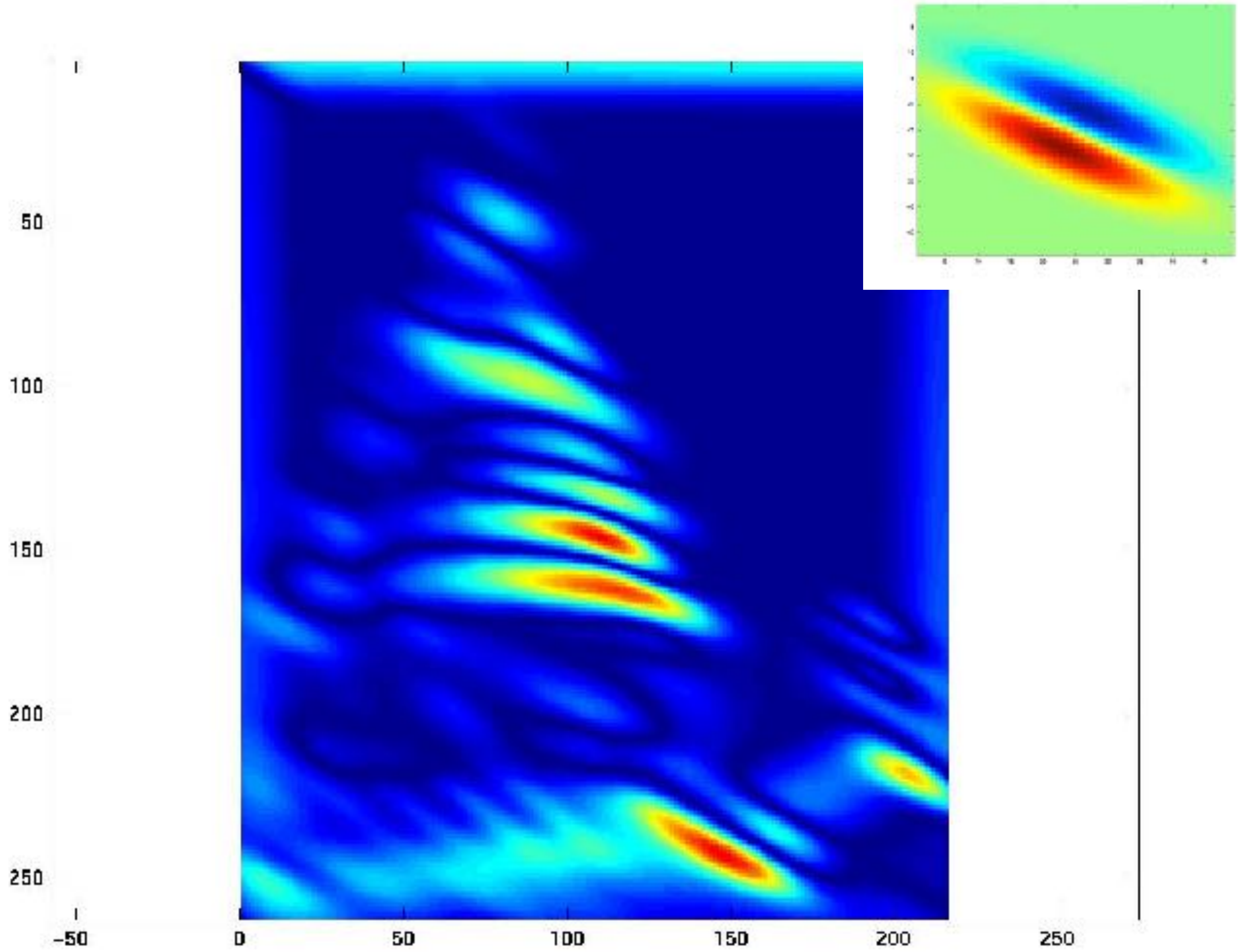

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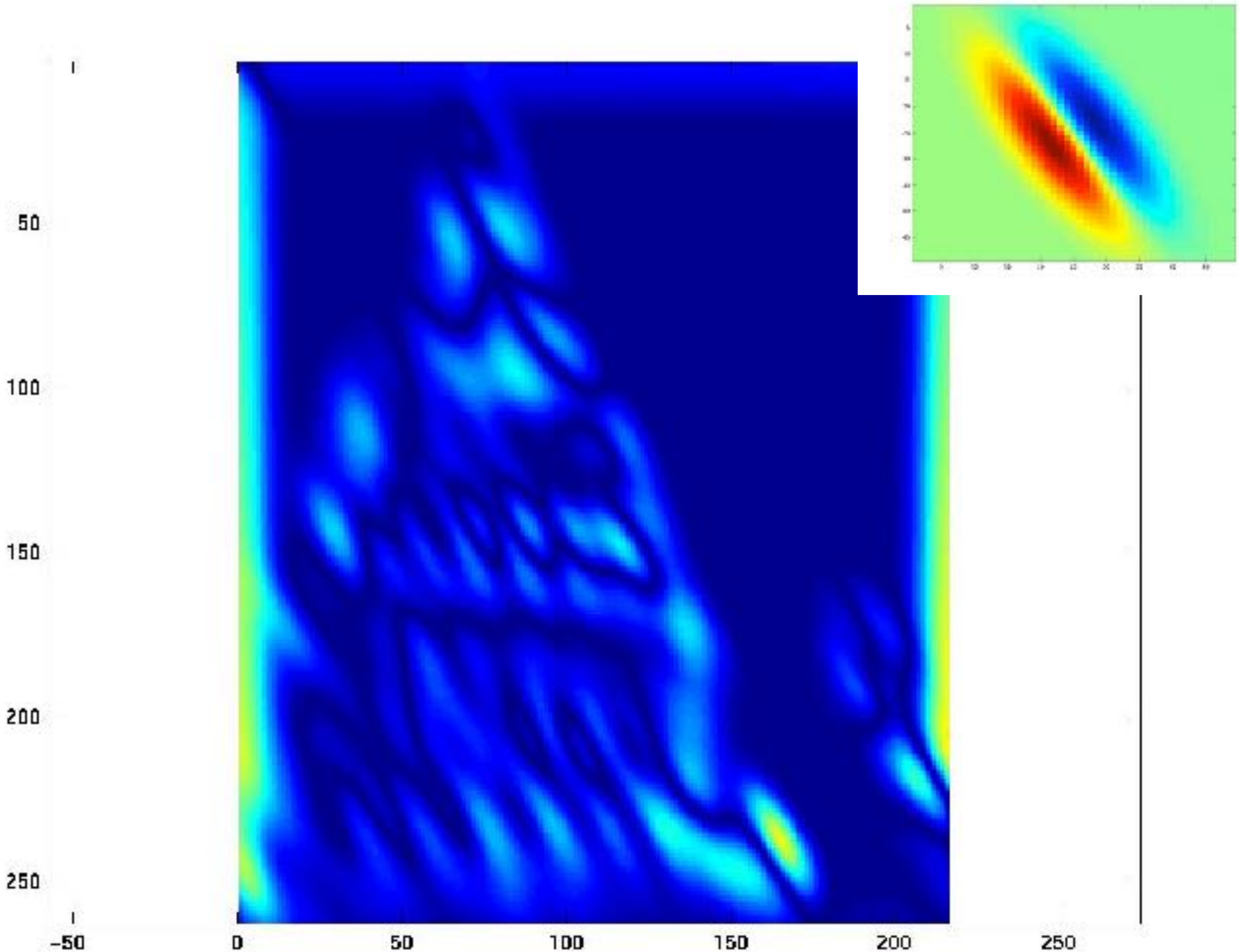

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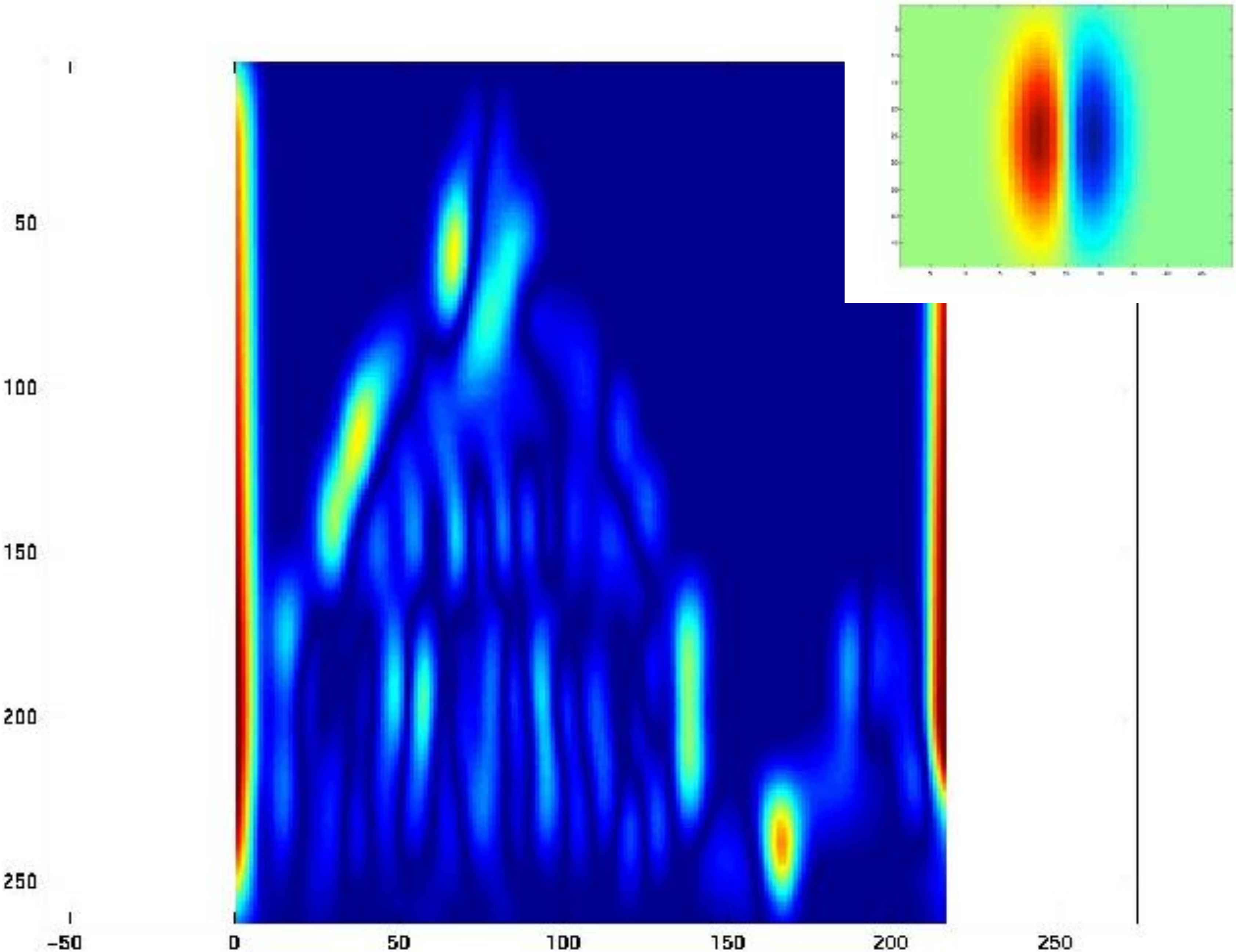

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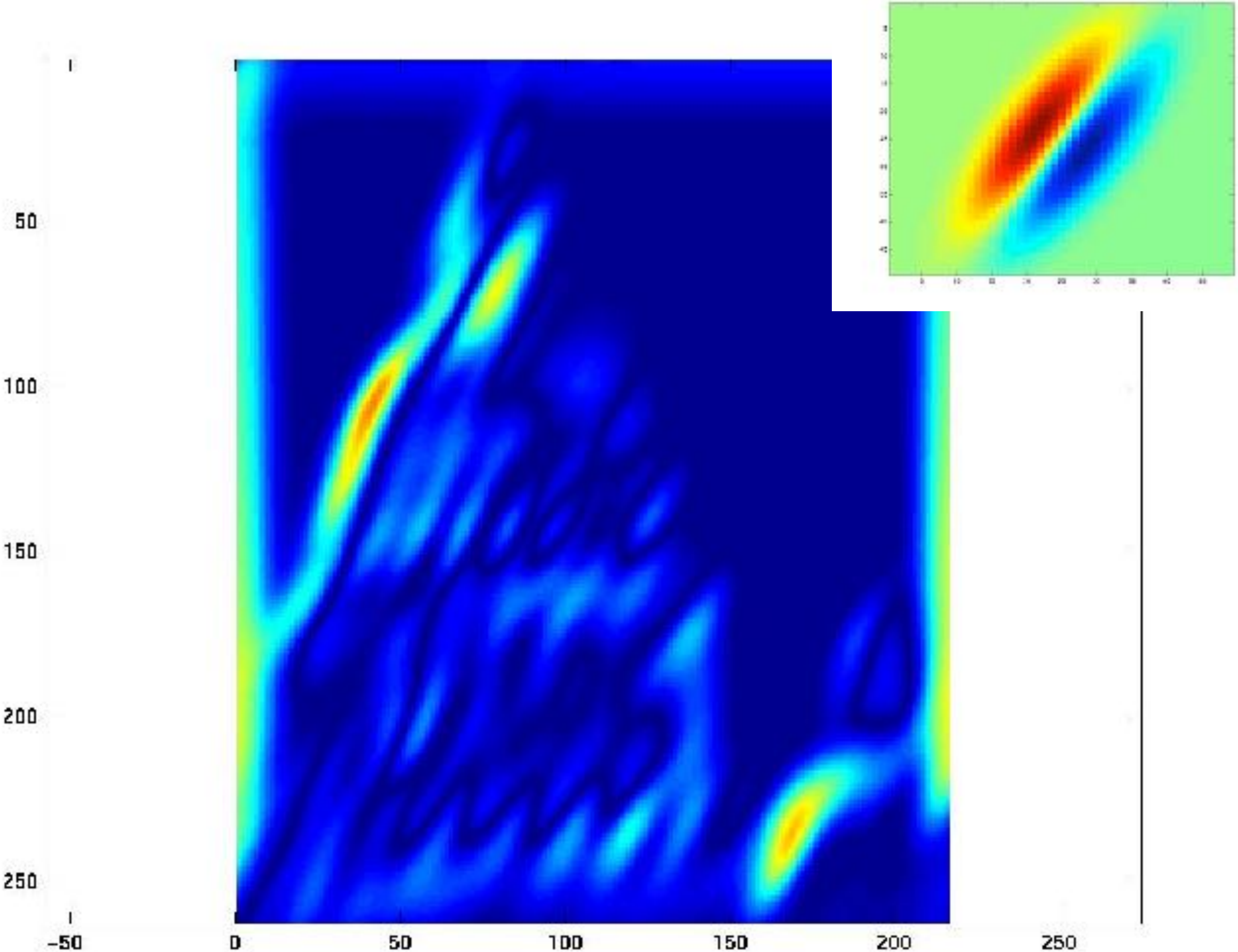

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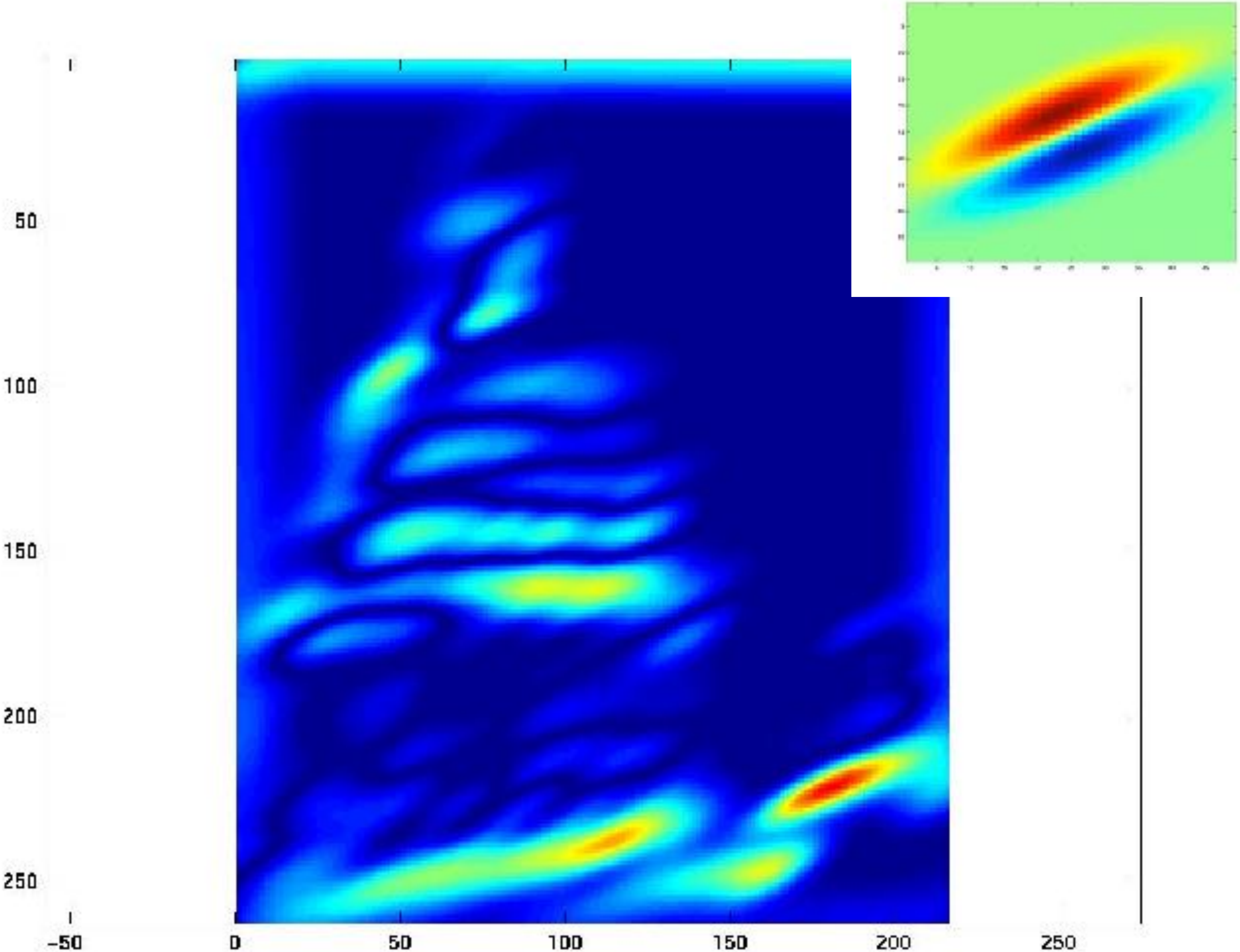

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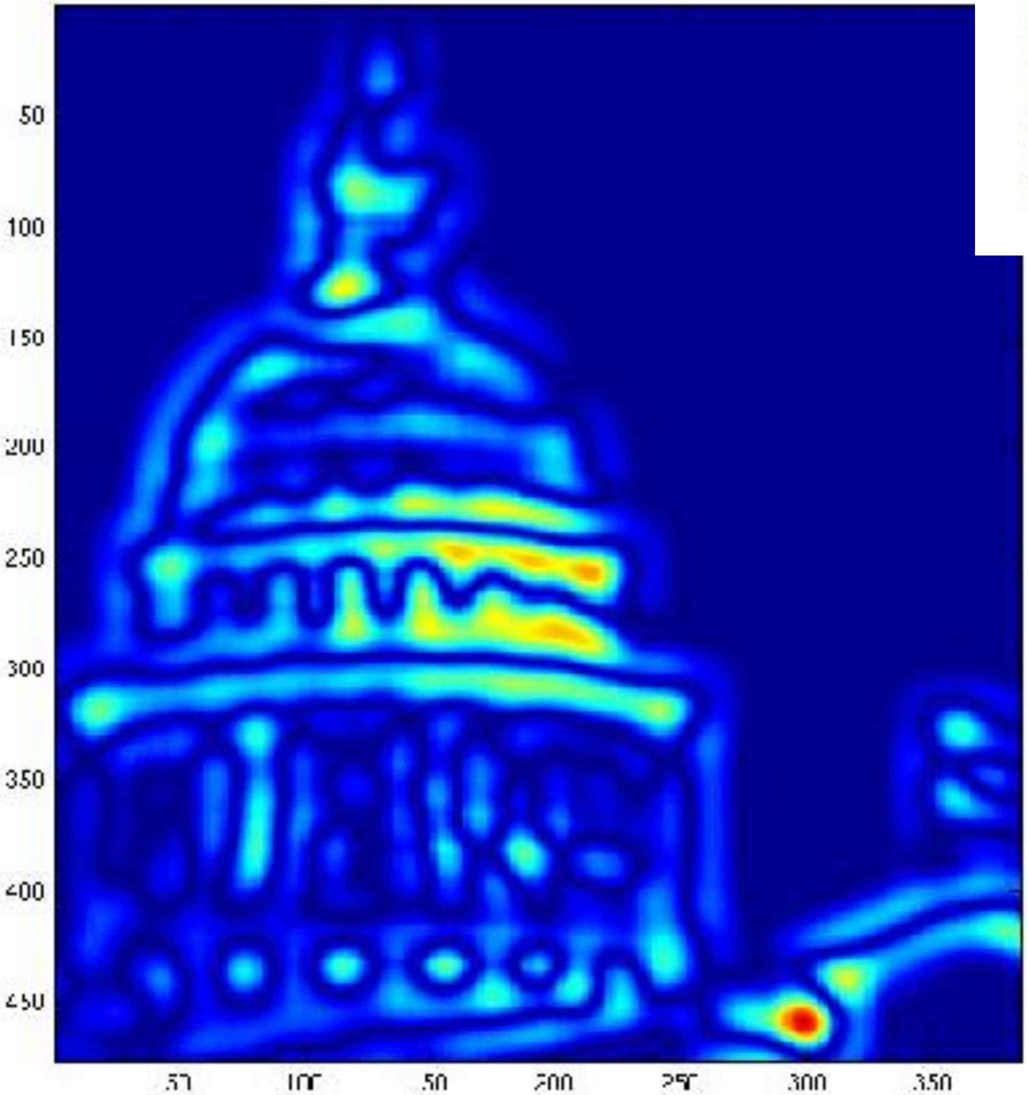

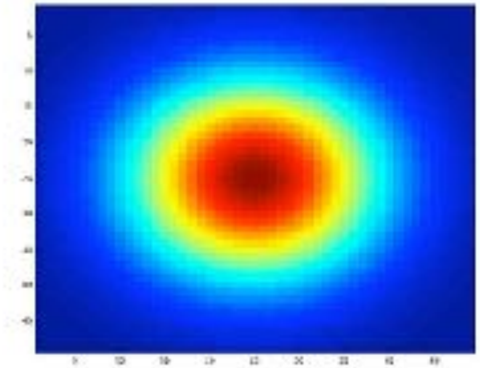

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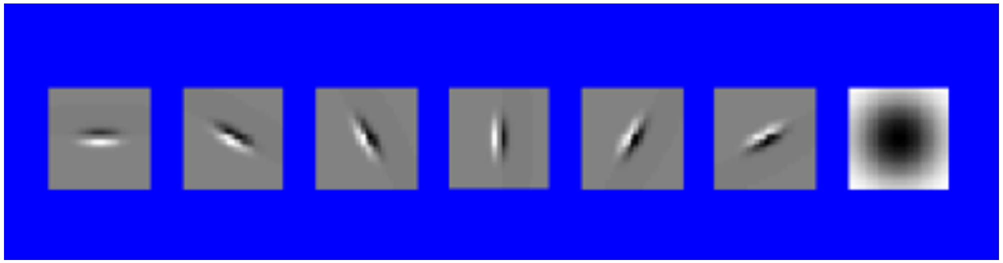
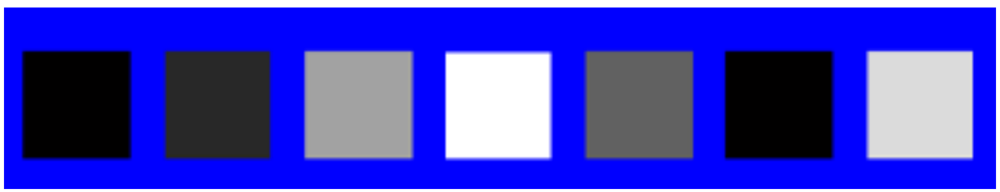
You Try: Can you match the texture to the response?

Filters

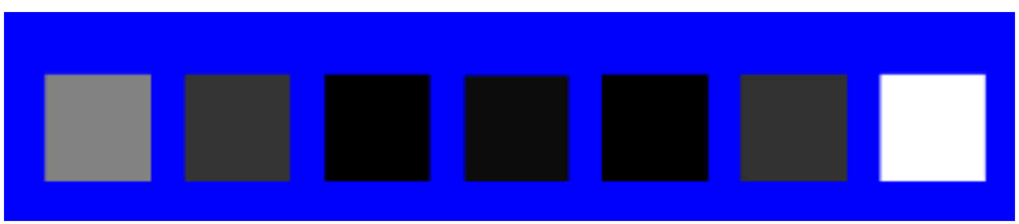


1



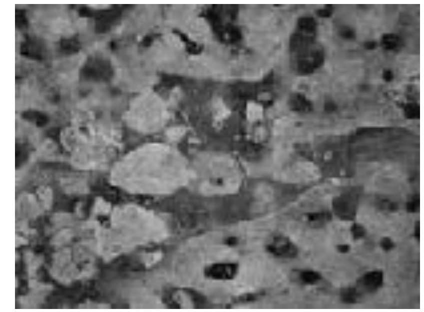
2

3



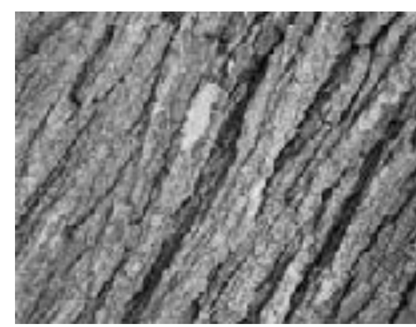
Mean abs responses

A



B

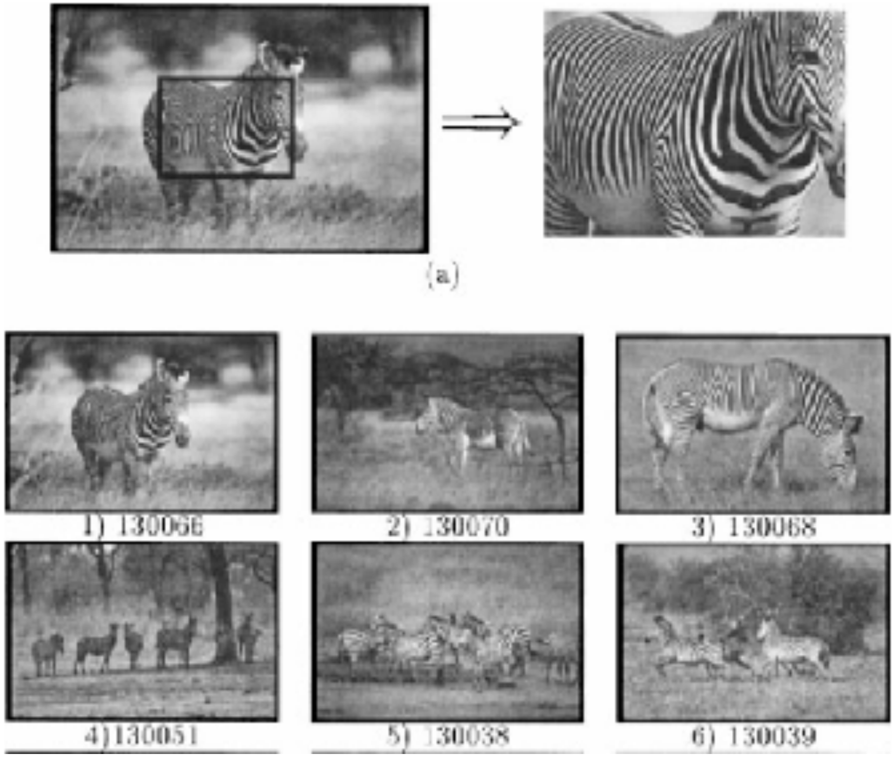
C



Derek Hoiem

Application: Retrieval

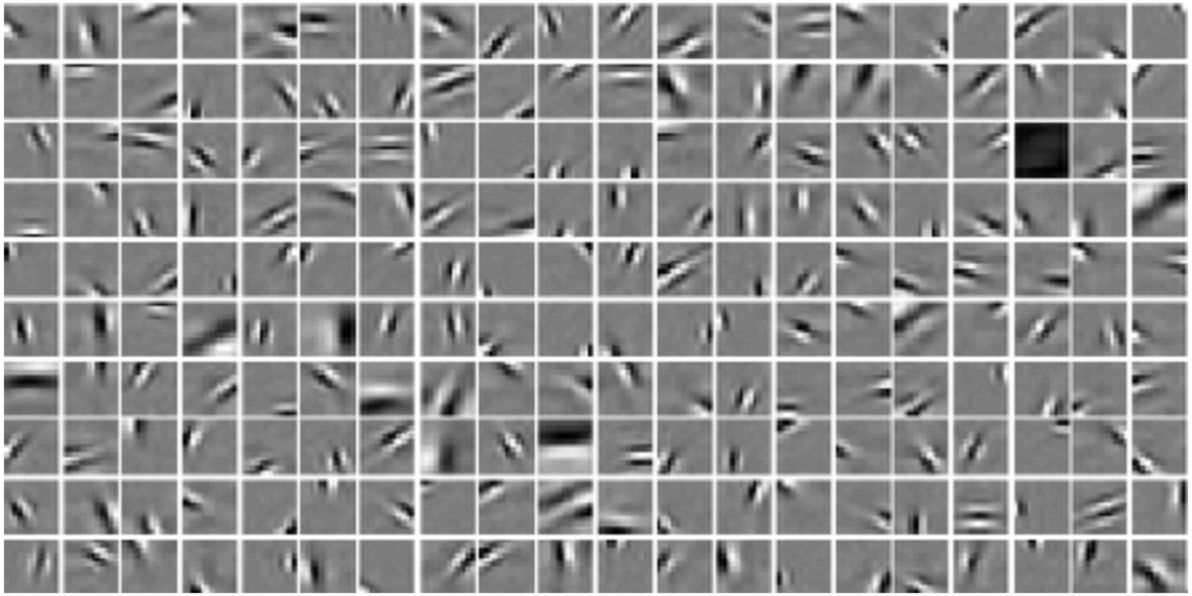
- Retrieve similar images based on texture



Y. Rubner, C. Tomasi, and L. J. Guibas. The earth mover's distance as a metric for image retrieval. *International Journal of Computer Vision*, 40(2): 99-121, November 2000,

Textons

- Elements ("textons") either identical or come from some statistical distribution
- Can analyze in natural images



Olhausen & Field

Clustering Textons

- Output of bank of *n* filters can be thought of as vector in *n*-dimensional space
- Can *cluster* these vectors using *k*-means [Malik et al.]
- Result: dictionary of most common textures

K-means clustering

Revisiting k-means

Most well-known and popular clustering algorithm:

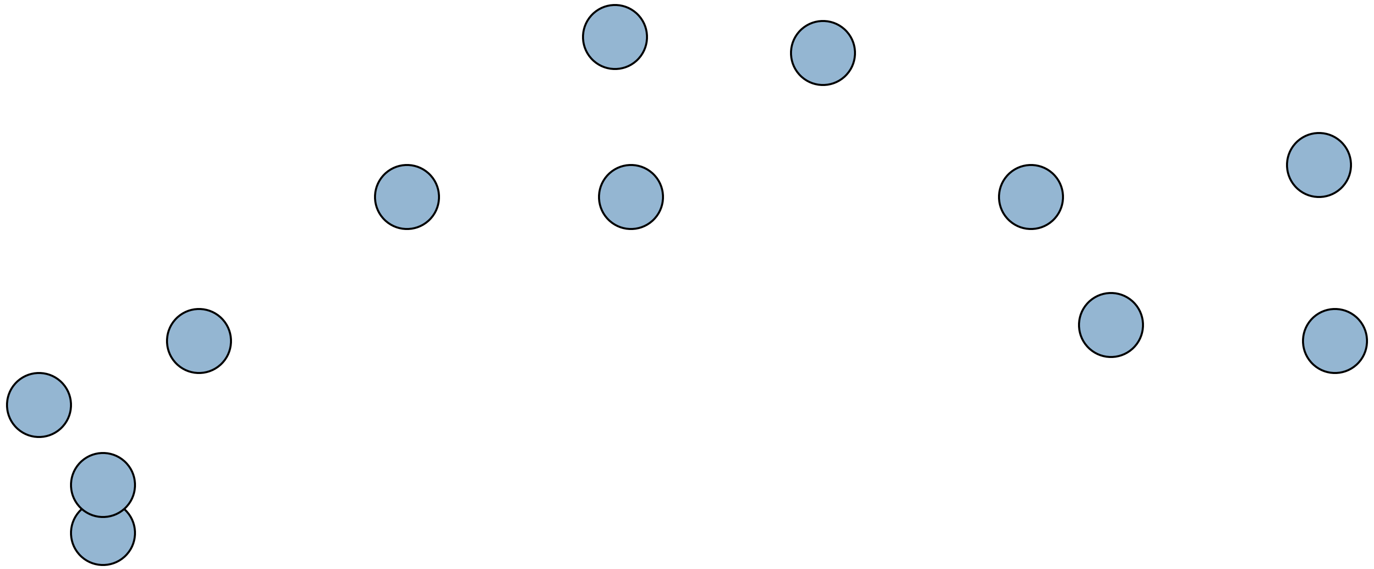
Start with some initial cluster centers

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster

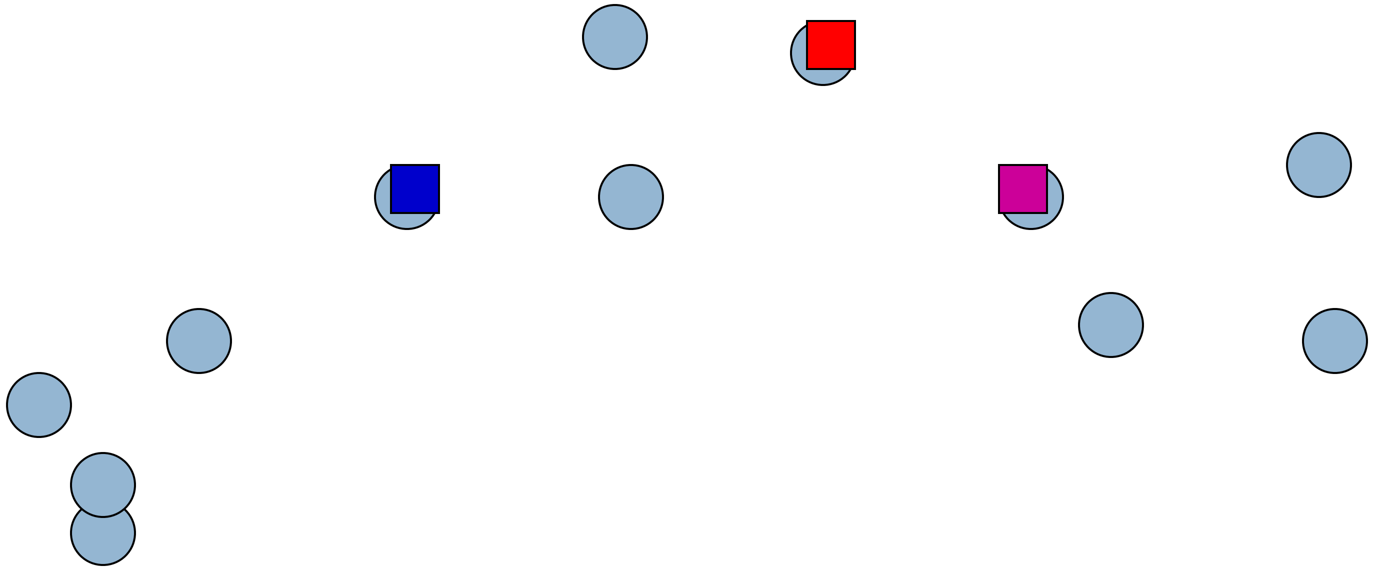
Credit: David Kauchak

K-means: an example



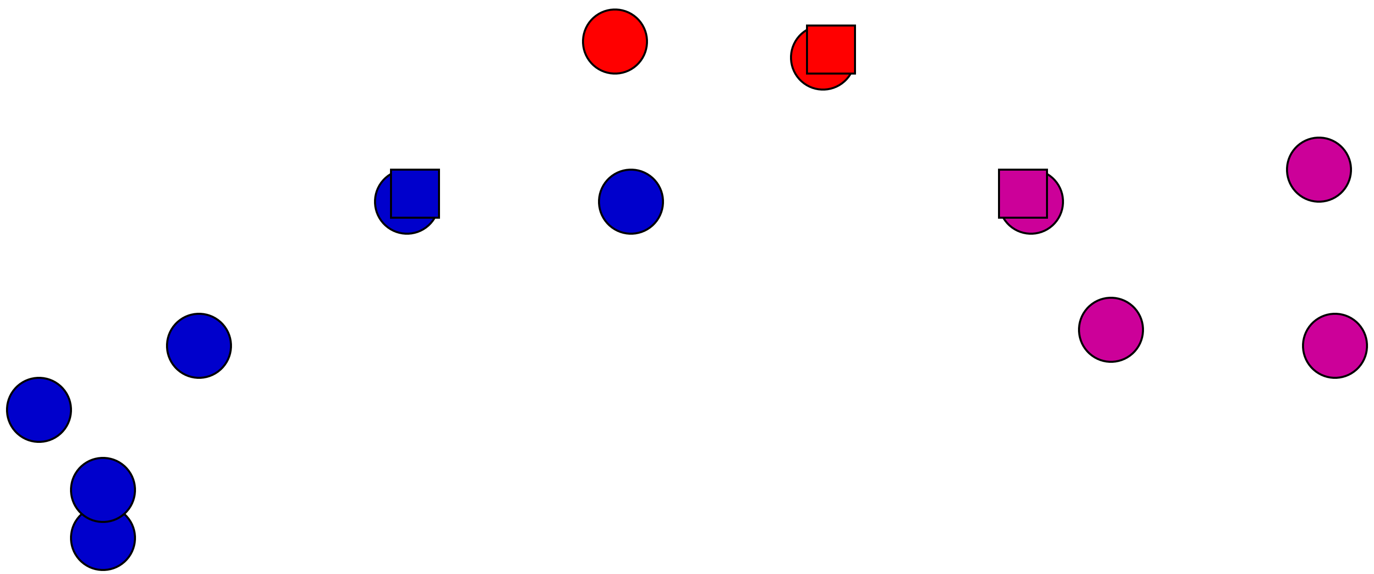
Credit: David Kauchak

K-means: Initialize centers randomly



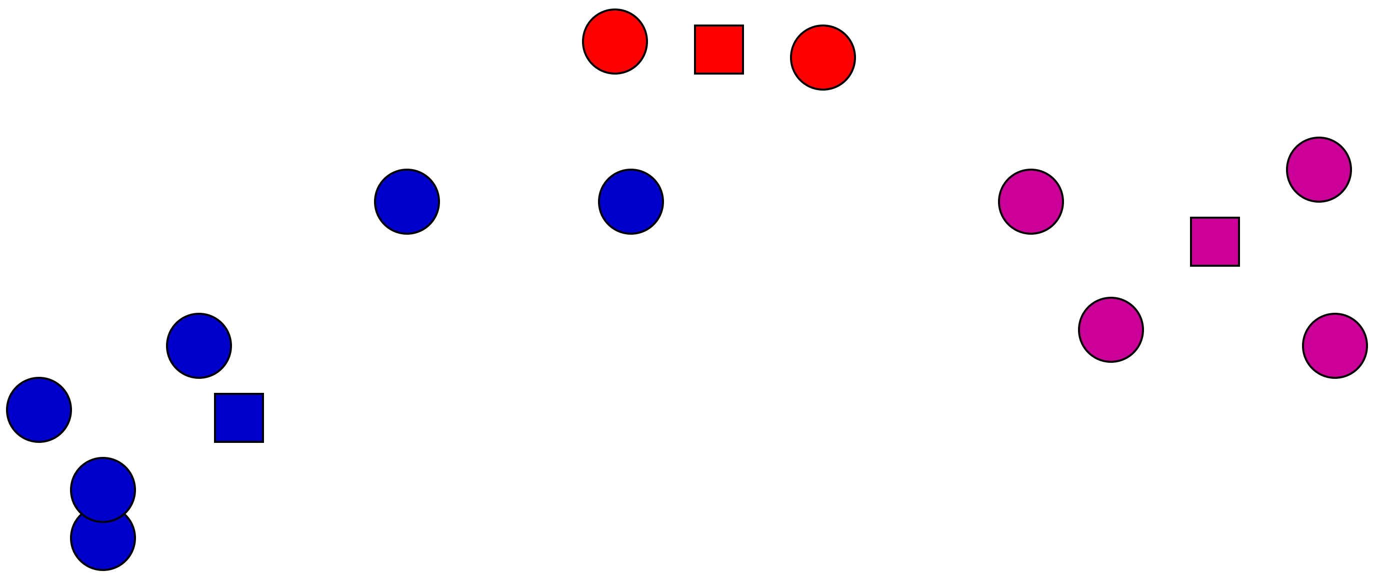
Credit: David Kauchak

K-means: assign points to nearest center



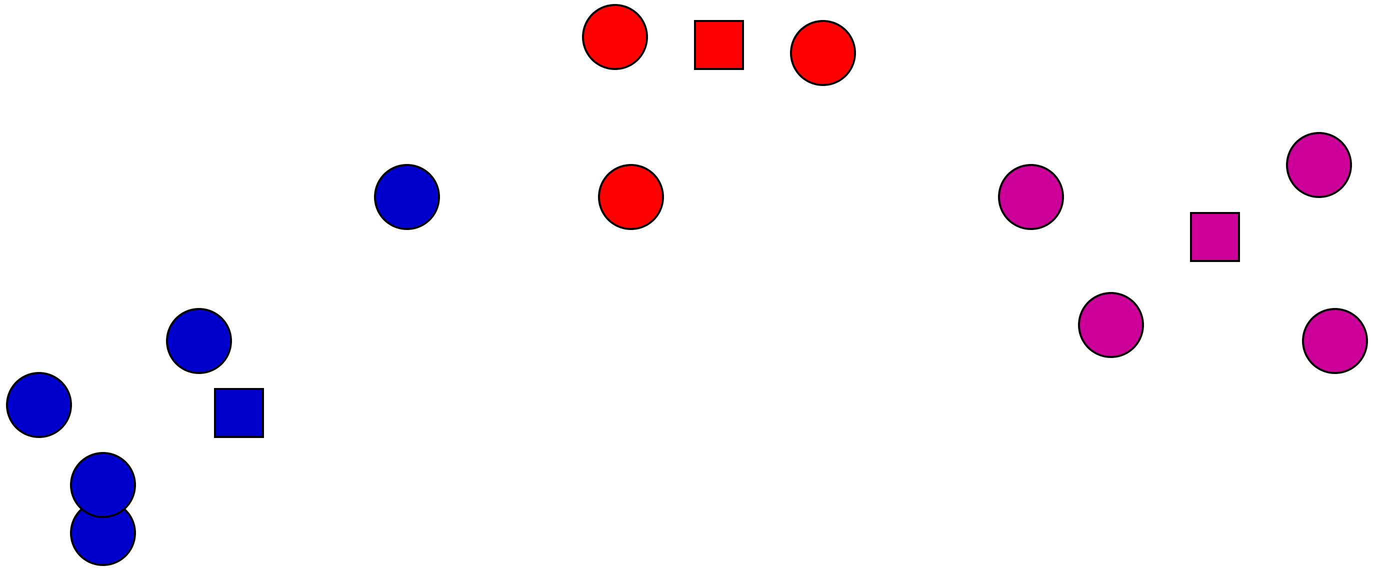
Credit: David Kauchak

K-means: readjust centers



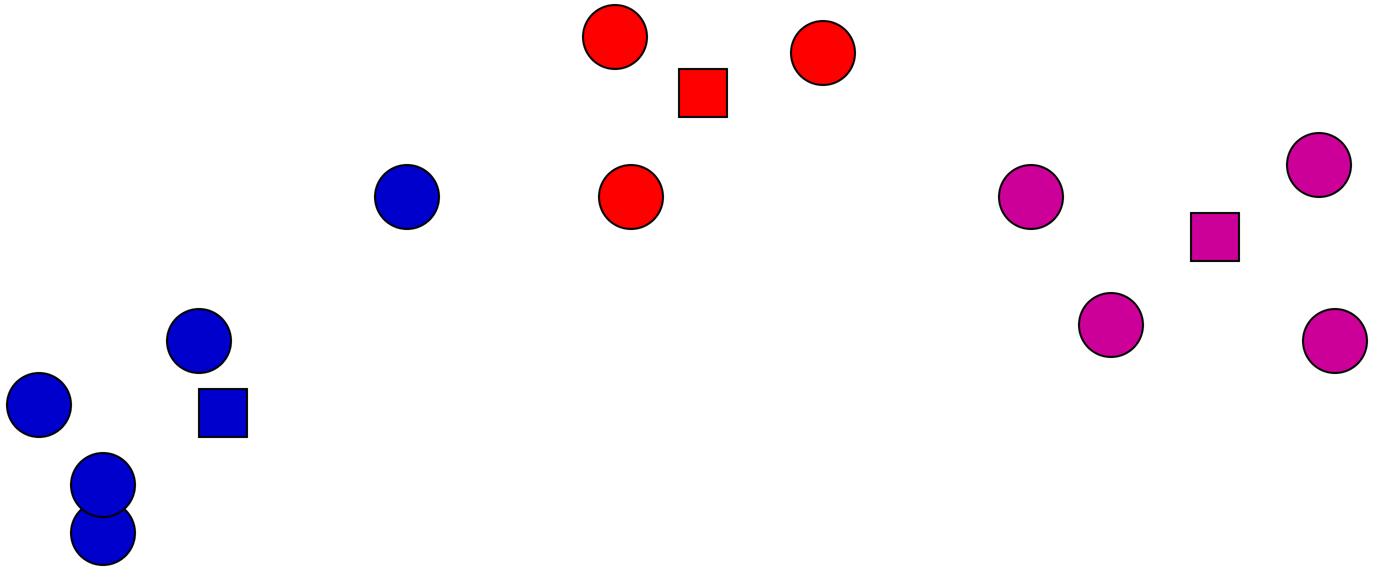
Credit: David Kauchak

K-means: assign points to nearest center



Credit: David Kauchak

K-means: readjust centers



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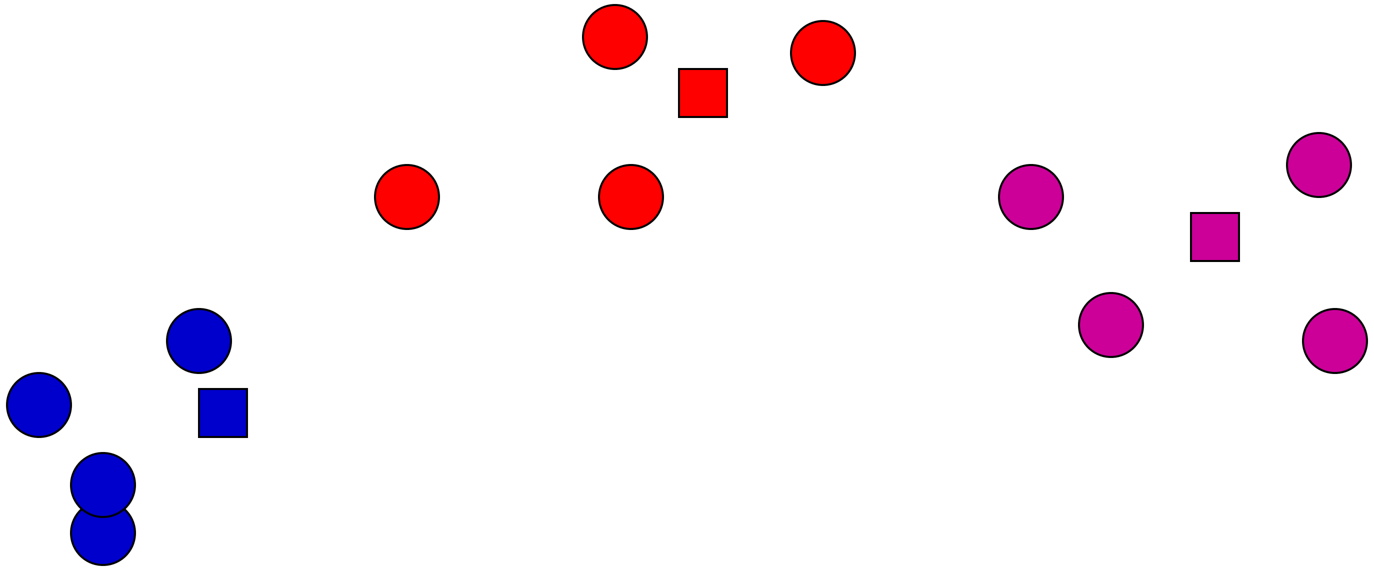
K-means: assign points to nearest center



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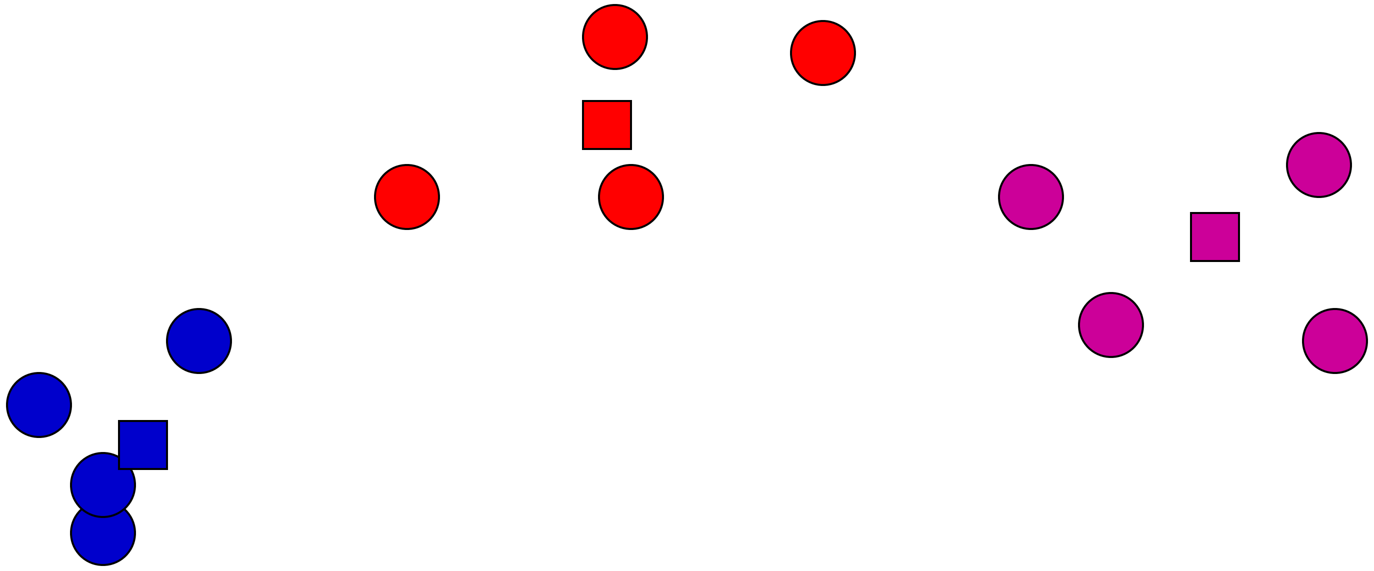
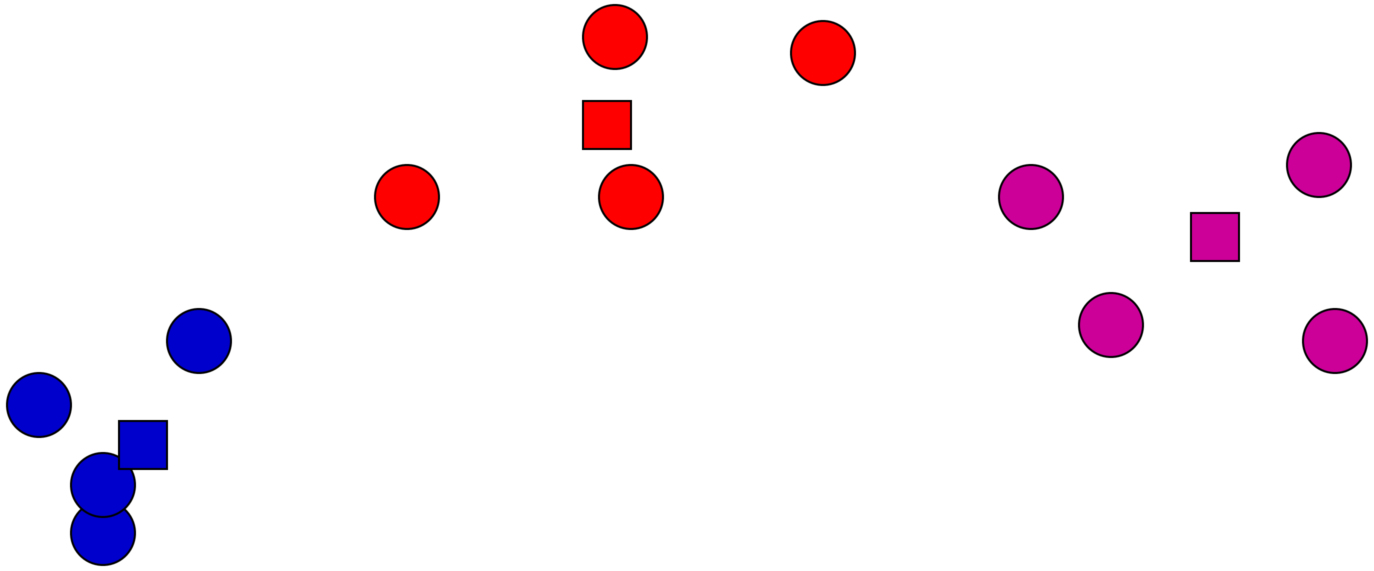
K-means: readjust centers



Credit: David Kauchak

K-means: assign points to nearest center



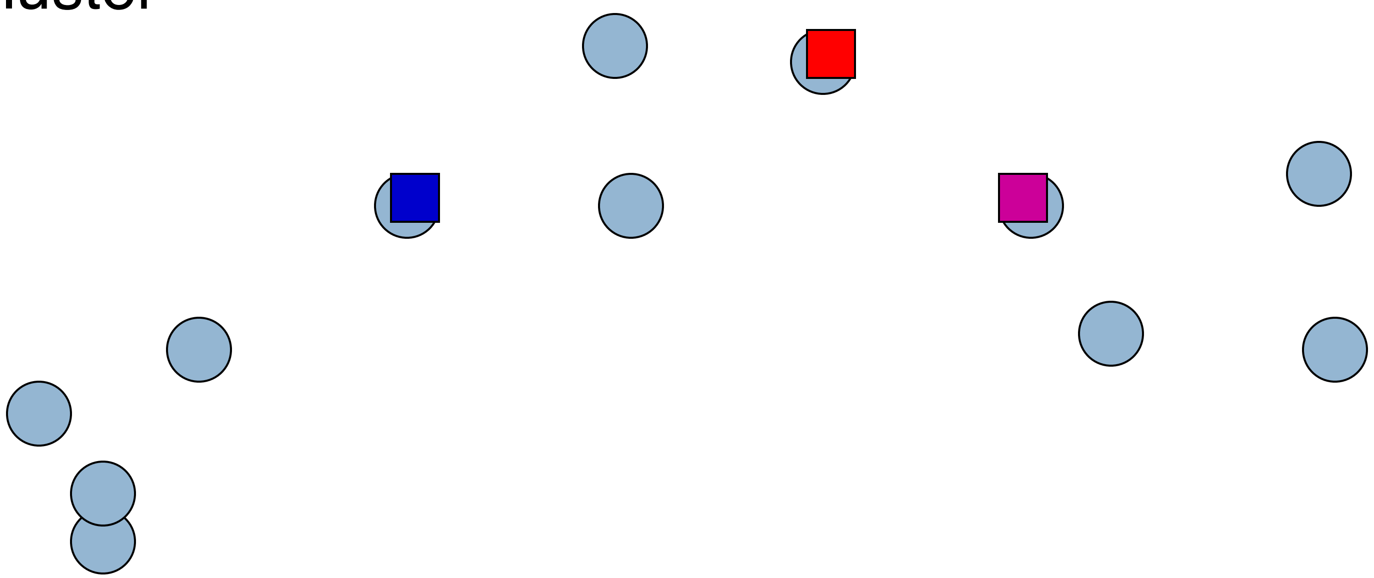
No changes: Done

Credit: David Kauchak

K-means

Iterate:

- **Assign/cluster each example to closest center**
- Recalculate centers as the mean of the points in a cluster



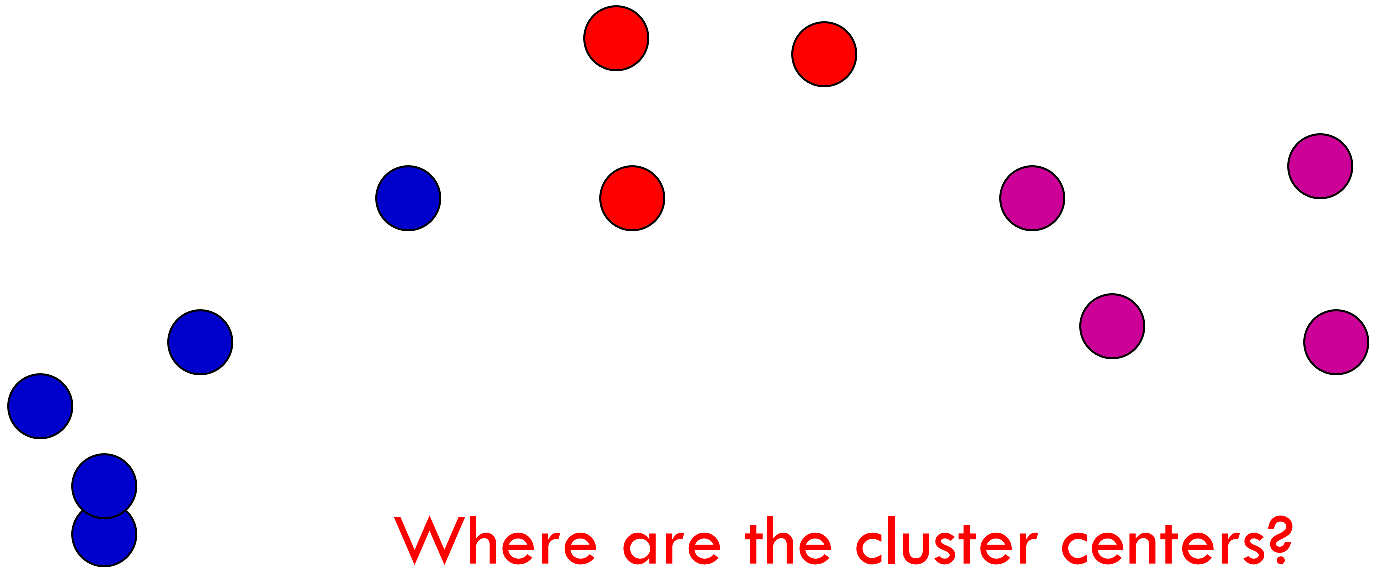
How do we do this?

Credit: David Kauchak

K-means

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster



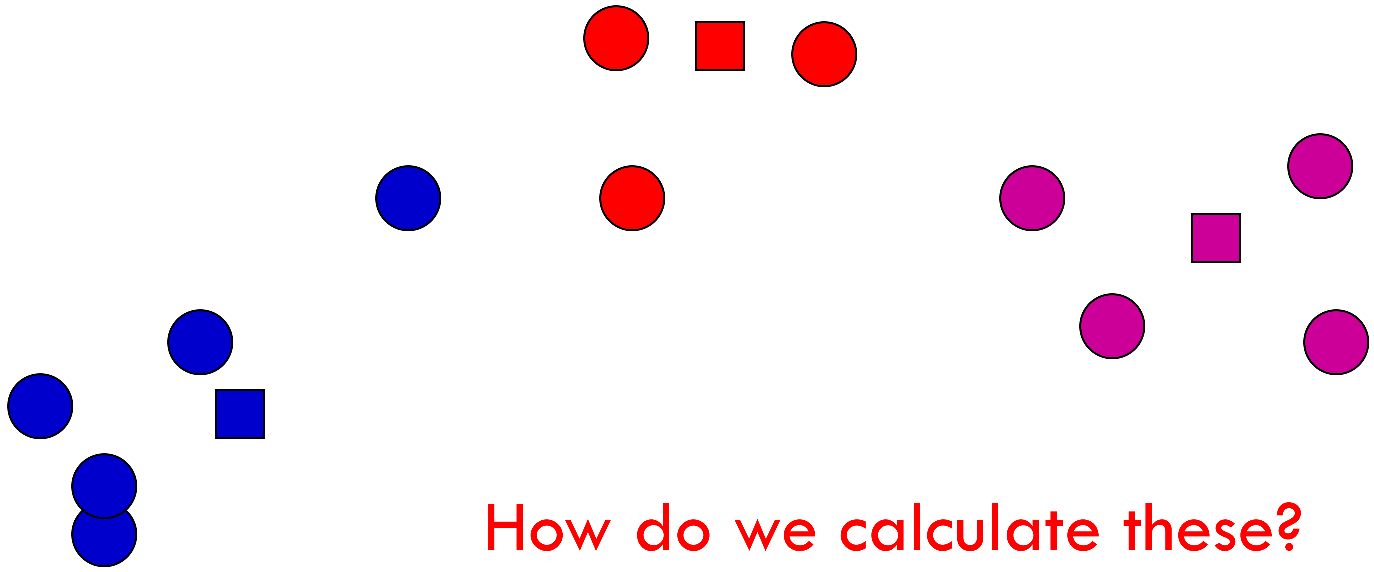
Where are the cluster centers?

Credit: David Kauchak

K-means

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster



How do we calculate these?

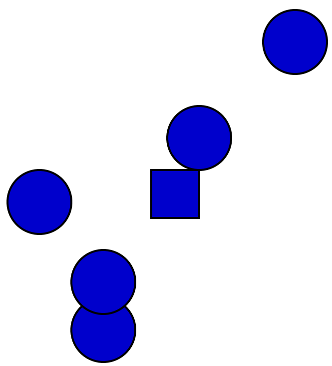
Credit: David Kauchak

K-means

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster

Mean of the points in the cluster:



$$\mu(C) = \frac{1}{|C|} \sum_{x \in C} x$$

Credit: David Kauchak

K-means loss function

K-means tries to minimize what is called the "k-means" loss function:

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

that is, the sum of the squared distances from each point to the associated cluster center

Credit: David Kauchak

Minimizing k-means loss

Iterate:

1. Assign/cluster each example to closest center
2. Recalculate centers as the mean of the points in a cluster

---

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

Does each step of k-means move towards reducing this loss function (or at least not increasing)?

Credit: David Kauchak

Minimizing k-means loss

Iterate:

1. Assign/cluster each example to closest center
2. Recalculate centers as the mean of the points in a cluster

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

This isn't quite a complete proof/argument, but:

1. Any other assignment would end up in a larger loss

1. The mean of a set of values minimizes the squared error

Credit: David Kauchak

Minimizing k-means loss

Iterate:

1. Assign/cluster each example to closest center
2. Recalculate centers as the mean of the points in a cluster

---

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

Does this mean that k-means will always find the minimum loss/clustering?

Minimizing k-means loss

Iterate:

1. Assign/cluster each example to closest center
2. Recalculate centers as the mean of the points in a cluster

---

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

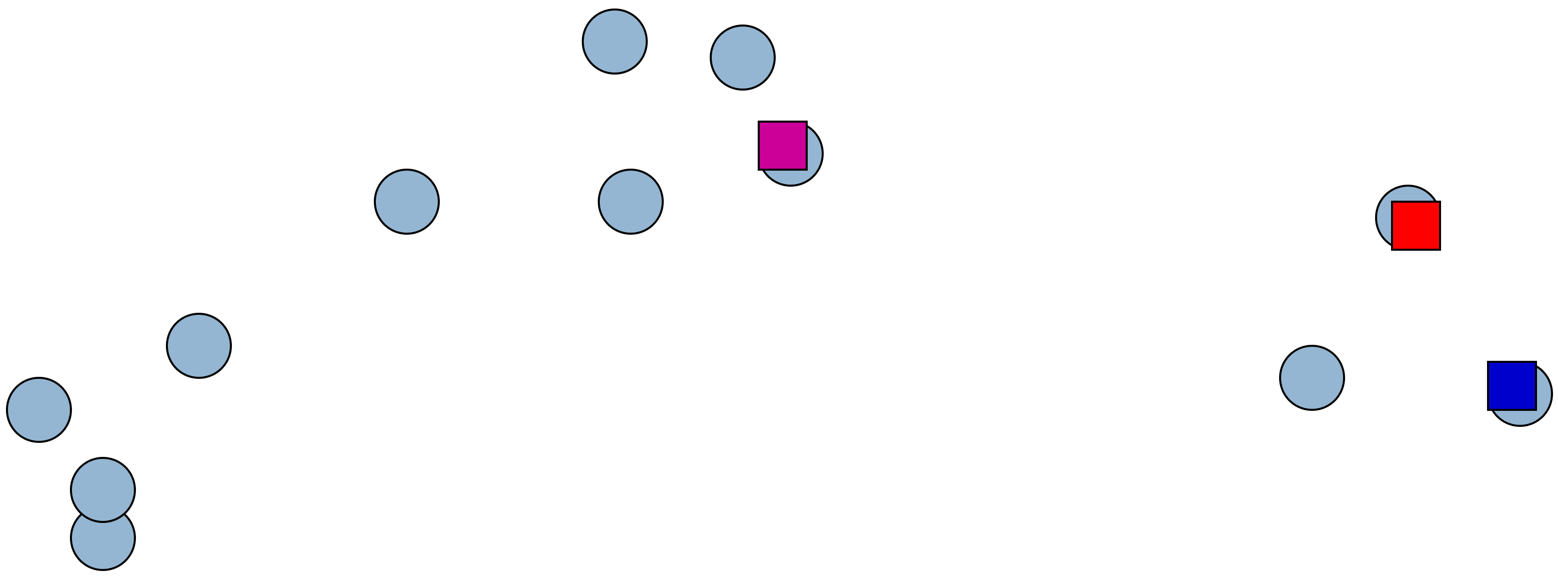
NO! It will find *a minimum*.

Unfortunately, the k-means loss function is generally not convex and for most problems has many, many minima

We're only guaranteed to find one of them

Credit: David Kauchak

K-means: Initialize centers randomly

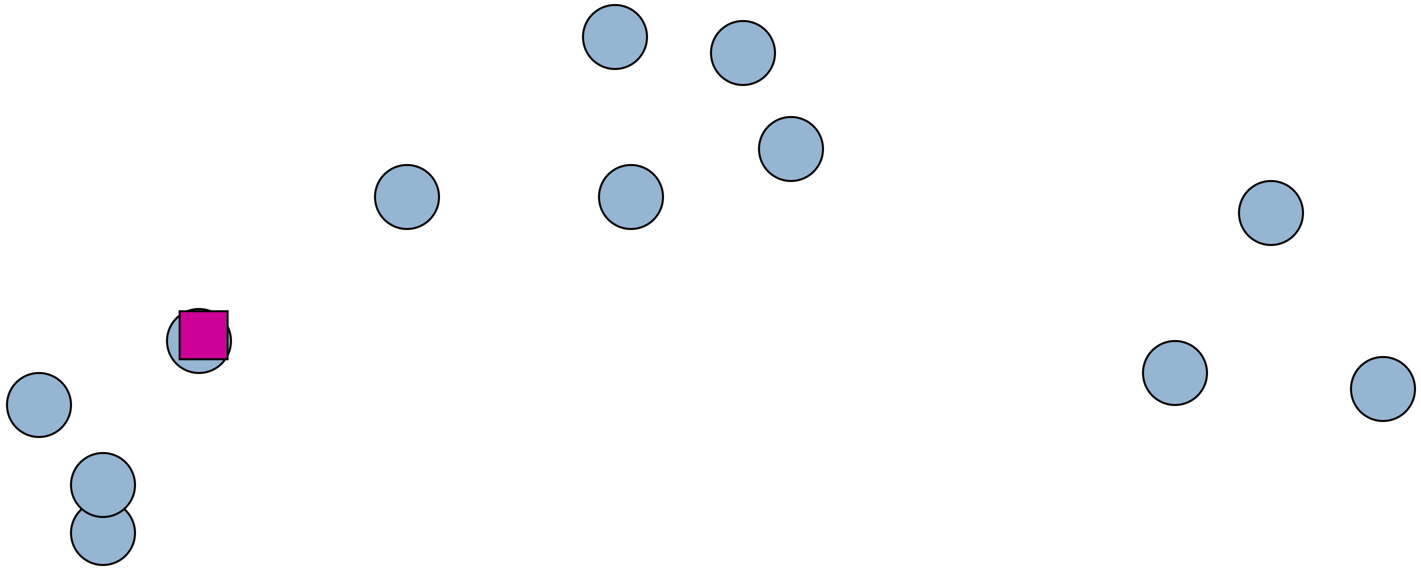


What would happen here?

Seed selection ideas?

Credit: David Kauchak

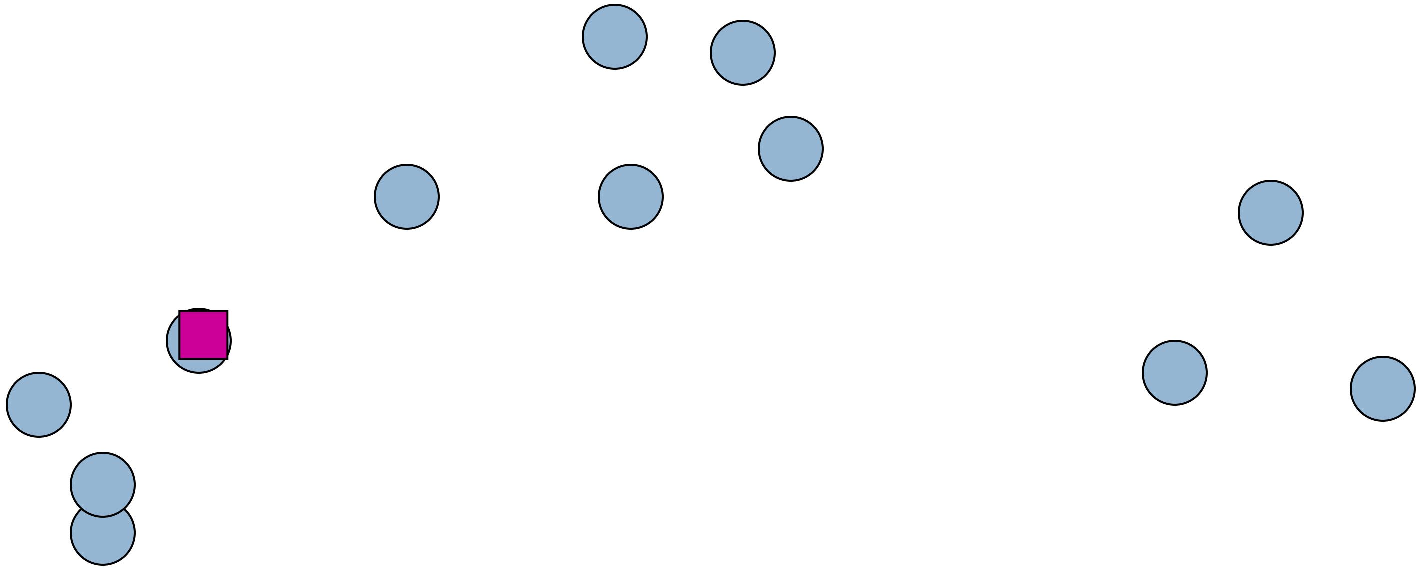
K-means: Initialize furthest from centers



Pick a random point for the first center

Credit: David Kauchak

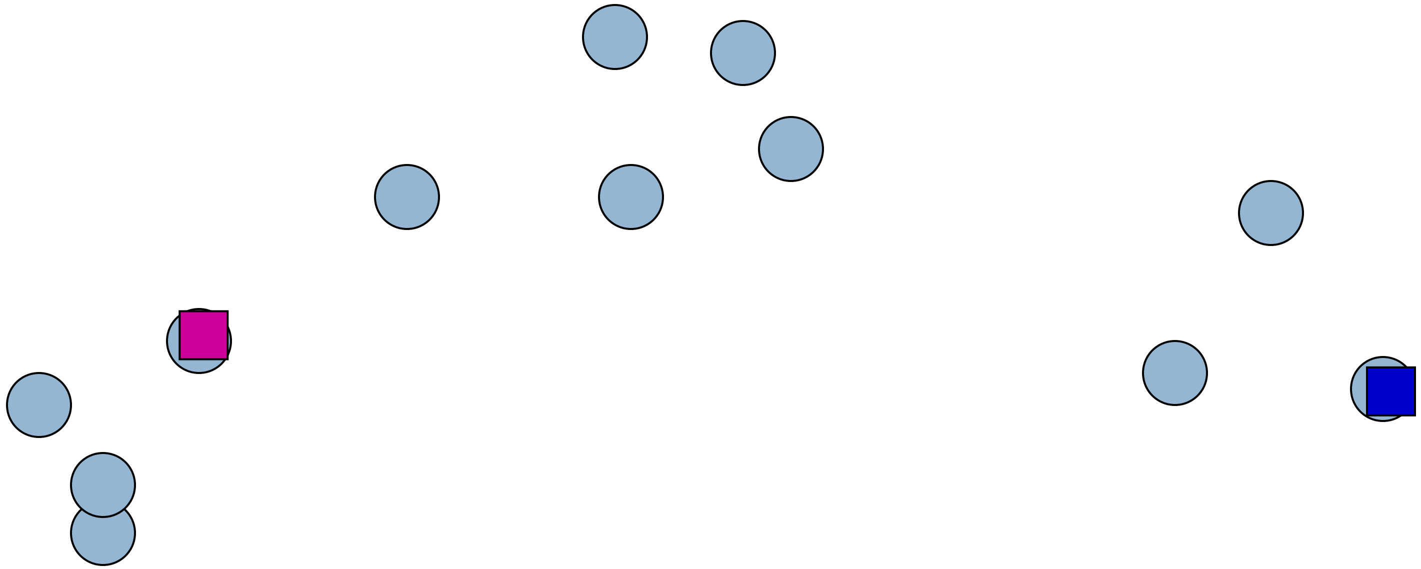
K-means: Initialize furthest from centers



What point will be chosen next?

Credit: David Kauchak

K-means: Initialize furthest from centers

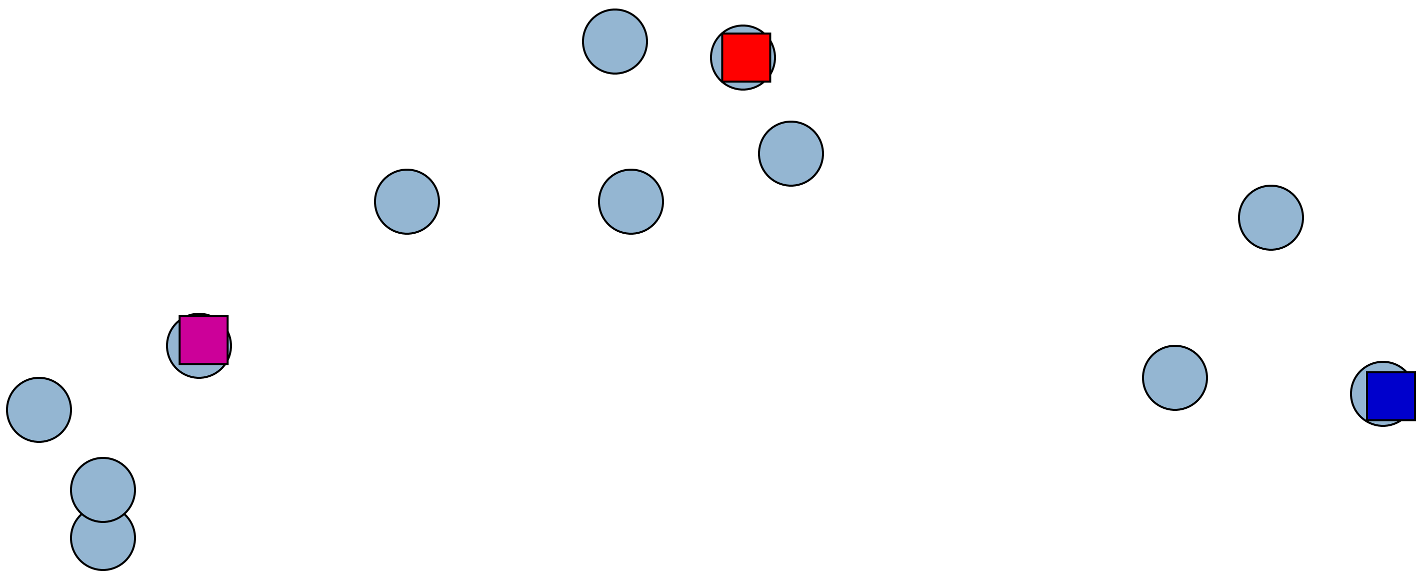


Furthest point from center

What point will be chosen next?

Credit: David Kauchak

K-means: Initialize furthest from centers

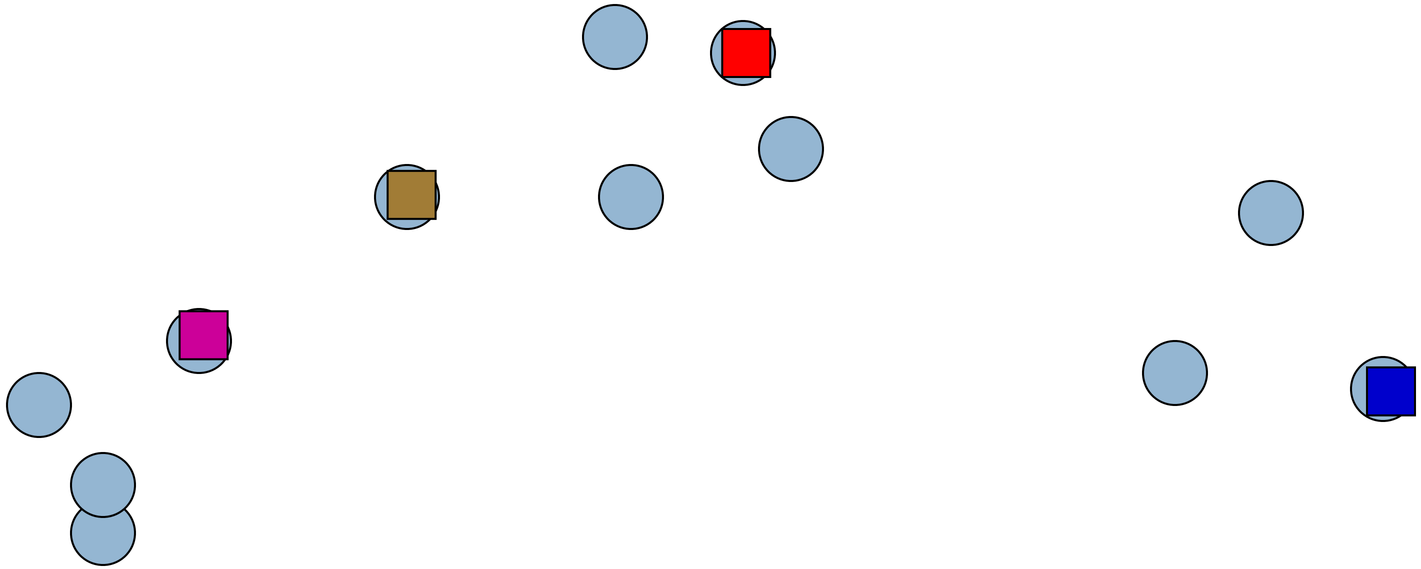


Furthest point from center

What point will be chosen next?

Credit: David Kauchak

K-means: Initialize furthest from centers

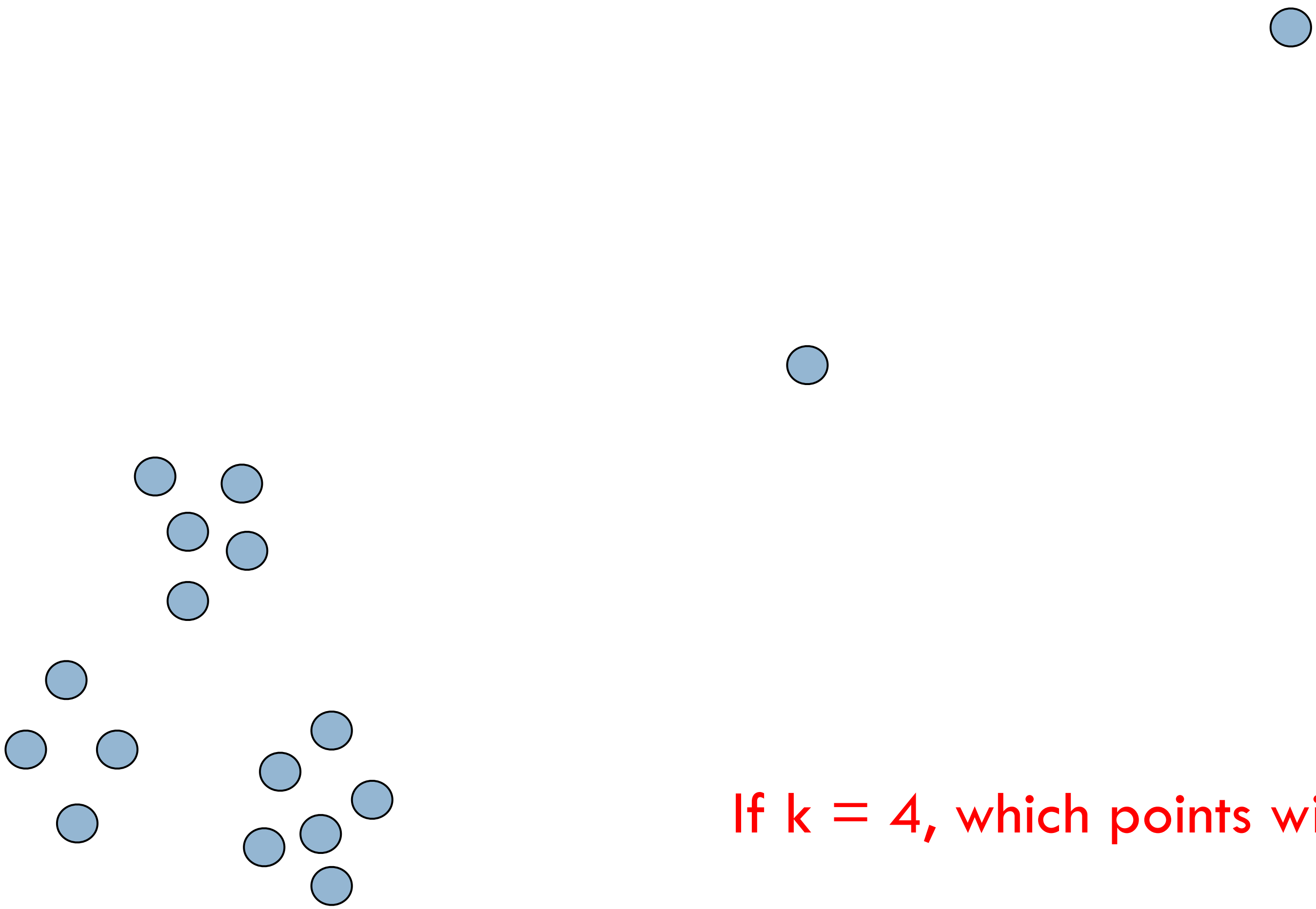


Furthest point from center

Any issues/concerns with this approach?

Credit: David Kauchak

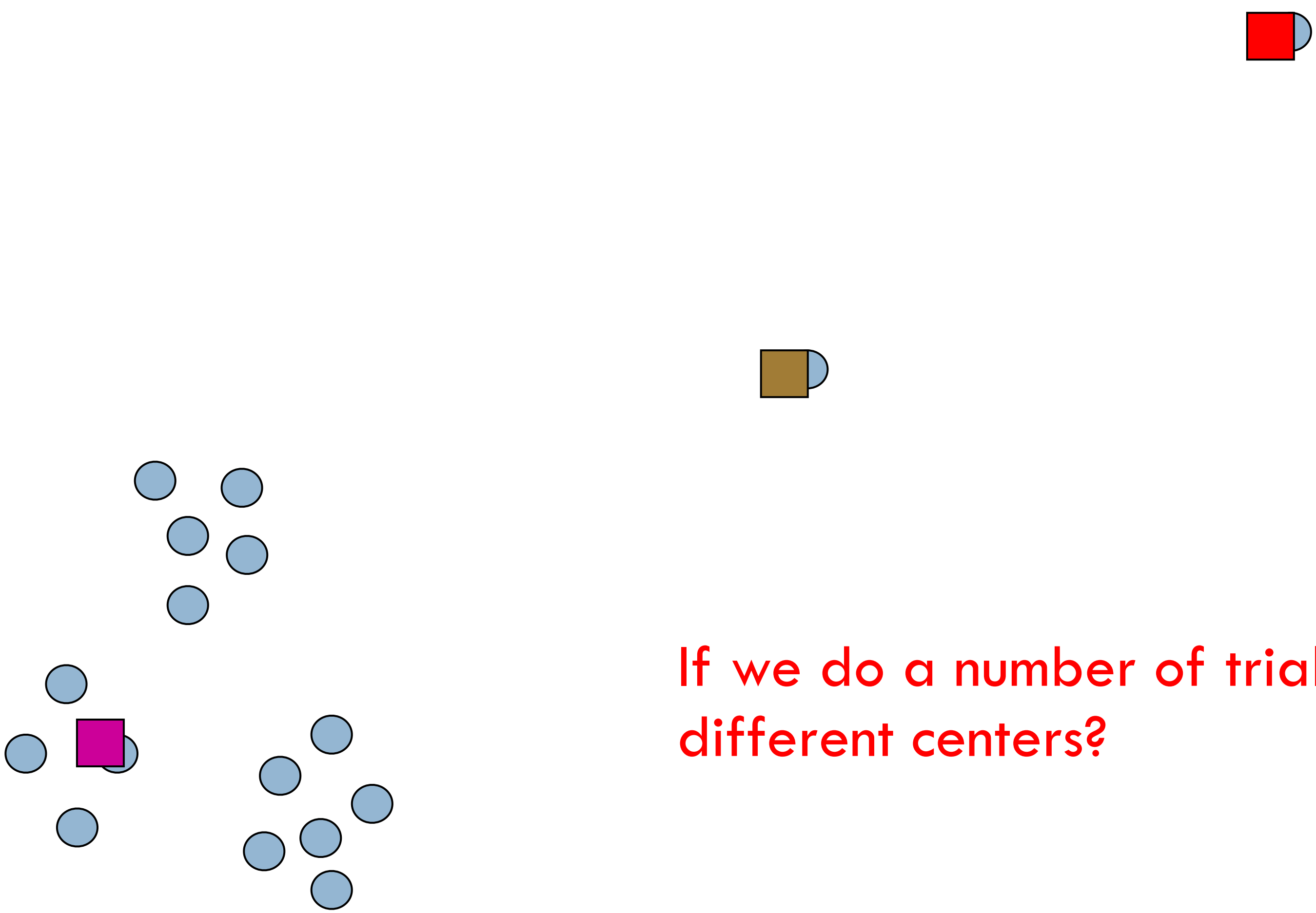
Furthest points concerns



If k = 4, which points will get chosen?

Credit: David Kauchak

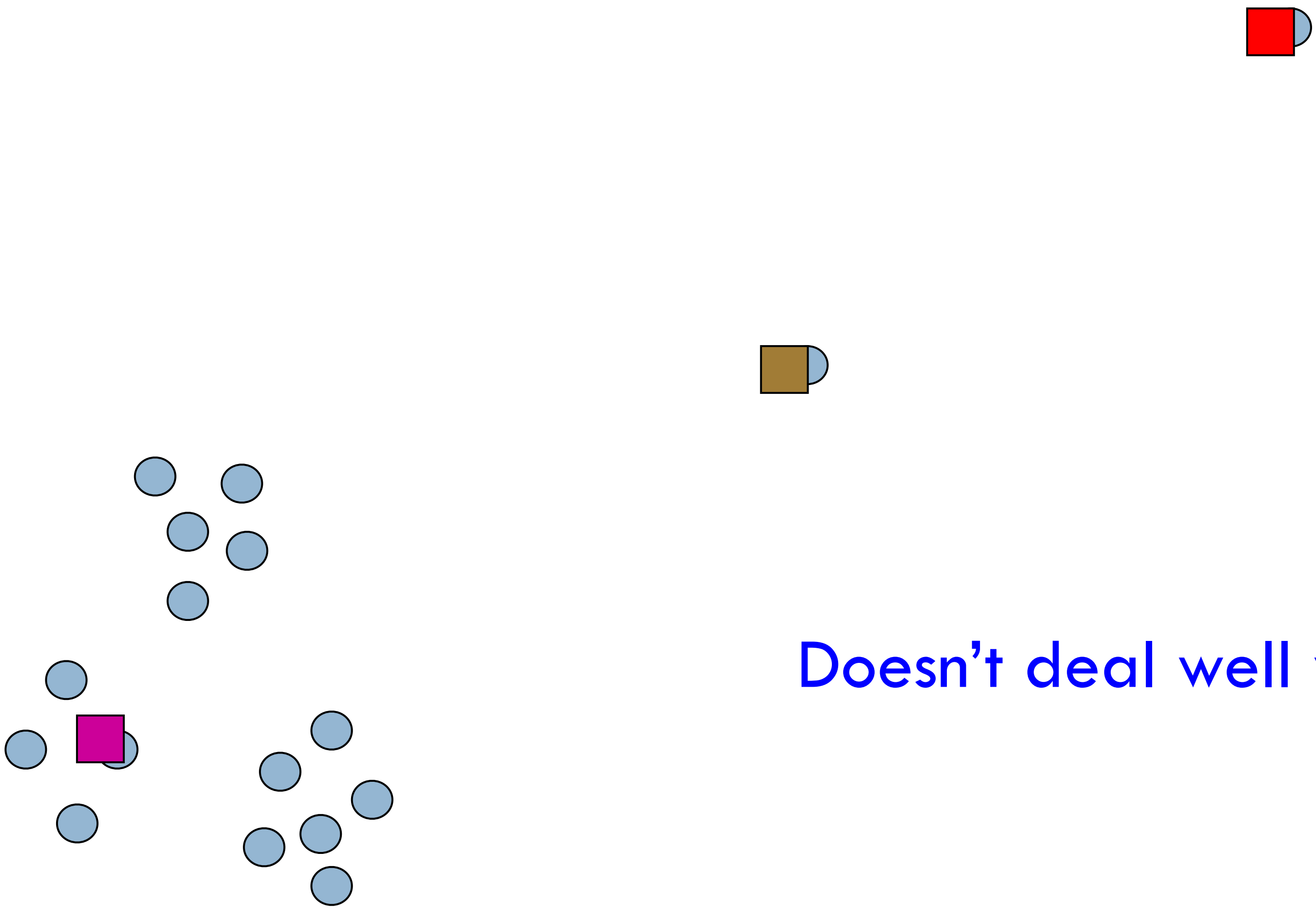
Furthest points concerns



If we do a number of trials, will we get different centers?

Credit: David Kauchak

Furthest points concerns



Doesn't deal well with outliers

Credit: David Kauchak

K-means

- But usually k-means works pretty well
  - Especially with large number of points and large number of centers k
- Variations: kmeans++, etc
- Alternatives: spectral clustering, hierarchical (bottom-up, agglomerative or top-down, divisive)

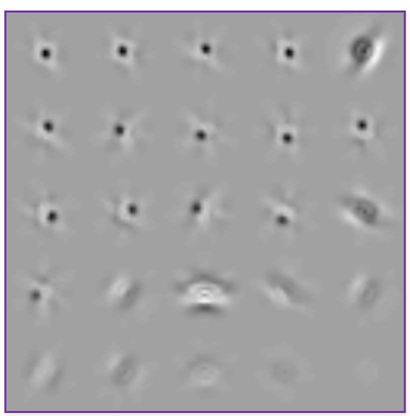
Coming back to textons

Clustering Textons

- Output of bank of *n* filters can be thought of as vector in *n*-dimensional space
- Can *cluster* these vectors using *k*-means [Malik et al.]
- Result: dictionary of most common textures

Clustering Textons

Image



Clustered Textons

Texton to Pixel Mapping

Malik

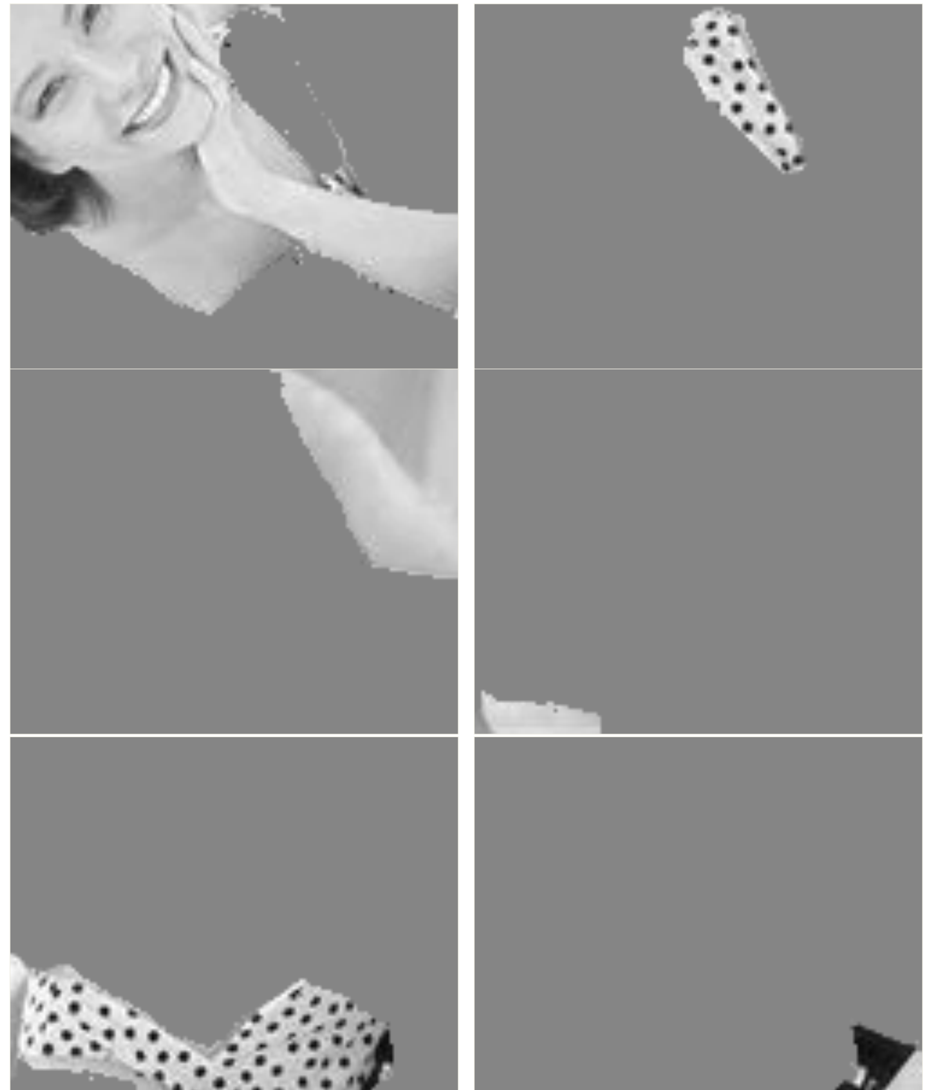
Using Texture in Segmentation

- Compute histogram of how many times each of the *k* clusters occurs in a neighborhood
- Define similarity of histograms h_i and h_j using χ^2

$$\chi^2 = \frac{1}{2} \sum_k \frac{(h_i(k) - h_j(k))^2}{h_i(k) + h_j(k)}$$

- Different histograms → separate regions

Application: Segmentation



Malik

Texture synthesis

Markov Random Fields

- Different way of thinking about textures
- Premise: probability distribution of a pixel depends on values of neighbors
- Probability the same throughout image
  - Extension of Markov chains

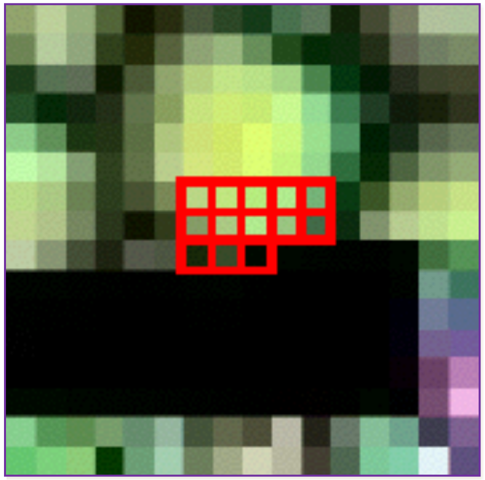
Motivation from Language

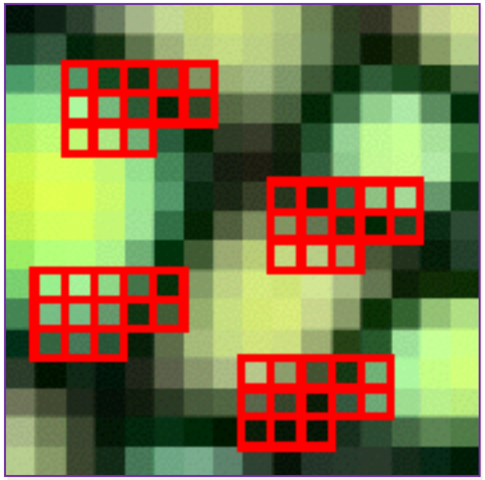
- Shannon (1948) proposed a way to synthesize new text using N-grams
  - Use a large text to compute probability distributions of each letter given N–1 previous letters
  - Starting from a seed repeatedly sample the conditional probabilities to generate new letters
  - Can do this with image patches!

Efros

Texture Synthesis Based on MRF

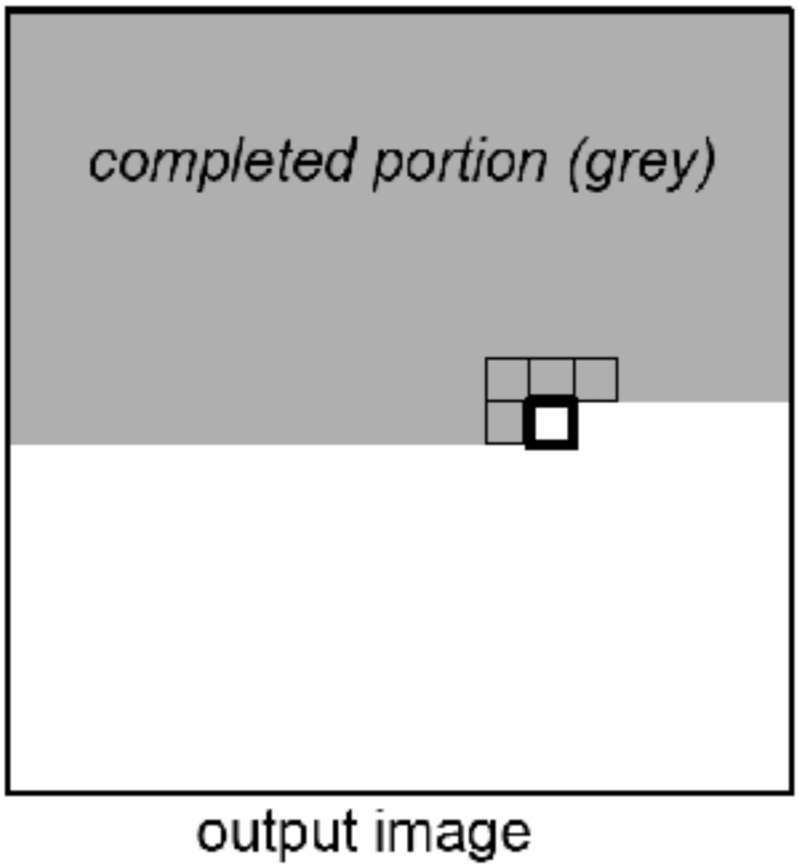
- For each pixel in destination:
  - Take already-synthesized neighbors
  - Find closest match in original texture
  - Copy pixel to destination
- Efros & Leung 1999
  - Speedup by Wei & Levoy 2000
  - Extension to copying whole blocks by Efros & Freeman 2001





Wei & Levoy

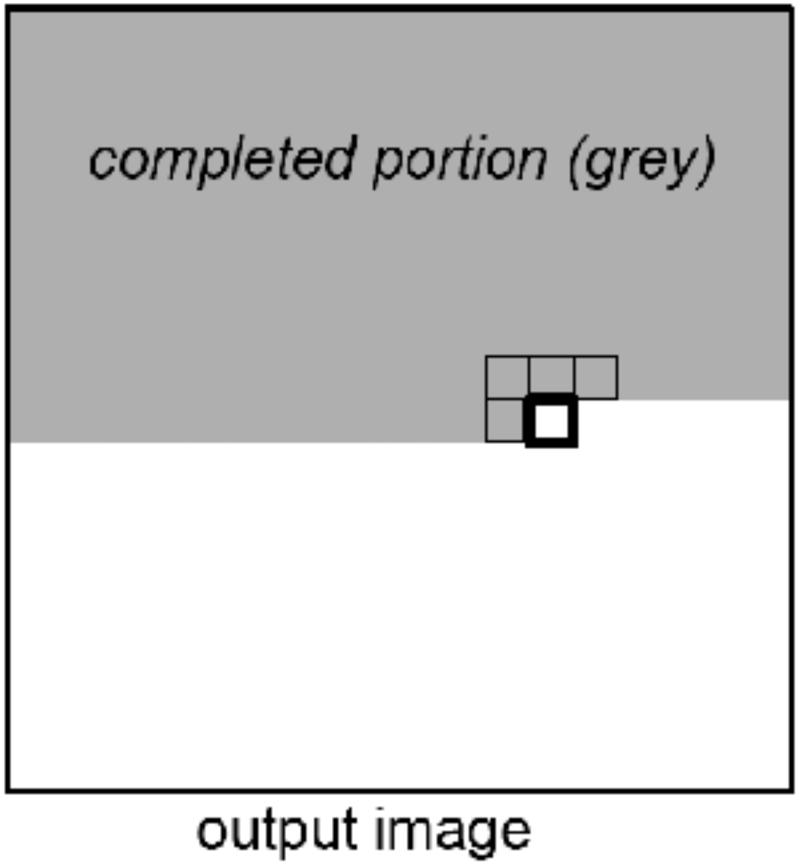
Efros & Leung Algorithm



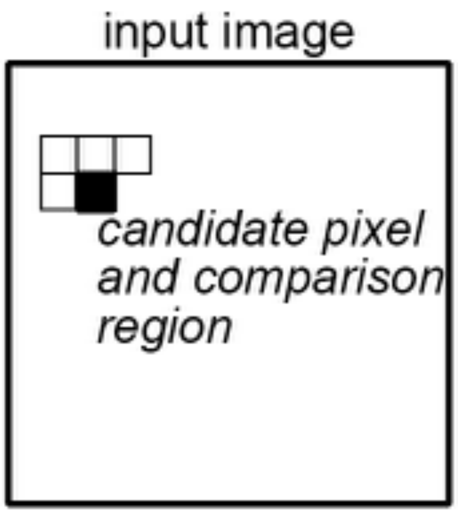
- Compute output pixels in scanline order (top-to-bottom, left-to-right)

Efros

Efros & Leung Algorithm



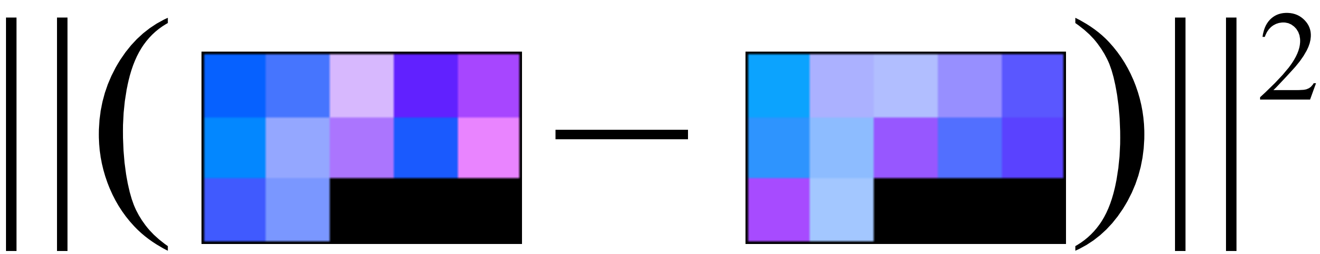
- Find candidate pixels based on similarities of pixel features in neighborhoods



Efros

Efros & Leung Algorithm

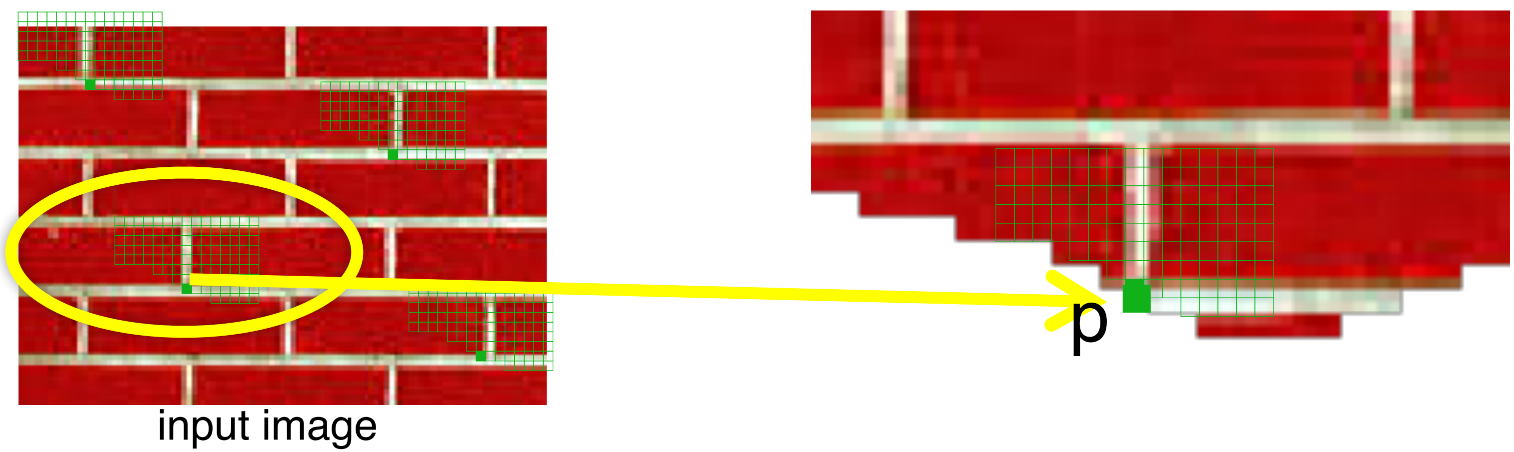
- Similarities of pixel neighborhoods can be computed with squared differences (SSD) of pixel colors and/or filter bank responses



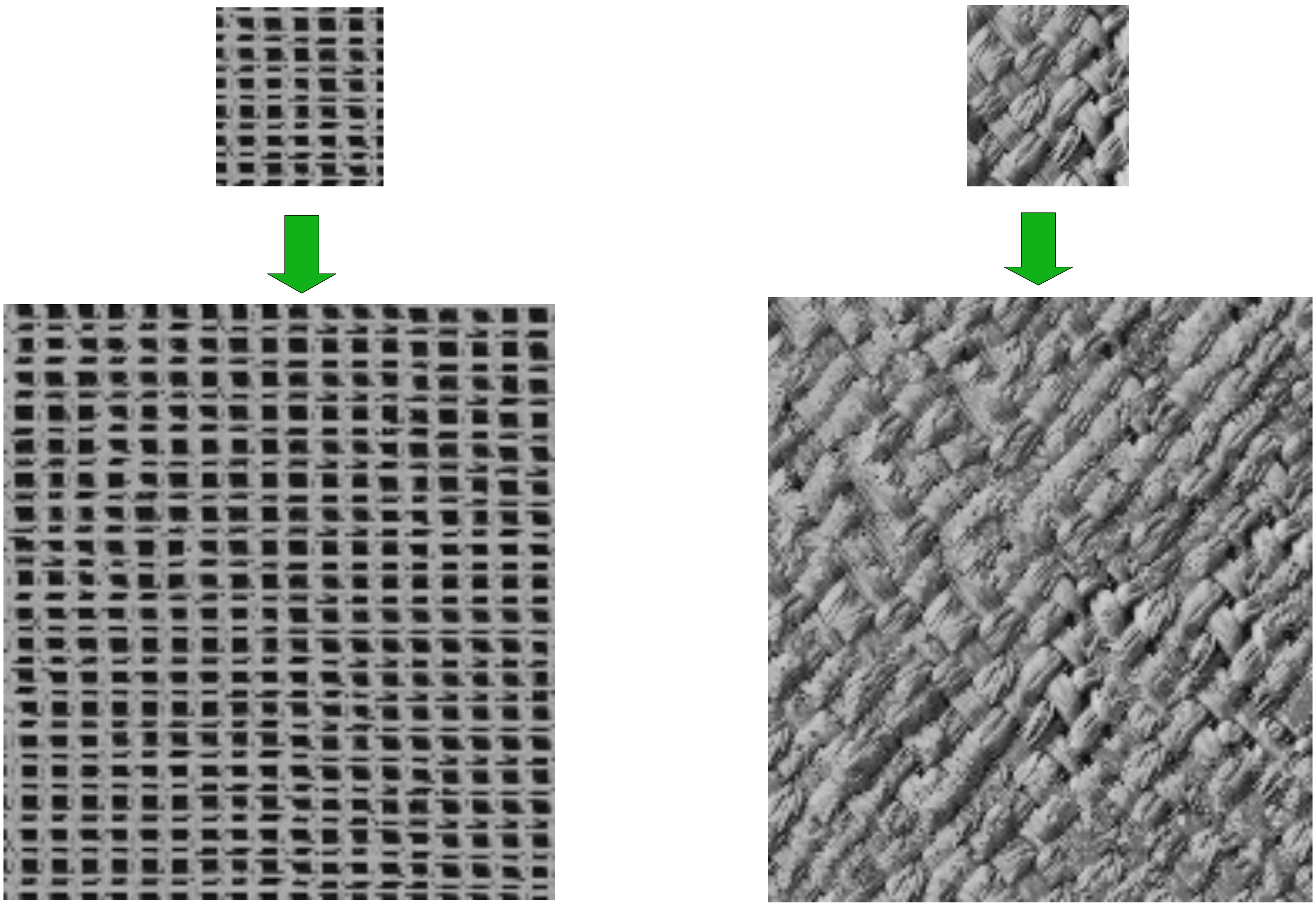
Efros

Efros & Leung Algorithm

- For each pixel p:
  - Find the best matching K windows from the input image
  - Pick one matching window at random
  - Assign p to be the center pixel of that window



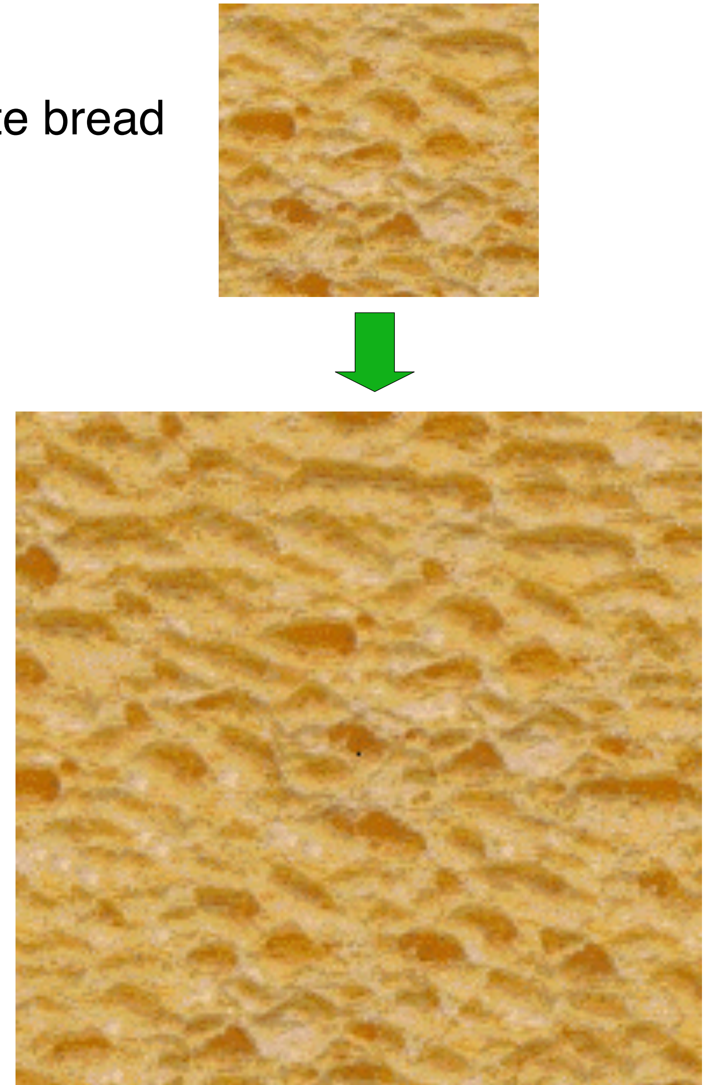
Synthesis Results



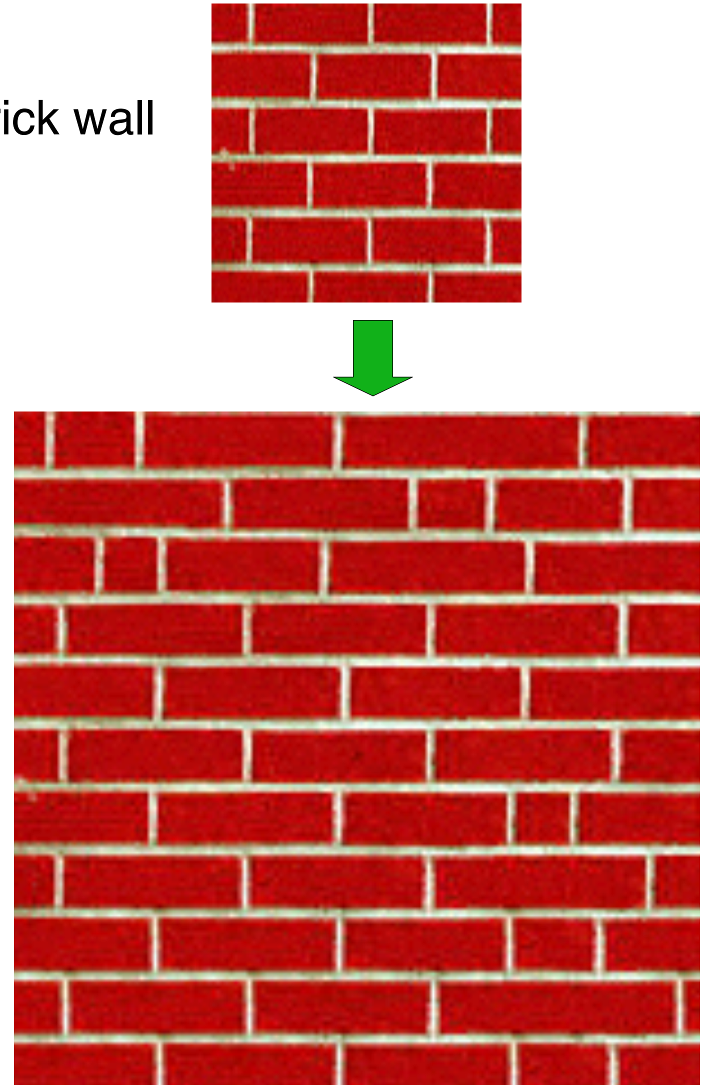
Efros

Synthesis Results

white bread



brick wall

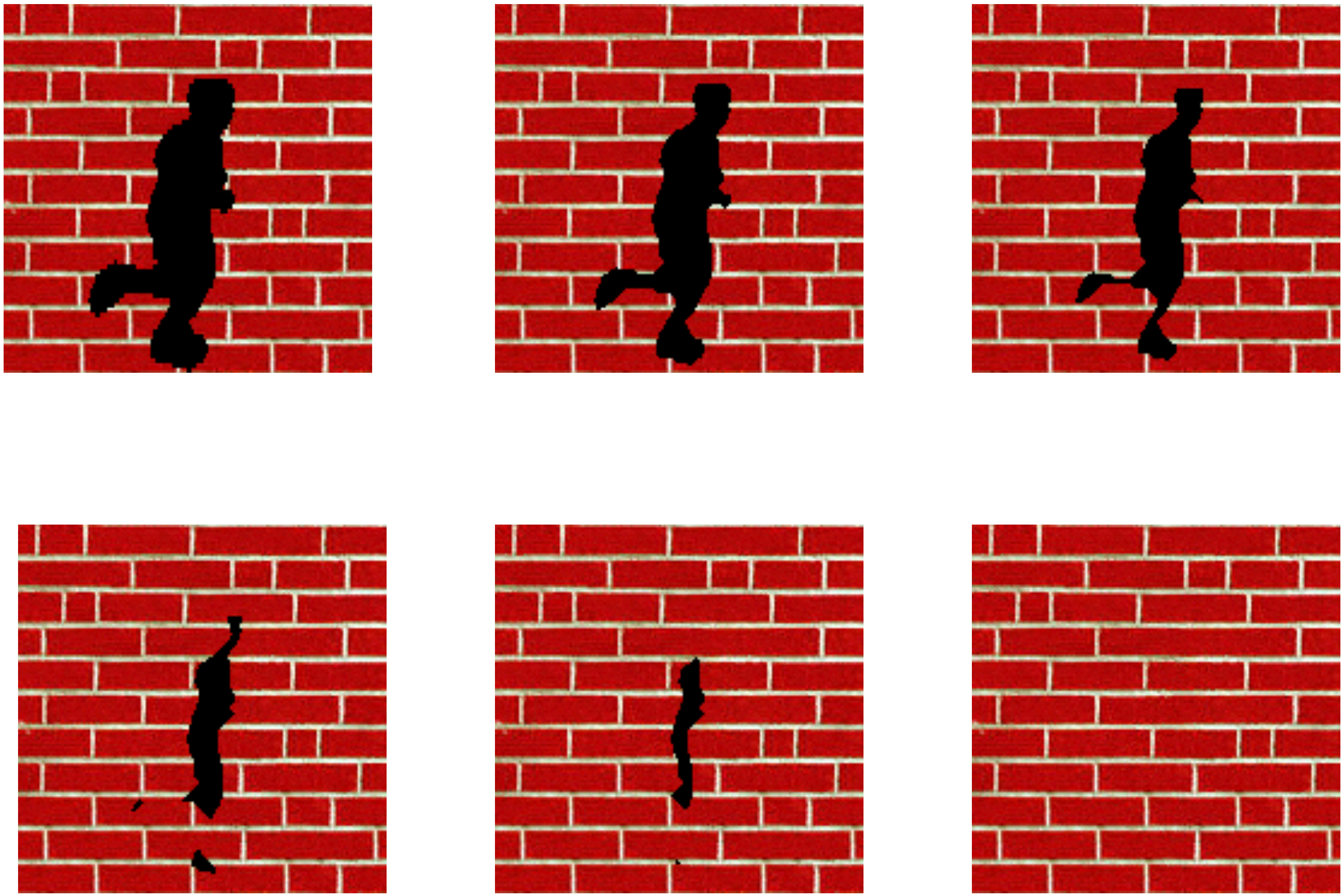


Efros

Hole Filling

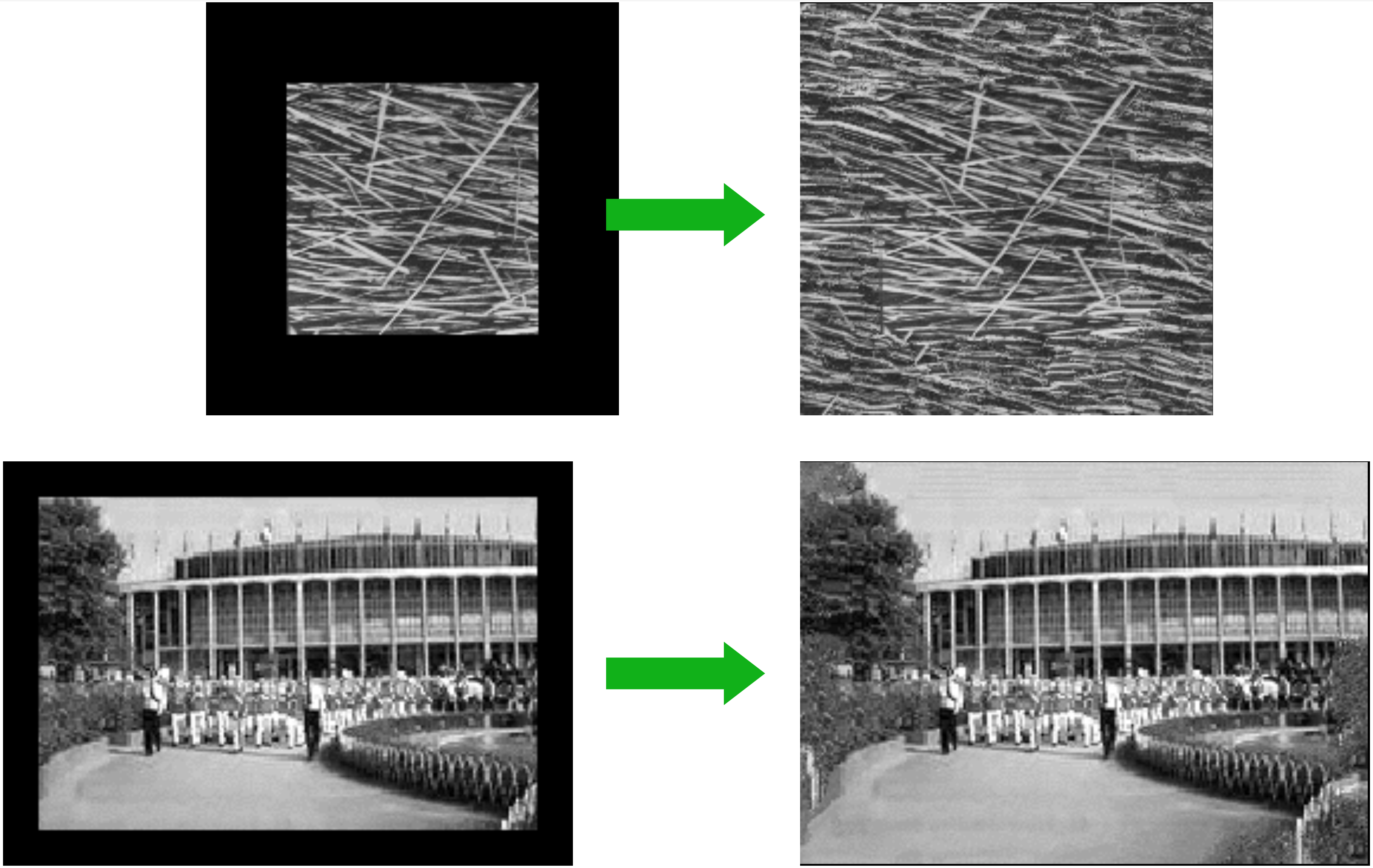
- Fill pixels in “onion skin” order
  - Within each “layer”, pixels with most neighbors are synthesized first
  - Normalize error by the number of known pixels
  - If no close match can be found, the pixel is not synthesized until the end

Hole Filling



Efros

Extrapolation



Special video

https://ghc.anitab.org/ghc-17-livestream/

(Wednesday keynote, 16:20 min - 44:00 min)