CS9840
Machine Learning in Computer Vision
Olga Veksler

Lecture 4

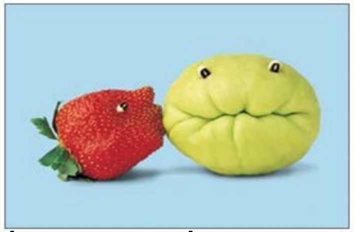
Image Representation

Outline

- How to represent an image as a feature vector?
- Basic image features
  - intensity, color, gradients, response to filter(s)
  - dense (at each pixel)
  - sparse (at a subset of locations)
- Representation of image through basic features
  - pixelwise
  - histogram
    - Global vs. Local histograms
    - Spatial pyramids

Basic Image Features

- Given image **I**, first compute *basic image features*
  - e.g. Intensity of a pixel, not enough for most applications
- Other image basic features commonly used

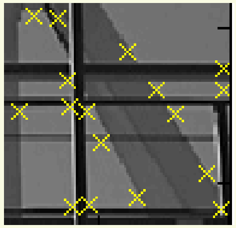


Color: 3 values per pixel

Edges: 1 or 2 values per pixel

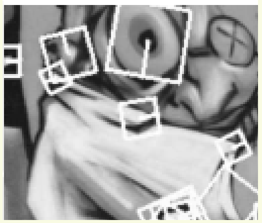
Texture: ≈ 48 values per pixel

- Basic features can be sparse or dense
- Common sparse basic features



Corners

Stable regions

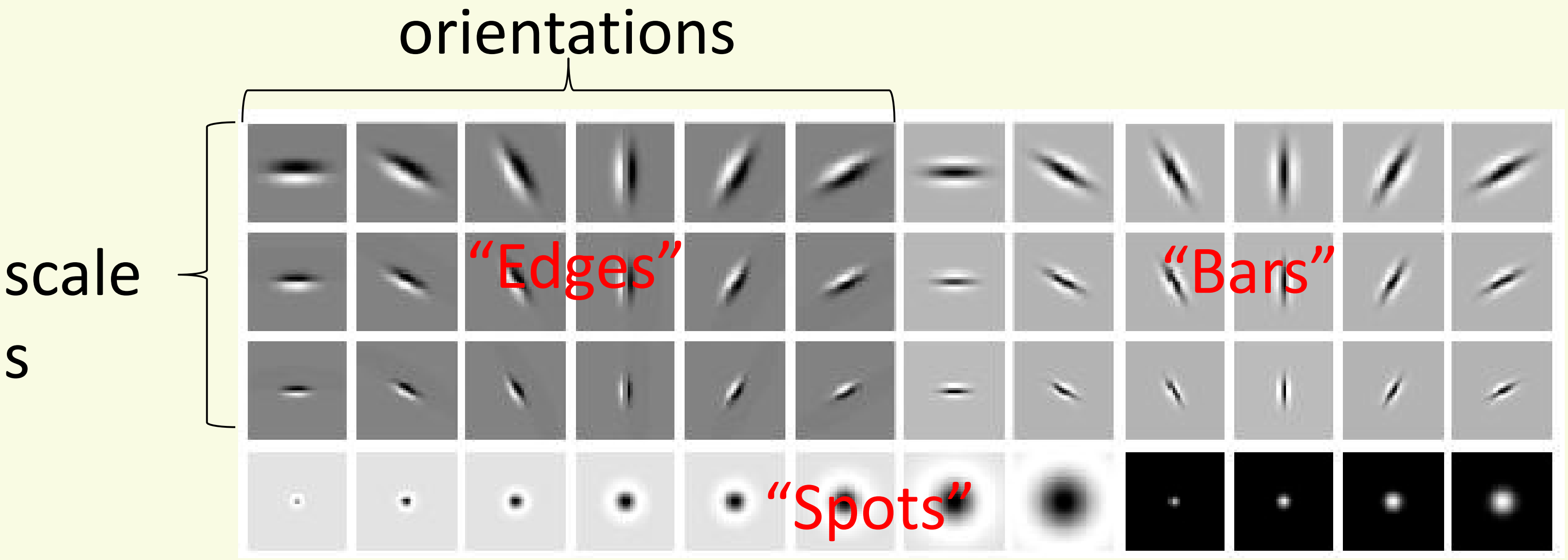


SIFT features

- Consolidate basic features into feature vector ***x*** that represents image **I**

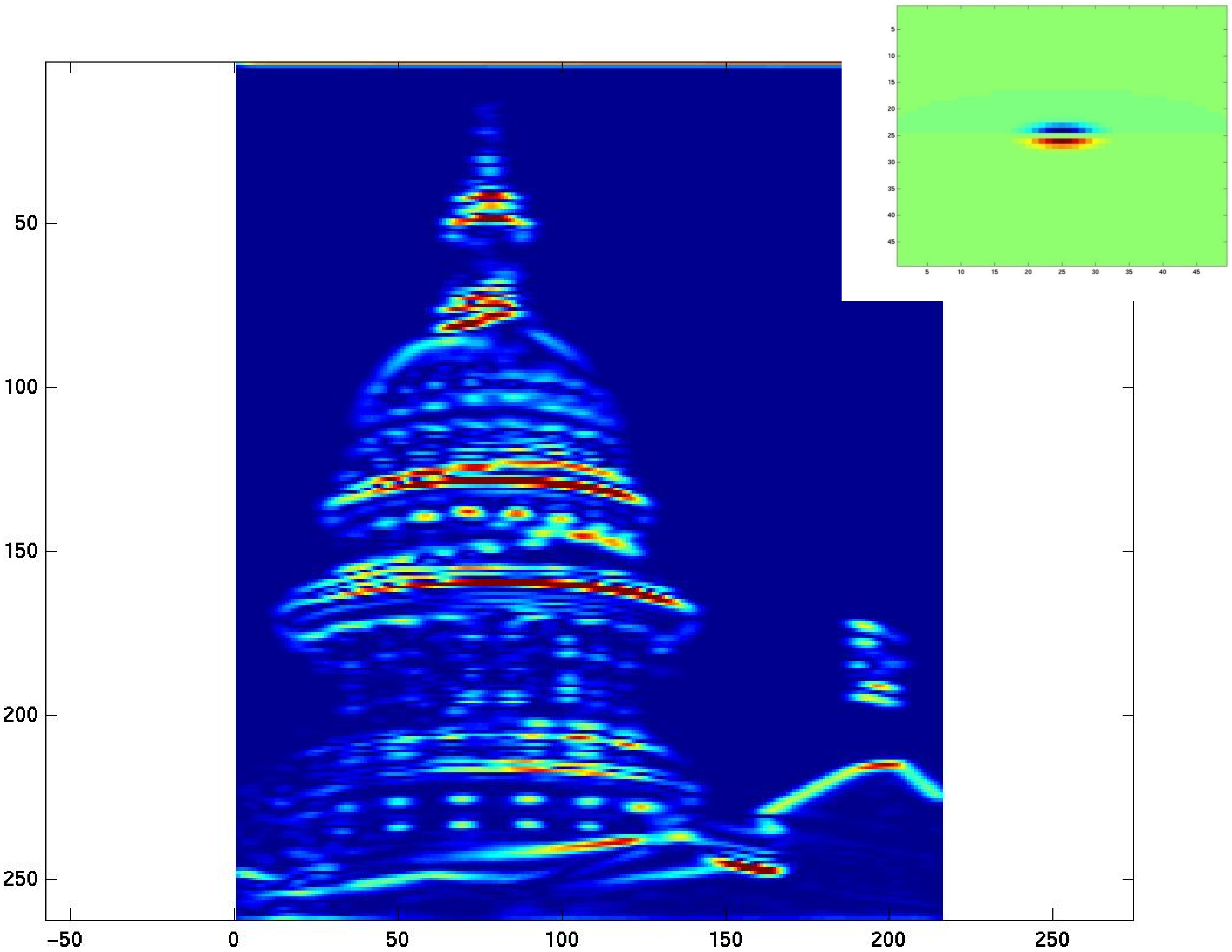
Extracting Texture (Texture Responses)

- Texture filter bank:

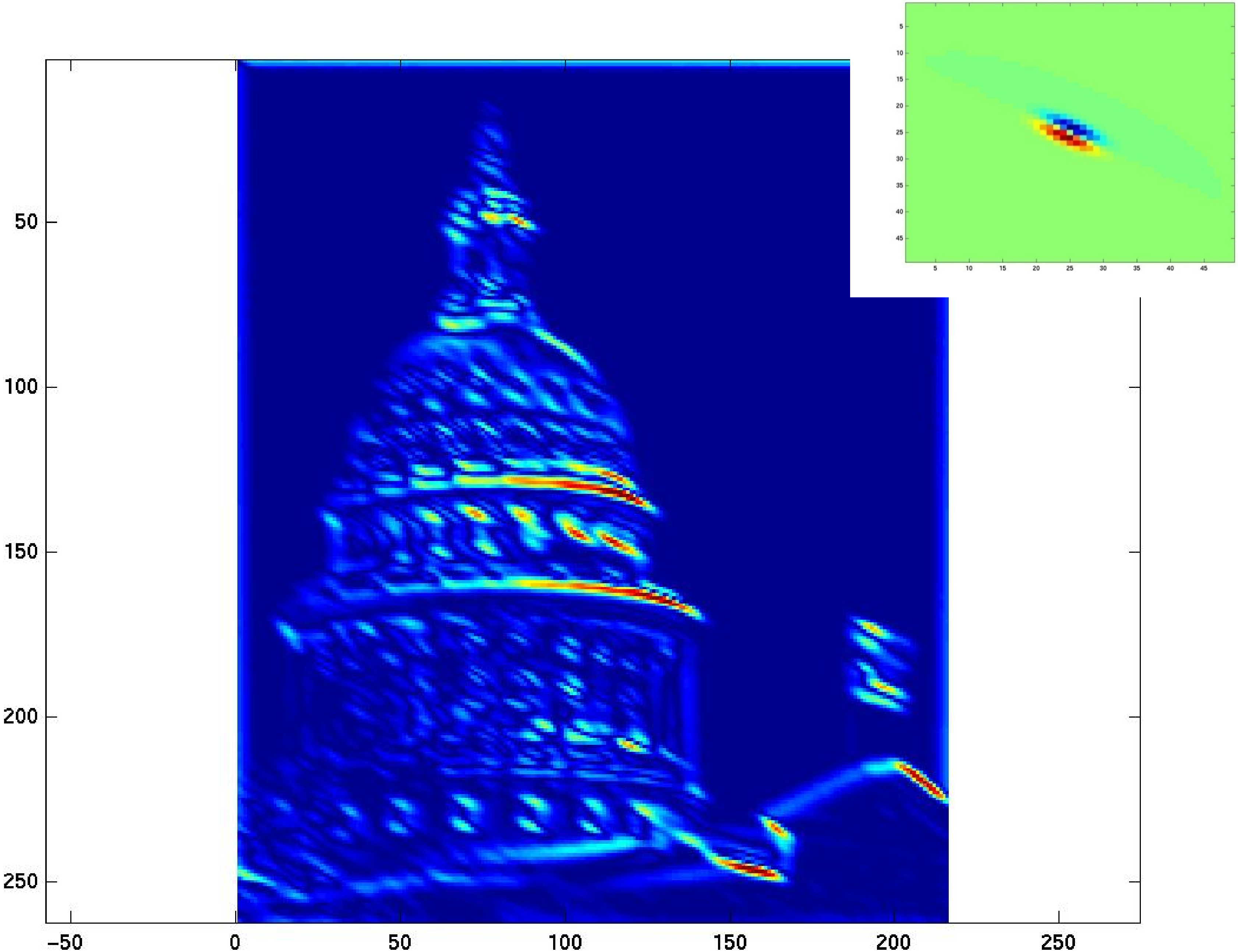


- Convolve image with each filter
  - 48 responses per pixel

Kristen Grauman



Kristen Grauman



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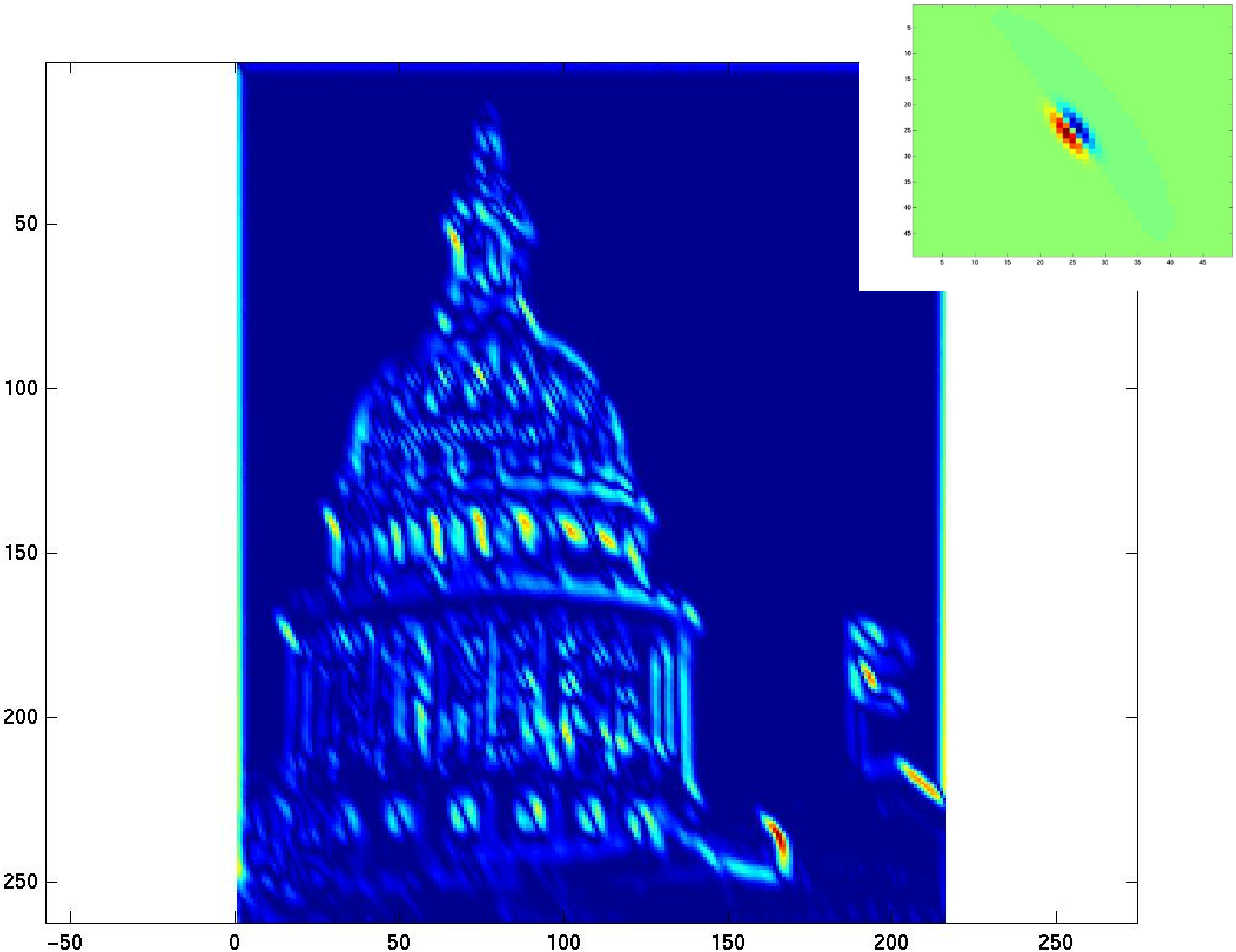

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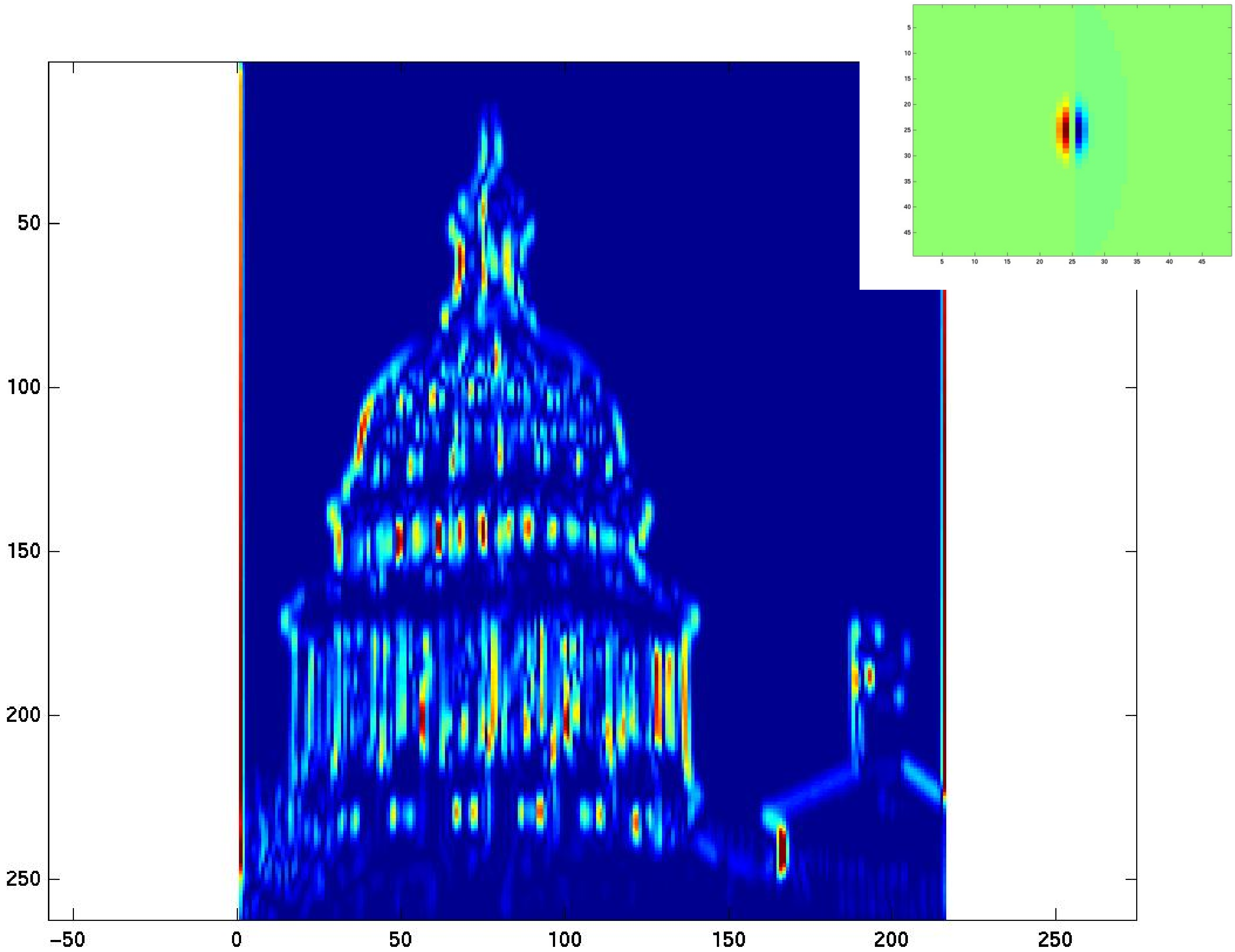
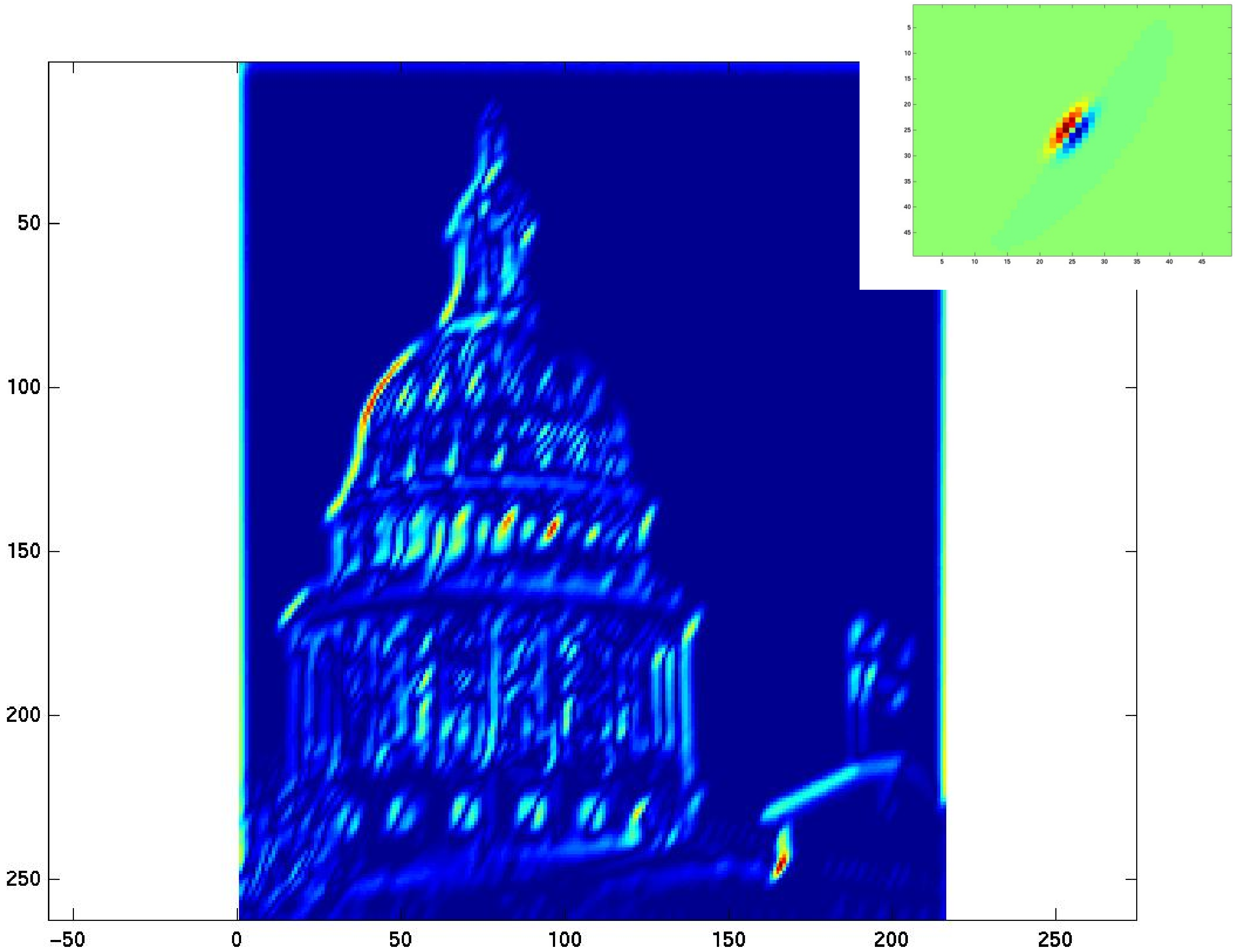

50
100
150
200
250
−50
0
50
100
150
200
250



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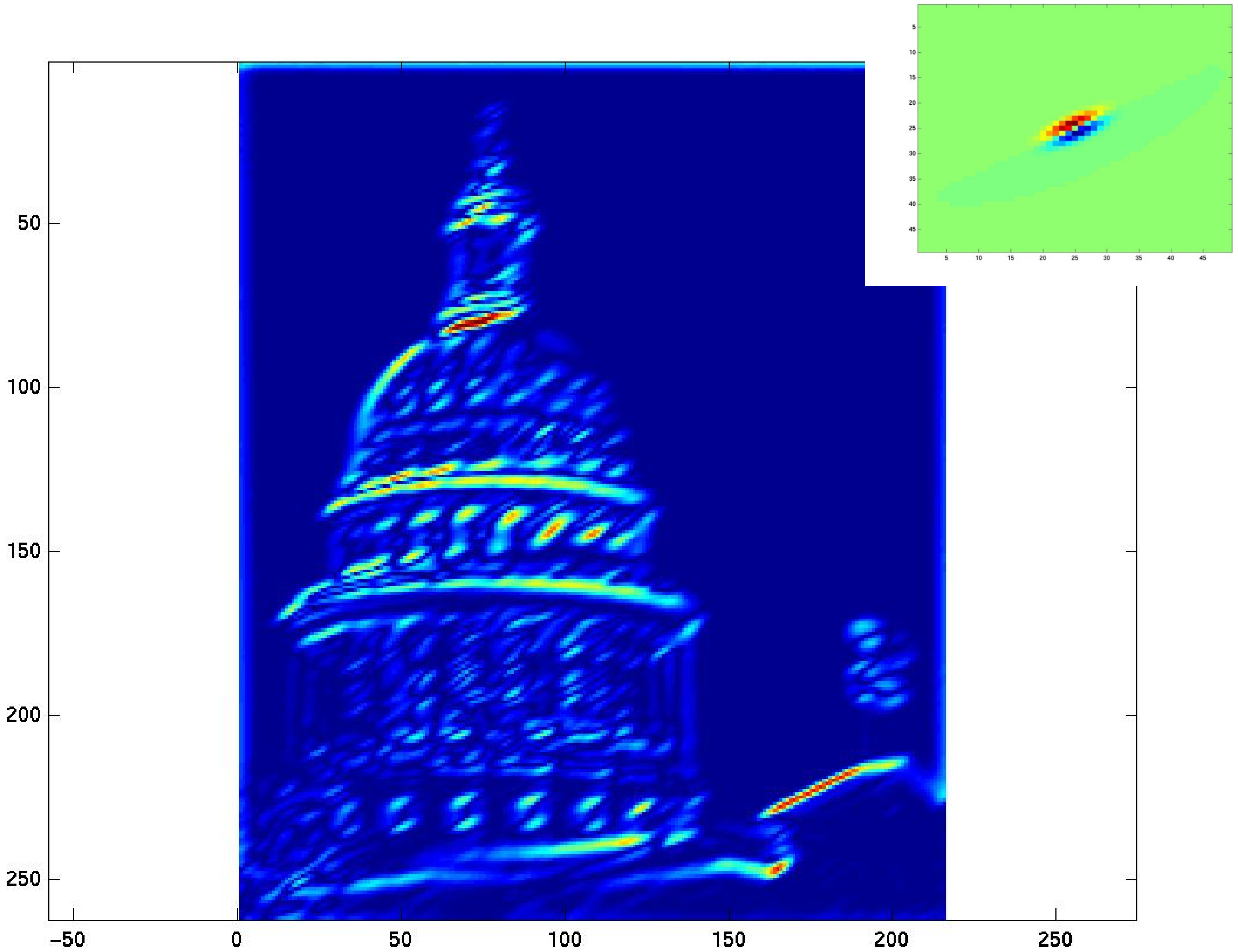

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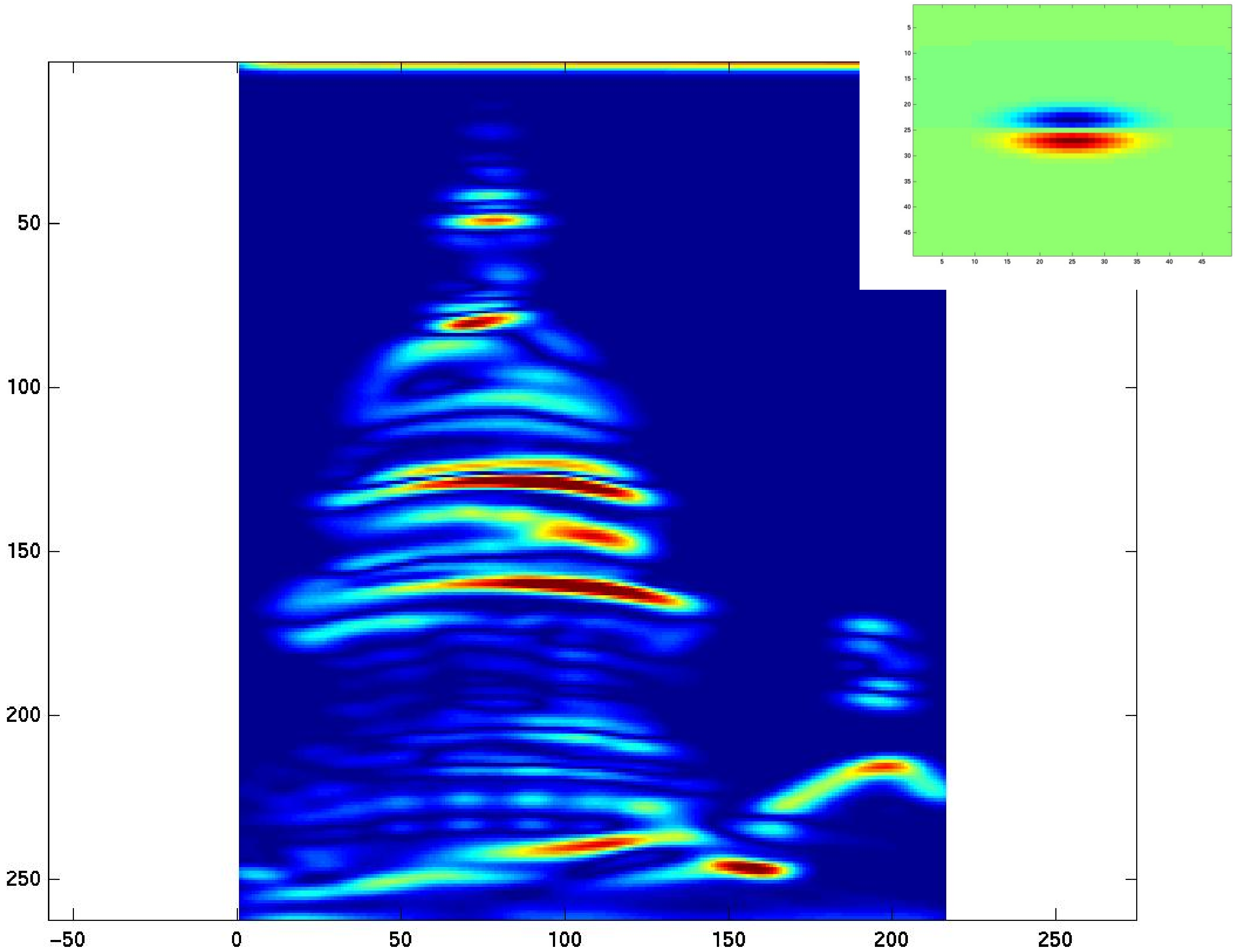

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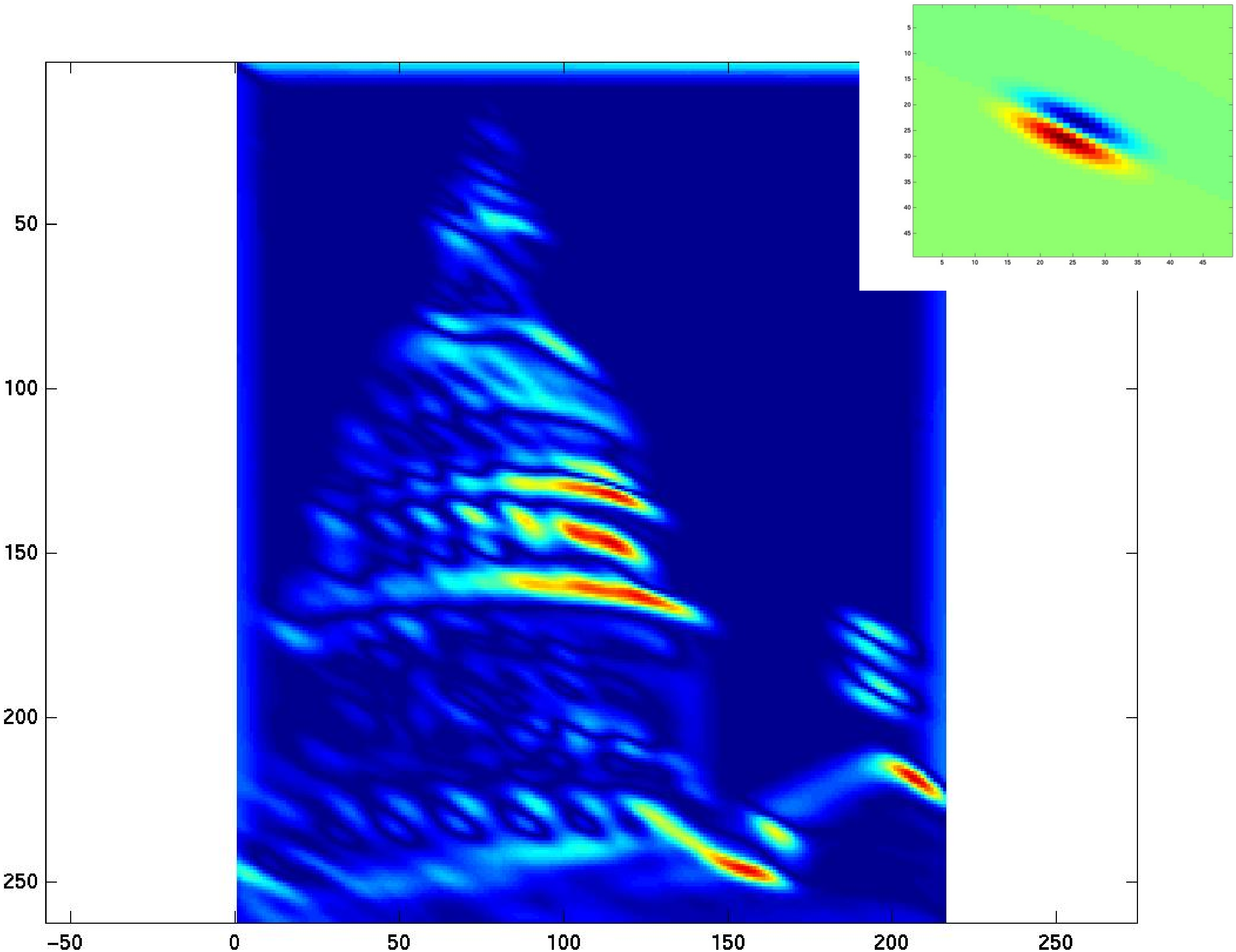

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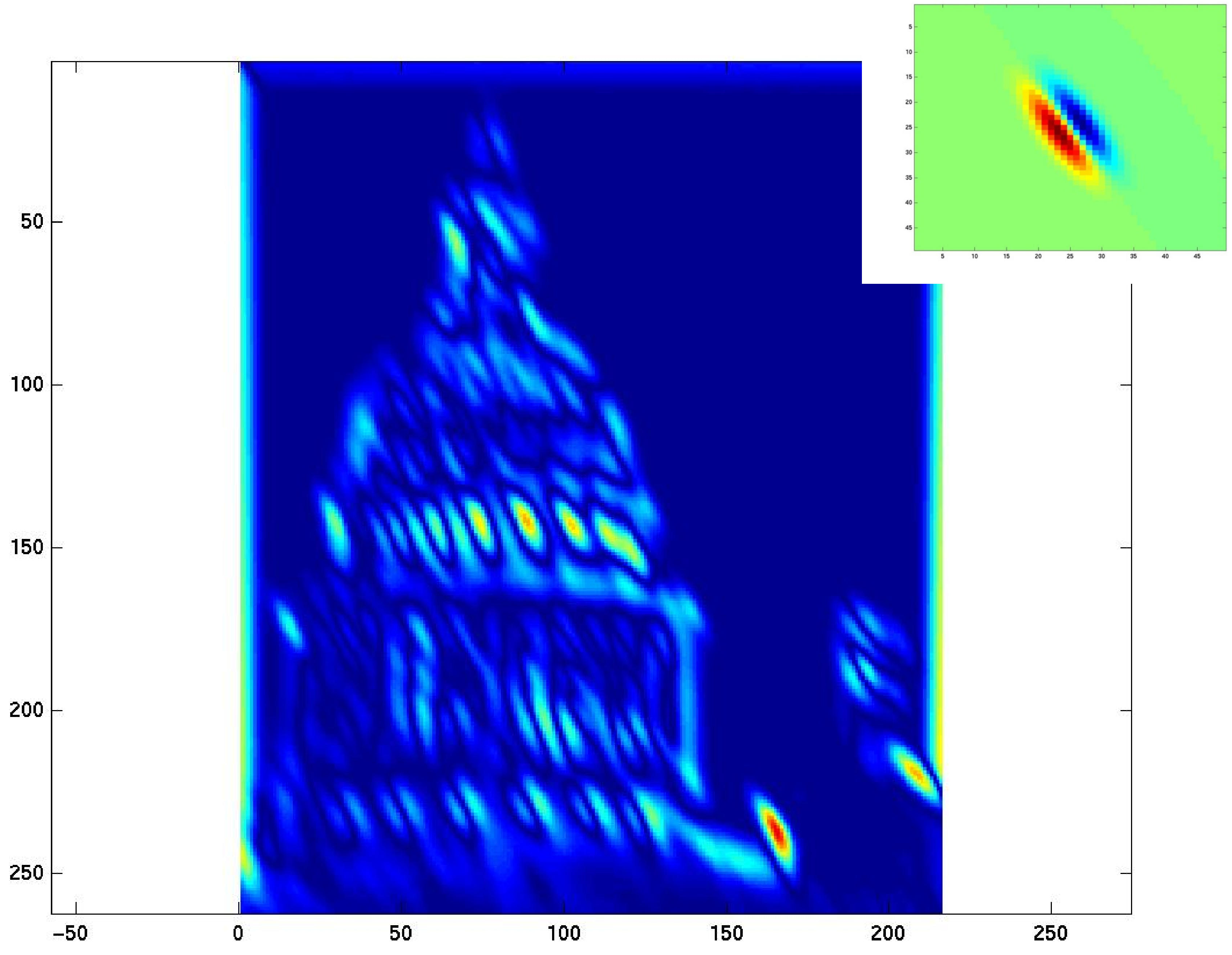

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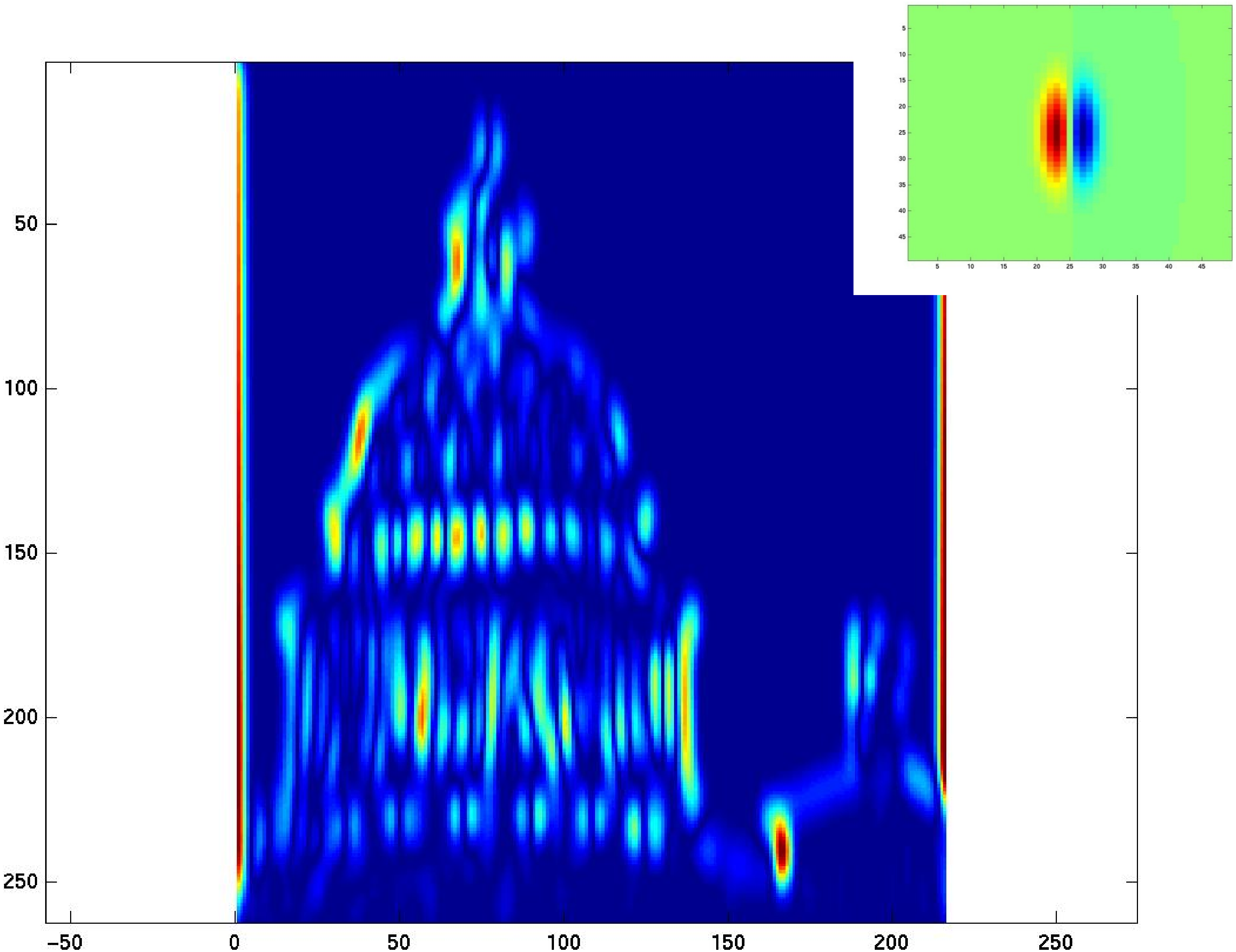

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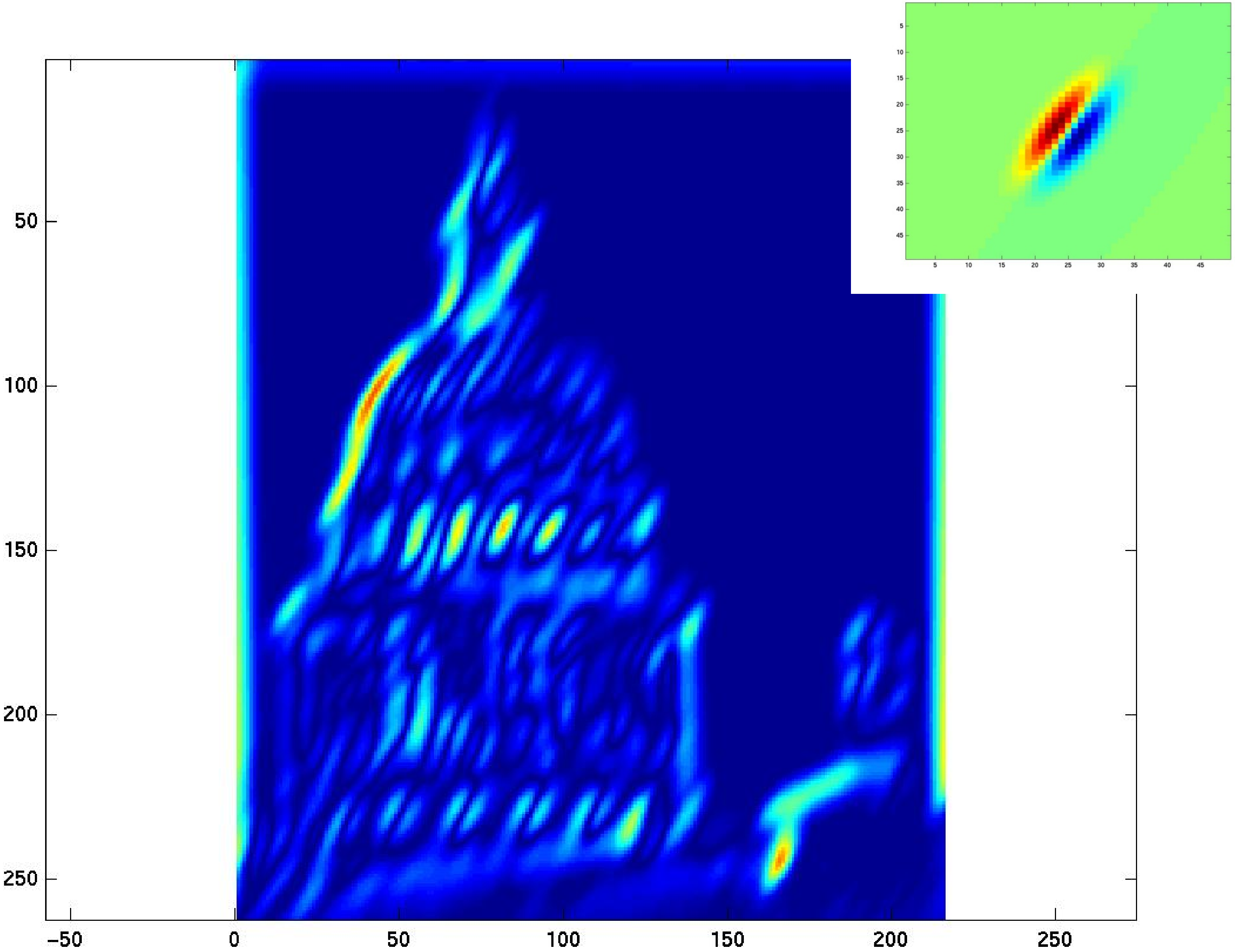

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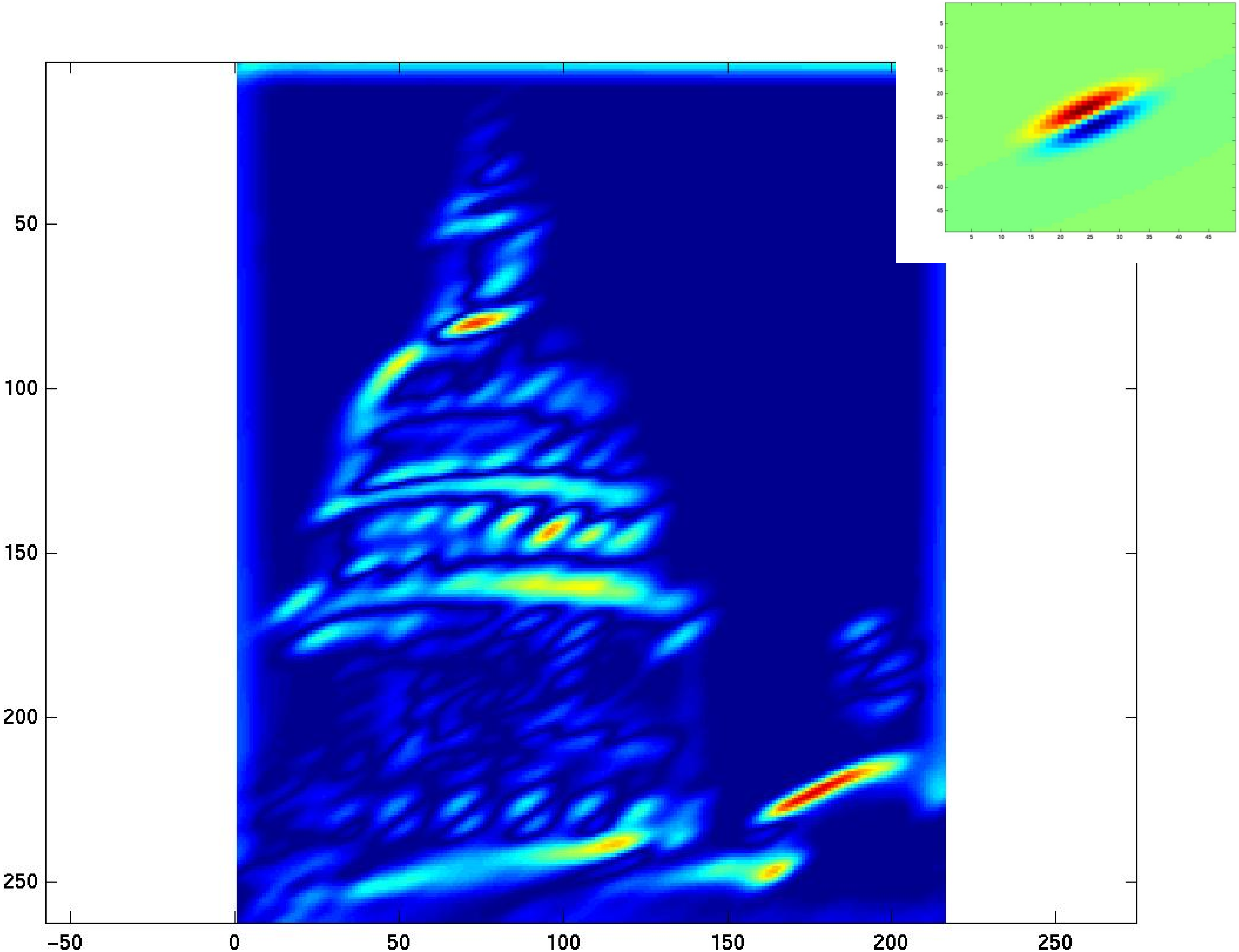

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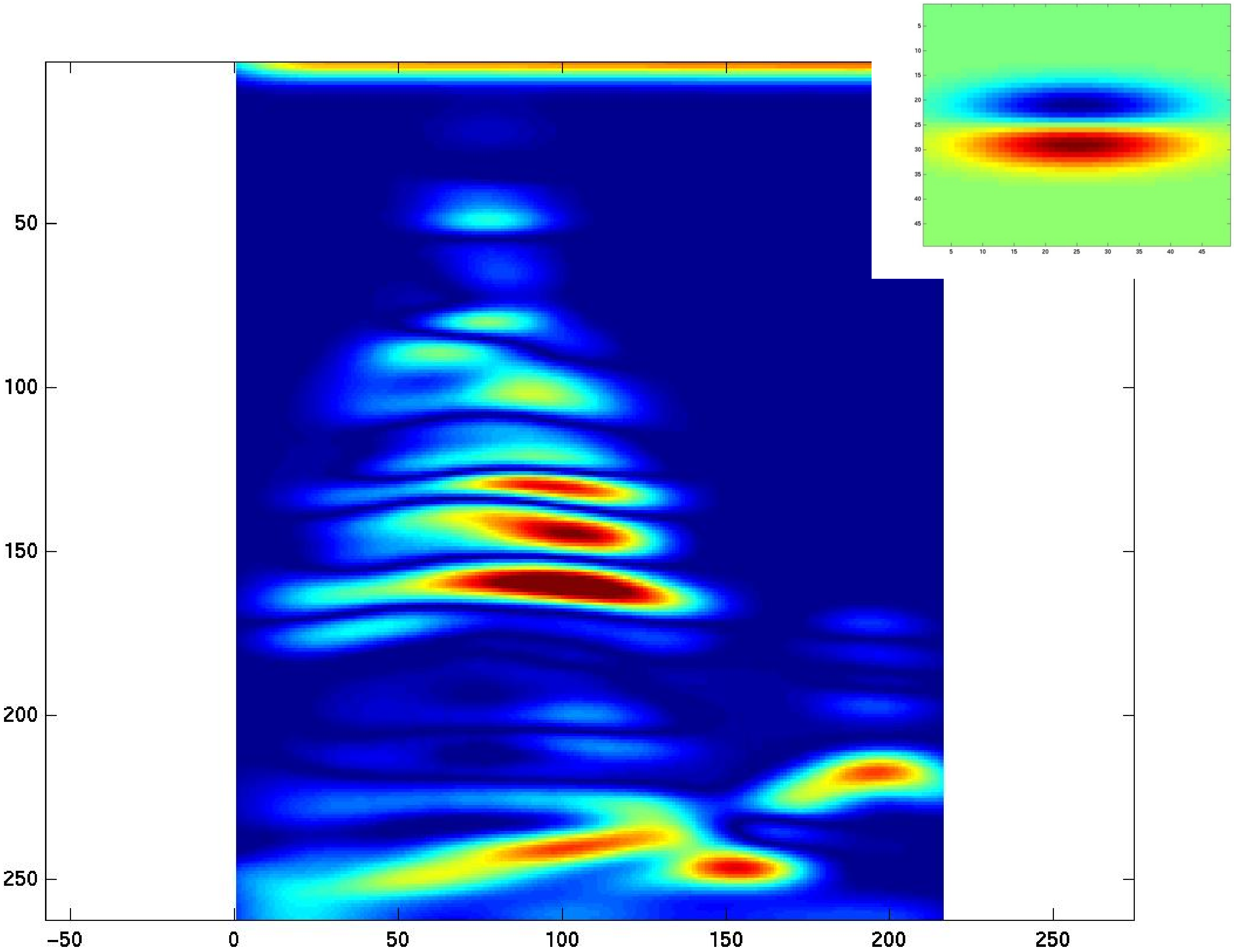

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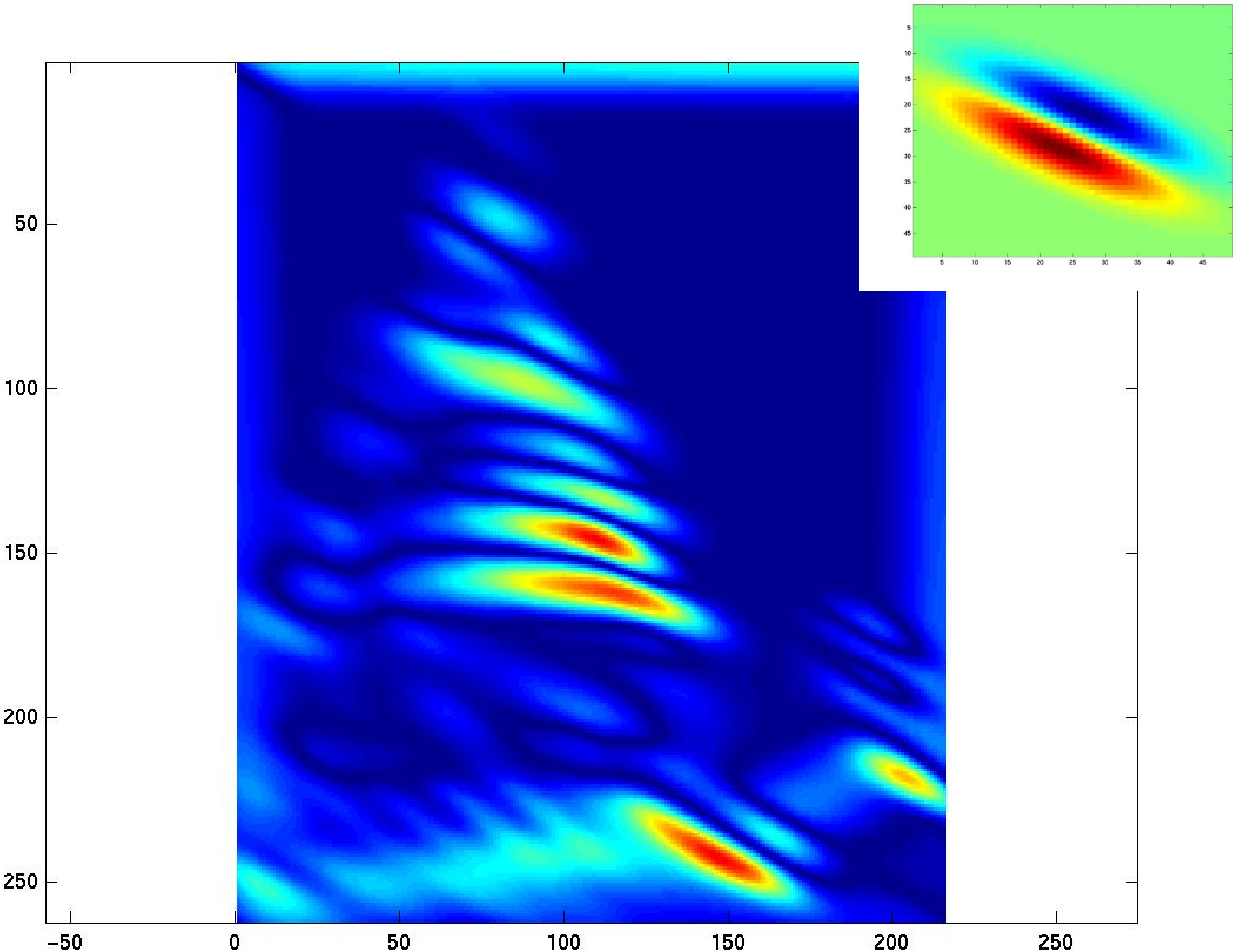

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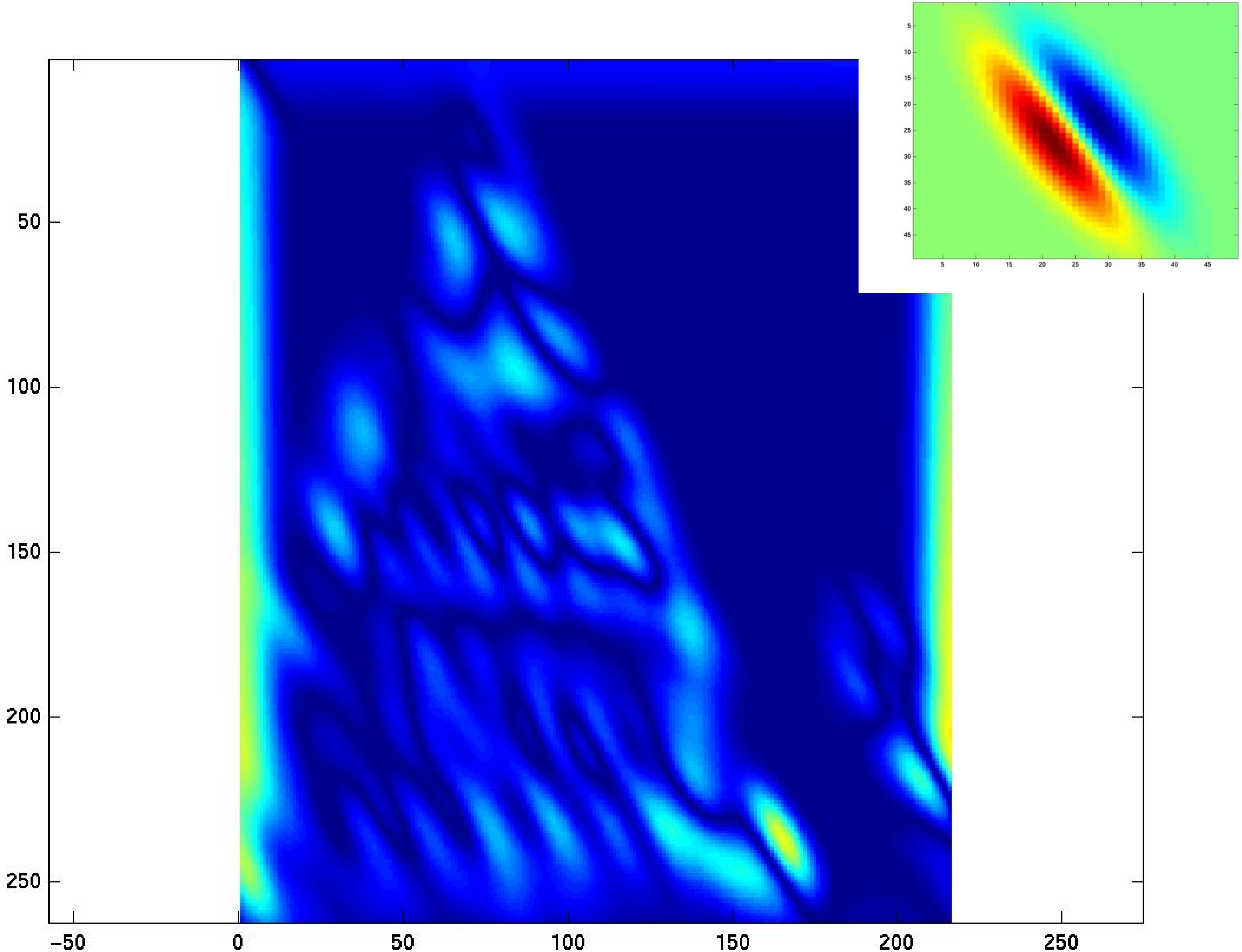

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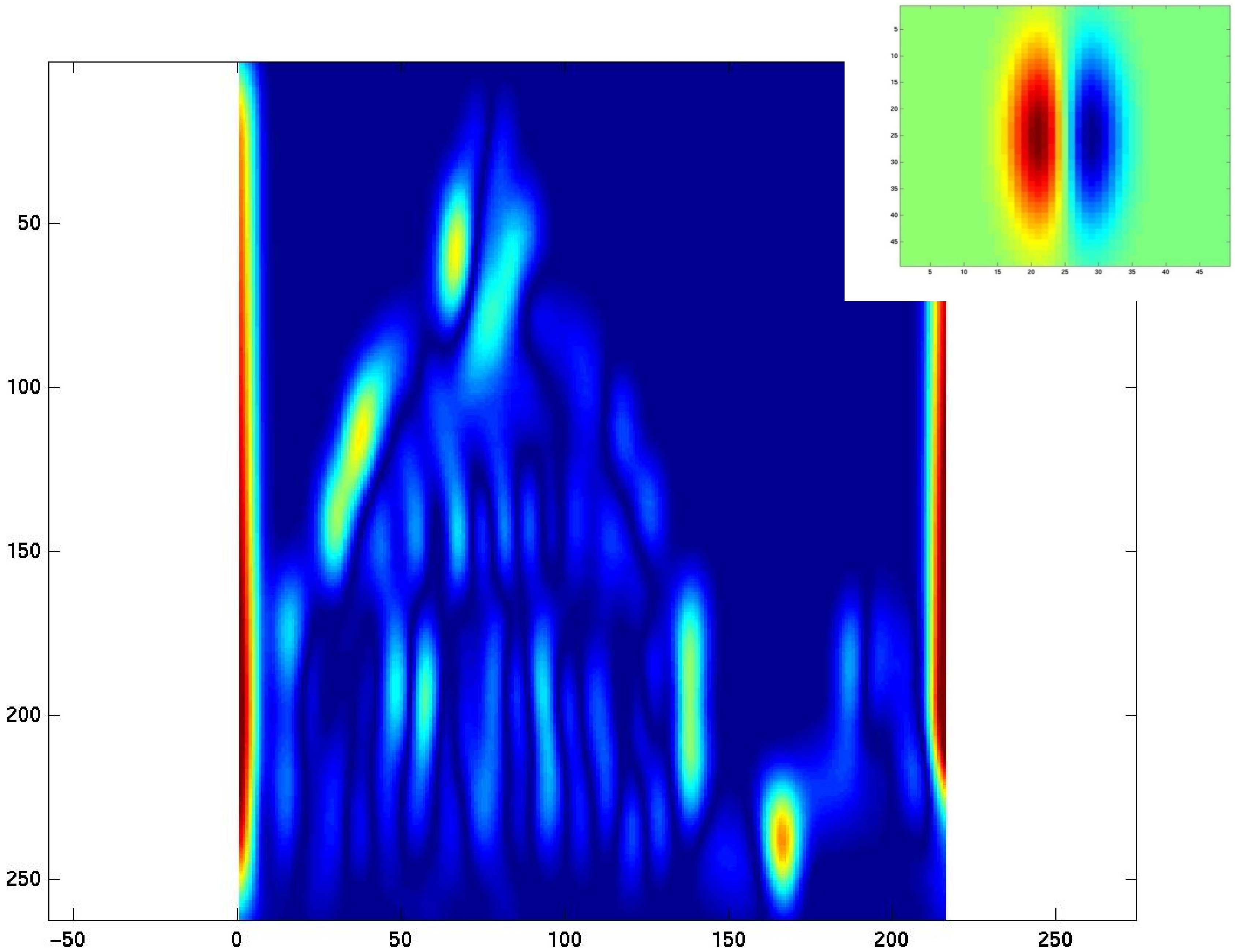

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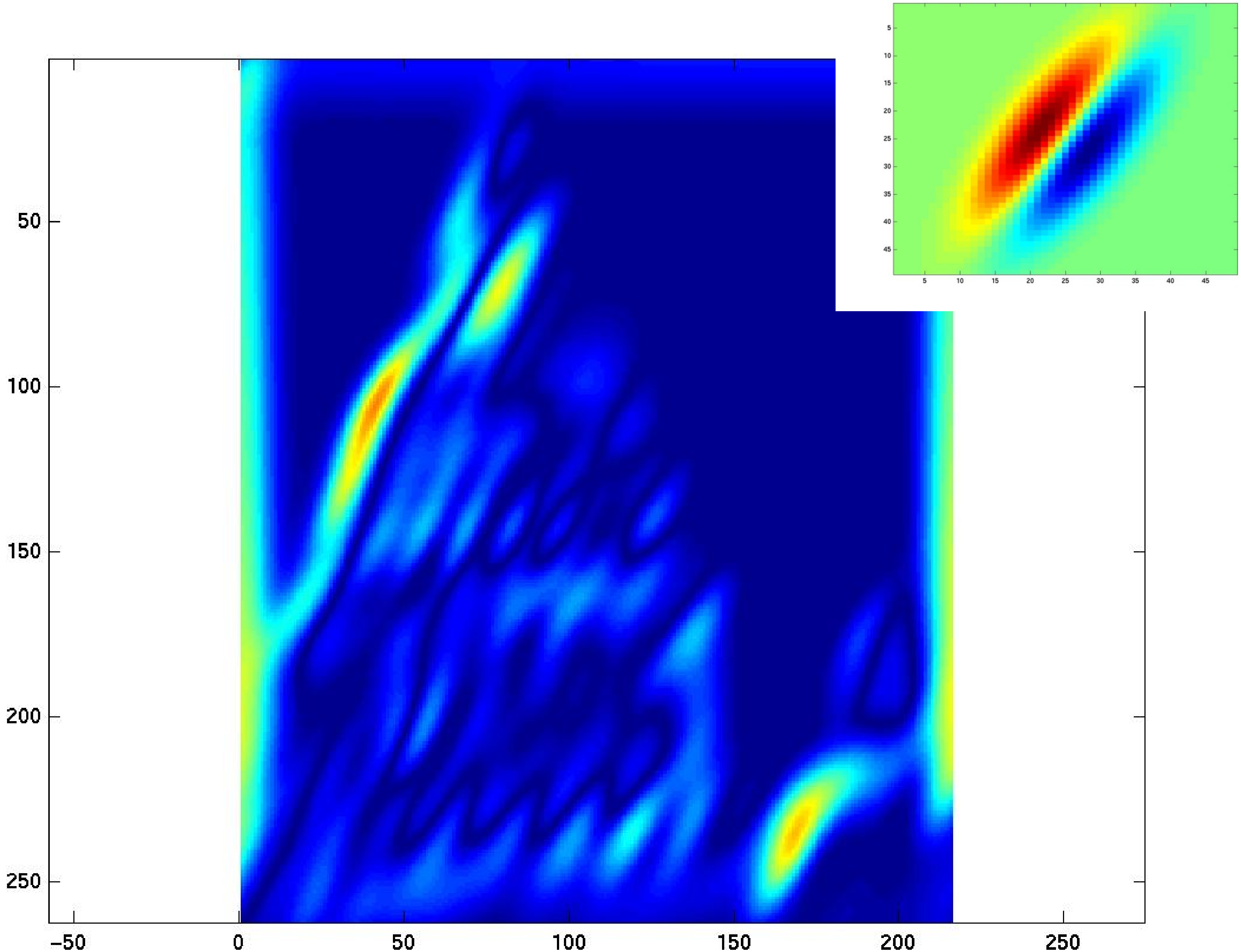

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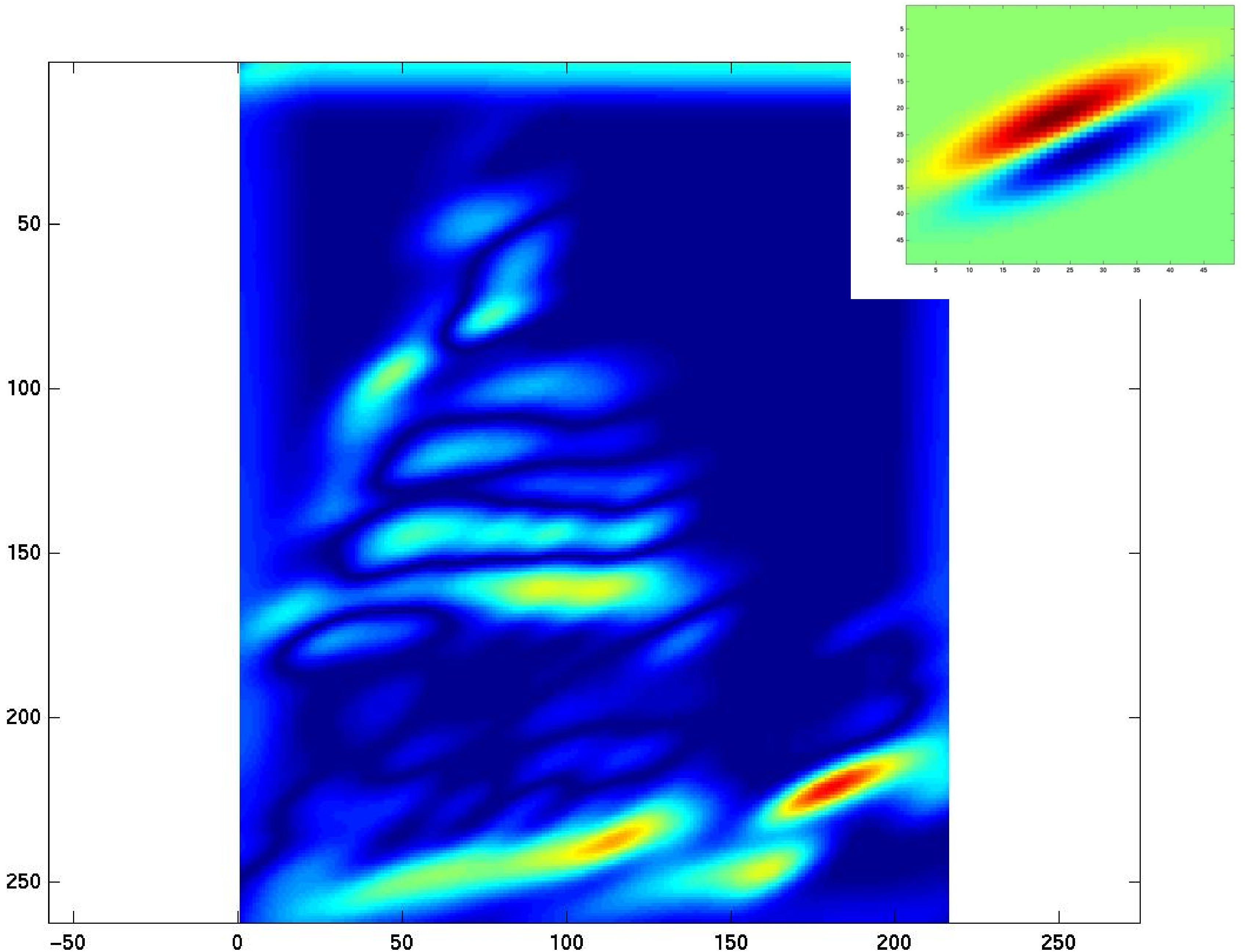

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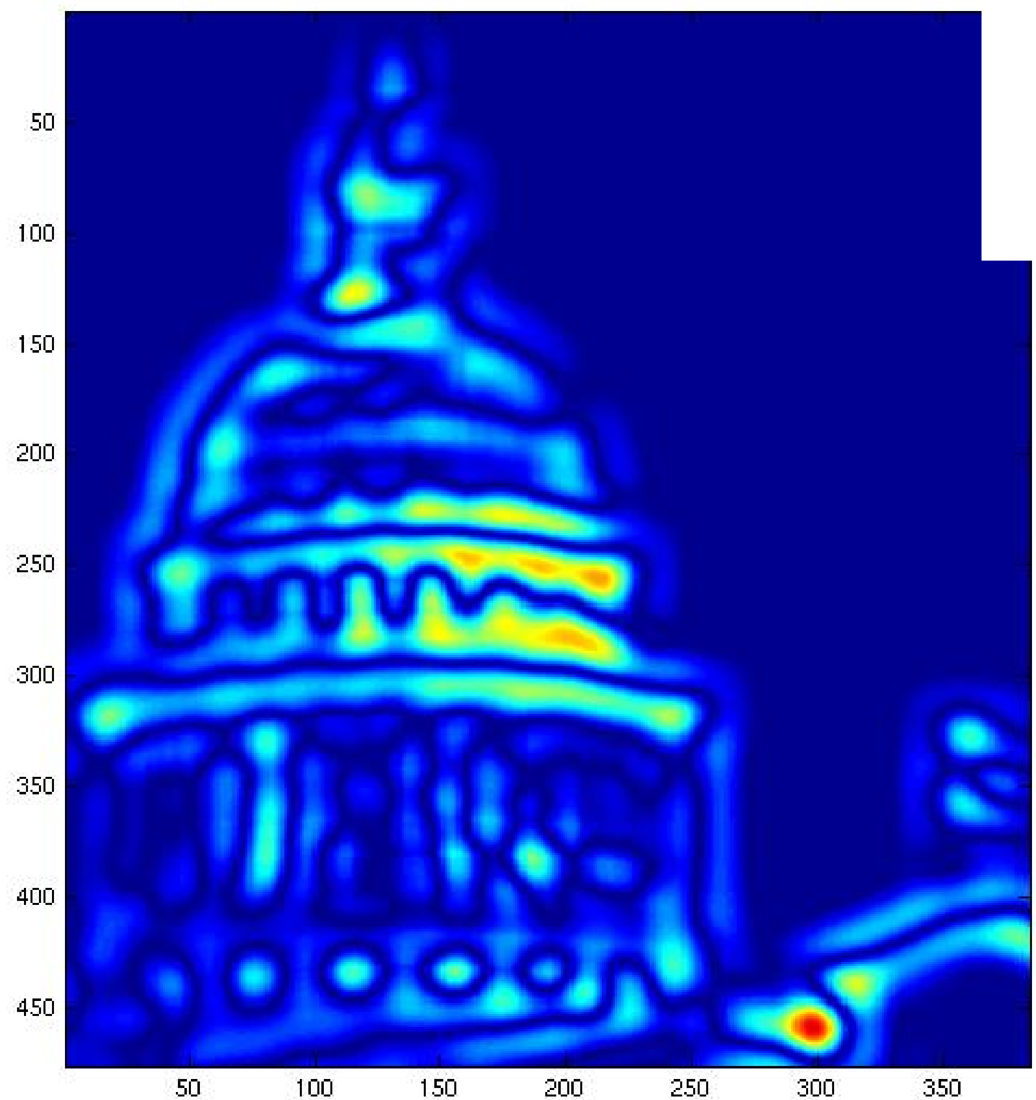

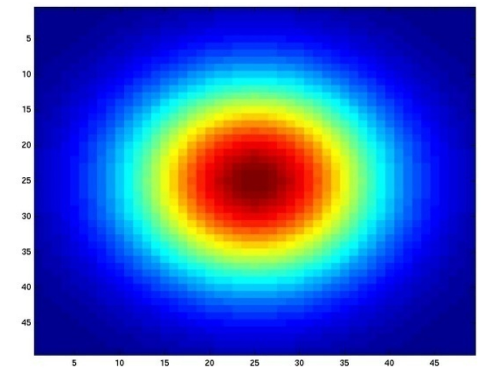

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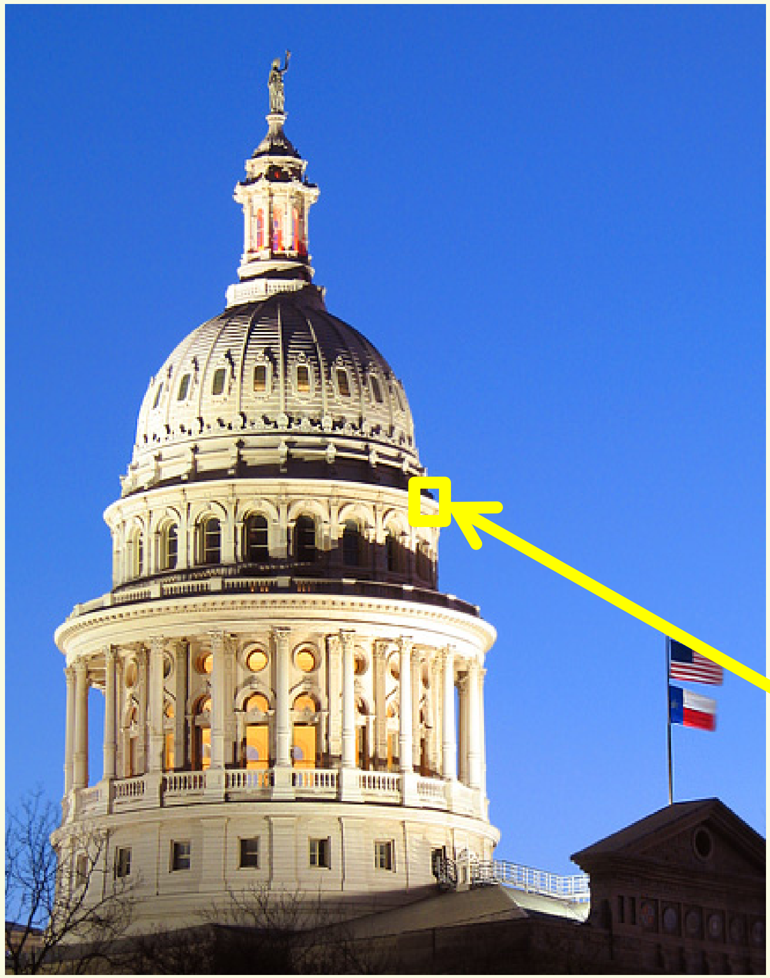
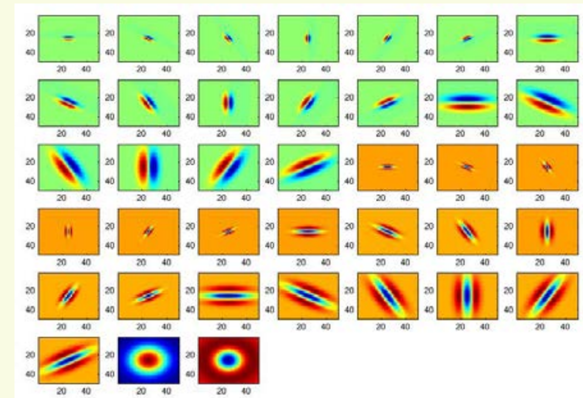
Extracting Texture



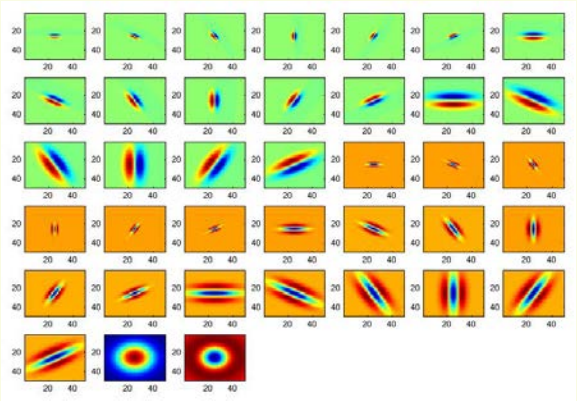


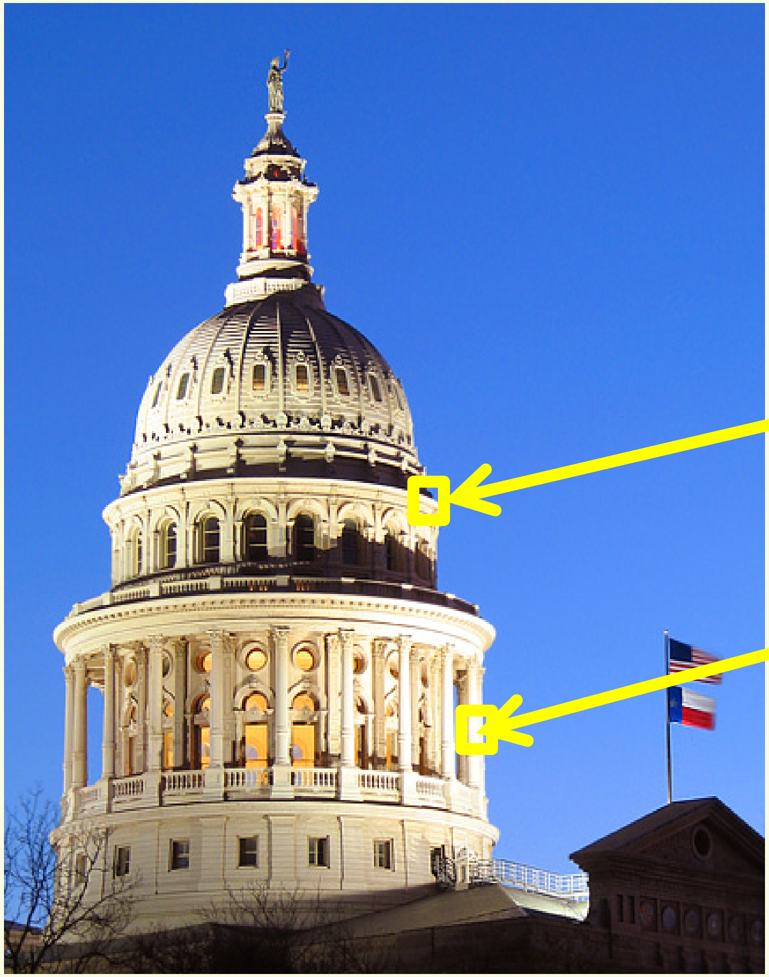
Form a descriptor vector from the list of responses at each pixel

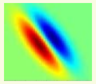
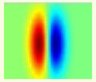
$[r_1, r_2, \ldots, r_{38}]$

Kristen Grauman

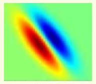
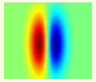
Extracting Texture





[r_1,..., large, ..., small, ..., r_{48}]

[r_1,..., small, ..., large, ..., r_{48}]

Right features depend on what you want to know

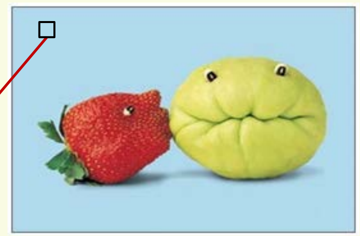
- Object: 2D shape
  - Local shape info, shading, shadows, texture
- Scene : overall layout
  - linear perspective, gradients
- Material properties: albedo, feel, hardness, …
  - Color, texture
- Motion
  - Optical flow, tracked points

Slide by Derek Hoiem

Basic Image Features

- Each basic feature is described by a multi-dimensional descriptor

Color



$$\begin{bmatrix}100\\120\\200\end{bmatrix}$$

SIFT features

$$\text{128 dimensions}\left\{\begin{bmatrix}100\\33\\\dots\\222\\11\end{bmatrix}\right.$$

- For machine learning, need to consolidate basic descriptors into feature vector ***x*** that represents image **I**

Pixelwise Representation

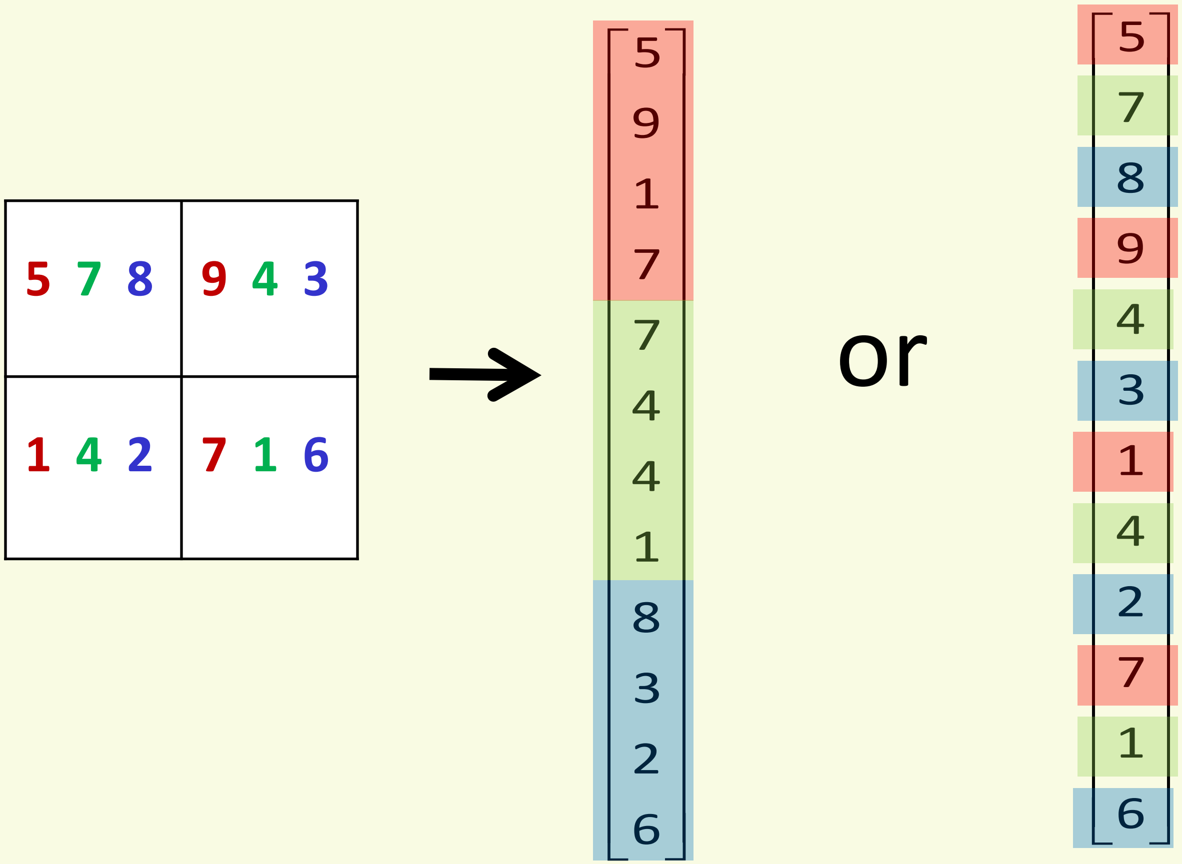
- Pile basic descriptors into one vector, say row order
- Example: intensity as a basic image feature
  - one value per pixel

10	12	30
20	17	21
33	91	24

$$\rightarrow \begin{bmatrix} 10 \\ 12 \\ 30 \\ 20 \\ 17 \\ 21 \\ 33 \\ 91 \\ 24 \end{bmatrix}$$

Pixelwise Representation

- Color as a basic image feature
  - three values per pixel, descriptor is 3-dimensional
- Pile all color channel into one vector



Pixelwise Representation

- Basic image feature has **n** dimensional descriptor
  - Sometimes each dimension is called a “channel”
- Pile each channel one after another into one vector

5 7 8 3	9 4 3 2
1 4 2 1	7 1 6 0

$$\rightarrow \begin{bmatrix} 5 \\ 9 \\ 1 \\ 7 \\ 7 \\ 4 \\ 4 \\ 1 \\ 8 \\ 3 \\ 2 \\ 6 \\ 3 \\ 2 \\ 1 \\ 0 \end{bmatrix}$$

Pixel Representations

- Small change in image appearance

Slide by Erik Learned-Miller

Pixel Representations

- Leads to a large change in feature vector

difference image

10	12	30
20	17	21
33	91	24

9	10	12
19	20	17
32	33	91

[10 12 30 20 17 21 33 91 24]

[9 10 12 19 20 17 32 33 91]

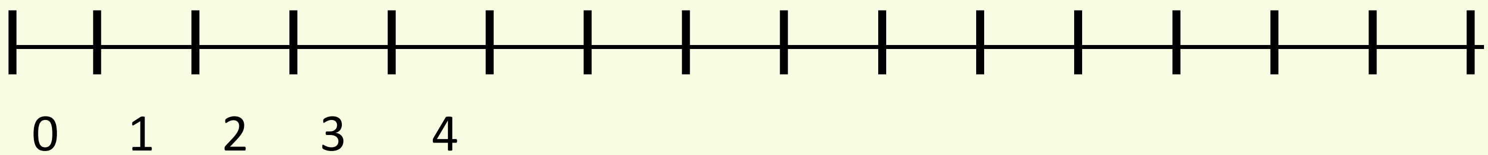
Slide modified from Erik Learned-Miller

Pixel Representations

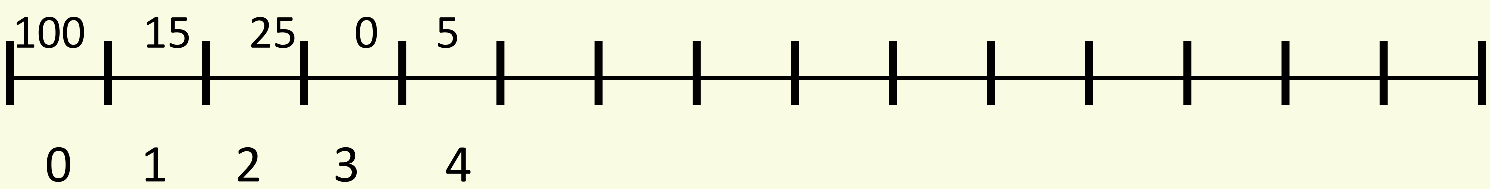
- Pixelwise representations:
  overly sensitive to position
- Nevertheless it has been successfully used in applications
  - eigenfaces, first successful face detection system

Global Intensity Histogram

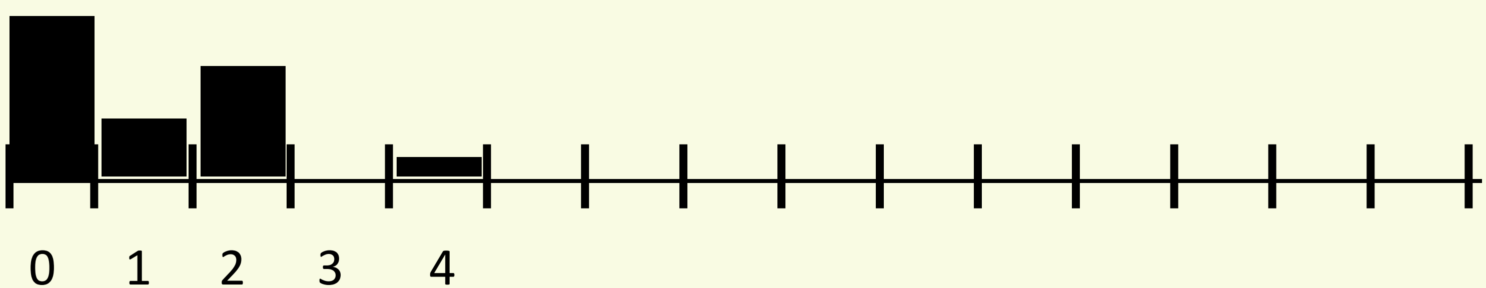
- Think of each intensity value as a “bin”



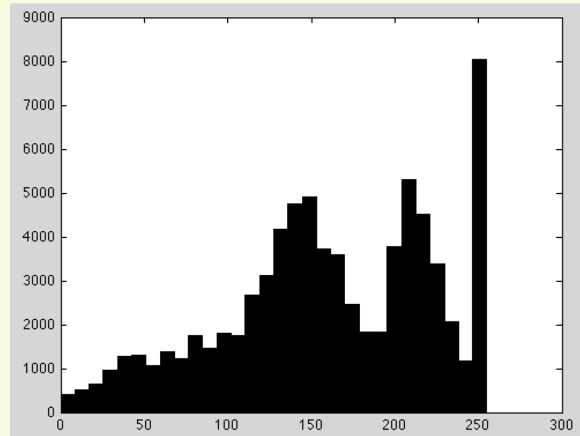
- Histogram counts the number of values that fall in each bin



- Visual plot:



Global Intensity Histogram



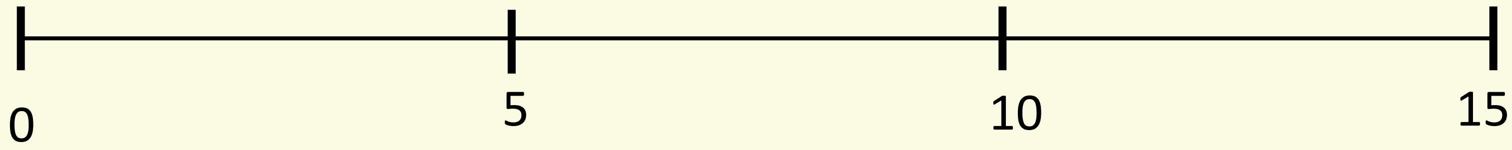
$$\begin{bmatrix} 5 \\ 10 \\ 4 \\ \dots \\ 100 \end{bmatrix}$$

$$\begin{bmatrix} 0.04 \\ 0.08 \\ 0.03 \\ \dots \\ 0.8 \end{bmatrix}$$

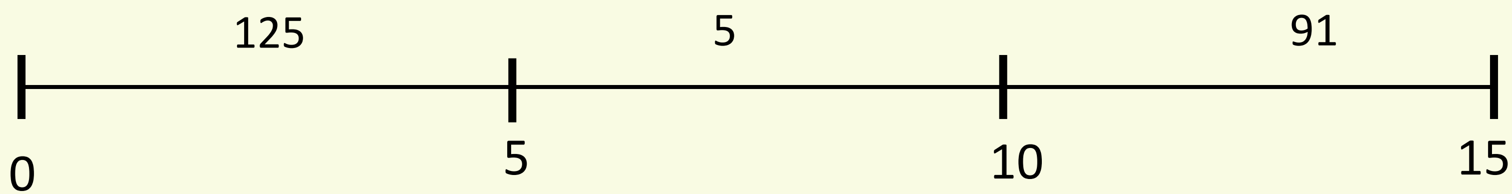
- Insensitive to changes in pixel location
- Often use normalized histogram
  - sums up to 1

Global Intensity Histogram Quantization

- Can quantize intensities (larger bins)



- Histogram: count number of values that fall in each bin



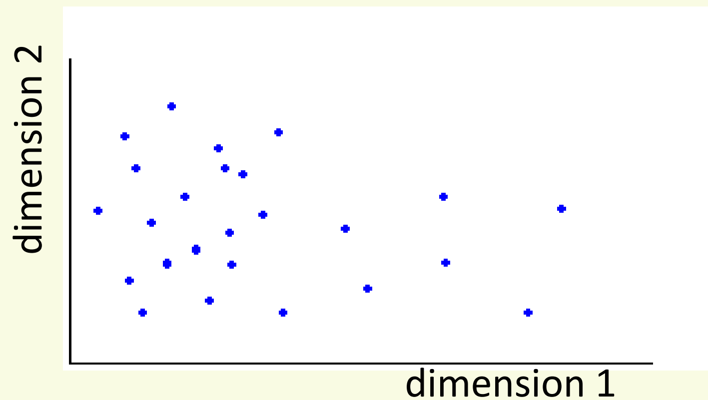
- Quantization
  - helps to improve efficiency
  - groups similar values together (i.e. removes fine distinction)
    - may help for recognition

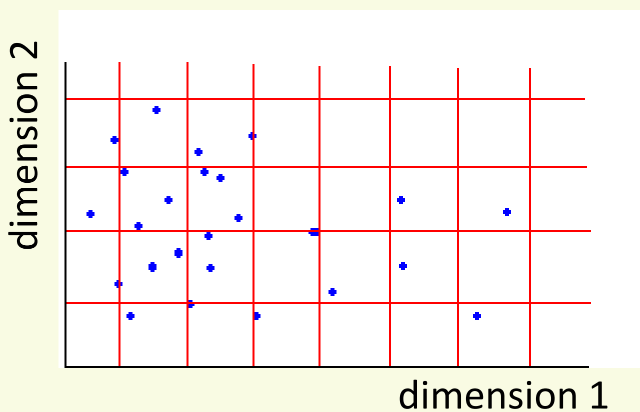
Multi-Dimensional Histograms

- Basic descriptors most often multi-dimensional
  - color, texture, optical flow, etc.
- How to build histogram?
- Have to quantize, too sparse without quantization

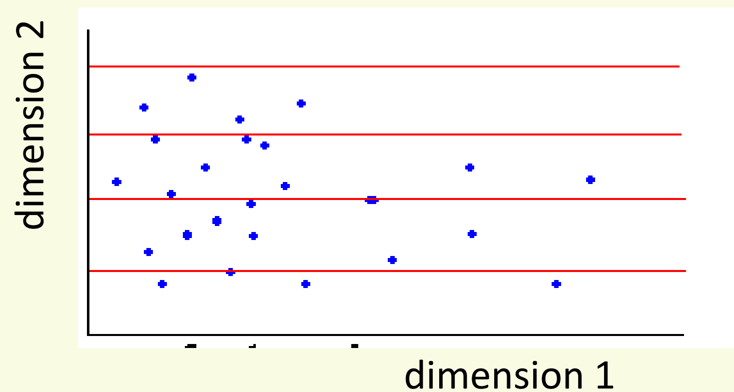
How to Quantize Multi-Dimensional Data?

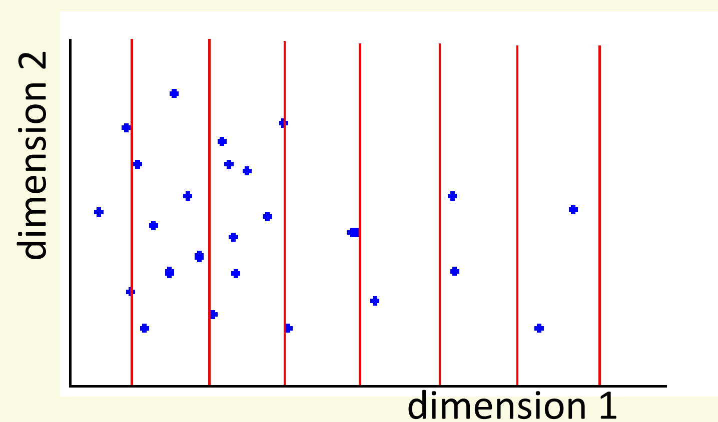
1. Joint histogram
    - Need lots of data to avoid empty bins
    - Make bins coarse to simulate lots of data $\rightarrow$ loose resolution





2. Marginal Histogram
    - More data per bin than joint histogram
    - Works best for independent features
        - Loose correlation information

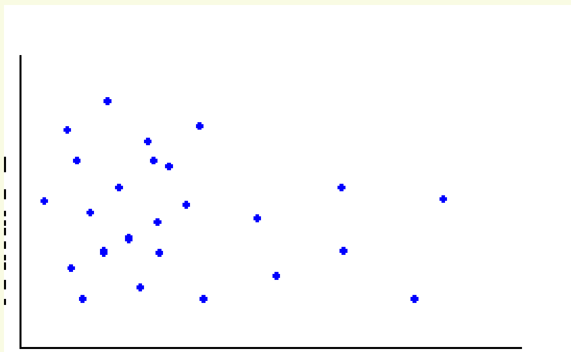


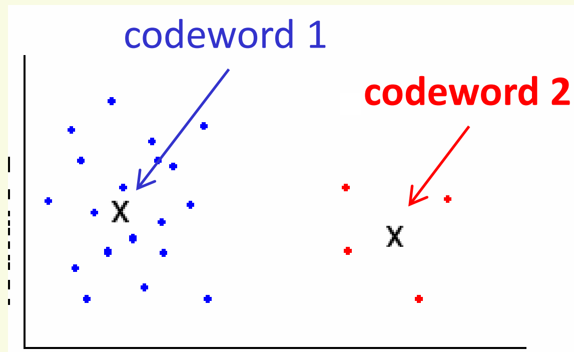


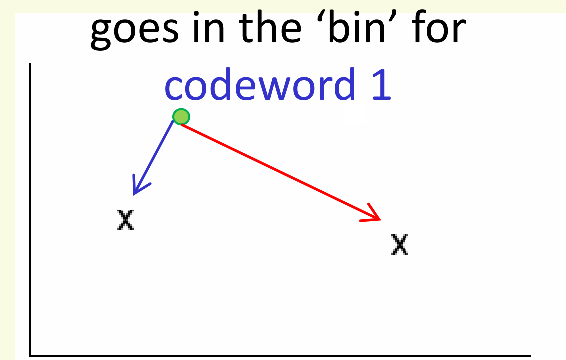
slide credit: Dave Kauchak

Histograms based on Irregular Partitioning

- Irregular quantization (clustering) gives meaningful bins that adapt to data
  - k-means clustering, etc.





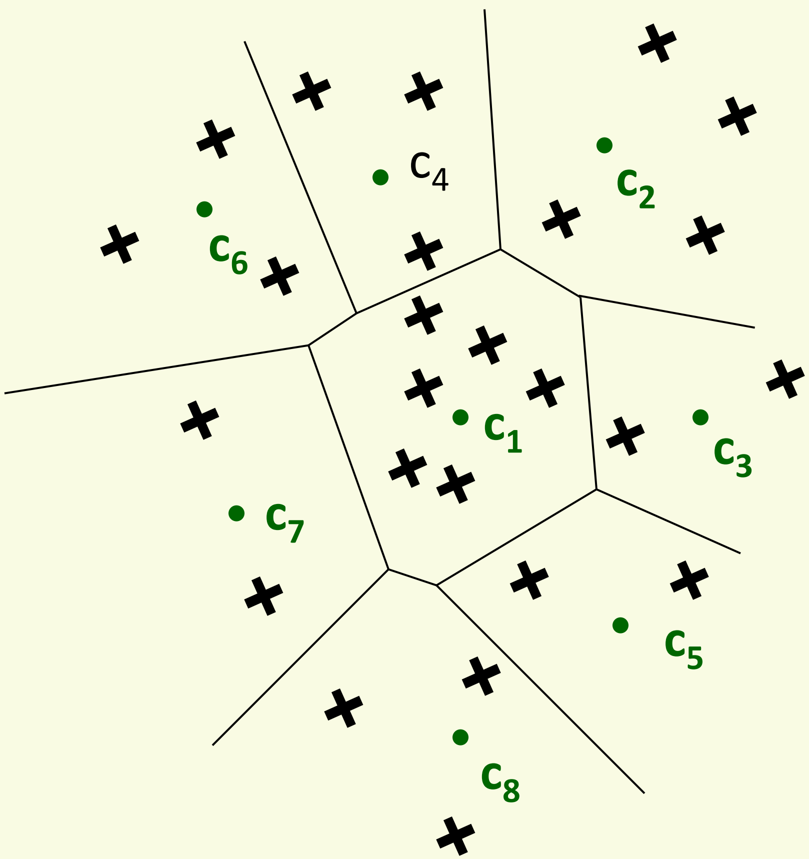


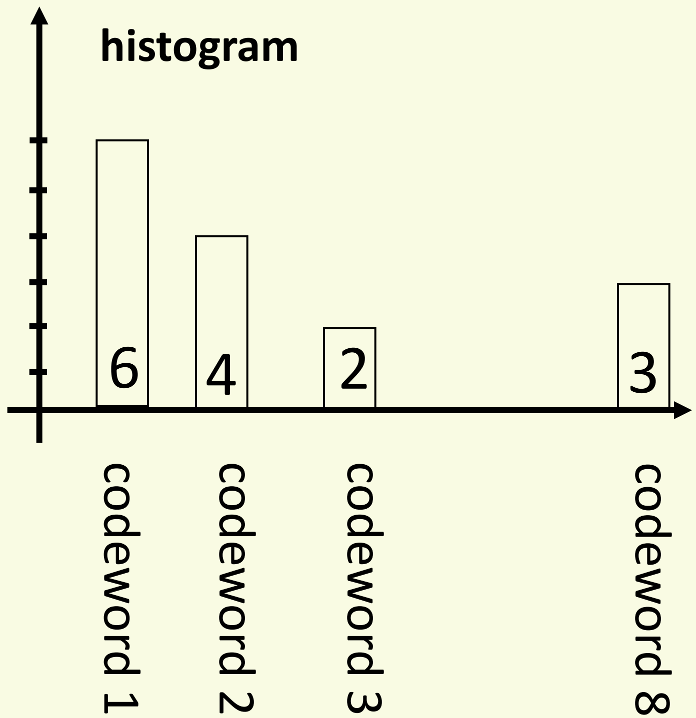
- Cluster centers are called **codewords**
- A sample is identified (assigned to) with the closest codeword
- Build histogram over the codeword
  - count how many samples are closest to codeword 1, codeword 2, etc.
- Need to store only the codewords

Slide Credit: Dave Kauchak

Encoding Image *I* as Feature Vector

- Pre-computed code-words in green
- Extract 2D features from image *I*



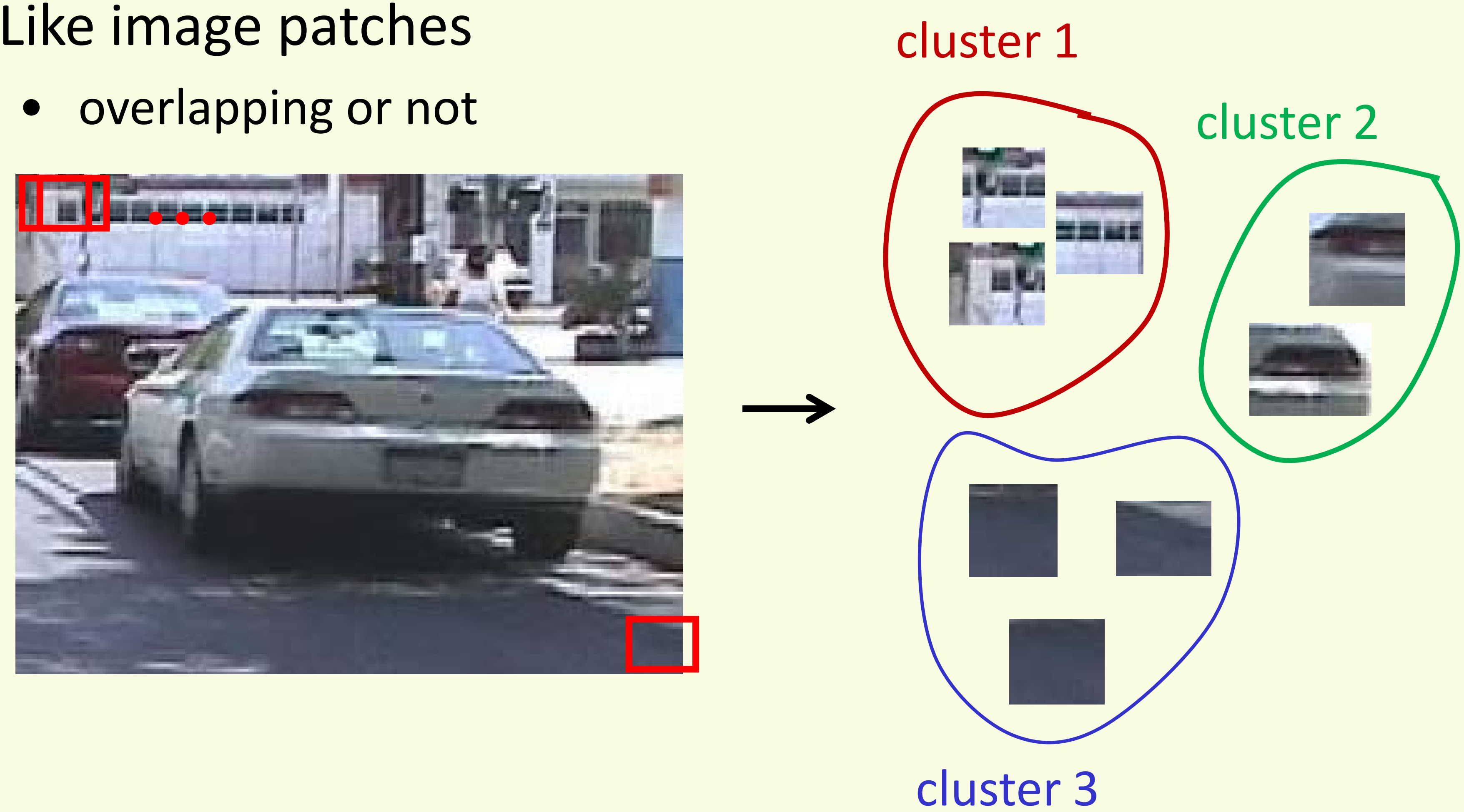


- Feature vector that represents image *I*
  - can also normalize it

$$\begin{bmatrix} 6 \\ 4 \\ 2 \\ \cdots \\ 3 \end{bmatrix}$$

Clustered Patches

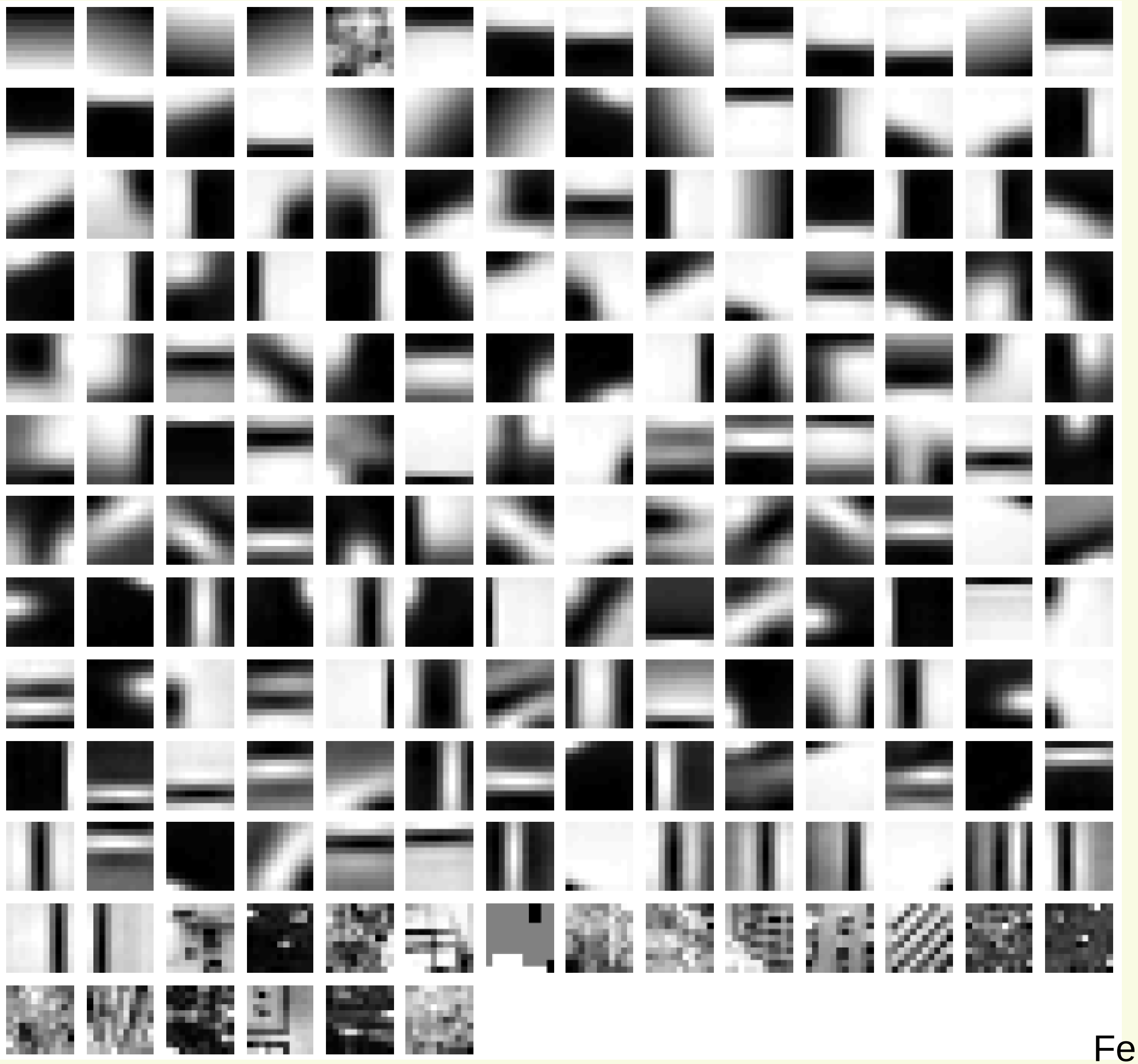
- So far clustered feature responses at each pixel
- Can cluster other things
- Like image patches
  - overlapping or not



Clustered Patches

- Take patches form many training data images
  - But not from test images
- Use only a subset of training data for speed
- Usually normalize patches to be of zero mean, unit variance
- Cluster centers become codewords

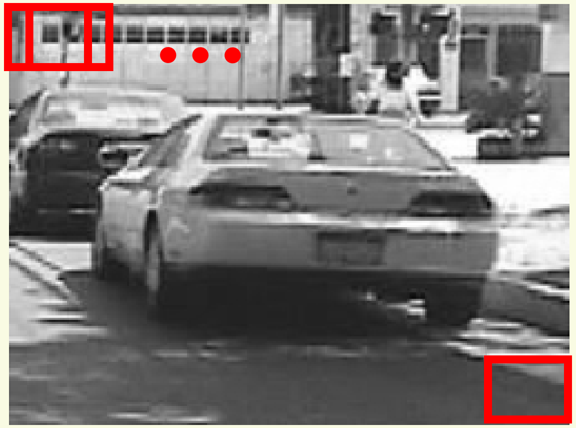
Centers of Clustered Patches (Codewords)

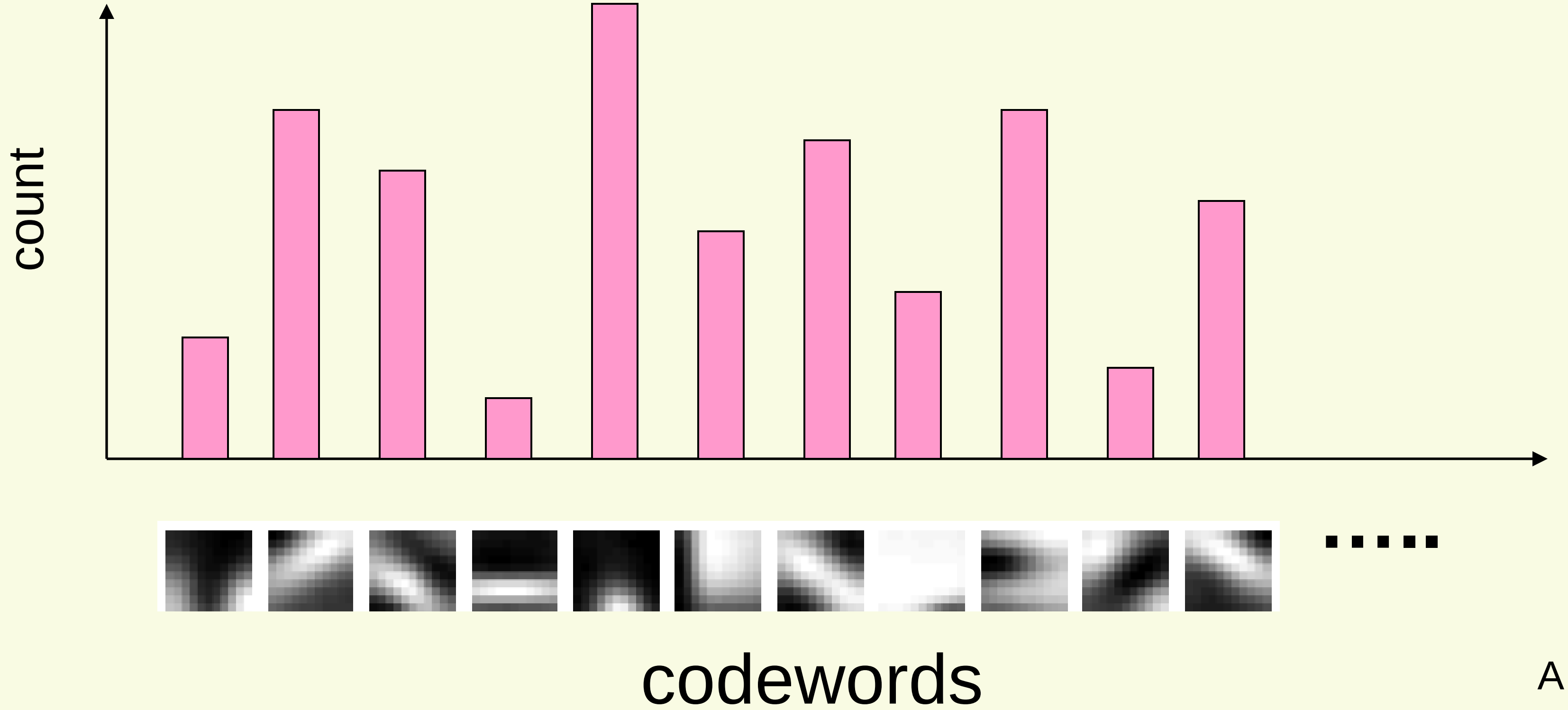


Fei-Fei et al. 2005

Feature Vector for image *I*

- To represent image I
  - Extract patches, overlapping or not
  - Find the closest codeword for each patch
  - Build histogram

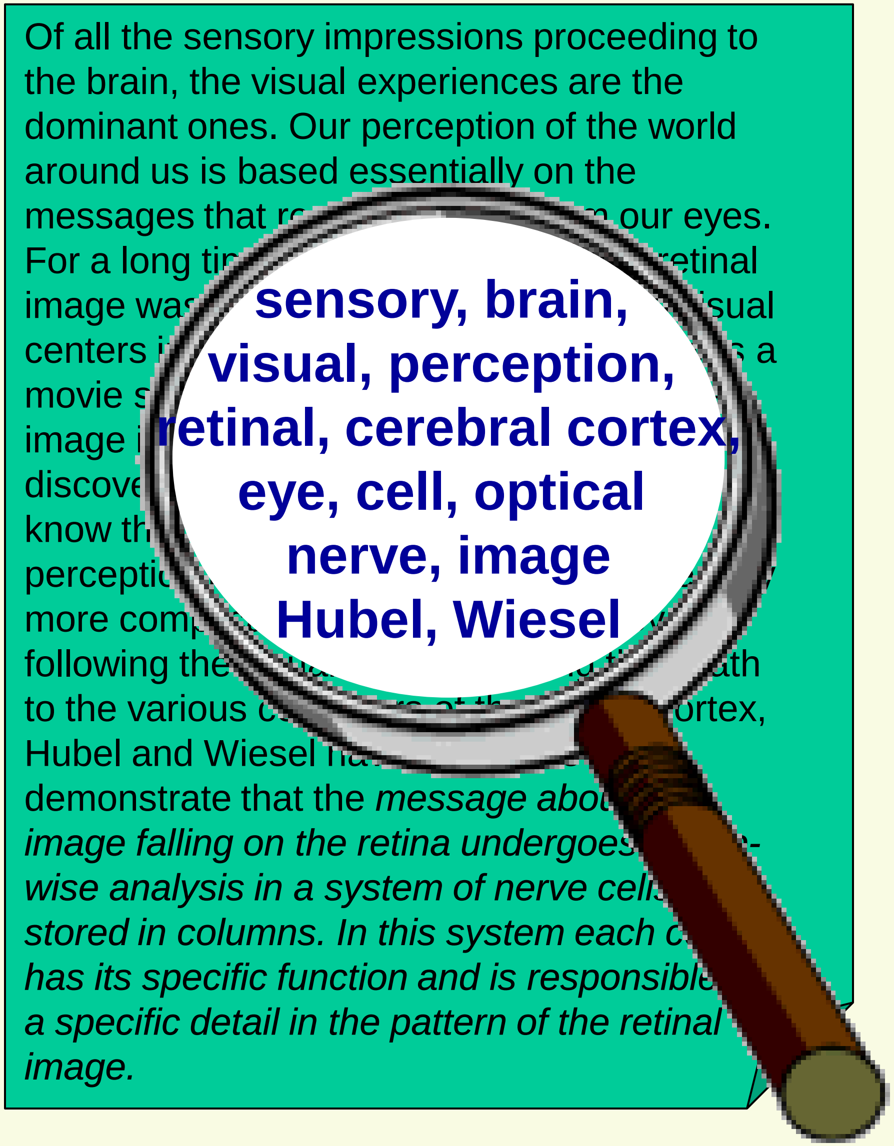




A. Efros

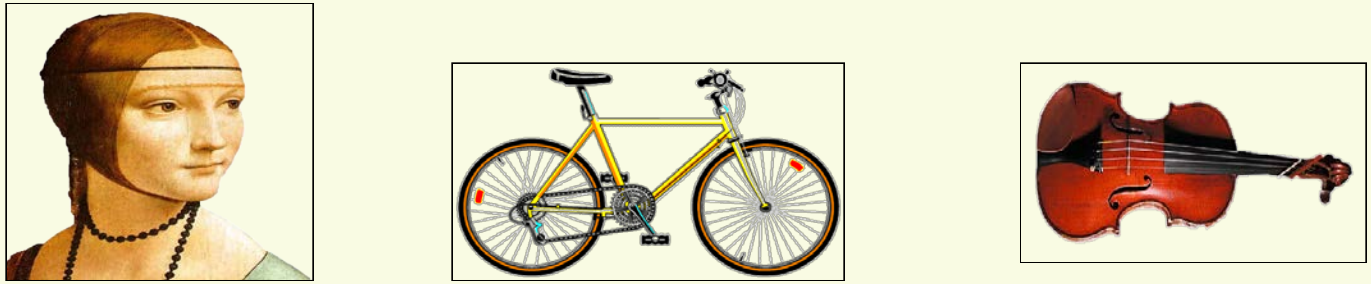
Analogy to documents: Bag of Words

- Inspiration comes from text classification

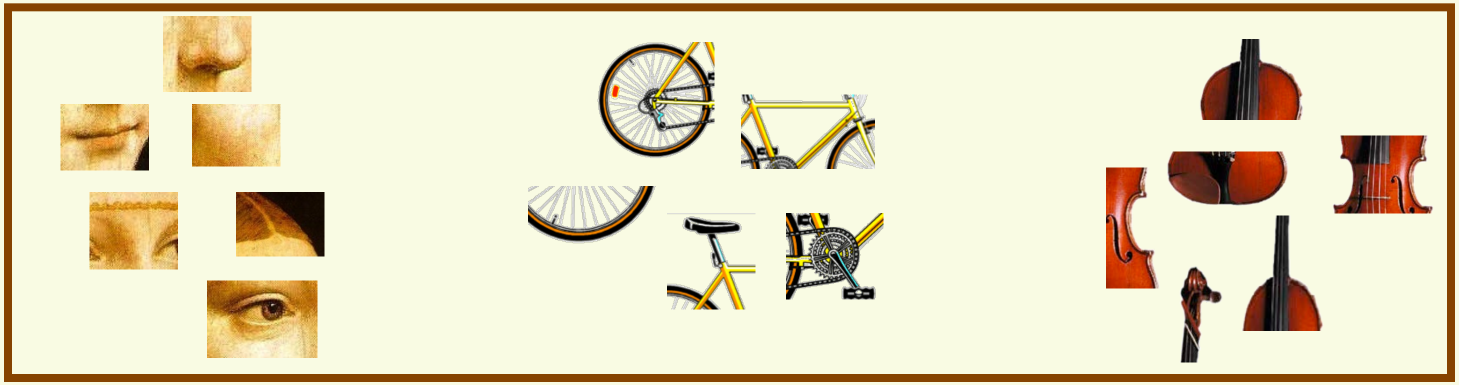


Bag of visual words

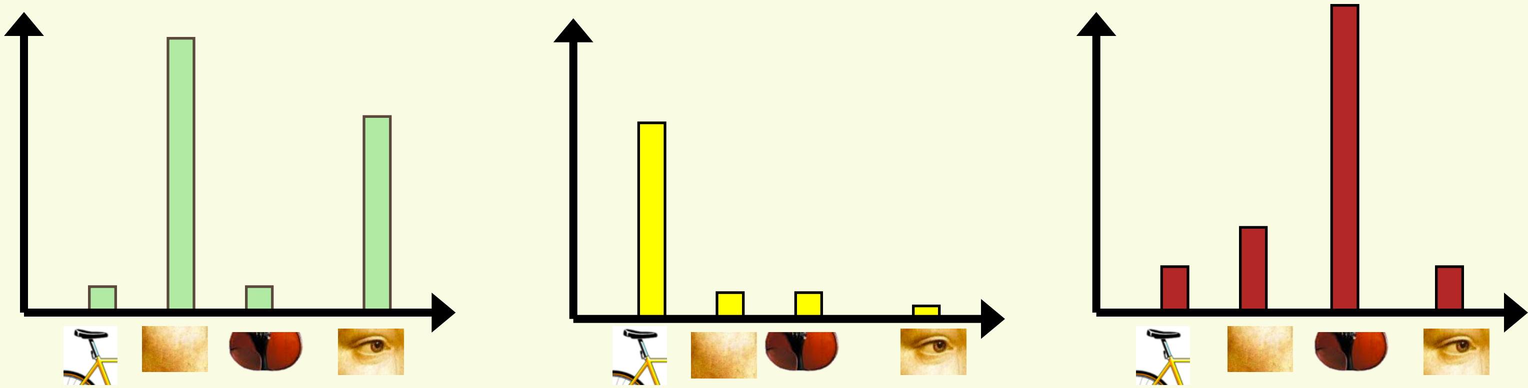
- Training images



- **codewords** or **visual words**

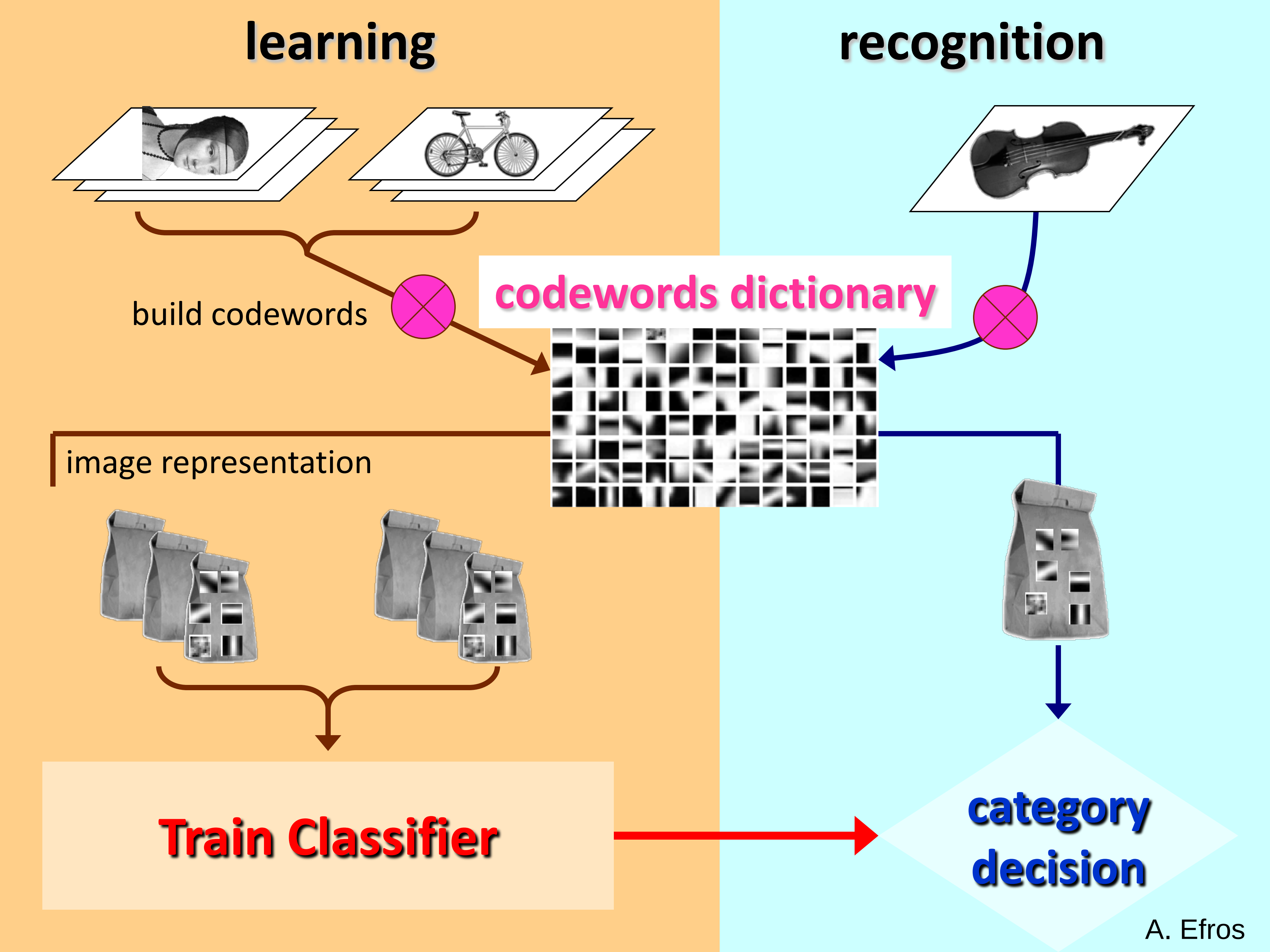


- Bow histogram



codewords

Slide by Derek Hoiem


learning
recognition
build codewords
codewords dictionary
image representation
Train Classifier
category decision
A. Efros

Histograms: Implementation issues

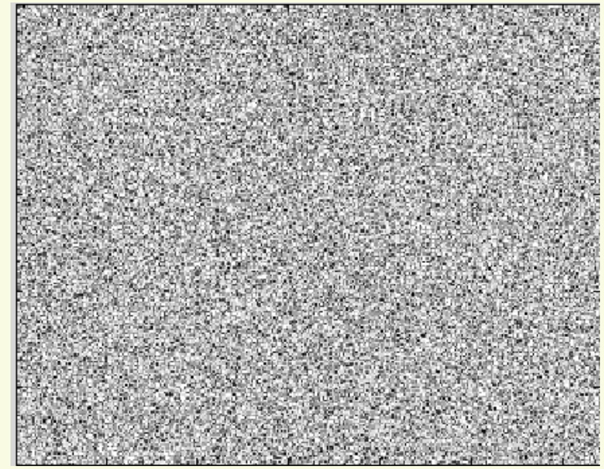
- Quantization
  - Grids: fast but applicable only with few dimensions
  - Clustering: slower but can quantize data in higher dimension
- How many bins (clusters)?

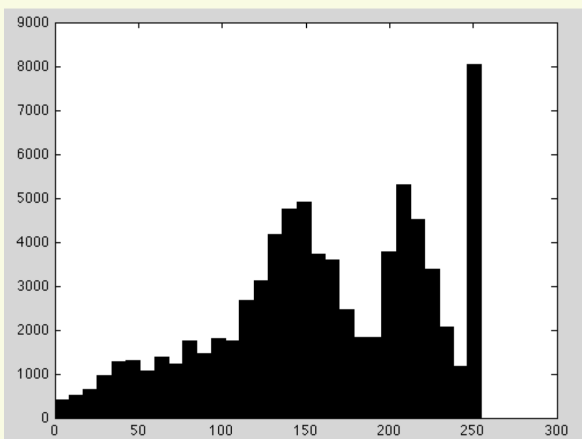
Few Bins
Need less data
Coarser representation
If too coarse, distinction is lost

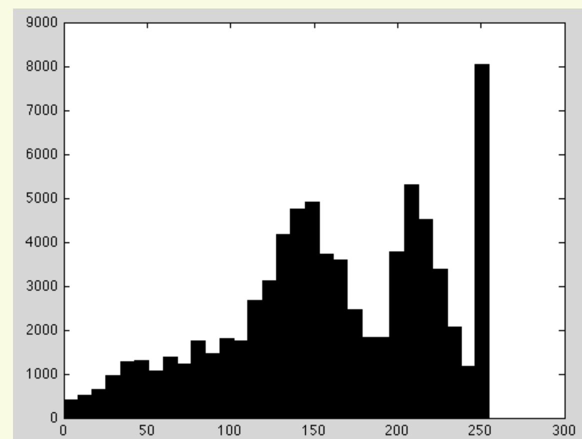
Many Bins
Need more data
Finer representation
If too fine, more distinction than necessary

Slide Credit: Derek Hoiem

Problem with Global Histogram

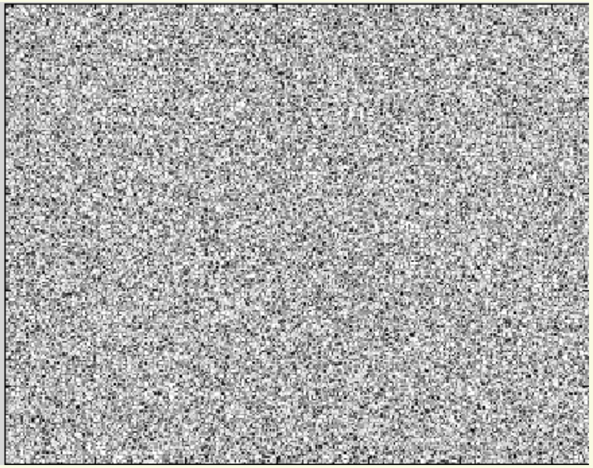






- Identical feature vectors!

Problem with Global Histogram



Have equal histograms!

Slide by Erik Learned-Miller

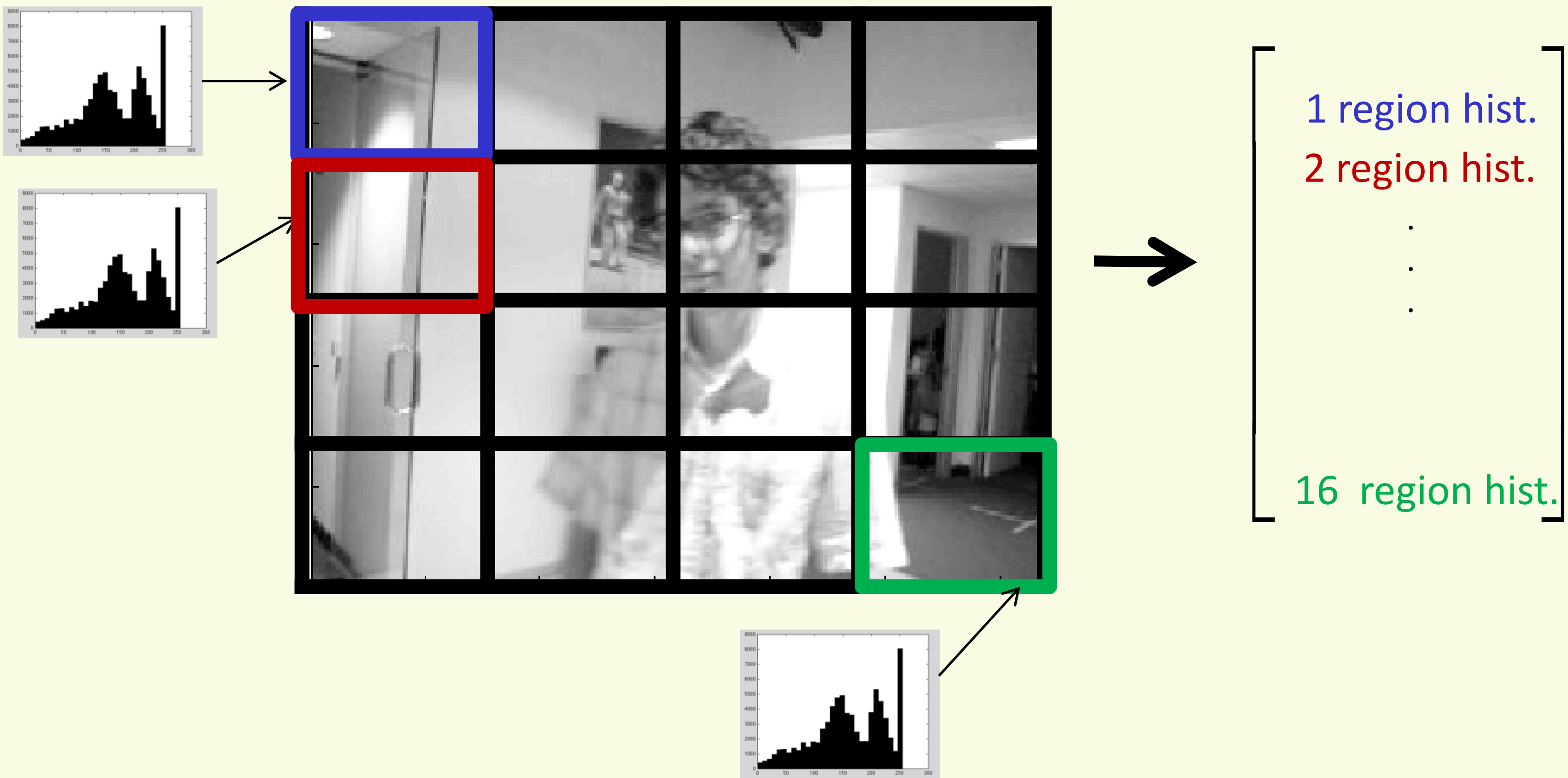
Conclusions

1. Pixel representations:
   overly sensitive to position
2. Global histogram representations:
   under-sensitive to position

Slide by Erik Learned-Miller

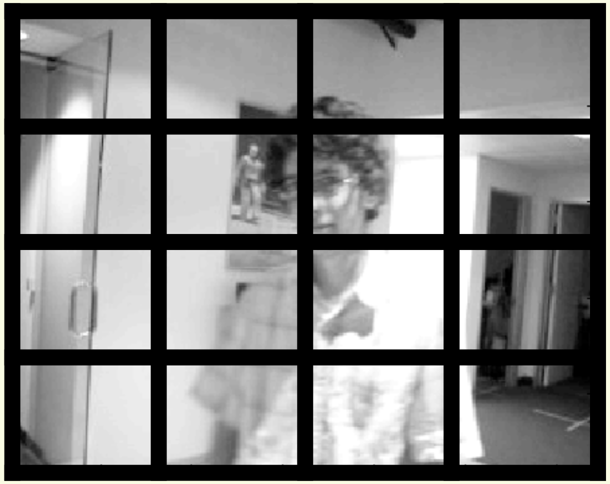
A Compromise: A local histogram

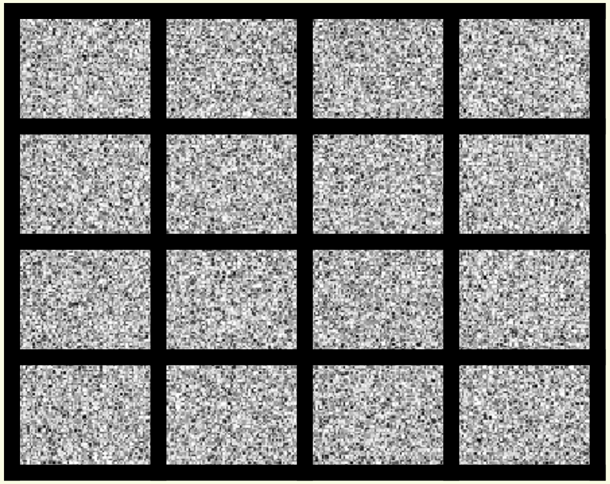
A separate (normalized) histogram for each region

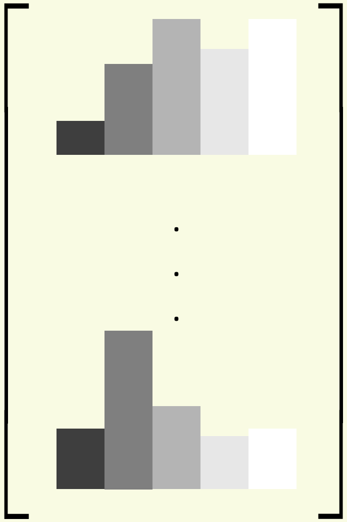


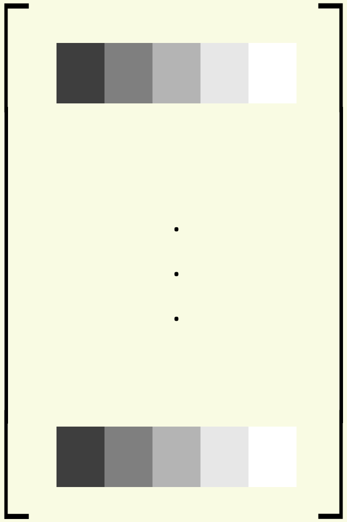
Slide by Erik Learned-Miller

Local Intensity Histogram

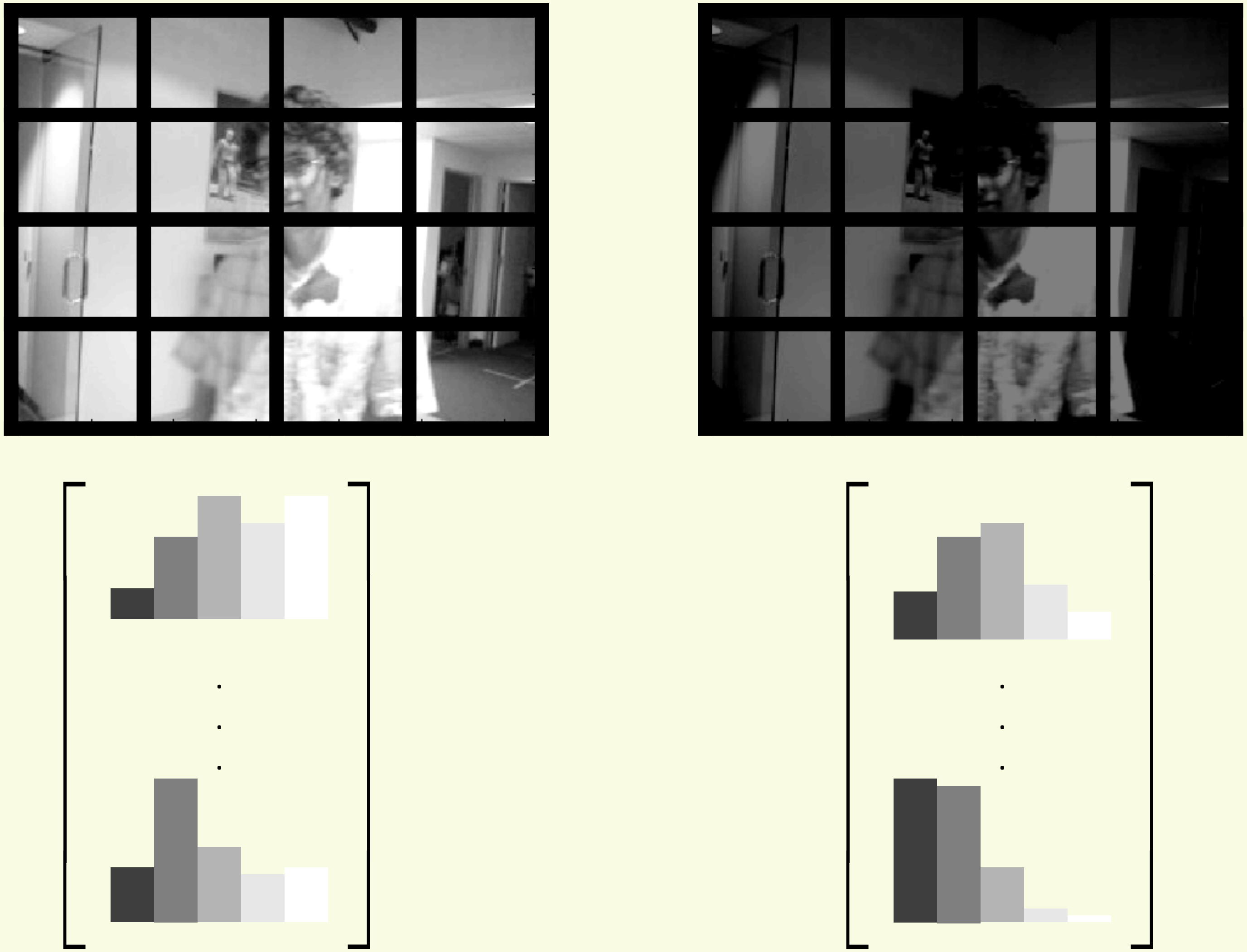






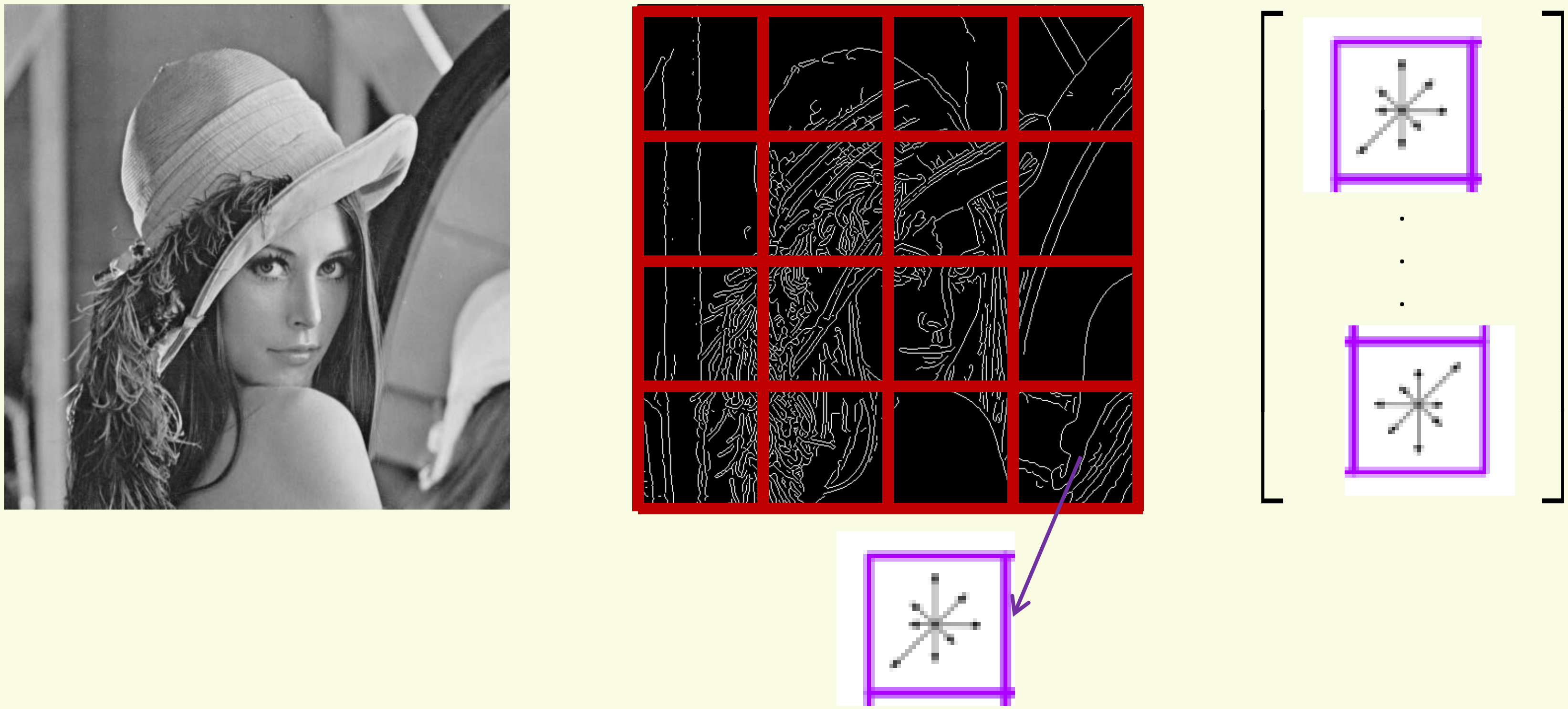


Local Intensity Histogram



- Intensity histogram is sensitive to lighting changes

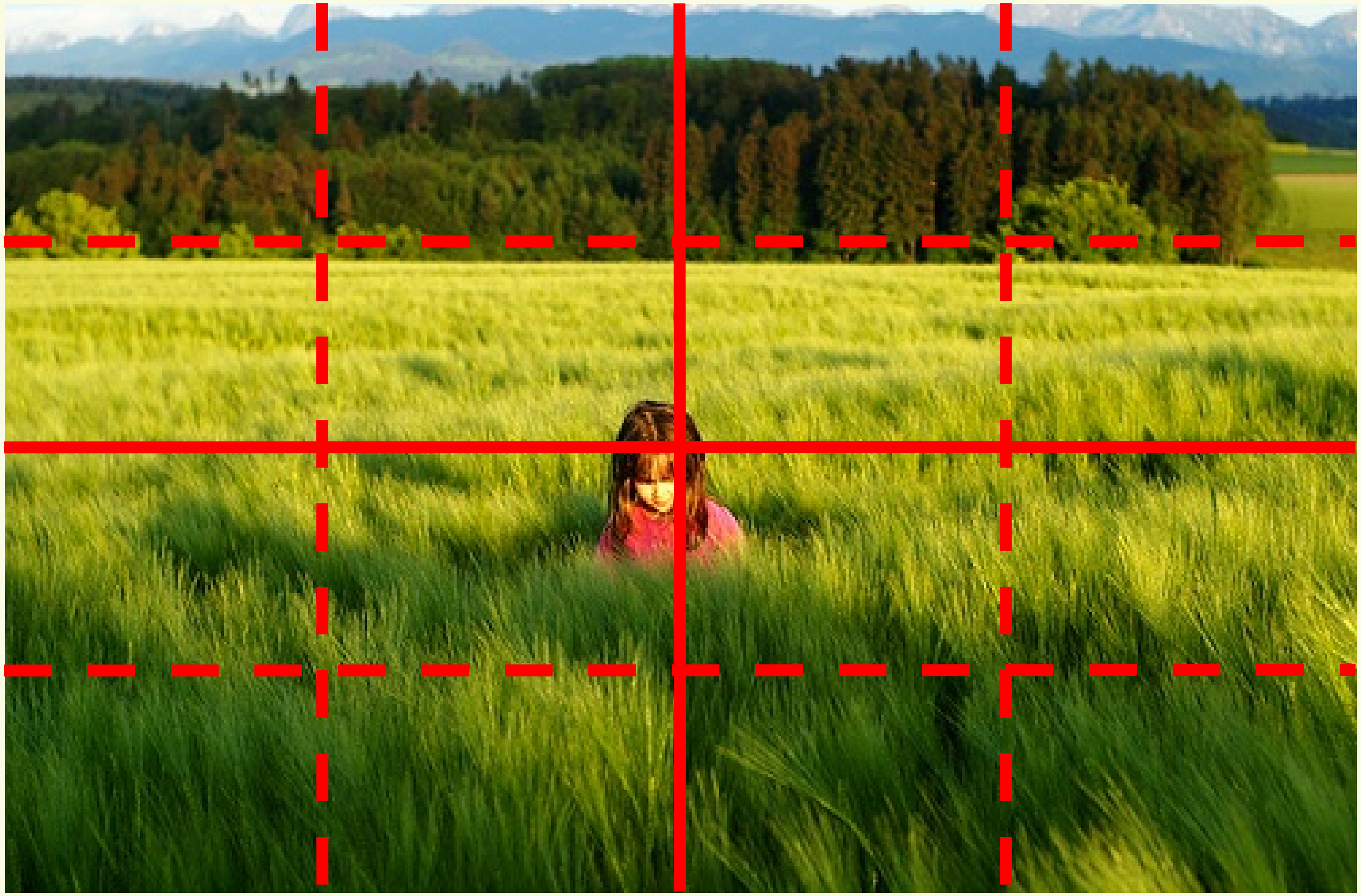
Local Edge Orientation Histogram



- Edges are not as sensitive to lighting changes
- Compute histogram of edges
  - typically consider only edge orientation
- How do we choose the right box size?

Spatial pyramid

- Use boxes of different sizes!



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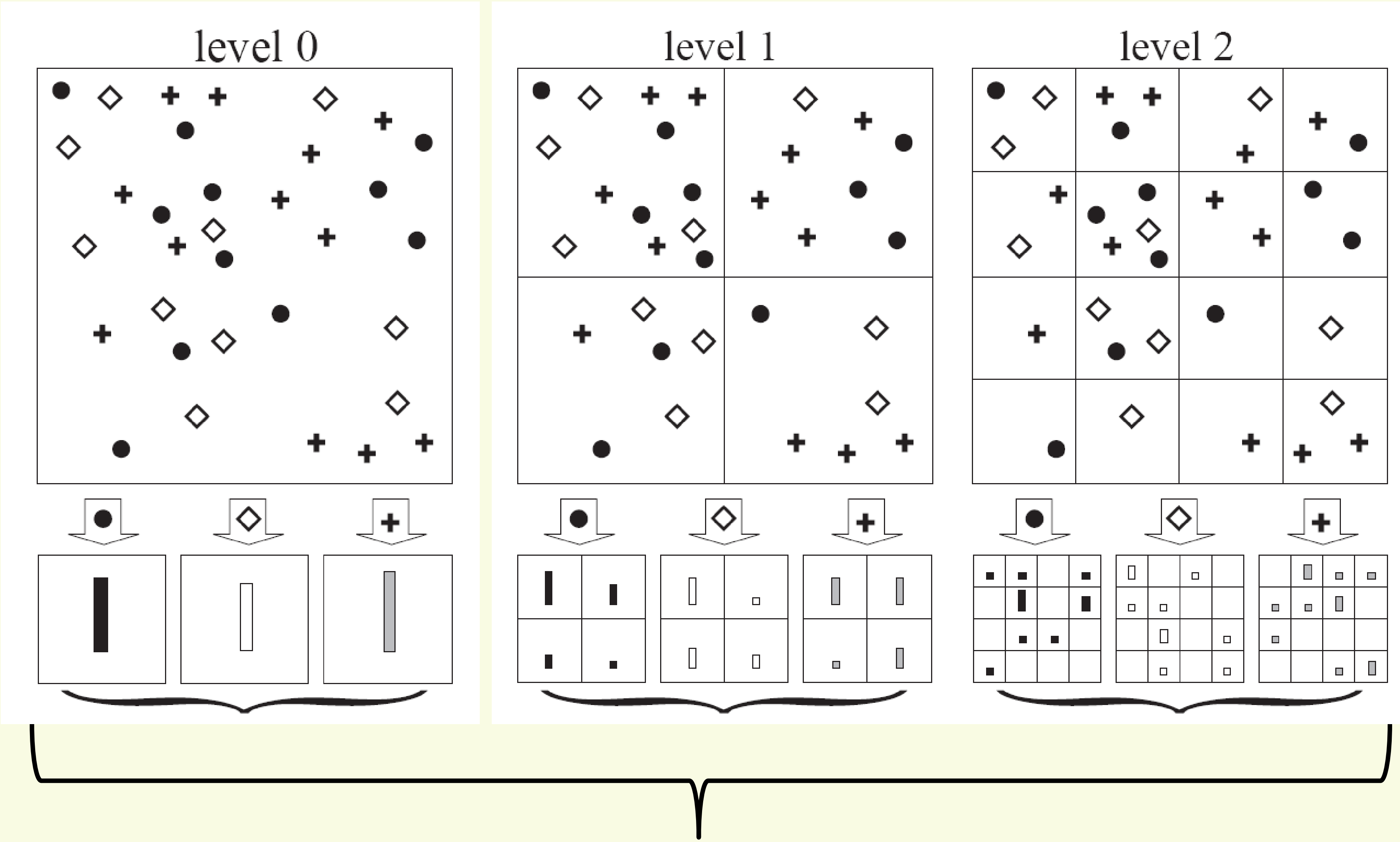
Spatial Pyramid



These get piled up into one feature vector

Slide Credit: Derek Hoiem

Other Representations

- Many image representation schemes are based on histogram of
  - texture
  - corner features
  - SIFT features
  - etc.
- There are other ways to represent an image as a feature vector