

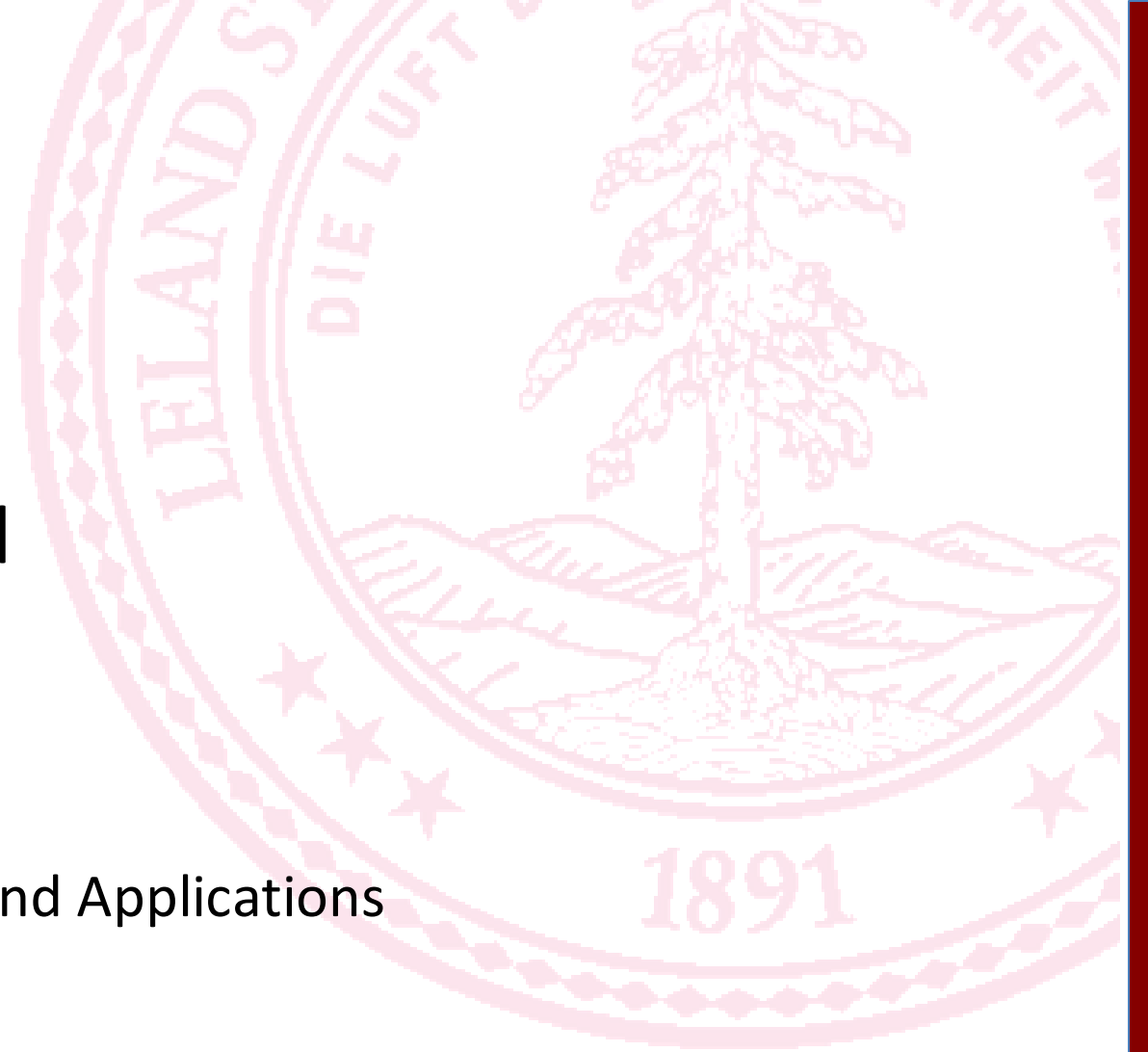


## Lecture 13: Visual Bag of Words

# Visual bag of words: method

Juan Carlos Niebles and Jiajun Wu

CS131 Computer Vision: Foundations and Applications



# What will we learn today?

- Visual bag of words: method
  - Background
  - Algorithm



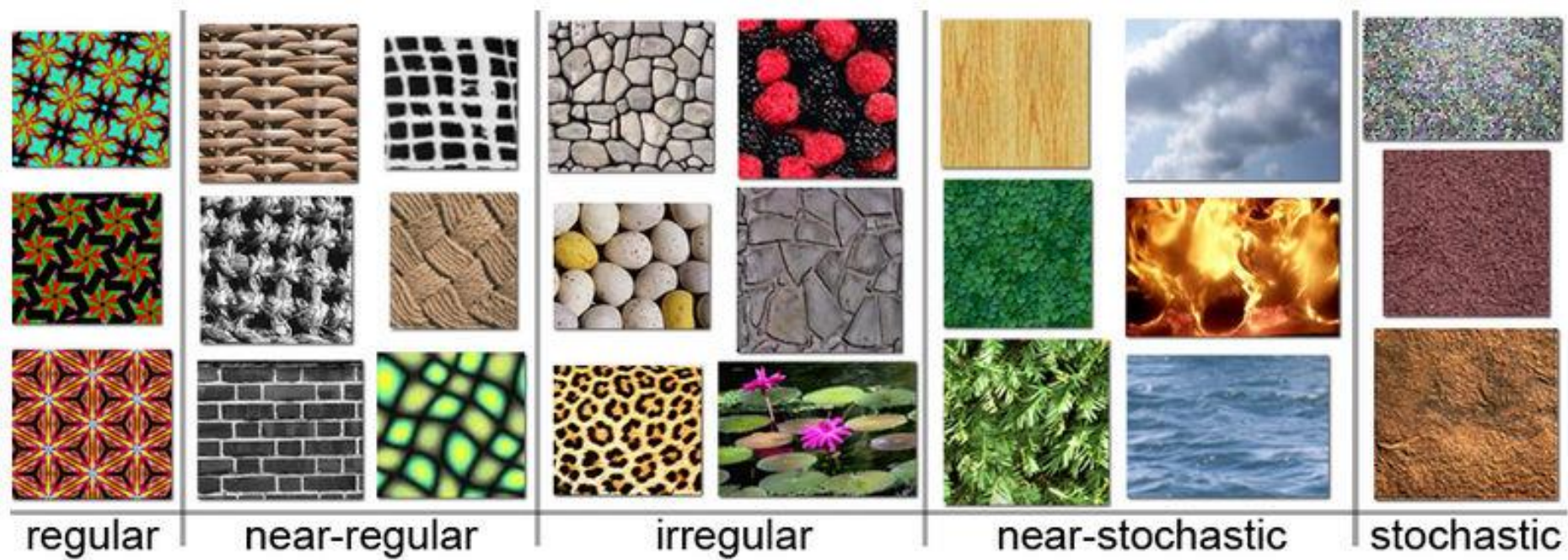
**Object**



**Bag of 'words'**



# Origin 1: Texture Recognition

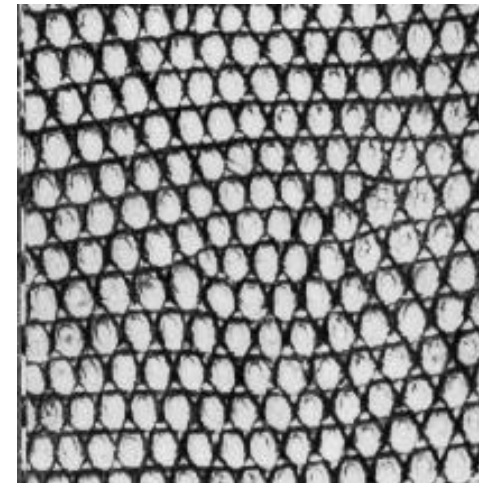
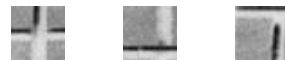
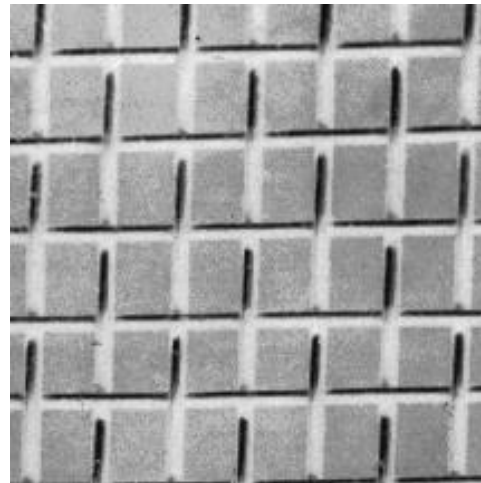
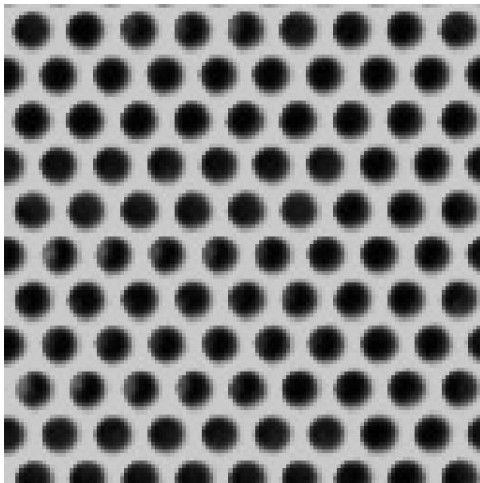


Example textures (from Wikipedia)



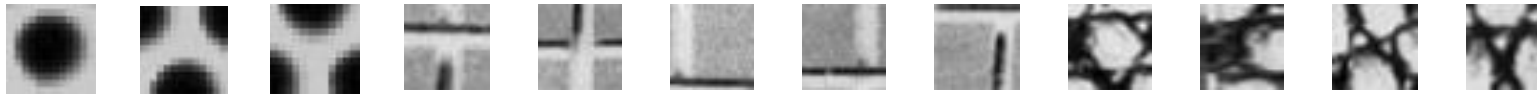
# Origin 1: Texture Recognition

- Texture is characterized by the repetition of basic elements or ***textons***



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

# Origin 1: Texture Recognition

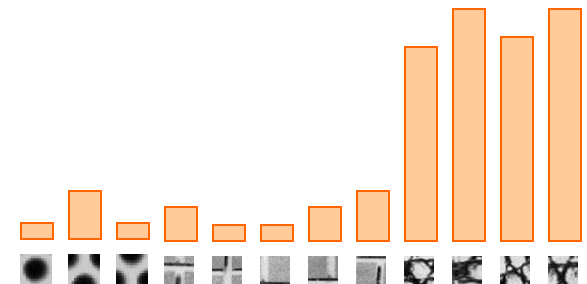
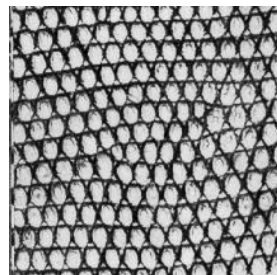
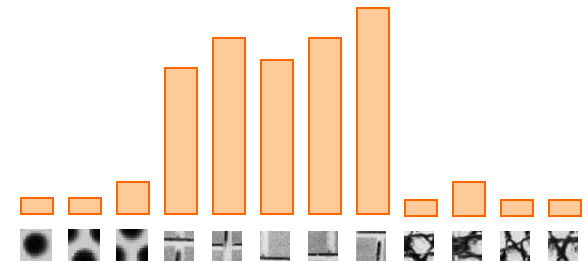
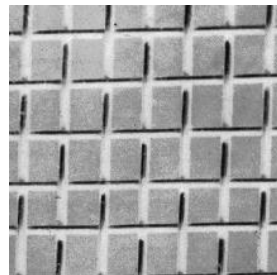
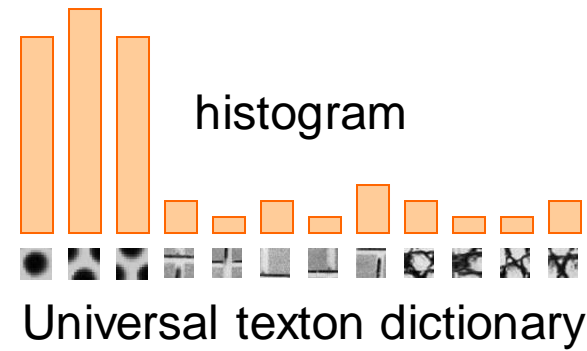
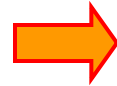
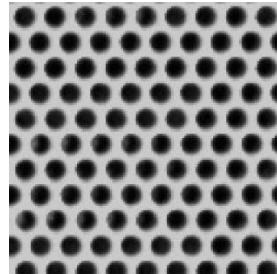


Universal texton dictionary





# Origin 1: Texture Recognition





## Origin 2: Bag-of-words models for text analysis

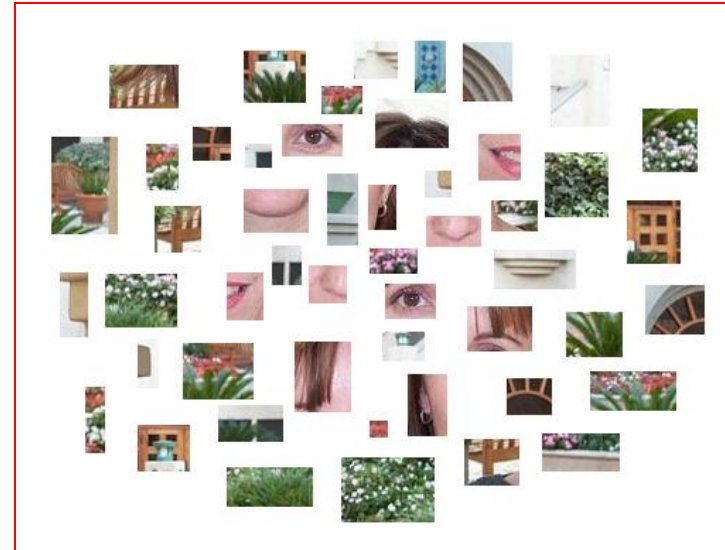
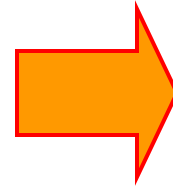
- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)



US Presidential Speeches Tag Cloud  
<http://chir.ag/phernalia/preztags/>



# Bags of features for object recognition



face, flowers, building

- Works pretty well for image-level classification and for recognizing object *instances*

# Bags of features for object recognition



class	bag of features	bag of features	Parts-and-shape model
	Zhang et al. (2005)	Willamowski et al. (2004)	Fergus et al. (2003)
airplanes	<b>98.8</b>	97.1	90.2
cars (rear)	98.3	<b>98.6</b>	90.3
cars (side)	<b>95.0</b>	87.3	88.5
faces	<b>100</b>	99.3	96.4
motorbikes	<b>98.5</b>	98.0	92.5
spotted cats	<b>97.0</b>	—	90.0

# What will we learn today?

- Visual bag of words: method
  - Background
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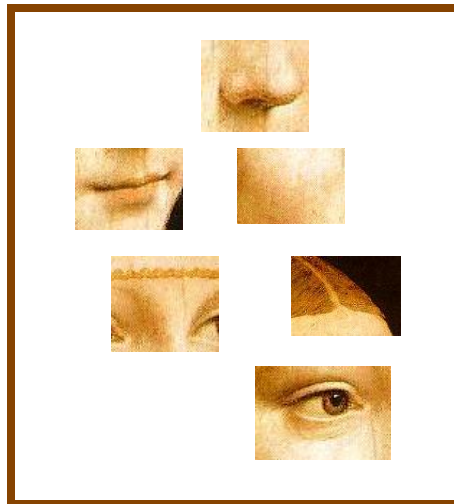


# Bag of features

- First, take a set of images, extract features, and build up a “dictionary” or “visual vocabulary” – a list of common features
- Given a new image, extract features and build a histogram – for each feature, find the closest visual word in the dictionary

# Bag of features: outline

## 1. Extract features



# Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”





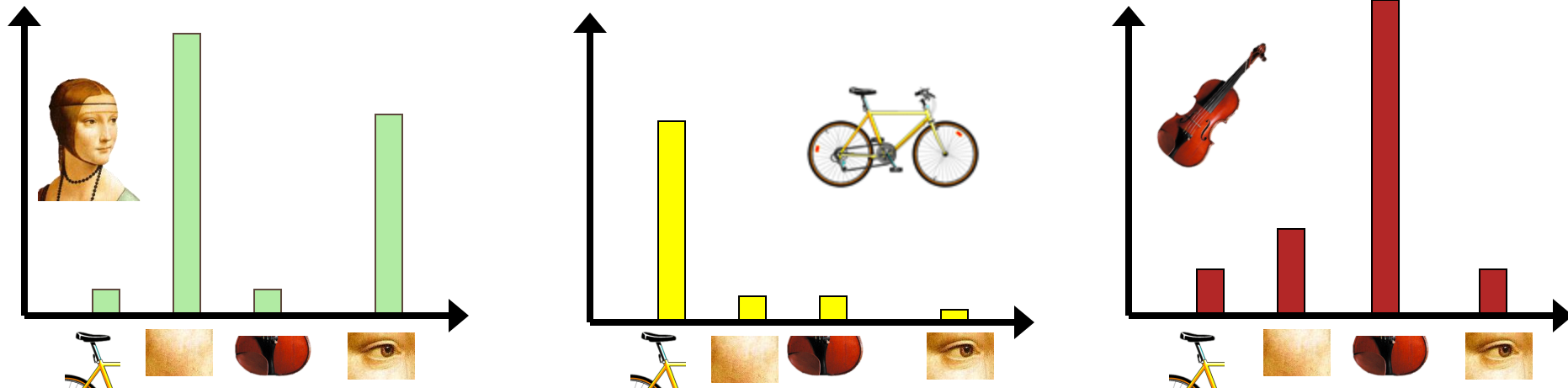


# Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary

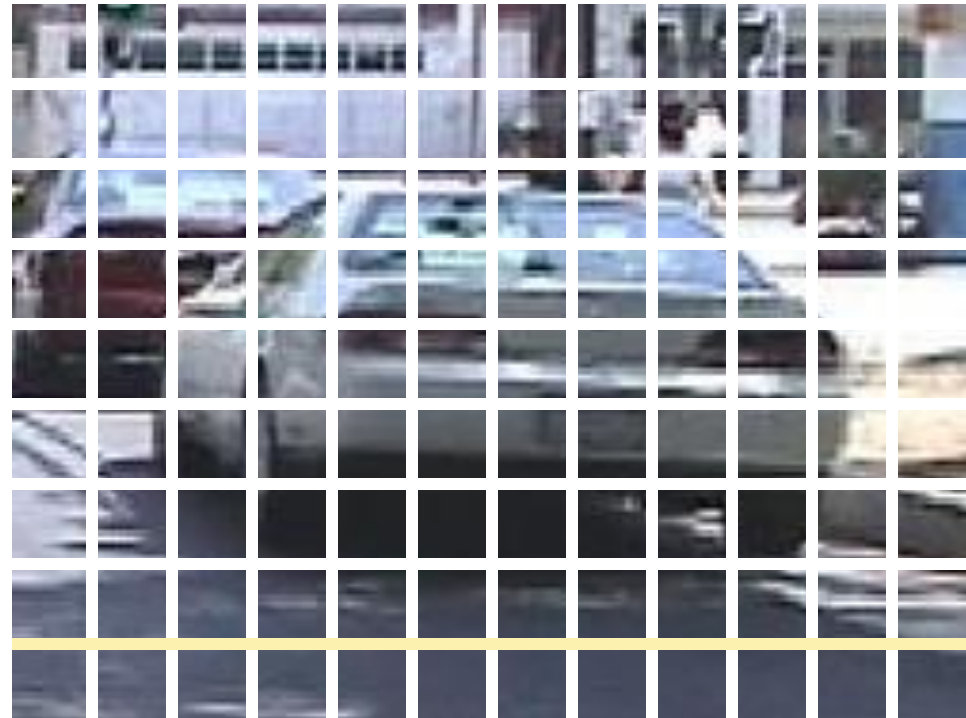
# Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



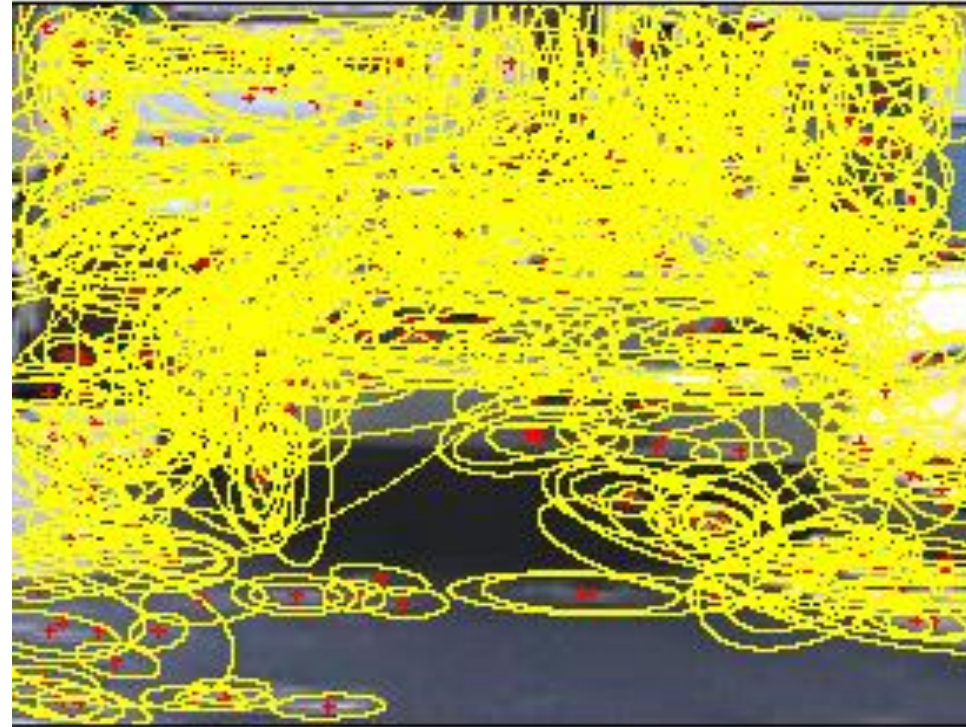
# 1. Feature extraction

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005



# 1. Feature extraction

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka et al. 2004
  - Fei-Fei & Perona, 2005
  - Sivic et al. 2005



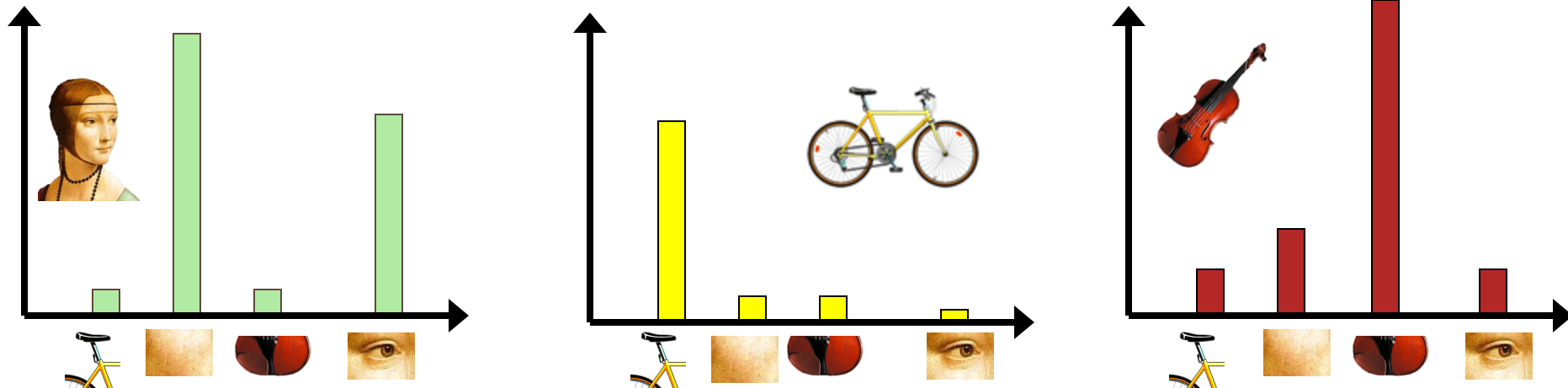


# 1. Feature extraction

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka et al. 2004
  - Fei-Fei & Perona, 2005
  - Sivic et al. 2005
- Other methods
  - Random sampling (Vidal-Naquet & Ullman, 2002)
  - Segmentation-based patches (Barnard et al. 2003)

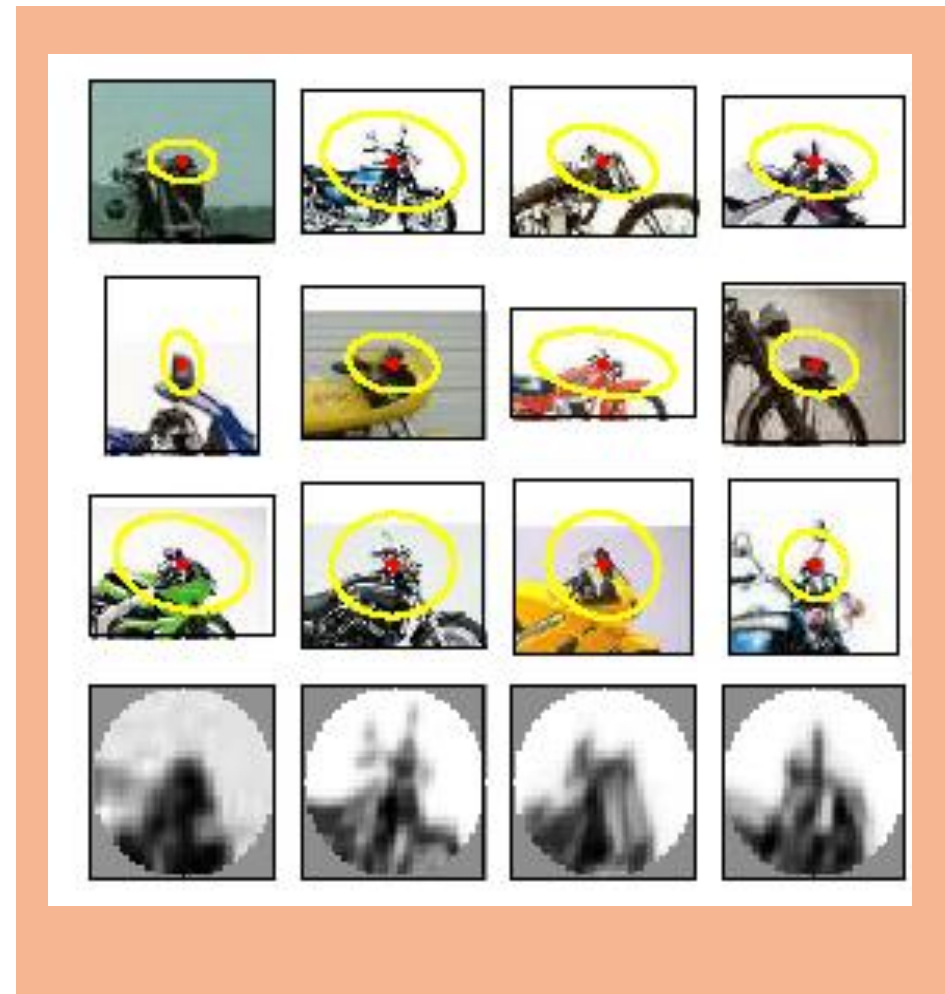
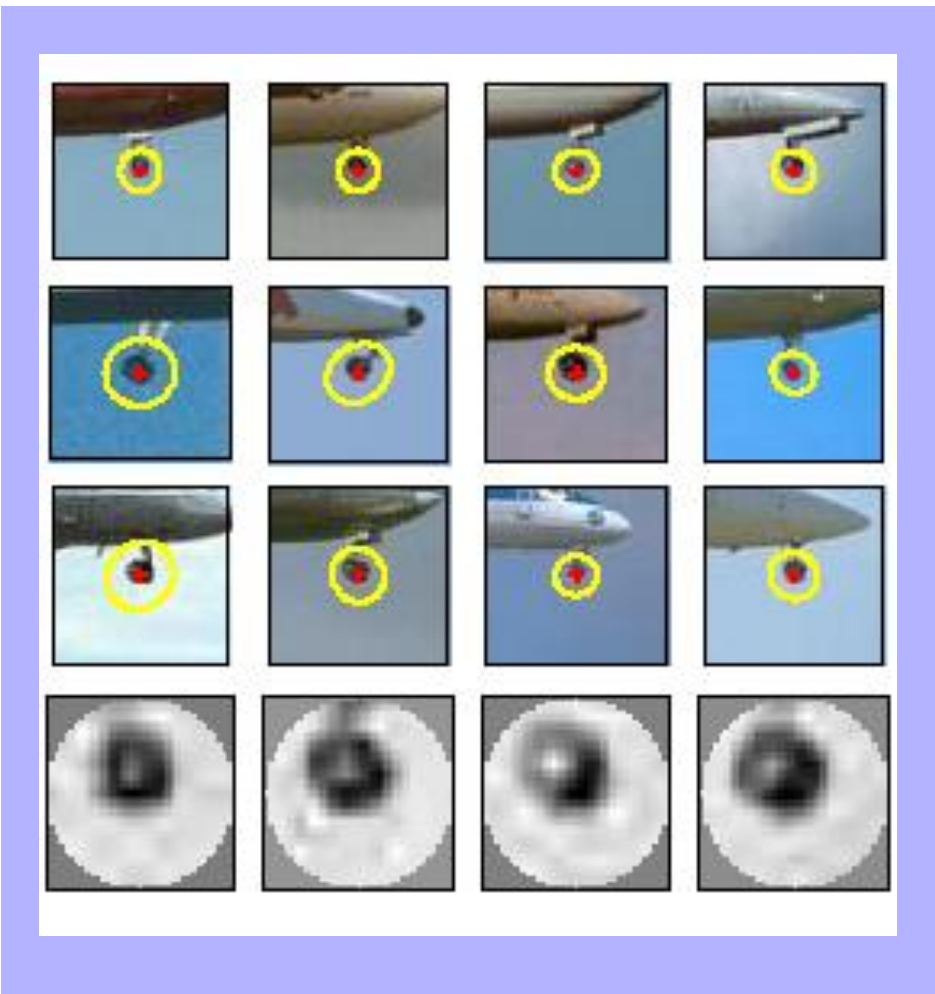
# Bag of features: outline

1. Extract features
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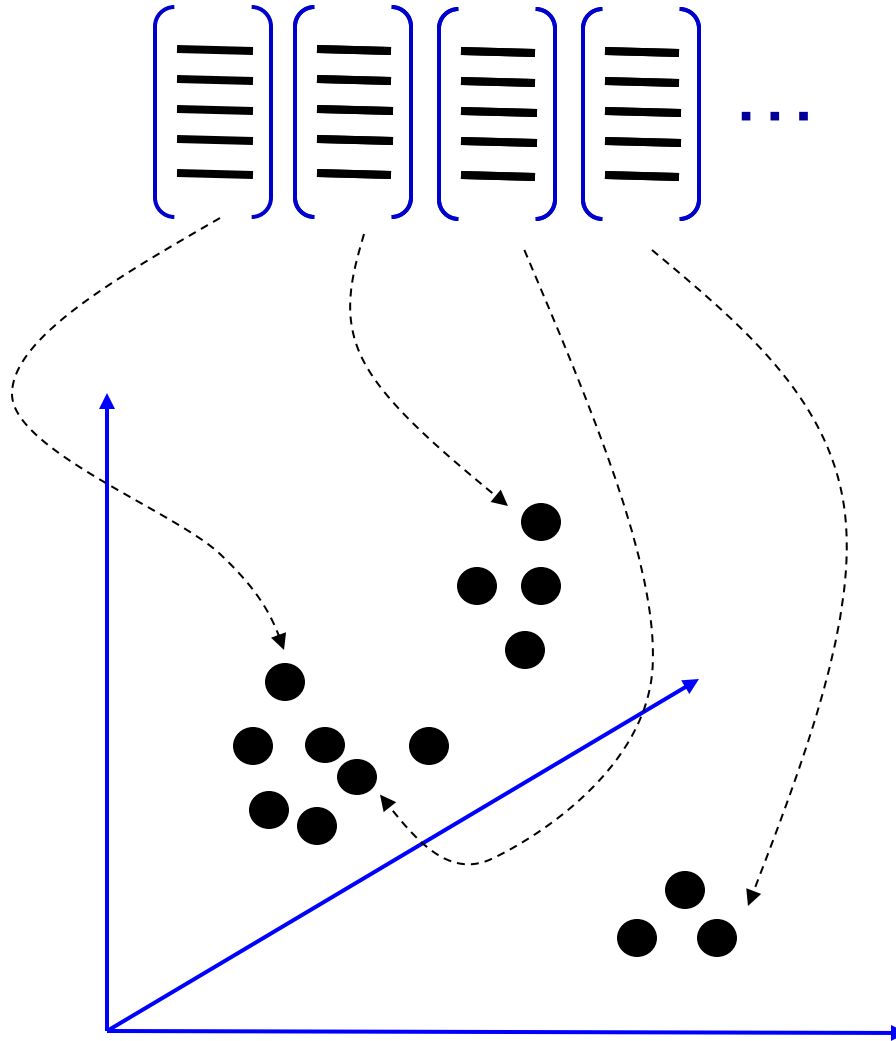




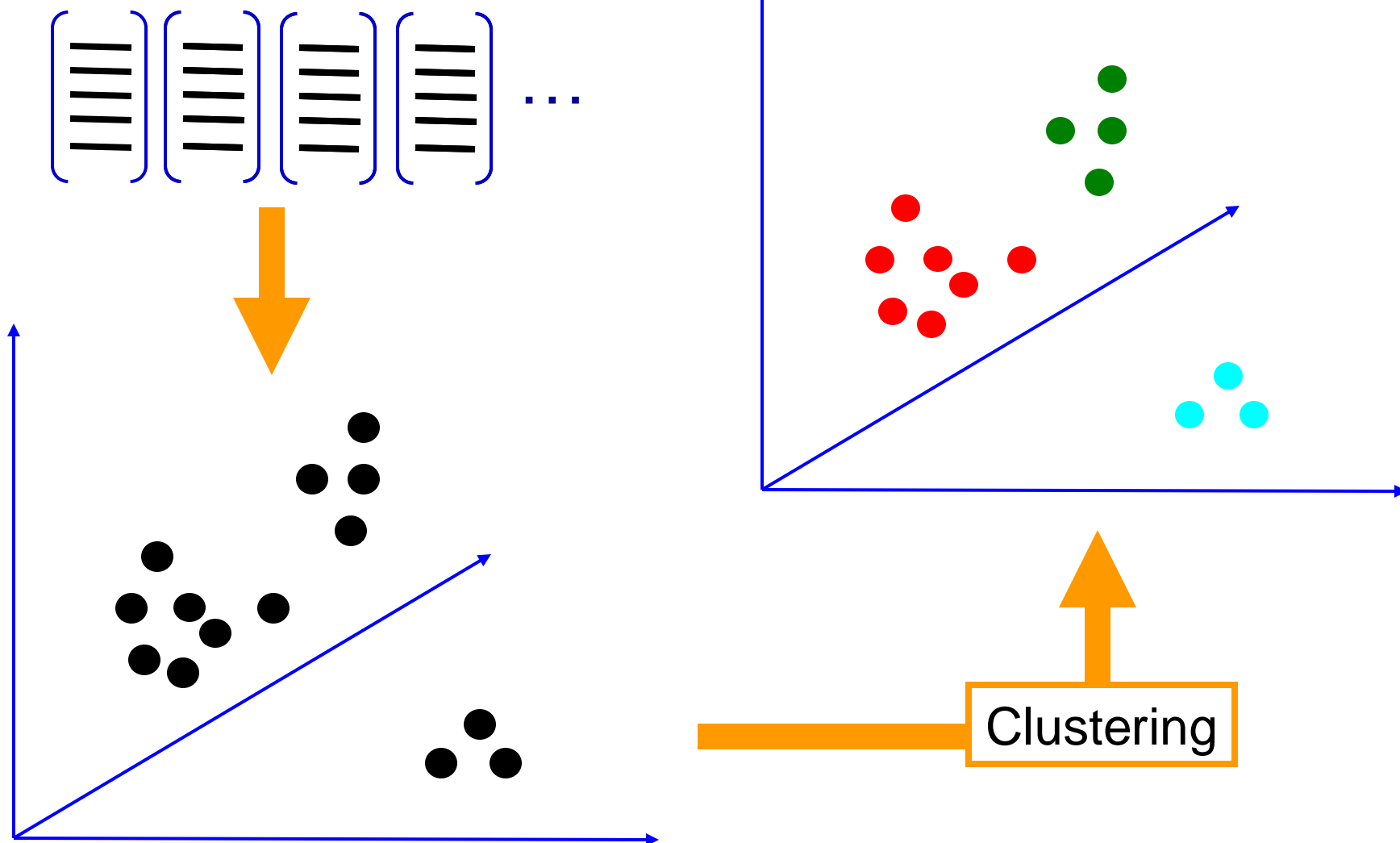
# Image patch examples of visual words



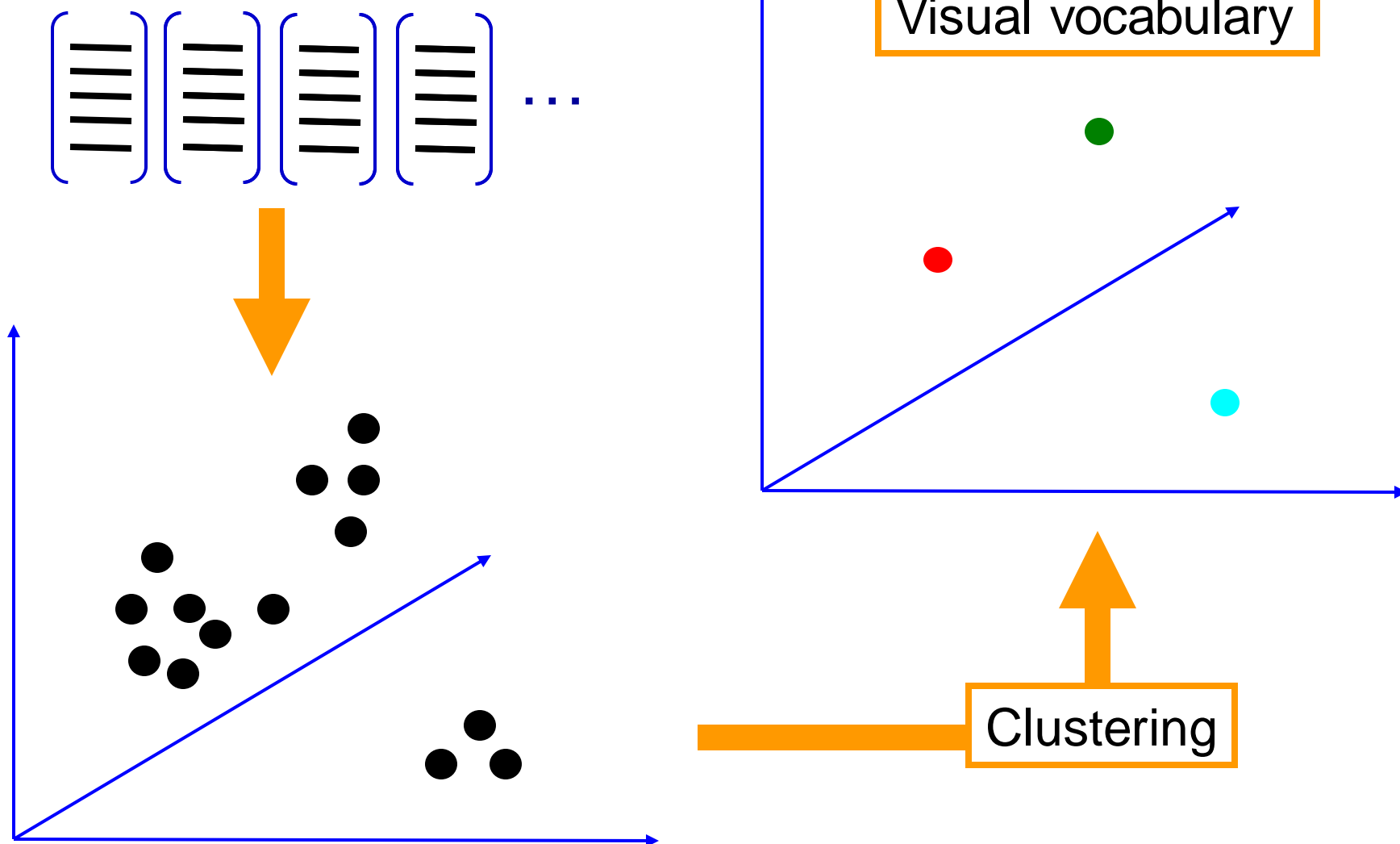
## 2. Learning the visual vocabulary



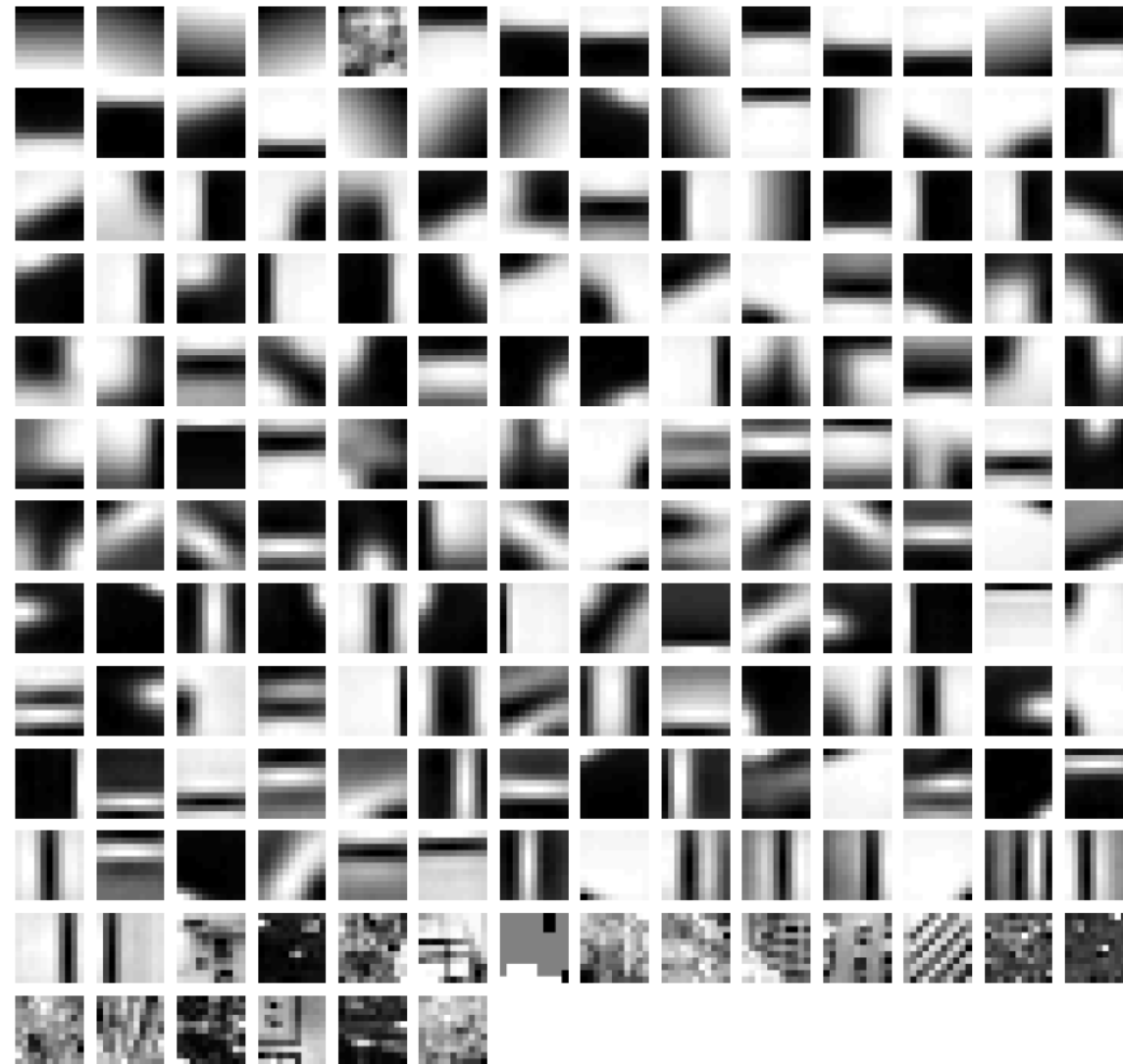
## 2. Learning the visual vocabulary



## 2. Learning the visual vocabulary

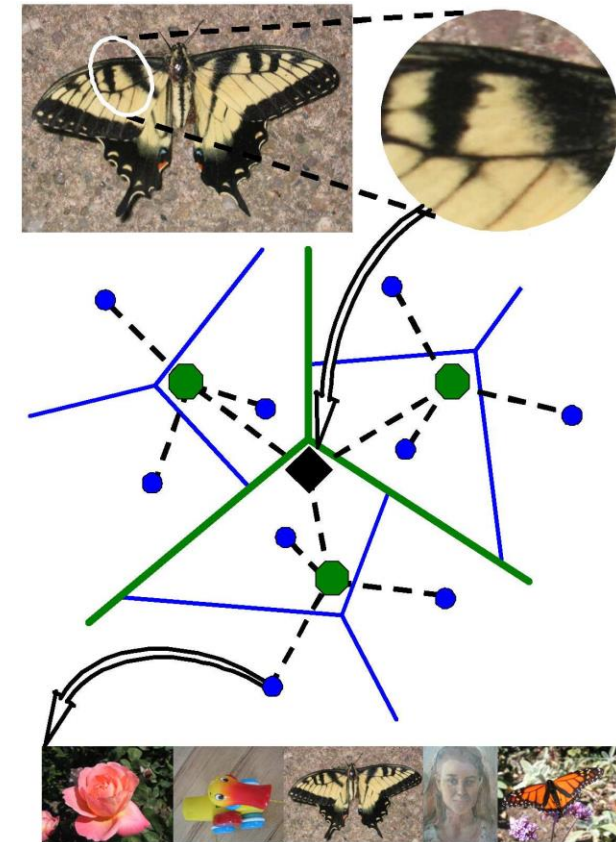


# Example visual vocabulary



# Visual vocabularies: Issues

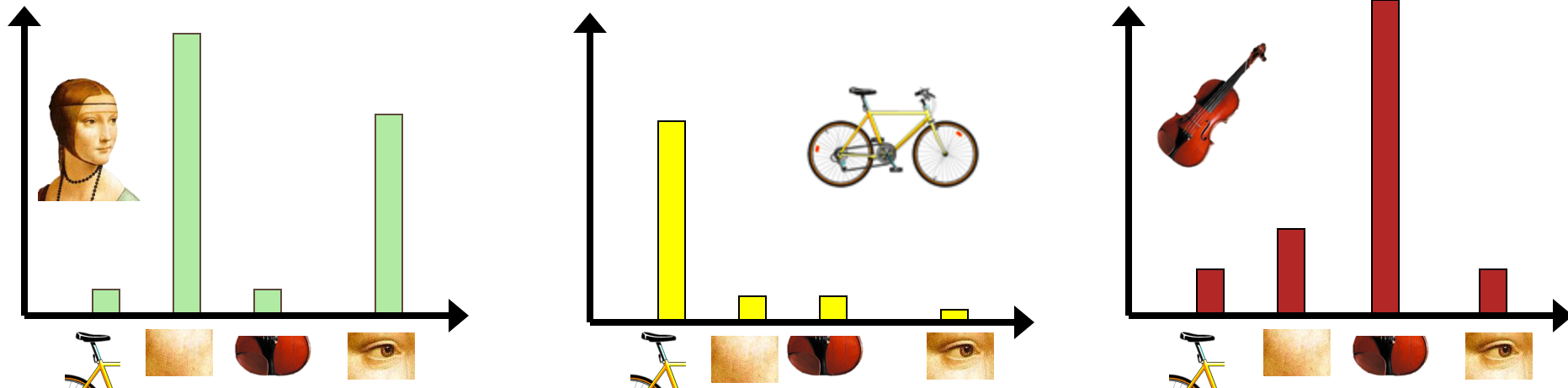
- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
- Computational efficiency
  - Vocabulary trees  
(Nister & Stewenius, 2006)





# Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



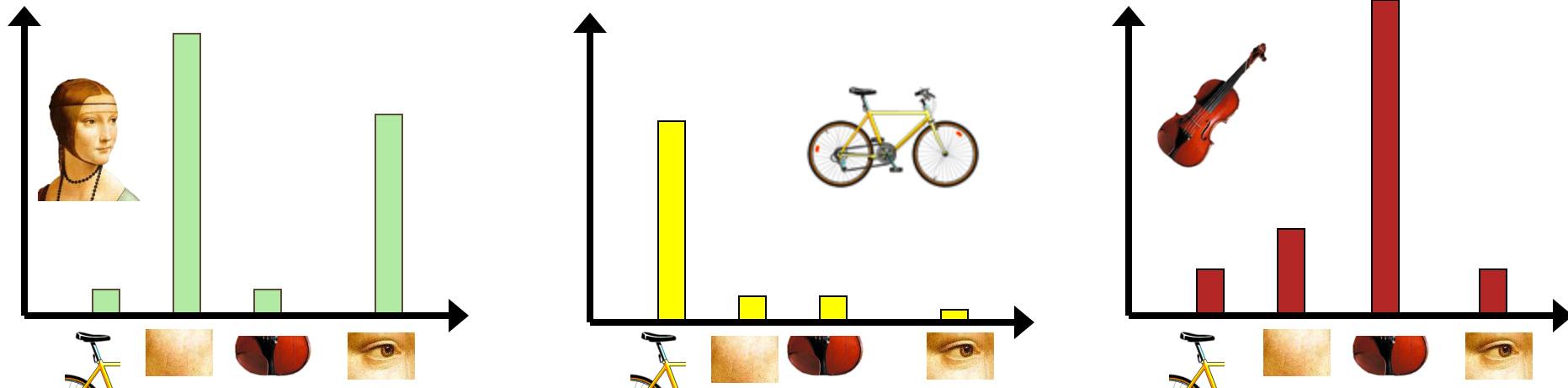


### 3. From clustering to vector quantization

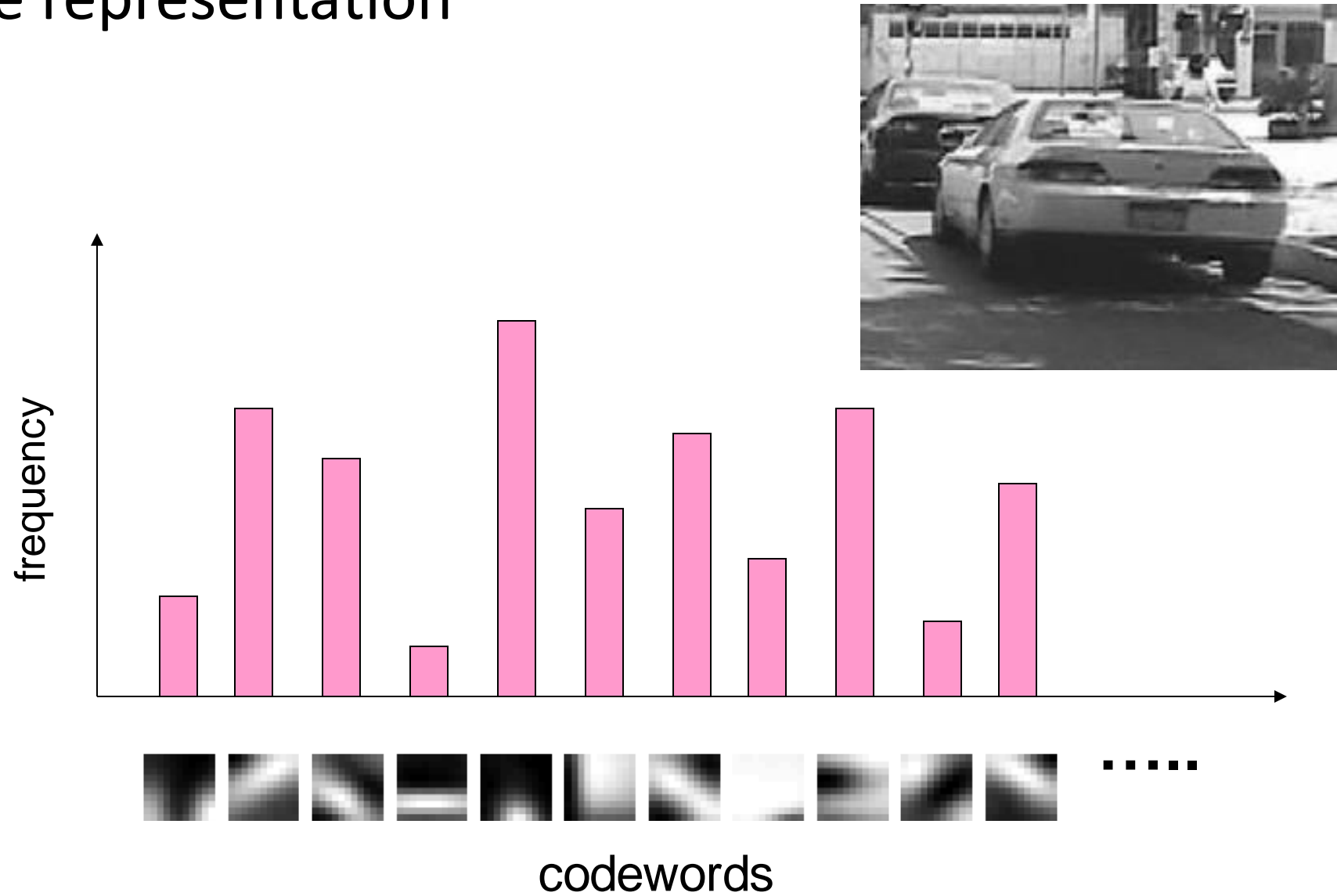
- Clustering is a common method for learning a visual vocabulary or codebook
  - Unsupervised learning process
  - Each cluster center produced by k-means becomes a codevector
  - Codebook can be learned on separate training set
  - Provided the training set is sufficiently representative, the codebook will be “universal”
- The codebook is used for quantizing features
  - A *vector quantizer* takes a feature vector and maps it to the index of the nearest codevector in a codebook
  - Codebook = visual vocabulary
  - Codevector = visual word

# Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



## 4. Image representation



# Summary

- Visual bag of words: method
  - Background
  - Algorithm

