

# Contents

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  - ‘Dictionary learning’ (clustering)
  - Recognition
  
- Tracking
  - Meanshift and CAMshift
  - Other approaches

# *Bag of features models*

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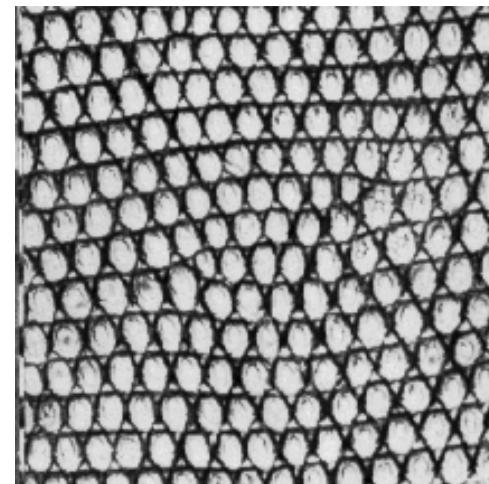
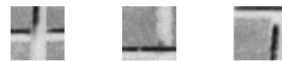
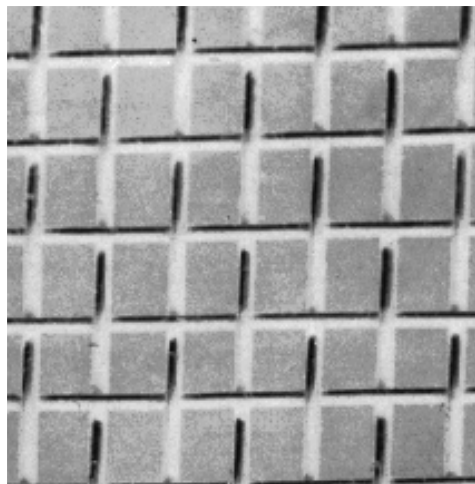
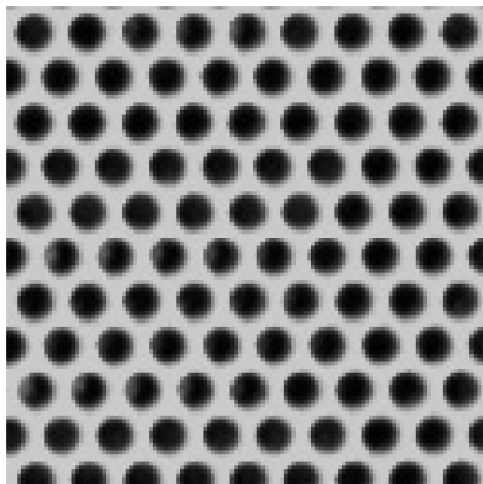


*Some slides adapted from Fei-Fei Li, Rob Fergus and Antonio Torralba*

# Origin 1: Texture recognition

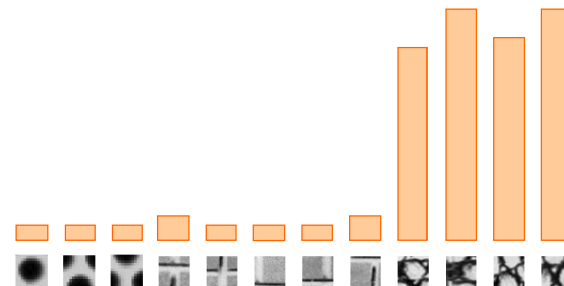
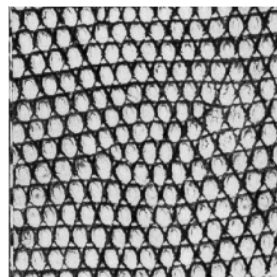
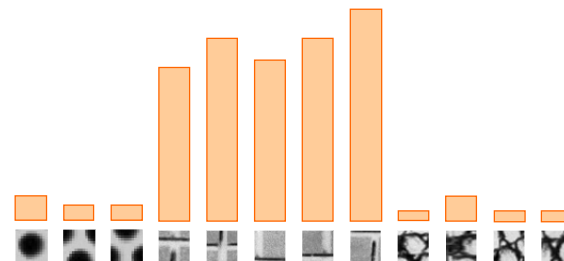
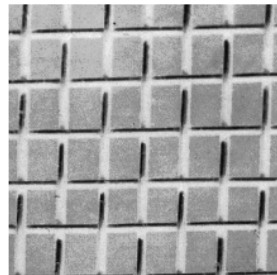
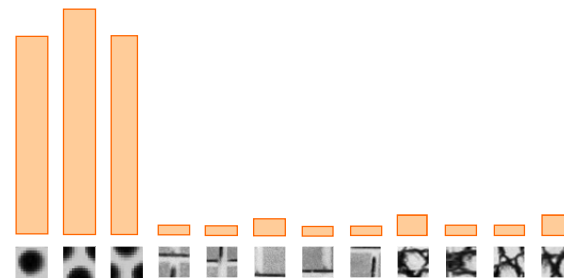
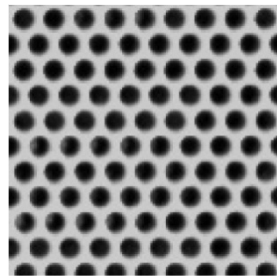
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Texture is characterized by the repetition of basic elements or *textons*. Arguably, for stochastic textures, the identity of the textons matters more than their spatial arrangement.



# Origin 1: Texture recognition

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## Origin 2: Bag-of-words models

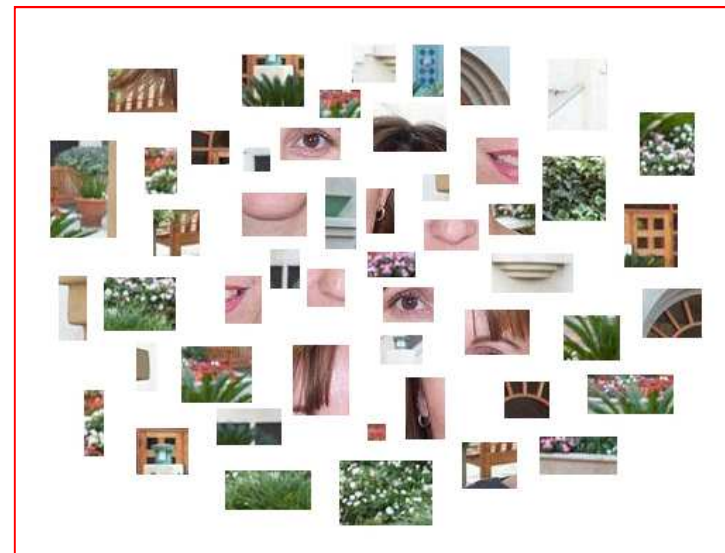
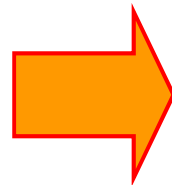
- ❖ **Orderless document representation: frequencies of words from a dictionary** Salton & McGill (1983)





# *Bags of features* for object recognition

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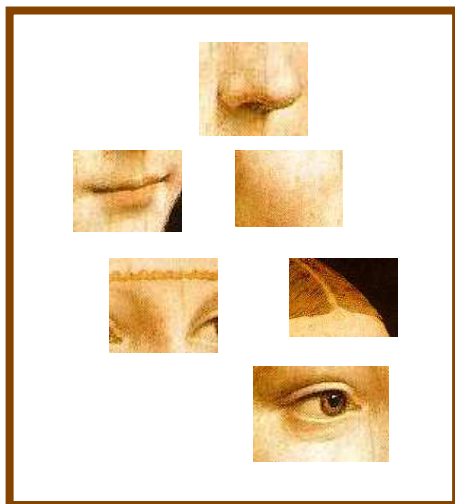
**face, flowers, building**

Quite effective for image-level classification

# Bag of features: overview

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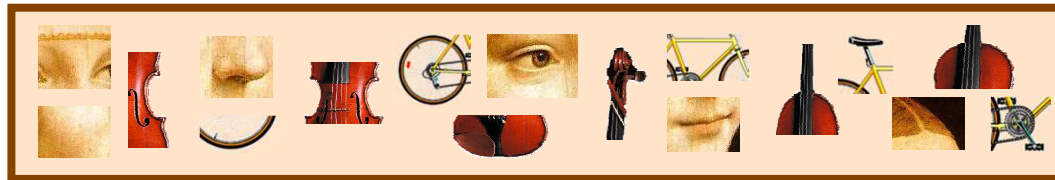
## 1. Extract features



# Bag of features: overview

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1. Extract features
2. Learn visual vocabulary ('dictionary' of visual 'words')





# Bag of features: overview

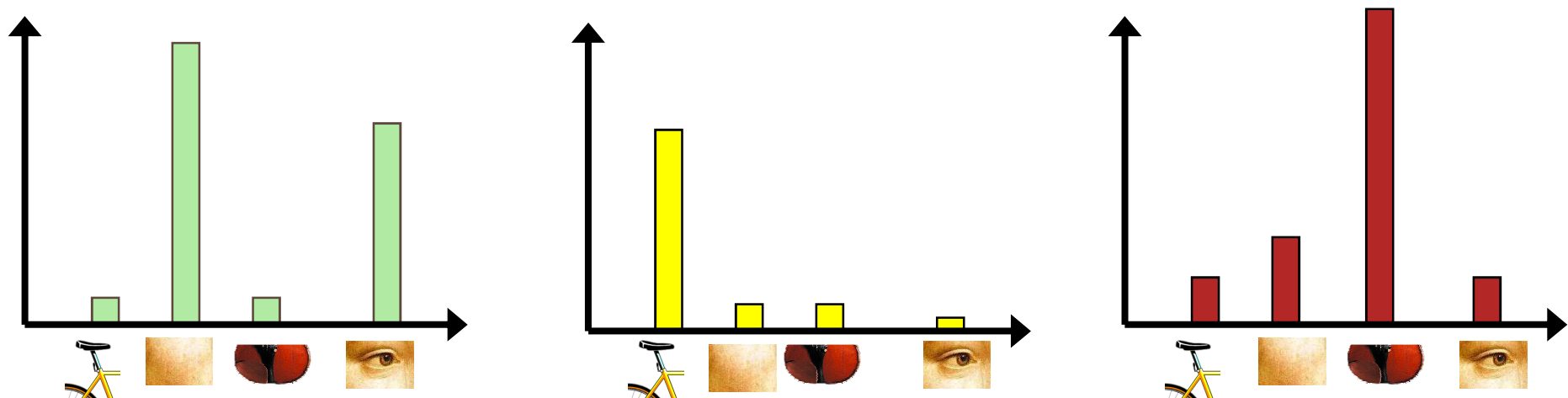
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1. Extract features
2. Learn visual vocabulary ('dictionary' of visual 'words')
3. Quantize features using visual vocabulary

# Bag of features: overview

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1. Extract features
2. Learn visual vocabulary ('dictionary' of visual 'words')
3. Quantize features using visual vocabulary
4. Represent images by frequencies of visual words



# 1. Feature extraction

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- Extract features at locations on a regular grid, at random locations, at detected feature points, from superpixels...



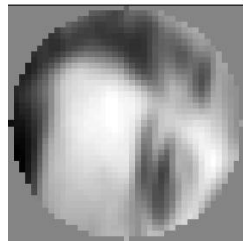
- Features: colour, texture, SIFT, SURF, etc.

# 1. Feature extraction

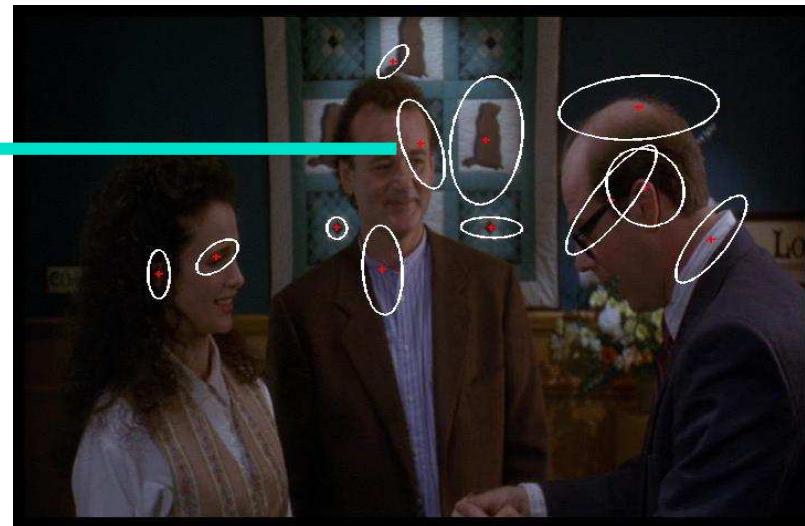
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**SIFT  
descriptor**



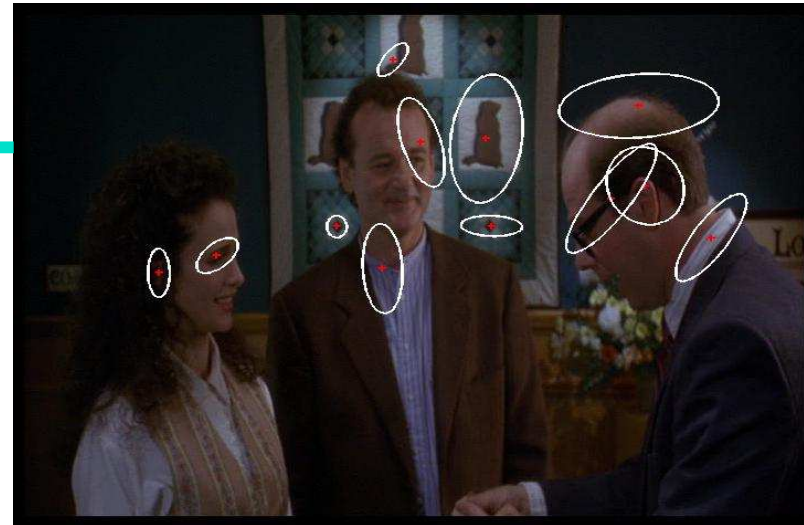
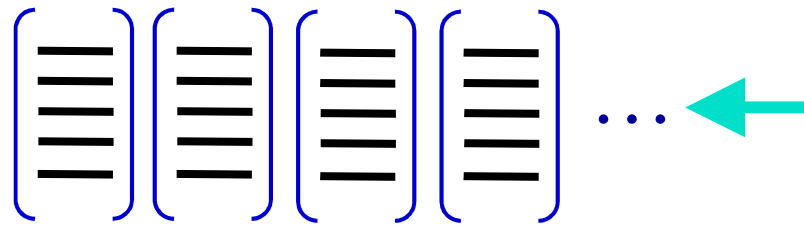
**Normalized  
patch**



**Patches (feature detection)**

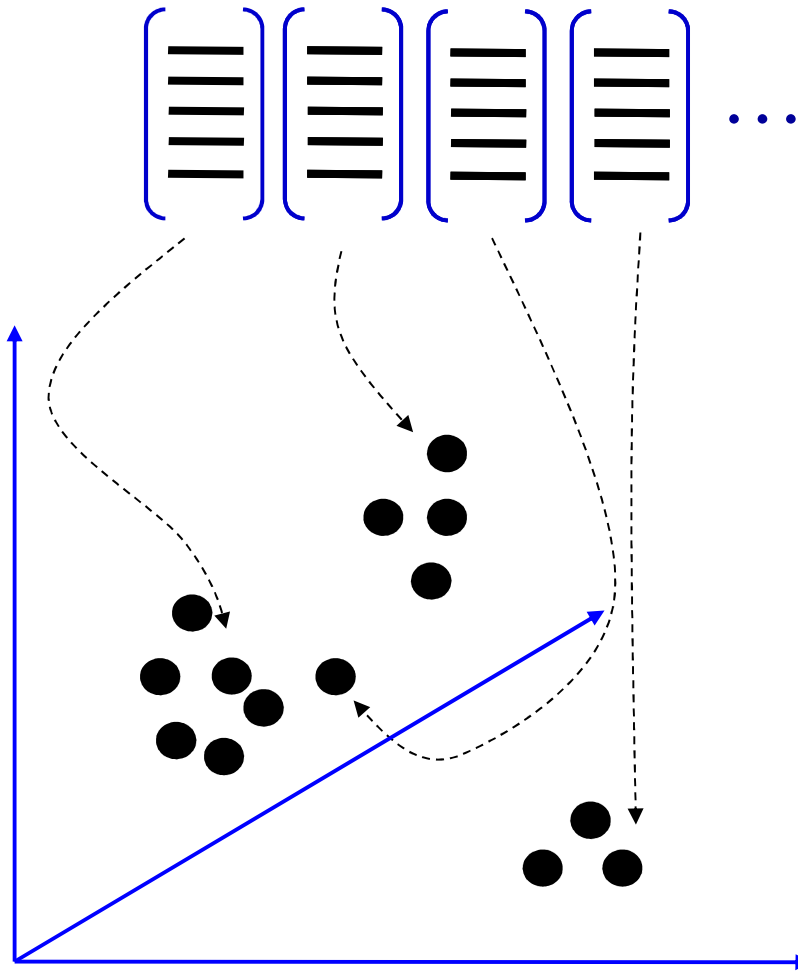
# 1. Feature extraction

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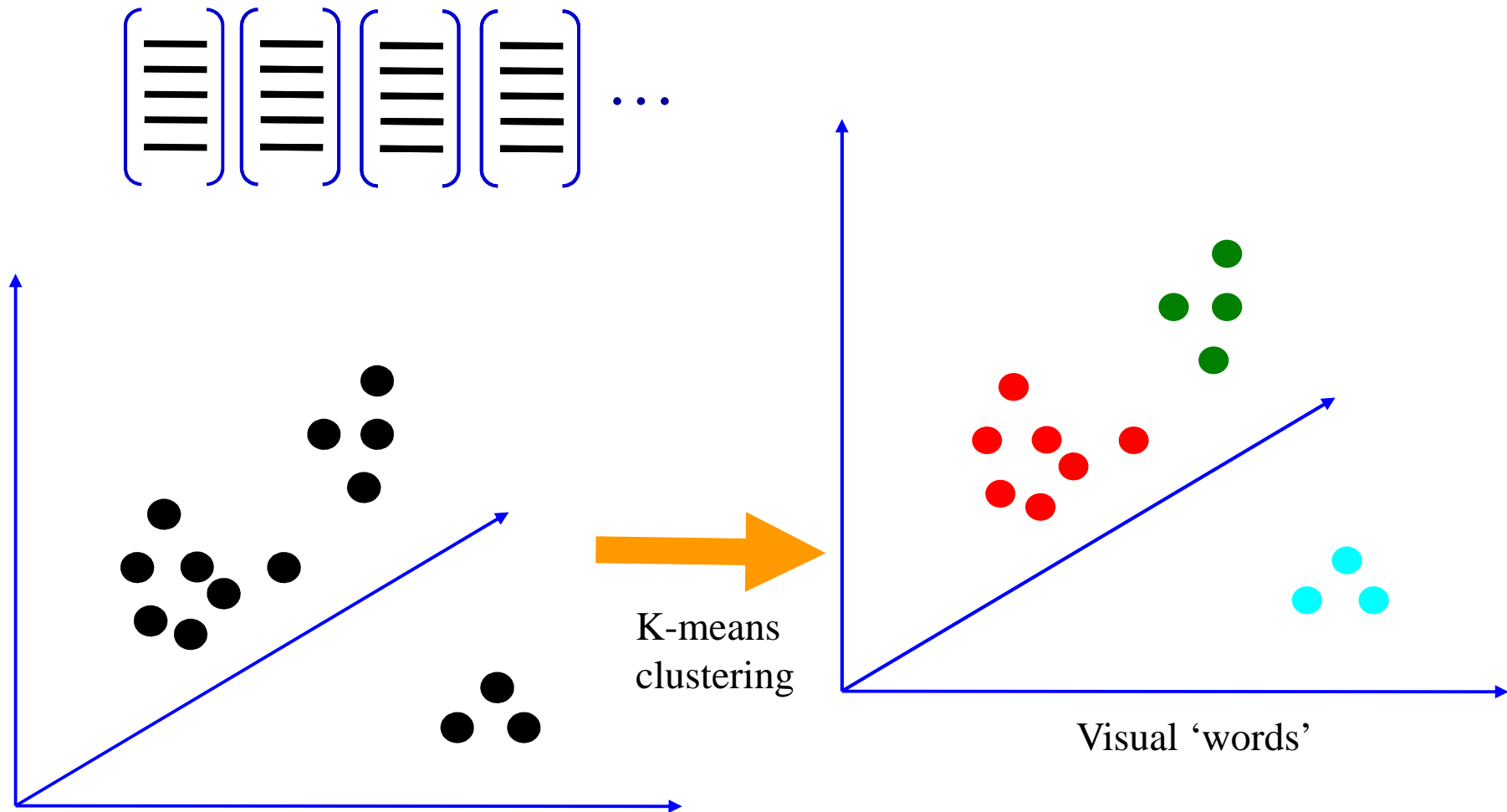
## 2. Learning the visual vocabulary

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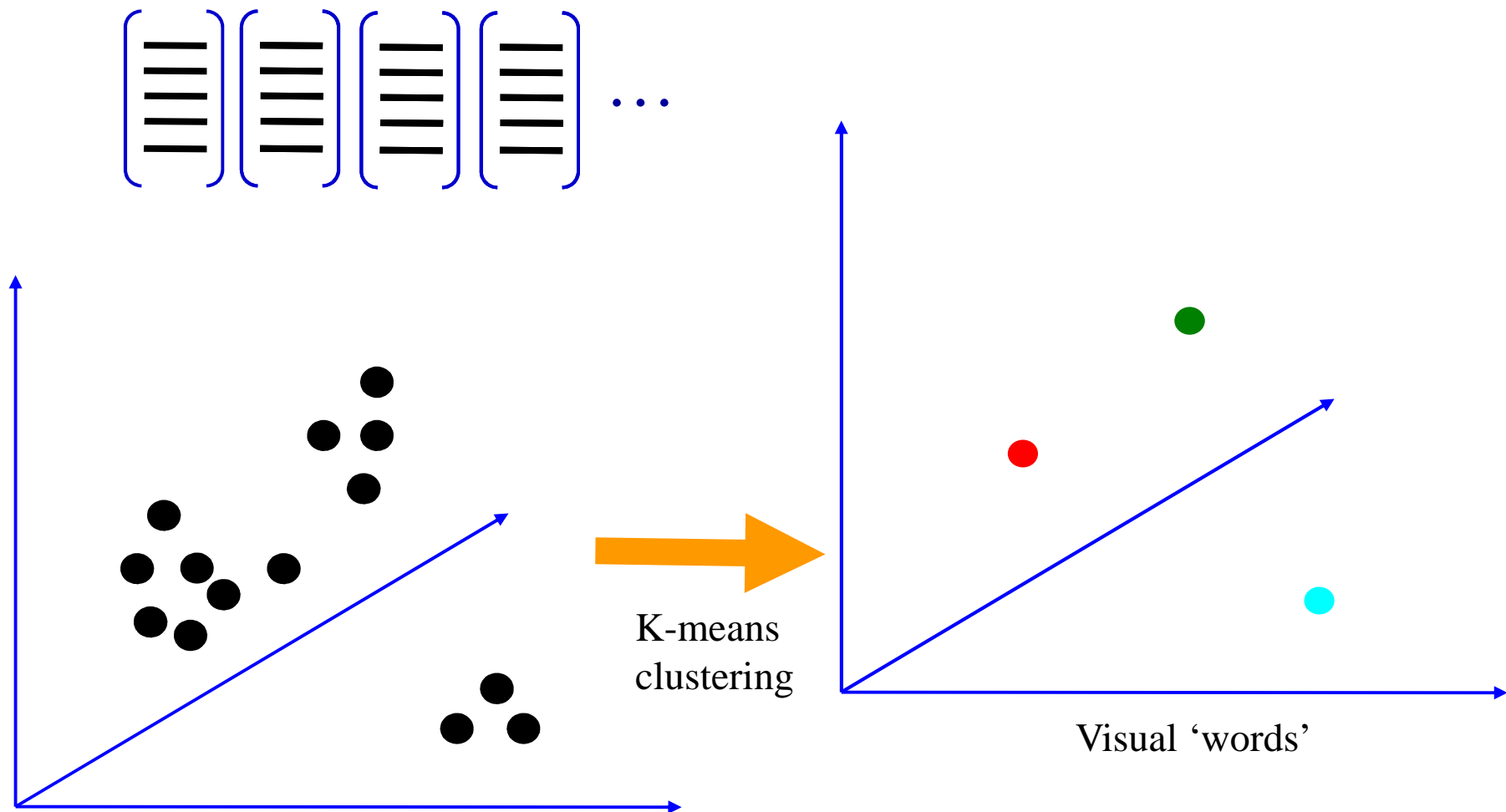


## 2. Learning the visual vocabulary



*Based on slide by Josef Sivic*

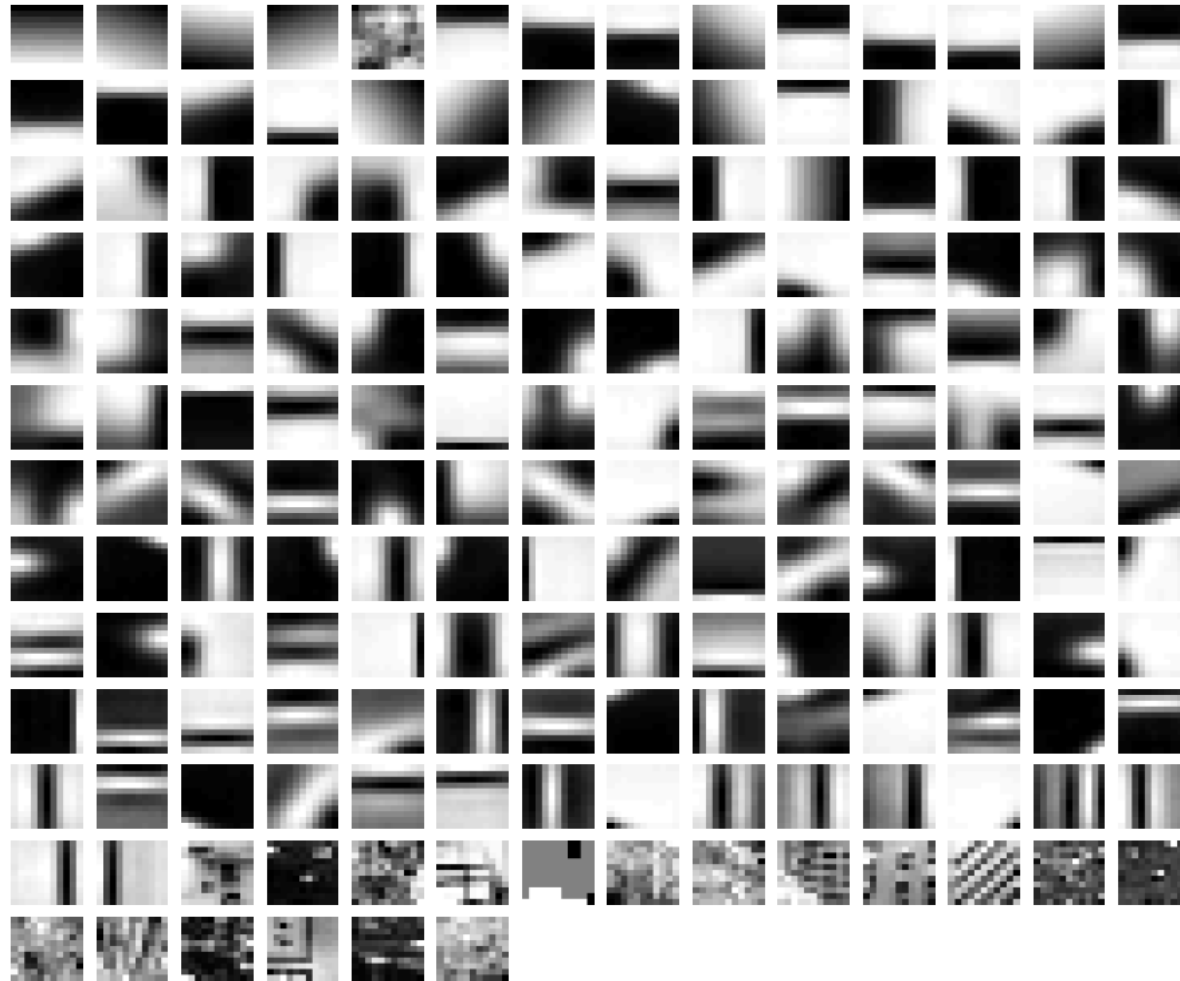
## 2. Learning the visual vocabulary



*Based on slide by Josef Sivic*

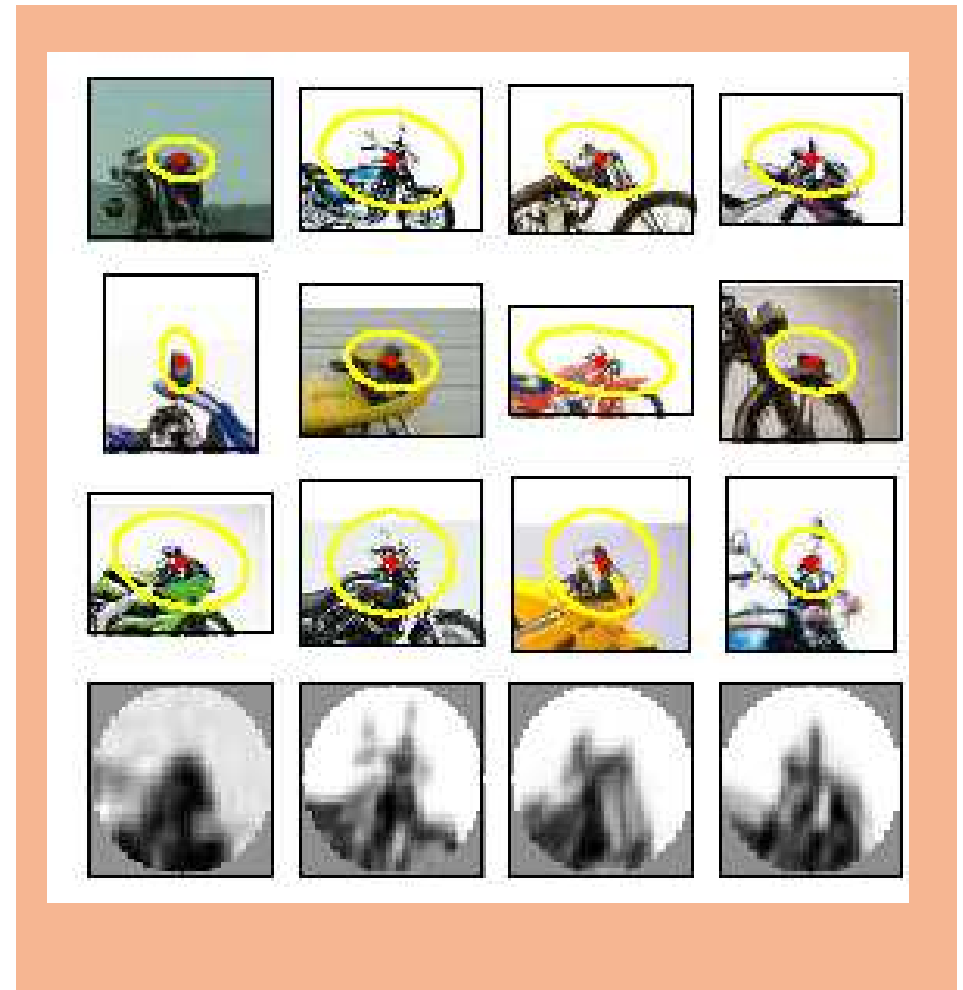
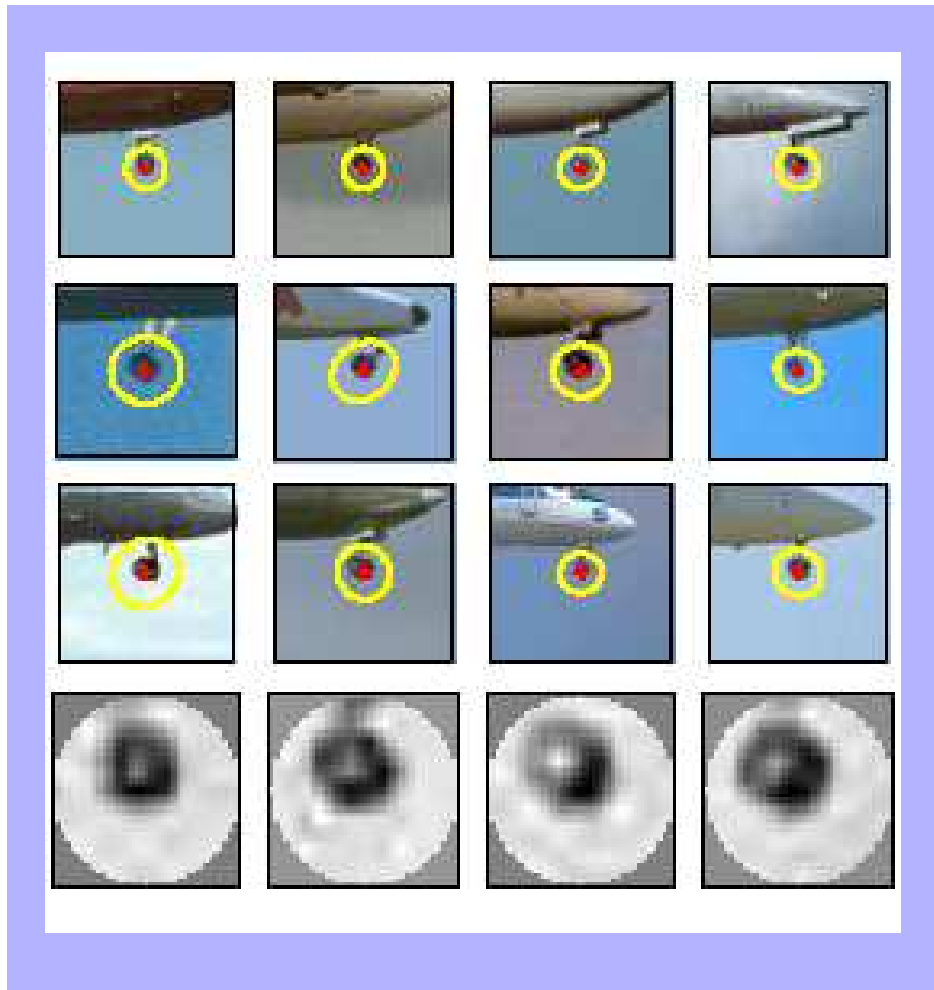
# Example visual vocabulary

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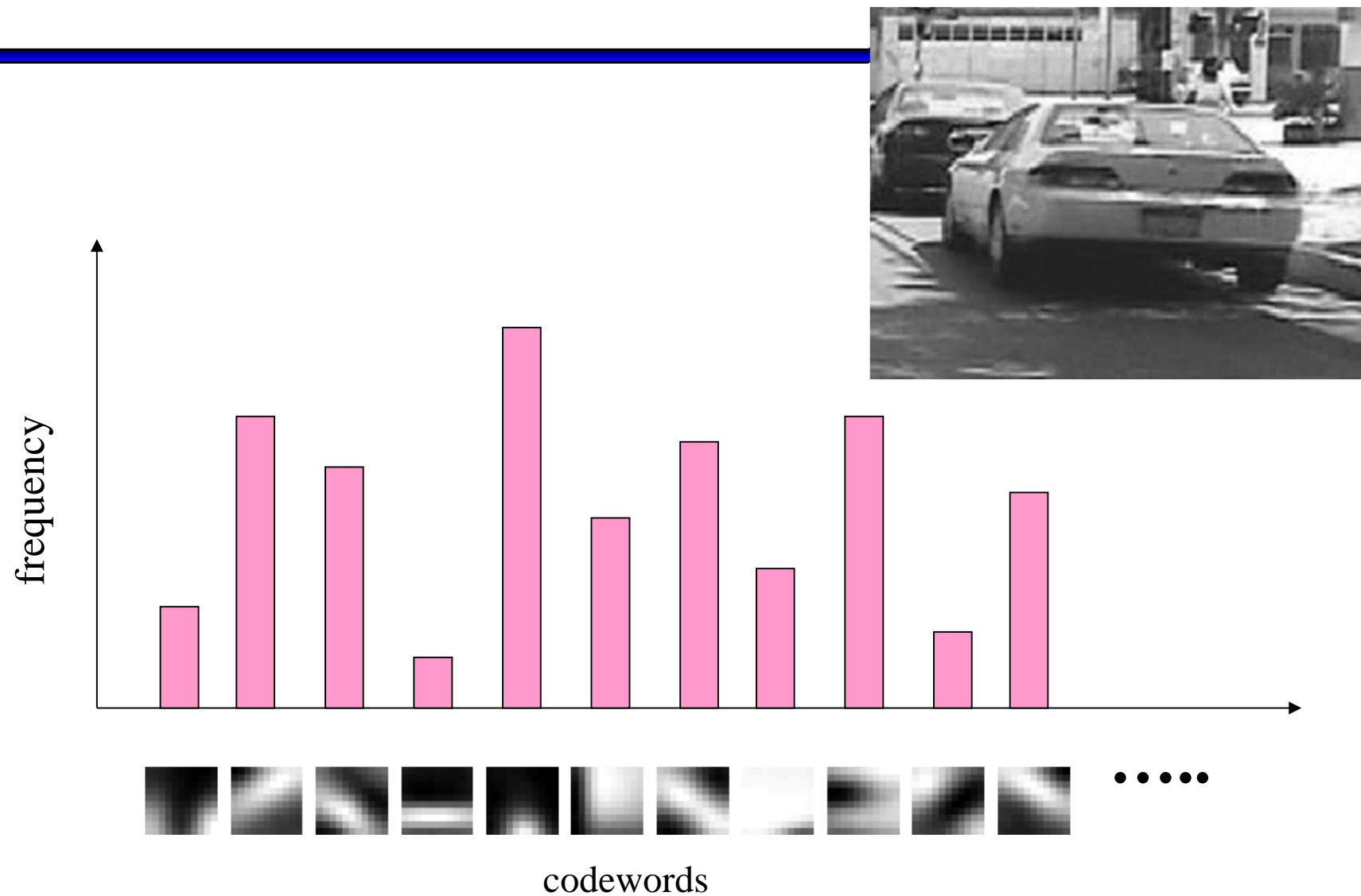
*Fei-Fei et al. 2005*

# Image patch examples of visual words



*Sivic et al. 2005*

### 3. Image representation

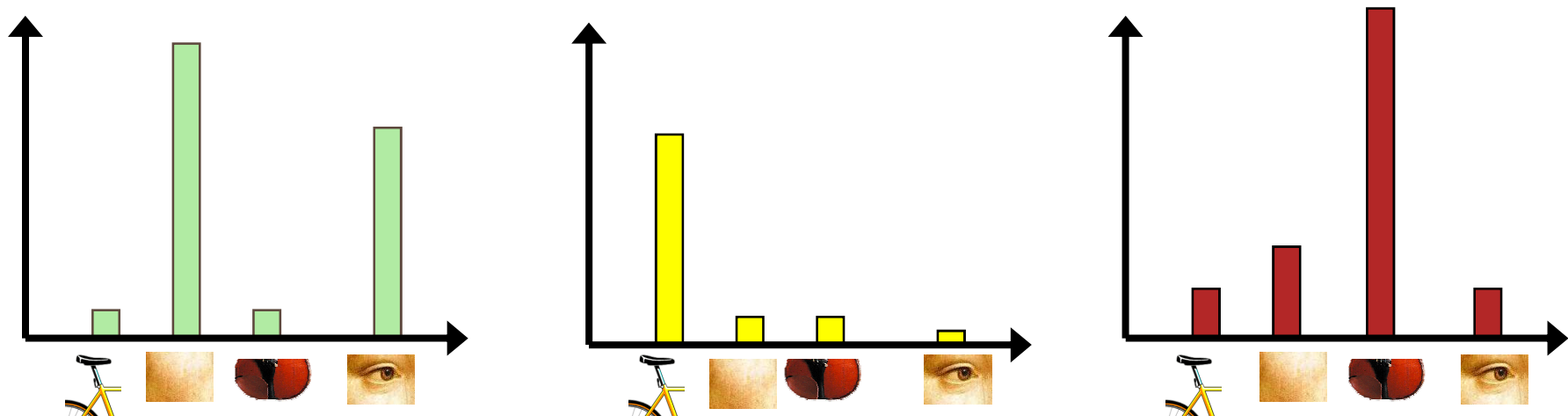


# Image classification

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Given a *bag-of-features* representation of each image:

- Train a classifier using the histograms as feature vectors
- Could involve defining a measure of histogram similarity





# Tracking

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- Following objects or features through an image sequence
- Estimating location (and orientation) in each frame
- Physical Constraints:
  - Inertia: motion cannot change abruptly
    - ⇒ No abrupt motion changes are observed *provided that* the frame rate is fast enough
  - If a 3D trajectory is smooth then its 2D projection is also smooth
- Useful Assumptions:
  - Location, speed and direction of motion do not change much between frames
  - Image motion is smooth

# Targets to Track

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- Local features (e.g. interest points, small objects)
- Contour fragments (e.g. partial object boundaries)
- Objects (possibly multiple parts, possibly deformable)

# Tracking example

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- ❖ Search in a local window
- ❖ Window position depends on previous estimate
- ❖ Extent of window depends on expected maximum speed of image motion



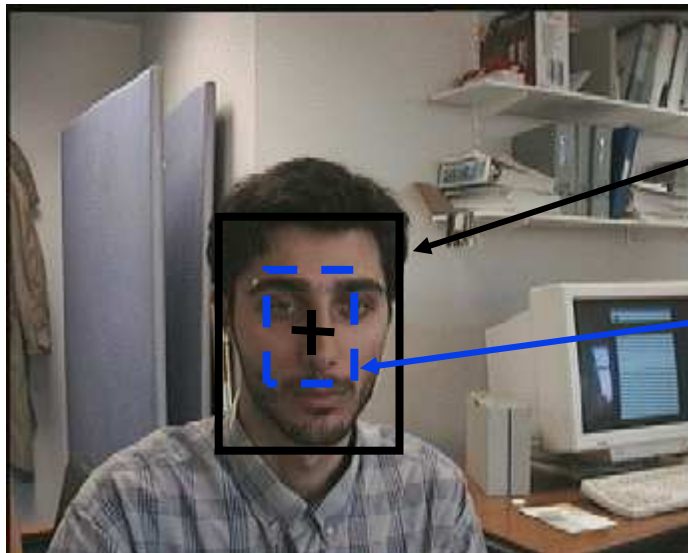
**Estimate at frame t**

**Search window for frame t+1**

# Face tracking example

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- Want to estimate location and scale (fixed aspect ratio)
- Search ranges depend on previous estimates



**Box indicates estimated location and scale at time  $t$**

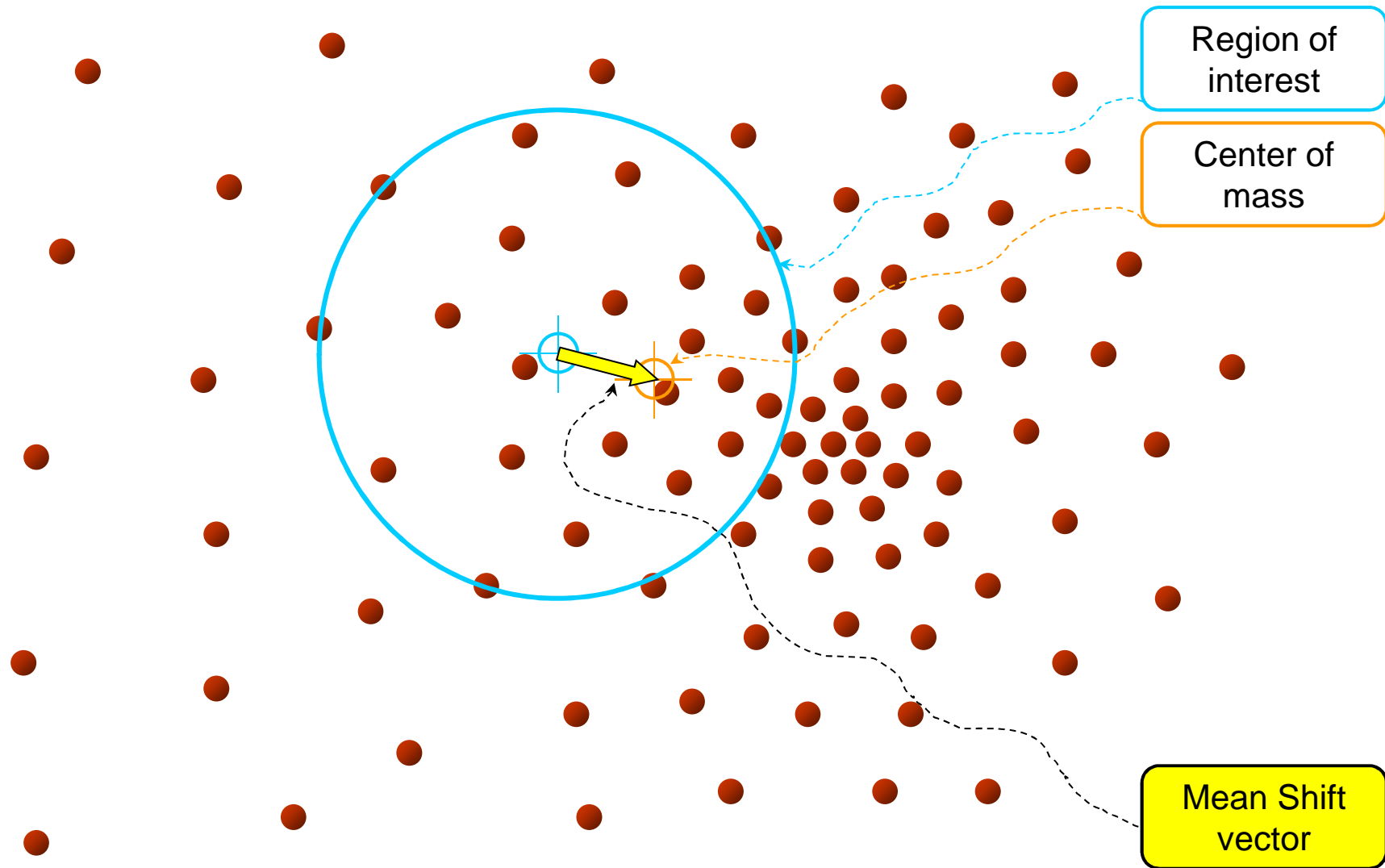
At  $t+1$ , search for object centred within this window and at a range of scales

# Example: Head Tracking

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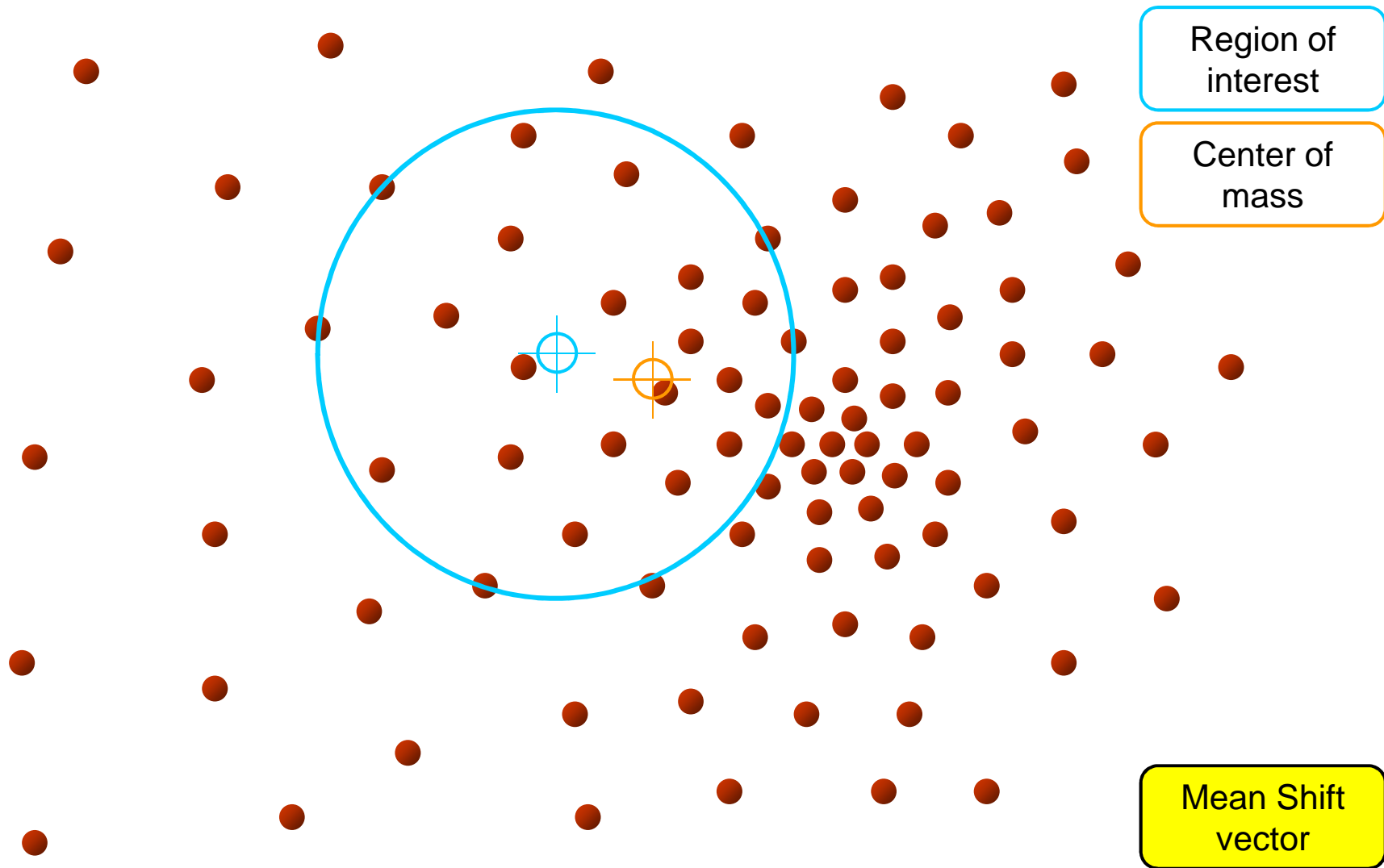
# Mean Shift: Intuitive Description



**Objective :** Find the densest region  
Distribution of identical billiard balls

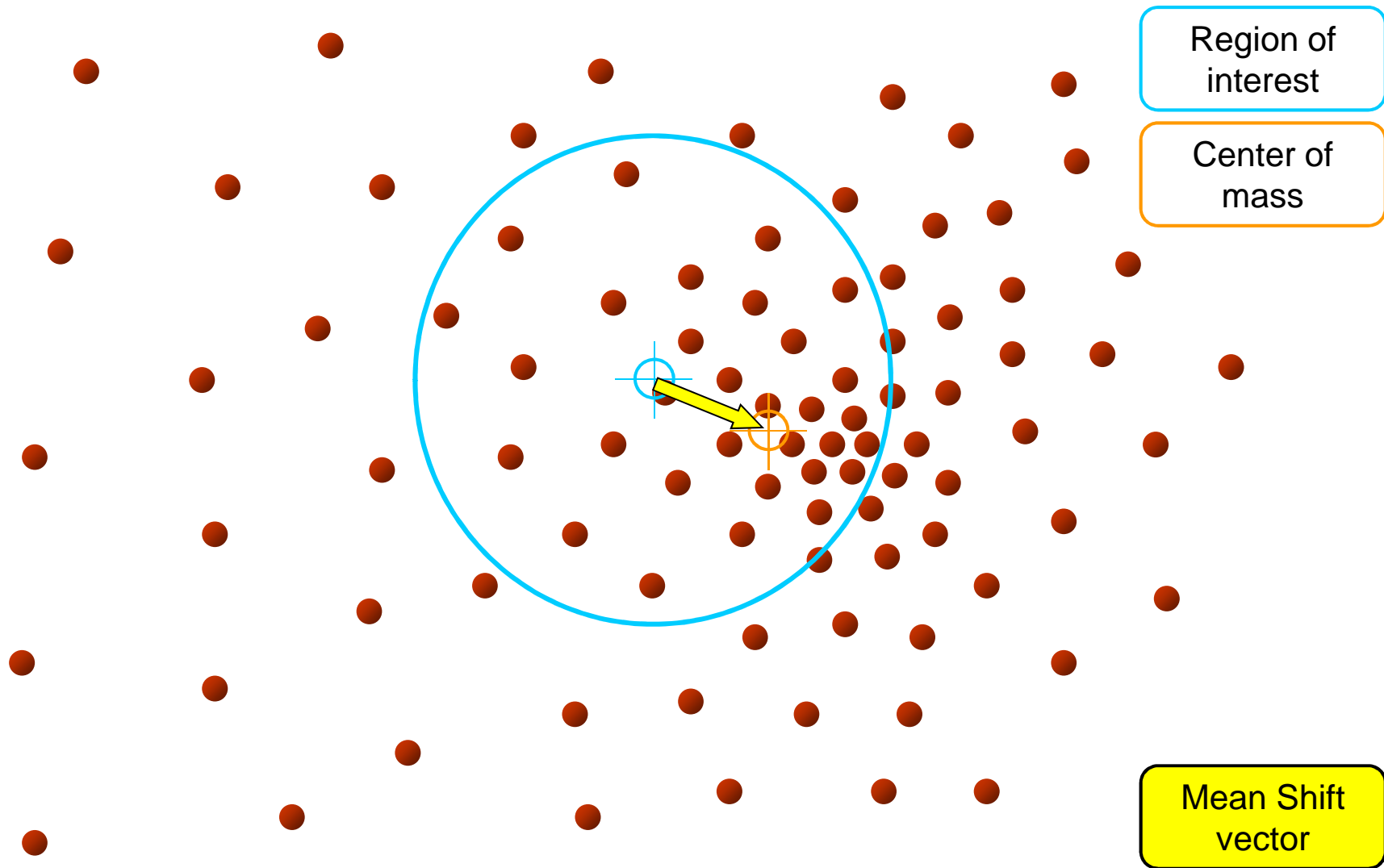
*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*





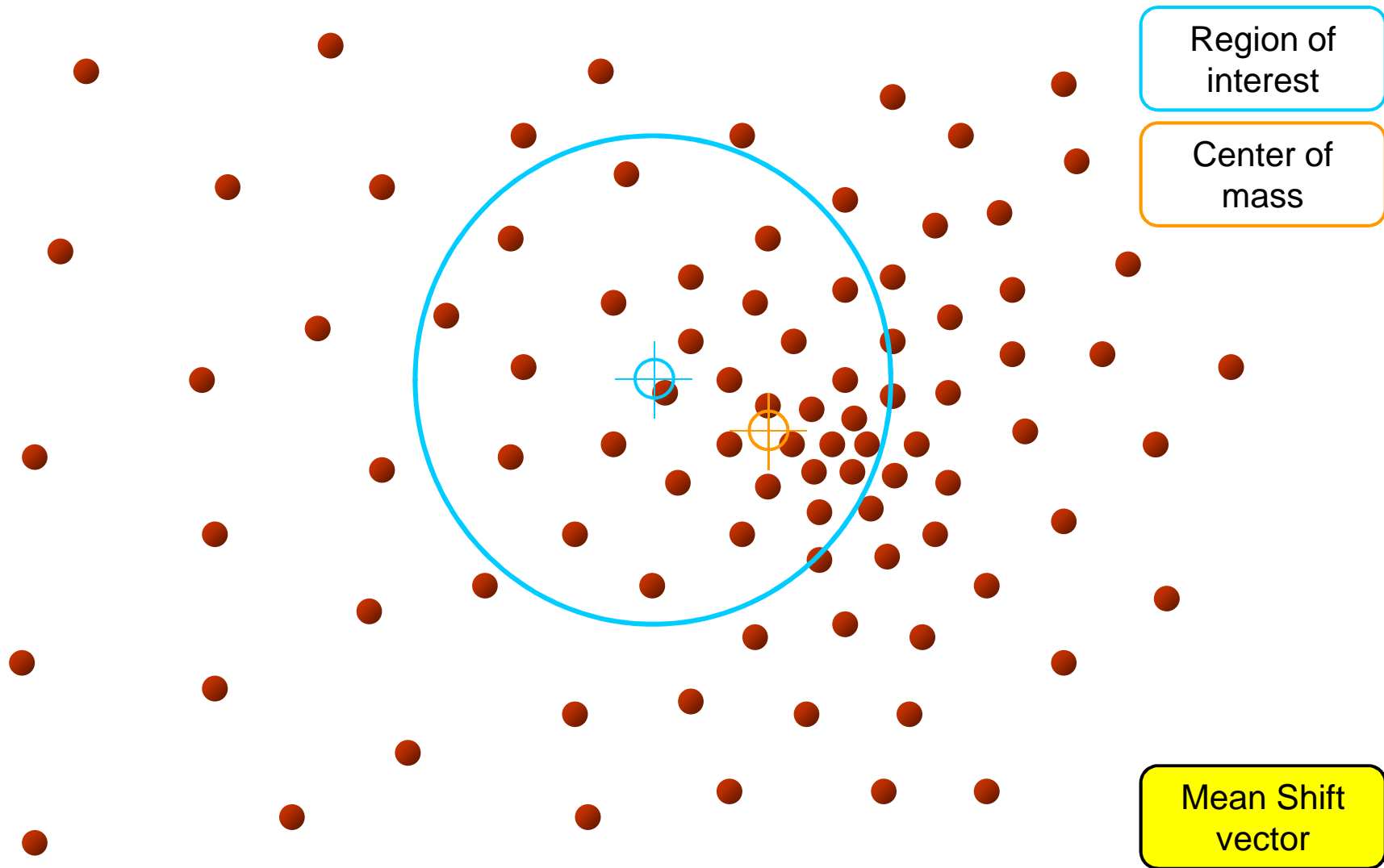
**Objective : Find the densest region**  
Distribution of identical billiard balls

*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



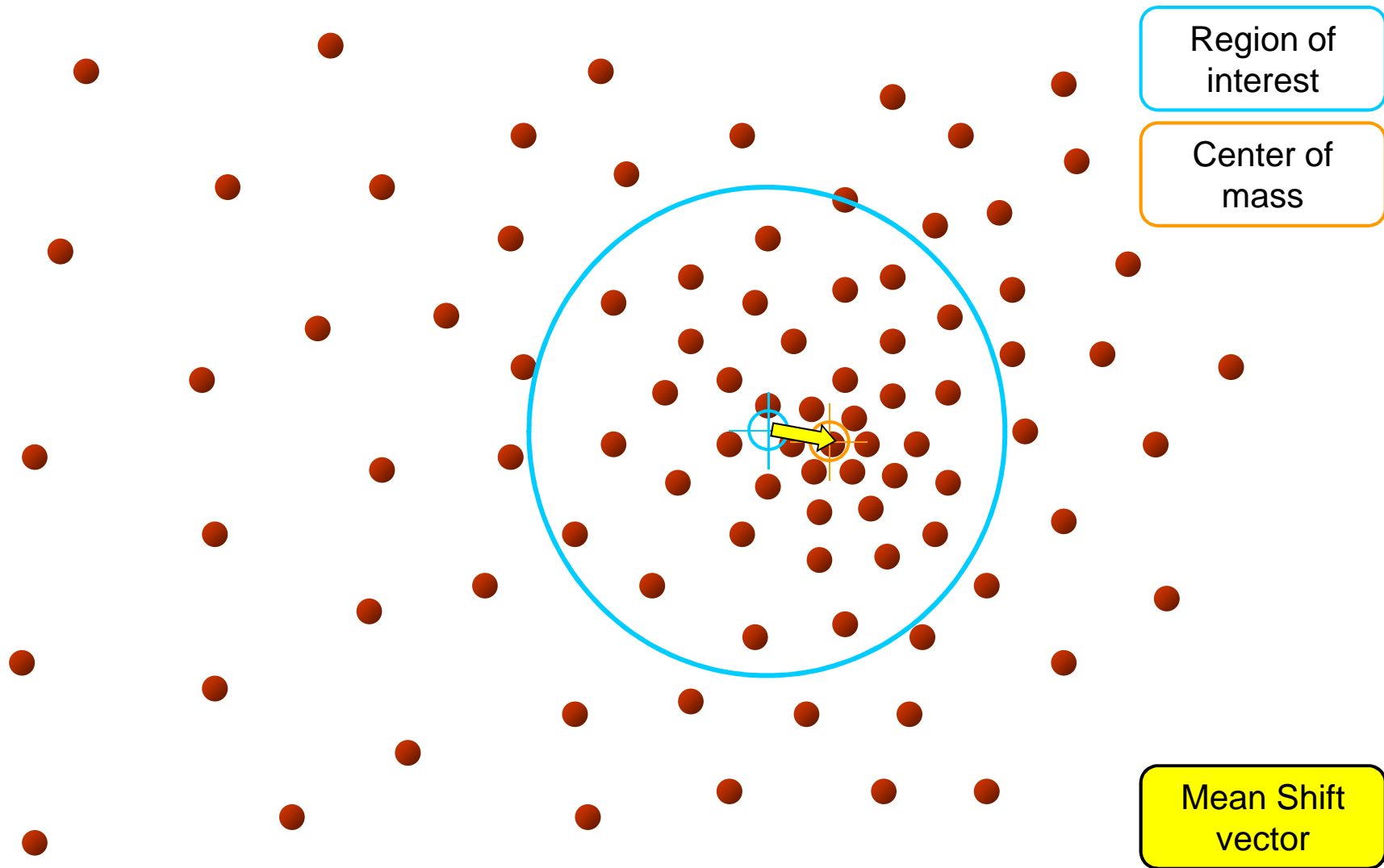
**Objective :** Find the densest region  
Distribution of identical billiard balls

*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



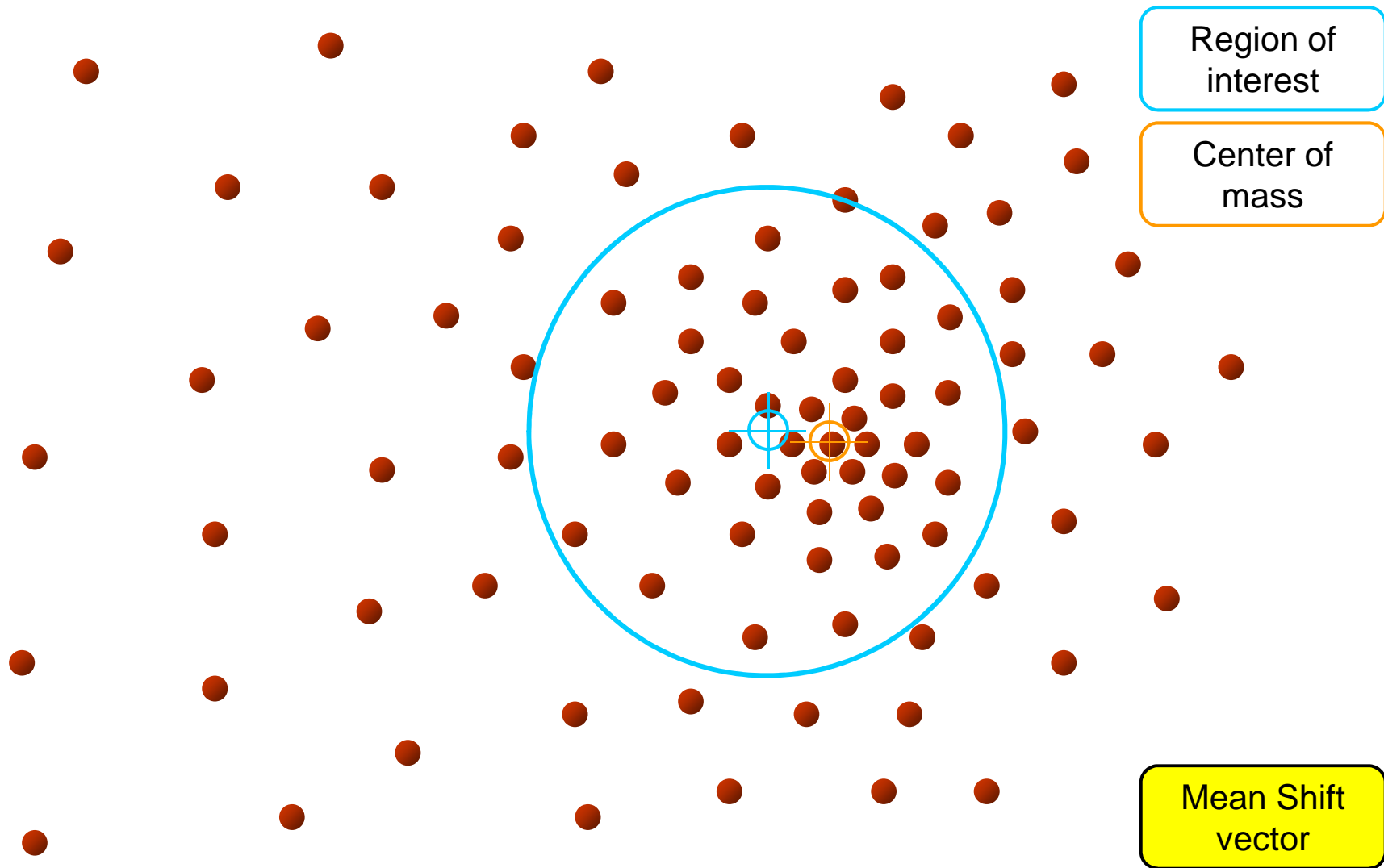
**Objective :** Find the densest region  
Distribution of identical billiard balls

*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



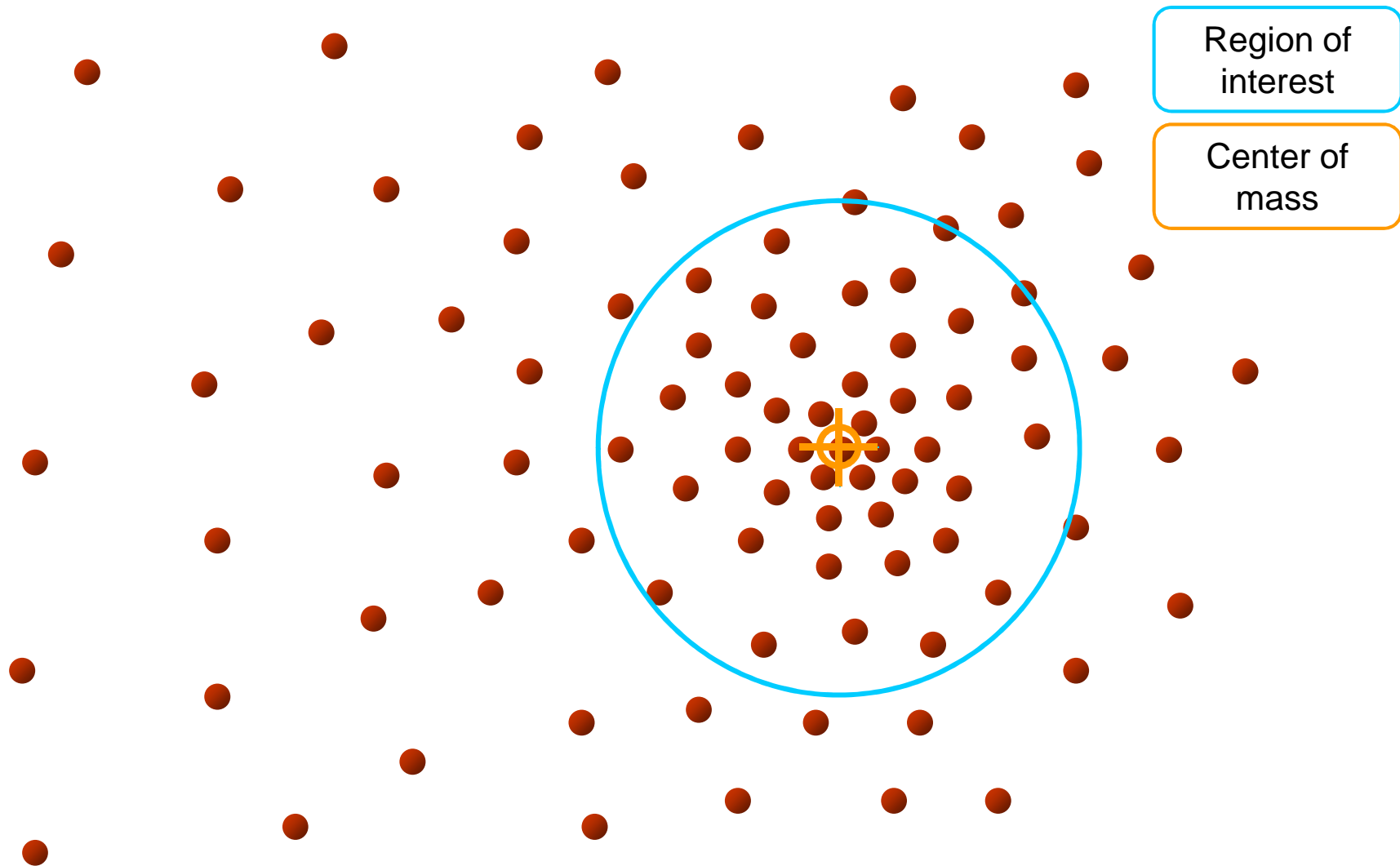
**Objective :** Find the densest region  
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*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



**Objective :** Find the densest region  
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*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



**Objective : Find the densest region**  
Distribution of identical billiard balls

*(Slide credit: Yaron Ukrainitz & Bernard Sarel)*



# What is Mean Shift ?

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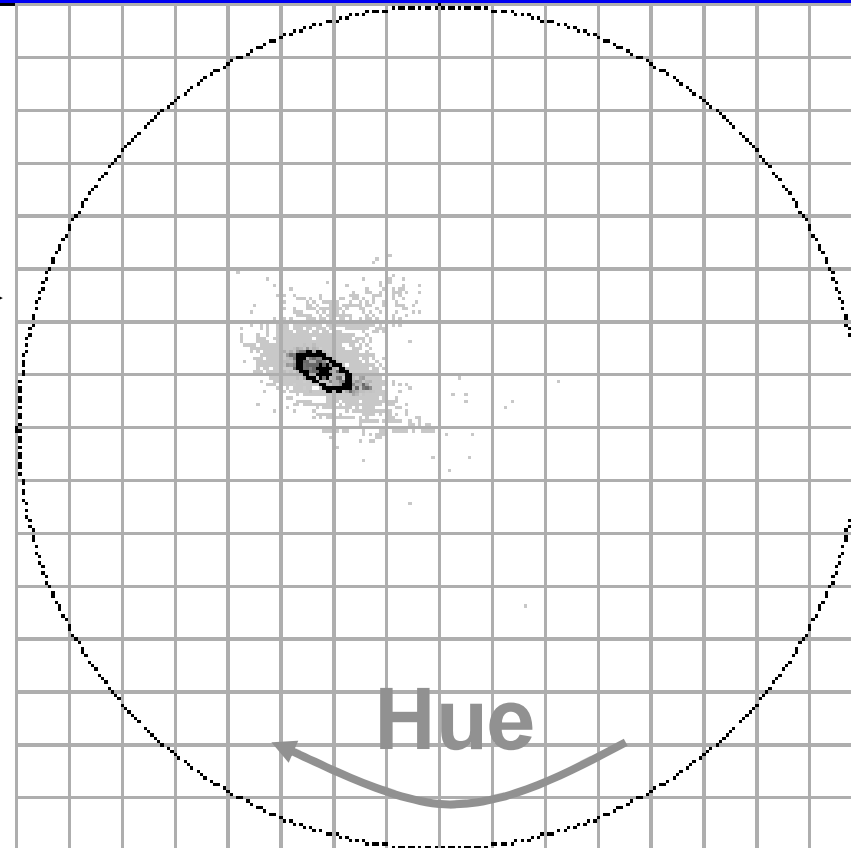
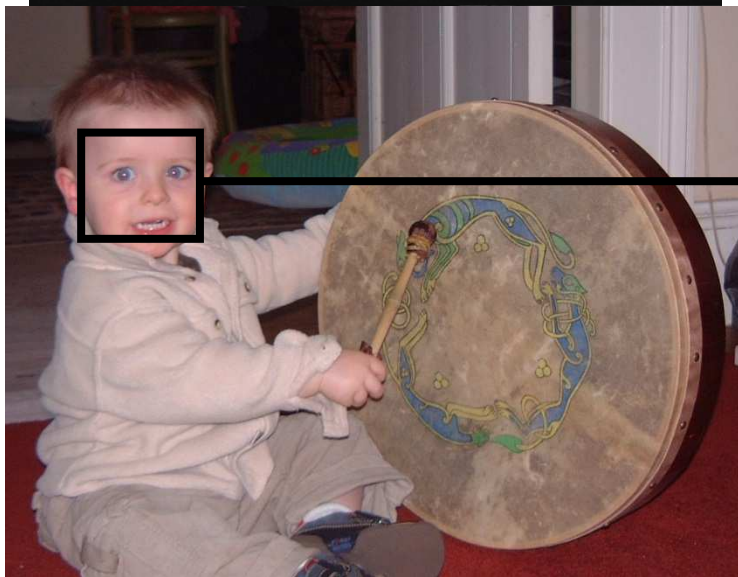
A tool for:

Finding modes in a set of data samples, manifesting an underlying probability distribution

The distribution could be in:

- Color space
- Image space
- Scale space
- Actually any feature space you can conceive
- ...

# Estimate histogram (model)



# Mean-Shift Tracking using Colour

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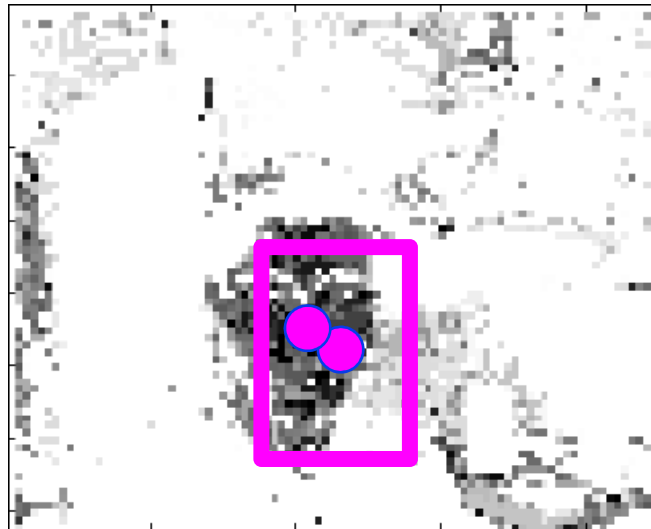
- Given each new video frame, compute a likelihood image from it by “looking up” each pixel in the histogram.
- Pixels form uniform grid of data points, each with a weight (pixel value) proportional to likelihood that the pixel is on the object we want to track.
- Perform mean-shift using this weighted set of points.



# Mean-Shift Tracking using Colour

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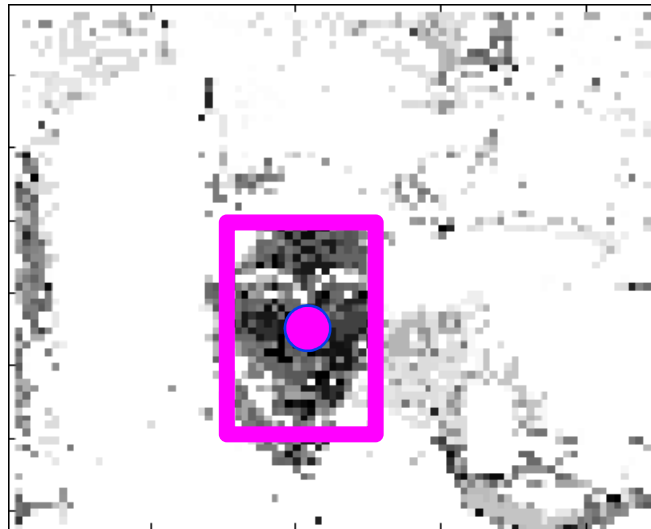
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# Mean-Shift Tracking using Colour

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# Mean-Shift Tracking using Colour

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- This is fast and can work well when histogram is unimodal (i.e. object is “one” colour)
- Alternative is to build a histogram from search window, compute similarity function of image and model histograms, and perform mean-shift search to maximise this function.
- Can also adapt scale (by searching nearby scales).
- Can also use other features (e.g. texture)

Further reading:

Collins, R. “Mean-shift Blob Tracking through Scale Space”  
IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2003

# Tracking

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CAMShift in Matlab Computer Vision System Toolbox:  
vision.HistogramBasedTracker System object

CAMShift uses a heuristic method to deal with scale.

G. Bradski, “Computer vision face tracking for use in a perceptual user interface”  
*Intel Technology Journal*, 2nd Quarter, 1998.

Further reading:

Y. Raja, S. J. McKenna, and S. Gong.

Tracking and segmenting people in varying lighting conditions using colour.  
*IEEE International Conference on Face & Gesture Recognition*, 228-233, 1998.

