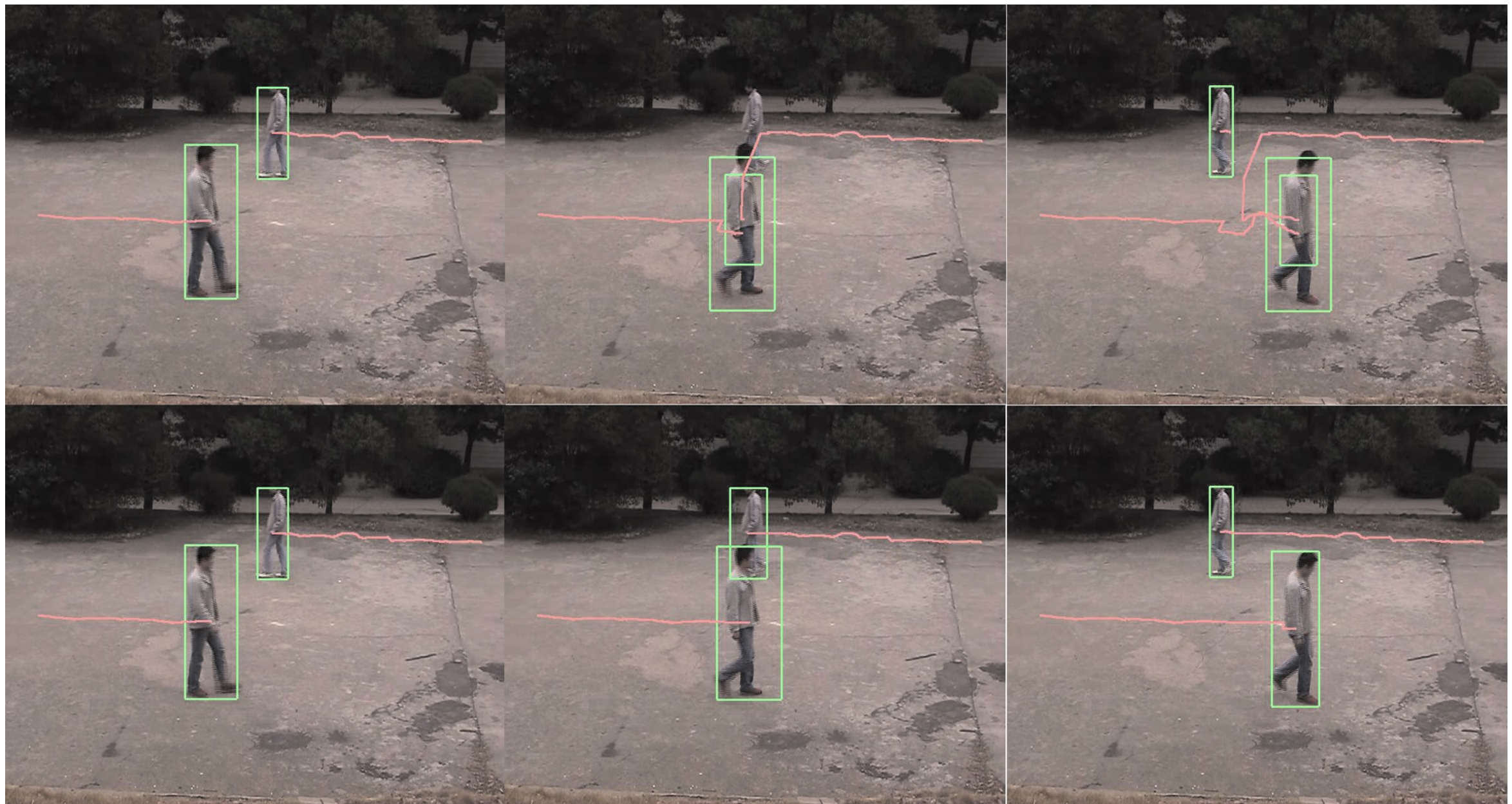


Alignment and tracking



Overview of today's lecture

- Motion magnification using optical flow.
- Image alignment.
- Lucas-Kanade alignment.
- Baker-Matthews alignment.
- Inverse alignment.
- KLT tracking.
- Mean-shift tracking.
- Modern trackers.

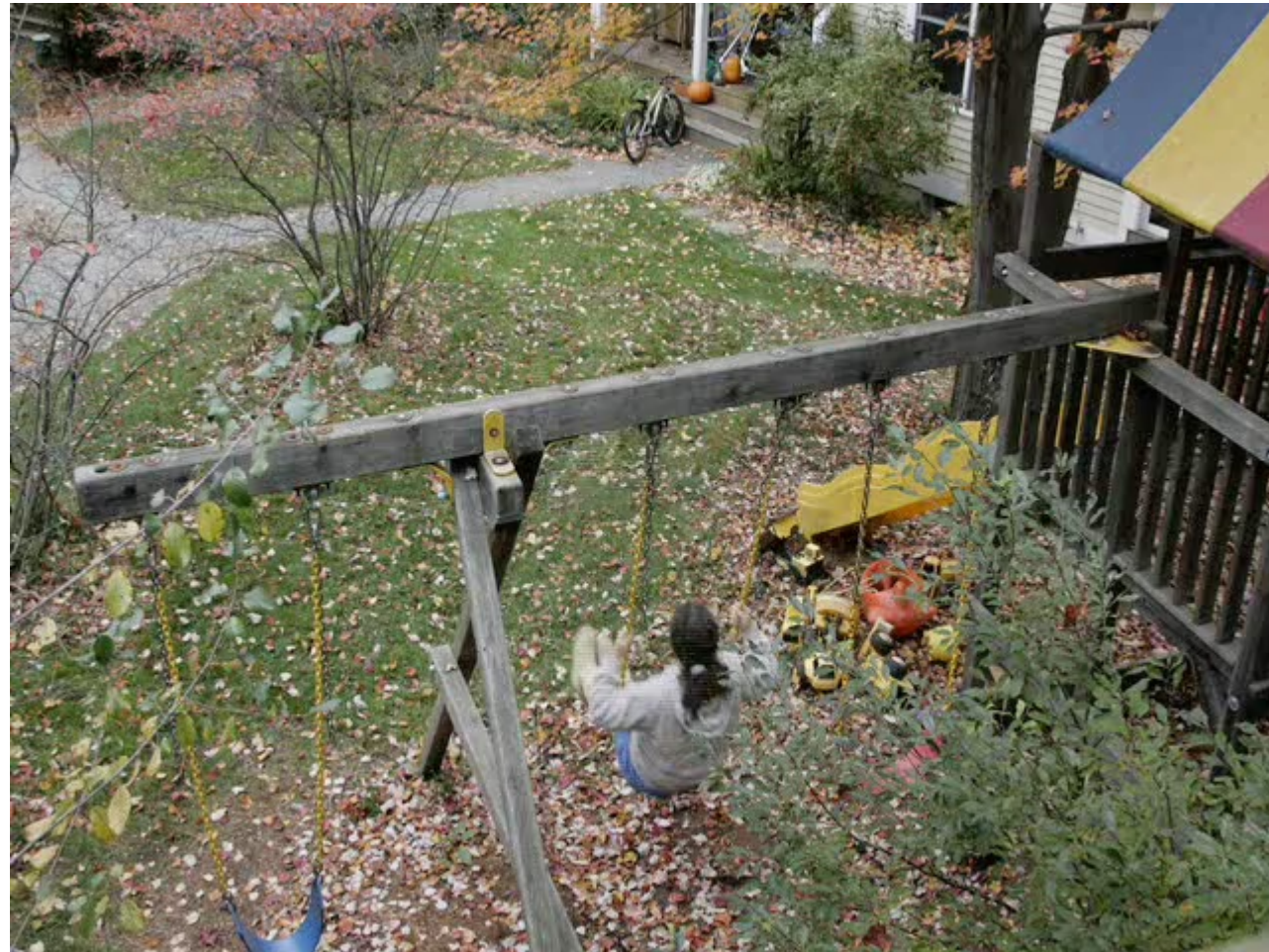
Slide credits

Most of these slides were adapted from:

- Kris Kitani (16-385, Spring 2017).

Motion magnification using optical flow

How would you achieve this effect?



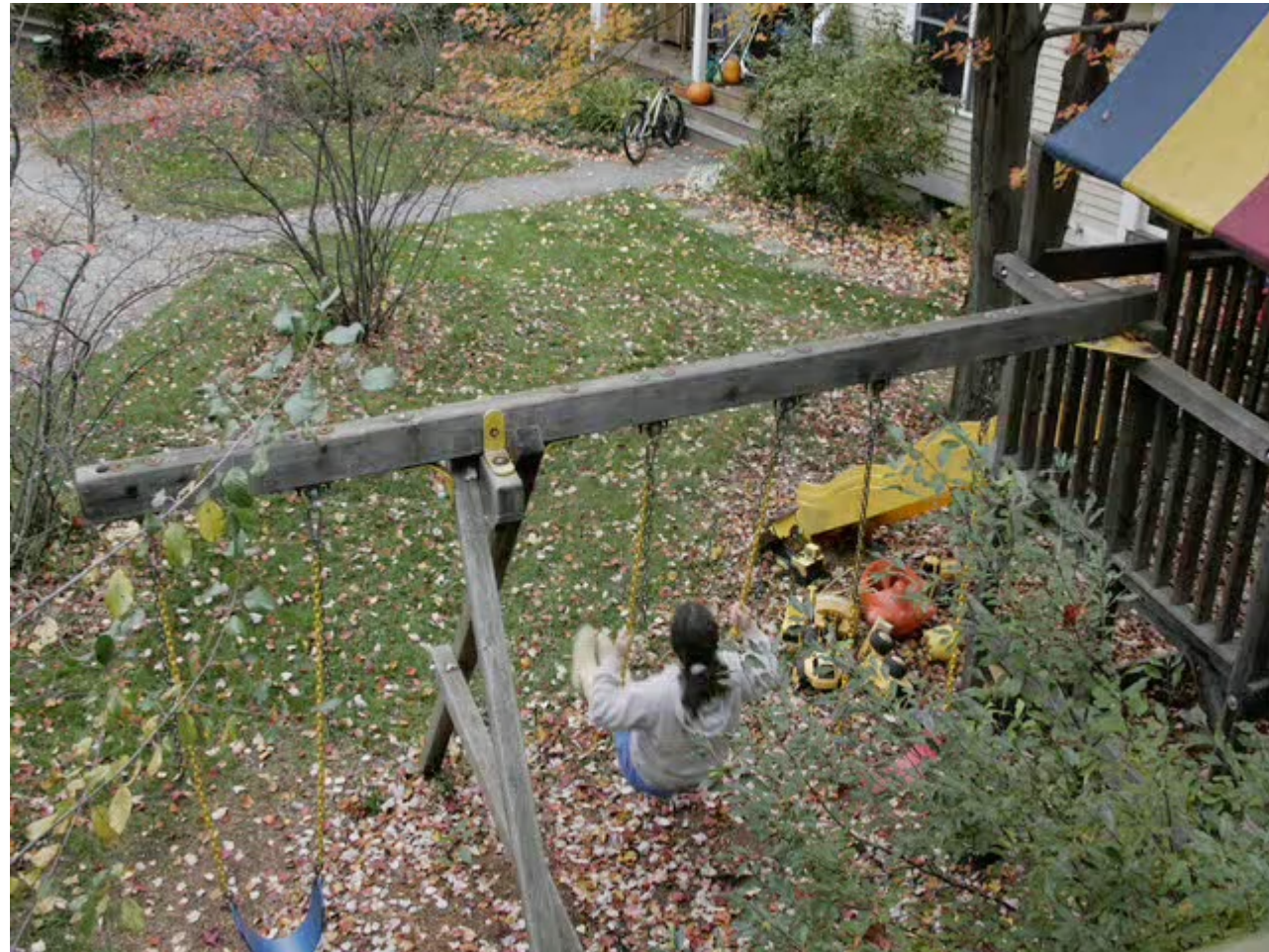
original



motion-magnified

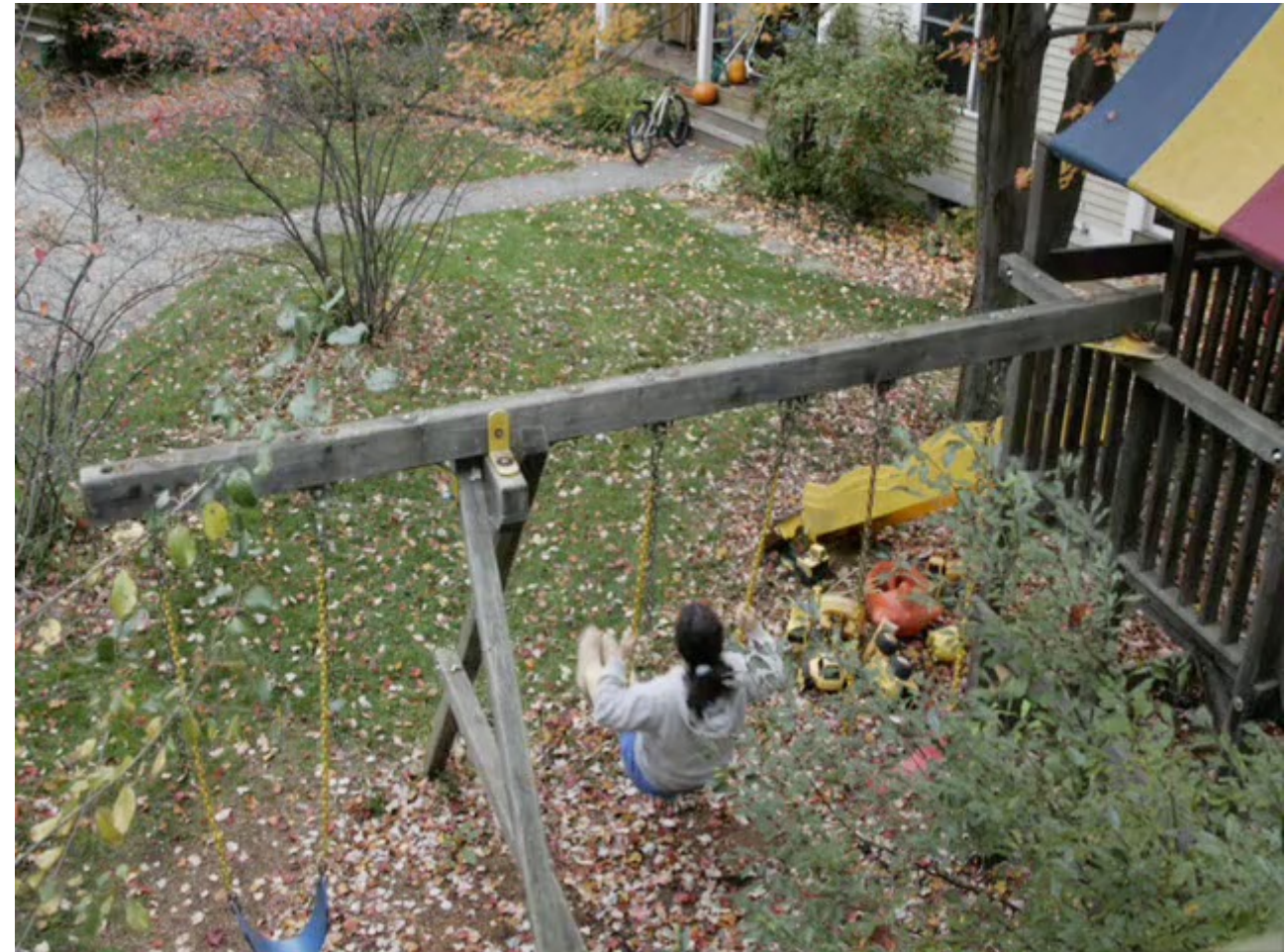
- Compute optical flow from frame to frame.
- Magnify optical flow velocities.
- Appropriately warp image intensities.

How would you achieve this effect?



naïvely motion-magnified

- Compute optical flow from frame to frame.
- Magnify optical flow velocities.
- Appropriately warp image intensities.



motion-magnified

In practice, many additional steps are required for a good result.

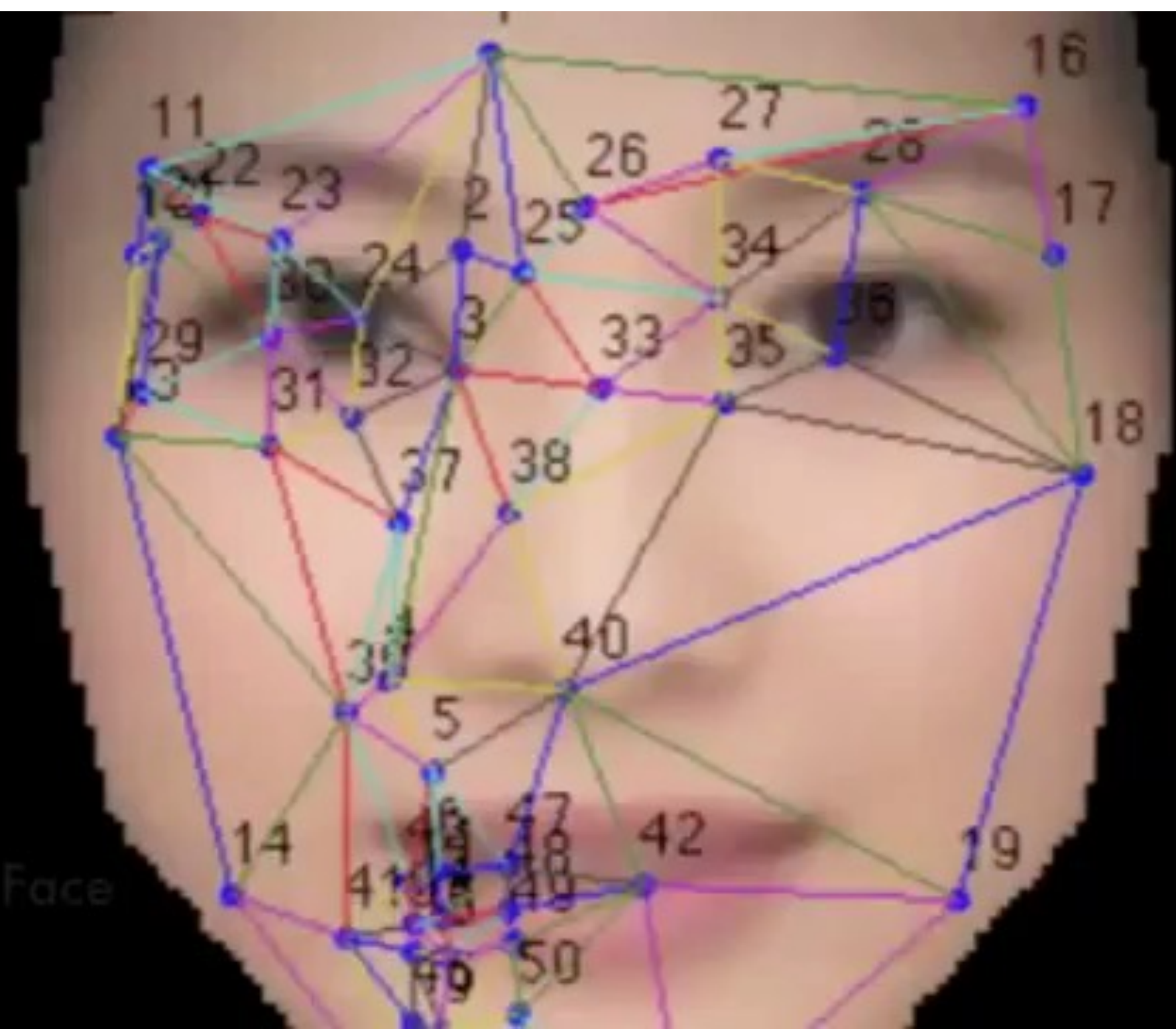
Some more examples



Some more examples

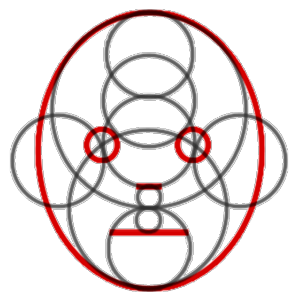
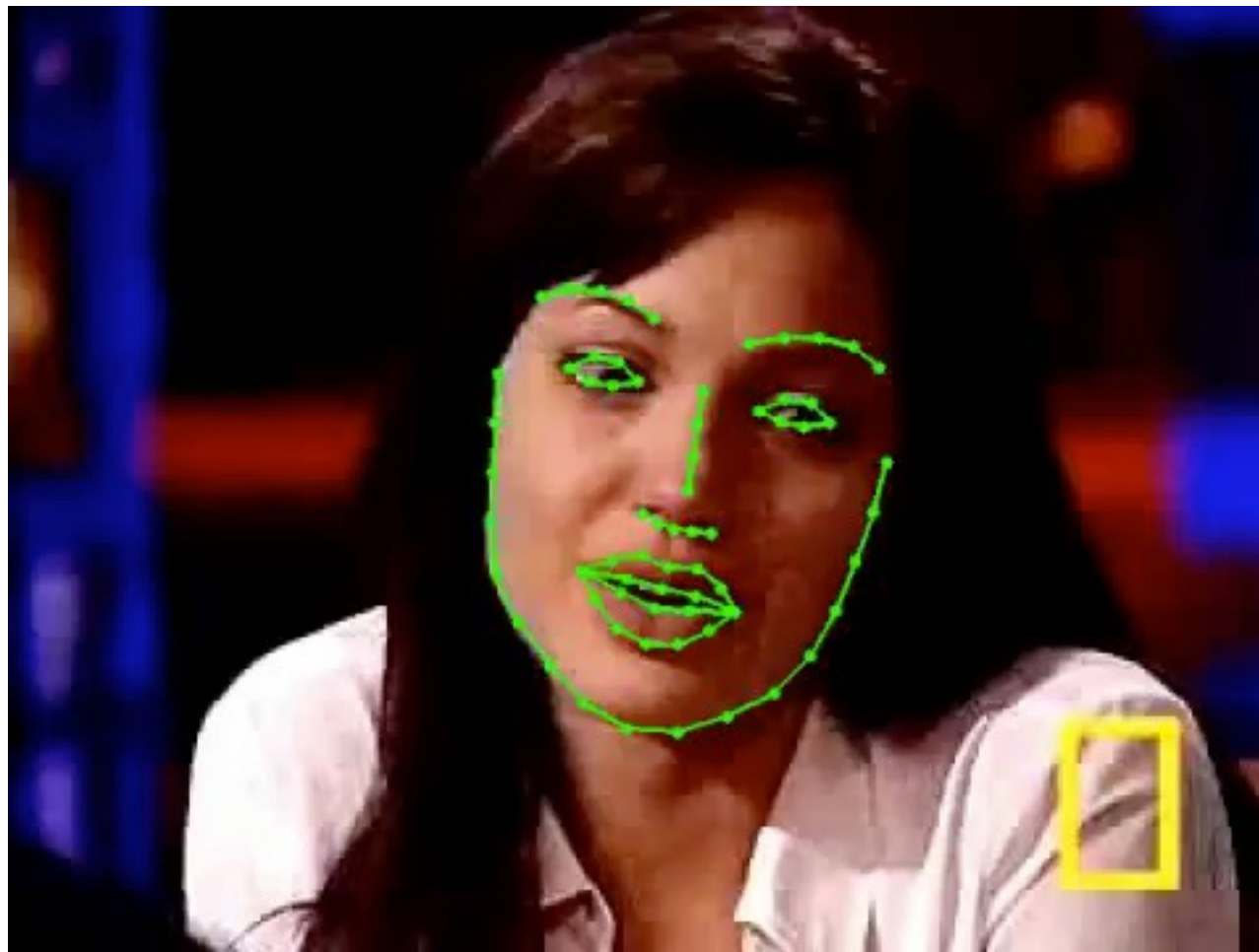


Image alignment



Average Face





IntraFace



How can I find



in the image?



Idea #1: Template Matching



Slow, combinatorial, global solution

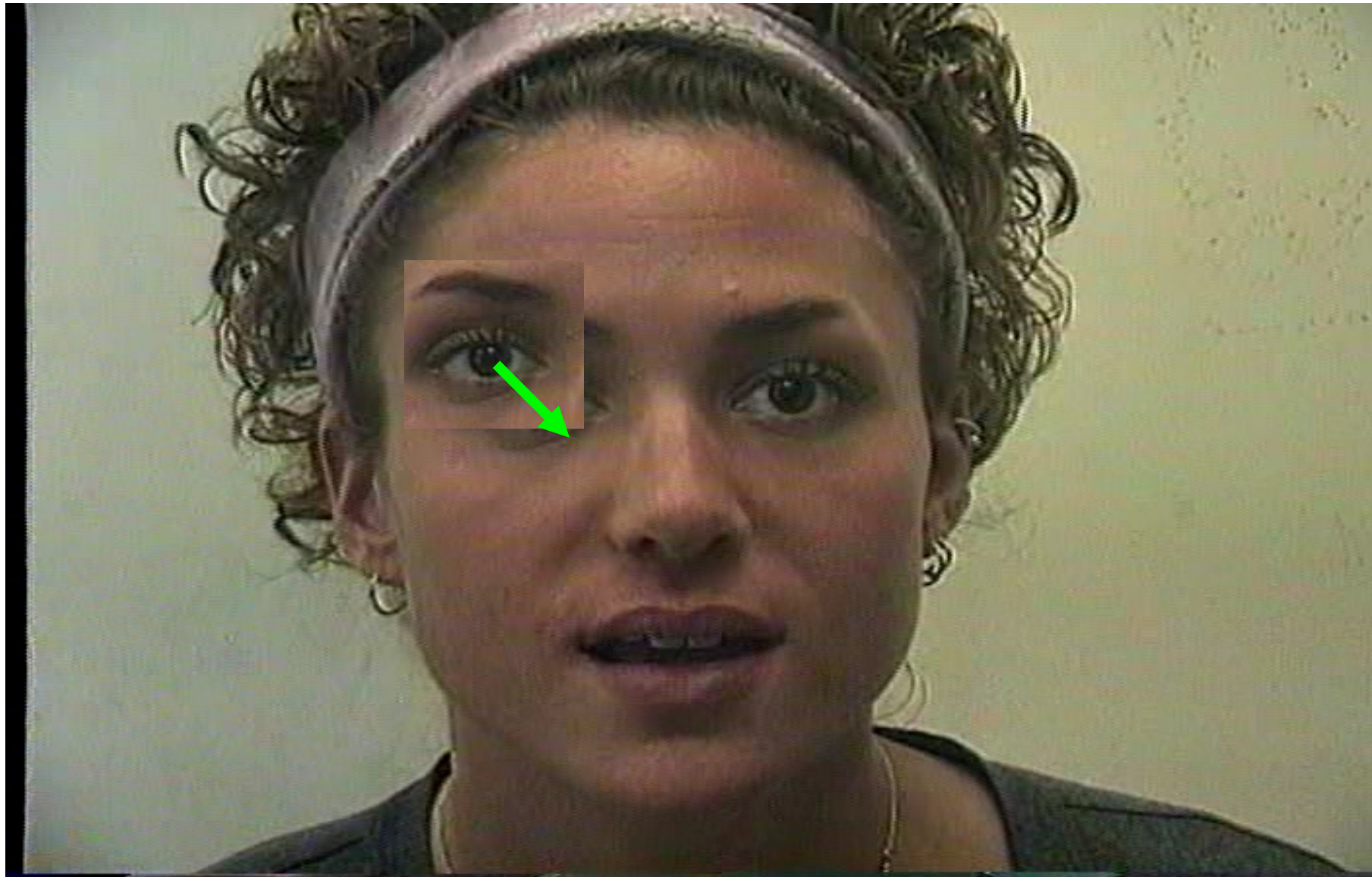
Idea #2: Pyramid Template Matching



Faster, combinatorial, locally optimal

Idea #3: Model refinement

(when you have a good initial solution)



Fastest, locally optimal

Some notation before we get into the math...

2D image transformation

$$\mathbf{W}(x; p)$$

2D image coordinate

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Parameters of the transformation

$$\mathbf{p} = \{p_1, \dots, p_N\}$$

Warped image

$$I(\mathbf{x}') = I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$$

Pixel value at a coordinate

Translation

Affine

Some notation before we get into the math...

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Pixel value at a coordinate

Translation

$$\begin{aligned} \mathbf{W}(\mathbf{x}; \mathbf{p}) &= \begin{bmatrix} x + p_1 \\ y + p_2 \end{bmatrix} \\ &= \underbrace{\begin{bmatrix} 1 & 0 & p_1 \\ 0 & 1 & p_2 \end{bmatrix}}_{\text{transform}} \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{\text{coordinate}} \end{aligned}$$

Affine

Some notation before we get into the math...

2D image transformation

$$\mathbf{W}(\mathbf{x}; \mathbf{p})$$

2D image coordinate

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

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$$\mathbf{p} = \{p_1, \dots, p_N\}$$

Warped image

$$I(\mathbf{x}') = I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$$

Pixel value at a coordinate

Translation

$$\begin{aligned} \mathbf{W}(\mathbf{x}; \mathbf{p}) &= \begin{bmatrix} x + p_1 \\ y + p_2 \end{bmatrix} \\ &= \underbrace{\begin{bmatrix} 1 & 0 & p_1 \\ 0 & 1 & p_2 \end{bmatrix}}_{\text{transform}} \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{\text{coordinate}} \end{aligned}$$

Affine

$$\begin{aligned} \mathbf{W}(\mathbf{x}; \mathbf{p}) &= \begin{bmatrix} p_1 x + p_2 y + p_3 \\ p_4 x + p_5 y + p_6 \end{bmatrix} \\ &= \underbrace{\begin{bmatrix} p_1 & p_2 & p_3 \\ p_4 & p_5 & p_6 \end{bmatrix}}_{\text{affine transform}} \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{\text{coordinate}} \end{aligned}$$

can be written in matrix form when linear
affine warp matrix can also be 3x3 when last row is [0 0 1]

$\mathbf{W}(\mathbf{x}; \mathbf{p})$ takes a _____ as input and returns a _____

$\mathbf{W}(\mathbf{x}; \mathbf{p})$ returns a _____ of dimension ____ x ____

$\mathbf{p} = \{p_1, \dots, p_N\}$ where N is _____ for an affine model

$I(\mathbf{x}') = I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$ this warp changes pixel values?

Image alignment

(problem definition)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

warped image template image

Find the warp parameters \mathbf{p} such that the
SSD is minimized

Find the warp parameters \mathbf{p} such that the SSD is minimized

$T(x)$



$I(x)$



$W(x; p)$



Image alignment

(problem definition)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

warped image template image

Find the warp parameters \mathbf{p} such that the
SSD is minimized

How could you find a solution to this problem?

This is a non-linear (quadratic) function of a non-parametric function!

(Function I is non-parametric)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Hard to optimize

What can you do to make it easier to solve?

This is a non-linear (quadratic) function of a non-parametric function!

(Function I is non-parametric)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Hard to optimize

What can you do to make it easier to solve?

assume good initialization,
linearized objective and update incrementally

Lucas-Kanade alignment

(pretty strong assumption)

If you have a good initial guess \mathbf{p} ...

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

can be written as ...

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

(a small incremental adjustment)
(this is what we are solving for now)

This is **still** a non-linear (quadratic) function of a non-parametric function!

(Function ***I*** is non-parametric)

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

*How can we linearize the function ***I*** for a really small perturbation of ***p***?*

This is **still** a non-linear (quadratic) function of a non-parametric function!

(Function ***I*** is non-parametric)

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

*How can we linearize the function ***I*** for a really small perturbation of ***p***?*

Taylor series approximation!

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Multivariable Taylor Series Expansion
(First order approximation)

$$f(x, y) \approx f(a, b) + f_x(a, b)(x - a) + f_y(a, b)(y - b)$$

Multivariable Taylor Series Expansion
(First order approximation)

$$f(x, y) \approx f(a, b) + f_x(a, b)(x - a) + f_y(a, b)(y - b)$$

Recall: $\mathbf{x}' = \mathbf{W}(\mathbf{x}; \mathbf{p})$

$$\begin{aligned} I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) &\approx I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \frac{\partial I(\mathbf{W}(\mathbf{x}; \mathbf{p}))}{\partial \mathbf{p}} \Delta \mathbf{p} \\ &\stackrel{\text{chain rule}}{=} I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \frac{\partial I(\mathbf{W}(\mathbf{x}; \mathbf{p}))}{\partial \mathbf{x}'} \frac{\partial \mathbf{W}(\mathbf{x}; \mathbf{p})}{\partial \mathbf{p}} \Delta \mathbf{p} \\ &\stackrel{\text{short-hand}}{=} I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} \end{aligned}$$

short-hand

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Multivariable Taylor Series Expansion
(First order approximation)

$$f(x, y) \approx f(a, b) + f_x(a, b)(x - a) + f_y(a, b)(y - b)$$

Linear approximation

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

What are the unknowns here?

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Multivariable Taylor Series Expansion
(First order approximation)

$$f(x, y) \approx f(a, b) + f_x(a, b)(x - a) + f_y(a, b)(y - b)$$

Linear approximation

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Now, the function is a linear function of the unknowns

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

\mathbf{x} is a _____ of dimension ____ x ____

output of \mathbf{W} is a _____ of dimension ____ x ____

\mathbf{p} is a _____ of dimension ____ x ____

$I(\cdot)$ is a function of _____ variables

The Jacobian $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$

(A matrix of partial derivatives)

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\mathbf{W} = \begin{bmatrix} W_x(x, y) \\ W_y(x, y) \end{bmatrix}$$

$$\frac{\partial \mathbf{W}}{\partial \mathbf{p}} = \begin{bmatrix} \frac{\partial W_x}{\partial p_1} & \frac{\partial W_x}{\partial p_2} & \dots & \frac{\partial W_x}{\partial p_N} \\ \frac{\partial W_y}{\partial p_1} & \frac{\partial W_y}{\partial p_2} & \dots & \frac{\partial W_y}{\partial p_N} \end{bmatrix}$$

Rate of change of the warp

Affine transform

$$\mathbf{W}(\mathbf{x}; \mathbf{p}) = \begin{bmatrix} p_1 x + p_3 y + p_5 \\ p_2 x + p_4 y + p_6 \end{bmatrix}$$

$$\frac{\partial W_x}{\partial p_1} = x \quad \frac{\partial W_x}{\partial p_2} = 0 \quad \dots$$

$$\frac{\partial W_y}{\partial p_1} = 0 \quad \dots$$


$$\frac{\partial \mathbf{W}}{\partial \mathbf{p}} = \begin{bmatrix} x & 0 & y & 0 & 1 & 0 \\ 0 & x & 0 & y & 0 & 1 \end{bmatrix}$$

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$


∇I is a _____ of dimension ____ x ____


$\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$ is a _____ of dimension ____ x ____

$\Delta \mathbf{p}$ is a _____ of dimension ____ x ____

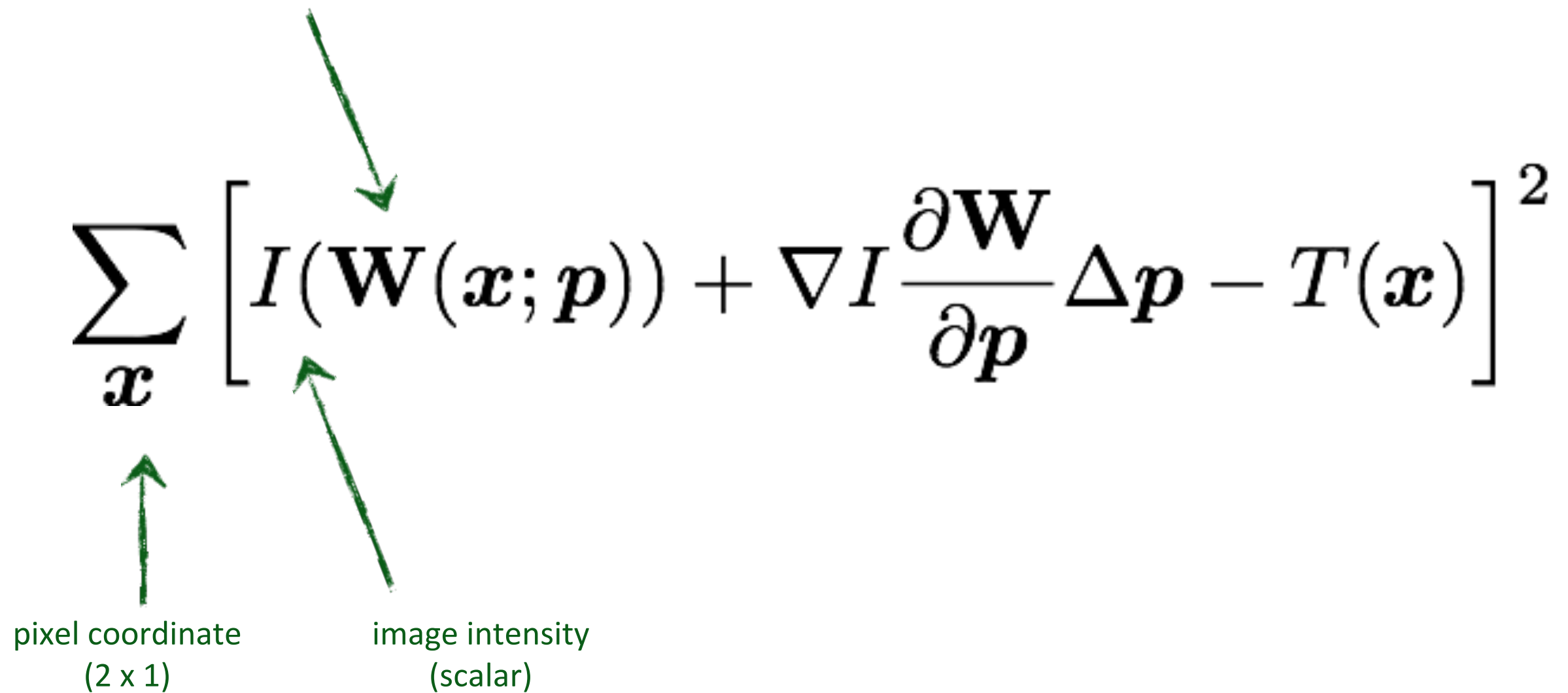
$$\sum_x \left[I(\mathbf{W}(x; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(x) \right]^2$$


$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$


 pixel coordinate
(2 x 1)



$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$



pixel coordinate
 (2 x 1)

image intensity
 (scalar)

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the equation:

- warp function (2 x 1)**: Points to $\mathbf{W}(\mathbf{x}; \mathbf{p})$.
- pixel coordinate (2 x 1)**: Points to \mathbf{x} .
- image intensity (scalar)**: Points to $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$.

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the image warping loss function:

- pixel coordinate** (2×1): Points to \mathbf{x} .
- warp function** (2×1): Points to \mathbf{W} .
- warp parameters** (6 for affine): Points to \mathbf{p} .
- image intensity** (scalar): Points to I .
- gradient** (∇): Points to the gradient term.

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the image warping loss function:

- pixel coordinate** (2×1): Points to \mathbf{x} .
- warp function** (2×1): Points to \mathbf{W} .
- warp parameters** (6 for affine): Points to \mathbf{p} .
- image intensity** (scalar): Points to I .
- image gradient** (1×2): Points to ∇I .
- Target image** (2×1): Points to $T(\mathbf{x})$.

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the image warping equation:

- Pixel coordinate** (2×1): Points to \mathbf{x} .
- Warp function** (2×1): Points to \mathbf{W} .
- Warp parameters** (6 for affine): Points to \mathbf{p} .
- Image intensity** (scalar): Points to I .
- Image gradient** (1×2): Points to ∇I .
- Partial derivatives of warp function** (2×6): Points to $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$.
- Delta parameters** ($\Delta \mathbf{p}$): Points to $\Delta \mathbf{p}$.

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the image warping equation:

- Pixel coordinate** (2×1): Points to \mathbf{x} .
- Warp function** (2×1): Points to \mathbf{W} .
- Warp parameters** (6 for affine): Points to \mathbf{p} .
- Image intensity** (scalar): Points to I .
- Image gradient** (1×2): Points to ∇I .
- Partial derivatives of warp function** (2×6): Points to $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$.
- Incremental warp** (6×1): Points to $\Delta \mathbf{p}$.
- Target image** (2×1): Points to $T(\mathbf{x})$.

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Diagram illustrating the components of the incremental warp function equation:

- Pixel coordinate** (2×1): Points to \mathbf{x} .
- Image intensity** (scalar): Points to $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$.
- Warp function** (2×1): Points to $\mathbf{W}(\mathbf{x}; \mathbf{p})$.
- Warp parameters** (6 for affine): Points to \mathbf{p} .
- Image gradient** (1×2): Points to ∇I .
- Partial derivatives of warp function** (2×6): Points to $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$.
- Incremental warp** (6×1): Points to $\Delta \mathbf{p}$.
- Template image intensity** (scalar): Points to $T(\mathbf{x})$.

When you implement this, you will compute everything in parallel and store as matrix ... don't loop over x!

Summary

(of Lucas-Kanade Image Alignment)

Problem:

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

warped imagetemplate image

Difficult non-linear optimization problem

Strategy:

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Assume known approximate solution
Solve for increment

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Taylor series approximation
Linearize

then solve for $\Delta \mathbf{p}$

OK, so how do we solve this?

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Another way to look at it...

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

(moving terms around)

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - \{T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))\} \right]^2$$

vector of
constants

vector of
variables

constant

Have you seen this form of optimization problem before?

Another way to look at it...

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - \{T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))\} \right]^2$$

Looks like

$$\mathbf{Ax} - \mathbf{b}$$

How do you solve this?

Least squares approximation

$$\hat{x} = \arg \min_x ||Ax - b||^2 \quad \text{is solved by} \quad x = (A^\top A)^{-1} A^\top b$$

Applied to our tasks:

$$\min_{\Delta \mathbf{p}} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - \{T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))\} \right]^2$$

is optimized when

$$\Delta \mathbf{p} = H^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

after applying
 $x = (A^\top A)^{-1} A^\top b$

$$\text{where } H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right] \quad A^\top A$$

Solve:

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

warped image template image

Difficult non-linear optimization problem

Strategy:

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Assume known approximate solution
Solve for increment

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Taylor series approximation
Linearize

Solution:

$$\Delta \mathbf{p} = H^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

Solution to least squares
approximation

$$H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

Hessian

This is called...

**Gauss-Newton gradient decent
non-linear optimization!**

Lucas Kanade (Additive alignment)

1. Warp image

$$I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$$

2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$

3. Compute gradient

$$\nabla I(\mathbf{x}')$$

\mathbf{x}' coordinates of the warped image
(gradients of the warped image)

4. Evaluate Jacobian

$$\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$$

5. Compute Hessian

$$H$$

$$H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

6. Compute

$$\Delta \mathbf{p}$$

$$\Delta \mathbf{p} = H^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

7. Update parameters

$$\mathbf{p} \leftarrow \mathbf{p} + \Delta \mathbf{p}$$

Just 8 lines of code!

Baker-Matthews alignment

Image Alignment

(start with an initial solution, match the image and template)

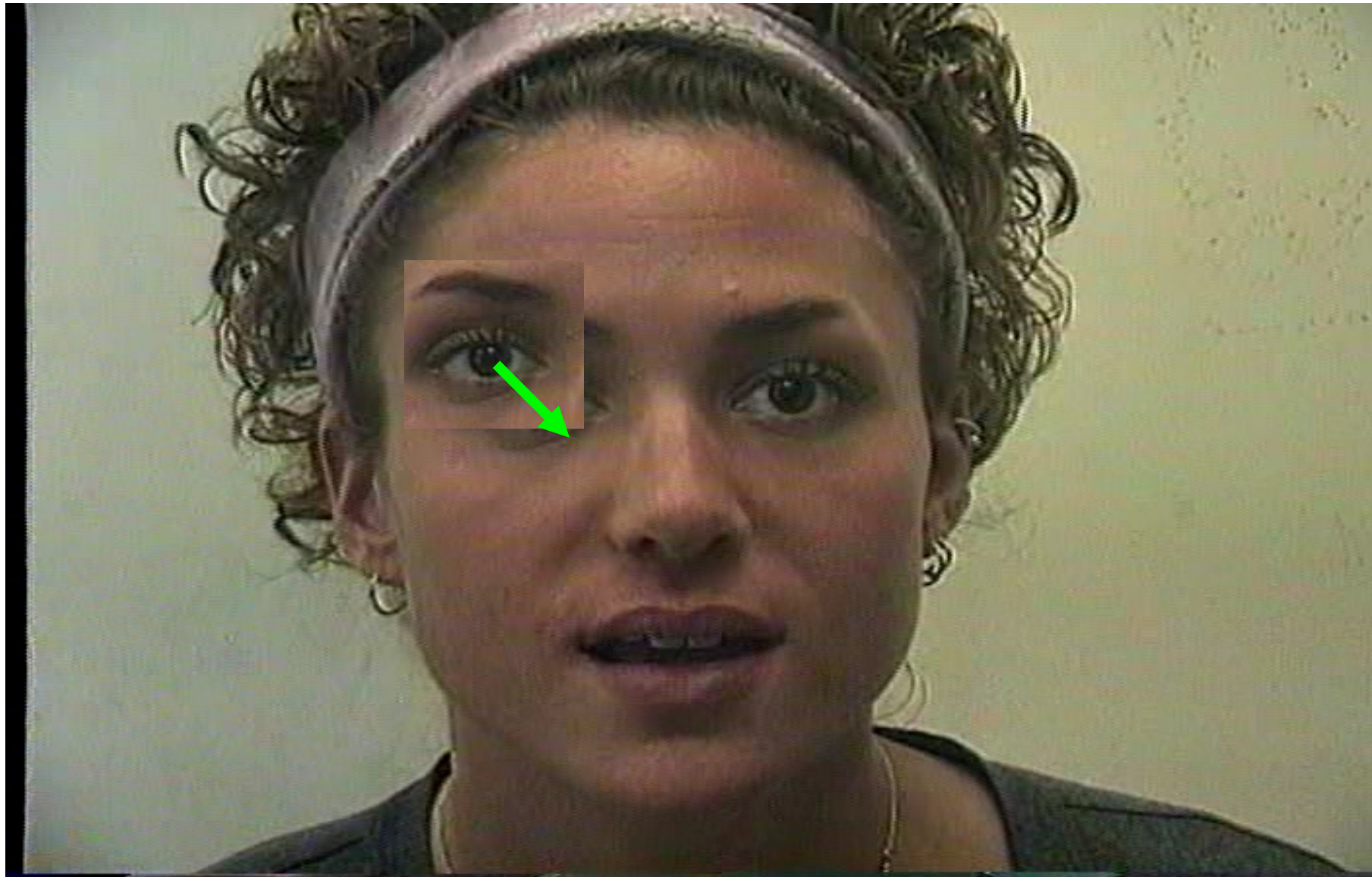


Image Alignment Objective Function

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Given an initial solution...several possible formulations

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

incremental perturbation of parameters

Image Alignment Objective Function

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Given an initial solution...several possible formulations

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

incremental perturbation of parameters

Compositional Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p}) - T(\mathbf{x})]^2$$

incremental warps of image

Additive strategy



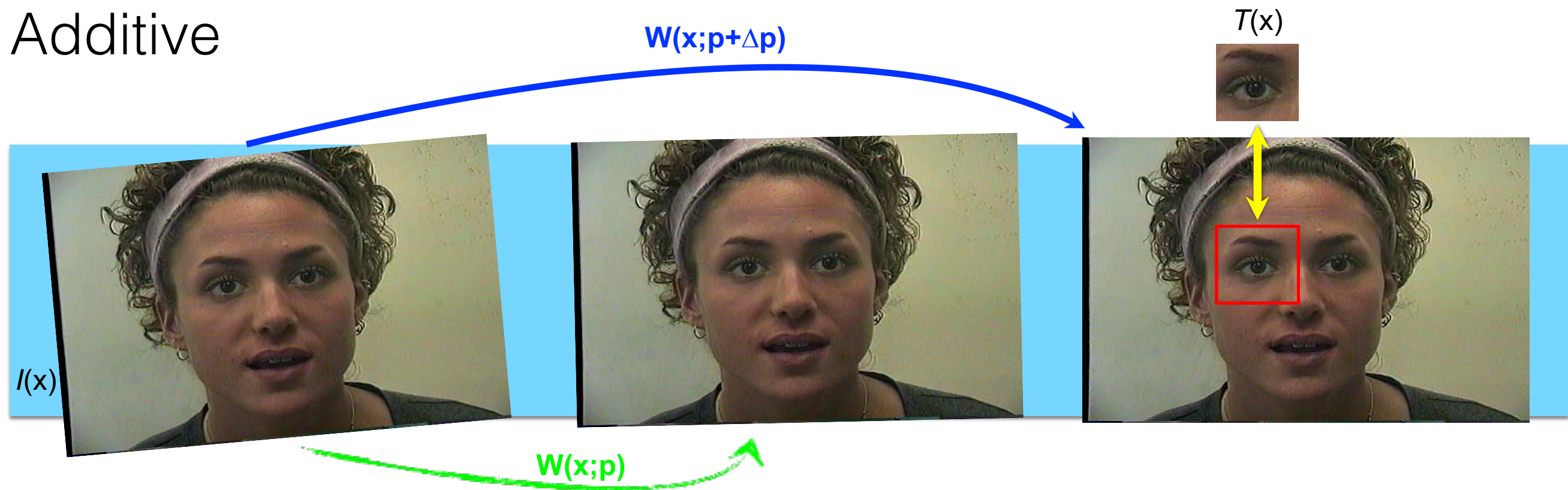
Compositional strategy



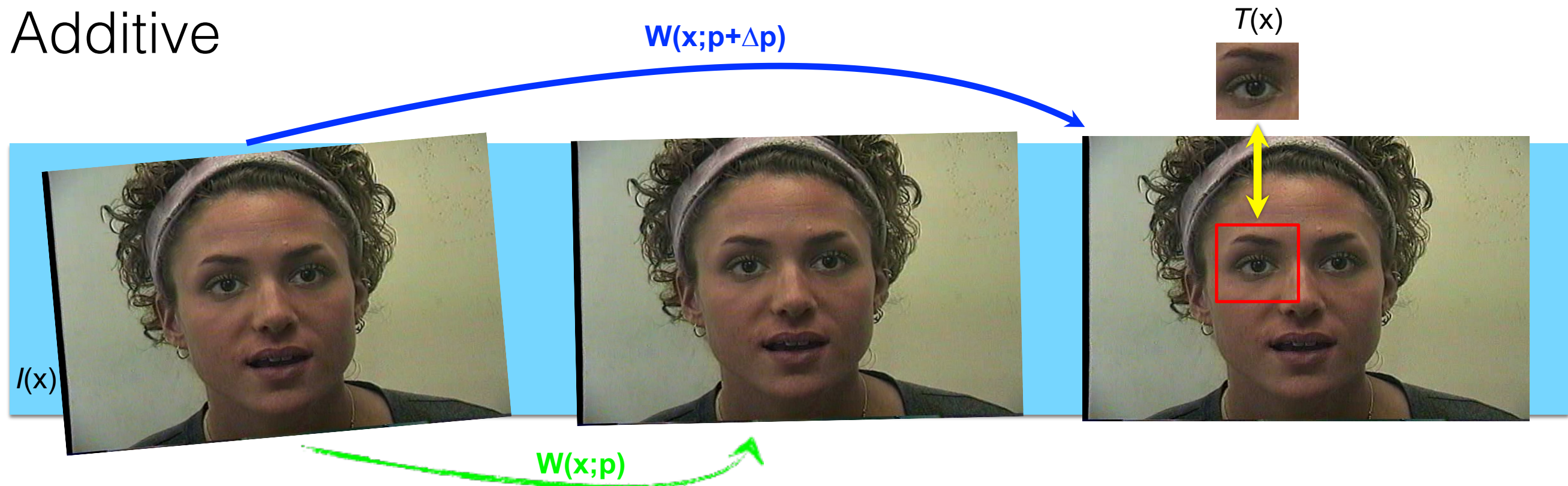
Additive



Additive



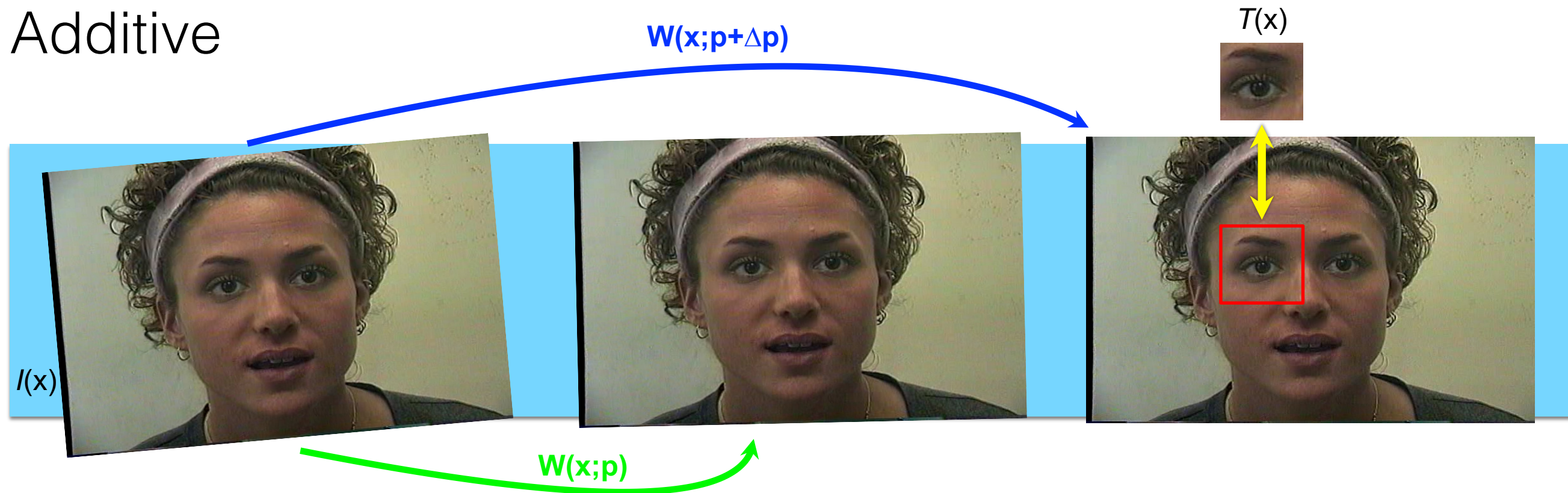
Additive



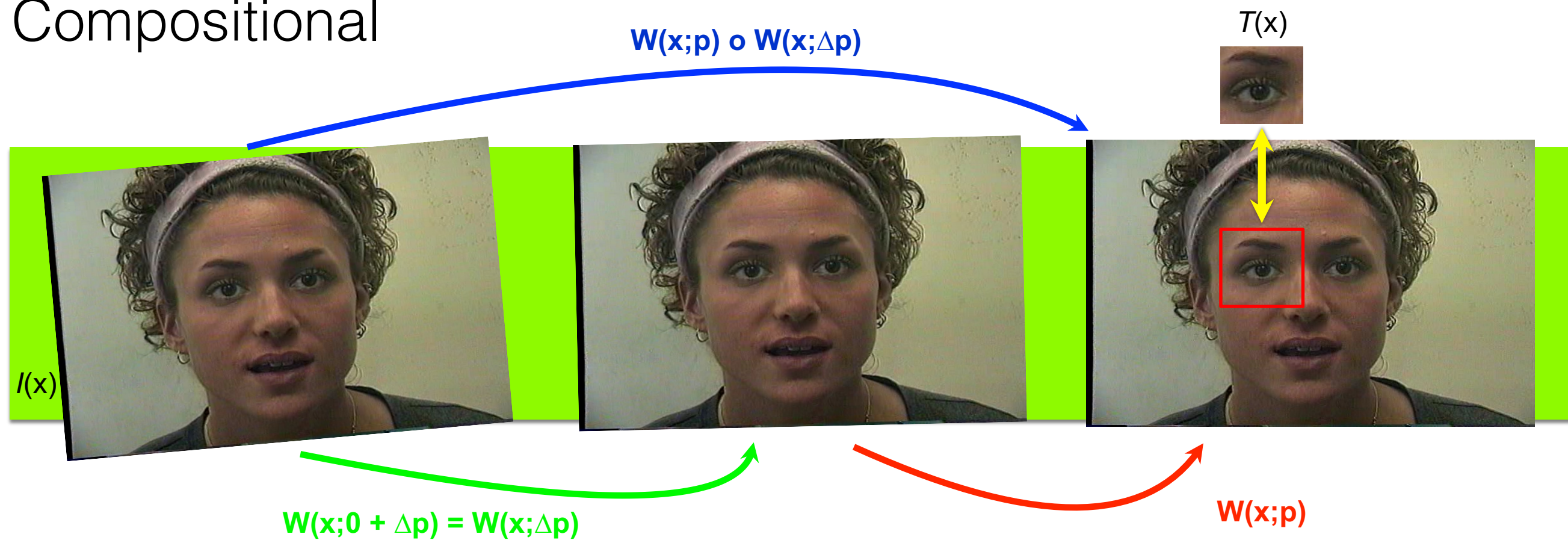
Compositional



Additive



Compositional



Compositional Alignment

Original objective function (SSD)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Assuming an initial solution \mathbf{p} and a compositional warp increment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})) - T(\mathbf{x})]^2$$

Compositional Alignment

Original objective function (SSD)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Assuming an initial solution \mathbf{p} and a compositional warp increment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})) - T(\mathbf{x})]^2$$

Another way to write the composition

$$\mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p}) \equiv \mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})$$

Identity warp

$$\mathbf{W}(\mathbf{x}; \mathbf{0})$$

Compositional Alignment

Original objective function (SSD)

$$\min_{\mathbf{p}} \sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$$

Assuming an initial solution \mathbf{p} and a compositional warp increment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})) - T(\mathbf{x})]^2$$

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$$\mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p}) \equiv \mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})$$

Identity warp

$$\mathbf{W}(\mathbf{x}; \mathbf{0})$$

Skipping over the derivation...the new update rule is

$$\mathbf{W}(\mathbf{x}; \mathbf{p}) \leftarrow \mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p})$$

So what's so great about this compositional form?

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

linearized form

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I(\mathbf{x}') \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Compositional Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p}) - T(\mathbf{x})]^2$$

linearized form

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I(\mathbf{x}') \frac{\partial \mathbf{W}(\mathbf{x}; \mathbf{0})}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

linearized form

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I(\mathbf{x}') \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

Jacobian of $\mathbf{W}(\mathbf{x}; \mathbf{p})$

Compositional Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p})) - T(\mathbf{x})]^2$$

linearized form

$$\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I(\mathbf{x}') \frac{\partial \mathbf{W}(\mathbf{x}; \mathbf{0})}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$$

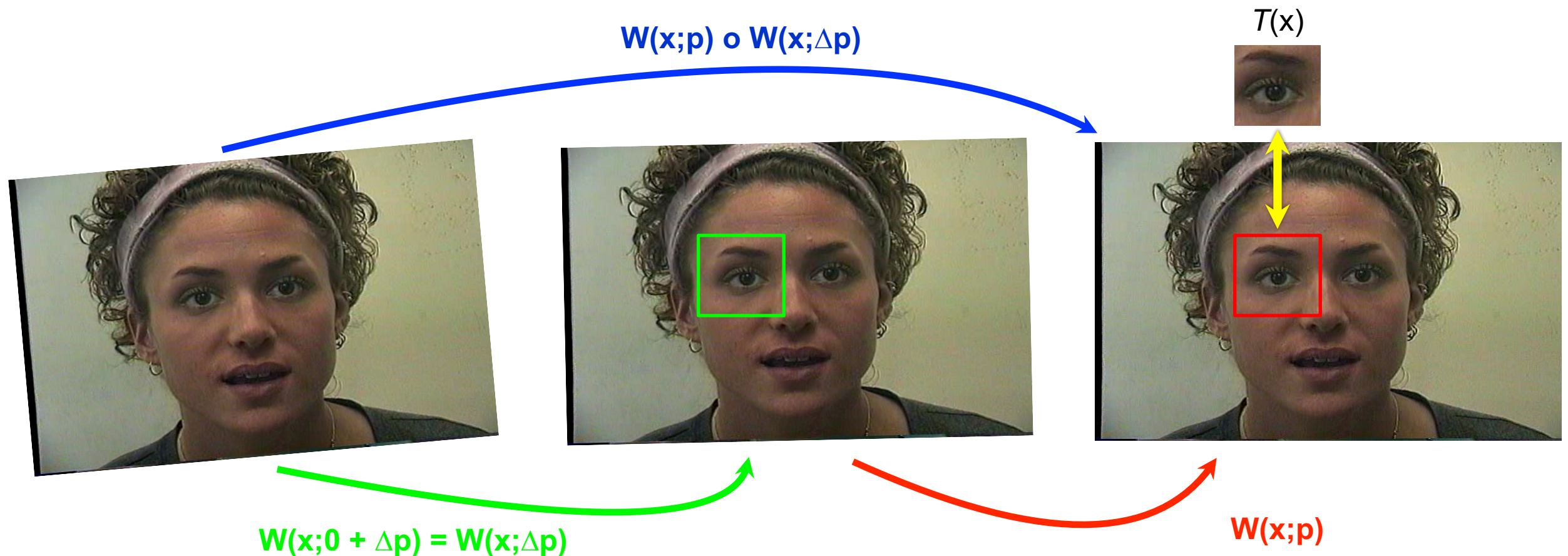
Jacobian of
 $\mathbf{W}(\mathbf{x}; \mathbf{0})$

**The Jacobian is constant.
Jacobian can be precomputed!**

Compositional Image Alignment

Minimize

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta\mathbf{p}); \mathbf{p})) - T(\mathbf{x})]^2 \approx \sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I(\mathbf{W}) \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta\mathbf{p} - T(\mathbf{x}) \right]^2$$



Jacobian is simple and can be precomputed

Lucas Kanade (Additive alignment)

1. Warp image $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$
2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]^2$
3. Compute gradient $\nabla I(\mathbf{x}')$
4. Evaluate Jacobian $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$
5. Compute Hessian H
6. Compute $\Delta \mathbf{p}$
7. Update parameters $\mathbf{p} \leftarrow \mathbf{p} + \Delta \mathbf{p}$

Shum-Szeliski (Compositional alignment)

1. Warp image $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$
2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]^2$
3. Compute gradient $\nabla I(\mathbf{x}')$
4. Evaluate Jacobian $\frac{\partial \mathbf{W}(\mathbf{x}; \mathbf{0})}{\partial \mathbf{p}}$
5. Compute Hessian H
6. Compute $\Delta \mathbf{p}$
7. Update parameters $\mathbf{W}(\mathbf{x}; \mathbf{p}) \leftarrow \mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p})$

Any other speed up techniques?

Inverse alignment

Why not compute warp updates on the template?

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Compositional Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p}) - T(\mathbf{x}))]^2$$

Why not compute warp updates on the template?

Additive Alignment

$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$$

Compositional Alignment

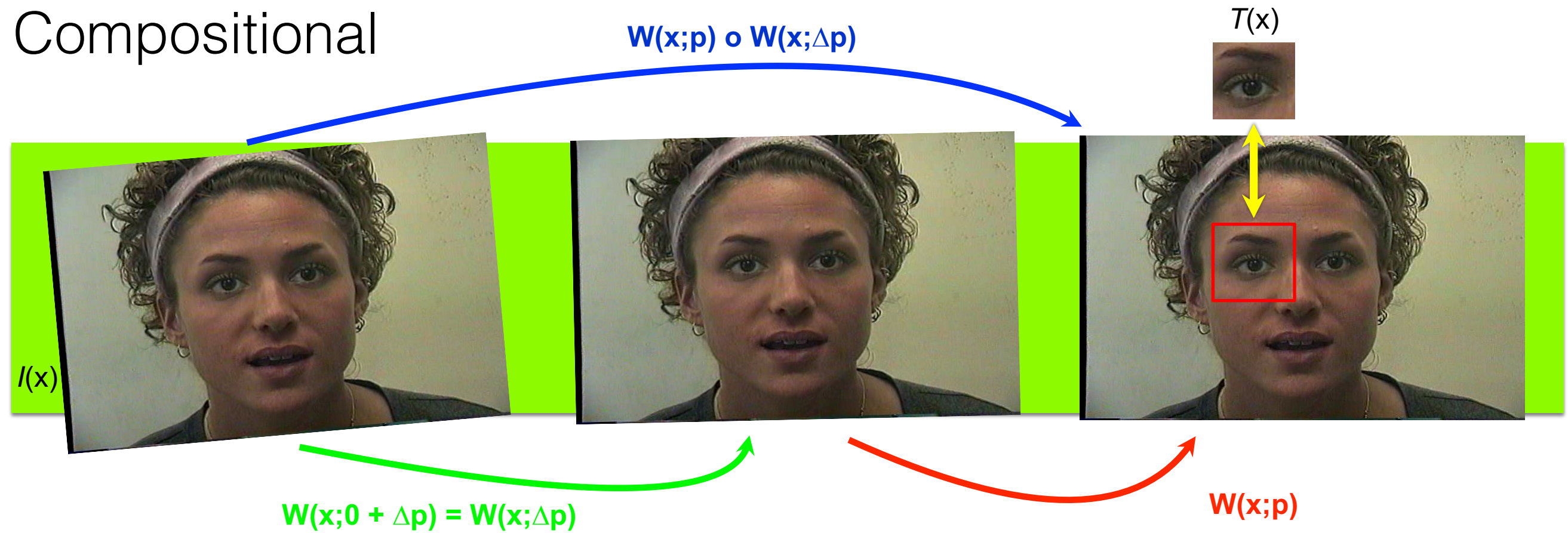
$$\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p}); \mathbf{p}) - T(\mathbf{x}))]^2$$

What happens if you let the template
be warped too?

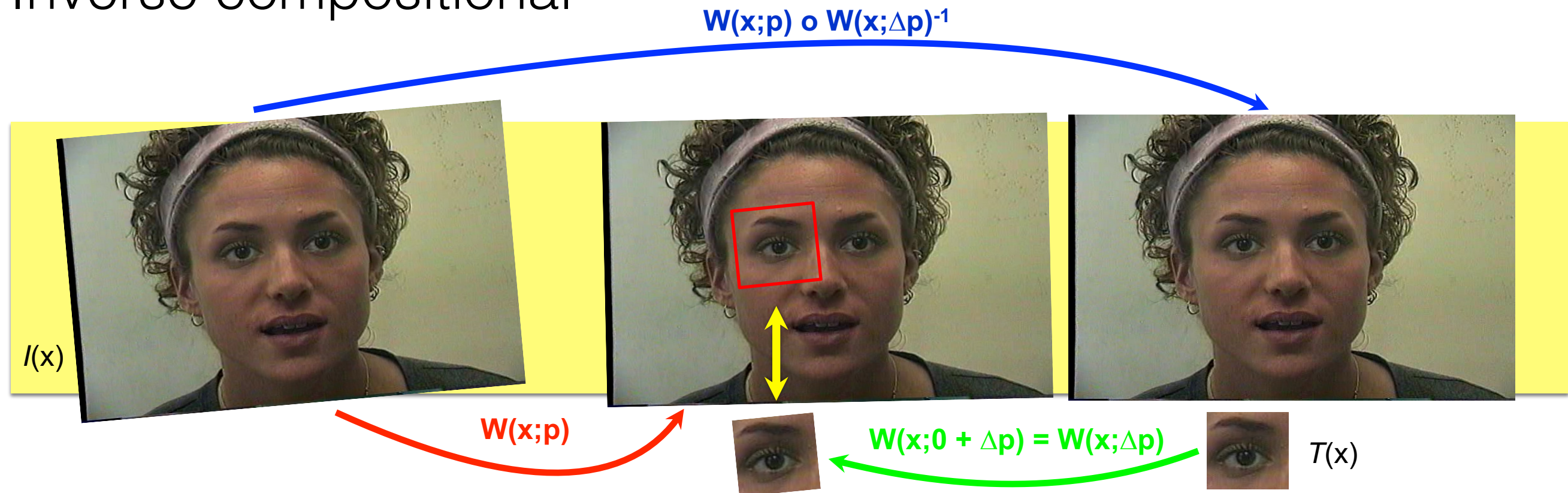
Inverse Compositional Alignment

$$\sum_{\mathbf{x}} [T(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p})) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]^2$$

Compositional



Inverse compositional



Compositional strategy



Inverse Compositional strategy



So what's so great about this inverse compositional form?

Inverse Compositional Alignment

Minimize

$$\sum_{\mathbf{x}} [T(\mathbf{W}(\mathbf{x}; \Delta \mathbf{p})) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]^2 \approx \sum_{\mathbf{x}} \left[T(\mathbf{W}(\mathbf{x}; \mathbf{0})) + \nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - I(\mathbf{W}(\mathbf{x}; \mathbf{p})) \right]^2$$

Solution

$$H = \sum_{\mathbf{x}} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right] \quad \text{can be precomputed from template!}$$

$$\Delta \mathbf{p} = \sum_{\mathbf{x}} H^{-1} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

Update

$$\mathbf{W}(\mathbf{x}; \mathbf{p}) \leftarrow \mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p})^{-1}$$

Properties of inverse compositional alignment

Jacobian can be precomputed

It is constant - evaluated at $W(x;0)$

Gradient of template can be precomputed

It is constant

Hessian can be precomputed

$$H = \sum_{\mathbf{x}} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

$$\Delta \mathbf{p} = \sum_{\mathbf{x}} H^{-1} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

(main term that needs to be computed)

Warp must be invertible

Lucas Kanade (Additive alignment)

1. Warp image $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$
2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]^2$
3. Compute gradient $\nabla I(\mathbf{W})$
4. Evaluate Jacobian $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$
5. Compute Hessian H
6. Compute $\Delta \mathbf{p}$
7. Update parameters $\mathbf{p} \leftarrow \mathbf{p} + \Delta \mathbf{p}$

Shum-Szeliski (Compositional alignment)

1. Warp image $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$
2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$
3. Compute gradient $\nabla I(\mathbf{x}')$
4. Evaluate Jacobian $\frac{\partial \mathbf{W}(\mathbf{x}; \mathbf{0})}{\partial \mathbf{p}}$
5. Compute Hessian H
6. Compute $\Delta \mathbf{p}$
7. Update parameters $\mathbf{W}(\mathbf{x}; \mathbf{p}) \leftarrow \mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p})$

Baker-Matthews (Inverse Compositional alignment)

1. Warp image $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$

2. Compute error image $[T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$

3. Compute gradient $\nabla T(\mathbf{W})$

4. Evaluate Jacobian $\frac{\partial \mathbf{W}}{\partial \mathbf{p}}$

5. Compute Hessian H
$$H = \sum_{\mathbf{x}} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

6. Compute $\Delta \mathbf{p}$
$$\Delta \mathbf{p} = \sum_{\mathbf{x}} H^{-1} \left[\nabla T \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

7. Update parameters $\mathbf{W}(\mathbf{x}; \mathbf{p}) \leftarrow \mathbf{W}(\mathbf{x}; \mathbf{p}) \circ \mathbf{W}(\mathbf{x}; \Delta \mathbf{p})^{-1}$

Algorithm	Efficient	Authors
Forwards Additive	No	Lucas, Kanade
Forwards compositional	No	Shum, Szeliski
Inverse Additive	Yes	Hager, Belhumeur
Inverse Compositional	Yes	Baker, Matthews

Kanade-Lucas-Tomasi (KLT) tracker



Feature-based tracking

Up to now, we've been aligning entire images
but we can also track just small image regions too!
(sometimes called sparse tracking or sparse alignment)

How should we select the 'small images' (features)?

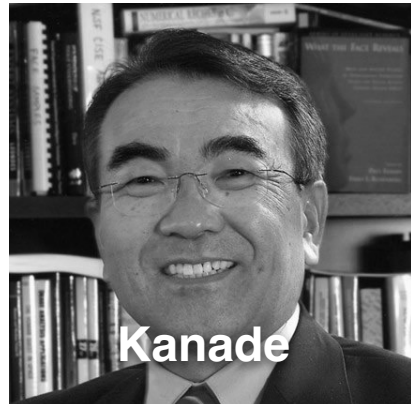
How should we track them from frame to frame?

History of the

Kanade-Lucas-Tomasi (KLT) Tracker



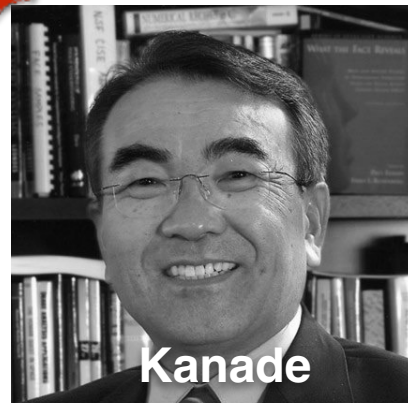
Lucas



Kanade

An Iterative Image Registration Technique
with an Application to Stereo Vision.

1981



Kanade



Tomasi

Detection and Tracking of Feature Points.

1991

The original KLT algorithm



Tomasi

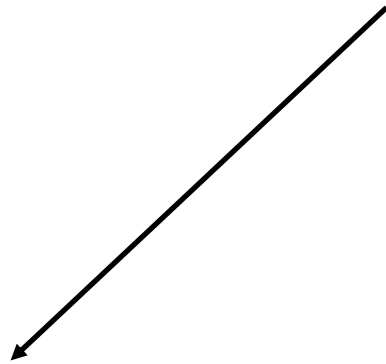


Shi

Good Features to Track.

1994

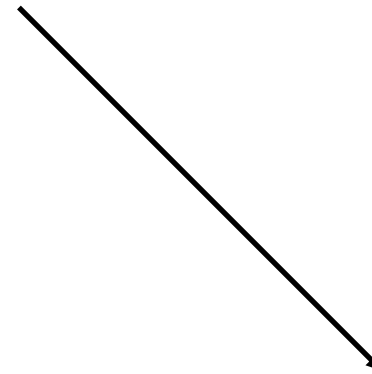
Kanade-Lucas-Tomasi



How should we track them from frame
to frame?

Lucas-Kanade

Method for aligning
(tracking) an image patch



How should we select features?

Tomasi-Kanade

Method for choosing the
best feature (image patch)
for tracking

What are good features for tracking?

What are good features for tracking?

Intuitively, we want to avoid smooth regions and edges.

But is there a more principled way to define good features?

What are good features for tracking?

Can be derived from the tracking algorithm

What are good features for tracking?

Can be derived from the tracking algorithm

‘A feature is good if it can be tracked well’

Recall the Lucas-Kanade image alignment method:

error function (SSD) $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$

incremental update $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$

Recall the Lucas-Kanade image alignment method:

error function (SSD) $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$

incremental update $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$

linearize $\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$

Recall the Lucas-Kanade image alignment method:

error function (SSD) $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$

incremental update $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$

linearize $\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$

Gradient update $\Delta \mathbf{p} = H^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$

$$H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

Recall the Lucas-Kanade image alignment method:

error function (SSD) $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - T(\mathbf{x})]^2$

incremental update $\sum_{\mathbf{x}} [I(\mathbf{W}(\mathbf{x}; \mathbf{p} + \Delta \mathbf{p})) - T(\mathbf{x})]^2$

linearize $\sum_{\mathbf{x}} \left[I(\mathbf{W}(\mathbf{x}; \mathbf{p})) + \nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \Delta \mathbf{p} - T(\mathbf{x}) \right]^2$

Gradient update $\Delta \mathbf{p} = H^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$

$$H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

Update $\mathbf{p} \leftarrow \mathbf{p} + \Delta \mathbf{p}$

Stability of gradient decent iterations depends on ...

$$\Delta \mathbf{p} = \underbrace{H^{-1}}_{\text{red circle}} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^{\top} [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

Stability of gradient decent iterations depends on ...

$$\Delta \mathbf{p} = \underbrace{H^{-1}} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

Inverting the Hessian

$$H = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

When does the inversion fail?

Stability of gradient decent iterations depends on ...

$$\Delta \mathbf{p} = \mathbf{H}^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top [T(\mathbf{x}) - I(\mathbf{W}(\mathbf{x}; \mathbf{p}))]$$

Inverting the Hessian

$$\mathbf{H} = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]$$

When does the inversion fail?

H is singular. But what does that mean?

Above the noise level

$$\lambda_1 \gg 0$$

$$\lambda_2 \gg 0$$

both Eigenvalues are large

Well-conditioned

both Eigenvalues have similar magnitude

Concrete example: Consider translation model

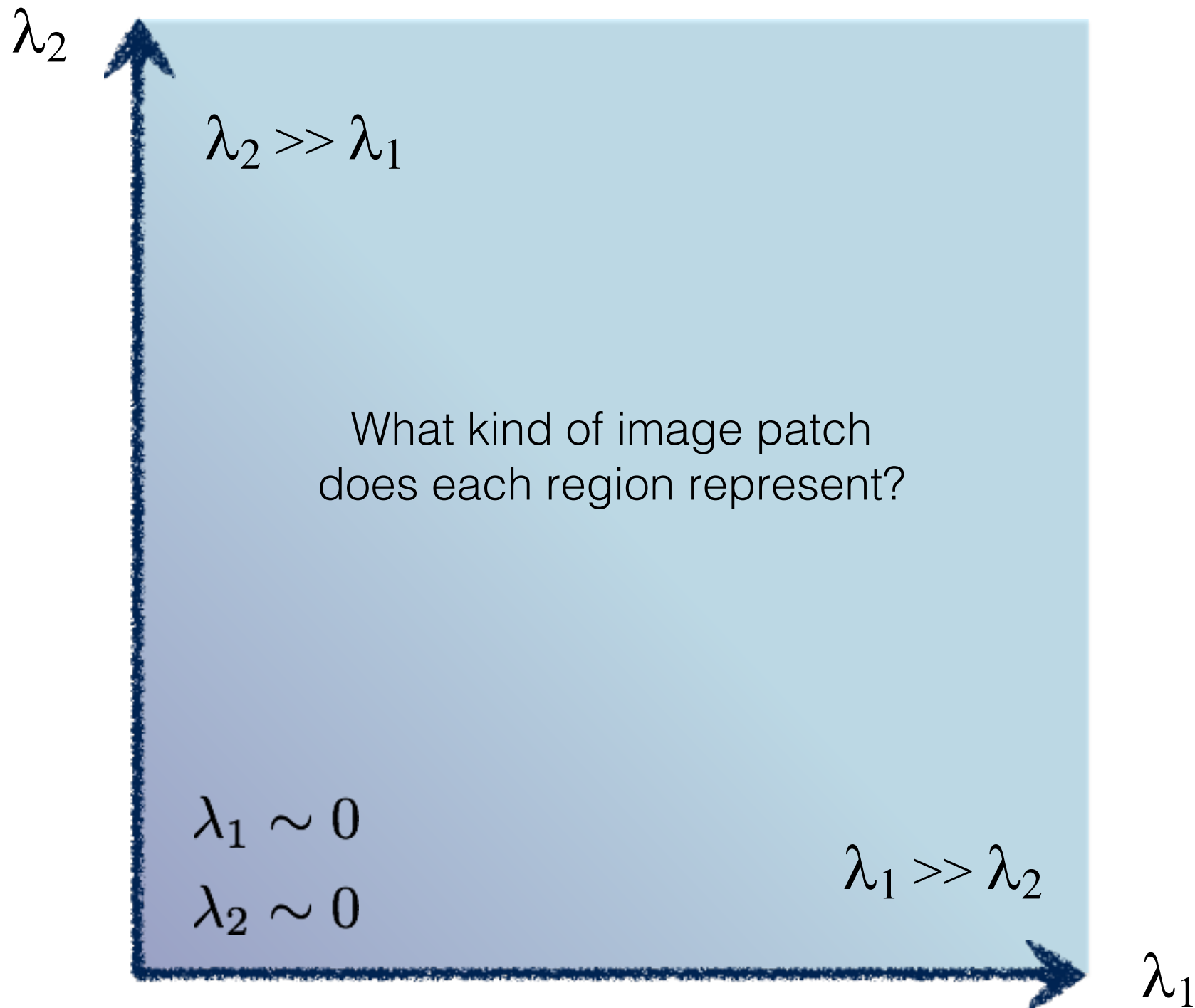
$$\mathbf{W}(\mathbf{x}; \mathbf{p}) = \begin{bmatrix} x + p_1 \\ y + p_2 \end{bmatrix} \quad \frac{\partial \mathbf{W}}{\partial \mathbf{p}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Hessian

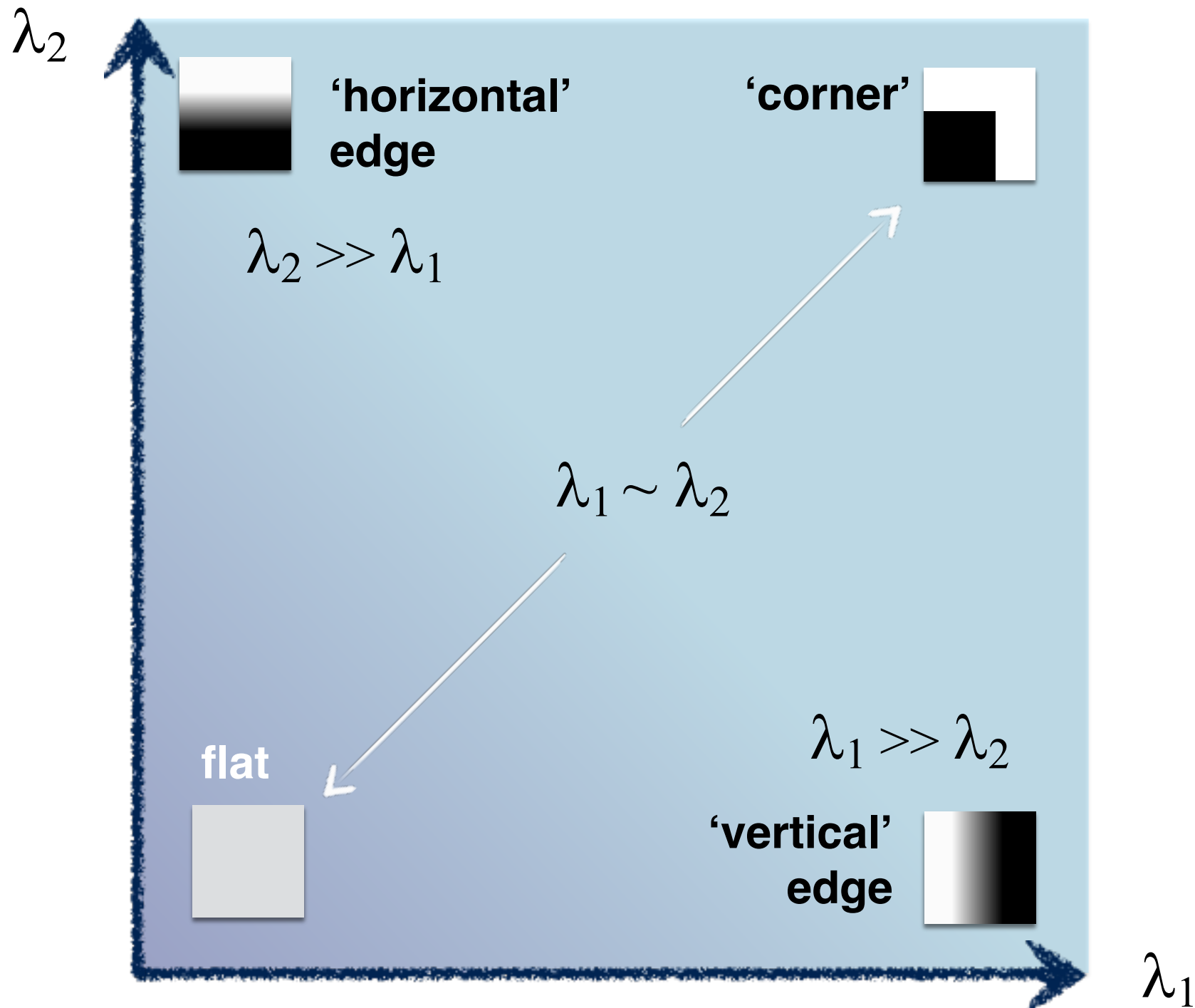
$$\begin{aligned} H &= \sum_{\mathbf{x}} \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right]^\top \left[\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}} \right] \\ &= \sum_{\mathbf{x}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_x \\ I_y \end{bmatrix} \begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} \sum_{\mathbf{x}} I_x I_x & \sum_{\mathbf{x}} I_y I_x \\ \sum_{\mathbf{x}} I_x I_y & \sum_{\mathbf{x}} I_y I_y \end{bmatrix} \quad \leftarrow \text{when is this singular?} \end{aligned}$$

How are the eigenvalues related to image content?

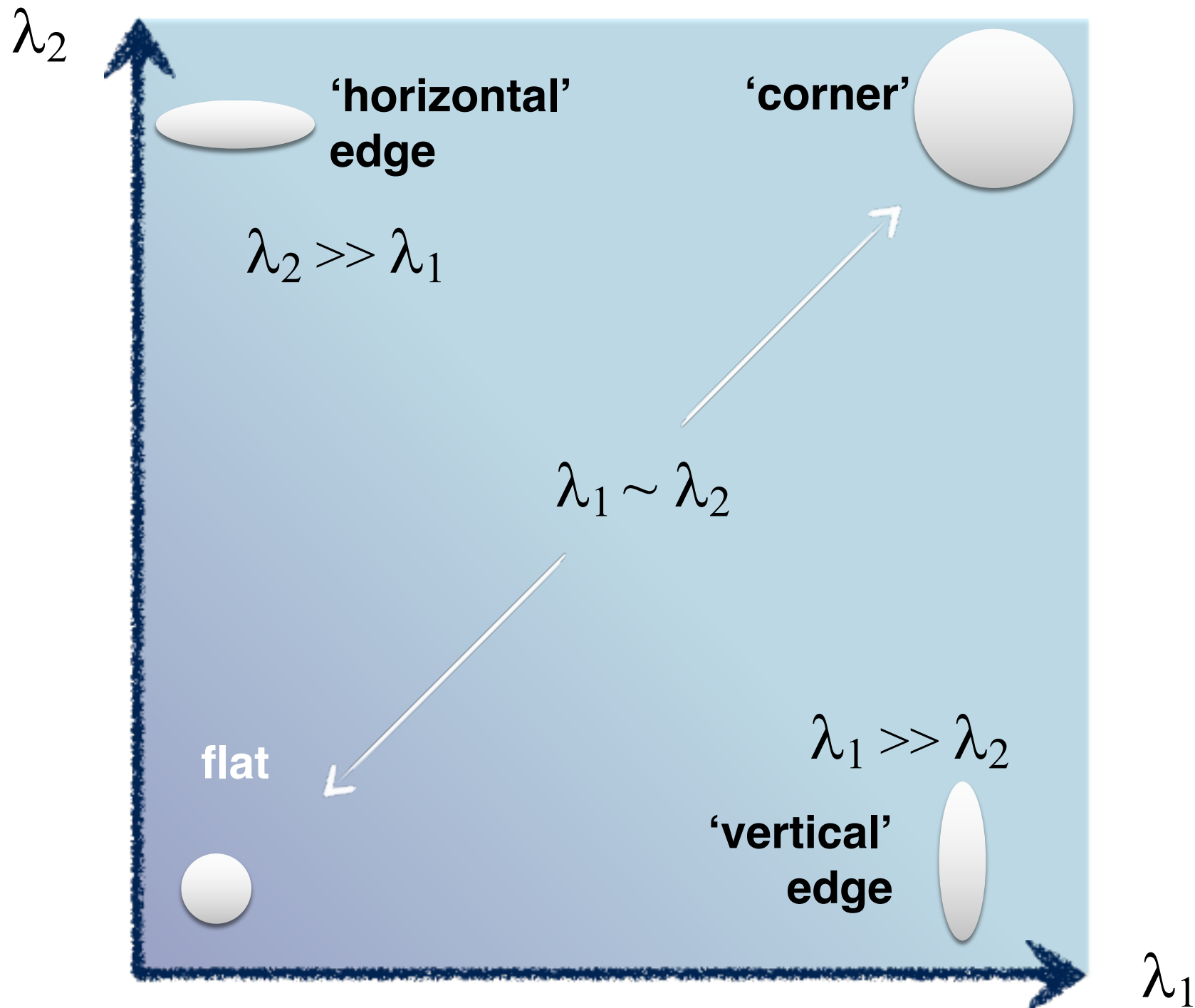
interpreting eigenvalues



interpreting eigenvalues



interpreting eigenvalues



What are good features for tracking?

What are good features for tracking?

$$\min(\lambda_1, \lambda_2) > \lambda$$

‘big Eigenvalues means good for tracking’

KLT algorithm

1. Find corners satisfying $\min(\lambda_1, \lambda_2) > \lambda$
2. For each corner compute displacement to next frame using the Lucas-Kanade method
3. Store displacement of each corner, update corner position
4. (optional) Add more corner points every M frames using 1
5. Repeat 2 to 3 (4)
6. Returns long trajectories for each corner point

Mean-shift algorithm



Mean Shift Algorithm

A 'mode seeking' algorithm

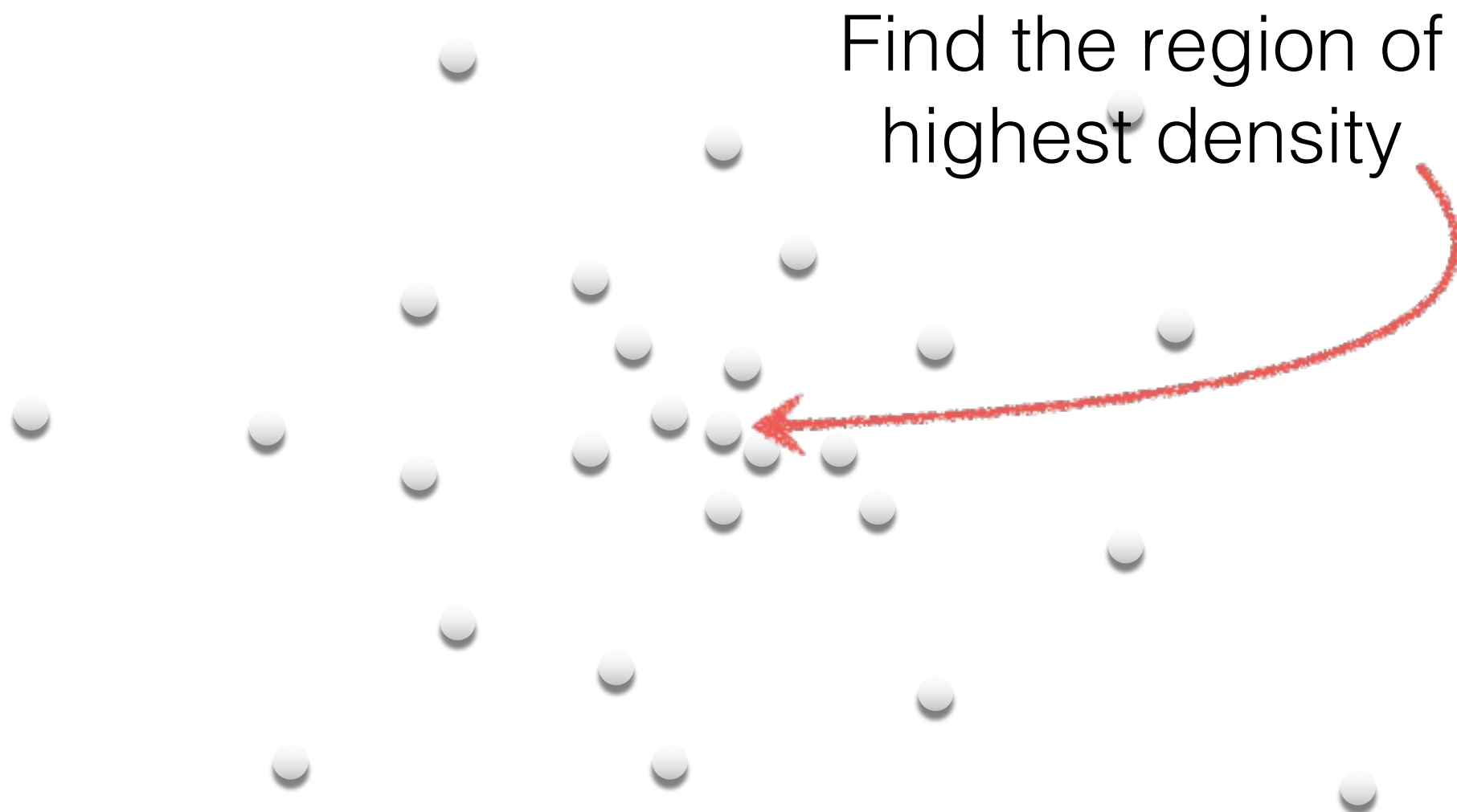
Fukunaga & Hostetler (1975)



Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

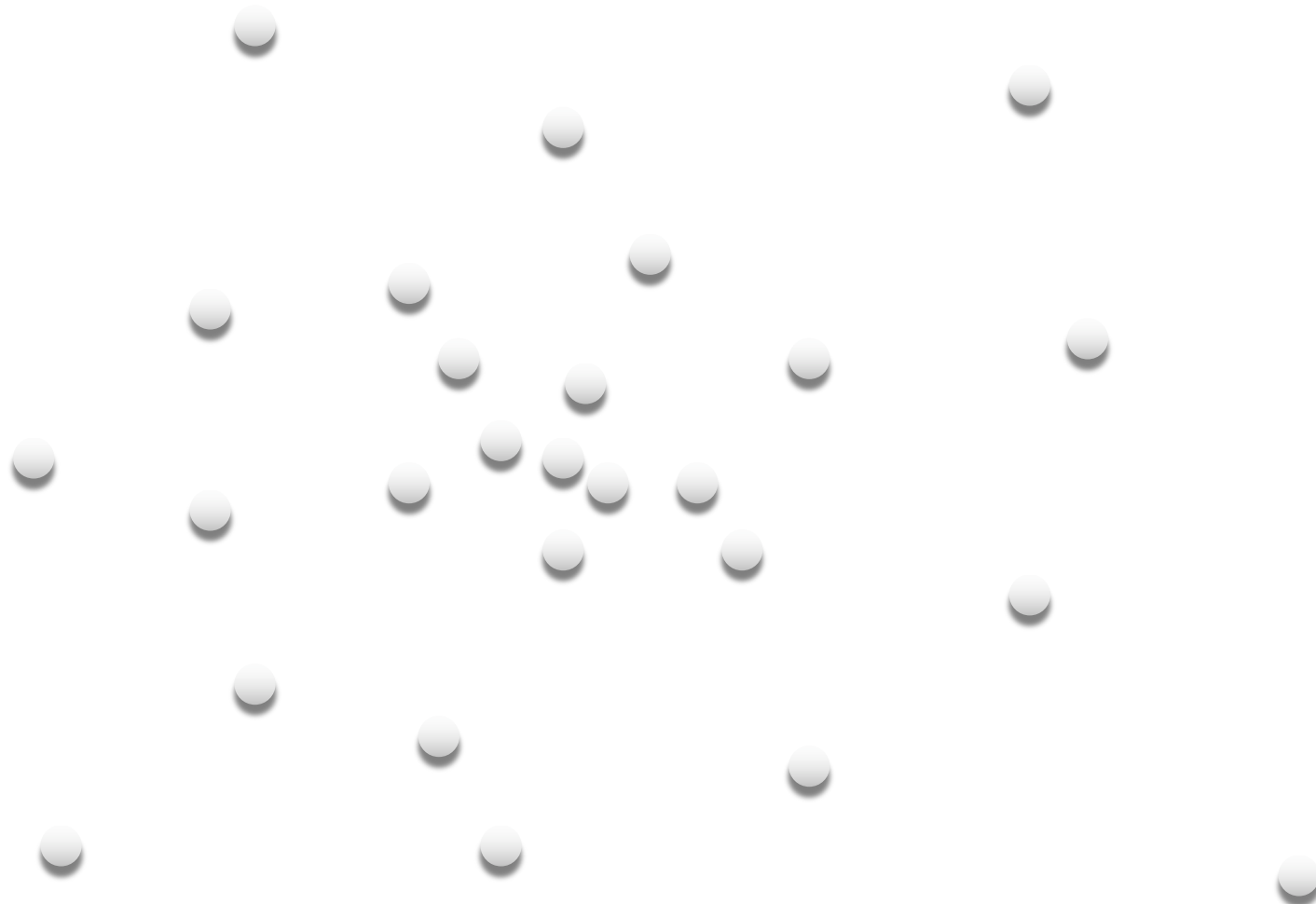


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Pick a point

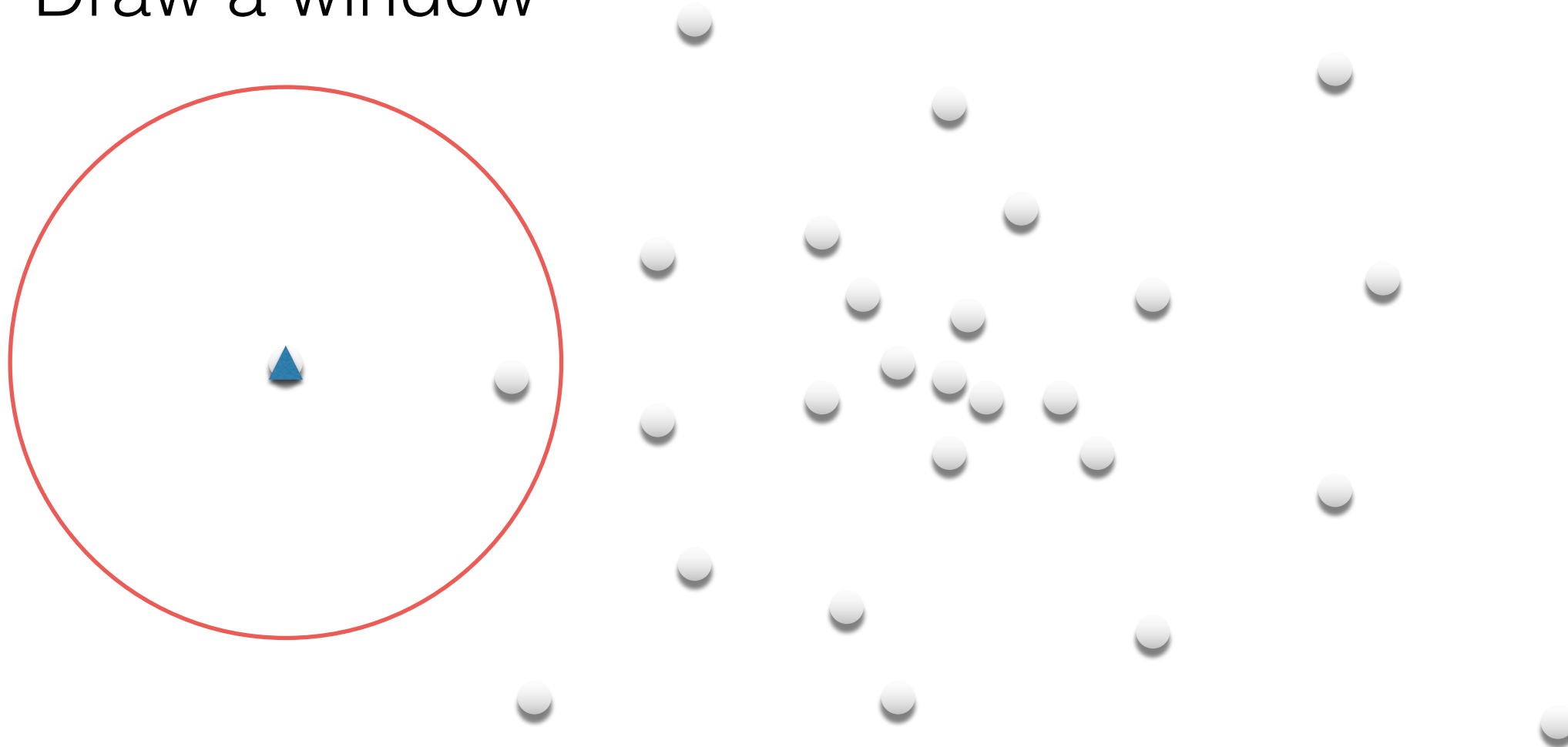


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Draw a window

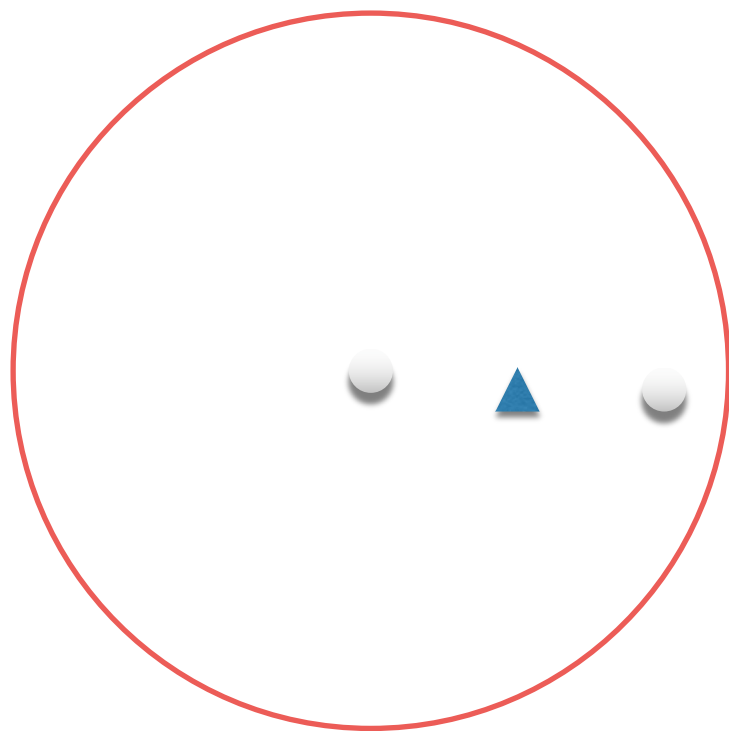


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Compute the
(weighted) **mean**

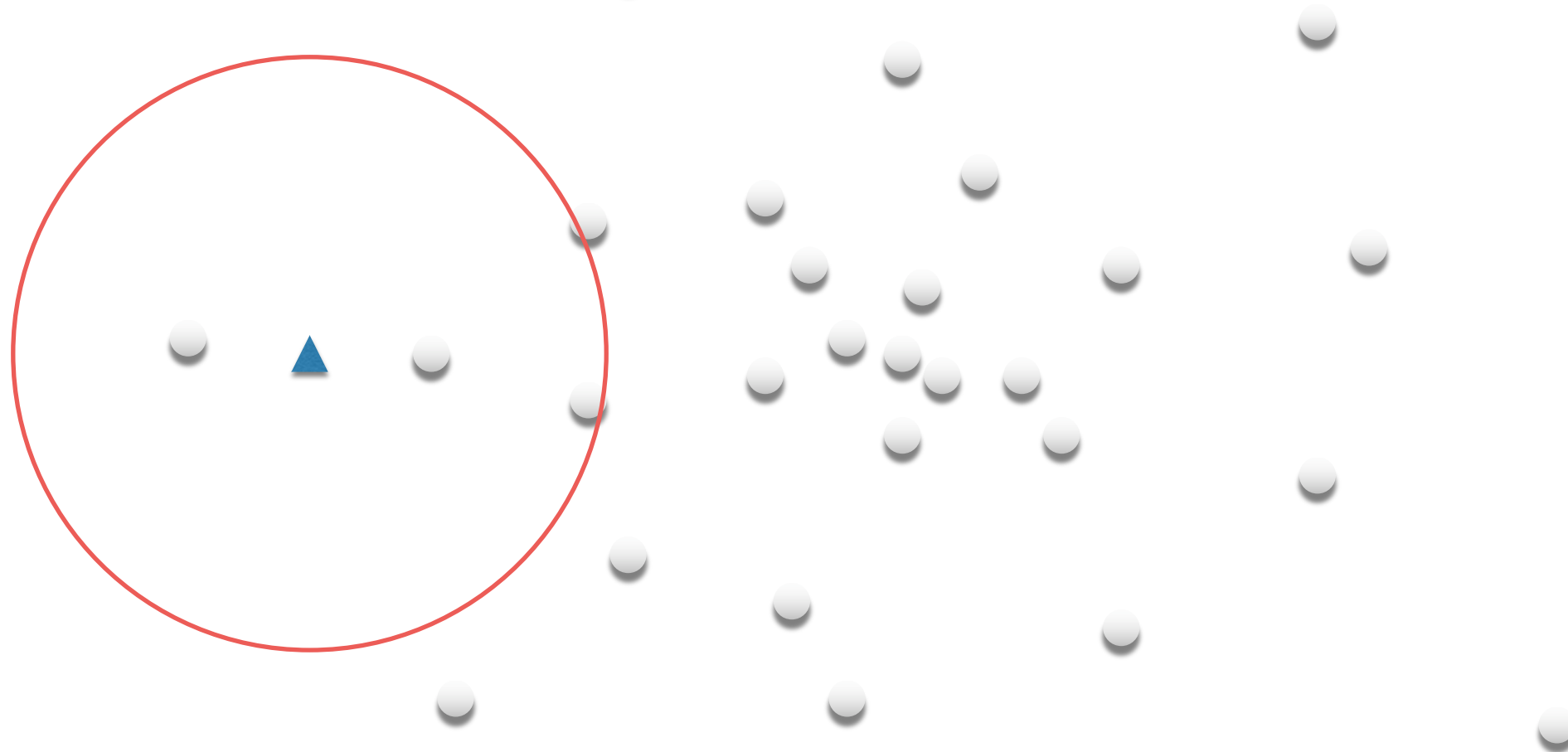


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Shift the window

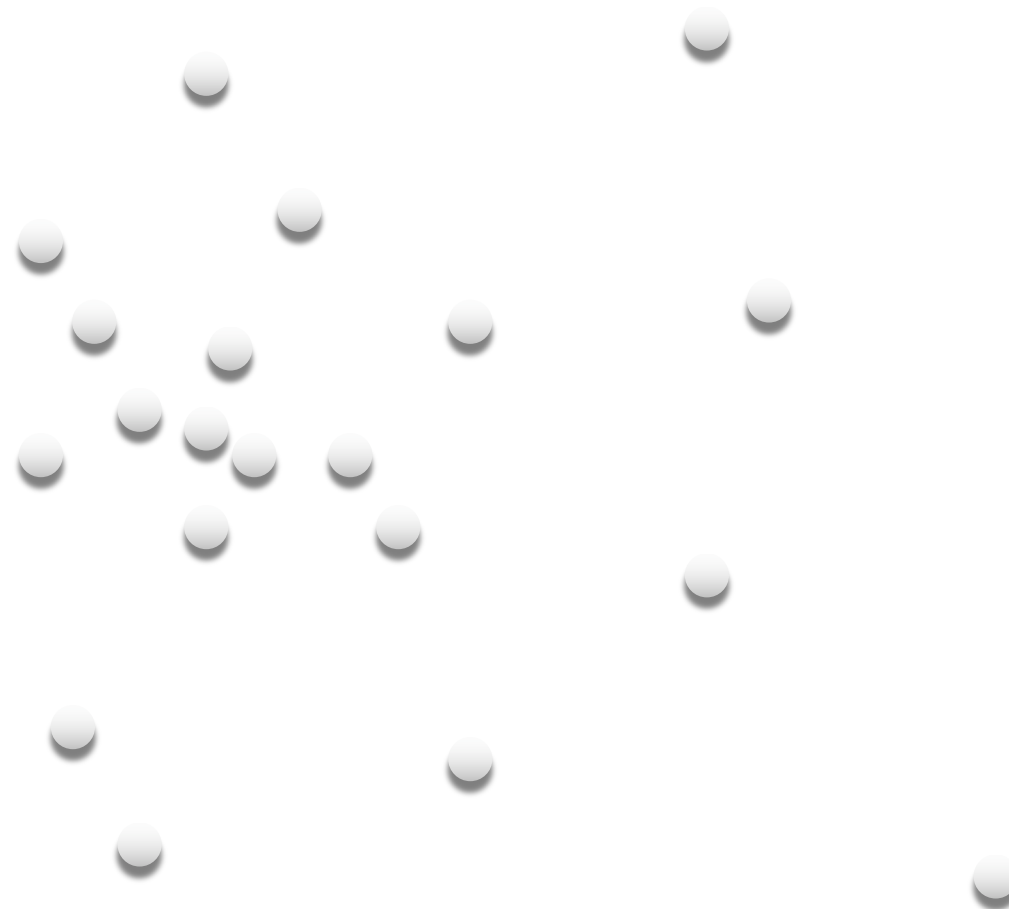
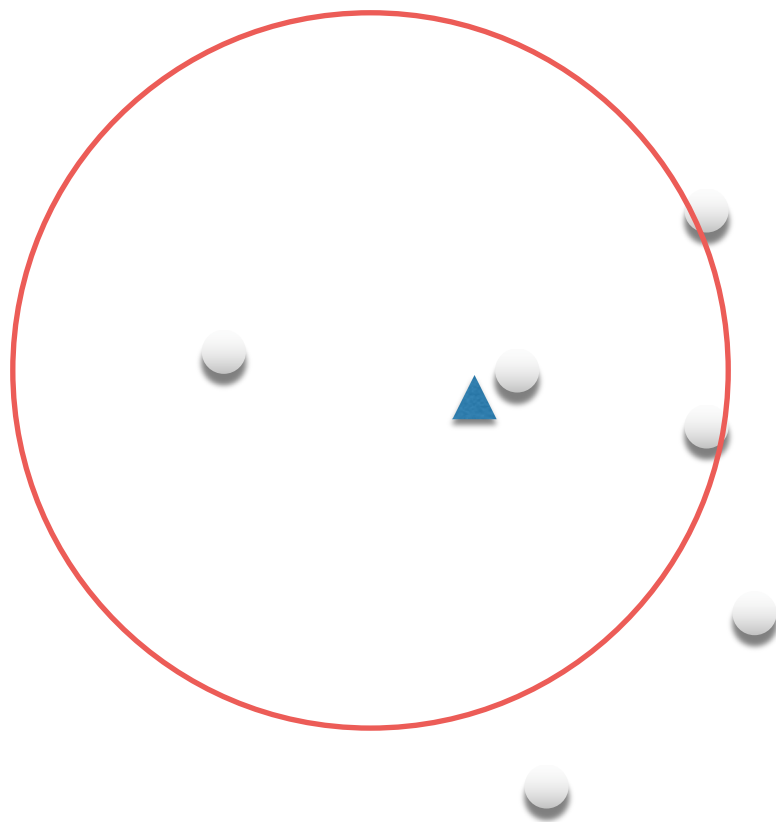


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

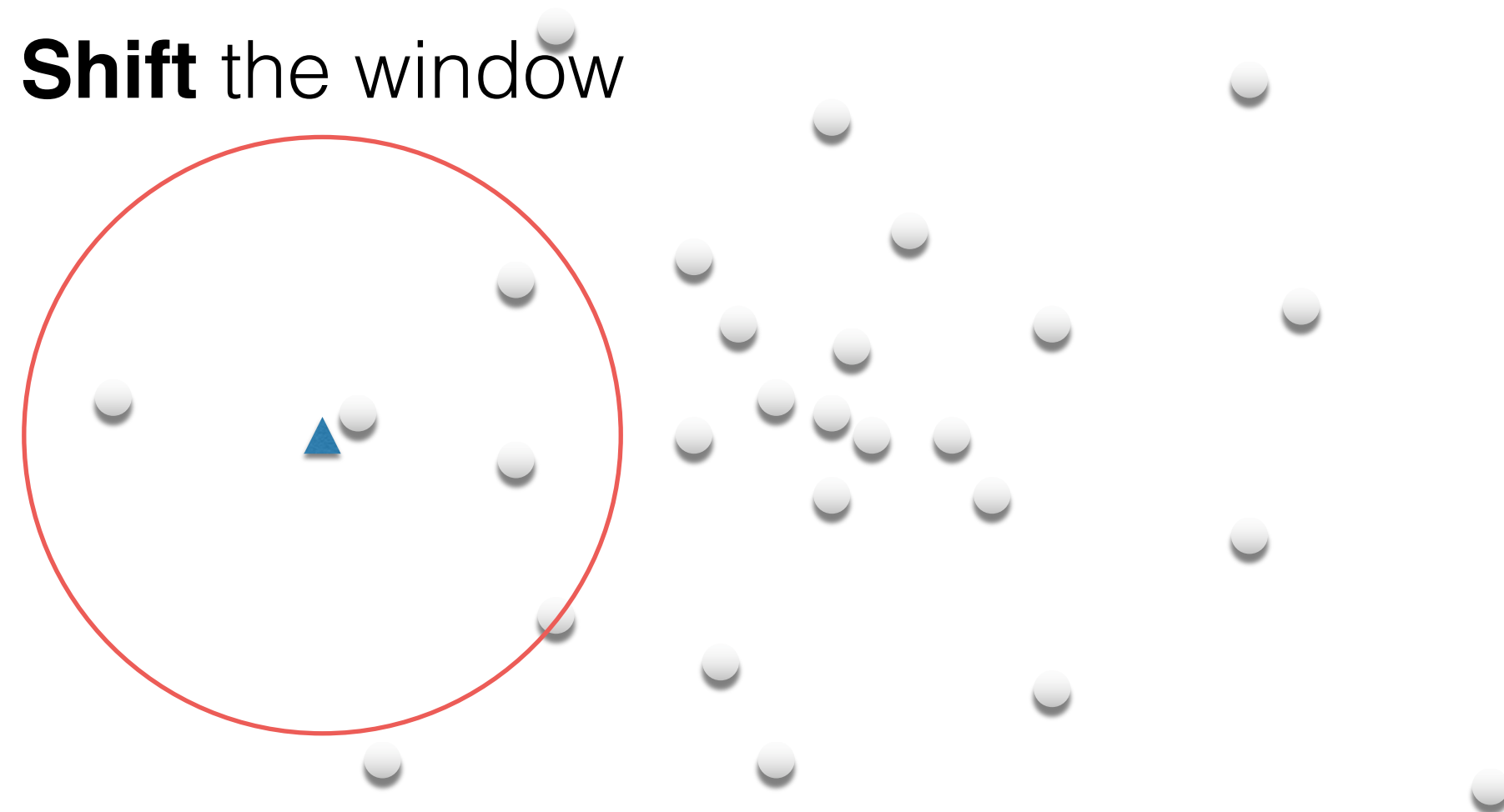
Compute the **mean**



Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

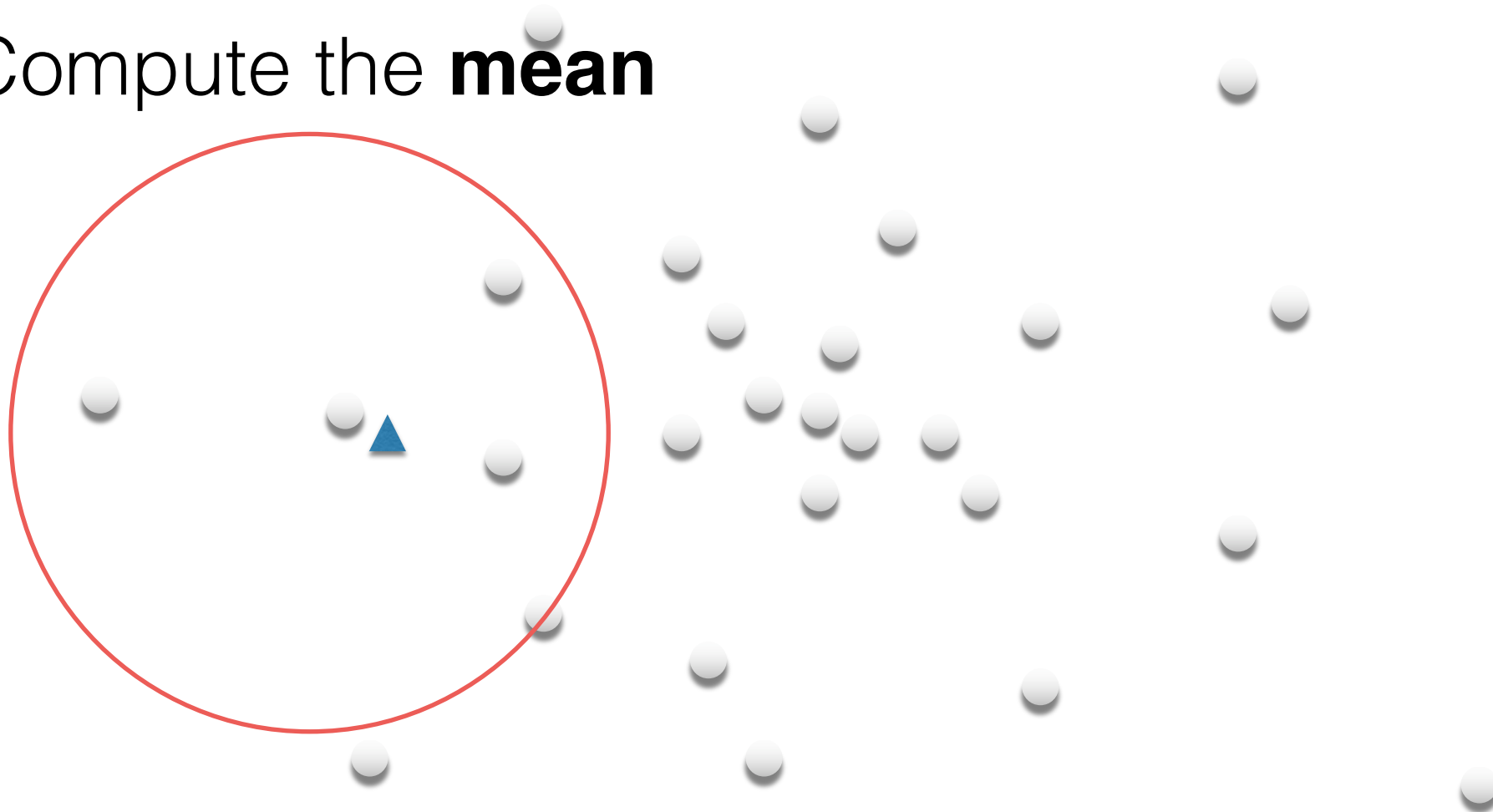


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

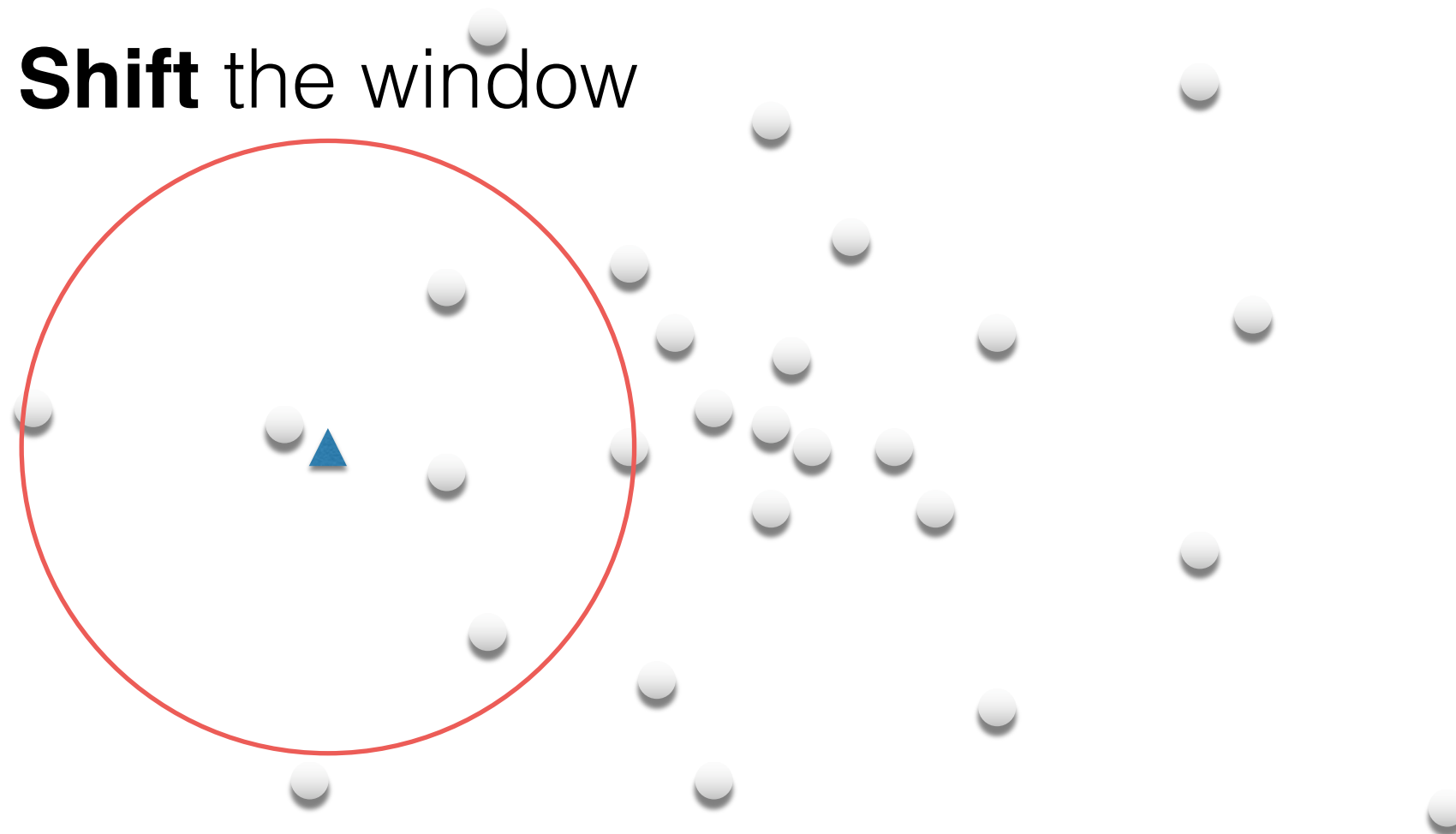
Compute the **mean**



Mean Shift Algorithm

A 'mode seeking' algorithm

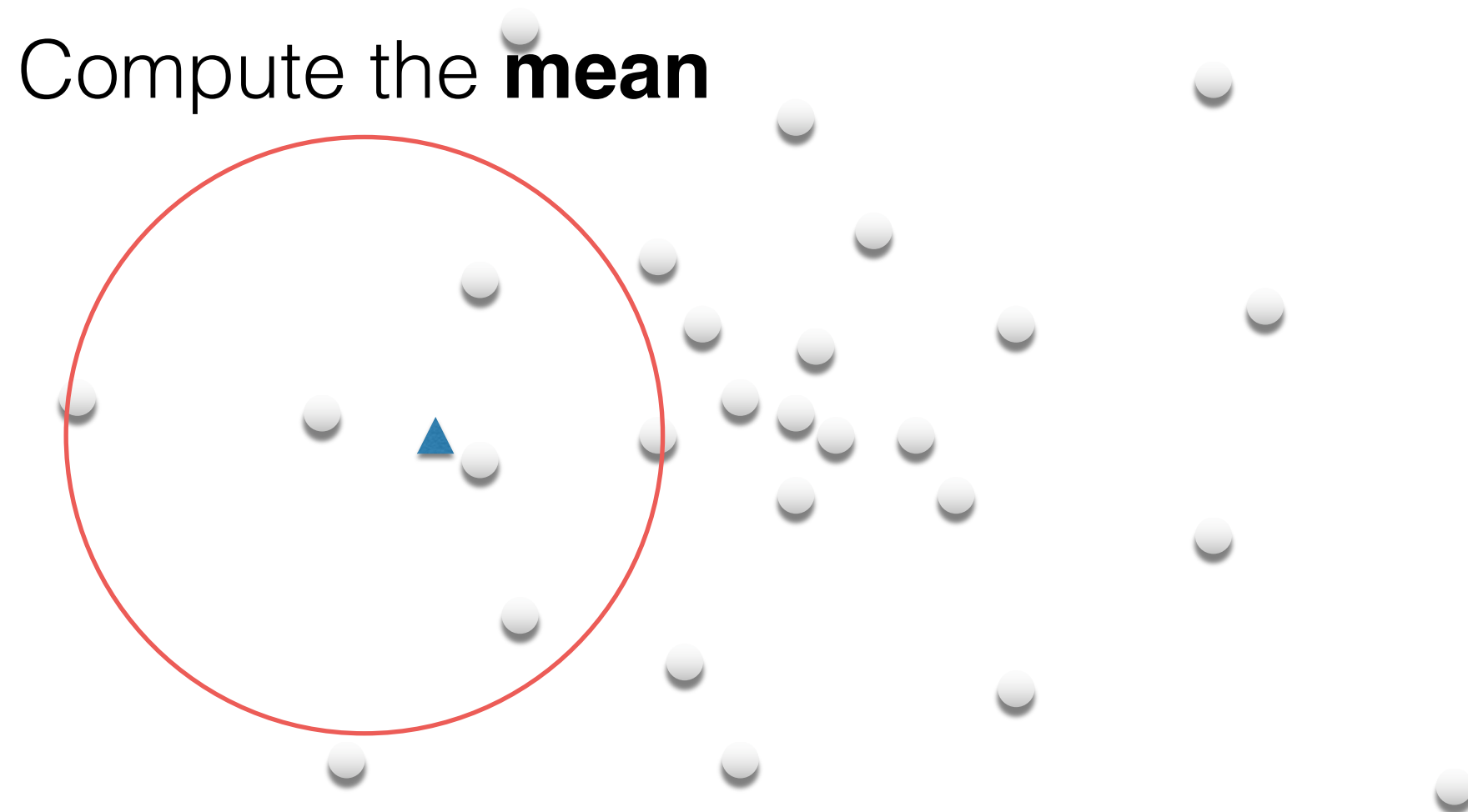
Fukunaga & Hostetler (1975)



Mean Shift Algorithm

A 'mode seeking' algorithm

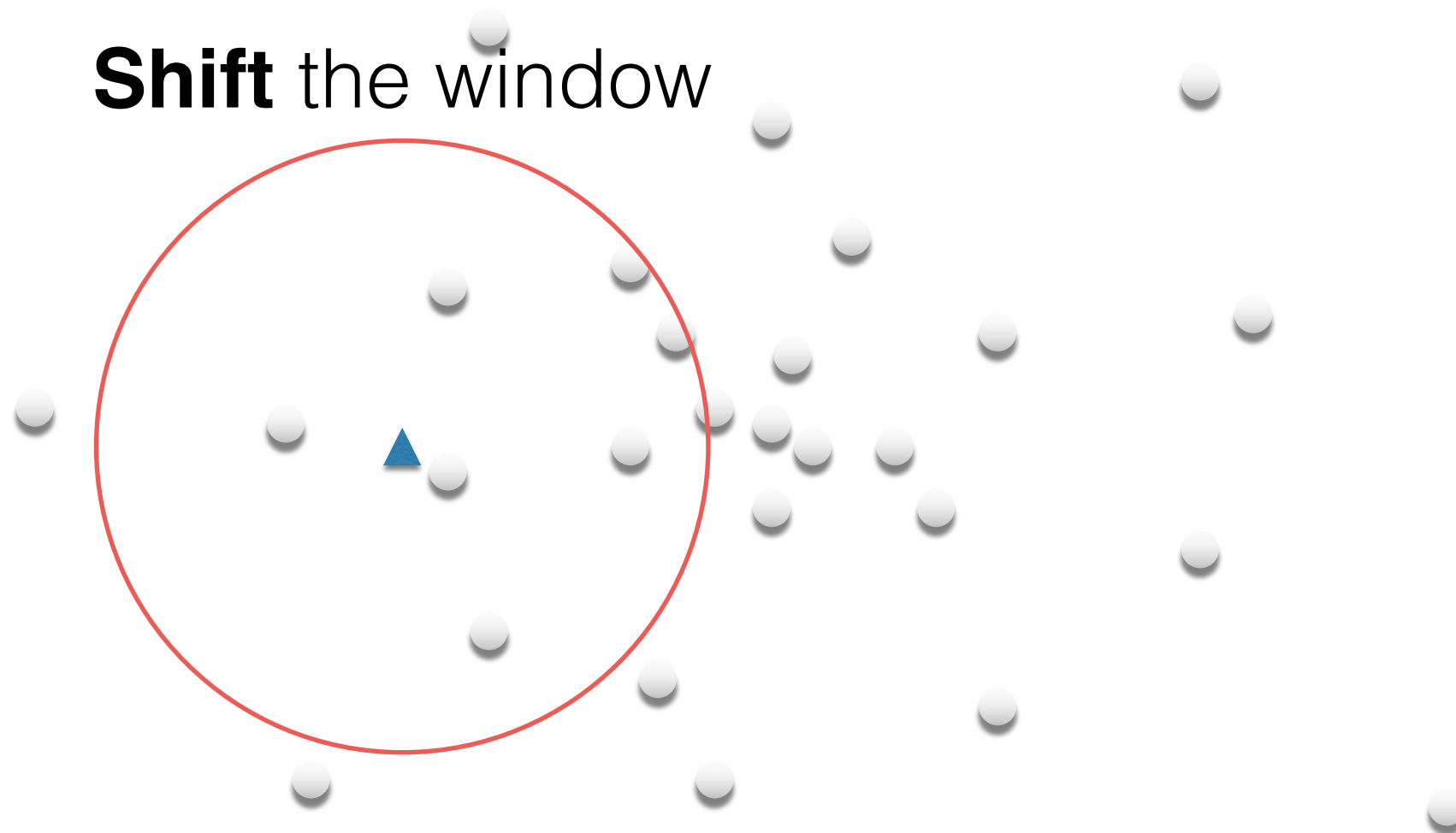
Fukunaga & Hostetler (1975)



Mean Shift Algorithm

A 'mode seeking' algorithm

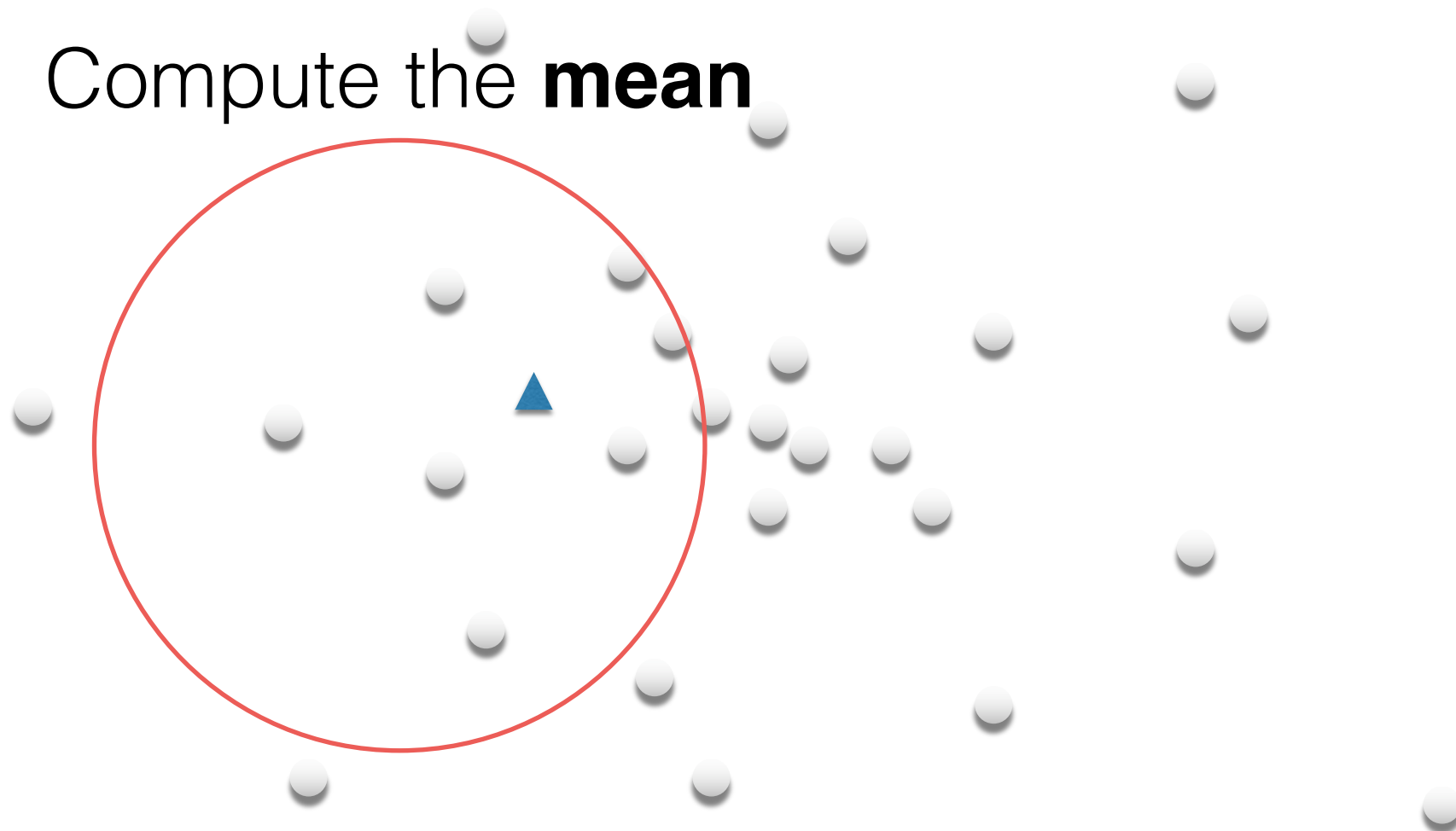
Fukunaga & Hostetler (1975)



Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

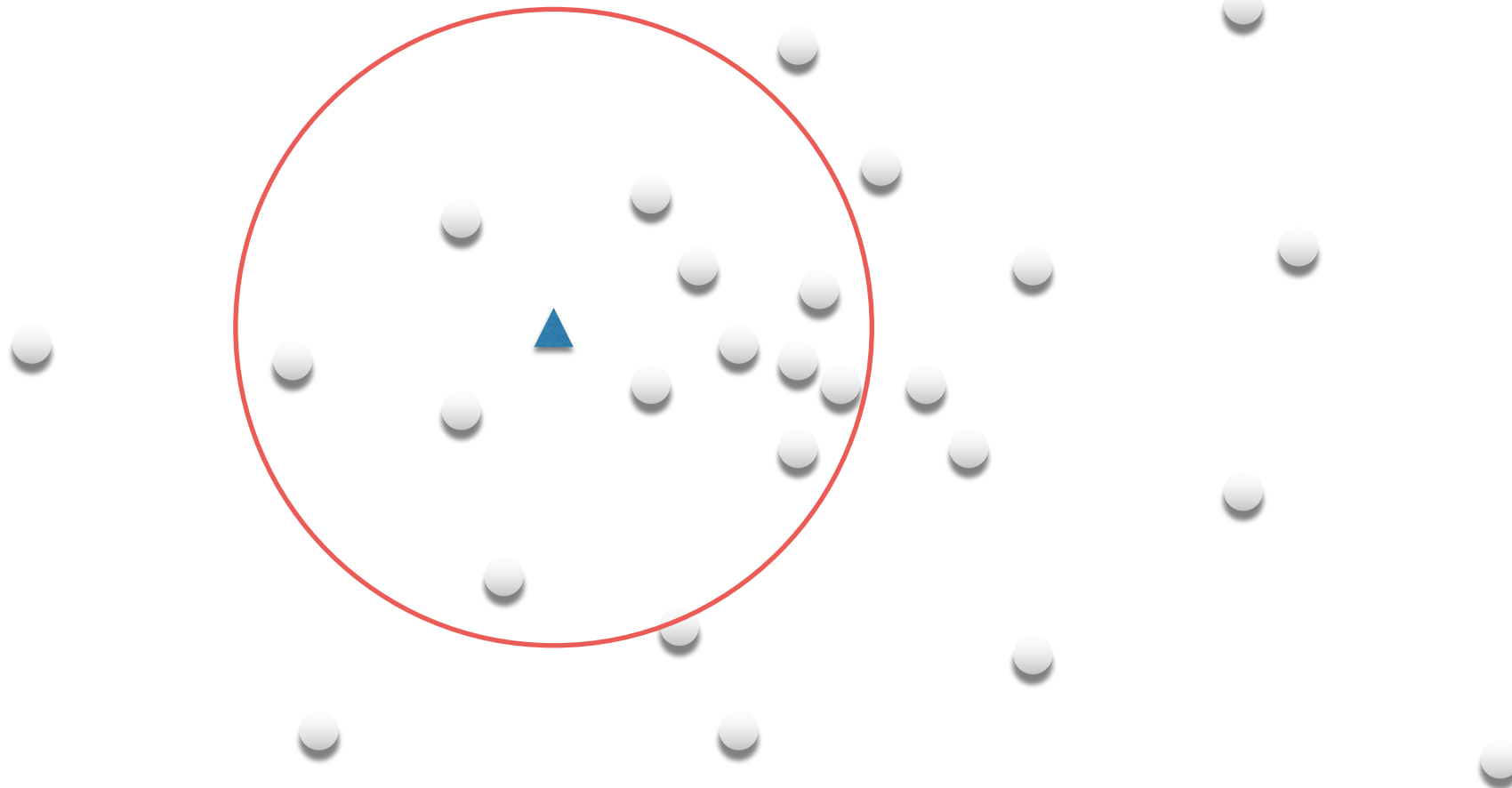


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Shift the window

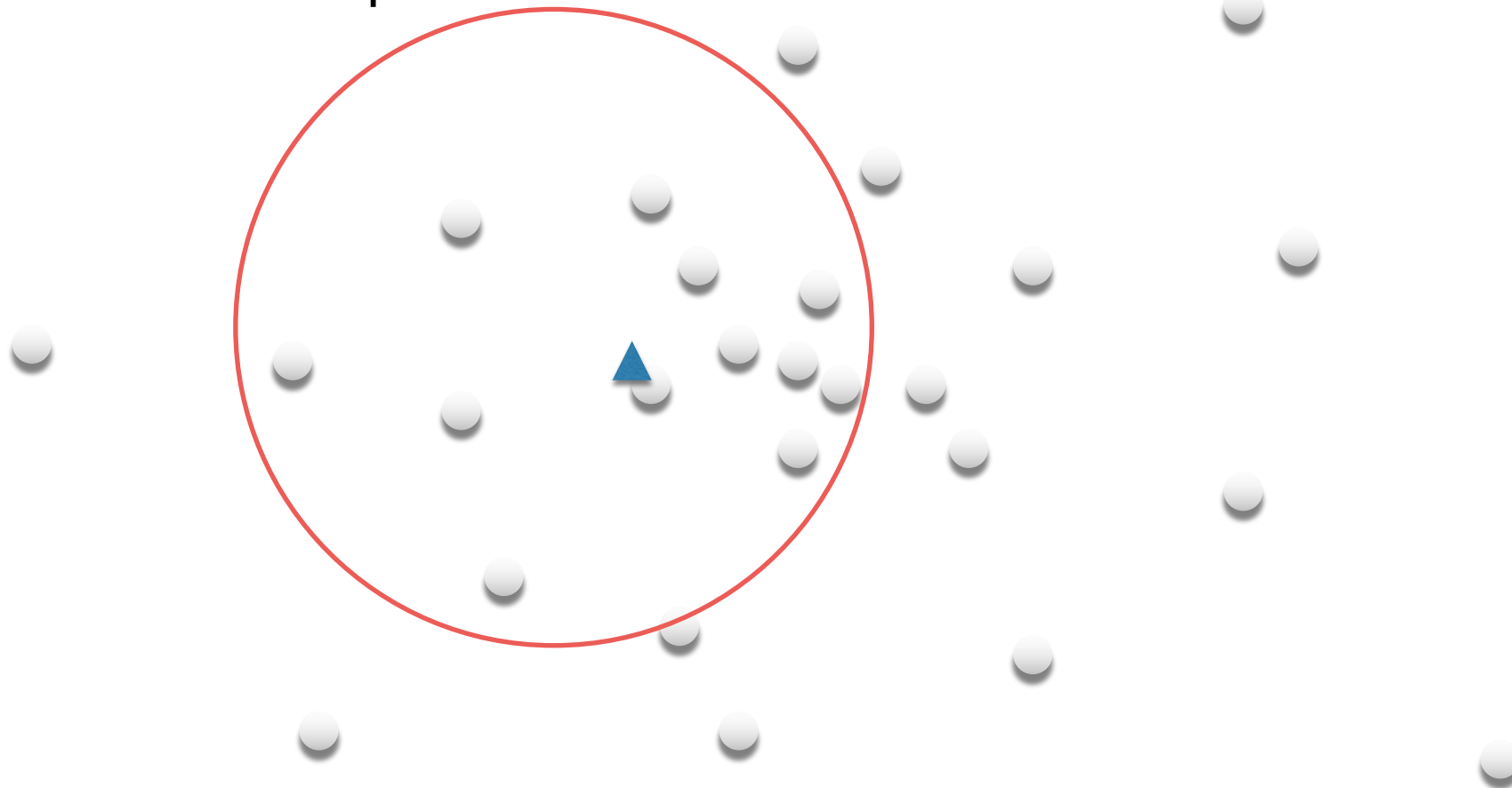


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

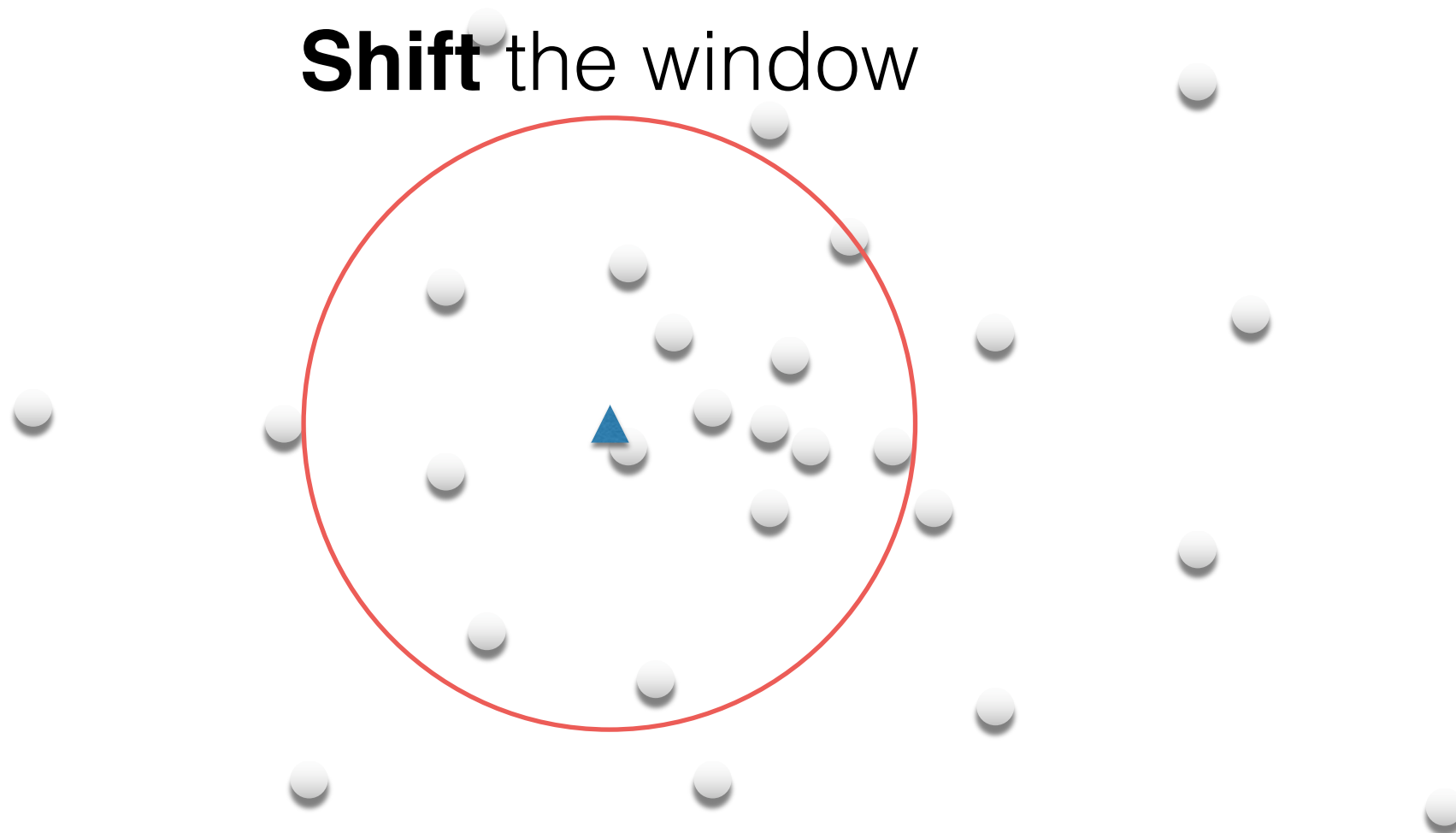
Compute the **mean**



Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

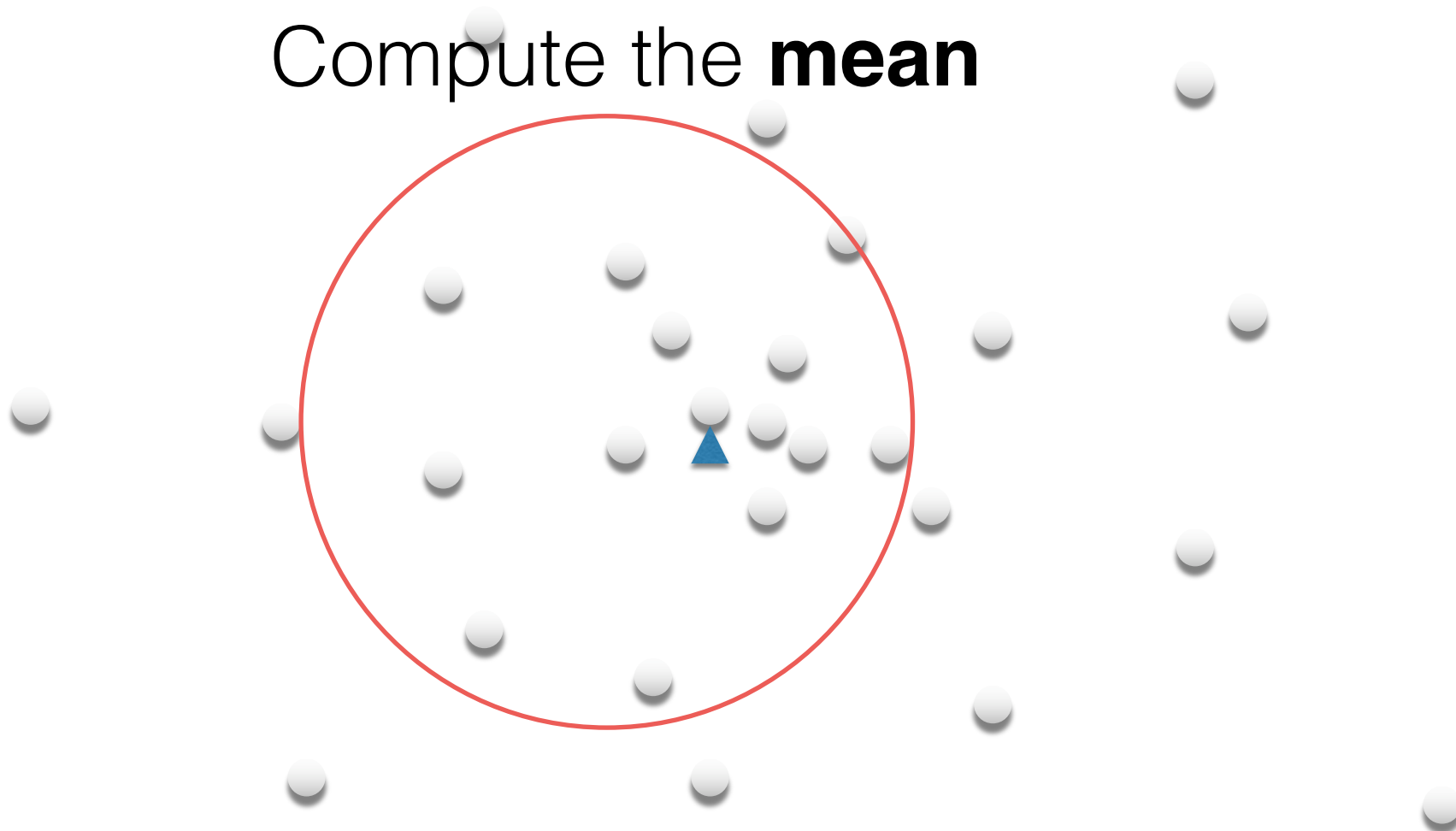


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Compute the **mean**

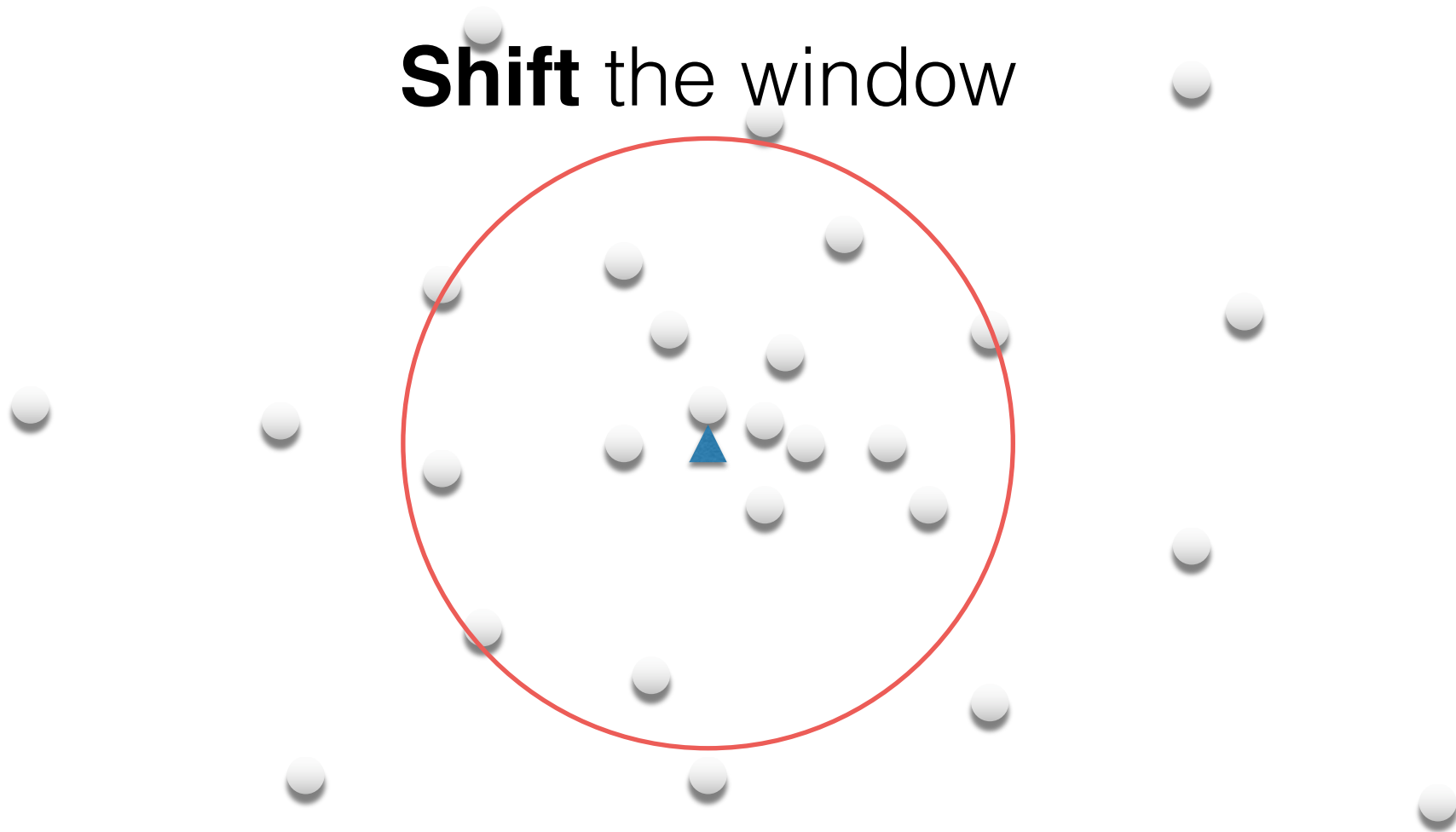


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Shift the window

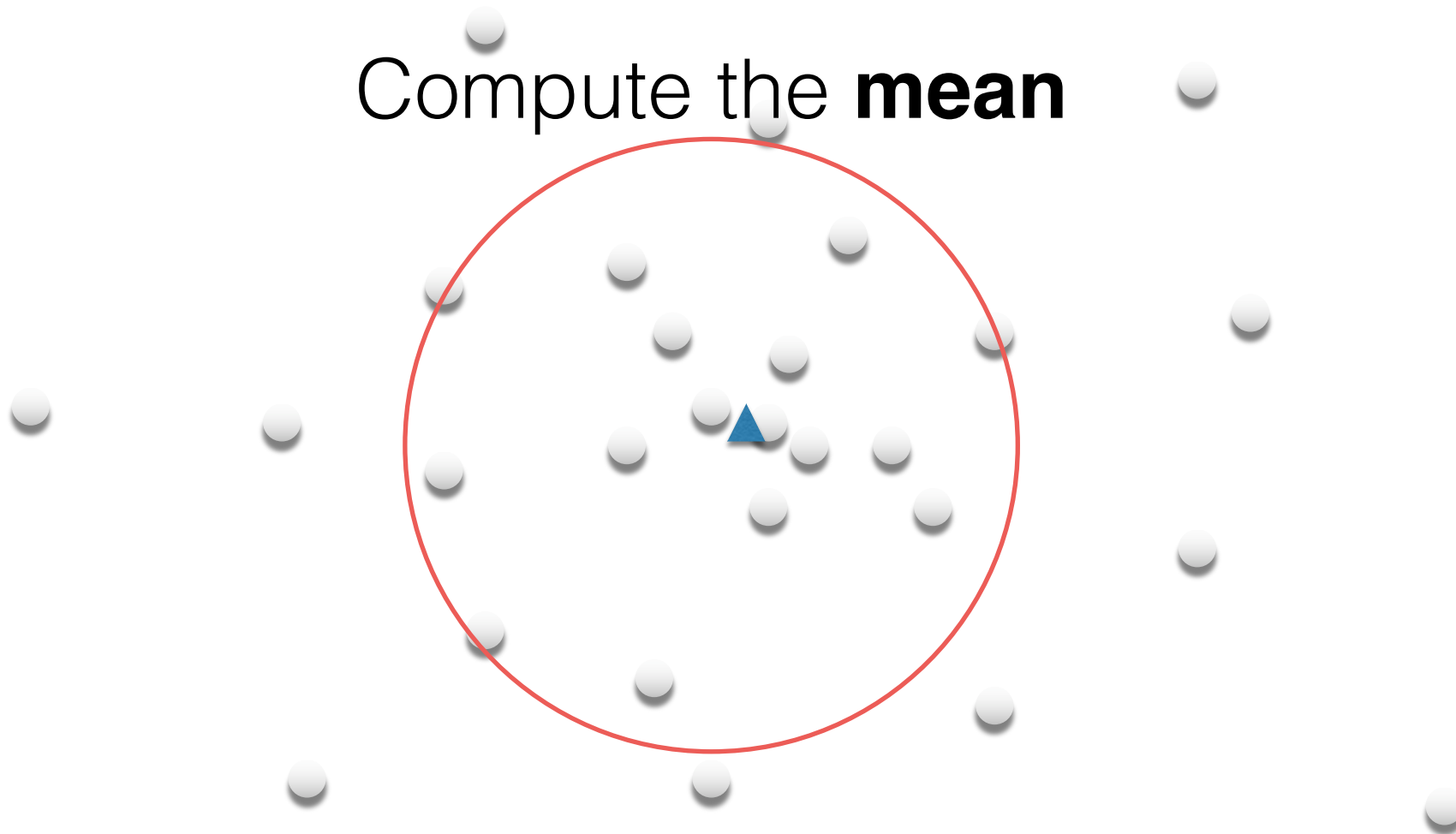


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Compute the **mean**

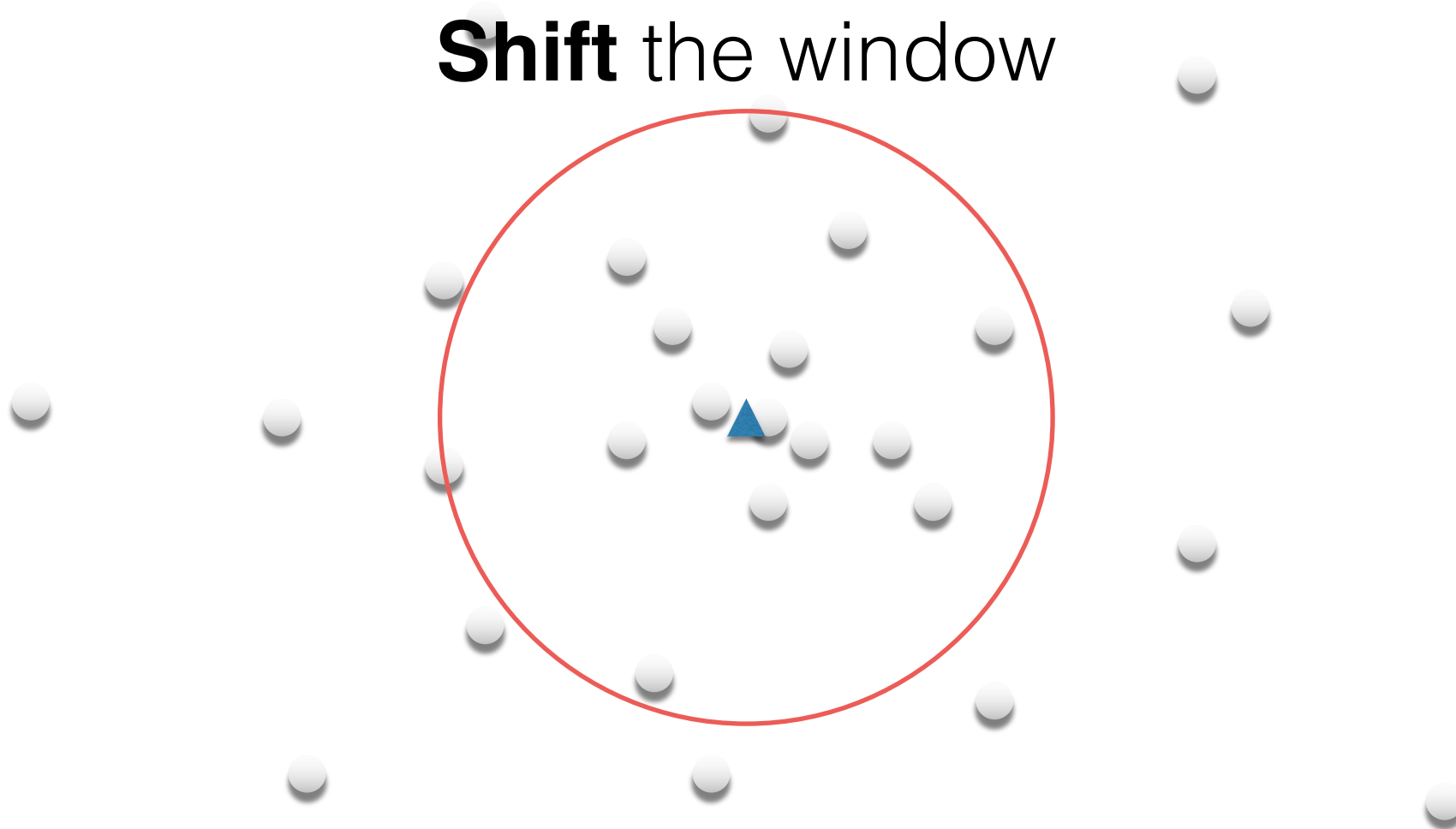


Mean Shift Algorithm

A 'mode seeking' algorithm

Fukunaga & Hostetler (1975)

Shift the window



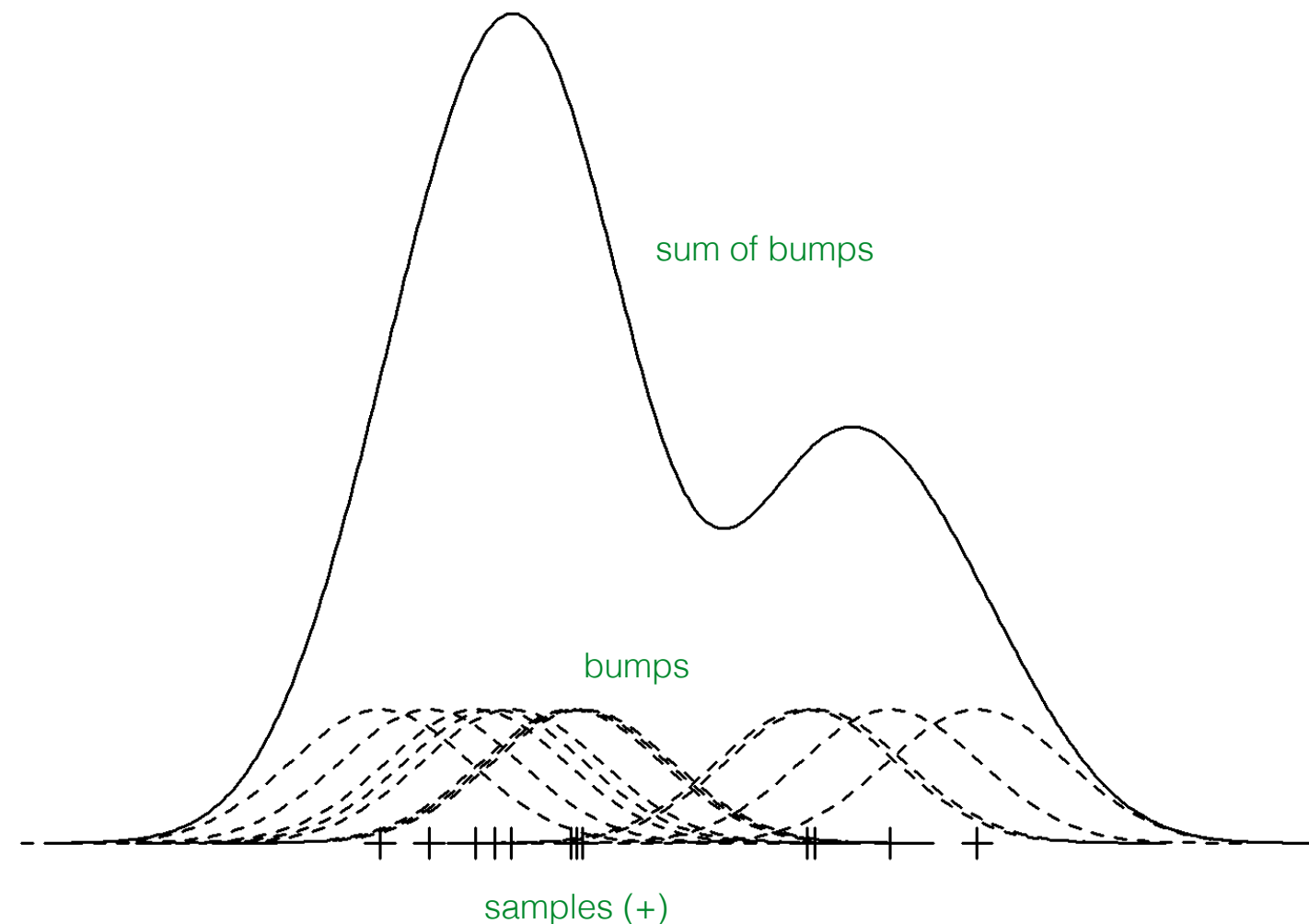
To understand the theory behind this we need to understand...

Kernel density estimation

To understand the mean shift algorithm ...

Kernel Density Estimation

A method to approximate an underlying PDF from samples



Put 'bump' on every sample to approximate the PDF

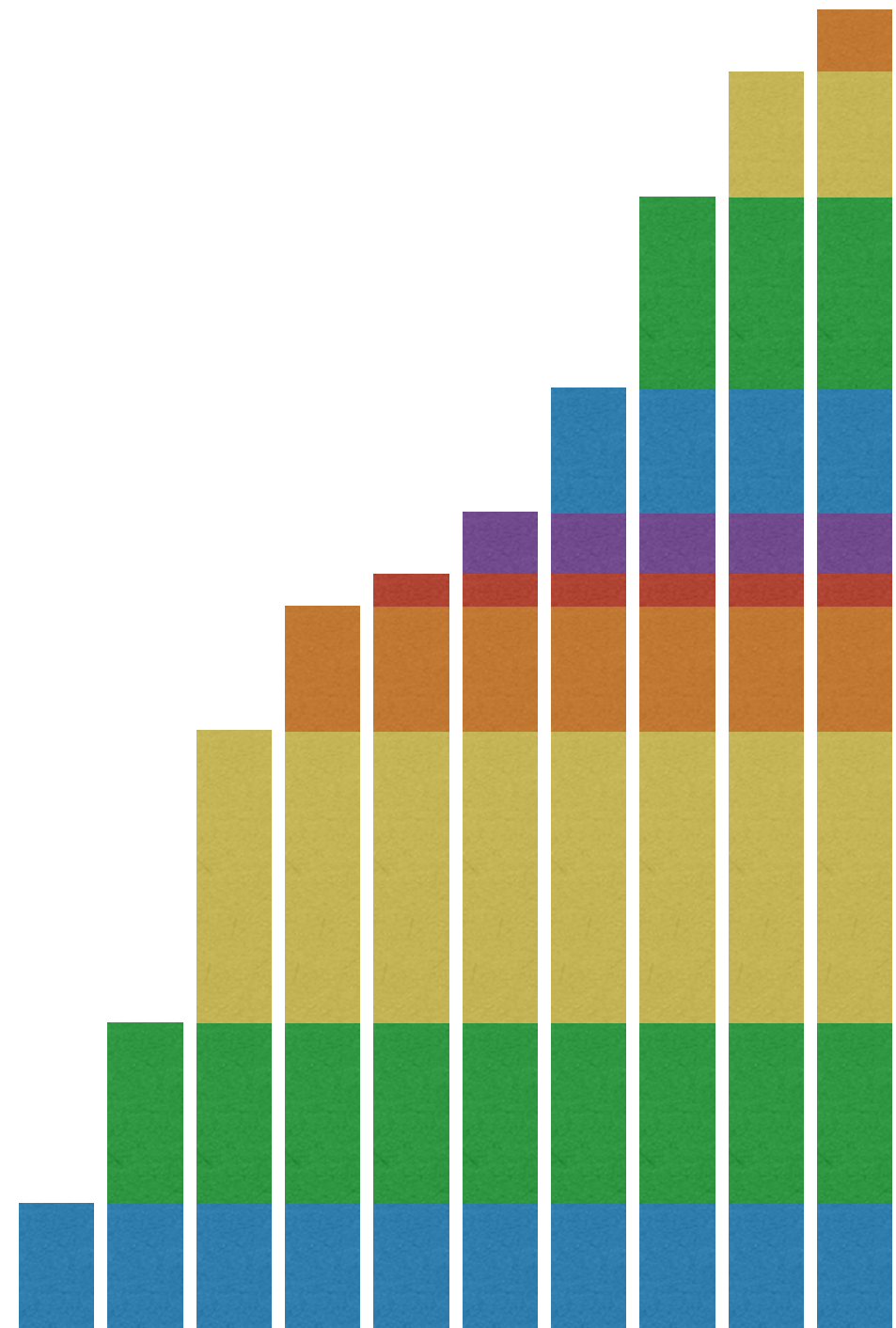
Say we have some hidden PDF...

$p(x)$

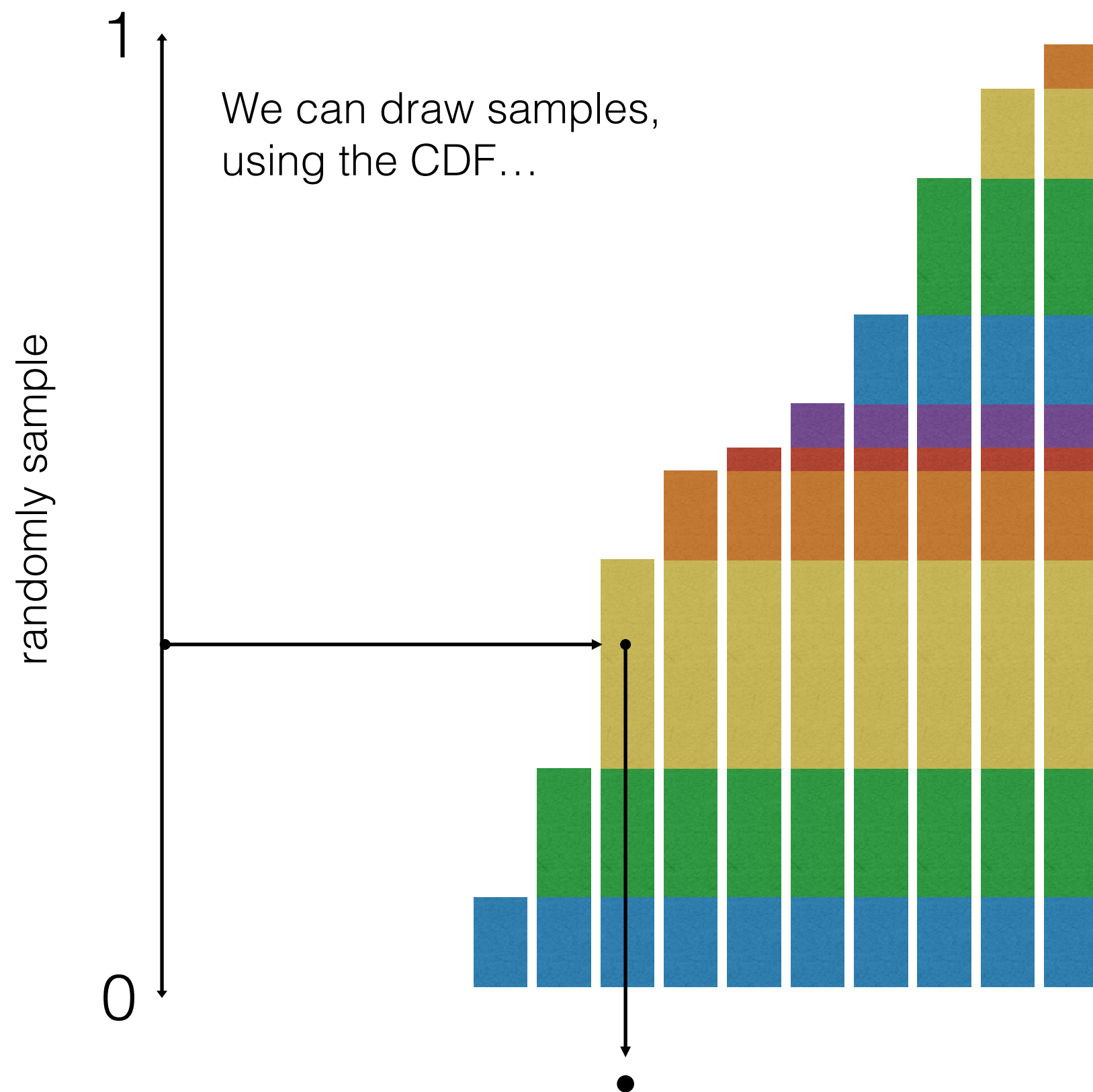


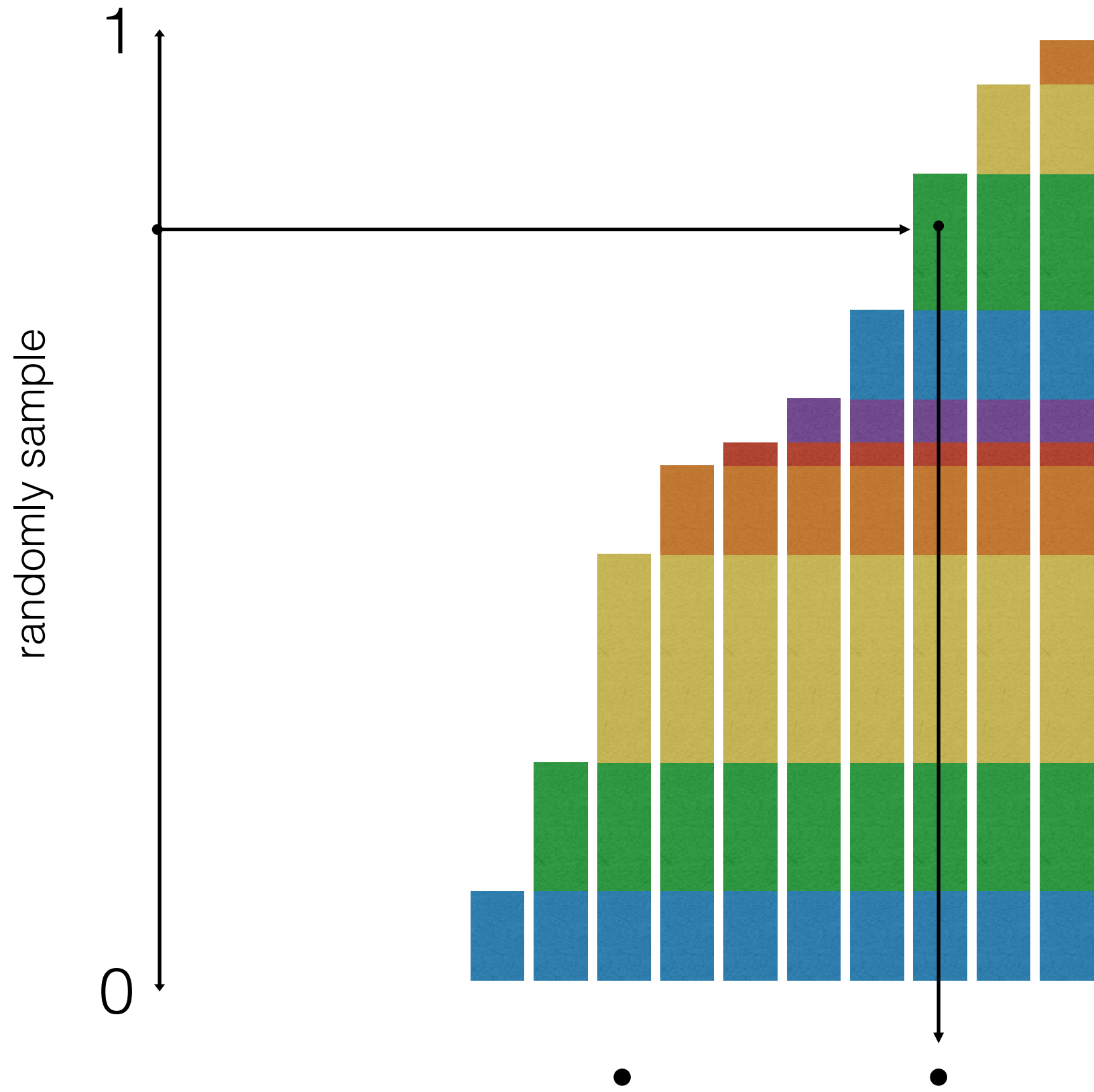
1 2 3 4 5 6 7 8 9 10

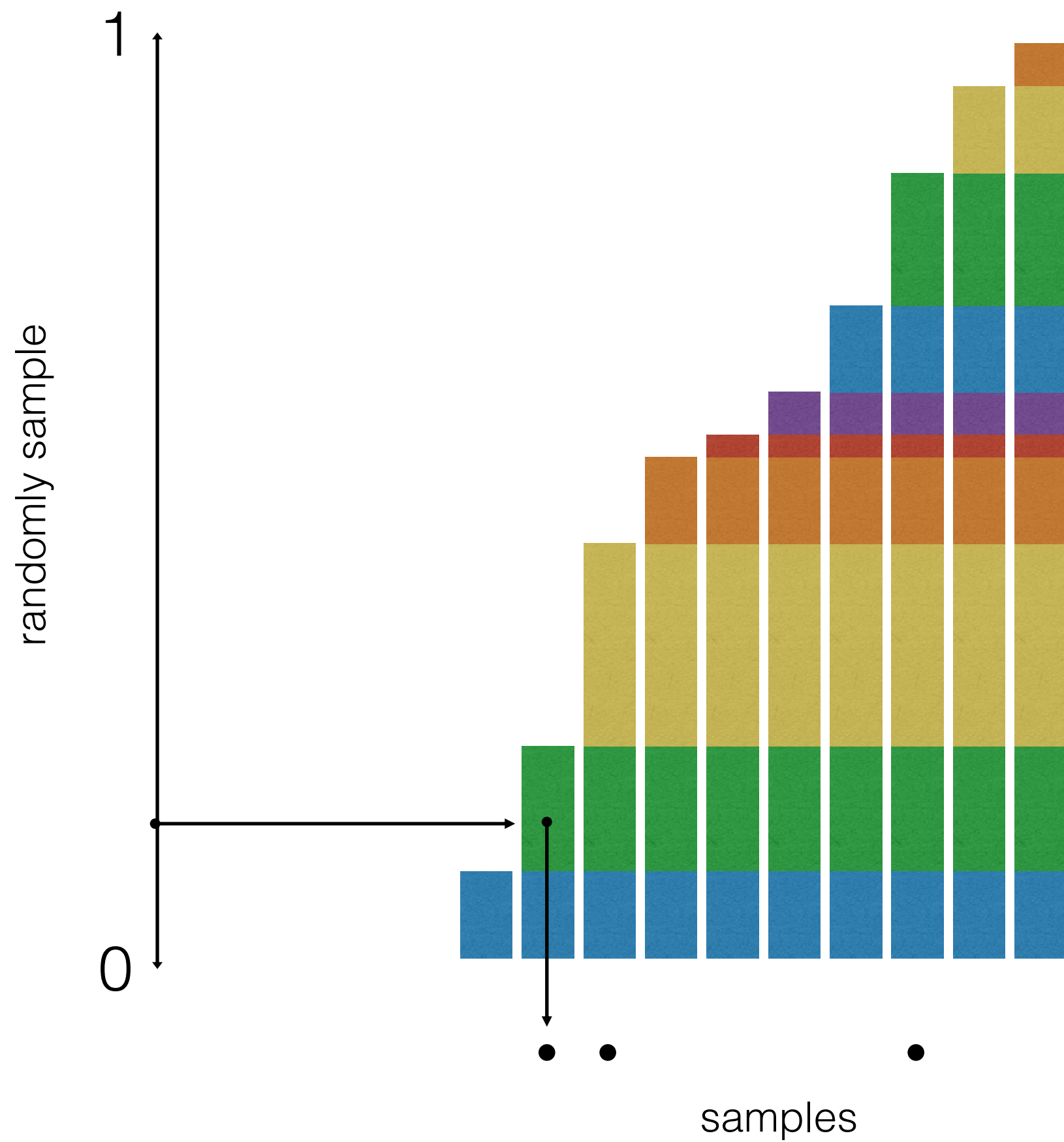
probability density function



cumulative density function







Now to estimate the 'hidden' PDF
place Gaussian bumps on the samples...

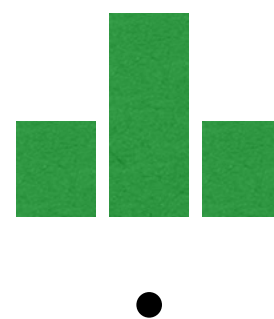
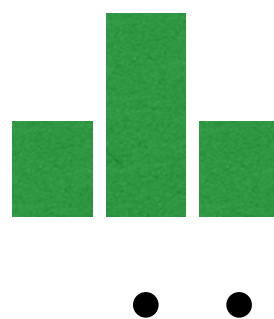


samples

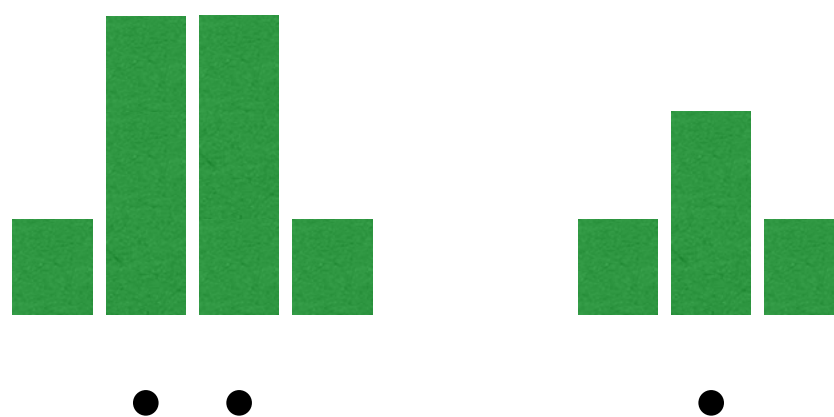


discretized 'bump'

samples

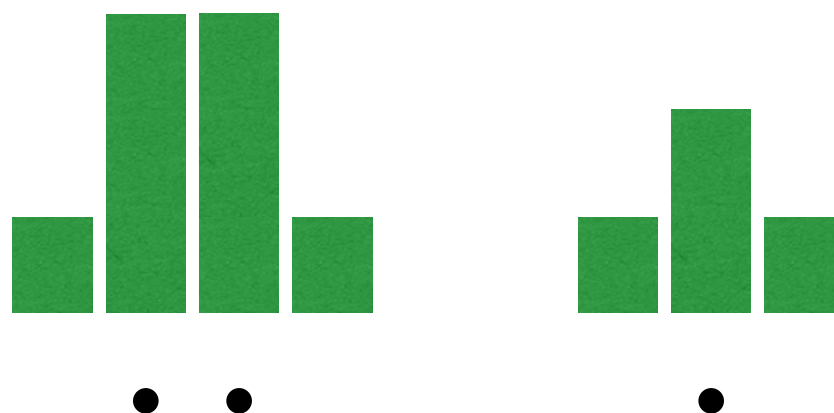
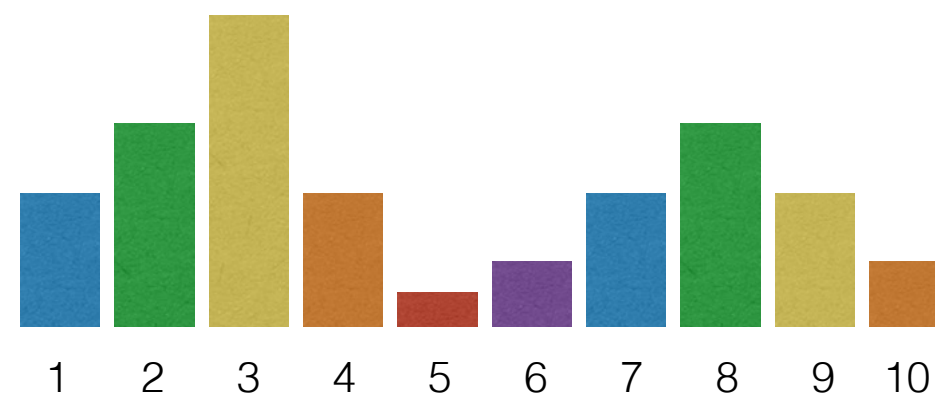


samples



samples

Kernel Density
Estimate
approximates the
original PDF



samples

Kernel Density Estimation

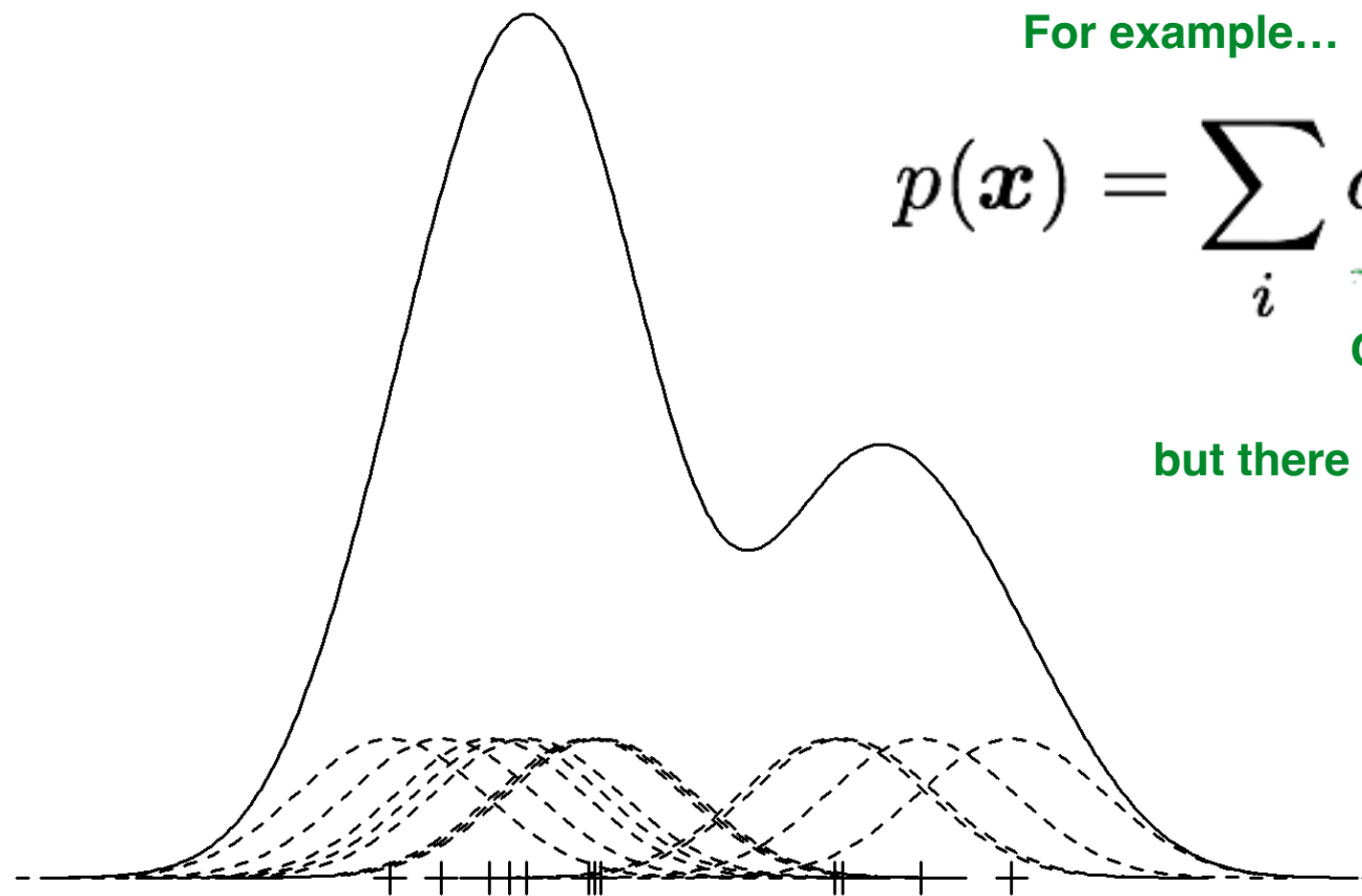
Approximate the underlying PDF from samples from it

For example...

$$p(\mathbf{x}) = \sum_i c_i \underbrace{e^{-\frac{(\mathbf{x} - \mathbf{x}_i)^2}{2\sigma^2}}}_{\text{Gaussian 'bump' aka 'kernel'}}$$

Gaussian 'bump' aka 'kernel'

but there are many types of kernels!



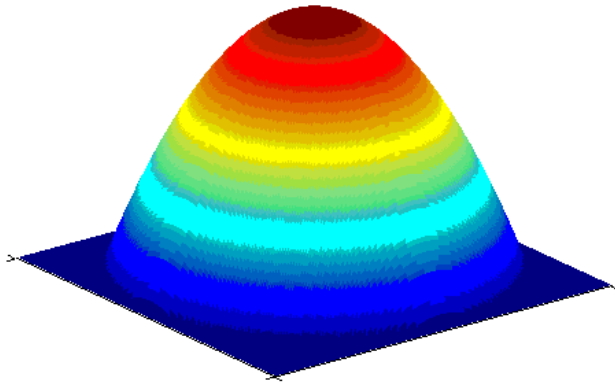
Put 'bump' on every sample to approximate the PDF

Kernel Function

$$K(\boldsymbol{x}, \boldsymbol{x}')$$

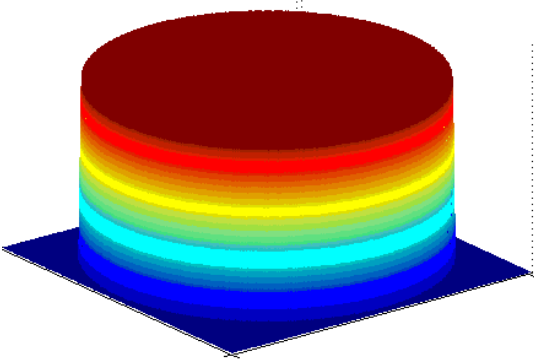
returns the 'distance' between two points

Epanechnikov kernel



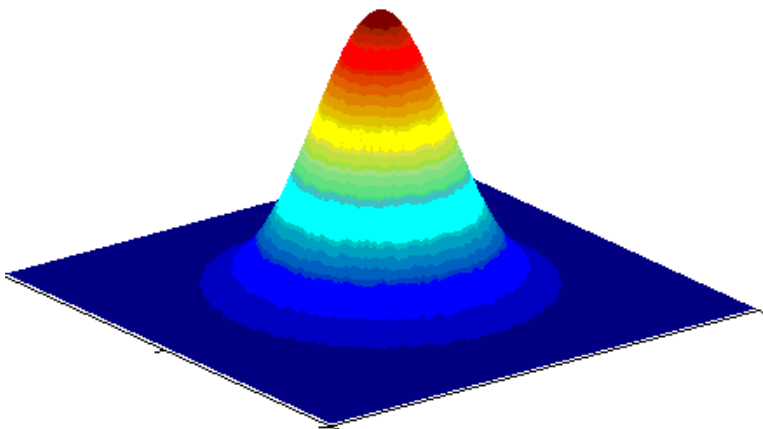
$$K(\mathbf{x}, \mathbf{x}') = \begin{cases} c(1 - \|\mathbf{x} - \mathbf{x}'\|^2) & \|\mathbf{x} - \mathbf{x}'\|^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Uniform kernel



$$K(\mathbf{x}, \mathbf{x}') = \begin{cases} c & \|\mathbf{x} - \mathbf{x}'\|^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Normal kernel




$$K(\mathbf{x}, \mathbf{x}') = c \exp \left(-\frac{1}{2} \|\mathbf{x} - \mathbf{x}'\|^2 \right)$$

These are all radially symmetric kernels

Radially symmetric kernels

...can be written in terms of its *profile*

$$K(\mathbf{x}, \mathbf{x}') = c \cdot k(\|\mathbf{x} - \mathbf{x}'\|^2)$$



profile

Connecting KDE and the Mean Shift Algorithm

Mean-Shift Tracking

Given a set of points:

$$\{\mathbf{x}_s\}_{s=1}^S \quad \mathbf{x}_s \in \mathcal{R}^d$$

and a kernel:

$$K(\mathbf{x}, \mathbf{x}')$$

Find the mean sample point:

$$\mathbf{x}$$

Mean-Shift Algorithm

Initialize \mathbf{x} place we start

While $v(\mathbf{x}) > \epsilon$ shift values becomes really small

1. Compute mean-shift

$$m(\mathbf{x}) = \frac{\sum_s K(\mathbf{x}, \mathbf{x}_s) \mathbf{x}_s}{\sum_s K(\mathbf{x}, \mathbf{x}_s)}$$

compute the 'mean'

$$v(\mathbf{x}) = m(\mathbf{x}) - \mathbf{x}$$

compute the 'shift'

2. Update $\mathbf{x} \leftarrow \mathbf{x} + v(\mathbf{x})$

update the point

Where does this algorithm come from?

Mean-Shift Algorithm

Initialize \mathbf{x}

While $v(\mathbf{x}) > \epsilon$

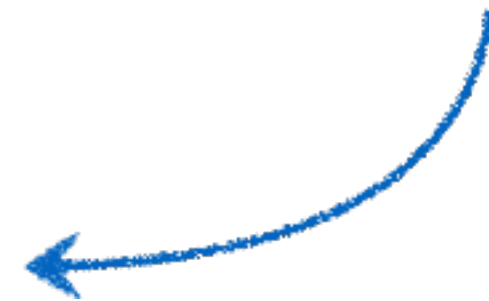
1. Compute mean-shift

$$m(\mathbf{x}) = \frac{\sum_s K(\mathbf{x}, \mathbf{x}_s) \mathbf{x}_s}{\sum_s K(\mathbf{x}, \mathbf{x}_s)}$$

$$v(\mathbf{x}) = m(\mathbf{x}) - \mathbf{x}$$

2. Update $\mathbf{x} \leftarrow \mathbf{x} + v(\mathbf{x})$

*Where does this
come from?*



Where does this algorithm come from?

How is the KDE related to the mean shift algorithm?

Recall:

Kernel density estimate

(radially symmetric kernels)

$$P(\mathbf{x}) = \frac{1}{N} c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

can compute probability for any point using the KDE!

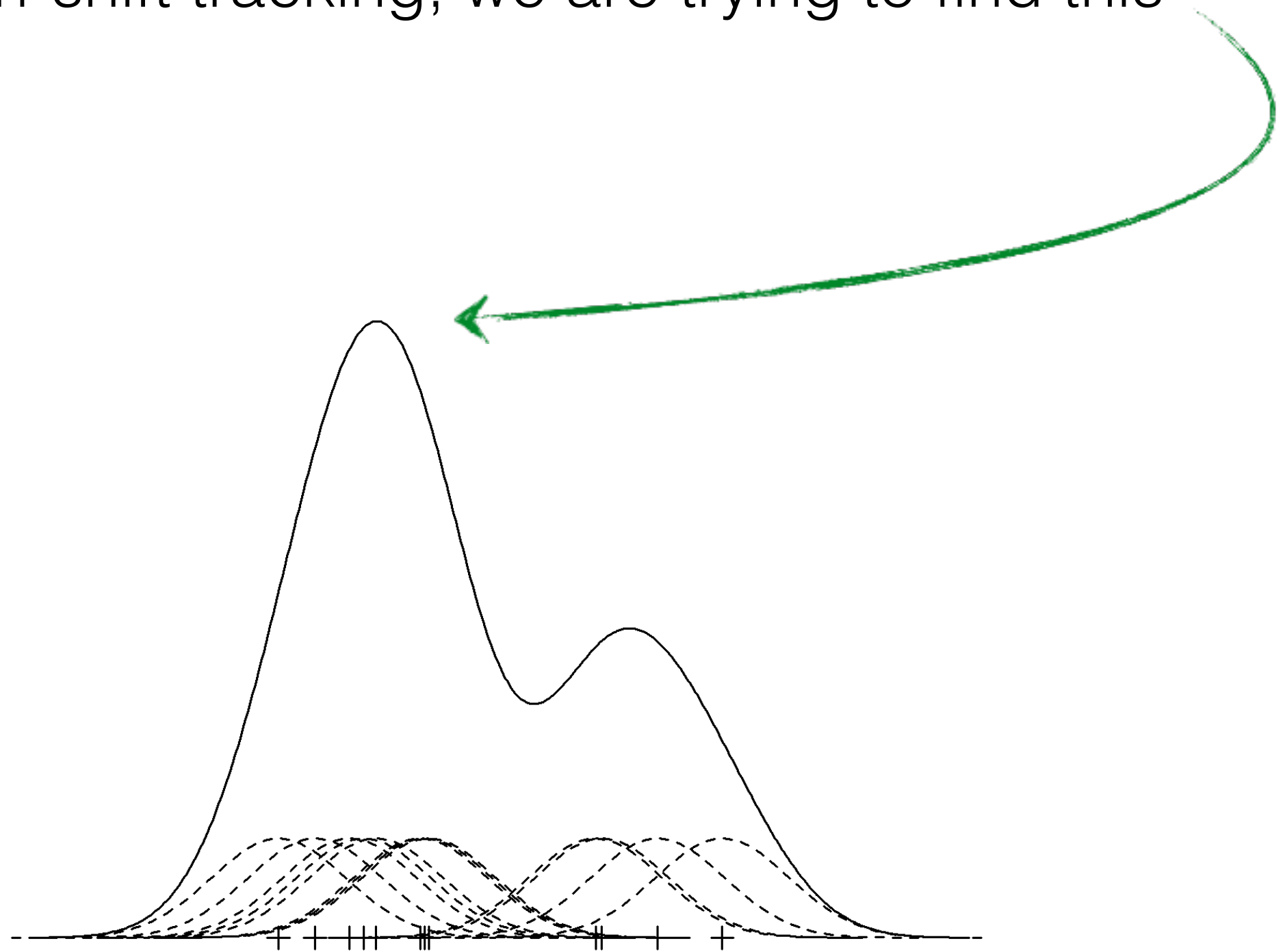
We can show that:

Gradient of the PDF is related to the mean shift vector

$$\nabla P(\mathbf{x}) \propto m(\mathbf{x})$$

The mean shift vector is a ‘step’ in the direction of the gradient of the KDE
mean-shift algorithm is maximizing the objective function

In mean-shift tracking, we are trying to find this



which means we are trying to...

We are trying to optimize this:

$$\mathbf{x} = \arg \max_{\mathbf{x}} P(\mathbf{x})$$

find the solution that has the highest probability

$$= \arg \max_{\mathbf{x}} \frac{1}{N} c \sum_n k(||\mathbf{x} - \mathbf{x}_n||^2)$$

usually non-linear

non-parametric

How do we optimize this non-linear function?

We are trying to optimize this:

$$\begin{aligned}\mathbf{x} &= \arg \max_{\mathbf{x}} P(\mathbf{x}) \\ &= \arg \max_{\mathbf{x}} \frac{1}{N} c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)\end{aligned}$$

usually non-linear non-parametric

How do we optimize this non-linear function?

compute partial derivatives ... **gradient descent!**

$$P(\boldsymbol{x}) = \frac{1}{N}c \sum_n k(\|\boldsymbol{x} - \boldsymbol{x}_n\|^2)$$

Compute the gradient

$$P(\mathbf{x}) = \frac{1}{N}c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}c \sum_n \nabla k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Expand the gradient (algebra)

$$P(\mathbf{x}) = \frac{1}{N}c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}c \sum_n \nabla k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Expand gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}2c \sum_n (\mathbf{x} - \mathbf{x}_n)k'(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

$$P(\mathbf{x}) = \frac{1}{N}c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}c \sum_n \nabla k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Expand gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}2c \sum_n (\mathbf{x} - \mathbf{x}_n)k'(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Call the gradient of the kernel function g

$$k'(\cdot) = -g(\cdot)$$

$$P(\mathbf{x}) = \frac{1}{N}c \sum_n k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}c \sum_n \nabla k(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

Expand gradient

$$\nabla P(\mathbf{x}) = \frac{1}{N}2c \sum_n (\mathbf{x} - \mathbf{x}_n)k'(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

change of notation
(kernel-shadow pairs)

$$\nabla P(\mathbf{x}) = \frac{1}{N}2c \sum_n (\mathbf{x}_n - \mathbf{x})g(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

keep this in memory: $k'(\cdot) = -g(\cdot)$

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n (\mathbf{x}_n - \mathbf{x}) g(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

multiply it out

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n \mathbf{x}_n g(\|\mathbf{x} - \mathbf{x}_n\|^2) - \frac{1}{N} 2c \sum_n \mathbf{x} g(\|\mathbf{x} - \mathbf{x}_n\|^2)$$

too long!

(use short hand notation)

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n \mathbf{x}_n g_n - \frac{1}{N} 2c \sum_n \mathbf{x} g_n$$

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n \mathbf{x}_n g_n - \frac{1}{N} 2c \sum_n \mathbf{x} g_n$$

multiply by one!

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n \mathbf{x}_n g_n \left(\frac{\sum_n g_n}{\sum_n g_n} \right) - \frac{1}{N} 2c \sum_n \mathbf{x} g_n$$

collecting like terms...

$$\nabla P(\mathbf{x}) = \frac{1}{N} 2c \sum_n g_n \left(\frac{\sum_n \mathbf{x}_n g_n}{\sum_n g_n} - \mathbf{x} \right)$$

What's happening here?

$$\nabla P(\mathbf{x}) = \underbrace{\frac{1}{N} 2c \sum_n g_n}_{\text{constant}} \underbrace{\left(\frac{\sum_n \mathbf{x}_n g_n}{\sum_n g_n} - \mathbf{x} \right)}_{\text{mean shift!}}$$

mean
shift

The **mean shift** is a 'step' in the direction of the gradient of the KDE

Let

$$\mathbf{v}(\mathbf{x}) = \left(\frac{\sum_n \mathbf{x}_n g_n}{\sum_n g_n} - \mathbf{x} \right) = \frac{\nabla P(\mathbf{x})}{\frac{1}{N} 2c \sum_n g_n}$$

Can interpret this to be
gradient ascent with
data dependent step size

Mean-Shift Algorithm

Initialize \mathbf{x}

While $v(\mathbf{x}) > \epsilon$

1. Compute mean-shift

$$m(\mathbf{x}) = \frac{\sum_s K(\mathbf{x}, \mathbf{x}_s) \mathbf{x}_s}{\sum_s K(\mathbf{x}, \mathbf{x}_s)}$$

$$v(\mathbf{x}) = m(\mathbf{x}) - \mathbf{x}$$

2. Update $\mathbf{x} \leftarrow \mathbf{x} + v(\mathbf{x})$

gradient with
adaptive step size

$$\frac{\nabla P(\mathbf{x})}{\frac{1}{N} 2c \sum_n g_n}$$

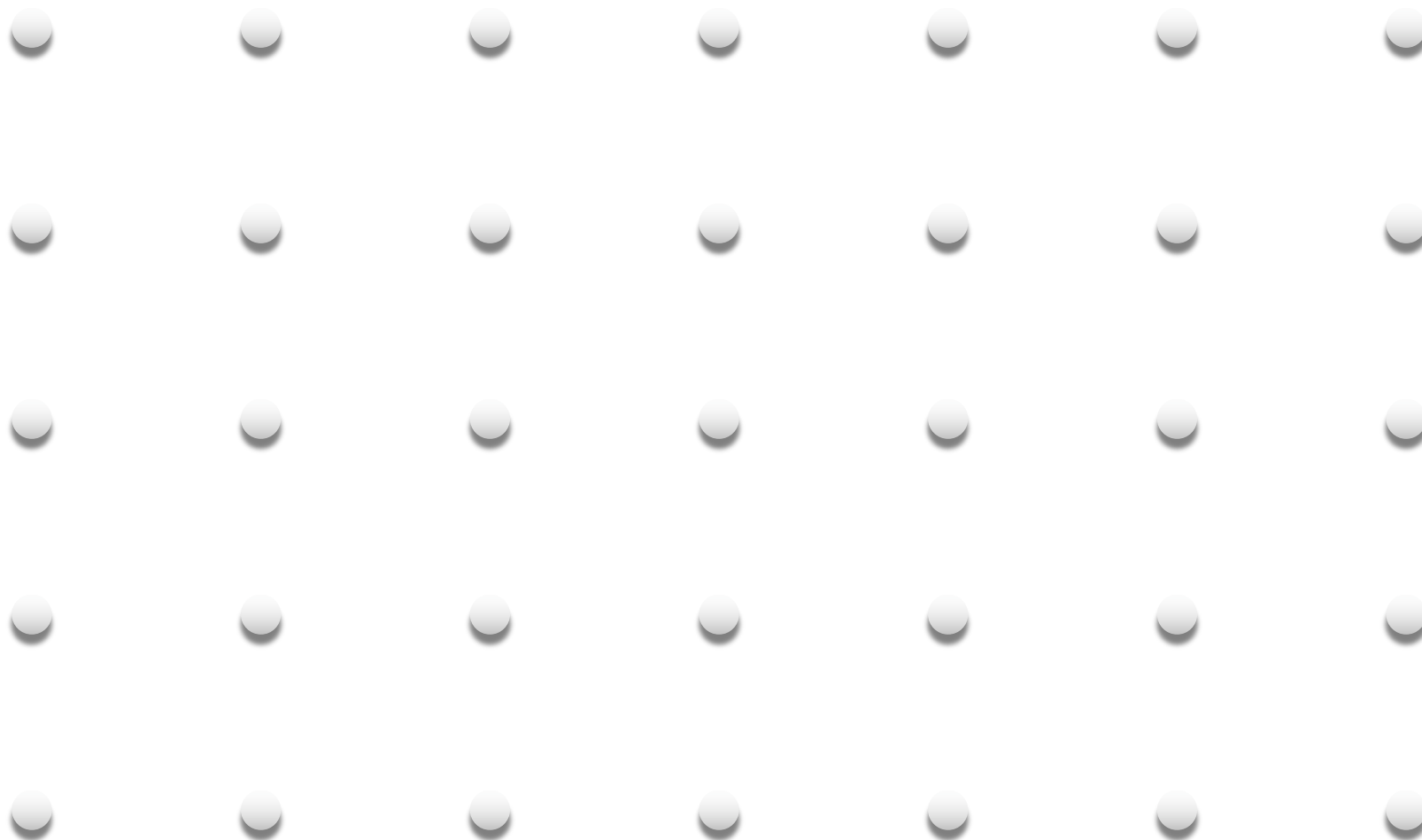
Just 5 lines of code!

Everything up to now has been about
distributions over samples...

Mean-shift tracker

Dealing with images

Pixels for a lattice, spatial density is the same everywhere!



What can we do?

same
Consider a set of points: $\{\mathbf{x}_s\}_{s=1}^S$ $\mathbf{x}_s \in \mathcal{R}^d$

Associated weights: $w(\mathbf{x}_s)$

Sample mean: $m(\mathbf{x}) = \frac{\sum_s K(\mathbf{x}, \mathbf{x}_s) w(\mathbf{x}_s) \mathbf{x}_s}{\sum_s K(\mathbf{x}, \mathbf{x}_s) w(\mathbf{x}_s)}$

same
Mean shift: $m(\mathbf{x}) - \mathbf{x}$

Mean-Shift Algorithm

(for images)

Initialize \mathbf{x}

While $v(\mathbf{x}) > \epsilon$

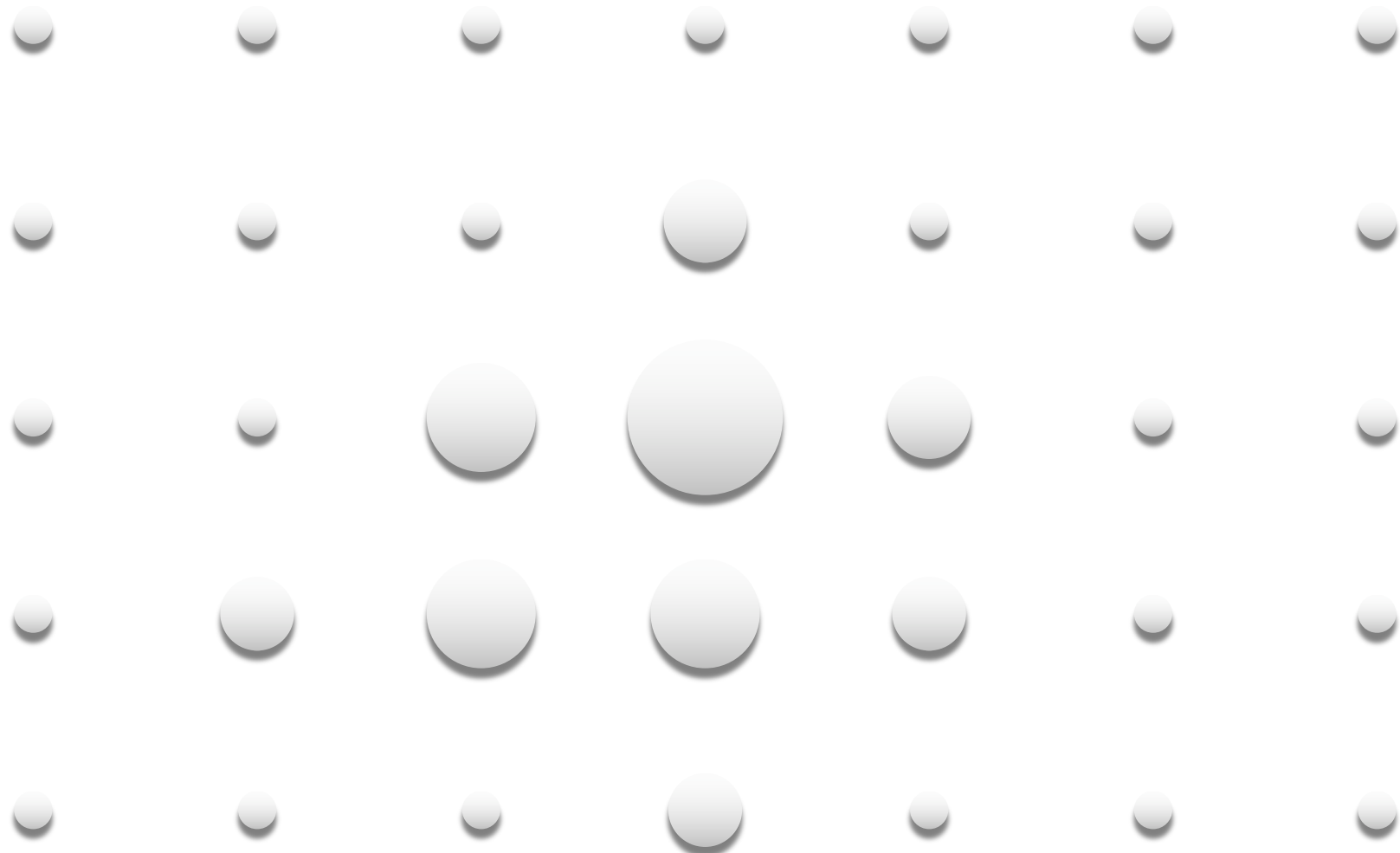
1. Compute mean-shift

$$m(\mathbf{x}) = \frac{\sum_s K(\mathbf{x}, \mathbf{x}_s) w(\mathbf{x}_s) \mathbf{x}_s}{\sum_s K(\mathbf{x}, \mathbf{x}_s) w(\mathbf{x}_s)}$$

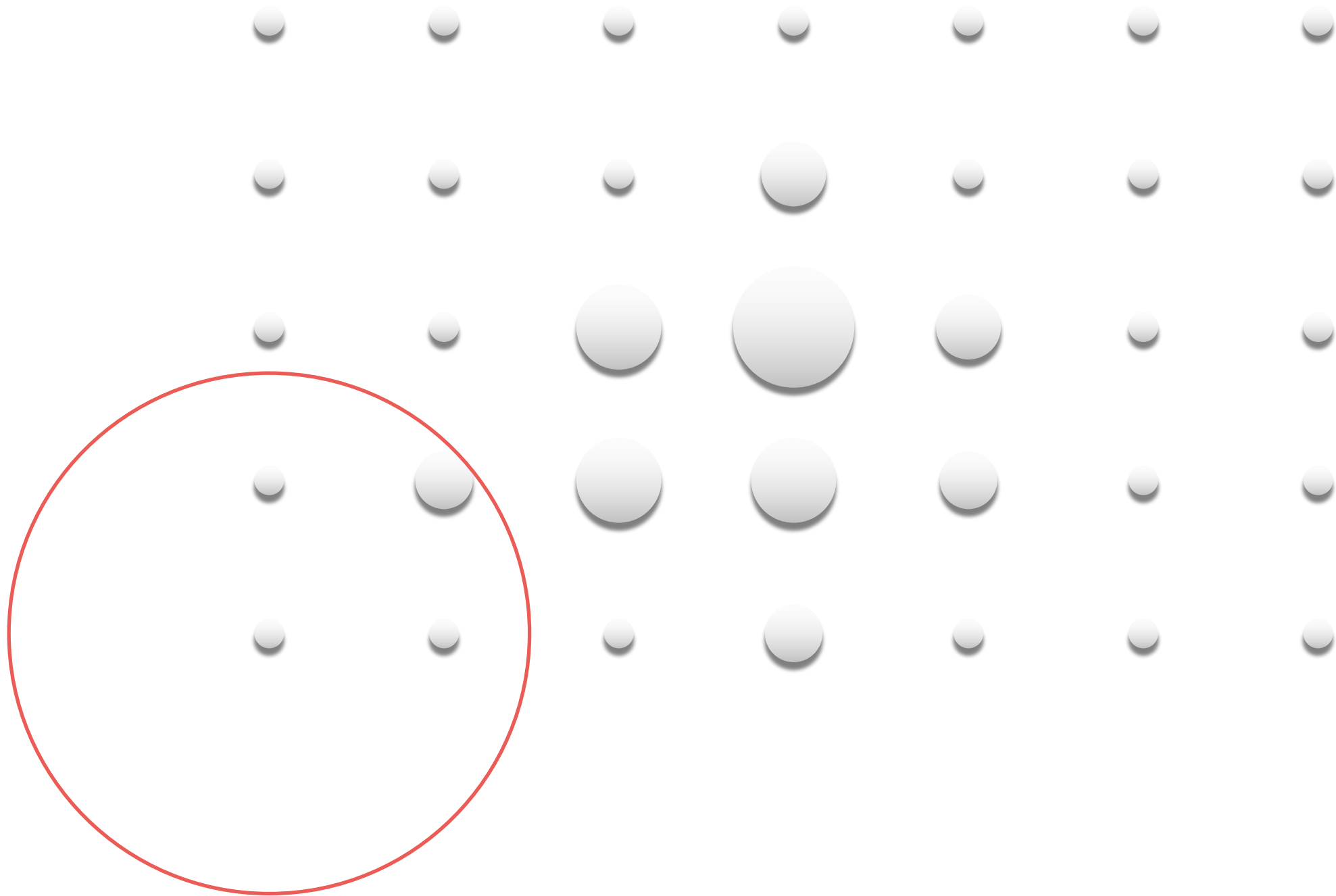
$$v(\mathbf{x}) = m(\mathbf{x}) - \mathbf{x}$$

2. Update $\mathbf{x} \leftarrow \mathbf{x} + v(\mathbf{x})$

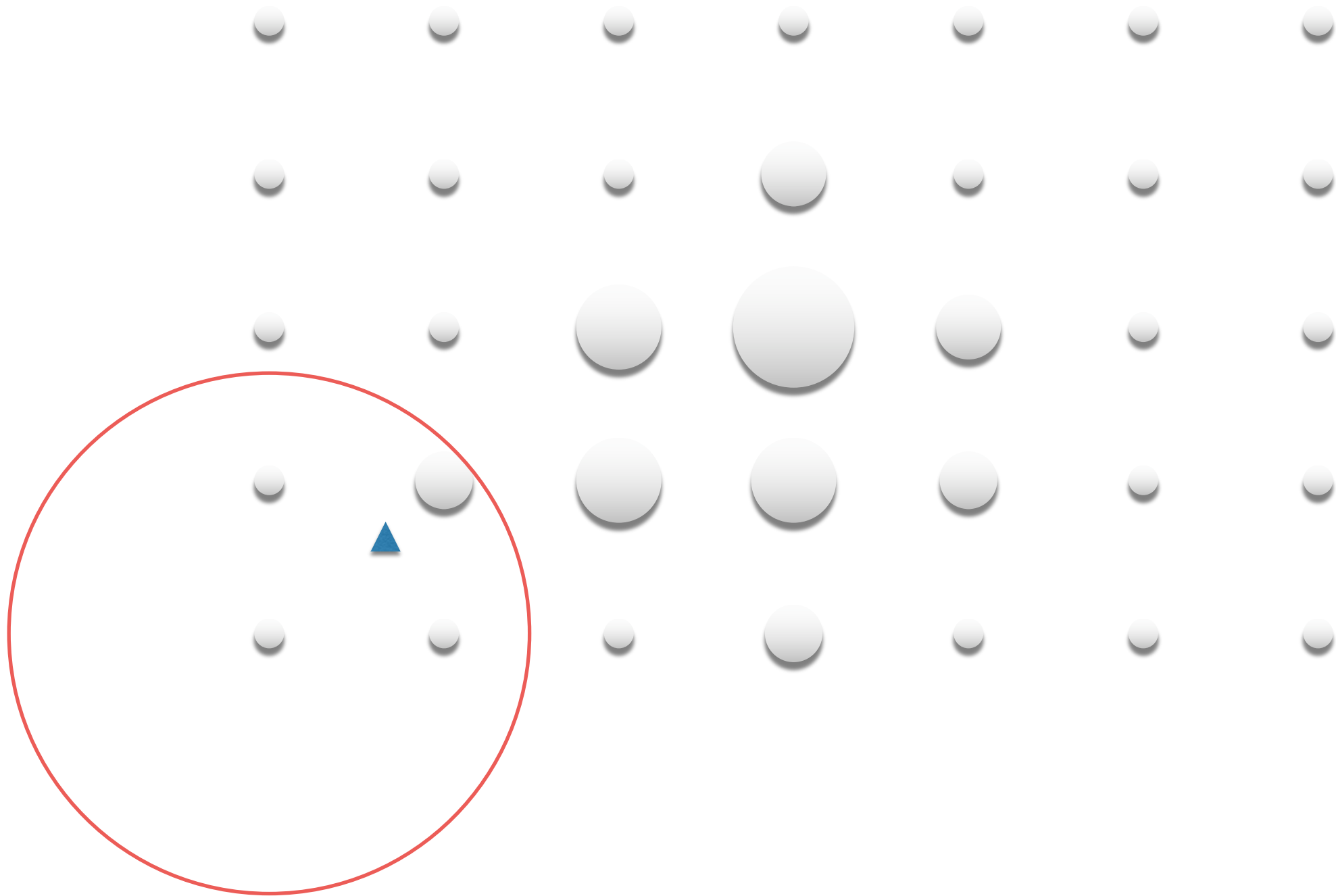
For images, each pixel is point with a weight



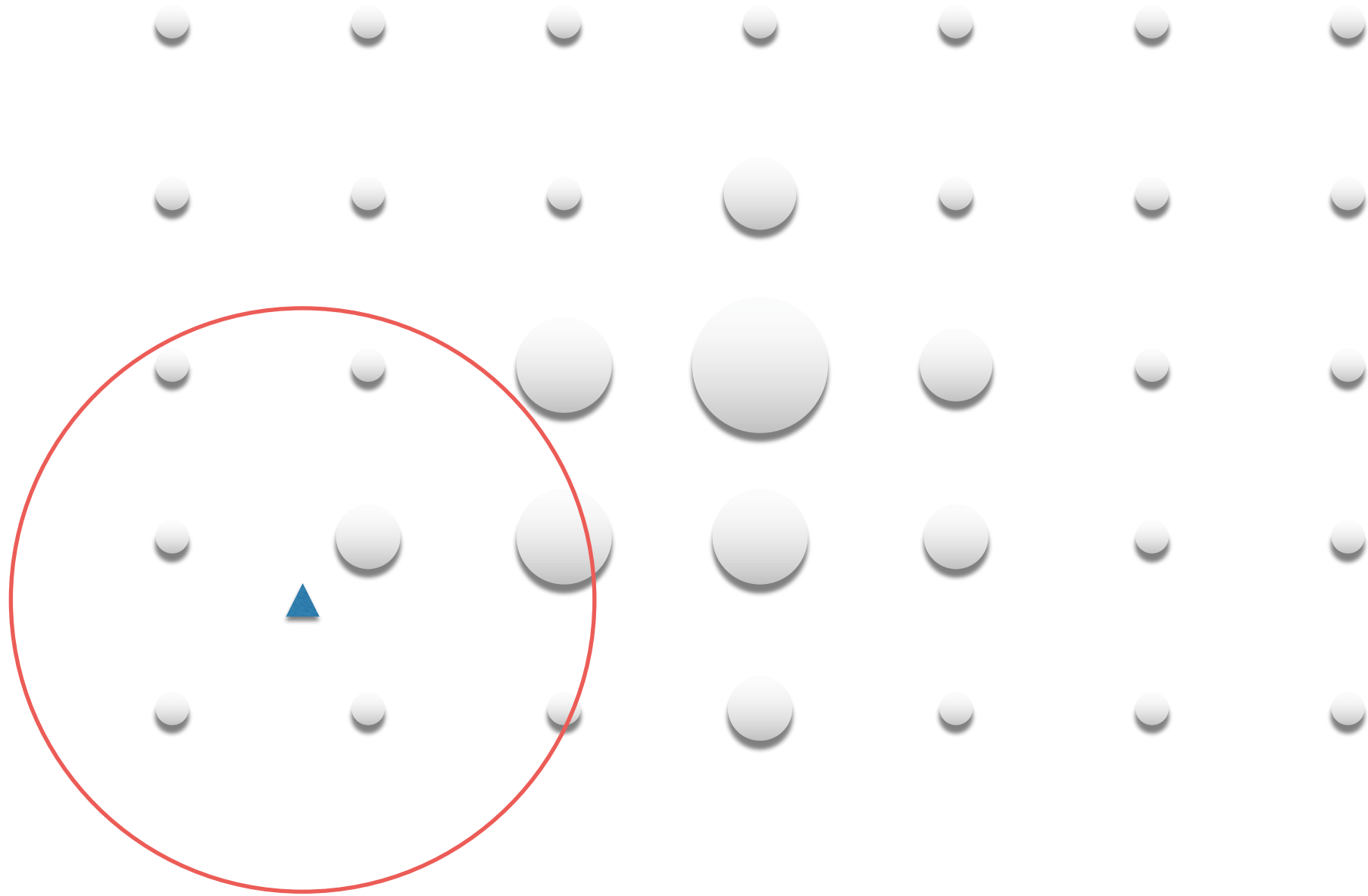
For images, each pixel is point with a weight



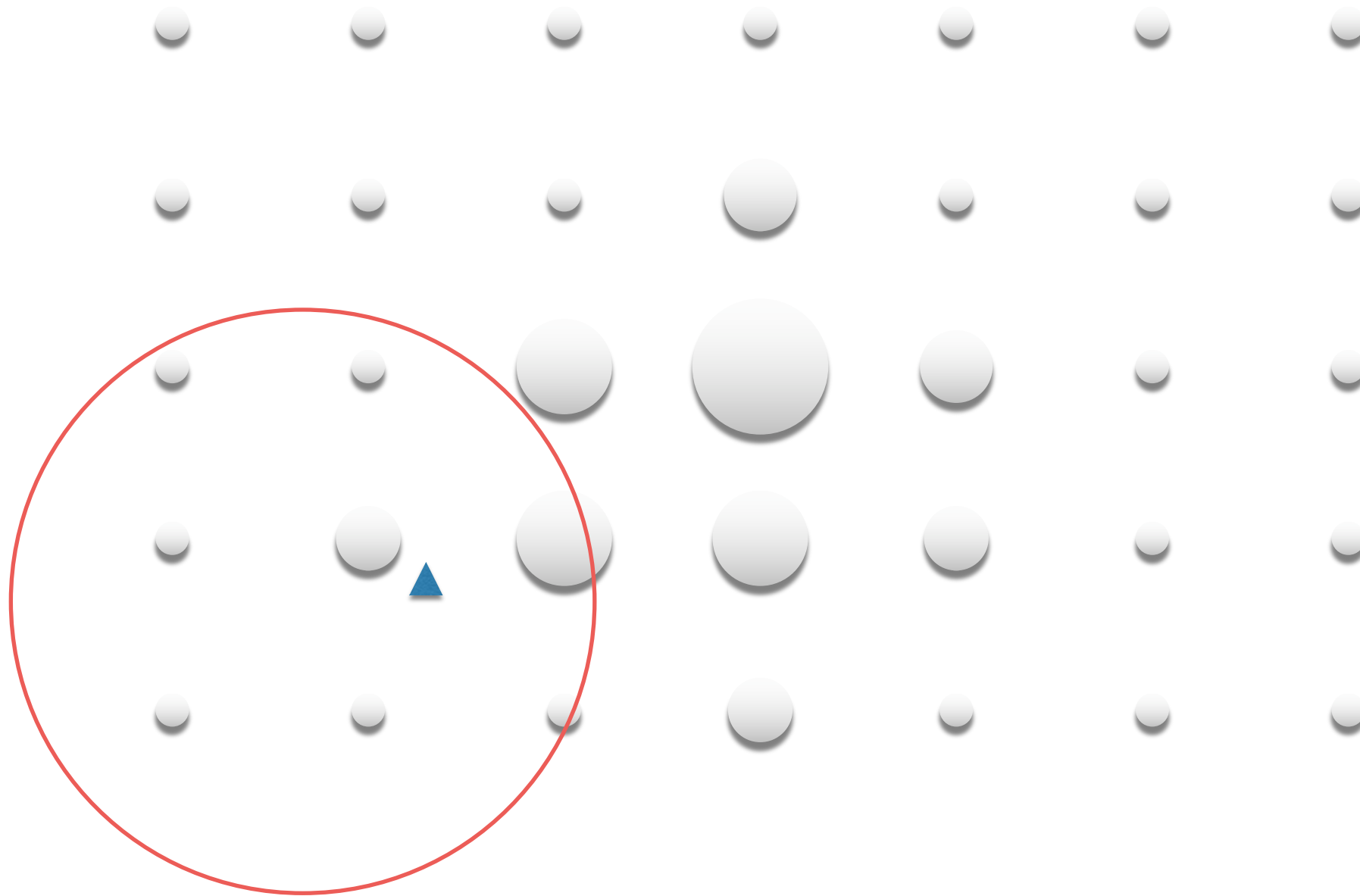
For images, each pixel is point with a weight



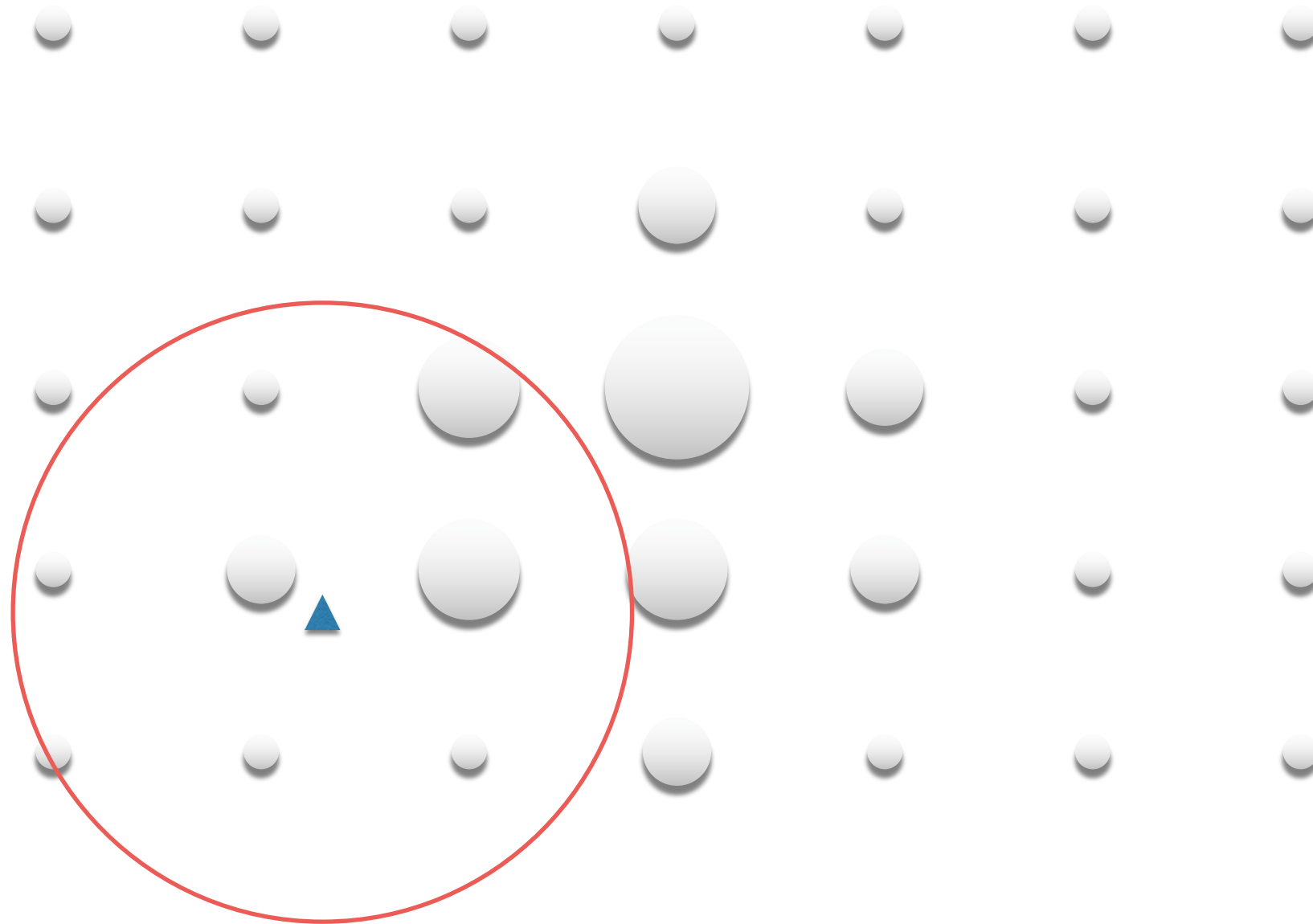
For images, each pixel is point with a weight



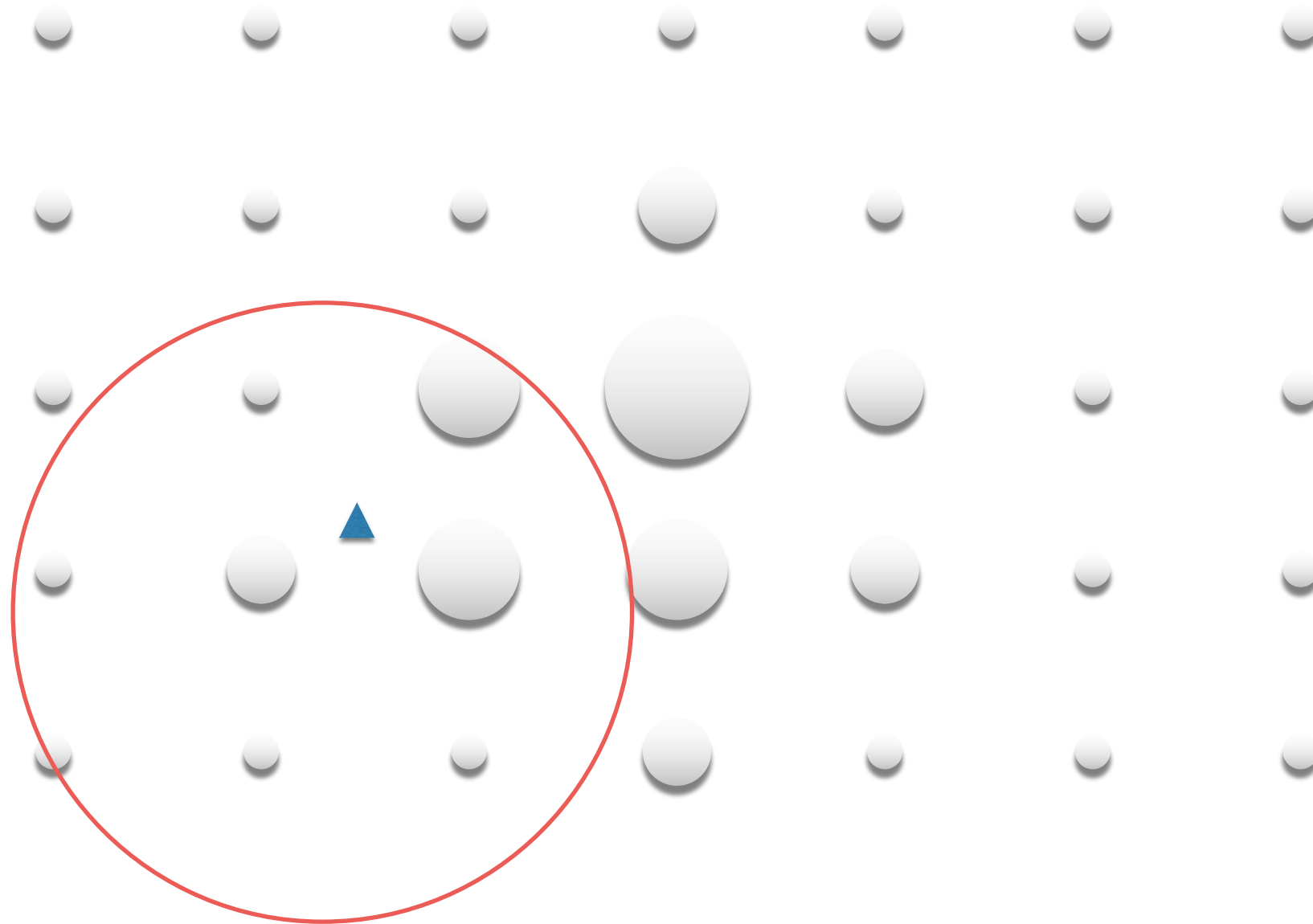
For images, each pixel is point with a weight



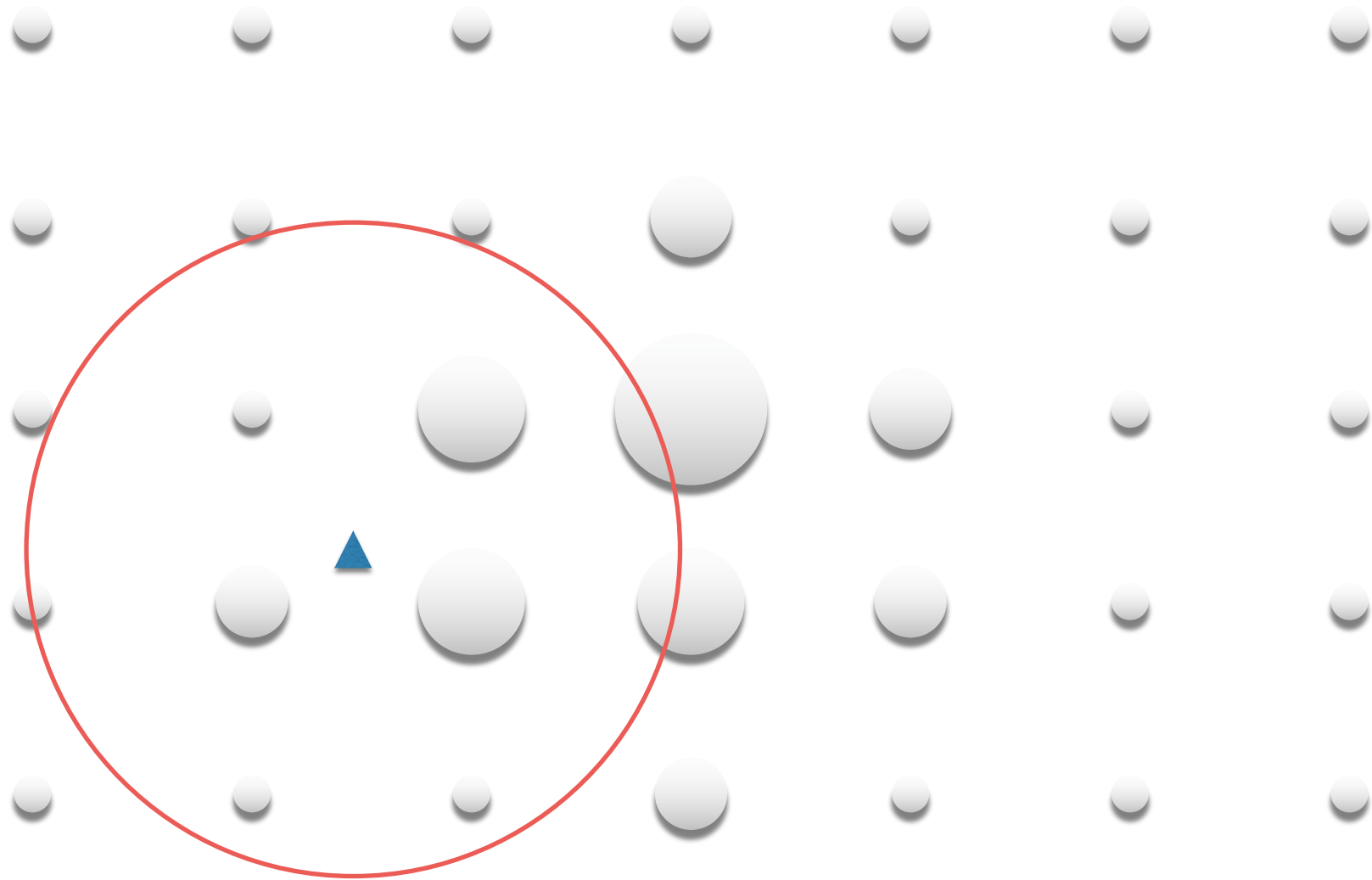
For images, each pixel is point with a weight



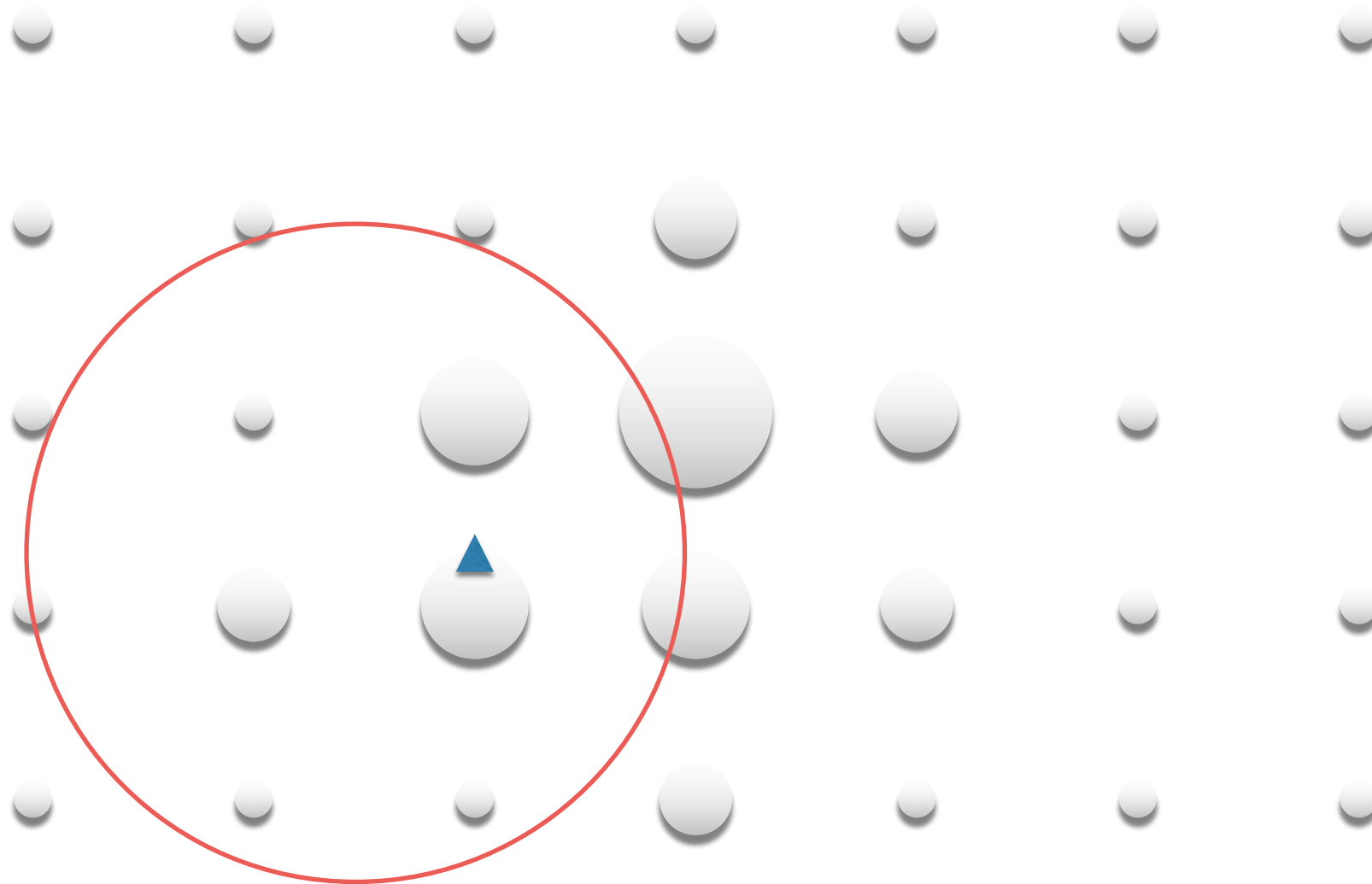
For images, each pixel is point with a weight



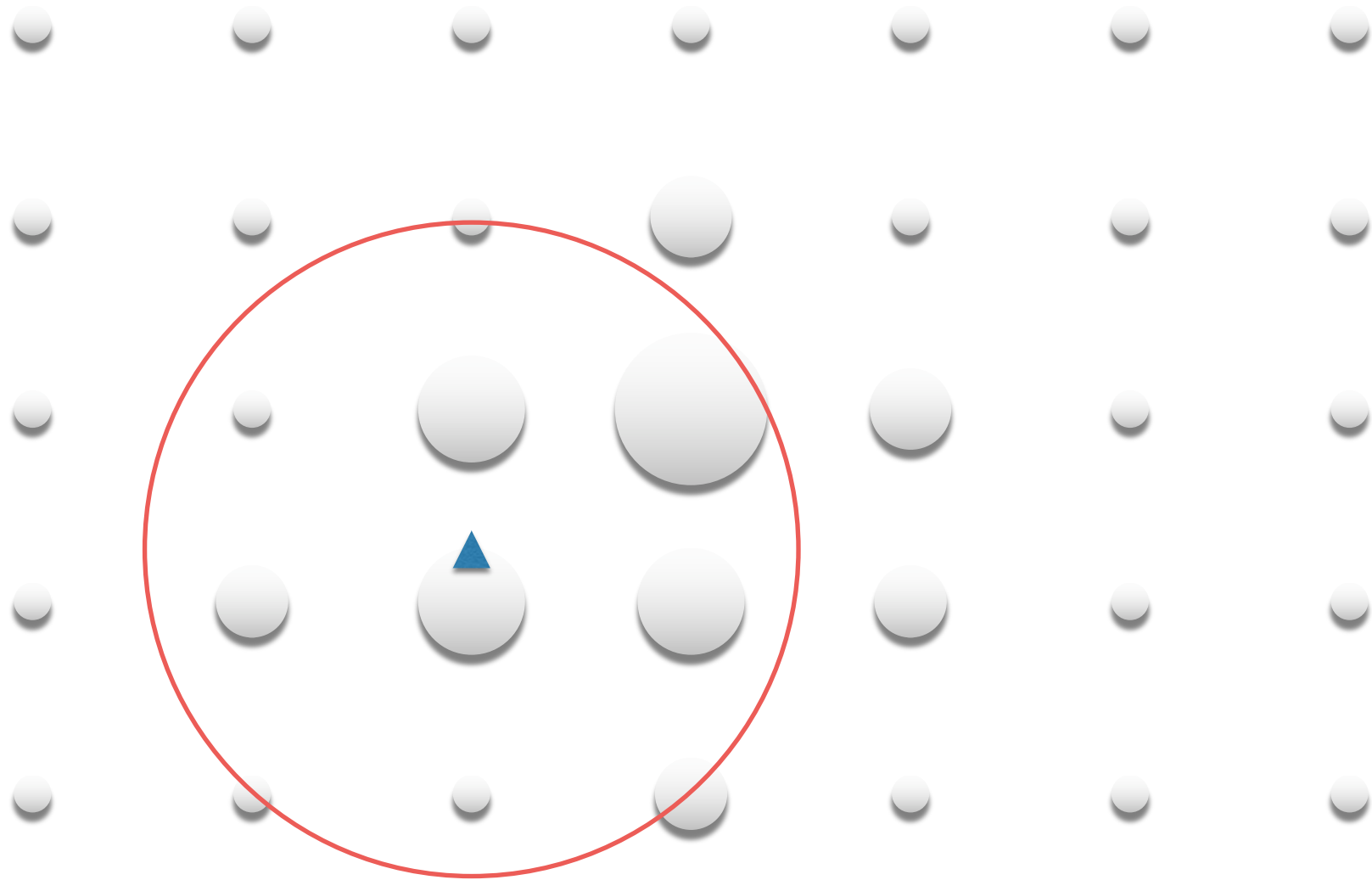
For images, each pixel is point with a weight



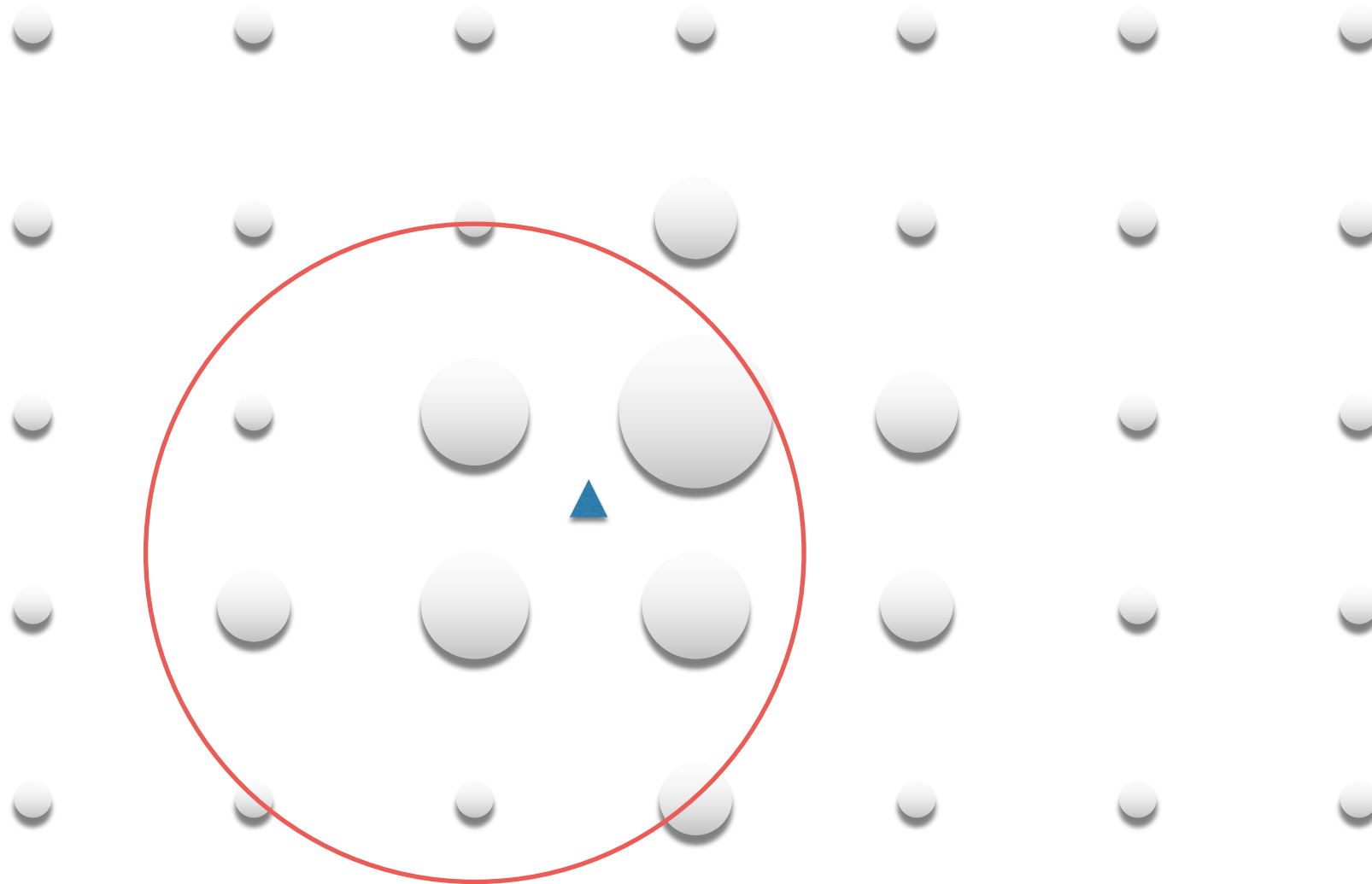
For images, each pixel is point with a weight



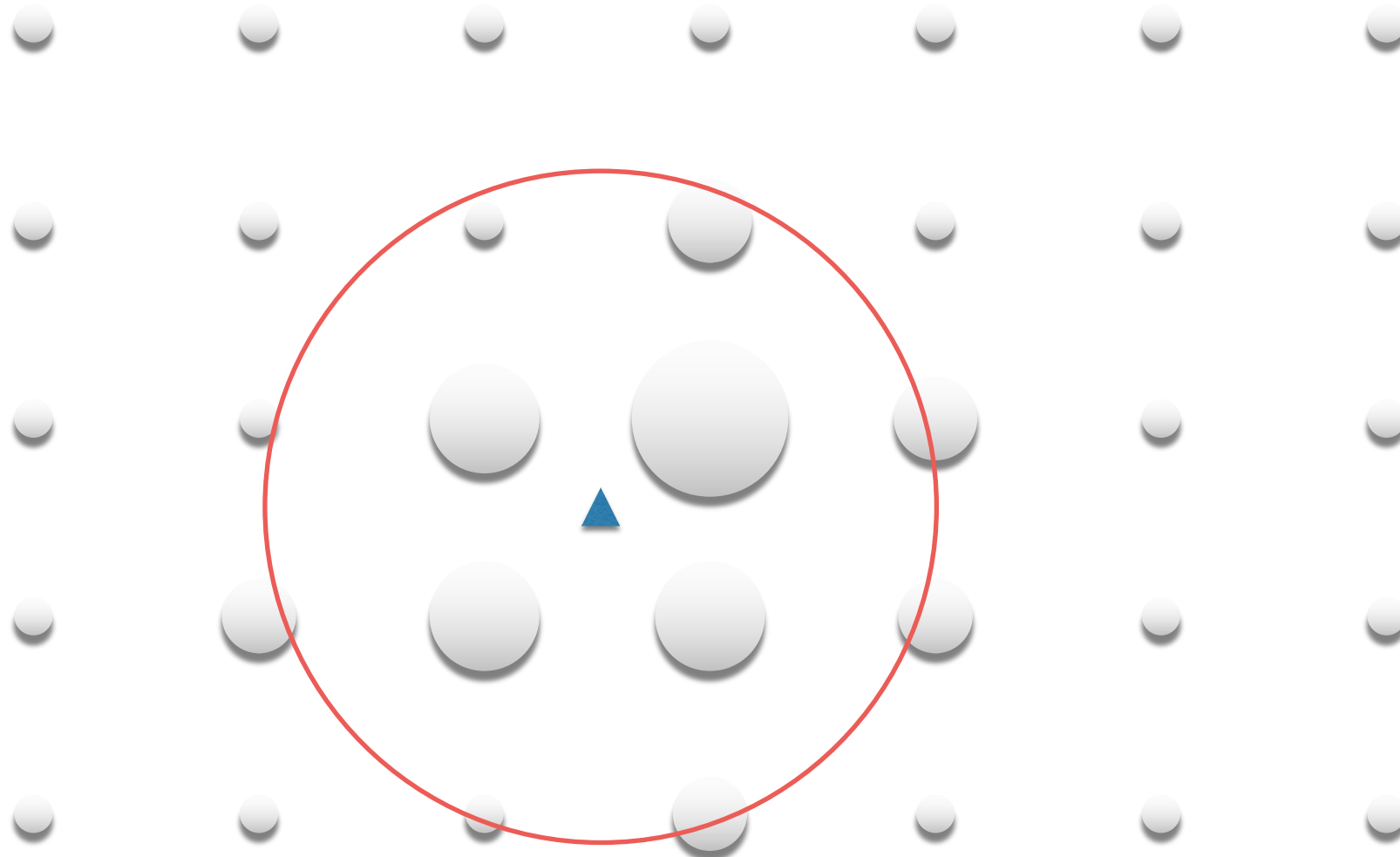
For images, each pixel is point with a weight



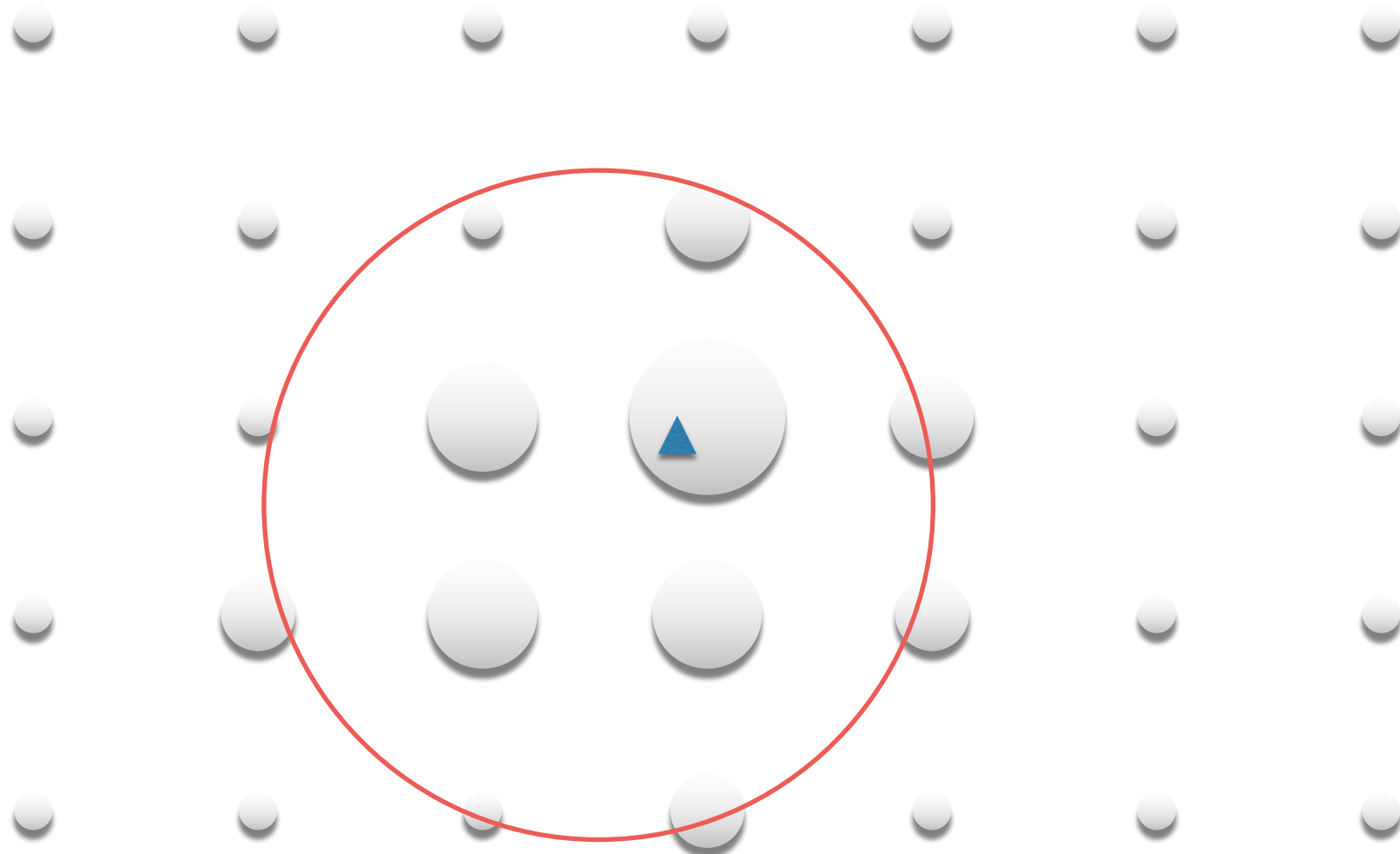
For images, each pixel is point with a weight



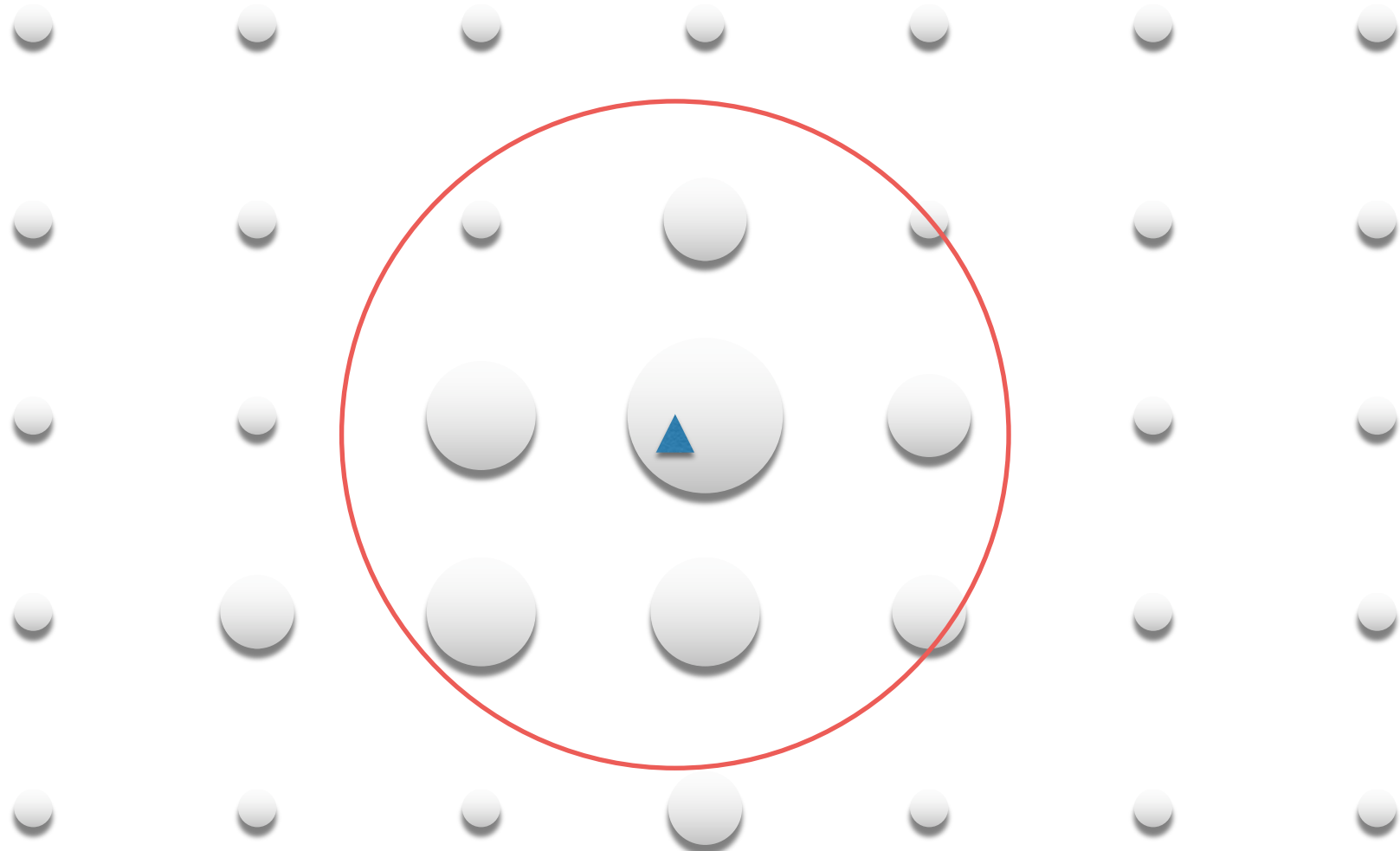
For images, each pixel is point with a weight



For images, each pixel is point with a weight

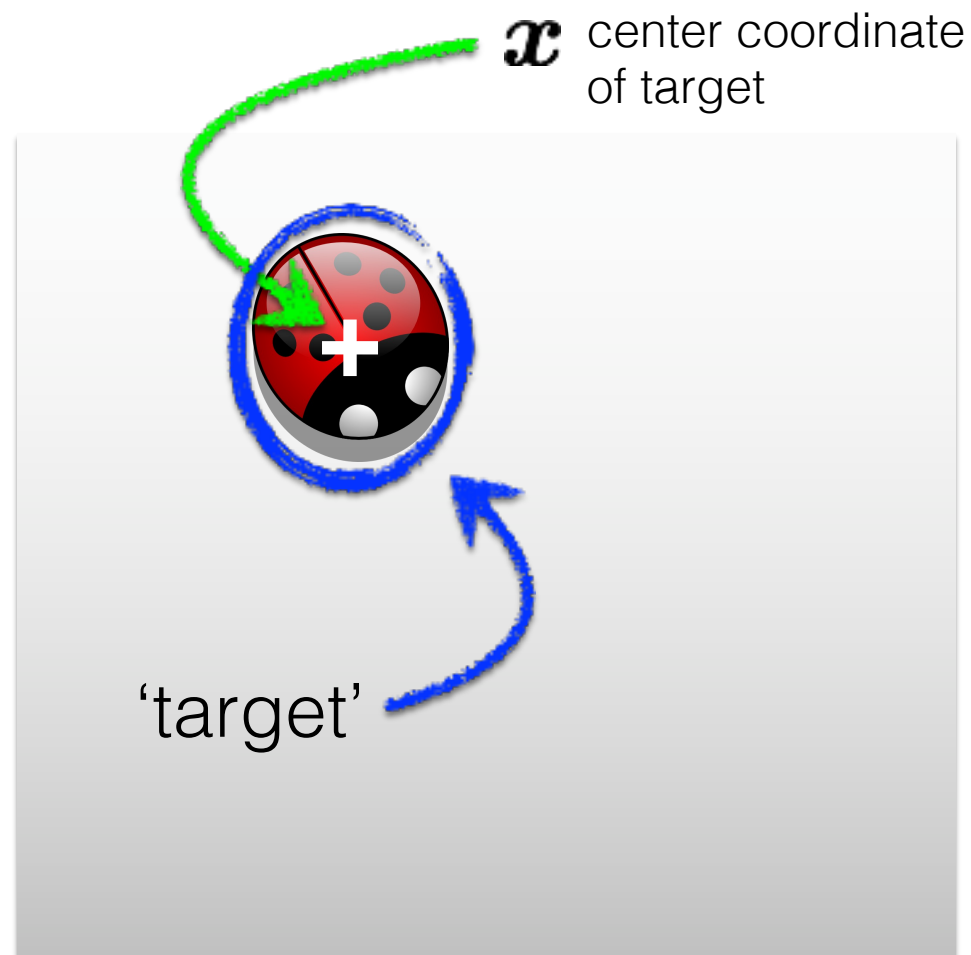


For images, each pixel is point with a weight



Finally... mean shift tracking in video!

Goal: find the best candidate location in frame 2



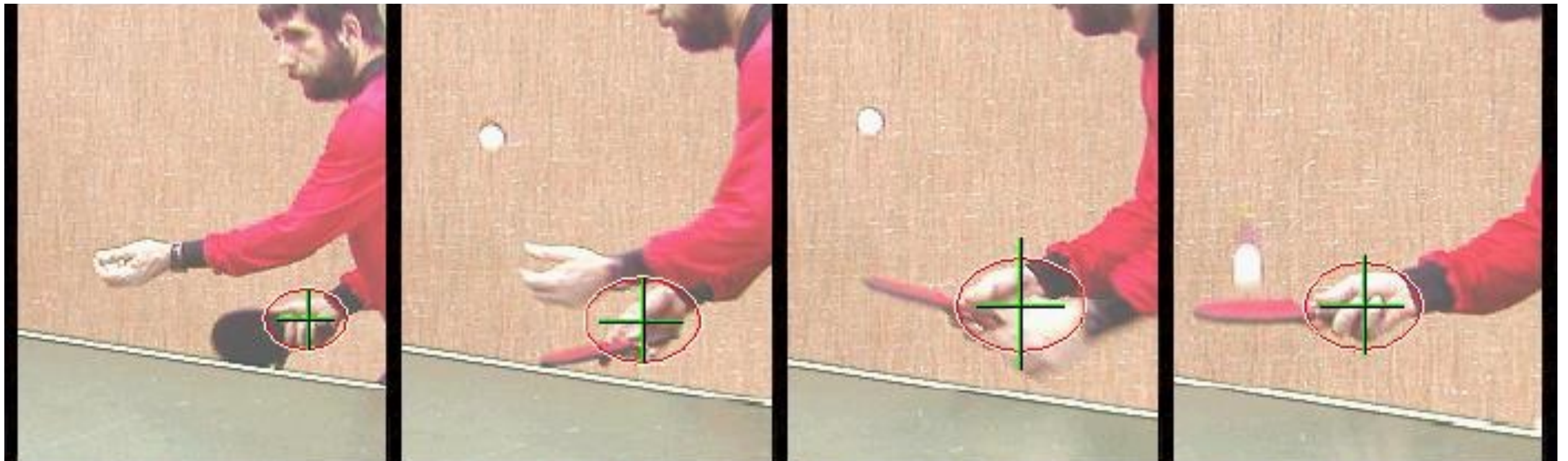
Frame 1



Frame 2

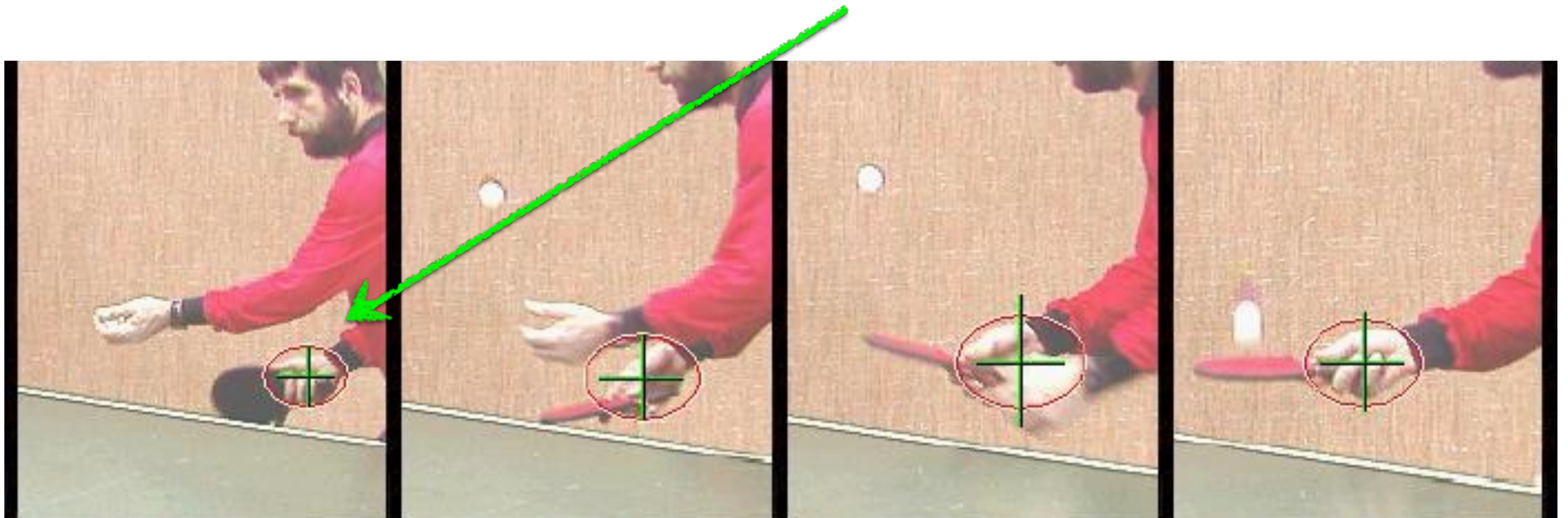
Use the mean shift algorithm
to find the best candidate location

Non-rigid object tracking



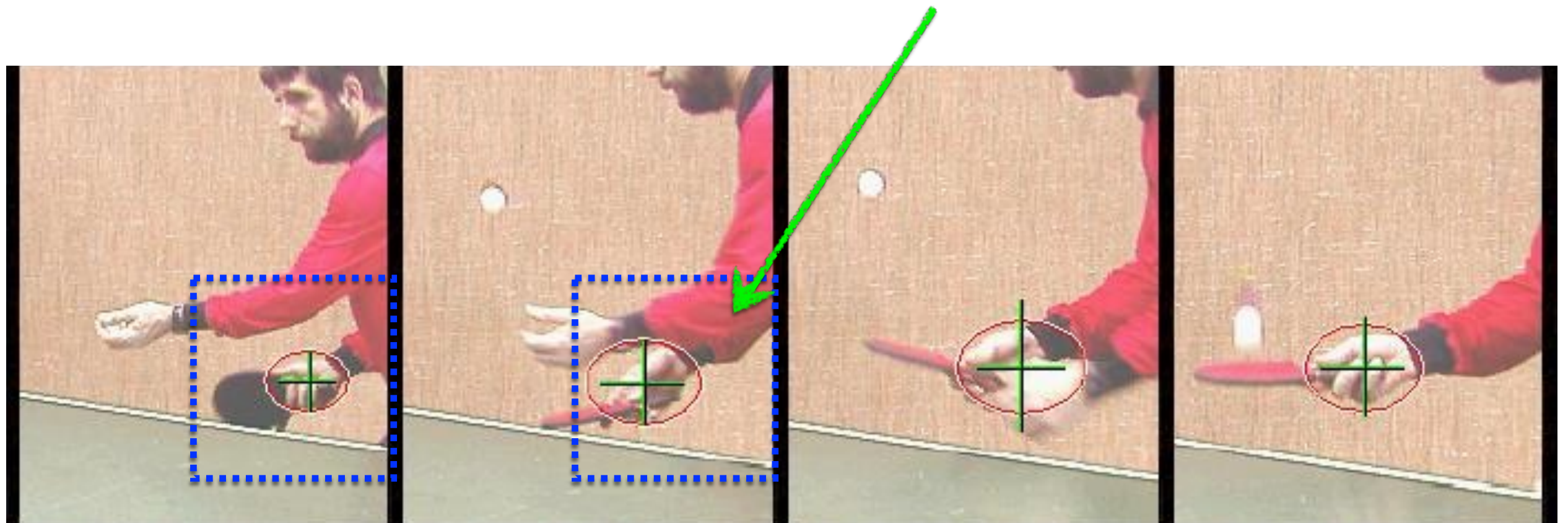
hand tracking

Compute a descriptor for the target



Target

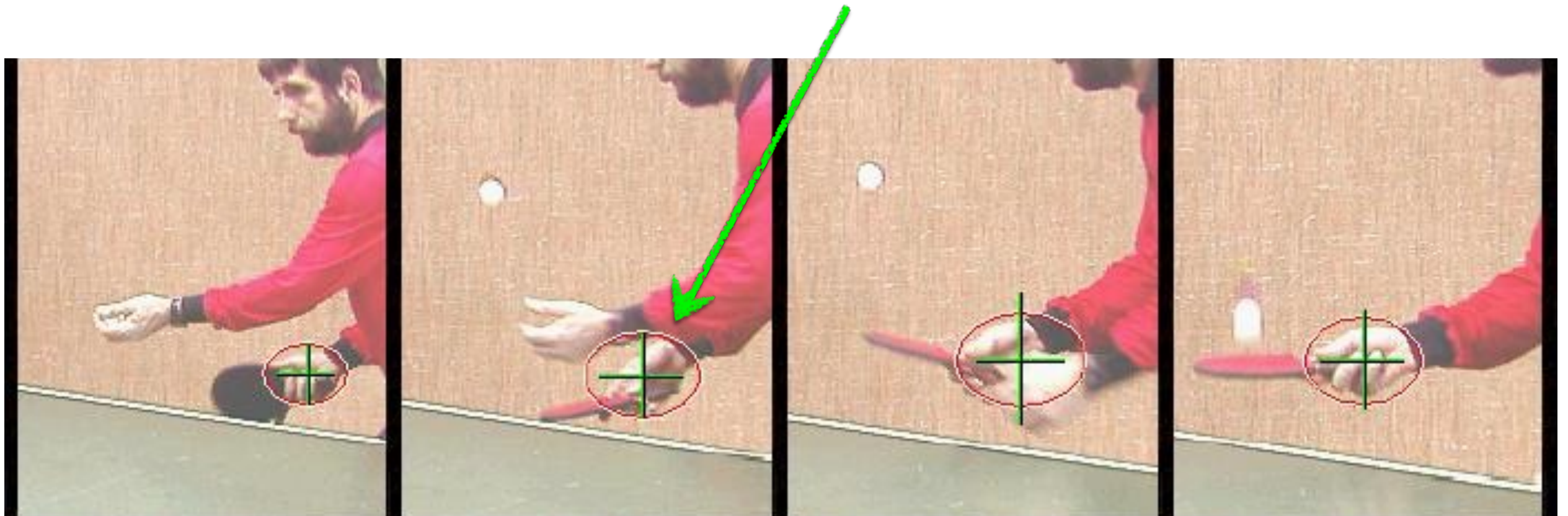
Search for similar descriptor in neighborhood in next frame



Target

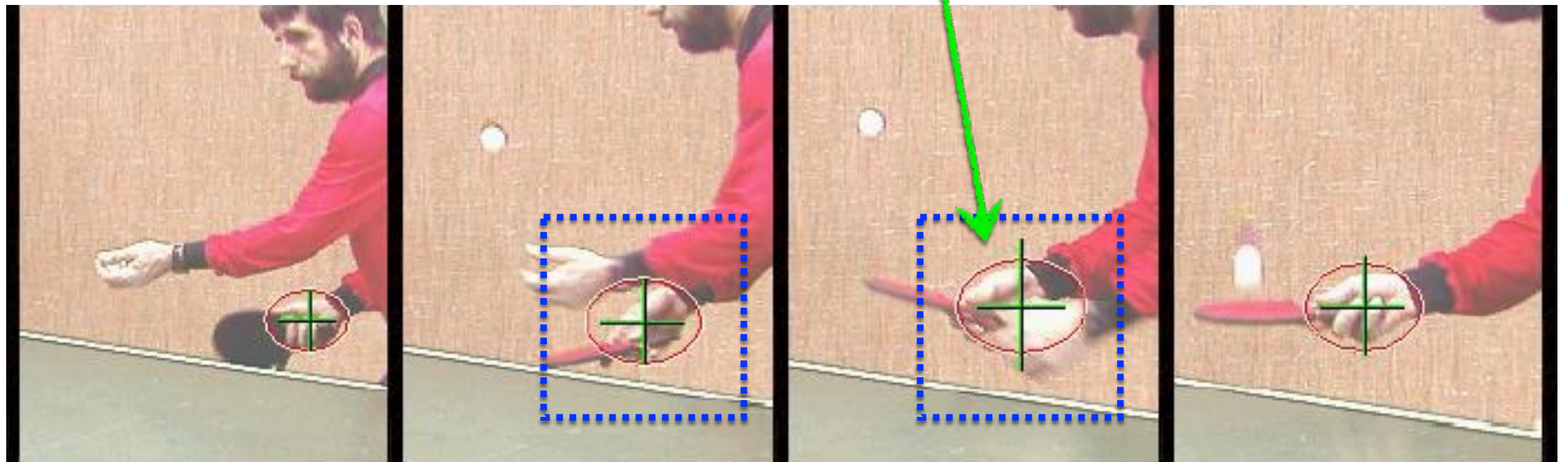
Candidate

Compute a descriptor for the new target



Target

Search for similar descriptor in neighborhood in next frame



Target

Candidate

How do we model the target and candidate regions?

Modeling the target



M-dimensional **target** descriptor

$$\mathbf{q} = \{q_1, \dots, q_M\}$$

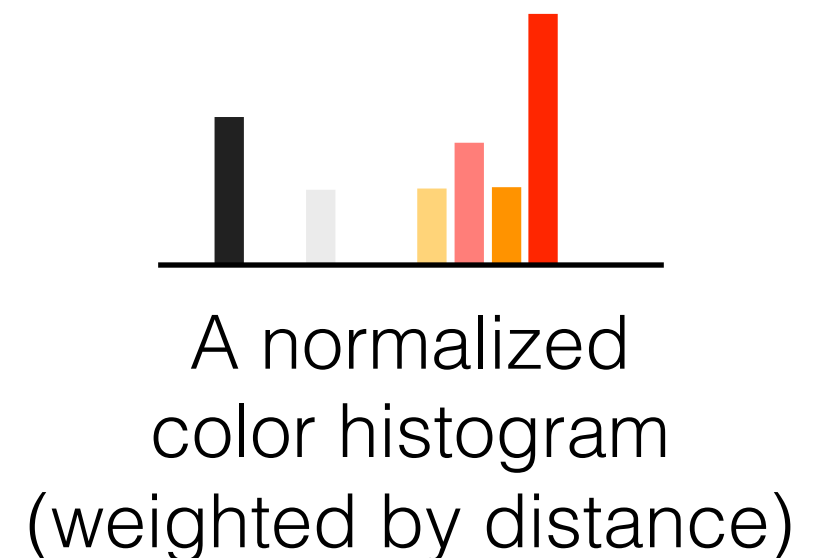
(centered at target center)

a 'fancy' (confusing) way to write a weighted histogram

$$q_m = C \sum_n k(\|\mathbf{x}_n\|^2) \delta[b(\mathbf{x}_n) - m]$$

Annotations for the equation:

- C : Normalization factor
- \sum_n : sum over all pixels
- $k(\|\mathbf{x}_n\|^2)$: function of inverse distance (weight)
- δ : Kronecker delta function
- $b(\mathbf{x}_n)$: quantization function
- m : bin ID



Modeling the candidate

M-dimensional **candidate** descriptor

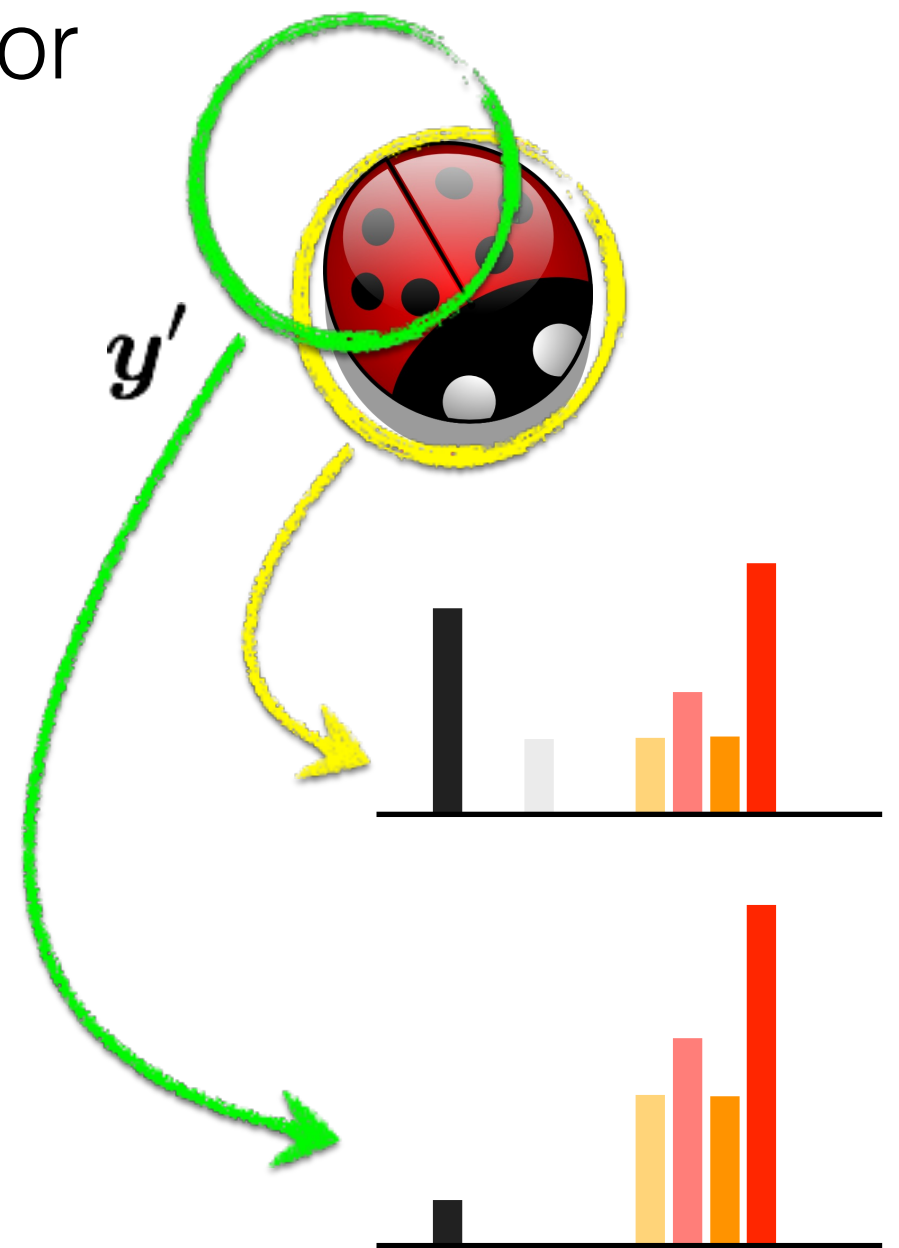
$$\mathbf{p}(\mathbf{y}) = \{p_1(\mathbf{y}), \dots, p_M(\mathbf{y})\}$$

(centered at location \mathbf{y})

a weighted histogram at \mathbf{y}

$$p_m = C_h \sum_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right) \delta[b(\mathbf{x}_n) - m]$$

bandwidth



Similarity between the target and candidate

Distance function

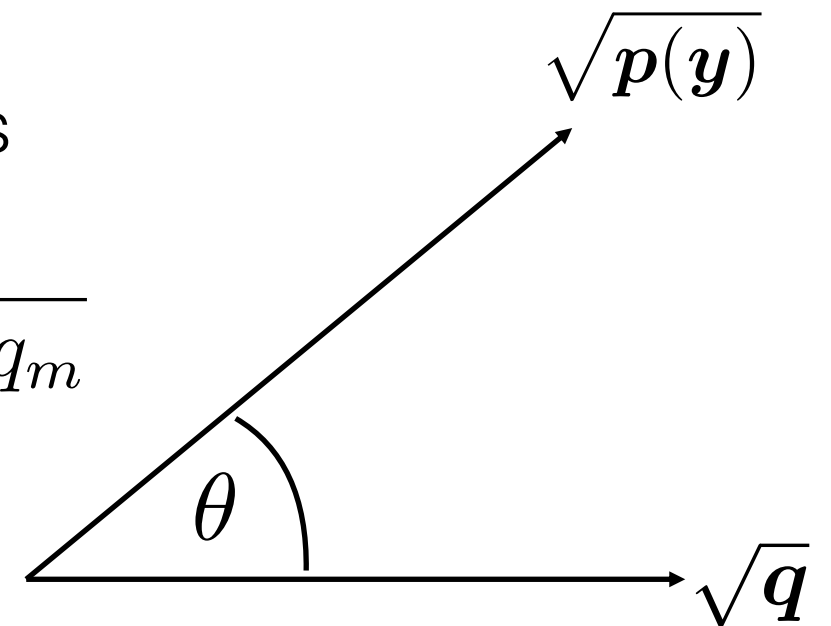
$$d(\mathbf{y}) = \sqrt{1 - \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]}$$

Bhattacharyya Coefficient

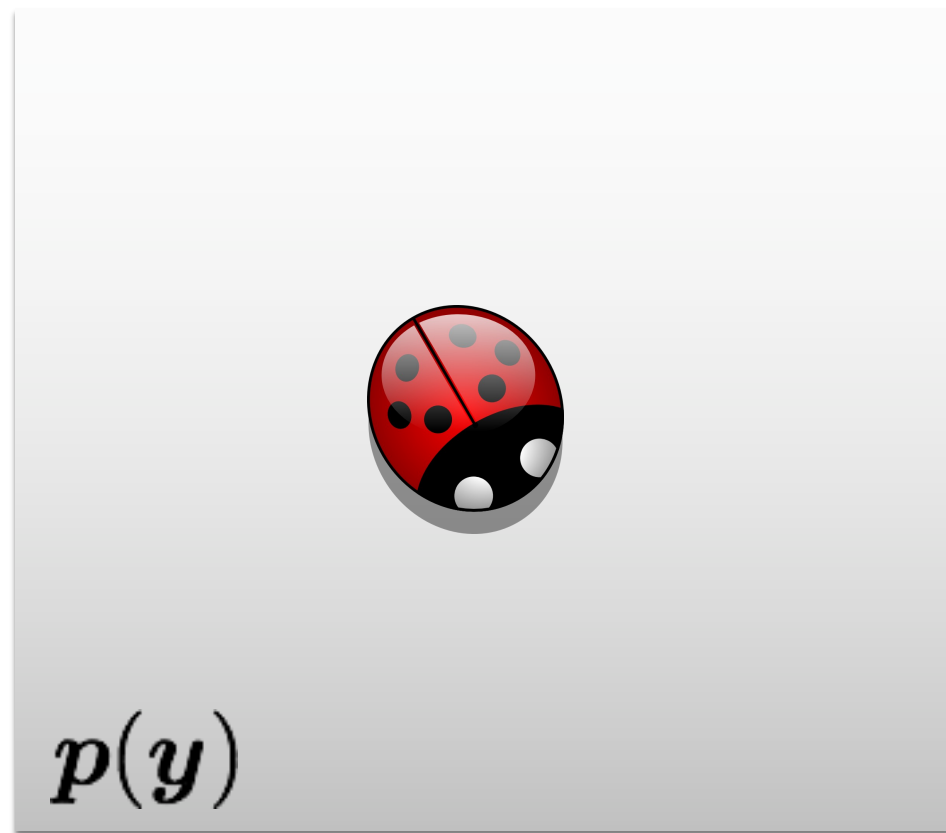
$$\rho(\mathbf{y}) \equiv \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] = \sum_m \sqrt{p_m(\mathbf{y}) q_m}$$

Just the Cosine distance between two unit vectors

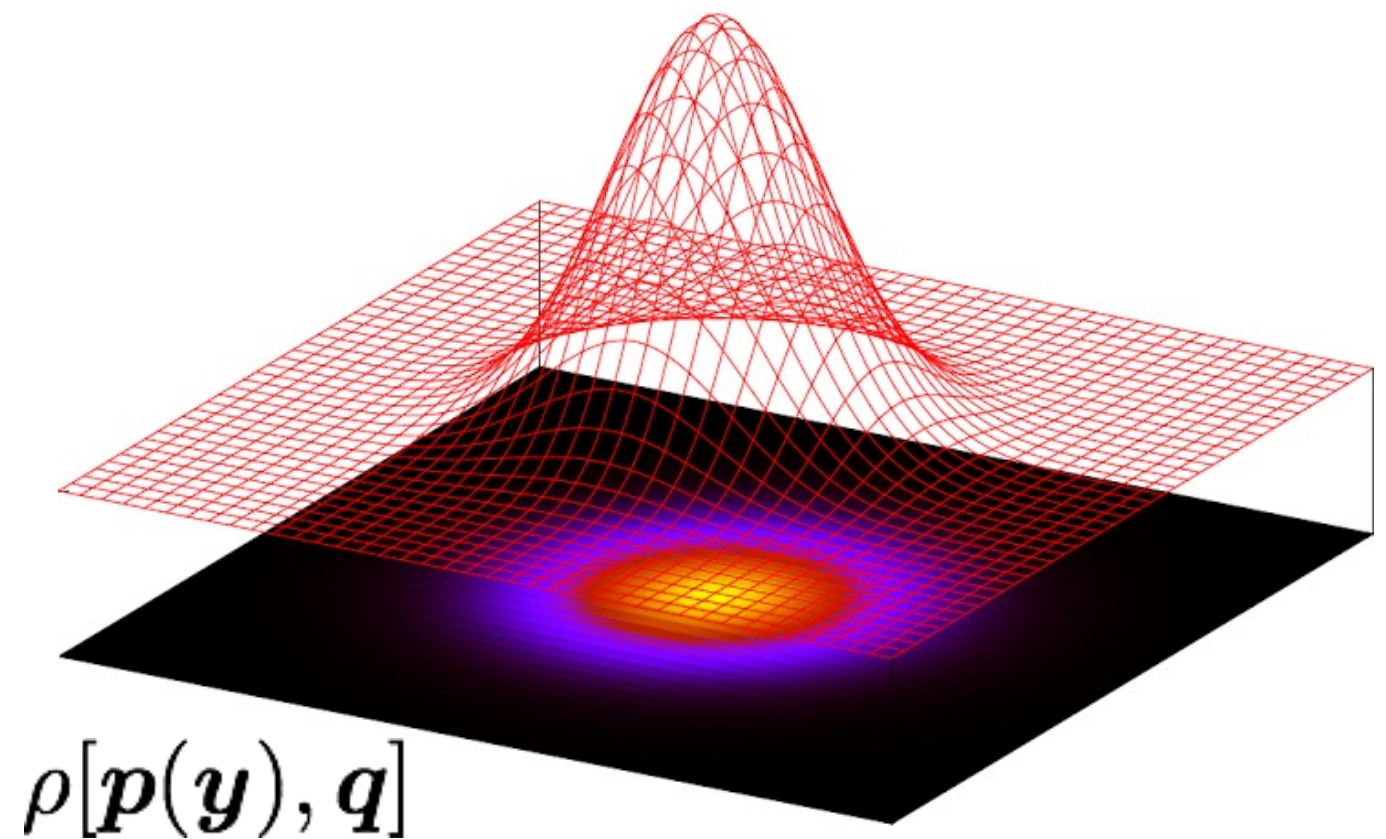
$$\rho(\mathbf{y}) = \cos \theta_{\mathbf{y}} = \frac{\sqrt{\mathbf{p}(\mathbf{y})}^T \sqrt{\mathbf{q}}}{\|\sqrt{\mathbf{p}(\mathbf{y})}\| \|\sqrt{\mathbf{q}}\|} = \sum_m \sqrt{p_m(\mathbf{y}) q_m}$$



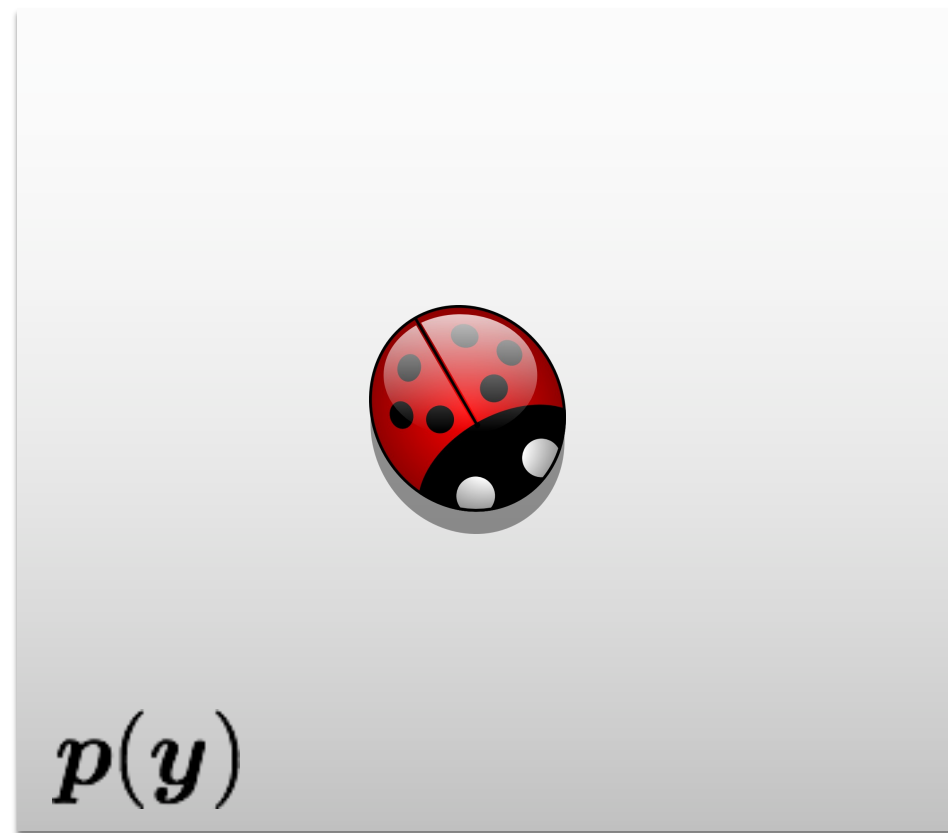
Now we can compute the similarity between
a target and multiple candidate regions



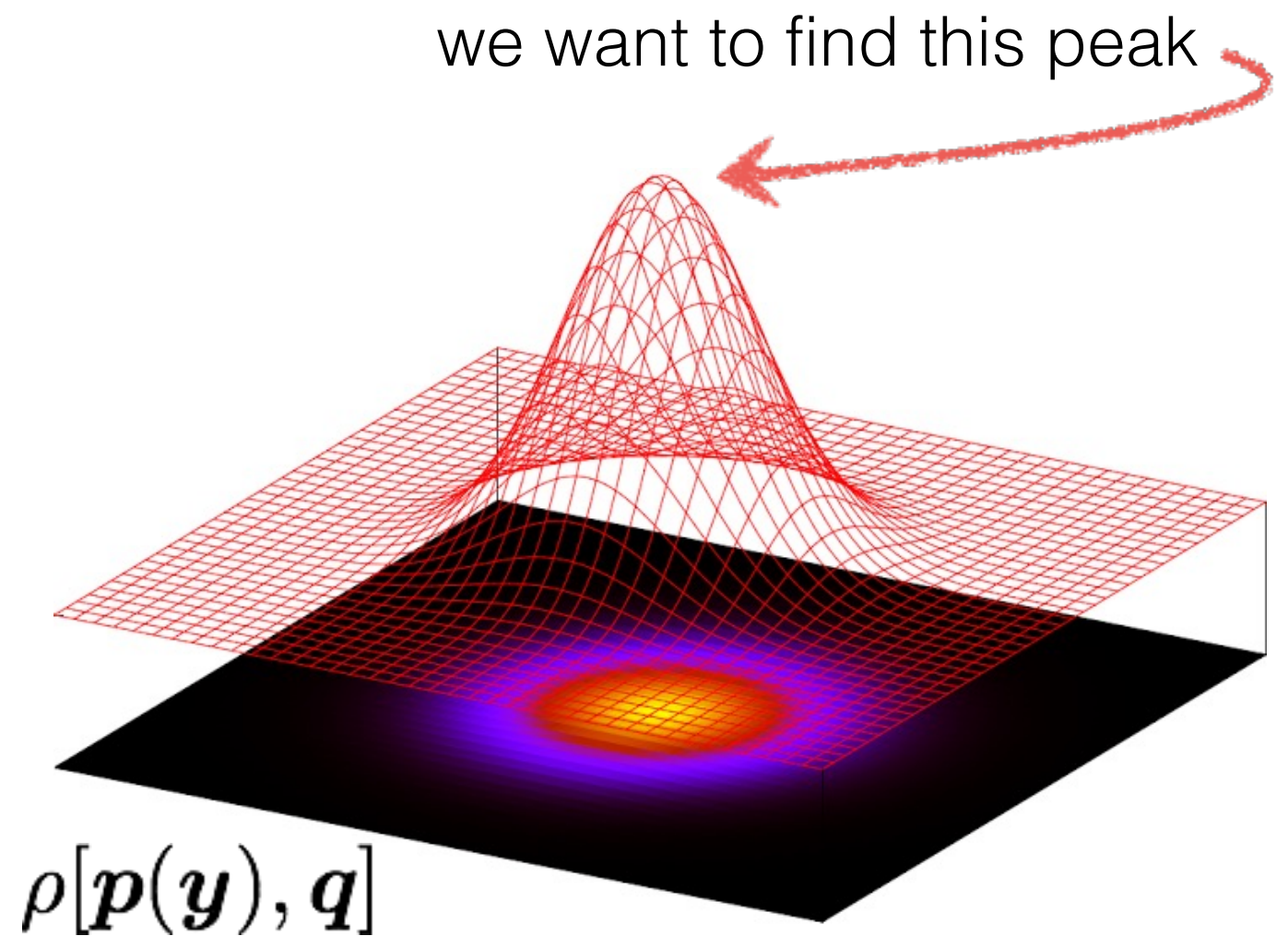
image



similarity over image



image



similarity over image

Objective function

$$\min_{\mathbf{y}} d(\mathbf{y}) \quad \text{same as} \quad \max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

Assuming a good initial guess

$$\rho[\mathbf{p}(\mathbf{y}_0 + \mathbf{y}), \mathbf{q}]$$

Linearize around the initial guess (Taylor series expansion)

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{1}{2} \sum_m p_m(\mathbf{y}) \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}}$$

function at specified value derivative

Linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{1}{2} \sum_m p_m(\mathbf{y}) \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}}$$

$$p_m = C_h \sum_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right) \delta[b(\mathbf{x}_n) - m]$$

Remember
definition of this?



Fully expanded

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{1}{2} \sum_m \left\{ C_h \sum_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right) \delta[b(\mathbf{x}_n) - m] \right\} \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}}$$

Fully expanded linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{1}{2} \sum_m \left\{ C_h \sum_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right) \delta[b(\mathbf{x}_n) - m] \right\} \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}}$$

Moving terms around...

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \underbrace{\frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m}}_{\text{Does not depend on unknown } \mathbf{y}} + \underbrace{\frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)}_{\text{Weighted kernel density estimate}}$$

where $w_n = \sum_m \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}} \delta[b(\mathbf{x}_n) - m]$

Weight is bigger when $q_m > p_m(\mathbf{y}_0)$

OK, why are we doing all this math?

We want to maximize this

$$\max_{\boldsymbol{y}} \rho[\boldsymbol{p}(\boldsymbol{y}), \boldsymbol{q}]$$

We want to maximize this

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

Fully expanded linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)$$

where $w_n = \sum_m \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}} \delta[b(\mathbf{x}_n) - m]$

We want to maximize this

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

Fully expanded linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m} + \frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)$$

doesn't depend on unknown \mathbf{y}

$$\text{where } w_n = \sum_m \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}} \delta[b(\mathbf{x}_n) - m]$$

We want to maximize this

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

only need to
maximize this!

Fully expanded linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \underbrace{\frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m}}_{\text{doesn't depend on unknown } \mathbf{y}} + \frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)$$

where

$$w_n = \sum_m \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}} \delta[b(\mathbf{x}_n) - m]$$

We want to maximize this

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

Fully expanded linearized objective

$$\rho[\mathbf{p}(\mathbf{y}), \mathbf{q}] \approx \underbrace{\frac{1}{2} \sum_m \sqrt{p_m(\mathbf{y}_0) q_m}}_{\text{doesn't depend on unknown } \mathbf{y}} + \frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)$$

where $w_n = \sum_m \sqrt{\frac{q_m}{p_m(\mathbf{y}_0)}} \delta[b(\mathbf{x}_n) - m]$

what can we use to solve this weighted KDE?

Mean Shift Algorithm!

$$\frac{C_h}{2} \sum_n w_n k \left(\left\| \frac{\mathbf{y} - \mathbf{x}_n}{h} \right\|^2 \right)$$

the new sample of mean of this KDE is

$$\mathbf{y}_1 = \frac{\sum_n \mathbf{x}_n w_n g \left(\left\| \frac{\mathbf{y}_0 - \mathbf{x}_n}{h} \right\|^2 \right)}{\sum_n w_n g \left(\left\| \frac{\mathbf{y}_0 - \mathbf{x}_n}{h} \right\|^2 \right)} \quad \text{(this was derived earlier)}$$

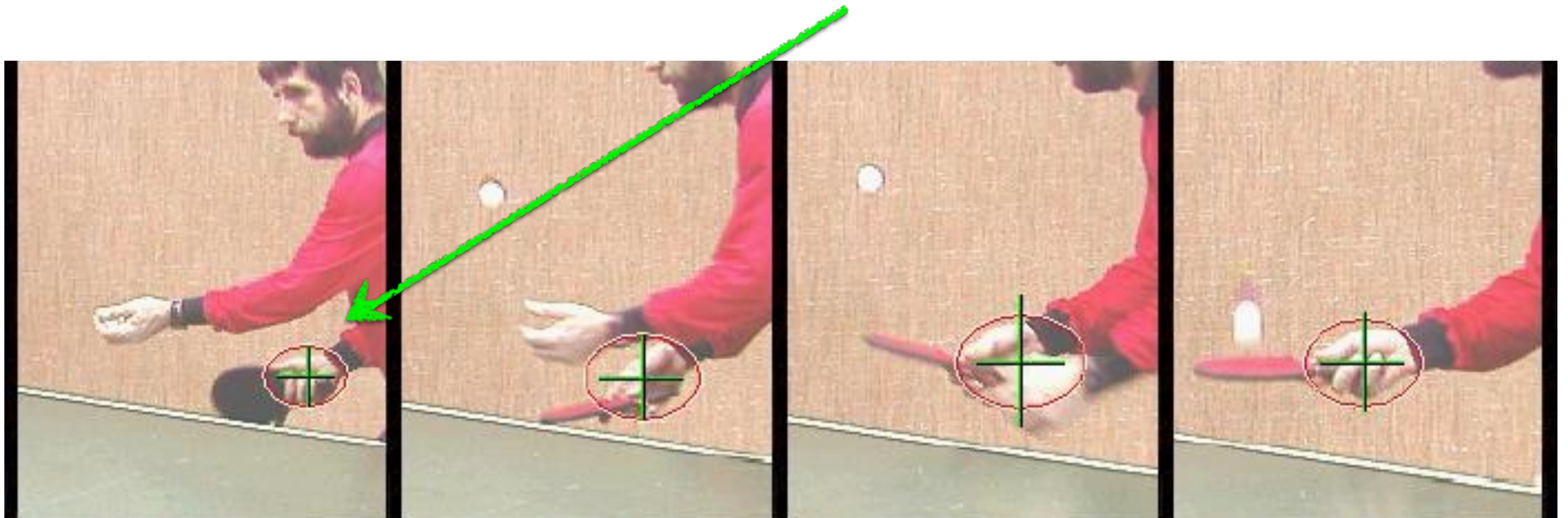
(new candidate location)

Mean-Shift Object Tracking

For each frame:

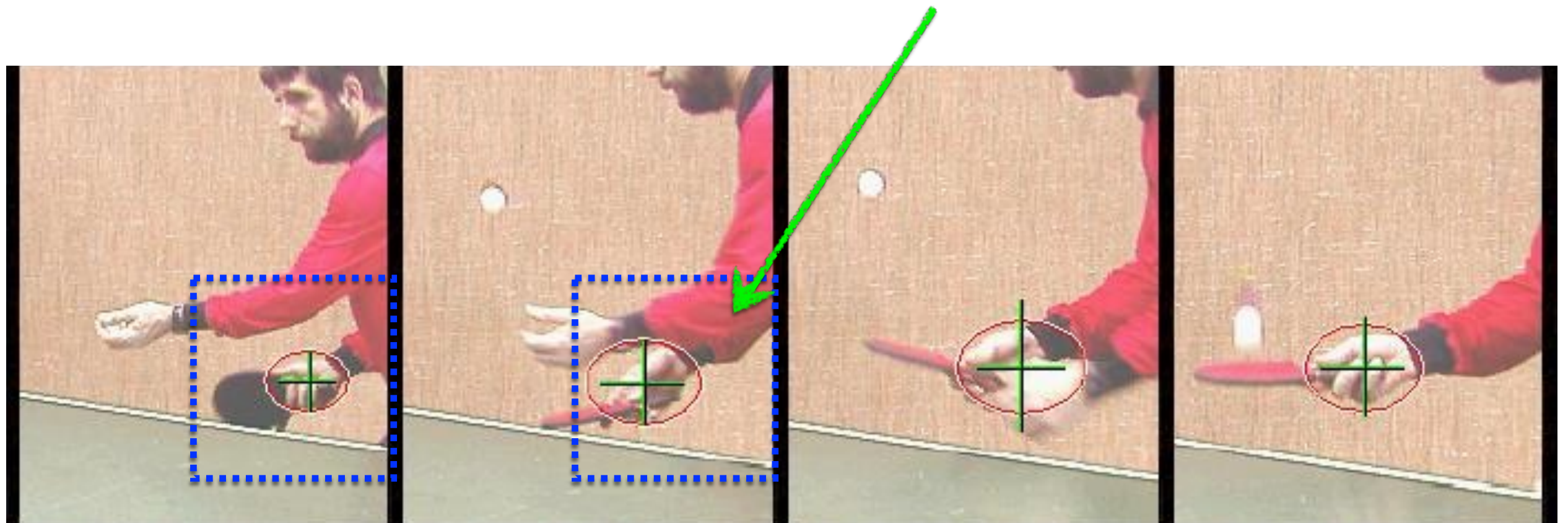
1. Initialize location \mathbf{y}_0
Compute \mathbf{q}
Compute $p(\mathbf{y}_0)$
2. Derive weights w_n
3. Shift to new candidate location (mean shift) \mathbf{y}_1
4. Compute $p(\mathbf{y}_1)$
5. If $\|\mathbf{y}_0 - \mathbf{y}_1\| < \epsilon$ return
Otherwise $\mathbf{y}_0 \leftarrow \mathbf{y}_1$ and go back to 2

Compute a descriptor for the target



Target
 q

Search for similar descriptor in neighborhood in next frame

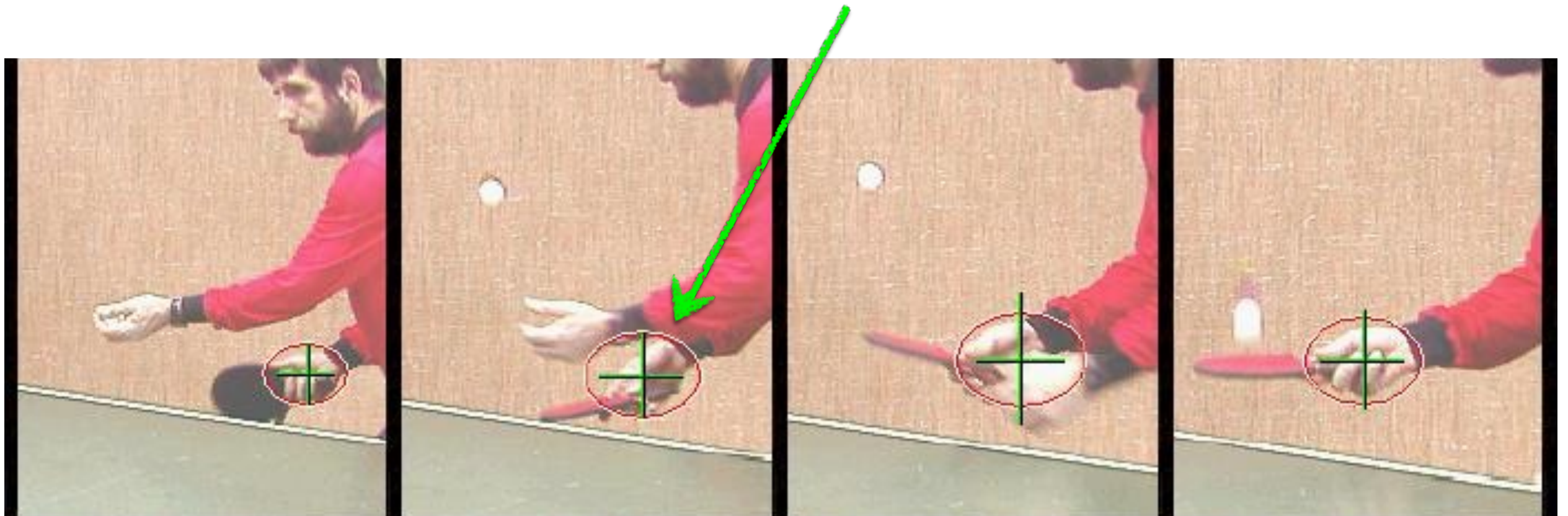


Target

Candidate

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$

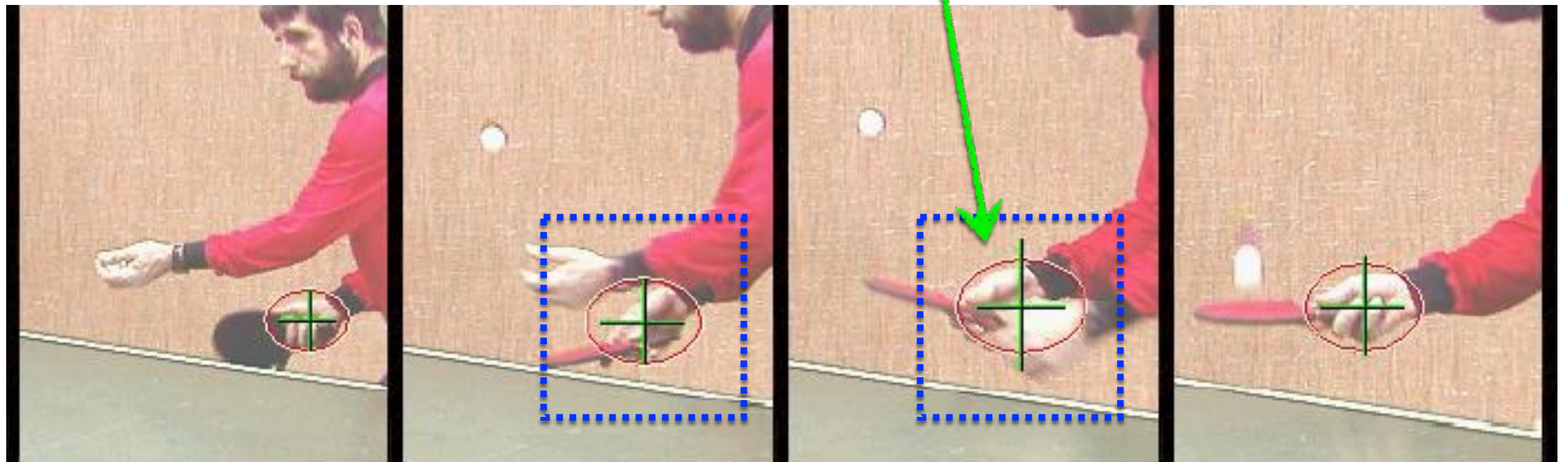
Compute a descriptor for the new target



Target

q

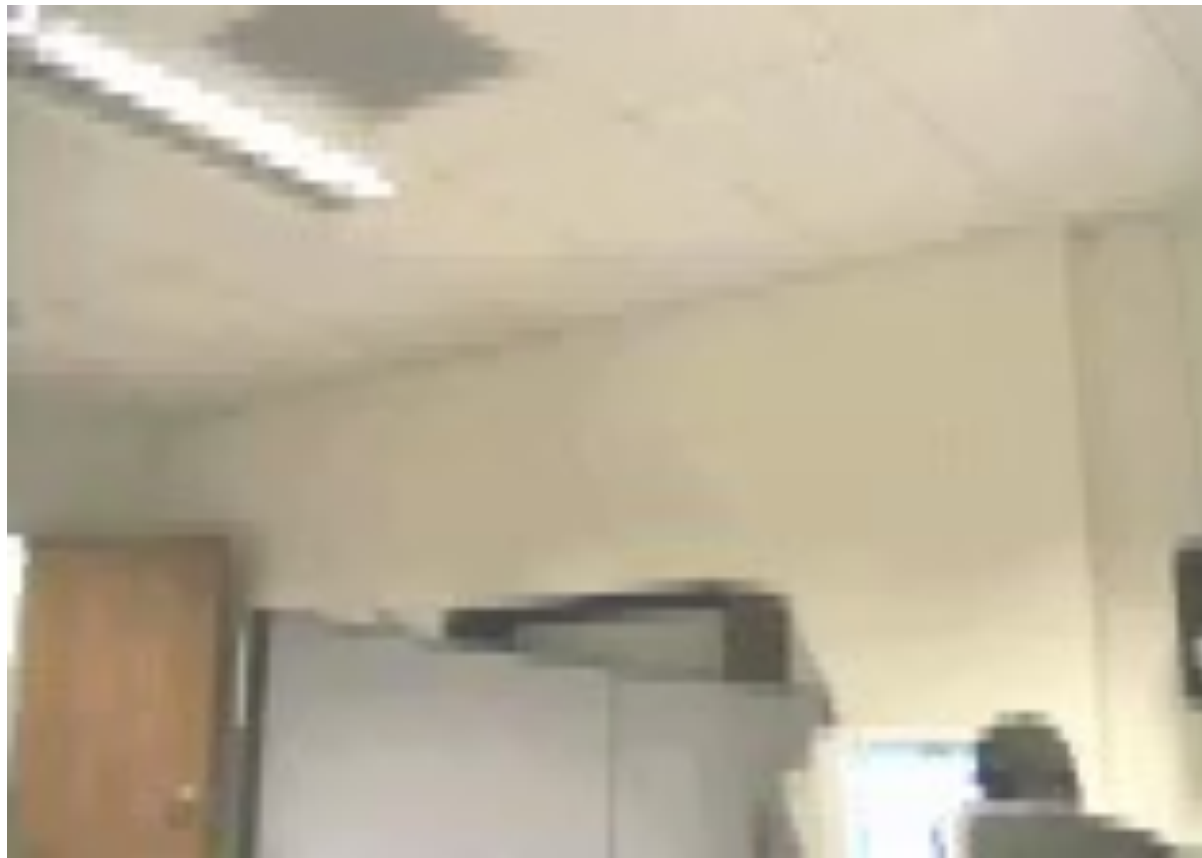
Search for similar descriptor in neighborhood in next frame



Target

Candidate

$$\max_{\mathbf{y}} \rho[\mathbf{p}(\mathbf{y}), \mathbf{q}]$$



Modern trackers

Learning Multi-Domain Convolutional Neural Networks for Visual Tracking

Hyeonseob Nam and Bohyung Han