



Capsule Networks

Aurélien Géron, November 2017

<https://youtu.be/pPN8d0E3900>

NIPS 2017 Paper

Dynamic Routing Between Capsules

by Sara Sabour, Nicholas Frosst, Geoffrey E. Hinton

October 2017: <https://arxiv.org/abs/1710.09829>

Computer Graphics

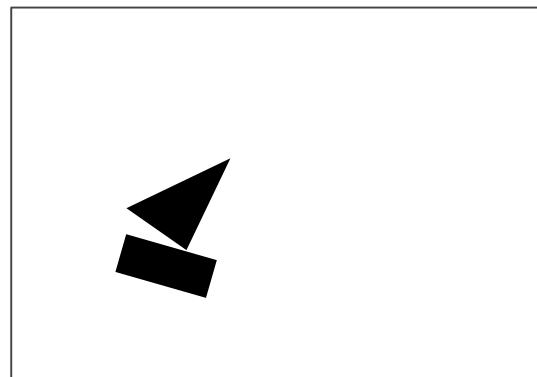
Rectangle
x=20 y=30 angle=16°

Instantiation parameters

Triangle
x=24 y=25 angle=-65°



Rendering



Image

Inverse Graphics

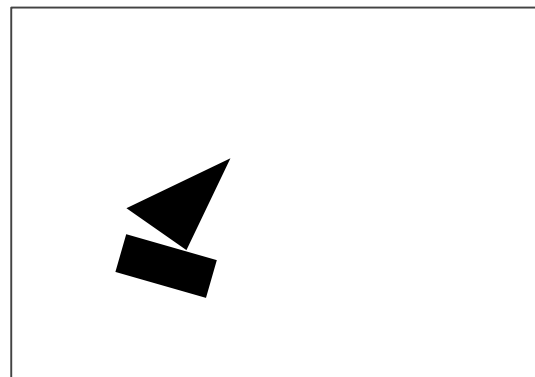
Rectangle
x=20 y=30 angle=16°

Instantiation parameters

Triangle
x=24 y=25 angle=-65°

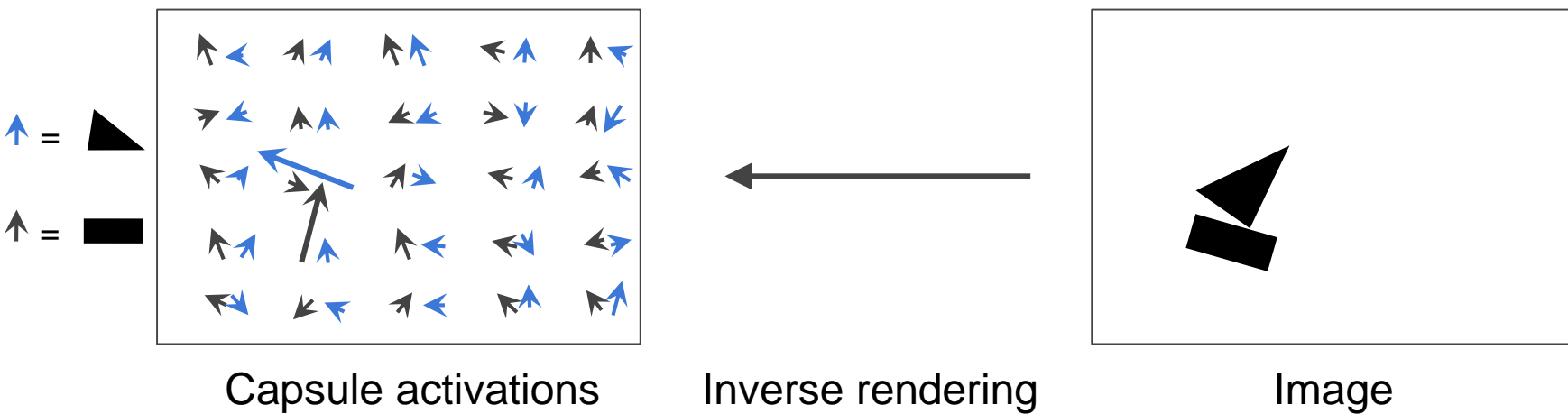


Inverse rendering

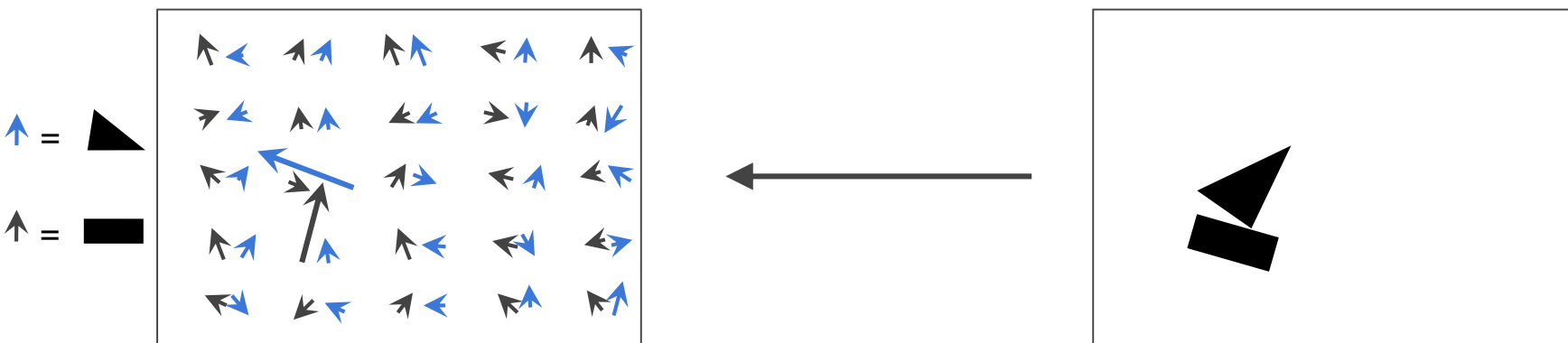


Image

Capsules



Capsules

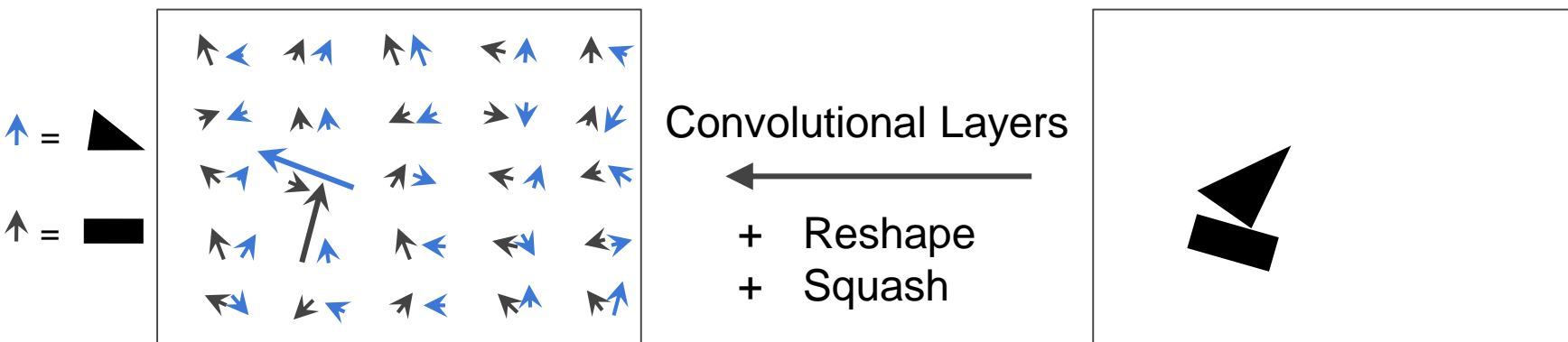


Activation vector:

Length = estimated probability of presence

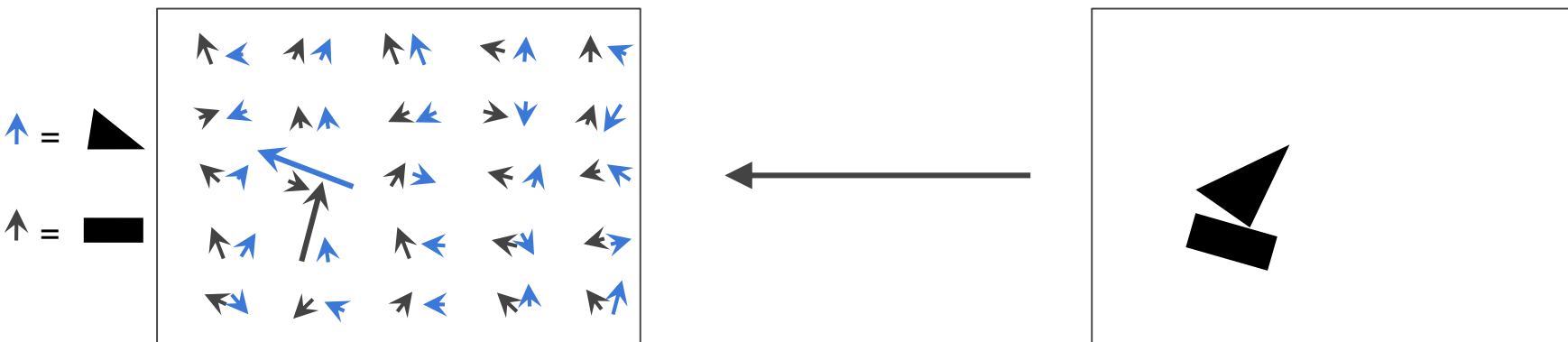
Orientation = object's estimated pose parameters

Capsules

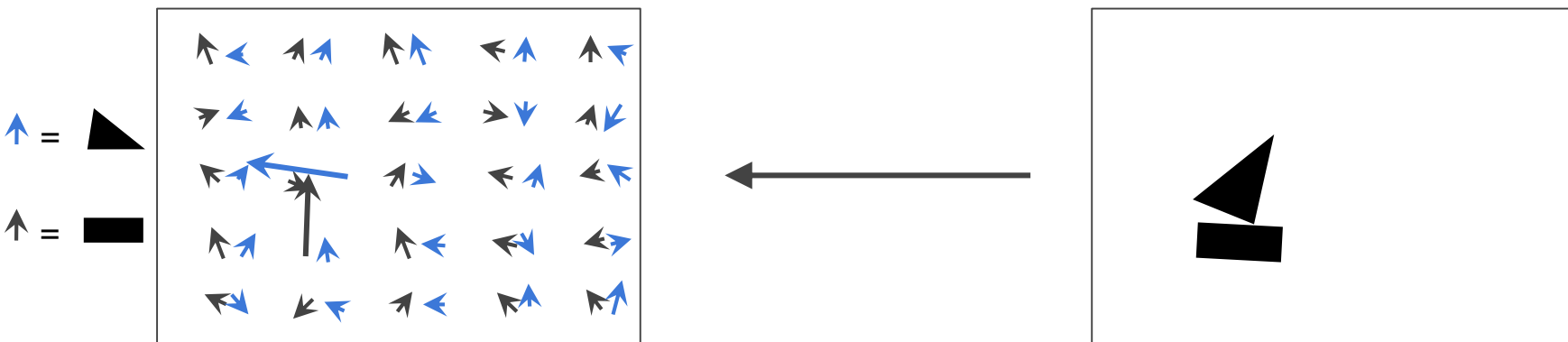


$$\text{Squash}(\mathbf{u}) = \frac{\|\mathbf{u}\|^2}{1 + \|\mathbf{u}\|^2} \frac{\mathbf{u}}{\|\mathbf{u}\|}$$

Equivariance



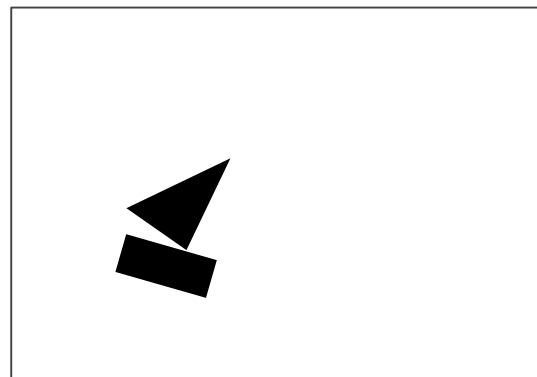
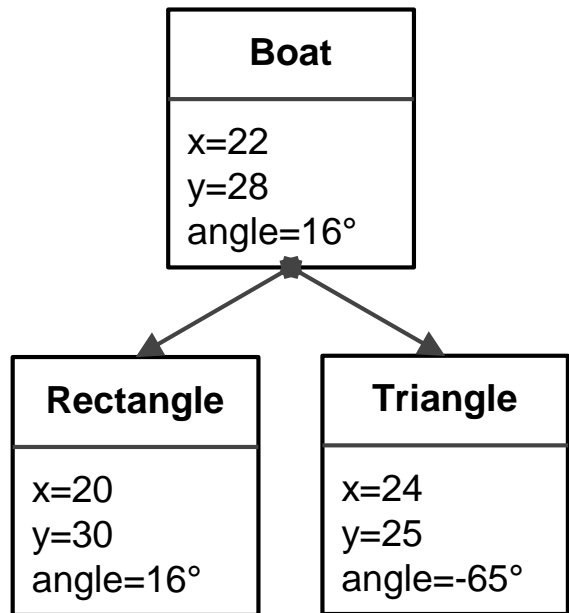
Equivariance



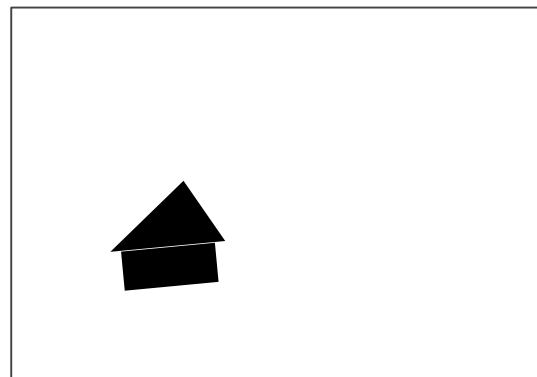
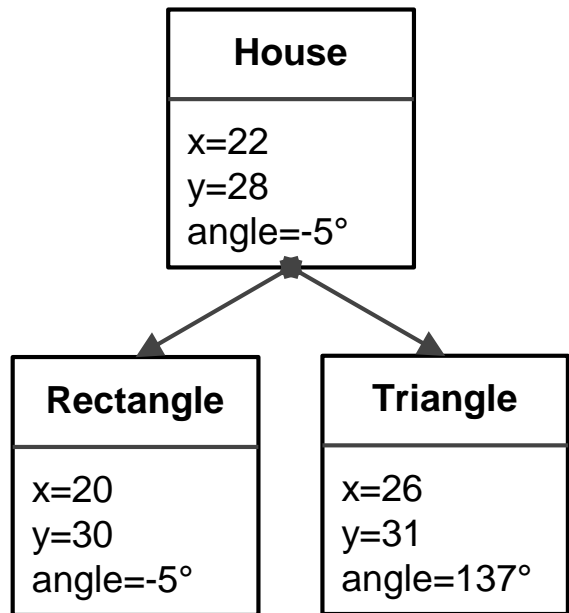
A hierarchy of parts

Boat
x=22 y=28 angle=16°

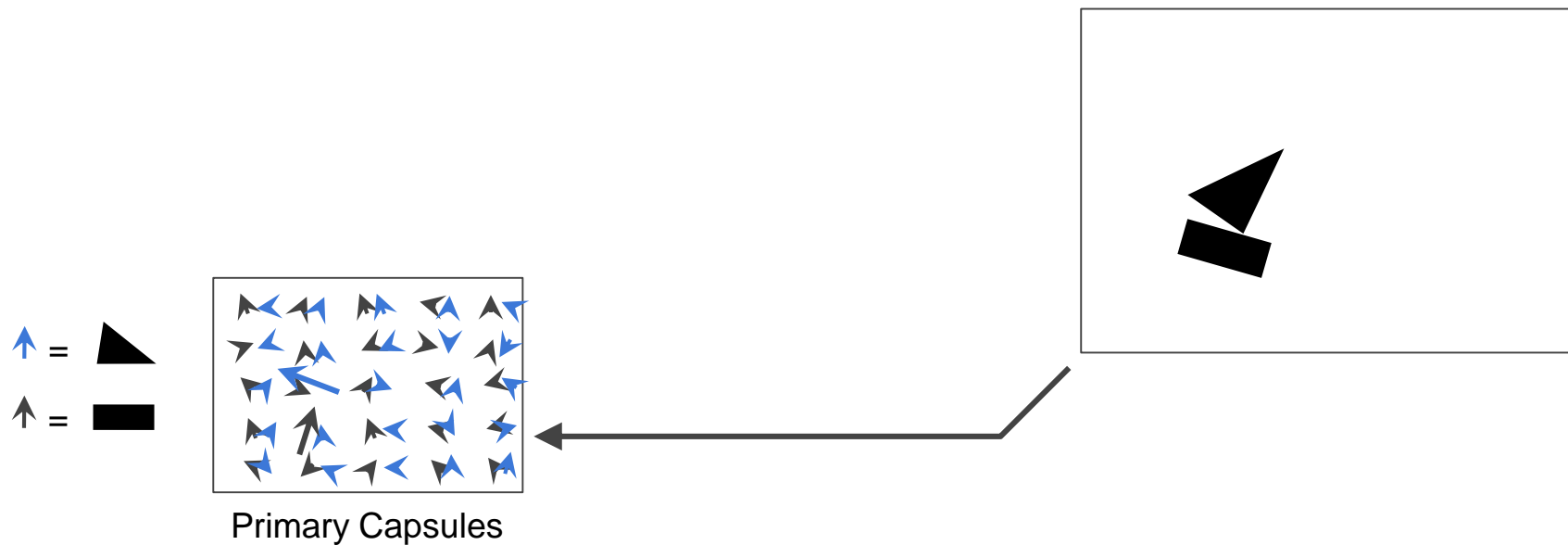
A hierarchy of parts



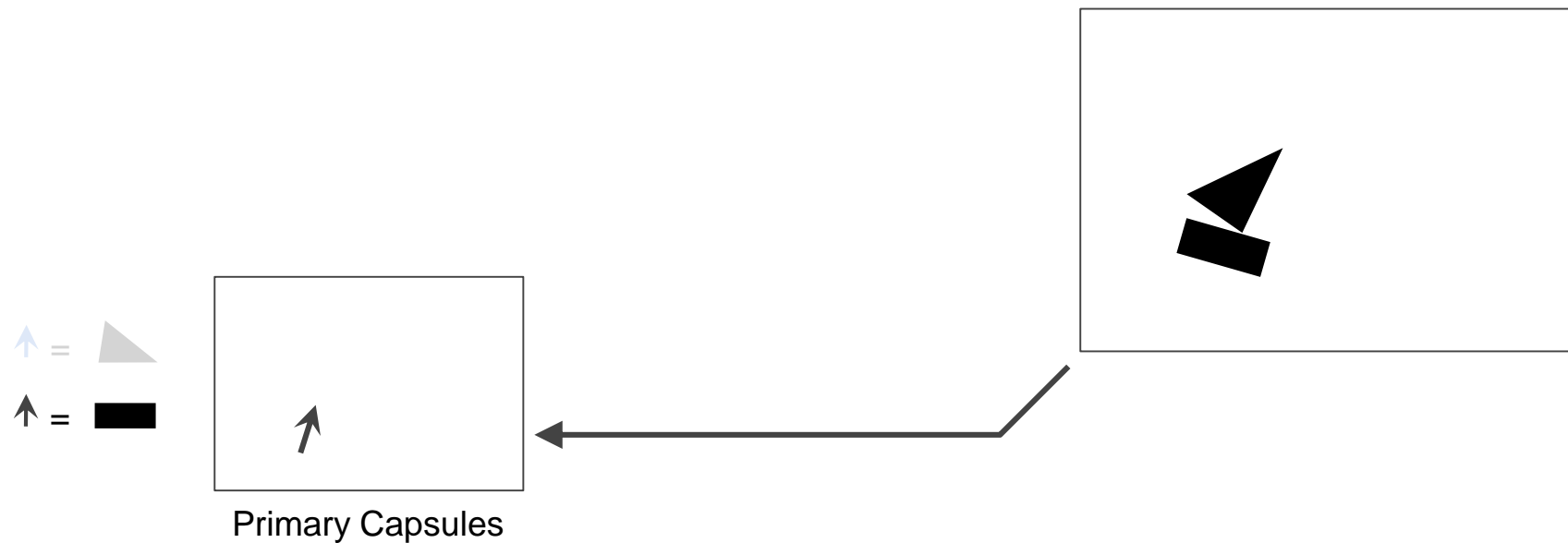
A hierarchy of parts



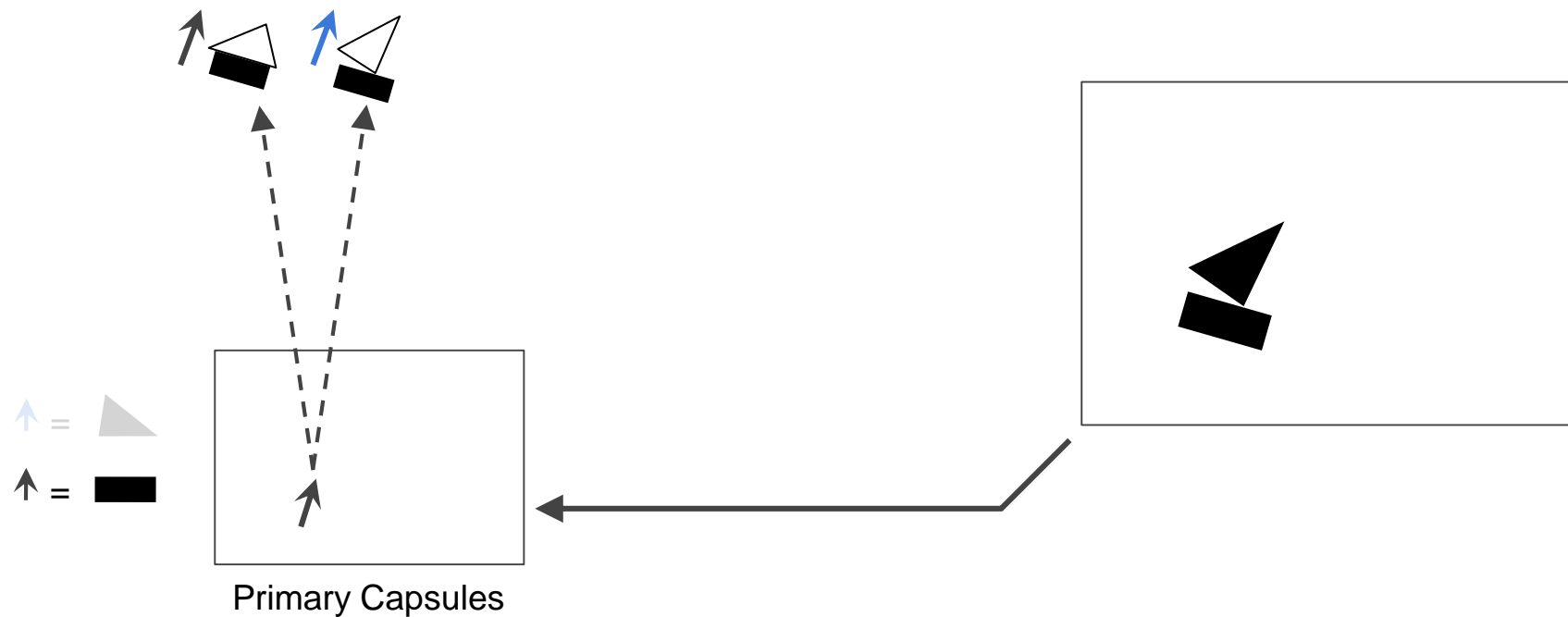
Primary Capsules



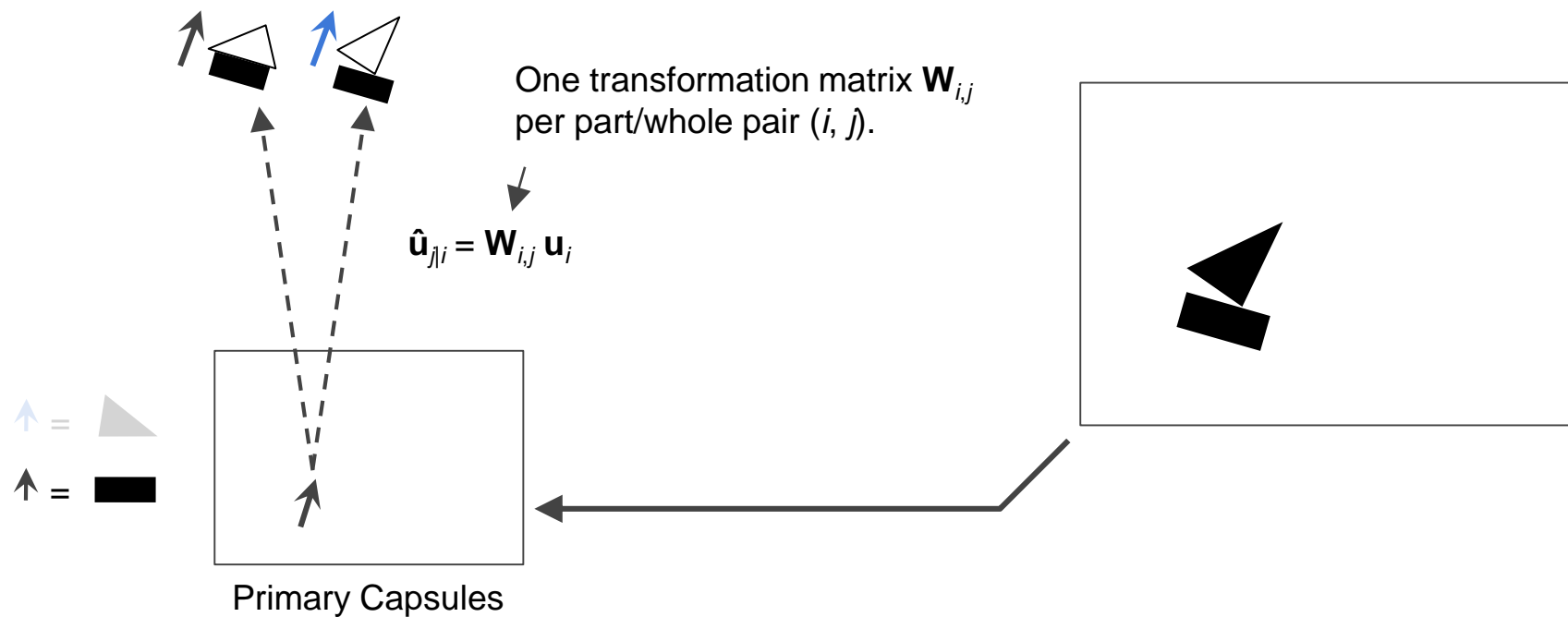
Predict Next Layer's Output



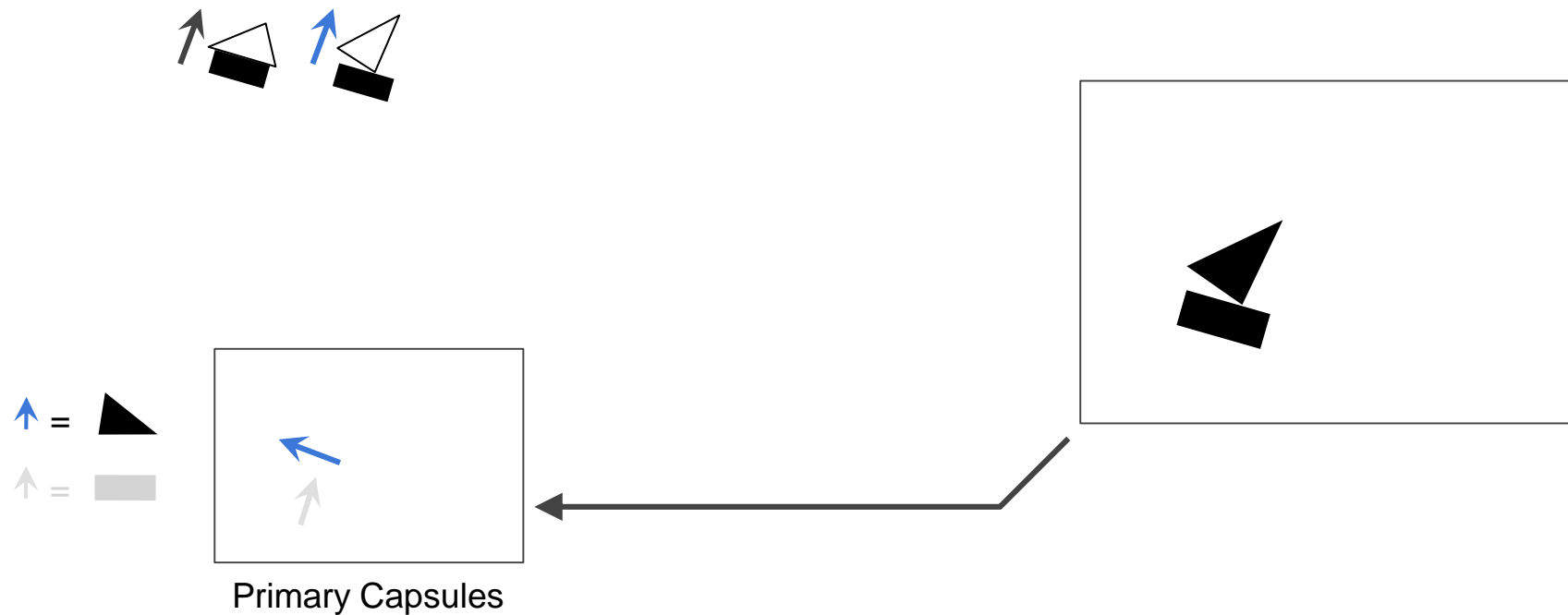
Predict Next Layer's Output



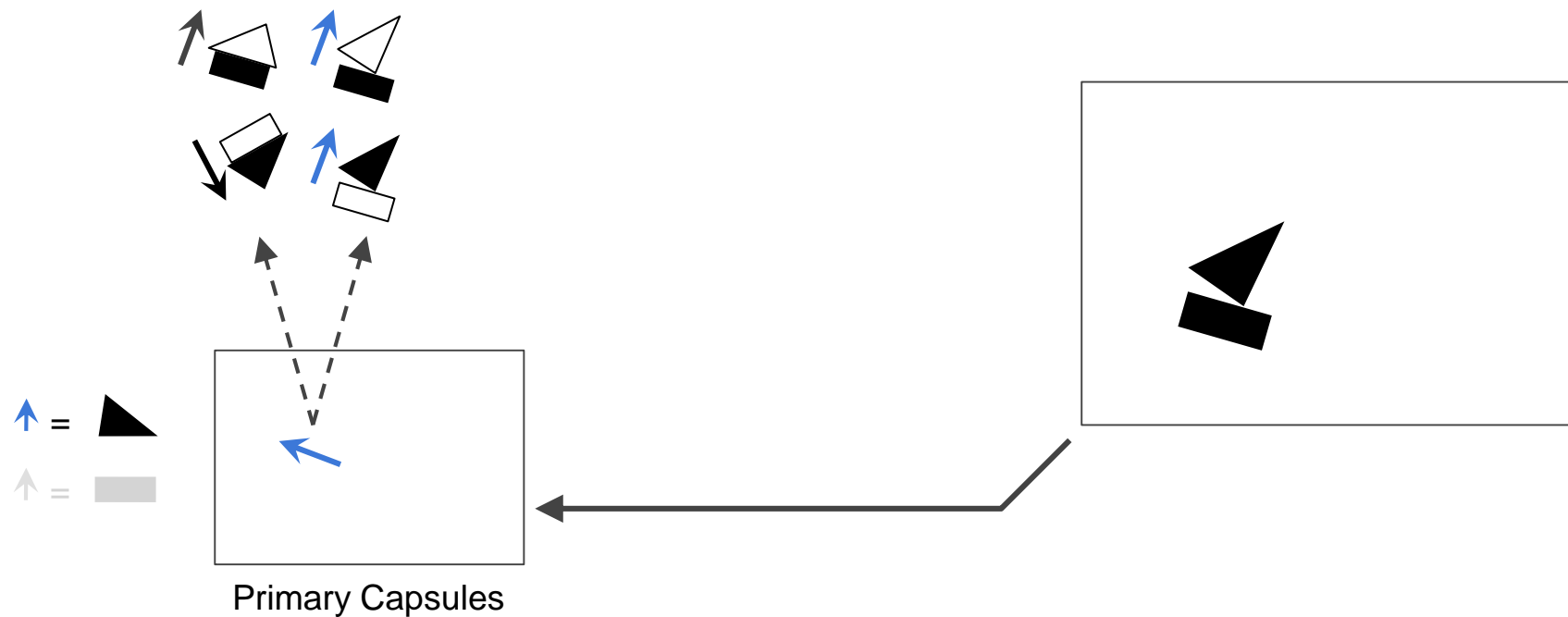
Predict Next Layer's Output



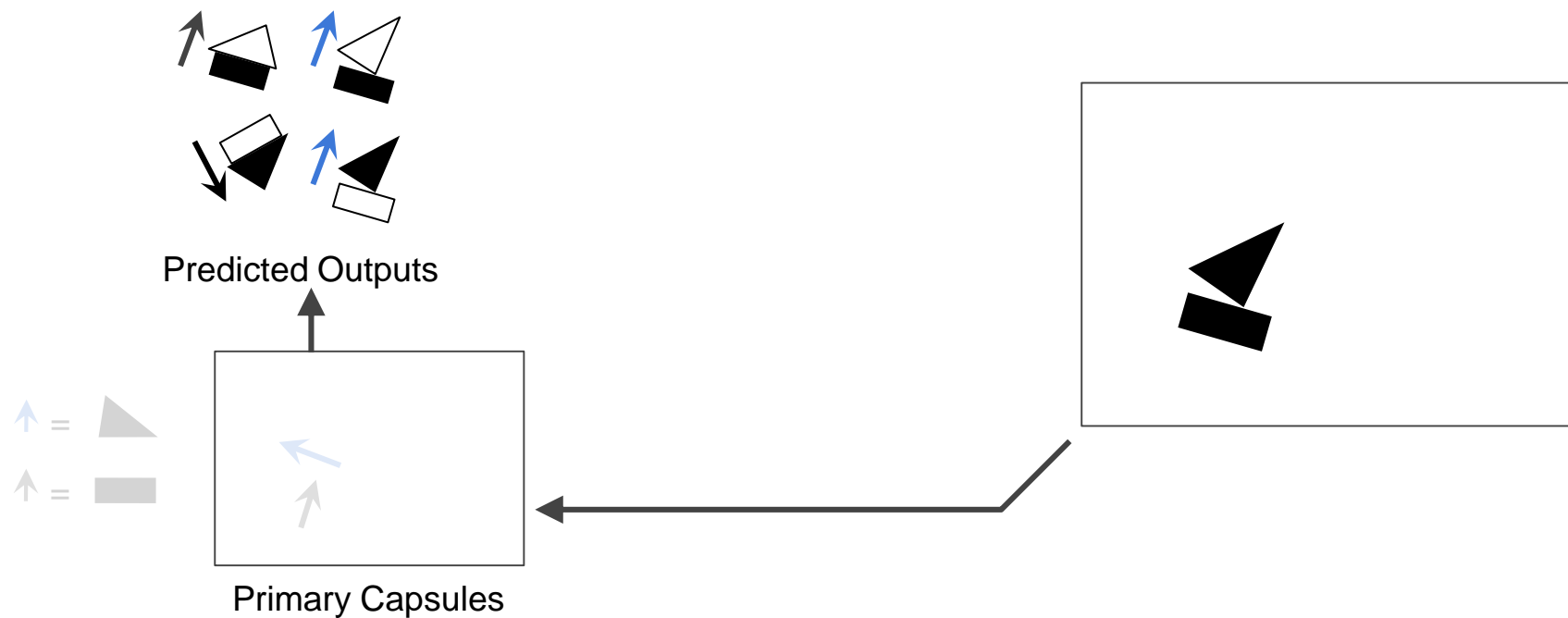
Predict Next Layer's Output



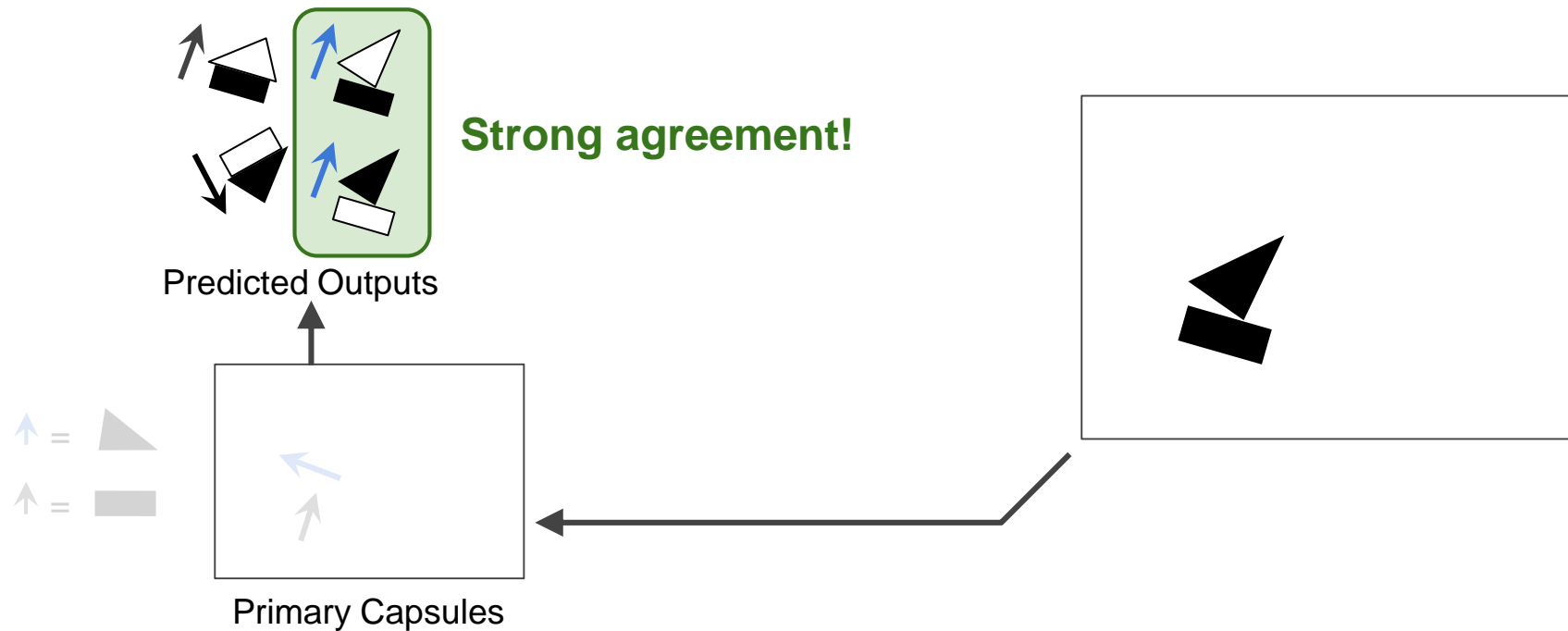
Predict Next Layer's Output



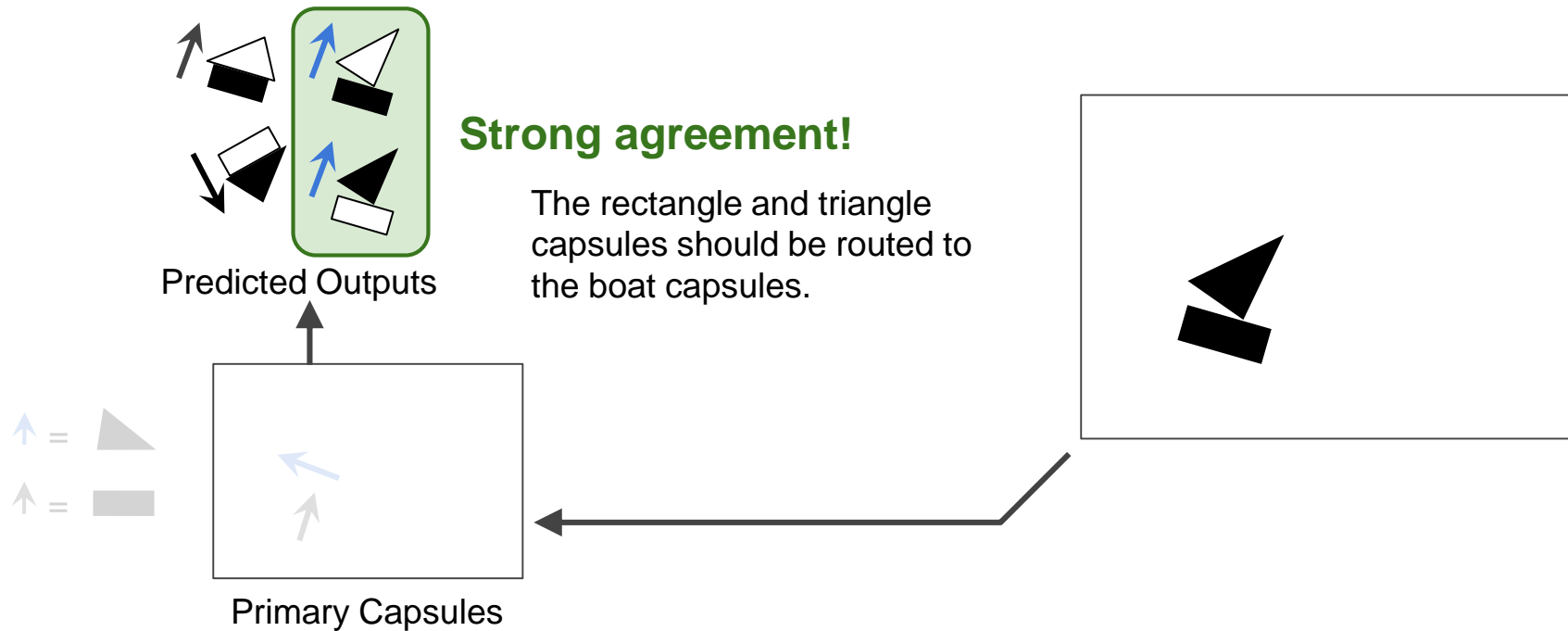
Compute Next Layer's Output



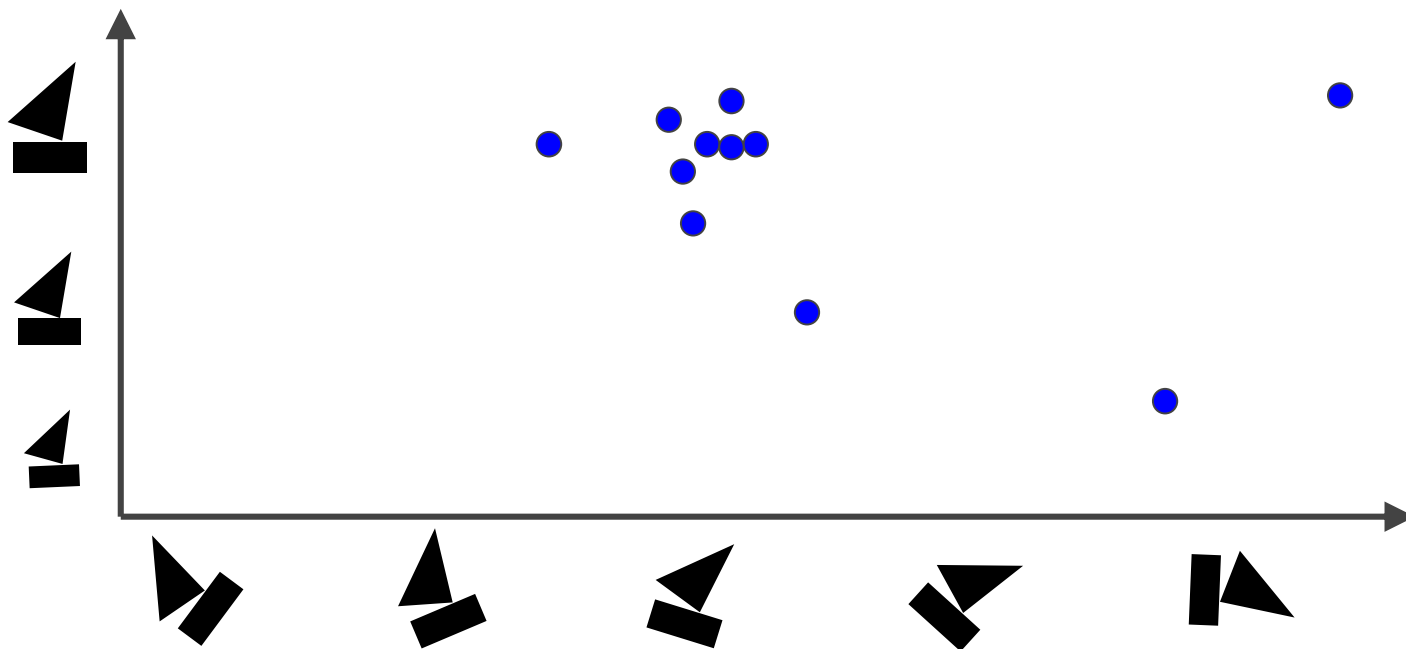
Routing by Agreement



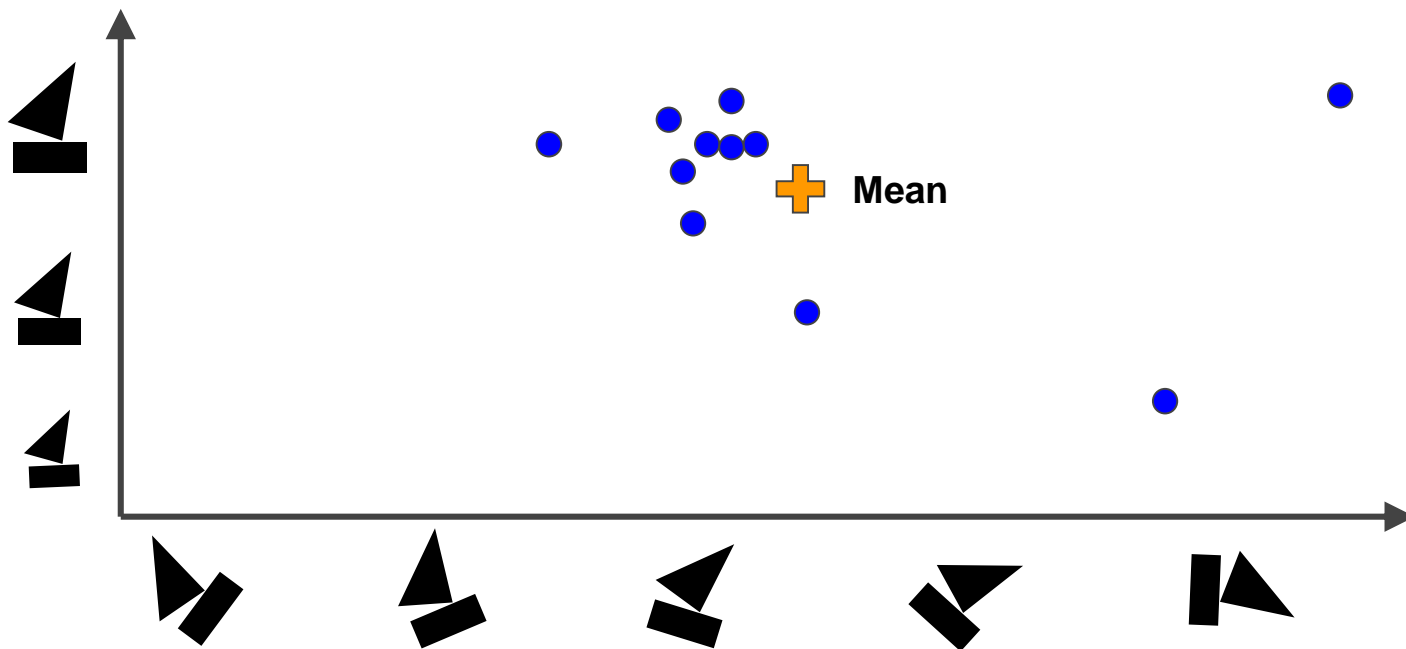
Routing by Agreement



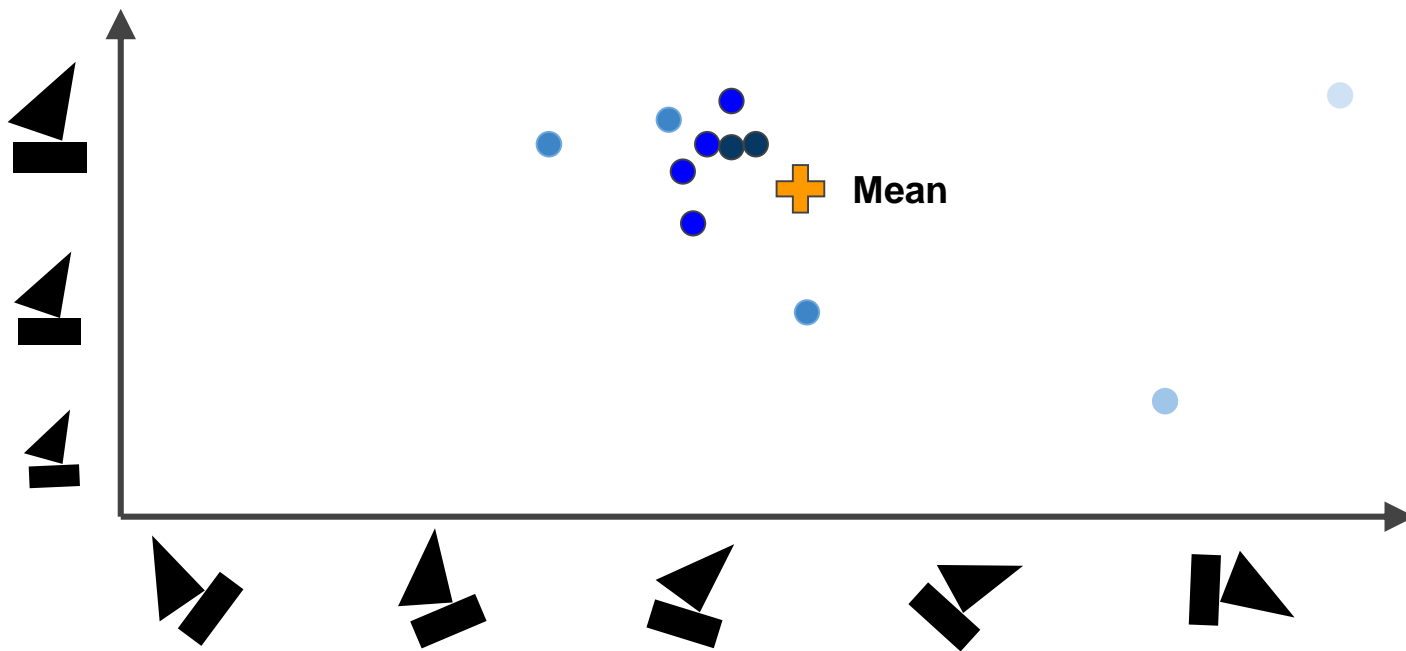
Clusters of Agreement



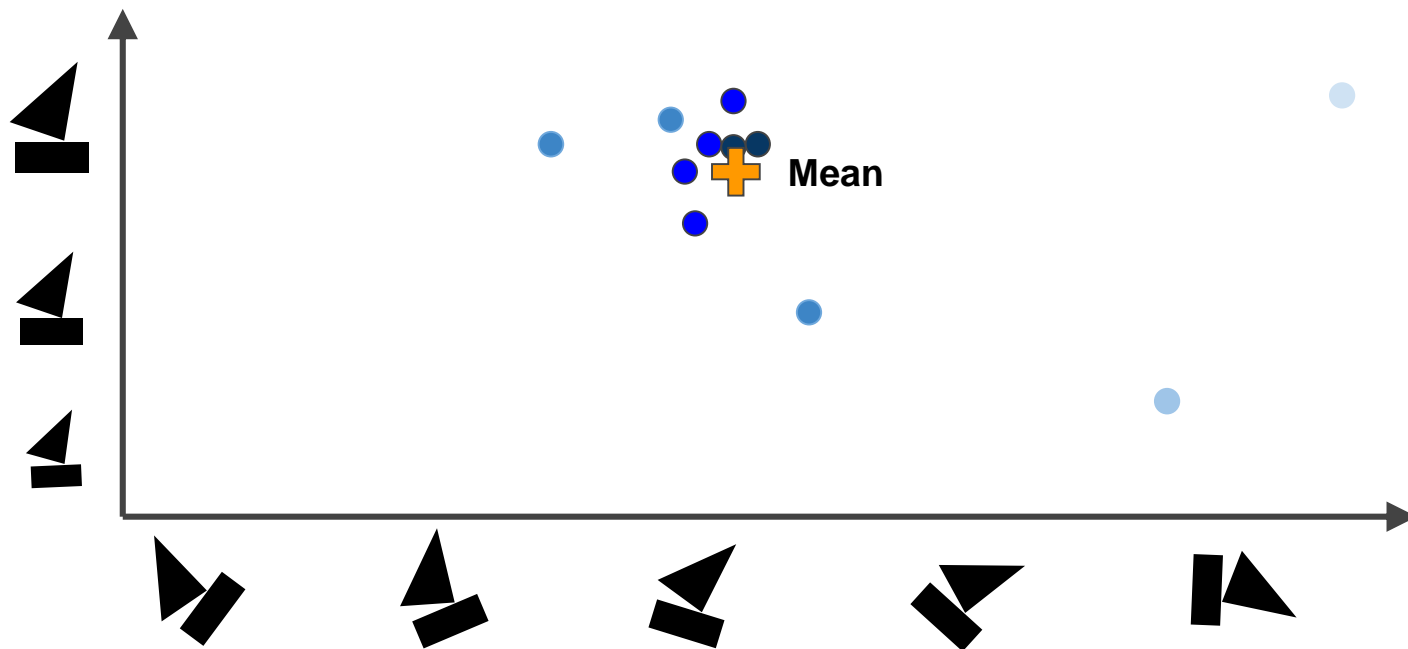
Clusters of Agreement



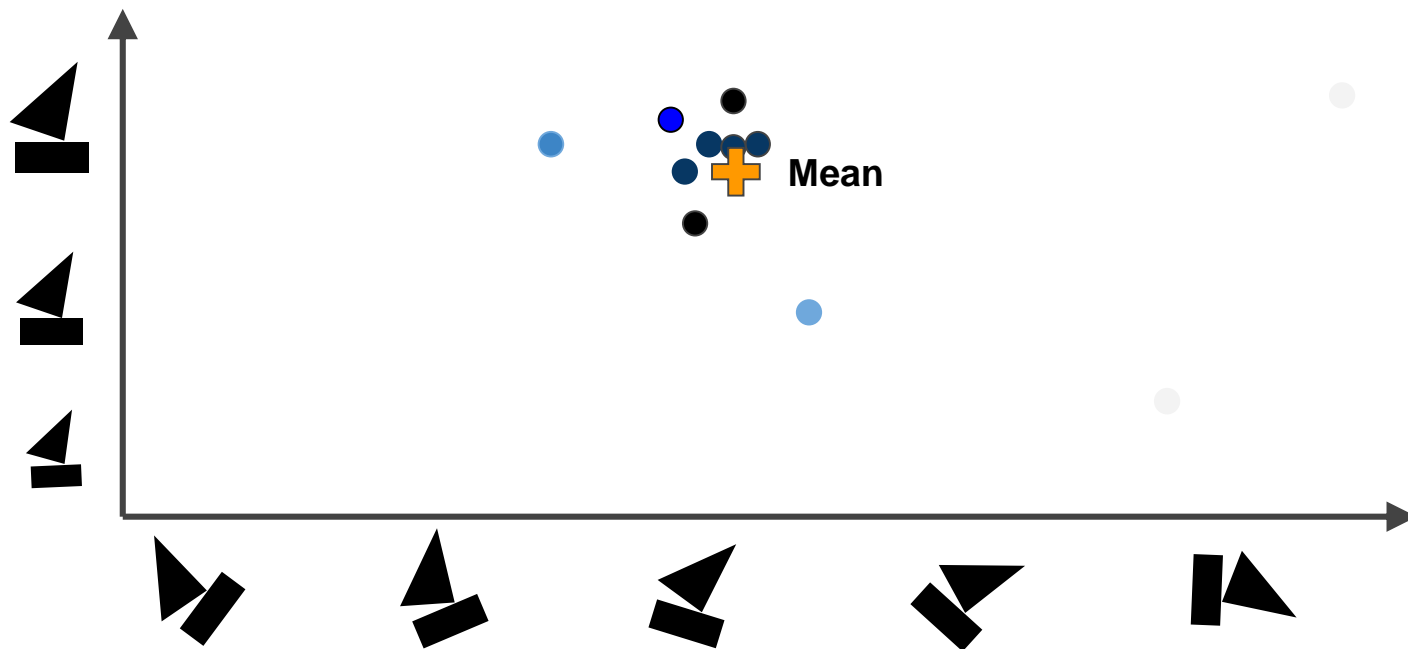
Aurélien Géron, 2017



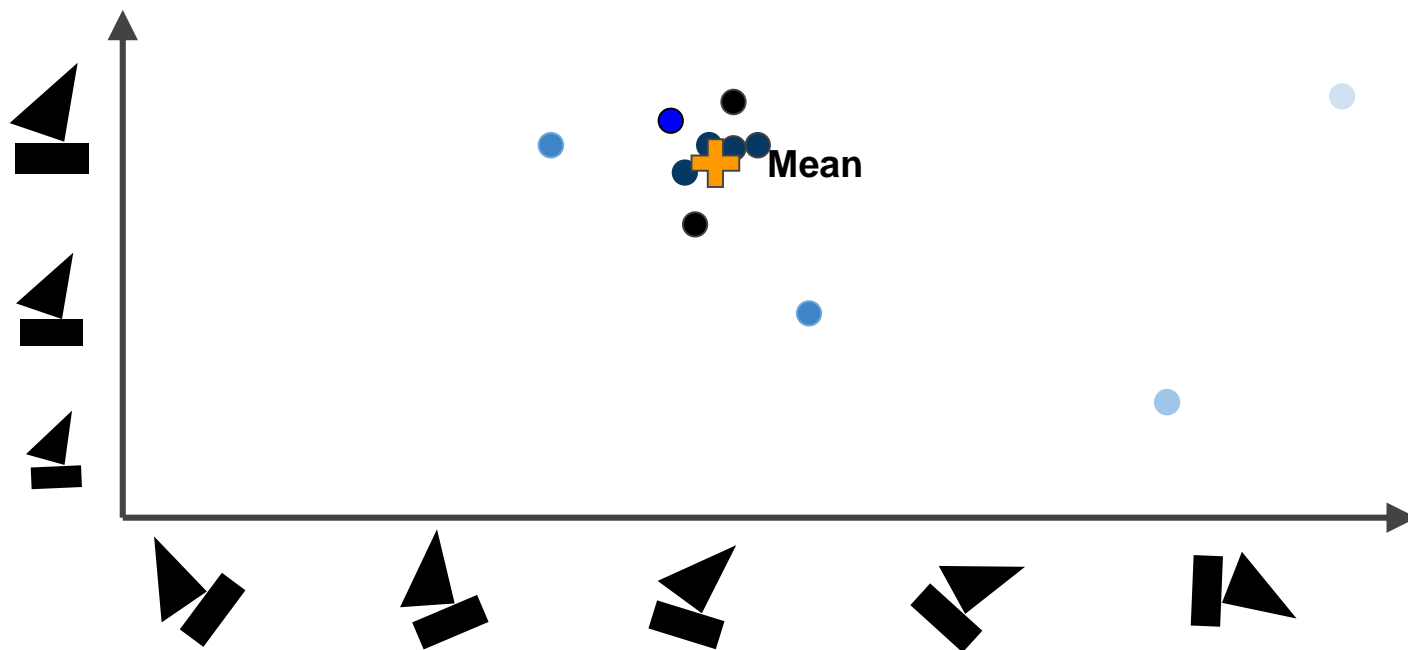
Clusters of Agreement



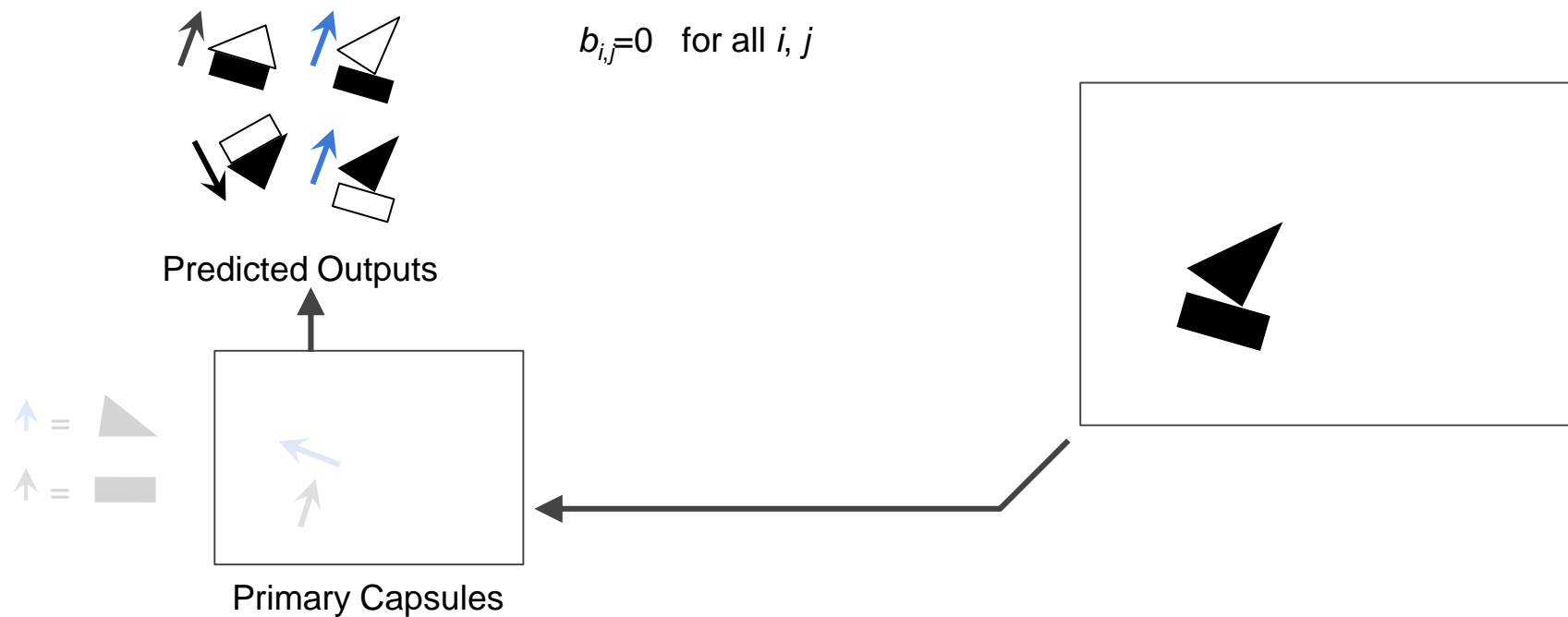
Clusters of Agreement



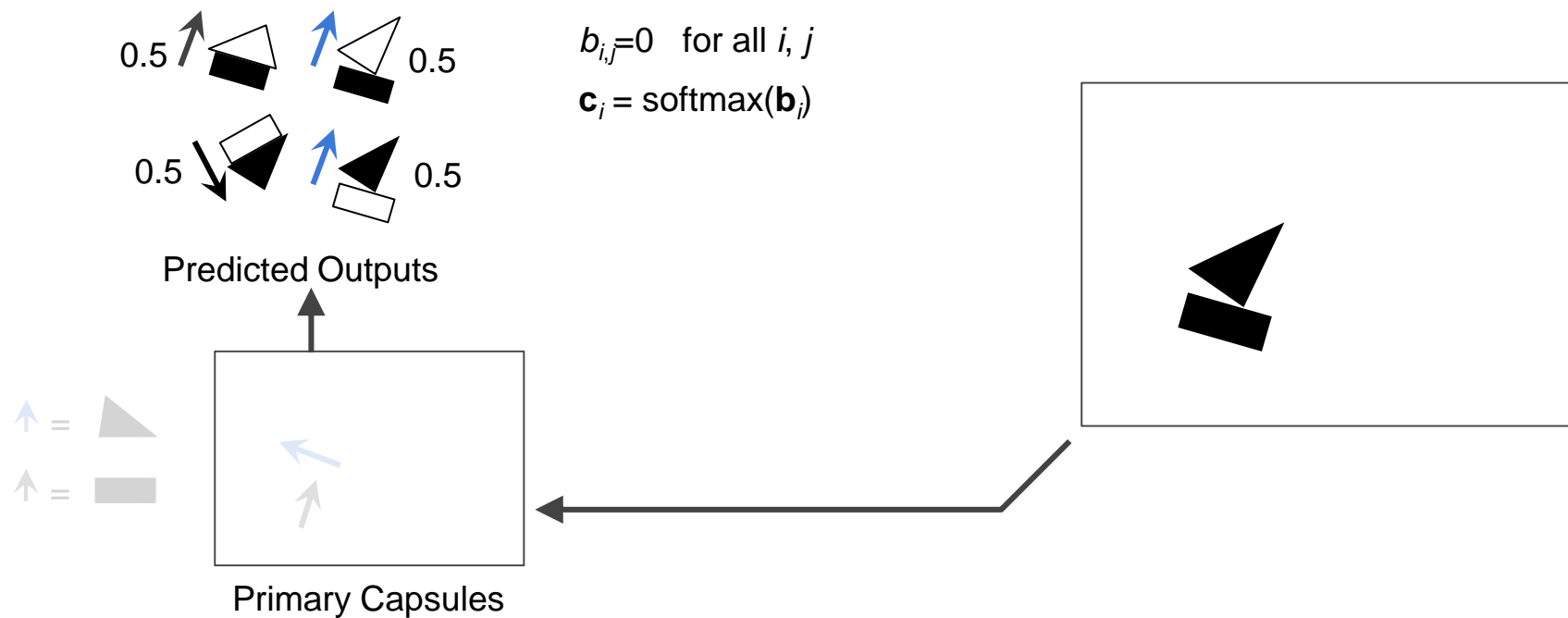
Clusters of Agreement



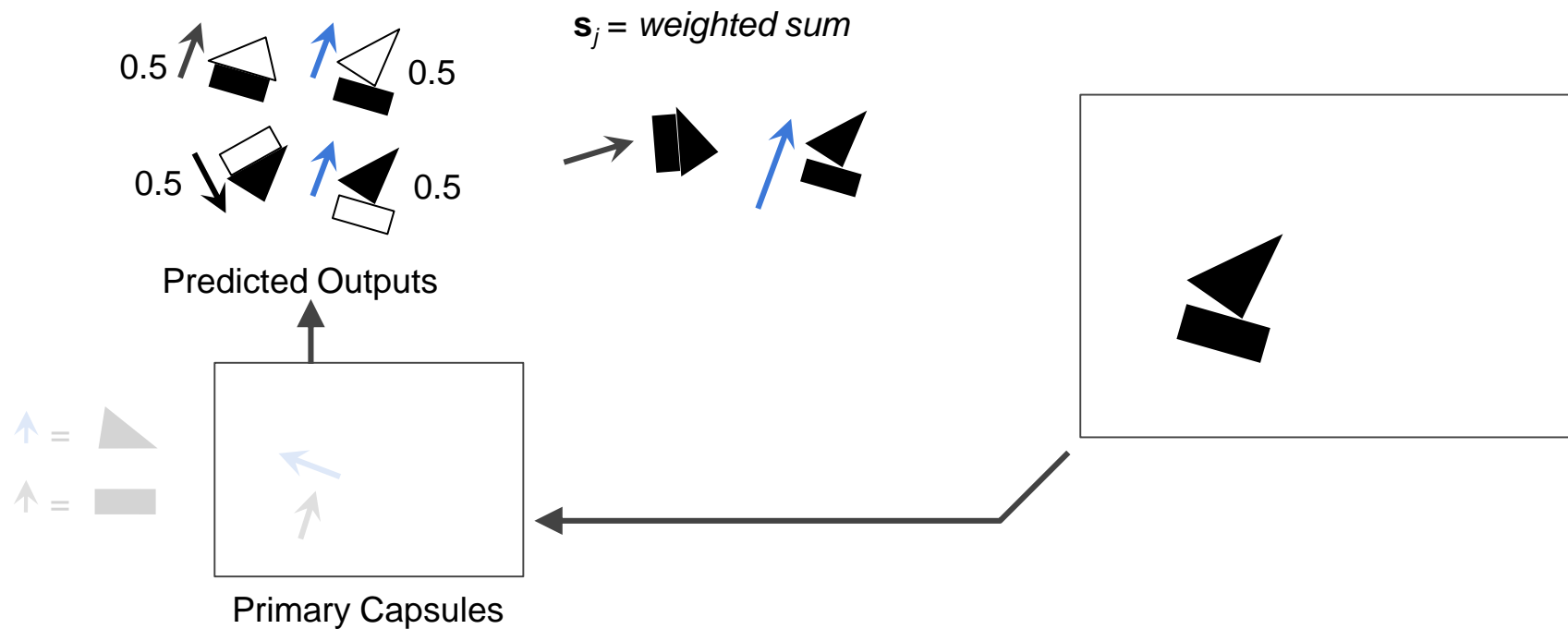
Routing Weights



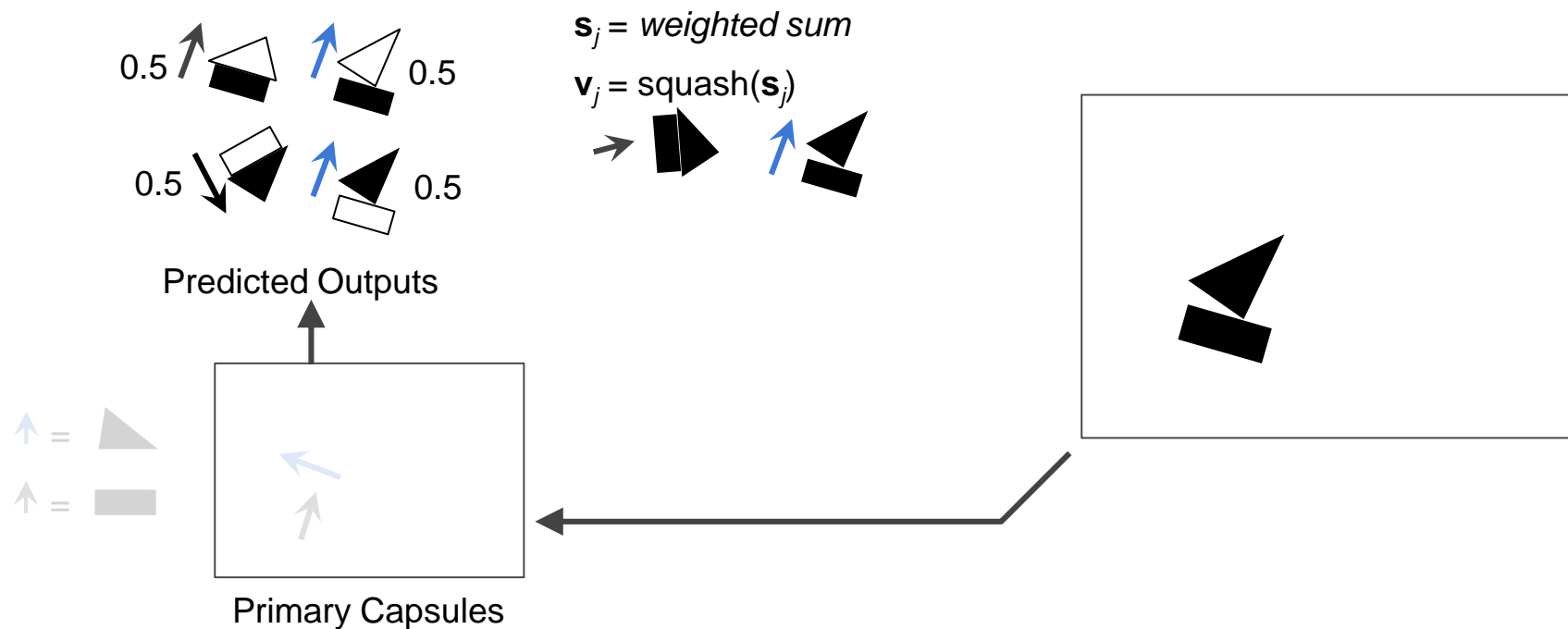
Routing Weights



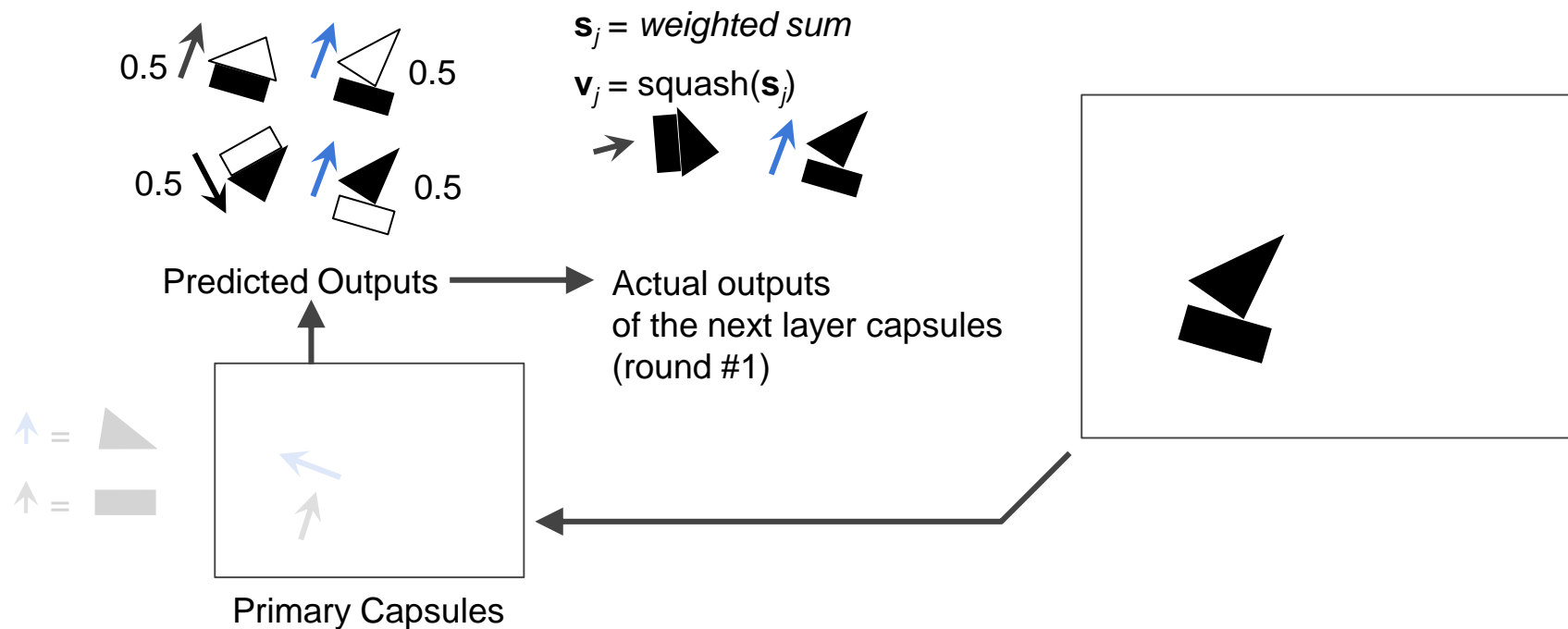
Compute Next Layer's Output



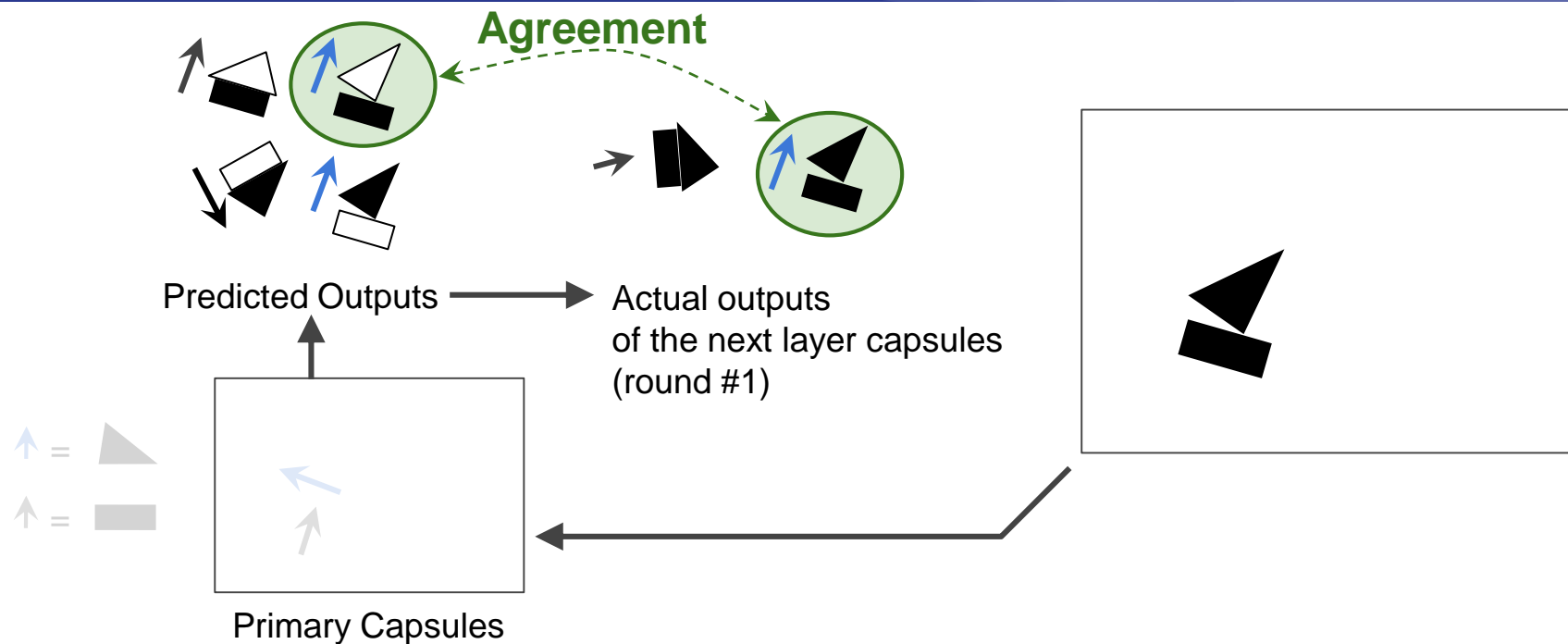
Compute Next Layer's Output



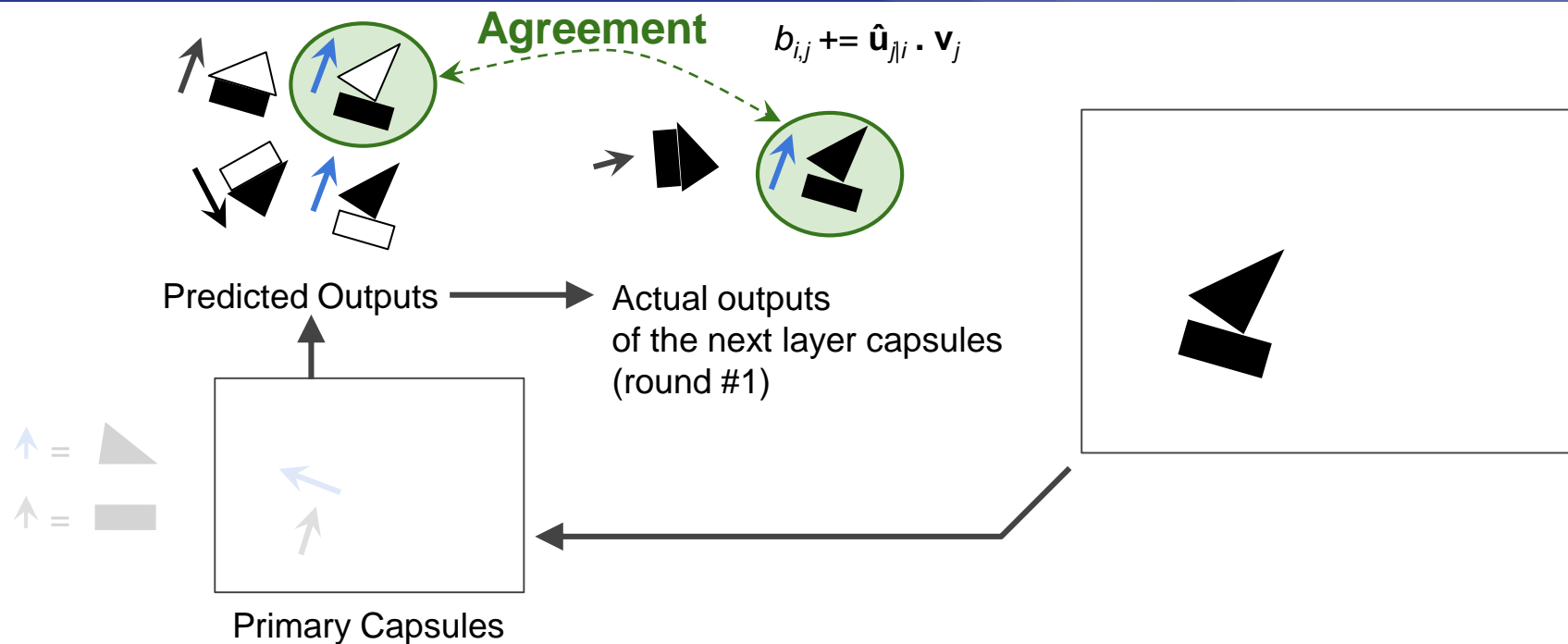
Compute Next Layer's Output



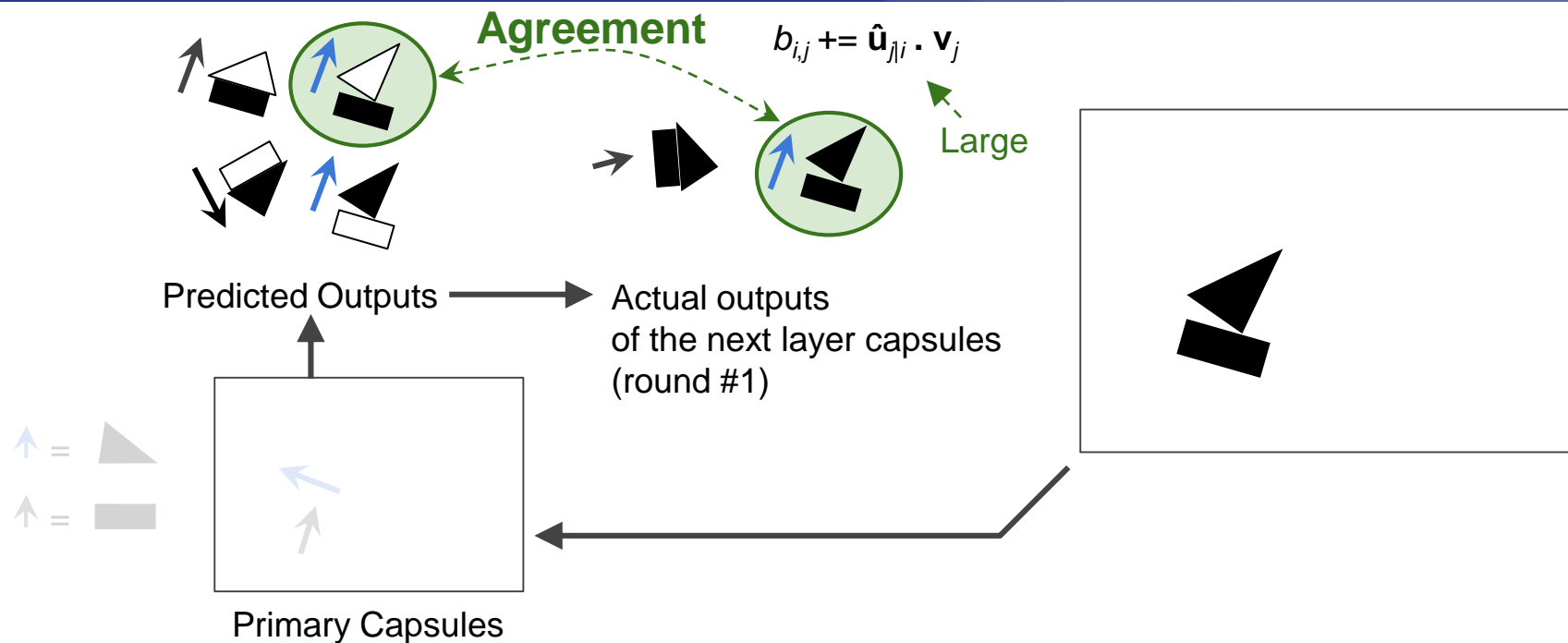
Update Routing Weights



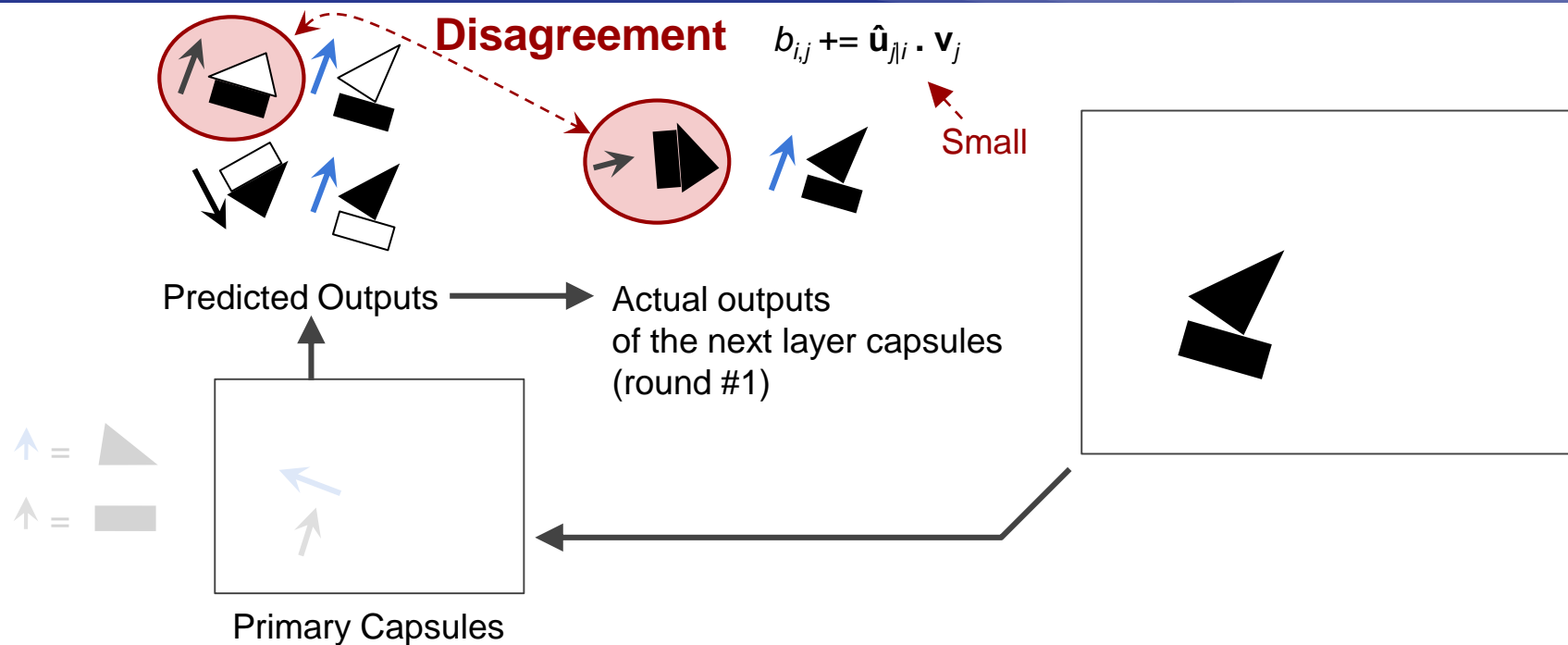
Update Routing Weights



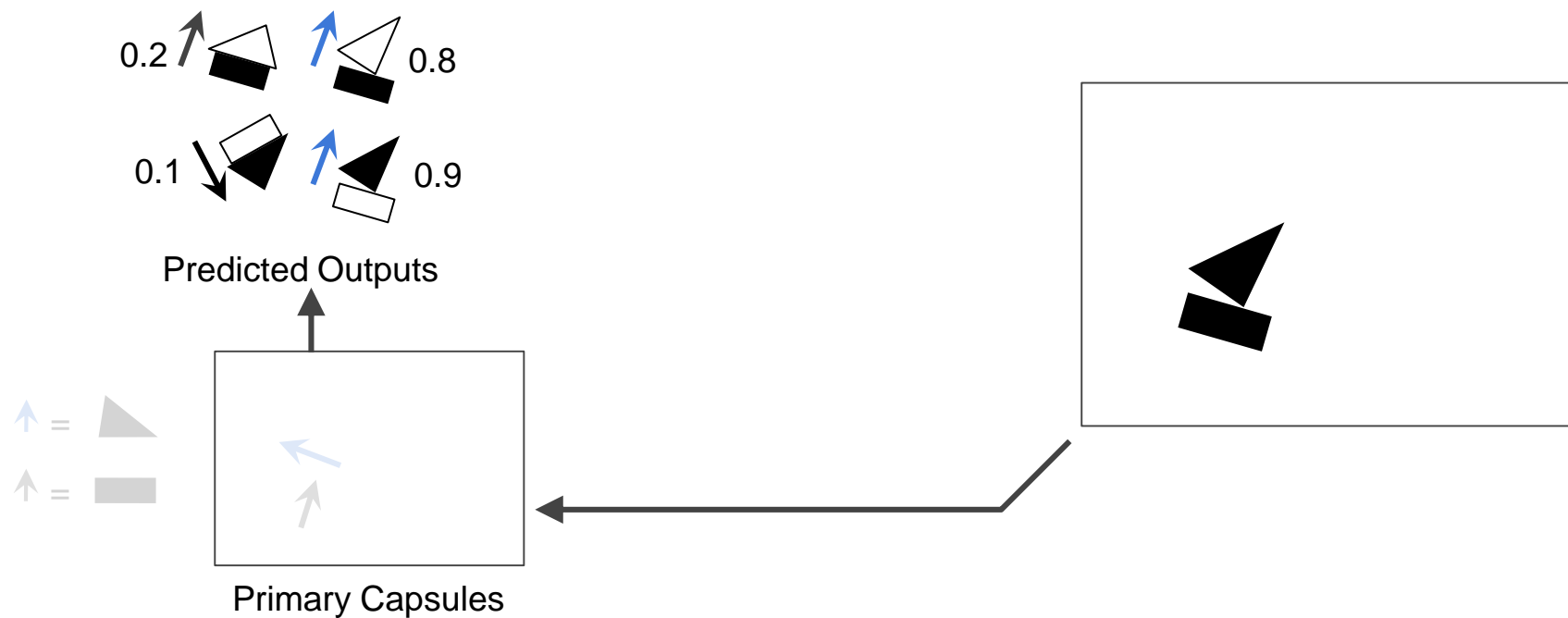
Update Routing Weights



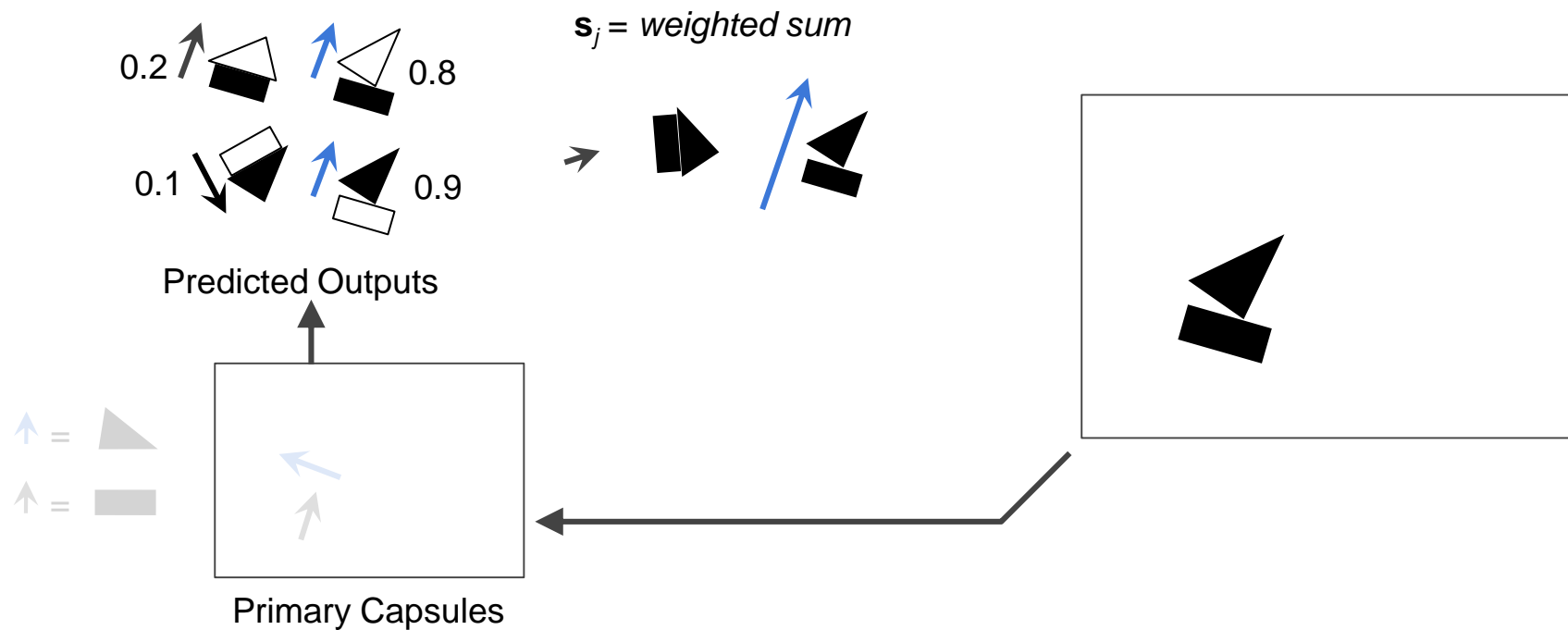
Update Routing Weights



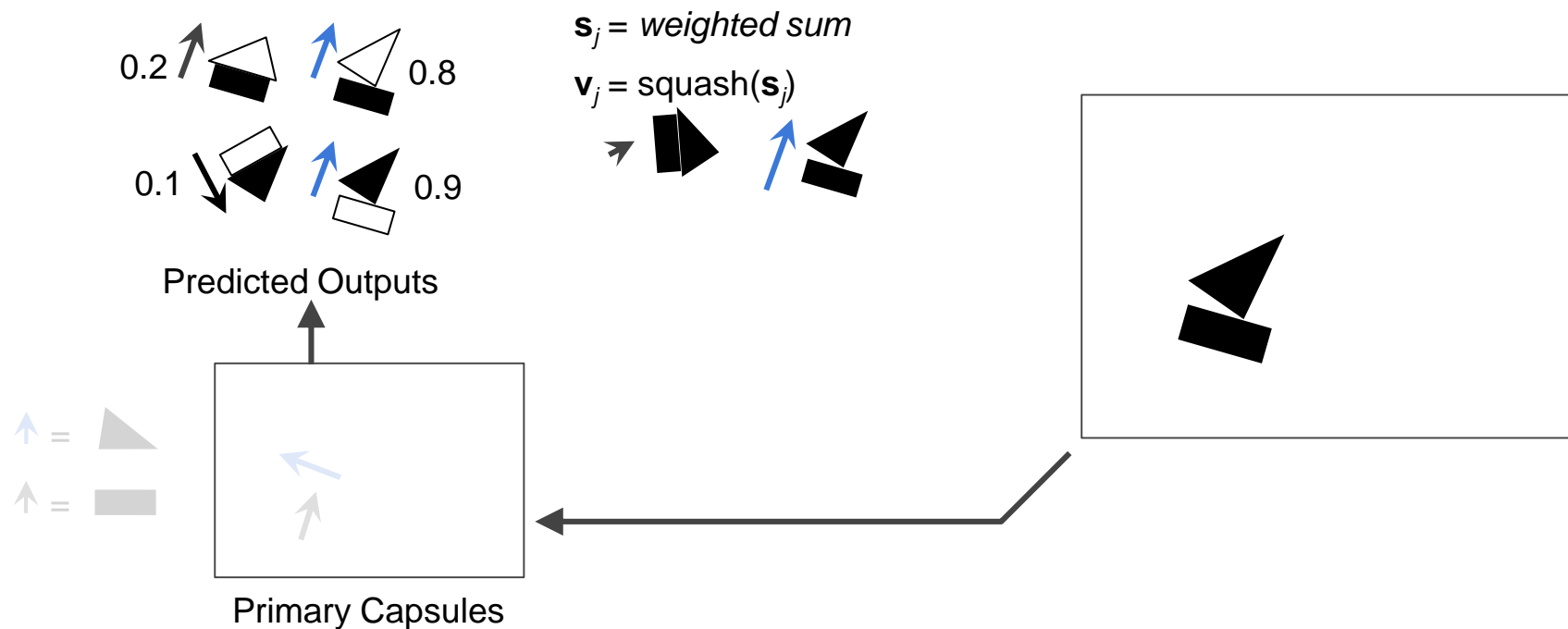
Compute Next Layer's Output



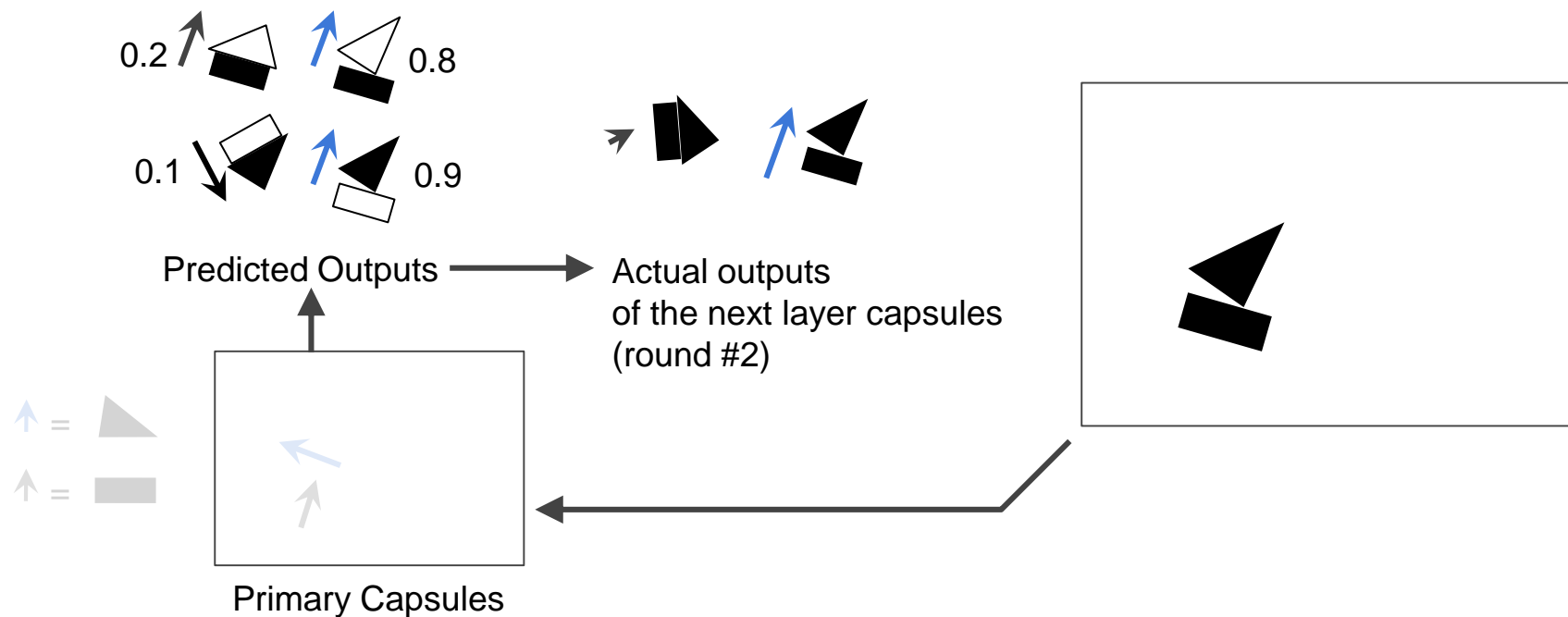
Compute Next Layer's Output



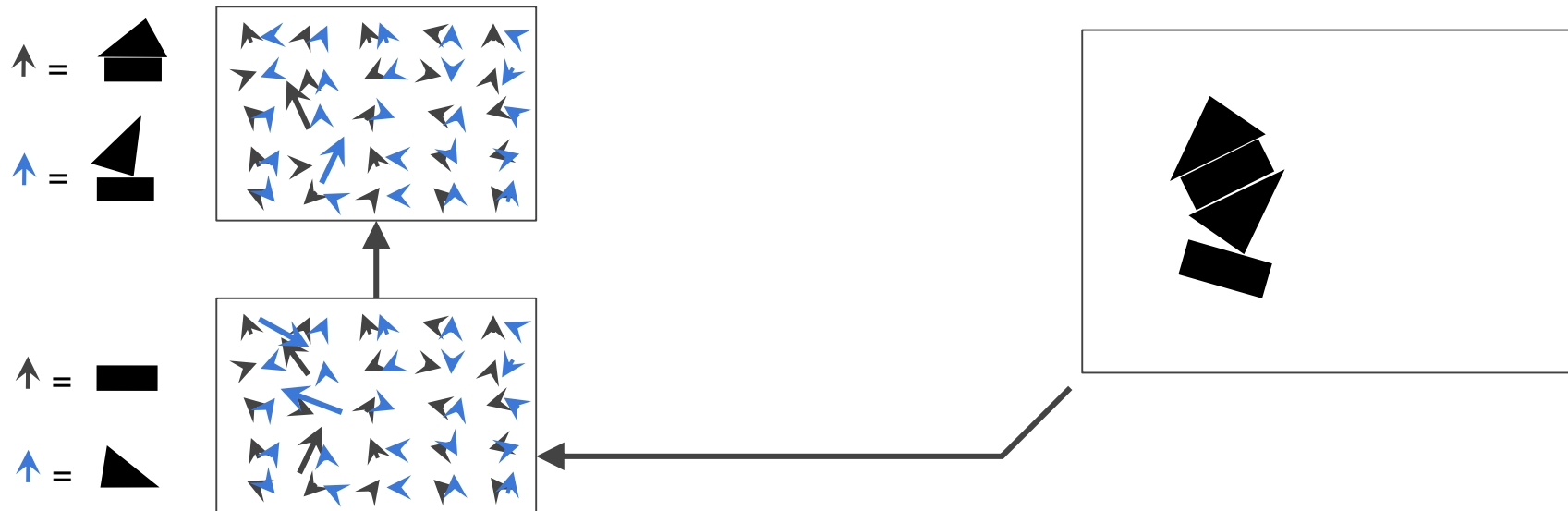
Compute Next Layer's Output



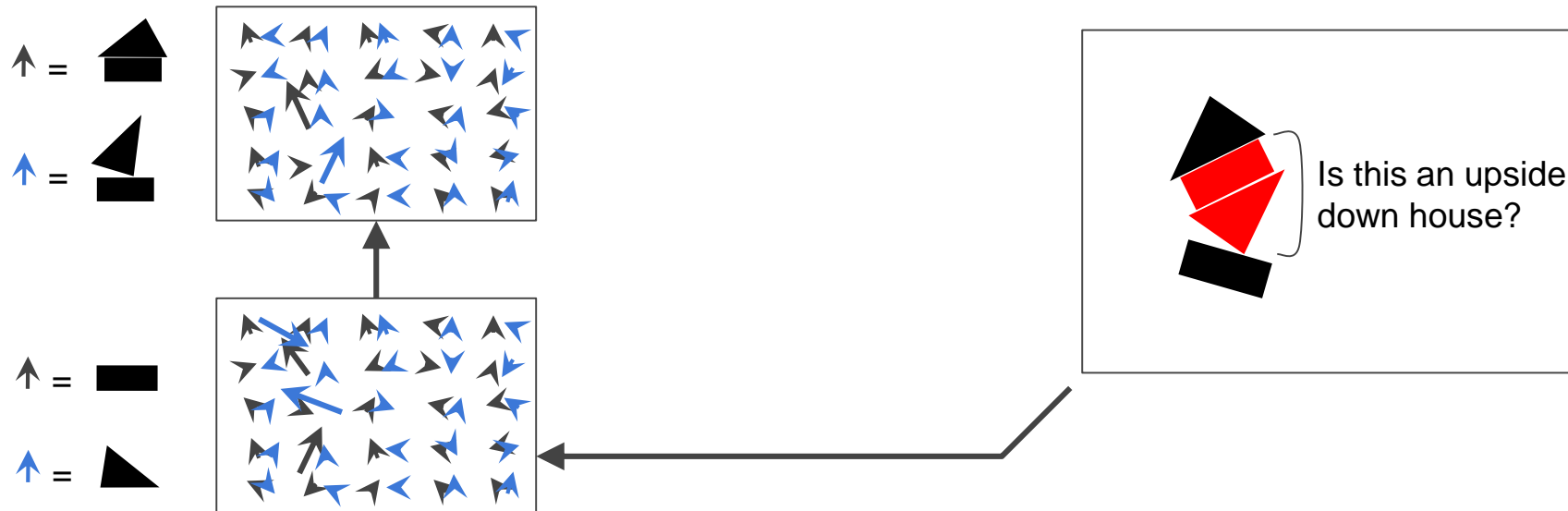
Compute Next Layer's Output



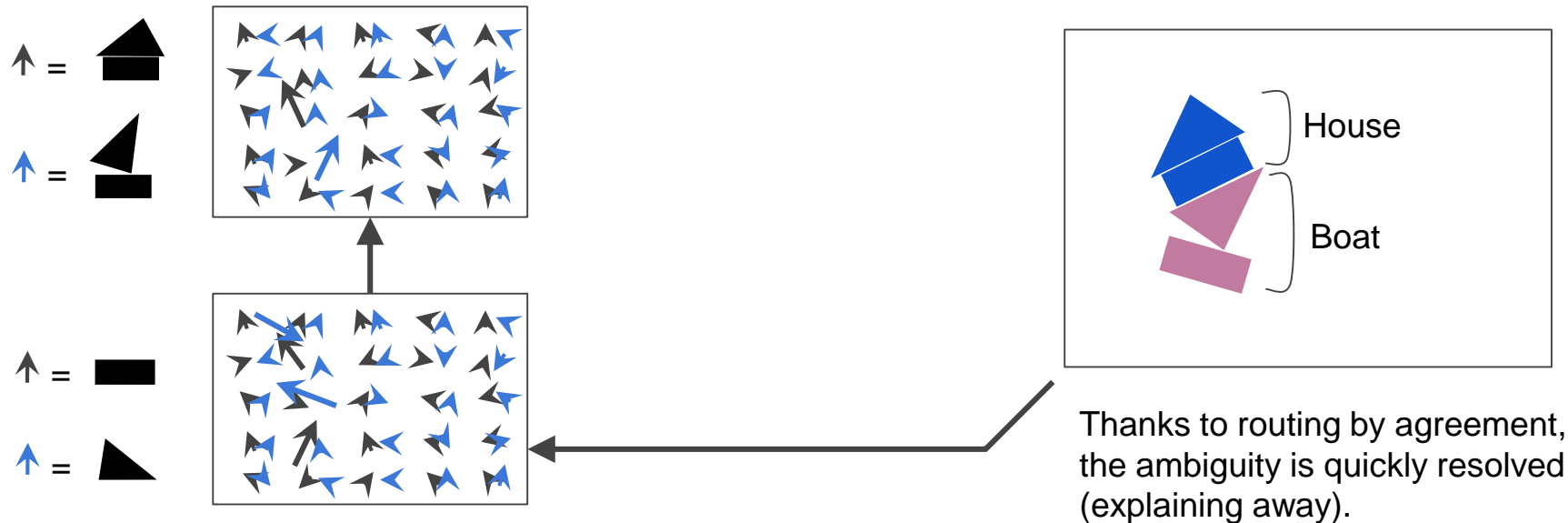
Handling Crowded Scenes



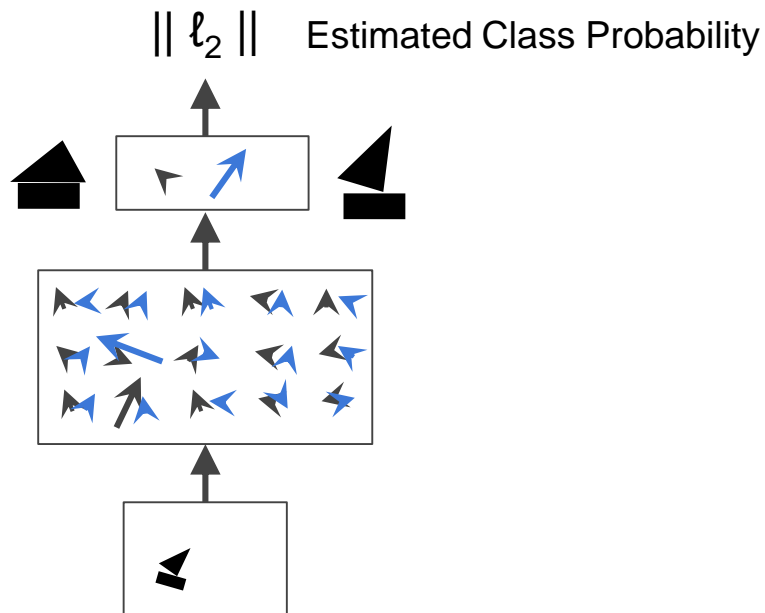
Handling Crowded Scenes



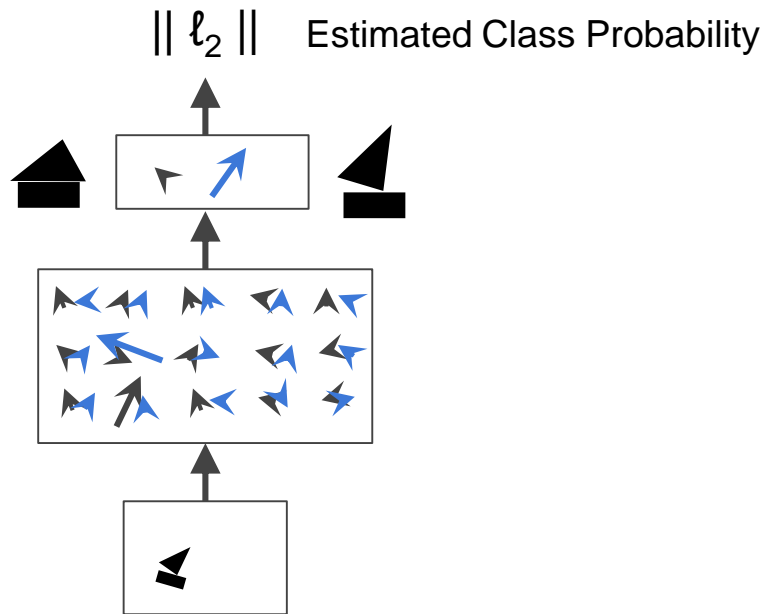
Handling Crowded Scenes



Classification CapsNet



Training



To allow multiple classes,
minimize margin loss:

$$L_k = T_k \max(0, m^+ - \|\mathbf{v}_k\|^2) \\ + \lambda (1 - T_k) \max(0, \|\mathbf{v}_k\|^2 - m^-)$$

$T_k = 1$ iff class k is present

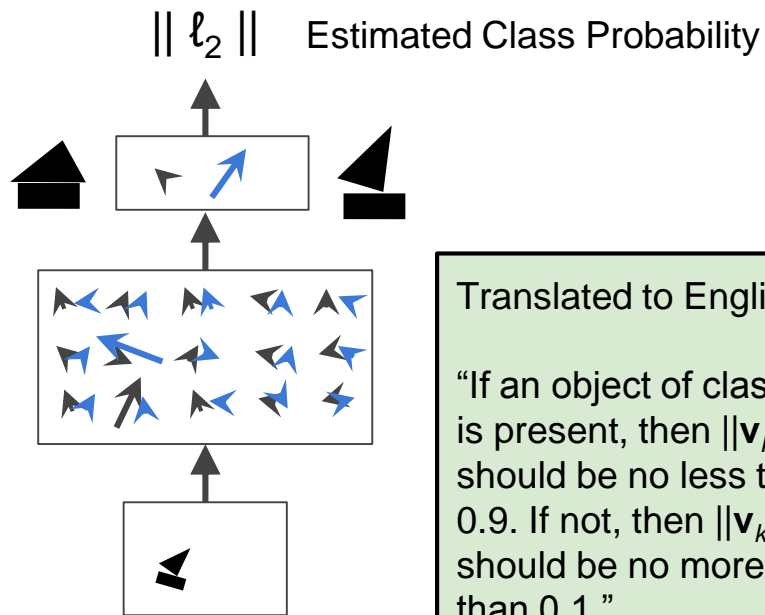
In the paper:

$$m^- = 0.1$$

$$m^+ = 0.9$$

$$\lambda = 0.5$$

Training



Translated to English:

“If an object of class k is present, then $\|\mathbf{v}_k\|^2$ should be no less than 0.9. If not, then $\|\mathbf{v}_k\|^2$ should be no more than 0.1.”

To allow multiple classes, minimize margin loss:

$$\mathcal{L}_k = T_k \max(0, m^+ - \|\mathbf{v}_k\|^2) + \lambda (1 - T_k) \max(0, \|\mathbf{v}_k\|^2 - m^-)$$

$T_k = 1$ iff class k is present

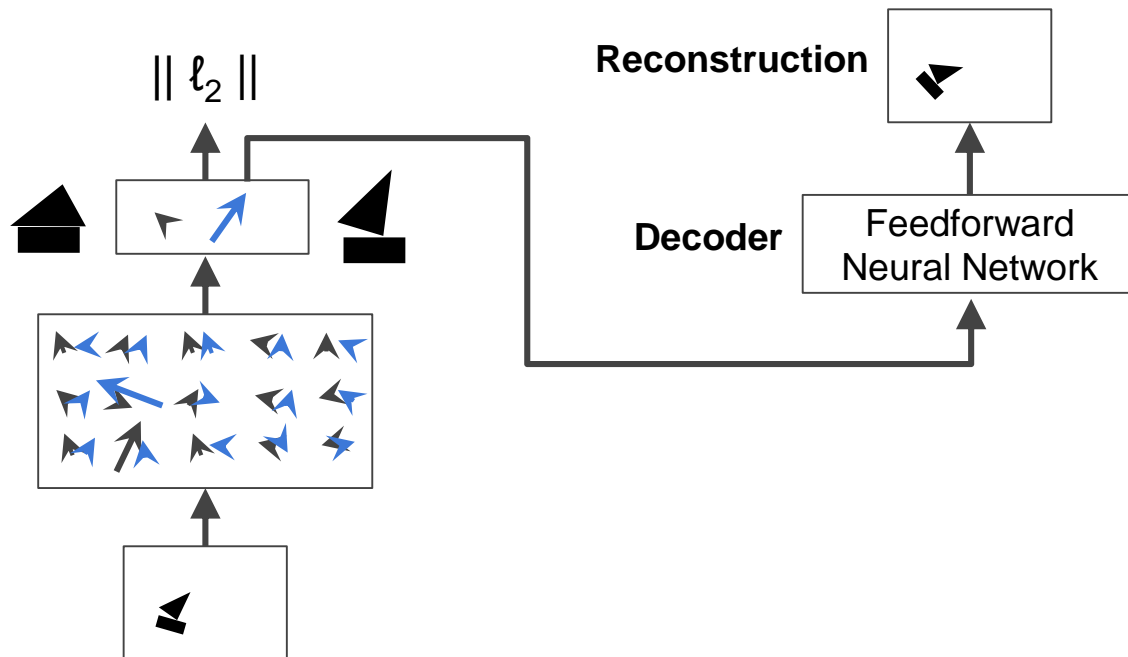
In the paper:

$$m^- = 0.1$$

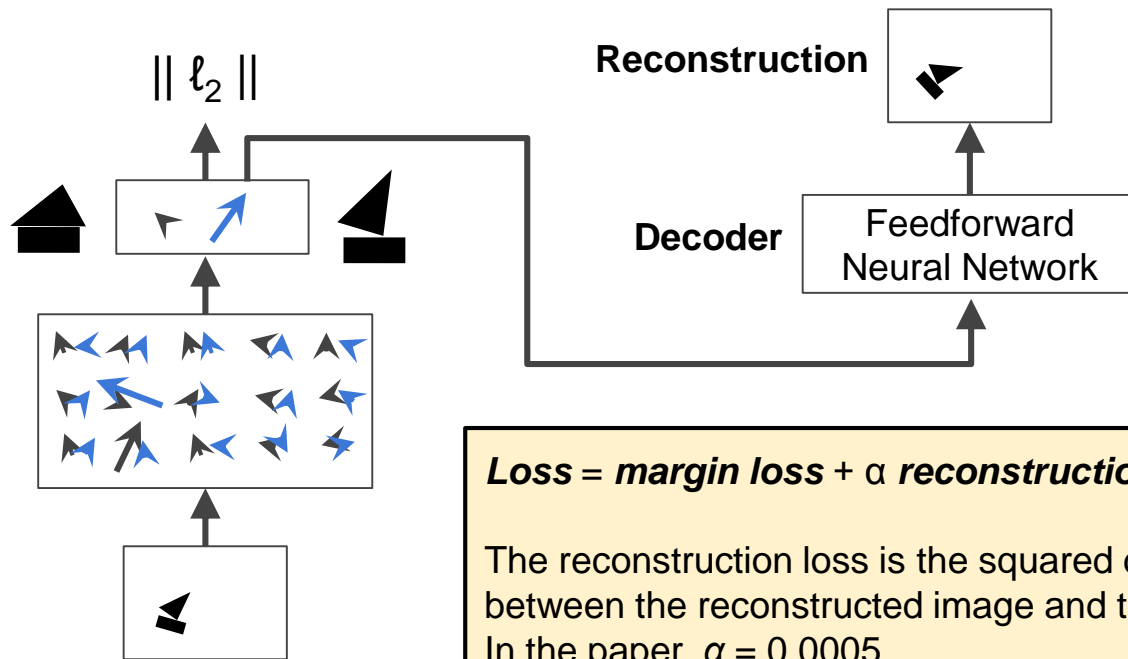
$$m^+ = 0.9$$

$$\lambda = 0.5$$

Regularization by Reconstruction



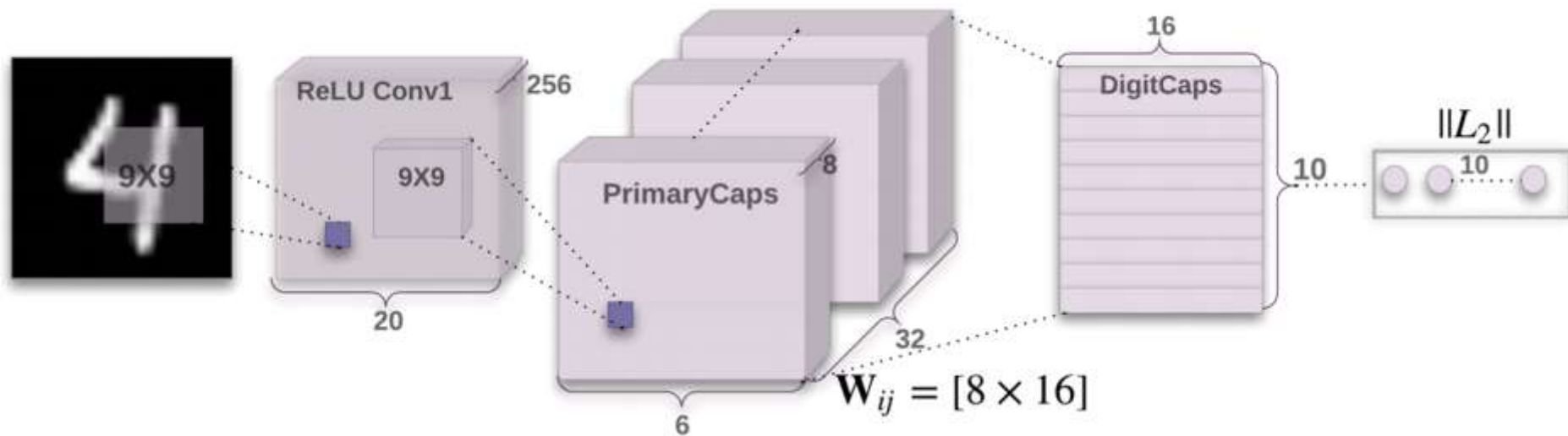
Regularization by Reconstruction



$$\text{Loss} = \text{margin loss} + \alpha \text{ reconstruction loss}$$

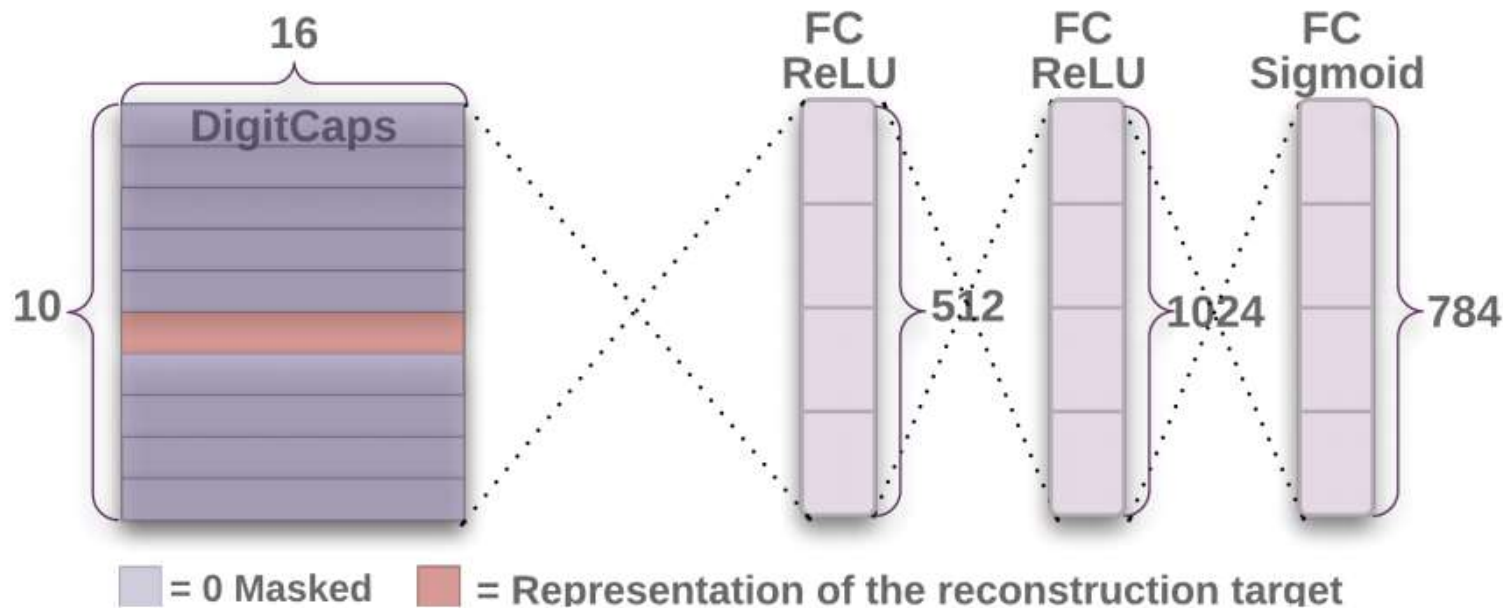
The reconstruction loss is the squared difference between the reconstructed image and the input image. In the paper, $\alpha = 0.0005$.

A CapsNet for MNIST








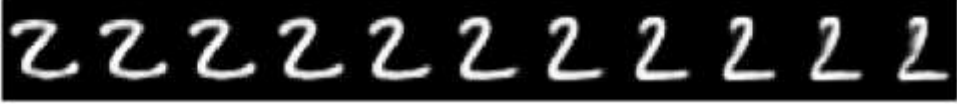
(Figure 1 from the paper)

A CapsNet for MNIST – Decoder



(Figure 2 from the paper)

Interpretable Activation Vectors

Scale and thickness	
Localized part	
Stroke thickness	
Localized skew	
Width and translation	
Localized part	

(Figure 4 from the paper)

Pros

- Reaches high accuracy on MNIST, and promising on CIFAR10
- Requires less training data
- Position and pose information are preserved (equivariance)
- This is promising for image segmentation and object detection
- Routing by agreement is great for overlapping objects (explaining away)
- Capsule activations nicely map the hierarchy of parts
- Offers robustness to affine transformations
- Activation vectors are easier to interpret (rotation, thickness, skew...)
- It's Hinton! ;-)

Cons

- Not state of the art on CIFAR10 (but it's a good start)
- Not tested yet on larger images (e.g., ImageNet): will it work well?
- Slow training, due to the inner loop (in the routing by agreement algorithm)
- A CapsNet cannot see two very close identical objects
 - This is called “crowding”, and it has been observed as well in human vision

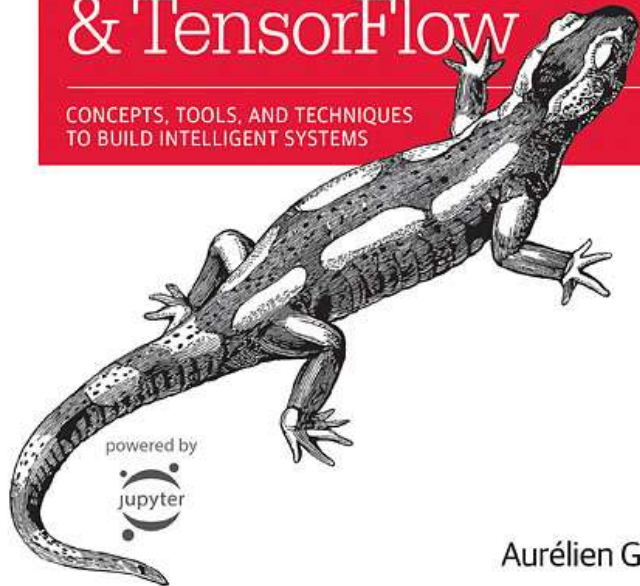
Implementations

- Keras w/ TensorFlow backend: <https://github.com/XifengGuo/CapsNet-Keras>
- TensorFlow: <https://github.com/naturomics/CapsNet-Tensorflow>
- PyTorch: <https://github.com/gram-ai/capsule-networks>

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