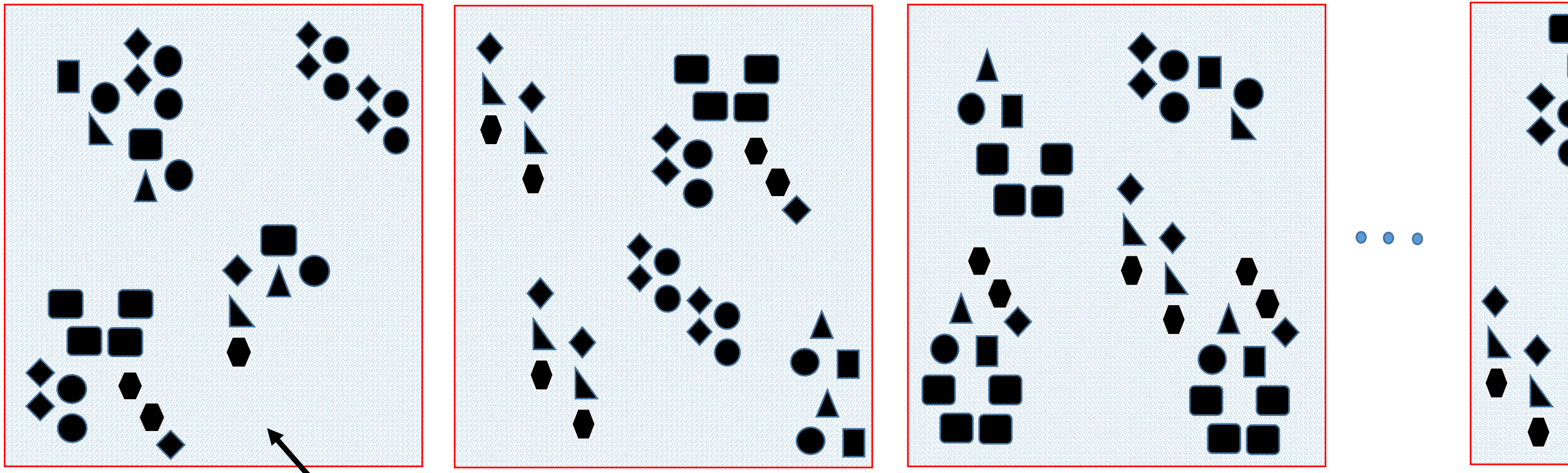
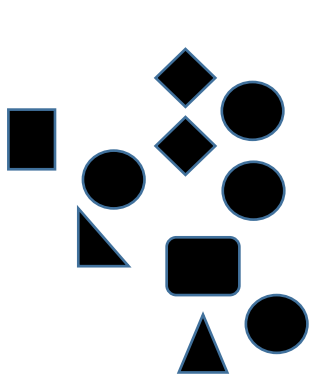
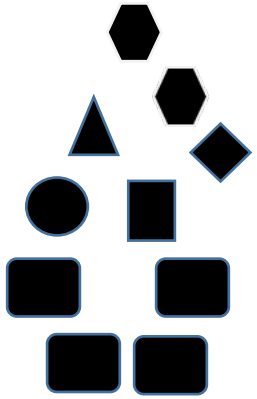
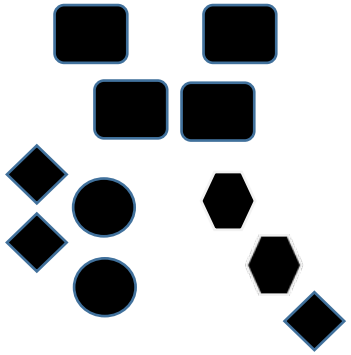
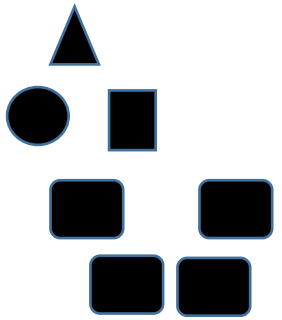
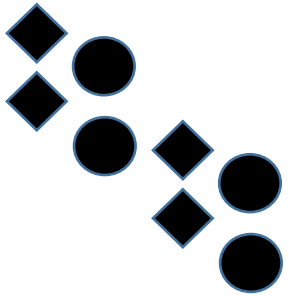
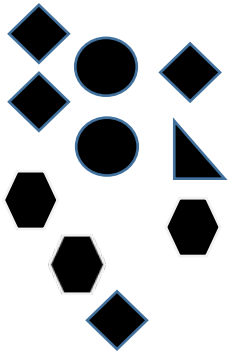
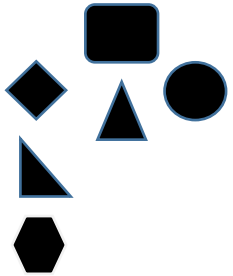
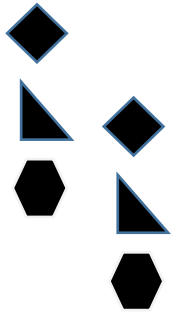
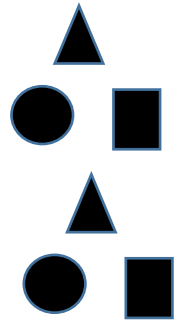
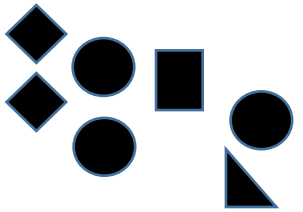
Deep Learning and Big Data

Lawrence Carin
Duke University

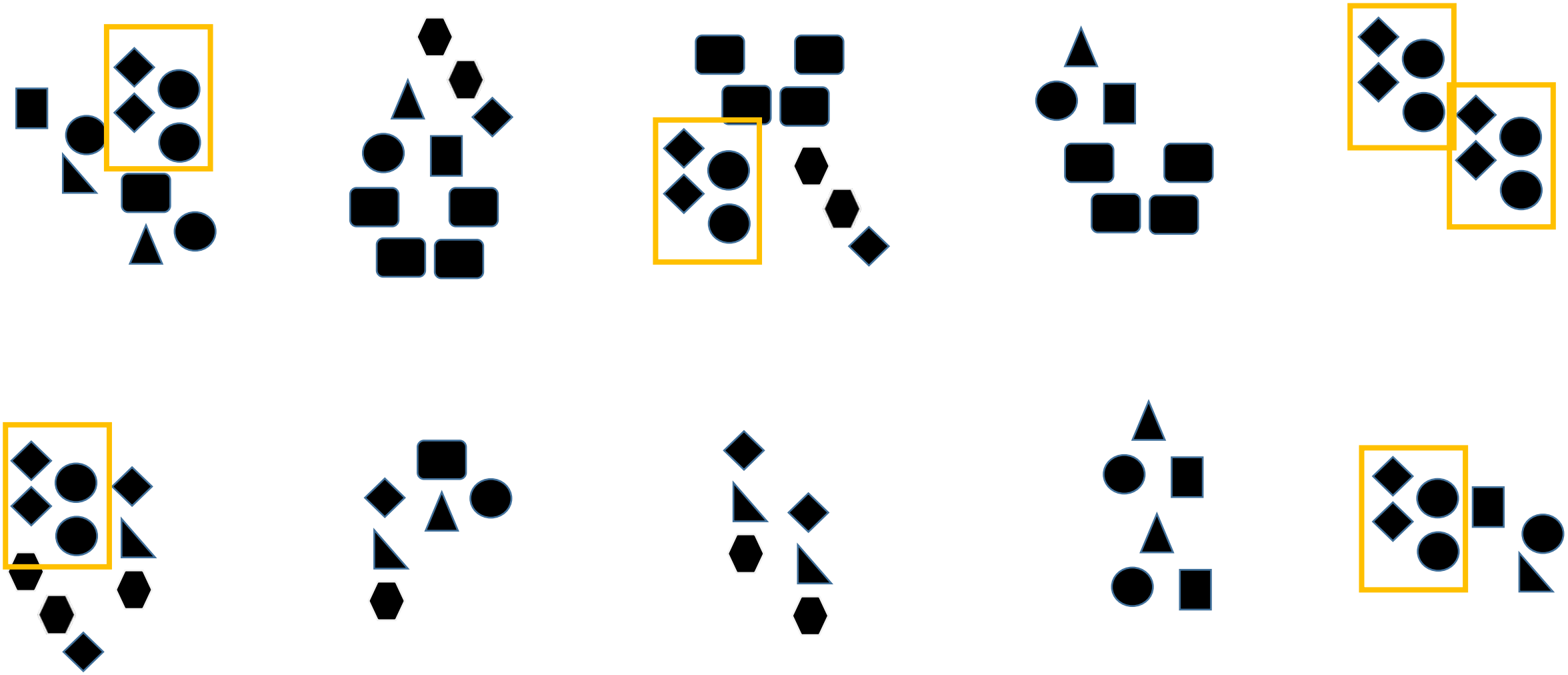
Consider a Set of “Toy” Images, for Illustration



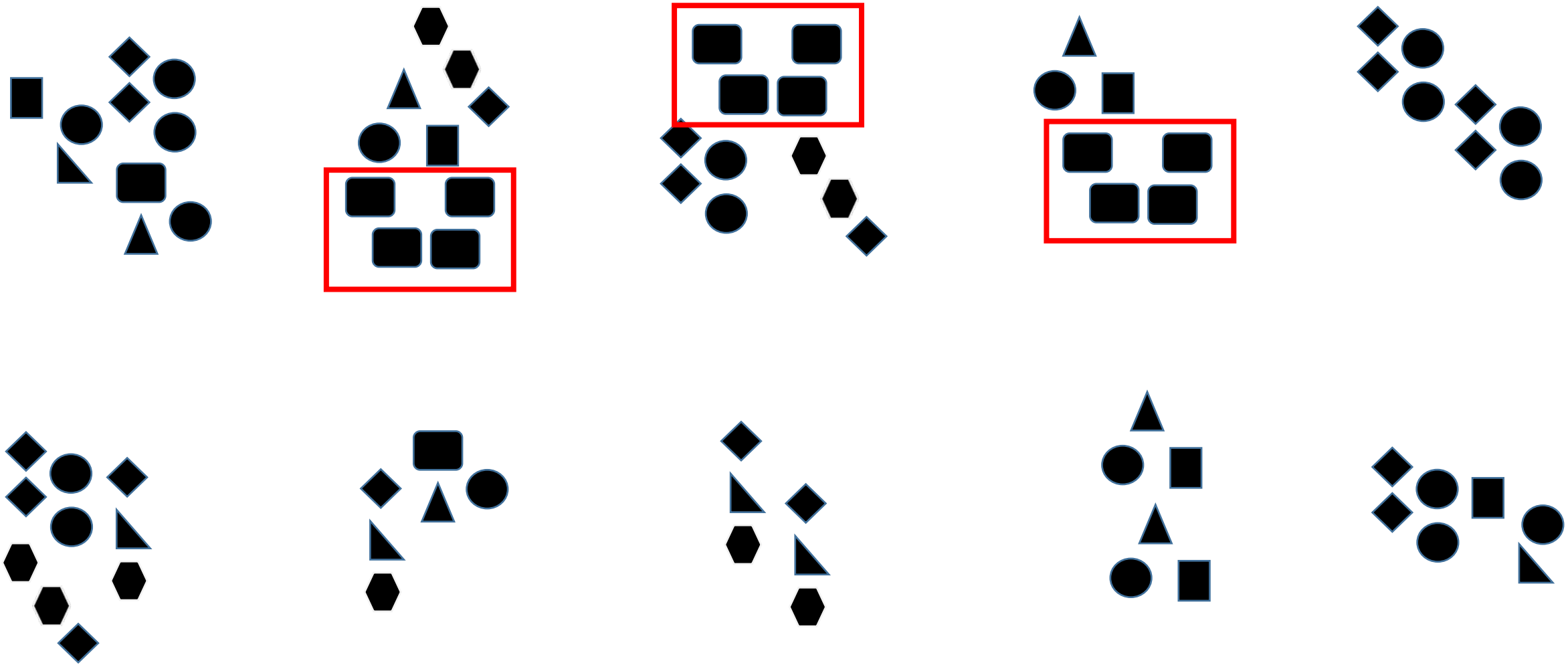
High-Level Motifs

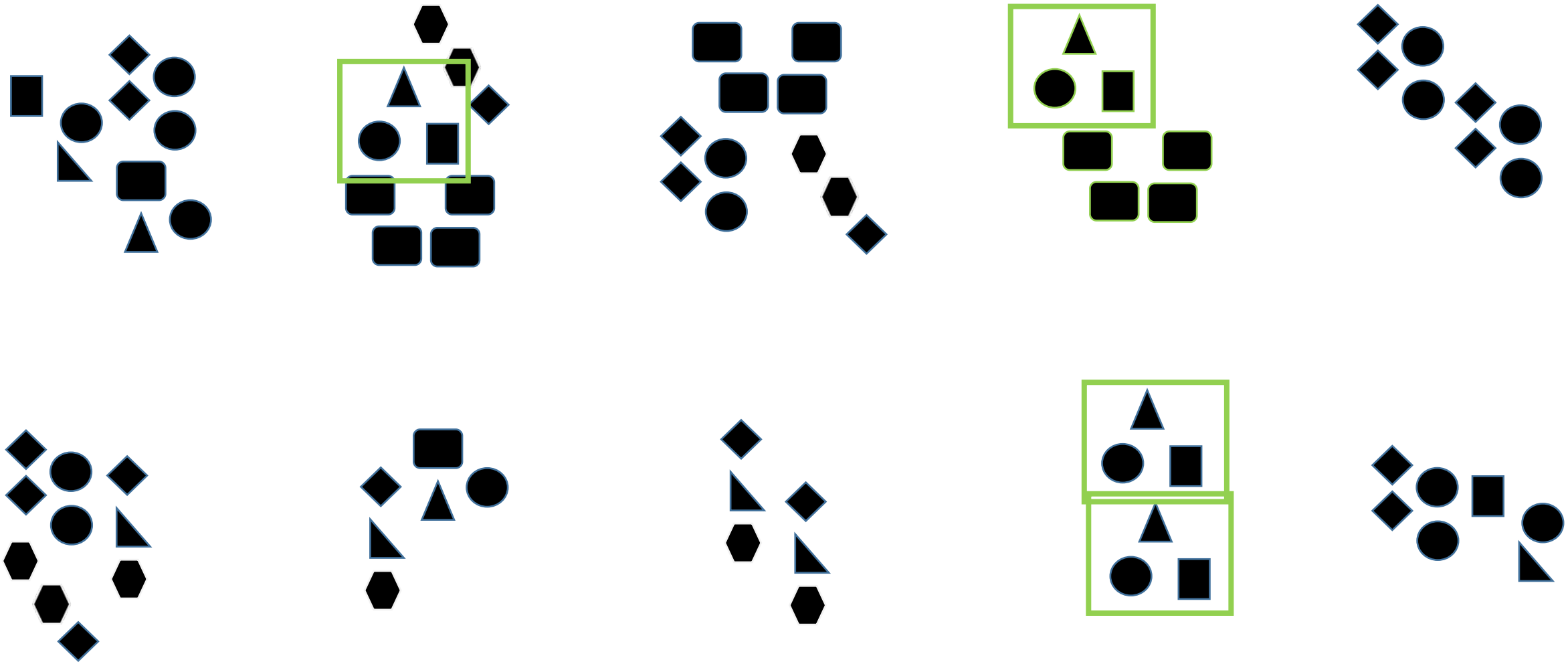
Shared Substructure Within Motifs



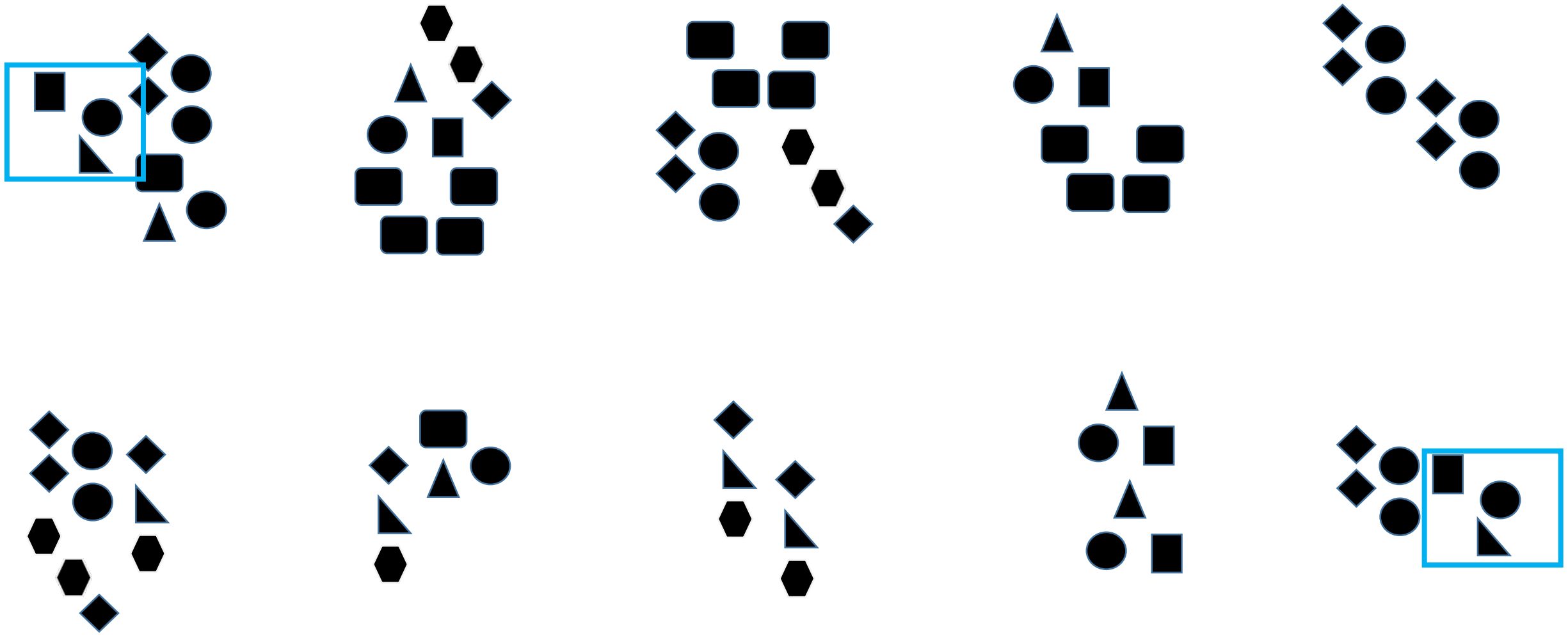
Shared Substructure Within Motifs



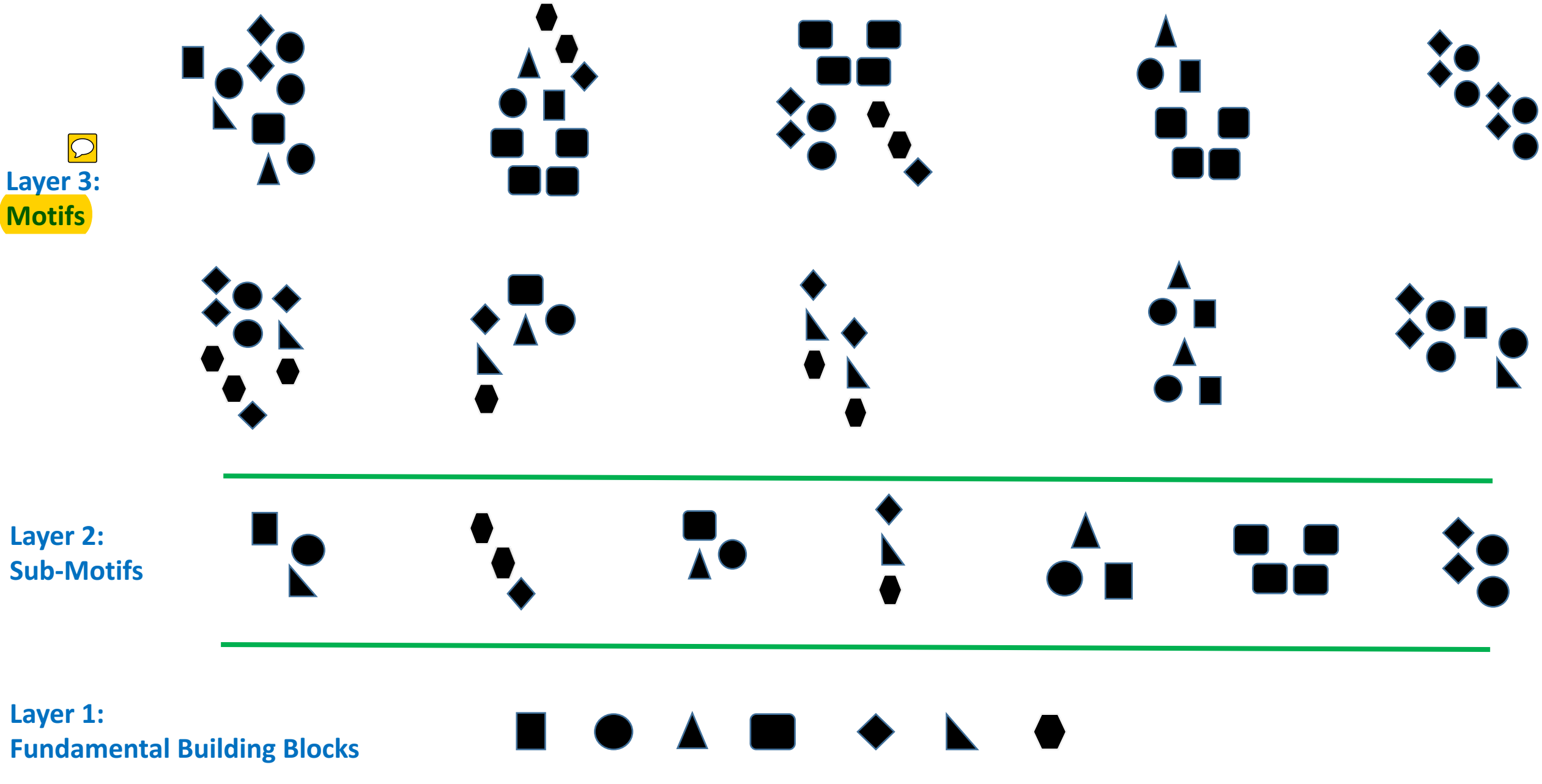
Shared Substructure Within Motifs



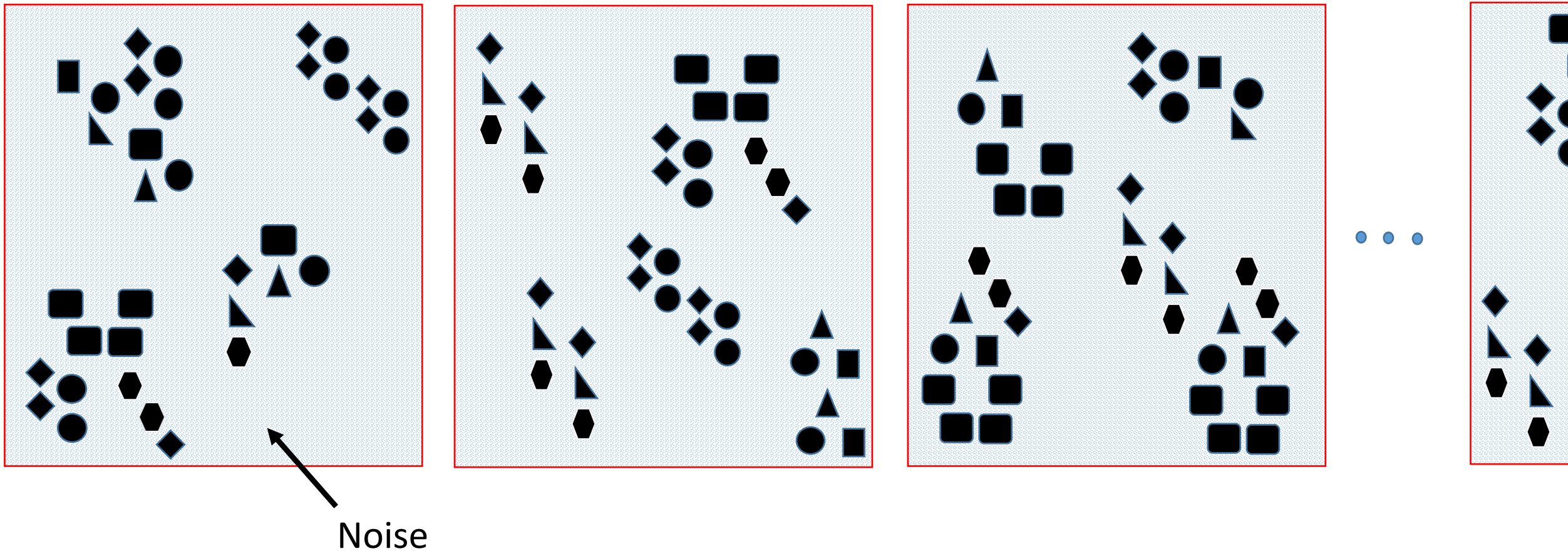
Shared Substructure Within Motifs



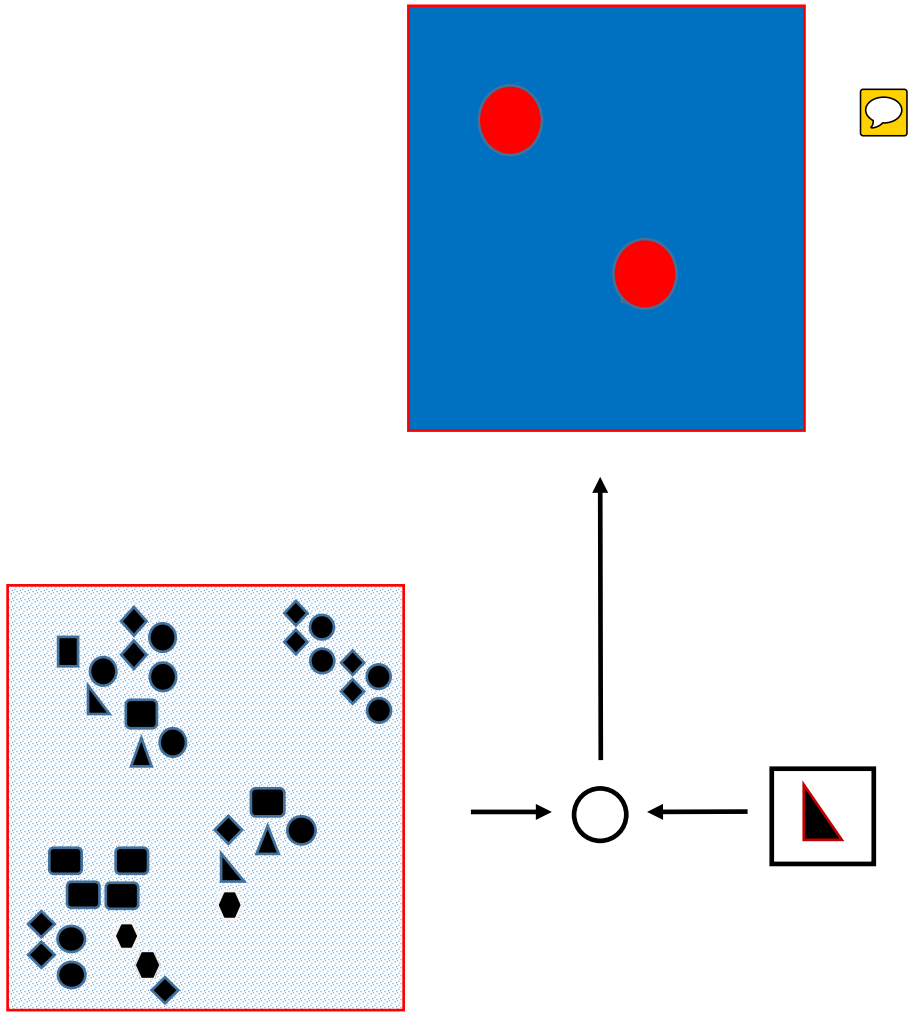
Hierarchical Representation of Images



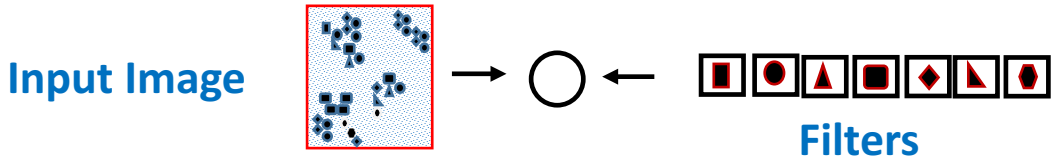
Recall the Data/Images

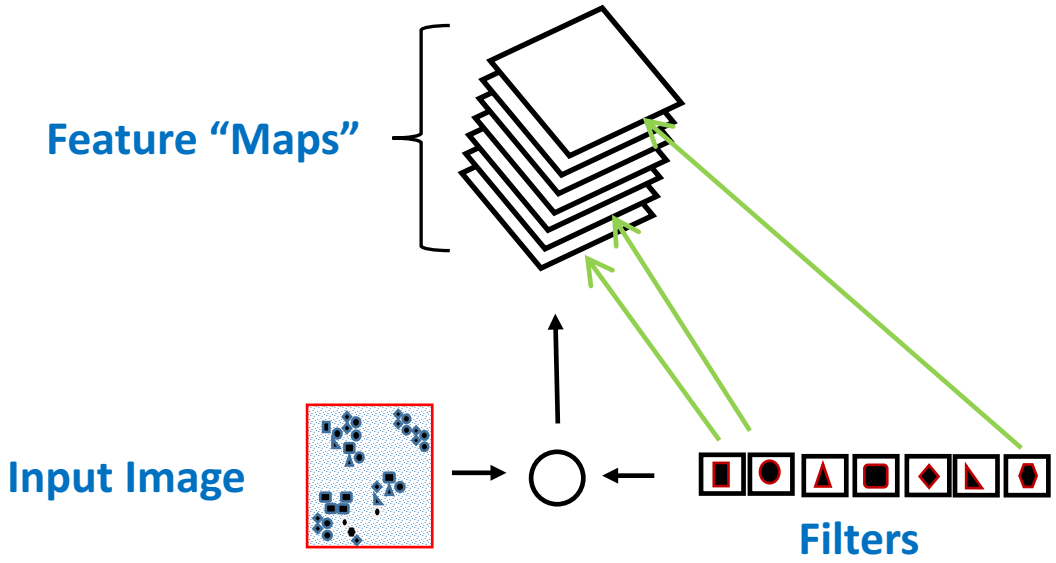


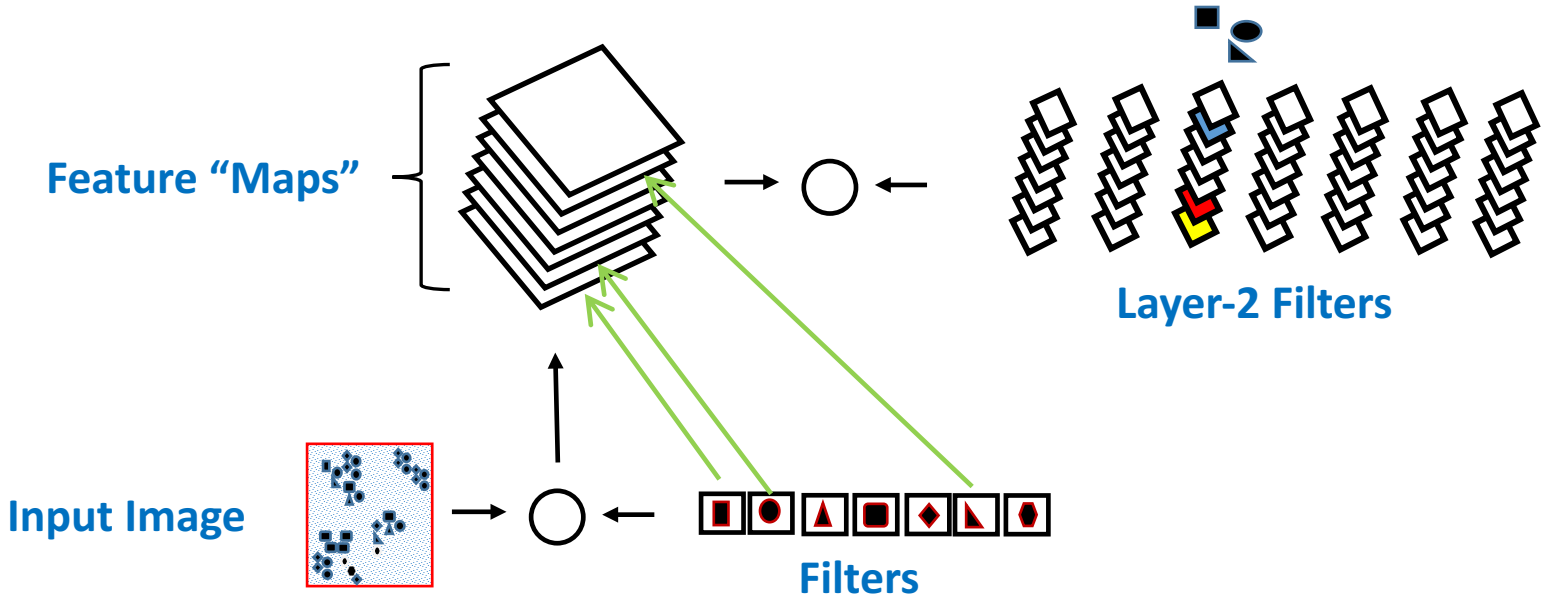
Convolutional Filter

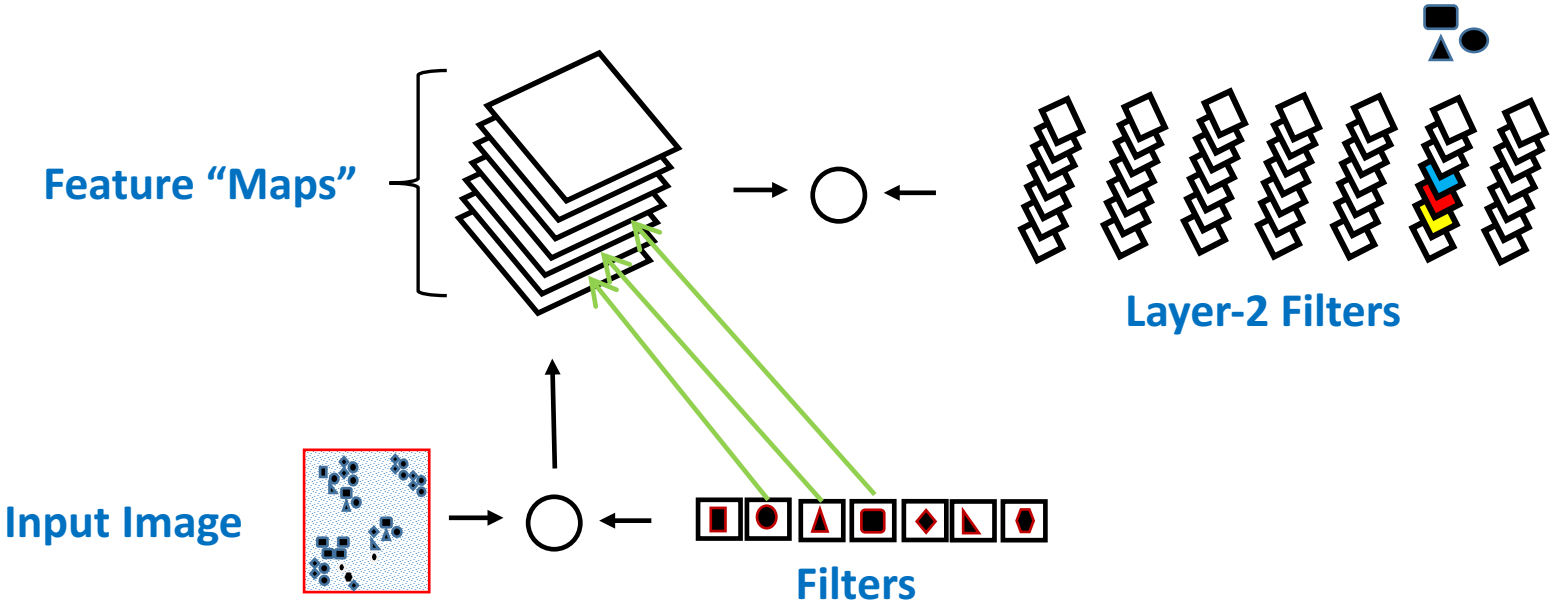


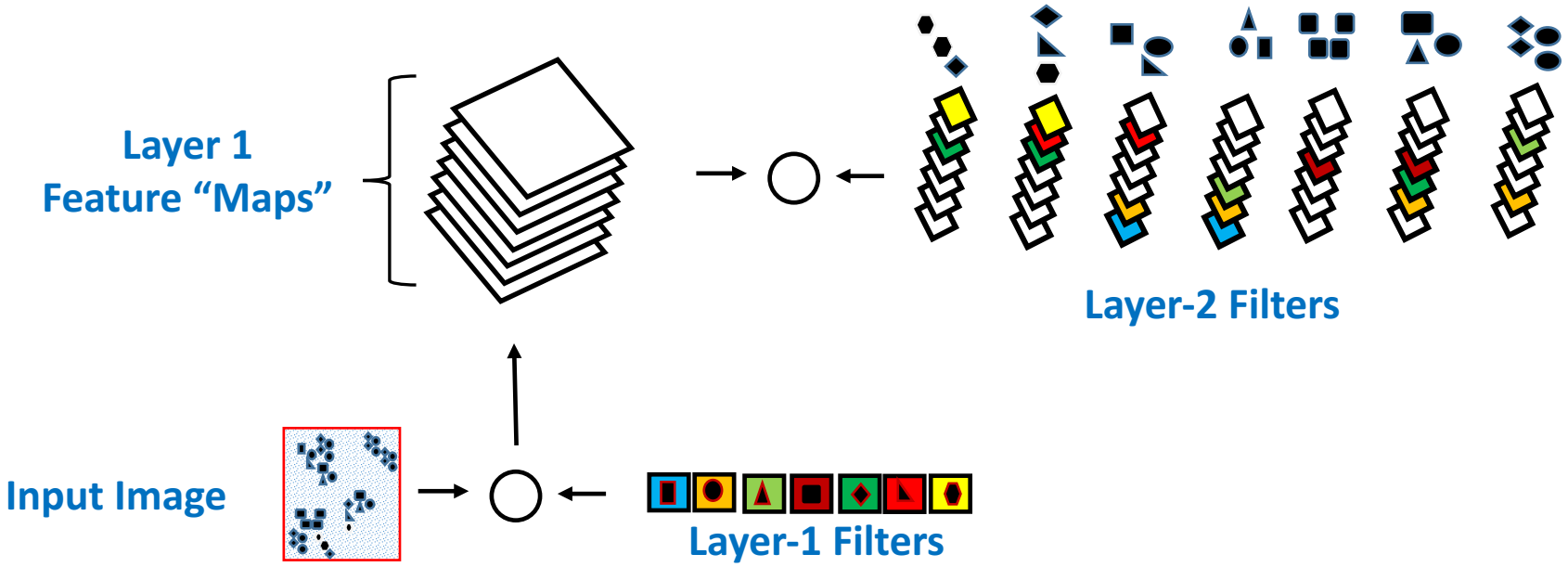
Multiple Filters, for Each Building Block

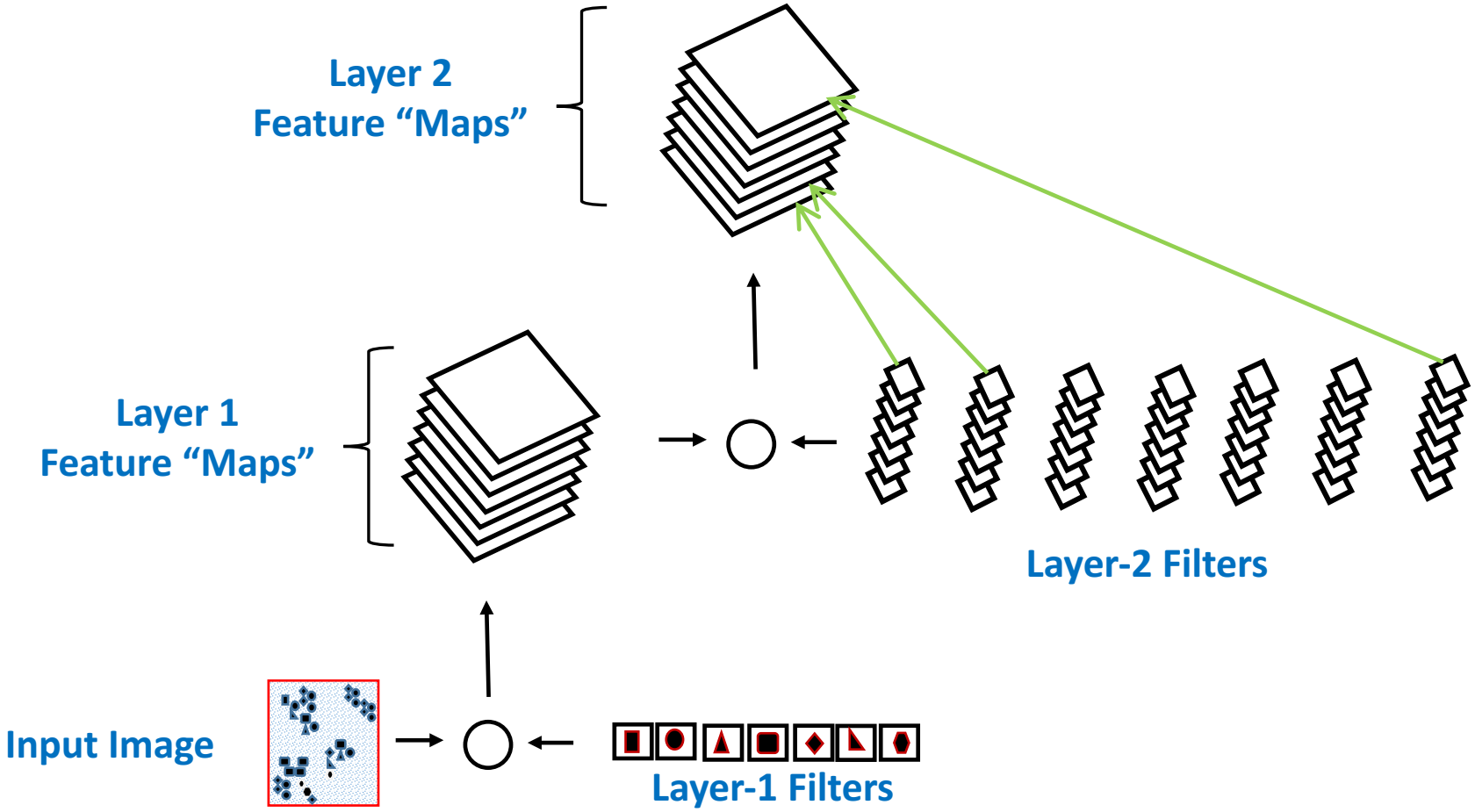


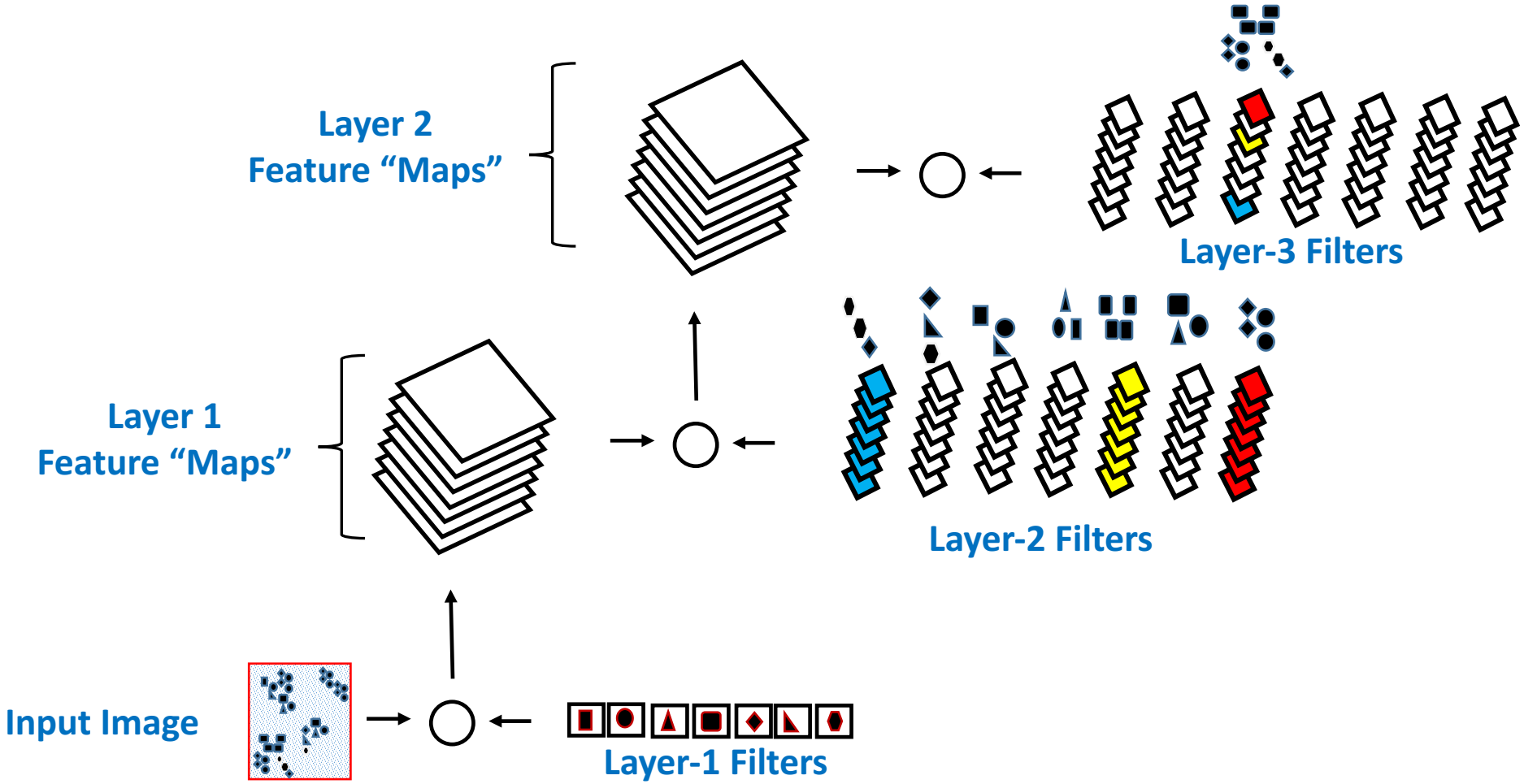

Feature “Maps”
Input Image
Filters

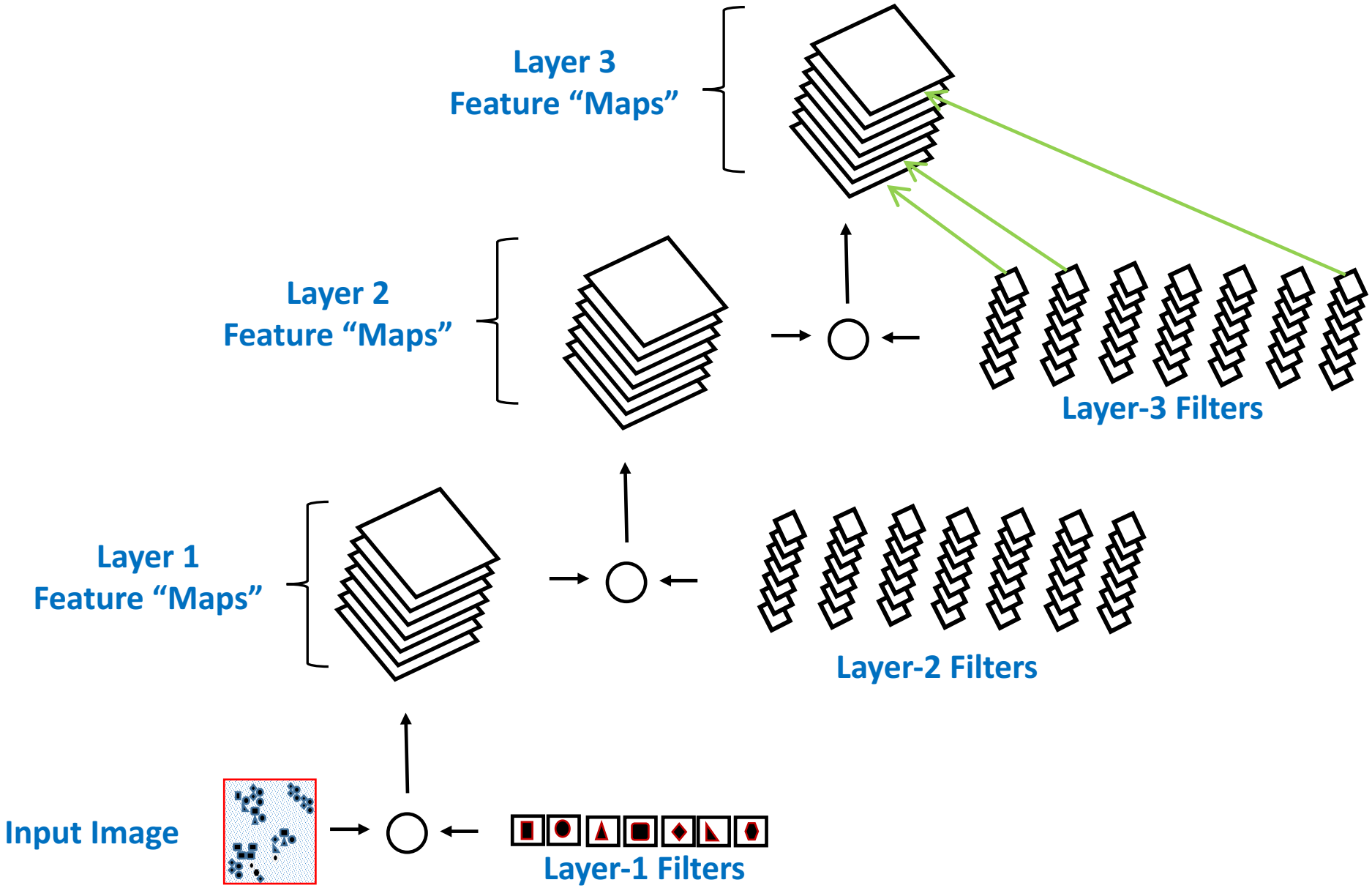

Feature “Maps”
Layer-2 Filters
Input Image
Filters


Feature “Maps”
Layer-2 Filters
Input Image
Filters

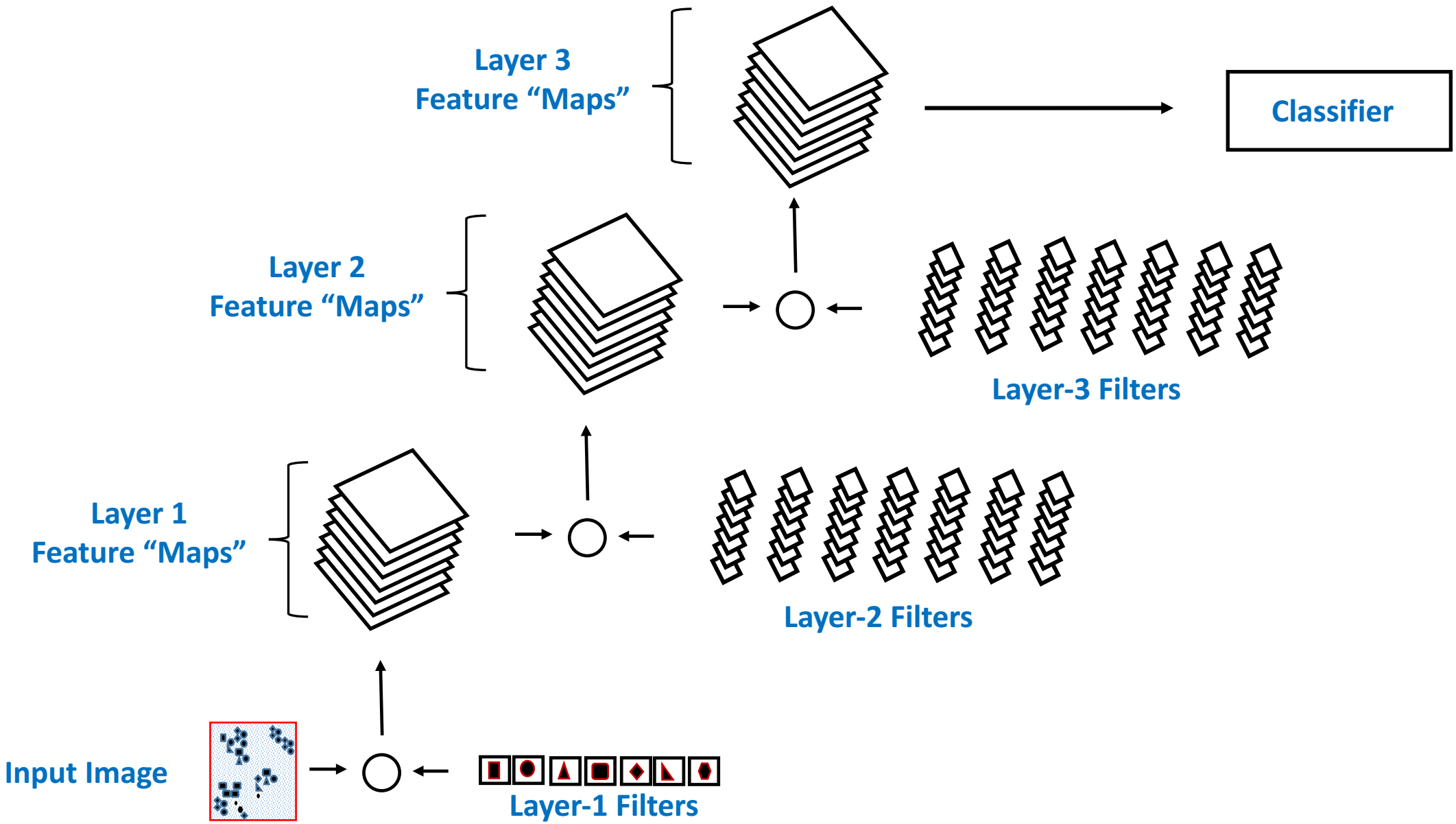

Layer 1
Feature "Maps"
Layer-2 Filters
Input Image
Layer-1 Filters


Layer 2
Feature "Maps"
Layer 1
Feature "Maps"
Layer-2 Filters
Input Image
Layer-1 Filters


Layer 2
Feature "Maps"
Layer-3 Filters
Layer 1
Feature "Maps"
Layer-2 Filters
Input Image
Layer-1 Filters

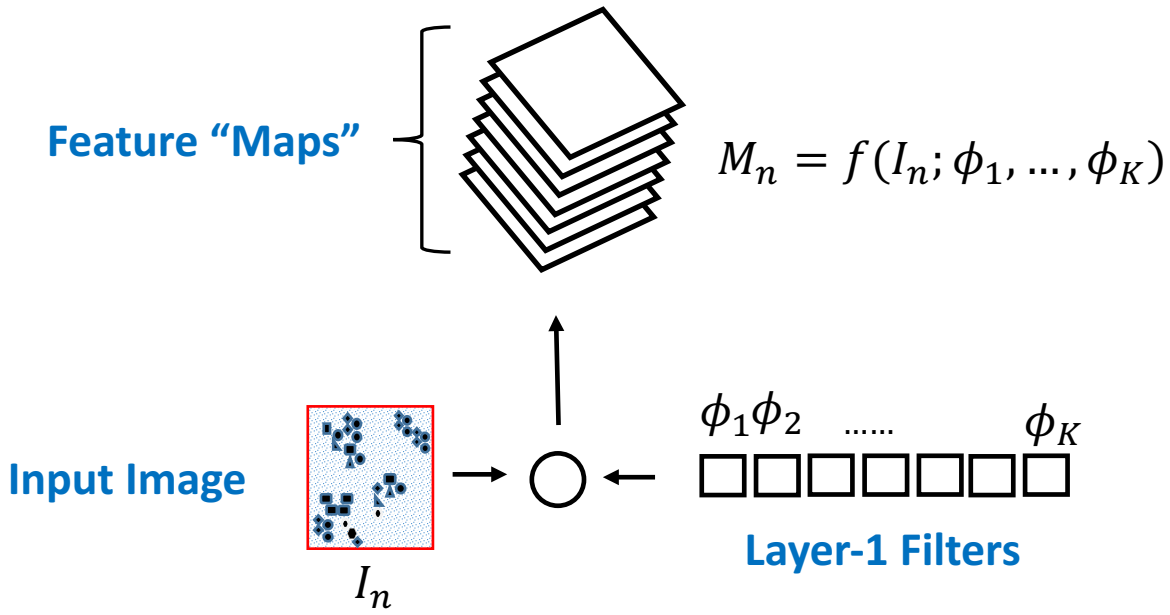

Layer 3
Feature “Maps”
Layer 2
Feature “Maps”
Layer-3 Filters
Layer 1
Feature “Maps”
Layer-2 Filters
Input Image
Layer-1 Filters

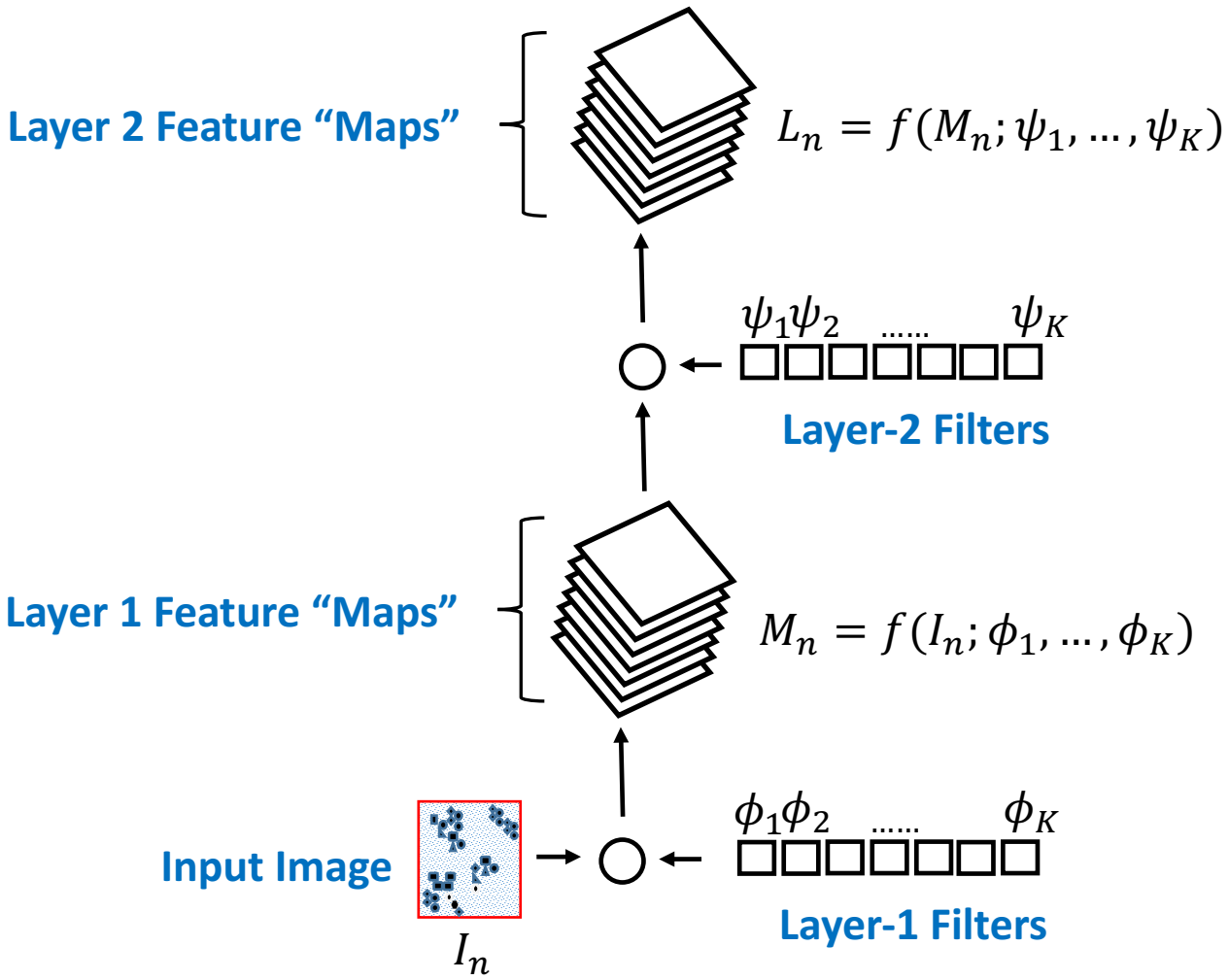
Deep Analysis Architecture

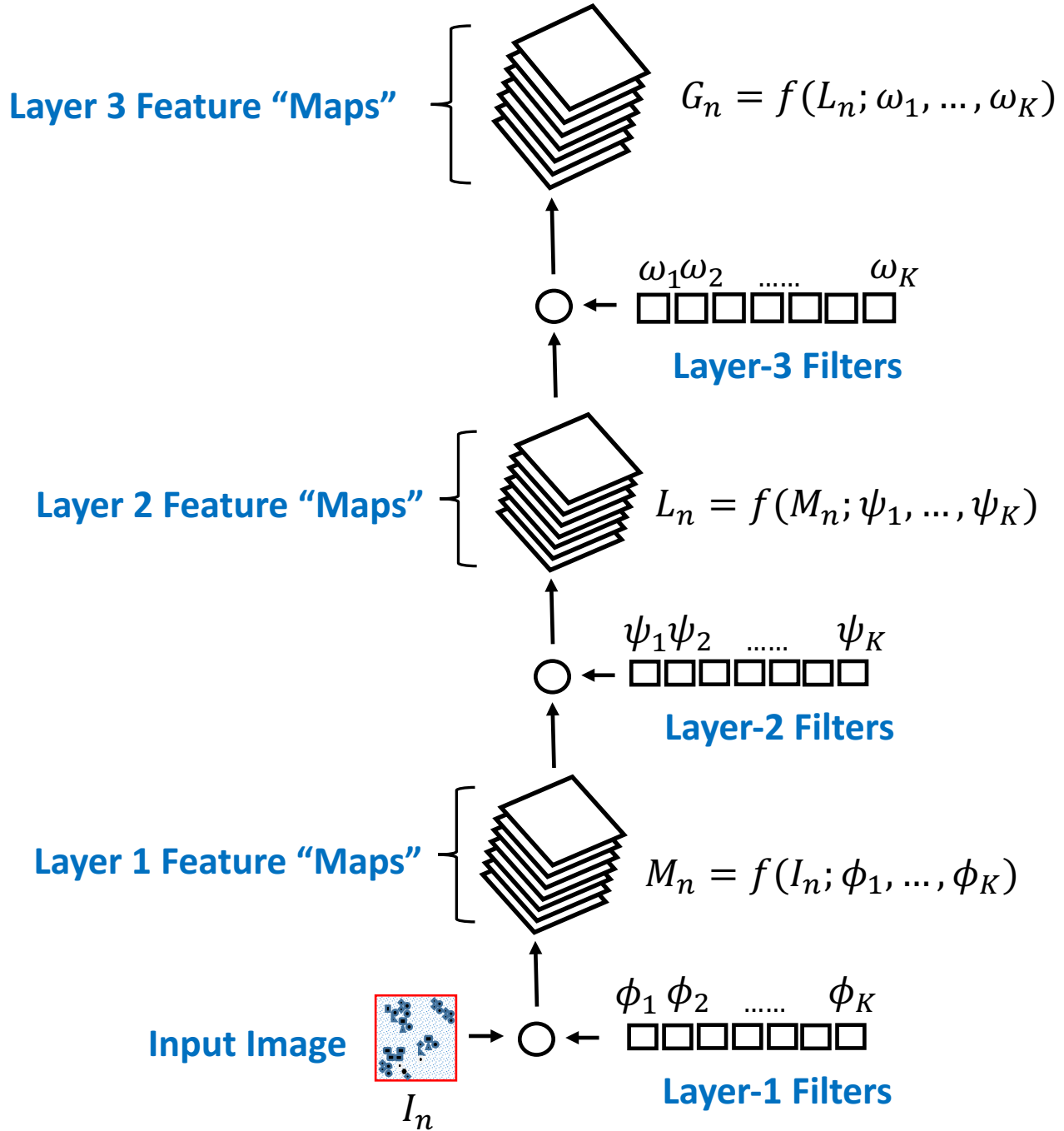


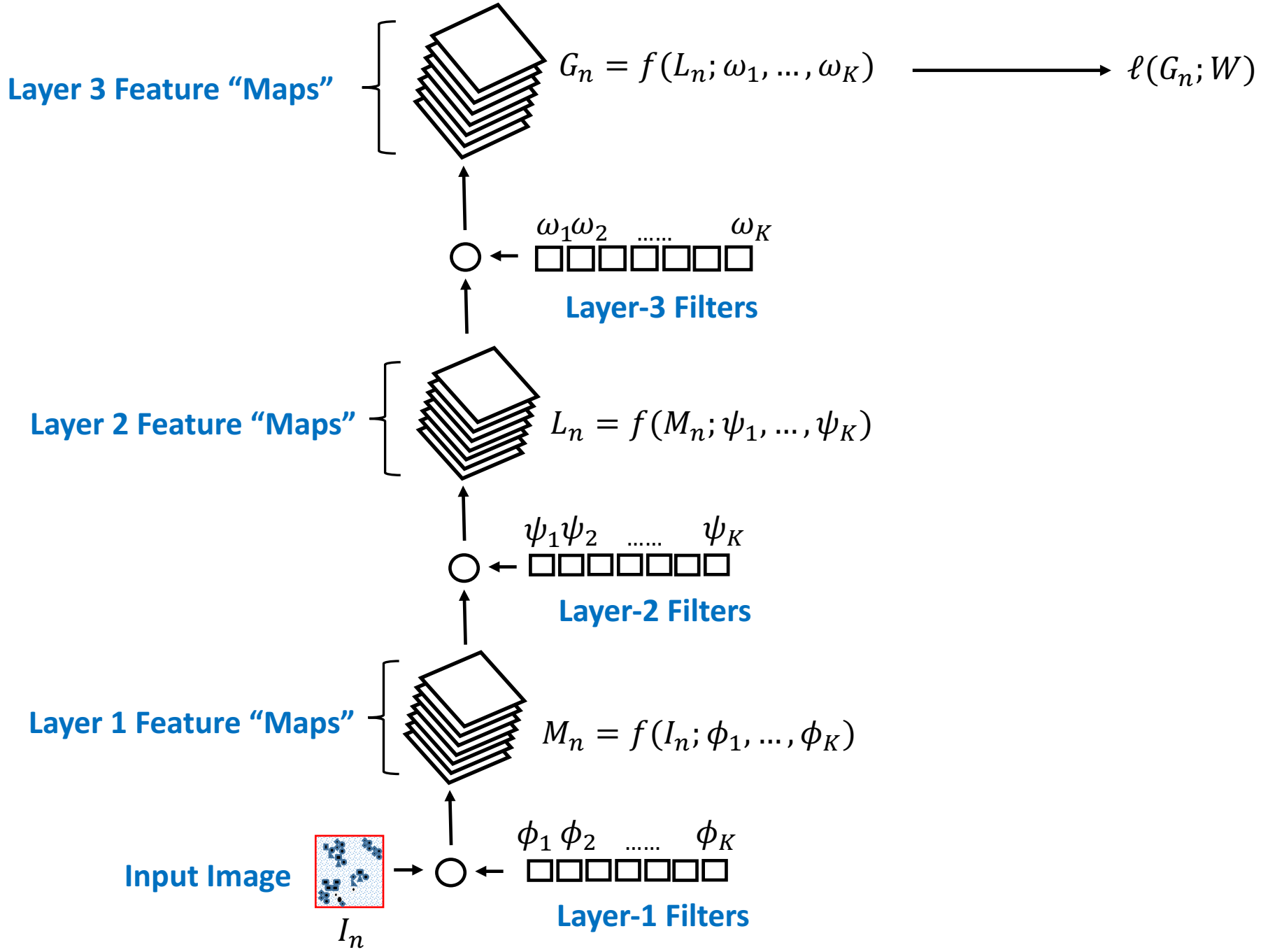
Given Images, How Do We Learn Model Parameters?

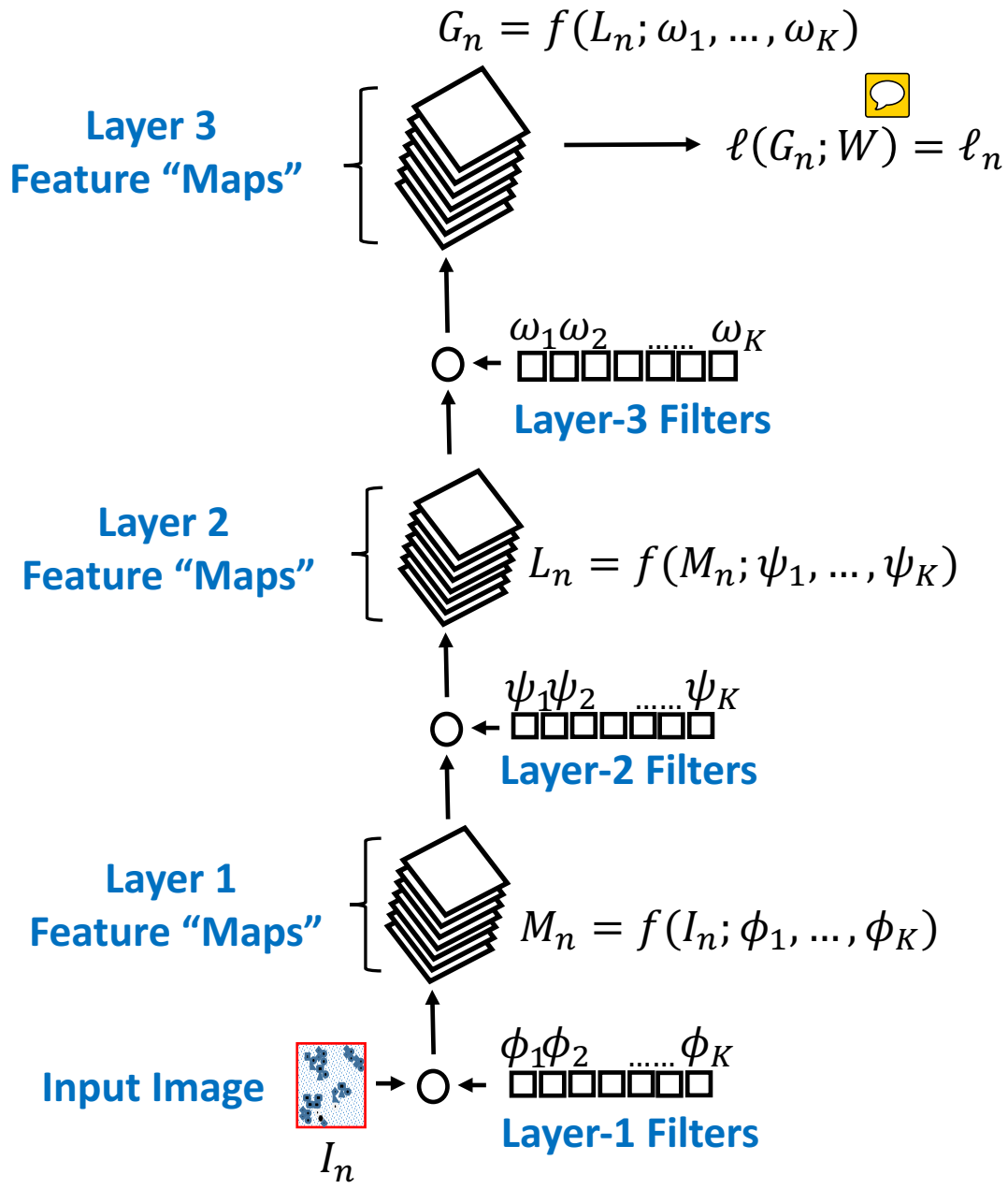
- The previous discussion was an illustration for motivating the “deep” algorithm concept
- Demonstrated using “toy” images
- How do we build such an algorithm in practice, given a large set of training images?


Feature "Maps"
$M_n = f(I_n; \phi_1, \ldots, \phi_K)$
Input Image
I_n
$\phi_1 \phi_2$ ..... ϕ_K
Layer-1 Filters


Layer 2 Feature "Maps"
$L_n = f(M_n; \psi_1, \ldots, \psi_K)$
$\psi_1 \psi_2$ ..... ψ_K
Layer-2 Filters
Layer 1 Feature "Maps"
$M_n = f(I_n; \phi_1, \ldots, \phi_K)$
Input Image
I_n
$\phi_1 \phi_2$ ..... ϕ_K
Layer-1 Filters


Layer 3 Feature "Maps"
$G_n = f(L_n; \omega_1, \ldots, \omega_K)$
$\omega_1 \omega_2$ ..... ω_K
Layer-3 Filters
Layer 2 Feature "Maps"
$L_n = f(M_n; \psi_1, \ldots, \psi_K)$
$\psi_1 \psi_2$ ..... ψ_K
Layer-2 Filters
Layer 1 Feature "Maps"
$M_n = f(I_n; \phi_1, \ldots, \phi_K)$
$\phi_1 \phi_2$ ..... ϕ_K
Input Image
I_n
Layer-1 Filters


Layer 3 Feature "Maps"
$G_n = f(L_n; \omega_1, \ldots, \omega_K)$
$\ell(G_n; W)$
$\omega_1 \omega_2$ ..... ω_K
Layer-3 Filters
Layer 2 Feature "Maps"
$L_n = f(M_n; \psi_1, \ldots, \psi_K)$
$\psi_1 \psi_2$ ..... ψ_K
Layer-2 Filters
Layer 1 Feature "Maps"
$M_n = f(I_n; \phi_1, \ldots, \phi_K)$
$\phi_1 \phi_2$ ..... ϕ_K
Input Image
I_n
Layer-1 Filters

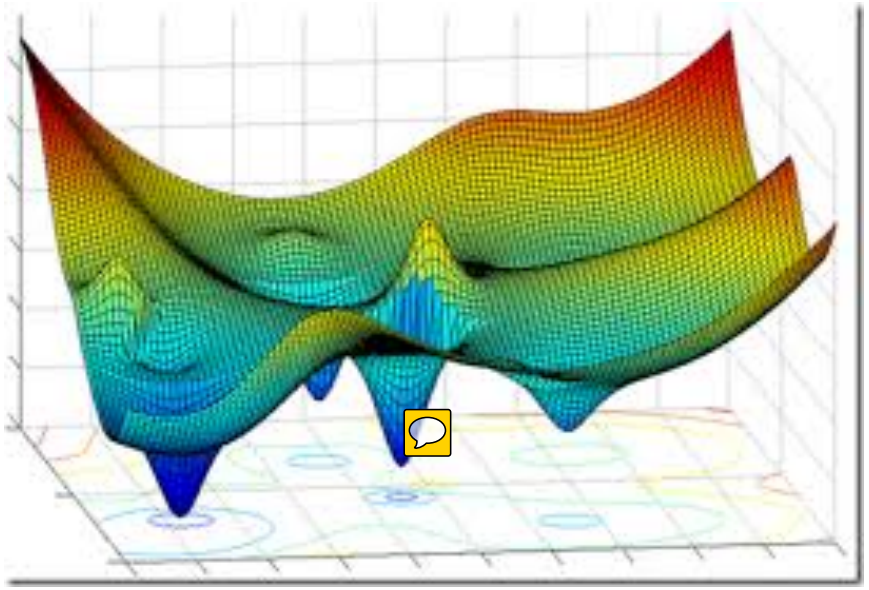


- Assume we have labeled images $\{I_n, y_n\}_{n=1,N}$
- I_n is image n, $y_n \in \{+1, -1\}$ is associated label
- Risk function of model parameters:

$$E(\Phi, \Psi, \Omega, W) = 1/N \sum_{n=1}^{N} loss(y_n, \ell_n)$$

- Find model parameters $\hat{\Phi}, \hat{\Psi}, \hat{\Omega}, \hat{W}$ that minimize $E(\Phi, \Psi, \Omega, W)$

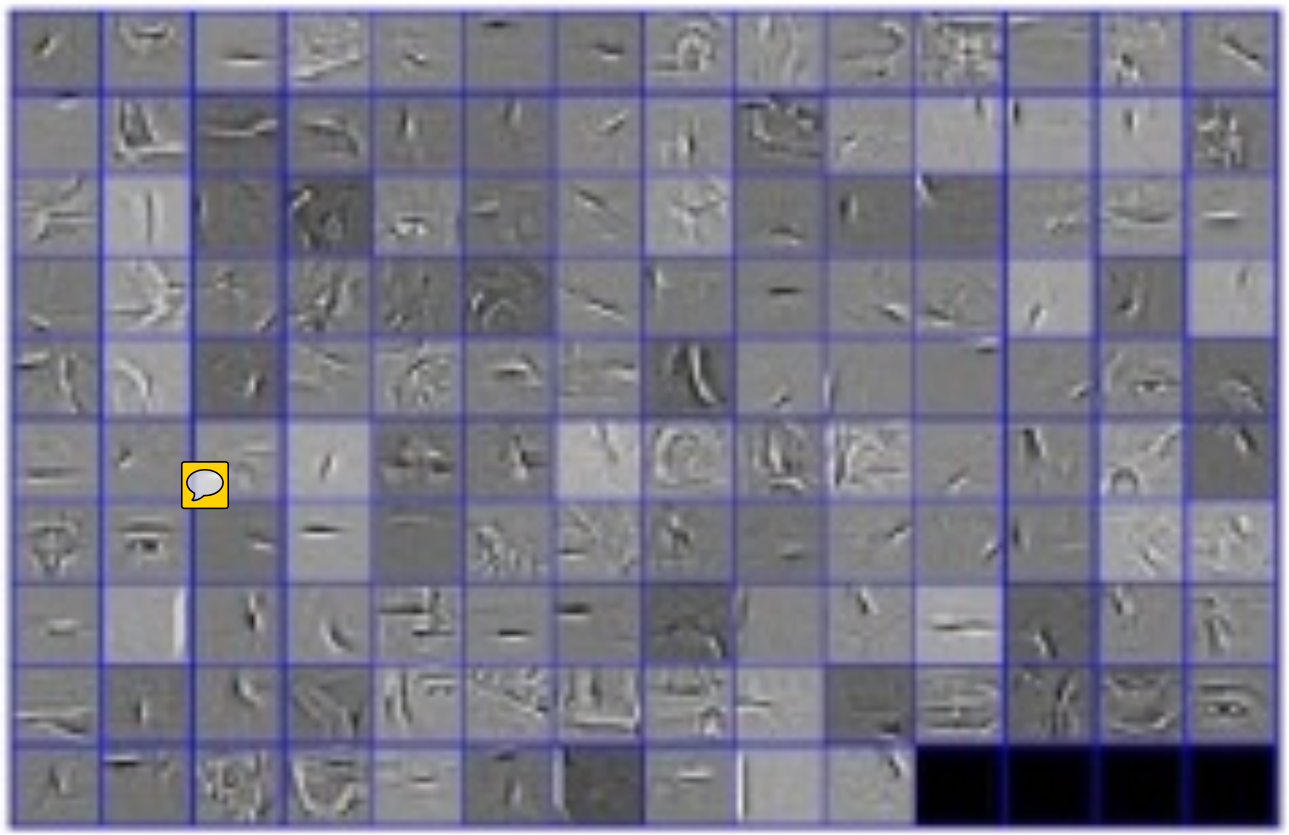
Cost Function vs. Model Parameters

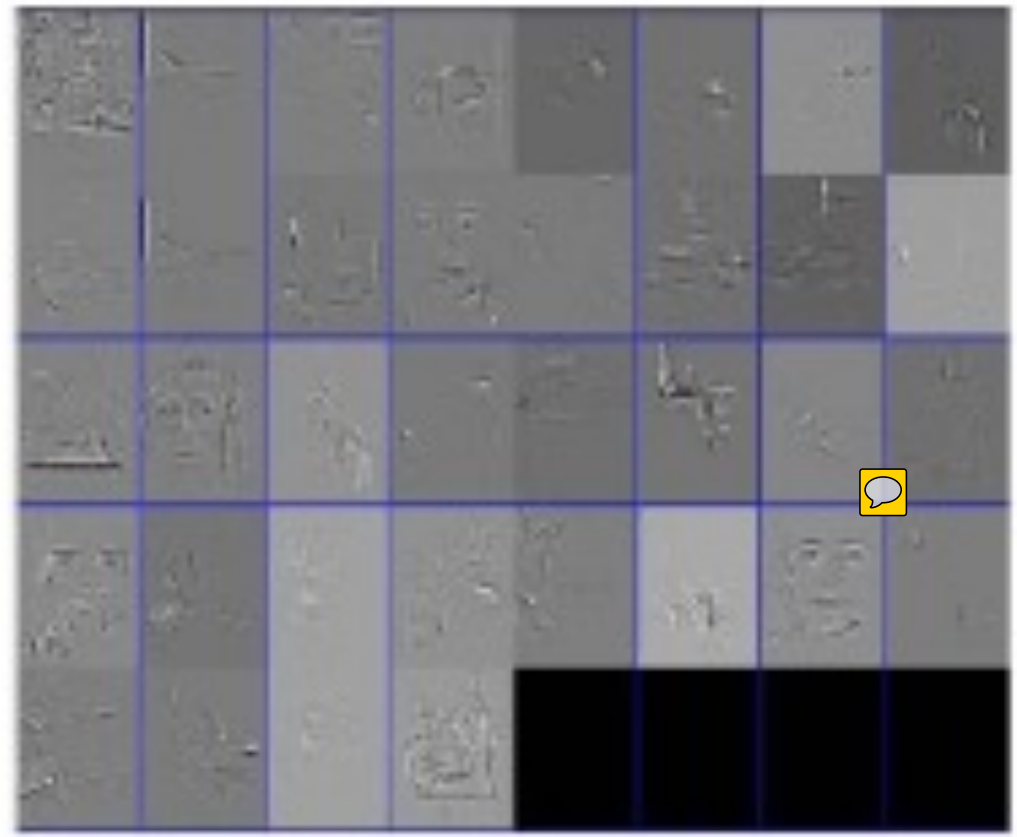


- High-dimensional function, as a consequence of a large number of model parameters
- Typically many local minima
- May be expensive to compute, for sophisticated models & large quantity of training images

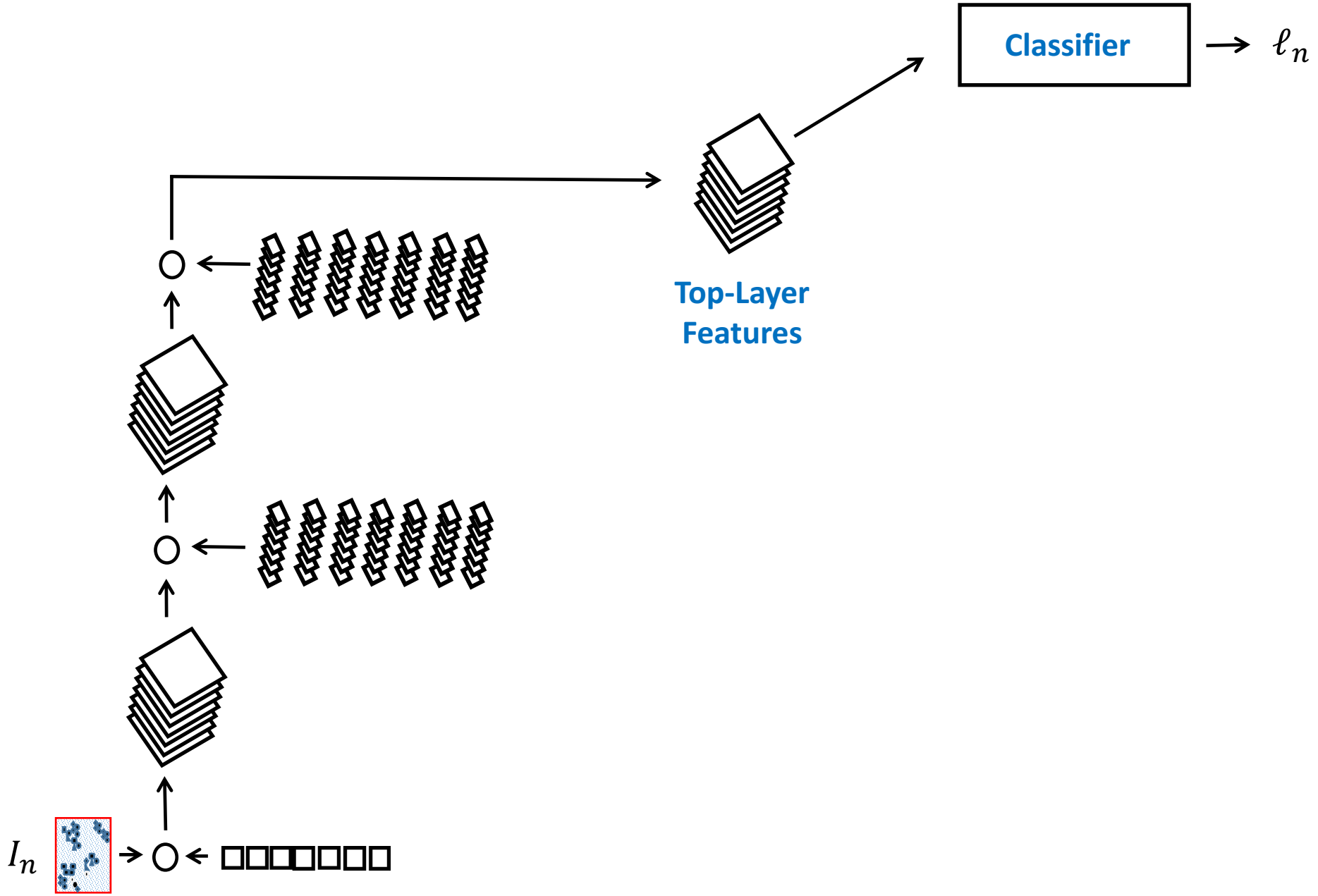
- Layer 1 dictionary elements:

- Second (left) and third (right) layer dictionary elements:

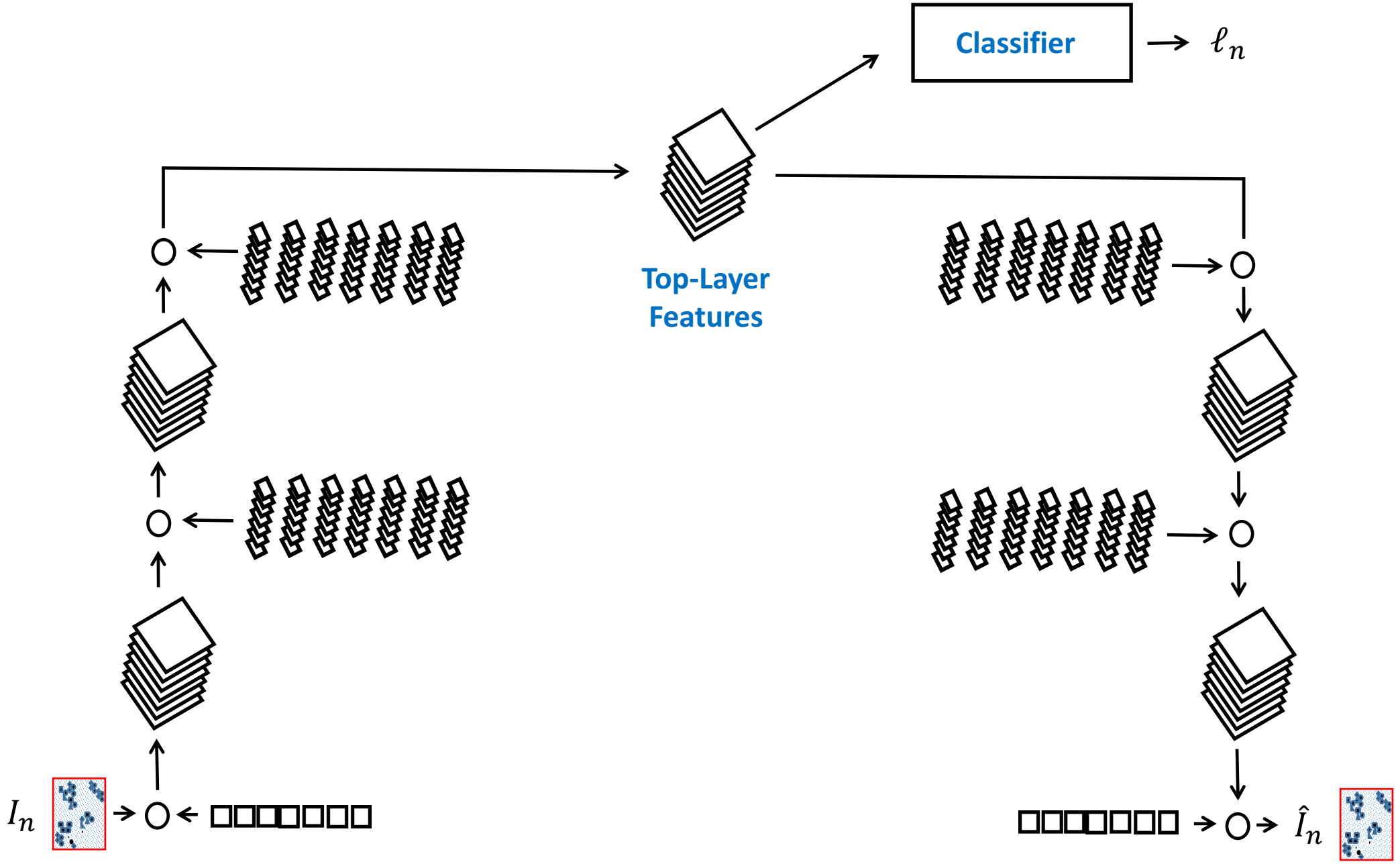




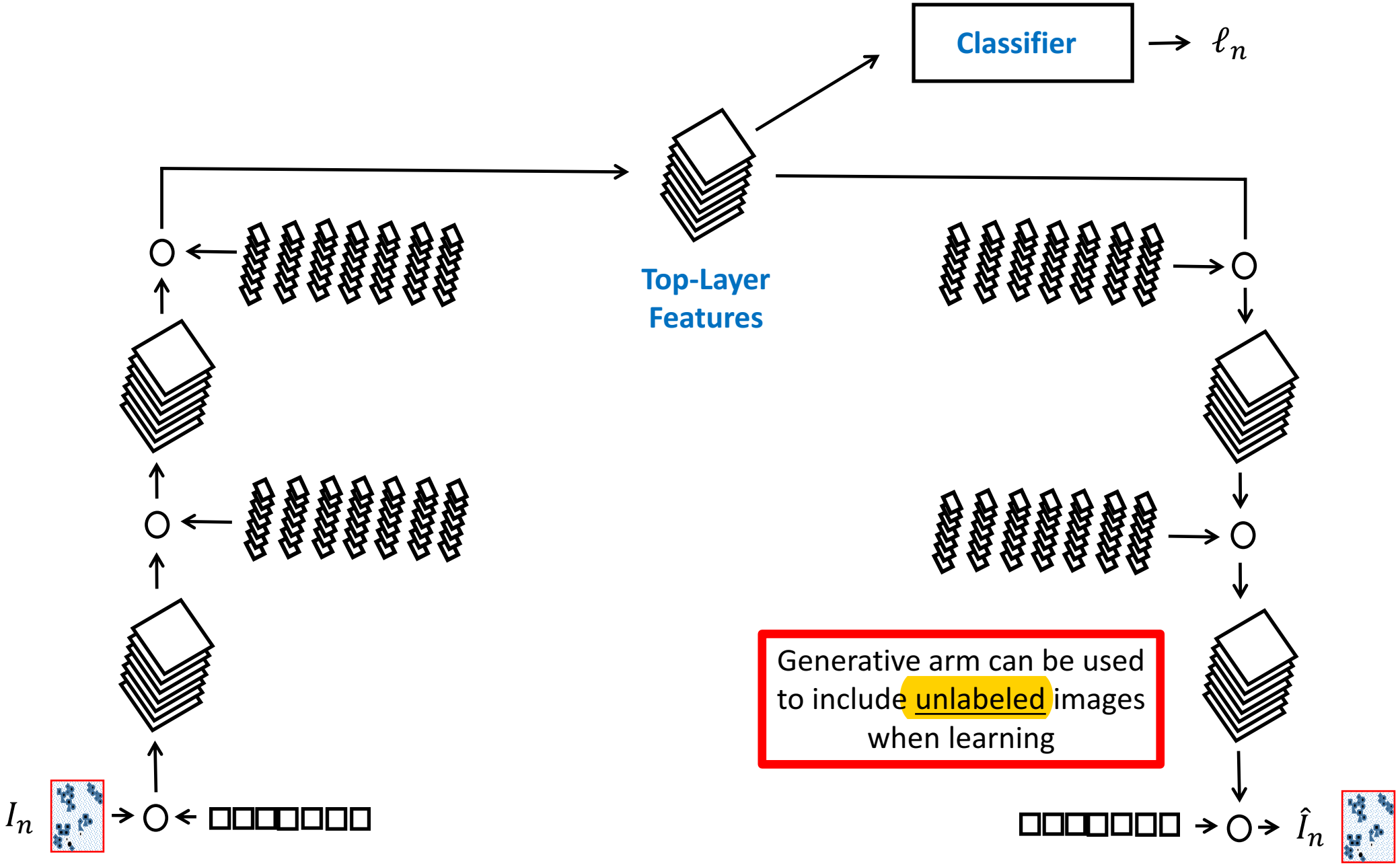
Deep Architecture



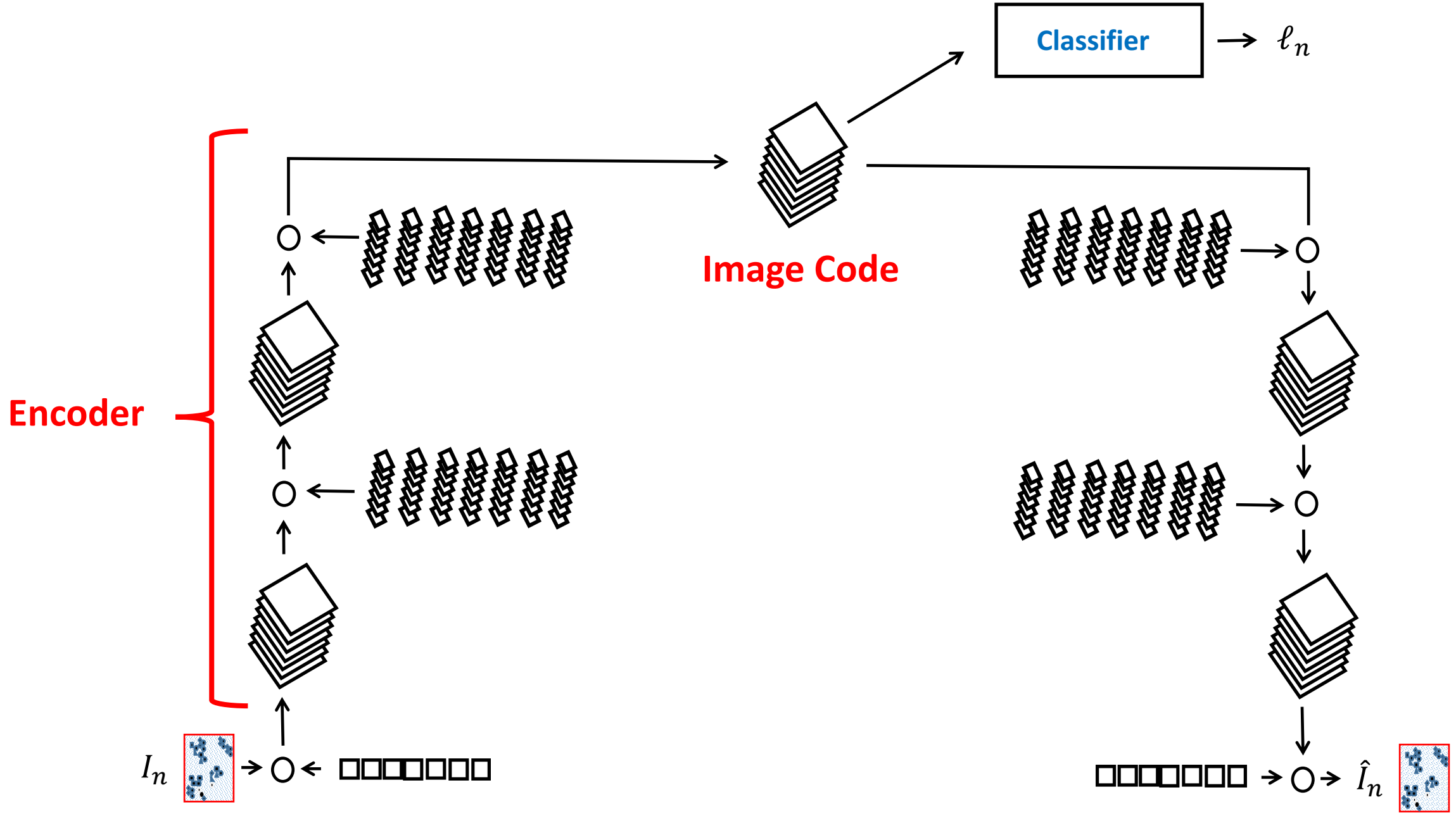
Add Generative Arm



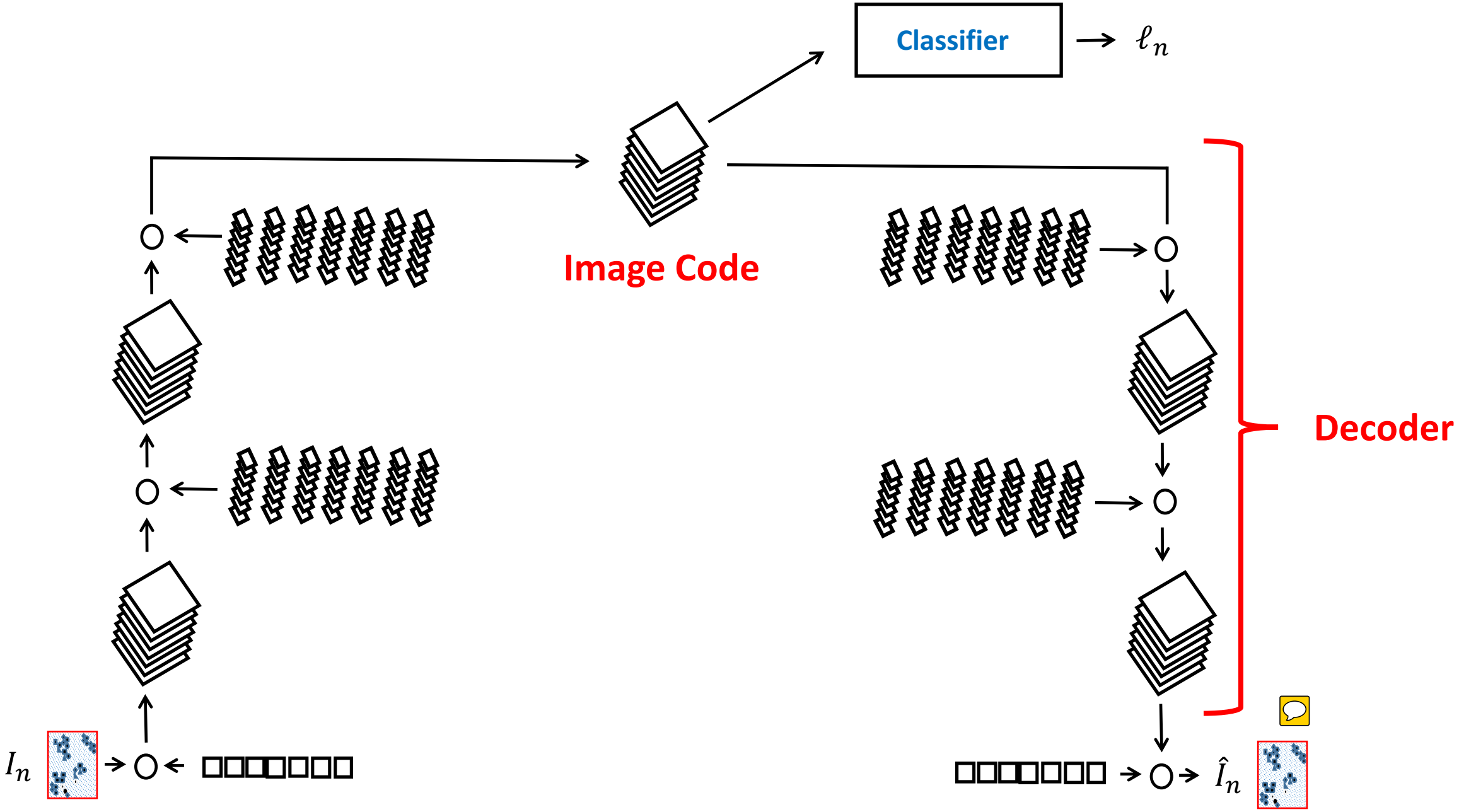
Add Generative Arm



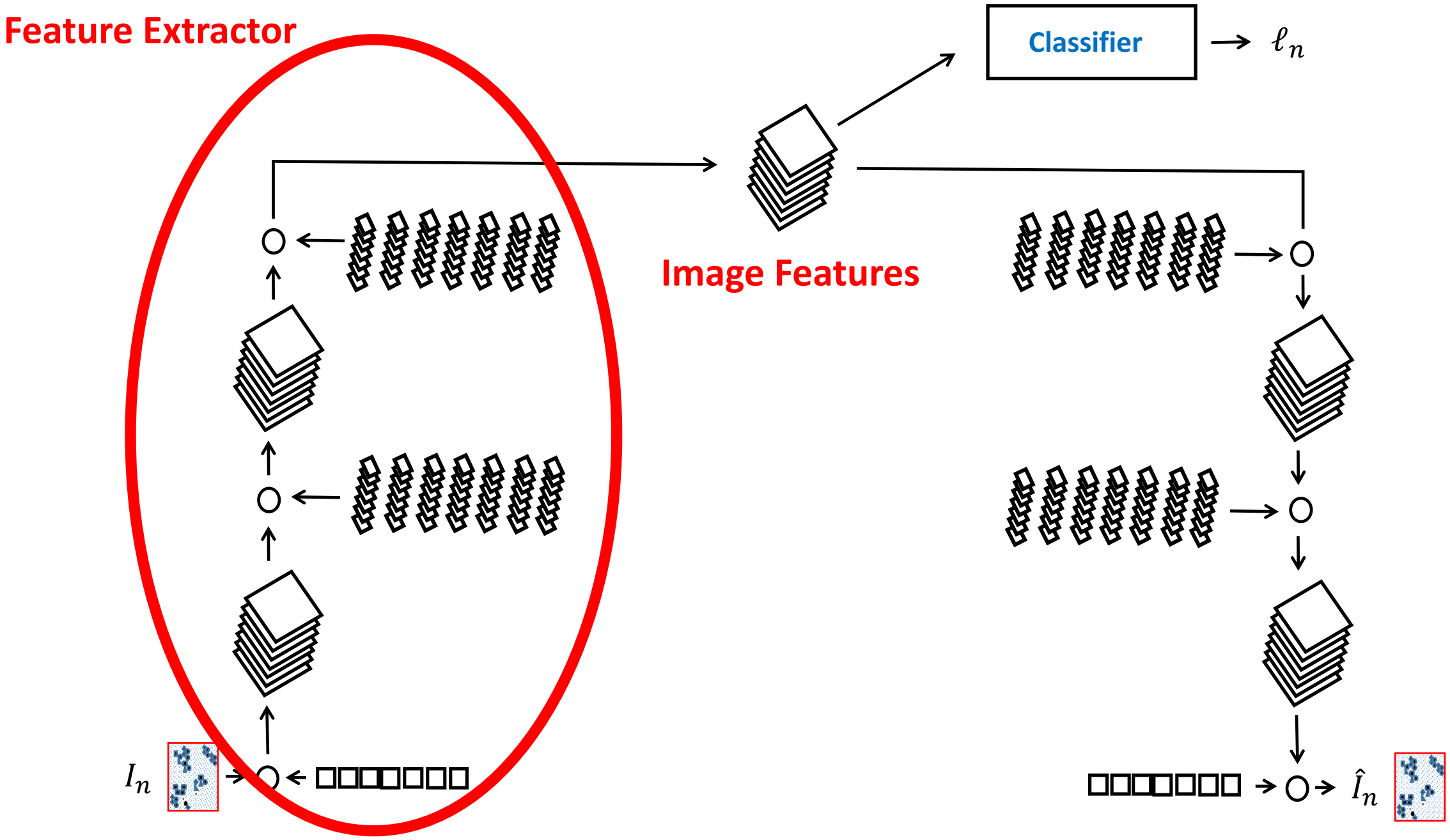
Deep Analysis Architecture



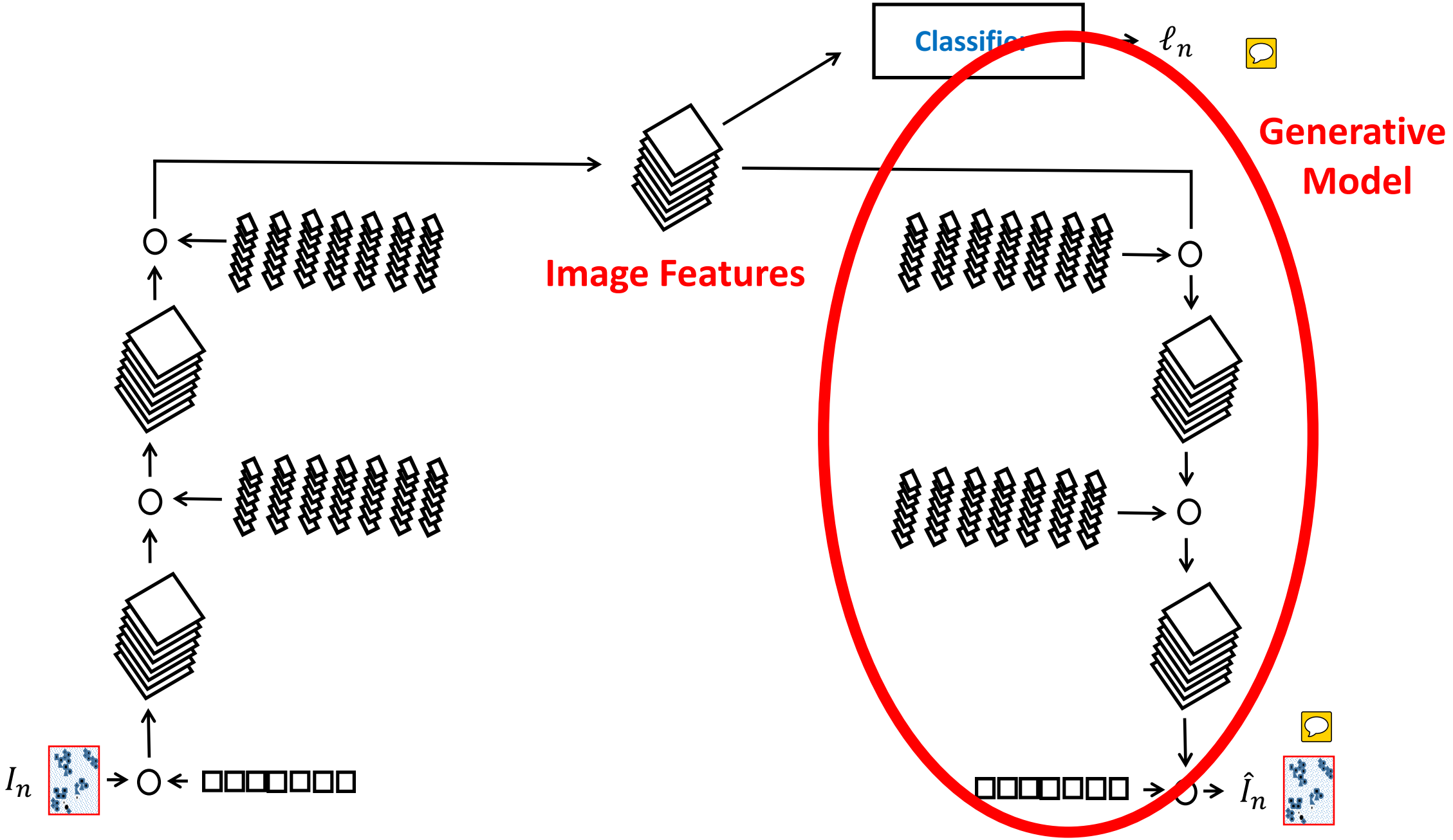
Deep Analysis Architecture



Deep Analysis Architecture



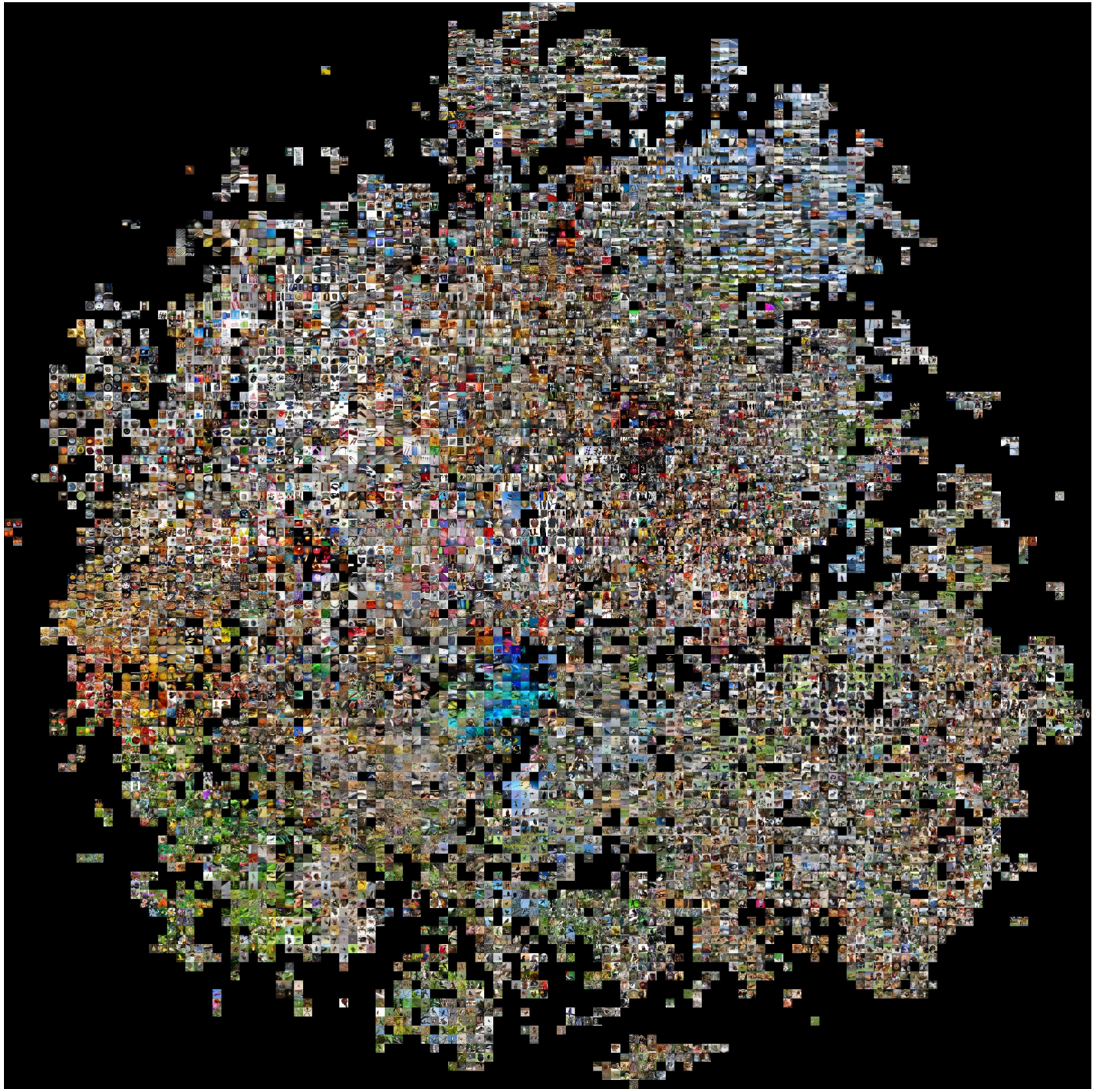
Deep Analysis Architecture



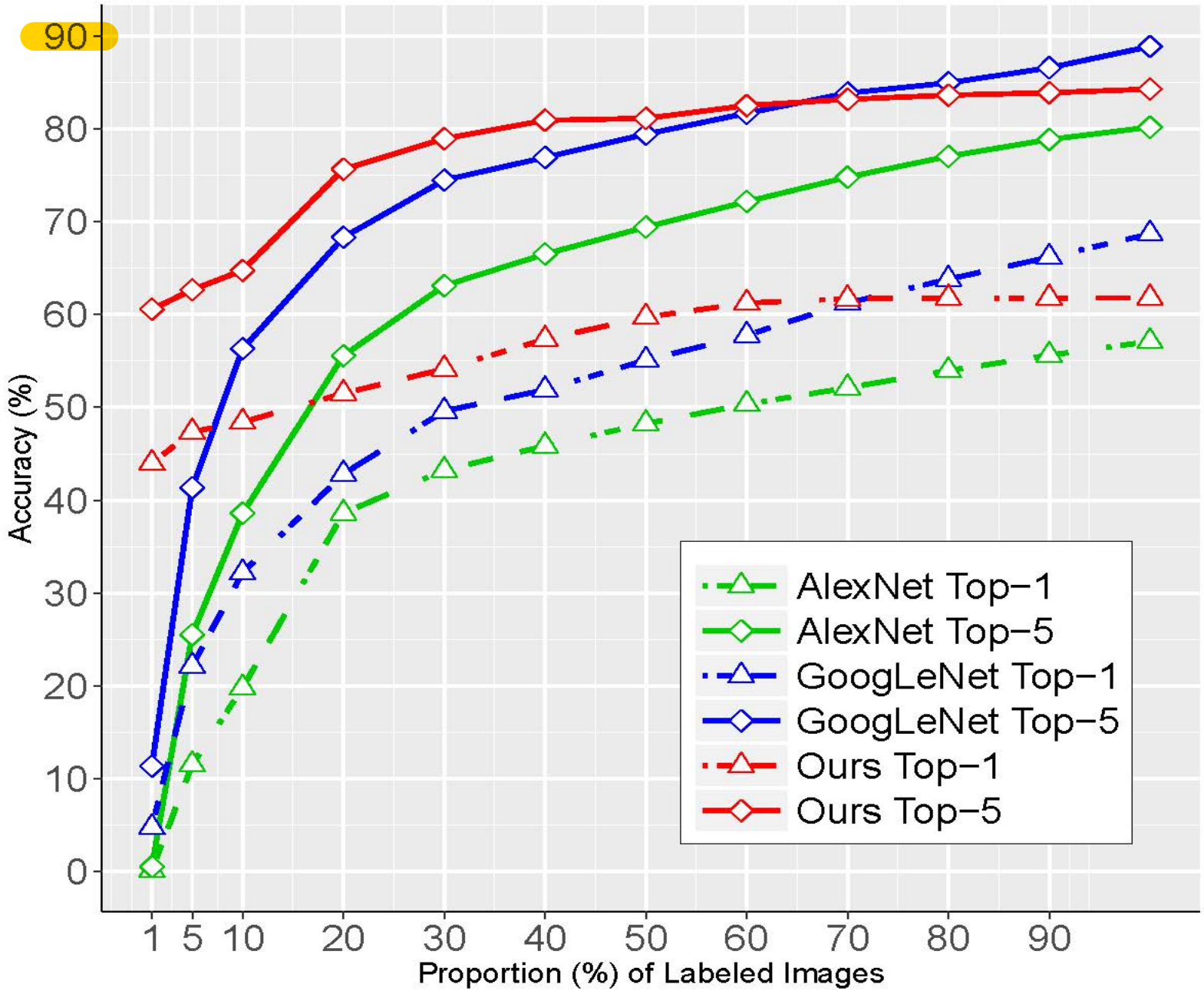
ImageNet Challenge

- 1000 image classes
- 1000 training images per class
- 1 million training images
- Real-life RGB images

Example Images



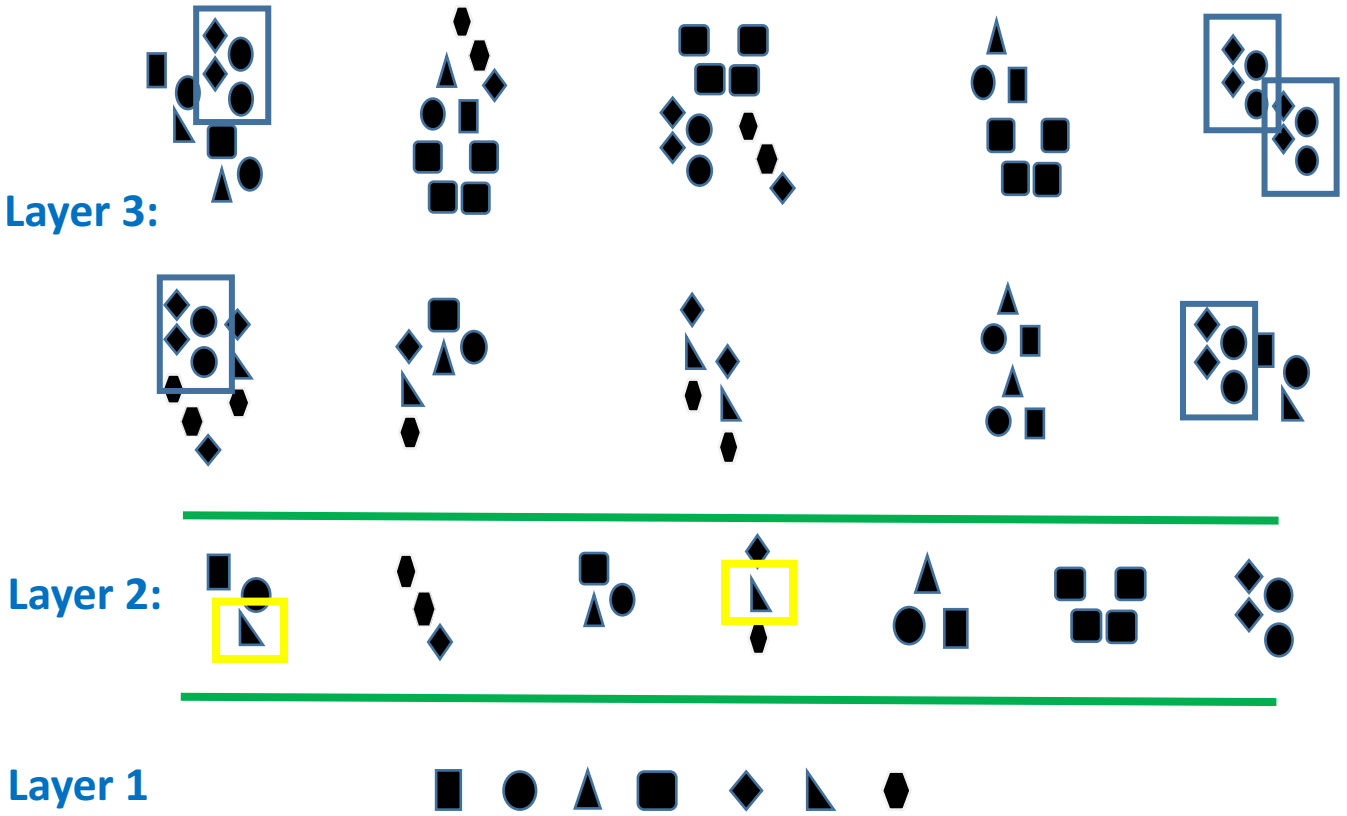
ImageNet Challenge



Semi-supervised classification error (%) on MNIST. N is the number of labeled images per class.

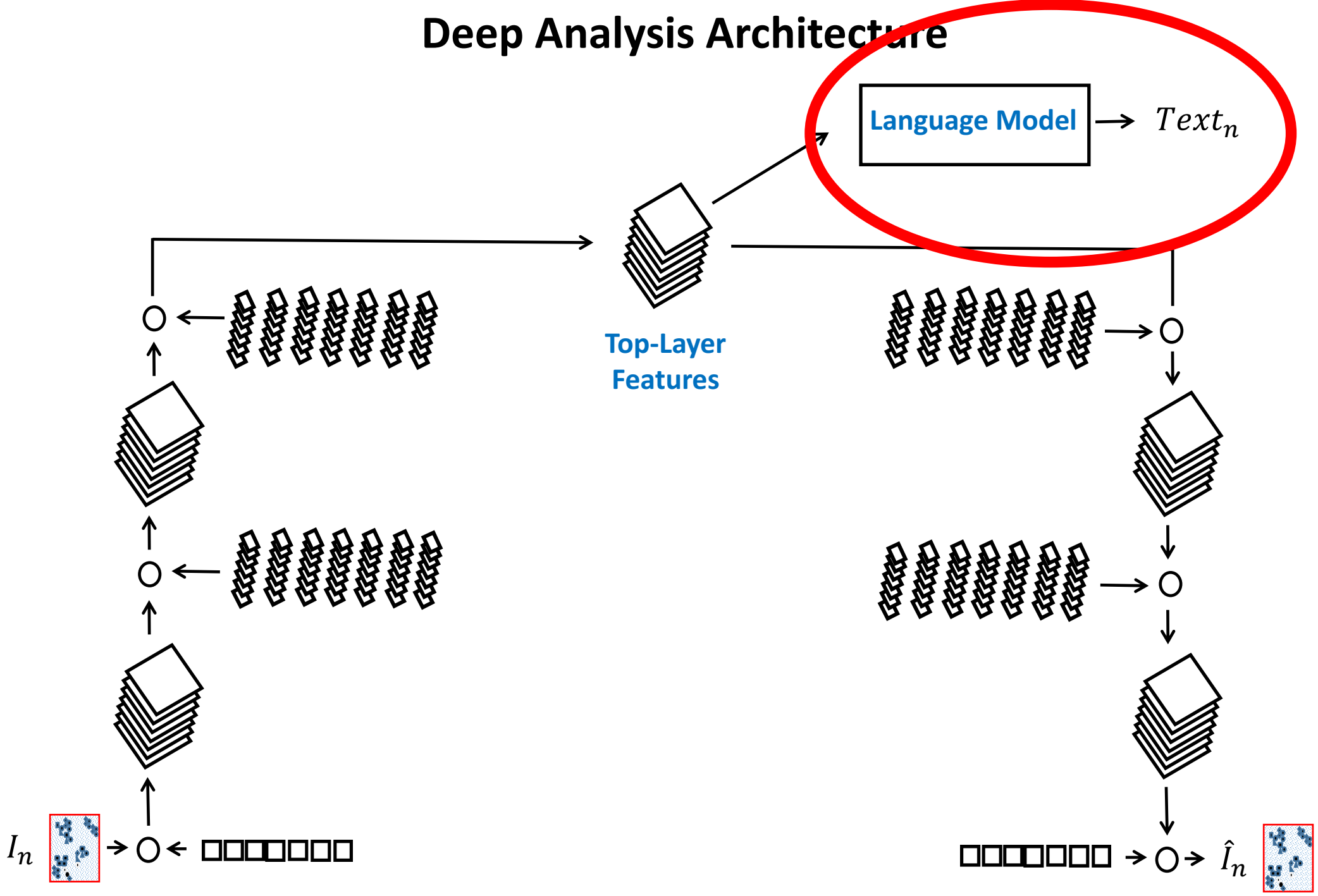
N	TSVM	Deep generative model [27]		Ladder network [28]		Our model	
		M1+TSVM	M1+M2	Γ-full	Γ-conv	$\xi = 0$	$\xi = N_x/(Cp)$
10	16.81	11.82± 0.25	3.33 ± 0.14	3.06 ± 1.44	**0.89**±0.50	5.83 ± 0.97	1.49 ± 0.36
60	6.16	5.72± 0.05	2.59 ±0.05	-	-	2.19 ± 0.19	**0.77** ± 0.09
100	5.38	4.24± 0.07	2.40 ±0.02	1.53 ± 0.10	-	1.75 ± 0.14	**0.63** ± 0.06
300	3.45	3.49± 0.04	2.18 ±0.04	-	-	1.42 ± 0.08	**0.51** ± 0.04

Advantage of Hierarchical Features?



- By learning and sharing statistical similarities within high-level motifs, we better leverage all training data
- If we do not use such a hierarchy, top-level motifs would be learned in isolation of each other

Deep Analysis Architecture



a man with a snowboard next to a man with glasses

a big black dog standing on the grass

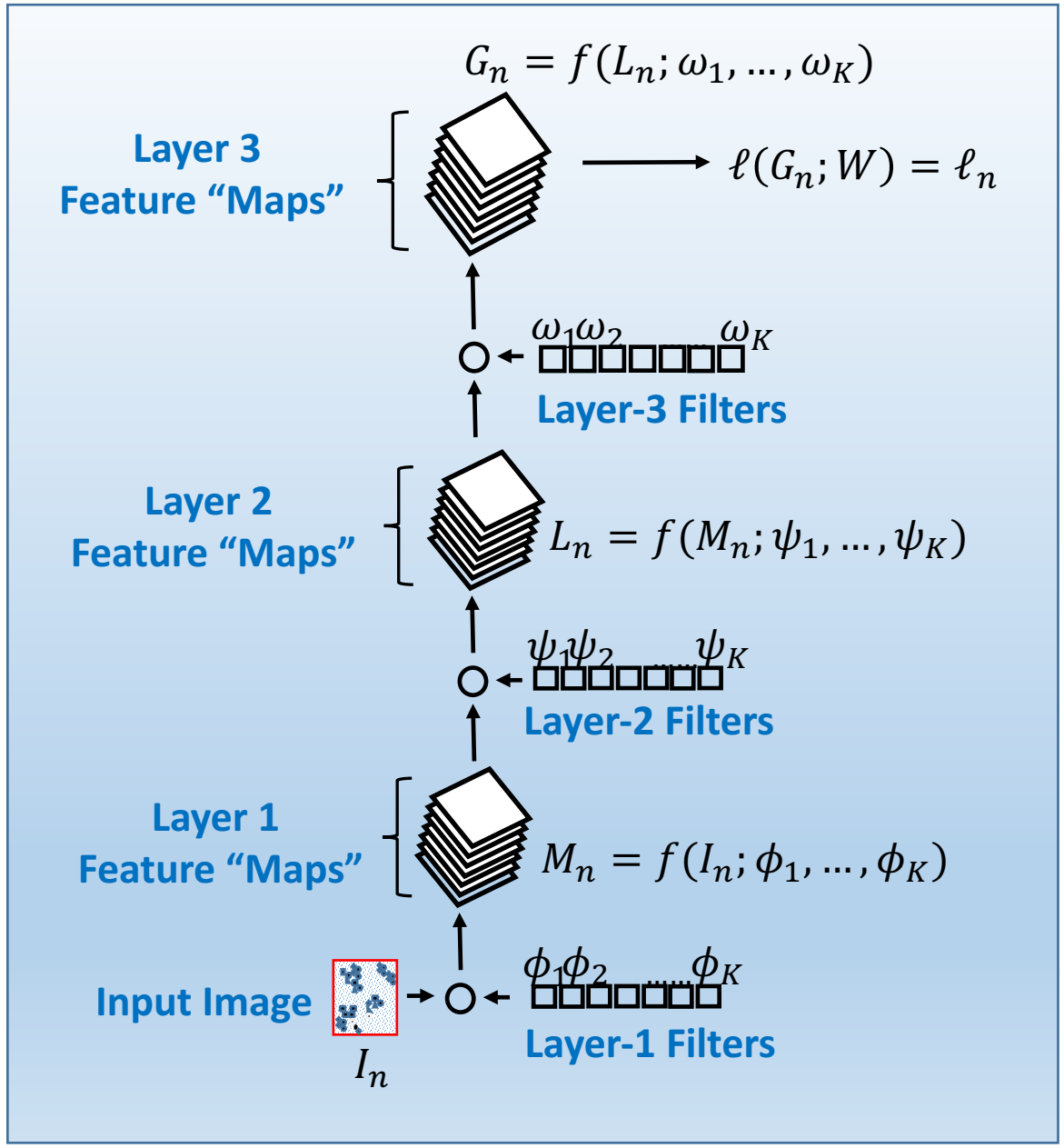
a player is holding a hockey stick

a desk with a keyboard

a man is standing next to a brown horse

a box full of apples and oranges

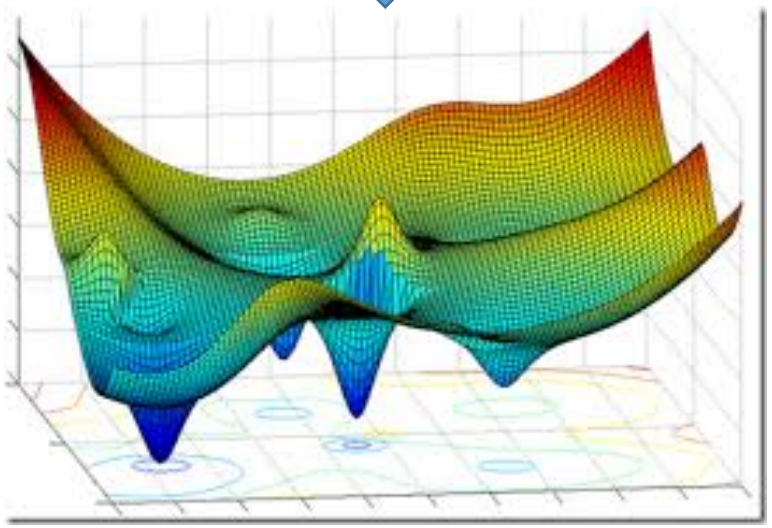
Big Picture



- Assume we have labeled images $\{I_n, y_n\}_{n=1,N}$
- I_n is image n, $y_n \in \{+1, -1\}$ is associated label
- Risk function of model parameters:

$$E(\Phi, \Psi, \Omega, W) = 1/N \sum_{n=1}^{N} loss(y_n, \ell_n)$$

- Find model parameters $\hat{\Phi}, \hat{\Psi}, \hat{\Omega}, \hat{W}$ that minimize $E(\Phi, \Psi, \Omega, \mathrm{W})$



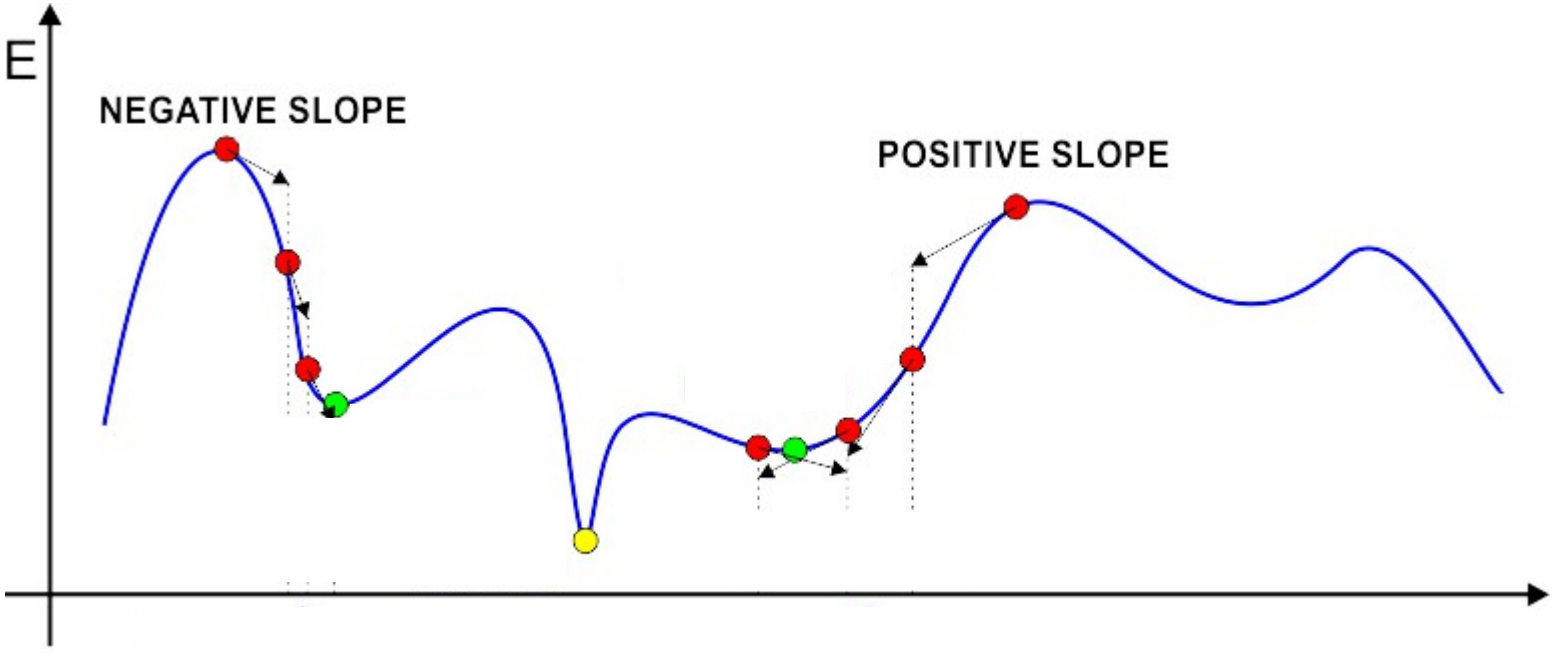
Technical Challenges

$$E(\Phi, \Psi, \Omega, W) = 1/N \sum_{n=1}^{N} loss(y_n, \ell_n)$$

- For large number of training pairs *N*, computation of risk $E(\cdot)$ could be prohibitive

- How do we optimize for Φ, Ψ, Ω, W?

Optimization for $\Theta = \{\Phi, \Psi, \Omega, \mathbf{W}\}$?



Gradient Descent

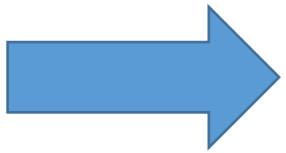
$$\Theta_t = \Theta_{t-1} - \alpha \nabla_{\Theta} E(\Theta_t)$$

Multi-dimensional "slope"

Massive N ?

Gradient Descent

$$\Theta_t = \Theta_{t-1} - \alpha \nabla_\Theta E(\Theta_t)$$



Stochastic Gradient Descent

$$\Theta_t = \Theta_{t-1} - \alpha \nabla_\Theta \hat{E}_t(\Theta_t)$$

$$\hat{E}_t(\Phi, \Psi, \Omega, W) = 1/|S_t| \sum_{n \in S_t} loss(y_n, \ell_n)$$

S_t a *random* subset of data, at iteration *t*

a cow is standing in front of a store

a group of elephants standing next to each other

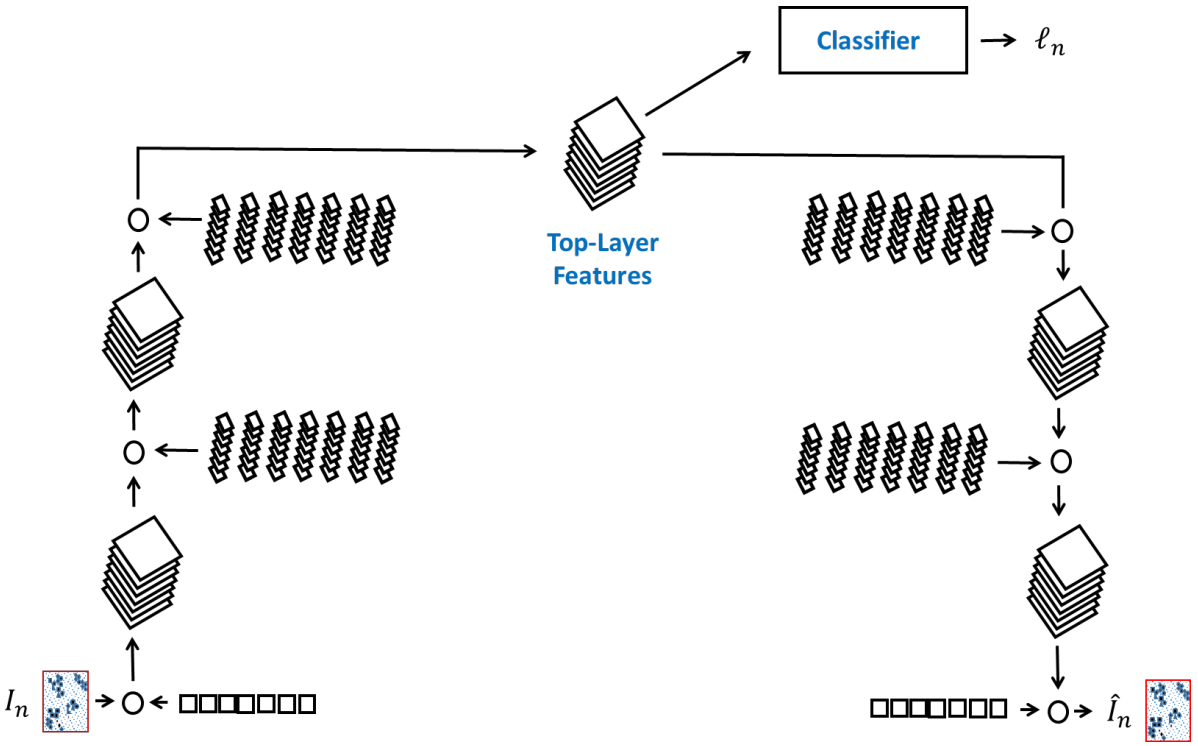
a table that has wooden spoons on it

a cat is eating some kind of food

a bunch of bananas are sitting on a table

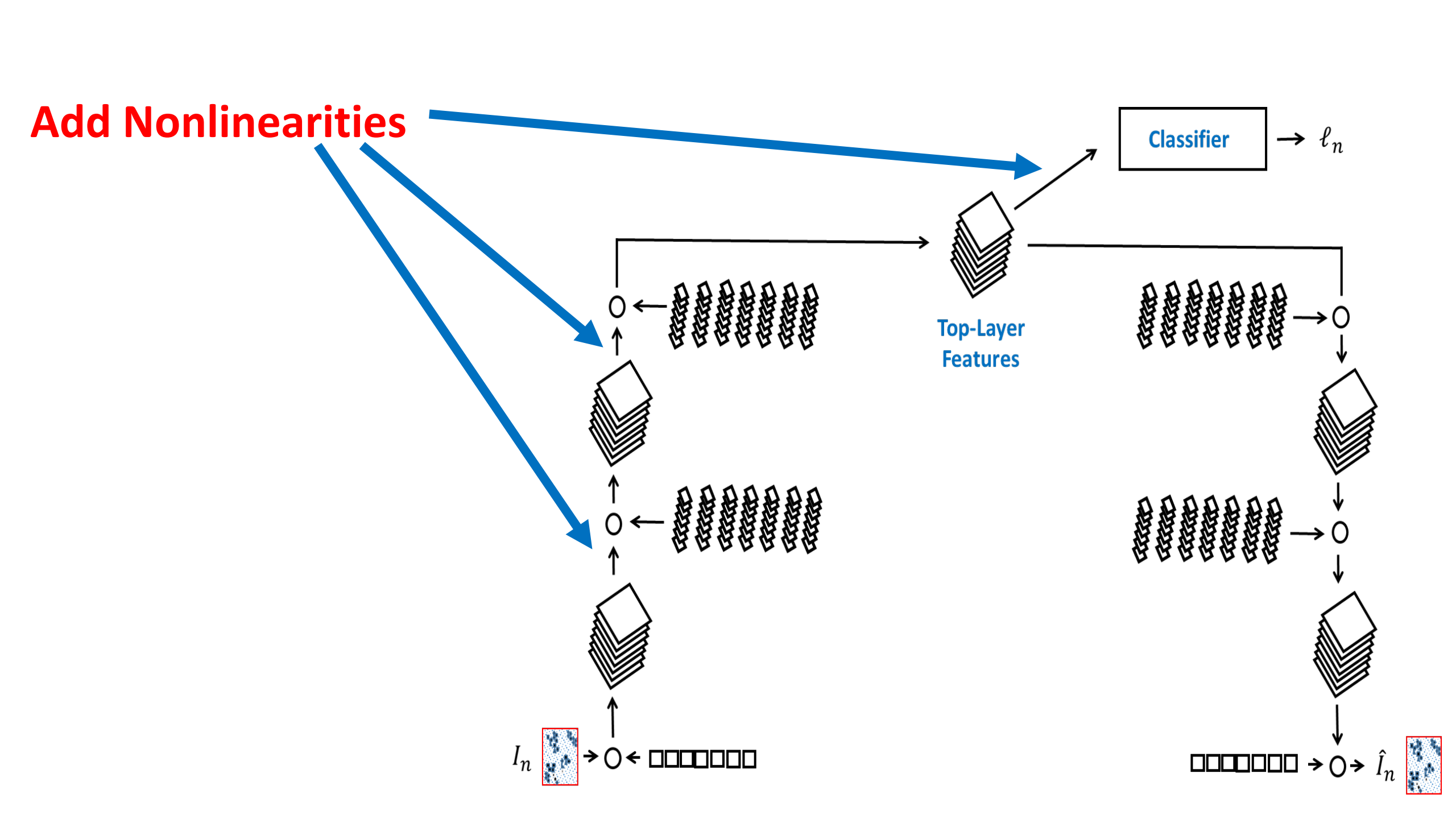
a motorcycle is parked next to a window

Important Technical Detail: Need for Nonlinearities



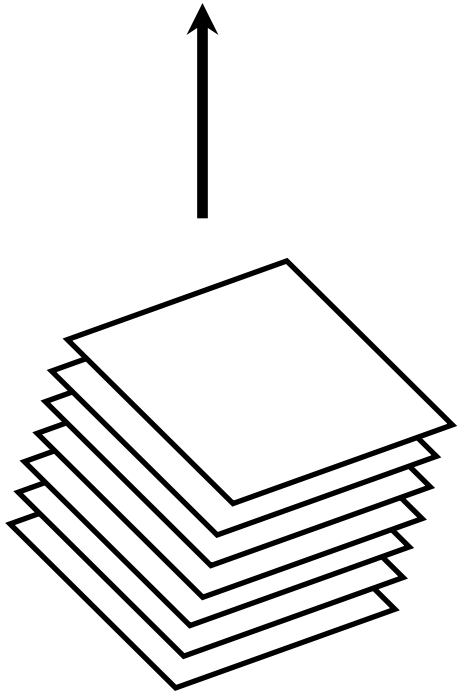
- As expressed, the model is <u>linear</u>
- If we consider image $I = I_n + I_m$ the top-layer features are the sum of the features from I_n and I_m separately
- Similarly, consider top-layer features f_n and f_m, that generate images I_n and I_m
- Top-layer features $f_n + f_m$ generate image $I_n + I_m$
- Such a linear model is overly restrictive

Add Nonlinearities



Pointwise Nonlinearity

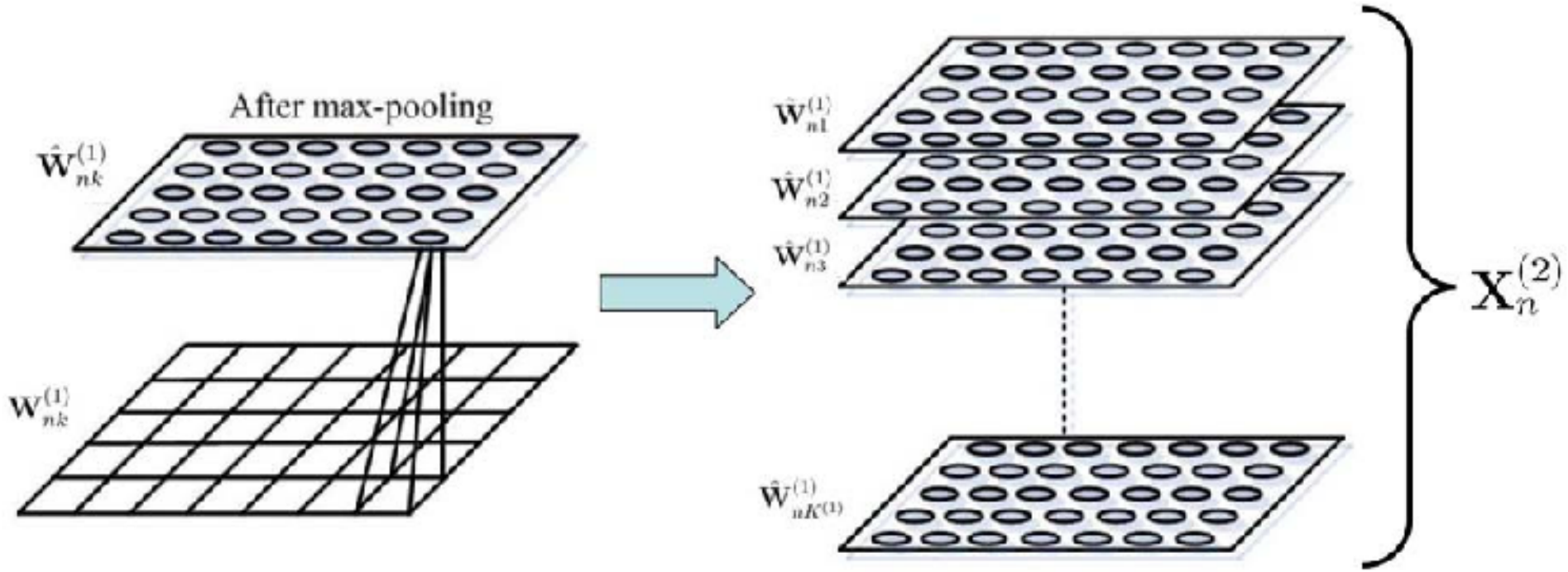
Pointwise Nonlinearity



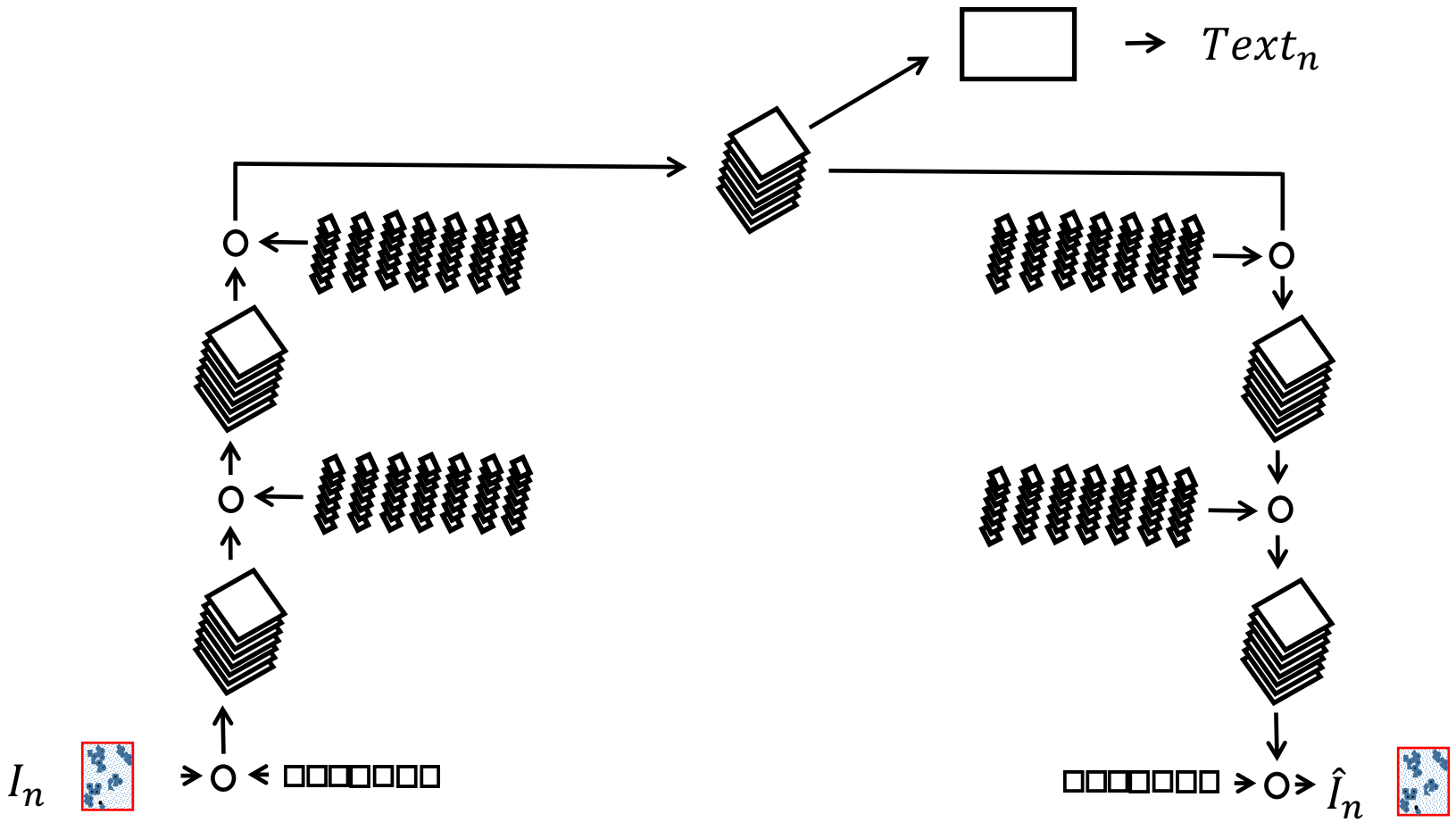
Convolutional filtering

- The feature map after the convolutional filters is sent through a pointwise nonlinear function
- Common example: $f(x) = \tanh(x)$
- Recent interest in $f(x) = 0 \; if \; x \leq 0, f(x) = x \; otherwise$

Pooling of Activation Maps

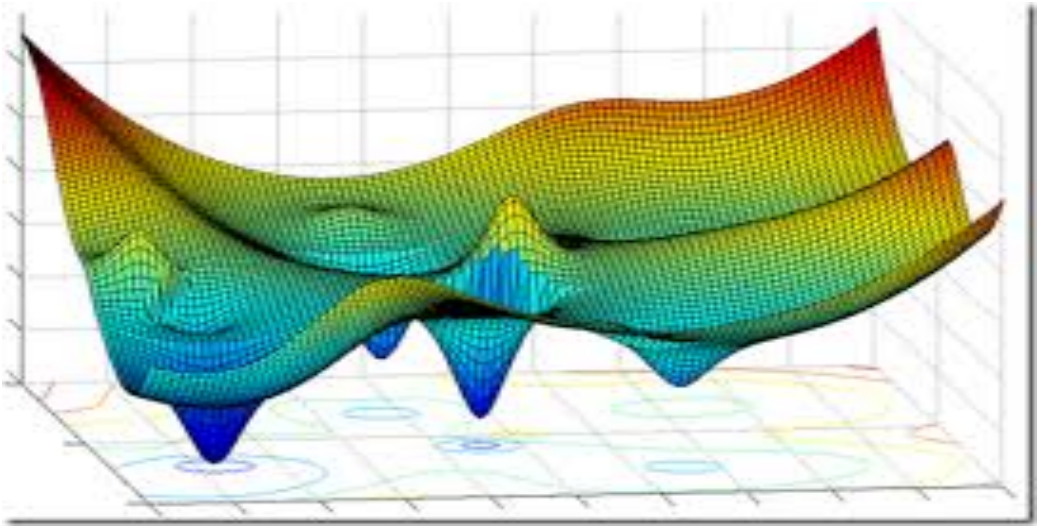


Summary



1. Deep architectures, data-driven feature learning

Summary



Stochastic Gradient Descent

$$\Theta_t = \Theta_{t-1} - \alpha \nabla_\Theta \hat{E}_t(\Theta_t)$$

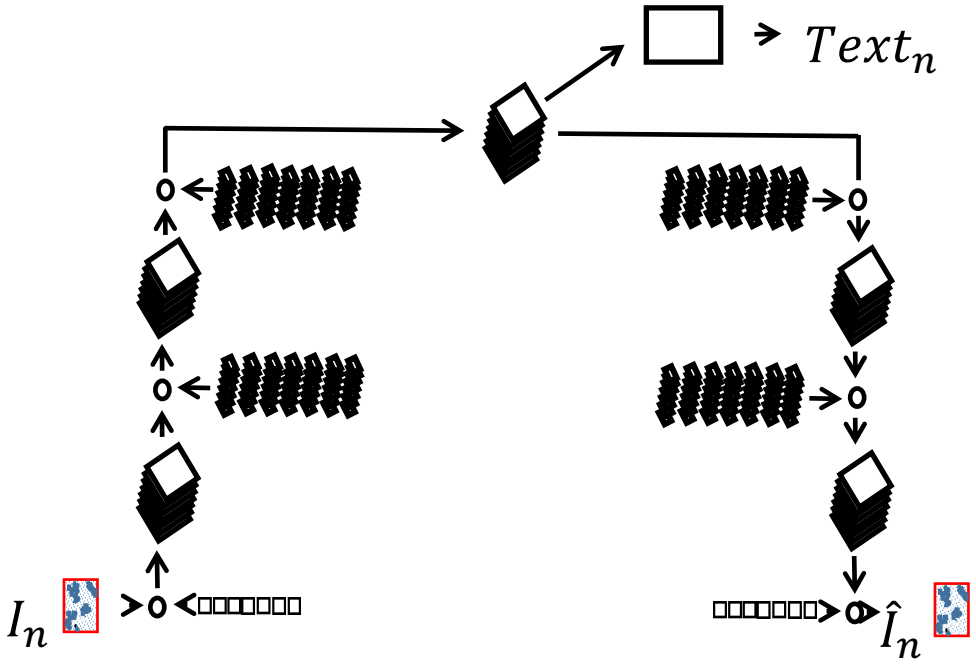
2. Scale to “Big Data”

Summary

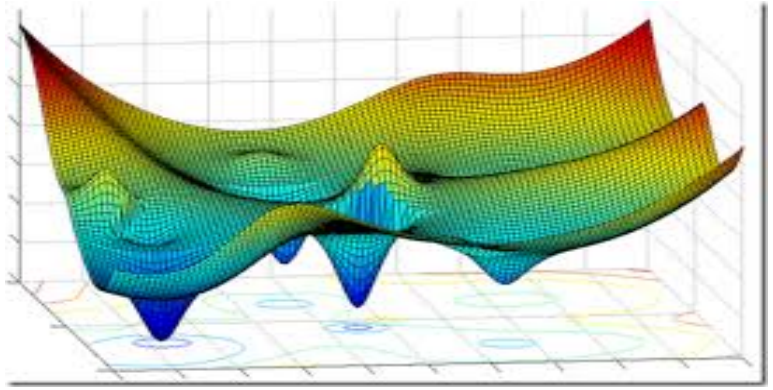
a man is standing next to a brown horse

3. Intriguing results on complex, large-scale data

Summary



1. Deep architectures, feature learning



Stochastic Gradient Descent

$$\Theta_t = \Theta_{t-1} - \alpha \nabla_\Theta \hat{E}_t(\Theta_t)$$

2. Scale to "Big Data"

a man is standing next to a brown horse

3. Intriguing results