Convolutional Cobweb:
A Model of Incremental Learning from 2D Images

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Mapping from Pixels to Symbols

- Many cognitive system approaches assume high-level (symbolic) representations are available for interfacing with the world
- To support learning from pixel-level inputs, they often utilize off-the-shelf, or pre-trained object detectors and classification algorithms
- The most common approach is to utilize Convolutional Neural Network (CNN) models (e.g., YOLO or ResNet) to translate 2D images into higher-level symbolic representations

Vision Module translates from low-level pixel representations to higher-level symbolic representations

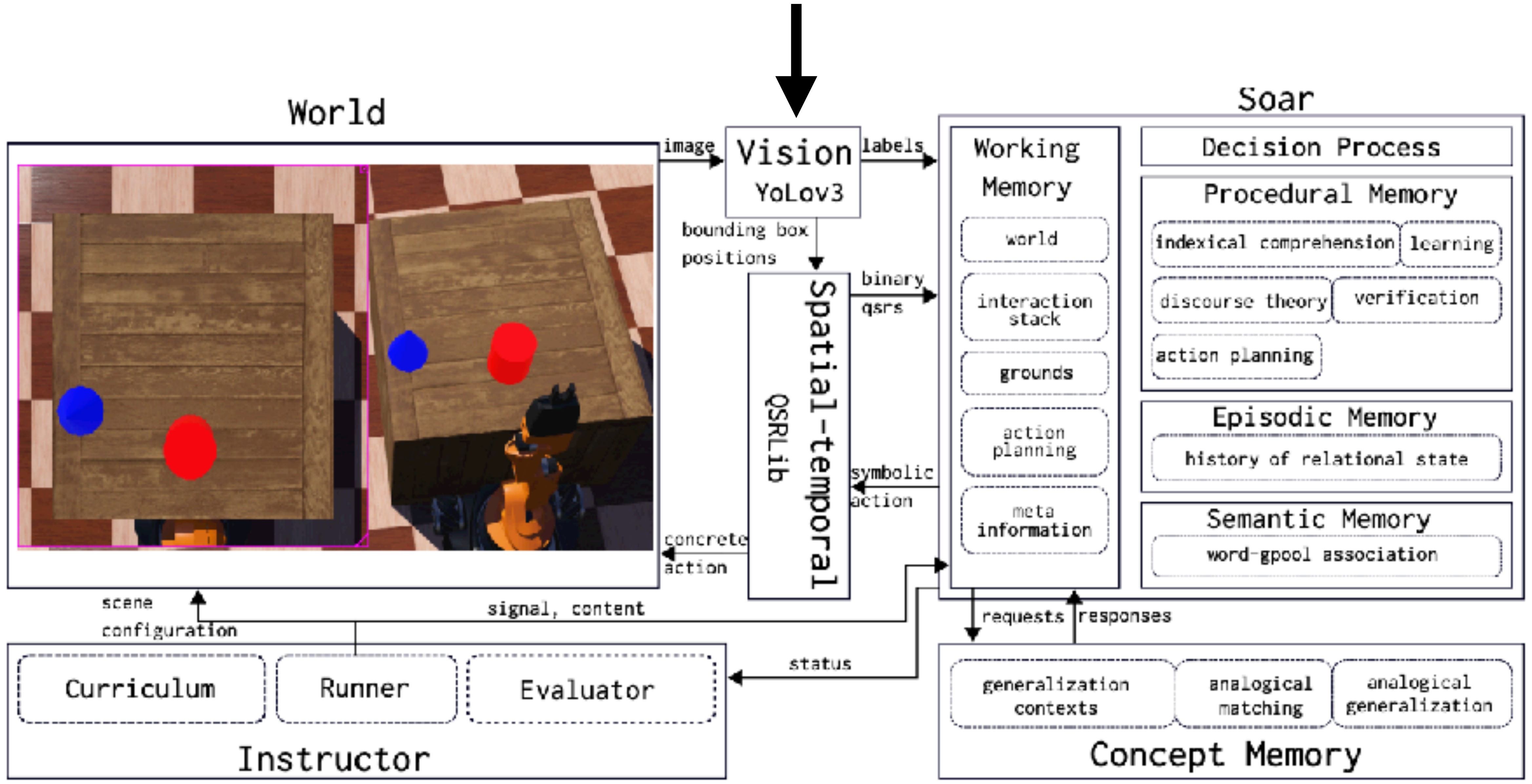


Figure 1: System diagram for Advanced cognItive LEarning for Embodied compreheNsion (AILEEN)

Figure from Mohan, Klenk, Shrive, Evans, Ang, and Maxwell (2020) Characterizing an Analogical Concept Memory for Architectures Implementing the Common Model of Cognition. Eight Annual Conference on Advances in Cognitive Systems.

Limitations of Current Approaches

Unfortunately, there are many limitations with CNN-based approaches:

- Training is **non-incremental** (i.e., offline, in batch)
- The **structure is fixed** at training time, it cannot adapt based on the input it receives (e.g., it cannot predict labels it does not have pre-existing outputs for)
- They require a **large amount of training data**

There are alternative approaches, such as probabilistic programs (e.g., see Lake, Salakhutdinov, and Tenenbaum, 2015)

- These approaches reduce the amount of training data required, but still use non-incremental training and adopt fixed model structures (only parameters are estimated)

A Concept Formation Approach

- To address these limitations, we have been exploring an approach that builds on prior *concept formation* models
- These models emphasize the **incremental nature of learning** and the **ability to adapt conceptual structures** to better reflect experience
- The basis for our approach is the *Cobweb* model of concept formation (Fisher, 1987)
- We utilize a variant called Cobweb/3 that supports both discrete and continuous-valued attributes (McKusick & Thompson, 1990)

Cobweb Example

New Instance

Atribute	Value
Color	Red
Shape	Square

Cobweb Tree

Attribute	Value	Probability

Cobweb Example

Atribute	Value
Color	Red
Shape	Square

Cobweb Tree

Attribute	Value	Probability

Cobweb Example

Atribute	Value
Color	Red
Shape	Square

Cobweb Tree

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

New Instance

Atribute	Value
Color	Green
Shape	Square

Cobweb Tree

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

Atribute	Value
Color	Green
Shape	Square

Cobweb Tree

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

Cobweb Tree

Attribute	Value	Probability
Color	Red	50%
	Green	50%
Shape	Square	100%

Atribute	Value
Color	Green
Shape	Square

Attribute	Value	Probability
Color	Green	100%
Shape	Square	100%

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

New Instance

Atribute	Value
Color	Green
Shape	Circle

Cobweb Tree

Attribute	Value	Probability
Color	Red	50%
	Green	50%
Shape	Square	100%

Attribute	Value	Probability
Color	Green	100%
Shape	Square	100%

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

Atribute	Value
Color	Green
Shape	Circle

Cobweb Tree

Attribute	Value	Probability
Color	Red	33%
	Green	66.6%
Shape	Square	66.6%
	Circle	33.3

Attribute	Value	Probability
Color	Green	100%
Shape	Square	100%

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

Cobweb Tree

Attribute	Value	Probability
Color	Red	33%
	Green	66.6%
Shape	Square	66.6%
	Circle	33.3

Atribute	Value
Color	Green
Shape	Circle

Attribute	Value	Probability
Color	Green	100%
Shape	Square	100%

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Cobweb Example

Cobweb Tree

Attribute	Value	Probability
Color	Red	33%
	Green	66.6%
Shape	Square	66.6%
	Circle	33.3

Attribute	Value	Probability
Color	Green	100%
Shape	Square	50%
	Circle	50%

Attribute	Value	Probability
Color	Red	100%
Shape	Square	100%

Atribute	Value
Color	Green
Shape	Circle

Attribute	Value	Probability
Color	Green	100%
Shape	Circle	100%

Attribute	Value	Probability
Color	Green	100%
Shape	Square	100%

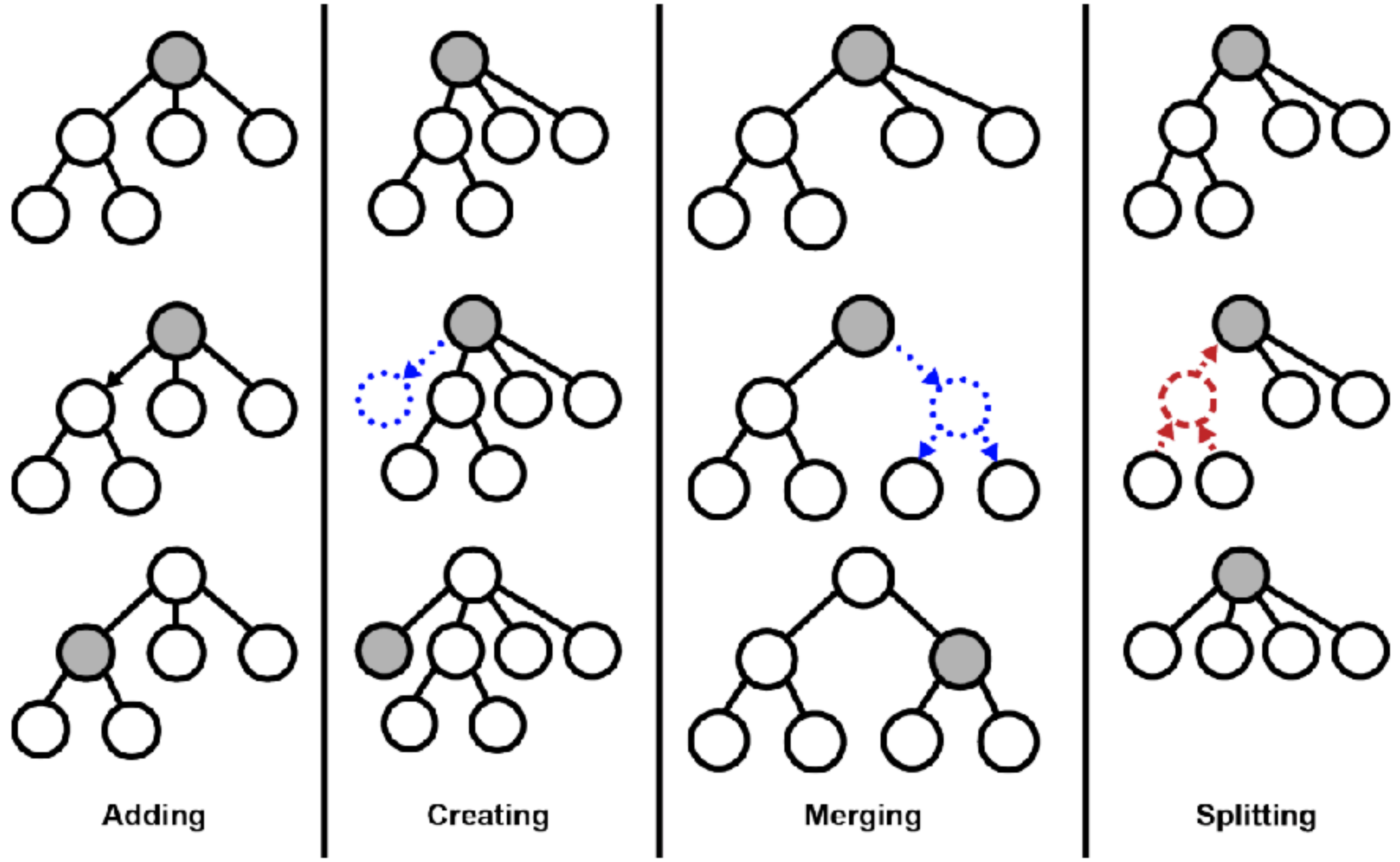
Cobweb Learning & Performance

During learning:

- Cobweb considers the four update operations at each node
- It chooses the operation that maximizes the category utility measure (Corter & Gluck, 1992)

At performance time:

- Cobweb only considers adding and creating, and does not update attribute-value counts/ probabilities during categorization
- The final node an instance ends up in is used to generate predictions about the instance



Four update operations considered by Cobweb at each node during learning

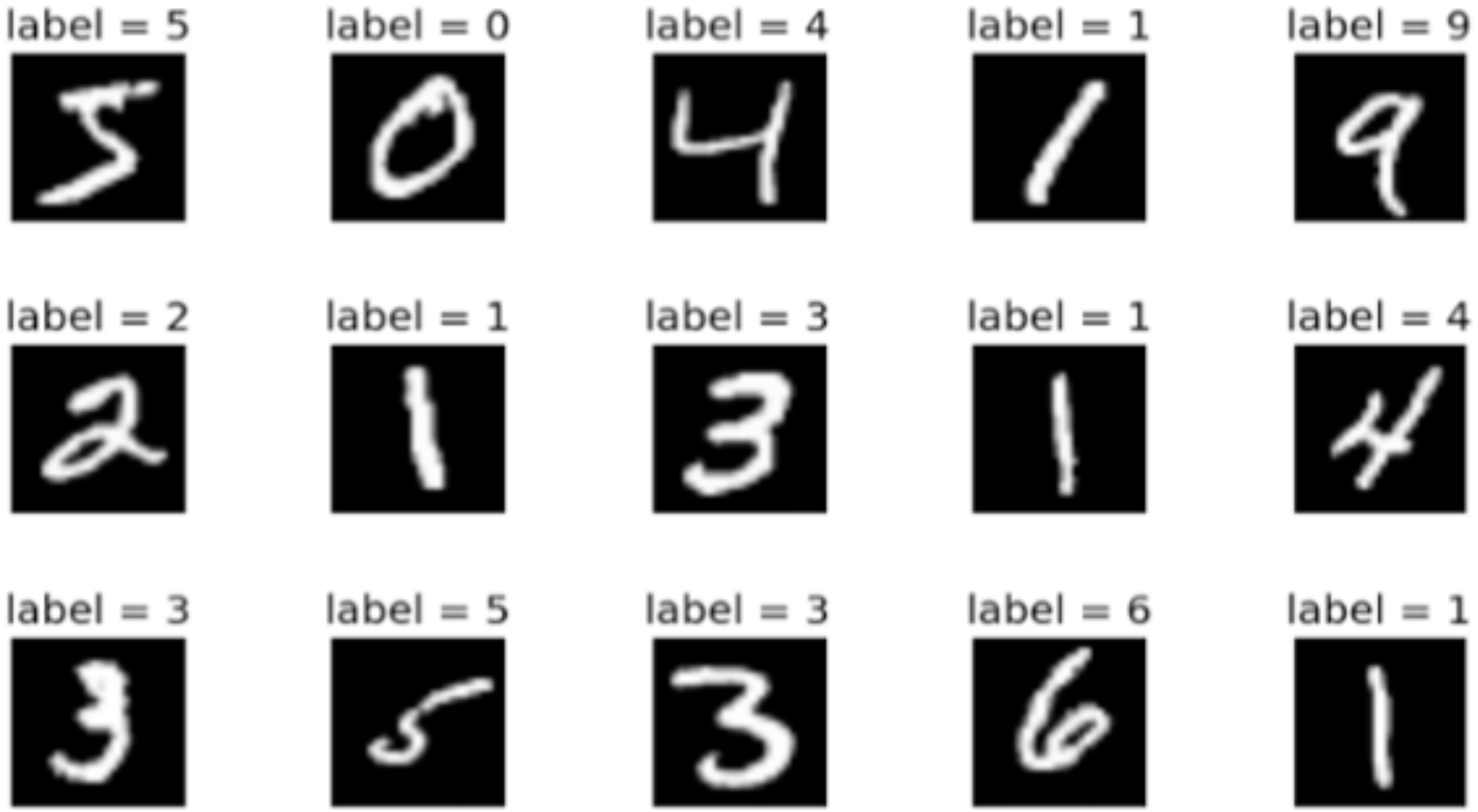
Figure from MacLellan, C.J., Harpstead, E., Aleven, V., Koedinger K.R. (2016). TRESTLE: A Model of Concept Formation in Structured Domains. Advances in Cognitive Systems, 4, 131-150.

Limitation of Cobweb

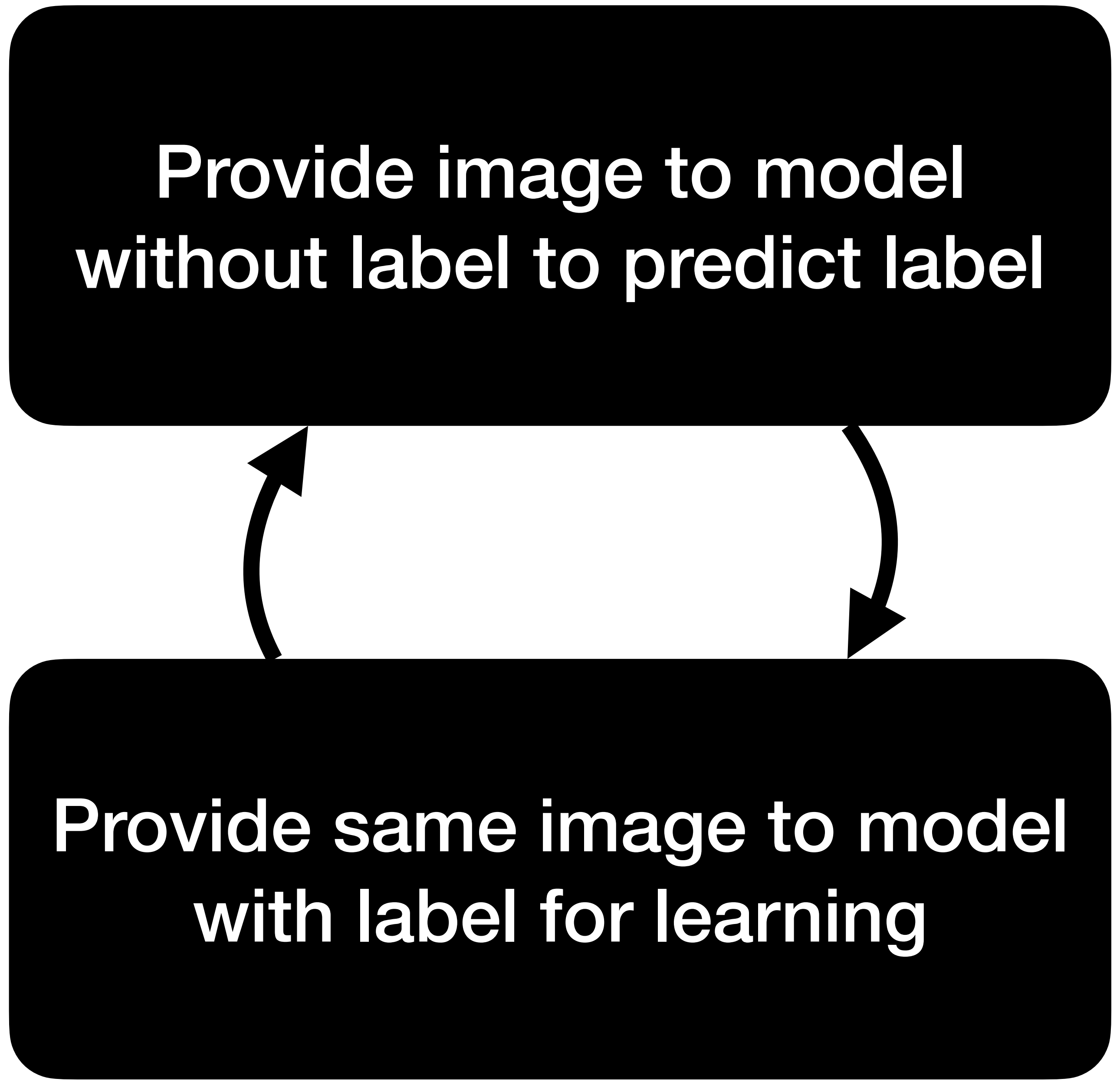
- Concept formation approaches have historically assumed higher-level representations, rather than lower-level (e.g., pixel) representations
- CNNs leverage convolutional processing to learn a representation of inputs
- Our work aims to explore how convolutional processing can be incorporated into the cobweb model to support concept formation from images

Incremental MNIST Digit Classification Task

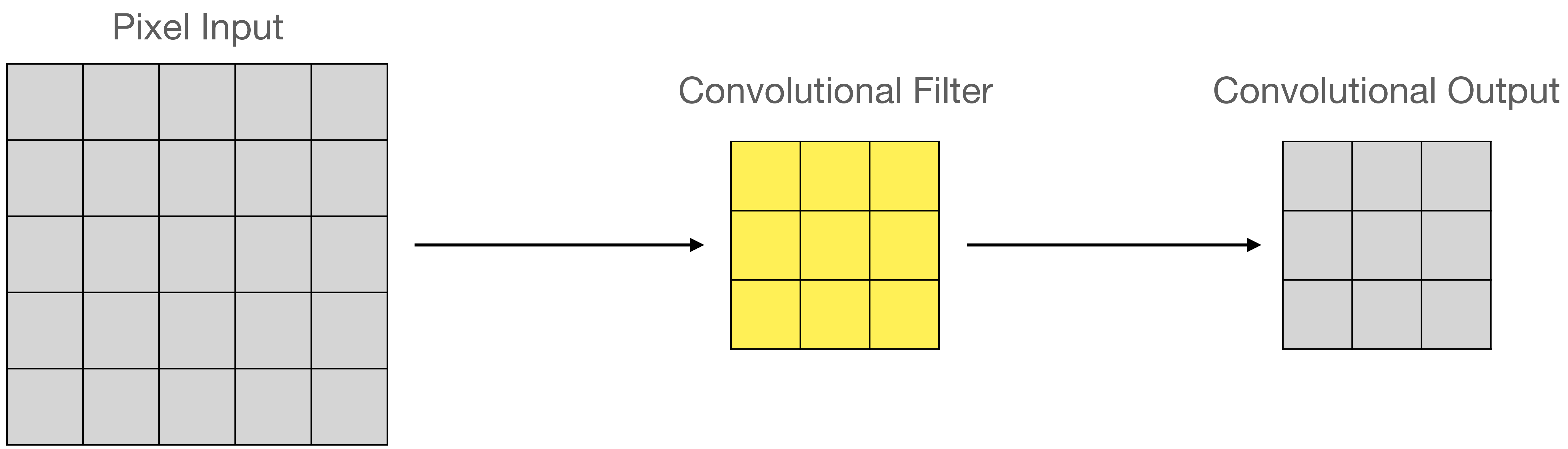
Examples of MNIST Images with Labels



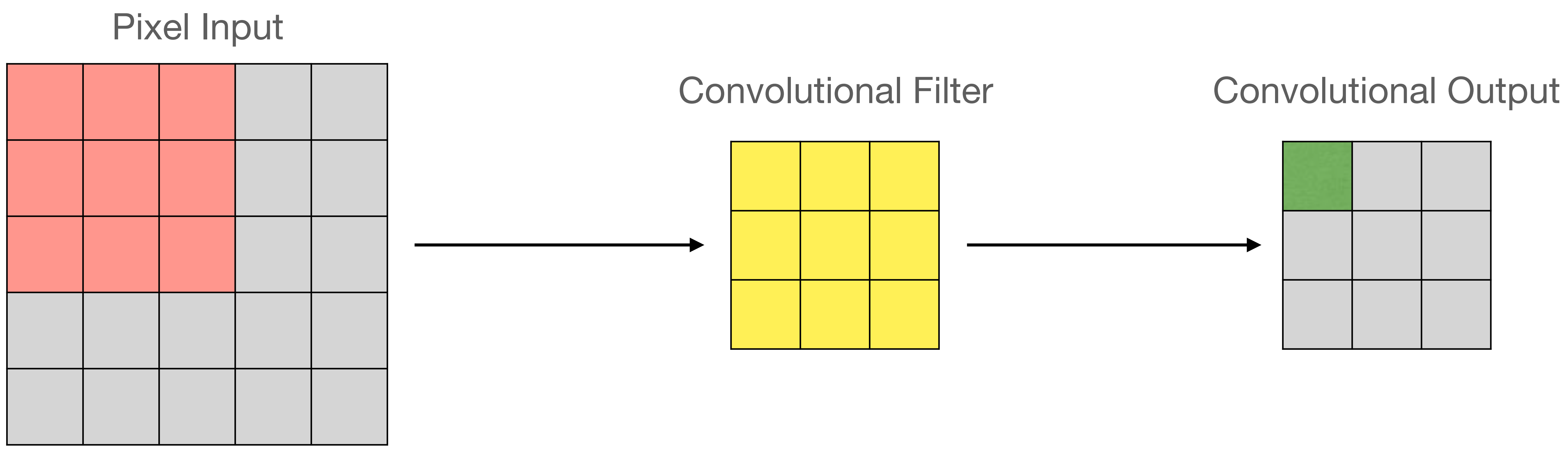
Incremental Prediction Approach



Convolutional Processing in a Simple CNN



Convolutional Processing in a Simple CNN



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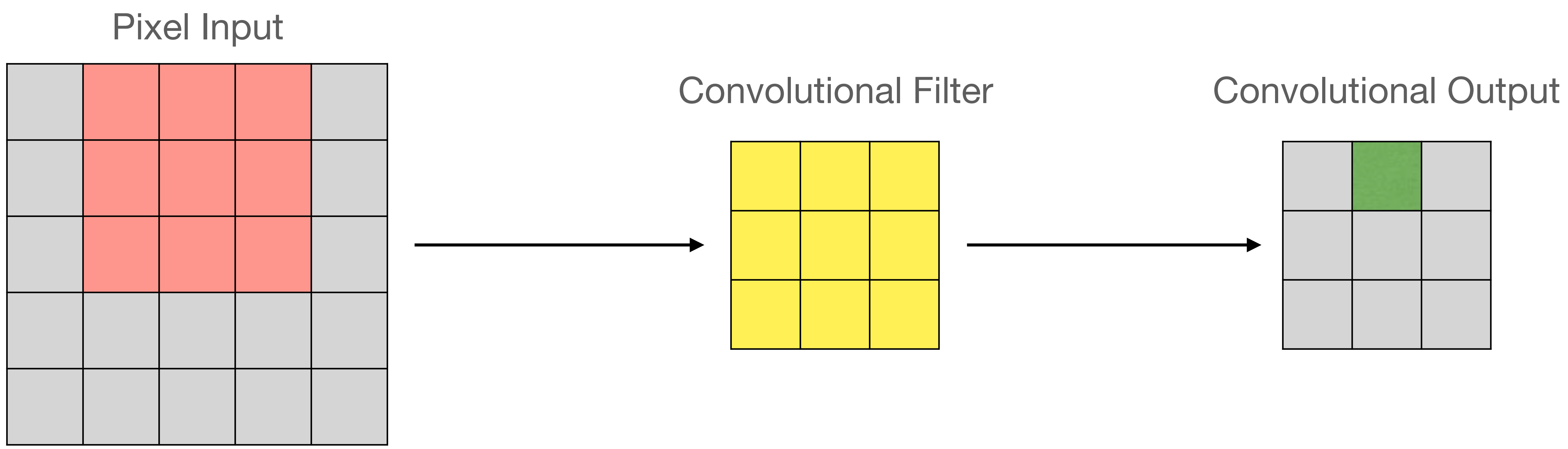

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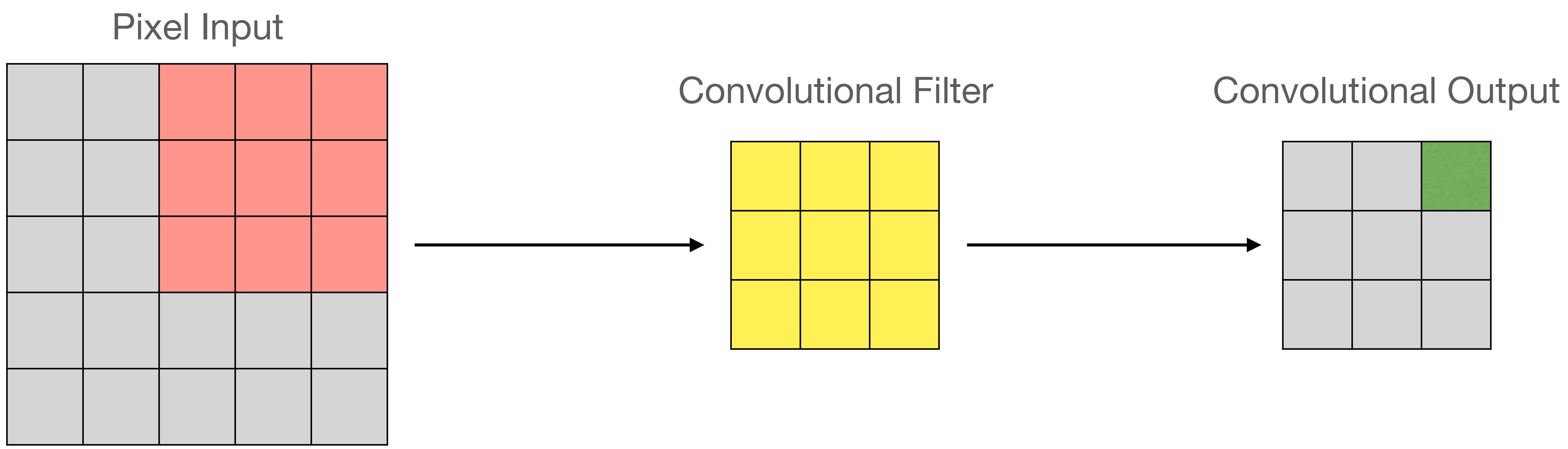

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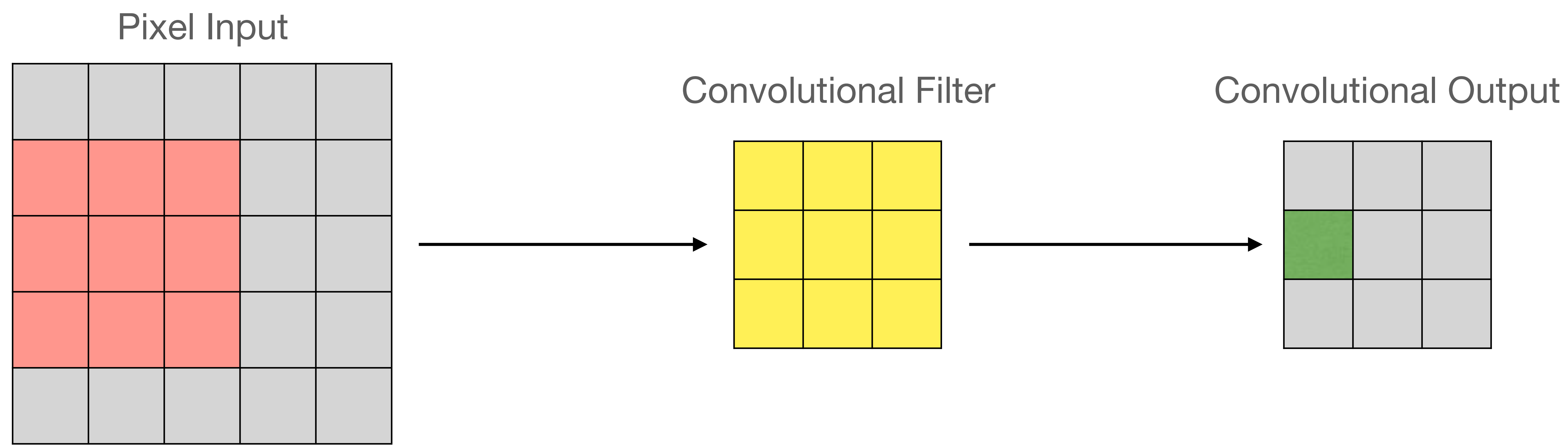

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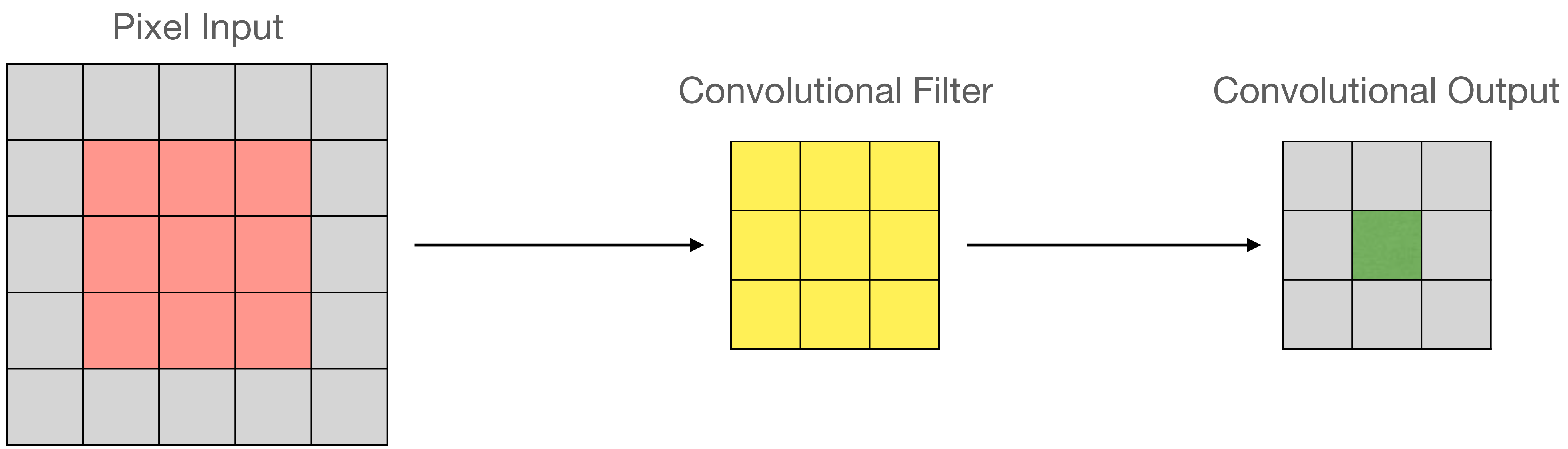

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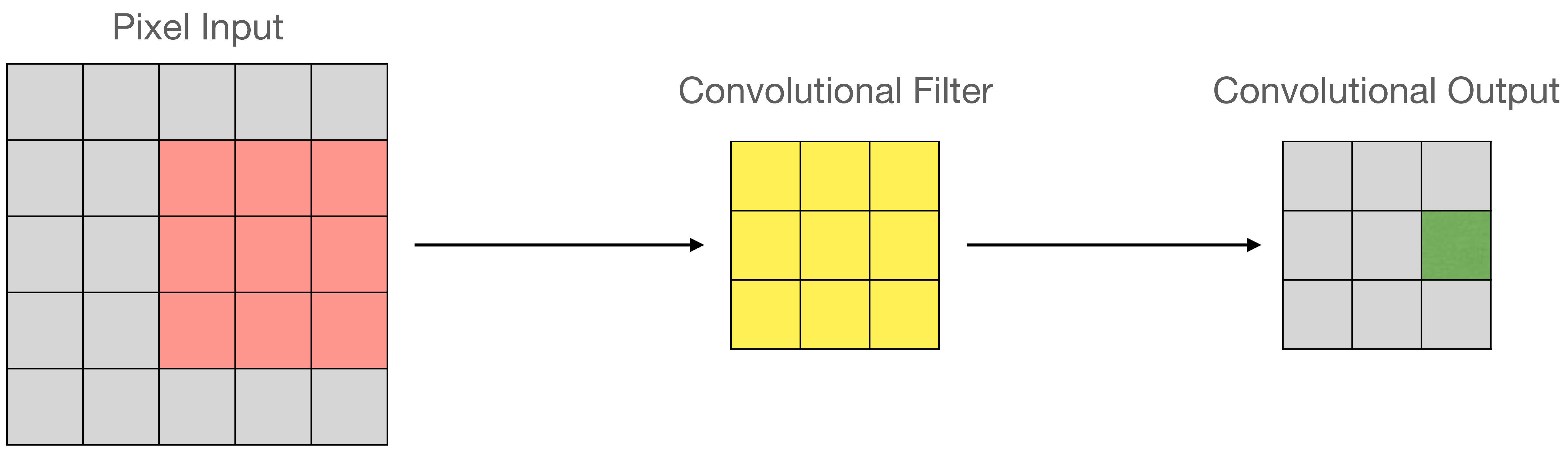

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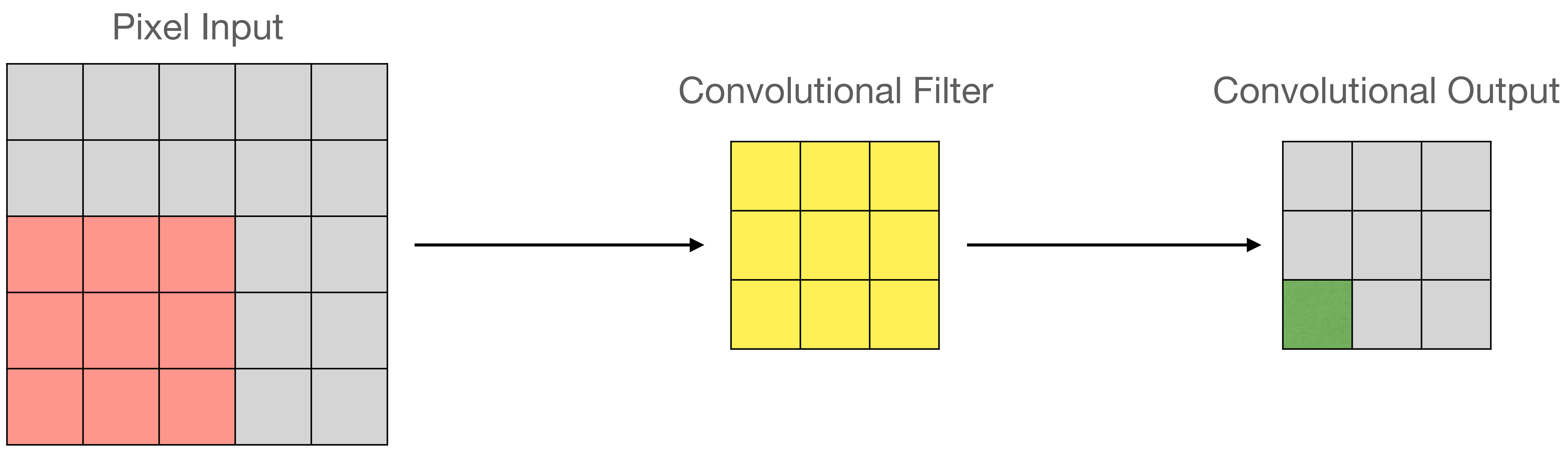

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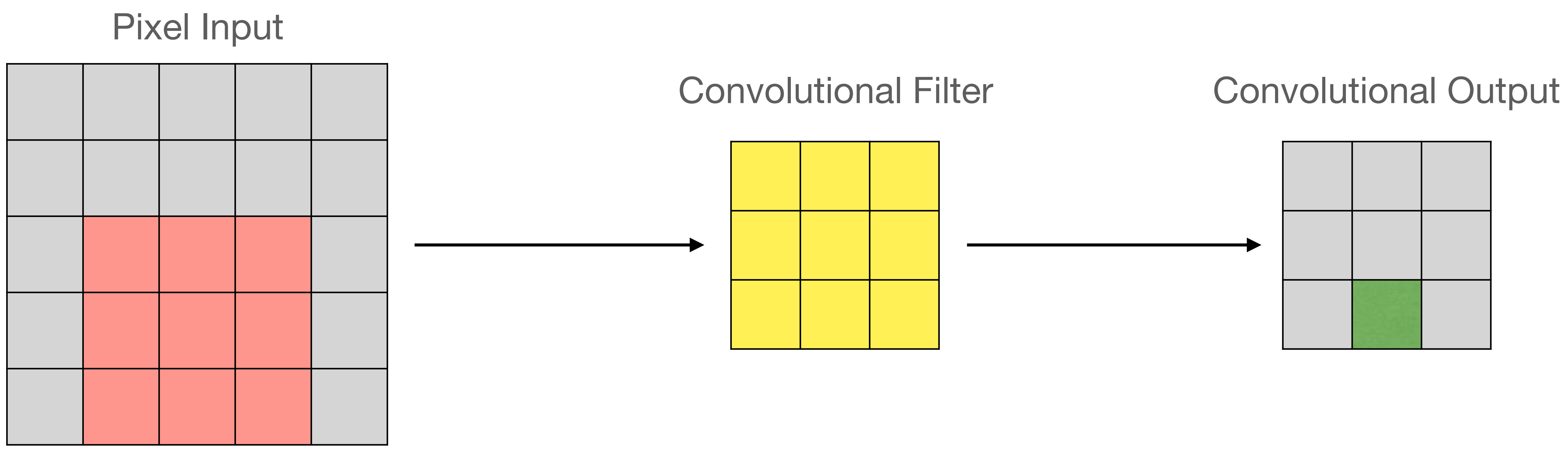

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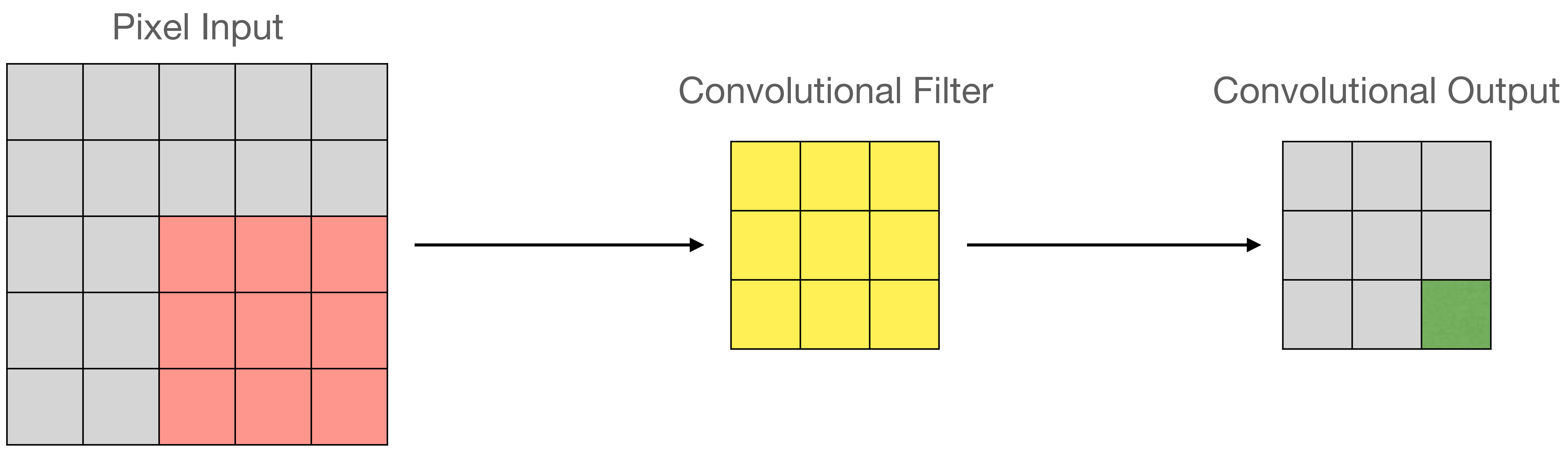

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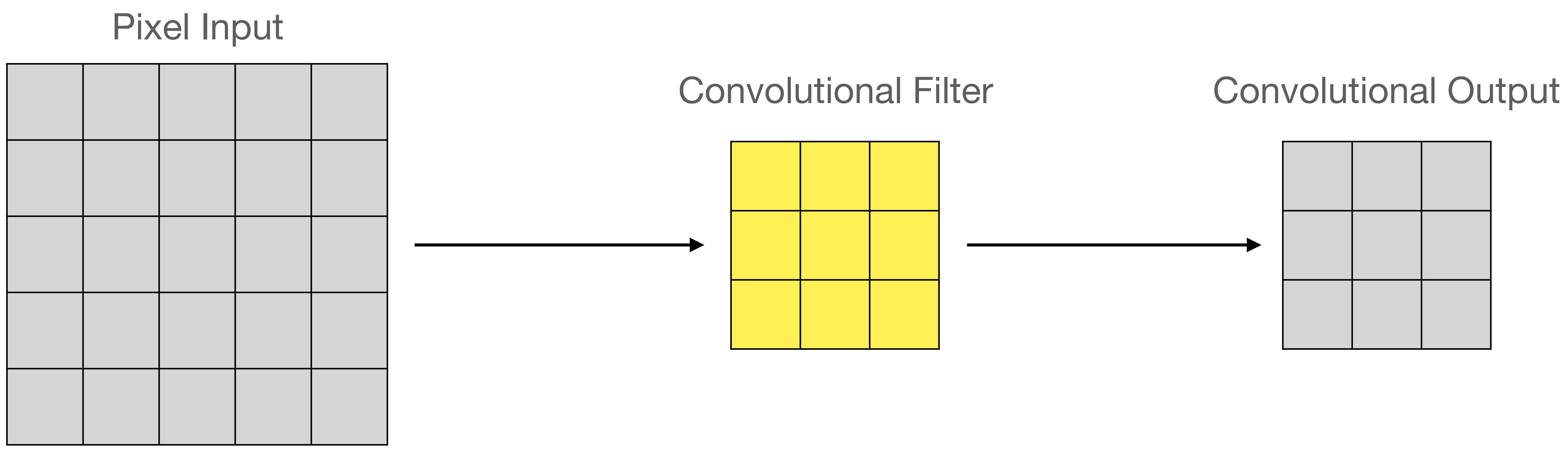
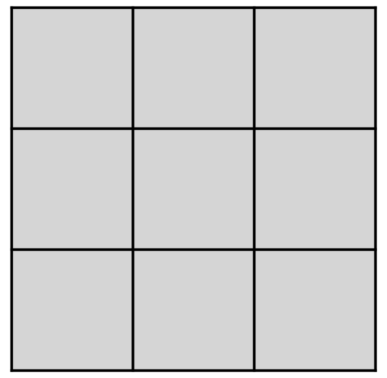


Convolutional Processing in a Simple CNN

Convolutional Output



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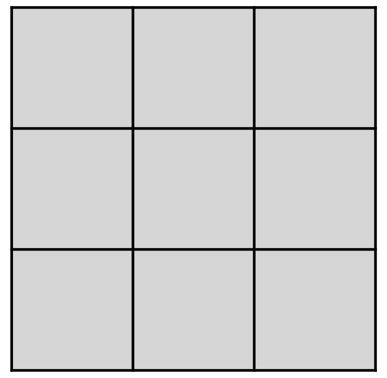

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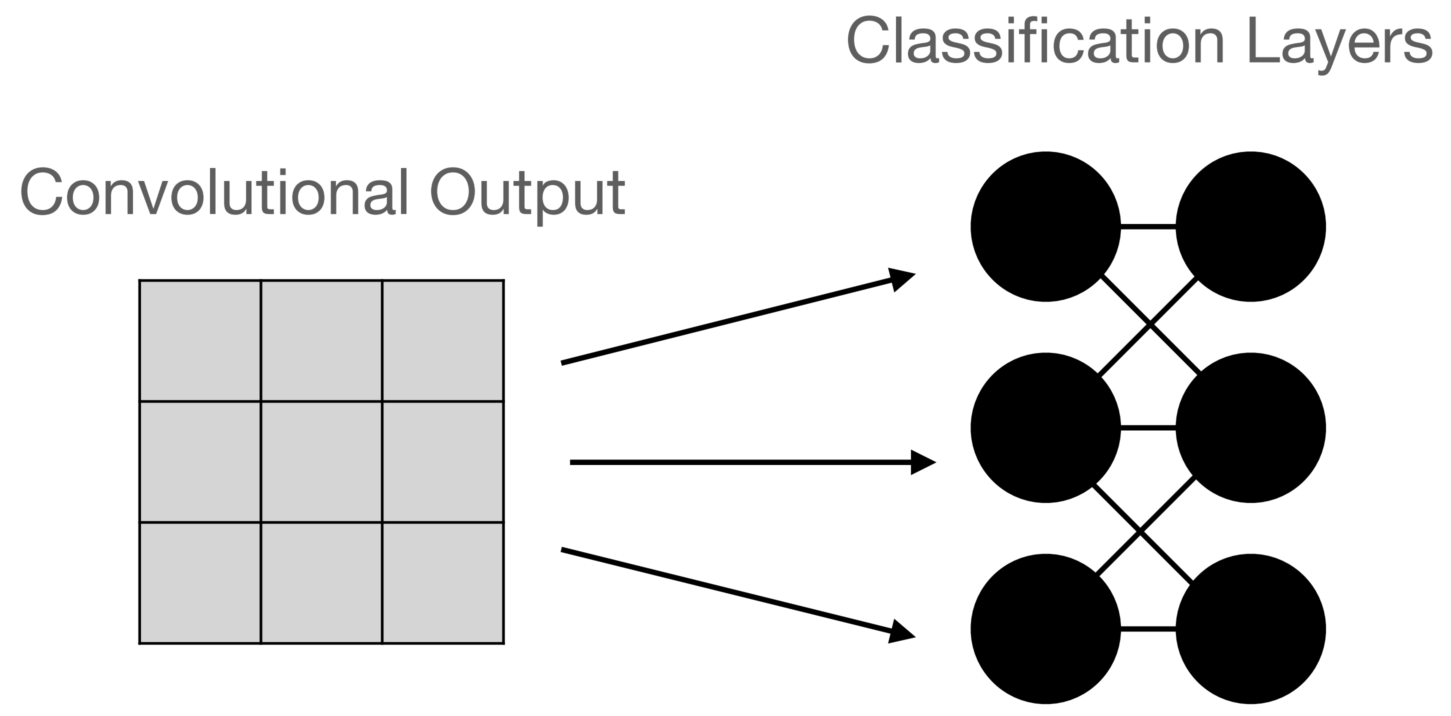

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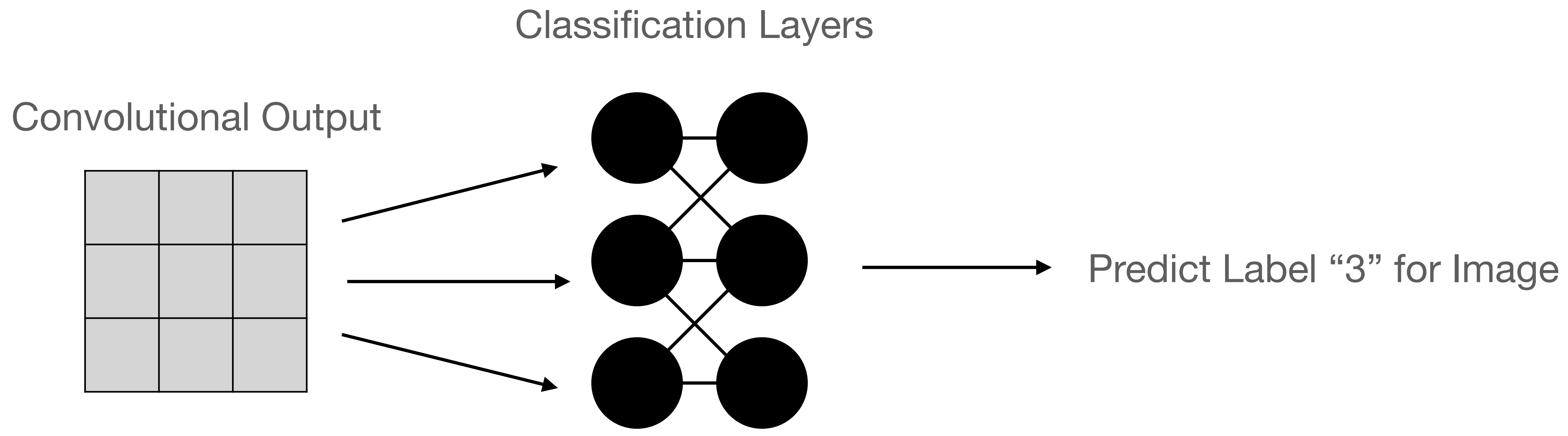
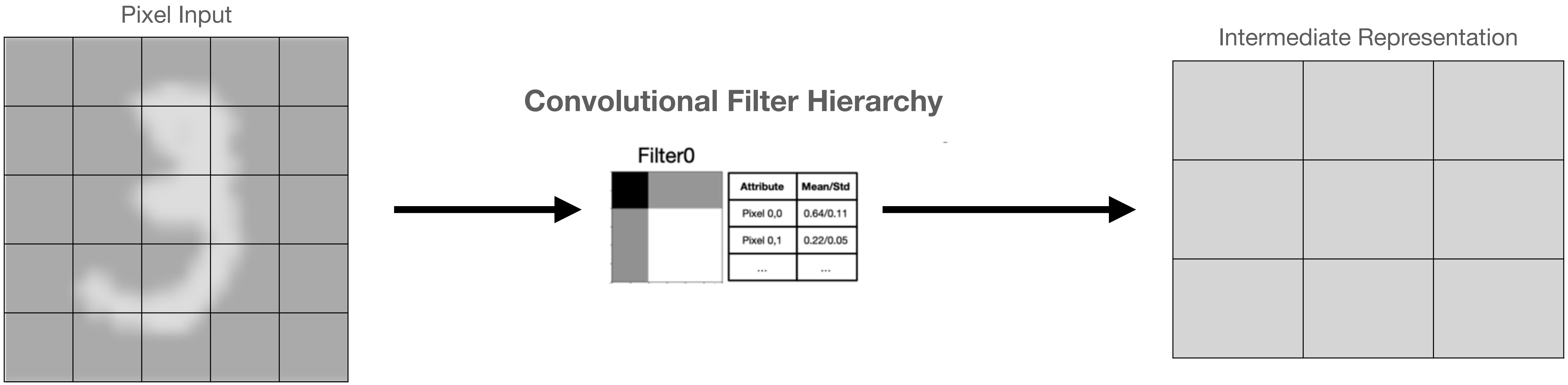


Convolutional Cobweb Approach



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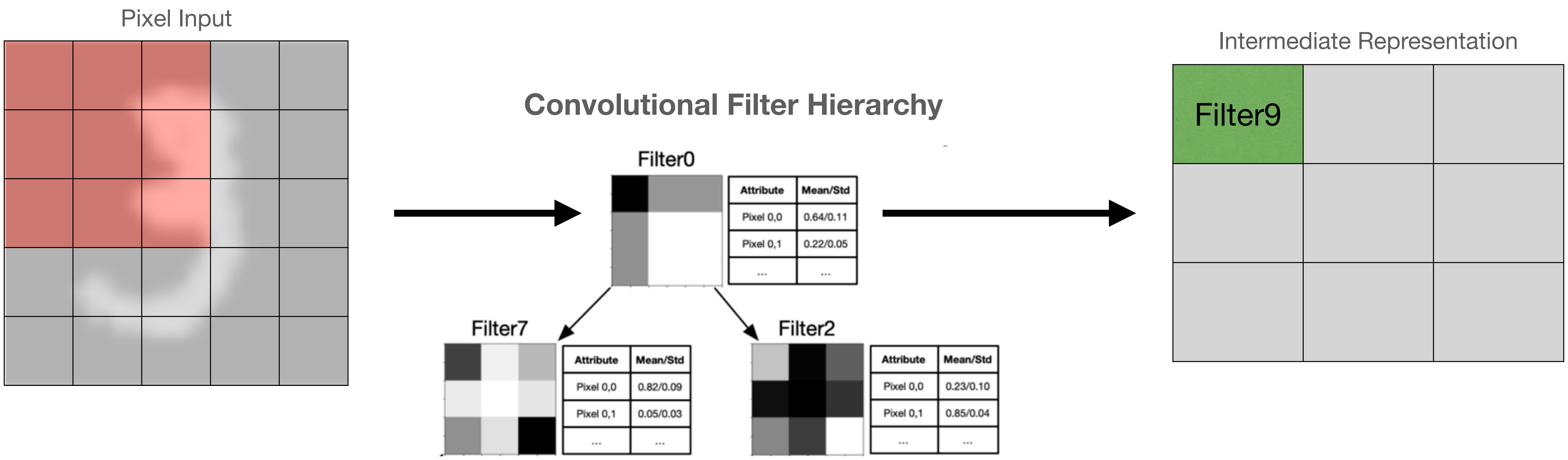

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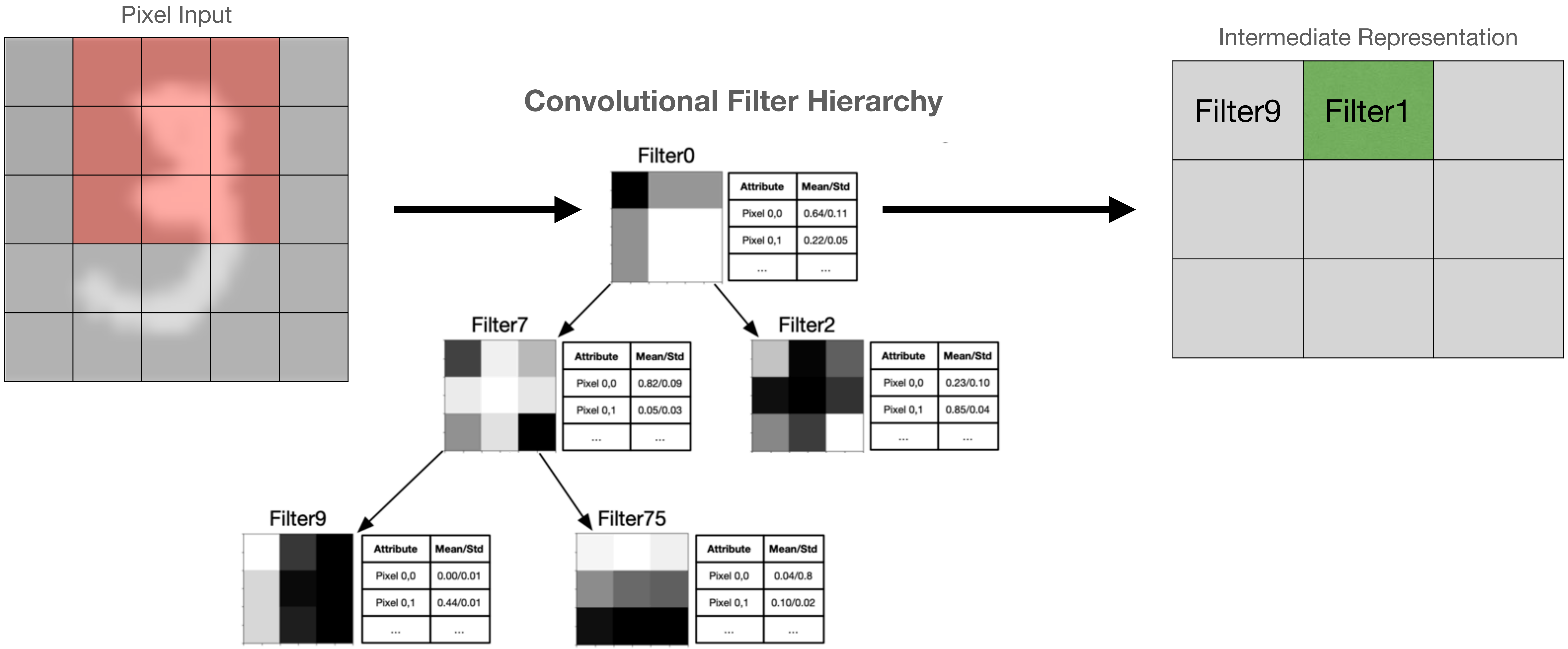

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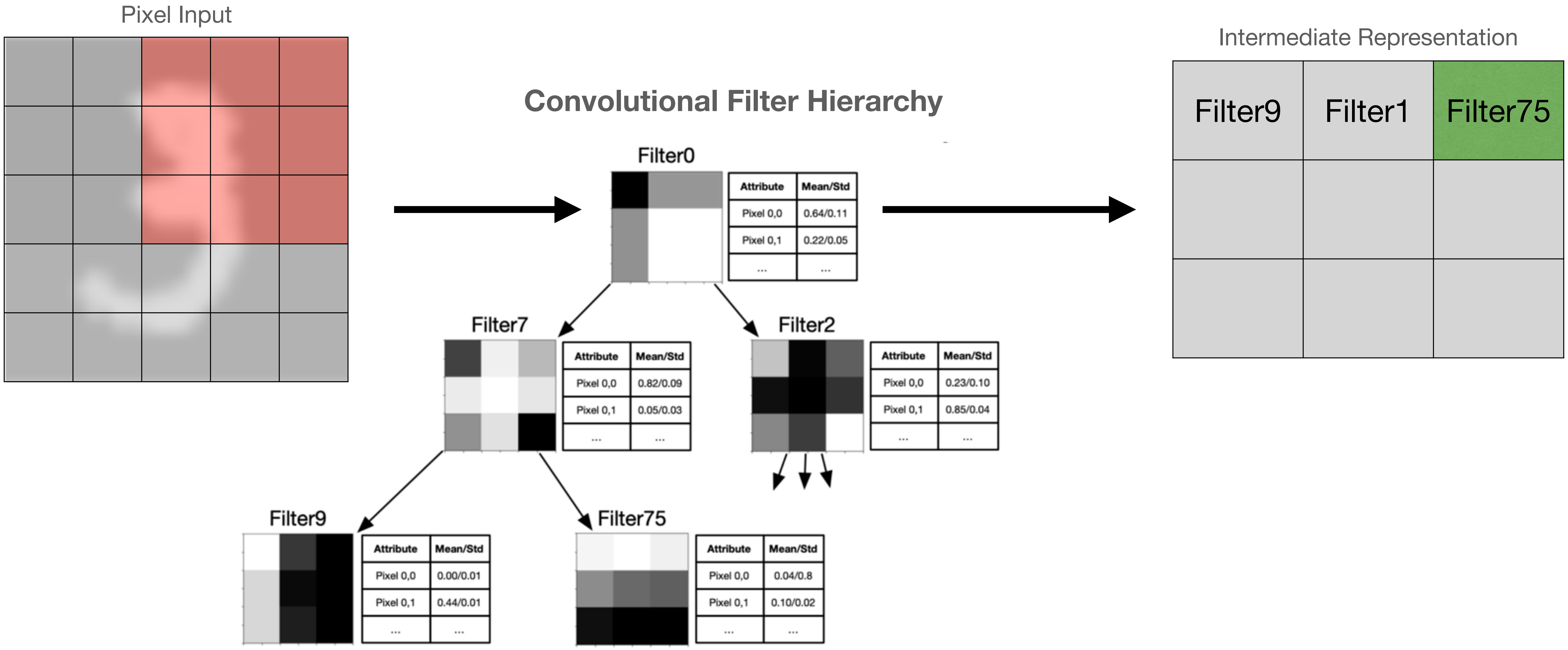

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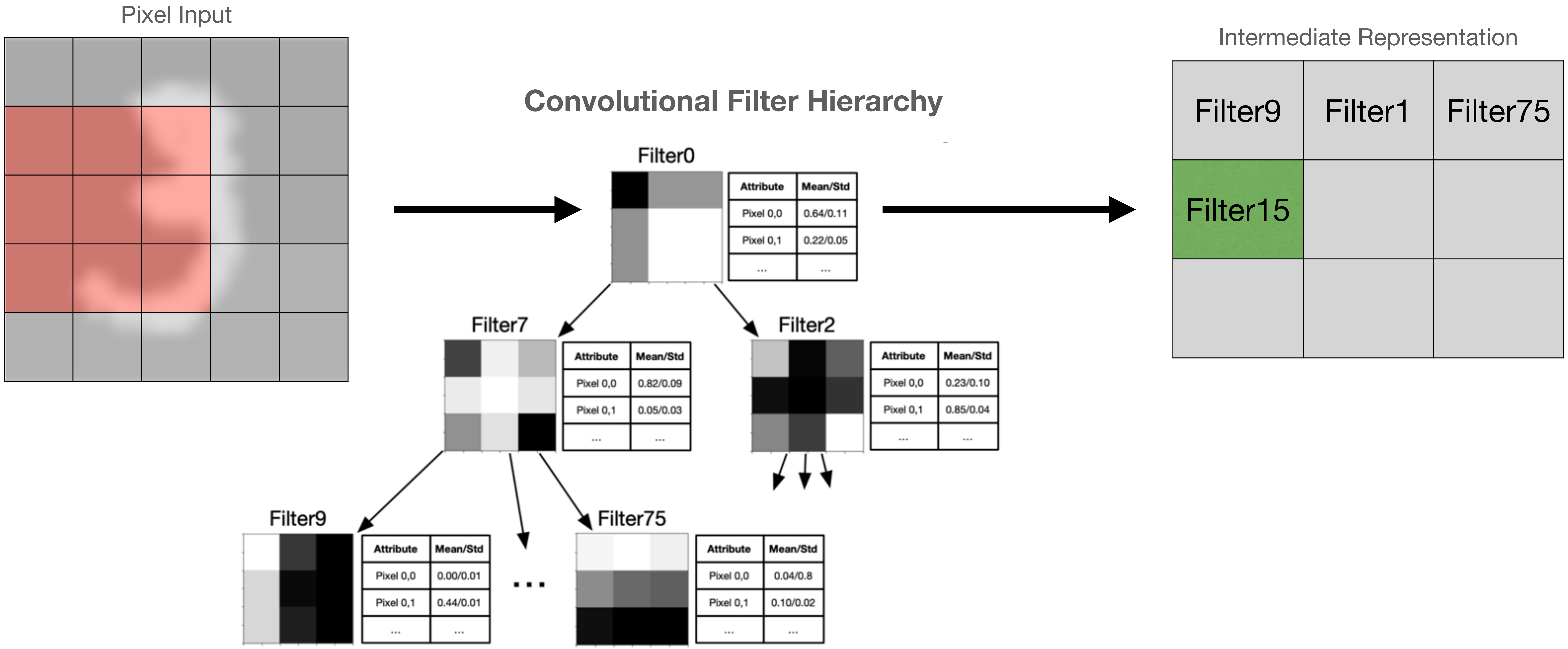

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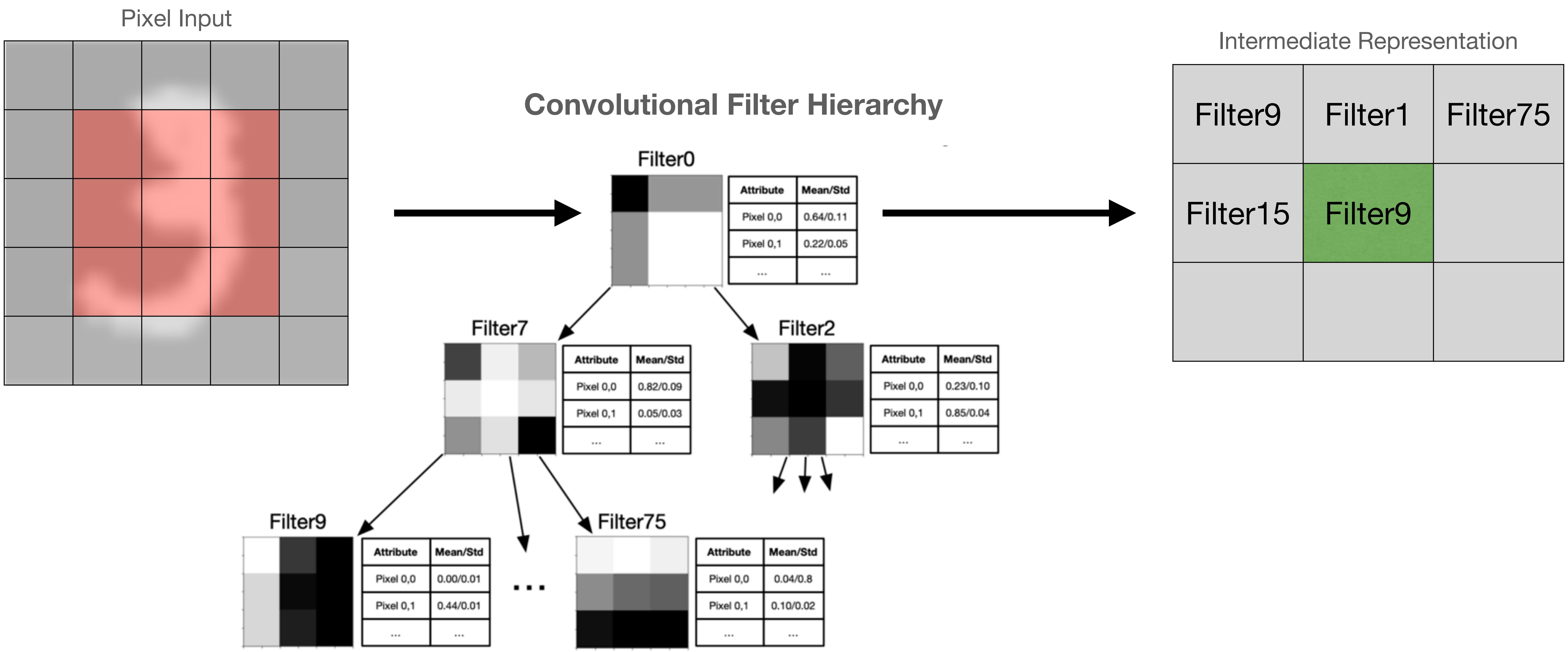

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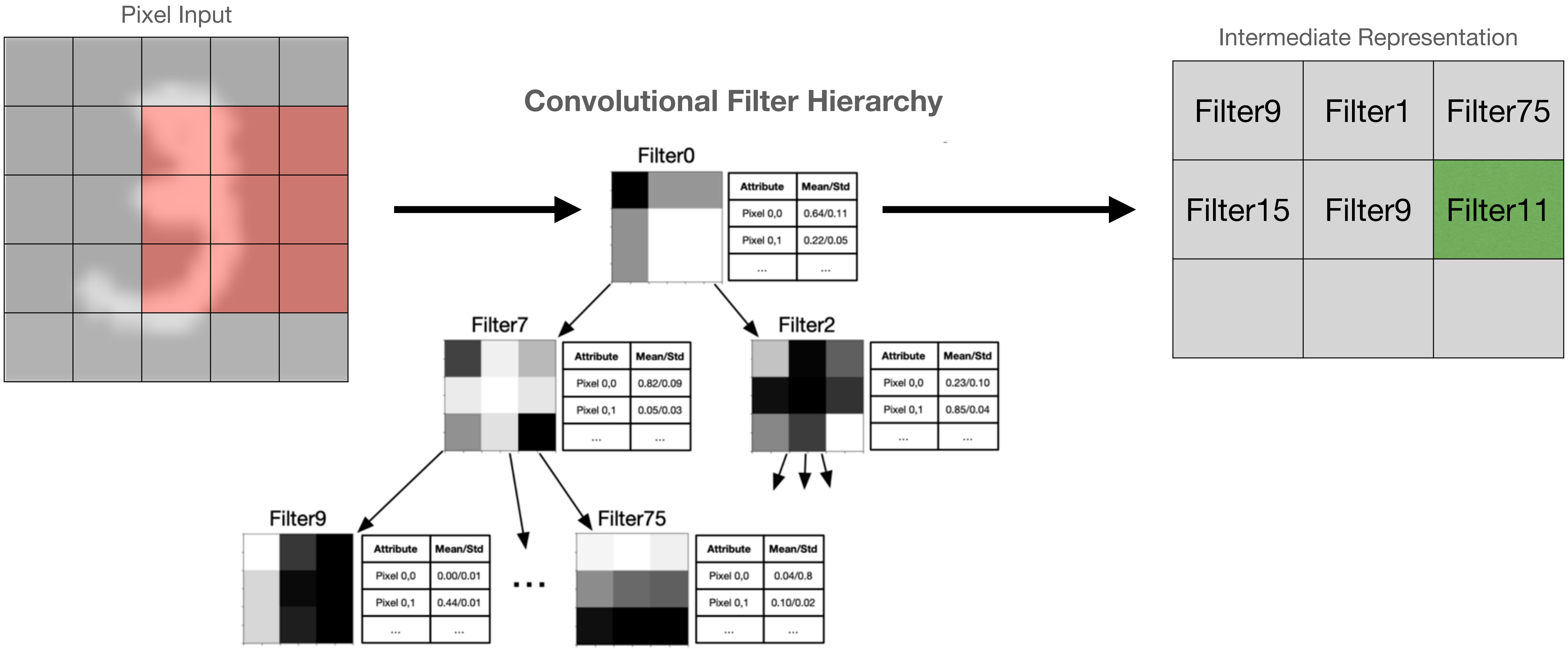

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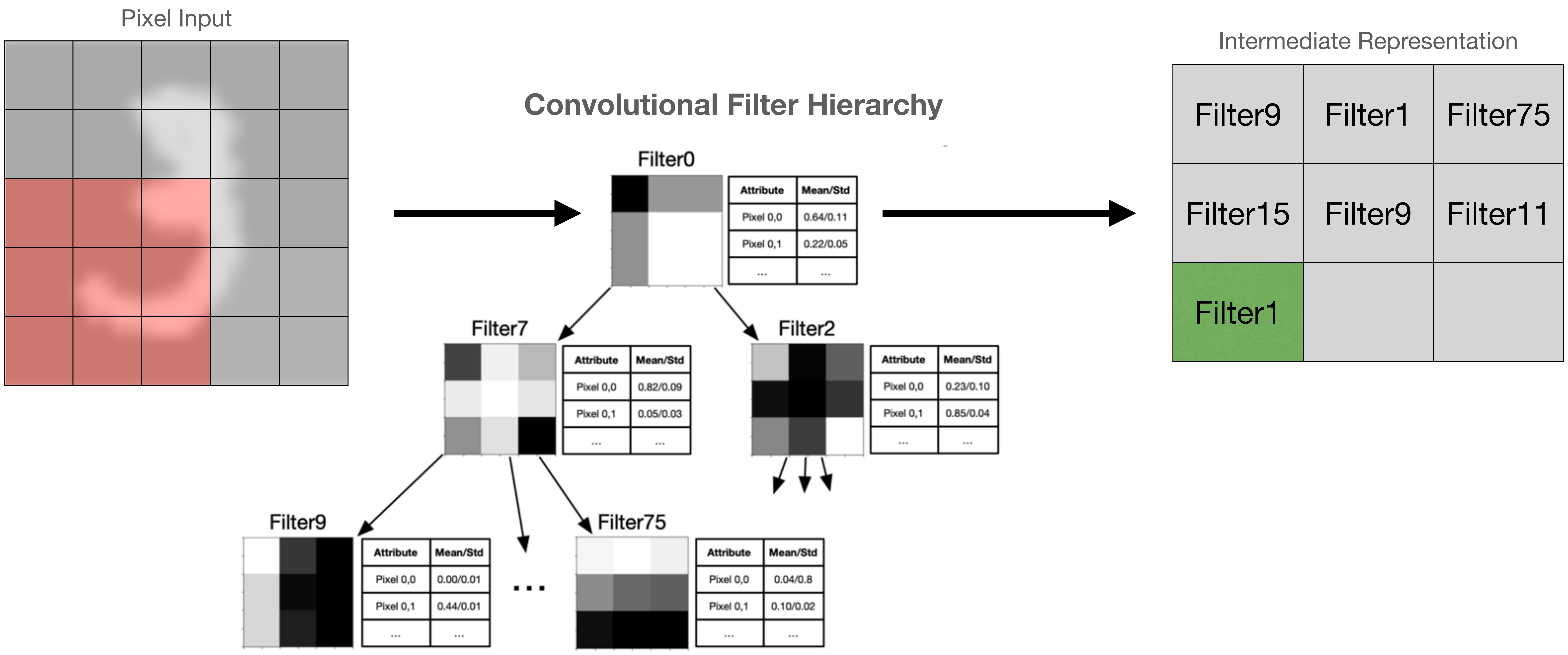

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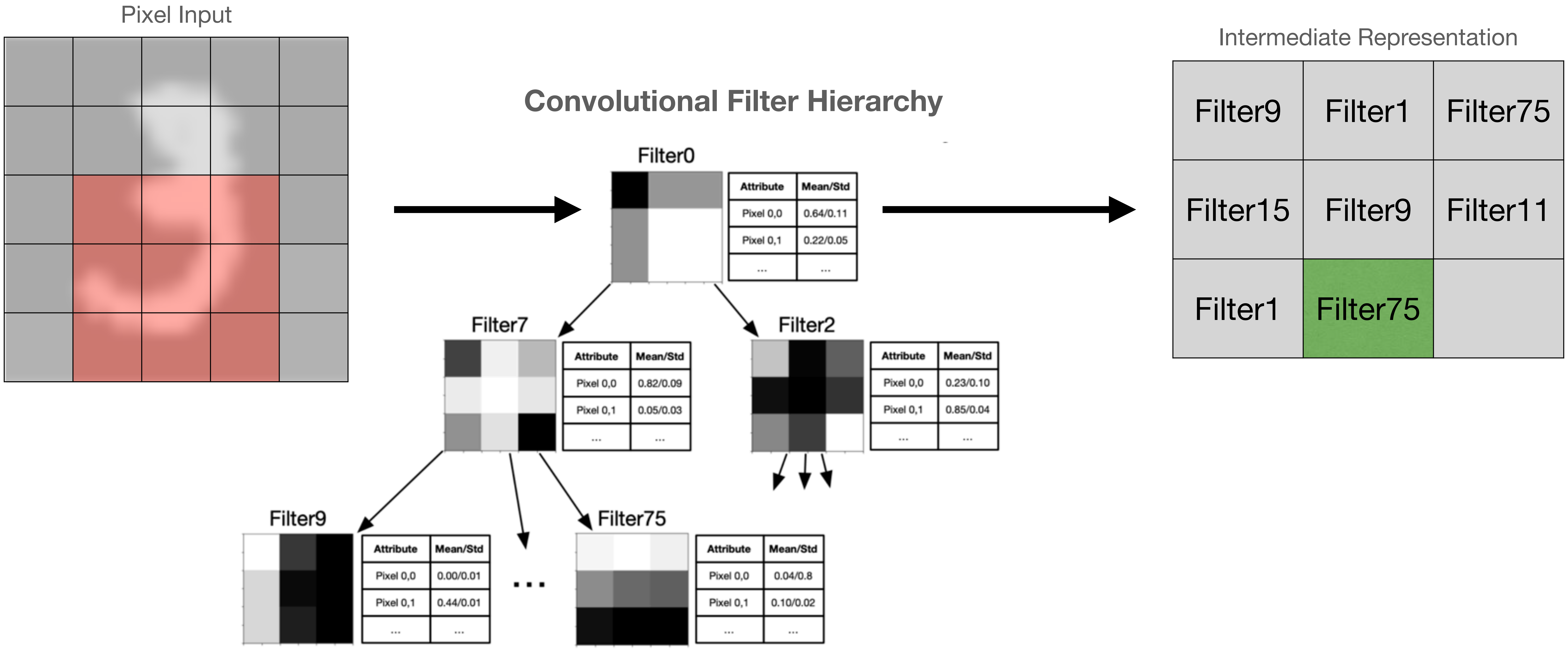

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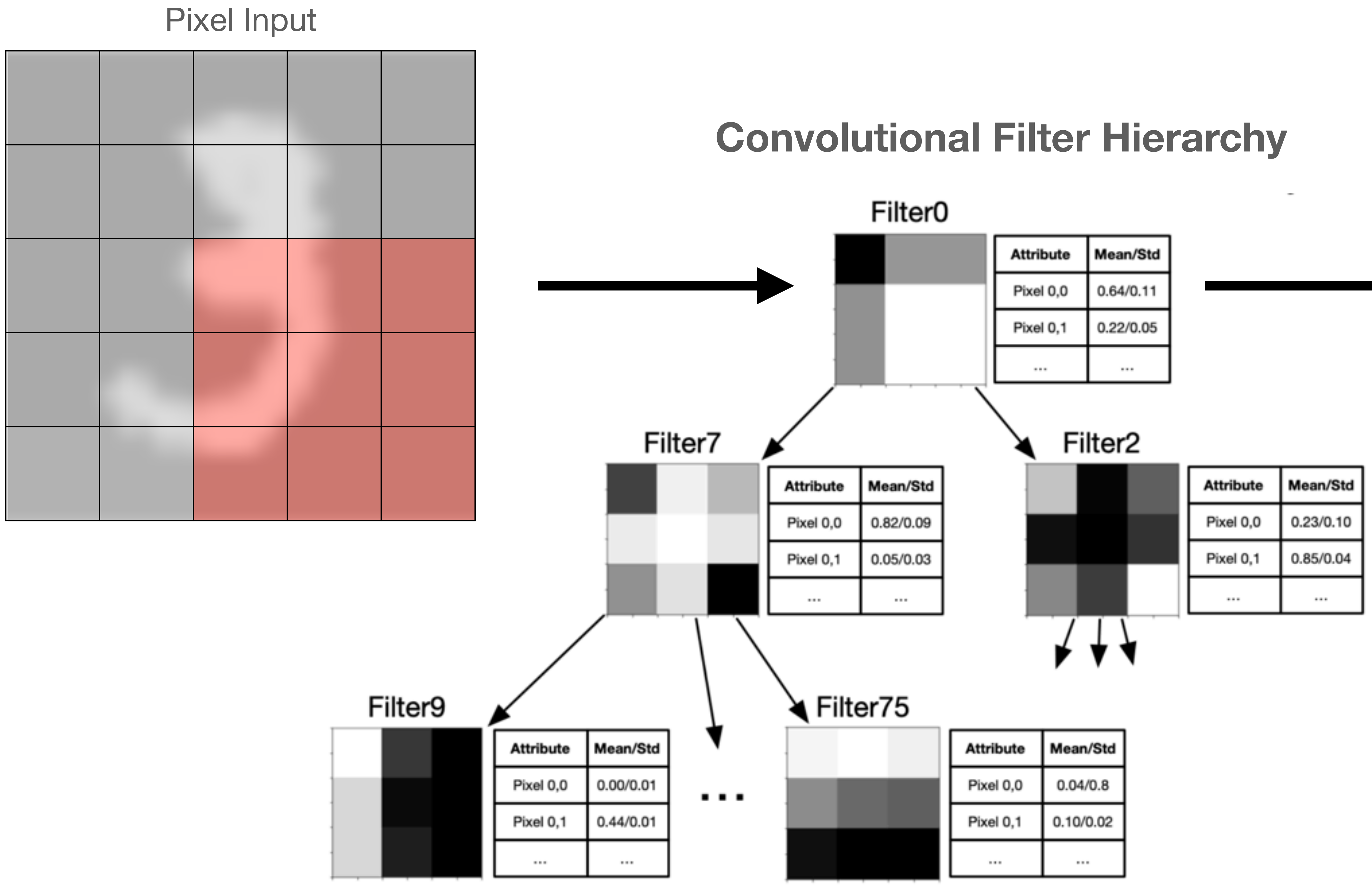
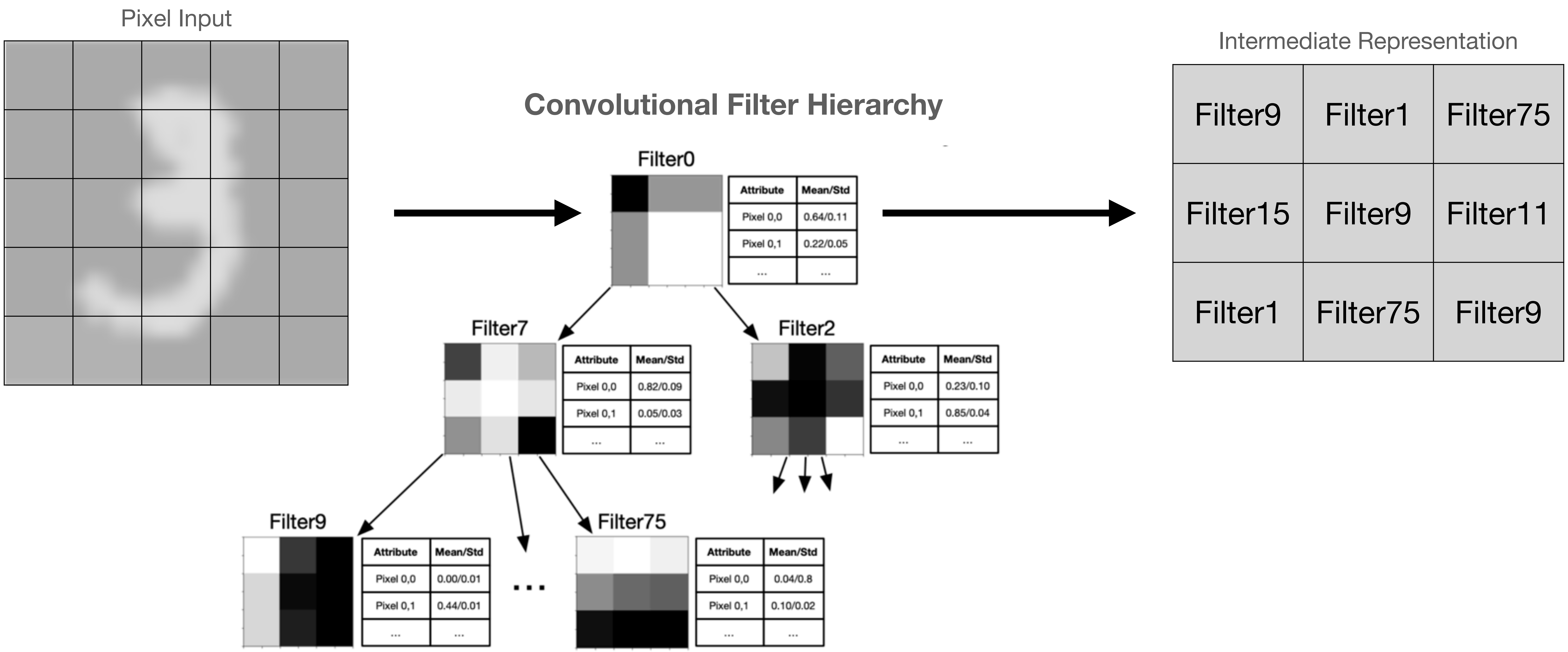


Intermediate Representation

Filter9	Filter1	Filter75
Filter15	Filter9	Filter11
Filter1	Filter75	Filter9

Convolutional Cobweb Approach



Convolutional Cobweb Approach

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Convolutional Cobweb Approach

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Convolutional Cobweb Approach

Intermediate Representation

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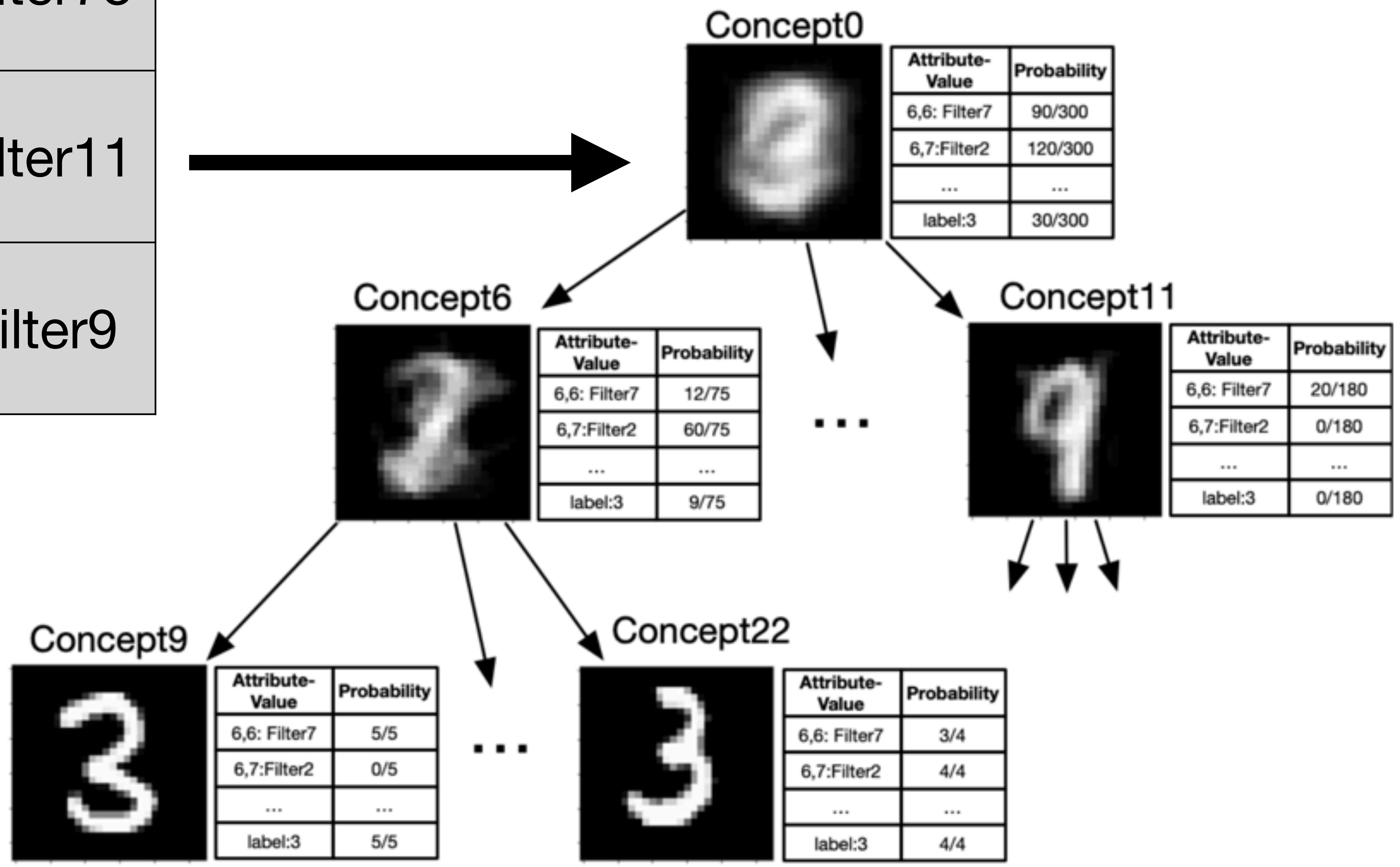
Classification Hierarchy



Convolutional Cobweb Approach

Intermediate Representation

Filter9	Filter1	Filter75
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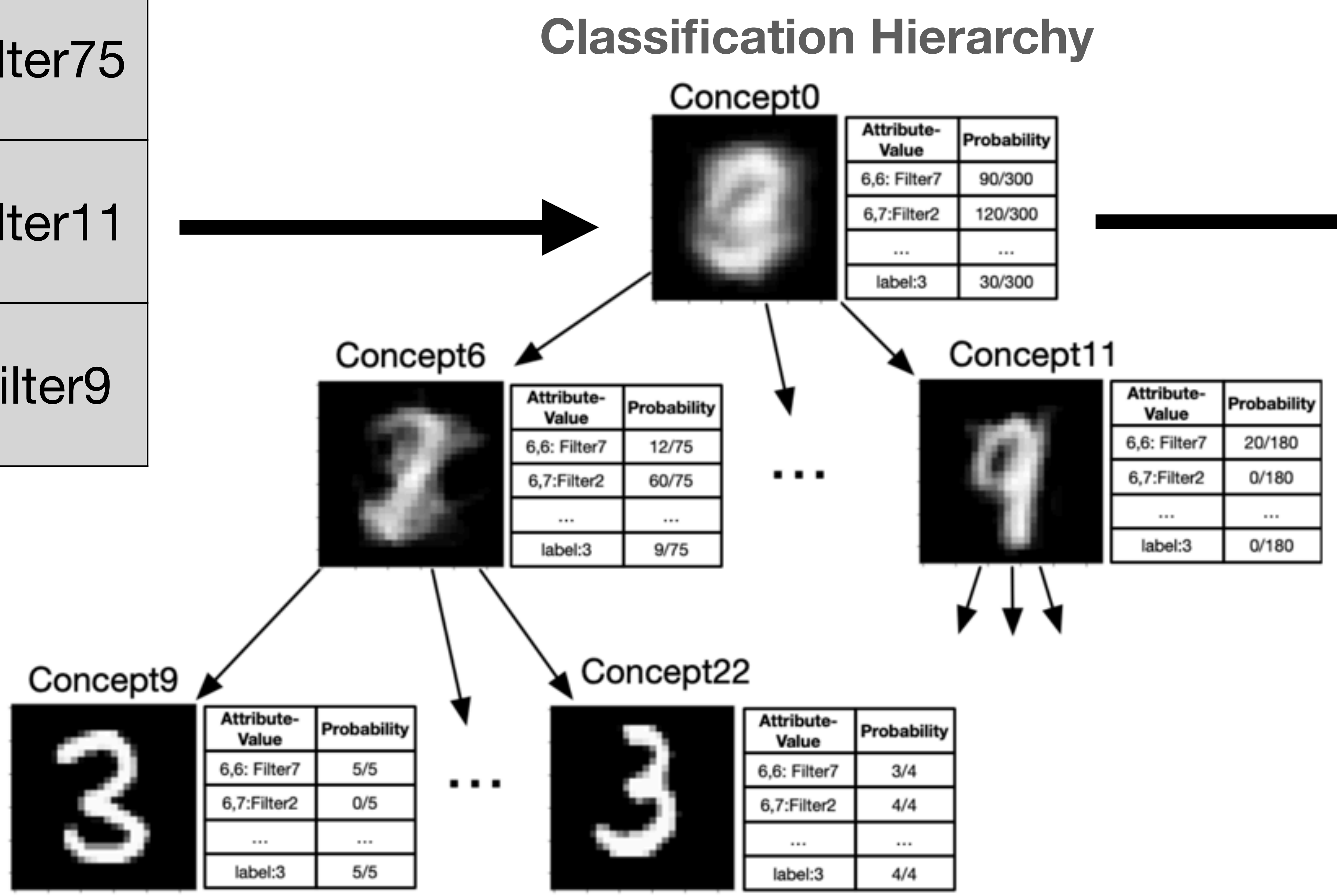


Final Concept: Concept15

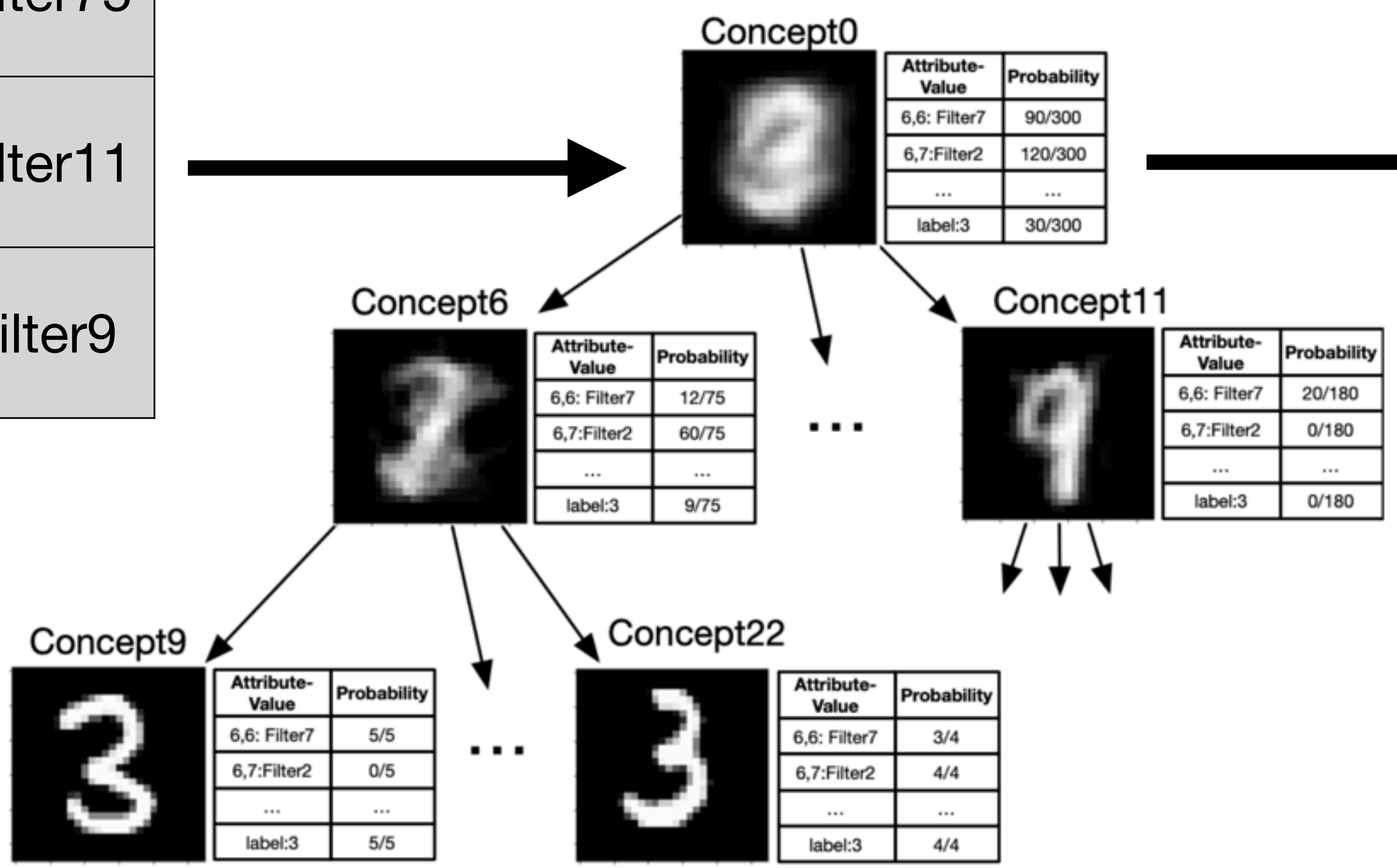
Attribute	Value	Probability
0,0	Filter9	88%
	Filter22	12%
0,1	Filter1	95%
	Filter7	5%
...	...	...
Label	"3"	100%

Convolutional Cobweb Approach

Intermediate Representation

Filter9	Filter1	Filter75
Filter15	Filter9	Filter11
Filter1	Filter75	Filter9

Classification Hierarchy



Final Concept: Concept15

Attribute	Value	Probability
0,0	Filter9	88%
	Filter22	12%
0,1	Filter1	95%
	Filter7	5%
…	…	…
Label	"3"	100%

Produces a Prediction of "3" for Image

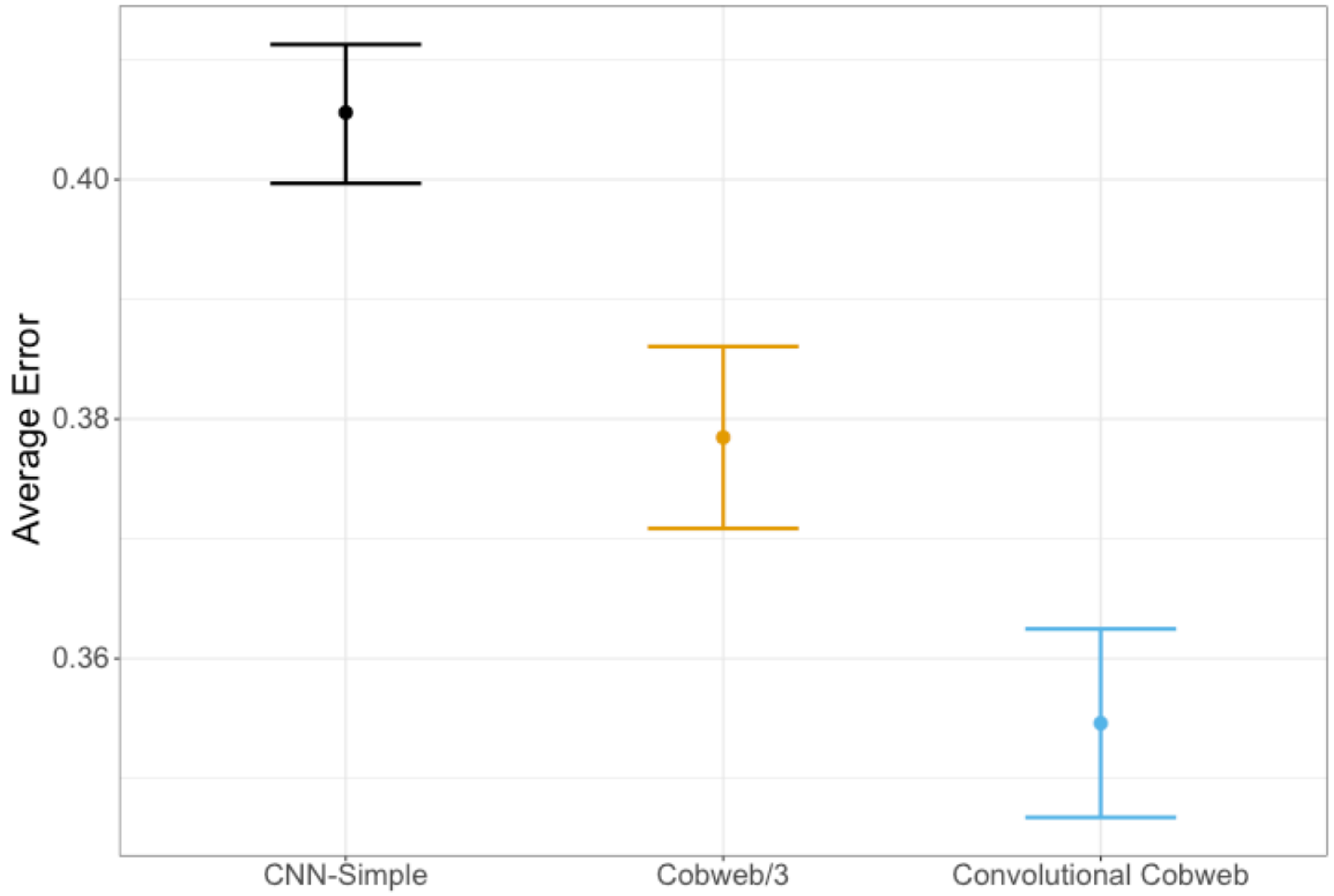
Evaluation

- As a preliminary test of our approach, we compared it to the two kinds of models we tried to unify:
    - A simple 1-layer CNN (no concept formation)
    - A Cobweb/3 model that maps pixels to features (no convolutional filters)

Overall Performance

- Each model was applied to the incremental MNIST prediction task
- Each model was presented with 300 images (30 images for each digit)
- Images were presented in a random order (same order across models)
- Our results average over 50 runs
- We find that our approach outperforms both approaches it was a based on

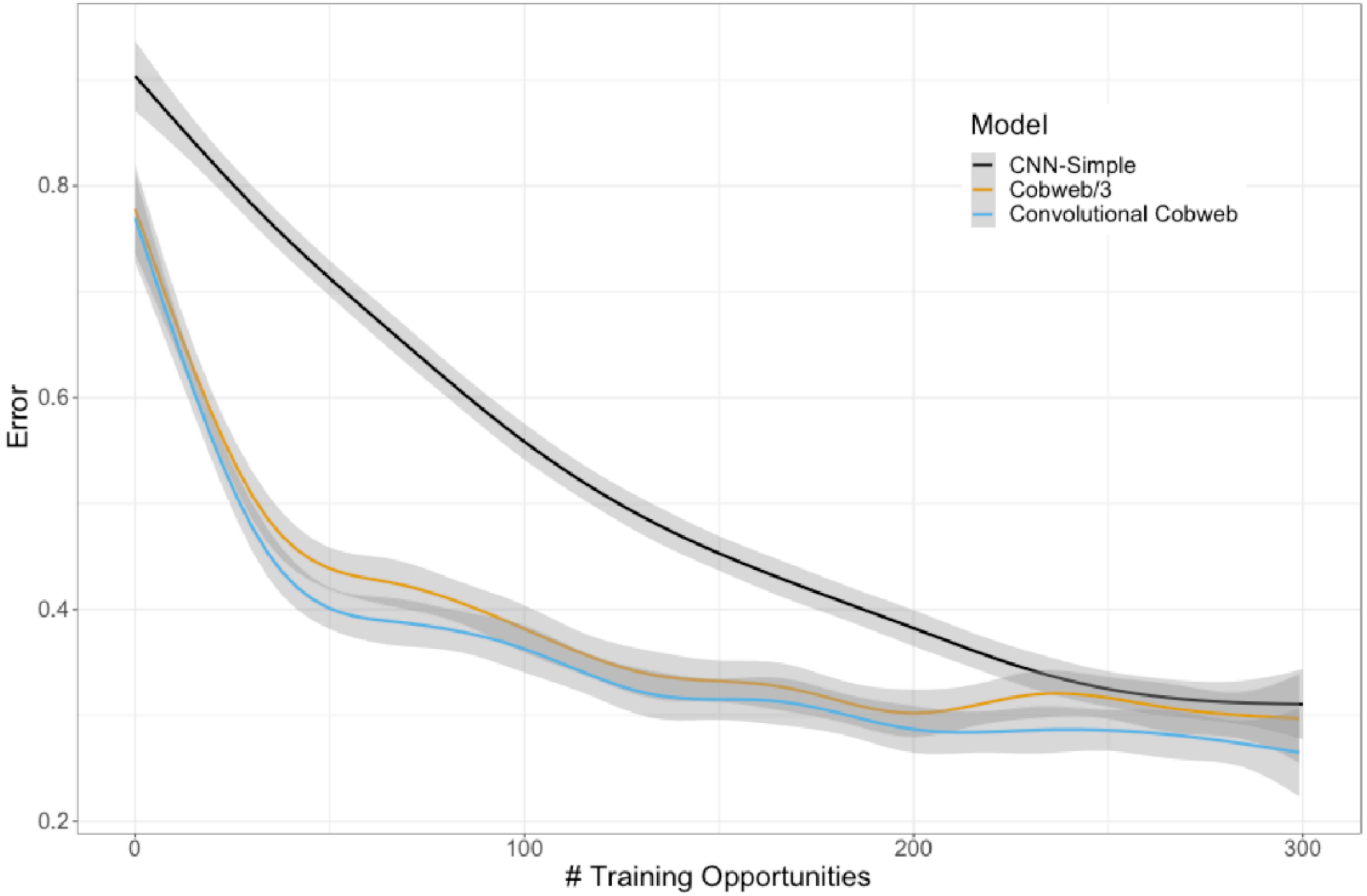
Note, we had to develop an incremental approach to training the CNN, which maintained a small FIFO buffer and used items in the buffer to do batch SGD updates; see paper for details.



Average performance of each model, whiskers denote bootstrapped 95% confidence intervals

Learning Curves

- We also investigated the performance of the models over the course training
- We find that both Cobweb models seem to converge much more quickly than the CNN (likely because they're not using SGD)
- During training, our approach is only slightly better than Cobweb, but the performance is consistent over runs and across training



Conclusions and Future Work

- We claim we have come up with a novel unification of convolutional processing ideas from computer vision research and classic ideas from the concept formation literature
- We believe our results shows some initial promise, but additional experiments are needed to better understand the behavior of our model
- We think there is potential to generalize this kind of idea beyond Cobweb to other concept formation approaches, such as SAGE (McLure, M., Friedman, S., & Forbus, K., 2015)
- Ultimately, we hope this research will lead to incremental learning modules that can serve as an alternative to CNN-based approaches within cognitive systems

Thank you!

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College of
Computing & Informatics