vDNN: Virtualized Deep Neural Networks for Scalable, Memory-Efficient Neural Network Design

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NVIDIA

Motivation

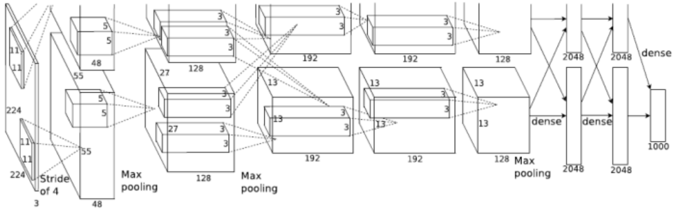
Trend: large and deep neural networks

Convolutional neural networks (CNNs)

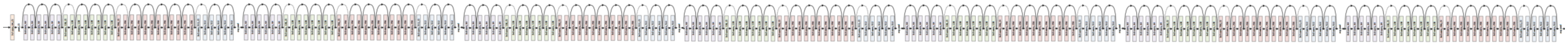
Grown from 7 layers to 152 layers (between 2012 to 2015)

Recurrent neural networks (RNNs)

Employ 100s to 1000s of layers (when the recurrence is unrolled)



AlexNet (2012)
7 layers



ResNet (2015)
152 layers

Motivation

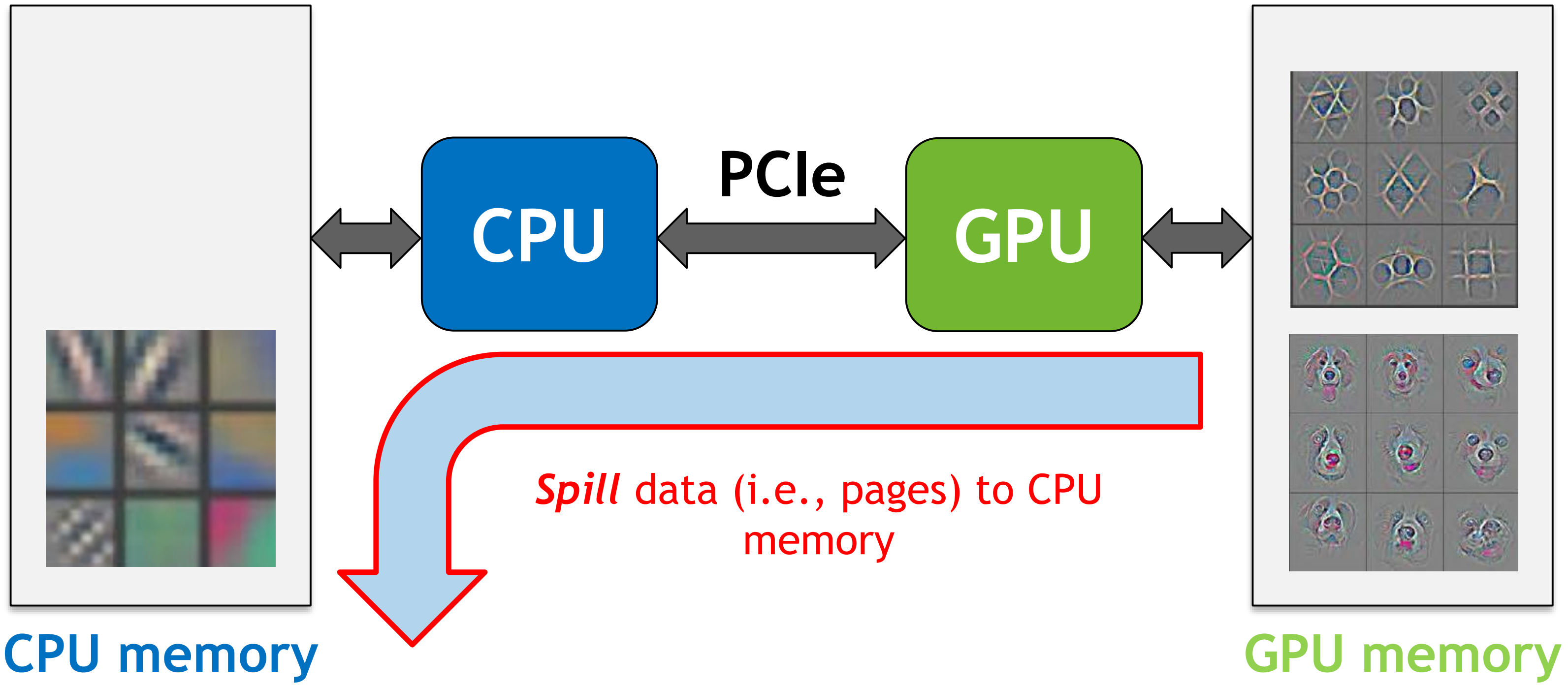
Challenges: deep networks require large GPU memory

> … It is clear why Baidu will be anxiously waiting for Pascal, because they're limited to 12 GB of memory per GPU, which is constraining. "We are constantly running into limitations because of memory." …

— The Next Platform, "Baidu eyes deep learning strategy in wake of new GPU options", April 2016

Motivation

Wait … what about CUDA UVM (Unified Virtual Memory) ?



< UVM page-migration from 10000 ft. >

Motivation

Wait … what about CUDA UVM (Unified Virtual Memory) ?

CPU-GPU page-migration in discrete GPU systems (via PCIe)

- 20 ~ 50 μs latency to bring in a single 4 KB page*
- PCIe bw. utilization is around 200 MB/sec (out of the 16 GB/sec under gen3)

Training deep neural networks incur 10s of GBs of memory allocations

- Performance bottlenecked by the throughput of CPU-GPU page-migration

* Zheng et al., "Towards High Performance Paged Memory for GPUs", HPCA-2016

AGENDA

Why does training DNNs require large memory?

What is our proposed solution to this problem?

How good & effective is our proposal?

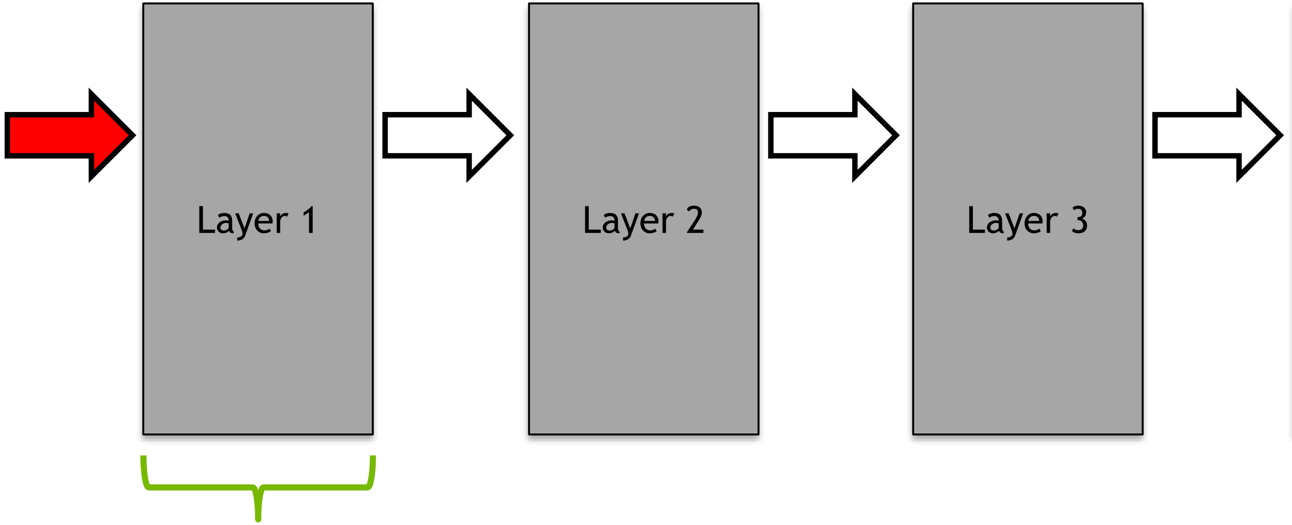
Q. Why does training DNNs incur such high GPU memory usage?

The Problem

GPU memory usage proportional to network depth

GPU memory

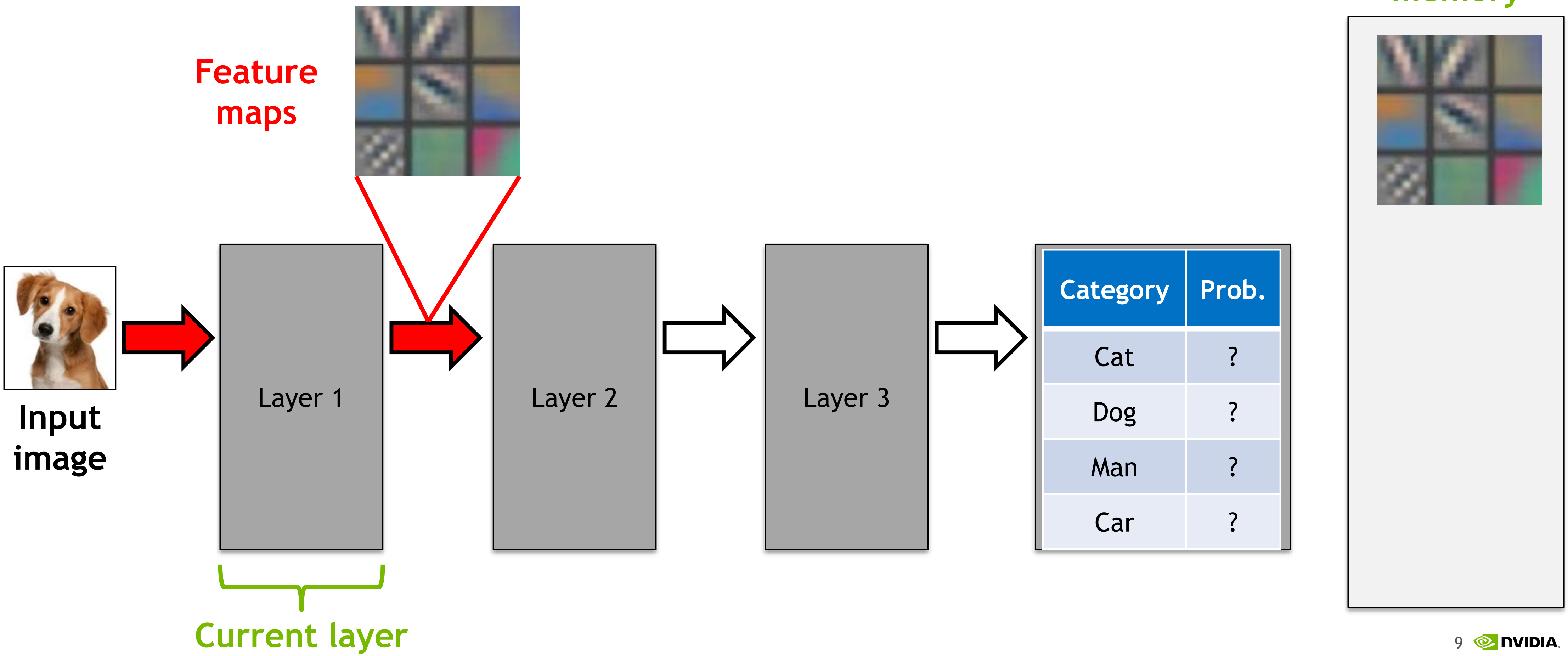
Input image



Category	Prob.
Cat	?
Dog	?
Man	?
Car	?

The Problem

GPU memory usage proportional to network depth



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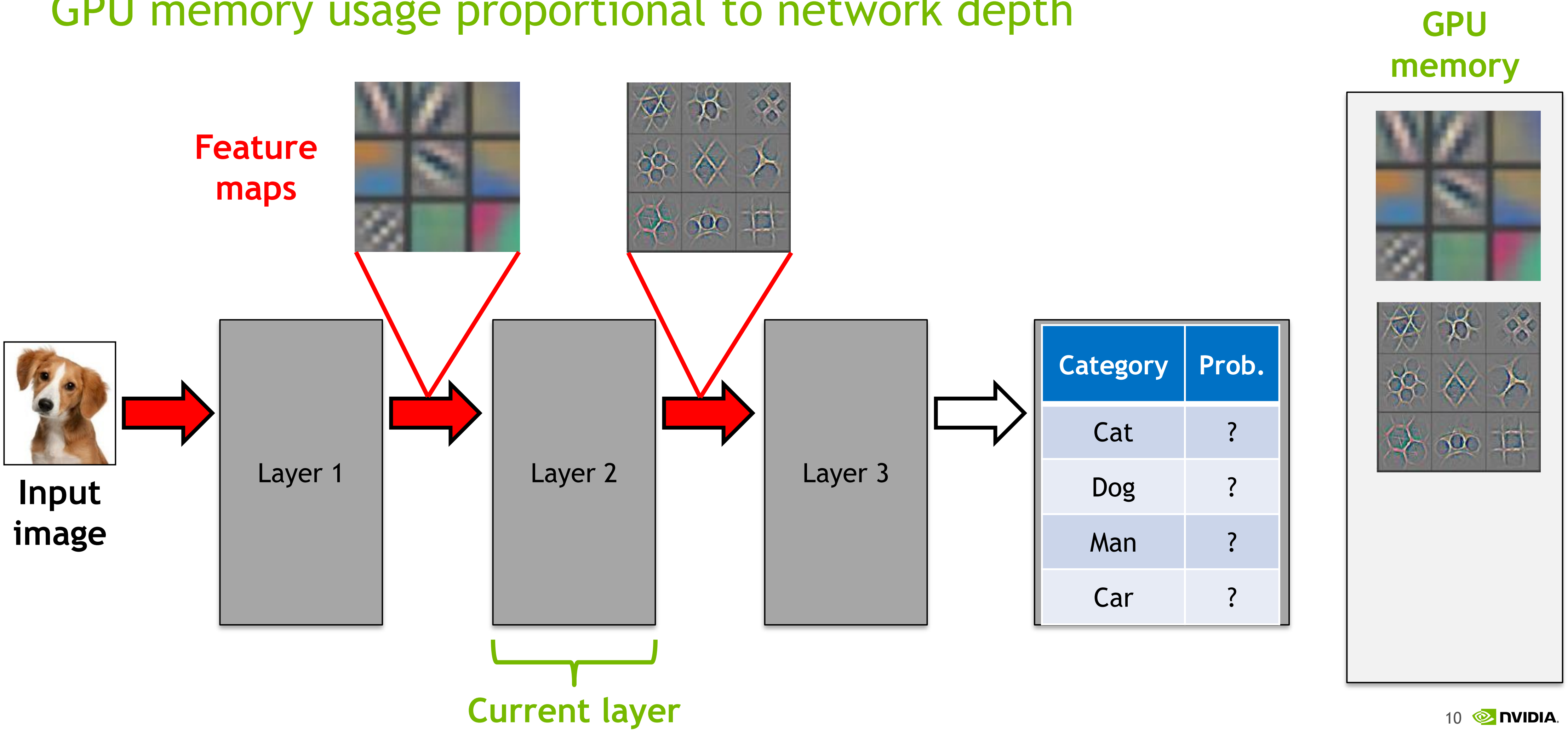

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People call this as: *forward propagation*

The Problem

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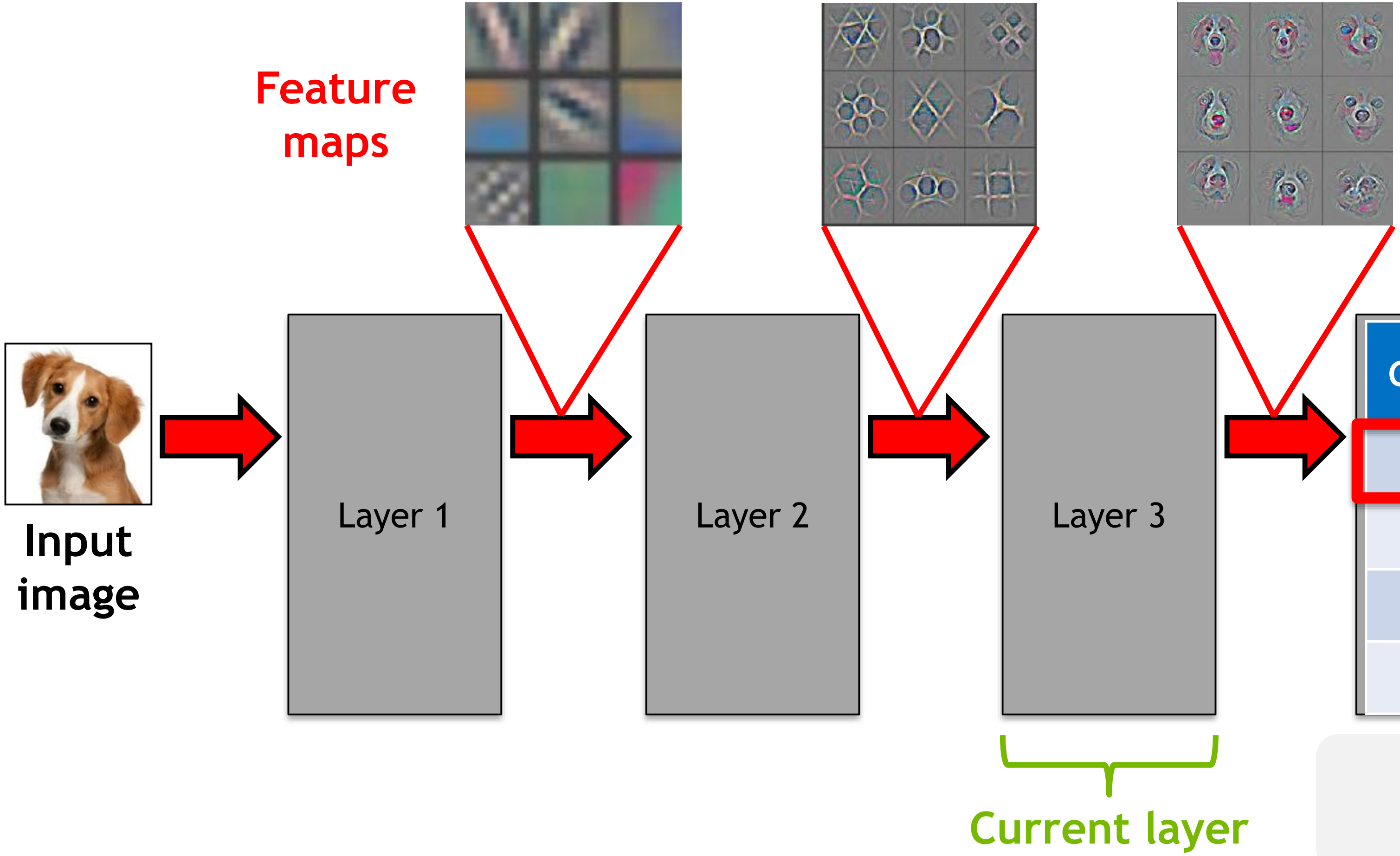
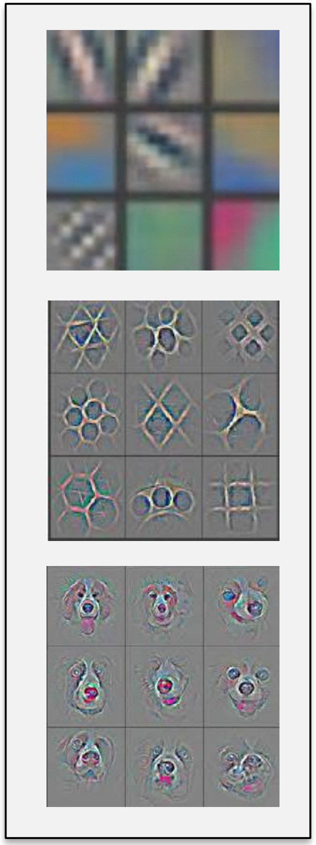


Category	Prob.
Cat	**80%**
Dog	10%
Man	5%
Car	5%

Prediction:
It's a **"Cat"**.

GPU memory



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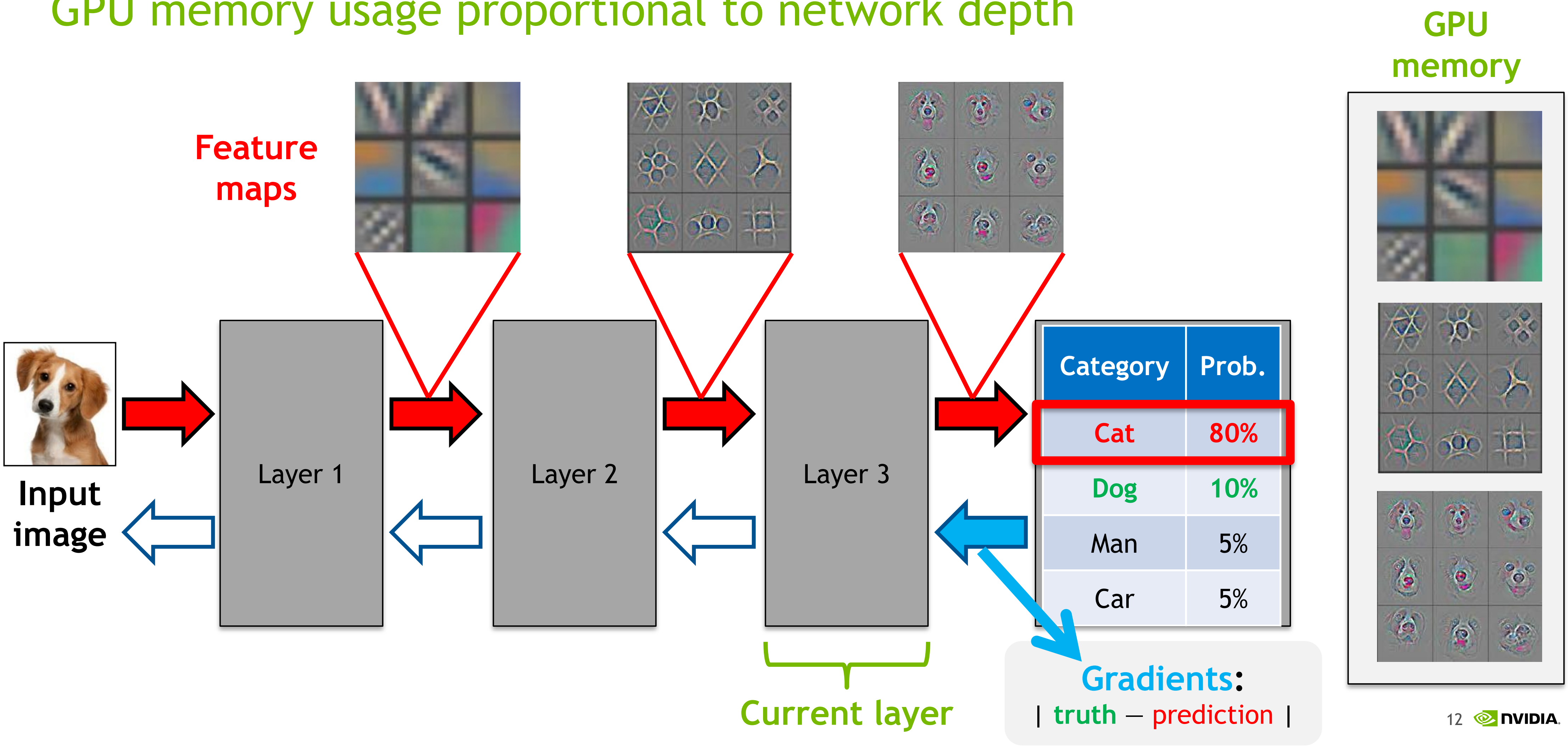

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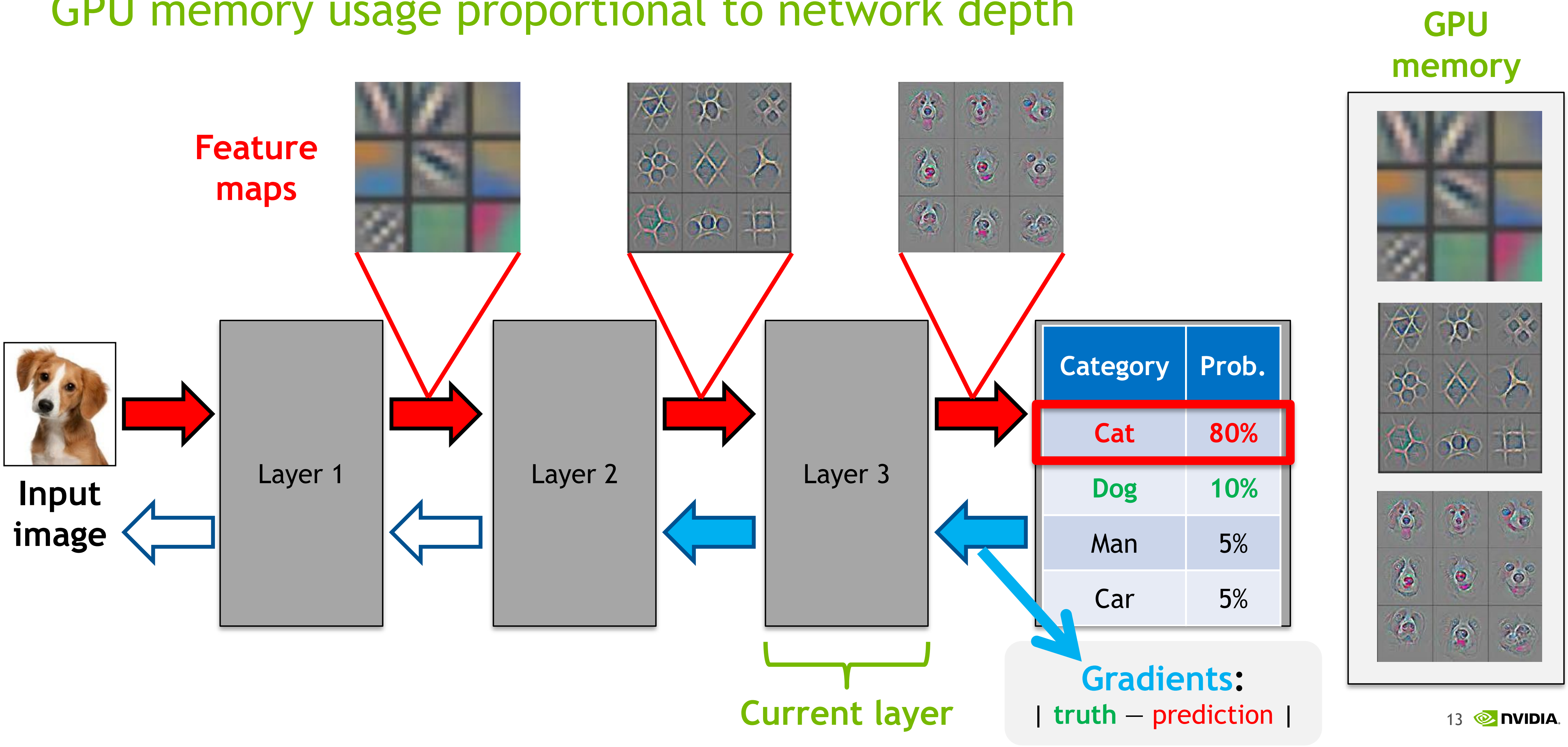

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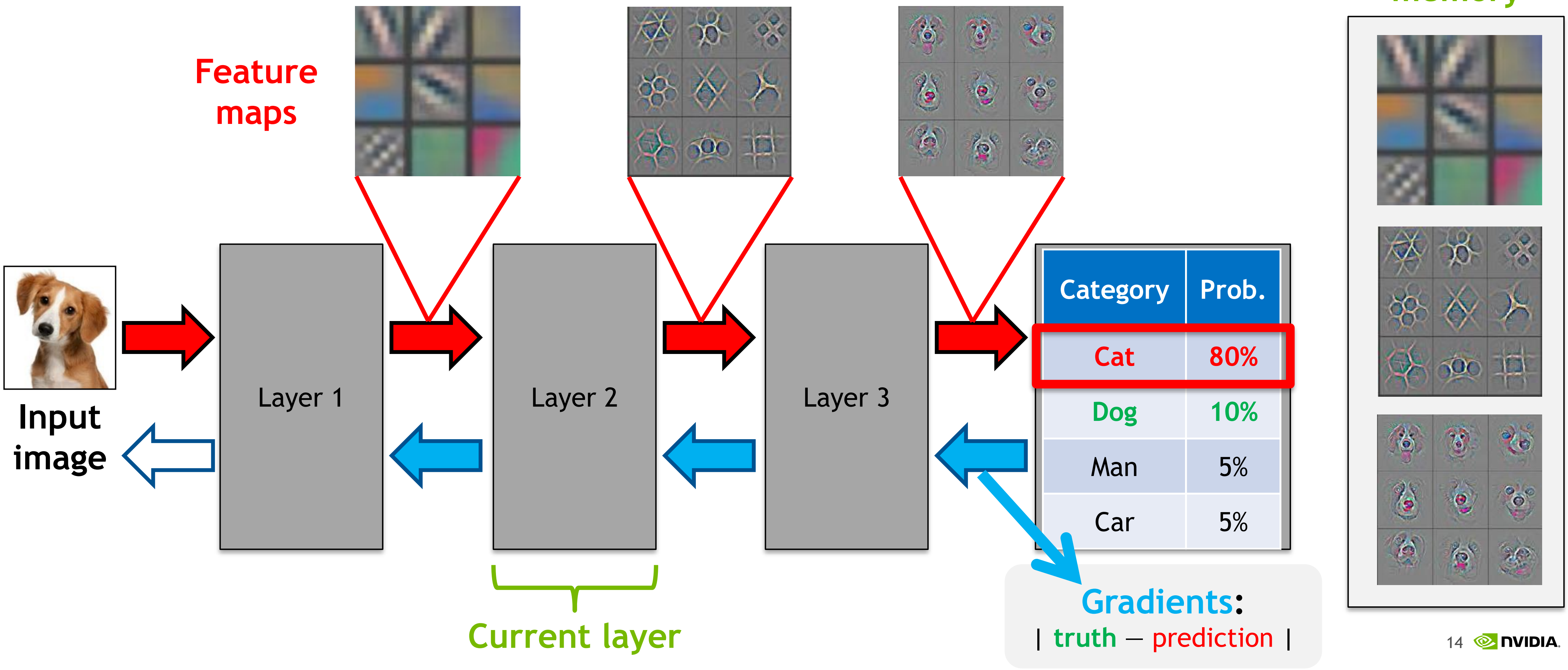

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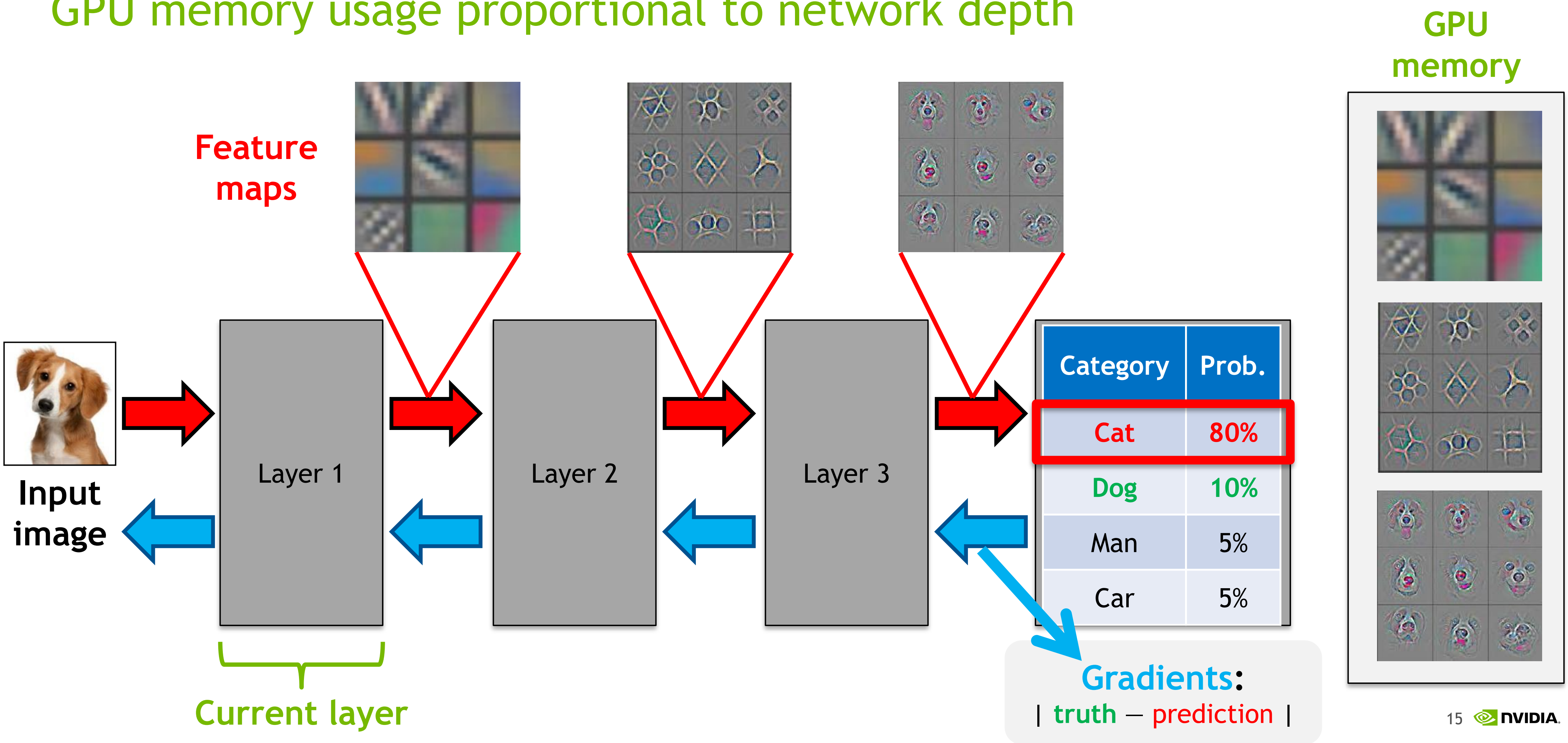

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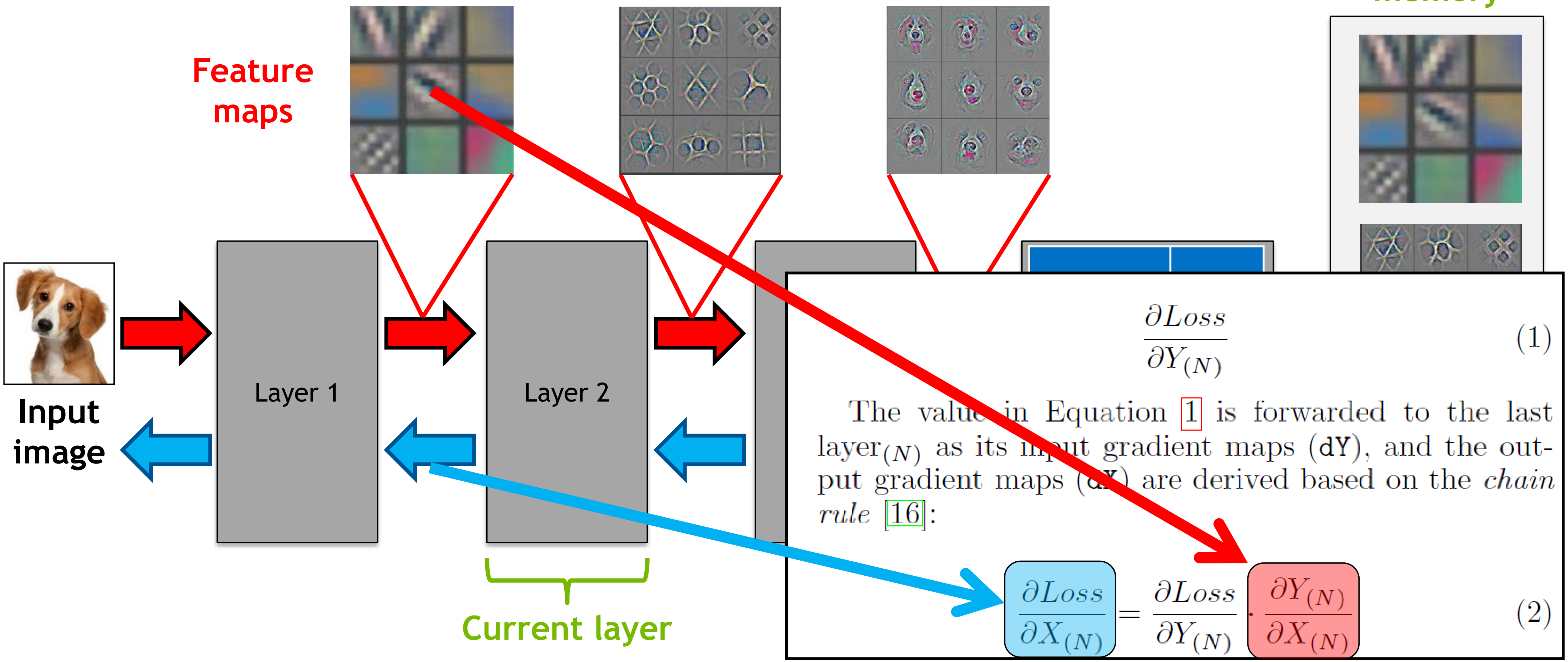


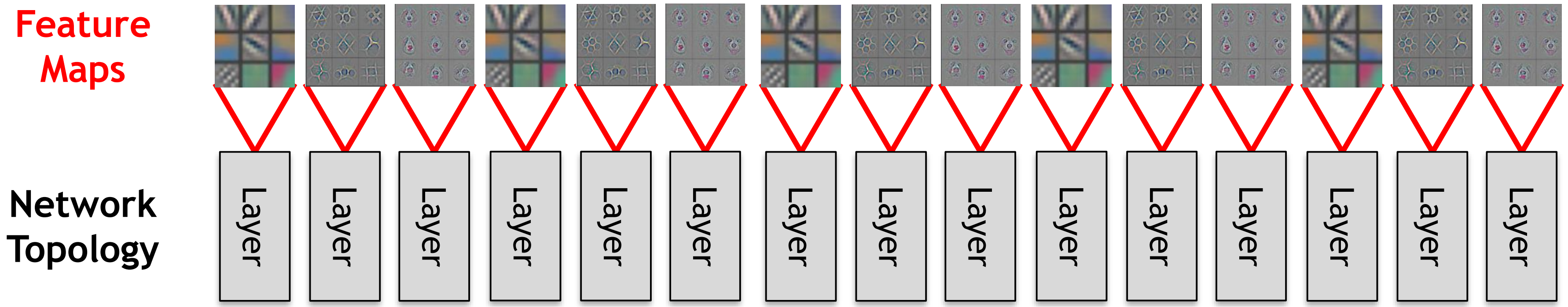
$$\frac{\partial Loss}{\partial Y_{(N)}} \quad (1)$$

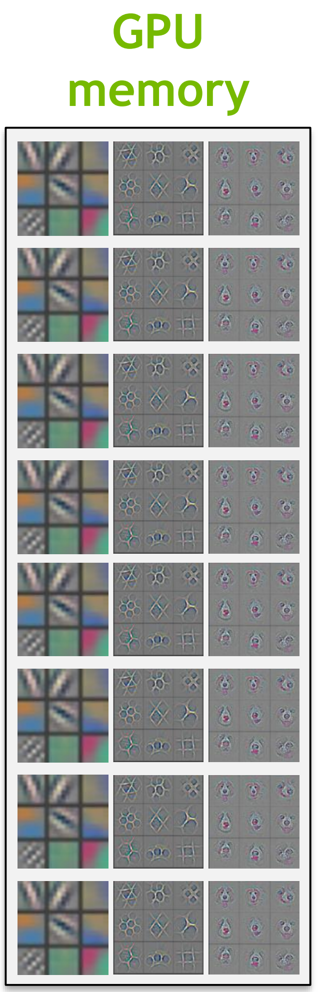
The value in Equation 1 is forwarded to the last layer$_{(N)}$ as its input gradient maps (dY), and the output gradient maps (dX) are derived based on the *chain rule* [16]:

$$\frac{\partial Loss}{\partial X_{(N)}} = \frac{\partial Loss}{\partial Y_{(N)}} \cdot \frac{\partial Y_{(N)}}{\partial X_{(N)}} \quad (2)$$

The Problem

GPU memory usage proportional to network depth





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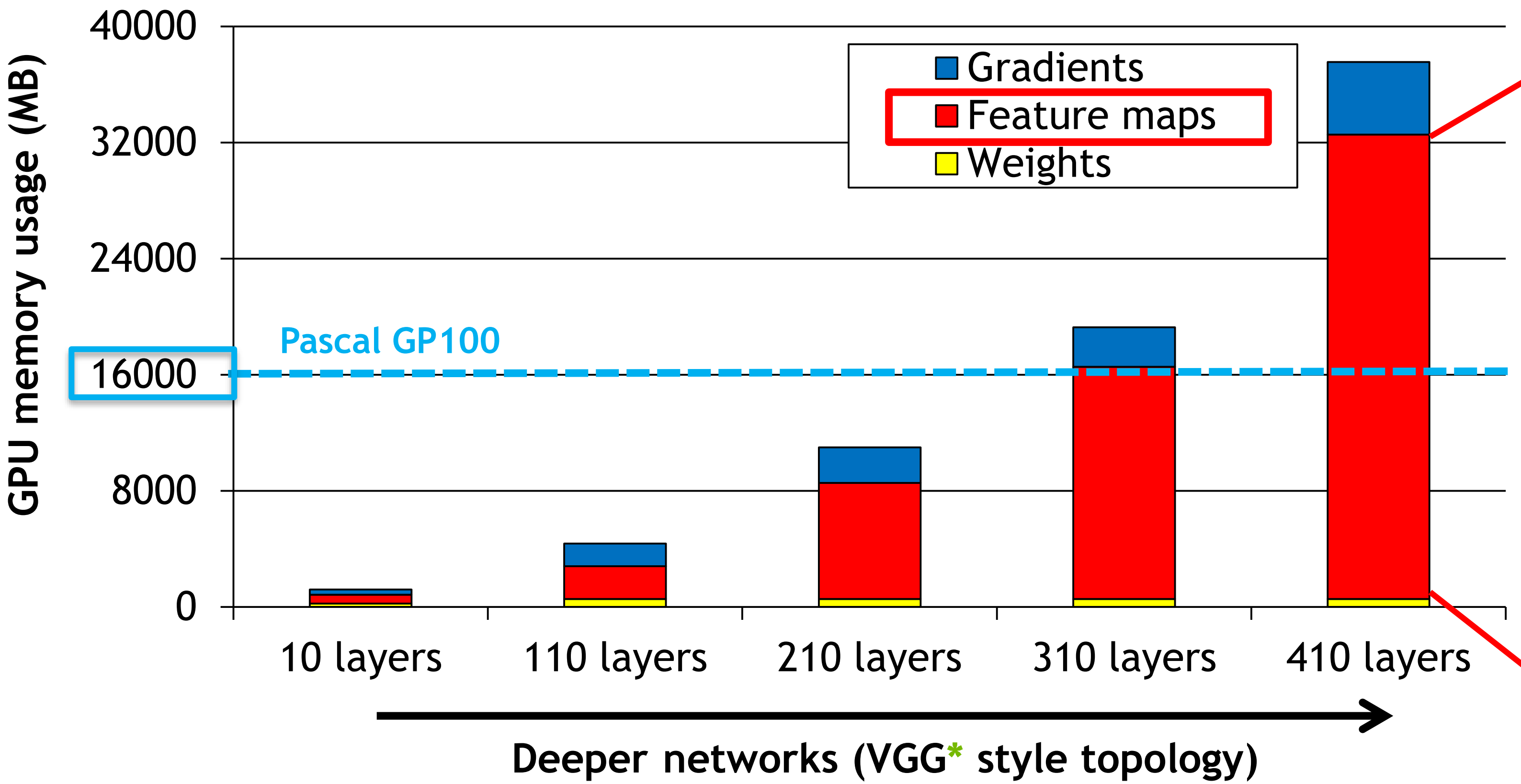
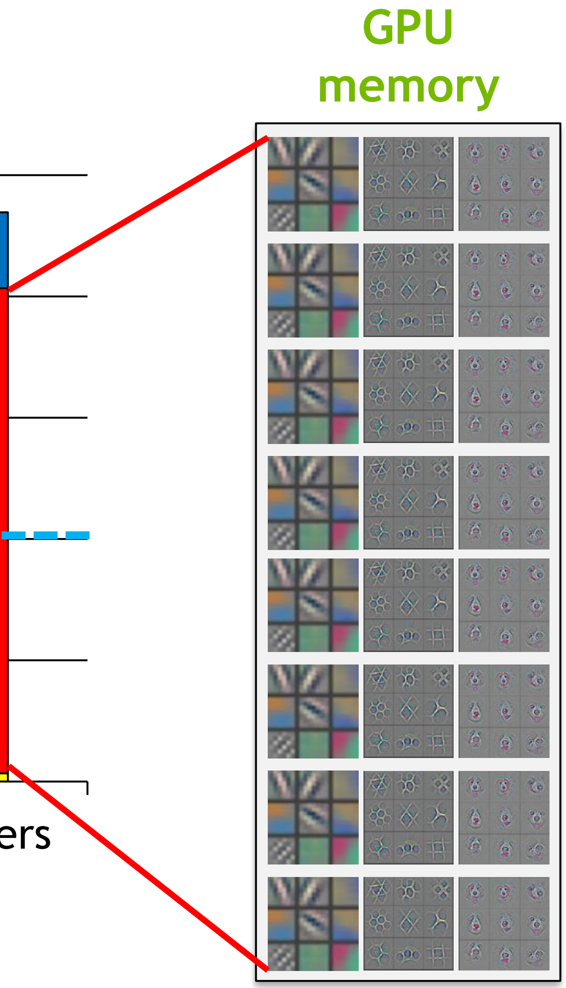




* Simonyan and Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", ICLR-2015

Our solution: virtualized DNN (vDNN)

Virtualized DNN (vDNN)

What is it?

CPU-side runtime memory manager tailored for DNNs

Functionality:

- *Virtualize* DNN memory usage across “***both***” CPU and GPU memory
- GPU memory acts as a fast ***cache*** for current layer’s memory usage

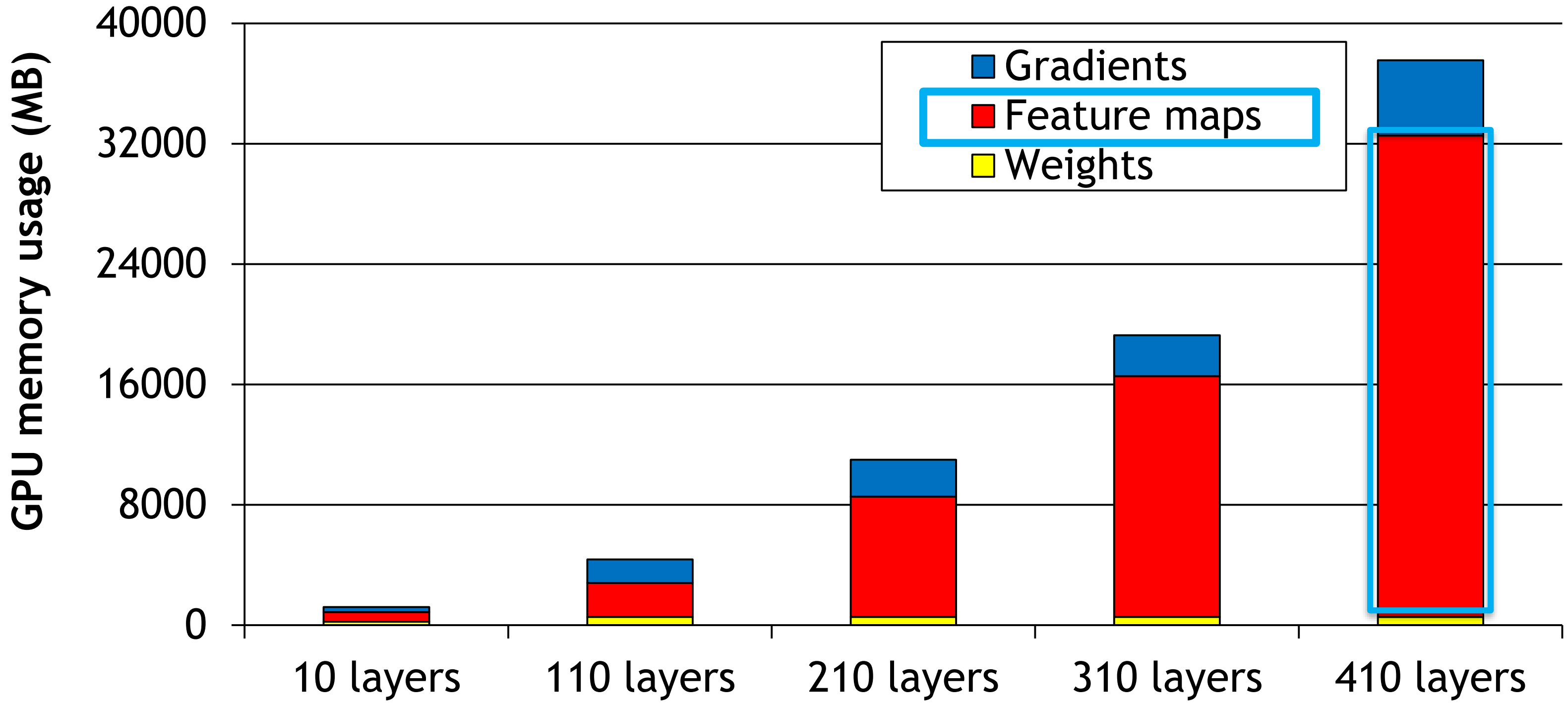
Virtualized DNN (vDNN)

Design principle

Exploits the following observations for performance optimizations

Virtualized DNN (vDNN)

Key observations

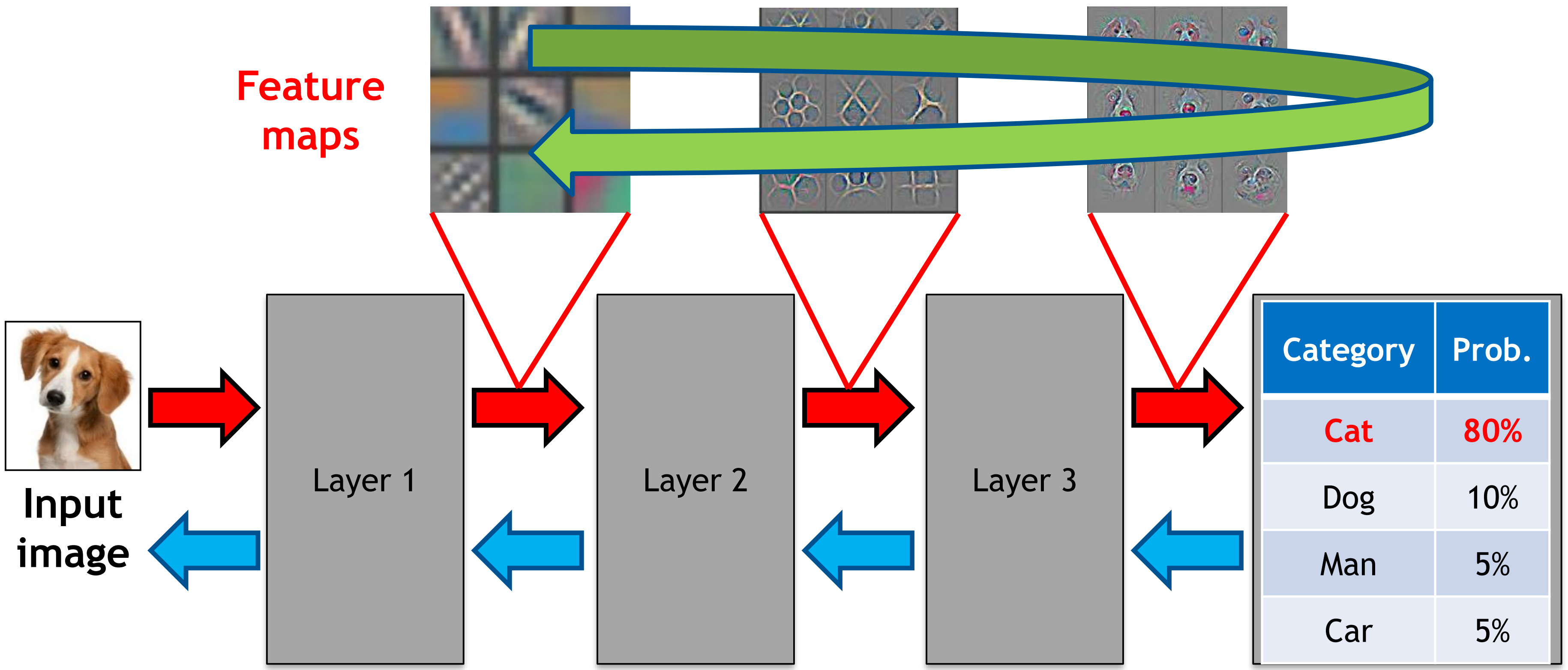


Key obstacle in designing a *scalable* DNN memory manager

Observation #1: feature maps dominate memory usage

Virtualized DNN (vDNN)

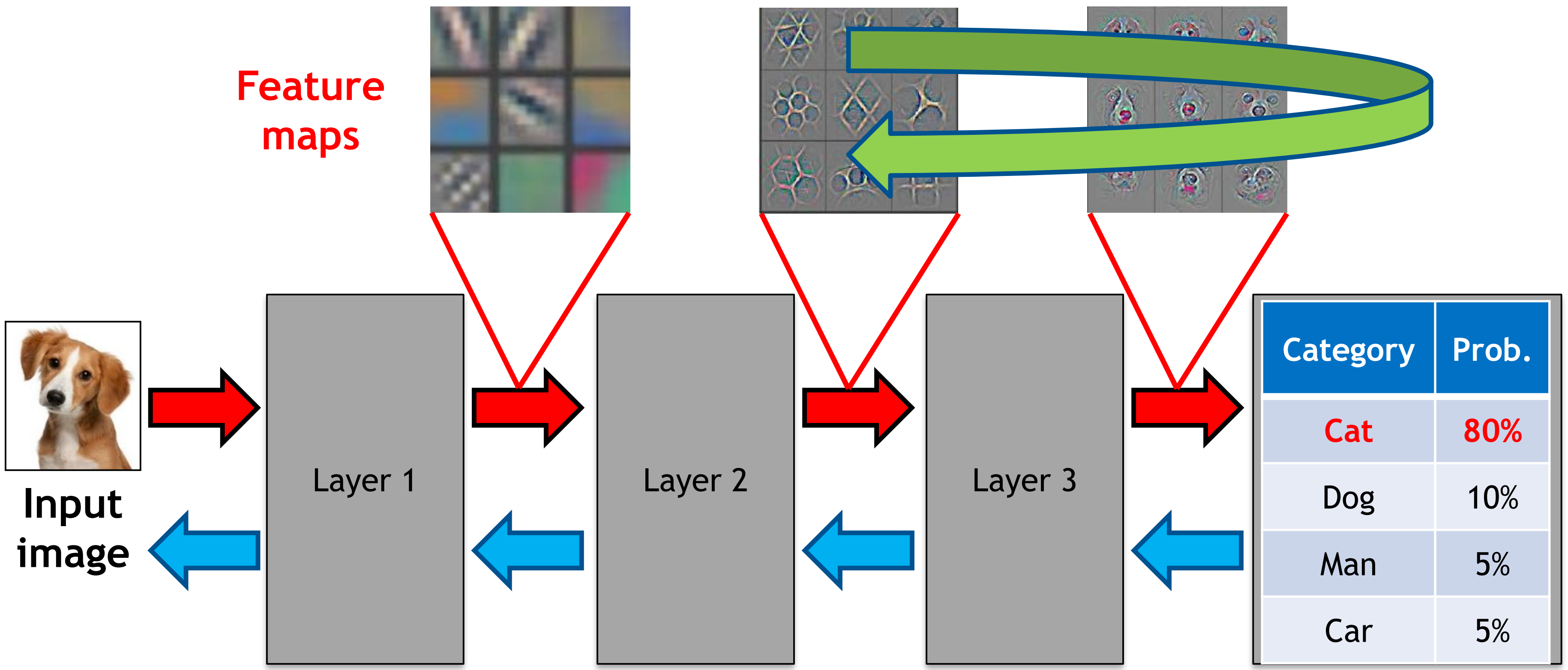
Key observations



Observation #2: long reuse distance of feature maps

Virtualized DNN (vDNN)

Key observations



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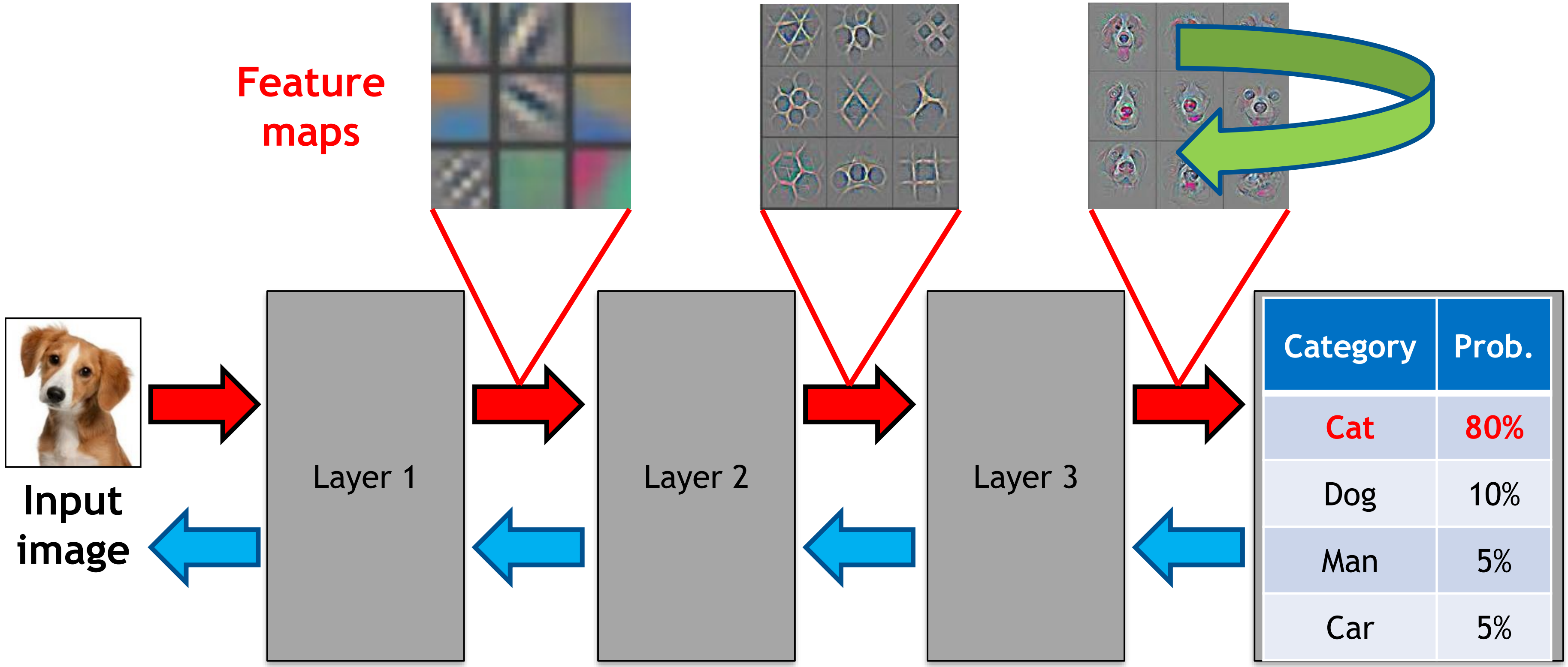

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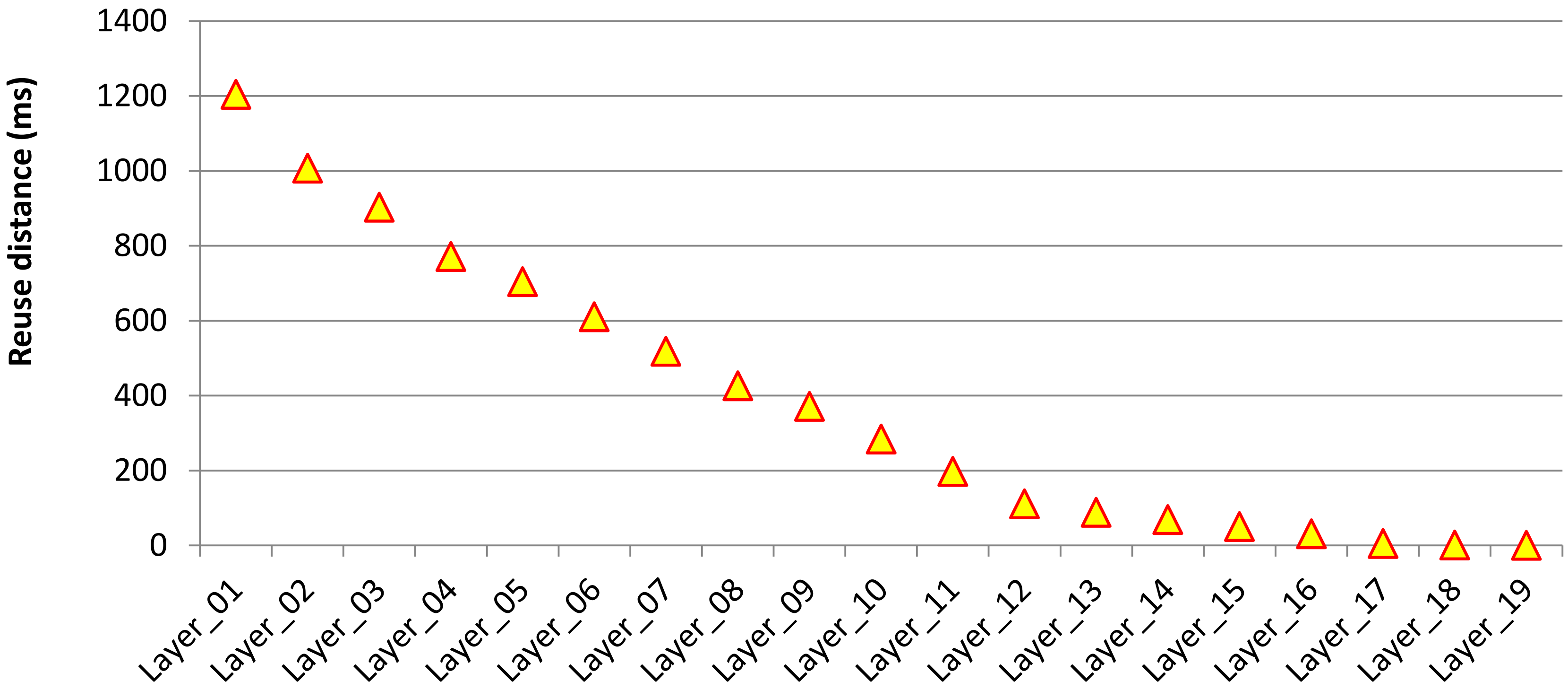

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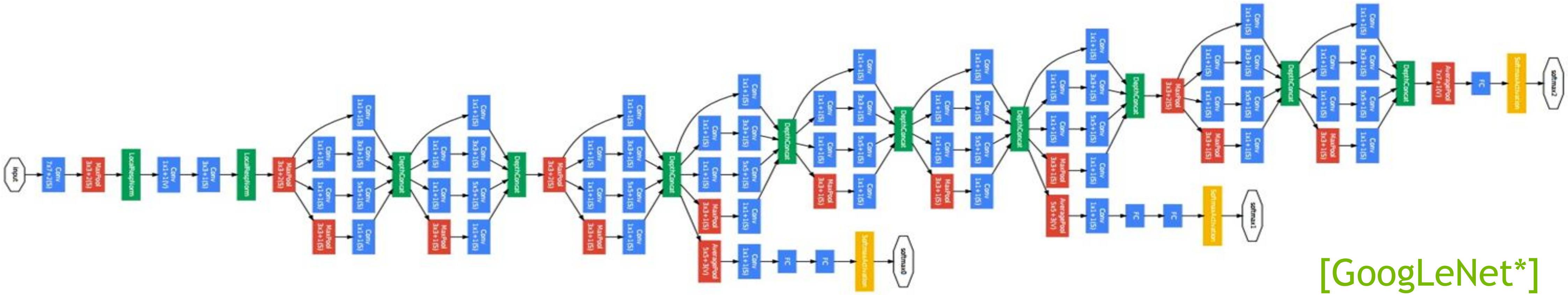

[GoogLeNet*]

Observation #3: DNN computation dataflow = DAG (direct acyclic graph)

* Szegedy et al., “Going Deeper With Convolutions”, CVPR-2015

Virtualized DNN (vDNN)

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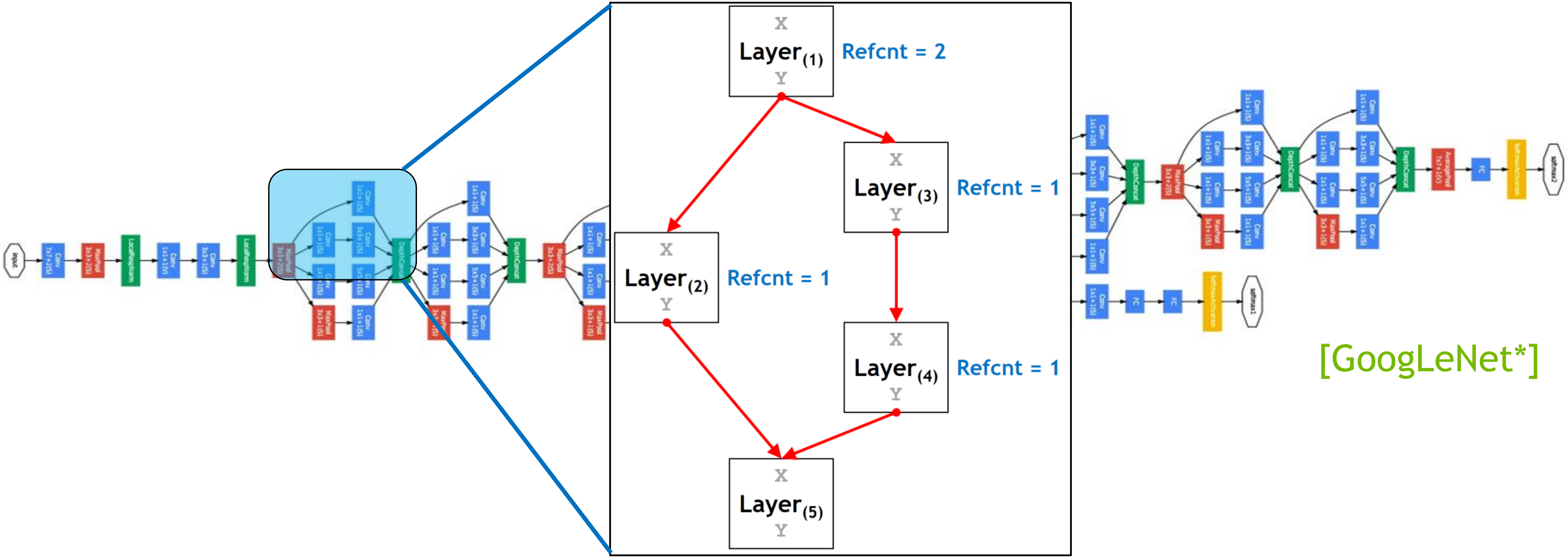

[GoogLeNet*]

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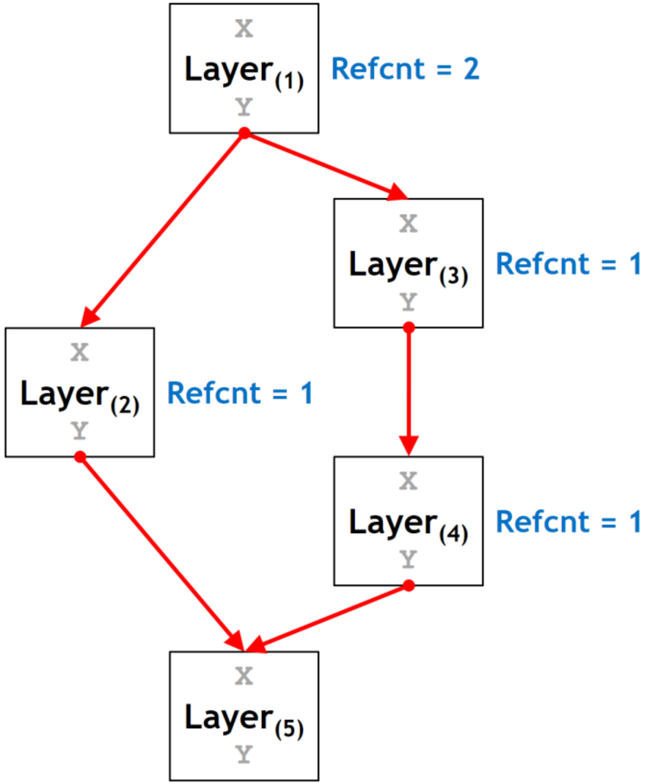
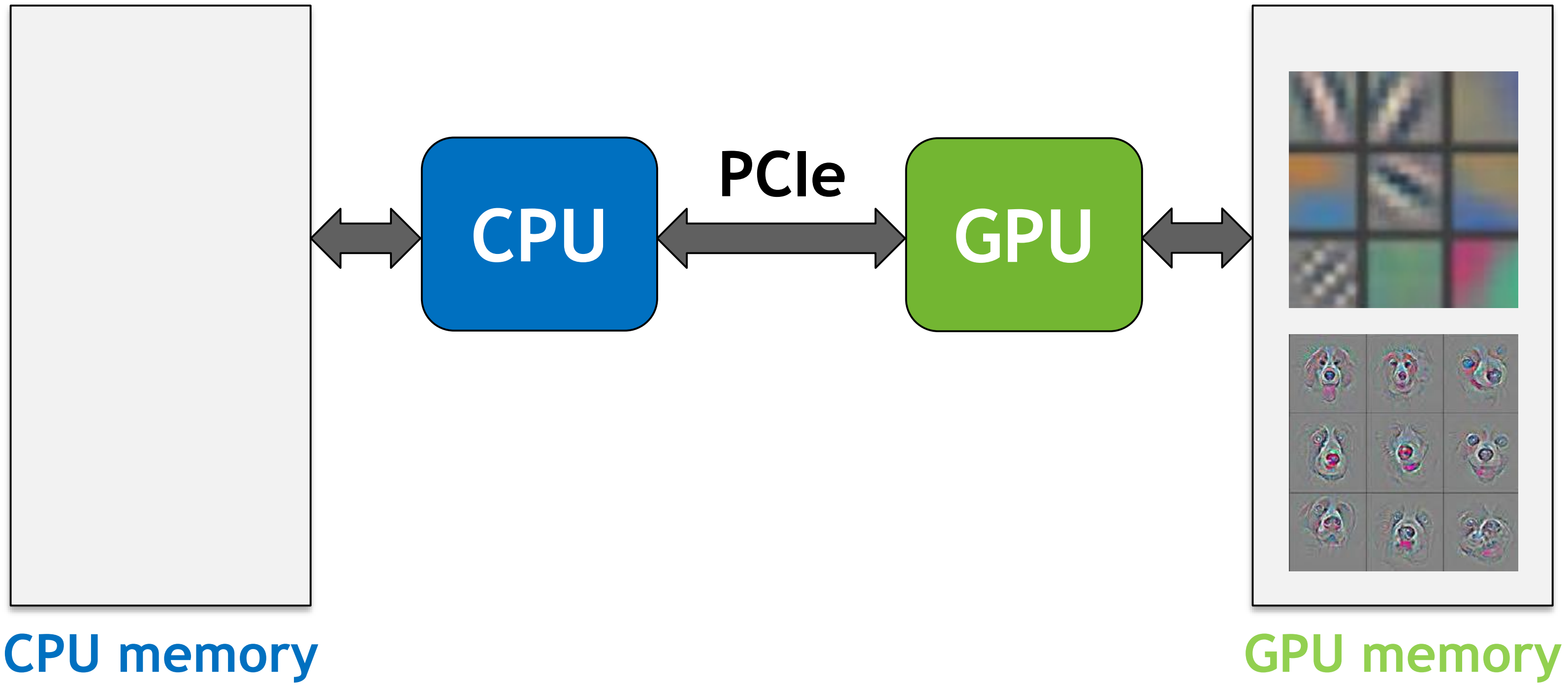


Refcnt: number of consumer layers of the current layer's output feature maps

Key idea) vDNN leverages the data dependencies of the feature maps revealed through the DAG to schedule intelligent CPU offload/prefetch operations.

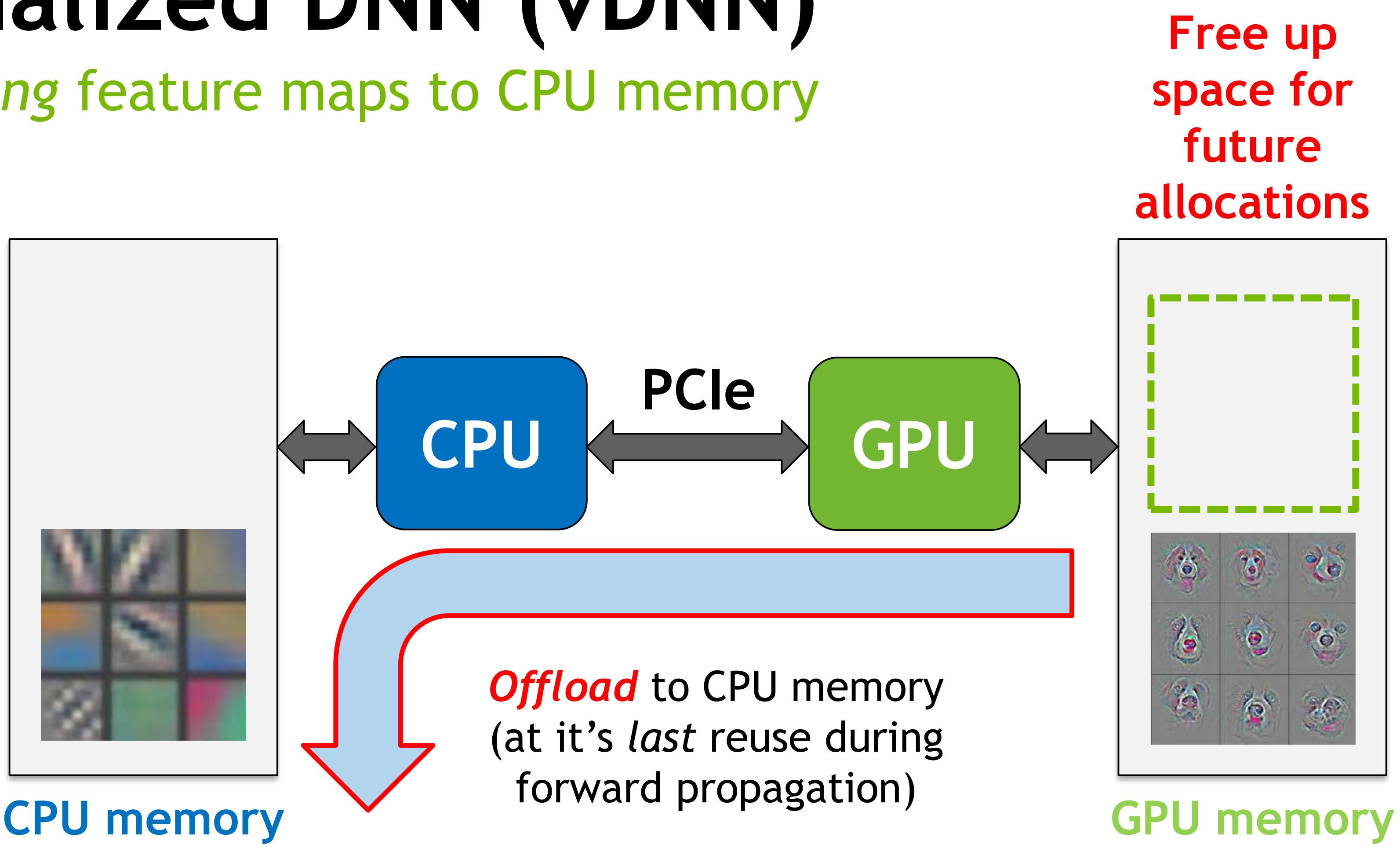
Virtualized DNN (vDNN)

Offloading feature maps to CPU memory



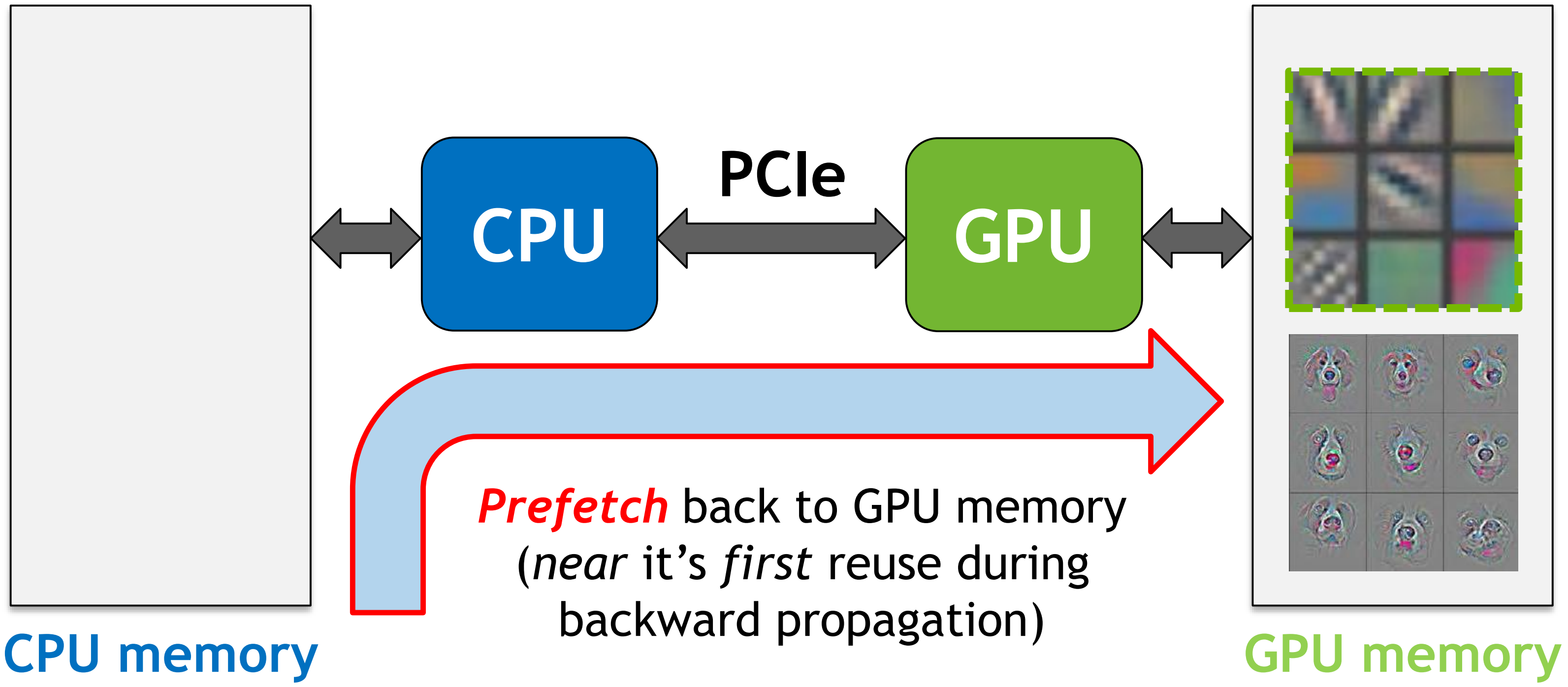
Virtualized DNN (vDNN)

Offloading feature maps to CPU memory



Virtualized DNN (vDNN)

Prefetching feature maps back into GPU memory



How good is vDNN?

Evaluation Methodology

Compute node configuration

CPU: Intel i7-5930K + 64 GB DDR4 memory

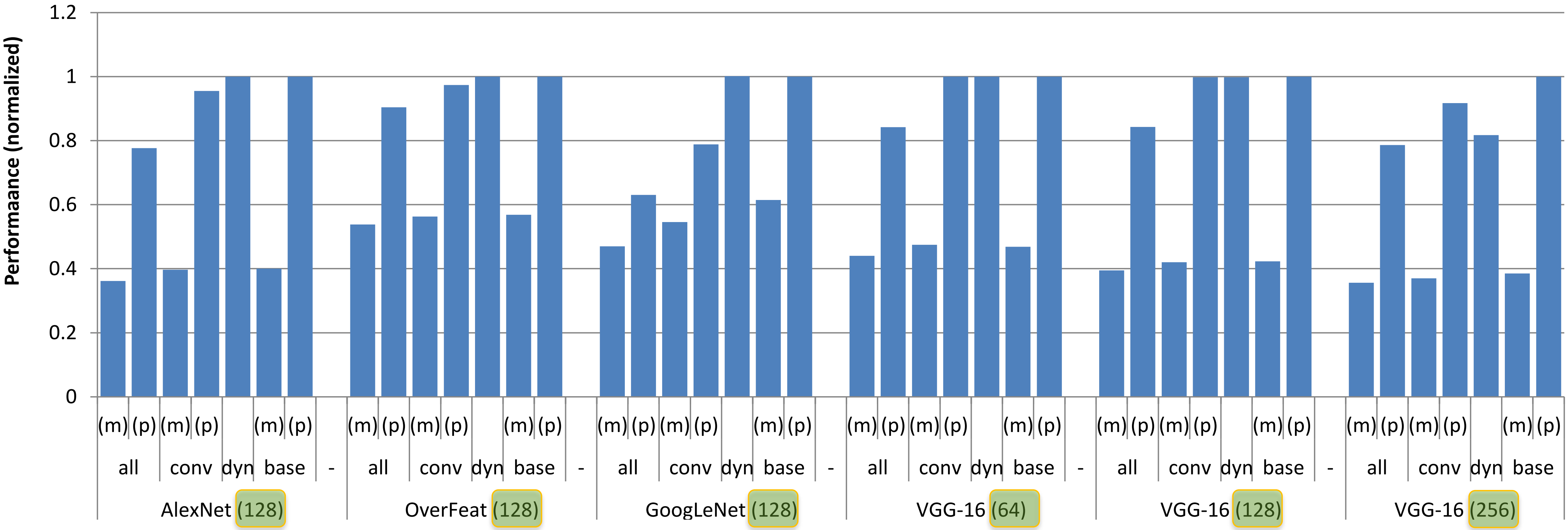
GPU: Maxwell Titan X + 12 GB GDDR5 memory

Can allocate data up to
(64+12) GB

PCIe: 16 GB/sec data transfer bandwidth (gen3)

Performance

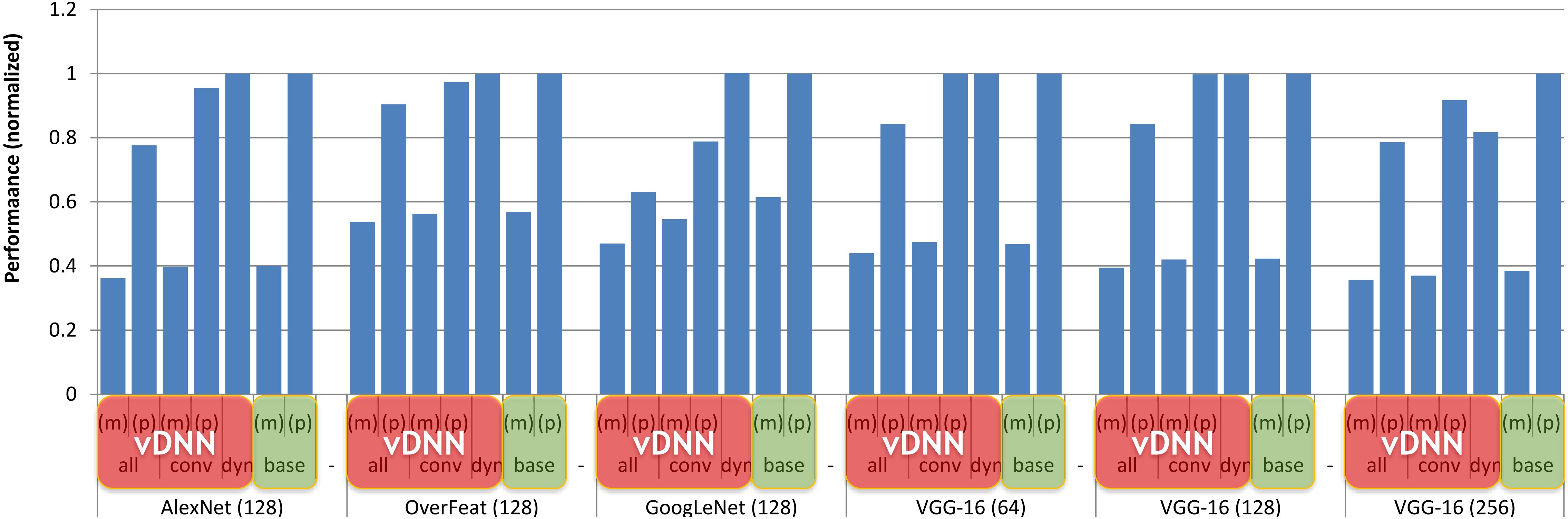
Higher is better



: mini-batch size used to train the target network

Performance

Higher is better

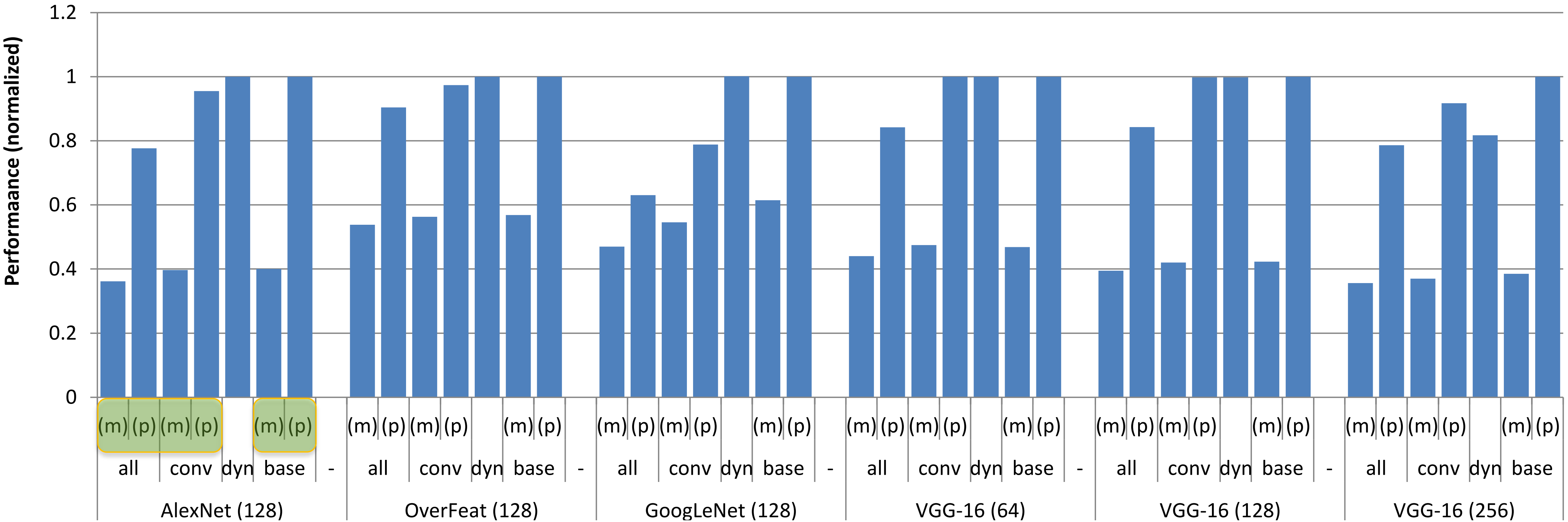


: vDNN (with different offload/prefetch policies, all / conv / dyn)

: Baseline

Performance

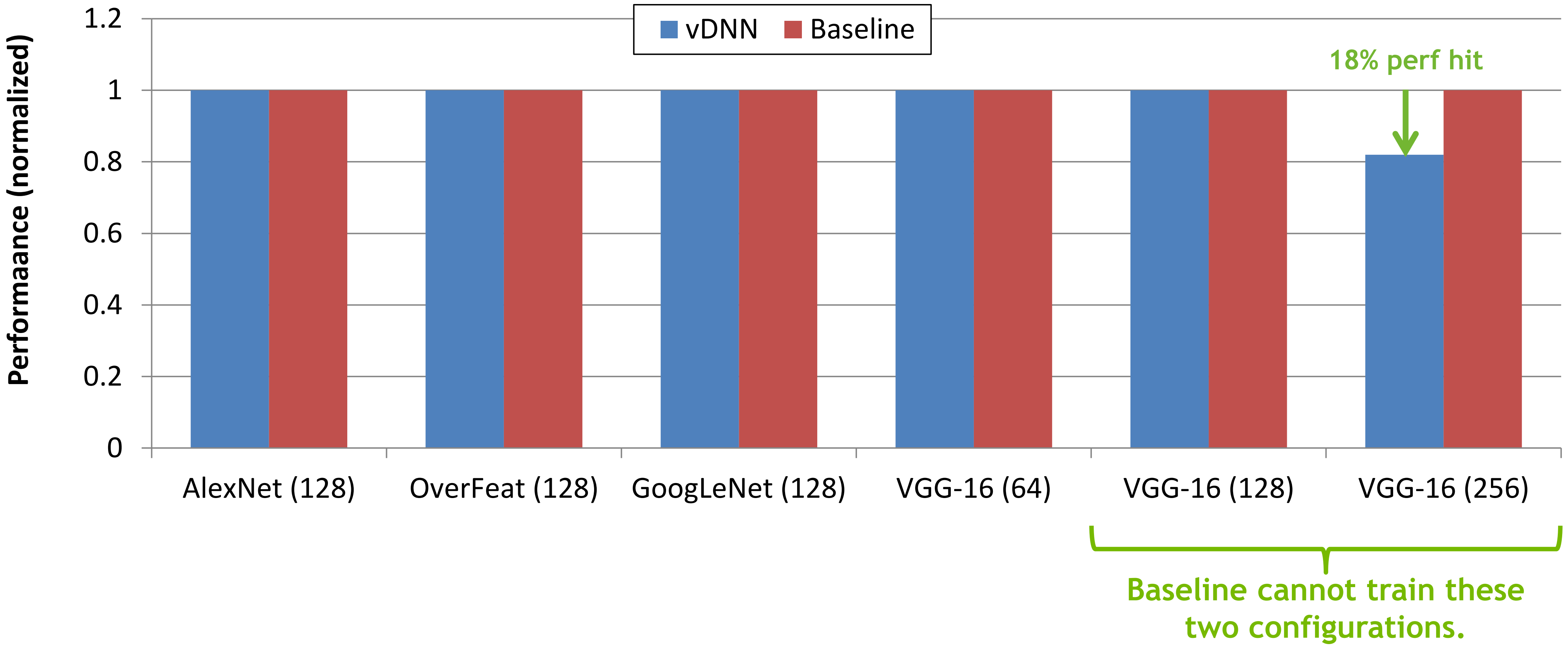
Higher is better



: convolutional algorithm chosen in cuDNN (v4), **(m)**: memory-optimal algo, **(p)**: perf-optimal algo

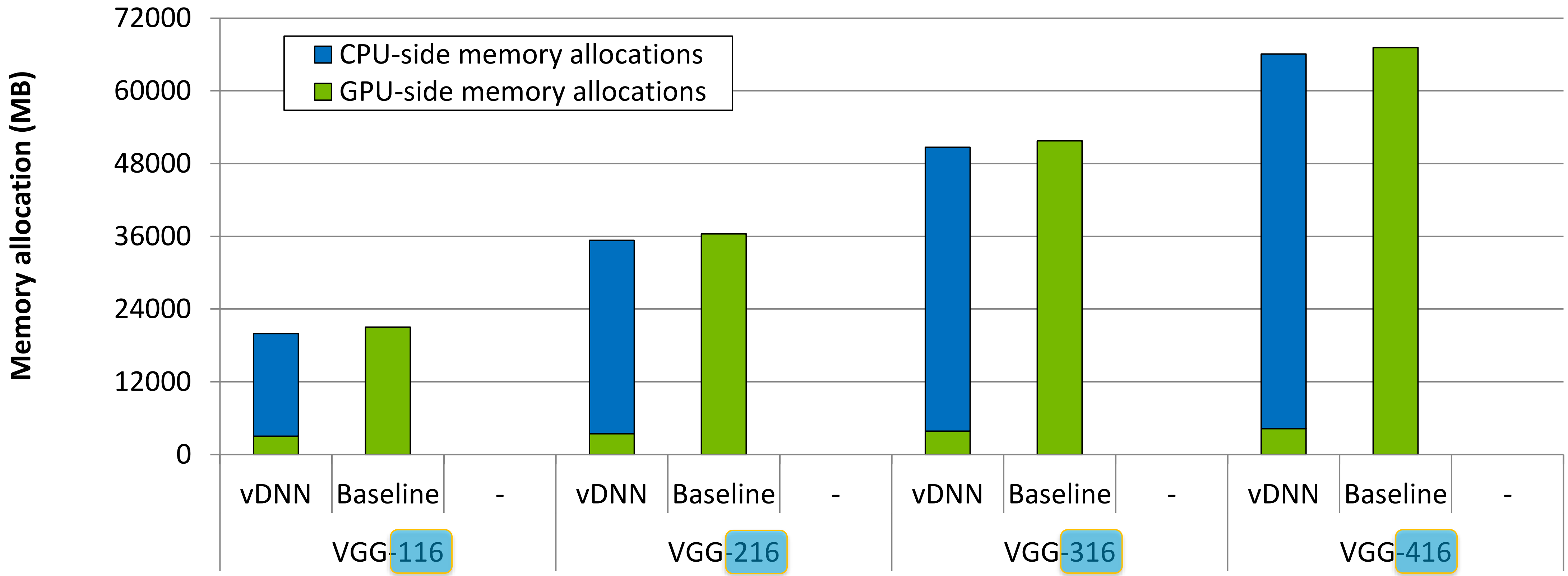
Performance

Higher is better



Scalability of vDNN

Testing the trainability of vDNN with *extremely* deep networks



: number of convolutional layers

Conclusion

vDNN is a scalable, performant virtual memory solution for DNNs

GPU memory capacity bottleneck is an important problem in the ML research space

- Page-migration VM solutions incur high overhead due to OS service requests
- PCIe bw. utilization becomes extremely low (200 MB/sec)

vDNN is an application-aware/software-level direct memory management solution

- Leverages the DAG dataflow for intelligent data movements across CPU-GPU
- Maximally utilizes PCIe bandwidth (12.8 GB/sec)

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