Achieving Predictability in the Execution of Deep Neural Networks in Safety Critical Applications

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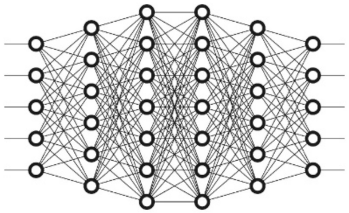
This Talk

Motivations



A case study

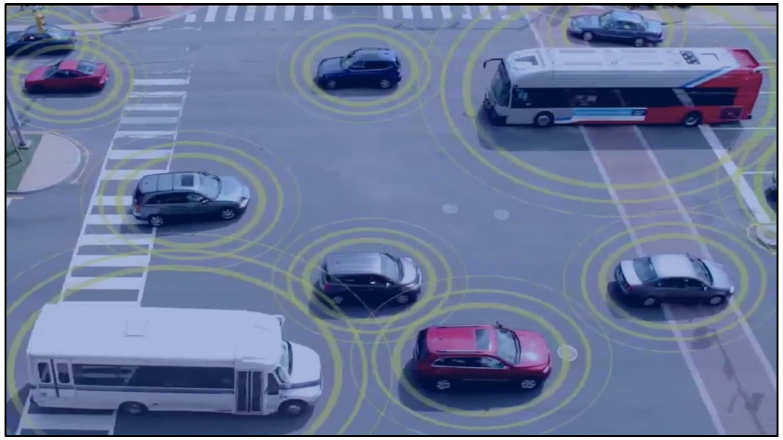
Understanding the workload generated by a Deep Neural Network

Our work

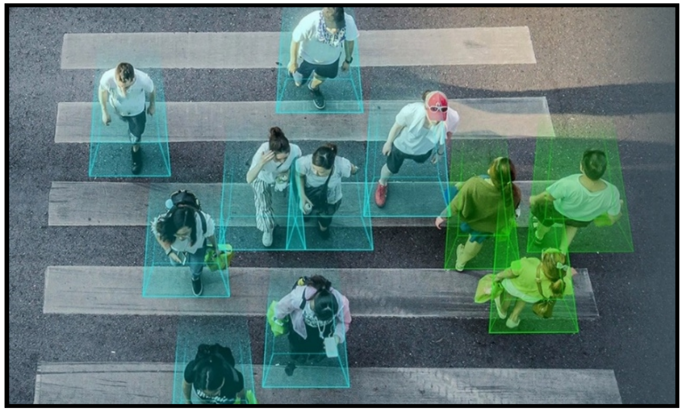
Timing isolation for DNN and real-time tasks executed on a multiprocessor platform

DNNs are everywhere

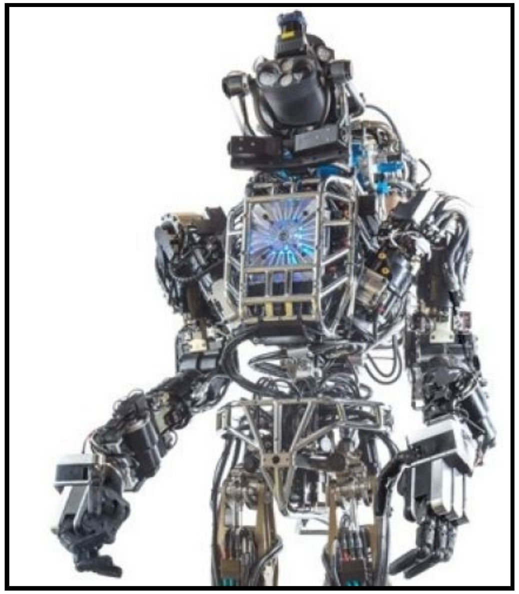
Autonomous Driving



Surveillance



Advanced Robotics



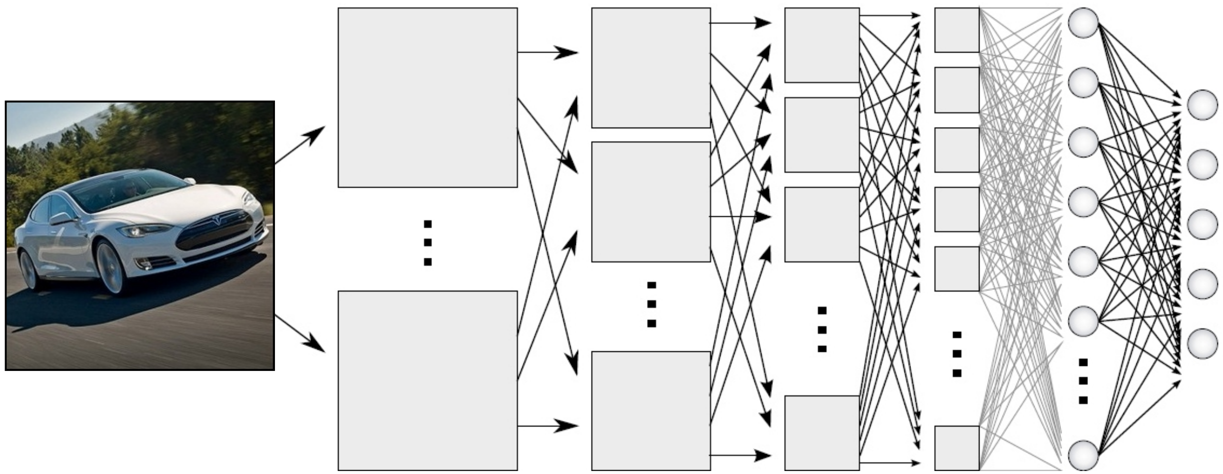
Healthcare

Image Recognition

- The ILSVRC Challenge is a competition held from 2010 in which networks compete in classifying objects from images to labels, with 1000 possible categories

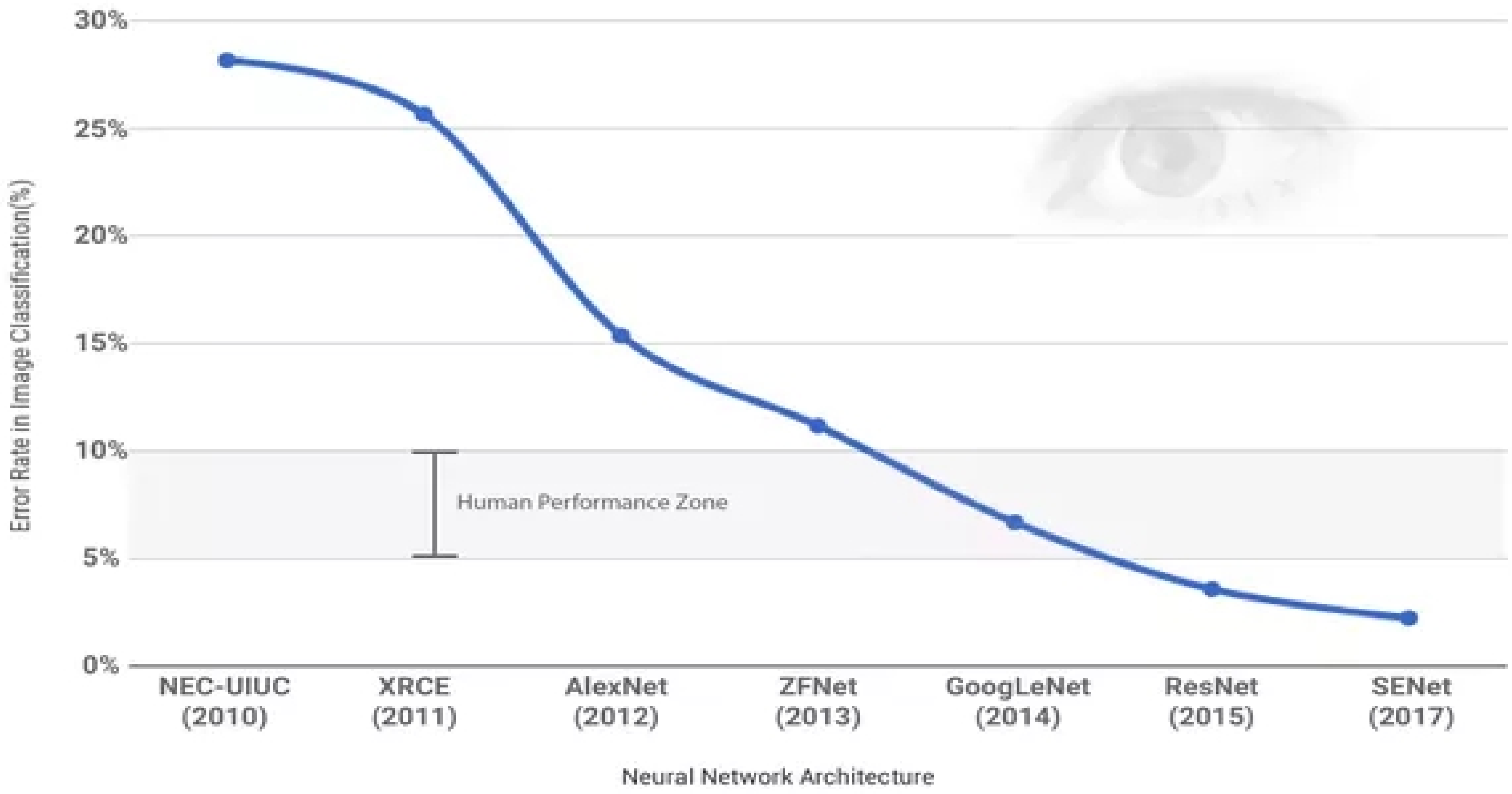
Training set: 1.2 million images (1,000 categories)

Test set: 150,000 images



Are DNNs good enough?

The winning network of 2017 (SENet), achieved an accuracy of 97.74%



Source: http://blog.paralleldots.com/data-science/must-read-path-breaking-papers-about-image-classification/

How to achieve predictability in the execution of DNN workload?

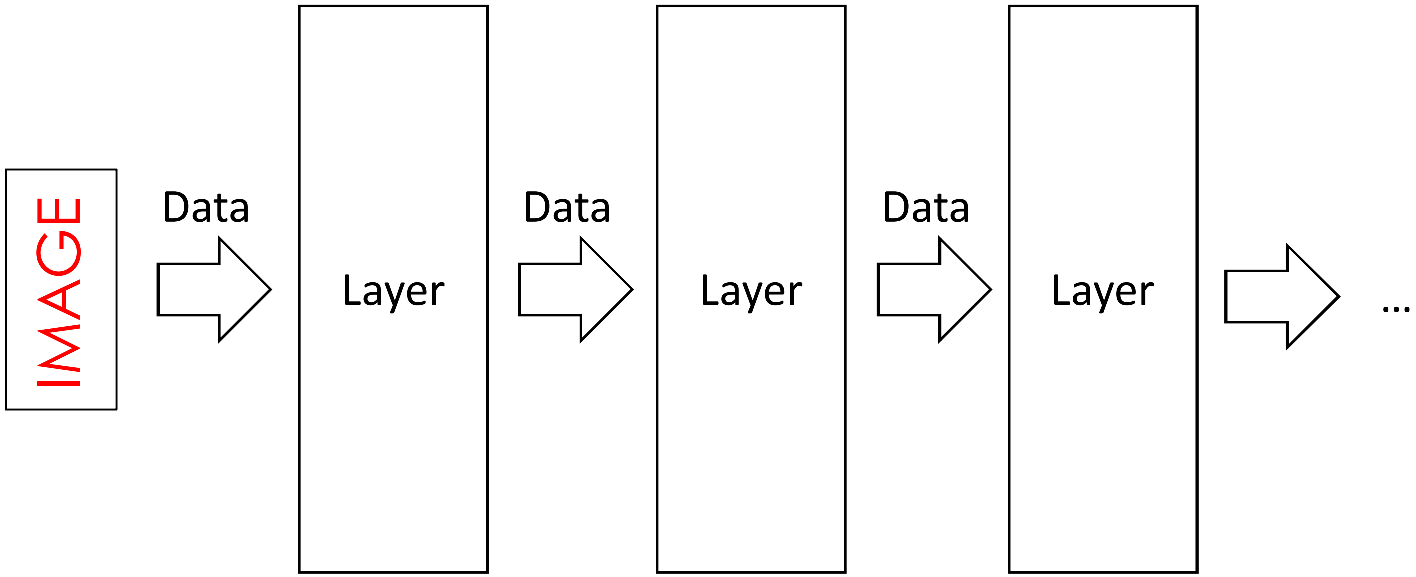
Understanding Complex DNN Workload

- What is a suitable model for the workload generated by complex DNNs?
- What is the resource consumption?
- Case study
  - InceptionV3: powerful image recognition DNN
  - Tensorflow: open-source machine learning framework by Google

- Stock Tensorflow with `eigen` math library on CPUs
- Strongly parallel workload with two levels of parallelism

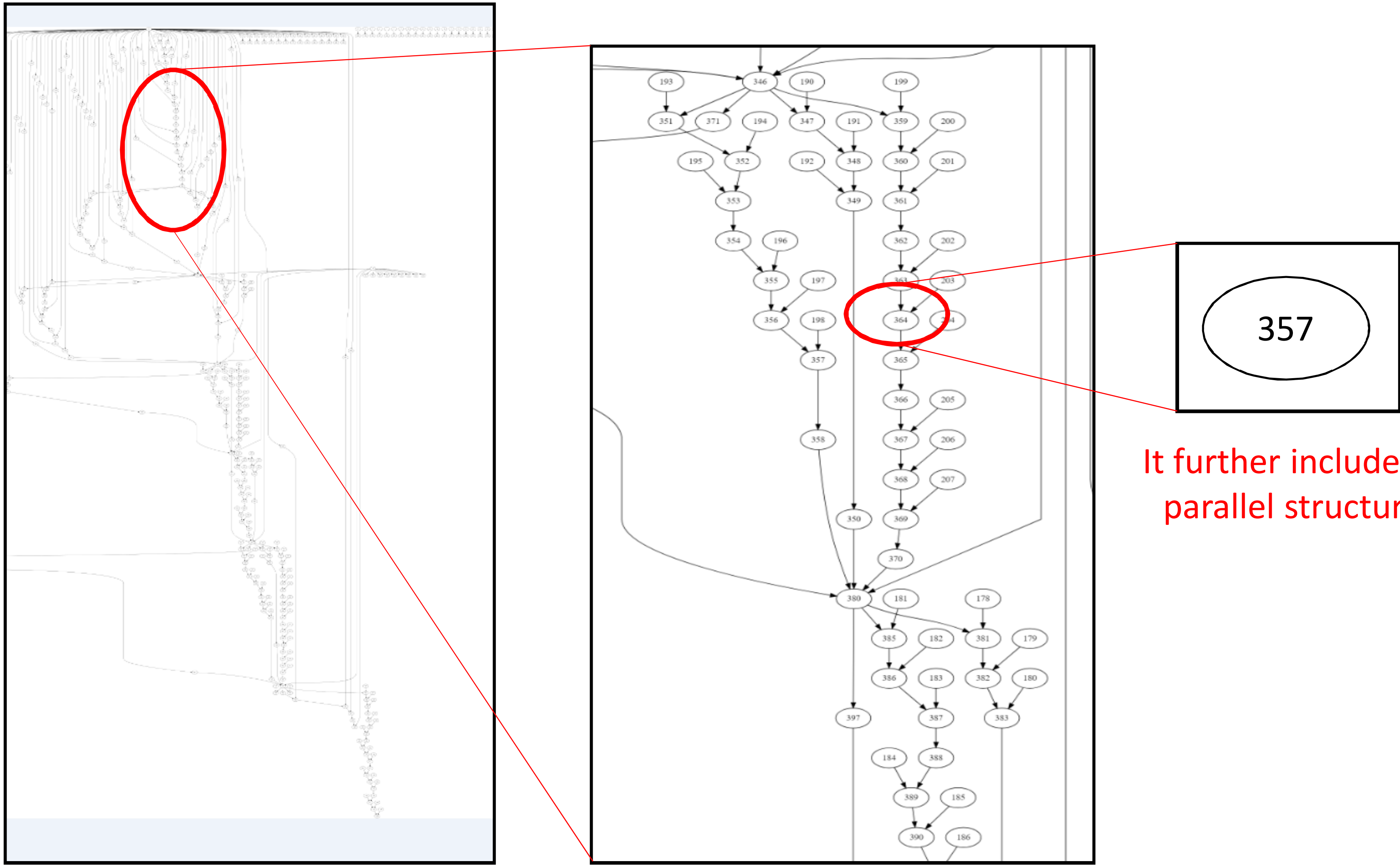
Understanding Complex DNN Workload

- A DNN is composed of a pipeline of layers, where each one implements an operation
- Key issue when it is used in a critical system: guaranteeing that a real-time workload composed of DNNs completes within a deadline (*inference* phase only)



InceptionV3 on Tensorflow

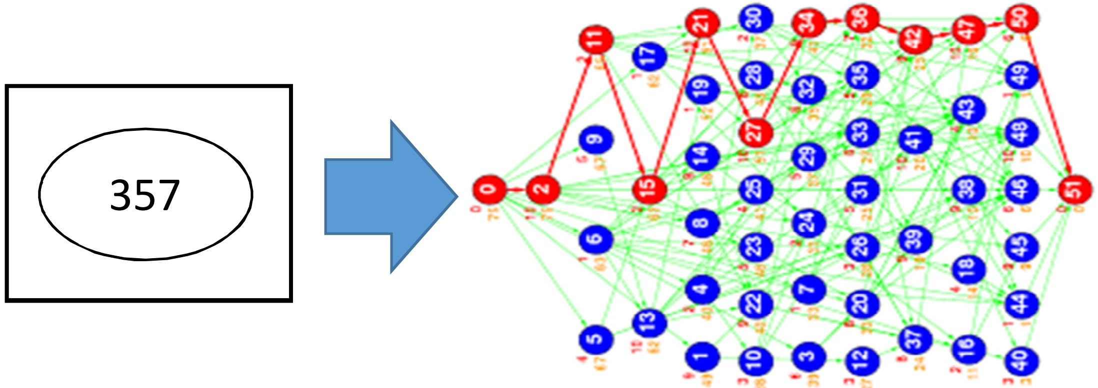
- First level is represented by a complex graph (~700 nodes)



It further includes a parallel structure

InceptionV3 on Tensorflow

- Nodes typically correspond to mathematical computations (e.g., tensor convolutions) whose implementation is platform-dependent and extremely parallel – this is the *second level* of parallelism

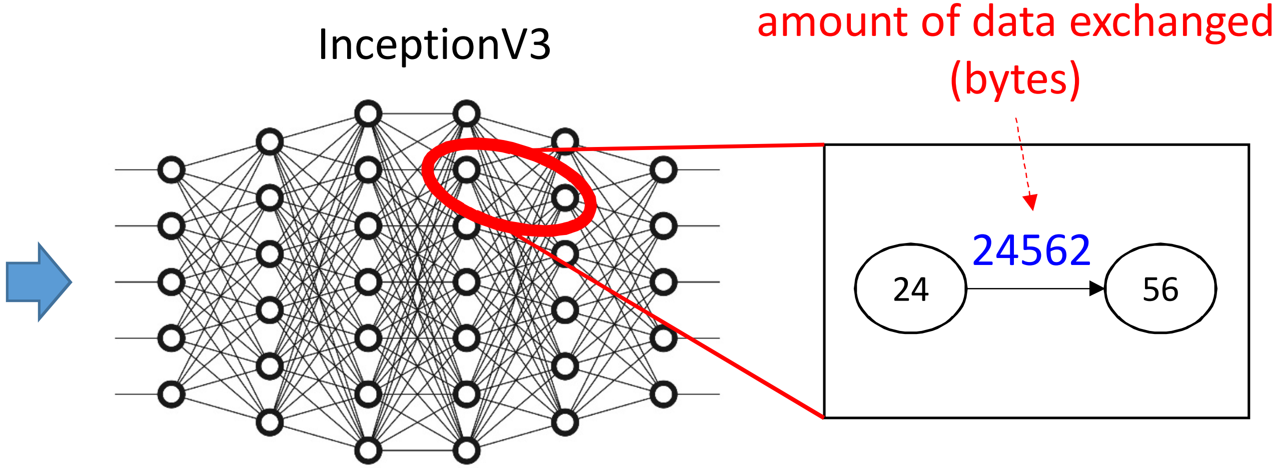


- InceptionV3 on a 8-core Intel i7 machine @ 3.5GHz
  - **More than 34000 nodes** (!) where only about **1.2%** of them have execution times larger than 100 microseconds
  - **Complex** workload with **extreme parallelism** → difficult to understand and manage

InceptionV3 on Tensorflow

- Nodes of the parallel tasks exchange a lot of data

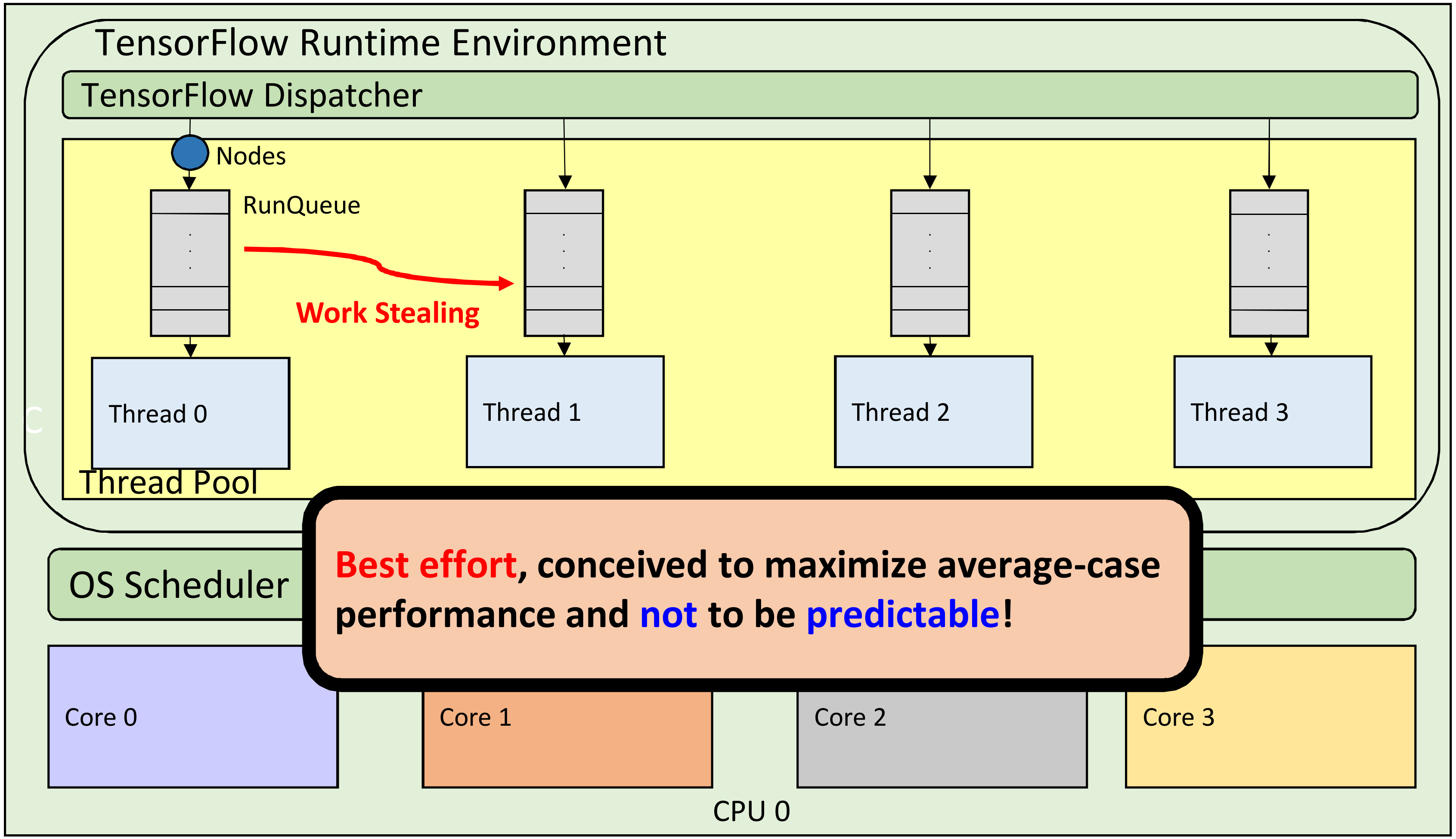
Input image (**60Kb**)



Total of data exchanged by nodes at the first level of parallelism amounts to **603856960 bytes ~= 604 Megabytes**

How Tensorflow works on CPUs?

- TensorFlow assigns ready nodes to threads of a thread pool, one for each level

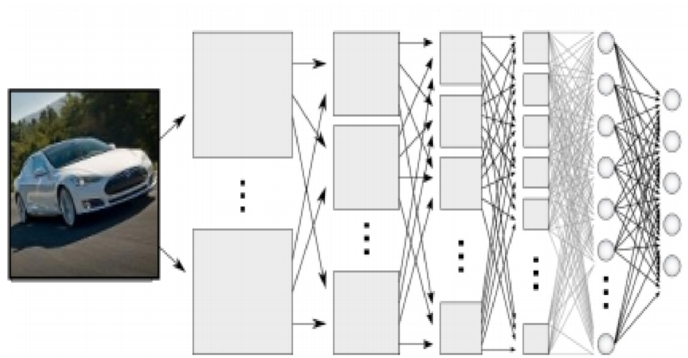


Best effort, conceived to maximize average-case performance and not to be predictable!

Predictable DNN Engines

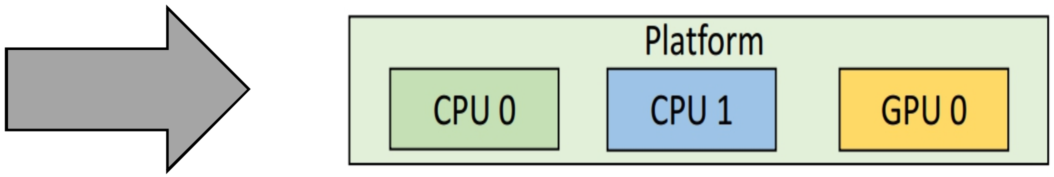
- Deep Neural Network (DNN) engines are typically conceived for best effort applications
  - No support for execution predictability
  - Prone to attacks and malfunctioning

- Need for improved inference engines to support predictable computing
  - Real-time scheduling and memory management, predictable allocation
  - Isolation to contain & control memory contention



DNN

Execution & Mapping



TensorFlow™

Caffe

TensorFlow for Safety-Critical Systems?

- TensorFlow is a complex software written in C++
- Large usage of dynamic memory
- Large usage of complex and advanced features of C++
- No safety programming guidelines are followed
- Wide usage of pointers
- …

Far from safety-critical software standards (e.g., ISO26262):

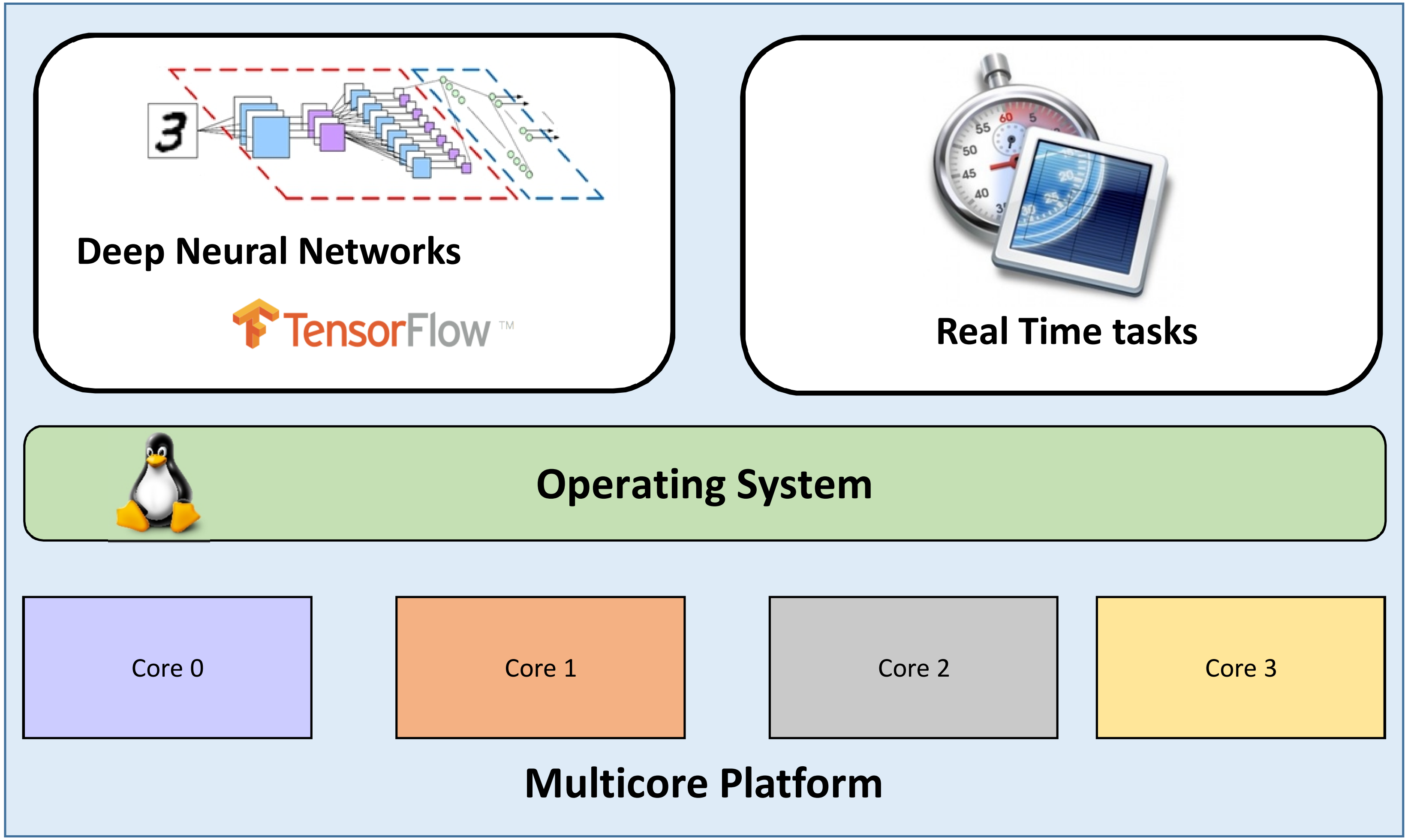
- **Static** memory
- Mandatory programming guidelines
- Limited use of pointers
- …

Large effort is required to make it usable in a safety-critical environment

Ongoing work

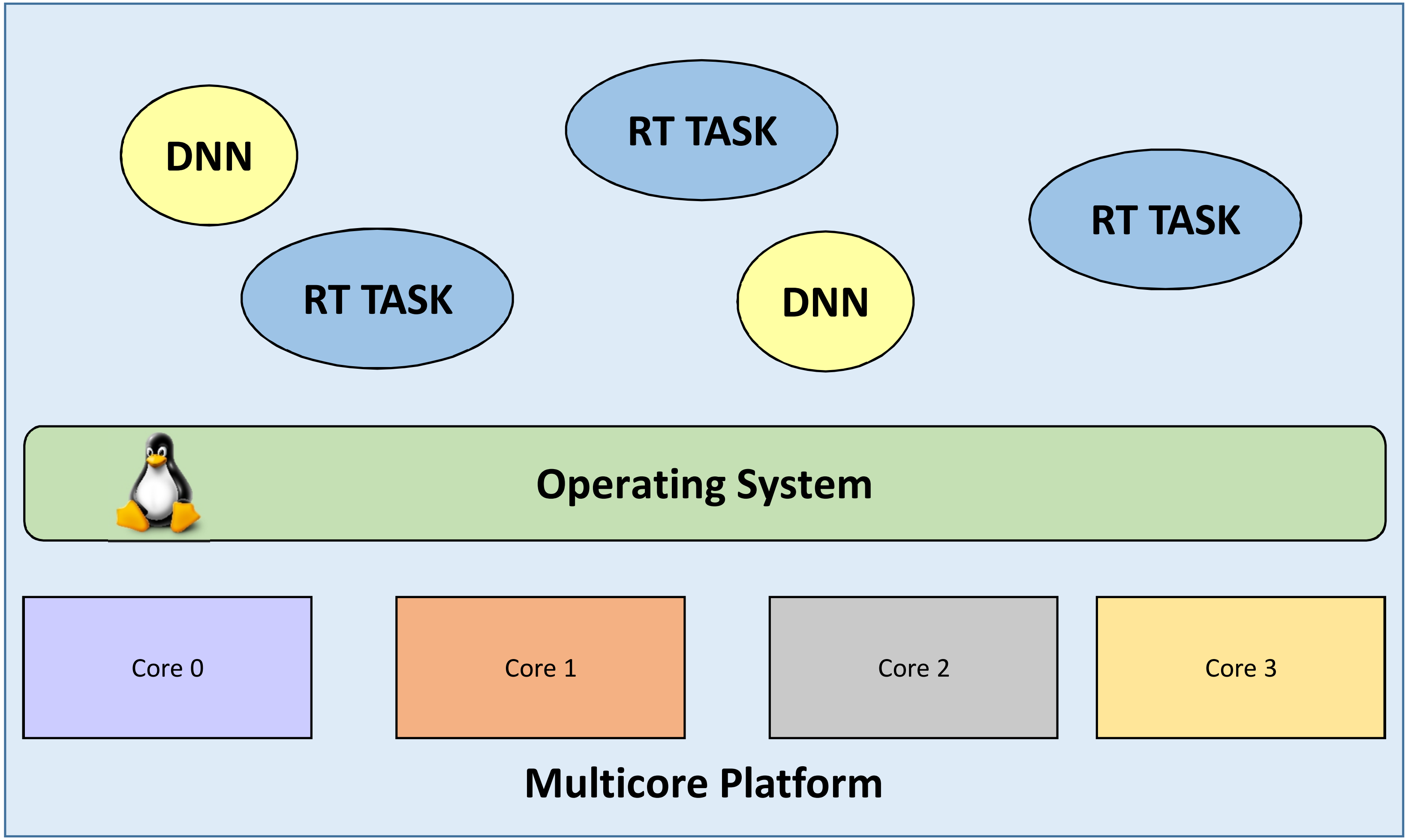
Scenario

Workload composed of DNN and regular real-time tasks



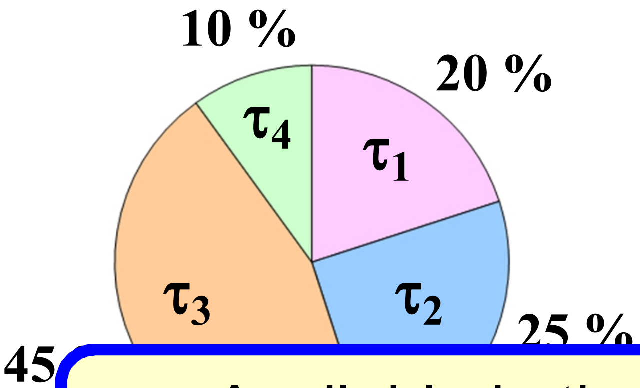
Scenario

but unfortunately they can interfere each other…



Resource Reservation

Resource partition



Resource enforcement

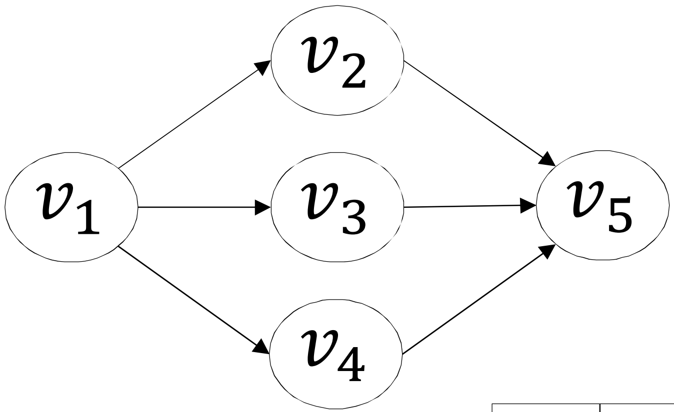
Available in the **SCHED_DEADLINE** scheduling class of **Linux**

Each task subset is assigned a fraction α_i of CPU bandwidth and behaves as it were executing alone on a slower processor of speed α_i

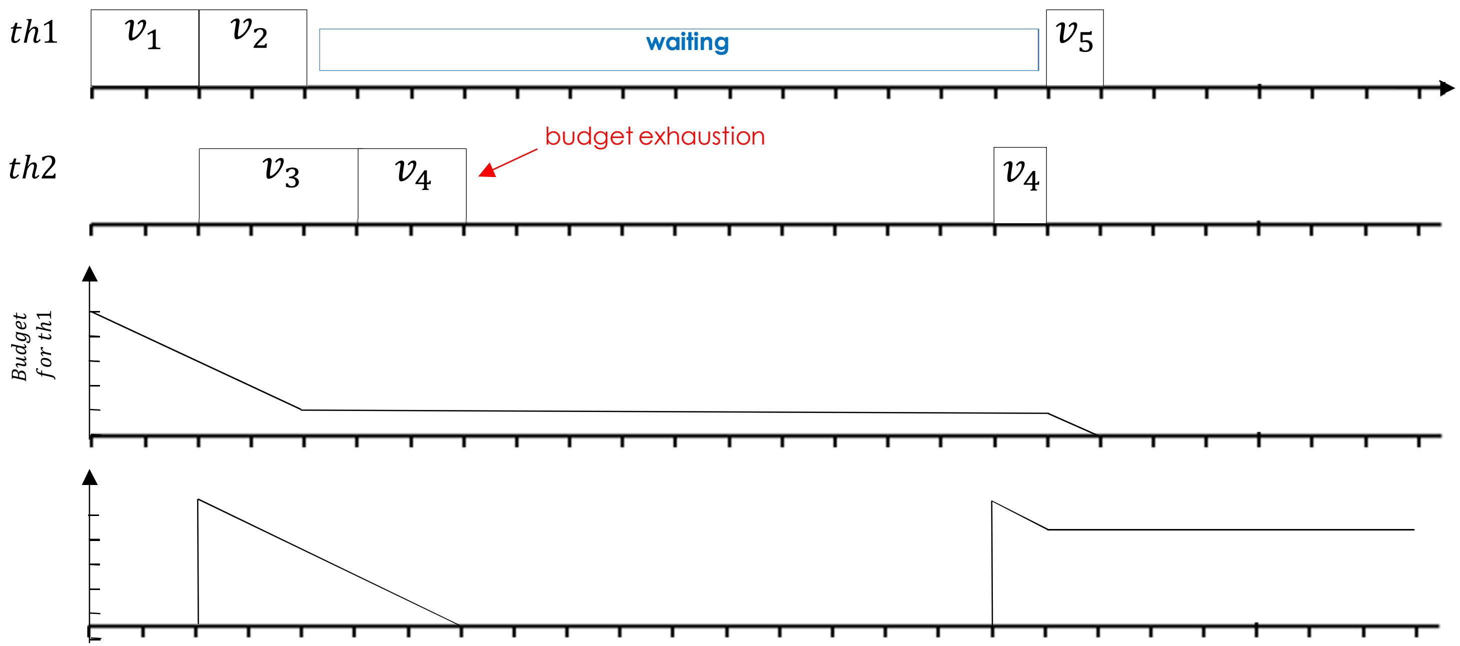
- … prevents … more than its reserved amount.
- If a task executes more, it is delayed, preserving the resource for other tasks.

Problem

- The usage of resource reservation when the workload is subject to precedence constraints can cause performance degradation



Budget exhaustion prevents successor nodes from being spawned



Our work

- Reduce the performance hit due to the usage of resource reservation by allowing budget overrun

Nodes are typically very small, allow them overrunning (with payback) can improve performance

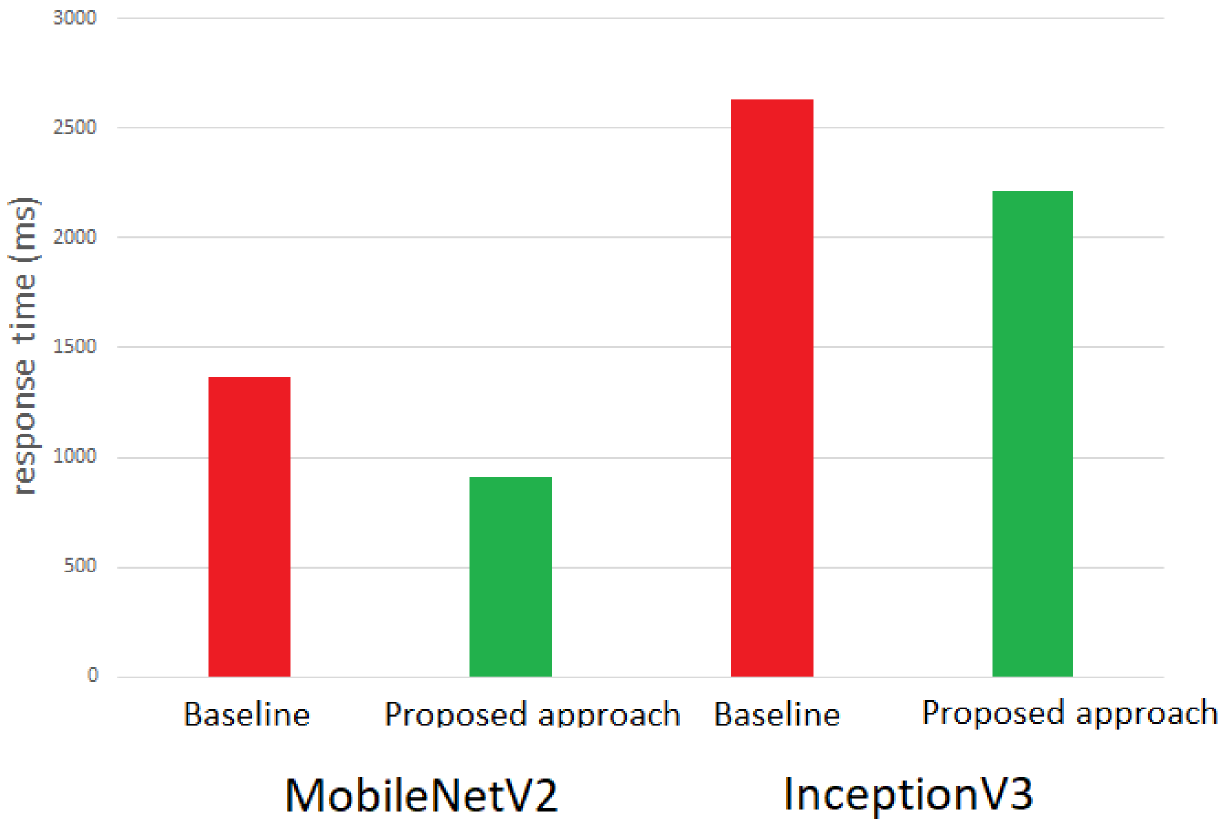
- Exploit **data locality** of DNN workload by implementing localized stealing

Nodes exchange a considerable amount of **memory:** Steal work from neighboring cores to take advantage of shared levels of cache

Some results

8-core Intel i7 running at 3.50Ghz, Tensorflow v1.5

2 DNNs + real-time tasks



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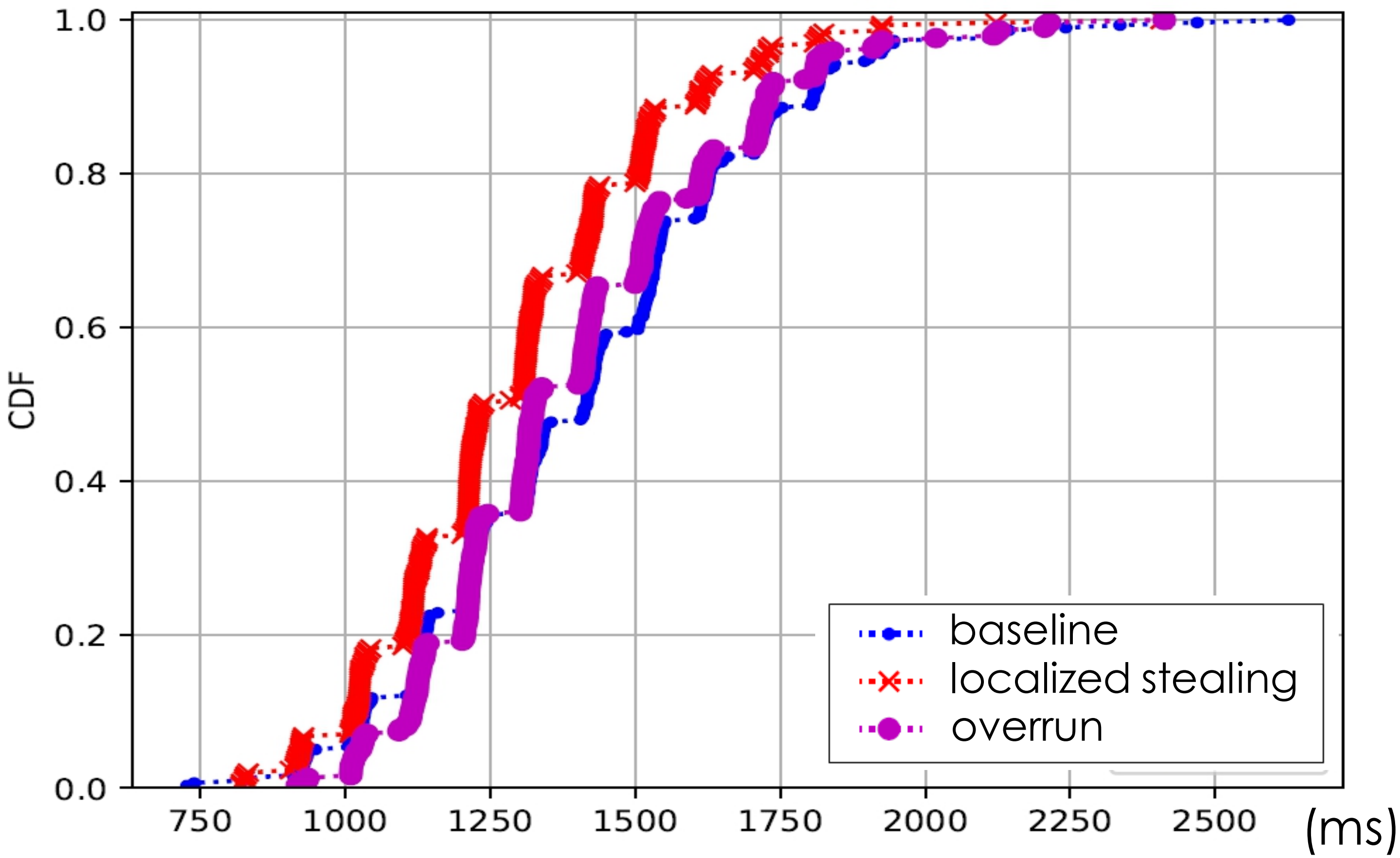

InceptionV3

Thank you!

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