

Small is the New Big: Designing Compact AI Models for Edge Devices

GOTO Chicago
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Brief Background: Why Deeplite?



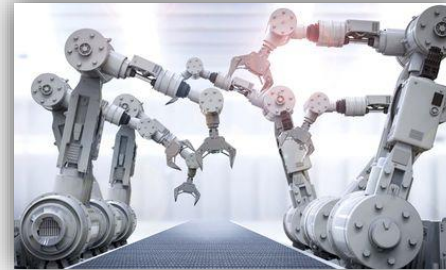
How do we bring the promise of AI models to benefit daily life?



Connected &
Autonomous Vehicles



Life-critical
Medical Devices

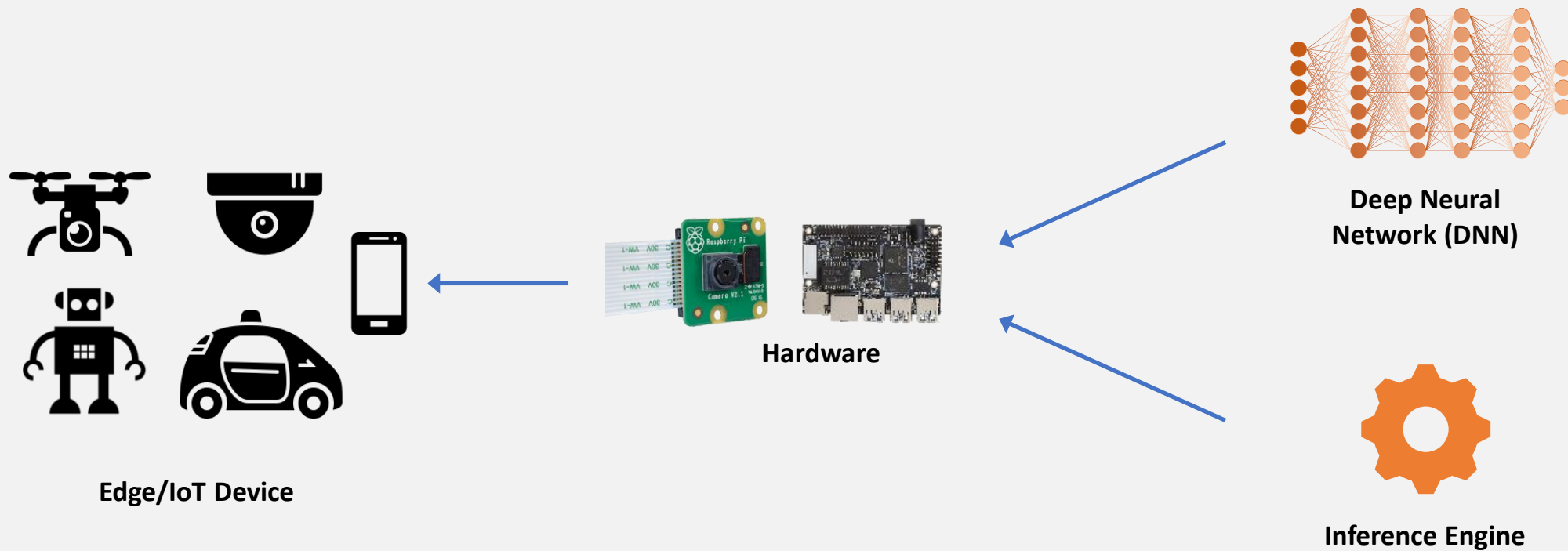


Robotics & Industrial
Automation



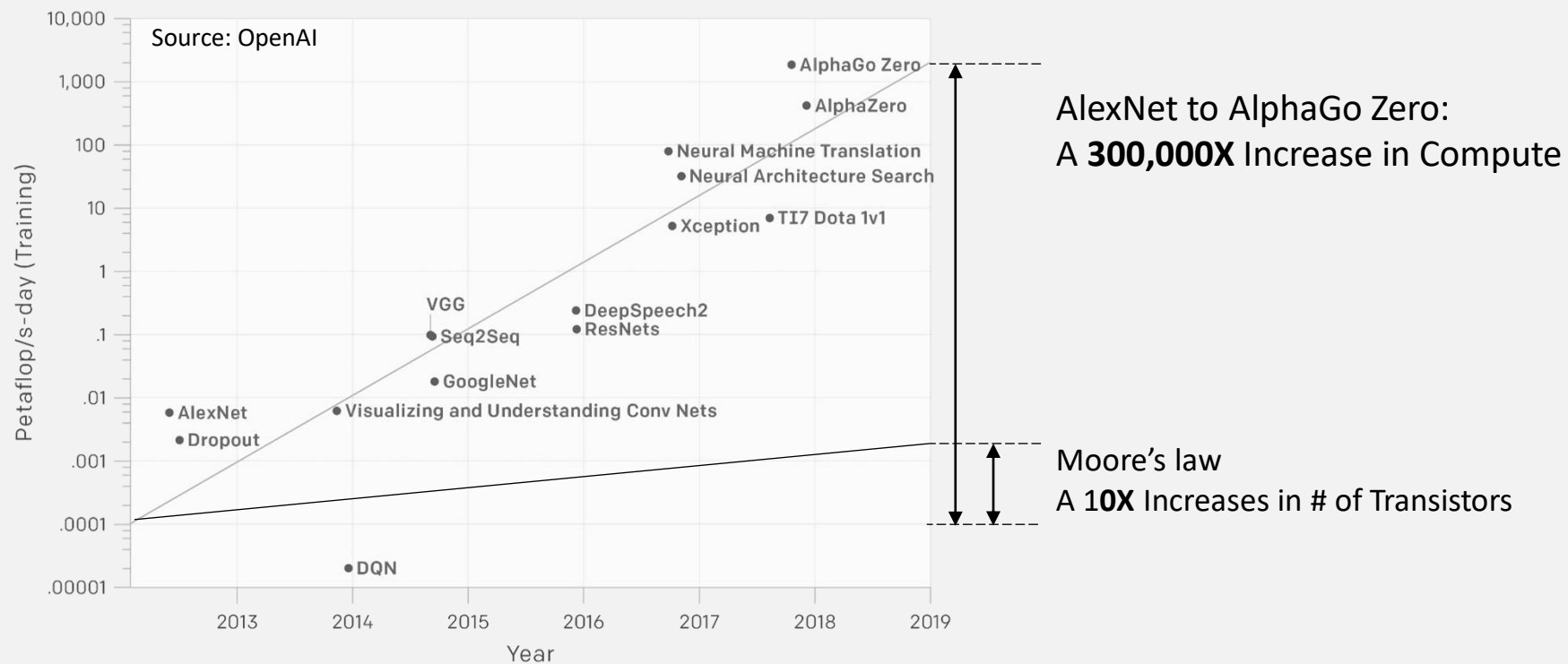
Drones, IoT &
Surveillance

Embedded AI 101



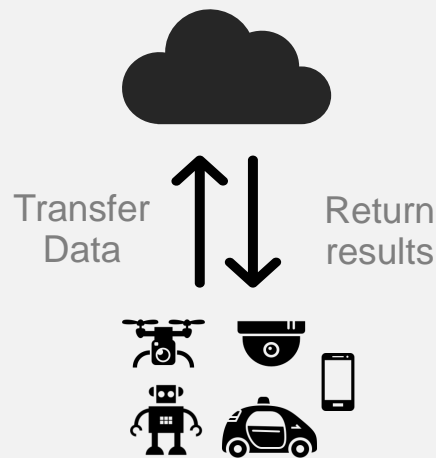
Deep learning models are growing rapidly

- Deep learning outperforms humans, but comes with **huge compute cost**
- **Deeper** neural network, **better** accuracy, **more** compute required



These demands force AI to the cloud

- **Expensive hardware** required for deep learning
- **Huge power consumption** for cloud AI hardware
- **Real-time critical AI** cannot rely on the internet connection



Typical Edge AI application workflow



Memory Footprint	~>10G
Power Consumption	>~300w
Computational Complexity	> 100 TOPs
Cost (ASP)	> \$5,000

Typical Cloud HW

Edge Computing Challenges



High Computational Complexity

Millions of expensive floating-point operations for each input classification are needed.



Memory Footprint

Huge amounts of weights and activations with limited on-chip memory and bandwidth.



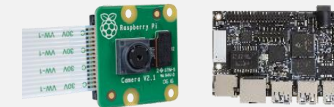
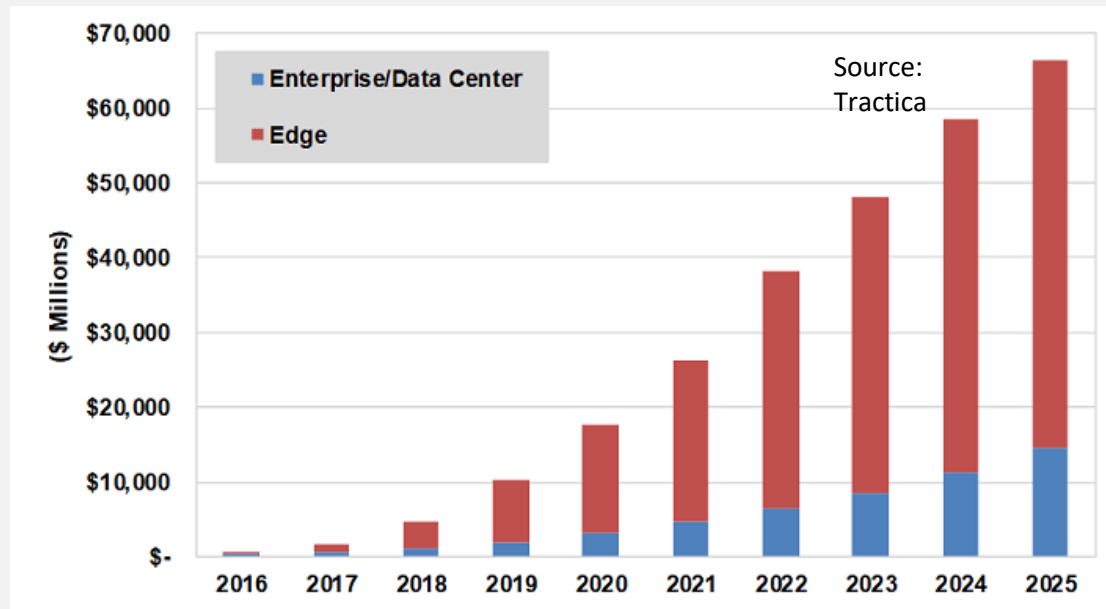
Power consumption

Deep learning requires significant power and can easily consume battery life



Time to deploy AI on edge devices

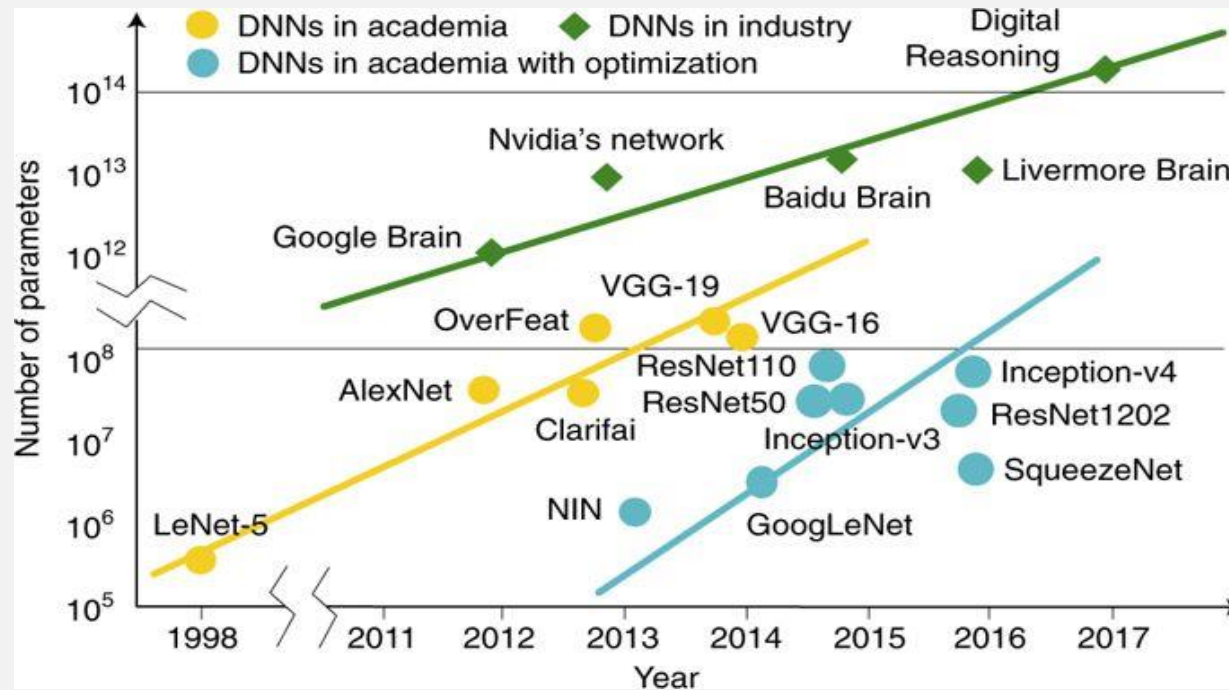
- Massive value unlocked by making AI applicable for cost-effective hardware
- **AI inference must meet strict power, speed, cost and resource constraints**



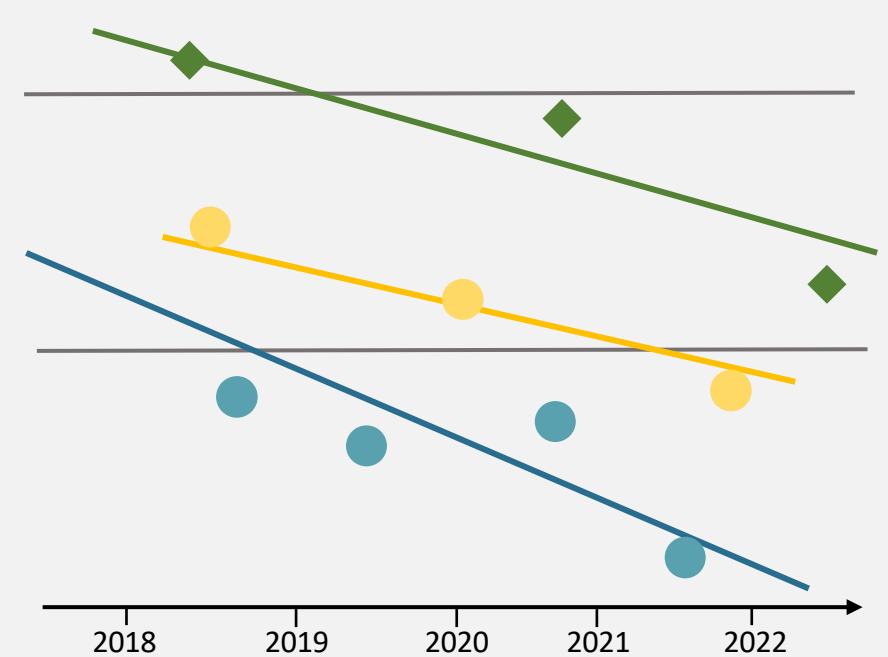
Memory Footprint	~<1M
Power Consumption	~<10w
Computational Complexity	~<10 TOPs
Cost (ASP)	~\$10

Typical Edge HW

Edge Computing Solution: Small is the New Big



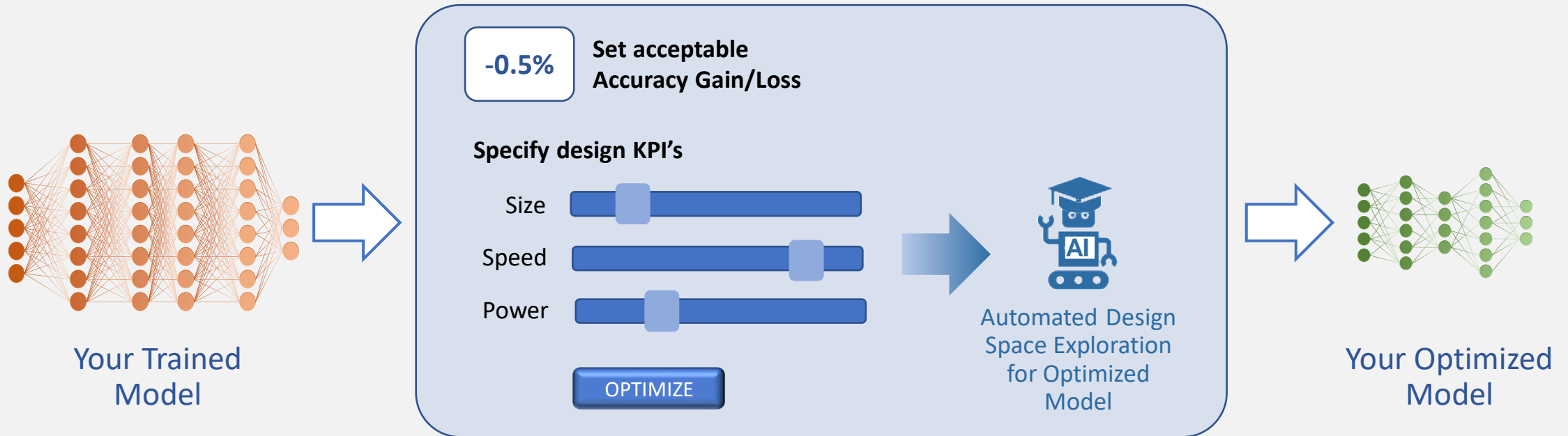
The Past



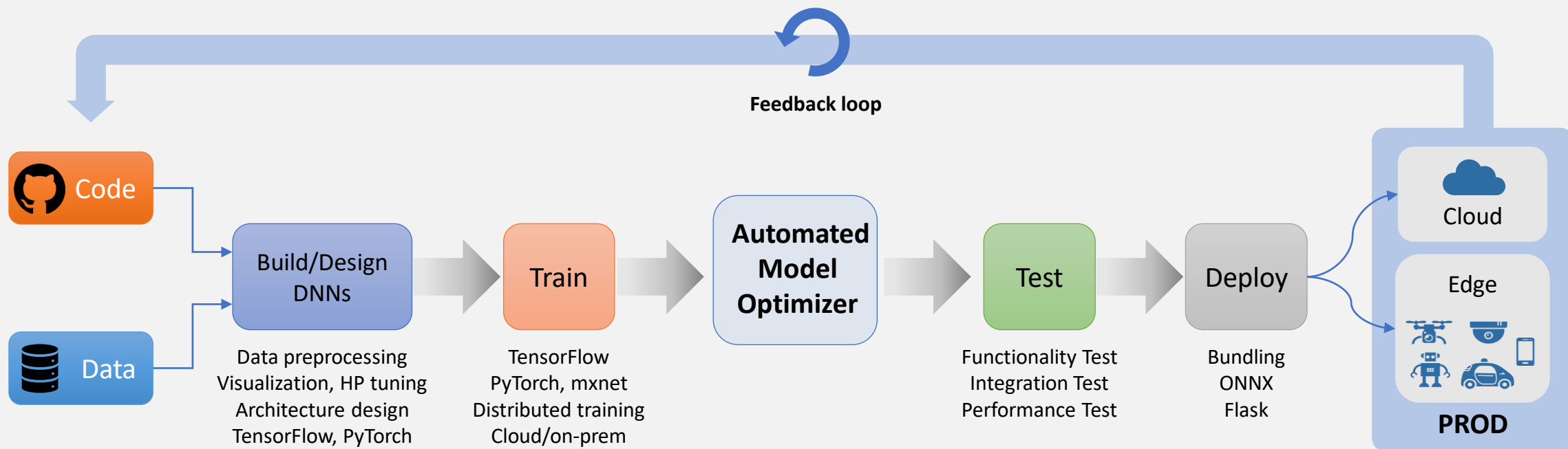
The Future

Designing compact deep learning models

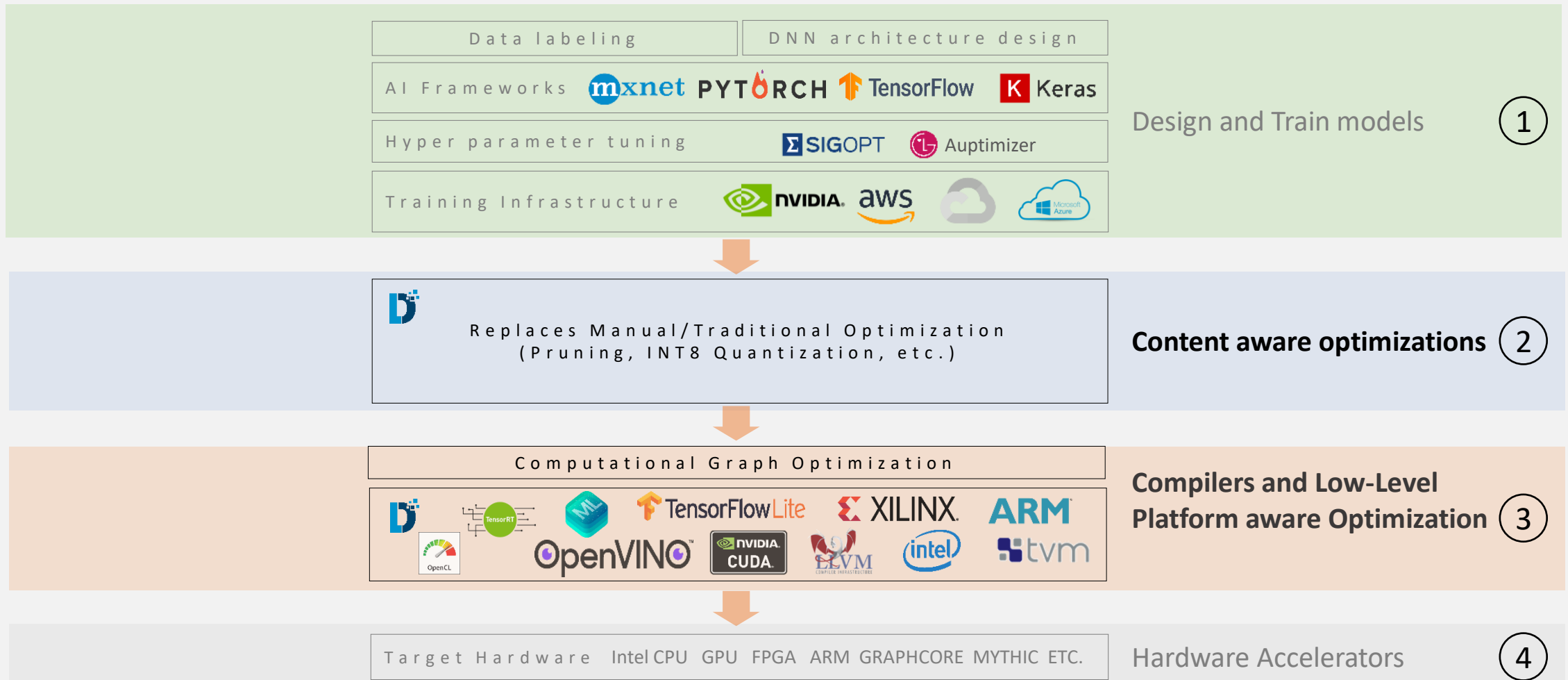
Automated, intelligent optimization methods help AI engineers to automatically create faster, smaller & more efficient model architectures for production edge devices.



Where does this fit in an ML/AI Workflow

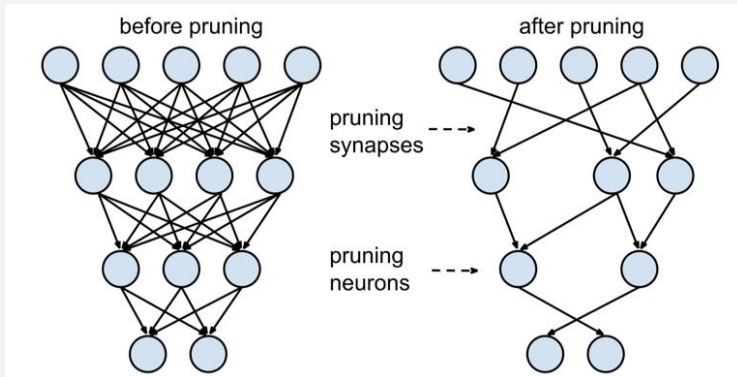


Levels of Optimization

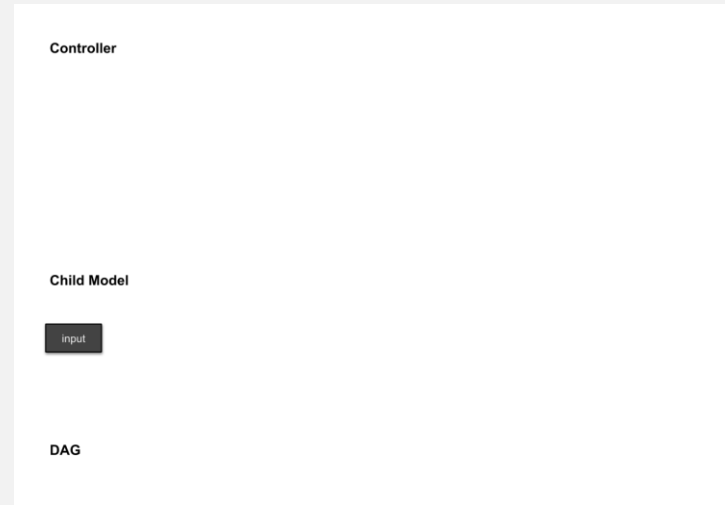


Types of Optimization

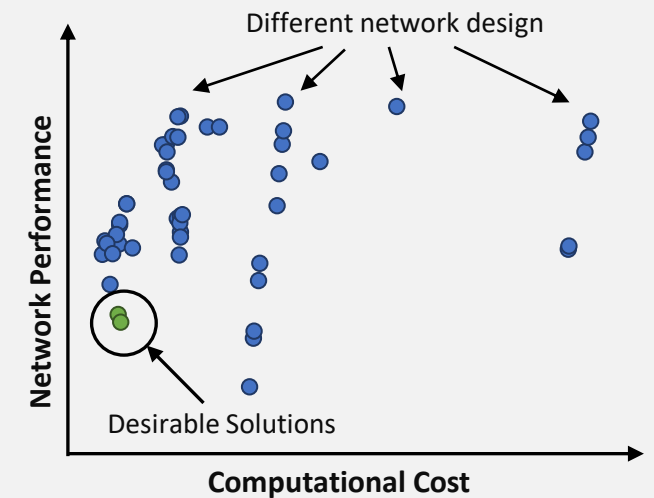
Pruning and Network Approximation



AutoML and Neural Architecture Search (NAS)



Automated Design Space Exploration



Our Focus

Optimization Benchmarks – Computer Vision

10x speedup on ARM mobile CPU

Application	Model	Compression ³			Complexity Reduction (FLOPs) ³	Accuracy Drop (%)	Dataset
		Original Size	Optimized Size	Improvement			
Image classification	VGG19	80MB	2.16MB	x37	x5	<1%	CIFAR100
	Resnet50	98MB	6.71MB	x14.6	x6	<1%	CIFAR100
	Resnet18	45MB	3.16MB	x14.2	x6	<1%	CIFAR100
	Mobilenet-v1.0	12.8MB	530KB	x22	x5	~1.5%	Visual Wake Words
	Industry use case ¹	45MB	1.8MB	x25	x4	<1%	Subset of Imagenet
Activity Recognition	Industry use case ²	1.9MB	59KB	x32	x100	~0%	Custom dataset
Object Detection	ResNet50-SSD300	54MB	18MB	x3	x3	~0%	Subset of COCO2017

¹ Based on ResNet18 architecture

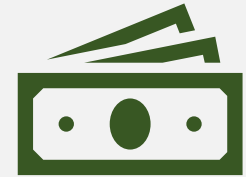
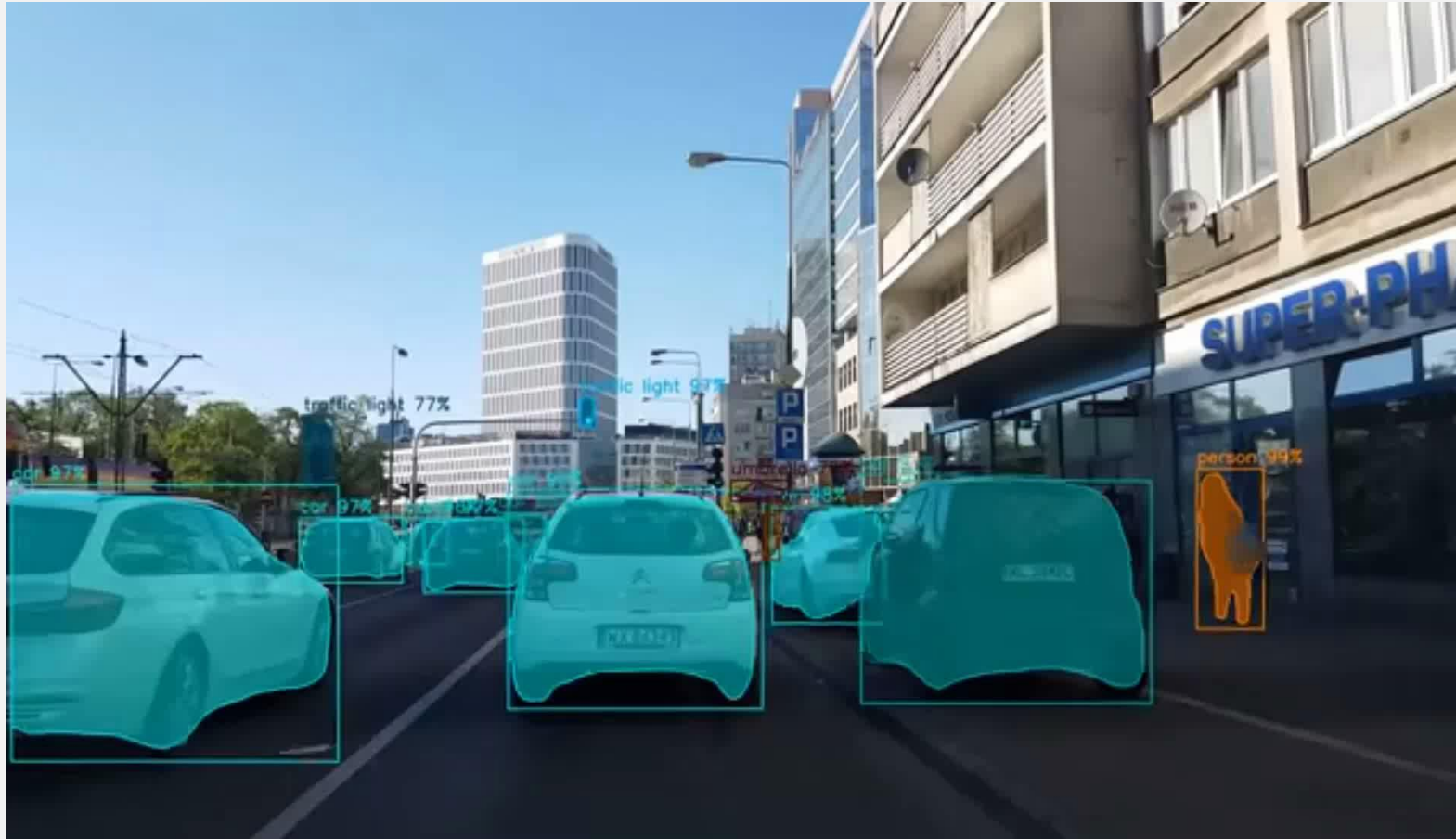
² Based on custom NN architecture

³ Results obtained purely using content-aware optimization (models in FP32). Further memory, speedup and energy savings available using platform-aware optimizations (INT8, mixed precision, binary weights etc.) and inference engine



Optimized vs. Unoptimized model on Android phone

Accelerating Autonomous Perception



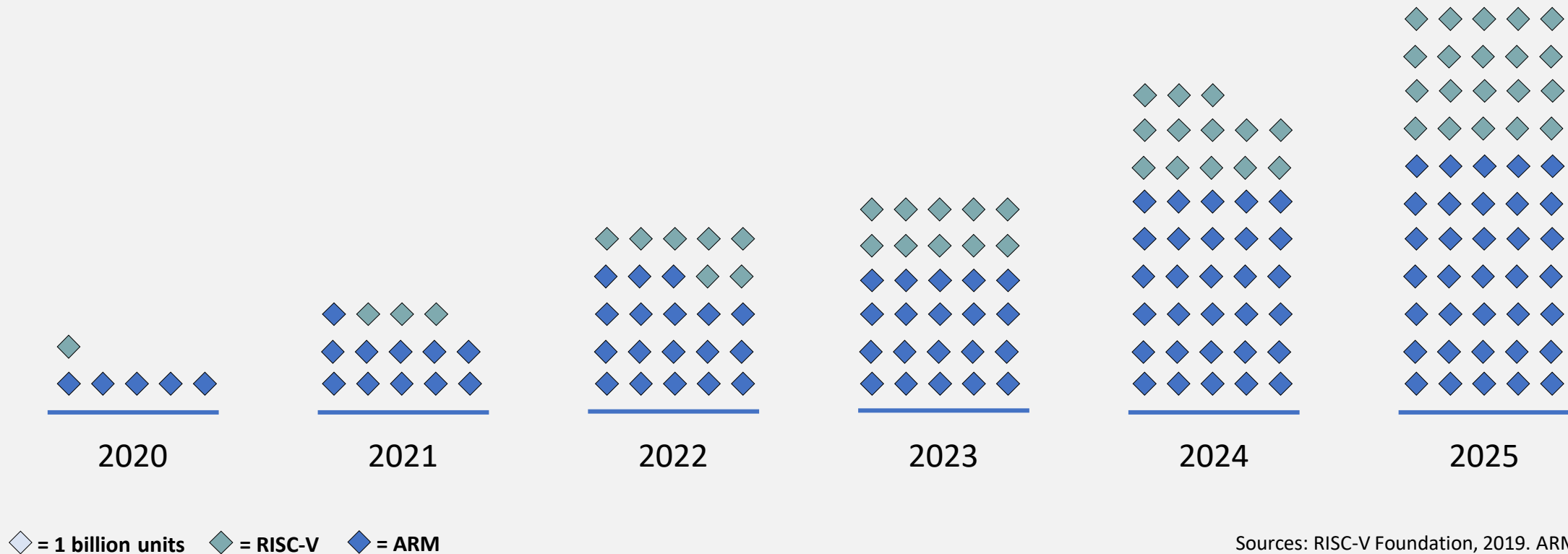
**Expensive hardware
required ~\$10,000/GPU**



**Deep learning consumes
~20% of battery**

AI on Low cost, low power chips

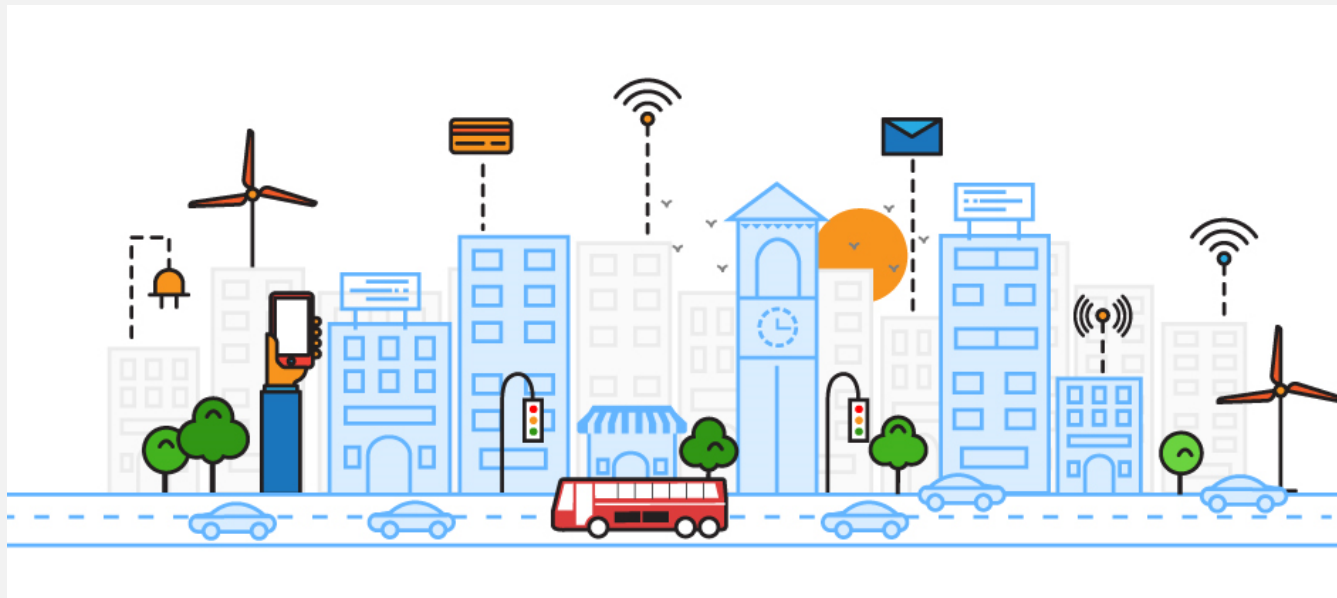
+100 billion IoT devices with ARM and RISC-V shipped over next 5 years



Sources: RISC-V Foundation, 2019. ARM IoT, 2020.

Bringing AI to daily life

- **Enable scalable** data centers and cloud services
- **Unlock new opportunities** by making DNNs applicable for edge computing
- **Reduce time to market** and engineering effort drastically



Thank you!

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