Developing an Efficient Automotive Augmented Reality Solution Using Teacher-Student Learning and Sprints

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CTO

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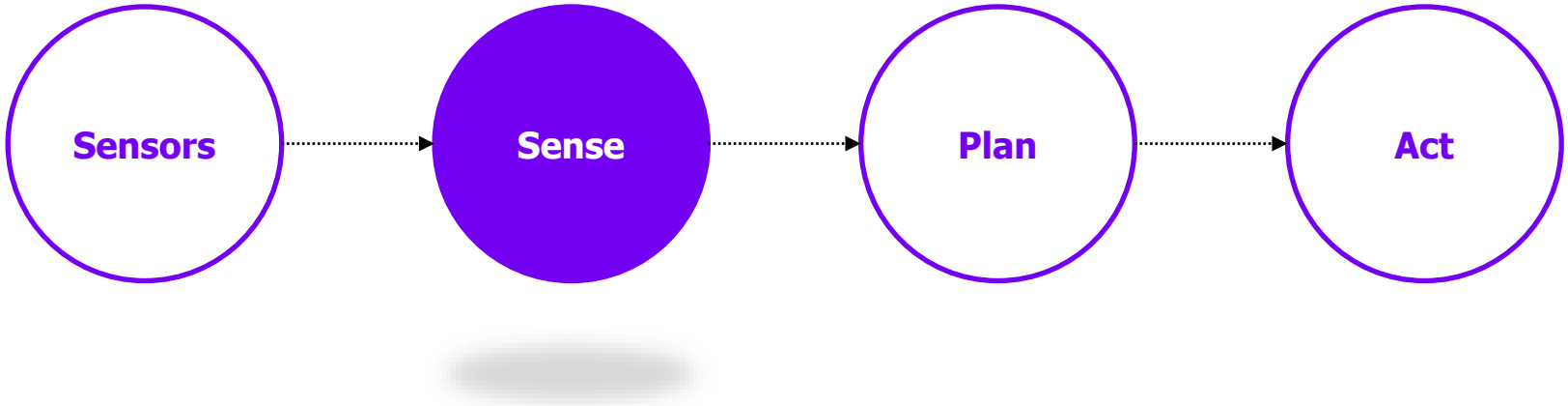
STRAD VISION

What We Do

Vison perception for active safety driving features



SVNet is part of the perception stack in ADAS, which provides key information for next stages such as planning and control

SVNet, Cutting Edge AI Technology

Deep learning-based vision perception algorithm + own know-how in automotive applications

Strong Performance

Expand and refine target algorithm through the state-of-the-art learning techniques

High Efficiency

Light weight and compact DNN[1)] Algo Less computing resource required

Maturity

Multiple commercial projects with automotive OEMs for mass-production of vehicle models

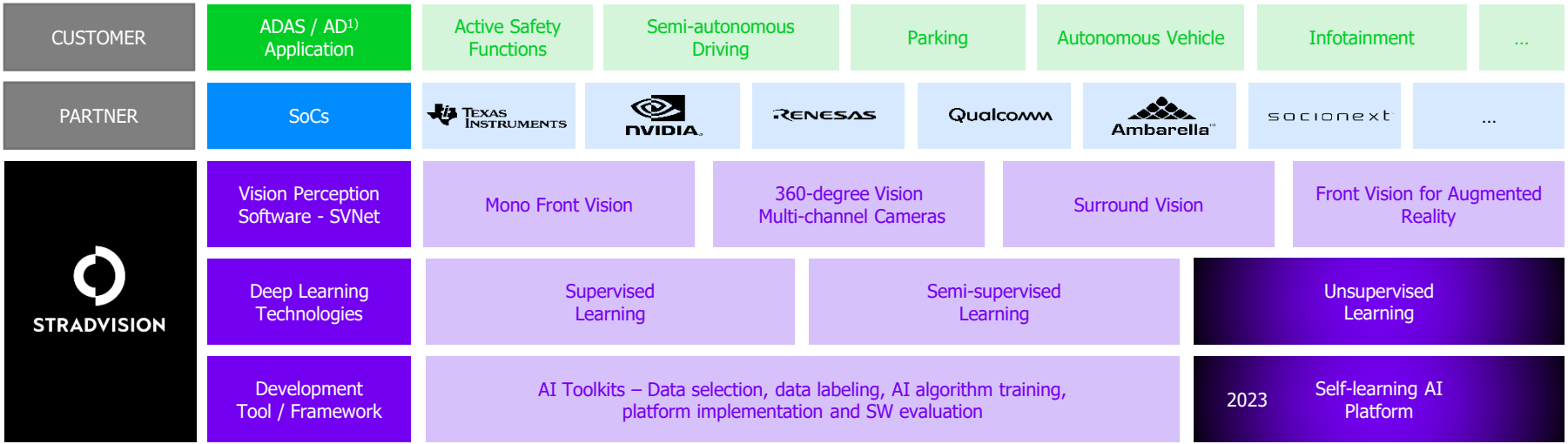
Industry Recognized Network

470+ patents with deep neural network ASPICE[2)] certification

DNN[1)] Deep Neural Network ASPICE[2)] Automotive Software Process Improvement and Capability dEtermination

Product Strategy

Versatile software for flexible and customized applications in the automotive industry



1) ADAS: Advanced Driver Assistance Systems / AD: Autonomous Driving

SVNet Product Lineup

1.ProDriver	2.ParkAgent	3.ImmersiView	4.CompliKit

EntryVision	BasicVision
CoreVision	UltraVision

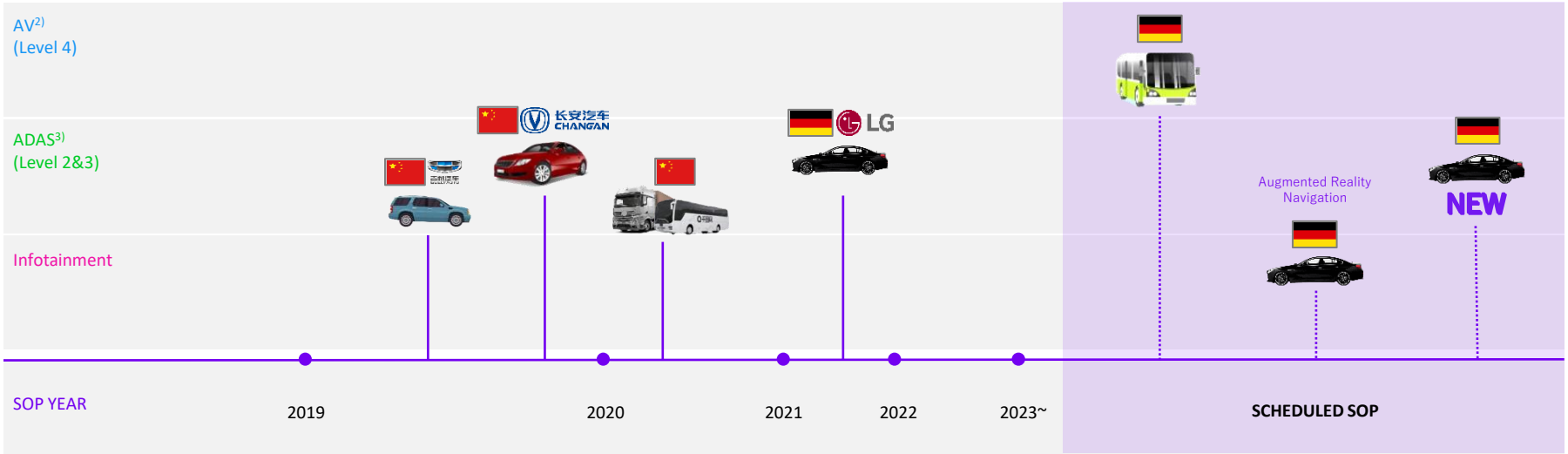
BasicAgent

AdvancedAgent

ValetAgent

Product Maturity – Design Wins with 13 OEMs

13 million vehicles in 50+ models on their way to the road with SVNet[1)] software embedded



SVNet[1)]: STRADVISION Deep Learning Network AV[2)]: Autonomous vehicles ADAS[3)]: Advanced Drivers' Assistance Systems

Key Techniques of SVNet

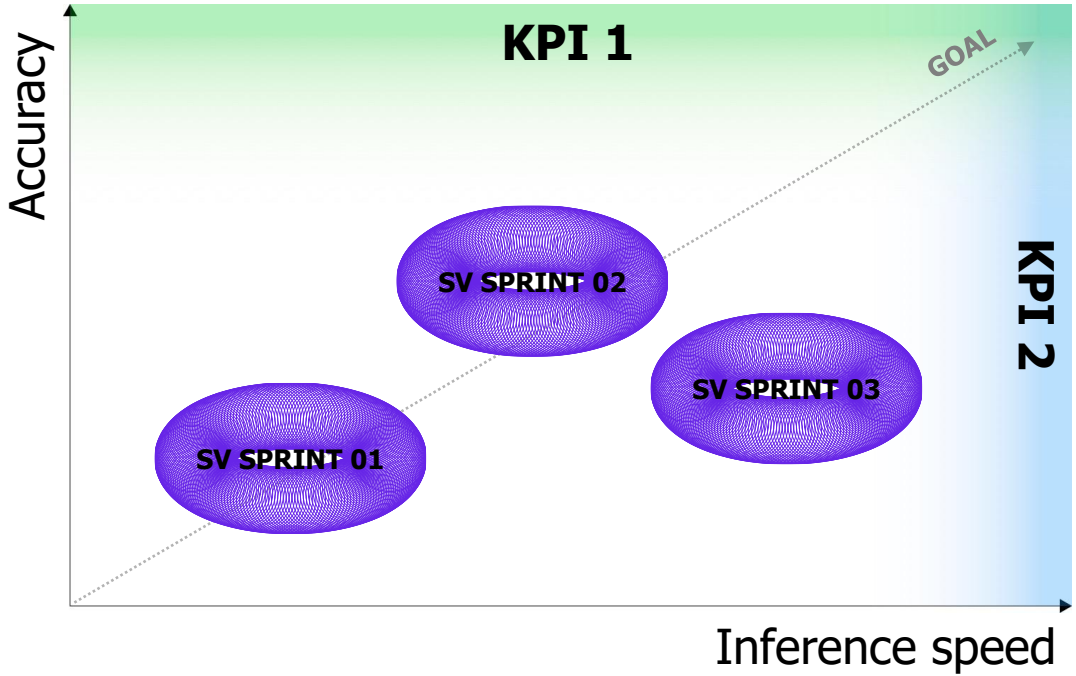
Deep Learning Projects

SV SPRINT MODEL

Prep Data

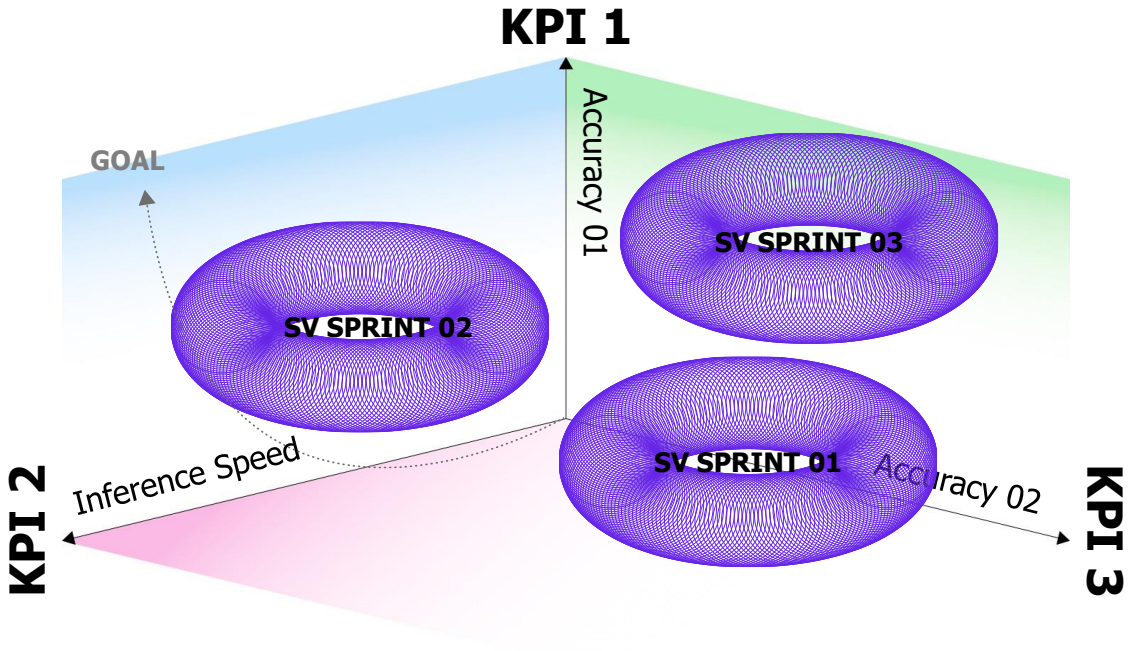
Challenges in Deep Learning Projects

- *Long* development cycles
- *Unpredictable* outcomes in each cycle (e.g., accuracy and speed)



Even More Challenges: Multi-Task DL Projects

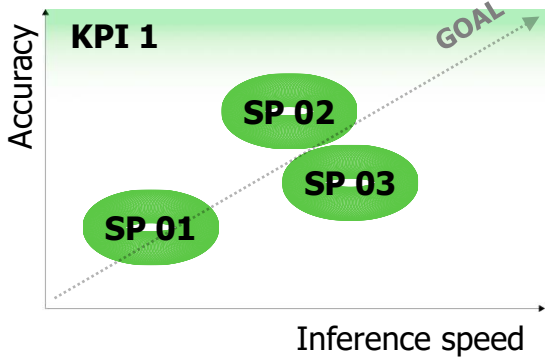
- *Looooonger* development cycles
- *Harder* to meet KPIs in *limited* time

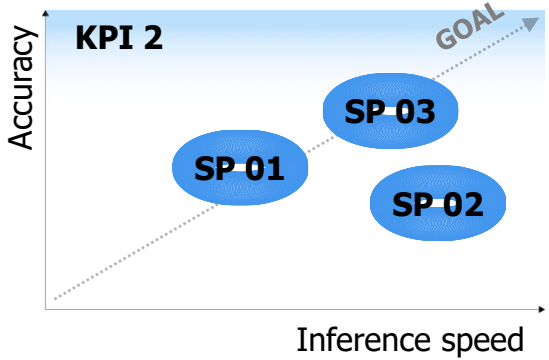


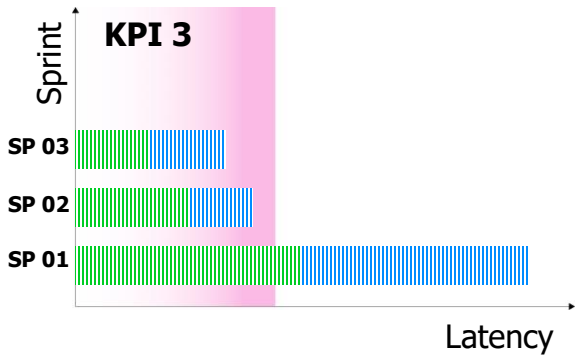
Naïve Approach to the Multi-Task DL Projects

- Train individual networks on *separate datasets*
- *Shorten* development cycles

- Causing resource *allocation* issues
- Inference speed in Task 1 vs. Task 2



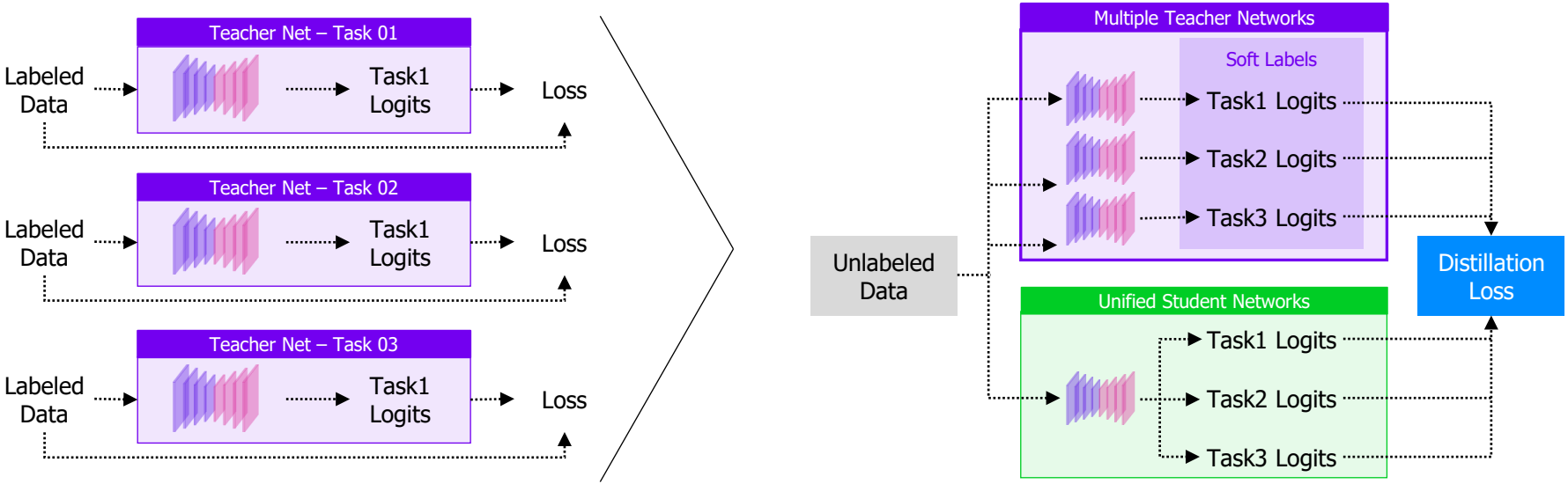




Proposed Development Process

Proposed Development Process

Multiple Teacher - Unified Student learning

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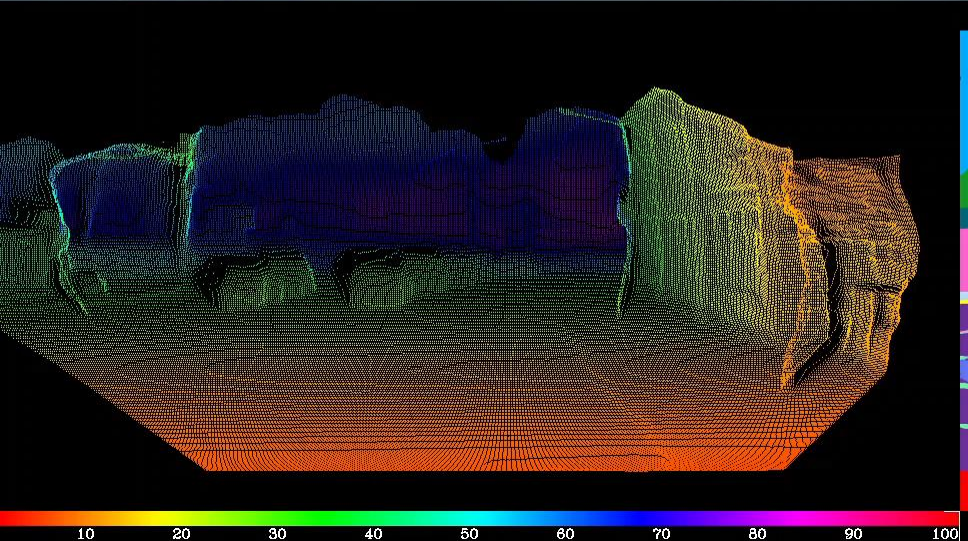
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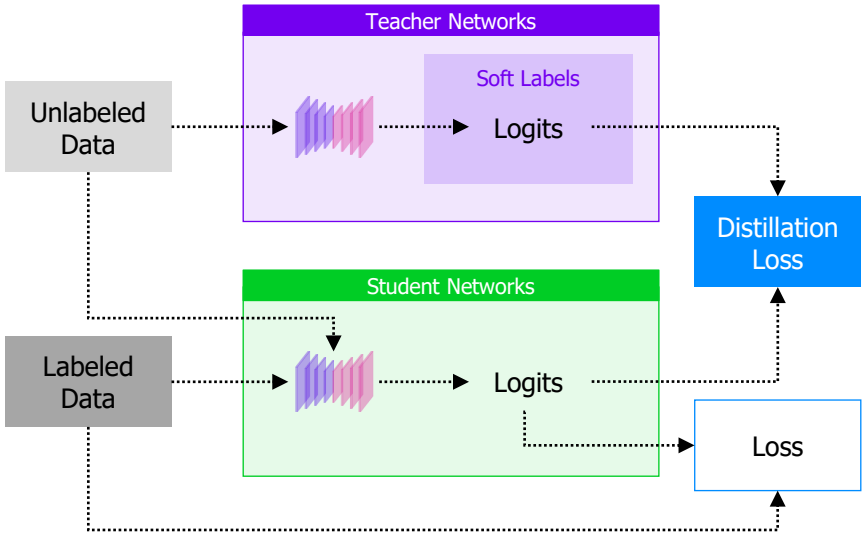
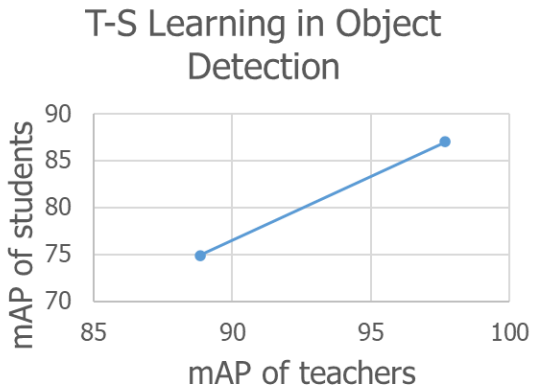
Teacher-Student Learning

Semi-supervised learning

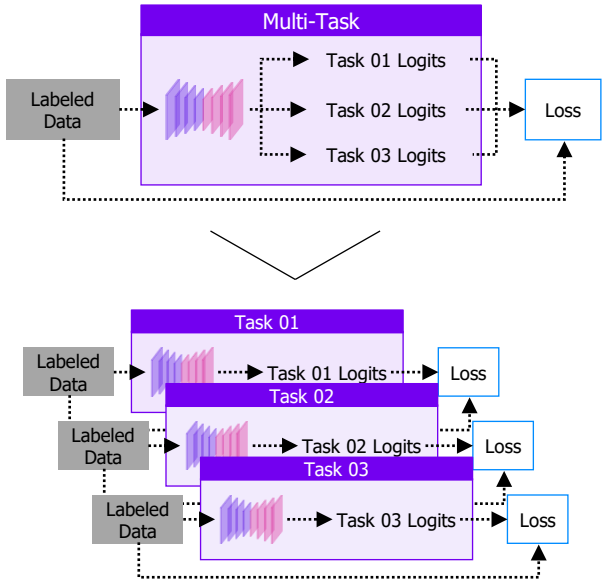


Better teachers, better students.

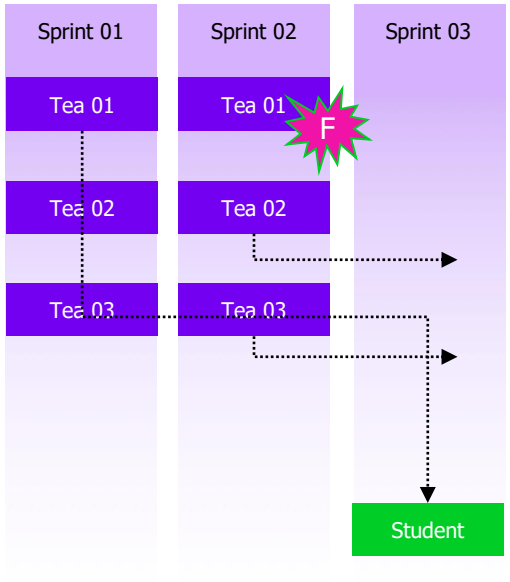


Decoupling Dependencies

Between Tasks

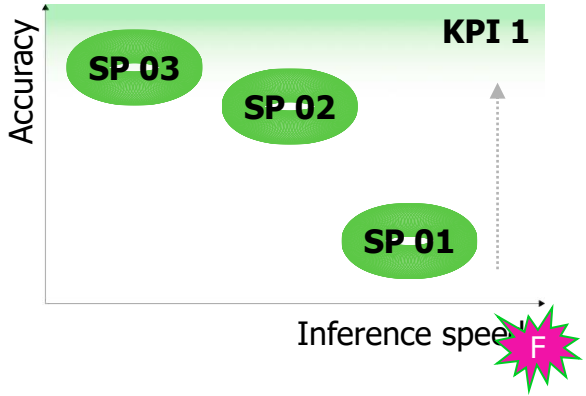


Between Sprints



Between KPIs

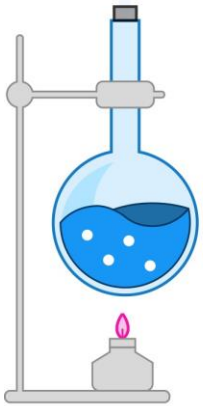
For teacher networks,
focus on improving accuracy only.



Benefits of Using Teacher-Student Learning

Teacher network	Student network
• Can develop **independently** of other networks. • Focus solely on improving **accuracy.** • Keep only the **most accurate** models. • **Not dependent** on target hardware. • Can **reuse** for other projects. • Can use **off-the-shelf** DNNs for the initial phase.	• Use **large-scale unlabeled** datasets. • Can use **partially labeled** datasets. • Improve accuracy **for free** with more accurate teacher networks.

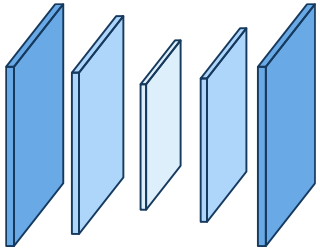
Teacher Network Training



1. Feed *more data* into *deeper and wider* models.
2. Apply *pre-training* if needed.
3. Apply *data augmentation* if needed.

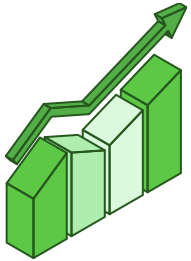
To improve accuracy

Unified Student Network Training



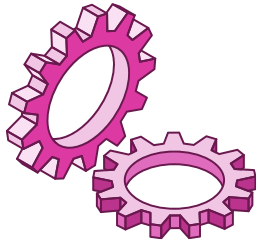
To meet KPIs for inference speed

1. Design your network.
2. Measure its inference speed before you start training.
3. Start training once the speed KPI is met.



To improve accuracy

1. Use more accurate teacher networks.
2. Use better losses, leveraging cross-task relationships.



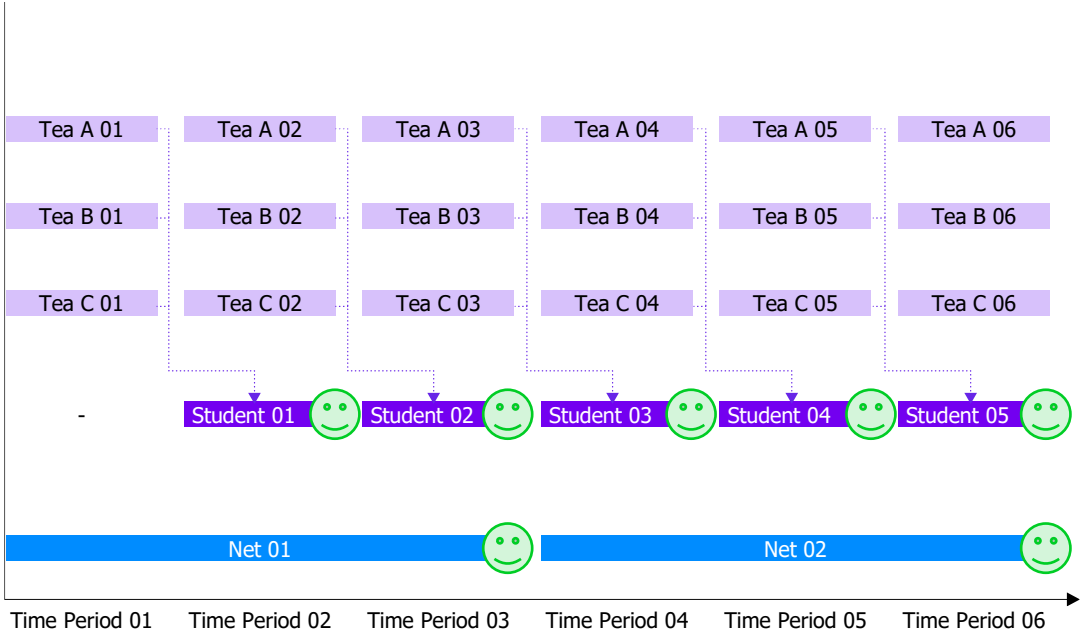
To accelerate training

1. Precompute and store soft labels to SSD.
2. Load the labels from SSD during training.

Benefits of The Proposed Process

Rapid prototyping & Continuous updating

Network Type	Target HW	KPIs	Task
Pipelined w/T-S learning			
Teacher	Cloud	Accuracy	A
			B
			C
Student	Embedded	Speed Accuracy	A,B,C
Non-pipelined w/o T-S learning			
-	Embedded	Speed Accuracy	A,B,C



Conclusions

- **Efficient SW development process for multiple DL tasks**
  - **using teacher-student learning.**
- **Concurrently improves accuracy and speed through sprints.**
  - **Reduced product development time by up to 50%.**

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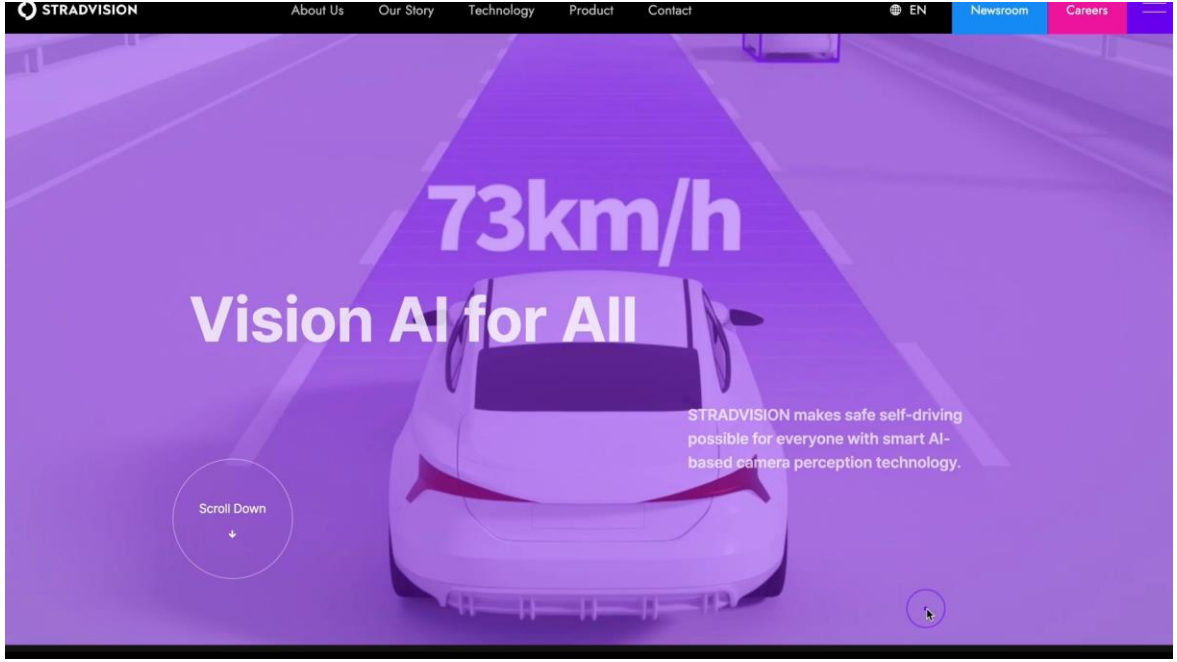

References

[1] Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. "Distilling the knowledge in a neural network." *arXiv preprint,* 2015. https://arxiv.org/abs/1503.02531

[2] Gou, Jianping, et al. "Knowledge distillation: A survey." *IJCV*, 2021. https://arxiv.org/abs/2006.05525

[3] Wang, Lin, and Kuk-Jin Yoon. "Knowledge distillation and student-teacher learning for visual intelligence: A review and new outlooks." *IEEE TPAMI,* 2021. https://arxiv.org/abs/2004.05937