

Motivation

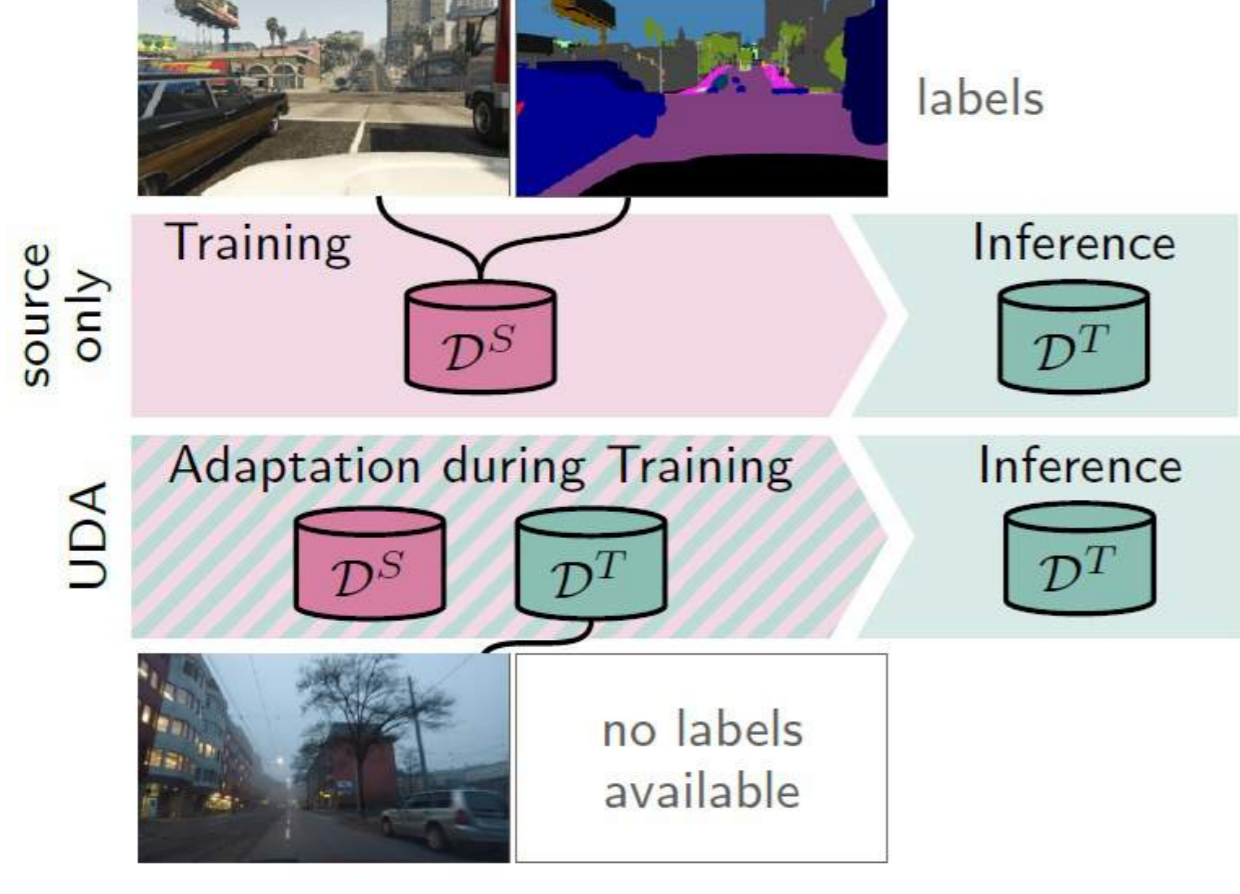


Figure 1: UDA Principle

- Unsupervised Domain Adaptation (UDA) without target labels
- Over 150 works on synthetic-to-real UDA since 2017

Overview

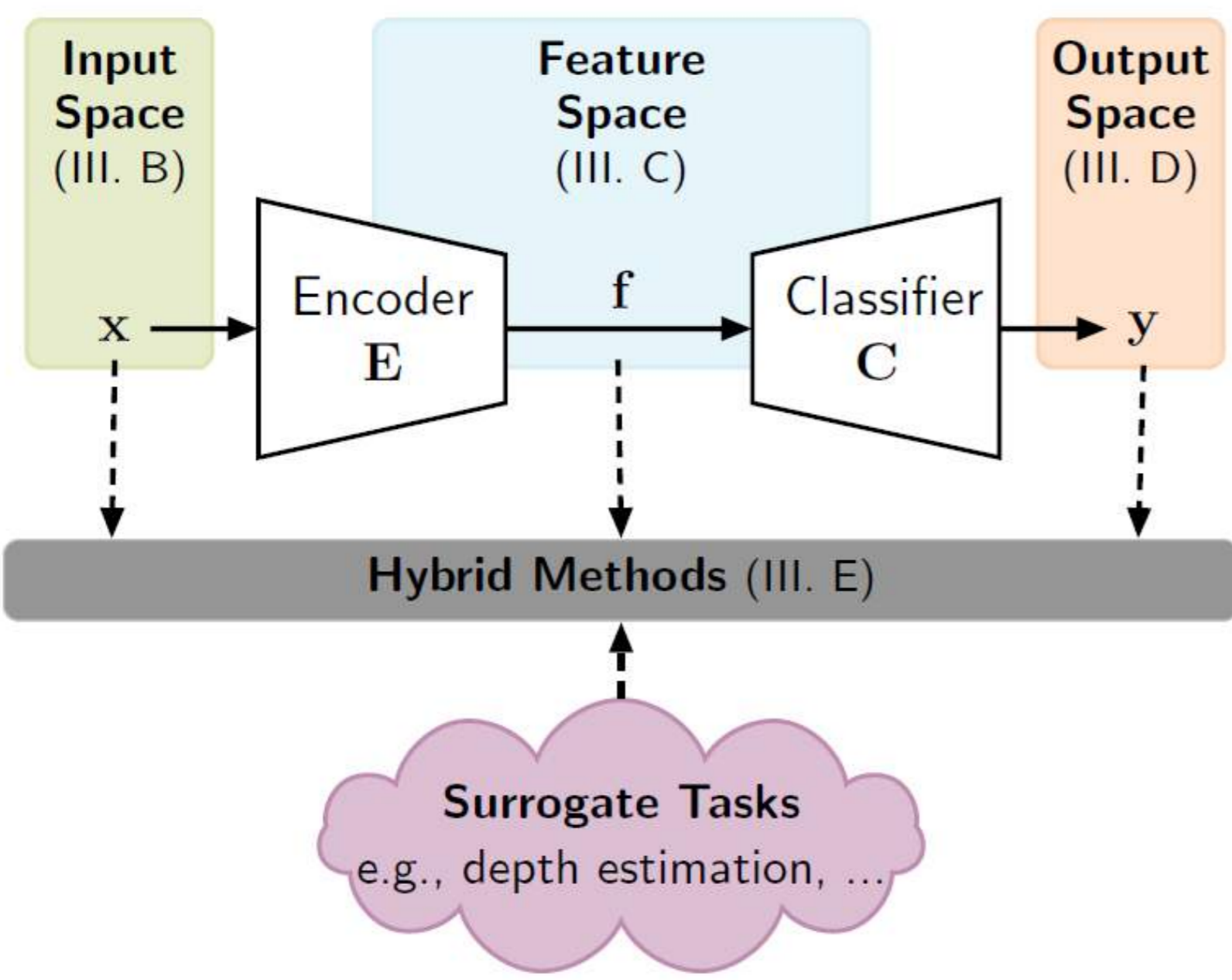


Figure 3: Taxonomy of UDA approaches

Categorization of approaches: Input, feature and output and if combined hybrid space

(1) Input Space

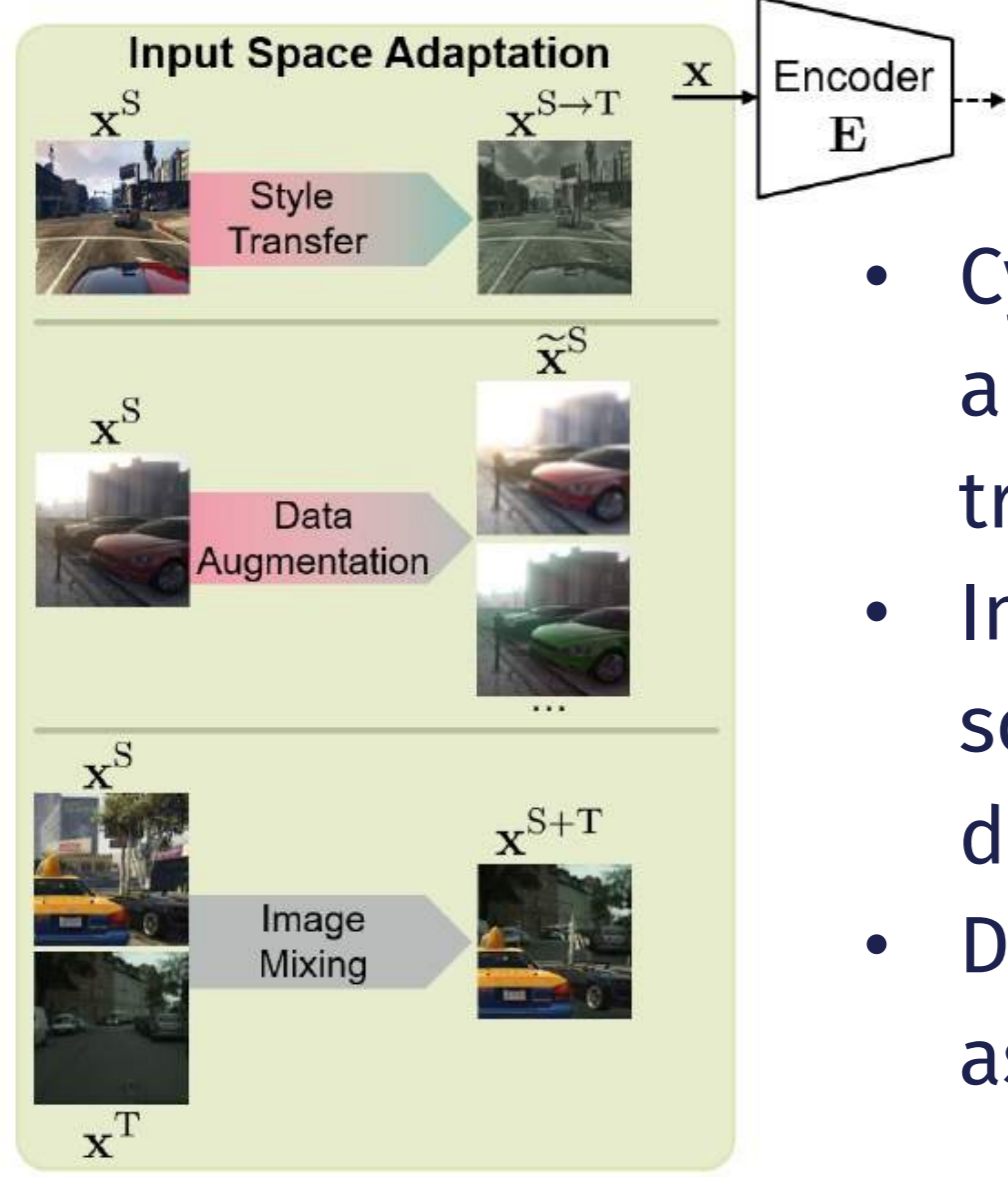


Figure 4: Input Space UDA approaches

- CycleGAN often applied for style transfer
- Image mixing to mix source and target domain
- Data augmentation as simple alternative

(2) Feature Space

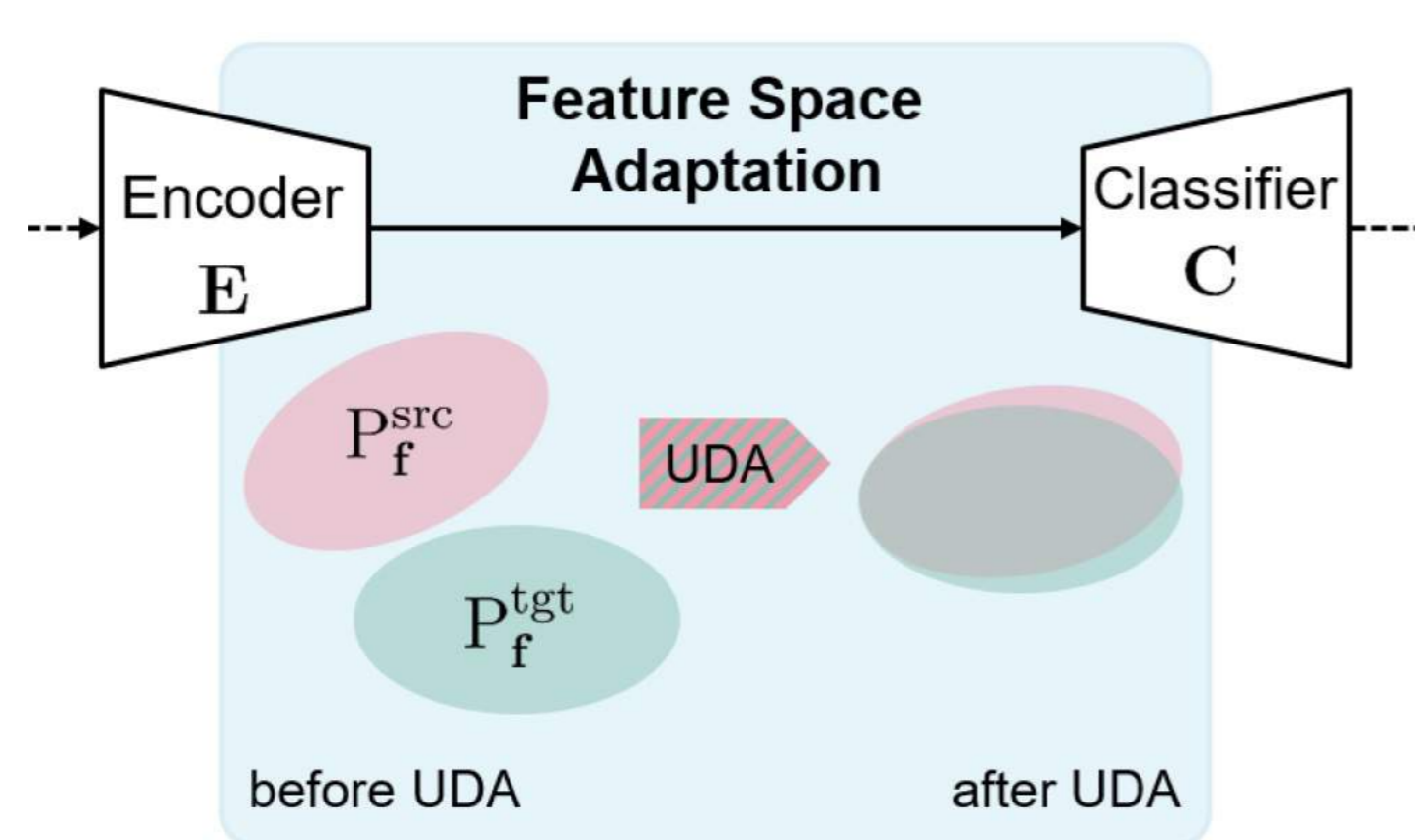


Figure 5: Feature Space UDA scheme

(3) Output Space

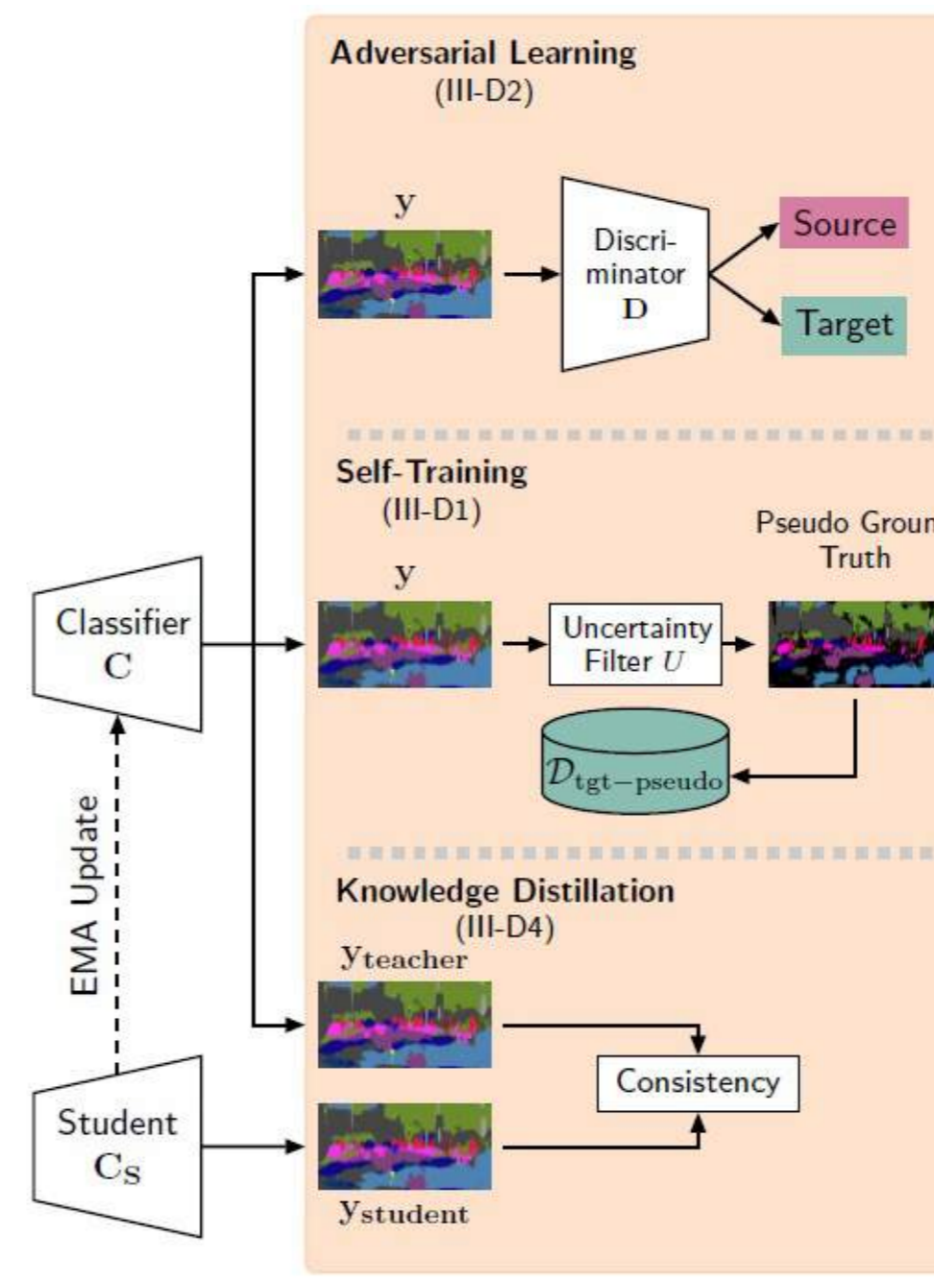


Figure 6: Output Space UDA Approaches

- Self-Training and adversarial learning most popular output space techniques
- knowledge distillation became more popular

Quantitative Analysis

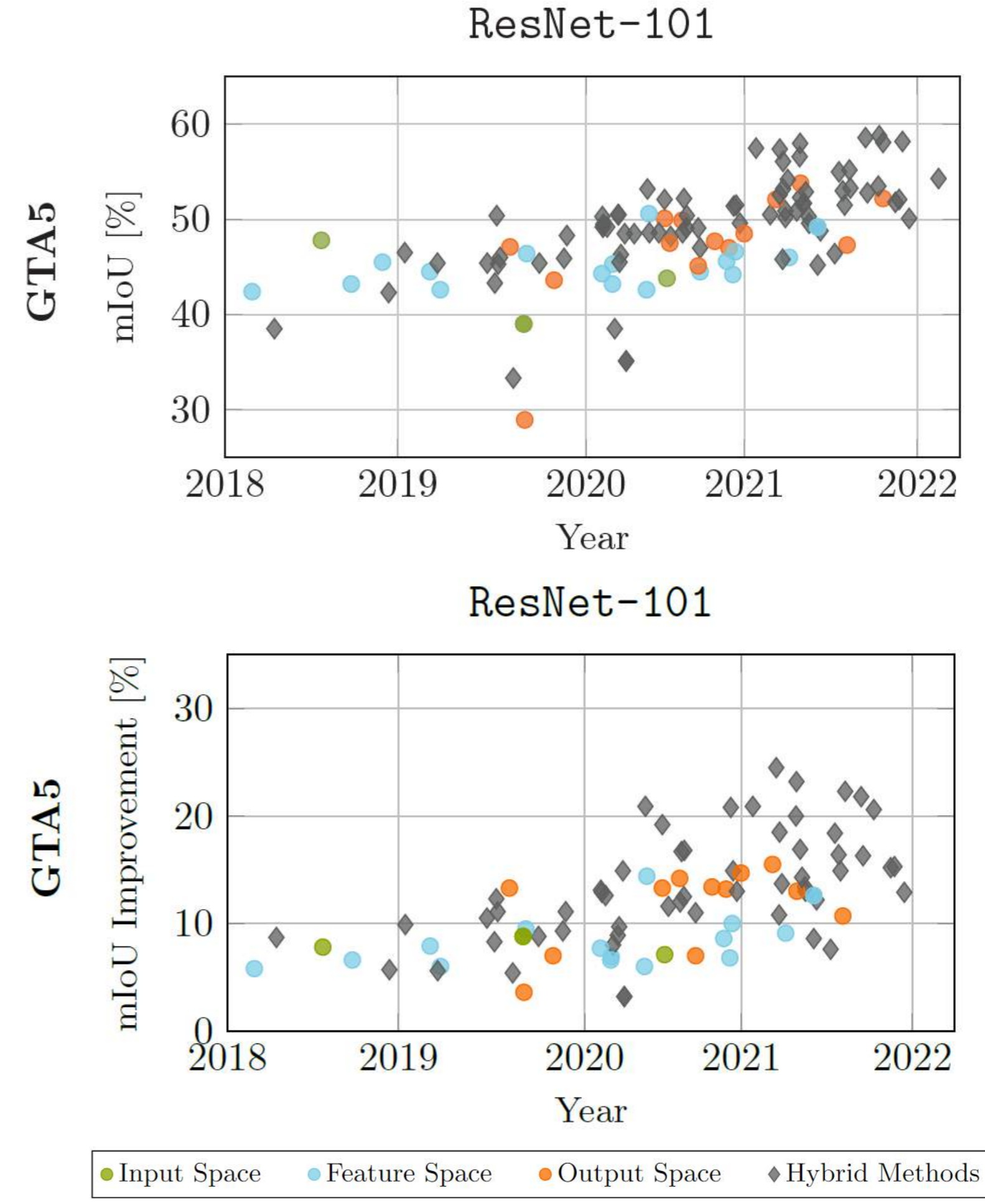


Figure 7: Meta Analysis over time of UDA approaches

→ Hybrid approaches cause significant performance boost but more complex
→ Vision transformer set new SOTA performance

Analysis

Several aspects impede UDA research and comparability:

- Dataset split, checkpoint selection
- Hyperparameters
- Complex hybrid frameworks

Conclusions & Future Work

UDA made significant progress over the past years, vision transformer raised the performance to a new-level.

Future Research Directions:

- New architectures
- Large-scale, industrial UDA
- Domain generalization

Partners



External partners

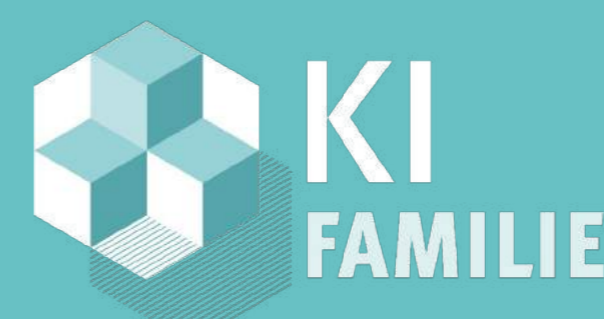


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Supported by:

