Continual Learning in Real-World Scenarios

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AI GRID

Promises of an AI-Driven Future

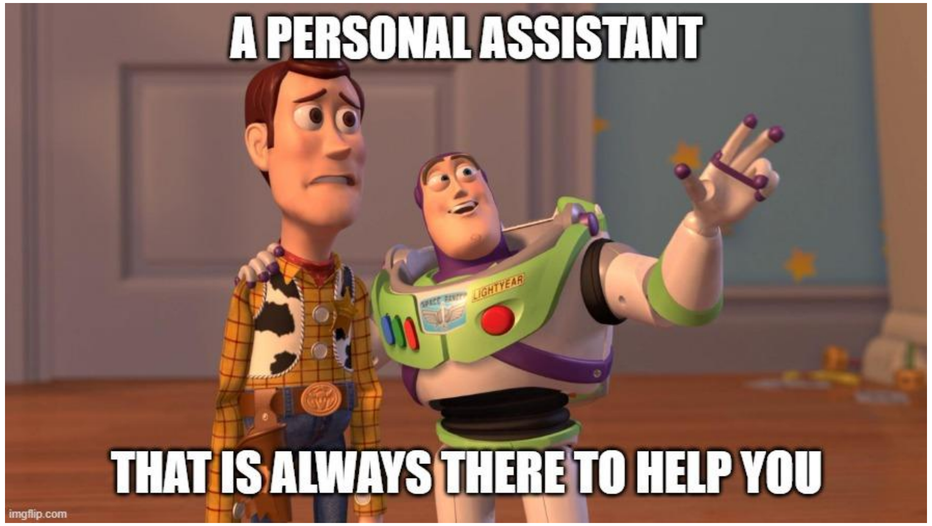
Smart Wearable Assistants

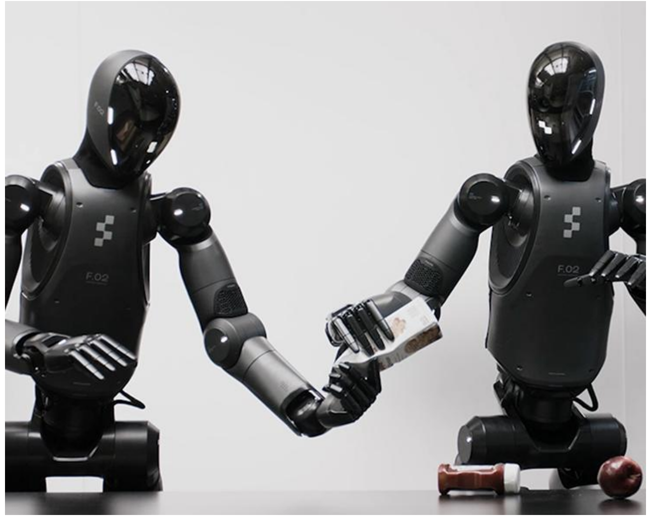
Embodied Agents

Sustainable Automation

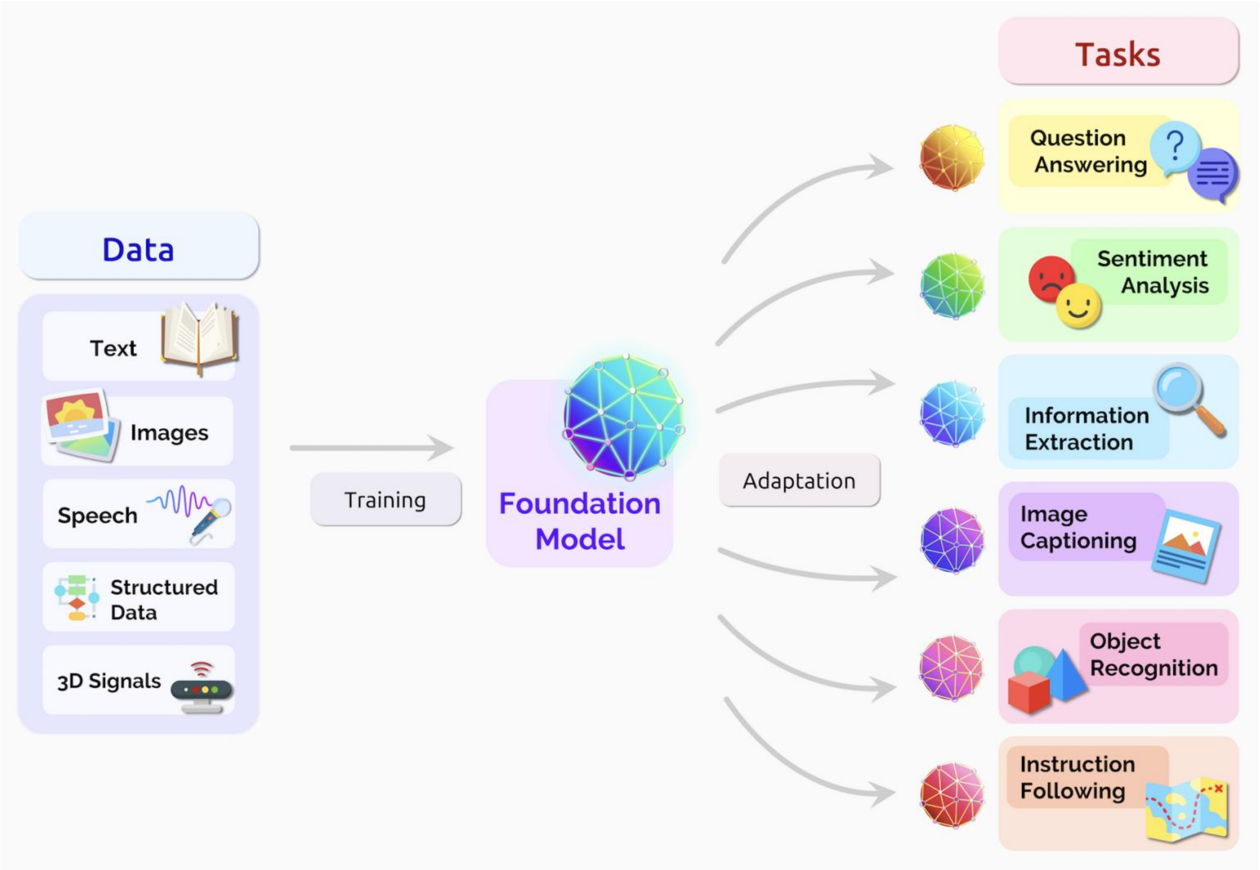
Human-AI Collaboration

- AI models are becoming increasingly more capable and powerful.
- Researchers and Policymakers anticipate development of Generally Intelligent systems, capable of increasing autonomy.
- But is this trend sustainable?





Foundation Models and AI Agents



- Current pretraining and post training recipes have mastered the art of scaling up data, compute and model size.
- This has led to ever-increasing capabilities in AI models and agentic pipelines.
- However, this cannot be conflated with "General Intelligence".
- Real-world changes necessitate such systems to be efficient and lifelong learners.
- Training these models is energy-intensive. Once trained, they cannot effectively learn from new data without **catastrophic forgetting**.
- This area of research is called **Continual Learning** or **Incremental Learning** or **Lifelong Learning**.

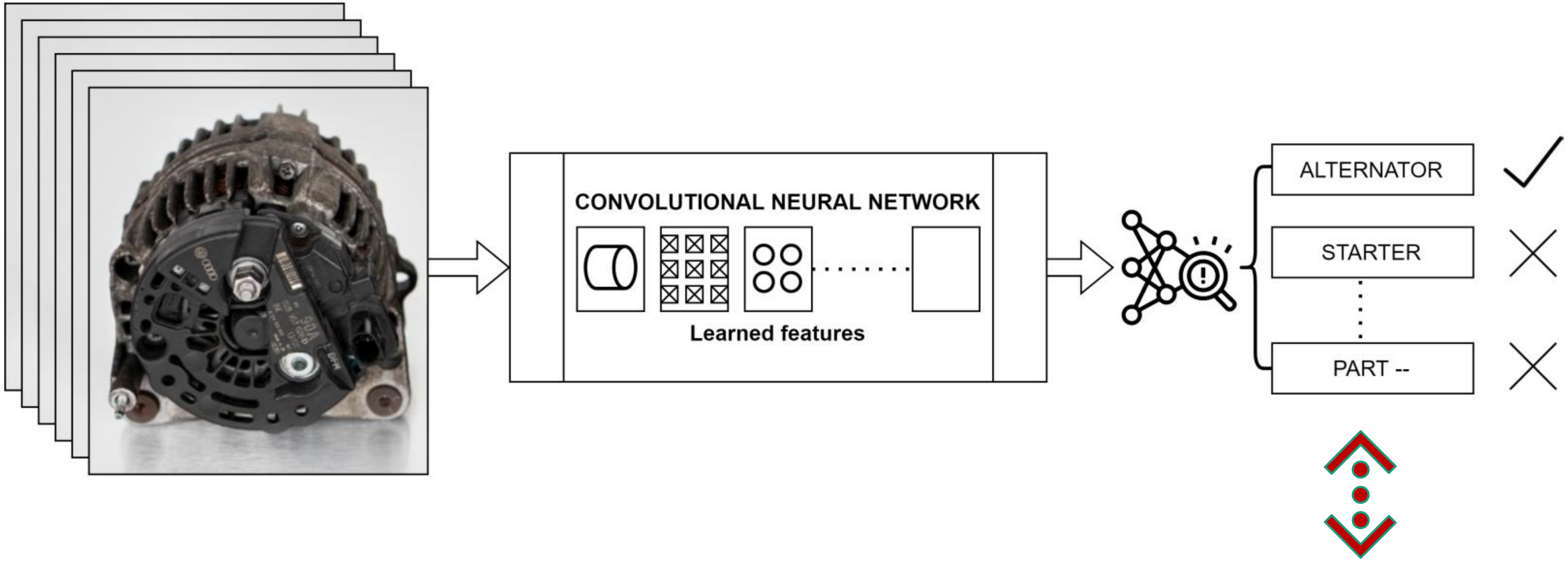
„Intelligence is the ability to adapt to change“

\- Stephen Hawking

Traditional Machine Learning Workflow

Traditional Continual Learning research considers simplified scenarios, with new data coming in periodically, which the model must learn from.

Model performance on a predefined task (e.g. Top-1 classification accuracy) is generally the benchmarking metric.

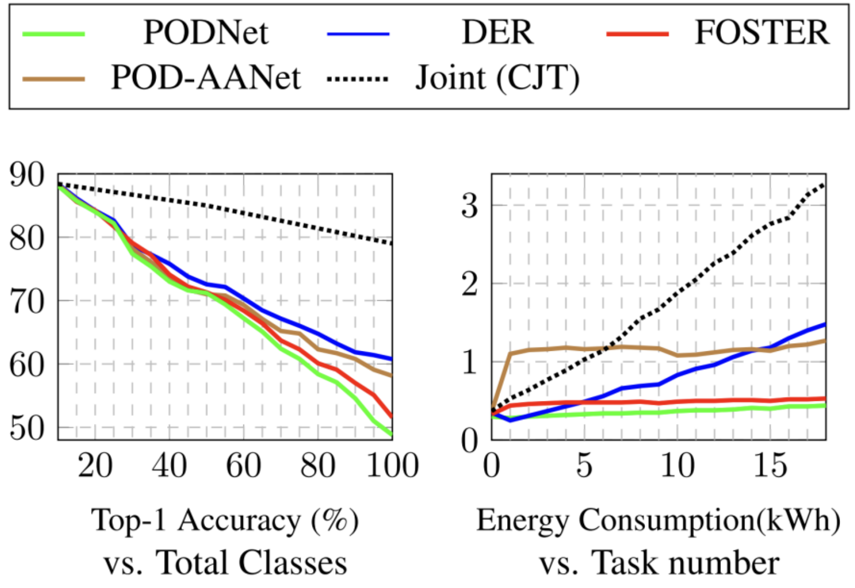


Our Contribution

We want Continual Learning to be practically adopted in industrial AI and real-world applications!

We argue that conventional research must consider additional factors for understanding the efficacy of a Continual Learning approach:

1. **Carbon Footprint or Energy Consumption.**
2. **The impact of data on the ability of ML models to learn continually.**



Top-1 Accuracy and **Task-wise Energy Consumption** for ImageNet-Subset for different Continual Learning approaches. The total energy consumption of an approach is given by the area under the curve. **Comparing the methods using only accuracy provides an incomplete understanding; computational footprint consideration is also important.**

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Carbon Footprint or Energy Consumption.

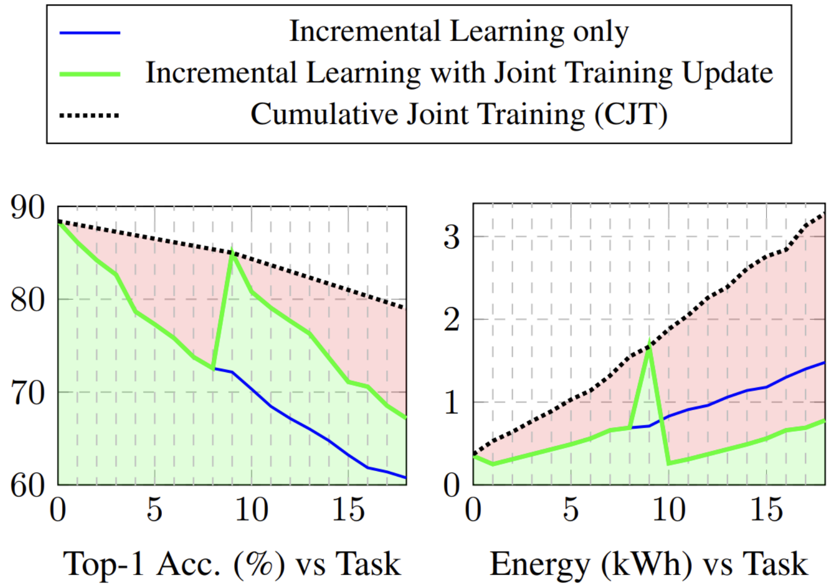
For computational footprint considerations, we measure the computational complexity in terms of Floating Point Operations (FLOPs) or Multiply–Accumulate Operations (MACs).

$$\#FLOPs = \sum_i FLOP_i = \sum_i \sum_{n_i} FLOP_s$$

We verify these calculations by measuring the energy consumption using a dedicated workstation connected to a smart power metering setup.

$$E_{CIL} = \sum_i^T E_i$$

We introduce the concept of periodic **Joint Training Update** for lifelong learning systems, where the model is retrained on all available data with the aim of minimizing the carbon footprint.



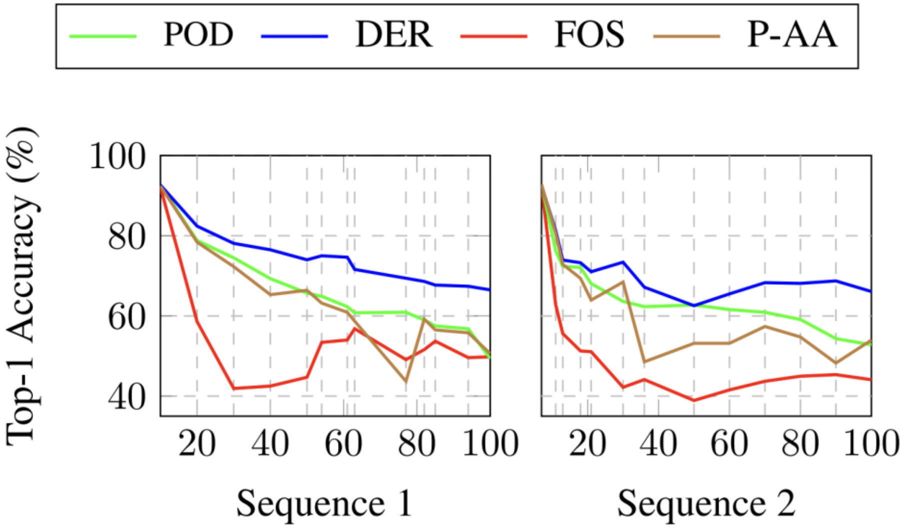
What is the optimal configuration of tasks T that can be performed using IL, in tandem with periodic update that yields acceptable performance based on accuracy and computational requirements for the application?

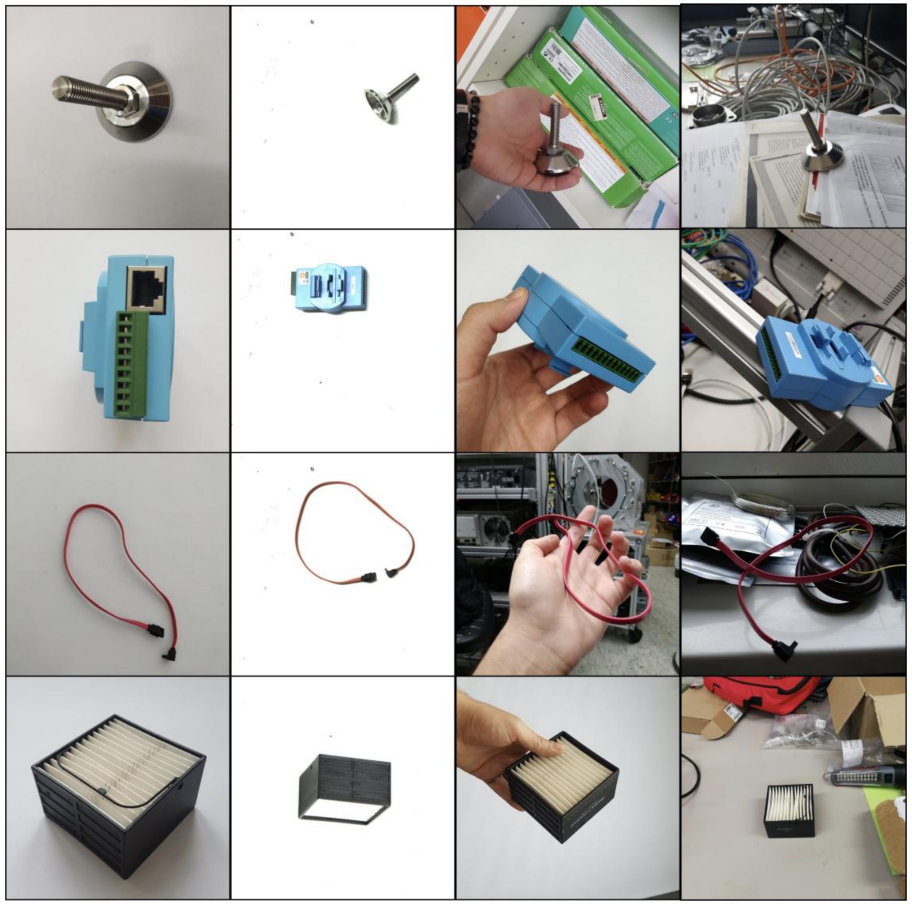
The impact of data on the ability of ML models to learn continually.

We introduce a novel dataset of **Industrial Objects in Varying Contexts (InVar-100).**

Additionally, we propose that real-world Continual Learning should be developed and benchmarked or **varying task increments** and contexts.

Current bemchmarks and methods fail to consider the impact of this variance on Continual Learning ability.





(a) White (b) Stationary (c) Handheld (d) Cluttered

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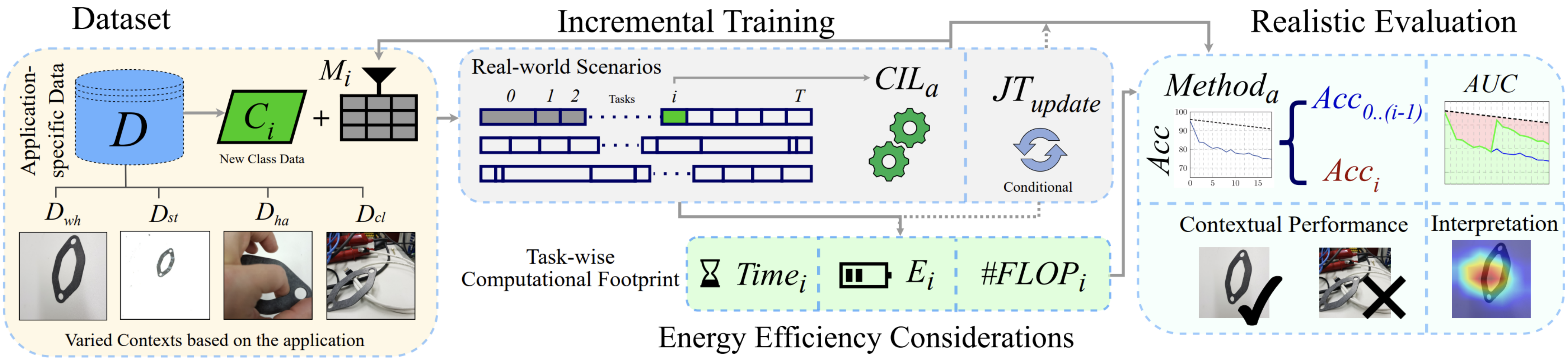
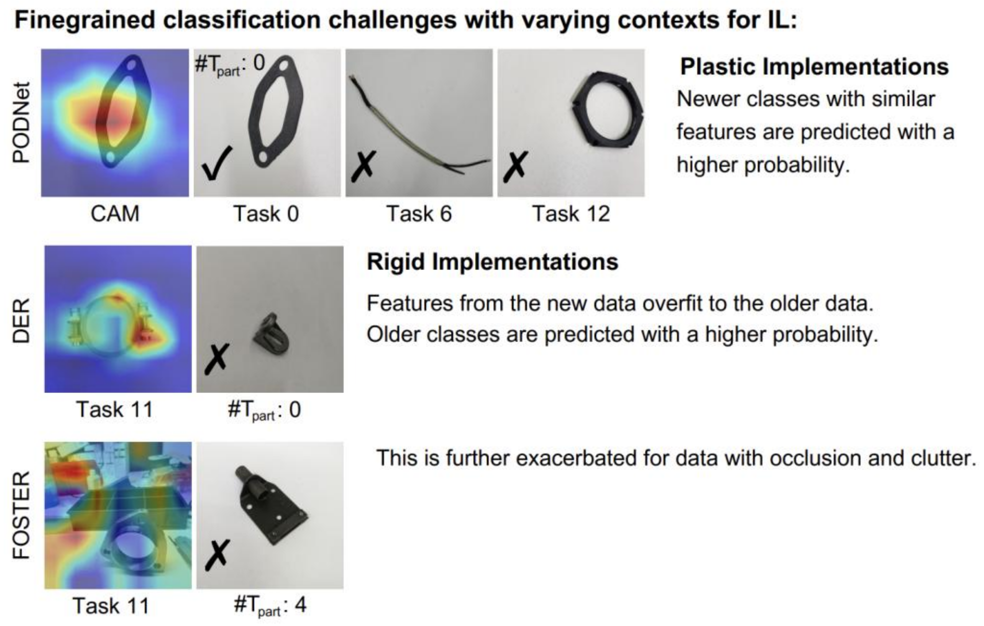
Real-world scenarios and Enegry Efficiency Considerations



A summary of the RECIL approach. The application-specific data is used to assess the CL implementations for different incremental learning scenarios. Task-wise model energy consumption (*Ei*) and model performance are reported (New classes: *Acci* , *Old classes: Acc0..(i-1))* for each task *i*. For long project timelines, AUC metrics are reported. Explainability (Class-Activations) are studied to understand model plasticity, rigidity and contextual performance.

Results and Observations

- Certain approaches to Continual Learning are more **plastic** (i.e. they readily learn from new data, but also forget old learning easily), and others are more **rigid** (i.e. they retain old learning easily, but struggle to learn from new data).
- Our experiments show that the **complexity of data** (e.g. visual clutter, occlusion) **negatively impacts the model accuracy** (i.e. the model can learn from clean data much easier than messy data).
- Performance on standardised benchmarks and well-curated data does not transfer to practical use cases.
- Putting the **model performance** in relation to the **energy consumption**, **training times** or **computational complexity** provides a fair and comprehensive comparison between CL approaches.
- An emphasis on **Green AI** is essential for a sustainable, broad-scale adoption of Continual Learning in real-world applications.



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Towards Realistic Evaluation of Industrial Continual Learning Scenarios with an Emphasis on Energy Consumption and Computational Footprint

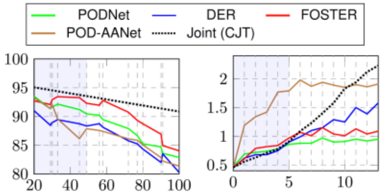
Vivek Chavan*, Paul Koch, Marian Schlüter, Clemens Briese

Code & Dataset

ICCV23 PARIS
International Conference on Computer Vision
October 2 - 6, 2023

Overview

Comparing the Incremental Learning (IL) methods using accuracy provides an incomplete understanding; Computational Footprint consideration is also important.



Top-1 Accuracy (%) vs. Total Classes

Energy Consumption (kWh) vs. Task Number

Industrial use cases: Reduction in training time and lower energy consumption are essential for adopting IL.

✗ Which IL implementation yields the highest incremental accuracy?

✓ Optimal configuration of IL-Tasks that yield acceptable performance based on accuracy and computational requirements for the application?

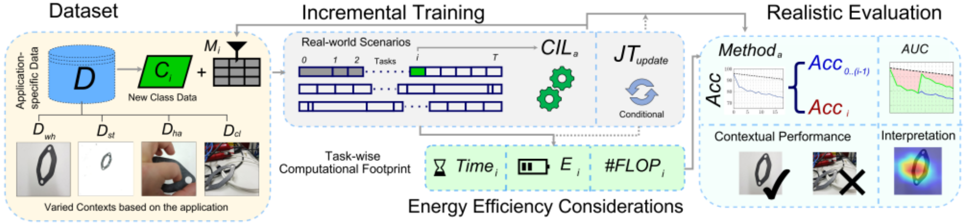
InVar-100 Dataset

Industrial Objects in Varied Contexts

Multimodal Dataset with object metadata.
Objects and Contexts relevant to industrial use cases.

D_{wh}	D_{st}	D_{ha}	D_{cl}
White Background	Stationary Setup	Handheld	Cluttered Background

Real-world scenarios and Enegry Efficiency Considerations



Extend the current CIL protocol to real-world use cases.

✓ Varying Task Sizes.

✓ Understanding Plasticity and Rigidity tradeoff better.

✓ Focus on overall sustainability of implementation.

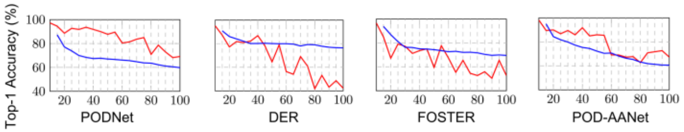
Extending Accuracy and Computaional Footprint Evaluation to practical use cases:

$$AUC_{acc} = \frac{\sum_{i=0}^{T} acc_i \times w_i}{\sum_{i=0}^{T} acc_i^{joint}} = \frac{AUC_{acc(CIL)}}{AUC_{acc(CJT)}} \qquad AUC_e = \frac{E_{CIL}}{E_{CJT}} = \frac{AUC_{e(CIL)}}{AUC_{e(CJT)}} \qquad \#FLOPs = \sum_i FLOP_i = \sum_i \sum_{n_i} FLOP_s$$

Experiments

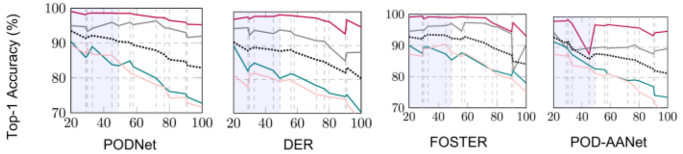
Old Classes (Rigidity) — New Classes (Plasticity)

Comparing performance on *Old* and *New* data provides a better understanding of *Plasticity* and *Rigidity*.



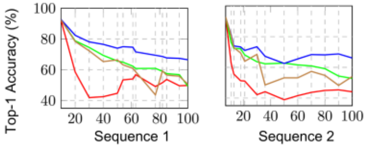
D_{wh} — D_{st} — D_{ha} — D_{cl} — Full

IL performance on data in varying visual contexts and varying task sizes. Performance on *Challenging* subcategories drops more rapidly.



POD — DER — FOS — P-AA

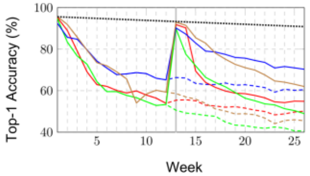
Two different sequences of IL Tasks. The class order remains identical; however, performance fluctuates considerably. This was not observed with constant task sizes.

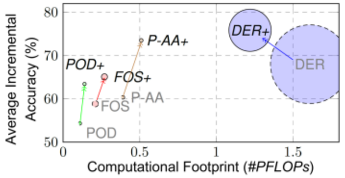


CIL only — CIL w/JT_{update}+ — CJT

Introducing a Joint Training Update in tandem with IL in long task sequences based on project requirements.

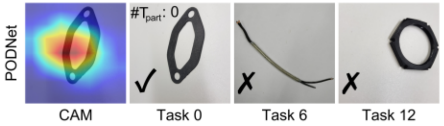
The radius corresponds to the model size at the end of IL-Training.



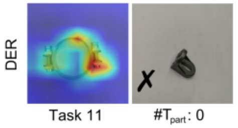


Discussion

Finegrained classification challenges with varying contexts for IL:



Plastic Implementations
Newer classes with similar features are predicted with a higher probability.



Rigid Implementations
Features from the new data overfit to the older data. Older classes are predicted with a higher probability.

This is further exacerbated for data with occlusion and clutter.

Project Implementability:

Optimal configuration of IL-Tasks in a continual project depends on the requirements, the quality of data and its availability.

Performance and computational footprint trade-off generally depends on the dataset, IL methods, and setup.

Conclusion

Putting the incremental accuracy in relation to the energy consumption, training times or computational complexity provides a fair and comprehensive comparison between IL approaches.

Performance on standardised benchmarks and well-curated data does not transfer to practical use cases.

An emphasis on Green AI is essential for a sustainable, broad-scale adoption of IL research in real-world applications.

References

[POD] Douillard et al., *PODNet: Pooled Outputs Distillation for Small-Tasks Incremental Learning.* In ECCV 2020
[DER] Yan et al., *DER: Dynamically Expandable Representation for Class Incremental Learning.* In CVPR 2021
[FOS] Wang et al., *Foster: Feature boosting and compression for class-incremental learning.* In ECCV 2022
[P-AA] Liu et al., *Adaptive Aggregation Networks for Class-Incremental Learning.* In CVPR 2020

Acknowledgements

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FONA Research for Sustainability

Further details and context in our paper:

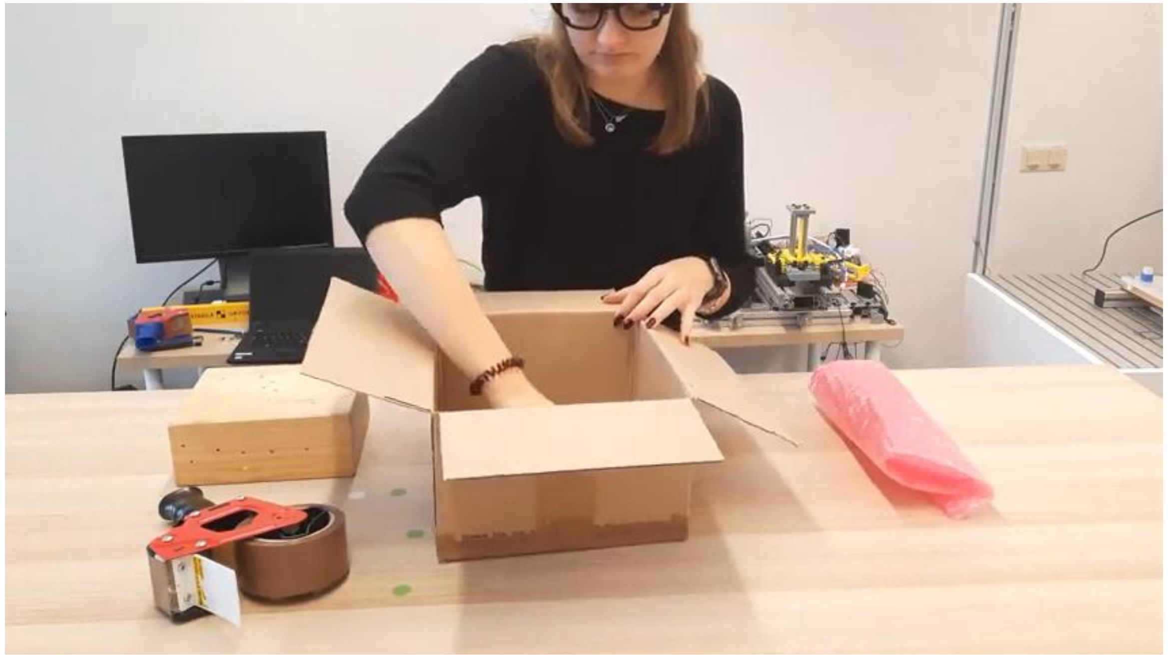
Towards Realistic Evaluation of Industrial Continual Learning Scenarios with an Emphasis on Energy Consumption and Computational Footprint

In ICCV 2023

Paper, Dataset and Code

Extension: Egocentric Vision and Video Data

- Video data, esp. from first person perspective introduces new challenges and opportunities.
- AI Agents and assistants must **continually learn** from always-on streams of multimodal data.



Exocentric/Allocentric/Third-Person View

Egocentric/First-Person View

Imagine a Future…

Smart Wearable Assistants

Embodied Agents

Sustainable Automation

Human-AI Collaboration

AI systems capable of robust, efficient and adaptable performance in real-world dynamic conditions can fulfil these promises of technological development and a sustainable future!