Continual Learning: On Machines that can Learn Continually

Official Open-Access Course @ University of Pisa, ContinualAI, AIDA

Lecture 4: Evaluation & Metrics

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Evaluation Protocols

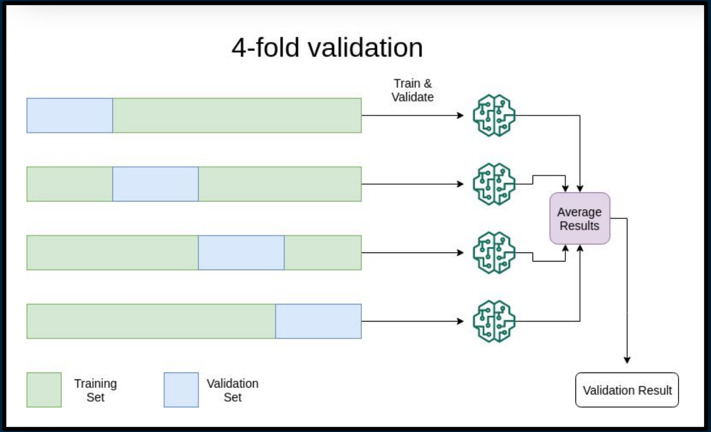
Classic ML Evaluation

Train - Validation - Test split

- **Model selection**: train on training set, eval on validation set
- **Model assessment**: train on training (+ validation) set, eval on test set

Variations allowed

- **K-fold** Cross-Validation
- Leave-one-out
- ...



Test, training and validation sets (brainstobytes.com)

Evaluating Machine Learning Models, by Alice Zheng, 2015.

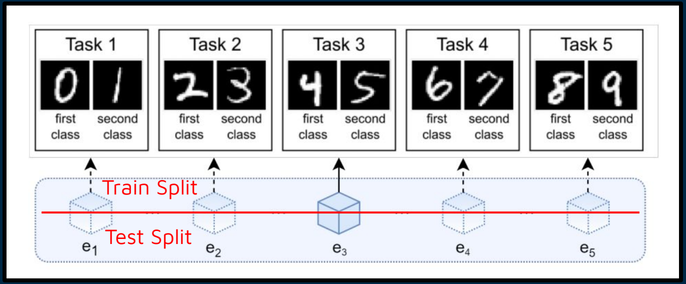
Basic CL Evaluation Protocol

Different Data

- Classic *Machine Learning* -> **static dataset**
- *Continual Learning* -> **stream of datasets** (experiences)

A Simple Extension to CL

- **Split by patterns**: one train-(validation)-test per experience (or *parallel streams* of experiences)
- This is the **simplest** and **most common** evaluation protocol



The objective of a CL algorithm is to minimize the loss $\mathcal{L}_S$ over the entire stream of data S:

$$\mathcal{L}_S(f_n^{CL}, n) = \frac{1}{\sum_{i=1}^{n} |\mathcal{D}_{test}^i|} \sum_{i=1}^{n} \mathcal{L}_{exp}(f_n^{CL}, \mathcal{D}_{test}^i) \tag{2}$$

$$\mathcal{L}_{exp}(f_n^{CL}, \mathcal{D}_{test}^i) = \sum_{j=1}^{|\mathcal{D}_{test}^i|} \mathcal{L}(f_n^{CL}(\boldsymbol{x}_j^i), y_j^i), \tag{3}$$

where the loss $\mathcal{L}(f_n^{CL}(\boldsymbol{x}), y)$ is computed on a single sample $\langle \boldsymbol{x}, y \rangle$, such as cross-entropy in classification problems.

Split by Patterns

- **Training phase**: train the model on **training sets** of each experience, sequentially
- **Test phase**: evaluate the model on **the sets** of the experiences (order does not matter)
- Examples in the training and test sets **are disjoint**!
- We may have a **single test set** or **one for each experience**
- **Multiple evaluation streams are possible** (Valid, Test, Out-of-Distribution, etc.)
- **Cross-Validation** & **Hyper-parameters** selection can be operated based on the final aggregate metric at the end of the training.

When and What to Test On

When to test?

- **At the end of each experience**, usually.
- A finer granularity is always possible (*epochs*, *iterations*, etc.)

On what to test?

- **Current** experience
- **Future** experiences
- **Past** experiences
- **All** experiences
- …

…depending also on the metrics you want to use!

Growing vs Fixed Test Set

Growing Test Set

- We consider only the test set of the **current and previously encountered** experiences
- Compute the performance metrics average over those

Fixed test set

- Common for some benchmarks
- Clear view on **overall system performance**
- Recover experience-wise performance, if needed

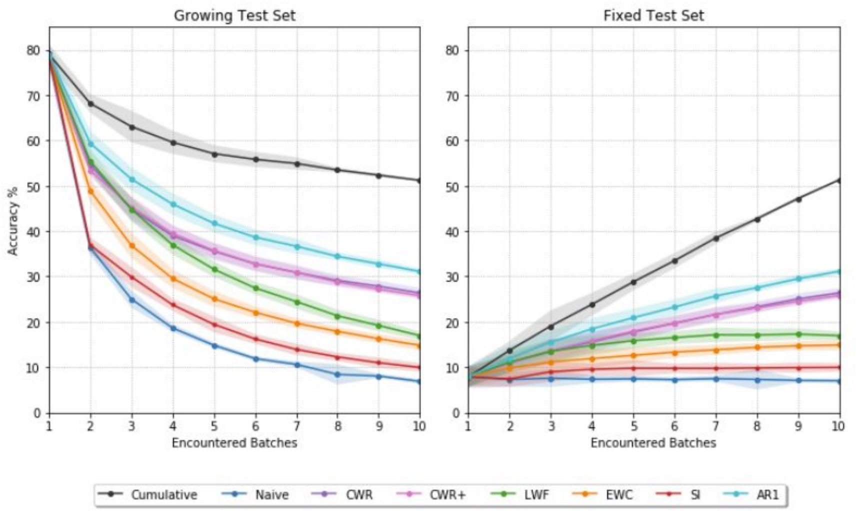
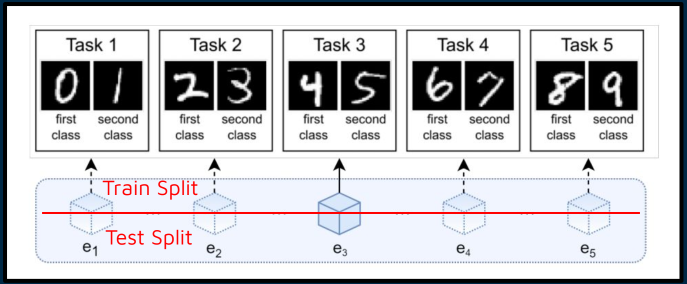


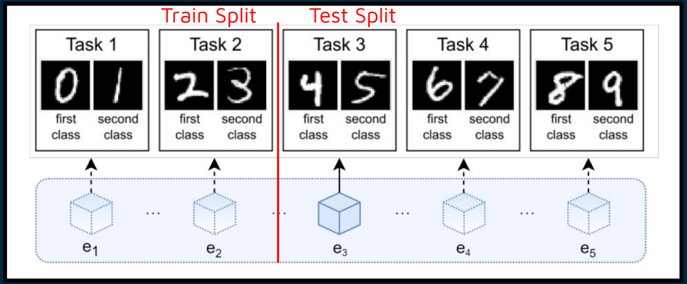
Figure 8: Accuracy on iCIFAR-100 with 10 batches (10 classes per batch). Results are averaged on 10 runs: for all the strategies hyperparameters have been tuned on run 1 and kept fixed in the other runs. The experiment on the right, consistently with CORe50 test protocol, considers a fixed test set including all the 100 classes, while on the left we include in the test set only the classes encountered so far (analogously to results reported in [28]). Colored areas represent the standard deviation of each curve. Better viewed in color.

Continuous Learning in Single-Incremental-Task Scenarios. Maltoni & Lomonaco, Neural Networks Journal 2019.

Is it Enough for CL?

- **Split by patterns**: one train-validation-test per experience (or *parallel streams* of experiences)
- *But is it enough for Continual Learning? ->* we would like a way to evaluate if we are **actually able** to learn continually!
- **Split by experiences**: **model selection** on a first set of experiences, **model assessment** on a second set of experiences
- Model assessment **should also involve training**.





Efficient Lifelong Learning with A-GEM Chaudhry et. al. ICLR, 2019.

Hyper-parameters Selection for CL

- We mentioned **Hyper-parameters** selection can be operated based on the final aggregate metric at the end of the training
- But this may be seen as **a form of cheating**: we select the best hyperparameters that maximize the the performance on a specific sequence of training experiences
- We may partially solve this with **several runs** with a **random order** of the training experiences
- This may be still **unfair**: we should calibrate hyper-parameters on a **limited set of experiences**

Class-incremental learning: survey and performance evaluation on image classification. Masana et al. 2020.
A continual learning survey: Defying forgetting in classification tasks. De Lange et al, 2019.

A more Articulated Protocol: An Example

- **Model selection**: train the model on a first split of experiences, select best *hyperparameters* with a cross-validation scheme.

- **Model assessment**: train & evaluate the CL algorithm on a second split of experiences

Algorithm 1 Learning and Evaluation Protocols

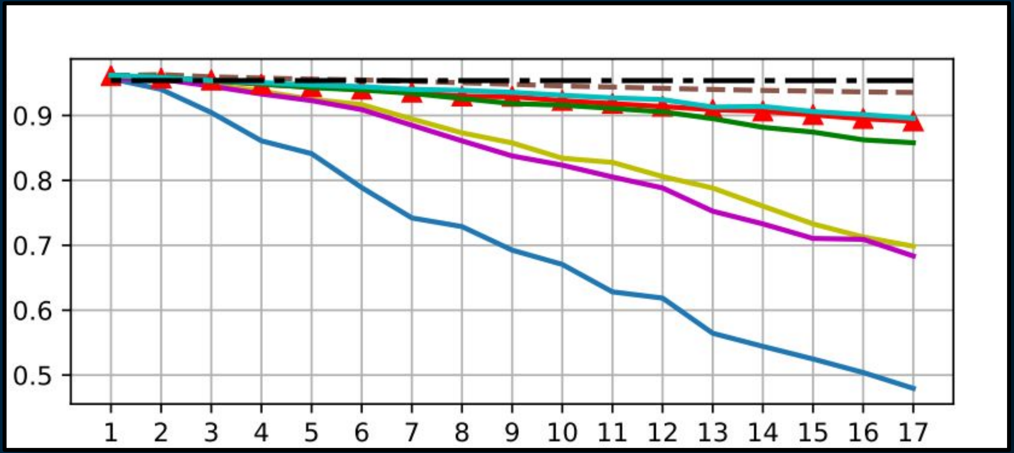
for h **in** hyper-parameter list **do** ▷ Cross-validation loop, executing multiple passes over $\mathcal{D}^{CV}$
  for $k = 1$ **to** T^{CV} **do** ▷ Learn over data stream $\mathcal{D}^{CV}$ using h
    for $i = 1$ **to** n_k **do** ▷ Single pass over $\mathcal{D}_k$
      Update f_θ using $(\mathbf{x}_i^k, t_i^k, y_i^k)$ and hyper-parameter h
      Update metrics on test set of $\mathcal{D}^{CV}$
    end for
  end for
end for
Select best hyper-parameter setting, h^*, based on average accuracy of test set of $\mathcal{D}^{CV}$, see Eq. 1.
Reset f_θ.
Reset all metrics.
for $k = T^{CV} + 1$ **to** T **do** ▷ Actual learning over datastream $\mathcal{D}^{EV}$
  for $i = 1$ **to** n_k **do** ▷ Single pass over $\mathcal{D}_k$
    Update f_θ using $(\mathbf{x}_i^k, t_i^k, y_i^k)$ and hyper-parameter h^*
    Update metrics on test set of $\mathcal{D}^{EV}$
  end for
end for
Report metrics on test set of $\mathcal{D}^{EV}$.

Efficient Lifelong Learning with A-GEM Chaudhry et. al. ICLR, 2019.

Continual Learning
Metrics

What to Monitor?

- Performance on **current experience**
- Performance on **past experiences**
- Performance on **future experiences**
- **Resource consumption**
  (Memory / CPU / GPU / Disk usage)
- **Model size growth**
  (with respect to the first model)
- Execution **time**
- **Data efficiency**
- …



Gradient Episodic Memory for Continual Learning, Lopez-Paz et al. NIPS, 2017.
Continual learning for robotics: Definition, framework, learning strategies, opportunities and challenges, Lesort et al. Information Fusion, 2020.

Accuracy

Q: How accurate is my model?

In many different sauces

- *Accuracy on the current experience*
- *Accuracy on previous experiences (plus the current one)*
- *Accuracy on future experiences (plus the current one)*

ACC Metric

- After training on all experiences, **average accuracy** over all the test experiences.

A Metric

- Average of the accuracy on all experiences **at any point in time**.

R	Te_1	Te_2	Te_3
Tr_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$
Tr_2	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$
Tr_3	$R_{3,1}$	$R_{3,2}$	$R_{3,3}$

$$\textbf{Average Accuracy: } \mathrm{ACC} = \frac{1}{T}\sum_{i=1}^{T} R_{T,i}$$

$$A = \frac{\sum_{i=1}^{N}\sum_{j=1}^{i} R_{i,j}}{\frac{N(N+1)}{2}}$$

Don't forget, there is more than forgetting: new metrics for Continual Learning, Rodriguez-Diaz et al. CL Workshop @ NeurIPS, 2018.
Gradient Episodic Memory for Continual Learning. Lopez-Paz & Ranzato, NeurIPS 2017.

Forward Transfer

Q: How much learning the current experience improves my performance on future experiences?

FWT Metric

- Accuracy on experience *i* after training on last experience Minus
- Accuracy on experience *i* before training on the first experience (model init)
- Averaged over $i=2,\dots,T$

R	Te_1	Te_2	Te_3
Tr_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$
Tr_2	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$
Tr_3	$R_{3,1}$	$R_{3,2}$	$R_{3,3}$

$$\text{FWT} = \frac{1}{T-1}\sum_{i=2}^{T} R_{i-1,i} - \bar{b}_i.$$

Gradient Episodic Memory for Continual Learning. Lopez-Paz & Ranzato, NeurIPS 2017.

Backward Transfer

Q: How much learning the current experience improves my performance on previous experiences?

BWT Metric

- Accuracy on experience *i* after training on experience T Minus
- Accuracy on experience *i* after training on experience *i*
- Averaged over i=1,...,T-1

FORGETTING = - BWT

R	Te_1	Te_2	Te_3
Tr_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$
Tr_2	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$
Tr_3	$R_{3,1}$	$R_{3,2}$	$R_{3,3}$

$$\text{BWT} = \frac{1}{T-1} \sum_{i=1}^{T-1} R_{T,i} - R_{i,i}$$

Gradient Episodic Memory for Continual Learning. Lopez-Paz & Ranzato, NeurIPS 2017.

Memory

Not only performance

- **How much space does your model occupy**? (MB, # of params, etc.)
- **What is the increment** in space required for each new experience?
- How much space do you require for **additional information** (replay buffer, past models…)?

$$MS = min(1, \frac{\sum_{i=1}^{N} \frac{Mem(\theta_1)}{Mem(\theta_i)}}{N})$$

$$SSS = 1 - min(1, \frac{\sum_{i=1}^{N} \frac{Mem(M_i)}{Mem(D)}}{N})$$

Don't forget, there is more than forgetting: new metrics for Continual Learning, Rrodriguez-Diaz et al. CL Workshop @ NeurIPS, 2018.

Computation

Not only performance

- What is the **computational overhead** during training? (# MACs, Running Time, GPU/CPU time, ...)
- What about its **increment over time**?
- What is the computational overhead **during inference**?

$$CE = min(1, \frac{\sum_{i=1}^{N} \frac{Ops\uparrow\downarrow(Tr_i)\cdot\varepsilon}{1+Ops(Tr_i)}}{N})$$

Don't forget, there is more than forgetting: new metrics for Continual Learning, Rrodriguez-Diaz et al. CL Workshop @ NeurIPS, 2018.

Don't Forget: There is More than Forgetting!

A plethora of other possible metrics

- *Accuracy vs offline baseline*
- *Model Robustness*
- *Model Plasticity & Capacity*
- *...*

More complex Score Functions

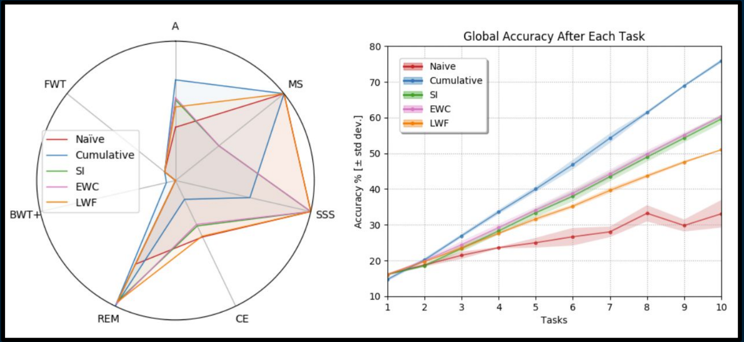
- Additional, more informative **derived metrics** can be devised as well.
- They can be **tuned depending on the specific application goals**.

$$CL_{score} = \sum_{i=1}^{\#\mathcal{C}} w_i c_i$$

$$CL_{stability} = 1 - \sum_{i=1}^{\#\mathcal{C}} w_i stddev(c_i)$$

Table 1: CL metrics and CL_{score} for each CL strategy evaluated (higher is better).

Strategy	A	REM	BWT⁺	FWT	MS	SSS	CE	CL_{score}	$CL_{stability}$
Naïve	0.3825	0.6664	0.0000	0.1000	**1.0000**	**1.0000**	**0.4492**	0.5140	**0.9986**
Cumul.	**0.7225**	**1.0000**	**0.0673**	0.1000	**1.0000**	0.5500	0.1496	0.5128	0.9979
EWC	0.5940	0.9821	0.0000	0.1000	0.4000	**1.0000**	0.3495	0.4894	0.9972
LWF	0.5278	0.9667	0.0000	0.1000	**1.0000**	**1.0000**	0.4429	**0.5768**	**0.9986**
SI	0.5795	0.9620	0.0000	0.1000	0.4000	**1.0000**	0.3613	0.4861	0.9970



[Don't forget, there is more than forgetting: new metrics for Continual Learning](), Rrodriguez-Diaz et al. CL Workshop @ NeurIPS, 2018.

Summing Up

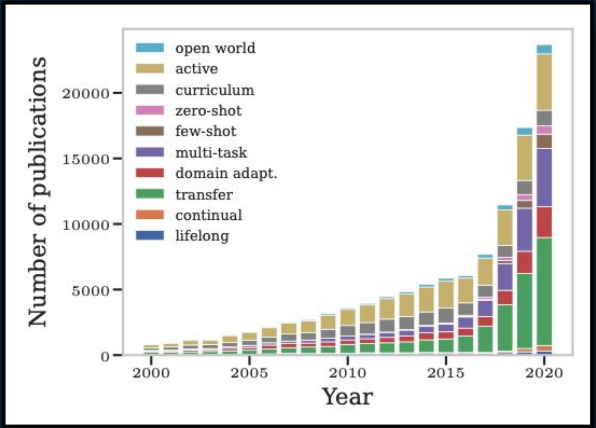
- Choose an evaluation protocol and **declare** it (no *standard*, yet)
- Choose the metrics you monitor wisely (**what are you interested in?**)
- **Do not focus exclusively on performance metrics**, if possible

Q: you can achieve low/zero forgetting by occupying a lot of space. How?

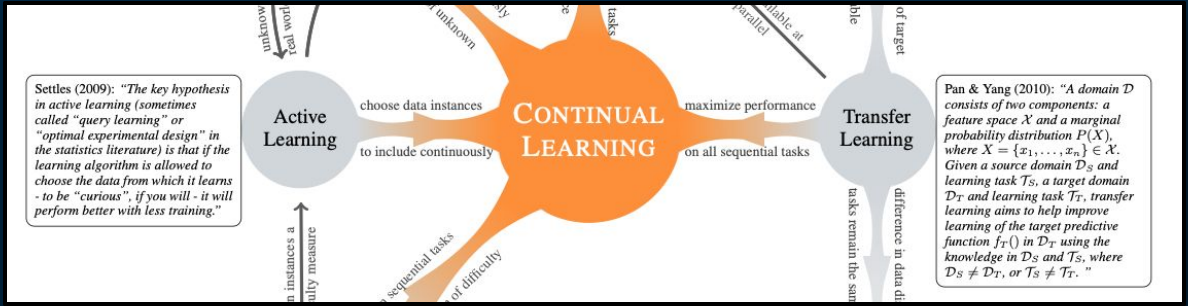
Q: which metrics would you monitor to evaluate a continual learner deployed and trained on the edge on image classification tasks?

CLEVA-Compass: A Continual Learning EValuation Assessment Compass

Recall lecture 1: there are various machine learning formulations that have continuous components



Depending on **where inspiration** has been drawn from, continual learning setups and **evaluation can vary dramatically**.



(a small snapshot from the overall paradigm relationships)

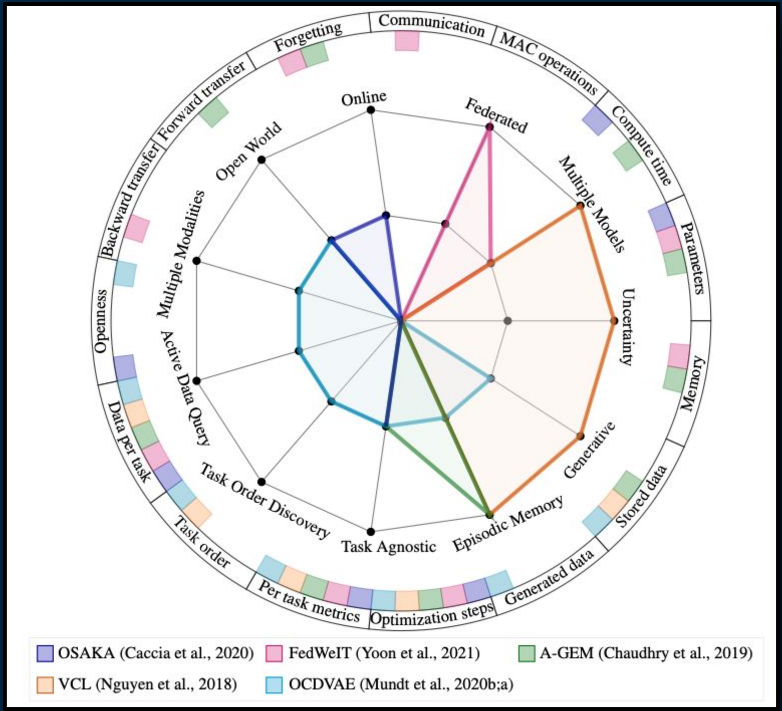
CLEVA-Compass: A Continual Learning EValuation Assessment Compass to Promote Research Transparency and Comparability, arXiv, 2021.

CLEVA-Compass: A Continual Learning EValuation Assessment Compass

Existence of various scenarios is not a problem, but actually meaningful because different applications can desire different things!

But **reproducibility & comparability can be problematic**, which is a constant subject in the scientific literature.

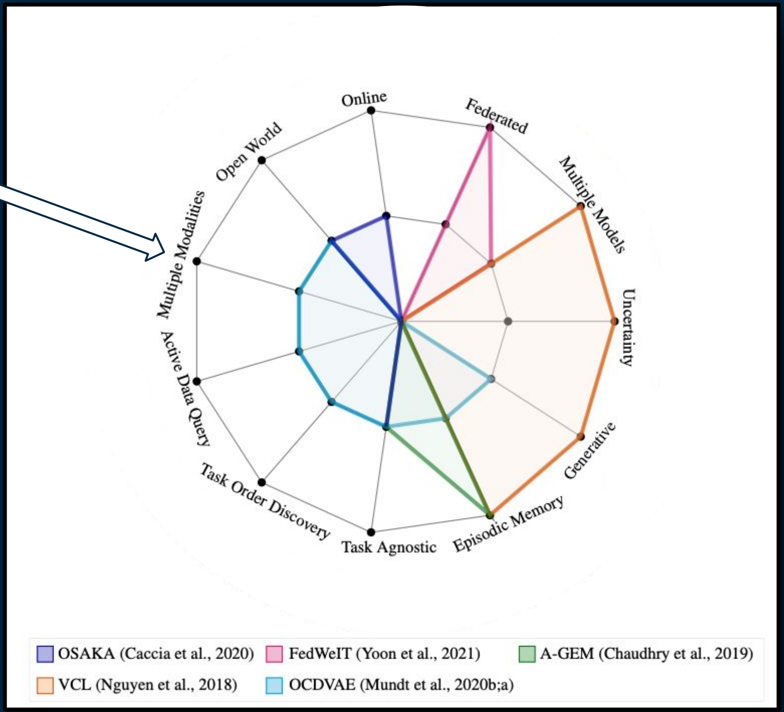
Recently, the **CLEVA-Compass** has been introduced to **promote transparency & comparability**



CLEVA-Compass: A Continual Learning EValuation Assessment Compass to Promote Research Transparency and Comparability, arXiv, 2021.

CLEVA-Compass: A Continual Learning EValuation Assessment Compass

Inner compass level (star plot):
indicates related paradigm inspiration & continual setting configuration (assumptions)



CLEVA-Compass: A Continual Learning EValuation Assessment Compass to Promote Research Transparency and Comparability, arXiv, 2021.

CLEVA-Compass: A Continual Learning EValuation Assessment Compass

Inner compass level (star plot):
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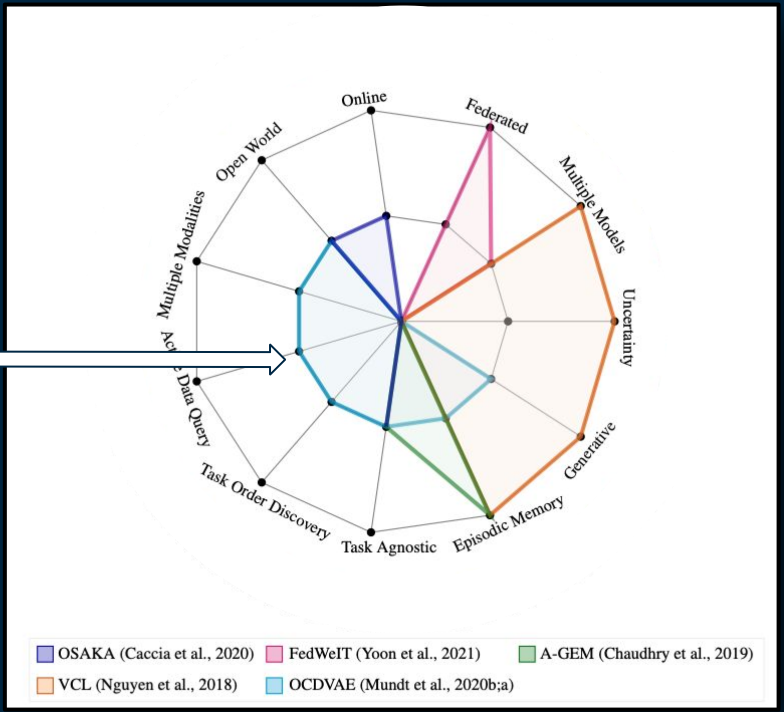
Inner compass level of supervision:
"rings" on the star plot indicate presence of supervision. Importantly: supervision is individual to each dimension!



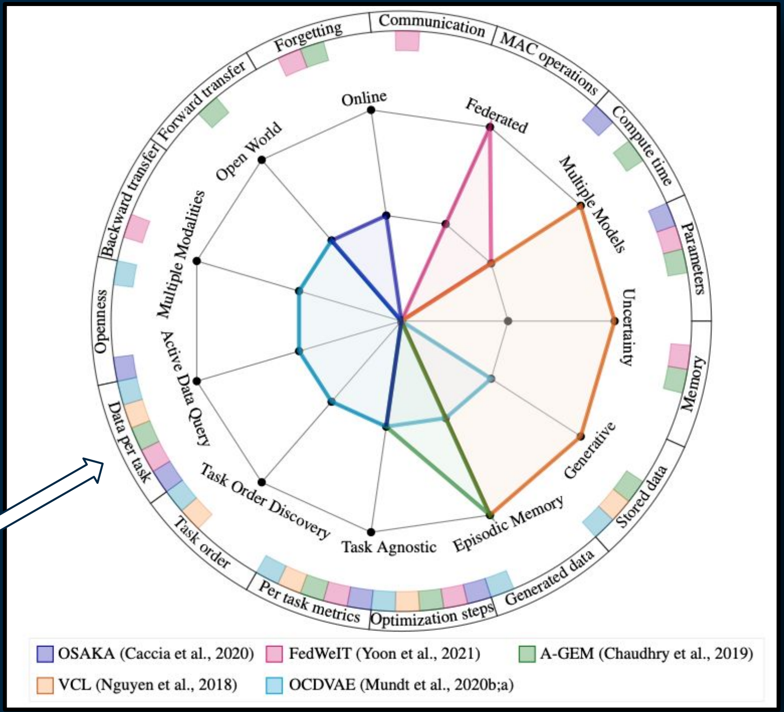
CLEVA-Compass: A Continual Learning EValuation Assessment Compass to Promote Research Transparency and Comparability, arXiv, 2021.

CLEVA-Compass: A Continual Learning EValuation Assessment Compass

Inner compass level (star plot):
indicates related paradigm inspiration & continual setting configuration (assumptions)

Inner compass level of supervision:
“rings” on the star plot indicate presence of supervision. Importantly: supervision is individual to each dimension!

Outer compass level:
Contains a comprehensive set of practically reported measures



CLEVA-Compass: A Continual Learning EValuation Assessment Compass to Promote Research Transparency and Comparability, arXiv, 2021.

Avalanche Metrics & Loggers

How to Monitor Experiments?

Evaluation module provides

- **Metrics** (accuracy, forgetting, CPU Usage…) - *you can create your own!*
- **Loggers** to report results in different ways - *you can create your own!*
- **Automatic integration in the training and evaluation loop** through the Evaluation Plugin
- **A dictionary with all recorded metrics** always available for custom use

V. Lomonaco et al. ***Avalanche: an End-to-End Library for Continual Learning***. CLVision Workshop at CVPR 2021.

Let’s Track our Experiments

```python
from avalanche.logging import InteractiveLogger, TextLogger, \
    TensorboardLogger
from avalanche.training.plugins import EvaluationPlugin
from avalanche.evaluation.metrics import ExperienceForgetting, \
    accuracy_metrics, loss_metrics, cpu_usage_metrics


eval_plugin = EvaluationPlugin(
  accuracy_metrics(minibatch=True, stream=True),
  loss_metrics(epoch=True, experience=True),
  ExperienceForgetting(),
  cpu_usage_metrics(stream=True),
  # add as many metrics as you need
  loggers=[TextLogger(open('out.txt', 'w')),
           InteractiveLogger(),
           TensorboardLogger()])

# just pass the evaluation plugin to the strategy
# strategy = EWC(..., evaluator=eval_plugin)

# {'metric name': [x values], [metric values]}
# empty since we have not trained, yet
metric_dict = eval_plugin.get_all_metrics()
```

V. Lomonaco et al. ***Avalanche: an End-to-End Library for Continual Learning***. CLVision Workshop at CVPR 2021.

Interactive Logger Output

```
-- >> Start of training phase << --
-- Starting training on experience 0 (Task 0) from train stream --
Epoch 0 ended.
  Loss_Epoch/train_phase/train_stream/Task000 = 1.1099
  Top1_Acc_Epoch/train_phase/train_stream/Task000 = 0.8926
...
-- >> End of training phase << --
-- >> Start of eval phase << --
-- Starting eval on experience 0 (Task 0) from test stream --
> Eval on experience 0 (Task 0)  from test stream ended.
     Loss_Exp/eval_phase/test_stream/Task000/Exp000 = 0.0208
     Top1_Acc_Exp/eval_phase/ test_stream/Task000/Exp000 = 0.9981
...
-- >> End of eval phase << --
     Loss_Stream/eval_phase/test_stream = 4.4492
```

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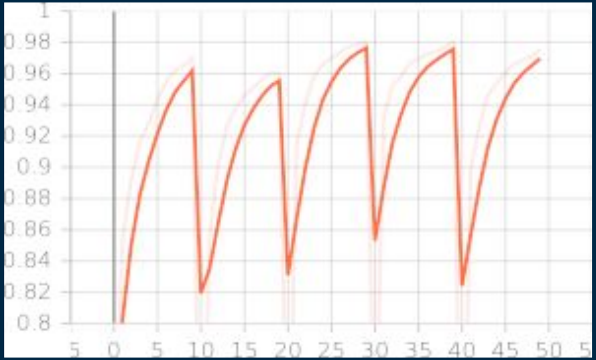
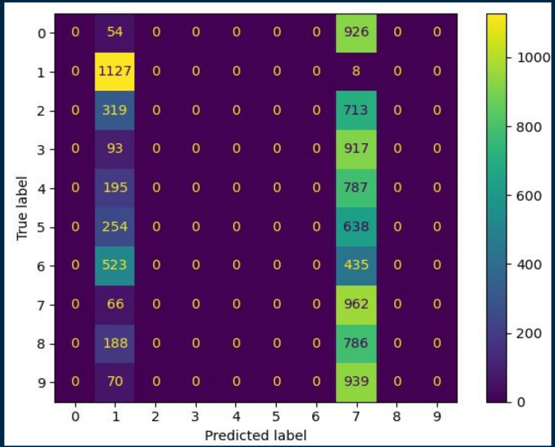
Tensorboard Logger in Action





V. Lomonaco et al. ***Avalanche: an End-to-End Library for Continual Learning***. CLVision Workshop at CVPR 2021.

Standalone Metrics

```python
import torch
from avalanche.evaluation.metrics import Accuracy

# create an instance of the standalone Accuracy metric
acc_metric = Accuracy()
print("Initial Accuracy: ", acc_metric.result())  # output 0

# two consecutive metric updates
real_y = torch.tensor([1, 2]).long()
predicted_y = torch.tensor([1, 0]).float()
acc_metric.update(real_y, predicted_y)
acc = acc_metric.result()
print("Average Accuracy: ", acc)  # output 0.5

predicted_y = torch.tensor([1,2]).float()
acc_metric.update(real_y, predicted_y)
acc = acc_metric.result()
print("Average Accuracy: ", acc)  # output 0.75

# reset accuracy to 0
acc_metric.reset()
print("After reset: ", acc_metric.result())  # output 0
```

V. Lomonaco et al. ***Avalanche: an End-to-End Library for Continual Learning***. CLVision Workshop at CVPR 2021.

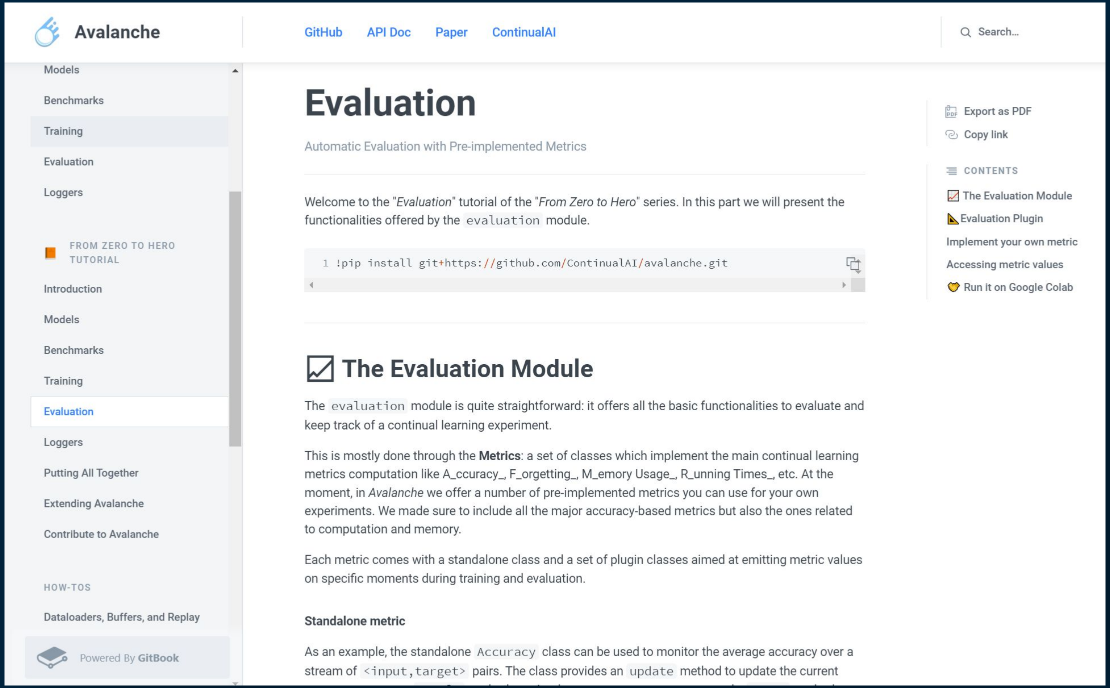
What's Next?

- Evaluation of a CL algorithm is not only about metrics and loggers.
- More support for the definition of **training and evaluation protocols**
    - How to perform **cross validation** in CL?
    - How to evaluate **multiple runs**?
- The objective of a **shared protocol** is possible only with the help of the community

V. Lomonaco et al. ***Avalanche: an End-to-End Library for Continual Learning***. CLVision Workshop at CVPR 2021.

Avalanche Evaluation Module

Demo Session!



Avalanche

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FROM ZERO TO HERO TUTORIAL

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Contribute to Avalanche

HOW-TOS

Dataloaders, Buffers, and Replay

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Evaluation

Automatic Evaluation with Pre-implemented Metrics

Welcome to the "*Evaluation*" tutorial of the "*From Zero to Hero*" series. In this part we will present the functionalities offered by the `evaluation` module.

```
!pip install git+https://github.com/ContinualAI/avalanche.git
```

The Evaluation Module

The `evaluation` module is quite straightforward: it offers all the basic functionalities to evaluate and keep track of a continual learning experiment.

This is mostly done through the **Metrics**: a set of classes which implement the main continual learning metrics computation like A_ccuracy_, F_orgetting_, M_emory Usage_, R_unning Times_, etc. At the moment, in *Avalanche* we offer a number of pre-implemented metrics you can use for your own experiments. We made sure to include all the major accuracy-based metrics but also the ones related to computation and memory.

Each metric comes with a standalone class and a set of plugin classes aimed at emitting metric values on specific moments during training and evaluation.

Standalone metric

As an example, the standalone `Accuracy` class can be used to monitor the average accuracy over a stream of `<input,target>` pairs. The class provides an `update` method to update the current

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[Avalanche, From Zero To Hero tutorial: Evaluation], [Avalanche, From Zero To Hero tutorial: Loggers]

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Methodologies [Part 1]

Do you have any questions?

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THANKS