







Continuum

Simple Management of Complex Continual Learning Scenarios



https://github.com/Continvvm/continuum

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Data Loading for Continual Learning

Continual data loading is complex

Each paper requires many different settings

Reinventing the wheel

```
dataset = MNIST("my/data/path", download=True, train=True)
scenario = ClassIncremental(dataset, increment=2)

for task_id, taskset in enumerate(scenario):
    train_taskset, val_taskset = split_train_val(|taskset, val_split=0.1)
    train_loader = DataLoader(train_taskset, batch_size=32, shuffle=True)
    val_loader = DataLoader(val_taskset, batch_size=32, shuffle=True)

for x, y, t in train_loader:
    # Do your cool stuff here
```

<u>UNIX Philosophy:</u>

Minimal

One Single Goal

Modular

- 1. Choose a dataset,
- Choose a scenario,
- and use torchvision loaders!

```
dataset = MNIST("my/data/path", download=True, train=True)
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for x, y, t in train_loader:
    # Do your cool stuff here
```

But wait there is already many libraries...

<u>Sequoia</u>

FACIL

<u>Avalanche</u>

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Sequoia

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Continuum

Released to public and used by several researchers since April 2020

Light-weight with only goal in mind: data loading, no models!

Easiest to **plug in** existing codebase

Also **good synergy** with large codebase such as <u>Sequoia!</u>

But wait there is already many libraries...

Sequoia

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<u>Avalanche</u>

Different goal than existing libraries

Continuum

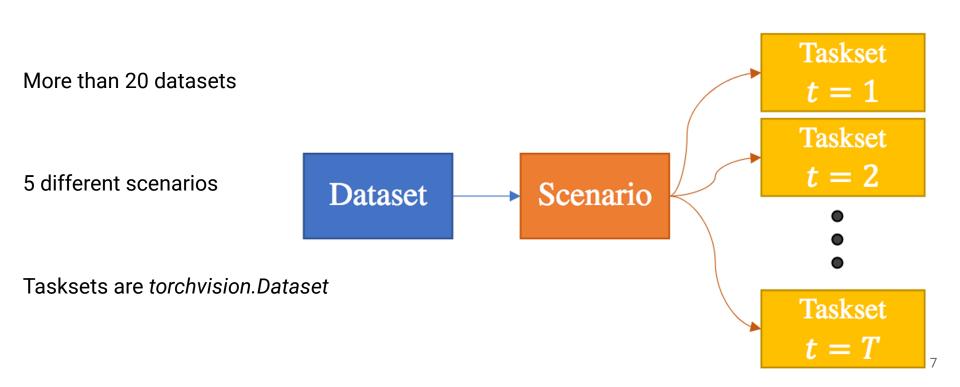
Released to public and used by several researchers since April 2020

Light-weight with only goal in mind: data loading, no models!

Easiest to **plug in** existing codebase

Also **good synergy** with large codebase such as Sequoia!

No big diagram



Smooth integration in Pytorch

```
from torch.utils.data import DataLoader
from continuum import ClassIncremental
from continuum.datasets import MNIST
dataset = MNIST("/data", train=True)
scenario = ClassIncremental(dataset, increment=2)
for task_id, train_taskset in enumerate(scenario):
    train loader = DataLoader(train_taskset, batch_size=32, shuffle=True)
    for x, y, t in train_loader:
```

Class-Incremental vs Task-Incremental

Use task ids, or not.

Your choice!

```
from torch.utils.data import DataLoader
from continuum import ClassIncremental
from continuum.datasets import MNIST
dataset = MNIST("/data", train=False)
scenario = ClassIncremental(dataset, increment=2)
for task id, test taskset in enumerate(scenario):
    test_loader = DataLoader(test_taskset, batch_size=32)
    for x, y, t in test_loader:
```

Tasks Flexibility

```
dataset = MNIST("/data", train=False)
scenario = ClassIncremental(dataset, increment=2)
third_taskset = scenario[2]
all_seen_tasksets = scenario[:3]
```

All usual python fancy indexing for scenario

Split MNIST

```
from continuum import ClassIncremental
from continuum.datasets import MNIST

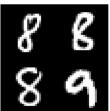
dataset = MNIST("/path", train=True)
scenario = ClassIncremental(dataset, increment=2)
```











Split MNIST

```
from continuum import ClassIncremental
from continuum.datasets import MNIST

dataset = MNIST("/path", train=True)
scenario = ClassIncremental(dataset, increment=[4, 4, 2])
```







New Instances

```
from continuum import InstanceIncremental
from continuum.datasets import Core50v2_79

dataset = Core50v2_79("/path", train=True, download=True)
scenario = InstanceIncremental(dataset)
```







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Segmentation

```
dataset = PascalVOC2012("/path", train=True, download=True)
scenario = SegmentationClassIncremental(
    dataset,
    increment=[19, 1], # Learning 19 classes then 1
    nb_classes=20,
    mode="overlap",
    transformations=[Resize((512, 512)), ToTensor()]
for taskset in scenario:
    loader = DataLoader(taskset, batch_size=12)
    for x, y, t in loaders:
```









Transformations Scenario



Task 0: 0° degree



Task 1: 45° degree



Task 2: 90° degree



Rehearsal Learning

Handle rehearsal memory as you want

Use memory in the taskset you want

Oversample with **native** pytorch samplers

```
from torch.utils.data import DataLoader
from continuum import ClassIncremental
from continuum.datasets import MNIST
dataset = MNIST("/path", train=True)
scenario = ClassIncremental(dataset, increment=2)
taskset = scenario[2]
taskset.add_samples(memory_x, memory_y)
loader = DataLoader(
    taskset,
    sampler=my pytorch sampler
```



- We don't want to increase complexity:
 - No addition of tons of options, attributes, etc.
 - No models, no losses, etc.
- ✓ We want to offer a large choice of simple interfaces:
 - More datasets (more segmentation, more NLP, etc.)
 - More scenarios

Don't use Continuum

- if you wants a whole ecosystem,
- many models,
- and a strict way to do continual learning

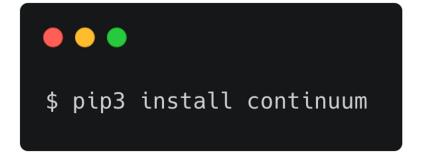
Do use Continuum

- if you wants a light-weight library,
- easily **pluggable** in any codebase, no matter how small or large it is
- with the most pytorchnic interface

Want more?

Documentation: continuum.readthedocs.io

Github: github.com/Continvvm/continuum



Colab tutorial: colab.research.google.com