

Avalanche An End-to-End Library for Continual Learning

avalanche.continualai.org

powered by



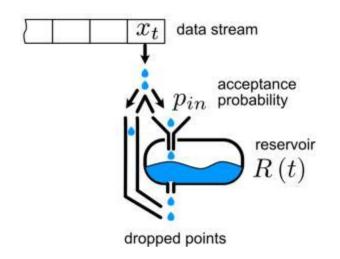
Antonio Carta, Andrea Cossu, Lorenzo Pellegrini, Gabriele Graffieti, Hamed Hemati, Vincenzo Lomonaco and many more contributors...

CL - Strategies



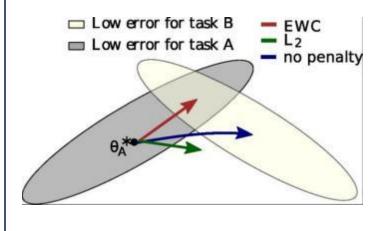
Replay

- Keep a buffer of old samples
- Rehearse old samples



Regularization

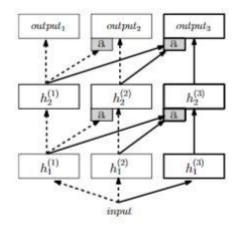
• Regularize the model to balance learning and forgetting



Elastic Weight Consolidation

Architectural

• Expand the model over time with new units/layers



Progressive Neural Networks

Avalanche – Design Principles



- 1. Comprehensive and Consistent
- 2. Easy to Use high-level APIs
- 3. Reproducibility and Portability
- 4. Easy to Extend modularity and independence of low-level APIs 5.

Community-driven – 40+ contributors from different institutions

Install with pip install avalanche-lib

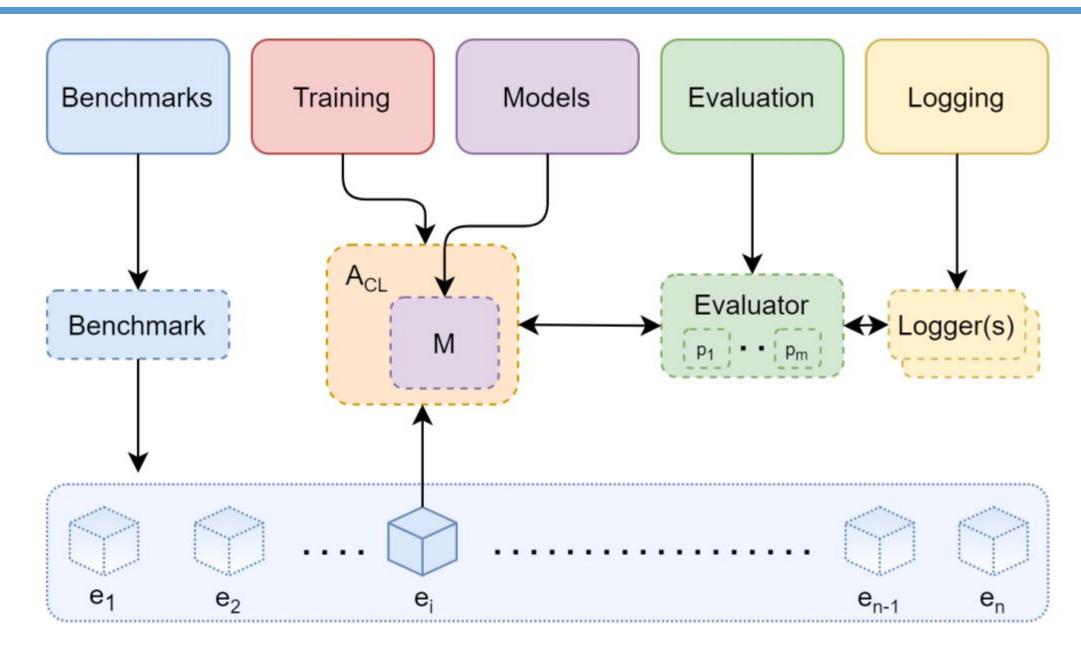
A Minimal Example



```
000
  1 # CL Benchmark Creation
  2 benchmark = PermutedMNIST(n_experiences=3)
  3 train_stream = benchmark.train_stream
  4 test_stream = benchmark.test_stream
  7 model = SimpleMLP(num_classes=10)
  8 optimizer = SGD(model.parameters(), lr=0.001, momentum=0.9)
  9 criterion = CrossEntropyLoss()
 10
 11 # Continual learning strategy
 12 cl_strategy = Naive(
 13
       model, optimizer, criterion,
       train_mb_size=32, train_epochs=2,
 14
 15
       eval_mb_size=32, device=device)
 16
 17 # train and test loop over the stream of experiences
 18 results = []
 19 for train_exp in train_stream:
        cl_strategy.train(train_exp)
 20
        results.append(cl_strategy.eval(test_stream))
```

Avalanche modules





Classic Benchmarks



Most common benchmarks from the literature are available

- ➤ MNIST: SplitMNIST, RotatedMNIST, PermutedMNIST, SplitFashionMNIST
- ➤ CIFAR10: SplitCIFAR10, SplitCIFAR100, SplitCIFAR110.
- CORe50: all the CORe50 scenarios are supported.
- ➤ Others: SplitCUB200, CLStream51, CLEAR.

Avalanche datasets add:

- train/eval transforms
- Management of class and task labels

```
1 benchmark = SplitMNIST(
     n_experiences=5,
      seed=1,
      return_task_id=False,
      fixed_class_order=[5,0,9, ...],
      train_transform=ToTensor(),
6
     eval_transform=ToTensor()
```

Benchmark – Data Iteration



```
train_stream = benchmark_instance.train_stream
test_stream = benchmark_instance.test_stream
for idx, experience in enumerate(train_stream):
   dataset = experience.dataset
    print('Train dataset contains',
        len(dataset), 'patterns')
   for x, y, t in dataset:
    test_experience = test_stream[idx]
    cumulative_test = test_stream[:idx+1]
```

Avalanche – Strategies



- Methods from the literature.
- Different methods can be combined together using plugins.
- You can also implement custom plugins to define your own strategies.
- **Baselines**: Naive, JointTraining, Cumulative.
- **Rehearsal**: Replay with reservoir sampling and balanced buffers, GSS greedy, CoPE, Generative Replay.
- Regularization: EWC, LwF, GEM, AGEM, CWR*, Synaptic Intelligence, MAS.
- Architectural: Progressive Neural Networks, multi-head, incremental classifier.
- Others: GDumb, iCaRL, AR1, Streaming LDA, LFL.

```
replay = ReplayPlugin(mem_size)
ewc = EWCPlugin(ewc_lambda)
strategy = BaseStrategy(
    model, optimizer,
    criterion, mem_size,
    plugins=[replay, ewc])
```

Example of Custom Plugin



```
from avalanche.training.plugins import StrategyPlugin
class ReplayPlugin(StrategyPlugin):
    """ Experience replay plugin. """
    def __init__(self, mem_size=200):
        super().__init__()
        self.mem_size = mem_size
        self.ext_mem = {} # a Dict<task_id, Dataset>
        self.rm add = None
    def adapt_train_dataset(self, strategy, **kwargs):
        0.00
        Expands the current training set with datapoints from
        the external memory before training.
        II II II
    def after_training_exp(self, strategy, **kwargs):
        After training we update the external memory with the patterns of
         the current training batch/task.
        11 H H
```

Models – Multi-Task



- Avalanche supports multitask models
- One task labels for each sample
- Standard models, like Multi-head classifiers, are already implemented
- •You can also implement custom modules.

 You implement the single-task forward,
 and Avalanche splits by task
 automatically

```
class MTSimpleMLP(MultiTaskModule):
    """Multi-layer perceptron with multi-head classifier"""
    def __init__(self, input_size=28 * 28, hidden_size=512):
        super().__init__()
        self.features = nn.Sequential(
            nn.Linear(input_size, hidden_size),
            nn.ReLU(inplace=True),
            nn.Dropout(),
        self.classifier = MultiHeadClassifier(hidden_size)
        self._input_size = input_size
    def forward(self, x, task_labels):
        x = x.contiquous()
        x = x.view(x.size(0), self._input_size)
        x = self.features(x)
        x = self.classifier(x, task_labels)
        return x
```

Models - Dynamic (growing) Modules



- Dynamic modules grow overtime by adding units/layers
 - Incremental classifier
 - Progressive neural network
- Adaptation is called automatically by the strategy

```
class IncrementalClassifier(DynamicModule):
   Output layer that incrementally adds units whenever new classes are
    encountered.
    def __init__(self, in_features, initial_out_features=2):
        :param in_features: number of input features.
        :param initial out features: initial number of classes (can be
            dynamically expanded).
        super().__init__()
        self.classifier = torch.nn.Linear(in_features, initial_out_features)
    @torch.no_grad()
    def adaptation(self, dataset: AvalancheDataset):
        """If 'dataset' contains unseen classes the classifier is expanded.
        :param dataset: data from the current experience.
        :return:
        in features = self.classifier.in features
        old_nclasses = self.classifier.out_features
        new_nclasses = max(
            self.classifier.out_features, max(dataset.targets) + 1
        if old_nclasses == new_nclasses:
        old_w, old_b = self.classifier.weight, self.classifier.bias
        self.classifier = torch.nn.Linear(in_features, new_nclasses)
        self.classifier.weight[:old_nclasses] = old_w
        self.classifier.bias[:old_nclasses] = old_b
    def forward(self, x, **kwargs):
        return self.classifier(x)
```

Metrics and Evaluation



Avalanche provides continuous evaluation of CL strategies with a large set of Metrics.

They are collected and logged automatically by the strategy during the training and evaluation loops.

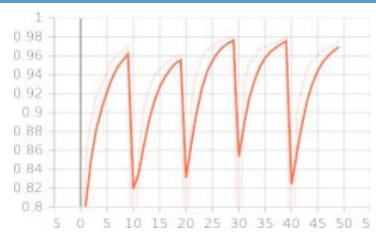
- Standard Performance Metrics: accuracy, loss, confusion (averaged over streams or experiences).
- CL-Metrics: backward/forward transfer, forgetting.
- Computational Resources: CPU and RAM usage, MAC, execution times.

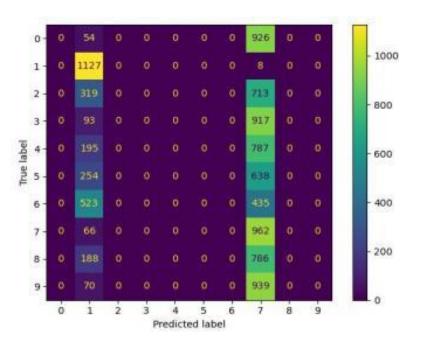
Metrics and Evaluation



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





Some Useful Links



- 1. Related Projects:
 - 1. Reproducibility: https://github.com/ContinualAI/reproducible-continual-learning
 - 2. Continual Reinforcement Learning: https://github.com/ContinualAI/avalanche-rl
- 2. Become familiar with all the avalanche features.
 - a. Official documentation: https://avalanche.continualai.org/
 - b. Learn avalanche in 5 minutes (link here).
 - c. From zero to hero tutorial (link here)
 - d. API doc can be consulted at https://avalanche-api.continualai.org/
- 3. If you don't understand something or you want to discuss a new feature or a possible improvement:
 - a. Join our slack channel #avalanche (here)
 - b. Open a discussion ongithub (here)
- 4. If you find an issue on Avalanche open an issue ongithub (here)