TorchIO

Search

Training

Patch samplers

Samplers are used to randomly extract patches from volumes. They are called with a sample generated by a `SubjectsDataset` and return a Python generator that yields cropped versions of the sample.

For more information about patch-based training, see this NiftyNet tutorial.

```
class torchio.data.UniformSampler(patch_size: Union[int, Tuple[int, int, int]])[source]
```

Bases: `torchio.data.sampler.sampler.RandomSampler`

Randomly extract patches from a volume with uniform probability.

PARAMETERS

patch_size – See `PatchSampler`.

```
class torchio.data.WeightedSampler(patch_size: Union[int, Tuple[int, int, int]],
    probability_map: str)                                                    [source]
```

Bases: `torchio.data.sampler.sampler.RandomSampler`

Randomly extract patches from a volume given a probability map.

The probability of sampling a patch centered on a specific voxel is the value of that voxel in the probability map. The probabilities need not be normalized. For example, voxels can have values 0, 1 and 5. Voxels with value 0 will never be at the center of a patch. Voxels with value 5 will have 5 times more chance of being at the center of a patch that voxels with a value of 1.

PARAMETERS

- **patch_size** – See `PatchSampler`.
- **probability_map** – Name of the image in the input subject that will be used as a sampling probability map.

RAISES

RuntimeError – If the probability map is empty.

EXAMPLE

```
>>> import torchio as tio
>>> subject = tio.Subject(
...     t1=tio.ScalarImage('t1_mri.nii.gz'),
...     sampling_map=tio.Image('sampling.nii.gz', type=tio.SAMPLING_MAP),
... )
>>> patch_size = 64
>>> sampler = tio.data.WeightedSampler(patch_size, 'sampling_map')
>>> for patch in sampler(subject):
...     print(patch[tio.LOCATION])
```

Note

The index of the center of a patch with even size s is arbitrarily set to $s/2$. This is an implementation detail that will typically not make any difference in practice.

Note

Values of the probability map near the border will be set to 0 as the center of the patch cannot be at the border (unless the patch has size 1 or 2 along that axis).

```
class torchio.data.LabelSampler(patch_size: Union[int, Tuple[int, int, int]],
    label_name: Optional[str] = None, label_probabilities: Optional[Dict[int, float]]
    = None)                                                                  [source]
```

Bases: `torchio.data.sampler.weighted.WeightedSampler`

Extract random patches with labeled voxels at their center.

This sampler yields patches whose center value is greater than 0 in the `label_name`.

PARAMETERS

- **patch_size** – See `PatchSampler`.
- **label_name** – Name of the label image in the subject that will be used to generate the sampling probability map. If `None`, the first image of type `torchio.LABEL` found in the subject subject will be used.
- **label_probabilities** – Dictionary containing the probability that each class will be sampled. Probabilities do not need to be normalized. For example, a value of `{0: 0, 1: 2, 2: 1, 3: 1}` will create a sampler whose patches centers will have 50% probability of being labeled as `1`, 25% of being `2` and 25% of being `3`. If `None`, the label map is binarized and the value is set to `{0: 0, 1: 1}`. If the input has multiple channels, a value of `{0: 0, 1: 2, 2: 1, 3: 1}` will create a sampler whose patches centers will have 50% probability of being taken from a non zero value of channel `1`, 25% from channel `2` and 25% from channel `3`.

EXAMPLE

```
>>> import torchio as tio
>>> subject = tio.datasets.Colin27()
>>> subject
Colin27(Keys: ('t1', 'head', 'brain'); images: 3)
>>> probabilities = {0: 0.5, 1: 0.5}
>>> sampler = tio.data.LabelSampler(
...     patch_size=64,
...     label_name='brain',
...     label_probabilities=probabilities,
```

CONTENTS

```
... )
>>> generator = sampler(subject)
>>> for patch in generator:
...     print(patch.shape)
```

If you want a specific number of patches from a volume, e.g. 10:

```
>>> generator = sampler(subject, num_patches=10)
>>> for patch in iterator:
...     print(patch.shape)
```

class torchio.data.**PatchSampler**(patch_size: Union[int, Tuple[int, int, int]]) [source]

Bases: `object`

Base class for TorchIO samplers.

PARAMETERS

patch_size – Tuple of integers (w, h, d) to generate patches of size $w \times h \times d$. If a single number n is provided, $w = h = d = n$.

> **Warning**
>
> This is an abstract class that should only be instantiated using child classes such as `UniformSampler` and `WeightedSampler`.

class torchio.data.**GridSampler**(subject: Optional[torchio.data.subject.Subject] = None, patch_size: Optional[Union[int, Tuple[int, int, int]]] = None, patch_overlap: Union[int, Tuple[int, int, int]] = (0, 0, 0), padding_mode: Optional[Union[str, float]] = None) [source]

Bases: `torchio.data.sampler.sampler.PatchSampler`

Extract patches across a whole volume.

Grid samplers are useful to perform inference using all patches from a volume. It is often used with a `GridAggregator`.

PARAMETERS

- **subject** – Instance of `Subject` from which patches will be extracted. This argument should only be used before instantiating a `GridAggregator`, or to precompute the number of patches that would be generated from a subject.
- **patch_size** – Tuple of integers (w, h, d) to generate patches of size $w \times h \times d$. If a single number n is provided, $w = h = d = n$. This argument is mandatory (it is a keyword argument for backward compatibility).
- **patch_overlap** – Tuple of even integers (w_o, h_o, d_o) specifying the overlap between patches for dense inference. If a single number n is provided, $w_o = h_o = d_o = n$.
- **padding_mode** – Same as `padding_mode` in `Pad`. If `None`, the volume will not be padded before sampling and patches at the border will not be cropped by the aggregator. Otherwise, the volume will be padded with $\left(\frac{w_o}{2}, \frac{h_o}{2}, \frac{d_o}{2}\right)$ on each side before sampling. If the sampler is passed to a `GridAggregator`, it will crop the output to its original size.

Example:

```
>>> import torchio as tio
>>> sampler = tio.GridSampler(patch_size=88)
>>> colin = tio.datasets.Colin27()
>>> for i, patch in enumerate(sampler(colin)):
...     patch.t1.save(f'patch_{i}.nii.gz')
...
>>> # To figure out the number of patches beforehand:
>>> sampler = tio.GridSampler(subject=colin, patch_size=88)
>>> len(sampler)
8
```

> **Note**
>
> Adapted from NiftyNet. See this NiftyNet tutorial for more information about patch based sampling. Note that `patch_overlap` is twice `border` in NiftyNet tutorial.

Queue

class torchio.data.**Queue**(subjects_dataset: torchio.data.dataset.SubjectsDataset, max_length: int, samples_per_volume: int, sampler: torchio.data.sampler.sampler.PatchSampler, num_workers: int = 0, shuffle_subjects: bool = True, shuffle_patches: bool = True, start_background: bool = True, verbose: bool = False) [source]

Bases: `torch.utils.data.dataset.Dataset`

Queue used for stochastic patch-based training.

A training iteration (i.e., forward and backward pass) performed on a GPU is usually faster than loading, preprocessing, augmenting, and cropping a volume on a CPU. Most preprocessing operations could be performed using a GPU, but these devices are typically reserved for training the CNN so that batch size and input tensor size can be as large as possible. Therefore, it is beneficial to prepare (i.e., load, preprocess and augment) the volumes using multiprocessing CPU techniques in parallel with the forward-backward passes of a training iteration. Once a volume is appropriately prepared, it is computationally beneficial to sample multiple patches from a volume rather than having to prepare the same volume each time a patch needs to be extracted. The sampled patches are then stored in a buffer or *queue* until the next training iteration, at which point they are loaded onto the GPU for inference. For this, TorchIO provides the `Queue` class, which also inherits from the PyTorch `Dataset`. In this queueing system, samplers behave as generators that yield patches from random locations in volumes contained in the `SubjectsDataset`.

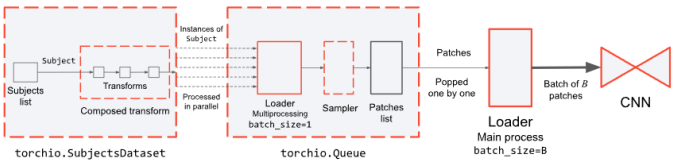
The end of a training epoch is defined as the moment after which patches from all subjects have been used for training. At the beginning of each training epoch, the subjects list in the

`SubjectsDataset` is shuffled, as is typically done in machine learning pipelines to increase variance of training instances during model optimization. A PyTorch loader queries the datasets copied in each process, which load and process the volumes in parallel on the CPU. A patches list is filled with patches extracted by the sampler, and the queue is shuffled once it has reached a specified maximum length so that batches are composed of patches from different subjects. The internal data loader continues querying the `SubjectsDataset` using multiprocessing. The patches list, when emptied, is refilled with new patches. A second data loader, external to the queue, may be used to collate batches of patches stored in the queue, which are passed to the neural network.

PARAMETERS

- **subjects_dataset** – Instance of `SubjectsDataset`.
- **max_length** – Maximum number of patches that can be stored in the queue. Using a large number means that the queue needs to be filled less often, but more CPU memory is needed to store the patches.
- **samples_per_volume** – Number of patches to extract from each volume. A small number of patches ensures a large variability in the queue, but training will be slower.
- **sampler** – A subclass of `PatchSampler` used to extract patches from the volumes.
- **num_workers** – Number of subprocesses to use for data loading (as in `torch.utils.data.DataLoader`). `0` means that the data will be loaded in the main process.
- **shuffle_subjects** – If `True`, the subjects dataset is shuffled at the beginning of each epoch, i.e. when all patches from all subjects have been processed.
- **shuffle_patches** – If `True`, patches are shuffled after filling the queue.
- **start_background** – If `True`, the loader will start working in the background as soon as the queue is instantiated.
- **verbose** – If `True`, some debugging messages will be printed.

This diagram represents the connection between a `SubjectsDataset`, a `Queue` and the `DataLoader` used to pop batches from the queue.



This sketch can be used to experiment and understand how the queue works. In this case, `shuffle_subjects` is `False` and `shuffle_patches` is `True`.

> **Note**
>
> `num_workers` refers to the number of workers used to load and transform the volumes. Multiprocessing is not needed to pop patches from the queue, so you should always use `num_workers=0` for the `DataLoader` you instantiate to generate training batches.

Example:

```
>>> import torch
>>> import torchio as tio
>>> from torch.utils.data import DataLoader
>>> patch_size = 96
>>> queue_length = 300
>>> samples_per_volume = 10
>>> sampler = tio.data.UniformSampler(patch_size)
>>> subject = tio.datasets.Colin27()
>>> subjects_dataset = tio.SubjectsDataset(10 * [subject])
>>> patches_queue = tio.Queue(
...     subjects_dataset,
...     queue_length,
...     samples_per_volume,
...     sampler,
...     num_workers=4,
... )
>>> patches_loader = DataLoader(
...     patches_queue,
...     batch_size=16,
...     num_workers=0,  # this must be 0
... )
>>> num_epochs = 2
>>> model = torch.nn.Identity()
>>> for epoch_index in range(num_epochs):
...     for patches_batch in patches_loader:
...         inputs = patches_batch['t1'][tio.DATA]  # key 't1' is in subject
...         targets = patches_batch['brain'][tio.DATA]  # key 'brain' is in subject
...         logits = model(inputs)  # model being an instance of torch.nn.Module
```

```
get_max_memory(subject: Optional[torchio.data.subject.Subject] = None) → int
```
[source]

Get the maximum RAM occupied by the patches queue in bytes.

PARAMETERS

subject – Sample subject to compute the size of a patch.

```
get_max_memory_pretty(subject: Optional[torchio.data.subject.Subject] = None) →
    str
```
[source]

Get human-readable maximum RAM occupied by the patches queue.

PARAMETERS

subject – Sample subject to compute the size of a patch.

‹ Previous
Patch-based pipelines

Next
Inference ›