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Visualization in Deep Learning: Tensorboard(X)

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PEP8

PEP8

- Style guide for Python code

- Check if your code is compliant with PEP8

    - Use of a linter:
        - tool that analyzes source code to flag programming errors, bugs, stylistic errors
        - E.g,: Flake8

    - flake8 --ignore W,F

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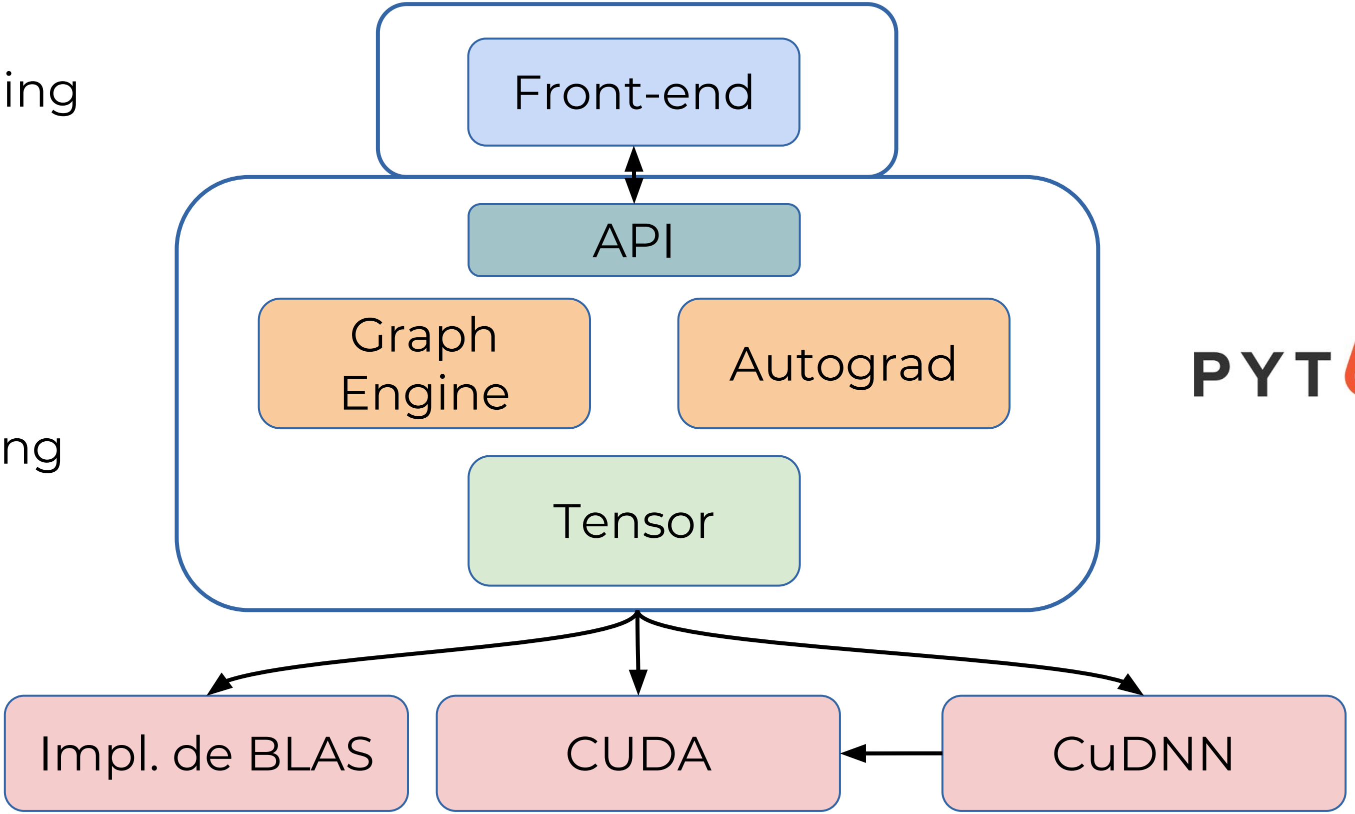
Tensorboard(X)

PyTorch

Deep Learning

Differential programming

Matrix calculation



PyTorch

Deep Learning

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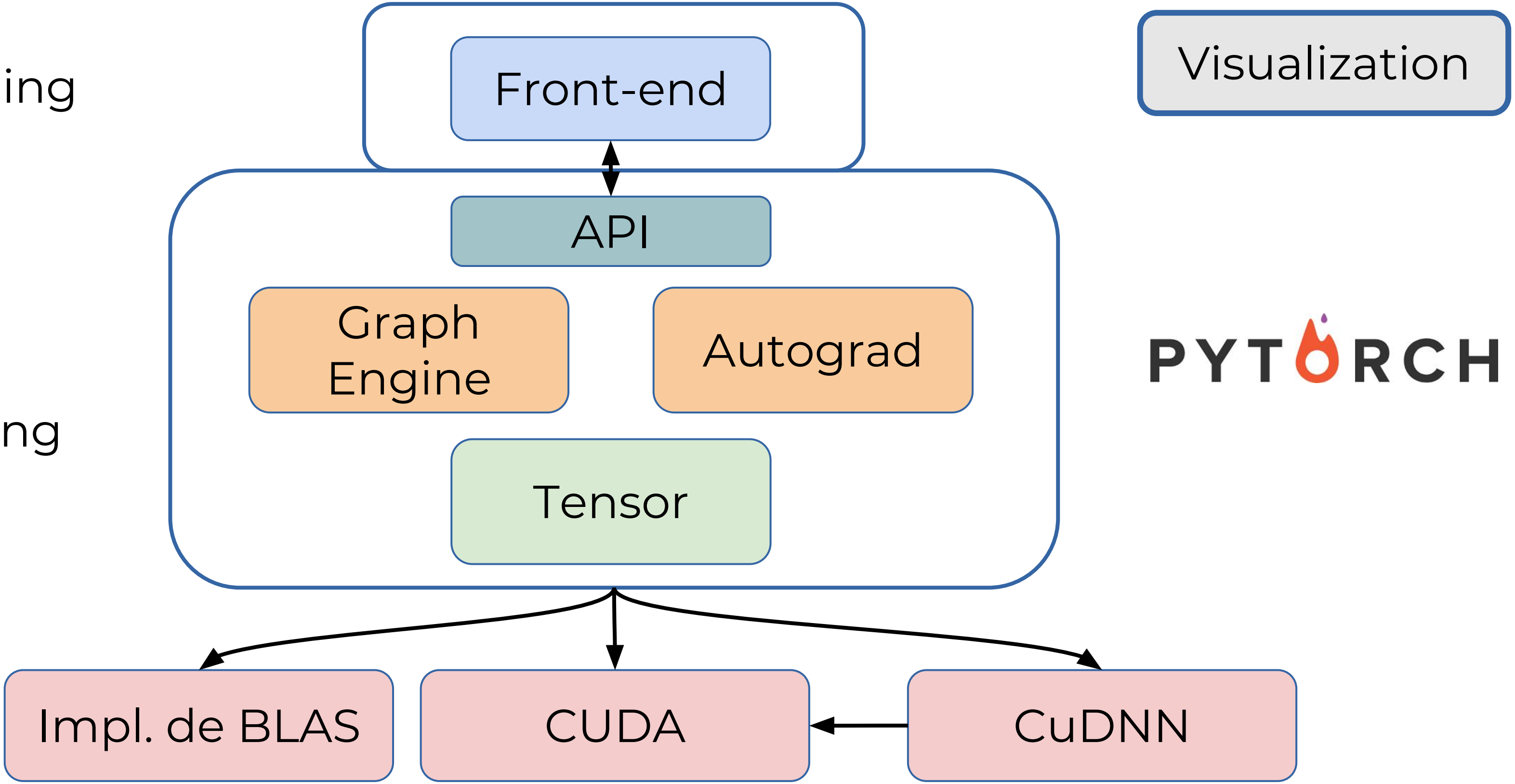

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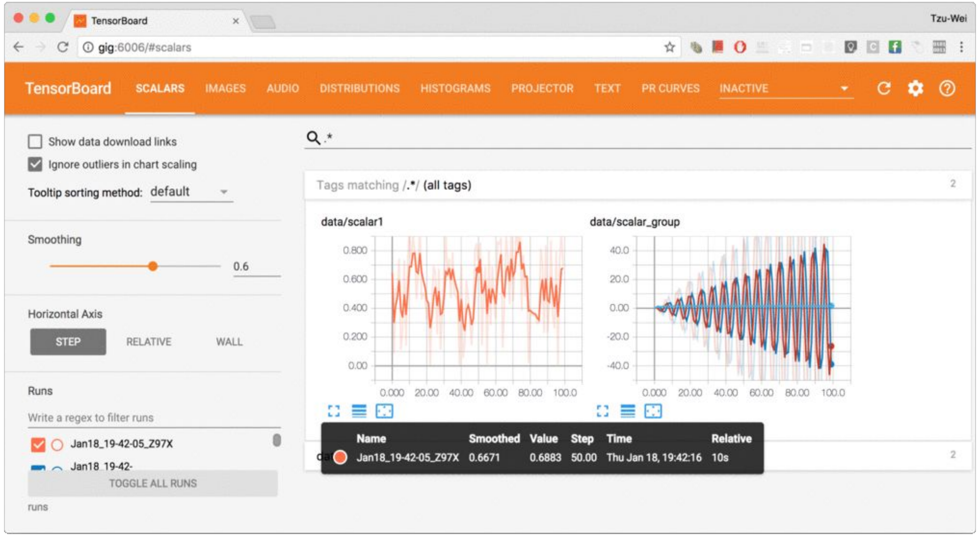
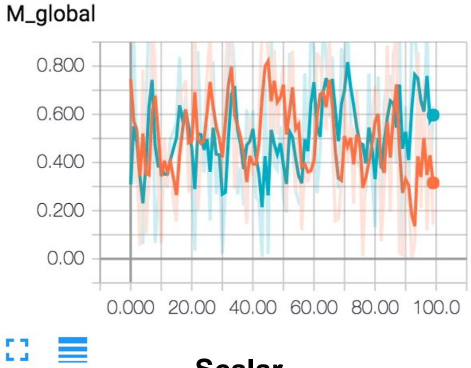
What is Tensorboard

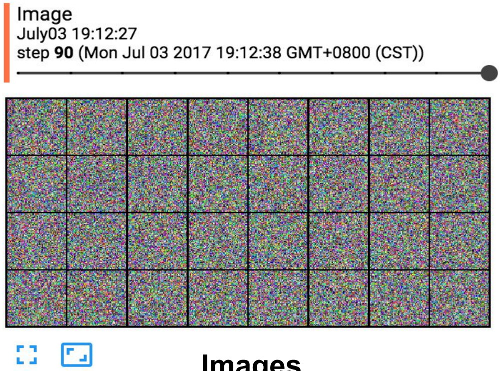
- A **TensorFlow** graphical interface useful for:
  - Graph visualization
  - Metric monitoring
  - Model Analysis
  - Debugging



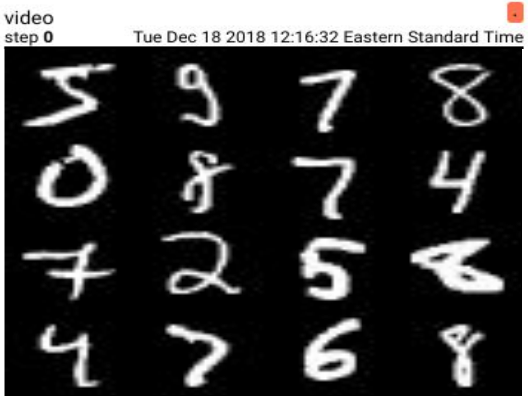
Levels of Information



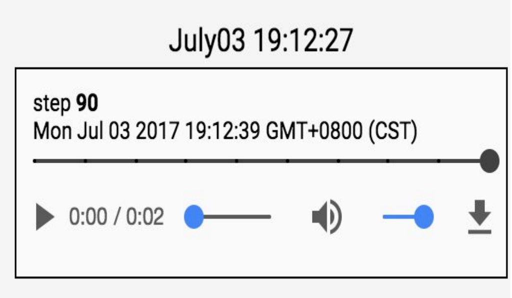
Scalar



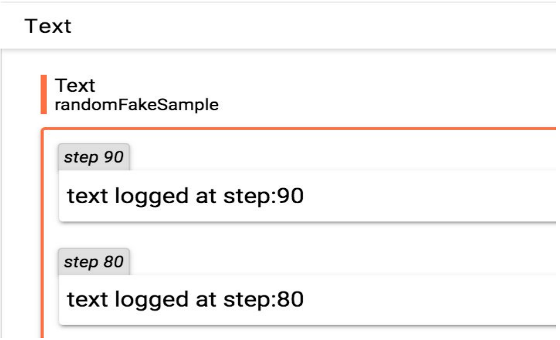
Images



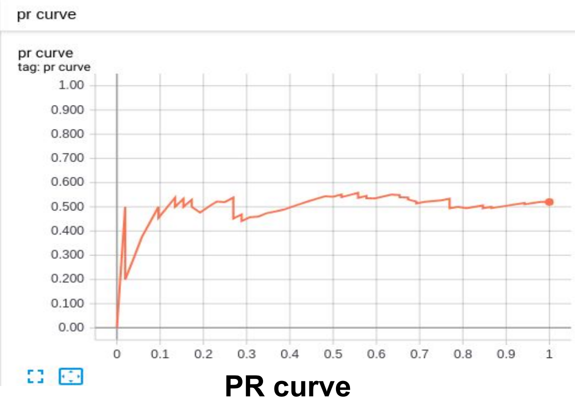
Video



Audio

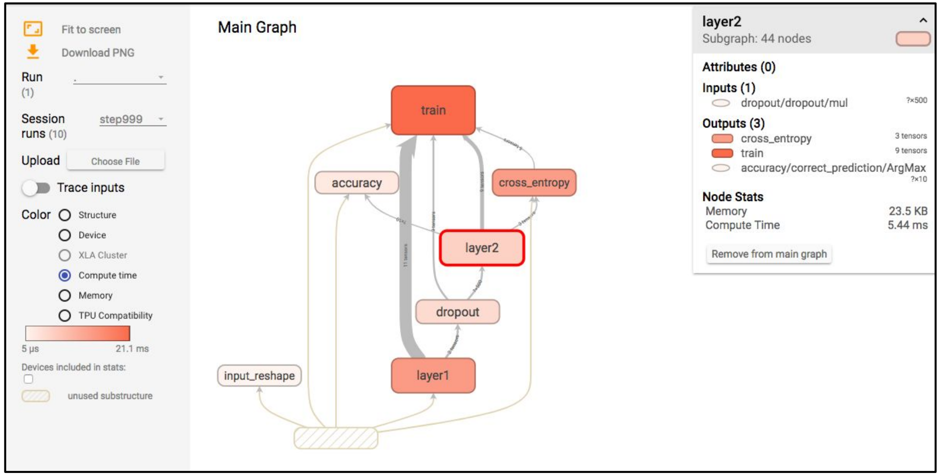


Text

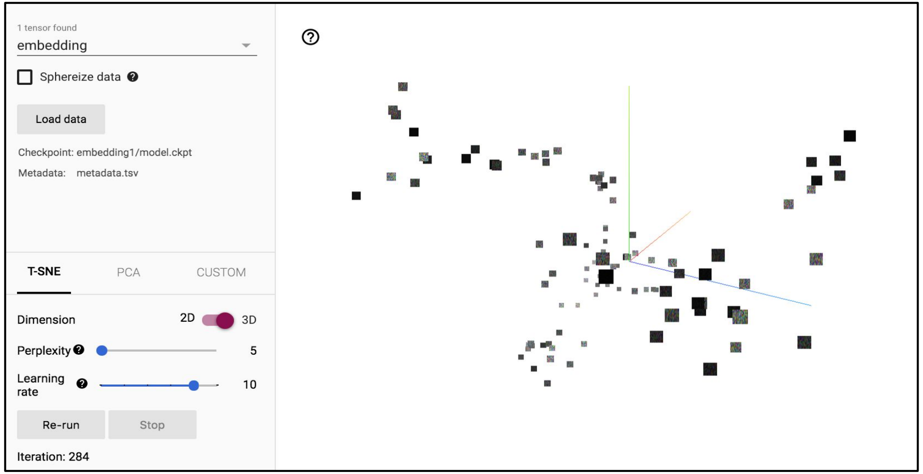


PR curve

Levels of Information

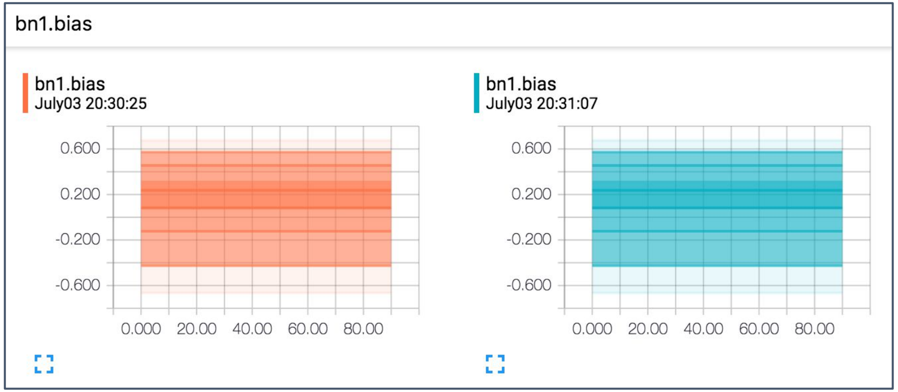


Computational Graphs

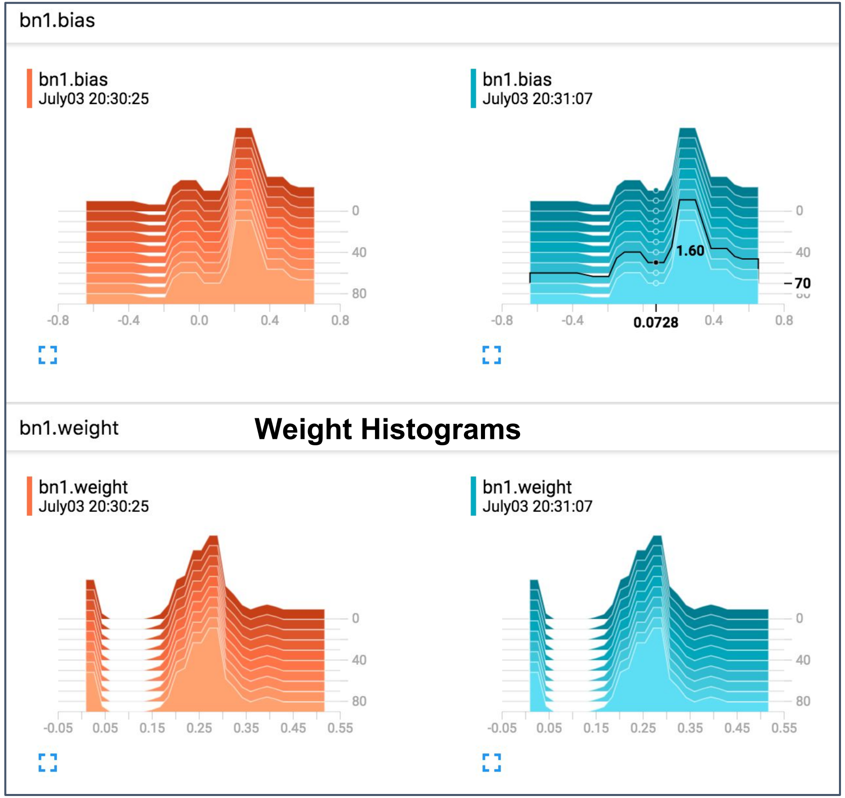


Embeddings

Levels of Information



Weight Distributions



Weight Histograms

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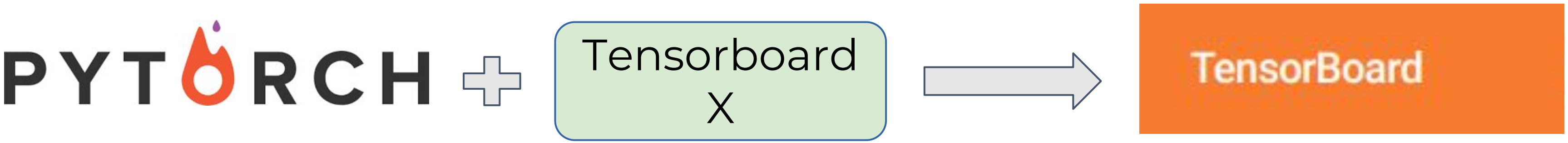
What is TensorboardX

- A module for visualization in tensorboard that works from **PyTorch**.



Interface for writing TensorBoard events with simple function calls

https://tensorboardx.readthedocs.io/en/latest/tensorboard.html

SummaryWriter

class **tensorboardX.SummaryWriter**(*log_dir=None, comment='', **kwargs*) [source]

Writes *Summary* directly to event files. The *SummaryWriter* class provides a high-level api to create an event file in a given directory and add summaries and events to it. The class updates the file contents asynchronously. This allows a training program to call methods to add data to the file directly from the training loop, without slowing down training.

- Class to directly write event files.
- General API format:

```
add_something(tag name, object, iteration number)
```

- Examples:
  - **add_scalar**(*tag, scalar_value, global_step=None, walltime=None*)
  - **add_image**(*tag, img_tensor, global_step=None, walltime=None*)
  - **add_video**(*tag, vid_tensor, global_step=None, fps=4, walltime=None*)
  - **add_audio**(*tag, snd_tensor, global_step=None, sample_rate=44100, walltime=None*)
  - **add_text**(*tag, text_string, global_step=None, walltime=None*)
  - **add_pr_curve**(*tag, labels, predictions, global_step=None, num_thresholds=127, weights=None, walltime=None*)
  - **add_graph**(*model, input_to_model=None, verbose=False, **kwargs*)
  - **add_embedding**(*mat, metadata=None, label_img=None, global_step=None, tag='default', metadata_header=None*)
  - **add_histogram**(*tag, values, global_step=None, bins='tensorflow', walltime=None*)

https://tensorboardx.readthedocs.io/en/latest/tensorboard.html

Example

```python
import torch
import torch.optim as optim
from tensorboardX import SummaryWriter

use_gpu = torch.cuda.is_available()
device = torch.device("cuda:0" if use_gpu else "cpu")
log_interval = 5


writer = SummaryWriter('runs')

model = ...

model.to(device)
optimizer = optim.SGD(model.parameters())

def train(epoch):
    model.train()
    torch.set_grad_enabled(True)
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))
            niter = epoch*len(train_loader)+batch_idx
            writer.add_scalar('Train/Loss', loss.data[0], niter)
```

https://tensorboardx.readthedocs.io/en/latest/tensorboard.html

Useful Commands

- **Installation**
  - pip install tensorboardX tensorboard
- **Execution**
  - tensorboard --logdir=<your_log_dir> [--port nPort]
- **Visualization** (on Browser)
  - http://localhost:nPort
- **Multiple run comparison**
  - tensorboard runs

https://tensorboardx.readthedocs.io/en/latest/tensorboard.html

Particularities on Helios

- No control of the computational nodes
  - You **can't run** tensorboard on those nodes
  - No **online monitoring** of your experiments

- But you can still do **offline monitoring**
  - Log your data as usual using **SummaryWriter**
  - **Copy the log files** at the end of the experiments on your local machines
  - Run tensorboard **locally**

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Checkpointing
Save and Resume your experiments

Checkpointing

- A way to save the current state of an experiment
  - Possibility to **pick up** from the saved point

- A way to keep track of the best weights of a model
  - Possibility to save the weights with the best validation performance

- A way to save multiple models
  - Possibility to average the weights of those models to generate an ensemble

When to set checkpoints

- Every n_batches of mini batches

- n_batches shouldn’t be too small because this might lead to:
    - Training slowdown if the validation set is large
    - Large disk space usage if the model weights at all checkpoints are saved

- n_batches shouldn’t be too large because this might lead to:
    - Missing the best model(s)

Checkpointing - What to save

- The architecture of the model
  - Possibility to re-create the model

- The weights of the model

- The training configuration
  - loss, epochs, and other meta-information (seed, hyperparameters, ...)

- The state of the optimizer
  - Possibility to resume training exactly where it left off

Checkpointing in PyTorch

- It is **recommended** to save only the model weights, not the model class

- Make use of the following functions:
  - torch.save
  - torch.load

Save a checkpoint in PyTorch

```
torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'loss': loss,
            ...
            }, PATH)
```

Load a checkpoint in PyTorch

```
model = TheModelClass(*args, **kwargs)
optimizer = TheOptimizerClass(*args, **kwargs)

checkpoint = torch.load(PATH)
model.load_state_dict(checkpoint['model_state_dict'])
optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
epoch = checkpoint['epoch']
loss = checkpoint['loss']

model.eval()
# - or -
model.train()
```

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Hyperparameter Tuning

What are Hyperparameters?

- In Machine Learning, a hyperparameter is a parameter whose value is set **before** the learning process begins.

- Hyperparameters **heavily affect the behaviour** of the underlying model.

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Examples of Hyperparameters in DL

- What is the network depth? How wide is it?
- Every layer: Feedforward or Convolutional?
- How do layers connect to each other?
- What type of activation functions to use?
- Which optimization algorithm to use?
- What’s the learning rate?
- How does the learning rate drop?
- Which initialization function to use?
- Is momentum necessary? What’s the rate?

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Examples of Hyperparameters in DL

- Is bias term needed in convolutional layers?
- Is dropout needed?
- Is batch norm needed?
- Is weight decay needed?
- What’s the weight decay speed?
- What’s the batch size?
- ...

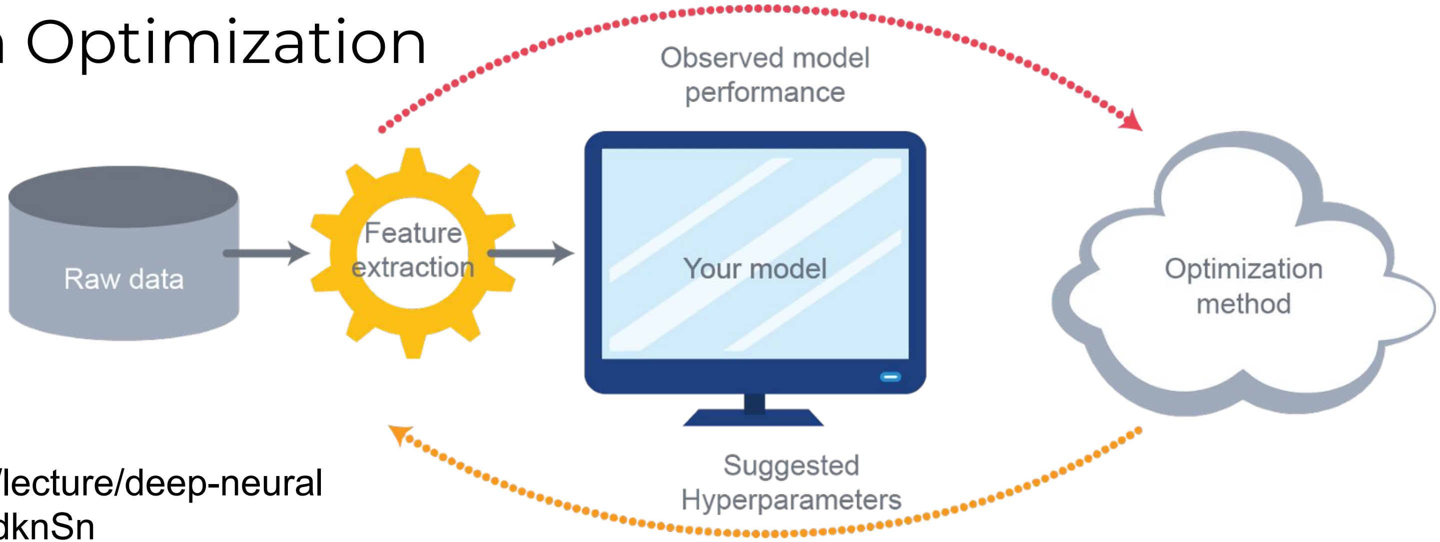
For each of these questions (hyperparameters), you have a **set of possible values** or a **range of values** associated. The combination of these values forms the **hyperparameter space**.

Hyperparameter Tuning

- From the hyperparameter space, find **a set of values** that lead to **optimal performances**.
  - E.g., Accuracy, MSE, ….

Some Existing approaches

- Grid Search
- Random Search
- Bayesian Optimization



https://www.coursera.org/lecture/deep-neural-network/tuning-process-dknSn

Grid Search

Explore **all** the possible hyperparameter configurations

- For each configuration, compute the related performance metric
    - Cross-validation for robustness

Keep the configuration with the highest performance.

Random Search

- Avoid exploration of the whole hyperparameter space
- Proceed by **randomly sampling a limited number** of configurations
  - For each sampled configuration, compute the related performance metric
    - Cross-validation for robustness

Keep the configuration with the highest performance.

Random Search: Strategies

- Set of discrete values:
  - Uniform sampling

- Range Values
  - Linear scale
  - Log-scale
  -
- For more information:
  https://www.coursera.org/lecture/deep-neural-network/using-an-appropriate-scale-to-pick-hyperparameters-3rdqN

Bayesian Optimization

- Set a **prior** over hyperparameter distribution

- Sequentially **update** it while observing different experiments using Bayes rule
  - Allows us to fit hyperparameter space better and, thus, find the configuration with highest performance.

Frameworks for Hyperparameter Tuning

scikit learn

tune

HyperSearch

SKORCH

Hyperopt

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