Development of the Pytorch Neuro Trigger

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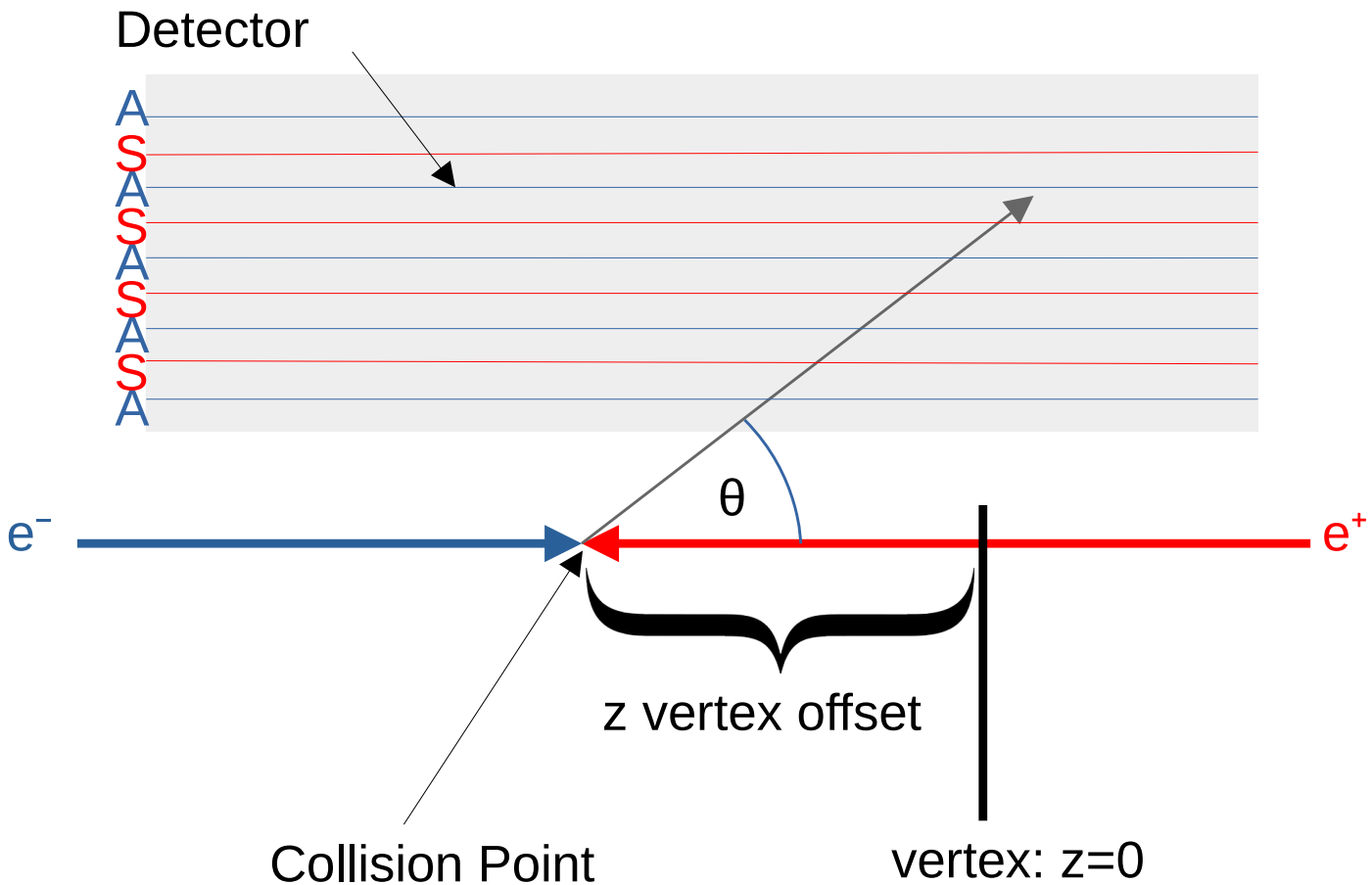
Max Planck Institute for Physics

Outline

Introduction

What do we want to predict?

- z-vertex
- θ angle
- Detector: 5 axial and 4 stereo superlayers



How to predict z and θ?

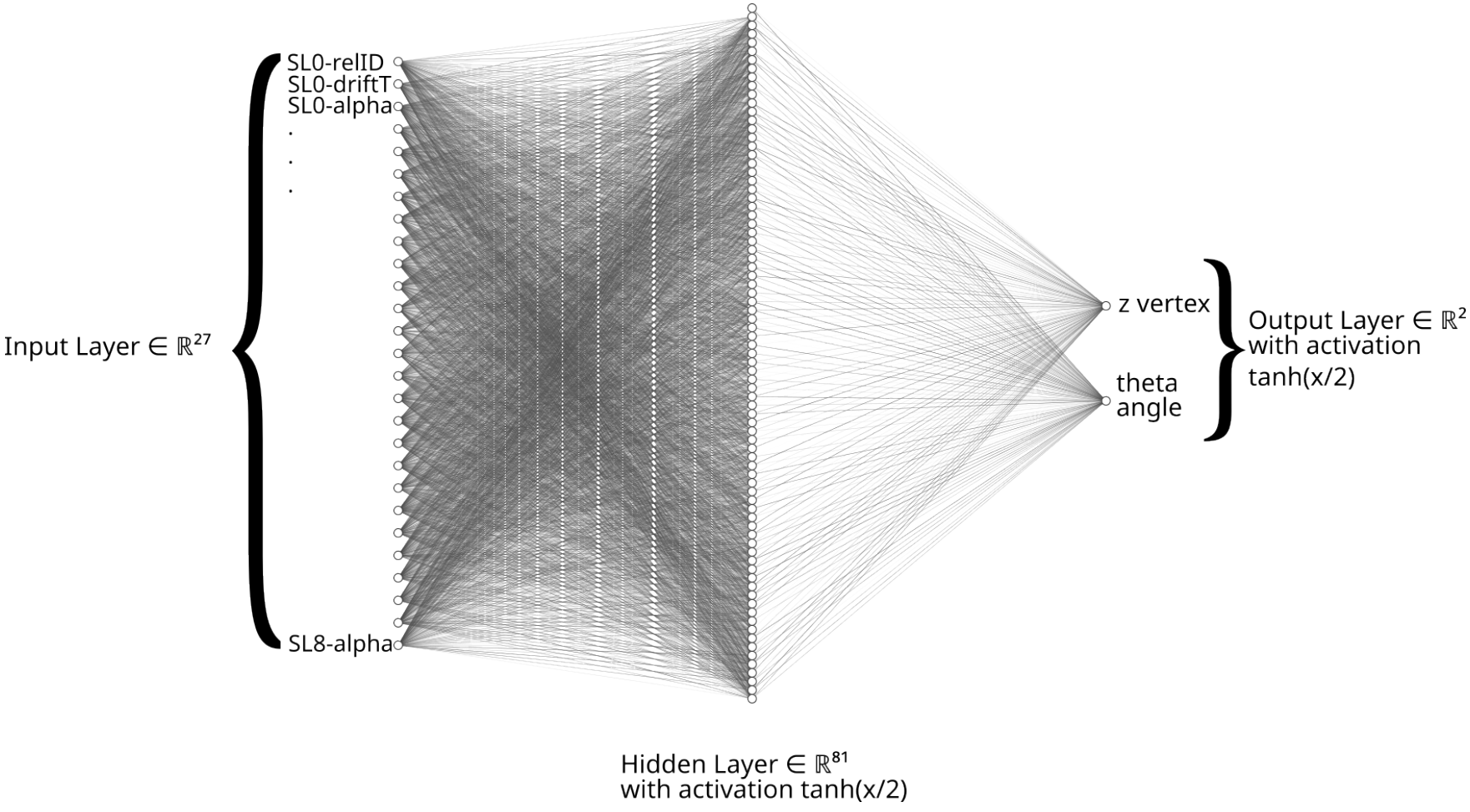
Neural Network for z and θ prediction of the e^+/e^- collision

- Input: 9 layers with
  - `SLx-relID`: Angle relative to 2D track ϕ
  - `SLx-driftT`: Drift time
  - `SLx-alpha`: Crossing angle α

  $\rightarrow \mathbb{R}^{27}$
- Output:
  - Collision's z-vertex
  - θ angle of the resulting partical

  $\rightarrow \mathbb{R}^2$
- One hidden layer with 81 neurons
- $\tanh(\frac{x}{2})$ as activation function

Network Architecture



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  - Sophisticated random weight initialization strategies

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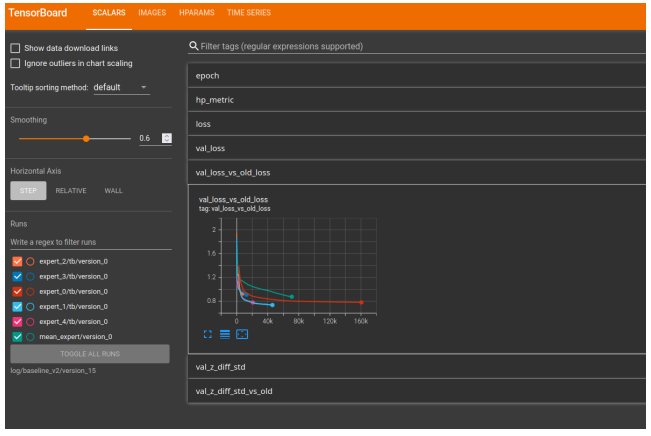

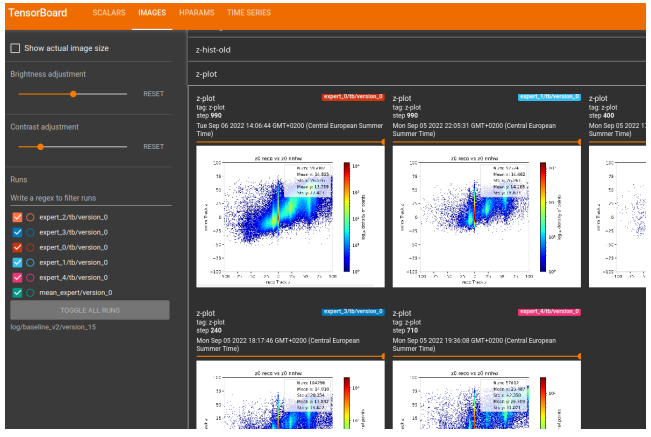

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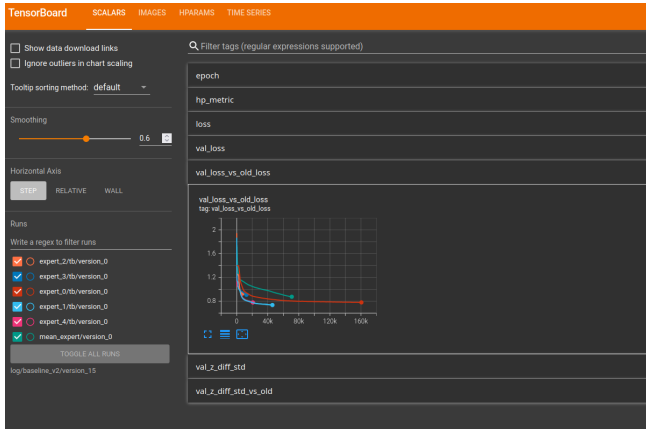

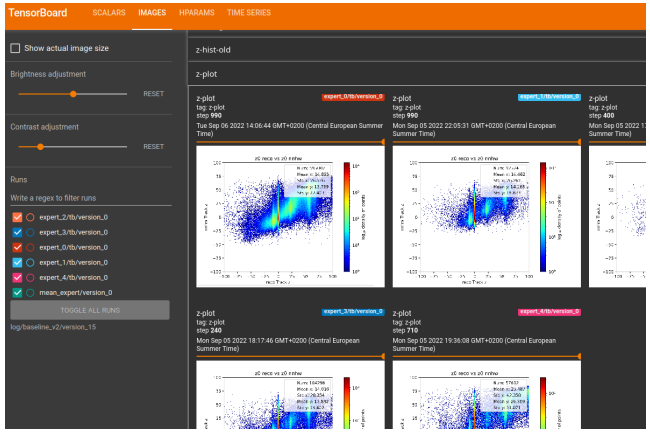

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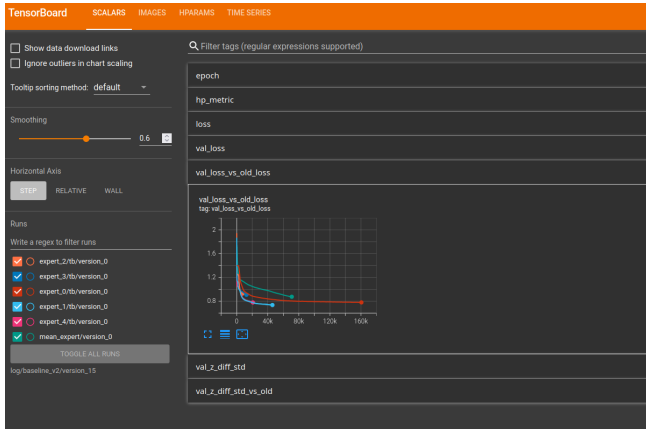

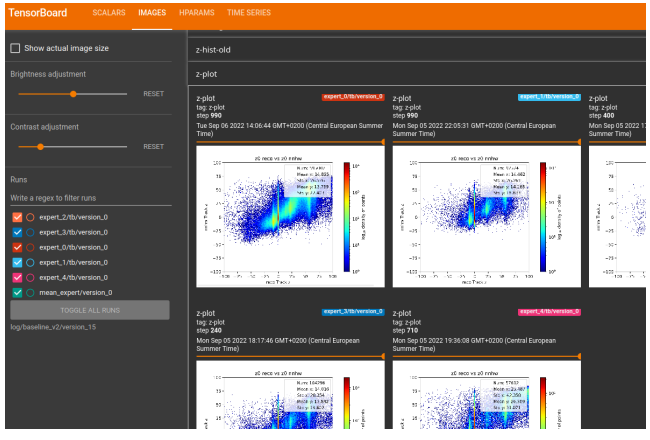

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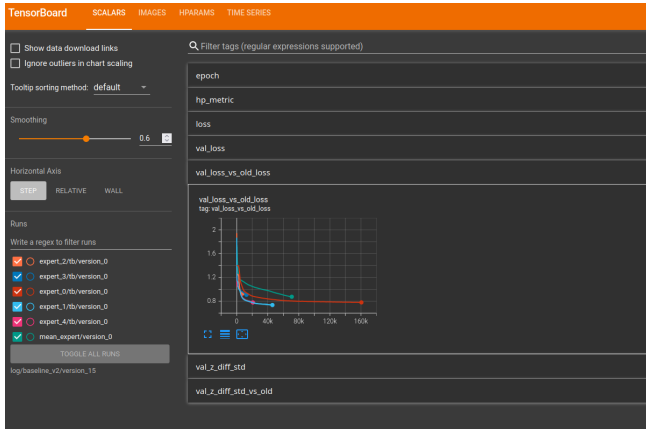
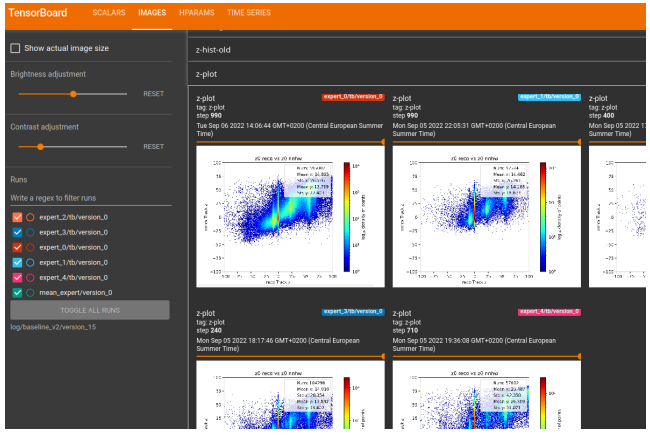
- Reproducability build-in through extensive logging





Configuration and Training

Folder Structure

```
nnt-pytorch
├── changelog.md
├── docs
│   ├── class_diagram.dia
│   ├── class_diagram.png
│   ├── class_diagram.svg
│   ├── norm_inf_bounds.png
│   ├── norm_non_inf_bounds.png
│   ├── uniform.png
│   └── zhist.png
├── README.md
├── requirements.txt
└── neuro_trigger
    ├── configs.py
    └── __init__.py
```

```
neuro_trigger
├── lightning
│   ├── __init__.py
│   ├── mean_tb_logger.py
│   └── pl_module.py
├── main.py
├── pytorch
│   ├── __init__.py
│   ├── dataset_filters.py
│   ├── dataset.py
│   └── model.py
├── tests
│   ├── __init__.py
│   ├── test_data.csv
│   ├── test_data_filter.csv
│   └── test.py
├── utils.py
└── visualize.py
```

Configure a Training

Trainings are configured in a python dictionary in `neuro_trigger/config.py`

- All training hyperparameter can be configured like learning rate, batch size, optimizer, network model, ... [1]
- Supports configurations inheritance
- Global hyperparameters vs per-expert hyperparameters
- Hierarchical: Flexible and extensible scheme

[1] Extensive list can be found in the README.md documentation

Configure a Training: Example

Base config to set default parameters:

```
"base": {
    "version": 1.0,
    "description": "Some desc.",
    "learning_rate": 1e-3,
    "batch_size": 2048,
    "weight_decay": 1e-6,
    "in_size": 27,
    "out_size": 2,
    "workers": 5,
    "epochs": 10,
    "model": "BaselineModel",
    "loss": "MSELoss",
    "optim": "Adam",
    "act": "tanh",
    "experts": [0, 1, 2, 3, 4],
    "compare_to": None,
    "load_pre_trained_weights":
        None,
}
```

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    "act": "tanh",
    "experts": [0, 1, 2, 3, 4],
    "compare_to": None,
    "load_pre_trained_weights":
        None,
}
```

Advanced config which inherits from base:

```
"my_base_extension": {
    "extends": "base",
    "description": "My ext.",
    "act": "tanh/2",
    "epochs": 1000,
    "expert_3": {
        "batch_size": 128,
        "epochs": 2000,
    },
    "expert_4": {
        "batch_size": 16,
        "epochs": 4000,
    },
    "compare_to":
        "base/version_4",
}
```

Training CLI

To start a training the `neuro_trigger/main.py` CLI has to be used:

```
usage: main.py [-h] [-p] [-s] mode

Tool to start the neuro trigger training.

positional arguments:
  mode                  Config mode to use, must be defined
                        in config.py

optional arguments:
  -h, --help            show this help message and exit
  -p, --production      If the flag is not given code will
                        run in debug mode otherwise production
                            mode
  -s, --solo_expert     Whether one or several experts are used
                        for training
```

Start Training and Tensorboard

- Start a production training

```
source venv/bin/activate
export PYTHONPATH="$PYTHONPATH:."
python neuro_trigger/main.py my_base_extension -p
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- View the log path

```
cat log/log.txt
```

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```

- View the log path

```
cat log/log.txt
```

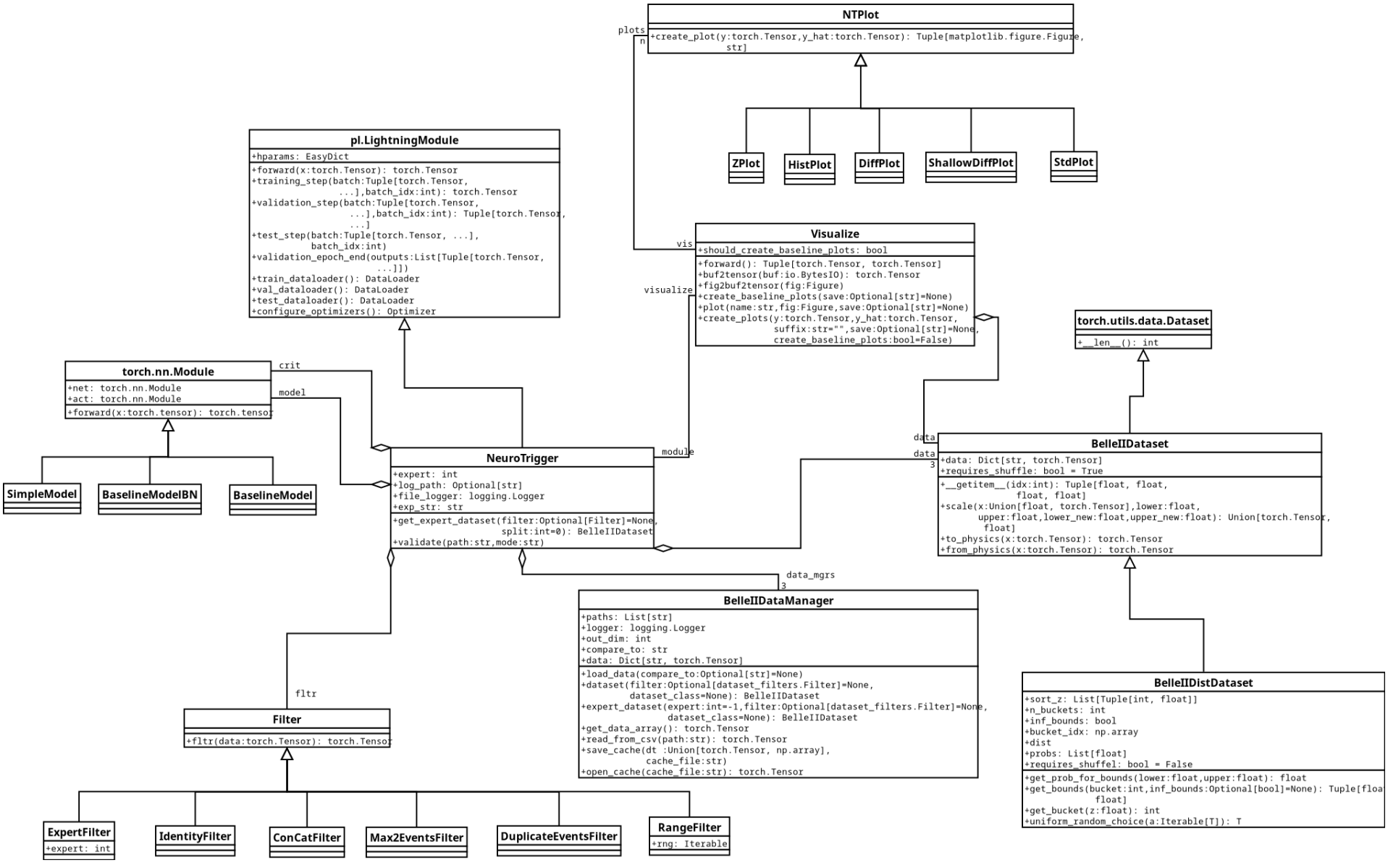
- Start Tensorboard

```
tensorboard --logdir=log/my_base_extension/
    version_0
```

Live Demo!

Extensibility

Software Architecture



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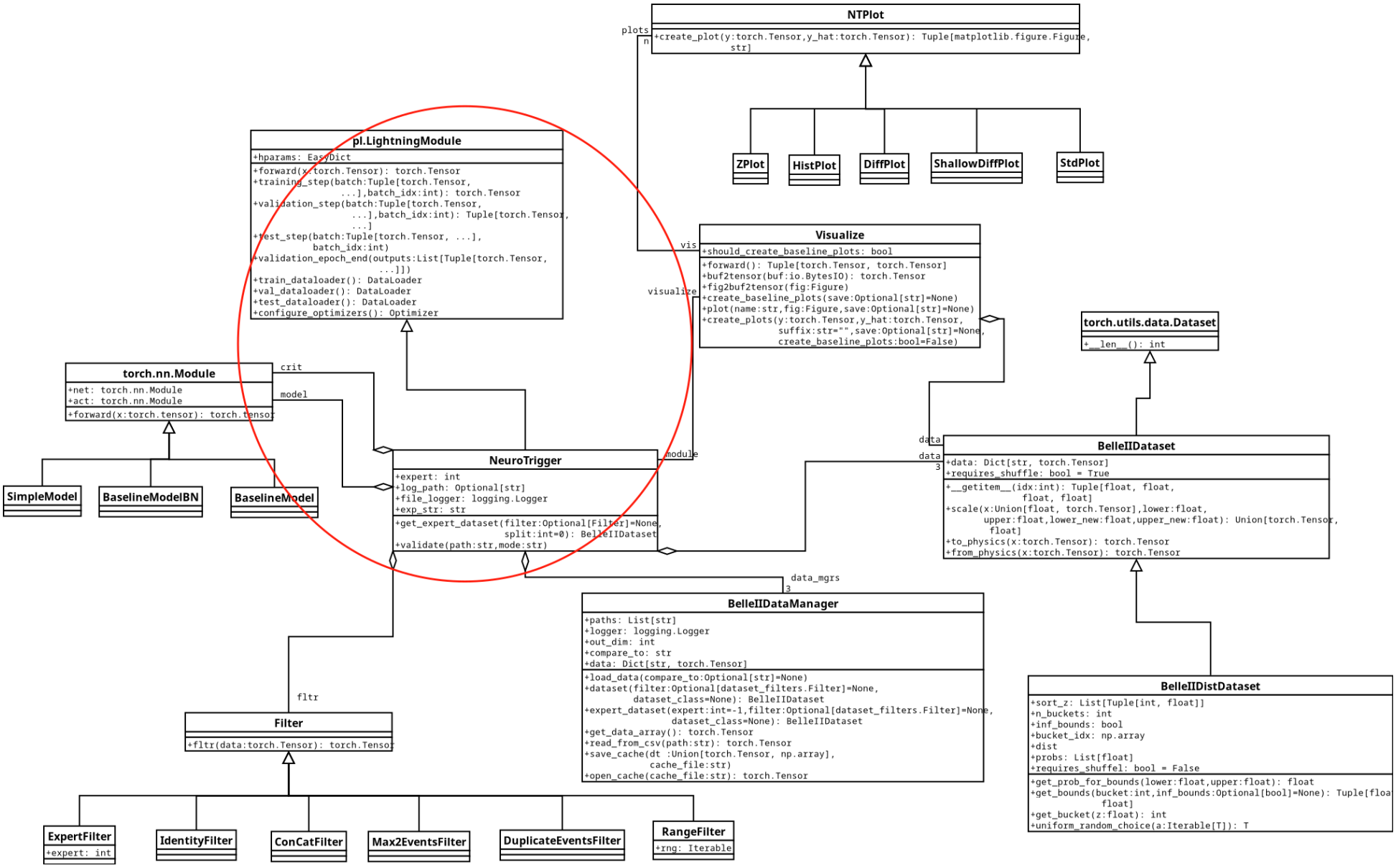

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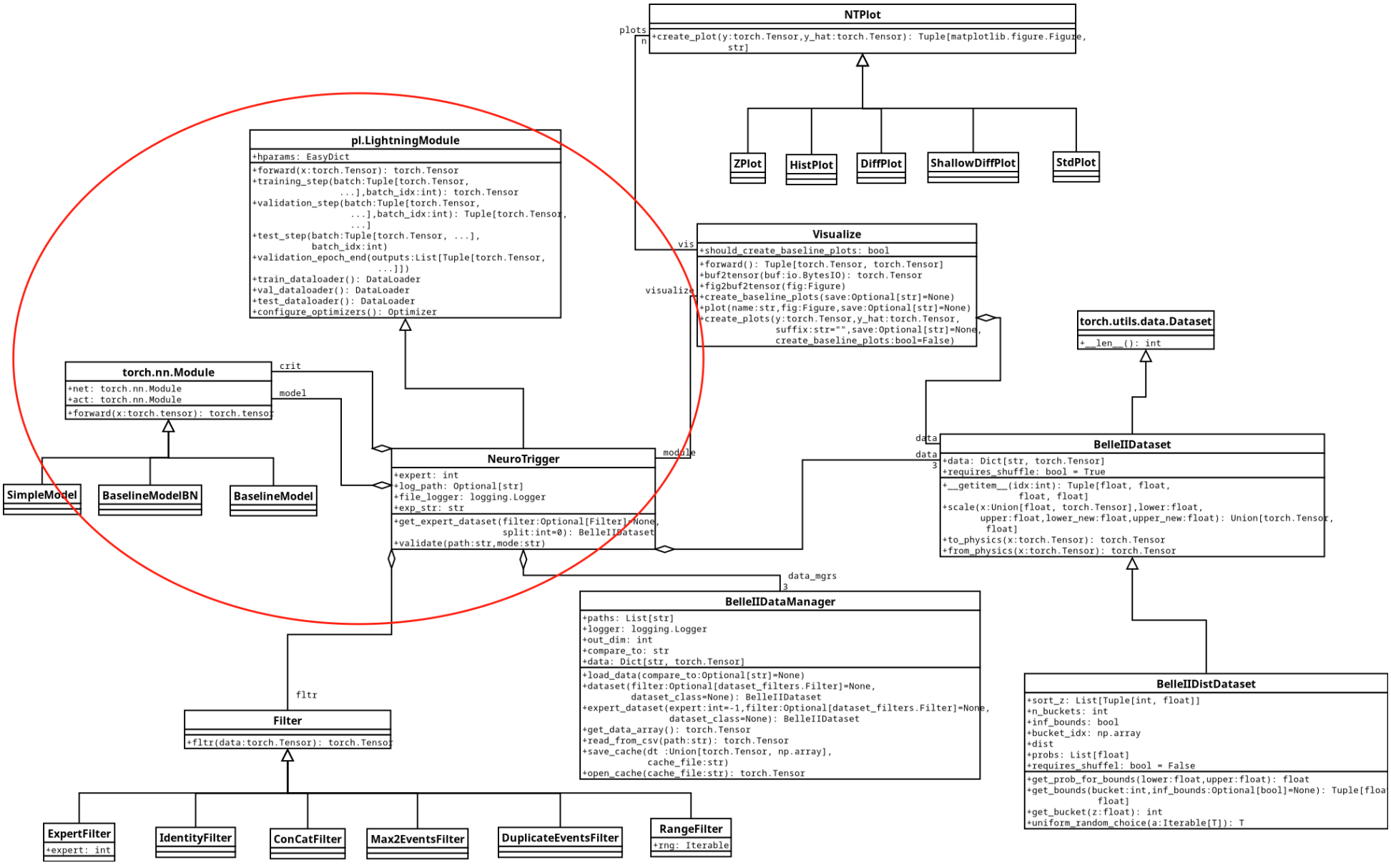

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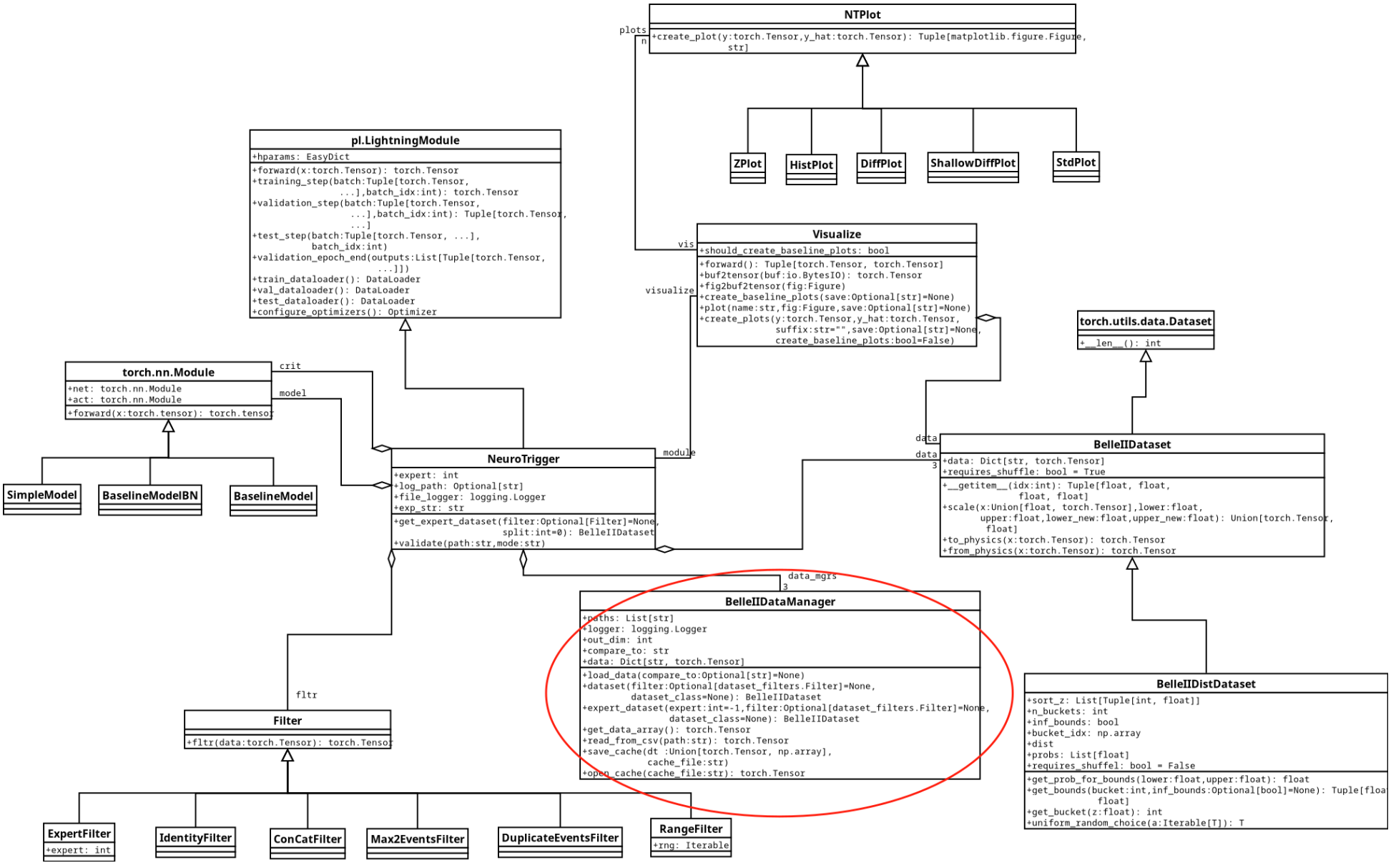

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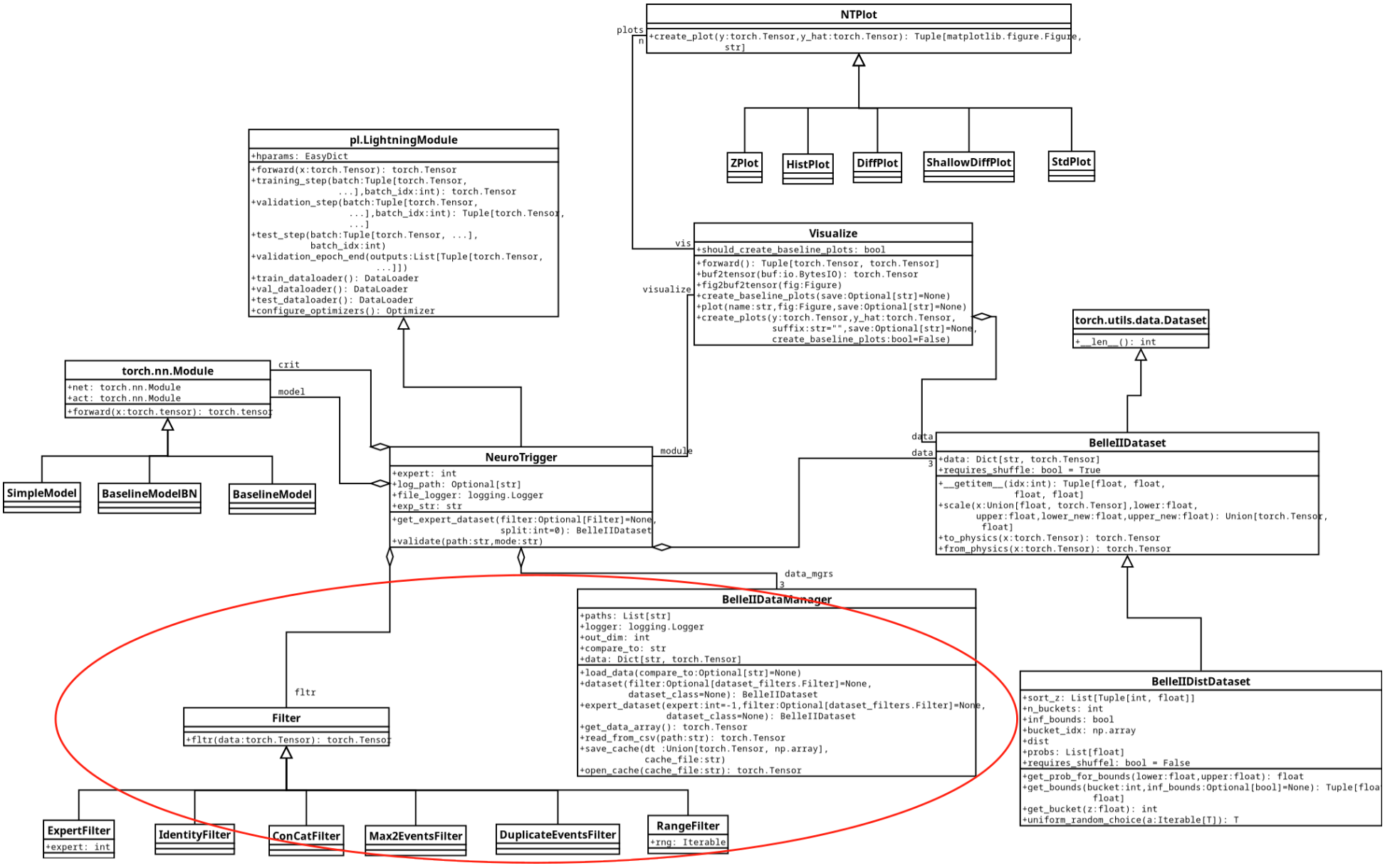

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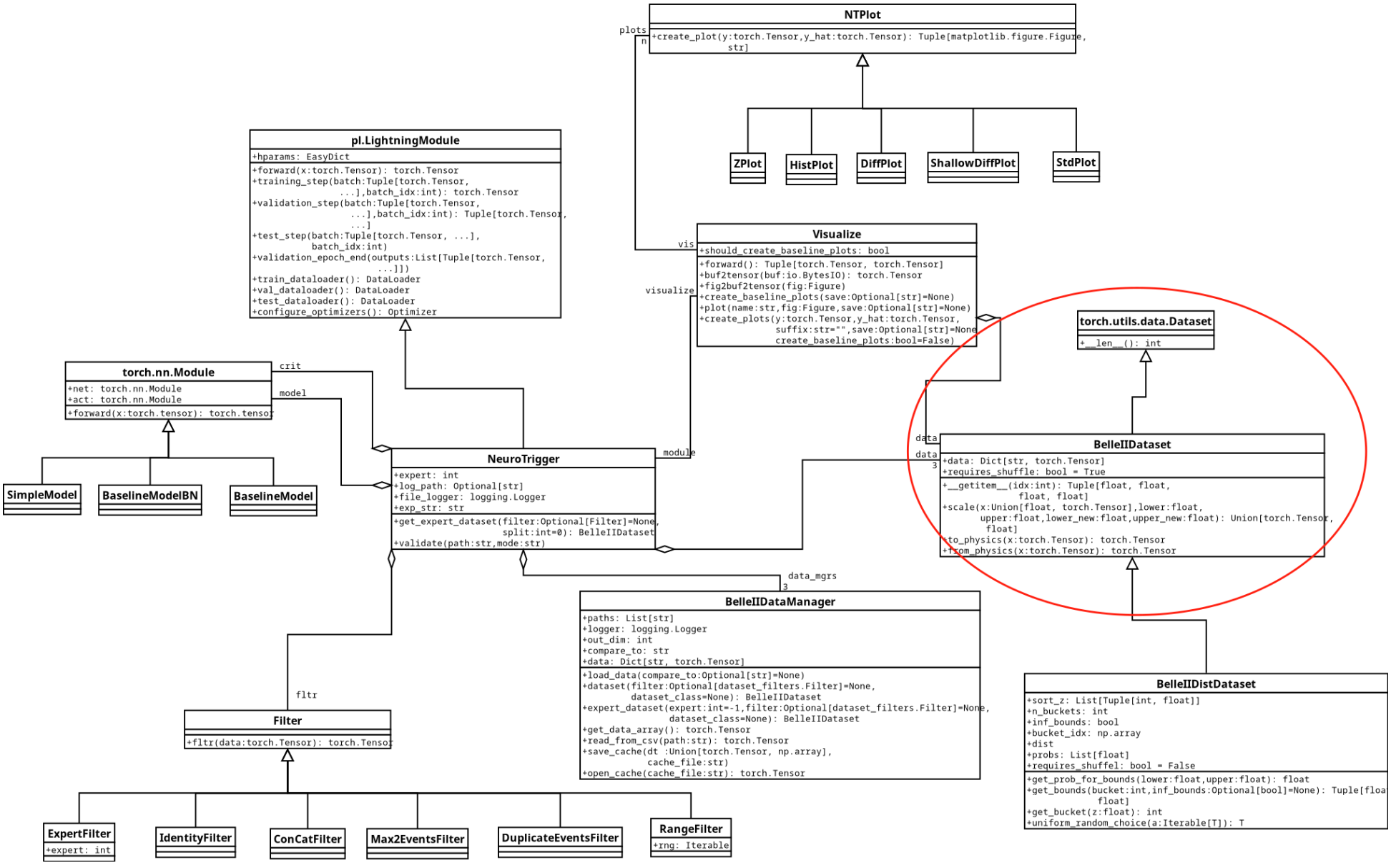

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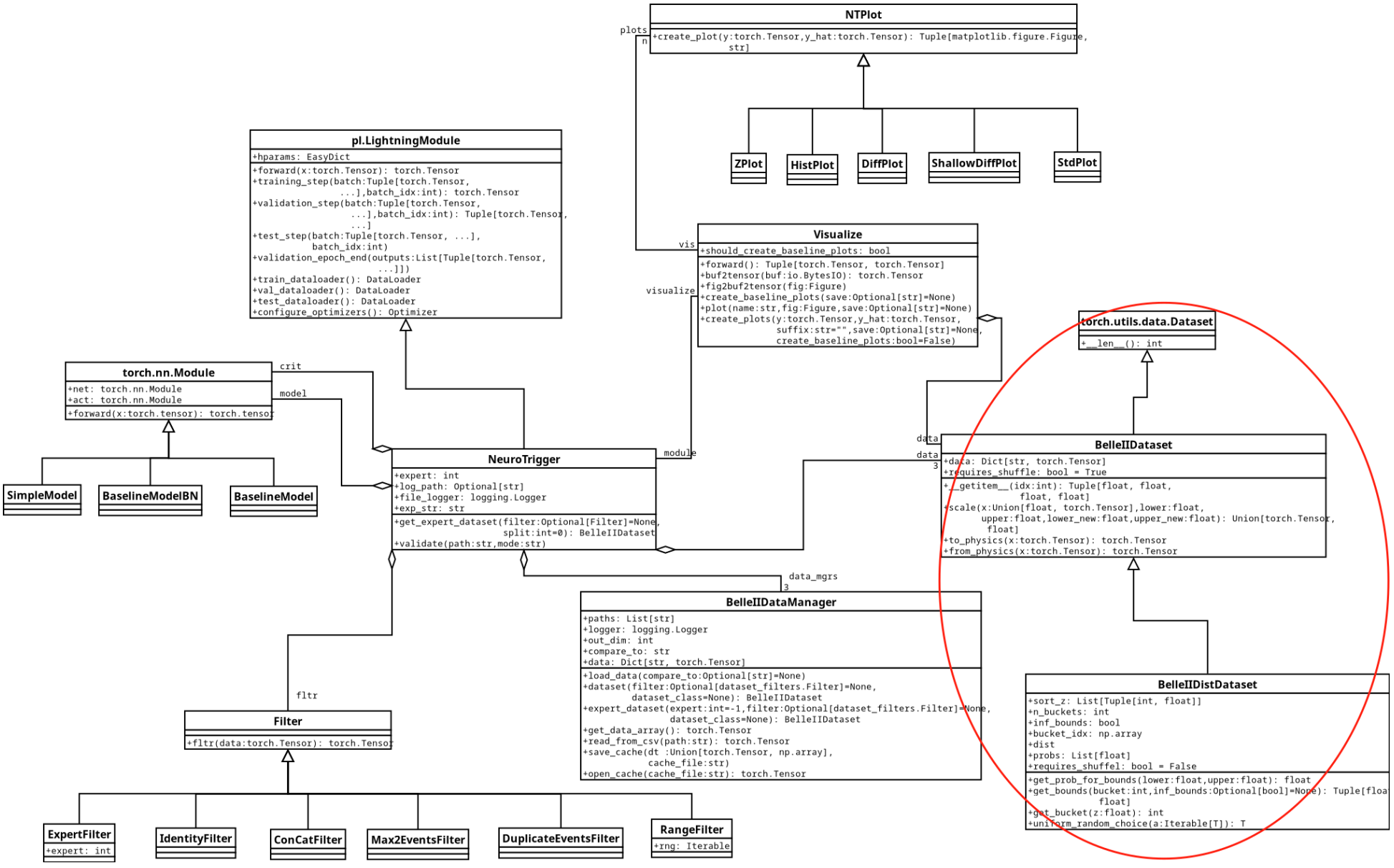

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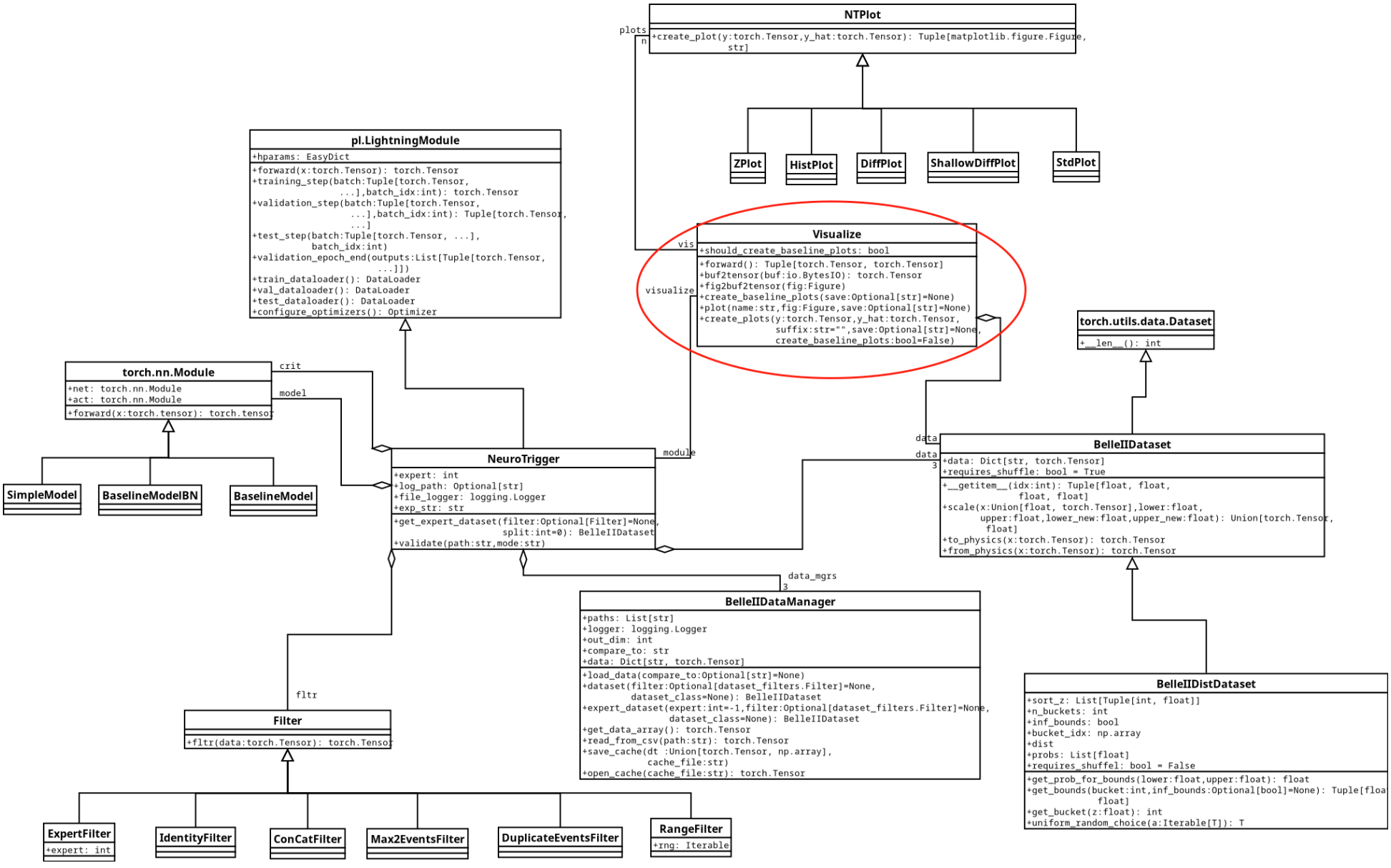

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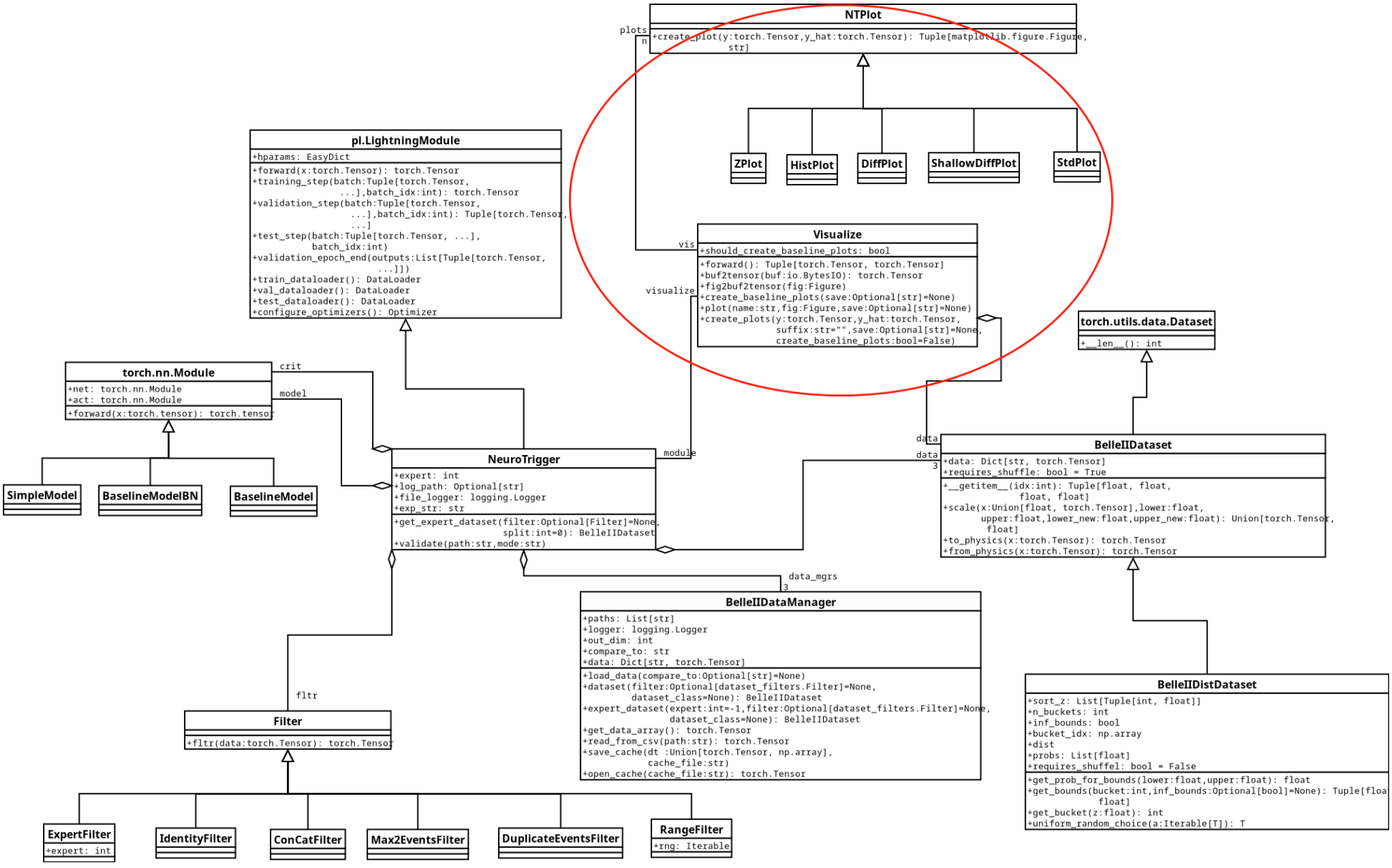

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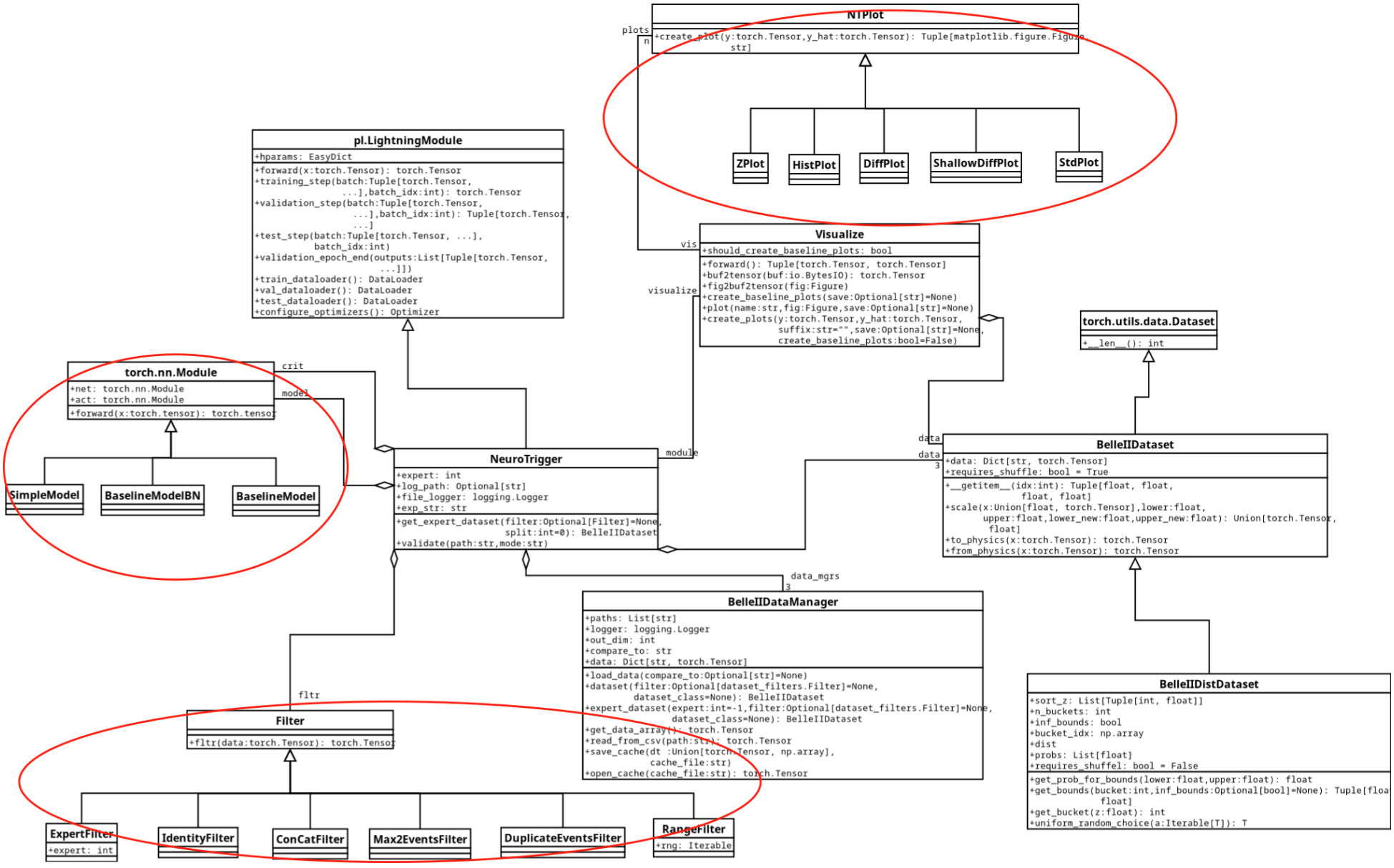
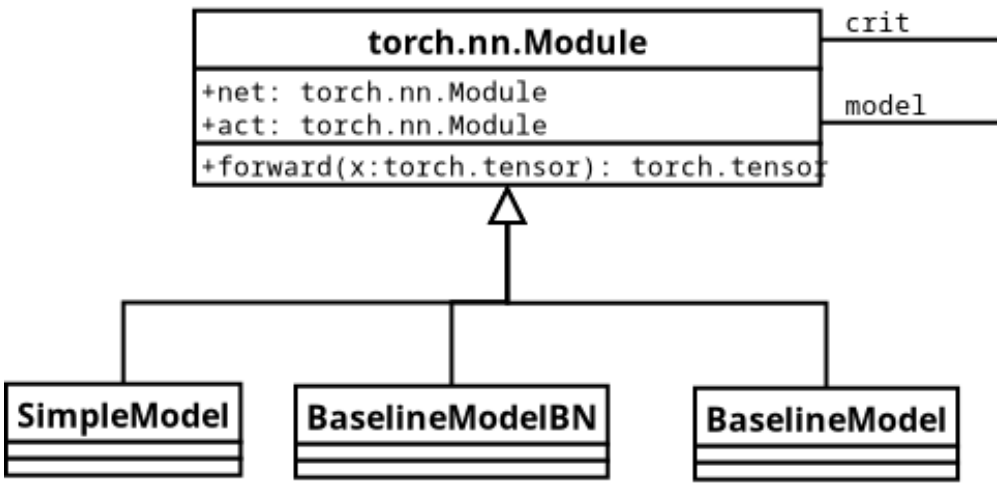


New Network Models

- Network models are defined using PyTorch Modules
- Expected contstructor arguments:
  - `inp`: input vector size, usally 27
  - `out`: output vector size, 2 for z and θ, 1 for only z
  - `act`: Activation function (PyTorch Module)
- PyTorch Module needs to implement the `forward` function



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Example: Current two layer FC network

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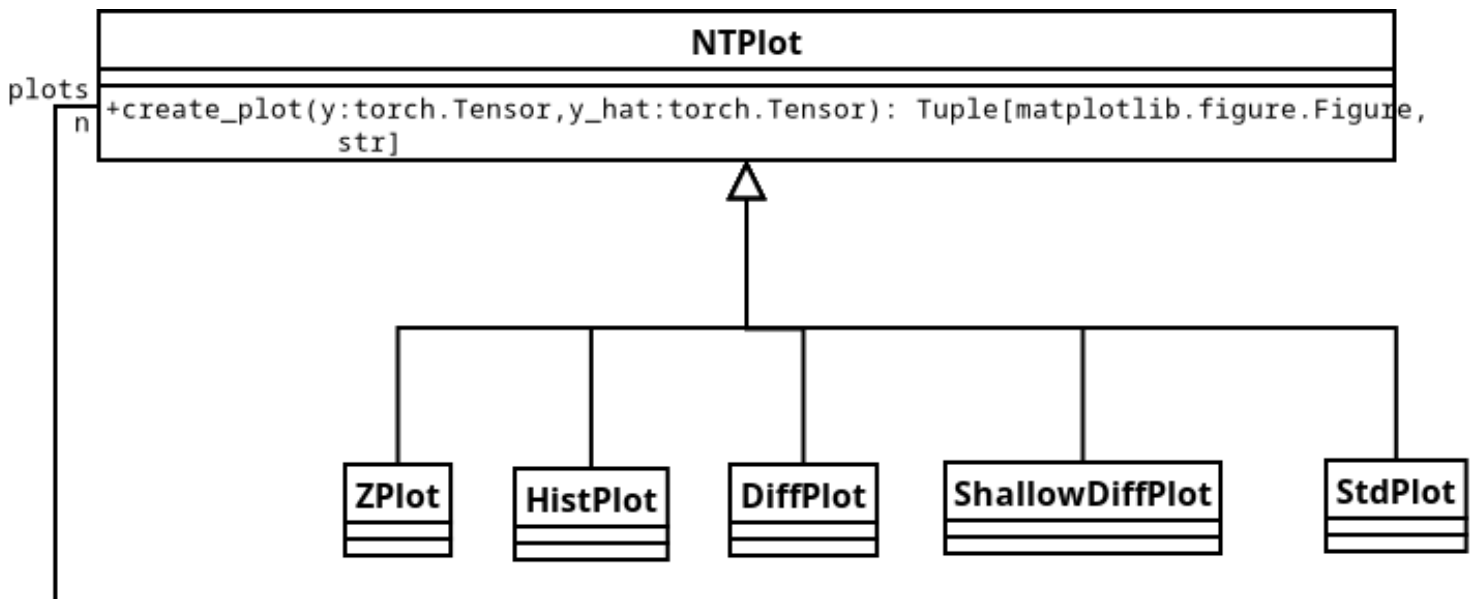
            nn.Linear(81, out),
            act,
        )
    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return self.net(x)
```

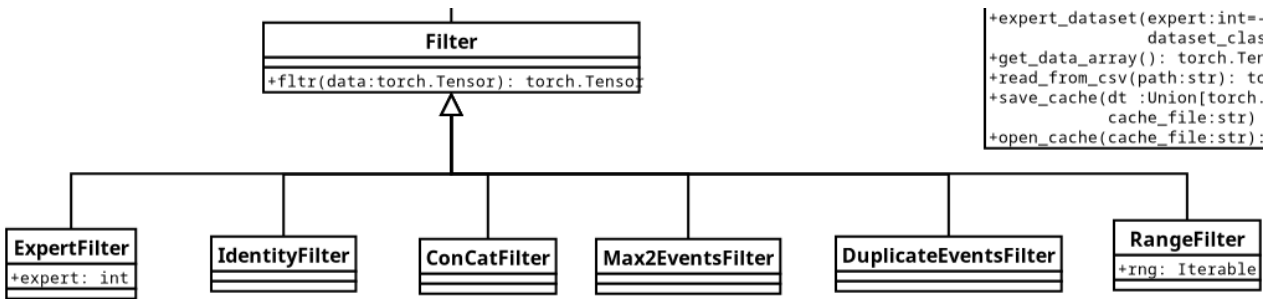
New Plots and Graphs

- Subclass from `visualize.NTPlot`
- Override the `create_plot` method
  - Gets prediction and ground truth (neuro and reco z)
  - Must return a matplotlib figure and a figure name



New Dataset filters

- Subclass from `dataset_filters.Filter`
- Override the `fltr` method
  - Gets data dictionary[2]
  - Must return boolean array with entries set to one that should be kept



[2] Keys and dimensions: `x` $\in \mathbb{R}^{N\times 27}$, `y` $\in \mathbb{R}^{N\times 2}$, `expert` $\in \mathbb{R}^{N}$, `y_hat_old` $\in \mathbb{R}^{N}$, ...

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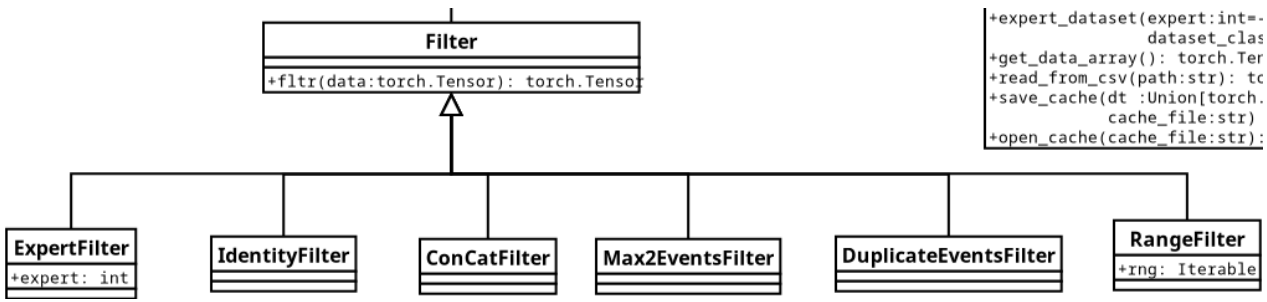

Example: Keep only positive z values

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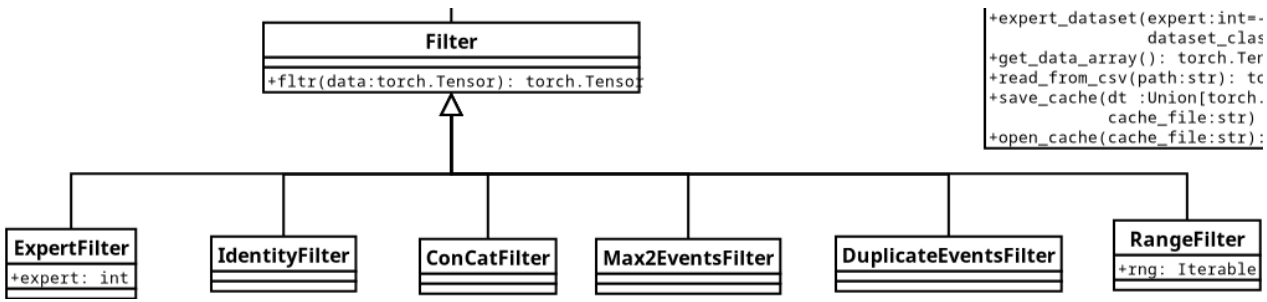

Example: Keep only positive z values

```
class PositiveZFilter(Filter):
    def fltr(self, data: Dict[str, torch.Tensor]) -> torch.Tensor:
        z_data = data['y'][:,0]
        return z_data > 0
```

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Dataset filters in Configuration

Use the new filter in your config (filter needs to be defined in `dataset_filters.py`):

```
"some_config": {
    # ...
    "filter": "dataset_filters.PositiveZFilter()",
}
```

Dataset filters in Configuration

Use the new filter in your config (filter needs to be defined in `dataset_filters.py`):

```
"some_config": {
    # ...
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}
```

Combine several filters with the `ConCatFilter`:

```
"some_config": {
    # ...
    "filter": "dataset_filters.ConCatFilter([
                    dataset_filters.PositiveZFilter(),
                    dataset_filters.RangeFilter(range(100))
                ])",
}
```

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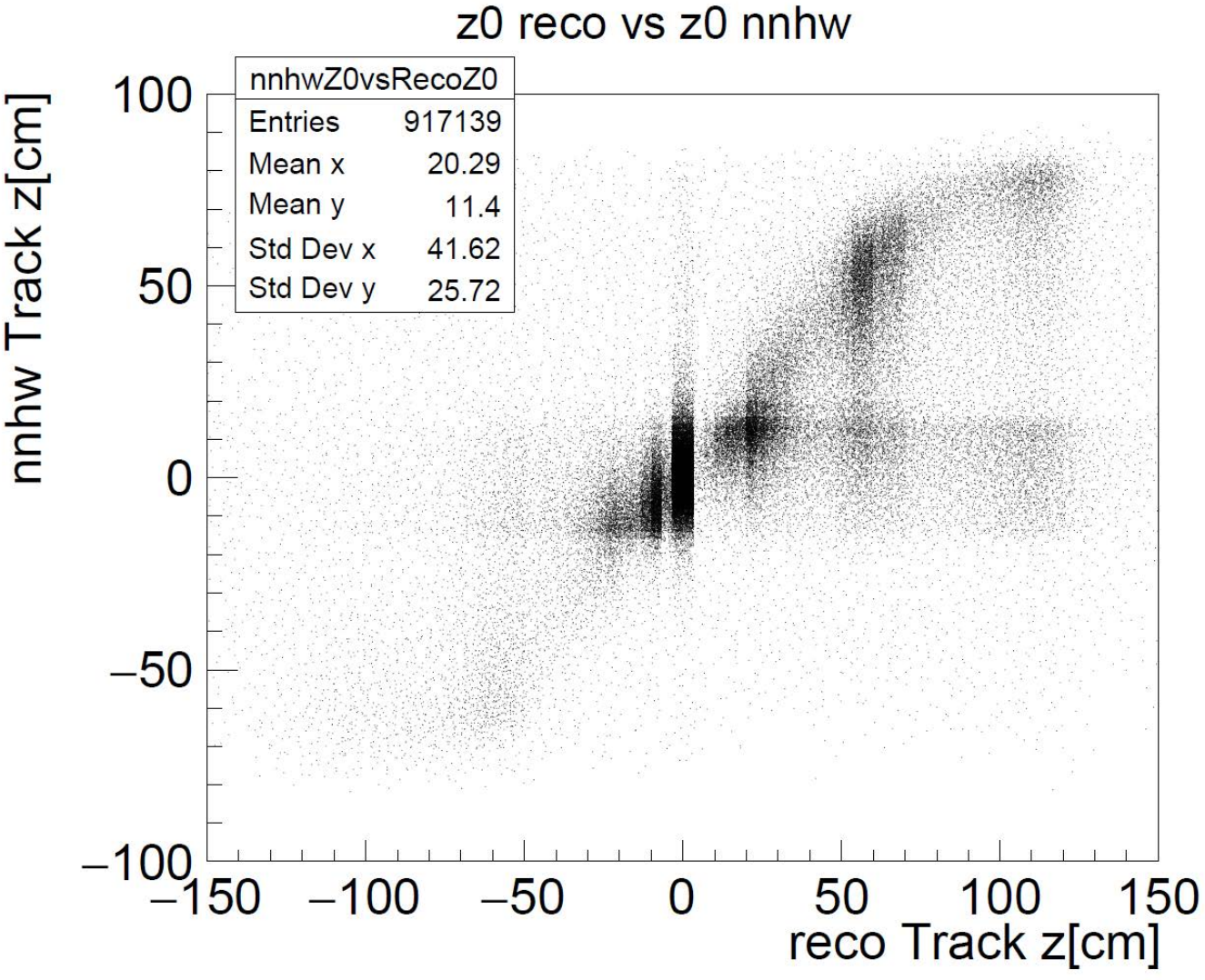
```

$\rightarrow$ Only positive z values **and** only the first one hundred samples

Feed-down Problem and Reweighting

The Feed-Down Problem

Feed-Down in the pre-PyTorch training:



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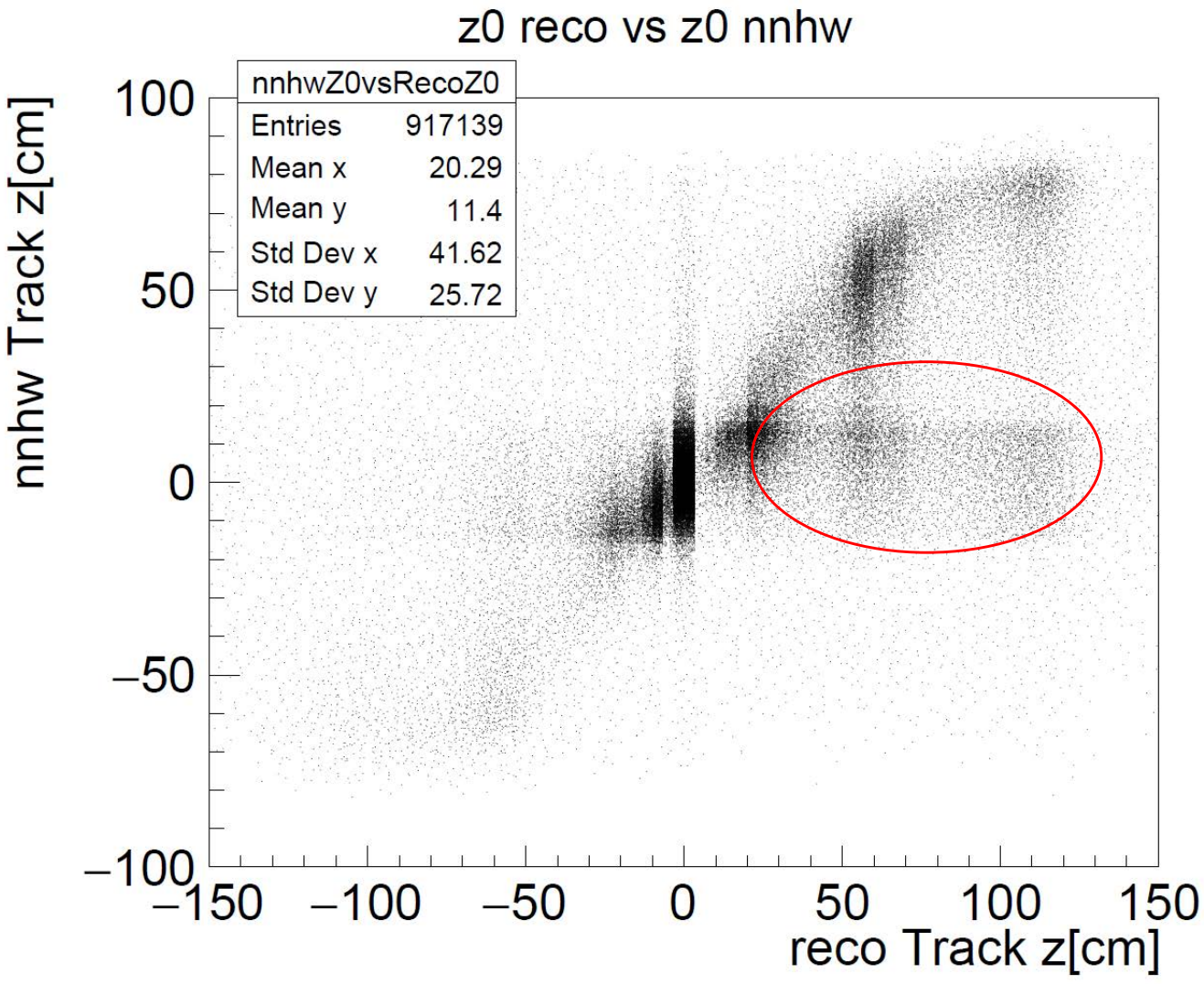
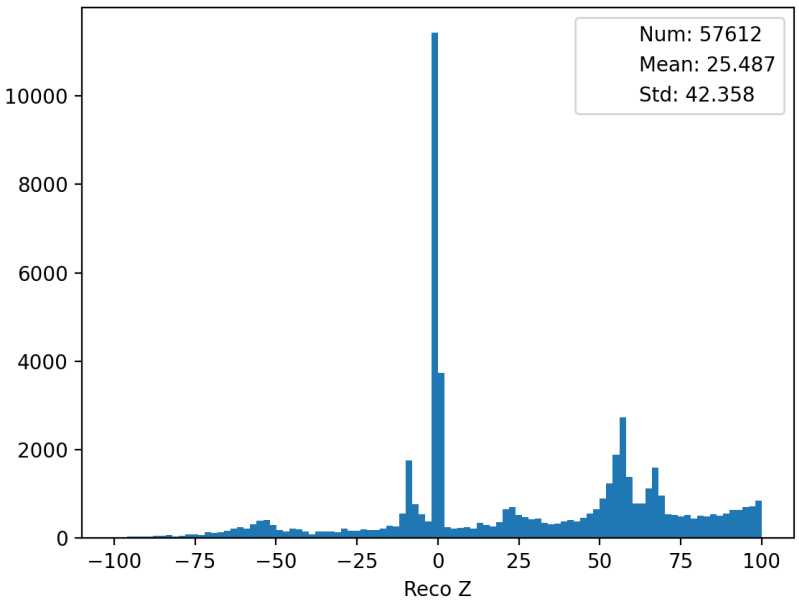


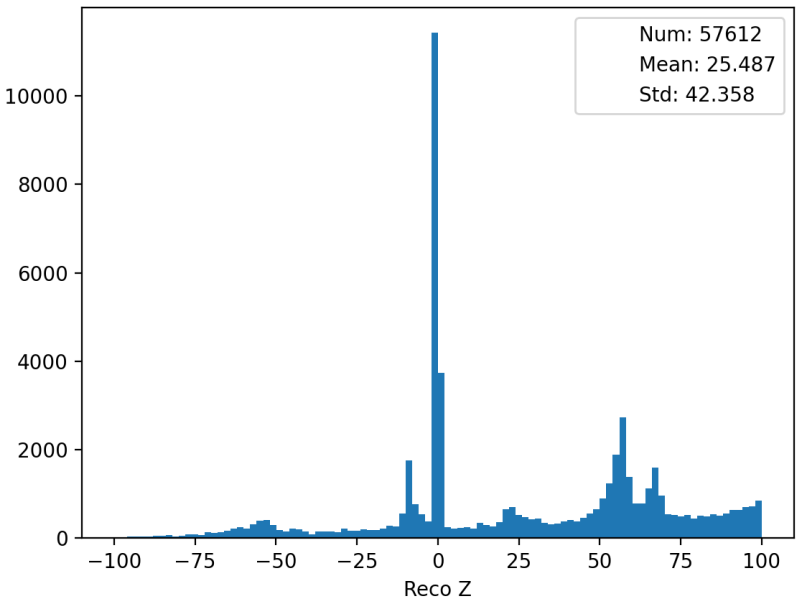
Reweighting: Root Problem & Idea

- A lot of data at $\hat{z} = 0$



Reweighting: Root Problem & Idea

- A lot of data at $\hat{z} = 0$
- Bias towards predicting $z = 0$



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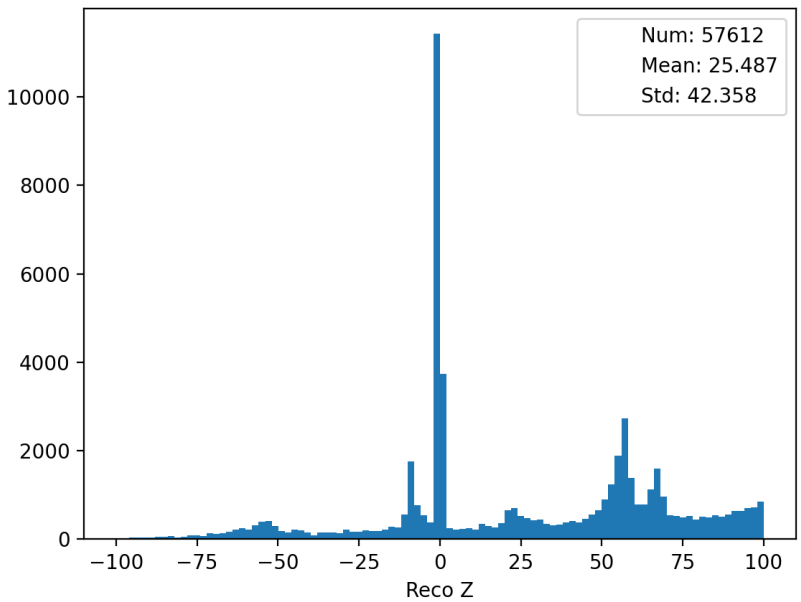

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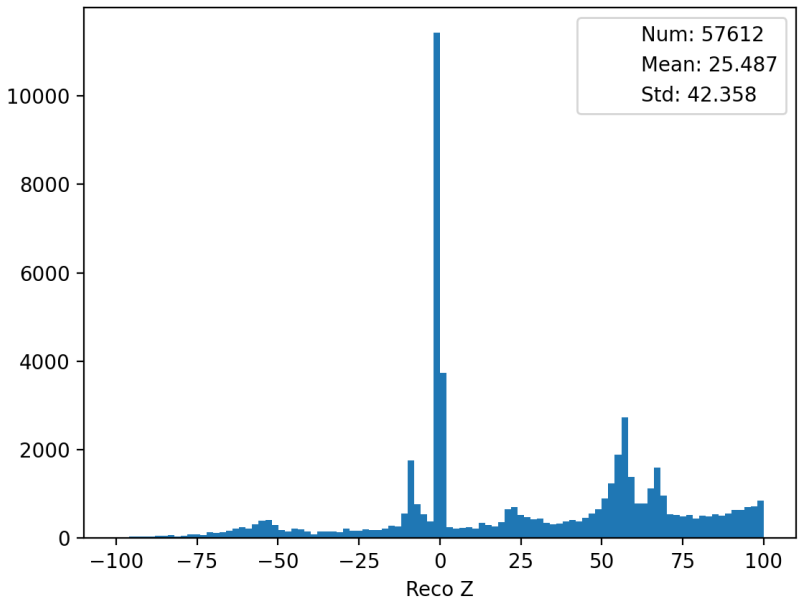

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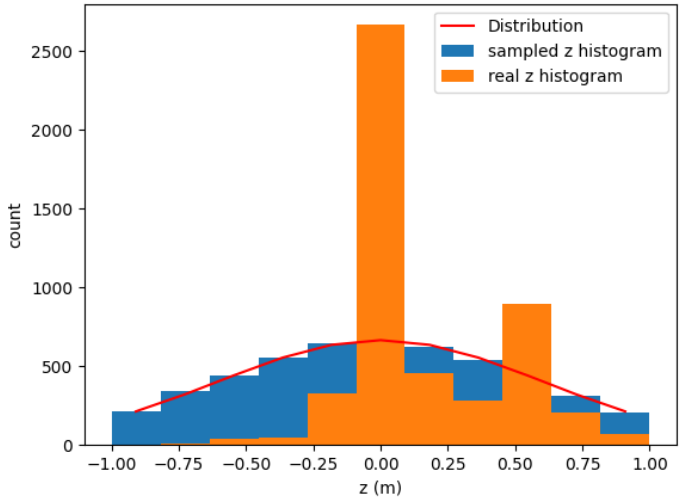

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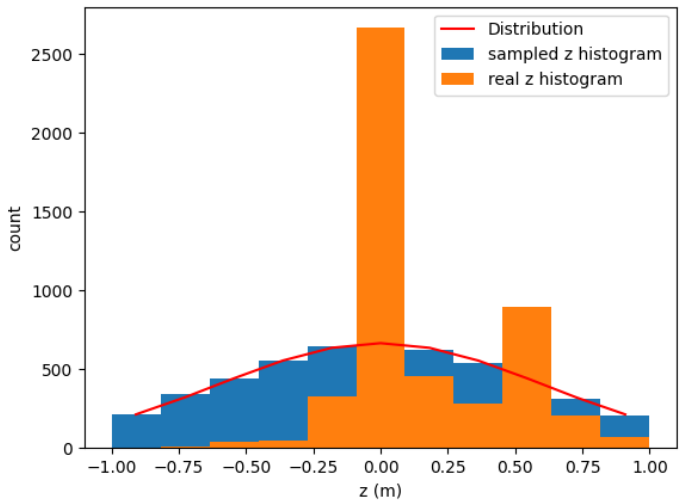

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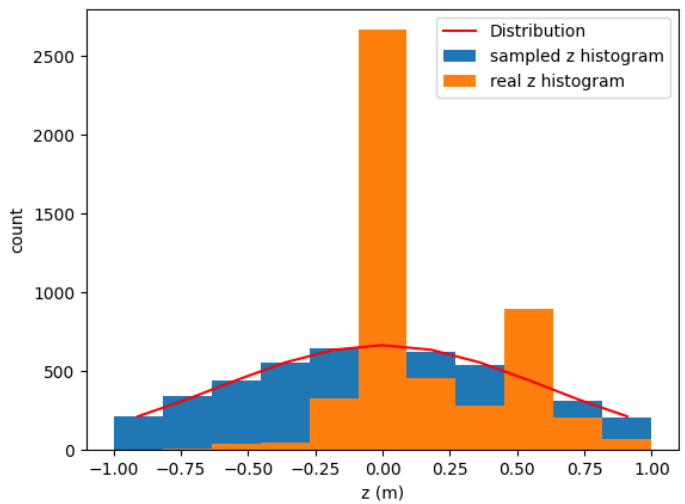

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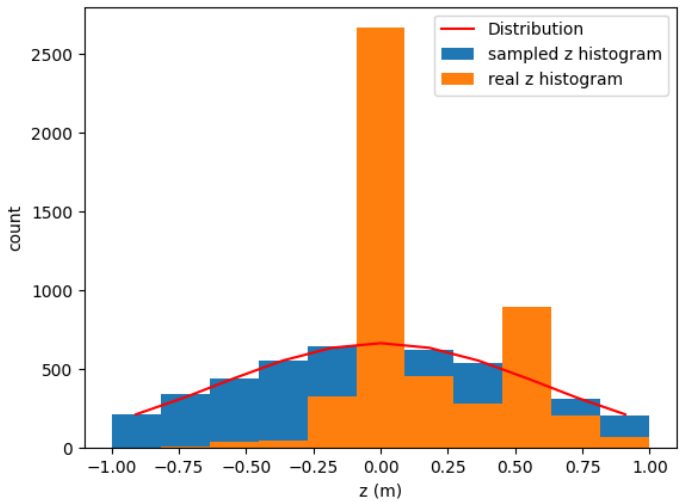

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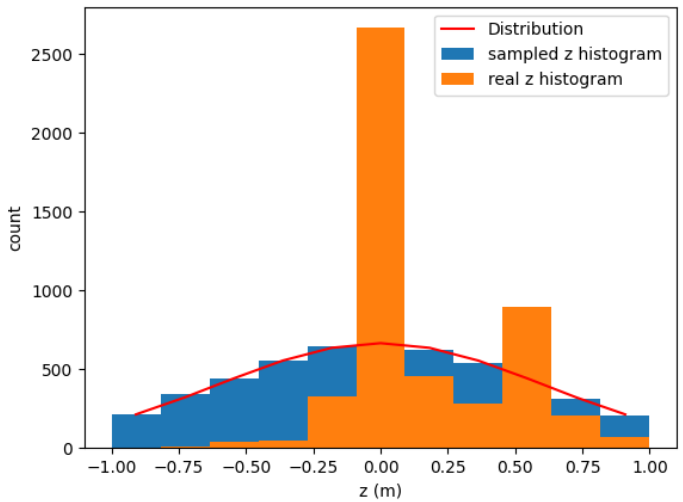

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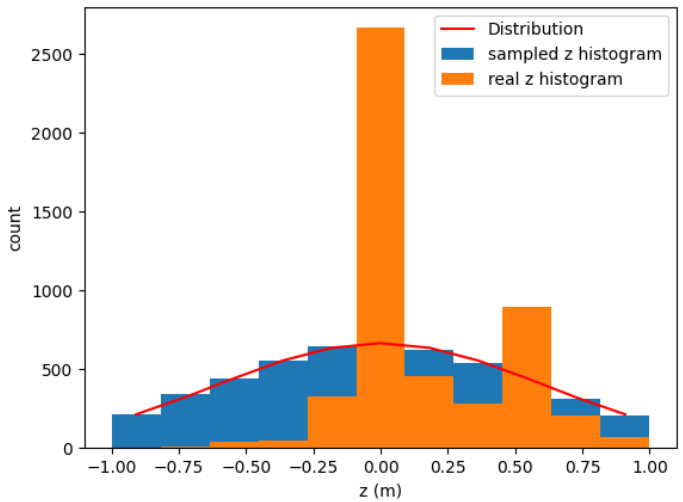

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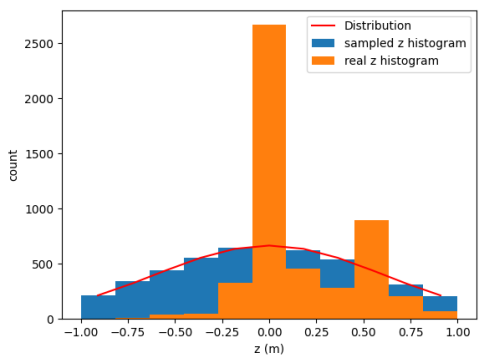
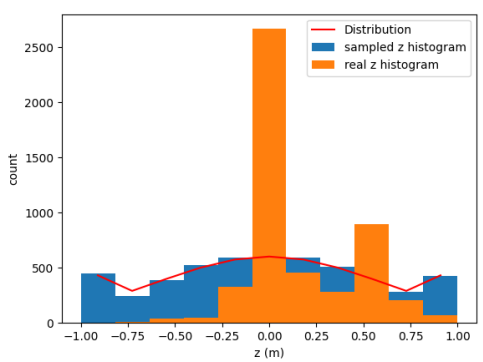
Infinite bounds vs non finite bounds:





Results

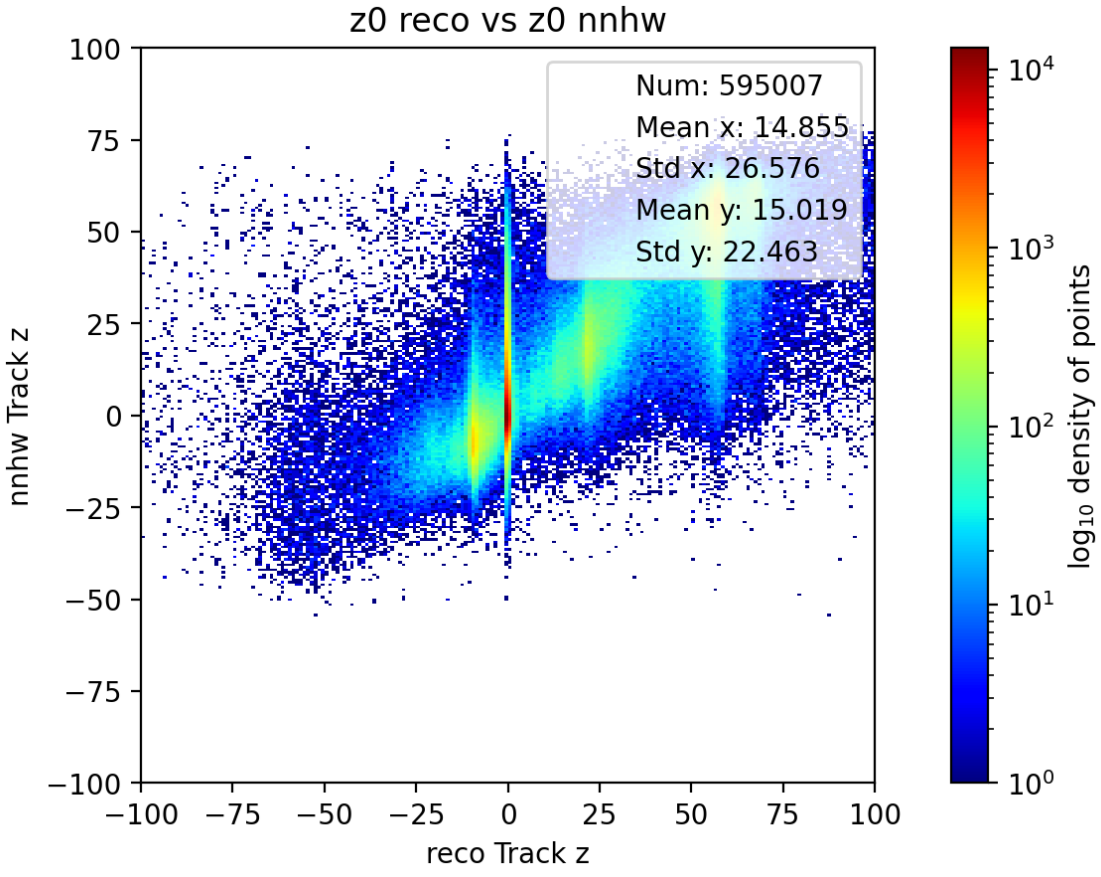
Numeric Results

Table 1: Validation loss vs Old loss

	Baseline	Tanh	Tanh BN	Softsign	Reweight	Events Filter
Expert 0	0.766	0.742	0.709	0.737	1.159	1.016
Expert 1	0.736	0.703	0.696	0.710	1.074	1.047
Expert 2	0.928	0.851	0.830	0.831	1.475	1.406
Expert 3	0.908	0.780	0.760	0.770	1.559	1.067
Expert 4	0.779	0.784	0.683	0.692	1.256	1.259
Mean	0.823	0.772	0.735	0.748	1.305	1.159

Z Plot

Neuro z vs reco z for expert 0 of the current Trigger:



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- Further Improvements
  - Open for potential for different network architectures
  - Large hyperparameter optimization should be done
  - Use more and more diverse data to train!
  - Overall plots: Cumbersome to look at all experts

Questions?