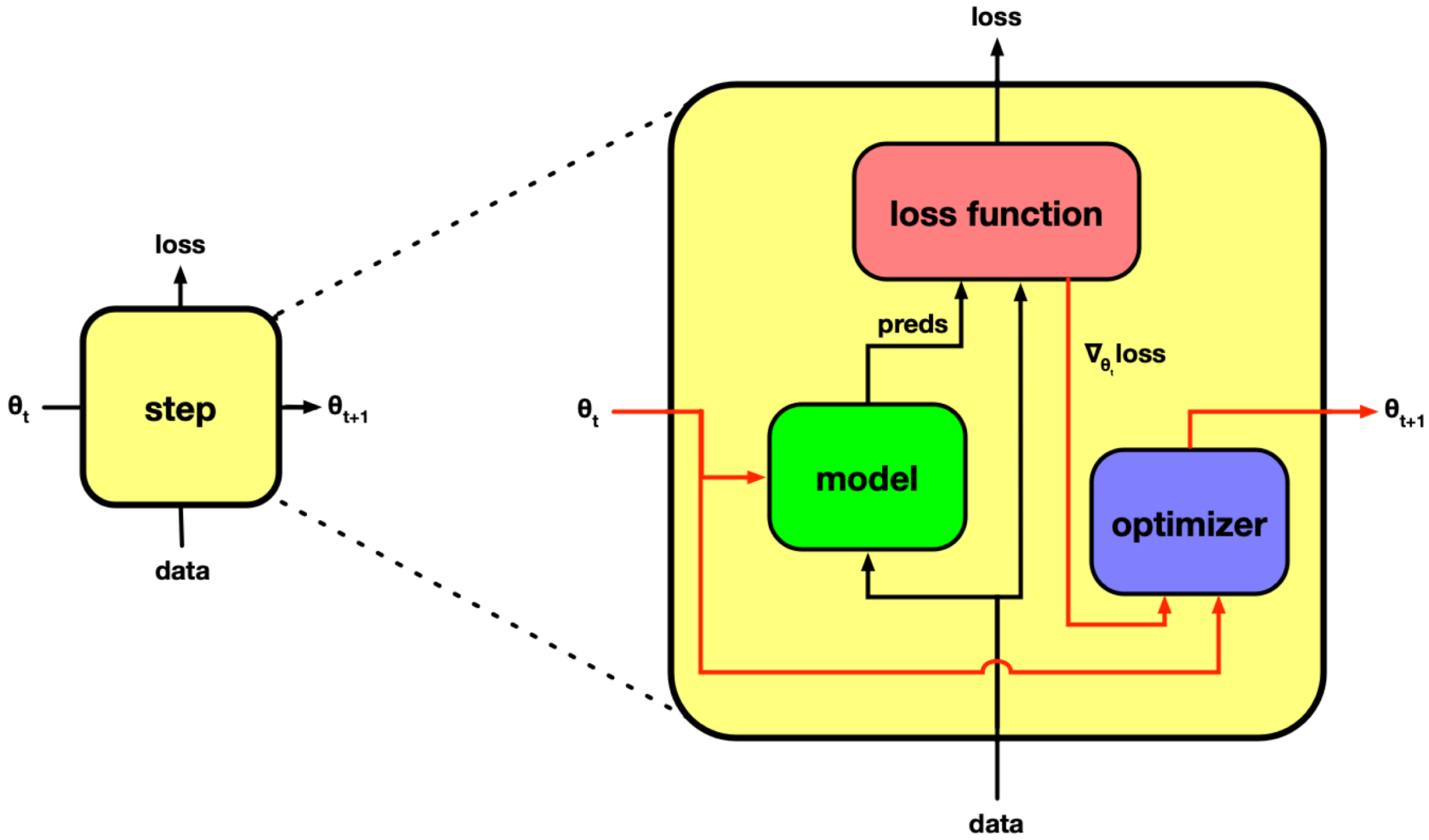
higher:
a pytorch metalearning library

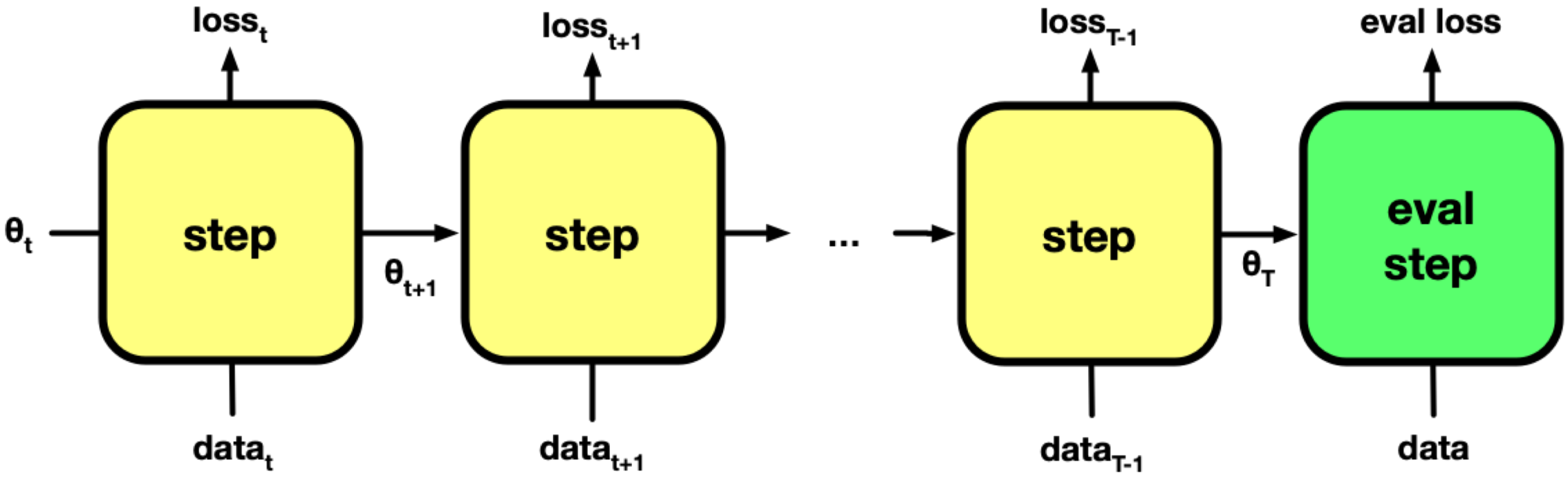
Edward Grefenstette

https://github.com/fairinternal/higher

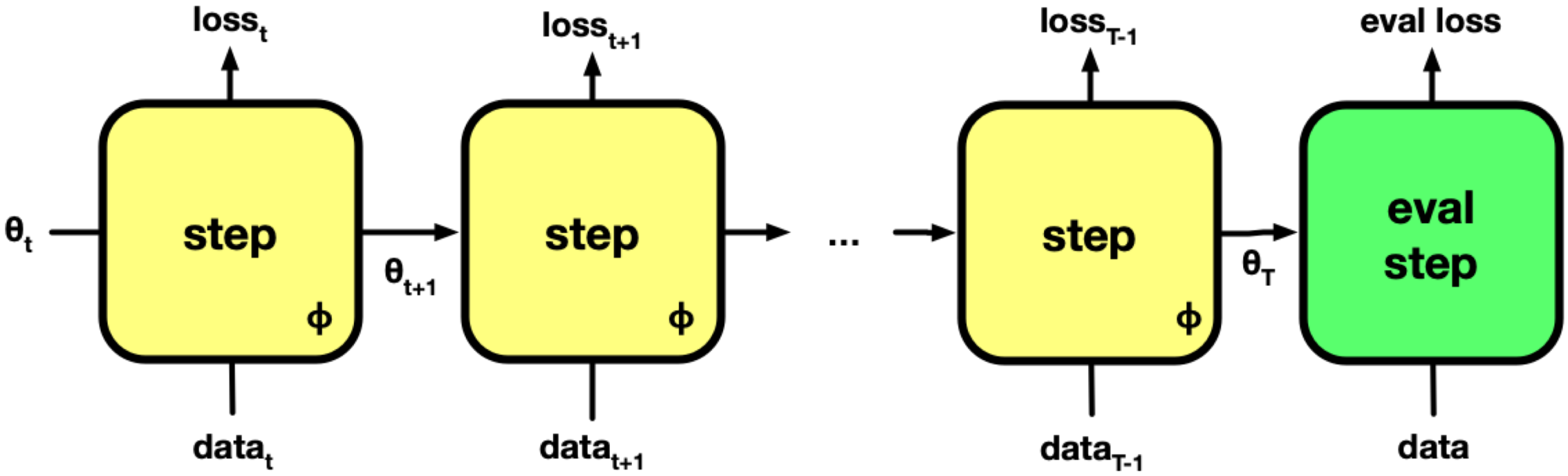
Anatomy of a training/eval step



An unrolled training + eval loop

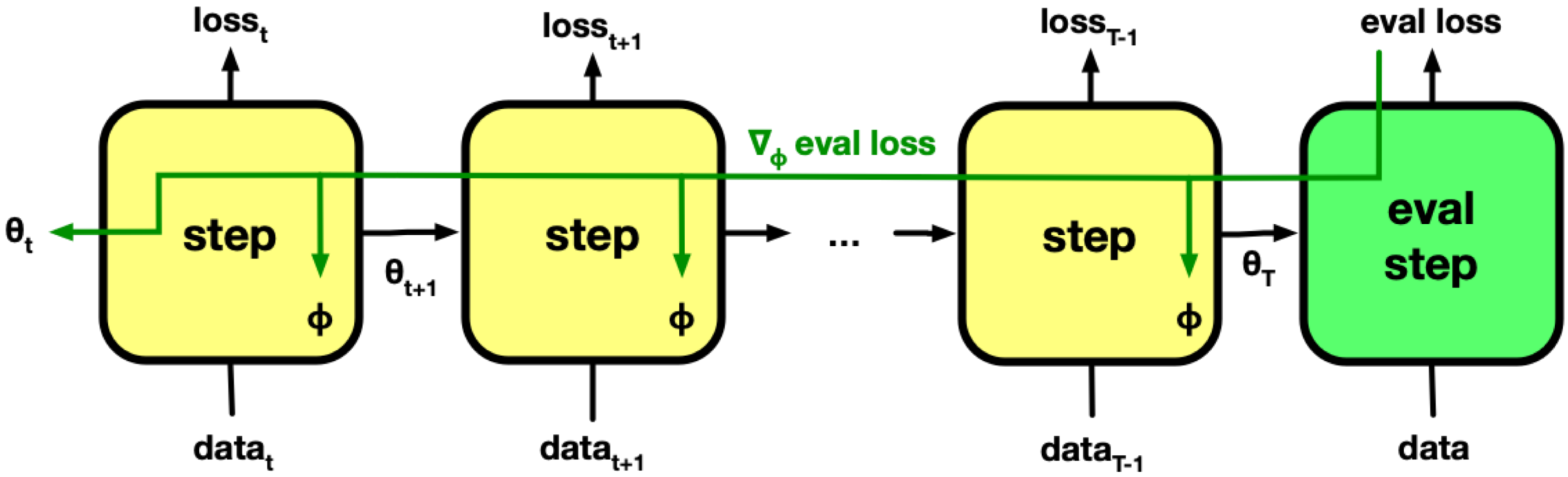


“Inner-loop” metalearning



φ: parameters corresponding to some aspect of your training loop (hyper-parameters, learned loss function, data mixture in multi-task learning, etc…)

“Inner-loop” metalearning



e.g. MAML == $\phi = \theta_t$

What you want to do

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model = MyModel(…)  # arbitrarily complex model
opt = torch.optim.MyOptim(…)  # favourite optim
init_params = model.parameters()  # get view on initial model params
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        loss.backward()
        opt.step()
```

↑↑↑↑↑↑ == some additional parameters that form part of your training process, e.g. per-example importance weights, learned loss function, etc.

You might want to metalearn these, rather than optimize them against normal training loss...

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↑↑↑↑↑↑ == $\nabla\theta_T$meta_loss != $\nabla\theta_t$meta_loss

↑↑↑↑↑↑ == model.parameters() # after training

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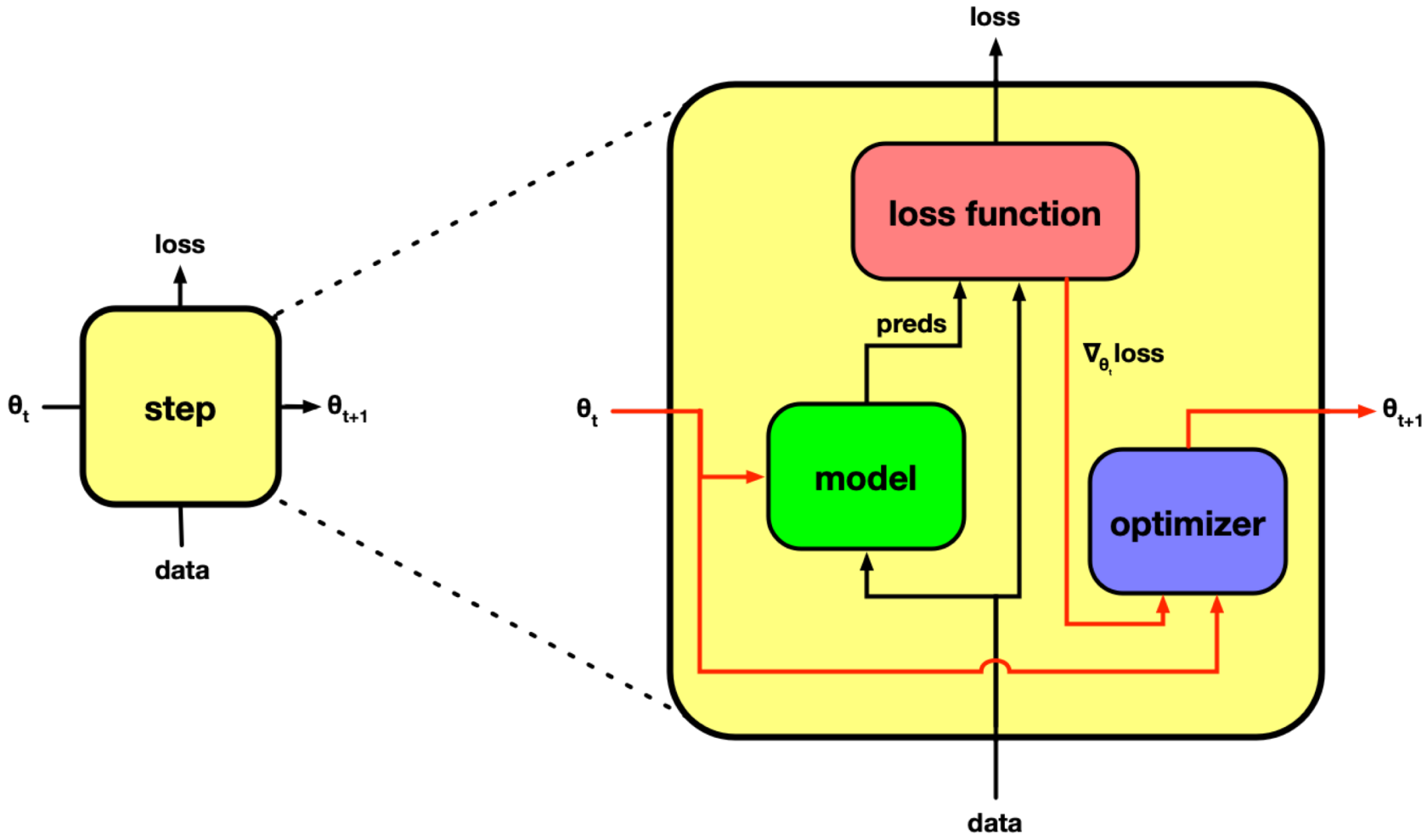
↑↑↑↑↑↑ == only gradients w.r.t. phi at last timestep

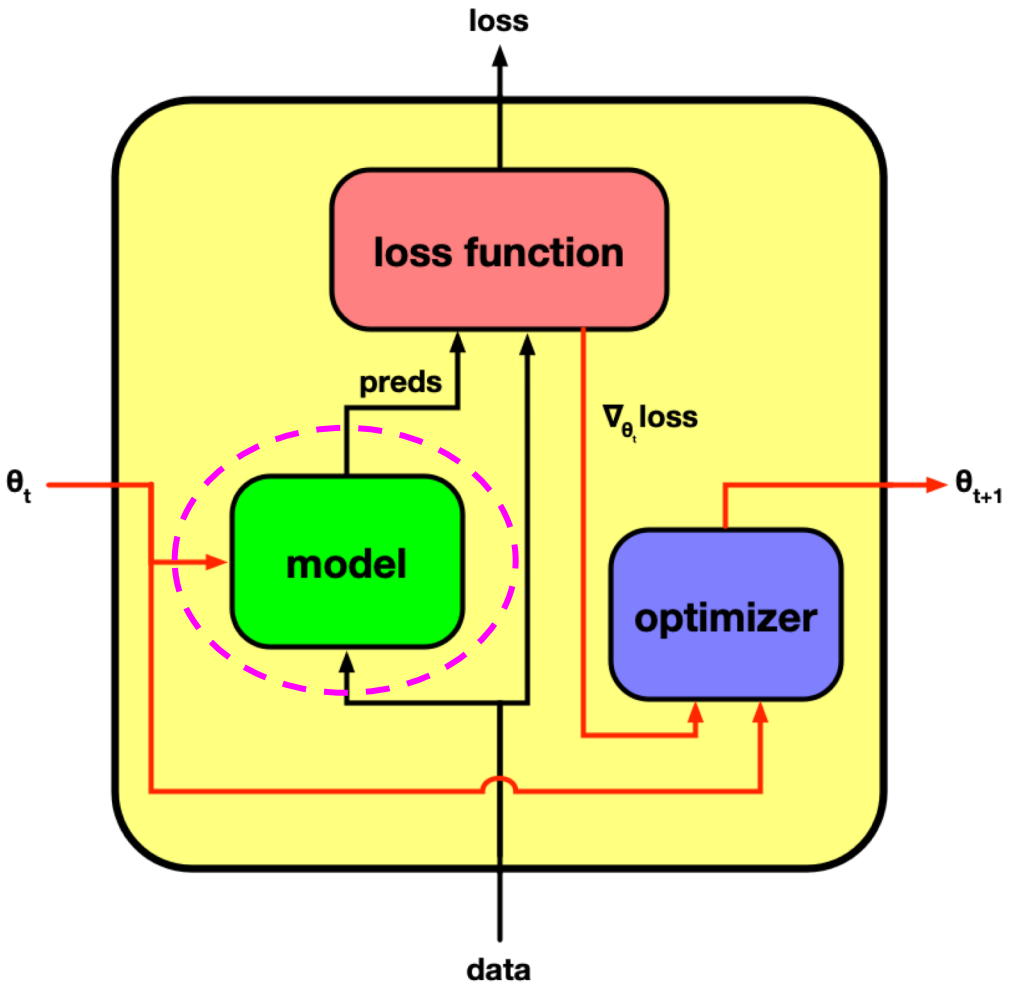
Why you can’t (easily) do it



Why you can't (easily) do it

We typically use **stateful** implementations of NN modules (torch.nn, tf.keras, etc).

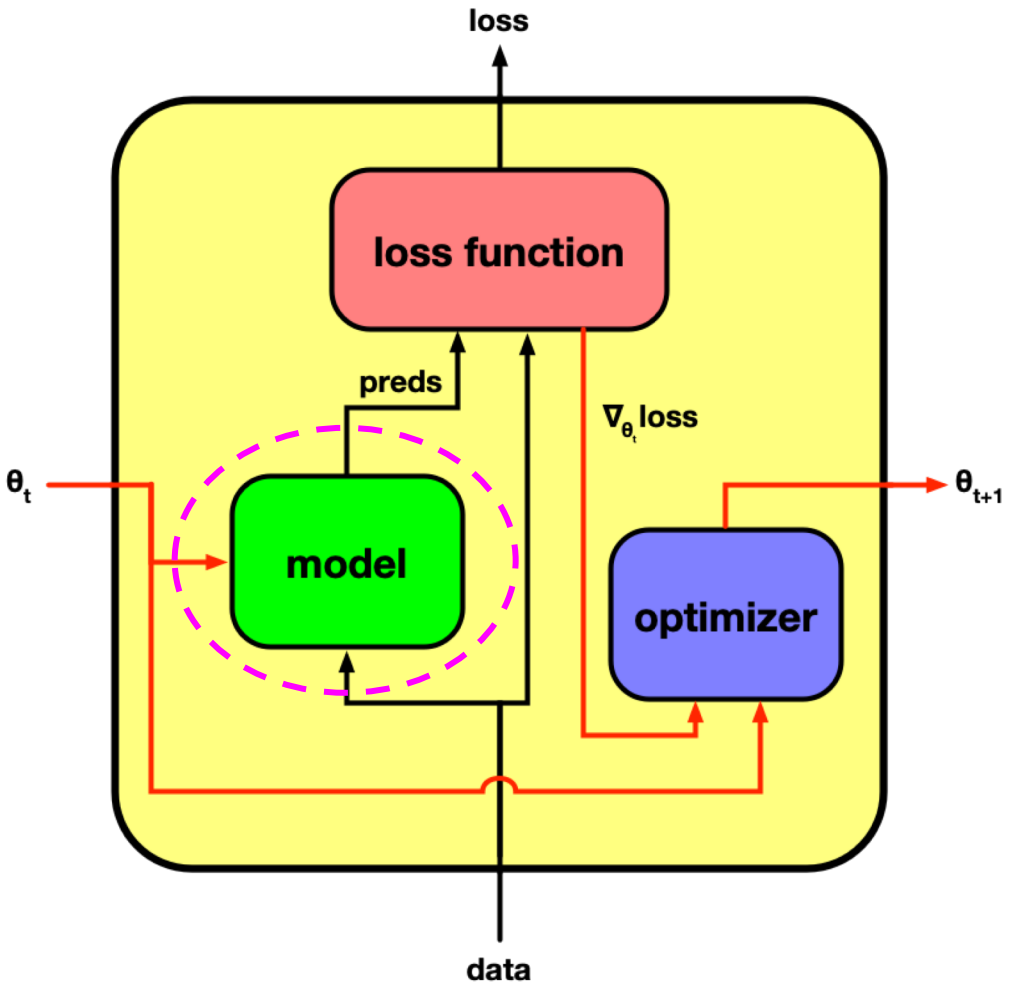
To track updates to params on the "gradient tape", we need to rewrite **functional** versions of our modules…



Why you can't (easily) do it

Re-implementing models functionally works but…

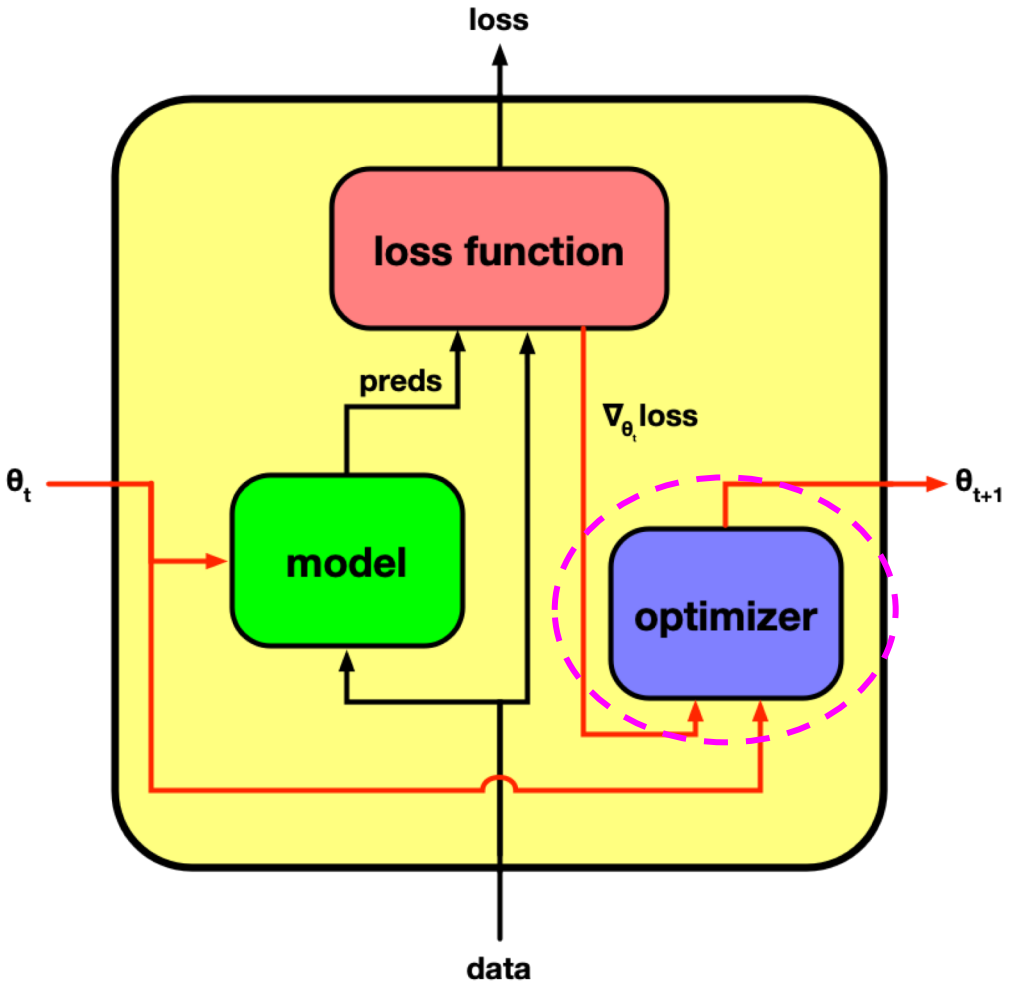
What if I want to metalearn with a pretrained BERT model, with saved weights, written by someone else, with a large and complicated codebase I don't want to mess with?



Why you can't (easily) do it

Optimizers apply grads to params **in place**, using ops that are differentiable, but **without tracking grad functions**.

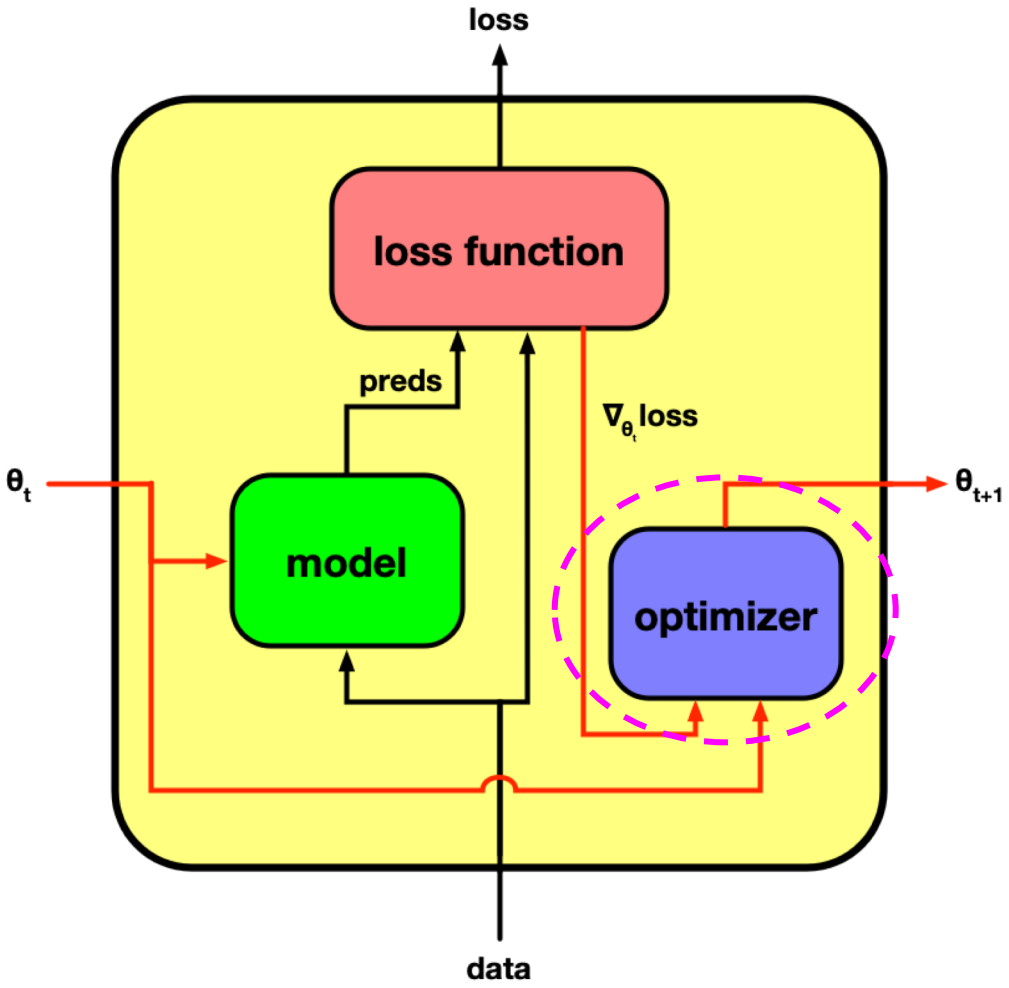
This is sensible to avoid **memory issues**, but we need to track these updates here…



Why you can't (easily) do it

Easy to write **vanilla SGD** in a differentiable way but…

What if I want to metalearn using a modern optimizer in my inner loop, or reflect my choice of outer loop optimizer?



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```

↑↑↑↑↑↑ == $\nabla_{\theta_{init}}$ meta_loss

↑↑↑↑↑↑ == θ_{init}

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Under the hood:

1. We **monkey-patch the torch module for the model** to use explicitly provided, or implicitly tracked, **fast weights** which can be updated through differentiable ops rather than in-place.

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1. We **monkey-patch the torch module for the model** to use explicitly provided, or implicitly tracked, **fast weights** which can be updated through differentiable ops rather than in-place.

2. **Differentiable versions of optimizers** wrap the regular optimizers, branching off their states, and perform updates on fast weights in a way which **yields grad functions**.

Patched modules

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fmodel = higher.monkeypatch(
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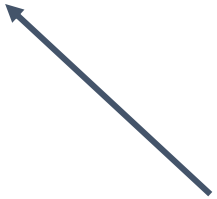

(optional) the device to do the unrolling on…

If None, use same device as module .

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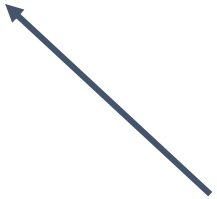

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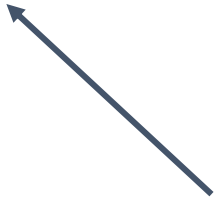

If True (default), creates a safe copy of the model to unroll. i.e. the weights of module do not receive gradient or form part of grad funcs as we unroll...

Only set to False if doing MAML, or if you are disciplined about clearing gradients after your metalearning loop...

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- fmodel.parameters() == latest_params
  fmodel.parameters(time=0) == init_params
  (i.e. model.parameters() when fmodel was created).
  The whole unroll history can be referenced this way…

Differentiable Optimizers

```
diffopt = higher.get_diff_optim(
    opt, reference_params, fmodel=None, device=None, track_higher_grads=True)
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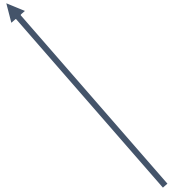

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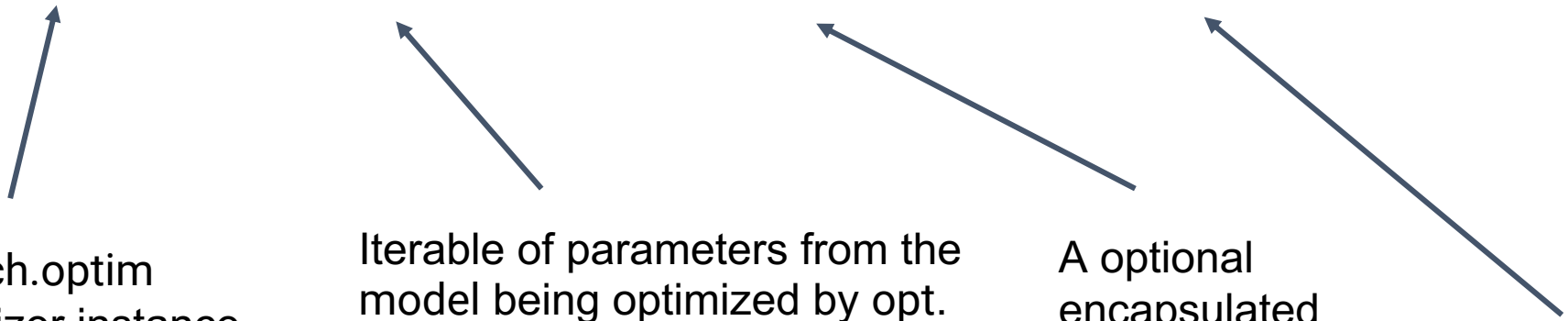

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Set to false to disable higher grad tracking (e.g. test mode)

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- **No need to call zero_grad()** on diffopt instances.

Keep it simple with innerloop_ctx

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with higher.innerloop_ctx(model, opt, **loop_kwargs) as (fmodel, diffopt):
        # write your inner loop here
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# ends (risk of memory problems).
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fmodel/diffopt branch from model/optim at context creation.

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Metalearning on **GPU**(s)

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- Thorough unit tests, but no blanket **correctness guarantees** for complex/exotic model architures. If in doubt, get in touch!
- Possible **grad stability issues** for differentiable optimizers as number of unroll steps increases. Mitigated for Adam, SGD, but other opts still experimental. If in doubt, get in touch!
- Other bugs, memory issues may arise. It's alpha software...

When can I use it?

Now!

git clone git@github.com:fairinternal/higher.git
cd higher
source activate my_favorite_env
pip install .

In your code, just import higher and start metalearning! 😀

Thanks!

https://github.com/fairinternal/higher

Contact egrefen@fb.com for questions/comments

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