In [1]: import torch 尽量不要自己给自己赋值 错误例子: 自己给自己赋值 In [2]: eta1 = torch.nn.Parameter(torch.rand(10), requires_grad=True) eta1 Parameter containing: tensor([0.0312, 0.6983, 0.4285, 0.4792, 0.2871, 0.7417, 0.1106, 0.9623, 0.9452, 0.4848], requires_grad=True) 这里本来想让 eta1 乘以2 In [3]: eta1 = eta1 * 2 In [4]: eta1 tensor([0.0625, 1.3966, 0.8570, 0.9584, 0.5741, 1.4835, 0.2212, 1.9247, 1.8905, 0.9695], grad fn=<MulBackward0>) In [5]: etal.sum().backward() 结果可以看出没有梯度了 In [6]: eta1.grad /Users/haibinzhao/miniconda3/envs/ML/lib/python3.8/site-packages/torch/_tensor.py:1104: UserWarning: The .grad attribute of a Tensor that is not a leaf Tensor is being accessed. Its .grad attribute won't be populated during autograd.backward (). If you indeed want the .grad field to be populated for a non-leaf Tensor, use .retain_grad() on the non-leaf Tensor. If you access the non-leaf Tensor by mistake, make sure you access the leaf Tensor instead. See github.com/pytorch/pytor ch/pull/30531 for more informations. (Triggered internally at /Users/distiller/project/conda/conda-bld/pytorch_16467559 22314/work/build/aten/src/ATen/core/TensorBody.h:475.) return self. grad 正确例子: 赋值给其他变量名 In [7]: eta2 = torch.nn.Parameter(torch.rand(10), requires_grad=True) eta2 Out[7]: Parameter containing: tensor([0.8627, 0.4348, 0.9095, 0.5124, 0.3881, 0.6686, 0.7270, 0.6214, 0.1460, 0.6846], requires_grad=True) In [8]: eta_temp = eta2 * 2 In [9]: eta_temp Out[9]: tensor([1.7255, 0.8697, 1.8190, 1.0247, 0.7762, 1.3372, 1.4540, 1.2428, 0.2920, 1.3692], grad_fn=<MulBackward0>) In [10]: eta_temp.sum().backward() In [11]: eta2.grad Out[11]: tensor([2., 2., 2., 2., 2., 2., 2., 2., 2.]) 小心直接赋值其他变量 错误例子:直接赋值给别的变量后,内存里还是同一个变量 In [12]: v1 = torch.nn.Parameter(torch.rand(10), requires grad=True) Out[12]: Parameter containing: tensor([0.2928, 0.7851, 0.0654, 0.9038, 0.8469, 0.8558, 0.8001, 0.8354, 0.2006, 0.9795], requires_grad=True) 把 v1 赋值给 a In [13]: a = v1[:4]修改 a 的值 In [15]: a.data.copy_(torch.rand(4)) Out[15]: tensor([0.1814, 0.2235, 0.1048, 0.1320], grad_fn=<SliceBackward0>) 发现 v1 的值也被改了 In [16]: Out[16]: Parameter containing: tensor([0.1814, 0.2235, 0.1048, 0.1320, 0.8469, 0.8558, 0.8001, 0.8354, 0.2006, 0.9795], requires_grad=True) 正确例子: 用克隆的方法 In [17]: v2 = torch.nn.Parameter(torch.rand(10), requires grad=True) v2 Parameter containing: Out[17]: tensor([0.6647, 0.6194, 0.3355, 0.2664, 0.4136, 0.1148, 0.5026, 0.8328, 0.2710, 0.9257], requires grad=True) In [18]: b = v2[:4].clone()In [19]: b.data.copy_(torch.rand(4)) tensor([0.3222, 0.6089, 0.8604, 0.0538], grad fn=<CloneBackward0>) In [20]: v2 Out[20]: Parameter containing: tensor([0.6647, 0.6194, 0.3355, 0.2664, 0.4136, 0.1148, 0.5026, 0.8328, 0.2710, 0.9257], requires_grad=True) 生成可学习参数时先生成,最后再包装 错误例子:先生成Parameter,再变形 In [21]: t = torch.nn.Parameter(torch.randn(12,1), requires grad=True) t Out[21]: Parameter containing: tensor([-0.5475], [2.0614], [-0.0118],[1.6362], [0.0855], [0.2819],[-1.6987], [-1.1044], [1.1377], [0.4085],[1.4628], [-0.2824]], requires_grad=True) In [23]: T = t.view(3,4)Out[23]: tensor([[-0.5475, 2.0614, -0.0118, 1.6362], [0.0855, 0.2819, -1.6987, -1.1044],[1.1377, 0.4085, 1.4628, -0.2824]], grad fn=<ViewBackward0>) In [24]: T.sum().backward() In [25]: t.grad /Users/haibinzhao/miniconda3/envs/ML/lib/python3.8/site-packages/torch/ tensor.py:1104: UserWarning: The .grad attribute of a Tensor that is not a leaf Tensor is being accessed. Its .grad attribute won't be populated during autograd.backward (). If you indeed want the .grad field to be populated for a non-leaf Tensor, use .retain_grad() on the non-leaf Tensor. If you access the non-leaf Tensor by mistake, make sure you access the leaf Tensor instead. See github.com/pytorch/pytor ch/pull/30531 for more informations. (Triggered internally at /Users/distiller/project/conda/conda-bld/pytorch 16467559 22314/work/build/aten/src/ATen/core/TensorBody.h:475.) return self. grad 正确例子:先全部初始化完成,再包装成Parameter In [24]: k = torch.randn(12,1)Out[24]: tensor([[-0.2693], [0.2612], [-0.8253], [0.5455],[1.5656], [-1.4120], [1.5922], [-1.7210], [0.8812], [0.9397],[-0.9860], [1.3318]]) In [25]: k = k.view(3,4)In [26]: kp = torch.nn.Parameter(k, requires grad=True) In [27]: kp.sum().backward() In [28]: kp.grad Out[28]: tensor([[1., 1., 1., 1.], [1., 1., 1., 1.],[1., 1., 1., 1.]组装变量时的错误 错误例子:用tensor把变量重新拼起来 In [26]: a = torch.nn.Parameter(torch.rand(5), requires grad=True) In [27]: a0 = a[0] * 2a1 = torch.log(a[1]+1)a2 = a[2] ** 2a3 = torch.nn.functional.softplus(a[3] * 2) a4 = a[4]a0, a1, a2, a3, a4 Out[27]: (tensor(0.1184, grad_fn=<MulBackward0>), tensor(0.3061, grad fn=<LogBackward0>), tensor(0.0003, grad fn=<PowBackward0>), tensor(1.3874, grad fn=<SoftplusBackward0>), tensor(0.5207, grad fn=<SelectBackward0>)) 组合成一个新变量 In [28]: A1 = torch.tensor([a0, a1, a2, a3, a4]) Α1 Out[28]: tensor([1.1843e-01, 3.0607e-01, 2.5946e-04, 1.3874e+00, 5.2072e-01]) 由于重新用 tensor 包装了变量,切断了反向传播 In [29]: A1.sum().backward() RuntimeError Traceback (most recent call last) Input In [29], in <cell line: 1>() ---> 1 A1.sum().backward() File ~/miniconda3/envs/ML/lib/python3.8/site-packages/torch/ tensor.py:363, in Tensor.backward(self, gradient, retain gr aph, create_graph, inputs) 354 if has_torch_function_unary(self): 355 return handle_torch_function(356 Tensor.backward, 357 (self,), (\ldots) 361 create_graph=create_graph, 362 inputs=inputs) --> 363 torch.autograd.backward(self, gradient, retain graph, create graph, inputs=inputs) File ~/miniconda3/envs/ML/lib/python3.8/site-packages/torch/autograd/__init__.py:173, in backward(tensors, grad_tensors, retain_graph, create_graph, grad_variables, inputs) 168 retain_graph = create_graph 170 # The reason we repeat same the comment below is that 171 # some Python versions print out the first line of a multi-line function 172 # calls in the traceback and some print out the last line --> 173 Variable. execution engine.run backward(# Calls into the C++ engine to run the backward pass 174 tensors, grad_tensors_, retain_graph, create_graph, inputs, 175 allow_unreachable=True, accumulate_grad=True) RuntimeError: element 0 of tensors does not require grad and does not have a grad fn 正确例子:建立一个变量,然后把值填进去 In [30]: Parameter containing: Out[30]: tensor([0.0592, 0.3581, 0.0161, 0.5500, 0.5207], requires_grad=True) In [32]: A2 = torch.zeros([5])In [33]: A2[0] = a[0] * 2 $A2[1] = torch \cdot log(a[1]+1)$ A2[2] = a[2] ** 2A2[3] = torch.nn.functional.softplus(a[3] * 2) A2[4] = a[4]A2 Out[33]: tensor([1.1843e-01, 3.0607e-01, 2.5946e-04, 1.3874e+00, 5.2072e-01], grad_fn=<CopySlices>) 就可以使用了 In [34]: A2.sum().backward() In [35]: a.grad Out[35]: tensor([2.0000, 0.7363, 0.0322, 1.5006, 1.0000]) 正确例子2: 用cat或stack拼起来 In [62]: A3 = torch.stack((a[0]*2, torch.log(a[1]+1), a[2]**2, torch.nn.functional.softplus(a[3]*2), a[4])) In [63]: a.grad.zero_() A3.sum().backward() In [64]: a.grad Out[64]: tensor([2.0000, 0.7363, 0.0322, 1.5006, 1.0000]) 可学习参数有相互组合时,不能填进去,只能cat/stack 在某些情况下,神经网络的可学习参数需要经过一些变化,然后继续进行计算。例如在某些问题中,可学习参数 R_1 , R_2 需要经过一个黑箱过程才能 变成 η ,然后 η 会参与后续的运算。也就是 $[R_1,R_2]
ightarrow Black\ Box
ightarrow \eta
ightarrow NeuralNetwork$ 这个黑箱转换过程可以通过神经网络来实现,也就是 $[R_1,R_2] o NN o \eta o NeuralNetwork$ 有的时候 R_1 和 R_2 的比值是一个重要的因素。但是这个比值会随着normalization而被削弱。在这种情况下,人们往往人为添加一个特征,也就是训练 一个3输入1输出的NN来拟合黑箱,也就是输入变成 R_1,R_2,k ,其中 $k=rac{R_1}{R_2}$ 。然后整个输入会被normalize成为 R_1^N,R_2^N,k^N ,注意 $k^N
eqrac{R_1^N}{R^N}$ 。 然而,我们明显能看出 R_1^N,R_2^N,k^N 只有2个自由度,也就是可学习参数最多只能有2个,否则就会产生矛盾。那么比如我们让可学习参数为 R_1^N 和 R_2^N 。然后推算出 $k^N = \mathcal{N}\left\{rac{\mathcal{D}(R_1^N)}{\mathcal{D}(R_2^N)}
ight\}$,其中 $\mathcal{N}(\cdot)$ 和 $\mathcal{D}(\cdot)$ 表示normalization和denormalization的操作。然后把 R_1^N 和 R_2^N 和推导出来的 k^N 拼起来, 放到NN里面计算 η 。然而,这个过程会出现问题: In [69]: torch.manual_seed(0) class Example(torch.nn.Module): def __init__(self): super().__init__() # learnable R1n and R2n self.paramn_ = torch.nn.Parameter(torch.rand(2),requires_grad=True) # exemplary NN convert [R1n, R2n, kn] to eta self.eta_estimator = torch.nn.Sequential(torch.nn.Linear(3,1)) self.eta estimator.train(False) # exemplary max and min of [R1, R2, k] for normalization and denormalization self.param_max = torch.tensor([2, 4, 2]) self.param_min = torch.tensor([1, 2, 0]) @property def Param(self): # calculate normalized R1 paramn = torch.zeros([3]) paramn[0] = self.paramn_[0] # R1n paramn[1] = self.paramn_[1] # R2n # denormalization param = paramn * (self.param_max - self.param_min) + self.param_min # calculate k=R1/R2 param[2] = param[0] / param[1] # normalization paramn = (param - self.param min) / (self.param max - self.param min) return paramn @property def eta(self): return self.eta estimator(self.Param) 可以看出上述代码以 R_1^N 和 R_2^N 为可学习参数,然后先经过denormalization求出真实值 R_1 和 R_2 ,然后在利用真实值求出k,再把真实的 $[R_1,R_2,k]$ 进行normalization,就可以用于放到NN里用于计算 η 了: In [70]: test = Example() print('可学习参数: ') print(test.paramn) print('经过处理后的可学习参数') print(test.Param) print('利用可学习参数转换成的eta') print(test.eta) 可学习参数: Parameter containing: tensor([0.4963, 0.7682], requires grad=True) 经过处理后的可学习参数 tensor([0.4963, 0.7682, 0.2115], grad fn=<DivBackward0>) 利用可学习参数转换成的eta tensor([-0.4544], grad fn=<AddBackward0>) 然而,由于 paramn 里的第三个参数k是前两个的组合,反向传递时会出现问题: In [71]: test.Param.sum().backward() RuntimeError Traceback (most recent call last) Input In [71], in <cell line: 1>() ---> 1 test.Param.sum().backward() File ~/miniconda3/envs/ML/lib/python3.8/site-packages/torch/ tensor.py:363, in Tensor.backward(self, gradient, retain gr aph, create graph, inputs) 354 if has torch function unary(self): return handle torch function(355 356 Tensor.backward, 357 (self,), (\ldots) 361 create graph=create graph, inputs=inputs) 362 --> 363 torch.autograd.backward(self, gradient, retain graph, create graph, inputs=inputs) File ~/miniconda3/envs/ML/lib/python3.8/site-packages/torch/autograd/ init .py:173, in backward(tensors, grad tensors, retain graph, create graph, grad variables, inputs) retain graph = create graph 170 # The reason we repeat same the comment below is that 171 # some Python versions print out the first line of a multi-line function 172 # calls in the traceback and some print out the last line --> 173 Variable. execution engine.run backward(# Calls into the C++ engine to run the backward pass tensors, grad tensors, retain graph, create graph, inputs, 174 175 allow unreachable=True, accumulate grad=True) RuntimeError: one of the variables needed for gradient computation has been modified by an inplace operation: [torch.Flo atTensor []], which is output 0 of AsStridedBackward0, is at version 1; expected version 0 instead. Hint: enable anomaly detection to find the operation that failed to compute its gradient, with torch.autograd.set detect anomaly(True). 问题就在于 param 的第三个参数k是用 param[2]=param[0]/param[1] 填进去的。应该用<math>cat(高维度)或者stack(0维)拼起来。 正确例子: In [72]: torch.manual seed(0) class Example(torch.nn.Module): def __init__(self): super().__init__() # learnable R1n and R2n self.paramn = torch.nn.Parameter(torch.rand(2),requires grad=True) # exemplary NN convert [R1n, R2n, kn] to eta self.eta estimator = torch.nn.Sequential(torch.nn.Linear(3,1)) self.eta estimator.train(False) # exemplary max and min of [R1, R2, k] for normalization and denormalization self.param max = torch.tensor([2, 4, 2]) self.param_min = torch.tensor([1, 2, 0]) @property def Param(self): # calculate normalized R1 paramn = torch.zeros([3]) paramn[0] = self.paramn [0] # R1n # R2n paramn[1] = self.paramn [1] # denormalization param = paramn * (self.param_max - self.param_min) + self.param_min # calculate k=R1/R2 param temp = torch.stack([param[0], param[1], param[0]/param[1]]) # normalization paramn = (param temp - self.param min) / (self.param max - self.param min) return paramn @property def eta(self): return self.eta_estimator(self.Param) In [73]: test = Example() print('可学习参数: ') print(test.paramn) print('经过处理后的可学习参数') print(test.Param) print('利用可学习参数转换成的eta') print(test.eta) 可学习参数: Parameter containing: tensor([0.4963, 0.7682], requires grad=True) 经过处理后的可学习参数 tensor([0.4963, 0.7682, 0.2115], grad fn=<DivBackward0>) 利用可学习参数转换成的eta tensor([-0.4544], grad fn=<AddBackward0>) In [74]: test.Param.sum().backward() test.paramn_.grad Out[74]: tensor([1.1414, 0.8804]) 其他解决方案 由于关键原因在于 paramn 的第三个元素是前两个元素的组合,这会使PyTorch出现问题。我们可以采取另外的解决方案:既然只有2个自由度可以 学习,可以将任意一个变量detach掉,这样也可以解决此问题,但是会牺牲掉detach掉的分支的信息,因此不推荐: In [78]: torch.manual seed(0) class Example(torch.nn.Module): def __init__(self): super(). init () # learnable R1n and R2n self.paramn_ = torch.nn.Parameter(torch.rand(2),requires grad=True) # exemplary NN convert [R1n, R2n, kn] to eta self.eta_estimator = torch.nn.Sequential(torch.nn.Linear(3,1)) self.eta_estimator.train(False) # exemplary max and min of [R1, R2, k] for normalization and denormalization self.param_max = torch.tensor([2, 4, 2]) self.param_min = torch.tensor([1, 2, 0]) @property def Param(self): # calculate normalized R1 paramn = torch.zeros([3]) # R1n paramn[0] = self.paramn_[0] # R2n paramn[1] = self.paramn [1] # denormalization param = paramn * (self.param max - self.param min) + self.param min # calculate k=R1/R2 param[2] = (param[0] / param[1]).detach() # normalization paramn = (param - self.param min) / (self.param max - self.param min) return paramn @property def eta(self): return self.eta estimator(self.Param) In [79]: test = Example() print('可学习参数: ') print(test.paramn_) print('经过处理后的可学习参数') print(test.Param) print('利用可学习参数转换成的eta') print(test.eta) 可学习参数: Parameter containing: tensor([0.4963, 0.7682], requires_grad=True) 经过处理后的可学习参数 tensor([0.4963, 0.7682, 0.2115], grad_fn=<DivBackward0>) 利用可学习参数转换成的eta tensor([-0.4544], grad fn=<AddBackward0>) In [77]: test.Param.sum().backward() test.paramn .grad Out[77]: tensor([1., 1.]) 总结 可以看出3个小实验的forward的结果都是一样的,但是第一个实验无法反向传播,后面两个可以。但是相比于第二个,第三个会把detach掉的分支 的信息给忽略,这不是最优的选择。 In []: In []: In []: In []: