Lab 4: Mindspore实现手写数字识别

Before we start

我们创建了实验课的github仓库，你可以在这里找到所有的实验指导书和相关资源。

由于众所周知的原因，我们会在智慧树平台上上传一份实验资源的拷贝，不使用git仓库**不会**影响你完成实验。

为什么使用git?

1. 你可以第一时间获取实验指导代码的更新，代码框架的修改等。
2. 你可以方便的在本地查看代码的变更和历史。
3. 你可以在issue中提出关于实验代码的问题，可以帮助到有相同问题的同学。

How to start:

初始化：

```
git clone git@github.com:Yujie-G/ML-2024Spring.git
```

之后，每次新实验发布，你可以通过以下命令来更新本地仓库：

```
git pull
```

TODO

1. 安装Mindspore
2. 阅读并理解全连接网络的实现代码
3. 实现LeNet5网络(部分代码已给出)

1. 安装Mindspore

进入官网获取下载命令， 建议选择2.1.1版本的Mindspore, 安装方式选择pip/conda安装均可

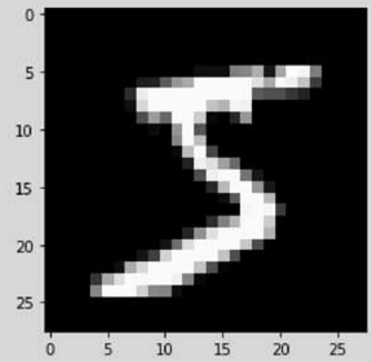
不会Mindspore?可以点击这里学习官方教程

你也可以参考官方的API文档

2. 利用Mindspore实现全连接网络手写数字识别

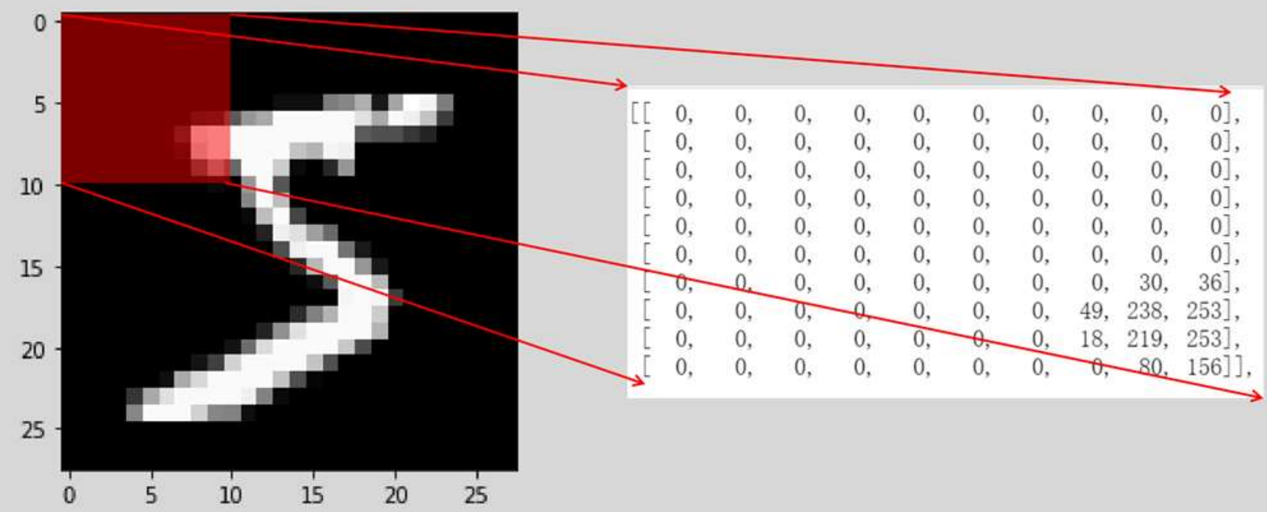
数据集介绍

手写识别数据集



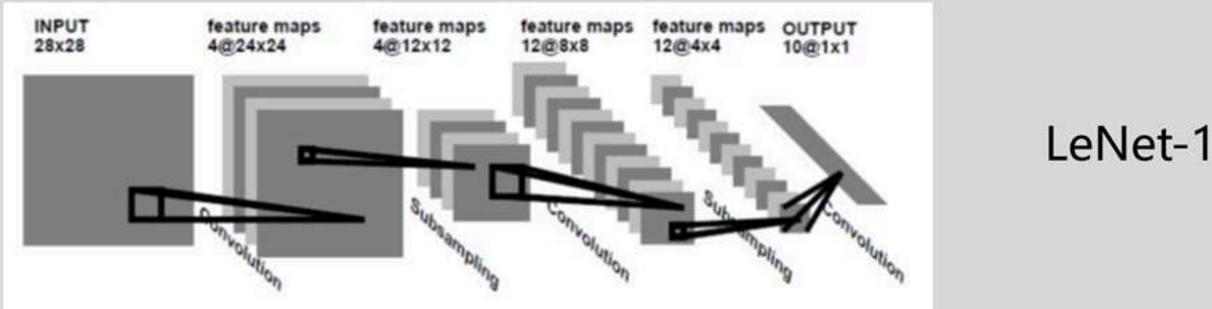
MNIST包含70000张手写数字图像：60000张用于训练；10000张用于测试。

28x28像素的灰度图。



Lenet5网络介绍

LeNet-5 发展历史



1989年：Yann LeCun等人，结合反向传播算法的卷积神经网络来识别手写数字，并成功地用于识别手写邮政编码。

1990年：他们的模型在美国邮政总局提供的邮政编码数字数据的测试结果表明，错误率仅为1%，拒绝率约为9%。

1998年：他们将手写数字识别的各种方法在标准的手写数字识别基准上进行比较，结果表明他们的网络优于所有其他模型，经过多年的研究和迭代，最终发展成为LeNet-5。

你可以参考这份华为官方的指导手册,查看Mindspore的教程

In [ ]:
```
import mindspore
from mindspore import ops
from mindspore import nn
from mindspore.dataset import vision, transforms
from mindspore.dataset import MnistDataset
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In [ ]:
```
# 加载MNIST数据集
train_dataset_dir = "./MNIST/train"
train_dataset = MnistDataset(dataset_dir=train_dataset_dir)
test_dataset_dir = "./MNIST/test"
test_dataset = MnistDataset(dataset_dir=test_dataset_dir)

print(train_dataset.get_col_names())
```

```
['image', 'label']
```

In [ ]:
```
def datapipe(dataset, batch_size):
    image_transforms = [
        vision.Rescale(1.0 / 255.0, 0),
        vision.Normalize(mean=(0.1307,), std=(0.3081,)),
        vision.HWC2CHW()
    ]
    label_transform = transforms.TypeCast(mindspore.int32)

    dataset = dataset.map(image_transforms, 'image')
    dataset = dataset.map(label_transform, 'label')
    dataset = dataset.batch(batch_size)
    return dataset

train_dataset = datapipe(train_dataset, 64)
test_dataset = datapipe(test_dataset, 64)
```

In [ ]:
```
for image, label in test_dataset.create_tuple_iterator():
    print(f"Shape of image [N, C, H, W]: {image.shape} {image.dtype}")
    print(f"Shape of label: {label.shape} {label.dtype}")
    break
```

```
Shape of image [N, C, H, W]: (64, 1, 28, 28) Float32
Shape of label: (64,) Int32
```

In [ ]:
```python
for image, label in test_dataset.create_tuple_iterator():
    print(f"Shape of image [N, C, H, W]: {image.shape} {image.dtype}")
    print(f"Shape of label: {label.shape} {label.dtype}")
    break
```

```
Shape of image [N, C, H, W]: (64, 1, 28, 28) Float32
Shape of label: (64,) Int32
```

In [ ]:
```python
# 网络构建
class Network(nn.Cell):
    def __init__(self):
        super().__init__()
        self.flatten = nn.Flatten()
        self.dense_relu_sequential = nn.SequentialCell(
            nn.Dense(28*28, 512),
            nn.ReLU(),
            nn.Dense(512, 512),
            nn.ReLU(),
            nn.Dense(512, 10)
        )

    def construct(self, x):
        x = self.flatten(x)
        logits = self.dense_relu_sequential(x)
        return logits

model = Network()
print(model)
```

```
Network<
  (flatten): Flatten<>
  (dense_relu_sequential): SequentialCell<
    (0): Dense<input_channels=784, output_channels=512, has_bias=True>
    (1): ReLU<>
    (2): Dense<input_channels=512, output_channels=512, has_bias=True>
    (3): ReLU<>
    (4): Dense<input_channels=512, output_channels=10, has_bias=True>
    >
  >
```

In [ ]:
```python
# 模型训练
loss_fn = nn.CrossEntropyLoss()
optimizer = nn.SGD(model.trainable_params(), 1e-2)
```

In [ ]:
```python
def train(model, dataset, loss_fn, optimizer):
    def forward_fn(data, label):
        logits = model(data)
        loss = loss_fn(logits, label)
        return loss, logits

    grad_fn = ops.value_and_grad(forward_fn, None, optimizer.parameters, has_aux=True)

    def train_step(data, label):
        (loss, _), grads = grad_fn(data, label)
        loss = ops.depend(loss, optimizer(grads))
        return loss

    size = dataset.get_dataset_size()
    model.set_train()
    for batch, (data, label) in enumerate(dataset.create_tuple_iterator()):
        loss = train_step(data, label)
```

```python
        if batch % 100 == 0:
            loss, current = loss.asnumpy(), batch
            print(f"loss: {loss:>7f}  [{current:>3d}/{size:>3d}]")
```

In [ ]:
```python
def test(model, dataset, loss_fn):
    num_batches = dataset.get_dataset_size()
    model.set_train(False)
    total, test_loss, correct = 0, 0, 0
    for data, label in dataset.create_tuple_iterator():
        pred = model(data)
        total += len(data)
        test_loss += loss_fn(pred, label).asnumpy()
        correct += (pred.argmax(1) == label).asnumpy().sum()
    test_loss /= num_batches
    correct /= total
    print(f"Test: \n Accuracy: {(100*correct):>0.1f}%, Avg loss: {test_loss:>8f} \n")
```

In [ ]:
```python
epochs = 3
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(model, train_dataset, loss_fn, optimizer)
    test(model, test_dataset, loss_fn)
print("Done!")
```

```
Epoch 1
-------------------------------
loss: 0.055614  [  0/938]
loss: 0.074898  [100/938]
loss: 0.090094  [200/938]
loss: 0.073458  [300/938]
loss: 0.036597  [400/938]
loss: 0.113472  [500/938]
loss: 0.090123  [600/938]
loss: 0.112469  [700/938]
loss: 0.081419  [800/938]
loss: 0.035383  [900/938]
Test: 
 Accuracy: 96.9%, Avg loss: 0.099123 

Epoch 2
-------------------------------
loss: 0.177960  [  0/938]
loss: 0.140007  [100/938]
loss: 0.079025  [200/938]
loss: 0.087178  [300/938]
loss: 0.230235  [400/938]
loss: 0.110756  [500/938]
loss: 0.053181  [600/938]
loss: 0.084230  [700/938]
loss: 0.024468  [800/938]
loss: 0.062206  [900/938]
Test: 
 Accuracy: 97.1%, Avg loss: 0.091054 

Epoch 3
-------------------------------
loss: 0.062178  [  0/938]
loss: 0.052646  [100/938]
loss: 0.132047  [200/938]
loss: 0.173868  [300/938]
loss: 0.158869  [400/938]
loss: 0.075314  [500/938]
loss: 0.180499  [600/938]
loss: 0.065313  [700/938]
loss: 0.088117  [800/938]
loss: 0.060853  [900/938]
Test: 
 Accuracy: 97.2%, Avg loss: 0.091232 

Done!
```

In [ ]:

```python
# Save checkpoint
mindspore.save_checkpoint(model, "model.ckpt")
print("Saved Model to model.ckpt")
```

```
Saved Model to model.ckpt
```

In [ ]:

```python
# Instantiate a random initialized model
model = Network()
# Load checkpoint and load parameter to model
param_dict = mindspore.load_checkpoint("model.ckpt")
param_not_load, _ = mindspore.load_param_into_net(model, param_dict)
print(param_not_load)
```

```
[]
```

In [ ]:

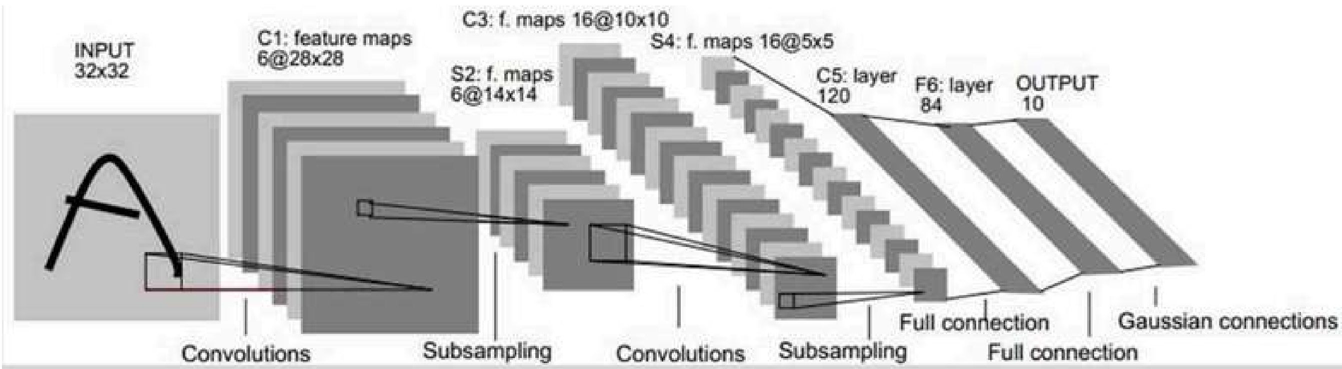
```python
model.set_train(False)
for data, label in test_dataset:
    pred = model(data)
```

```
    predicted = pred.argmax(1)
    print(f'Predicted: "{predicted[:10]}", Actual: "{label[:10]}"')
    break
```

Out[ ]:

```
Network<
  (flatten): Flatten<>
  (dense_relu_sequential): SequentialCell<
    (0): Dense<input_channels=784, output_channels=512, has_bias=True>
    (1): ReLU<>
    (2): Dense<input_channels=512, output_channels=512, has_bias=True>
    (3): ReLU<>
    (4): Dense<input_channels=512, output_channels=10, has_bias=True>
    >
  >
Predicted: "[7 1 1 3 8 0 4 0 9 7]", Actual: "[7 1 1 3 8 0 4 0 9 7]"
```

3. 实现LeNet5网络



	输入	卷积、池化、神经元	输出	训练参数
输入层*			32*32	0
卷积层1	32*32	6个 5*5卷积核 步长为1	6*28*28（32-5+0）/1+1	1*（5*5）*6 +6=156
池化层1	6*28*28	2*2 步长为2	6*14*14	0
卷积层2	6*14*14	16个 5*5卷积核 步长为1	16*10*10 （14-5+0）/1+1	6*（5*5）*16 +16=2416
池化层2	16*10*10	2*2 步长为2	16*5*5	0
全连接层1	16*5*5	120个 5*5卷积核 步长为1	120*1*1（5-5+0）/1+1	16*（5*5）*120+120=48120
全连接层2	120		84	120*84+84=10164
输出层	84		10	84*10+10=850

根据上图说明的参数，实现LeNet5网络，完成手写数字识别任务，部分代码已给出，你需要补全代码

你可能会用到的MindSpore卷积神经网络API

In [ ]:

```
# Classify MNIST digits
import os
import numpy as np
import mindspore as ms
import mindspore.nn as nn
from mindspore import Model
from mindspore.train.callback import Callback
from mindspore.train.callback import LossMonitor
import mindspore.dataset as ds
import mindspore.dataset.vision as CV
import mindspore.dataset.transforms as C
from mindspore.dataset.vision import Inter
from mindspore import dtype as mstype
import matplotlib.pyplot as plt
```

In [ ]:
```python
# !设置全局种子，这里改成你的学号后四位
np.random.seed(777)
ms.set_seed(777)


## hyperparameters
batch_size = 32
epoch_size = 10
learning_rate = 0.01
## dataset loading

dataset_dir = "./MNIST"
```

In [ ]:
```python
# 导入你需要的包
## pkgs import
import mindspore.dataset as ds
import mindspore.dataset.vision as CV
import mindspore.dataset.transforms as C
from mindspore import dtype as mstype

resize_height, resize_width = 32, 32
rescale = 1.0 / 255.0
shift = 0.0
rescale_nml = 1 / 0.3081
shift_nml = -1 * 0.1307 / 0.3081


def create_dataset(data_path, batch_size=32, repeat_size=1, num_parallel_workers=1):

    # 创建数据集
    mnist_ds = ds.MnistDataset(data_path)

    # 实现数据增强和处理(不要忘记处理label)
    # 1. 将图像缩放到模型需要的输入，比如32x32，插值方式为线性插值。
    # [附加题] 将图像的对比度和亮度做适当的调整，调整幅度任意。 [提示：需要先对色彩空间进行转化]
    """
    ==========================修改这部分代码=======================
    """
    image_trans = [
        CV.Rescale(rescale_nml, shift_nml),
        CV.Rescale(rescale, shift),
        CV.HWC2CHW(),
    ]
    label_trans = C.TypeCast(mstype.int32)
    mnist_ds = mnist_ds.map(operations=image_trans,input_columns=["image"], num_parallel_workers
    """
    ===============================================================
    """

    # 当需要对**指定标签**的数据进行增强时，可以使用类似下面的双变量迭代方式，例如：
    # mnist_ds = mnist_ds.map(operations=(lambda img, lb: ... if lb == ... else ...),input_colum
    # 处理生成的数据集
    buffer_size = 10000
    mnist_ds = mnist_ds.shuffle(buffer_size=buffer_size)
    mnist_ds = mnist_ds.batch(batch_size, drop_remainder=True)
    mnist_ds = mnist_ds.repeat(repeat_size)

    return mnist_ds


train_dataset = create_dataset(os.path.join(dataset_dir, "train"), batch_size=batch_size)
test_dataset = create_dataset(os.path.join(dataset_dir, "test"), batch_size=batch_size)
```

In [ ]:
```
# this part is for debug use
image, label = next(train_dataset.create_tuple_iterator())
print(train_dataset.get_dataset_size())
print(image.shape, image.dtype, f", the result should be ({batch_size}, 1, {resize_height}, {res
print(label.shape, label.dtype, f", the result should be ({batch_size},) Int32")
```

```
1875
(32, 1, 32, 32) Float32 , the result should be (32, 1, 32, 32) Float32
(32,) Int32 , the result should be (32,) Int32
```

In [ ]:
```
class LeNet5(nn.Cell):
    '''
    code here
    '''
```

In [ ]:
```
net = LeNet5()
loss = nn.SoftmaxCrossEntropyWithLogits(sparse=True, reduction='mean')
optim = nn.Momentum(params=net.trainable_params(), learning_rate=learning_rate, momentum=0.9)
model = Model(network = net, loss_fn=loss, optimizer=optim, metrics={"Accuracy": nn.Accuracy()})
```

In [ ]:
```
# 实现训练部分代码，并打印训练过程中的loss值，建议可视化查看loss值的变化

"""
code here
"""
```

```
[WARNING] ME(66948:51340,MainProcess):2023-05-22-19:29:48.935.820 [mindspore\train\model.py:107
7] For StepLossAccInfo callback, {'step_end'} methods may not be supported in later version, Use
methods prefixed with 'on_train' or 'on_eval' instead when using customized callbacks.
epoch: 1 step: 700, loss is 2.299285650253296
epoch: 1 step: 1400, loss is 2.2985246181488037
epoch: 2 step: 225, loss is 2.317354440689087
epoch: 2 step: 925, loss is 2.31984281539917
epoch: 2 step: 1625, loss is 2.315185785293579
epoch: 3 step: 450, loss is 2.2975192070007324
epoch: 3 step: 1150, loss is 2.316565752029419
epoch: 3 step: 1850, loss is 1.741559386253357
epoch: 4 step: 675, loss is 0.2549223005771637
epoch: 4 step: 1375, loss is 0.011149514466524124
epoch: 5 step: 200, loss is 0.002960966667160392
epoch: 5 step: 900, loss is 0.030207134783267975
epoch: 5 step: 1600, loss is 0.0054566883482038975
epoch: 6 step: 425, loss is 0.003726671449840069
epoch: 6 step: 1125, loss is 0.03973142430186272
epoch: 6 step: 1825, loss is 0.07755744457244873
epoch: 7 step: 650, loss is 0.00104424764867872
epoch: 7 step: 1350, loss is 0.003242630511522293
epoch: 8 step: 175, loss is 0.05023606866598129
epoch: 8 step: 875, loss is 0.02776007540524006
epoch: 8 step: 1575, loss is 0.008360585197806358
epoch: 9 step: 400, loss is 0.004078148398548365
epoch: 9 step: 1100, loss is 0.0006239300710149109
epoch: 9 step: 1800, loss is 0.0003876787959598005
epoch: 10 step: 625, loss is 0.0019181546522304416
epoch: 10 step: 1325, loss is 0.0034030776005238295
```

In [ ]:
```
## test
def test_net(network, model, path):
    """Define the evaluation method."""
    # 加载已保存的模型
    param_dict = ms.load_checkpoint(path)
    # Load parameter to the network
    ms.load_param_into_net(network, param_dict)
```

```
    # evaluation
    acc = model.eval(test_dataset, dataset_sink_mode=False)
    print("============== Accuracy:{} ==============".format(acc))

# 修改为你的checkpoint路径
test_net(net, model, "/path/to/your/ckpt")
```

```
============== Accuracy:{'Accuracy': 0.9878806089743589} ==============
```