

## features

2021 年 4 月 8 日

```
[2]: from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# 输入 daseCV 所在的路径
# 'daseCV' 文件夹包括 '.py', 'classifiers' 和 'datasets' 文件夹
# 例如 'CV/assignments/assignment1/daseCV/'
FOLDERNAME = 'CV/assignments/assignment1/daseCV/'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd daseCV/datasets/
!bash get_datasets.sh
%cd ../../
```

Mounted at /content/drive

/content/drive/My Drive

/content

/content/daseCV/datasets

--2021-04-03 11:54:41-- http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz

Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30

Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...

connected.

HTTP request sent, awaiting response... 200 OK

Length: 170498071 (163M) [application/x-gzip]

```
Saving to: 'cifar-10-python.tar.gz'
```

```
cifar-10-python.tar 100%[=====>] 162.60M 95.8MB/s in 1.7s
```

```
2021-04-03 11:54:43 (95.8 MB/s) - 'cifar-10-python.tar.gz' saved  
[170498071/170498071]
```

```
cifar-10-batches-py/  
cifar-10-batches-py/data_batch_4  
cifar-10-batches-py/readme.html  
cifar-10-batches-py/test_batch  
cifar-10-batches-py/data_batch_3  
cifar-10-batches-py/batches.meta  
cifar-10-batches-py/data_batch_2  
cifar-10-batches-py/data_batch_5  
cifar-10-batches-py/data_batch_1  
/content
```

## 1 图像特征练习

补充并完成本练习。

我们已经看到，通过在输入图像的像素上训练线性分类器，从而在图像分类任务上达到一个合理的性能。在本练习中，我们将展示我们可以通过对线性分类器（不是在原始像素上，而是在根据原始像素计算出的特征上）进行训练来改善分类性能。

你将在此 notebook 中完成本练习的所有工作。

```
[4]: import random  
import numpy as np  
from daseCV.data_utils import load_CIFAR10  
import matplotlib.pyplot as plt  
  
%matplotlib inline  
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots  
plt.rcParams['image.interpolation'] = 'nearest'
```

```
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
# → autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

## 1.1 数据加载

与之前的练习类似，我们将从磁盘加载 CIFAR-10 数据。

```
[5]: from daseCV.features import color_histogram_hsv, hog_feature

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # Load the raw CIFAR-10 data
    cifar10_dir = 'daseCV/datasets/cifar-10-batches-py'

    # Cleaning up variables to prevent loading data multiple times (which may
    # → cause memory issue)
    try:
        del X_train, y_train
        del X_test, y_test
        print('Clear previously loaded data.')
    except:
        pass

    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # Subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
```

```

mask = list(range(num_training))
X_train = X_train[mask]
y_train = y_train[mask]
mask = list(range(num_test))
X_test = X_test[mask]
y_test = y_test[mask]

return X_train, y_train, X_val, y_val, X_test, y_test

X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()

```

## 1.2 特征提取

对于每一张图片我们将会计算它的方向梯度直方图（英语：Histogram of oriented gradient，简称 HOG）以及在 HSV 颜色空间使用色相通道的颜色直方图。

简单来讲，HOG 能提取图片的纹理信息而忽略颜色信息，颜色直方图则提取出颜色信息而忽略纹理信息。因此，我们希望将两者结合使用而不是单独使用任一个。去实现这个设想是一个十分有趣的事情。

hog\_feature 和 color\_histogram\_hsv 两个函数都可以对单个图像进行运算并返回改图像的一个特征向量。extract\_features 函数输入一个图像集合和一个特征函数列表然后对每张图片运行每个特征函数，然后将结果存储在一个矩阵中，矩阵的每一列是单个图像的所有特征向量的串联。

```

[6]: from daseCV.features import *

num_color_bins = 10 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img,
    ↪nbin=num_color_bins)]

X_train_feats = extract_features(X_train, feature_fns, verbose=True)
X_val_feats = extract_features(X_val, feature_fns)
X_test_feats = extract_features(X_test, feature_fns)

# Preprocessing: Subtract the mean feature
mean_feat = np.mean(X_train_feats, axis=0, keepdims=True)
X_train_feats -= mean_feat
X_val_feats -= mean_feat

```

```
X_test_feats -= mean_feat

# Preprocessing: Divide by standard deviation. This ensures that each feature
# has roughly the same scale.
std_feat = np.std(X_train_feats, axis=0, keepdims=True)
X_train_feats /= std_feat
X_val_feats /= std_feat
X_test_feats /= std_feat

# Preprocessing: Add a bias dimension
X_train_feats = np.hstack([X_train_feats, np.ones((X_train_feats.shape[0], 1))])
X_val_feats = np.hstack([X_val_feats, np.ones((X_val_feats.shape[0], 1))])
X_test_feats = np.hstack([X_test_feats, np.ones((X_test_feats.shape[0], 1))])
```

```
Done extracting features for 1000 / 49000 images
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
Done extracting features for 14000 / 49000 images
Done extracting features for 15000 / 49000 images
Done extracting features for 16000 / 49000 images
Done extracting features for 17000 / 49000 images
Done extracting features for 18000 / 49000 images
Done extracting features for 19000 / 49000 images
Done extracting features for 20000 / 49000 images
Done extracting features for 21000 / 49000 images
Done extracting features for 22000 / 49000 images
```

```
Done extracting features for 23000 / 49000 images
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Done extracting features for 25000 / 49000 images
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Done extracting features for 48000 / 49000 images
Done extracting features for 49000 / 49000 images
```

### 1.3 使用特征训练 SVM

使用之前作业完成的多分类 SVM 代码来训练上面提取的特征。这应该比原始数据直接在 SVM 上训练会去的更好的效果。

[40]: # 使用验证集调整学习率和正则化强度

```
from daseCV.classifiers.linear_classifier import LinearSVM
```

```

learning_rates = [1e-1, 1e-2, 1e-3]
regularization_strengths = [5e4, 5e5, 5e6, 5]
#learning_rates=[5e-2, 7.5e-2, 1e-1]
#regularization_strengths = [(5+i)*1e6 for i in range(-3,4)]

results = {}
best_val = -1
best_svm = None

#####
# 你需要做的:
# 使用验证集设置学习率和正则化强度。
# 这应该与你对 SVM 所做的验证相同;
# 将训练最好的的分类器保存在 best_svm 中。
# 你可能还想在颜色直方图中使用不同数量的 bins。
# 如果你细心一点应该能够在验证集上获得接近 0.44 的准确性。
#####
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

svm = LinearSVM()
for lr in learning_rates:
    for reg in regularization_strengths:
        svm.train(X_train_feats, y_train, lr, reg, 200)
        train_accuracy = np.mean(svm.predict(X_train_feats) == y_train)
        val_accuracy = np.mean(svm.predict(X_val_feats) == y_val)
        results[(lr, reg)] = (train_accuracy, val_accuracy)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out results.
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (

```

```

        lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' %_
      ↪best_val)

```

```

lr 1.000000e-03 reg 5.000000e+00 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-03 reg 5.000000e+04 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-03 reg 5.000000e+05 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-03 reg 5.000000e+06 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-02 reg 5.000000e+00 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-02 reg 5.000000e+04 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-02 reg 5.000000e+05 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-02 reg 5.000000e+06 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-01 reg 5.000000e+00 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-01 reg 5.000000e+04 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-01 reg 5.000000e+05 train accuracy: 0.115204 val accuracy: 0.126000
lr 1.000000e-01 reg 5.000000e+06 train accuracy: 0.115204 val accuracy: 0.126000
best validation accuracy achieved during cross-validation: 0.126000

```

```

[41]: # Evaluate your trained SVM on the test set
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)

```

0.098

```

[14]: np.random.choice([], 8, replace=False)

```

```

-----
ValueError                                Traceback (most recent call last)
<ipython-input-14-a3b8a0cf64f6> in <module>()
----> 1 np.random.choice([], 8, replace=False)

mtrand.pyx in numpy.random.mtrand.RandomState.choice()

ValueError: 'a' cannot be empty unless no samples are taken

```



```
[24]: # 直观了解算法工作原理的一种重要方法是可视化它所犯的错误。
# 在此可视化中，我们显示了当前系统未正确分类的图像示例。
# 第一列显示的图像是我们的系统标记为 “plane”，但其真实标记不是 “plane”。

examples_per_class = 8
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',
           ↪ 'ship', 'truck']
for cls, cls_name in enumerate(classes):
    idxs = np.where((y_test != cls) & (y_test_pred == cls))[0]
    idxs=[0,1,2,3,4,5,6,7]
    #print(idxs)
    idxs = np.random.choice(idxs, examples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt.subplot(examples_per_class, len(classes), i * len(classes) + cls +
           ↪ 1)

        plt.imshow(X_test[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls_name)
plt.show()
```



### 问题 1:

描述你看到的错误分类结果。你认为他们有道理吗？

答：毫无道理 0.1 也基本说明了他就在瞎猜而已

## 1.4 图像特征神经网络

在之前的练习中，我们看到在原始像素上训练两层神经网络比线性分类器具有更好的分类精度。在这里，我们已经看到使用图像特征的线性分类器优于使用原始像素的线性分类器。为了完整起见，我们还应该尝试在图像特征上训练神经网络。这种方法应优于以前所有的方法：你应该能够轻松地在测试集上达到 55% 以上的分类精度；我们最好的模型可达到约 60% 的精度。

```
[25]: # Preprocessing: Remove the bias dimension
# Make sure to run this cell only ONCE
print(X_train_feats.shape)
X_train_feats = X_train_feats[:, :-1]
X_val_feats = X_val_feats[:, :-1]
X_test_feats = X_test_feats[:, :-1]

print(X_train_feats.shape)
```

```
(49000, 155)
```

```
(49000, 154)
```

```
[45]: from daseCV.classifiers.neural_net import TwoLayerNet

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10
best_acc = 0.0

net = TwoLayerNet(input_dim, hidden_dim, num_classes)
best_net = None

#####
# TODO: 使用图像特征训练两层神经网络。
# 您可能希望像上一节中那样对各种参数进行交叉验证。
# 将最佳的模型存储在 best_net 变量中。
↪

#####
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

results = {}
best_val = -1
best_net = None

learning_rates = [1e-2, 1e-1, 5e-1, 1, 5]
regularization_strengths = [1e-3, 5e-3, 1e-2, 1e-1, 0.5, 1]
```

```

for lr in learning_rates:
    for reg in regularization_strengths:
        net = TwoLayerNet(input_dim, hidden_dim, num_classes)
        # Train the network
        stats = net.train(X_train_feats, y_train, X_val_feats, y_val,
                           num_iters=1500, batch_size=200,
                           learning_rate=lr, learning_rate_decay=0.95,
                           reg=reg, verbose=False)
        val_acc = (net.predict(X_val_feats) == y_val).mean()
        if val_acc > best_val:
            best_val = val_acc
            best_net = net
        results[(lr,reg)] = val_acc

# Print out results.
for lr, reg in sorted(results):
    val_acc = results[(lr, reg)]
    print ('lr %e reg %e val accuracy: %f' % (
        lr, reg, val_acc))

print ('best validation accuracy achieved during cross-validation: %f' %
    ↪best_val)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

```

/content/daseCV/classifiers/neural\_net.py:103: RuntimeWarning: divide by zero encountered in log

/content/daseCV/classifiers/neural\_net.py:101: RuntimeWarning: overflow encountered in subtract

/content/daseCV/classifiers/neural\_net.py:101: RuntimeWarning: invalid value encountered in subtract

/content/daseCV/classifiers/neural\_net.py:105: RuntimeWarning: overflow encountered in multiply

```
grads = {}
/content/daseCV/classifiers/neural_net.py:105: RuntimeWarning: overflow
encountered in double_scalars
grads = {}
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:87:
RuntimeWarning: overflow encountered in reduce
return ufunc.reduce(obj, axis, dtype, out, **passkwargs)

lr 1.000000e-02 reg 1.000000e-03 val accuracy: 0.221000
lr 1.000000e-02 reg 5.000000e-03 val accuracy: 0.187000
lr 1.000000e-02 reg 1.000000e-02 val accuracy: 0.087000
lr 1.000000e-02 reg 1.000000e-01 val accuracy: 0.078000
lr 1.000000e-02 reg 5.000000e-01 val accuracy: 0.102000
lr 1.000000e-02 reg 1.000000e+00 val accuracy: 0.078000
lr 1.000000e-01 reg 1.000000e-03 val accuracy: 0.526000
lr 1.000000e-01 reg 5.000000e-03 val accuracy: 0.527000
lr 1.000000e-01 reg 1.000000e-02 val accuracy: 0.520000
lr 1.000000e-01 reg 1.000000e-01 val accuracy: 0.428000
lr 1.000000e-01 reg 5.000000e-01 val accuracy: 0.079000
lr 1.000000e-01 reg 1.000000e+00 val accuracy: 0.079000
lr 5.000000e-01 reg 1.000000e-03 val accuracy: 0.583000
lr 5.000000e-01 reg 5.000000e-03 val accuracy: 0.570000
lr 5.000000e-01 reg 1.000000e-02 val accuracy: 0.570000
lr 5.000000e-01 reg 1.000000e-01 val accuracy: 0.368000
lr 5.000000e-01 reg 5.000000e-01 val accuracy: 0.102000
lr 5.000000e-01 reg 1.000000e+00 val accuracy: 0.105000
lr 1.000000e+00 reg 1.000000e-03 val accuracy: 0.549000
lr 1.000000e+00 reg 5.000000e-03 val accuracy: 0.549000
lr 1.000000e+00 reg 1.000000e-02 val accuracy: 0.560000
lr 1.000000e+00 reg 1.000000e-01 val accuracy: 0.375000
lr 1.000000e+00 reg 5.000000e-01 val accuracy: 0.151000
lr 1.000000e+00 reg 1.000000e+00 val accuracy: 0.113000
lr 5.000000e+00 reg 1.000000e-03 val accuracy: 0.087000
lr 5.000000e+00 reg 5.000000e-03 val accuracy: 0.087000
lr 5.000000e+00 reg 1.000000e-02 val accuracy: 0.087000
lr 5.000000e+00 reg 1.000000e-01 val accuracy: 0.087000
lr 5.000000e+00 reg 5.000000e-01 val accuracy: 0.087000
```

```
lr 5.000000e+00 reg 1.000000e+00 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.583000
```

[46]: # 在测试集上运行得到的最好的神经网络分类器，应该能够获得 55%以上的准确性。

```
test_acc = (best_net.predict(X_test_feats) == y_test).mean()
print(test_acc)
```

0.574

---

## 2 重要

这里是作业的结尾处，请执行以下步骤：

1. 点击 File -> Save 或者用 control+s 组合键，确保你最新的的 notebook 的作业已经保存到谷歌云。
2. 执行以下代码确保 .py 文件保存回你的谷歌云。

```
[48]: import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = []

for files in FILES_TO_SAVE:
    with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w') as f:
        f.write(''.join(open(files).readlines()))
```