

★ Assignment 1

⇒ Goals:

- * Understand the basic **Image Classification pipeline** & data-driven approach (**train/predict** stages)
- * Understand the **train/val/test** splits.
 - ↳ Use of validation data for **hyperparameter tuning**.
- * Develop proficiency in writing efficient **vectorized code** with numpy.
- * Implement and apply a **k-Nearest Neighbor (kNN) classifier**.
- * Implement and apply a **multiclass SVM classifier**.
- * Implement & apply **Softmax classifier**.
- * Implement & apply **Two layer neural network classifier**.
- * Understand the difference & tradeoffs between these classifiers.
- * Get a basic understanding of performance improvements from using **higher-level representation** than raw pixels.
 - { Color Histogram, Histogram of Gradients (HOG) features }

★ Setup Instructions

{ Working remotely on Google Colaboratory }

{ Combination of Jupyter notebook
and Google Drive }

⇒ GC runs entirely in the cloud & comes preinstalled with many packages (e.g. PyTorch & TensorFlow), so everyone has access to the same dependencies.

⇒ Colab benefits from free access to hardware accelerators like GPUs (K80, P100) and TPUs.

1. KNN Classifier (knnipythb)

★ CIFAR-10 dataset

→ 10 classes

→ Canadian Institute for Advanced Research

⇒ Contains 60,000 $32 \times 32 \times 3$ color images in 10 classes

→ 6,000 image per class

→ (50,000 training image) + (10,000 test image)

⇒ The dataset is divided as follows:

~~① 5 - test batch~~

① 1 - test batch

→ 1000 randomly selected images for each class.

② 5 - training batch

→ 5 sets of 10,000 randomly selected images from the remaining images.

⇒ Class:

- | | |
|-------------------------|-----------|
| 1. aeroplane | 6. dog |
| 2. automobile | 7. frog |
| 3. bird | 8. horse |
| 4. cat | 9. ship |
| 5. deer | 10. truck |

{The classes are completely mutually exclusive, no overlap}

⇒ Each file in dataset is a Python "pickled" object produced with pickle.

⇒ Python 3 routine which will open such file & return a dictionary:

```
def unpickle(file):  
    import pickle  
    with open(file, 'rb') as fo:  
        dict = pickle.load(fo, encoding='bytes')  
    return dict
```

⇒ Each of the batch files contain a dictionary with the following elements:

- **data**

↳ 10,000 × 3072 numpy array of unit 8s.

	← 1024 →	← 1024 →	← 1024 →
0	red	green	blue
1			
⋮			
10,000			

One row contains one image, stored in row-major order.

- **labels**

↳ A list of 10,000 numbers in the range 0-9.

⇒ batches, meta, contain the following ~~dictionary~~ Dictionary:

- **label_name**

↳ 10-element list which gives meaningful names to the numeric labels in the labels array.

Inline Question 1

* black \rightarrow Small distance

* White \rightarrow Large distance



(a) distinctly bright row

\rightarrow The test image corresponding to that row
is far away from every image.

train

(b) distinctly bright column

\rightarrow The train image corresponding to that column
is far away from every test image.

Inline Question 2

$P_{ij}^{(k)}$ \rightarrow Pixel value at location (i,j) of some image I_k

$h \rightarrow$ height of images

$w \rightarrow$ width of images

$n \rightarrow$ Total number of images

$$M = \frac{1}{nhw} \sum_{k=1}^n \sum_{i=1}^h \sum_{j=1}^w P_{ij}^{(k)} \quad \left\{ \begin{array}{l} \text{Mean across all} \\ \text{pixels over all} \\ \text{images} \end{array} \right\}$$

$$M_{ij} = \frac{1}{n} \sum_{k=1}^n P_{ij}^{(k)} \quad \left\{ \begin{array}{l} \text{Pixel-wise mean } M_{ij} \\ \text{across all images} \end{array} \right\}$$

$\Rightarrow \sigma$ & σ_{ij} are defined similarly

$$(1) \quad \tilde{P}_{ij}^{(k)} = P_{ij}^{(k)} - M$$

$$\begin{aligned} \text{dist}_{ij} &= \tilde{P}_{ij}^{(k_2)} - \tilde{P}_{ij}^{(k_1)} \\ &= P_{ij}^{(k_2)} - P_{ij}^{(k_1)} \end{aligned}$$

Will not change
Performance

$$(2) \quad \tilde{P}_{ij}^{(k)} = P_{ij}^{(k)} - M_{ij}$$

$$\begin{aligned} \text{dist}_{ij} &= \tilde{P}_{ij}^{(k_2)} - \tilde{P}_{ij}^{(k_1)} \\ &= P_{ij}^{(k_2)} - P_{ij}^{(k_1)} \end{aligned}$$

Will not change
Performance

$$(3) \quad \tilde{P}_{ij}^{(k)} = \frac{P_{ij}^{(k)} - M}{\sigma}$$

$$\text{dist}_{ij} = \frac{P_{ij}^{(k_2)} - P_{ij}^{(k_1)}}{\sigma}$$

Will not change
Performance

$$\text{dist} = \frac{1}{\sigma} \sum_{ij} |P_{ij}^{(k_2)} - P_{ij}^{(k_1)}|$$

④ $\hat{p}_{ij}^{(k)} = \frac{p_{ij}^{(k)} - \mu_{ij}}{\sigma_{ij}}$

Will change
Performance

$dist_{ij} = \frac{p_{ij}^{(k_1)} - p_{ij}^{(k_2)}}{\sigma_{ij}}$

~~$dist = \sum_{i,j} \left(\frac{p_{ij}^{(k_1)} - p_{ij}^{(k_2)}}{\sigma_{ij}} \right)^2$~~

$dist = \sum_{i,j} \left| \frac{p_{ij}^{(k_1)} - p_{ij}^{(k_2)}}{\sigma_{ij}} \right|$

⑤ Will Change
Performance

Inline Question 3

1. No
2. Yes
3. No
4. Yes