# Image Classification using K-Nearest Neighbor and Convolutional Neural Networks

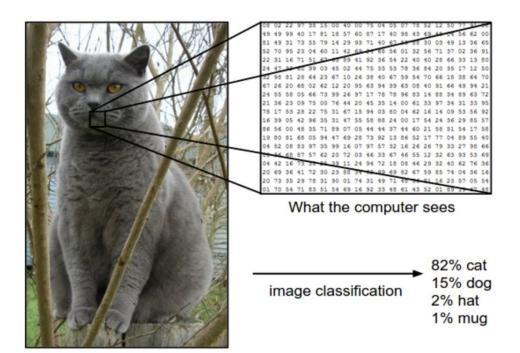
By Rumaisa Abdulhai

#### Why Image Classification?

#### Many Applications, including:

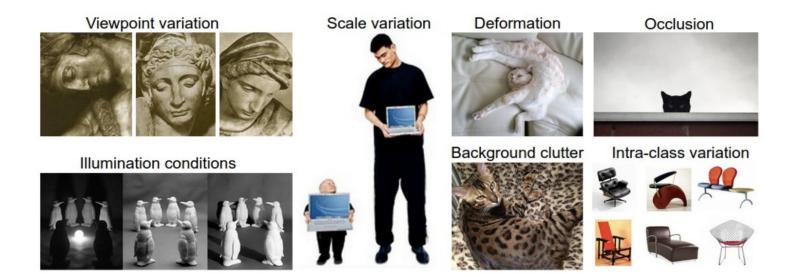
- Medical Diagnosis
  - Identify cancers & tumors using CT Scans
- Image Searching
  - Law Enforcement to identify suspects
- Autonomous vehicles such as self-driving cars
  - Obstacle avoidance
  - Navigation
- And much more...





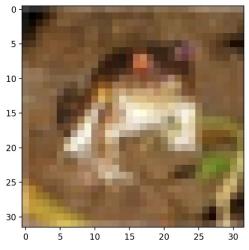
 Turn the matrix of numbers (pixels) into a single label...

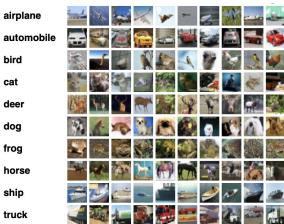
#### Strength of the Classification Model



#### **CIFAR-10 Dataset**

- 60,000 32x32 RGB images with labels
- 10 classes of images so 6000 images per class
- 1/6 images reserved for testing







- 2012 Challenge
  - 1.4 Million 256 x 256 RGB images with labels
  - 1000 classes of images so roughly 1000 images per class
  - 1.2 Million Training, 50,000 Validation, 150,000
     Testing

These are popular datasets, but there are many more



### Machine Learning Techniques for Image Classification

- K-Nearest Neighbor (KNN)
  - Simplest method
- Convolutional Neural Networks (CNN)
  - Dominant method

#### ML: Training, Validation, & Testing Sets

- Dataset divided into Training and Testing (~80% Training & 20% Testing)
- Within Training dataset, a small portion is reserved for validation
- Training set: Used to form the weights/params of the model
- Validation set: Used in between runs of training to further tune parameters
- Test set: Used at the very end after model is completed to evaluate performance

# K-Nearest Neighbor (KNN)

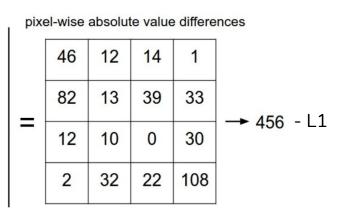
#### L1 & L2 Distances - Definitions

- Calculates distances between two vectors (images)
  - Numerical measure of proximity between two images
- L1: sum of absolute value differences between corresponding pixel values
- L2: square root of the sum of the squares of the pixel-wise differences

| test image |    |     |     |  |  |
|------------|----|-----|-----|--|--|
| 56         | 32 | 10  | 18  |  |  |
| 90         | 23 | 128 | 133 |  |  |
| 24         | 26 | 178 | 200 |  |  |
| 2          | 0  | 255 | 220 |  |  |

|   | training image |    |     |     |  |  |  |  |
|---|----------------|----|-----|-----|--|--|--|--|
|   | 10             | 20 | 24  | 17  |  |  |  |  |
| - | 8              | 10 | 89  | 100 |  |  |  |  |
|   | 12             | 16 | 178 | 170 |  |  |  |  |
|   | 4              | 32 | 233 | 112 |  |  |  |  |

tunining image



#### Nearest Neighbor for Classifying Images

- Take the L2 distance between every training image and desired test image
- The label of the training image with the smallest L2 dist with the test image is assigned to test image
- Repeat for all desired test images...

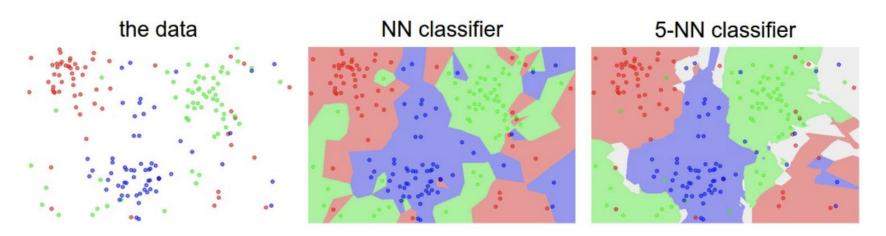
```
In [14]: from sklearn.metrics import accuracy_score
# making predictions
predictions = k_nearest_neighbor(x_train, y_train, x_test, 7)

# evaluating accuracy
accuracy = accuracy_score(y_test, predictions)
print("Accuracy: {}".format(100*accuracy))
```

Accuracy: 27.400000000000002



- Find K Smallest L2 Distances and take most common label
- As K increases, more bias and less variance (smooth boundaries)
- K > 1 always better than k = 1



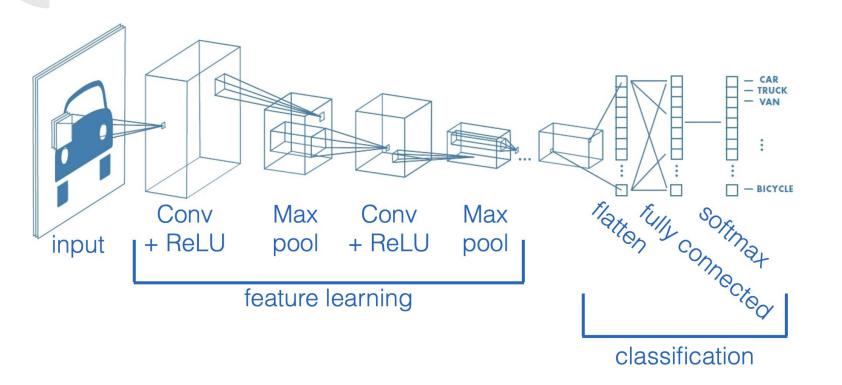
# K-NN: Accuracies with Different Training Data

| K                              | Accuracy |   | K                              | Accuracy |
|--------------------------------|----------|---|--------------------------------|----------|
| 1                              | 31.97    |   | 1                              | 35.39    |
| 3                              | 31.21    |   | 3                              | 33.02    |
| 5                              | 32.43    |   | 5                              | 33.98    |
| 7                              | 32.01    | 7 | 33.58                          |          |
| 9                              | 32.42    |   | 9                              | 33.98    |
| 25,000 Training<br>10,000 Test |          |   | 50,000 Training<br>10,000 Test |          |



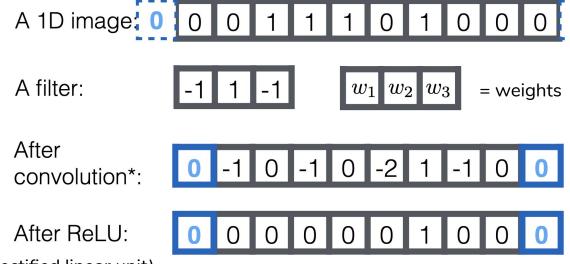
#### Convolutional Neural Networks (CNNs)

#### Components of a CNN Model



#### What is a Convolution Layer?

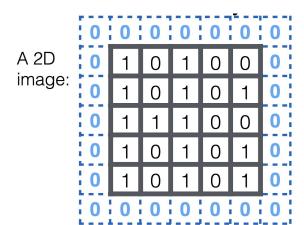
- Convolution is the scalar/dot product of two vectors/matrices
- Used to detect patterns in target images where pattern is specified by filter
- Example:



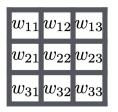
ReLU = activation function where pos #s are kept & neg #s =0

(rectified linear unit)

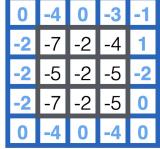
#### 2D Convolution Example (B&W Image)



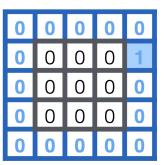
A filter: -1 -1 -1 -1 -1 -1



After convolution:



After convolution & ReLU:

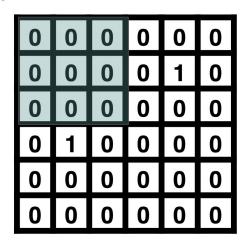


#### What is a Max Pooling Layer?

- Max Pooling is the reduction in the size of an image (matrix) by taking maximum pixel values from certain areas of the image
- Goal: Summarize the patterns it discovered during convolution + relu layer
- Use a kernel for specifying the part of the image you take the maximum of
- Stride specifies how your kernel slides over the image, can be from 1 to length of the kernel
  - If stride = kernel length, then image size reduces by the factor of the kernel's length

#### 2D Max Pooling Example

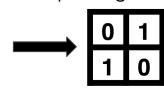
Output from the convolutional layer & ReLU:



Max pooling: returns max of its arguments

- size 3x3 ("size 3")
- stride 3

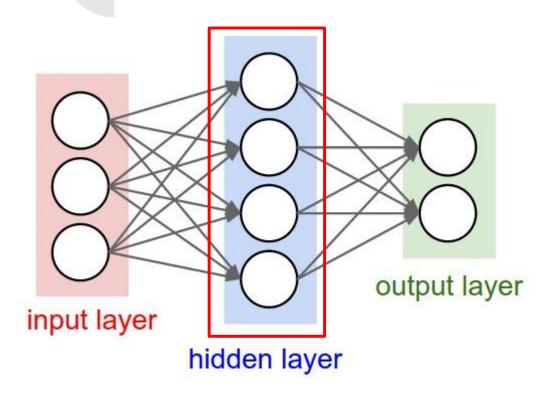
After max pooling:



6x6 B&W Image

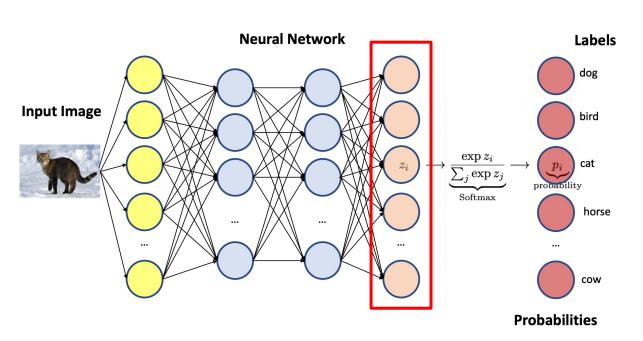
2x2 B&W Image





- Performs the classification part
- Ultimately needed for ML
- Known as Hidden Layer
- Where all inputs are connected to each node at the next level with a seperate weight.
- Images must be flattened or converted to 1D array before passed into hidden layer

#### What is a Softmax Layer?



- An activation function for multicategory classification
- Converts the output of the final fully-connected layer into probabilities of the test image falling into a certain category
- These probabilities are compared against one-hot-encoded actual label

## Preliminary Results on CIFAR-10 with CNN Models

|         | Layers                                    | Parameters | % Test Error with 5 Epochs | % Test Accuracy with 5 Epochs | % Test Error<br>with 10<br>Epochs | % Test Accuracy with 10 Epochs |
|---------|---|------------|----------------------------|-------------------------------|-----------------------------------|--------------------------------|
| Model 1 | 1 conv, 1 maxpool,<br>1 hidden, 1 softmax | 806,666    | 37.42                      | 62.58                         | 34.41                             | 65.59                          |
| Model 2 | 2 conv, 1 maxpool,<br>1 hidden, 1 softmax | 619,306    | 34.58                      | 65.42                         | 31.39                             | 68.61                          |
| Model 3 | 3 conv, 1 maxpool,<br>1 hidden, 1 softmax | 464,714    | 35.59                      | 64.41                         | 30.86                             | 69.14                          |
| Model 4 | 4 conv, 1 maxpool,<br>1 hidden, 1 softmax | 342,890    | 40.12                      | 59.88                         | 32.45                             | 67.55                          |

#### **Future Work**

- Fine tune the model further to achieve a higher accuracy
  - Save best weights throughout training that minimize classification error between training and test sets
  - Train for more epochs
- Use a different, larger dataset such as ImageNet and develop an accurate model if time permits

#### Extras

#### Model 1- Convolutional Layer

model.add(Conv2D(32, (5, 5), activation='relu', input\_shape=(32,32,3))

Input Image- 32x32x3

For every input image, make 32 copies of image and apply a different filter each of size 5x5 for each copy of the image

Output Image: 28x28x32

Total weights/parameters needed:  $5x5 \times 32 \times 3 + 32 = 2432$ 

No padding is used, so images are reduced by 2 pixels on each side

#### Model 1- Max Pooling Layer

```
model.add(MaxPooling2D(pool_size=(2, 2)), data_format='channels_last')
```

Input Image: 28x28x32

Apply Max Pooling with a size 2x2 kernel with stride 2, which divides the row and column of each image in half

Result Image: 14x14x32

#### Model 1: Hidden Layer

```
model.add(Flatten())
model.add(Dense(128, activation='relu'))
```

Flatten Image First: 14x14x32 = 6272 pixels

Hidden Layer has 6272 inputs, and 128 outputs

Total weights/parameters required:  $6272 \times 128 + 128 = 802,944$ 

#### Model 1: Final Softmax Layer

```
model.add(Dense(num_classes, activation='softmax'))
```

Now Hidden Layer to Softmax

Softmax has 128 inputs, and 10 outputs (for the 10 classes)

Total weights/parameters needed:  $128 * 10 + 10 = \underline{1290}$ 

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Total Tunable Parameters: 6272 + 802,944 + 1290 = 806,666