

# Machine Learning

# Lecture 6:

# KNN

# Image Classification

# Image Classification

## Multi-class classification

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- ▶ Direct approaches –
  - ▶  $k$ -NN classifier
  - ▶ Bayesian classifier
  - ▶ Decision trees
  - ▶ Artificial Neural network → (e.g., Convolution neural nets)
  - ▶  $k$ -class SVM (support vector machines)
- ▶ Indirect approaches (i.e., using a binary classifier) –
  - ▶ One-vs-All strategy
  - ▶ All-vs-All strategy
  - ▶ Error correcting codes

# Image Classification

A core task in Computer Vision



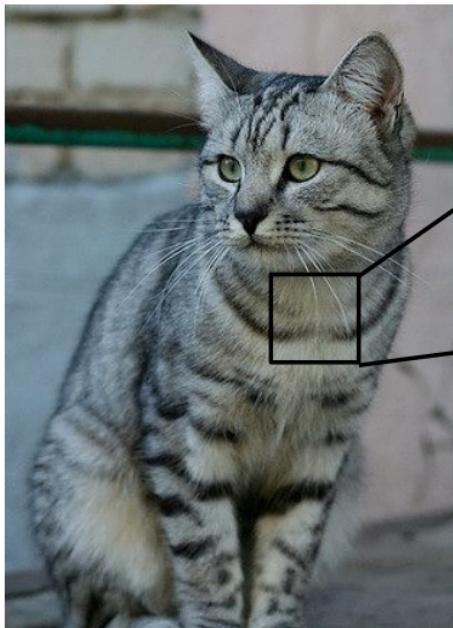
(assume given set of discrete labels) {dog,  
cat, truck, plane, ...}

→ cat

# Image Classification

## A core task in Computer Vision

### The Problem: Semantic Gap



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```
[ [105 112 108 111 104 99 106 99 96 103 112 119 104 97 93 87]
[ 91 98 102 106 104 79 98 103 99 105 123 136 110 105 94 85]
[ 76 85 90 105 128 105 87 96 95 99 115 112 106 103 99 85]
[ 99 81 81 93 128 131 127 180 95 98 102 99 96 93 101 94]
[106 91 61 64 69 91 88 101 107 109 98 75 84 96 95]
[114 108 85 55 55 69 64 54 64 87 112 129 98 74 84 91]
[133 137 147 103 65 81 80 65 52 54 74 84 102 93 85 82]
[128 137 144 140 109 95 86 70 62 65 63 63 60 73 86 101]
[125 133 148 137 119 121 117 94 65 79 80 65 54 64 72 98]
[127 125 131 147 133 127 126 131 111 96 89 75 61 64 72 84]
[115 114 109 123 150 148 131 118 113 109 100 92 74 65 72 78]
[ 89 93 90 97 108 147 131 118 113 114 113 109 106 95 77 80]
[ 63 77 86 81 77 79 102 123 117 115 117 125 125 130 115 87]
[ 62 65 82 89 78 71 80 101 124 126 119 101 107 114 131 119]
[ 63 65 75 88 89 71 62 81 128 138 135 105 81 98 110 118]
[ 87 65 71 87 106 95 69 45 76 130 126 107 92 94 105 112]
[118 97 82 86 117 123 116 66 41 51 95 93 89 95 102 107]
[164 146 112 80 82 120 124 104 76 48 45 66 88 101 102 109]
[157 170 157 120 93 86 114 132 112 97 69 55 70 82 99 94]
[130 128 134 161 139 100 109 118 121 134 114 87 65 53 69 86]
[128 112 96 117 150 144 126 115 104 107 102 93 87 81 72 79]
[123 107 96 86 83 112 153 149 122 109 104 75 80 107 112 99]
[122 121 102 80 82 86 94 117 145 148 153 102 58 78 92 107]
[122 164 148 103 71 56 78 63 93 103 119 139 102 61 69 84]]
```

What the computer sees

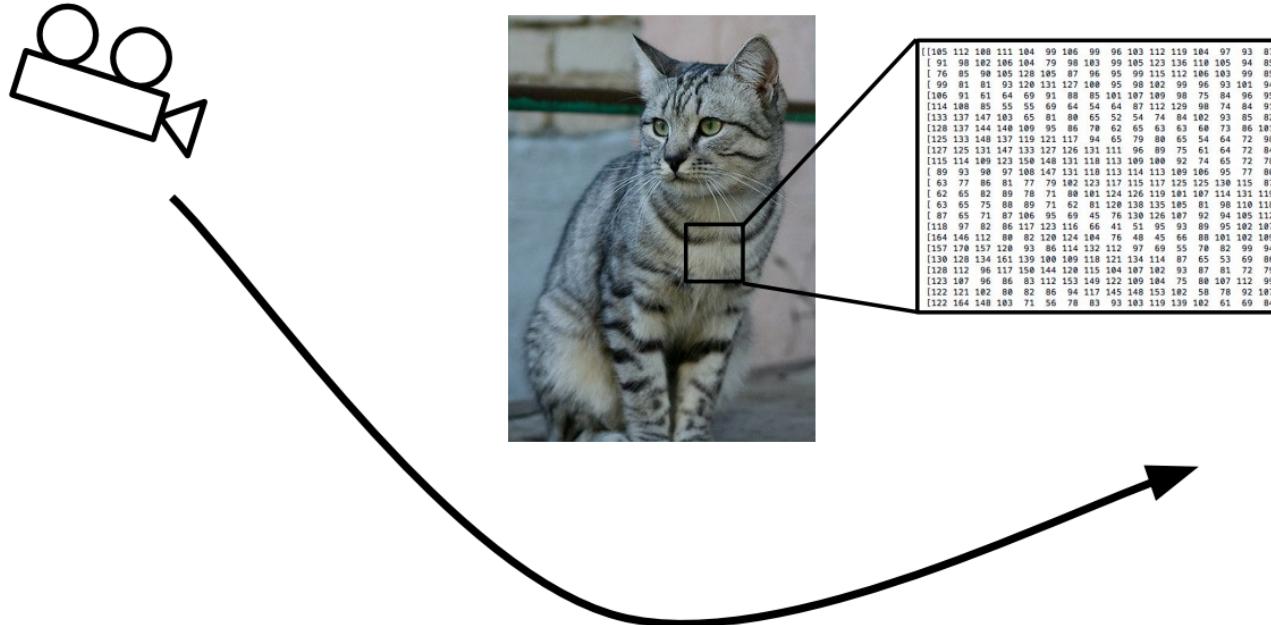
An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3  
(3 channels RGB)

# Image Classification

## A core task in Computer Vision

**Challenges:** Viewpoint variation



# Image Classification

## A core task in Computer Vision

### Challenges: Illumination



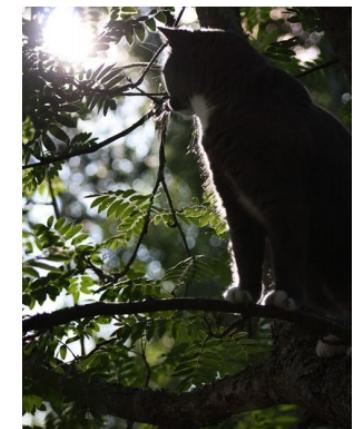
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[This image is CC0 1.0 public domain](#)



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# Image Classification

## A core task in Computer Vision

### Challenges: Deformation



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# Image Classification

A core task in Computer Vision

## Challenges: Occlusion



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# Image Classification

A core task in Computer Vision

Challenges: Background Clutter



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# Image Classification

A core task in Computer Vision

**Challenges:** Intraclass variation



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# Image Classification

## A core task in Computer Vision

An image classifier

```
def classify_image(image):  
    # Some magic here?  
    return class_label
```

Unlike e.g. sorting a list of numbers,

**no obvious way** to hard-code the algorithm for  
recognizing a cat, or other classes.

# Image Classification

A core task in Computer Vision

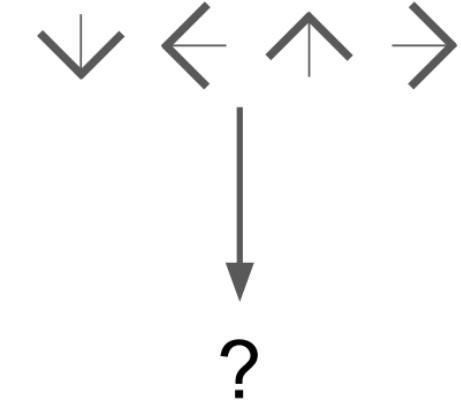
Attempts have been made



Find edges



Find corners



# Image Classification

## A core task in Computer Vision

### Machine Learning: Data-Driven Approach

1. Collect a dataset of images and labels
2. Use Machine Learning to train a classifier
3. Evaluate the classifier on new images

Example training set

```
def train(images, labels):  
    # Machine learning!  
    return model
```

```
def predict(model, test_images):  
    # Use model to predict labels  
    return test_labels
```

**airplane**



**automobile**



**bird**



**cat**



**deer**



# Image Classification

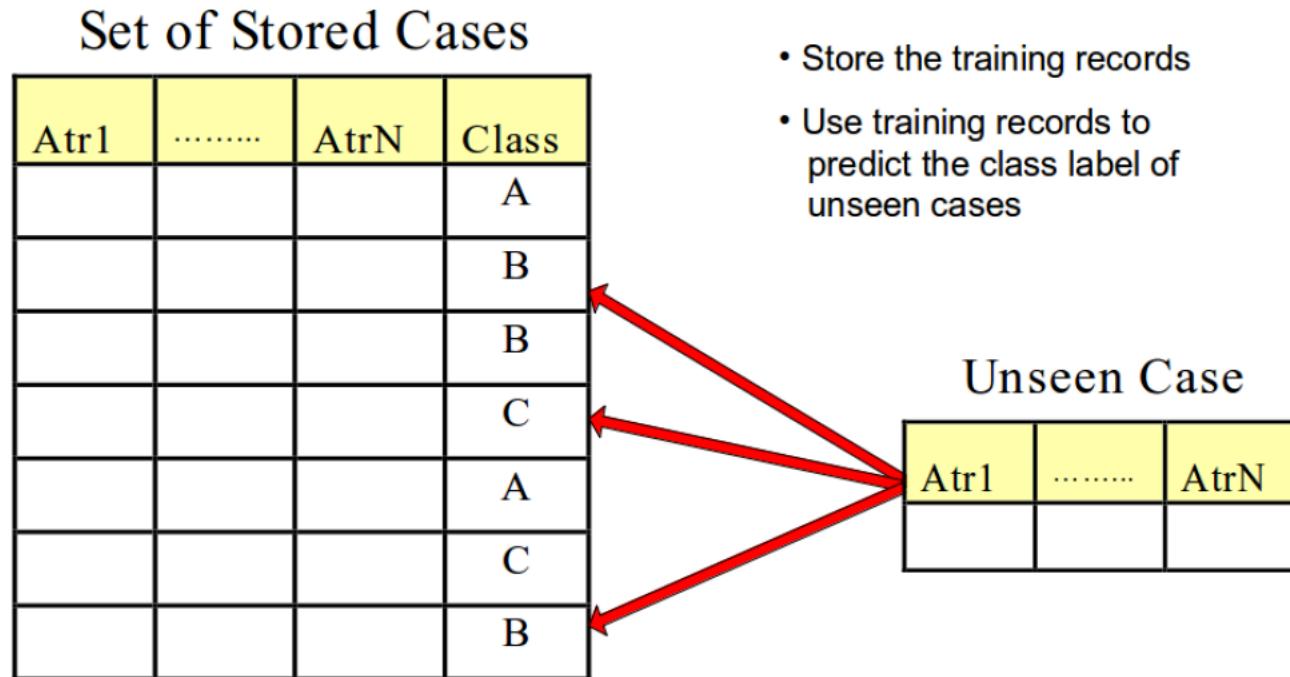
---

**Nearest Neighbor classifier**  
**K-Nearest Neighbors classifier**  
**Assignment**

# Image Classification

## Nearest Neighbor classifier

### Instance based classifier



# Image Classification

## Nearest Neighbor classifier

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**Training:** Nothing just records

**Testing:** Compare (distance)

**Question:**

**How to compare ?**

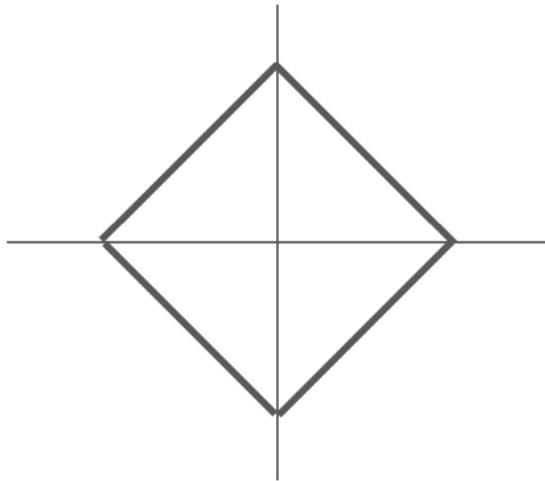
**How to compute the distance, difference?**

# Image Classification

## Nearest Neighbor classifier

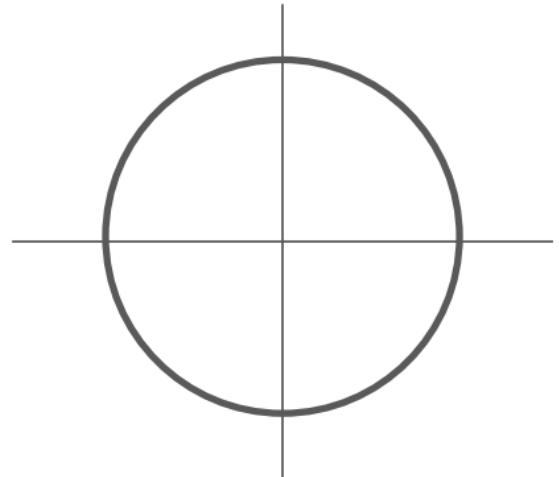
L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$



# Image Classification

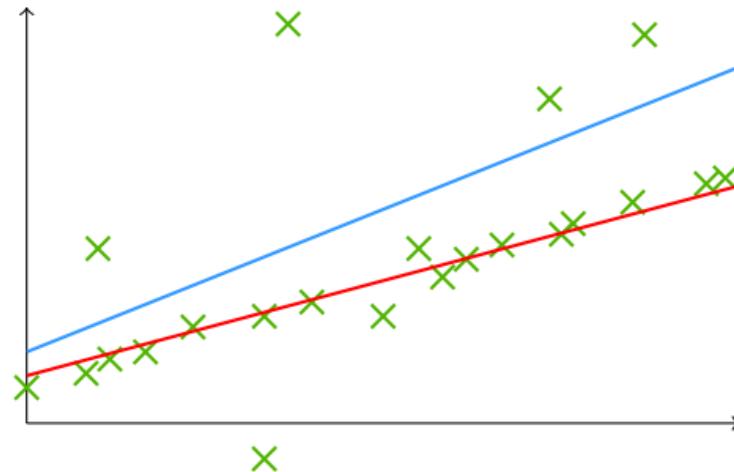
## Nearest Neighbor classifier

Given : A set of **points** in 2-dimension

Goal : Find a line to fit those points

Output :  $\ell_2$  minimizer **line**,  $\ell_1$  minimizer **line**

L1 is more robust to outlier

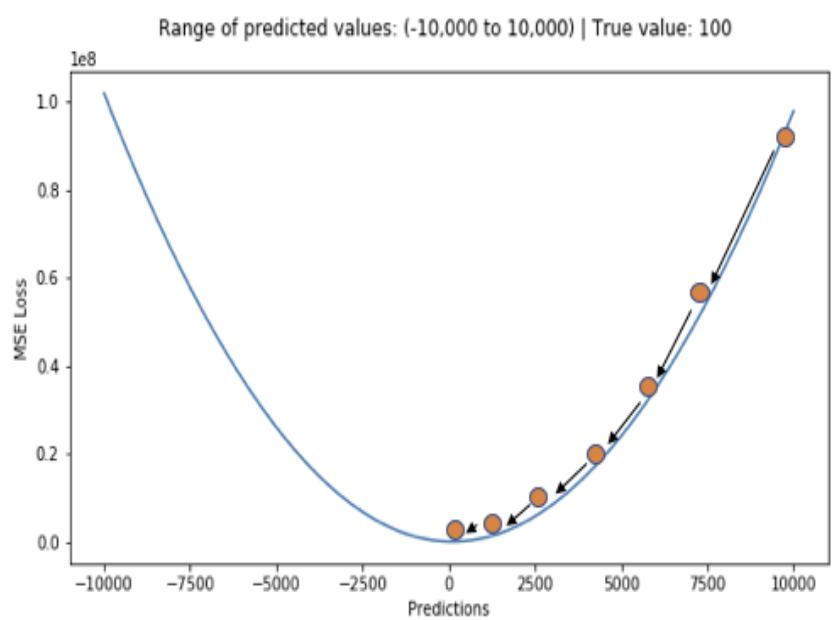
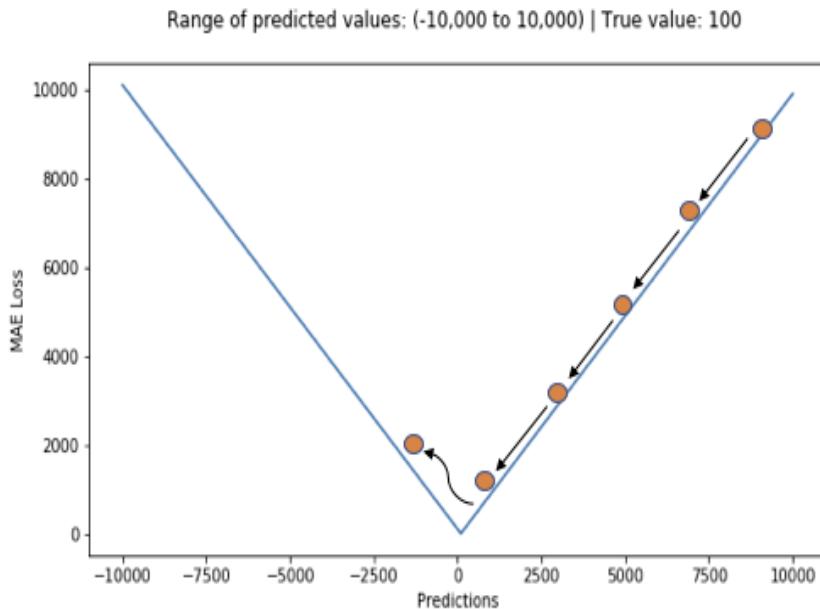


<http://www.chioka.in/differences-between-the-l1-norm-and-the-l2-norm-least-absolute-deviations-and-least-squares/>

# Image Classification

## Nearest Neighbor classifier

L2 loss is sensitive to outliers, but gives a more stable and closed form solution (by setting its derivative to 0.)



# Image Classification

## Nearest Neighbor classifier

```
import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
        # the nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        """ X is N x D where each row is an example we wish to predict label for """
        num_test = X.shape[0]
        # lets make sure that the output type matches the input type
        Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

        # loop over all test rows
        for i in xrange(num_test):
            # find the nearest training image to the i'th test image
            # using the L1 distance (sum of absolute value differences)
            distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred
```

Memorize training data

For each test image:  
Find closest train image  
Predict label of nearest image

# Image Classification

## Nearest Neighbor classifier

```
import numpy as np

class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        """ X is N x D where each row is an example. Y is 1-dimension of size N """
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            min_index = np.argmin(distances) # get the index with smallest distance
            Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

        return Ypred
```

**Q:** With N examples, how fast are training and prediction?

**A:** Train O(1), predict O(N)

This is bad: we want classifiers that are **fast** at prediction; **slow** for training is ok

# Image Classification

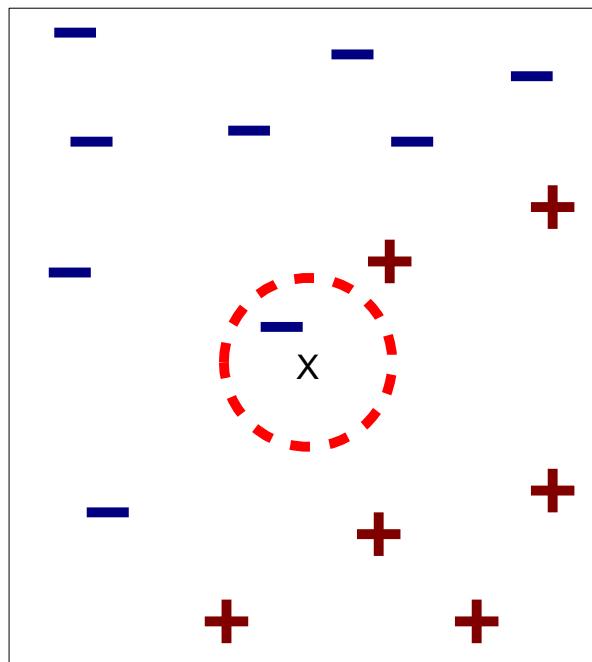
## K-Nearest Neighbor classifier

---

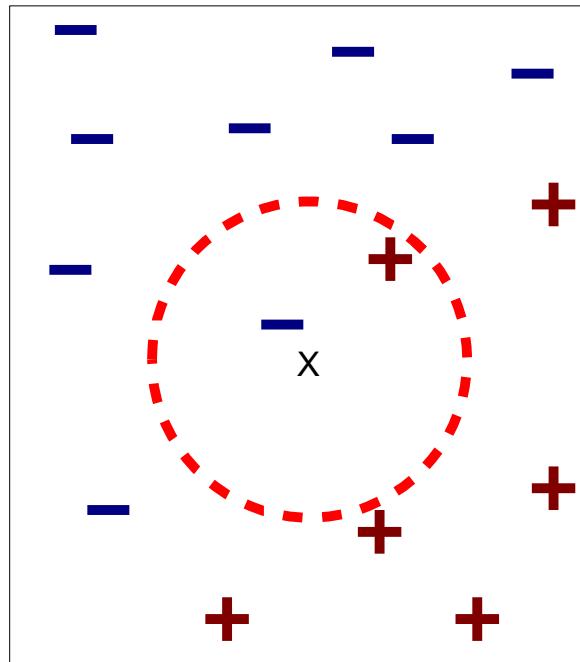
You may have noticed that it is strange to only use the label of the nearest image when we wish to make a prediction. Indeed, it is almost always the case that one can do better by using what's called a **k-Nearest Neighbor Classifier**. The idea is very simple: instead of finding the single closest image in the training set, we will find the top  $k$  closest images, and have them vote on the label of the test image. In particular, when  $k = 1$ , we recover the Nearest Neighbor classifier.

# Image Classification

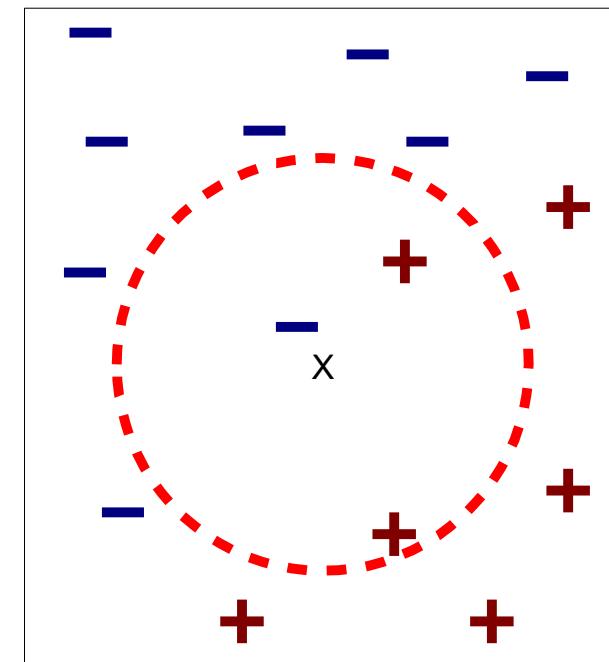
## K-Nearest Neighbor classifier



(a) 1-nearest neighbor



(b) 2-nearest neighbor

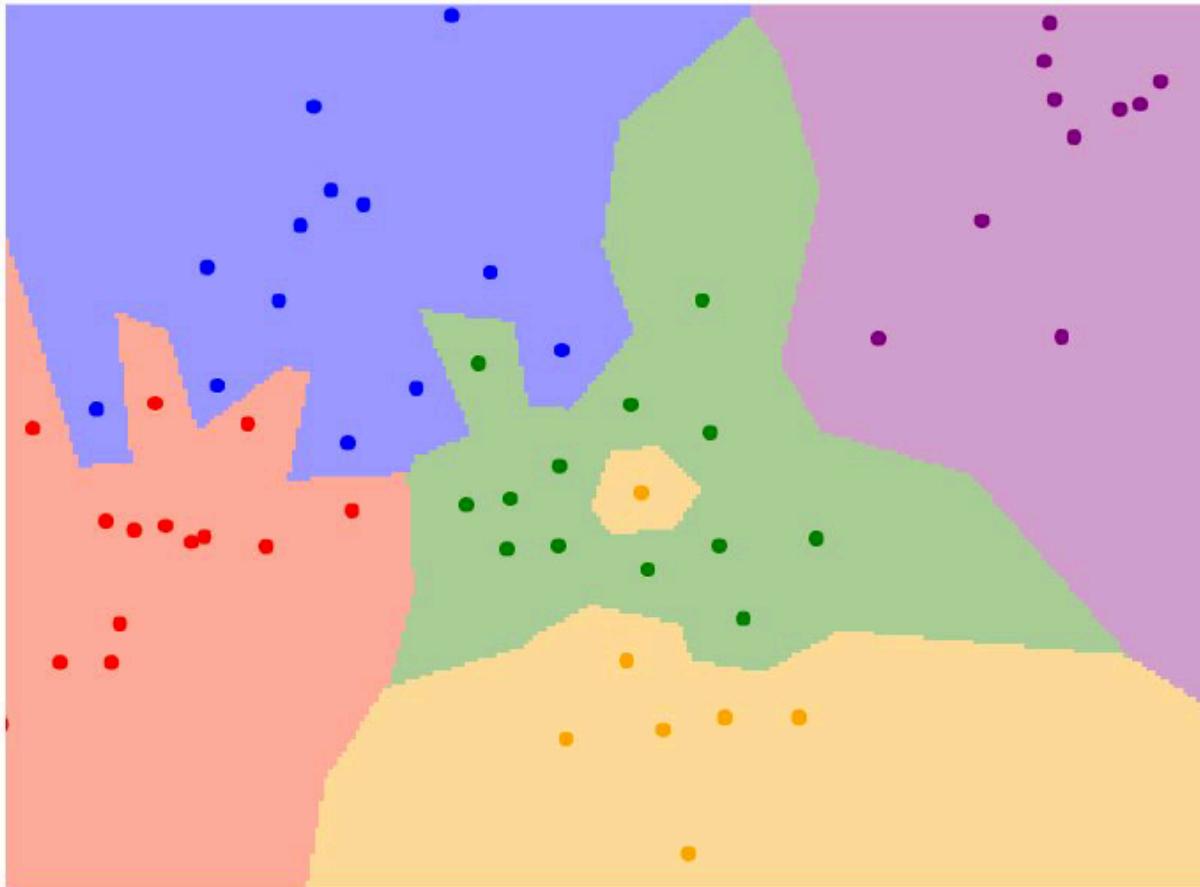


(c) 3-nearest neighbor

# Image Classification

## K-Nearest Neighbor classifier

<http://vision.stanford.edu/teaching/cs231n-demos/knn/>

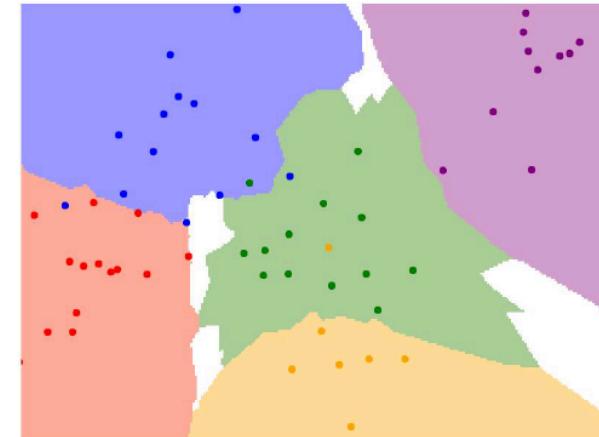
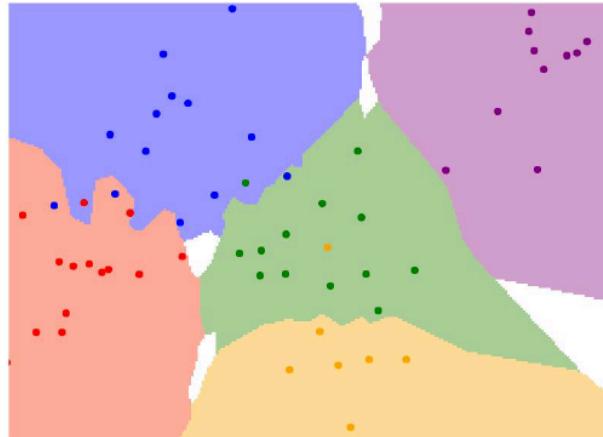
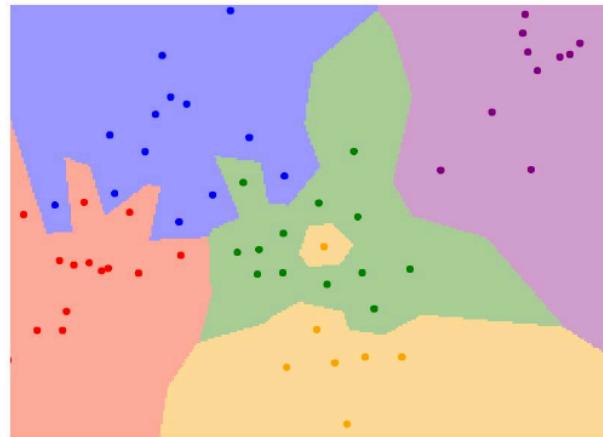


# Image Classification

## K-Nearest Neighbor classifier

<http://vision.stanford.edu/teaching/cs231n-demos/knn/>

Instead of copying label from nearest neighbor,  
take **majority vote** from K closest points

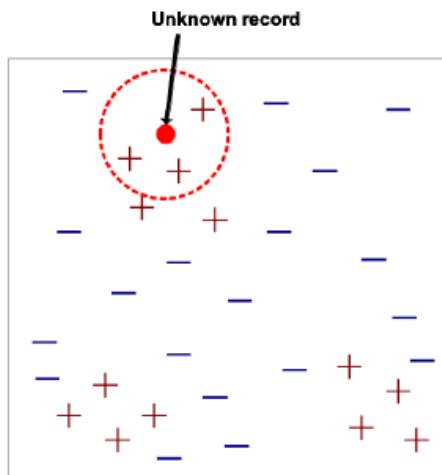


# Image Classification

## K-Nearest Neighbor classifier

Requires 3 things:

- ▶ The set of stored samples
- ▶ A Distance metric to compute distance between two samples
- ▶ The value of  $k$ , the number of nearest neighbors to retrieve.



To classify an unknown record:

- ▶ Compute distance to other training samples.
- ▶ Identify its  $k$  nearest neighbors
- ▶ Use class labels of nearest neighbors to determine the class label of the unknown sample. (e.g., by taking majority vote).

# Image Classification

## K-Nearest Neighbor classifier

- ▶ Compute distance between two data points:
  - ▶ Given  $\vec{p}$ ,  $\vec{q}$  be two  $n$  dimensional data points,
  - ▶ Euclidean distance between the two is defined as

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^n (p_i - q_i)^2}$$

- ▶ Determine the class from the nearest neighbor list
  - ▶ take the majority vote of class labels among the  $k$  nearest neighbors
  - ▶ Weight the vote according to distance,  $w = \frac{1}{d^2}$

# Image Classification

## K-Nearest Neighbor classifier

Consider the following 10 points in the 2-D space and their corresponding class labels. Predict the class label for point (4,5), using  $k$ -nearest neighbors,  $k \in \{1, 3, 5, 9\}$

x	y	class	d	1NN	3NN	5NN	9NN
1	5	B	3.00		B	B	B
1	6	B	3.16		B	B	B
2	1	C	4.47				C
3	9	C	4.12				C
4	0	C	5.00				C
5	4	A	1.41	A	A	A	A
6	8	B	3.61			B	B
7	7	C	3.61			C	C
8	2	C	5.00				
0	5	C	4.00				C
4	5	?		A	B	B	C

# Image Classification

## K-Nearest Neighbor classifier (apply to images)

L1 distance:

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

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

-

pixel-wise absolute value differences

46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

=

add → 456

# Image Classification

## K-Nearest Neighbor classifier (apply to images)

### Example Dataset: CIFAR10

10 classes

50,000 training images

10,000 testing images

airplane



automobile



bird



cat



deer



dog



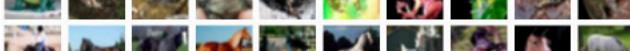
frog



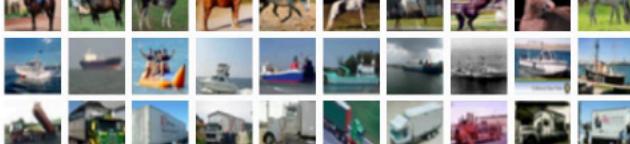
horse



ship



truck

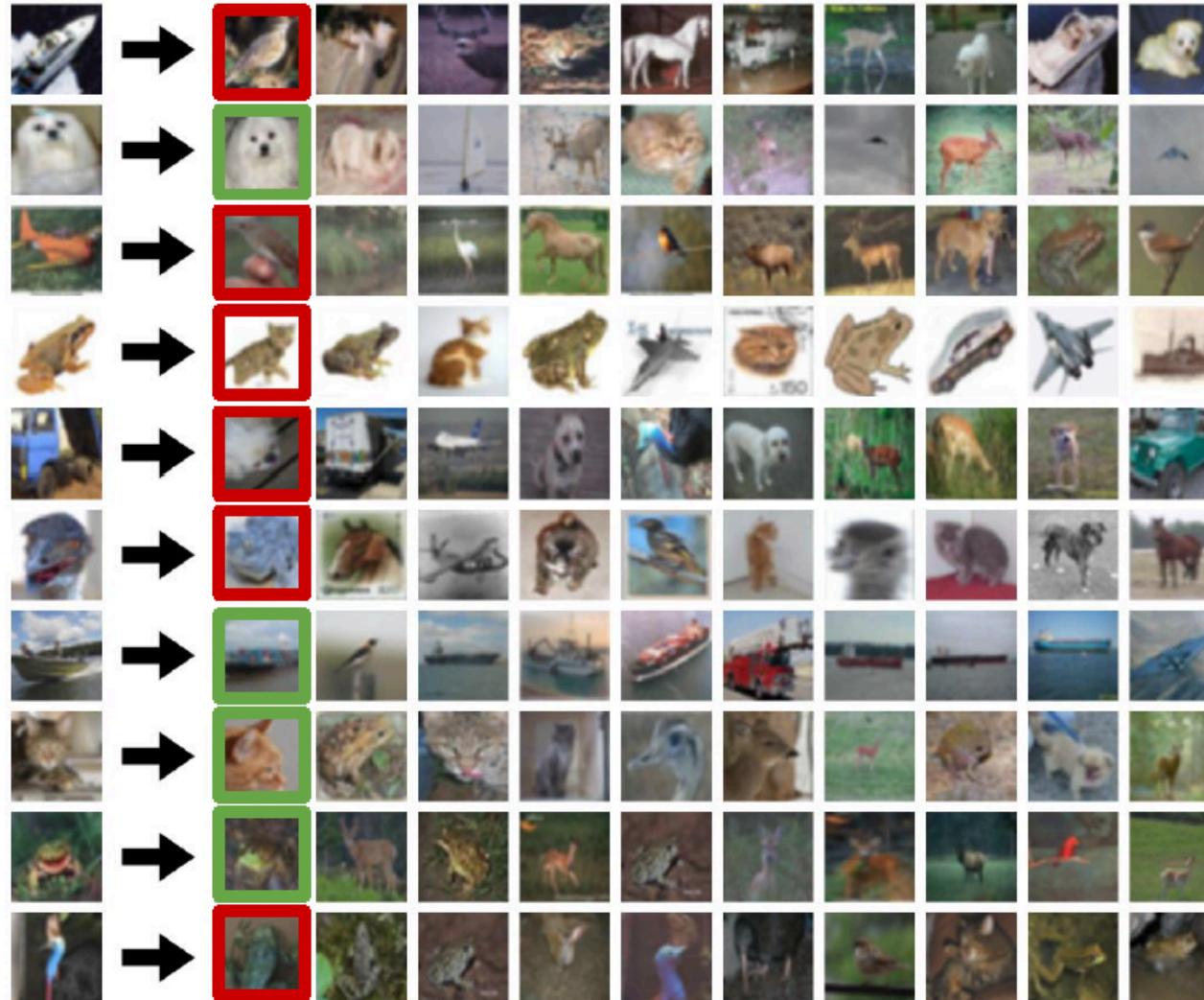


Test images and nearest neighbors



# Image Classification

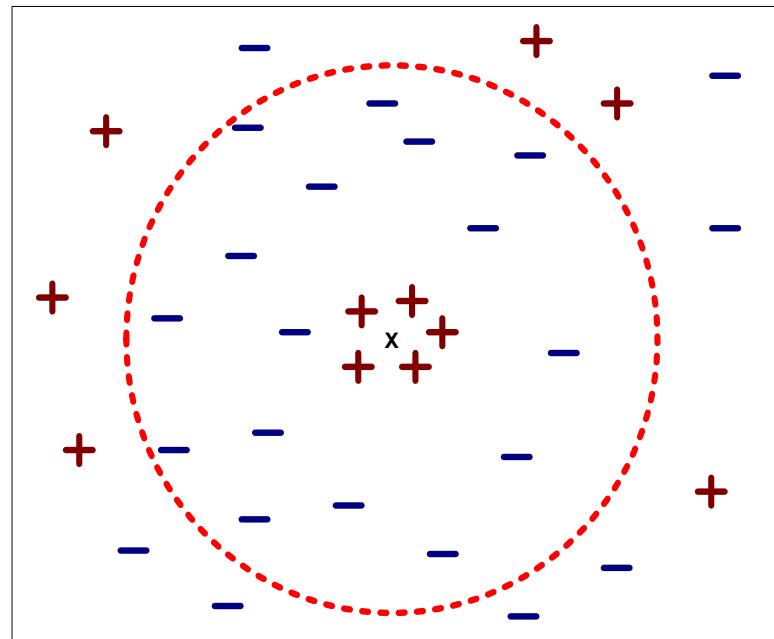
## K-Nearest Neighbor classifier (apply to images)



# Image Classification

## K-Nearest Neighbor classifier

- Choosing the value of k:
  - If k is too small, sensitive to noise points
  - If k is too large, neighborhood may include points from other classes



# Image Classification

## K-Nearest Neighbor classifier

### Hyperparameters

What is the best value of  $k$  to use?  
What is the best **distance** to use?

These are **hyperparameters**: choices about the algorithm that we set rather than learn

Very problem-dependent.  
Must try them all out and see what works best.

# Image Classification

## K- Nearest Neighbor Classifier

### Hyperparameters

What is the best value of **k** to use?  
What is the best **distance** to use?

These are **hyperparameters**: choices about the algorithm that we set rather than learn

Very problem-dependent.  
Must try them all out and see what works best.

# Image Classification

## K- Nearest Neighbor Classifier

### Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

Your Dataset

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

train

test

**Idea #3:** Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

Better!

train

validation

test

# Image Classification

## K- Nearest Neighbor Classifier

### Setting Hyperparameters

Your Dataset

**Idea #4: Cross-Validation:** Split data into **folds**,  
try each fold as validation and average the results

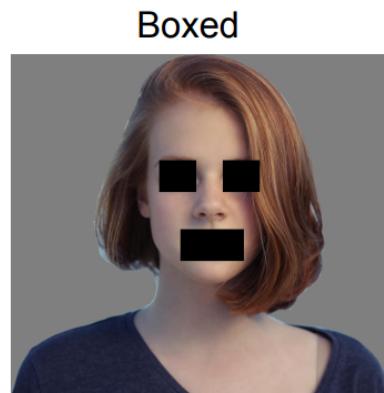
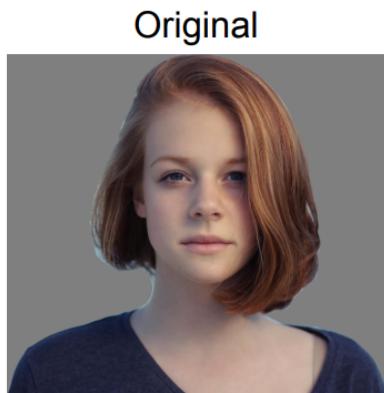
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test

# Image Classification

## K- Nearest Neighbor Classifier

k-Nearest Neighbor on images **never used**.

- Very slow at test time
- Distance metrics on pixels are not informative



(all 3 images have same L2 distance to the one on the left)

# Image Classification

## K- Nearest Neighbor Classifier

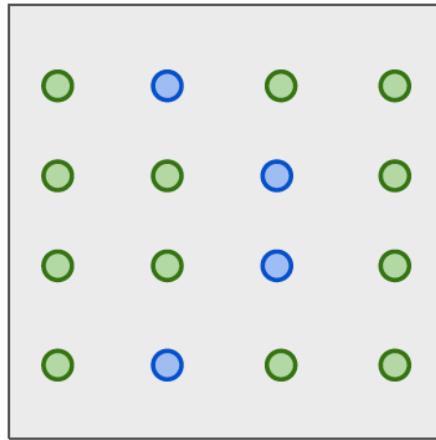
k-Nearest Neighbor on images **never used**.

- Curse of dimensionality

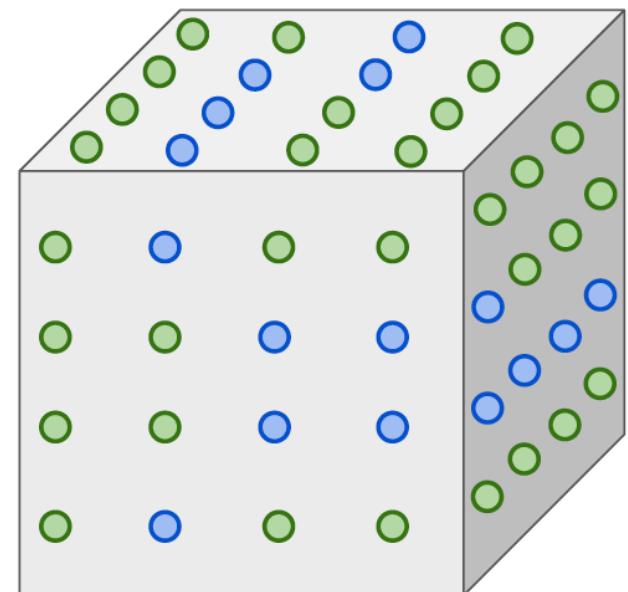
Dimensions = 1  
Points = 4



Dimensions = 2  
Points =  $4^2$



Dimensions = 3  
Points =  $4^3$



# Image Classification

## K- Nearest Neighbor Classifier

---

- One main advantage of the k-NN algorithm is that it's **extremely simple** to implement and understand.
- Furthermore, the classifier takes absolutely **no time to train**, since all we need to do is store our data points for the purpose of later computing distances to them and obtaining our final classification.
- However, we pay for this simplicity at classification time. Classifying a new testing point requires a comparison to every single data point in our training data, which scales  $O(N)$ , making working with larger datasets computationally prohibitive.

# Image Classification

## K- Nearest Neighbor Classifier

### K-Nearest Neighbors: Summary

In **Image classification** we start with a **training set** of images and labels, and must predict labels on the **test set**

The **K-Nearest Neighbors** classifier predicts labels based on nearest training examples

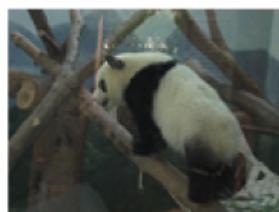
Distance metric and K are **hyperparameters**

Choose hyperparameters using the **validation set**; only run on the test set once at the very end!

# Image Classification

## K- Nearest Neighbor Classifier

HW : 3-class animals classification using K-nearest neighbor classifier



# Image Classification

## K- Nearest Neighbor Classifier

**HW :** 3-class animals classification using K-nearest neighbor classifier

- 1. Gather the Dataset:** The Animals datasets consists of 3,000 images with 1,000 images per dog, cat, and panda class, respectively. Each image is represented in the RGB color space. You will preprocess each image by resizing it to 32x32 pixels. Taking into account the three RGB channels, the resized image dimensions imply that each image in the dataset is represented by  $32 \times 32 \times 3 = 3,072$  integers.

# Image Classification

## K- Nearest Neighbor Classifier

---

**HW :** 3-class animals classification using K-nearest neighbor classifier

**2. Split the Dataset:** You'll be using three splits of the data. One split for training, one split for validation and the other for testing. Please **randomly** partition the data into these three splits. For example, 70% for training, 10% for validation and 20% for testing.

# Image Classification

## K- Nearest Neighbor Classifier

---

**HW :** 3-class animals classification using K-nearest neighbor classifier

**3. Train the Classifier:** Your k-NN classifier will be trained on the raw pixel intensities of the images in the training set. You need to convert the images to data vectors with label (how?). What is the best value of K to use? What is the best distance to use?

# Image Classification

## K- Nearest Neighbor Classifier

---

**HW :** 3-class animals classification using K-nearest neighbor classifier

**4. Evaluate:** Once your k-NN classifier is trained, you should evaluate performance (accuracy, precision, recall, F-measure) on the test set. You need to provide the details of your evaluation steps.

# Image Classification

## K- Nearest Neighbor Classifier

---

**HW:** 3-class animals classification using K-nearest neighbor classifier

### Submission:

- Write a report to describe the detailed steps of your design and include your evaluation results.
- Upload your code with comments as a separate .zip file

# Image Classification

## K- Nearest Neighbor Classifier

### Example:

<https://www.datacamp.com/community/tutorials/k-nearest-neighbor-classification-scikit-learn>

```
# Assigning features and label variables
```

```
# First Feature
```

```
weather=['Sunny','Sunny','Overcast','Rainy','Rainy','Rainy','Overcast','Sunny','Sunny',
```

```
'Rainy','Sunny','Overcast','Overcast','Rainy'] # Second Feature
```

```
temp=['Hot','Hot','Hot','Mild','Cool','Cool','Cool','Mild','Cool','Mild','Mild','Mild','Hot',  
'Mild'] # Label or target variable
```

```
play=['No','No','Yes','Yes','Yes','No','Yes','No','Yes','Yes','Yes','Yes','Yes','Yes','Yes','No']
```

# Image Classification

## K- Nearest Neighbor Classifier

**Example:**

<https://www.datacamp.com/community/tutorials/k-nearest-neighbor-classification-scikit-learn>

```
#Import LabelEncoder from sklearn import preprocessing  
#creating labelEncoder  
le = preprocessing.LabelEncoder()  
  
# Converting string labels into numbers.  
weather_encoded=le.fit_transform(weather)  
print(weather_encoded)  
  
>> [2 2 0 1 1 1 0 2 2 1 2 0 0 1]
```

# Image Classification

## K- Nearest Neighbor Classifier

### Example:

<https://www.datacamp.com/community/tutorials/k-nearest-neighbor-classification-scikit-learn>

```
# converting string labels into numbers  
temp_encoded=le.fit_transform(temp)  
label=le.fit_transform(play)
```

```
#combinig weather and temp into single list of tuples  
features=list(zip(weather_encoded,temp_encoded))
```

# Image Classification

## K- Nearest Neighbor Classifier

### Example:

<https://www.datacamp.com/community/tutorials/k-nearest-neighbor-classification-scikit-learn>

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=3)

# Train the model using the training sets
model.fit(features,label)

#Predict Output
predicted= model.predict([[0,2]]) # 0:Overcast, 2:Mild
print(predicted)

>> [1]
```

# Image Classification

## K- Nearest Neighbor Classifier

HW:

Pip3 install opencv-python

Import cv2

<https://pypi.org/project/opencv-python/>

Import os

Import cv2

Dataset\_path = "../Data/"

```
image_list = os.listdir(Dataset_path)
for image_name in image_list:
    image = cv2.imread(Dataset_path+image_name)
    image = cv2.resize(image, (32, 32), interpolation=cv2.INTER_CUBIC)
```

# Image Classification

## K- Nearest Neighbor Classifier

HW:

Pip3 install opencv-python

Import cv2

<https://pypi.org/project/opencv-python/>

Import os

Import cv2

```
Dataset_path = "../Data/"
```

```
data=[]
```

```
#labels=[]
```

```
image_list = os.listdir(Dataset_path)
```

```
for image_name in image_list:
```

```
...
```

```
# read image append as list
```

```
data.append(image)
```

```
mydata=np.array(data)
```

# Image Classification

## K- Nearest Neighbor Classifier

HW:

Pip3 install opencv-python

Import cv2

<https://pypi.org/project/opencv-python/>

Import os

Import cv2

```
Dataset_path = "../Data/KNN/animals/"
```

```
class_folders = os.listdir(Dataset_path)
for class_name in class_folders:
    image_list = os.listdir(Dataset_path+class_name)
    for image_name in image_list:
        print("Folder Done")
```

# Image Classification

## K- Nearest Neighbor Classifier

**HW-V1:**

```
def load(Dataset_path):
    return (np.array(data),np.array(labels))

def KNN_pred(trainX, trainY, testX, k)
    return Ypred

#if your data is (3000, 32,32,3) you need data.reshape((data.shape[0],3072))

Le=LabelEncode()
labels=le.fit_transform(labels)

(trainX, testX,
trainY,testY)=Train_test_split(data,labels,test_size=0.3,random_state=number)

print(classification_report(testY, Ypred, target_names=le.classes_))
```

# Image Classification

## K- Nearest Neighbor Classifier

### HW\_V2:

```
def load(Dataset_path):
    return (np.array(data),np.array(labels))

#if your data is (3000, 32,32,3) you need data.reshape((data.shape[0],3072))
Le=LabelEncode()
labels=le.fit_transform(labels)

(trainX, testX,
trainY,testY)=Train_test_split(data,labels,test_size=0.3,random_state=number)

print(classification_report(testY, Ypred, target_names=le.classes_))

model = KNeighborsClassifier(n_neighbors=number)
model.fit(data,labels)
Ypred=model.predict(testX)
```

# Image Classification

## K- Nearest Neighbor Classifier

HW:

for a selected K, L#:

```
X_train, X_tv, y_train, y_tv = train_test_split(X, y, test_size=0.30, random_state=42)
```

```
X_test, X_valid, y_test, y_valid = train_test_split(X_tv, y_tv, test_size=0.33, random_state=42)
```

```
print ('Train Test Validate Split Done')
```

# Image Classification

## K- Nearest Neighbor Classifier

HW:

**for k in Krange:**

**plot\_report (k, L1)**

**plot\_report (k, L2)**

**Analysis :**

**What K**

**What L**

# Image Classification

## K- Nearest Neighbor Classifier

HW:

Your own KNN

```
def predict(trainX,trainY,testX,k):

    num_test = testX.shape[0]
    # lets make sure that the output type matches the input type
    Ypred = np.zeros(num_test, dtype=trainY.dtype)

    for i in range(num_test):
        L1_distances = np.sum(np.abs(trainX - testX[i, :]), axis=-1)
        #L2_distances = np.sqrt(np.sum(np.square(trainX - testX[i,:])), axis = 1)
        #min_index = np.argmin(L1_distances) # get the index with smallest distance
        K_index = np.argsort(L1_distances)[:k]
        #K_labels=np.zeros(len(K_index))
        K_labels=[]
        for j in range(len(K_index)):
            K_labels.append(trainY[K_index[j]])

        Ypred[i] = max(set(K_labels), key = K_labels.count)

    return Ypred
```