ROB 498/599: Deep Learning for Robot Perception (DeepRob)

Lecture 2: Image Classification; K Nearest Neighbors

https://deeprob.org/w25/

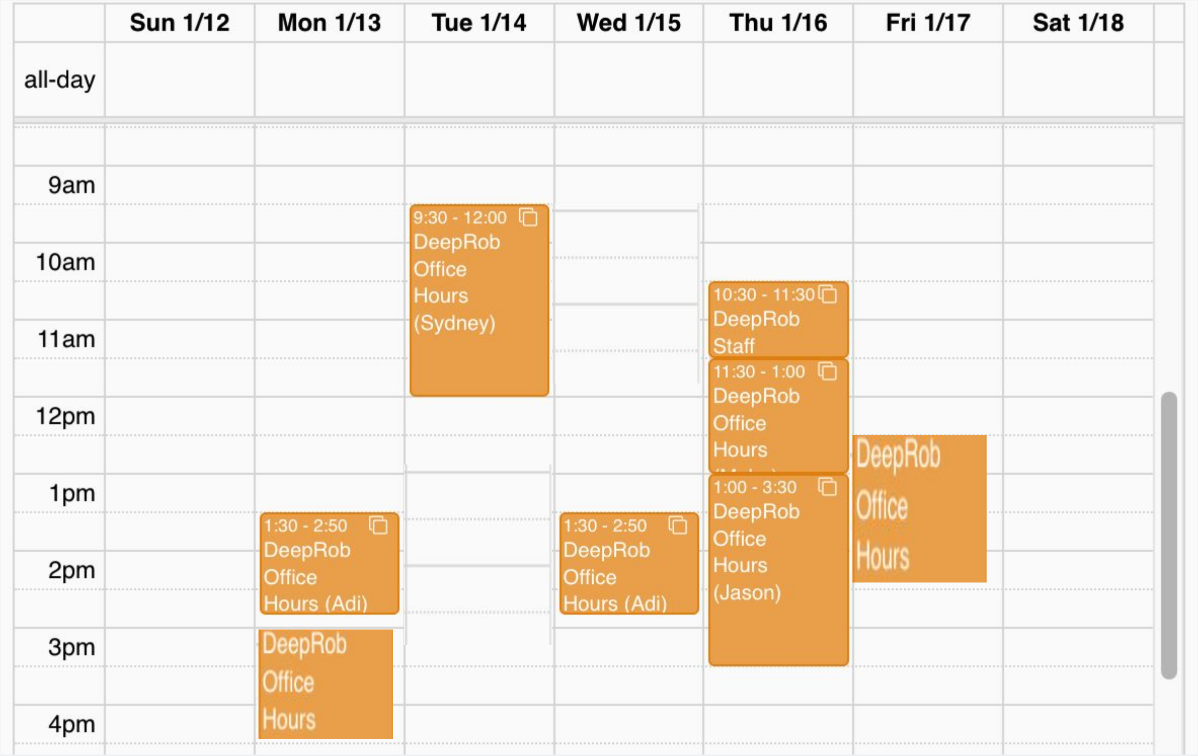
ROBOTICS

Today

- Logistics (Office Hours, P0 starter) (5min)
- Image Classification (KNN)
  - K Nearest Neighbors - Basics (15 min)
  - K Nearest Neighbors - in-class activity (20min)
  - Hyperparameters (15min)
  - Universal Approximation (20min)
- Summary and Takeaways (5min)

Office Hours

- See Course Info doc



*May have small changes - stay tuned

ROBOTICS

Office Hours

- Specifically, this week Jan.13- Jan.17

- Monday 3:00pm-4:30pm (Prof. Du) or by appointment 3257 FRB
- Tuesday 2:00pm-3:30pm (Cale- GSI) CSRB Lounge (outside classroom)
- Tuesday 5:30-7pm (after lab) or by appointment (Sydney - IA) CSRB
- Wednesday 1:30pm (after lecture) (Adi - IA)
- Thursday 11:30am-2pm (Meha - IA) 3310 FRB
- Thursday 1pm-3:30pm (Jason - IA) 3310 FRB

Always available on Piazza

P0 Starter

P0 folder:
https://drive.google.com/drive/folders/1gJKZlMKRuLmA4EsICxrREa3dujlyY9XC?usp=drive_link

Please create a "DeepRob" folder in your own Google Drive, and put P0 folder under there. This will be your individual private copy of the code - do NOT change the starter code in shared folder!

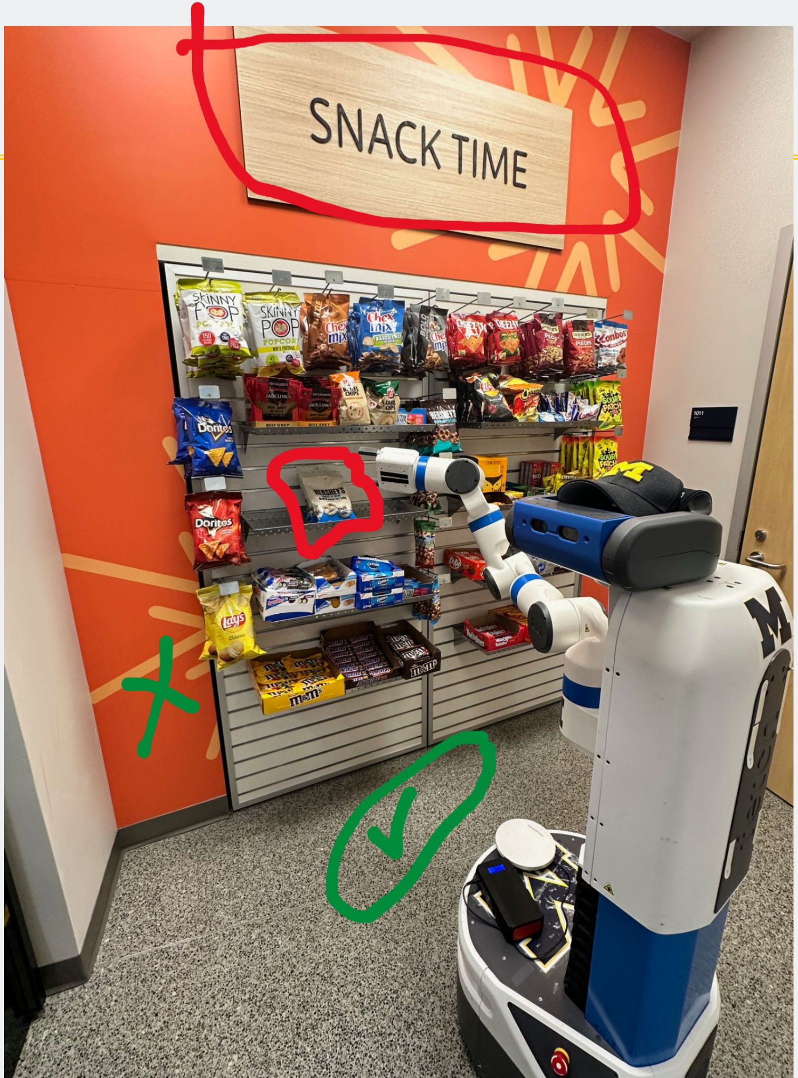
M | ROBOTICS

Reminder

About waitlist

About access (Google Colab etc.)

M | ROBOTICS



- How do you "classify" which part is traversable for the robot, which part is not?
- How do you tell which one is the correct snack?

Image Classification
—A Core Computer Vision/Robot Perception Task

Input: image

Output: assign image to one of a fixed set of categories

Chocolate Pretzels

Granola Bar

Potato Chips

Water Bottle

Popcorn

"Semantic Gap"

Input: image

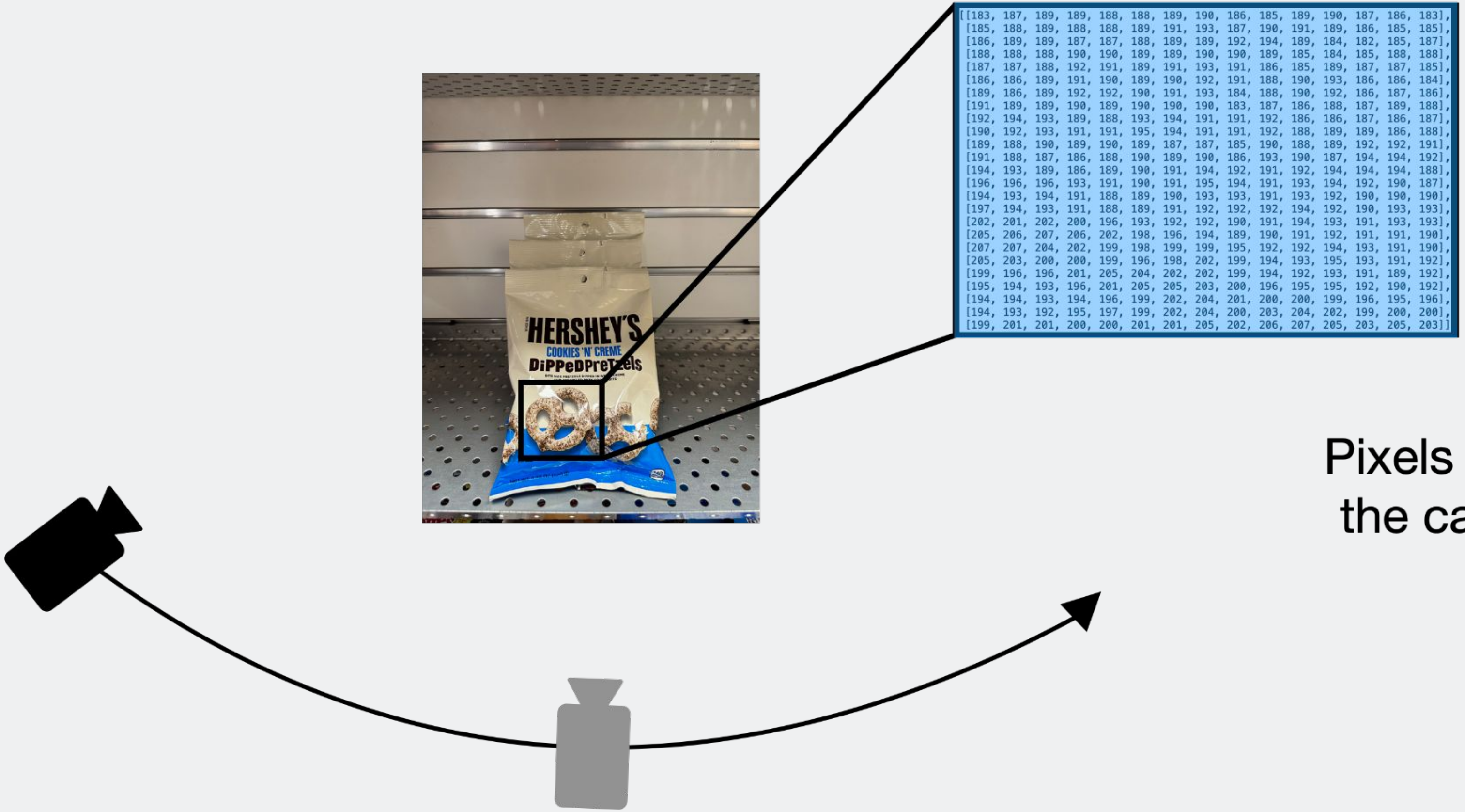

```
[[183, 187, 189, 189, 188, 188, 189, 190, 186, 185, 189, 190, 187, 186, 183],
 [185, 188, 189, 188, 188, 189, 191, 193, 187, 190, 191, 189, 186, 185, 185],
 [186, 189, 189, 187, 187, 188, 189, 189, 192, 194, 189, 184, 182, 185, 187],
 [188, 188, 188, 190, 190, 189, 189, 190, 190, 189, 185, 184, 185, 188, 188],
 [187, 187, 188, 192, 191, 189, 191, 193, 191, 186, 185, 189, 187, 187, 185],
 [186, 186, 189, 191, 190, 189, 190, 192, 191, 188, 190, 193, 186, 186, 184],
 [189, 186, 189, 192, 192, 190, 191, 193, 184, 188, 190, 192, 186, 187, 186],
 [191, 189, 189, 190, 189, 190, 190, 190, 183, 187, 186, 188, 187, 189, 188],
 [192, 194, 193, 189, 188, 193, 194, 191, 191, 192, 186, 186, 187, 186, 187],
 [190, 192, 193, 191, 191, 195, 194, 191, 191, 192, 188, 189, 189, 186, 188],
 [189, 188, 190, 189, 190, 189, 187, 187, 185, 190, 188, 189, 192, 192, 191],
 [191, 188, 187, 186, 188, 190, 189, 190, 186, 193, 190, 187, 194, 194, 192],
 [194, 193, 189, 186, 189, 190, 191, 194, 192, 191, 192, 194, 194, 194, 188],
 [196, 196, 196, 193, 191, 190, 191, 195, 194, 191, 193, 194, 192, 190, 187],
 [194, 193, 194, 191, 188, 189, 190, 193, 193, 191, 193, 192, 190, 190, 190],
 [197, 194, 193, 191, 188, 189, 191, 192, 192, 192, 194, 192, 190, 193, 193],
 [202, 201, 202, 200, 196, 193, 192, 192, 190, 191, 194, 193, 191, 193, 193],
 [205, 206, 207, 206, 202, 198, 196, 194, 189, 190, 191, 192, 191, 191, 190],
 [207, 207, 204, 202, 199, 198, 199, 199, 195, 192, 192, 194, 193, 191, 190],
 [205, 203, 200, 200, 199, 196, 198, 202, 199, 194, 193, 195, 193, 191, 192],
 [199, 196, 196, 201, 205, 204, 202, 202, 199, 194, 192, 193, 191, 189, 192],
 [195, 194, 193, 196, 201, 205, 205, 203, 200, 196, 195, 195, 192, 190, 192],
 [194, 194, 193, 194, 196, 199, 202, 204, 201, 200, 200, 199, 196, 195, 196],
 [194, 193, 192, 195, 197, 199, 202, 204, 200, 203, 204, 202, 199, 200, 200],
 [199, 201, 201, 200, 200, 201, 201, 205, 202, 206, 207, 205, 203, 205, 203]]
```

What the computer sees

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

M | ROBOTICS

Challenges—Viewpoint Variation



Pixels change when the camera moves

Challenges—Intraclass variation

M | ROBOTICS

Challenges—Fine Grained Categories

e.g.,

Milk Chocolate

White Chocolate

Cookies N' Creme

Peanut Butter

Ambiguous Category

ROBOTICS

Challenges— Background Clutter

ROBOTICS

Challenges—Image Resolution

iPhone 14 Camera

4032x3024

ASUS RGB-D Camera

640x480

Challenges—Illumination Changes

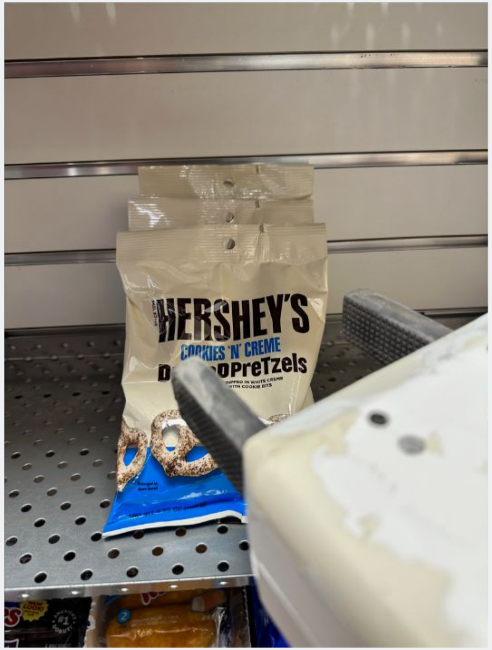
Want our robot's perception system to be reliable in all conditions

Challenges—Subject Deformation

Challenges—Occlusion

Scene Clutter

Robot Actuator



Transparency

M | ROBOTICS

Challenges—Semantic Relationship

Reflections

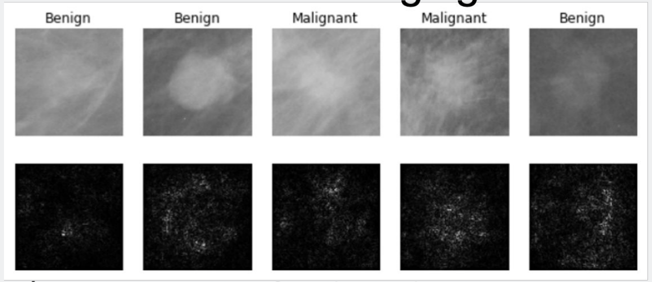
Contact Relationships

<u>Robots have to act</u> on the state they perceive

M | ROBOTICS

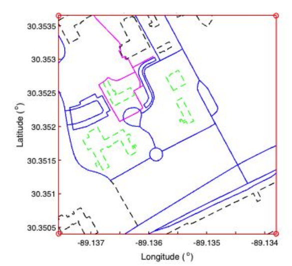
Application of Image Classification

Medical Imaging

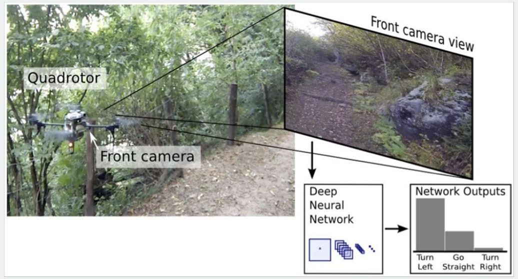


Lévy et al., "Breast Mass Classification from Mammograms using Deep Convolutional Neural Networks", arXiv:1612.00542, 2016

Hyperspectral Imaging



Trail Direction Classification



Giusti et al., "A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robots", IEEE RAL, 2016

Tomato Ripeness Classification

Name	Color	Storage Time (Days)	Sample
LV1	Breakers	21 ~ 28	
LV2	Turning	15 ~ 20	
LV3	Pink	7 ~ 14	
LV4	Light red	5 ~ 6	
LV5	Red	2 ~ 4	

Zhang et al., "Deep Learning Based Improved Classification System for Designing Tomato Harvesting Robot", IEEE Access, 2016

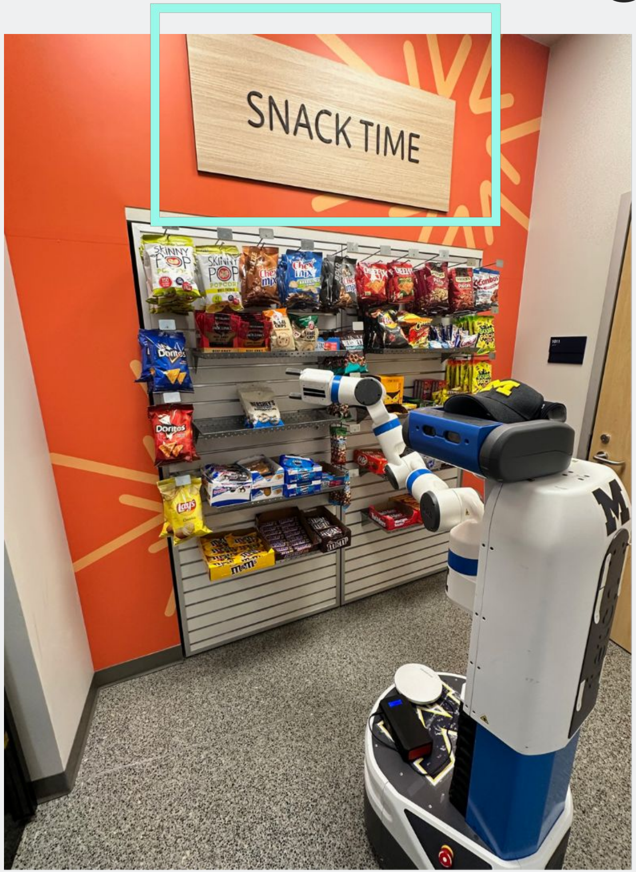
Galaxy Classification

Dieleman et al., "Rotation-invariant convolutional neural networks for galaxy morphology prediction", 2015

From left to right: public domain by NASA, usage permitted by ESA/Hubble, public domain by NASA, and public domain

ROBOTICS

Image Classification — Building Block for Other Tasks



Example: Object Detection

Wall

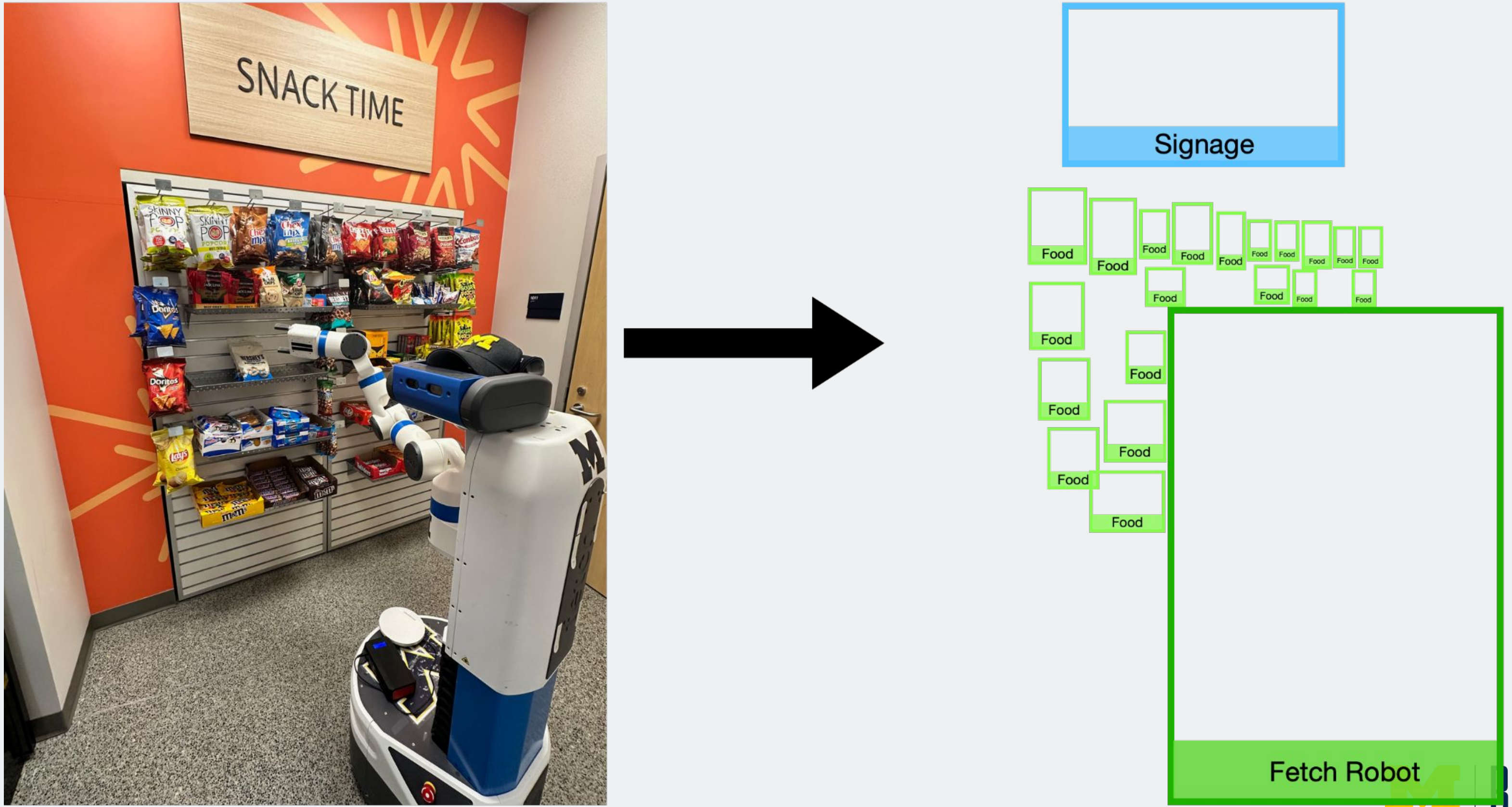
Floor

Signage

Fetch Robot

Snacks

Image Classification — Building Block for Other Tasks



An Image Classifier

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

Unlike well defined programming (e.g. sorting a list)

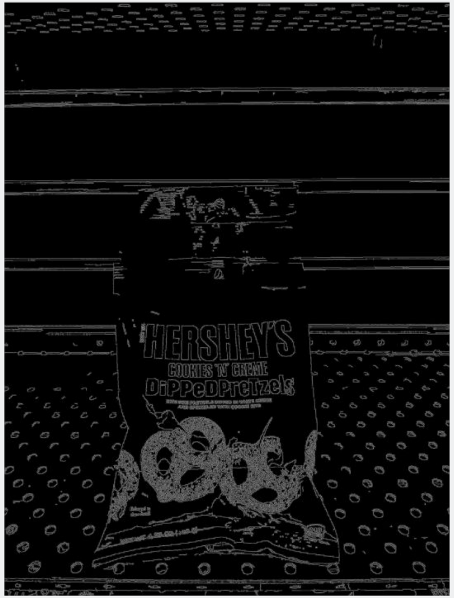
No obvious way to hard-code the algorithm for recognizing each class

One “classifical” Computer Vision approach

(example)

Input: image

Detect: Edges



Detect: Corners

???

Deep Learning — A Data-Driven Approach

1. Collect a dataset of images + labels
2. Use ML/DL to train a classifier
3. Evaluate the classifier on new images

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

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

Some examples of Deep Learning Datasets

MNIST

Handwritten digits

10 classes: Digits 0 to 9
28x28 grayscale images
50k training images
10k test images

Due to relatively small size, results on MNIST often do not hold on more complex datasets

Some examples of Deep Learning Datasets

CIFAR10

10 classes

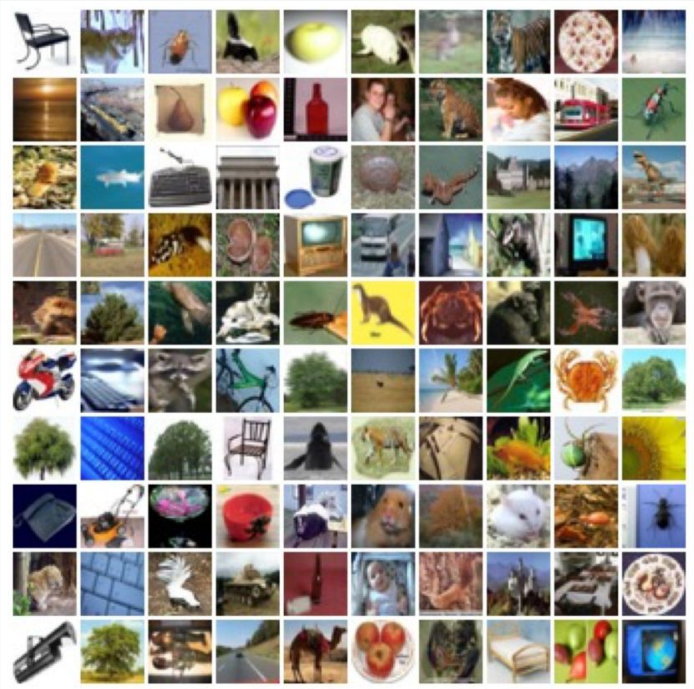
32x32 RGB images

50k training images (5k per class)

10k test images (1k per class)

Alex Krizhevsky, “Learning Multiple Layers of Features from Tiny Images”, Technical Report, 2009.

Some examples of Deep Learning Datasets



CIFAR100

100 classes
32x32 RGB images
50k training images (500 per class)
10k test images (100 per class)

20 superclasses with 5 classes each:

Aquatic mammals: beaver, dolphin, otter, seal, whale

Some examples of Deep Learning Datasets

ImageNet

Deng et al., "ImageNet: A Large-Scale Hierarchical Image Database", CVPR, 2009.

Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge", IJCV, 2015.

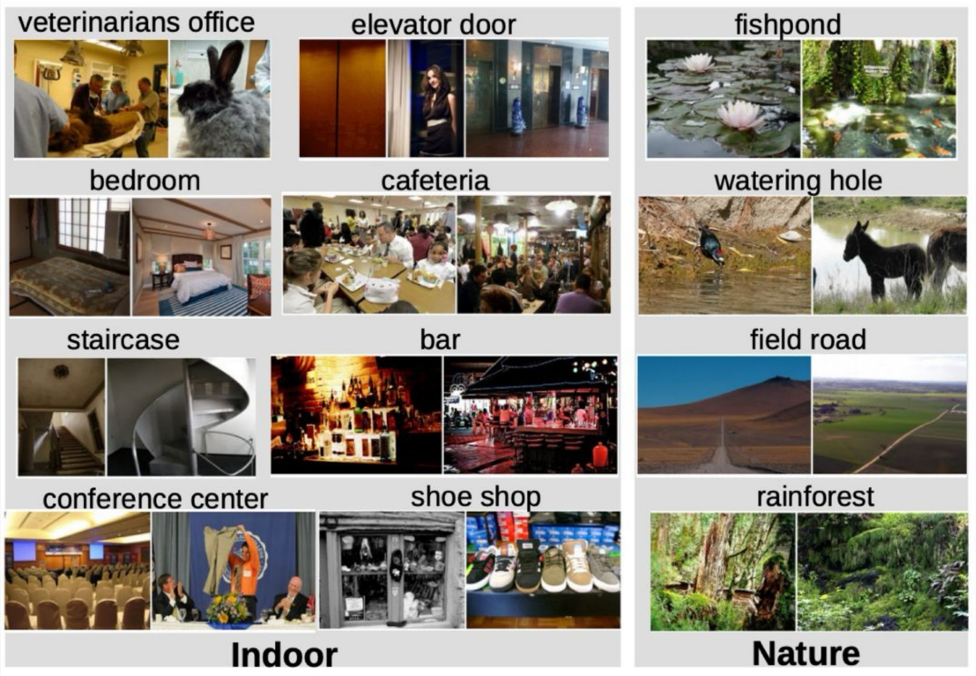
1000 classes

~1.3M training images (~1.3K per class)
50k validation images (50 per class)
100K test images (100 per class)

Images have variable size, but often resized to **256x256** for training

Some examples of Deep Learning Datasets

MIT Places



Zhou et al., "Places: A 10 million Image Database for Scene Recognition", TPAMI, 2017.

365 classes of different scene types

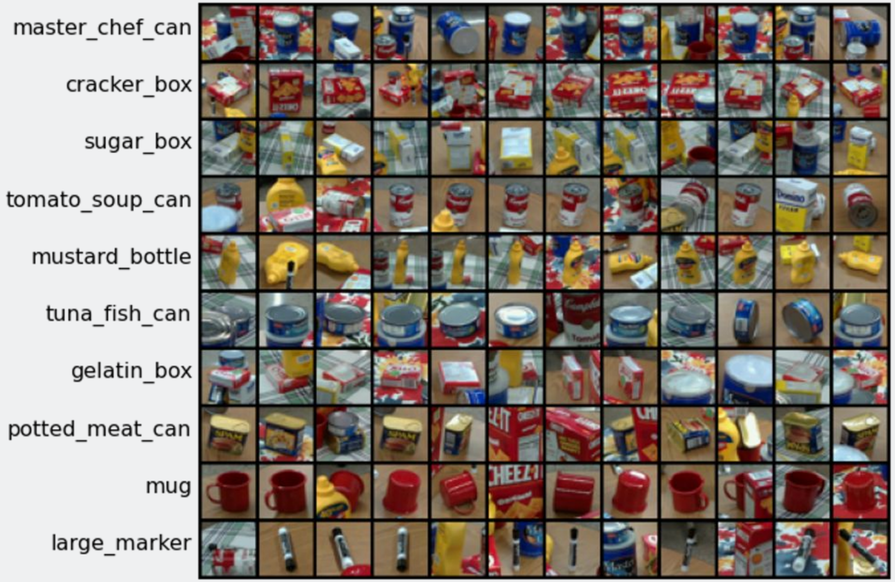
~8M training images
18.25K val images (50 per class)
328.5K test images (900 per class)

Images have variable size, but often resized to **256x256** for training

ROBOTICS

Image Classification Dataset

Progress **R**obot **O**bject **P**erception **S**amples **D**ataset

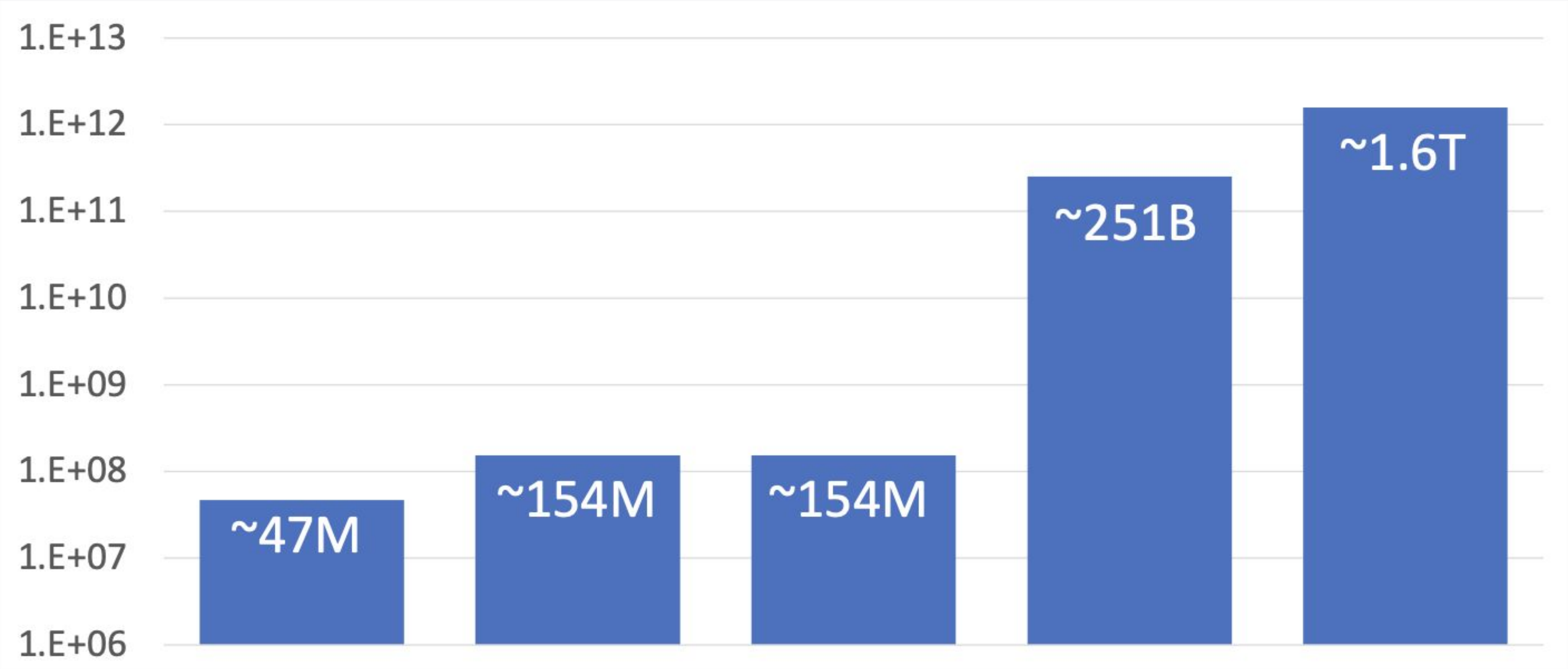


Chen et al., "ProgressLabeller: Visual Data Stream Annotation for Training Object-Centric 3D Perception", IROS, 2022.

(PROPS)

10 classes
32x32 RGB images
50k training images (5k per class)
10k test images (1k per class)

Size of Dataset - # of Training Pixels



Our first classifier - Nearest Neighbor

Aha Slides
(In-class participation)

https://ahaslides.com/DMOPW

Q1, Q2

Our first classifier - Nearest Neighbor

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

→ Memorize all data and labels

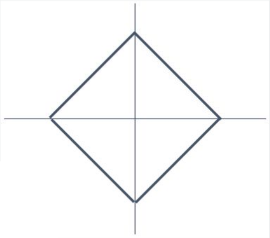
```python
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

→ Predict the label of the most similar training image

Distance Metric to Compare Images

“How do you know which one is the `nearest` neighbor?”

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

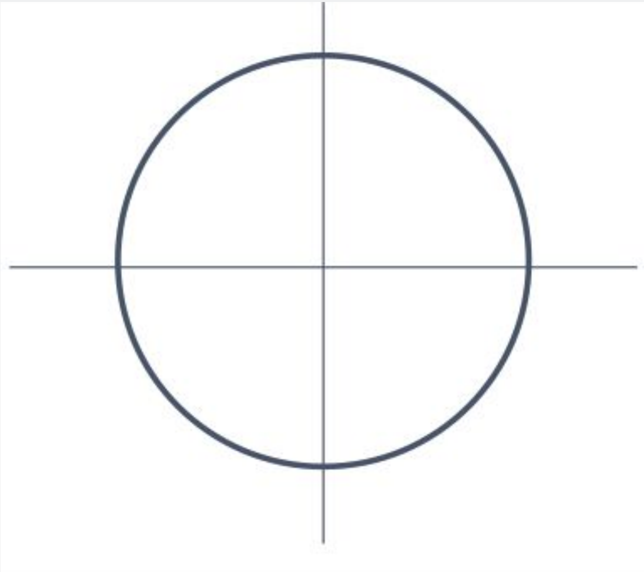
46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

add → 456

Distance Metric to Compare Images

“How do you know which one is the \`nearest\` neighbor?”

L2 (Euclidean) distance $d_2(I_1, I_2) = \left(\sum_p (I_1^p - I_2^p)^2\right)^{\frac{1}{2}}$



Nearest Neighbor Classifier Algorithm

```
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

      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
```

https://ahaslides.com/DMOPW

Q3

Nearest Neighbor Classifier Algorithm

```
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

Nearest Neighbor Classifier Algorithm

```python
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
```

For each test image:
Find <u>nearest</u> training image
Return label of nearest image

ROBOTICS

Nearest Neighbor Classifier Algorithm

```python
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
```

Q: With N examples how fast is training?

A: O(1)

Q: With N examples how fast is testing?

A: $\boxed{\text{O(N)}}$

This is a problem: we can train slow offline but need fast testing!

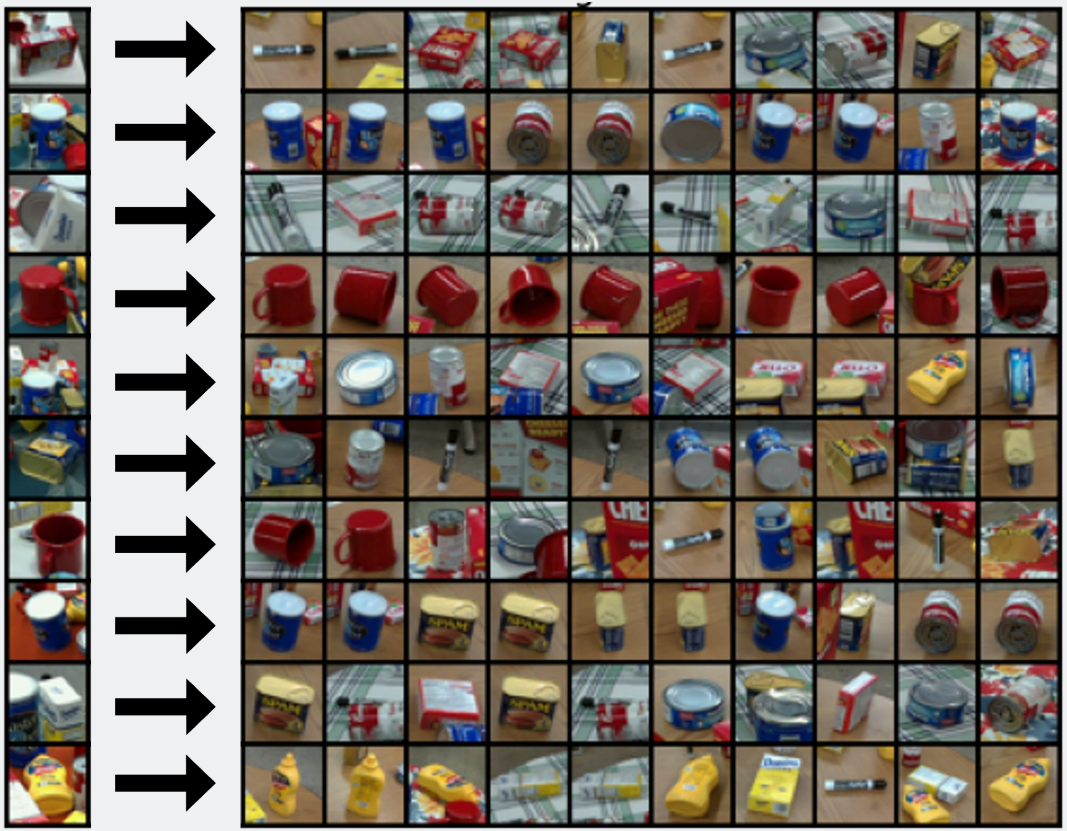
Further reading: faster/more efficient nearest neighbors

Example:
https://github.com/facebookresearch/faiss

More distance metrics

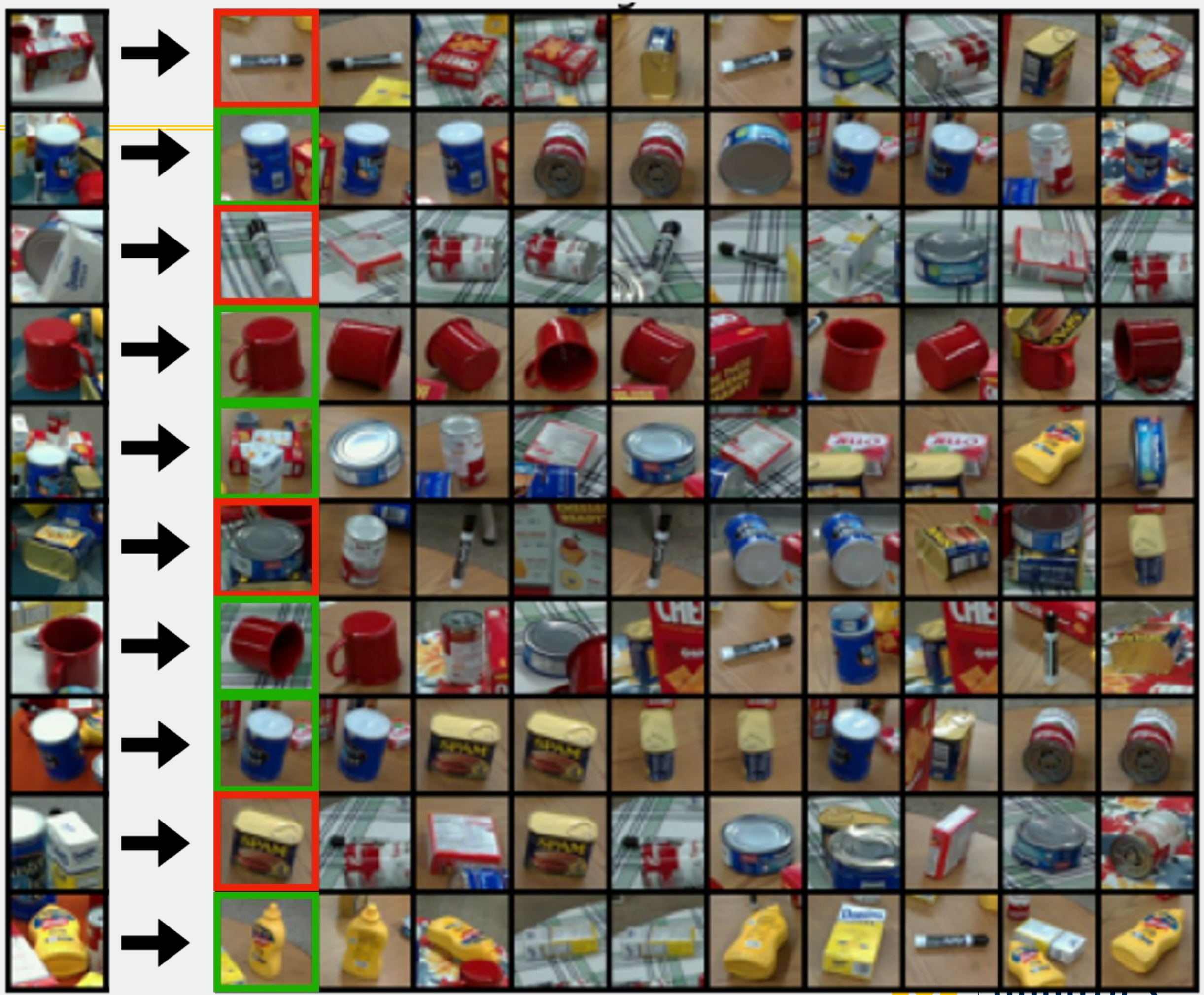
- Similarity/dissimilarity metrics
  - Euclidean distance: $d_E = \sqrt{(\mathbf{x}_1 - \mathbf{x}_2)^T (\mathbf{x}_1 - \mathbf{x}_2)}$
  - City block distance: $d_C = \sum_{i=1}^{d} |x_{1i} - x_{2i}|$
  - Mahalanobis distance: $(\mathbf{x}_1 - \mathbf{x}_2)^T \Sigma^{-1} (\mathbf{x}_1 - \mathbf{x}_2)$
  - Geodesic distance
  - Cosine angle similarity: $\cos\theta = \dfrac{\mathbf{x}_1^T \mathbf{x}_2}{|\mathbf{x}_1|_2^2 |\mathbf{x}_2|_2^2}$
  - and many more...

What does this look like in PROPS dataset?



ROBOTICS

PROPS dataset is instance-level



CIFAR10 dataset is category-level

In-Class Activity

20250113_knn.ipynb

K-Nearest Neighbors—Web Demo

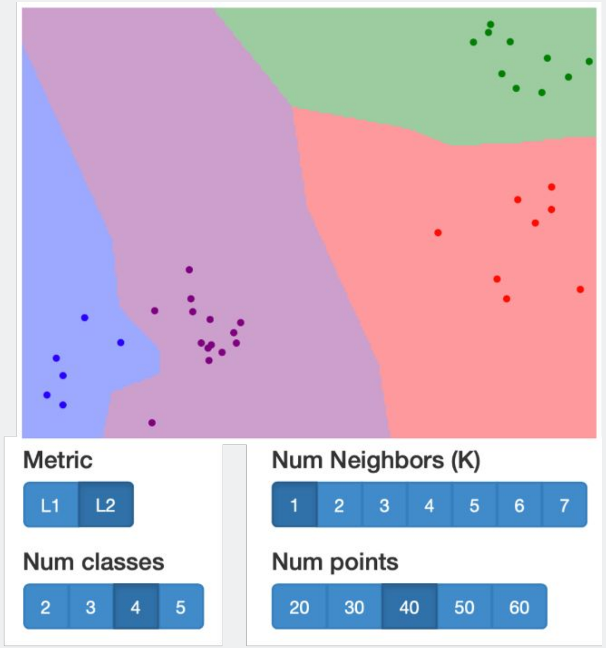
(for fun!)

Interactively move points around
and see decision boundaries change

Observe results with L1 vs L2 metrics

Observe results with changing number
of training points and value of K

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



ROBOTICS

Hyperparameters

What is the best value of K to use?

What is the best **distance metric** to use?

Setting Hyperparameters

What is the best value of K to use?

What is the best **distance metric** to use?

These are examples of hyperparameters: choices about our learning algorithm that we don't learn from the training data. Instead, we can set them at the start of the learning process.

Very problem-dependent - In general may need to try them all and observe what works best for our data

Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data

Your Dataset

Setting Hyperparameters

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

BAD: No idea how algorithm will perform on new data

Setting Hyperparameters

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

Better!

ROBOTICS

Setting Hyperparameters

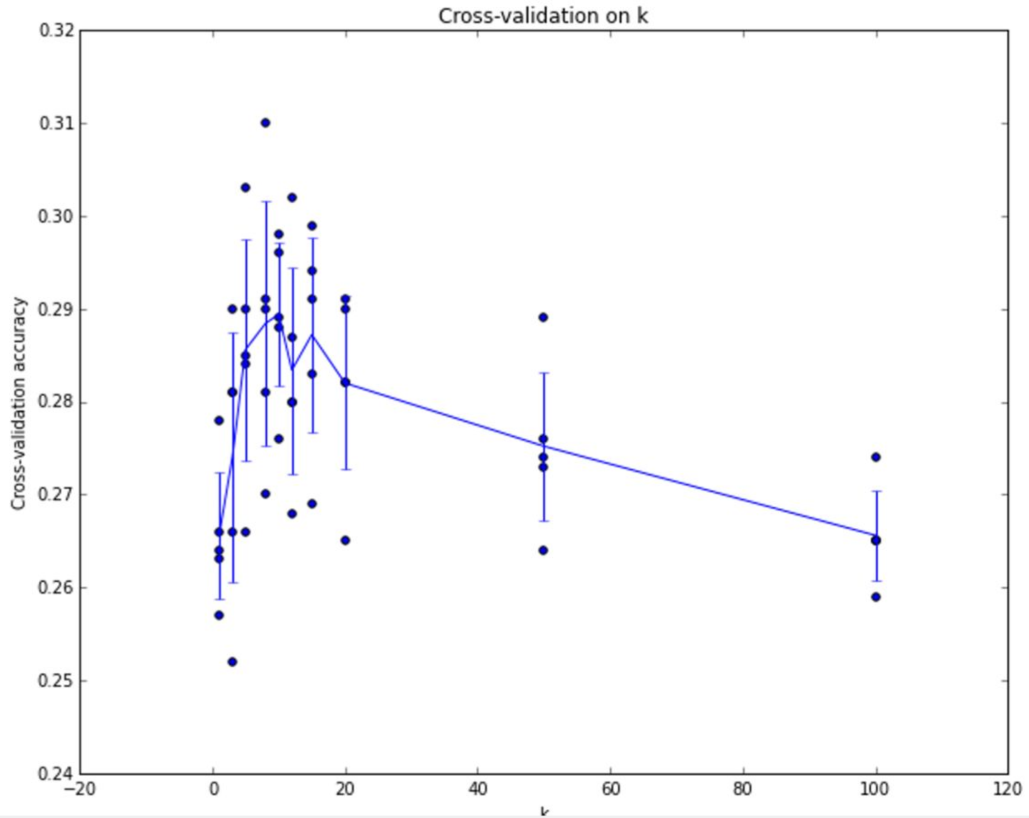
Your Dataset

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

Useful for small datasets, but (unfortunately) not used too frequently in deep learning

Setting Hyperparameters - KNN example



Example of 5-fold cross-validation for the value of **k.**

Each point: single outcome.

The line goes through the mean, bars indicated standard deviation

(Seems that k ~ 7 works best for this data)

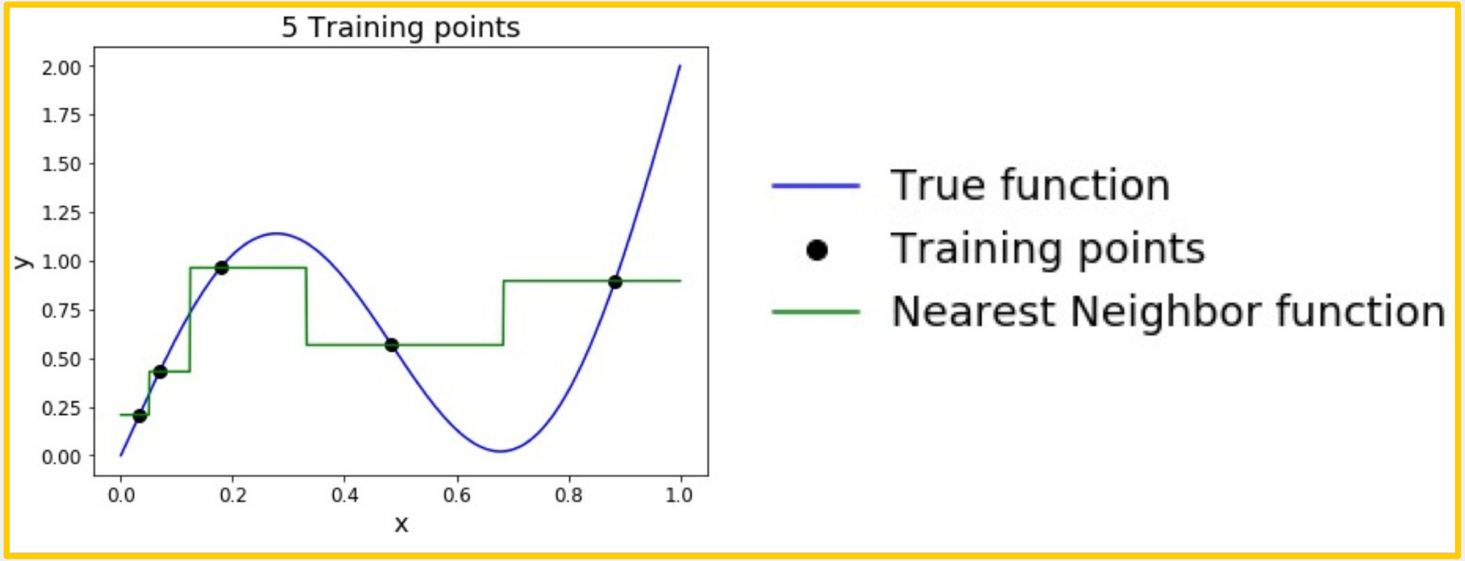
KNN - Universal Approximation

As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!

(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

KNN - Universal Approximation

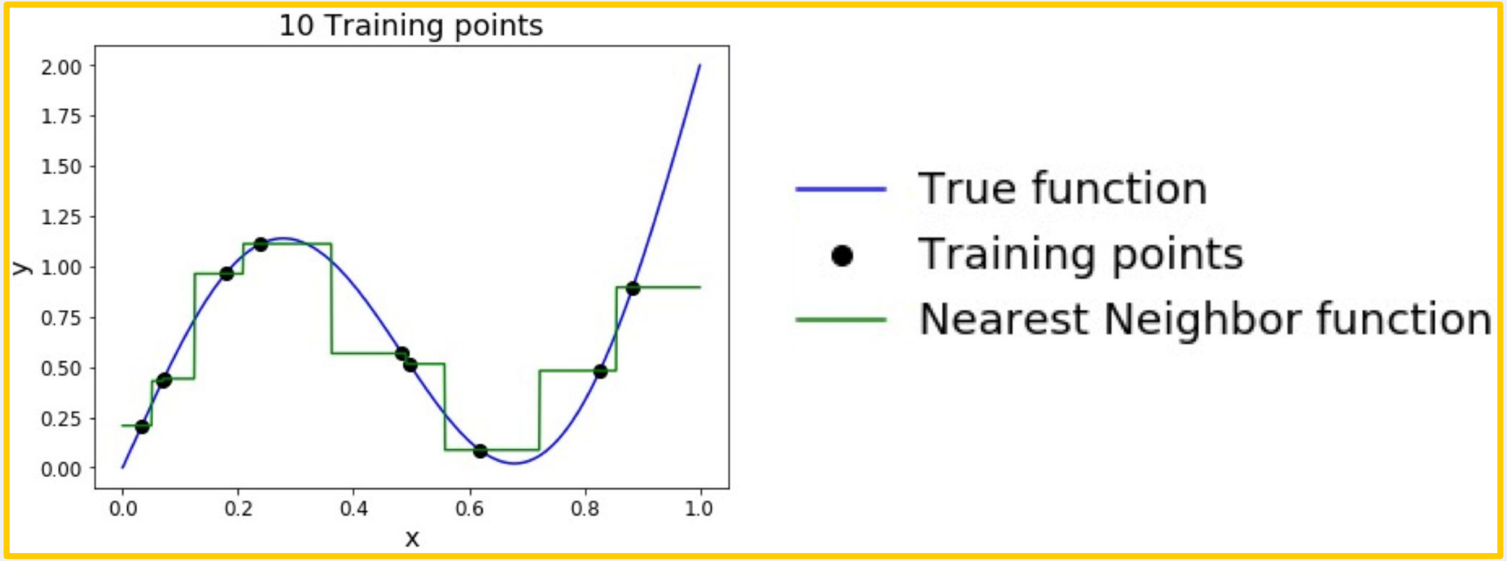
As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!



(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

KNN - Universal Approximation

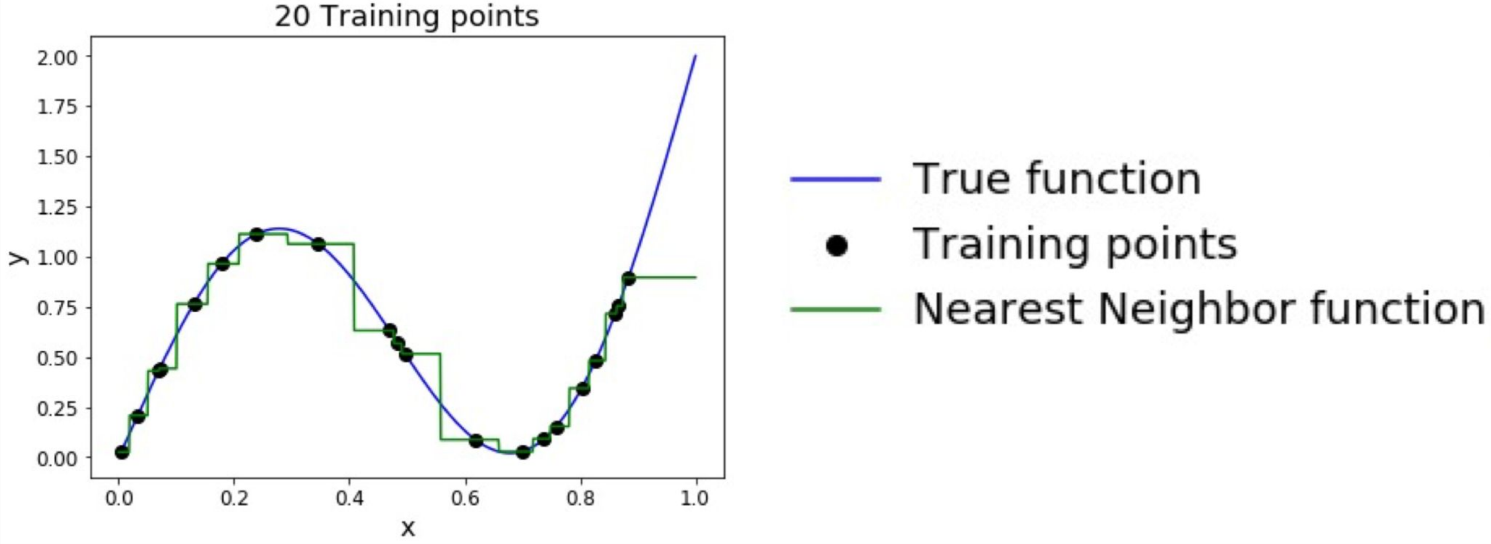
As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!



(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

KNN - Universal Approximation

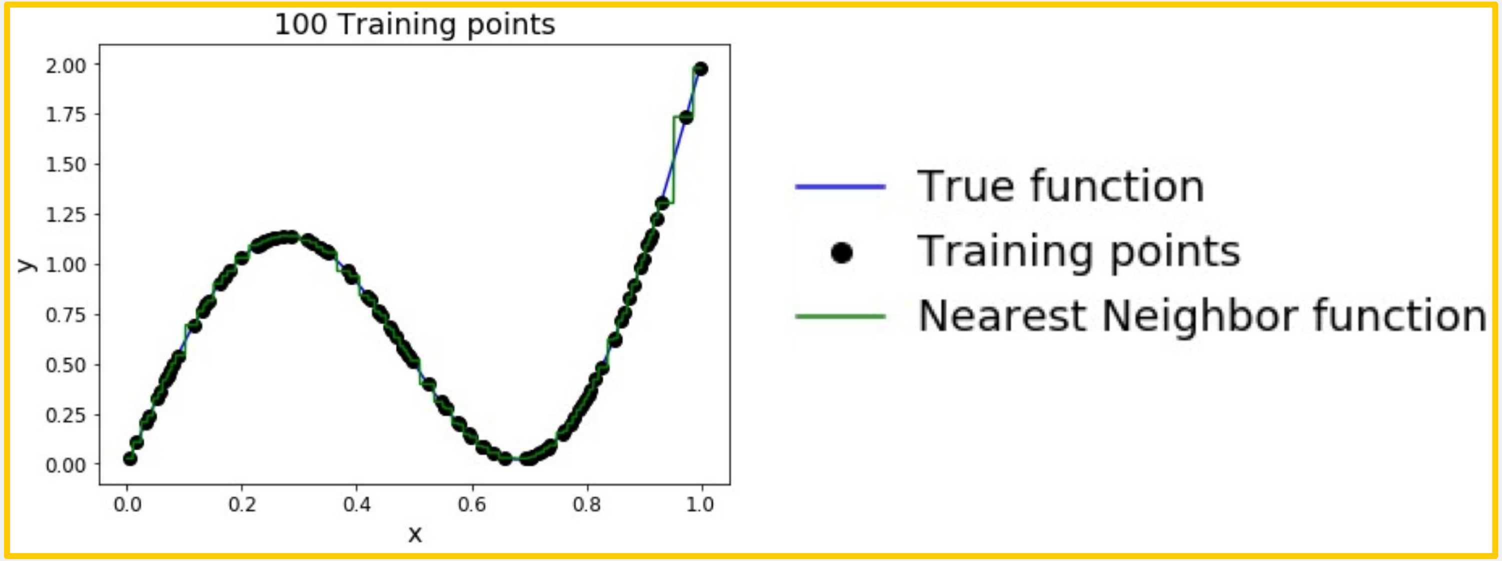
As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!



(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

KNN - Universal Approximation

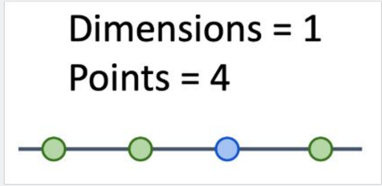
As the number of training samples goes to infinity, nearest neighbor can represent any(*) function!

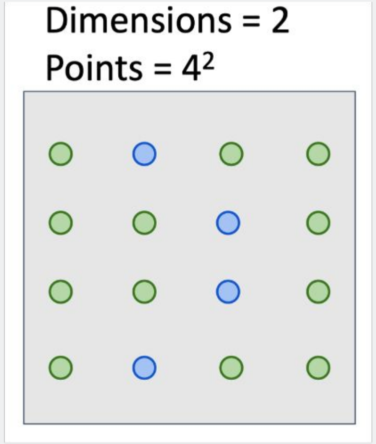


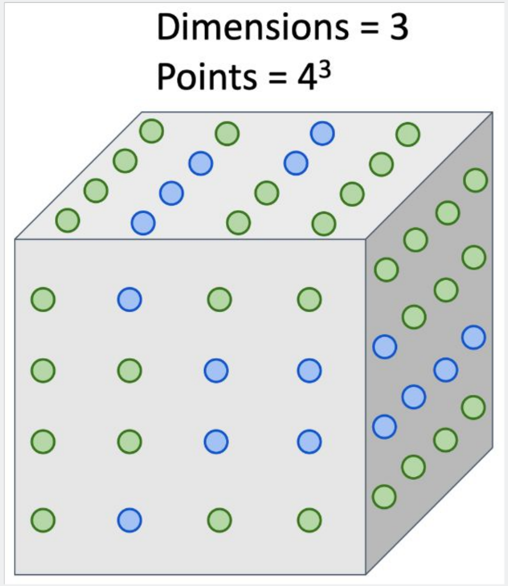
(*) Subject to many technical conditions. Only continuous functions on a compact domain; need to make assumptions about spacing of training points; etc.

Problem - Curse of Dimensionality

Curse of dimensionality: For uniform coverage of space, number of training points needed grows exponentially with dimension







Problem - Curse of Dimensionality

Curse of dimensionality: For uniform coverage of space, number of training points needed grows exponentially with dimension

Number of possible
32x32 binary images

$$2^{32X32} \approx 10^{308}$$

Notes

- K-Nearest Neighbors Seldom Used on Raw Pixels
- Very slow at test time
- Distance metrics on pixels are not informative

(Example)

All 3 images have same L2 distance to the original

K-Nearest Neighbors with ConvNet Features Works Well

Devlin et al., “Exploring Nearest Neighbor Approaches for Image Captioning”, 2015.

Summary

In **image classification** we start with a training set of images and labels, and must predict labels for a test set

Image classification is challenging due to the **semantic gap**:

we need invariance to occlusion, deformation, lighting, sensor variation, etc.

Image classification is a **building block** for other vision tasks

The **K-Nearest Neighbors** classifier predicts labels from nearest training samples

Distance metric and K are **hyperparameters**

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

Aha Slides
(In-class participation)

https://ahaslides.com/DMOPW

Q4

Due dates

Canvas Assignment: 20250113 KNN Quiz

Scored - individual (as part of in-class activity points)

Due Jan. 15, 2025

P0

5 submissions per day - Start today!!!

Due Jan. 19, 2025