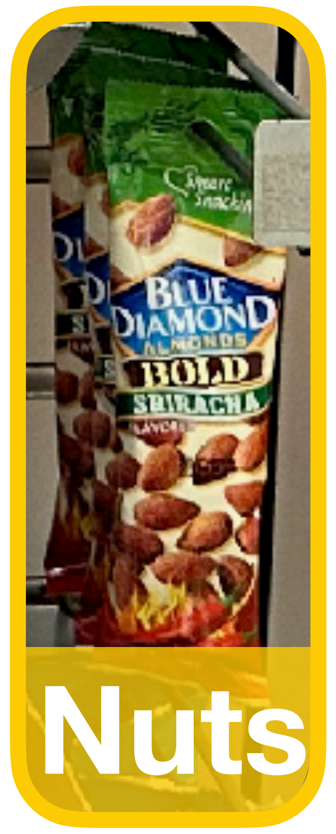

DeepRob

Lecture 2
Image Classification
University of Michigan and University of Minnesota

Project 0

- Instructions and code available on the website
  - Here: deeprob.org/projects/project0/

- Uses Python, PyTorch and Google Colab

- Introduction to PyTorch Tensors

- **Due this Thursday (January 12th), 11:59 PM EST**

Project 0 Suggestions

- If you choose to develop locally
  - **PyTorch Version 1.13.0**

- Ensure you save your notebook file before uploading submission

- Close any Colab notebooks not in use to avoid usage limits

Discussion Forum

- Ed Stem available for course discussion and questions
  - Forum is shared across UMich and UMinn students
  - Participation and use is not required
  - Opt-in using this Google form
  - **Discussion of quizzes and verbatim code must be private**

Enrollment

- Additional class permissions being issued
  - Both sections (498 & 599)
- If you haven’t received a class permission contact Anthony and Prof. Jenkins

Image Classification

Image Classification—A Core Computer Vision Task

Input: image

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

Chocolate Pretzels

Granola Bar

Potato Chips

Water Bottle

Popcorn

Problem—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],
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 [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]

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

Challenges—Viewpoint Variation


```
[[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],
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Challenges—Viewpoint Variation


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```
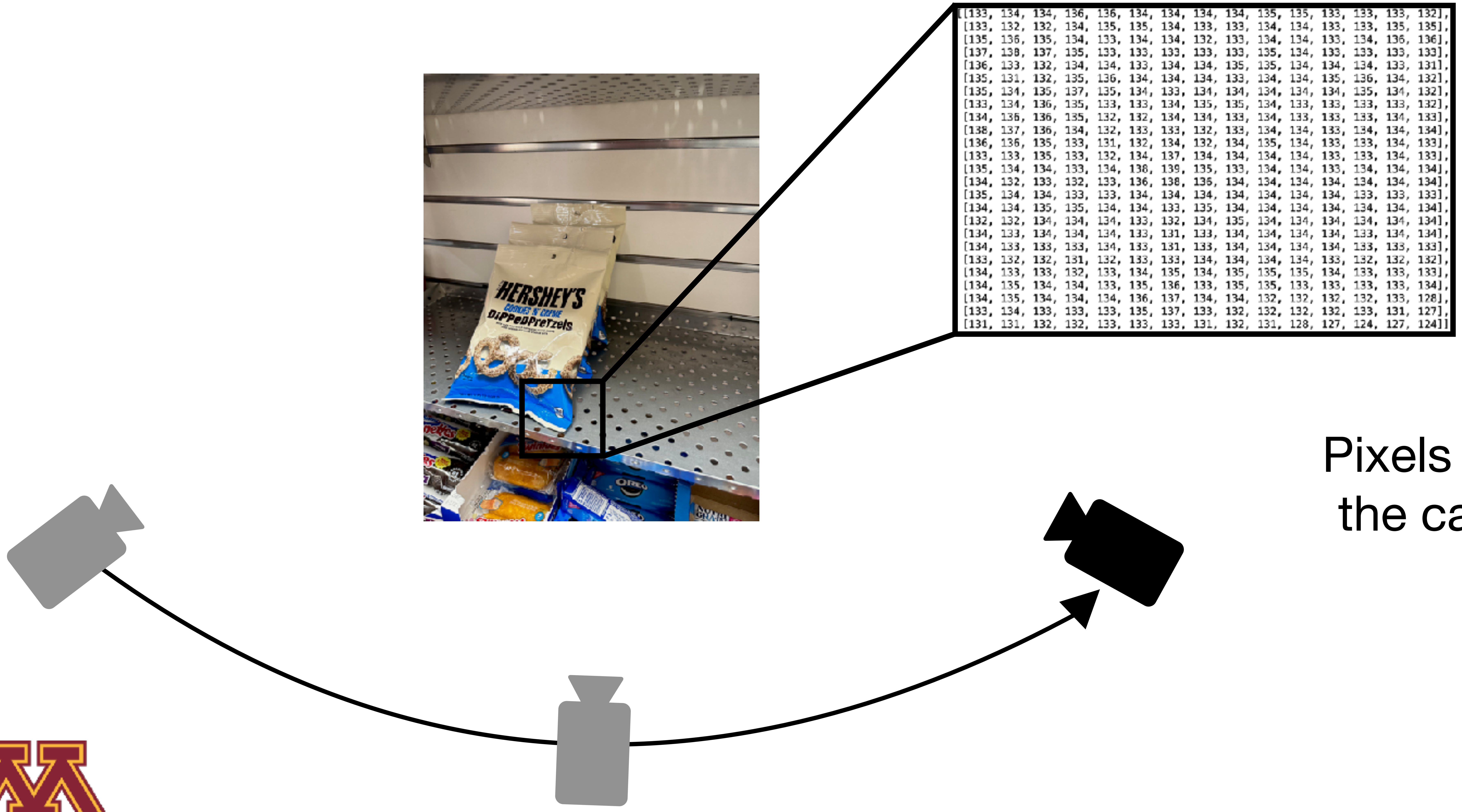

Challenges—Viewpoint Variation



Pixels change when the camera moves

Challenges—Intraclass Variation

Challenges—Fine-Grained Categories

Milk Chocolate

White Chocolate

Cookies N' Creme

Peanut Butter

Ambiguous Category

Challenges—Background Clutter

Challenges—Image Resolution

iPhone 14 Camera

4032x3024

ASUS RGB-D Camera

640x480

Challenges—Illumination Changes

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

Challenges—Semantic Relationships

Reflections

Contact Relationships

Challenges—Semantic Relationships

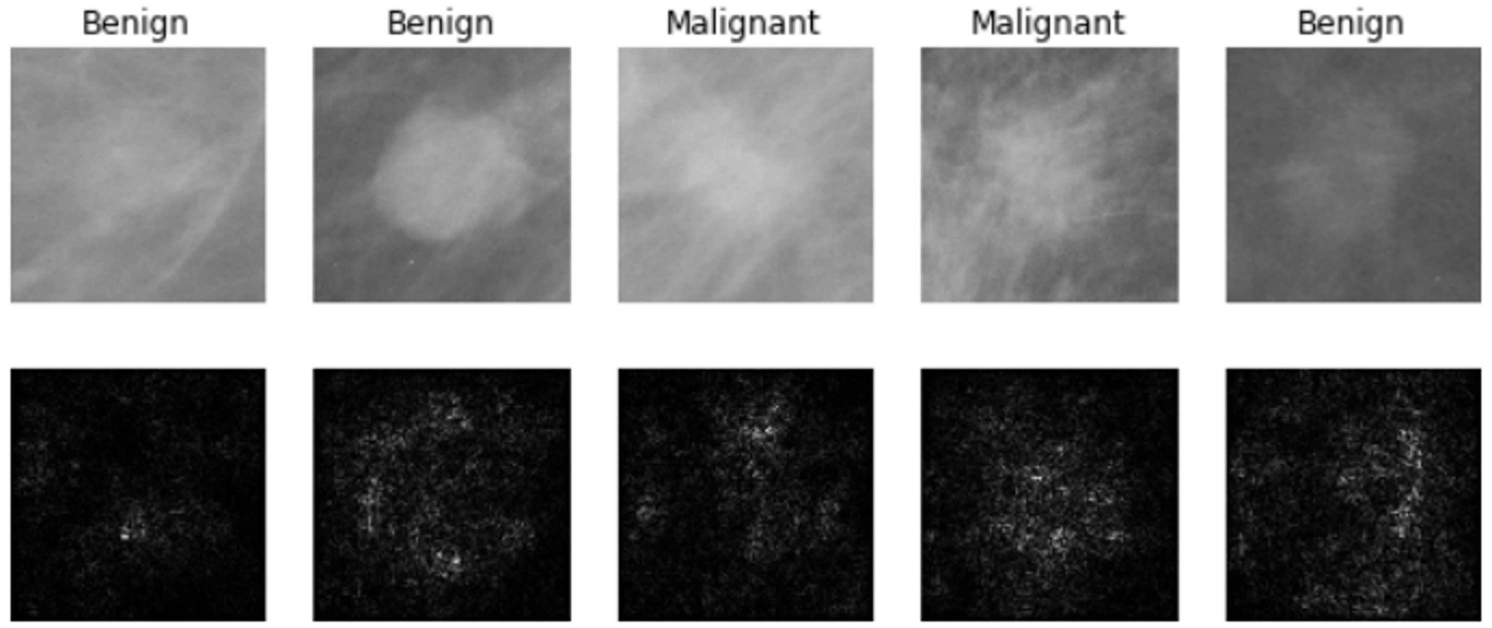
Reflections

Contact Relationships

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

Applications of Image Classification

Medical Imaging



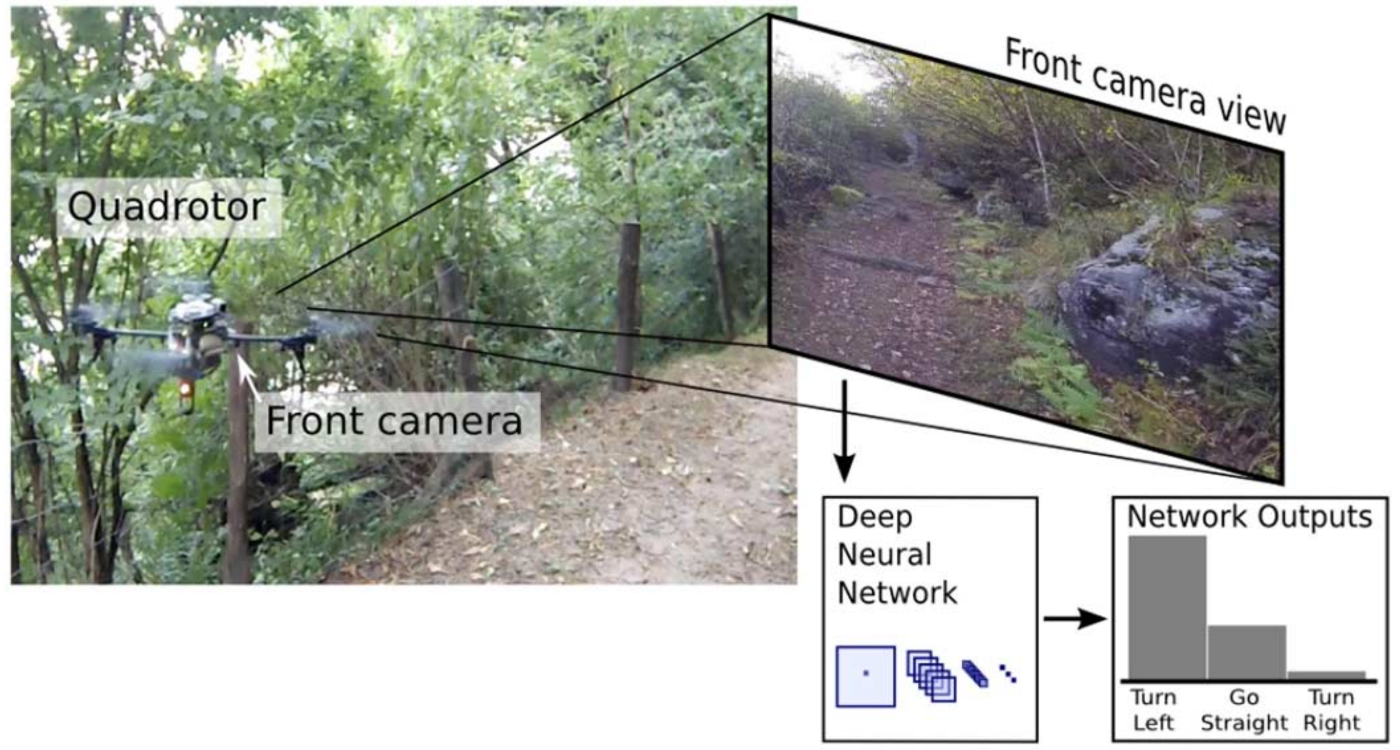
Lévy et al., "Breast Mass Classification from Mammograms using Deep Convolutional Neural Networks", arXiv:1612.00542, 2016

Galaxy Classification

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

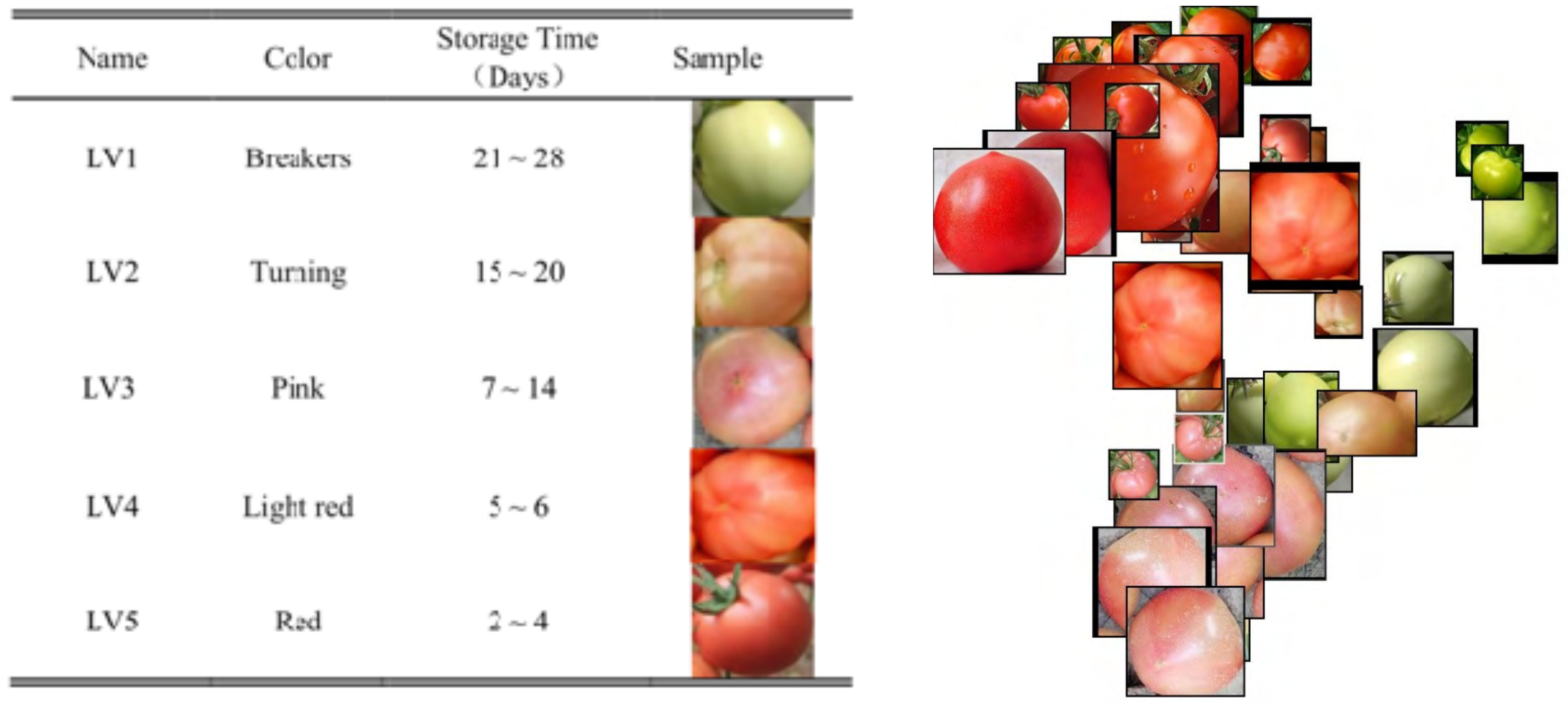
From left to right: public domain by NASA, usage permitted by ESA/Hubble, public domain by NASA, and public domain

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

Image Classification—Building Block for Other Tasks

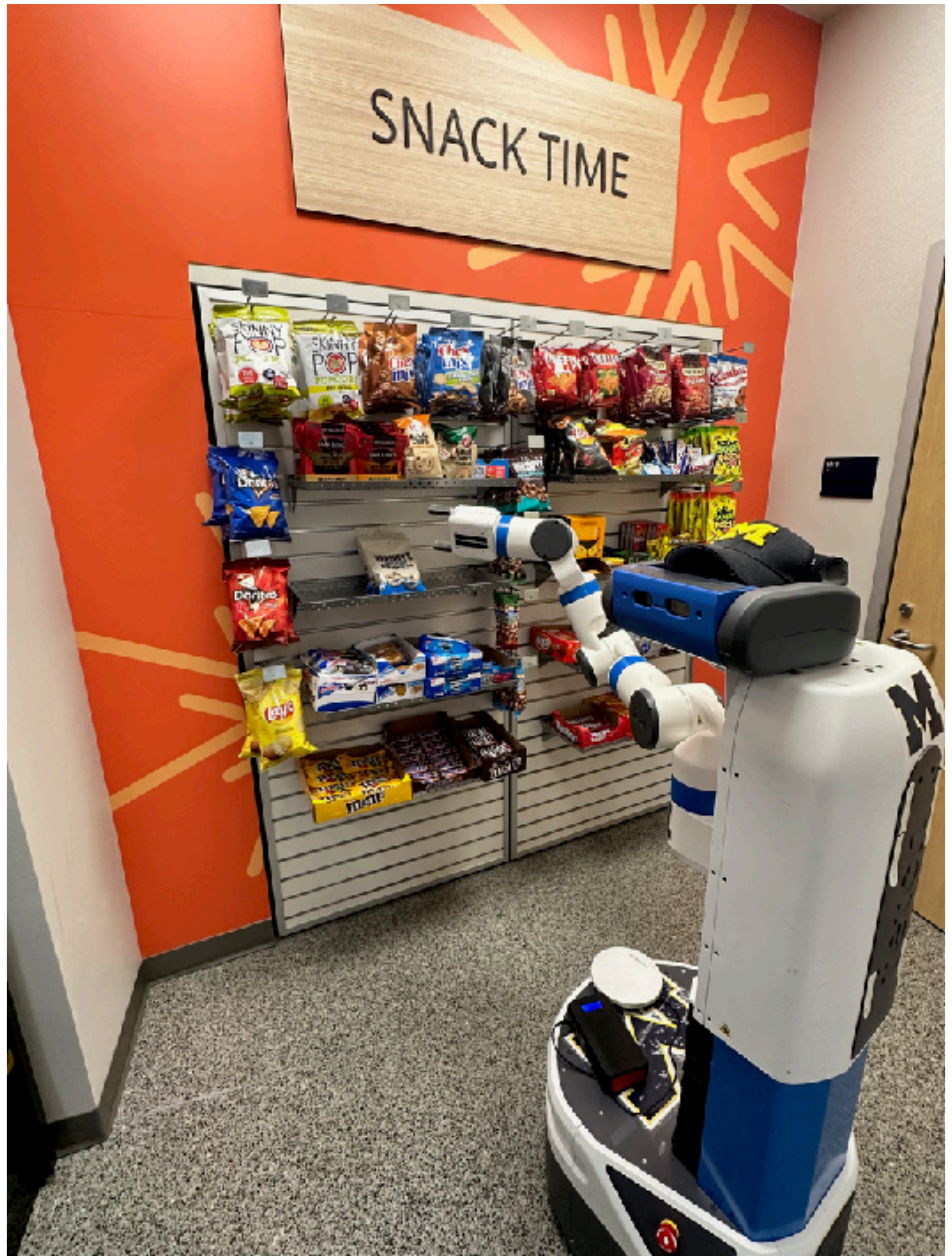
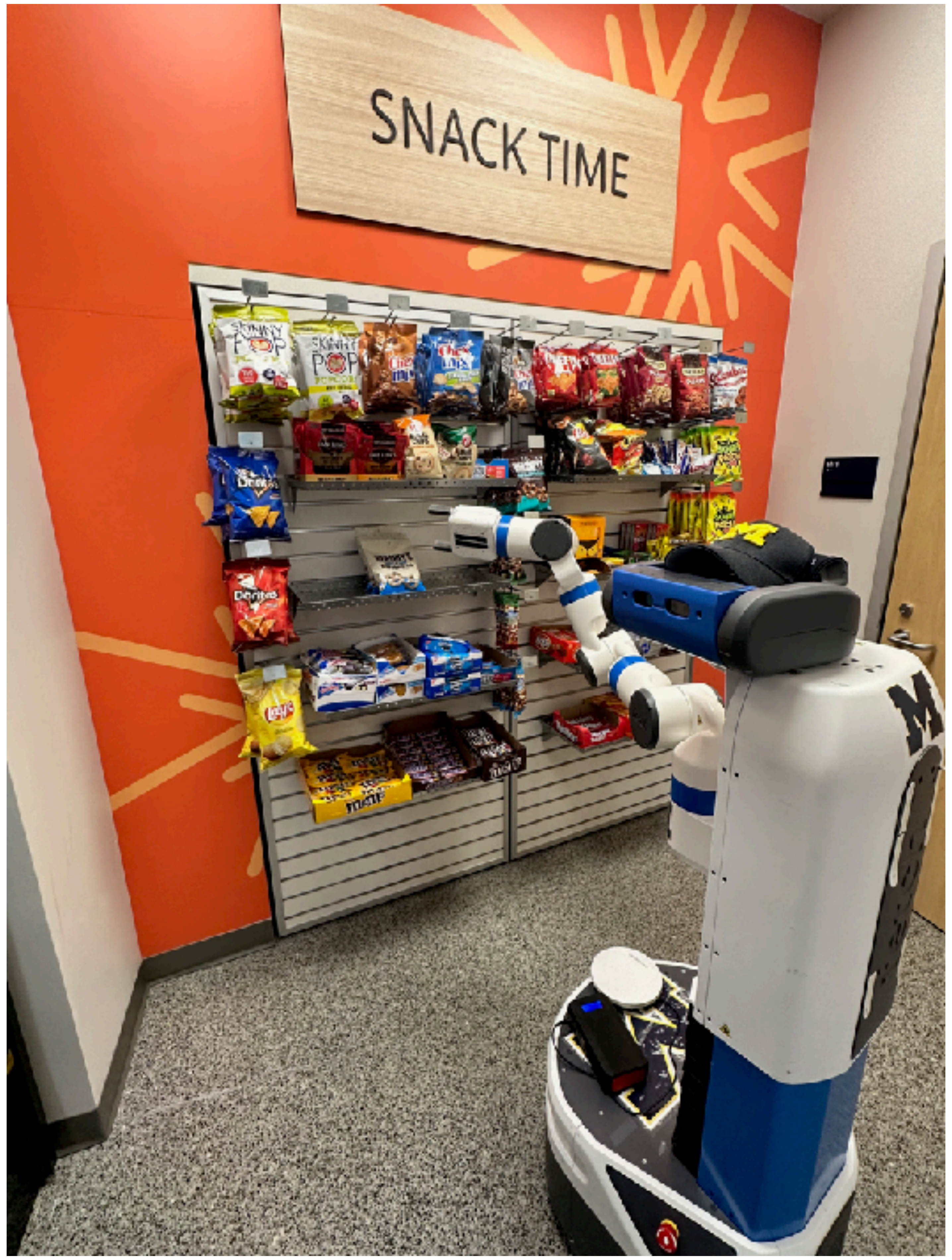


Image Classification—Building Block for Other Tasks



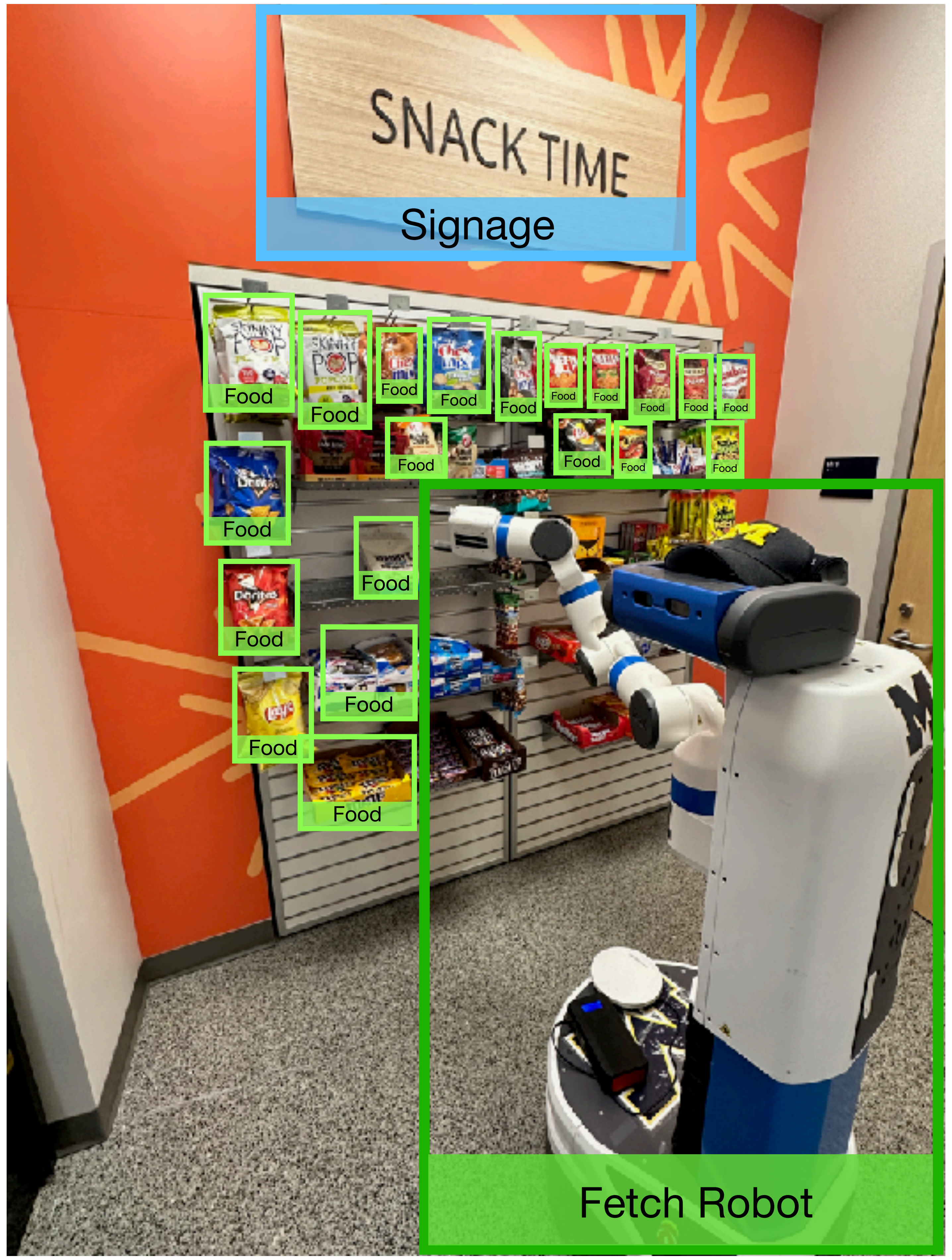
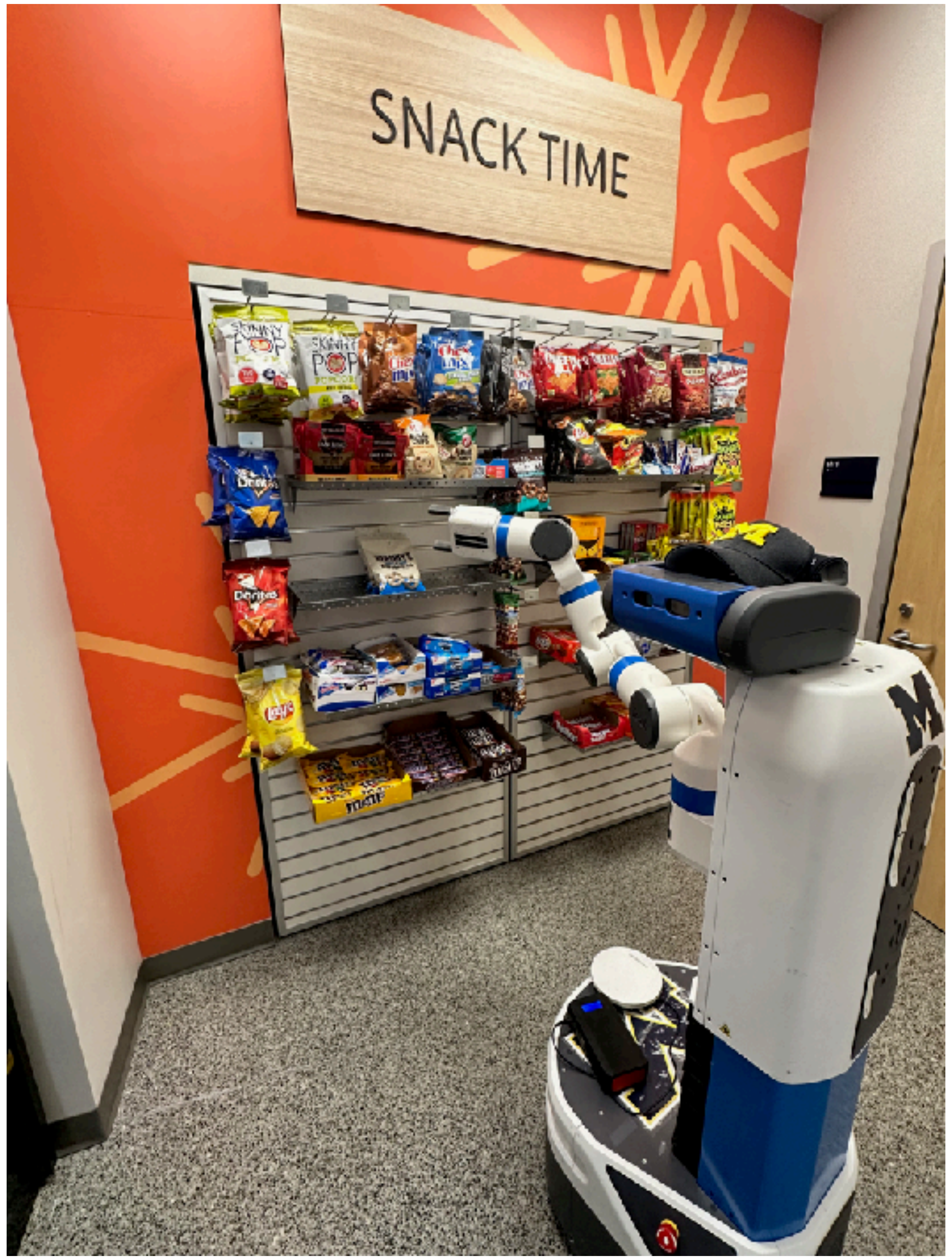


Image Classification—Building Block for Other Tasks



Example: Object Detection

Wall

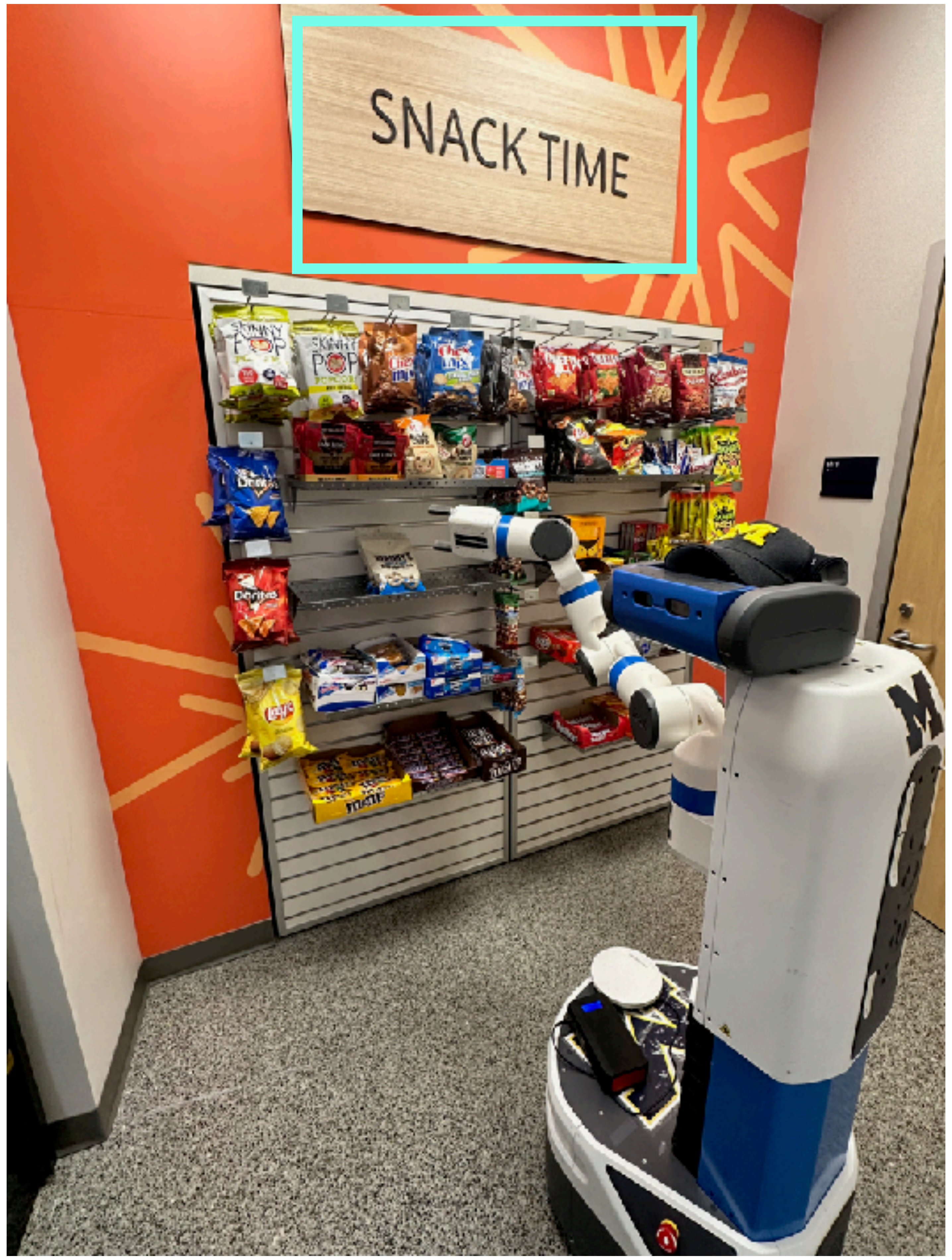
Floor

Signage

Fetch Robot

Snacks

Image Classification—Building Block for Other Tasks



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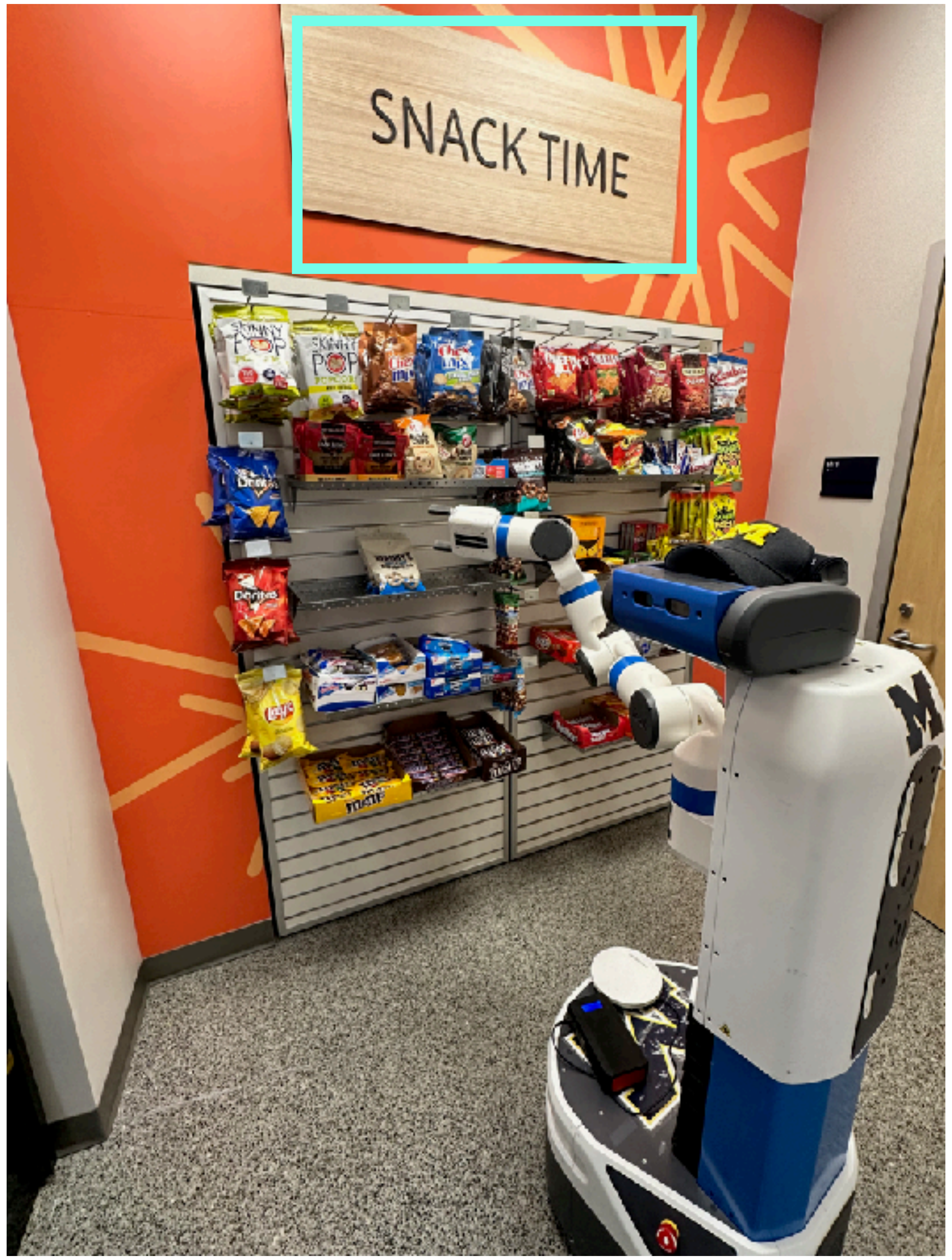

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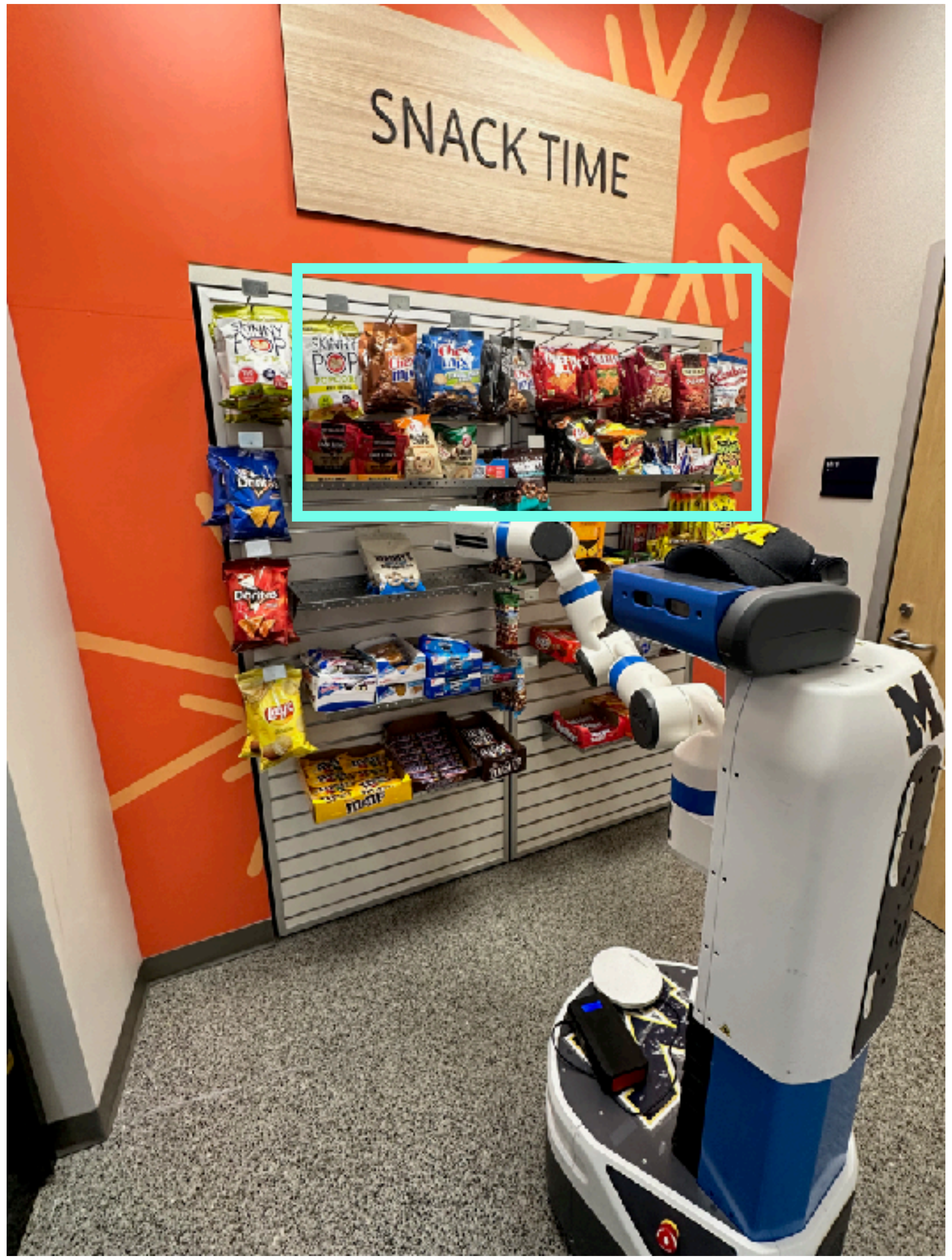

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Snacks

Image Classification—Building Block for Other Tasks

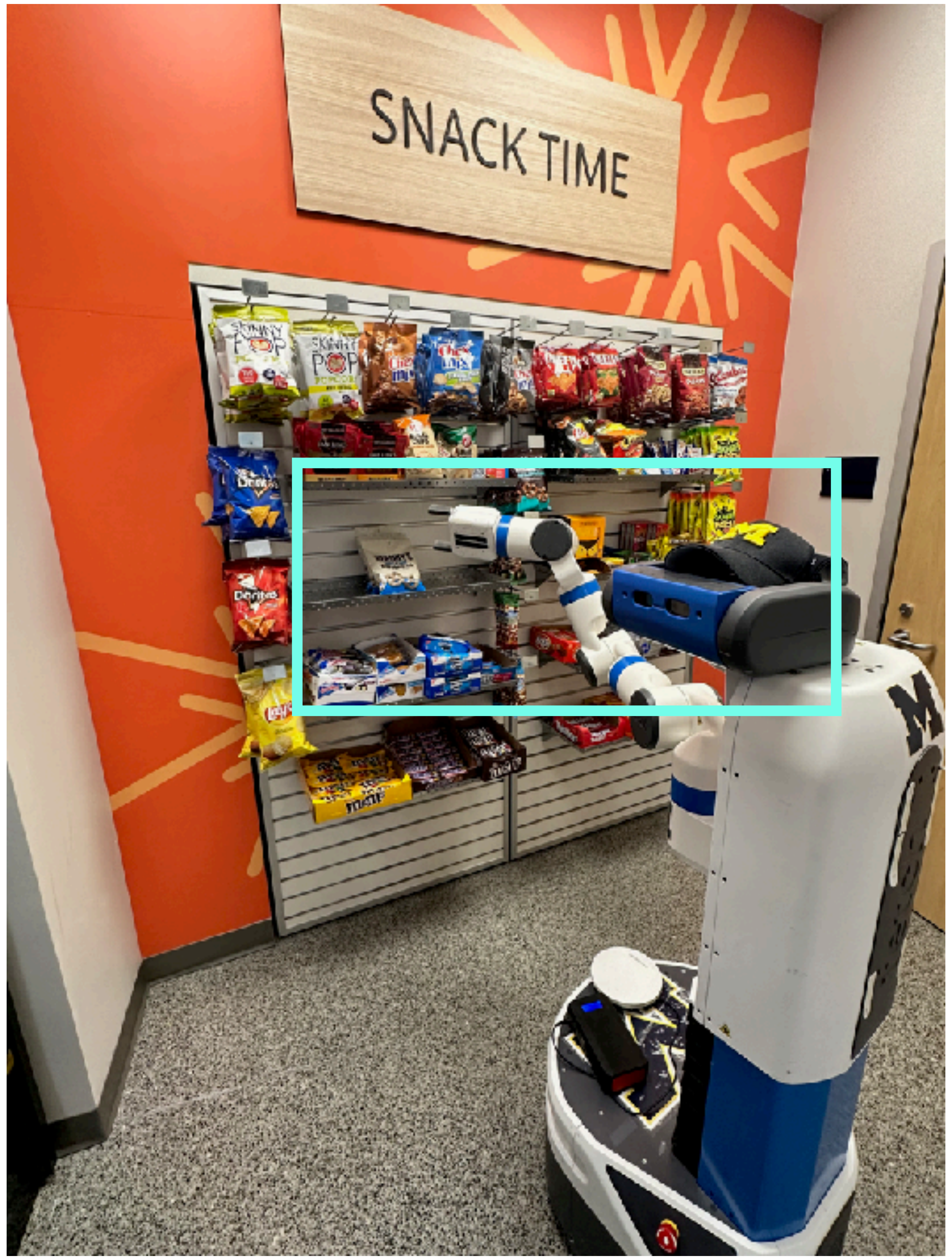

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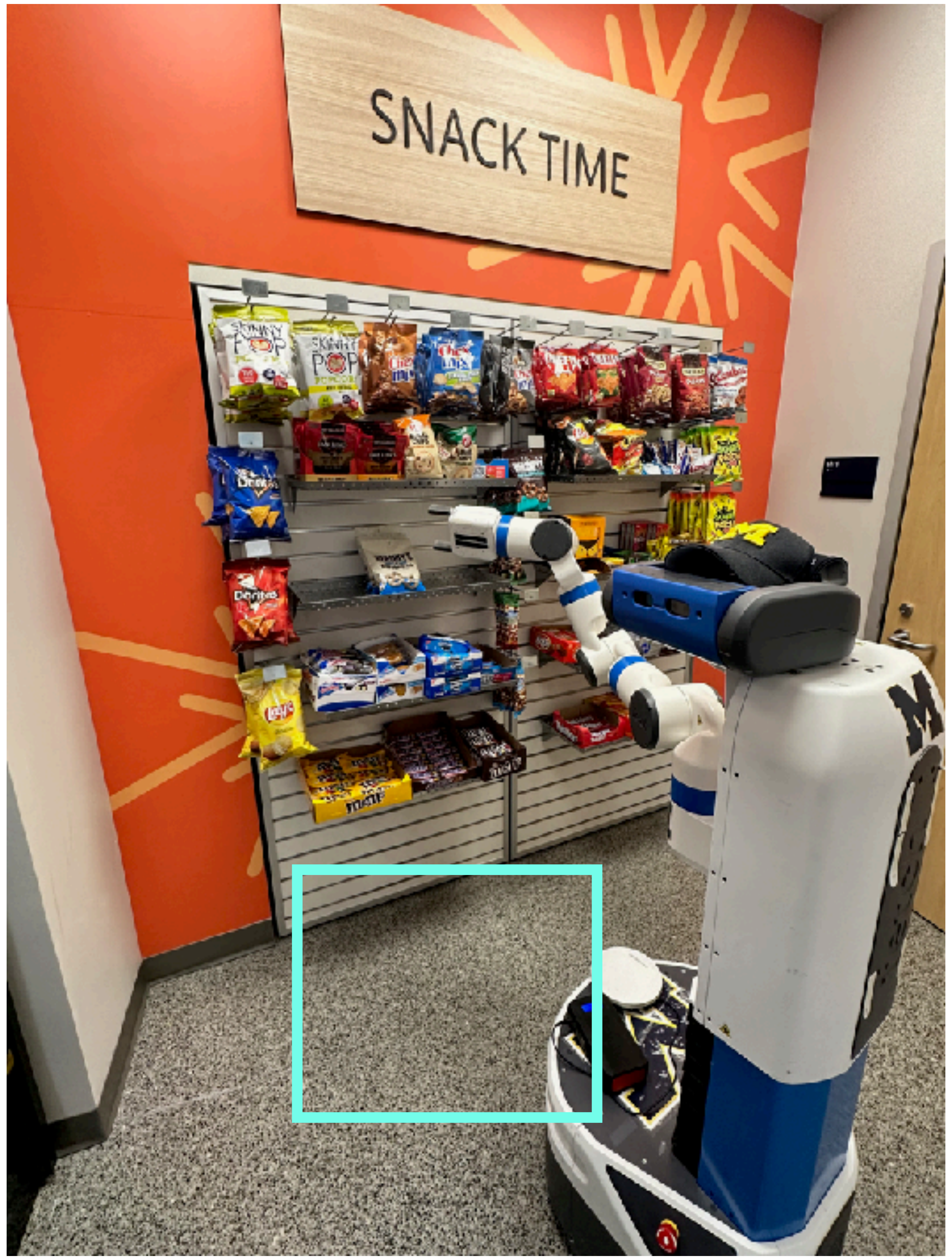
Image Classification—Building Block for Other Tasks



Example: Object Detection

Wall

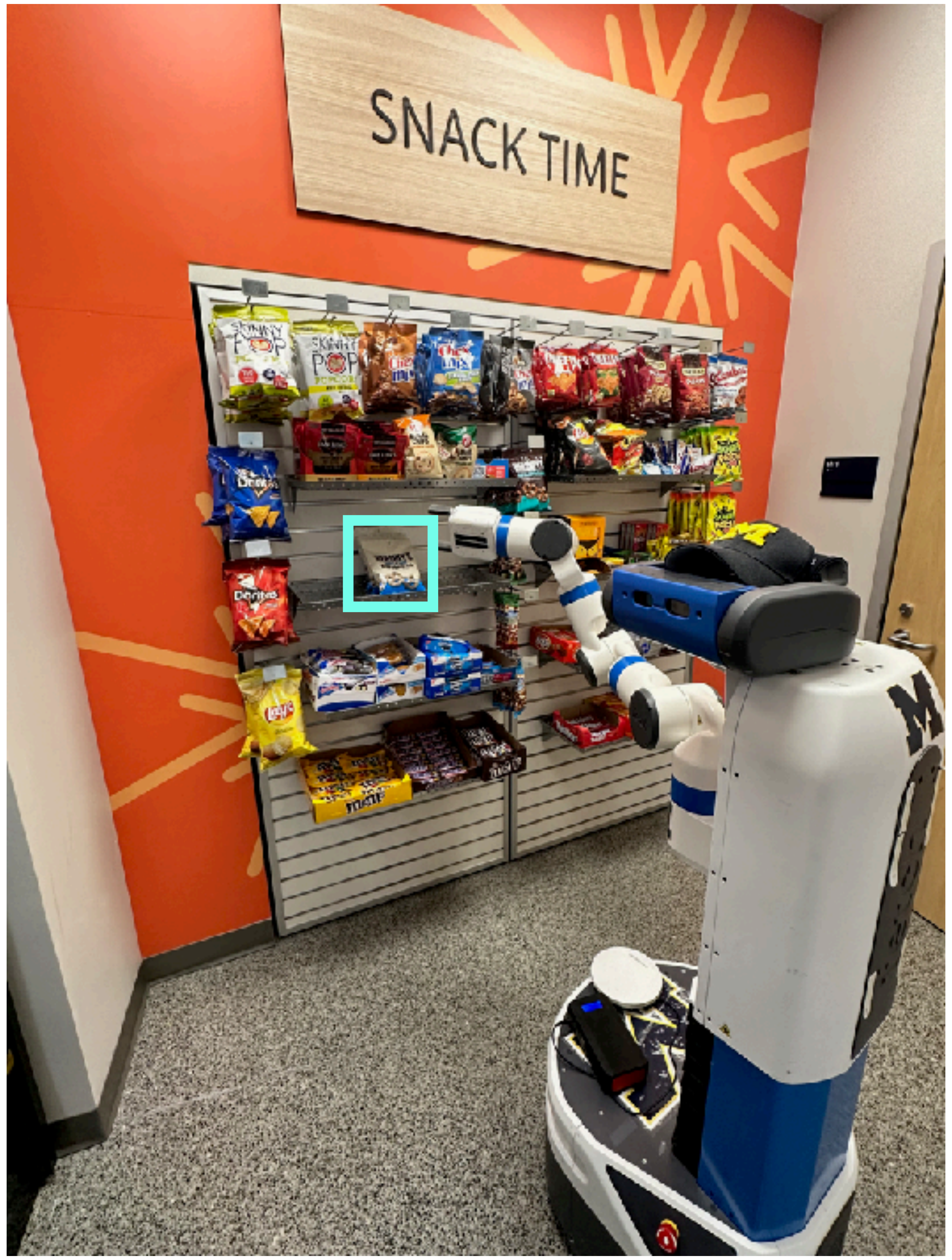
Floor

Signage

Fetch Robot

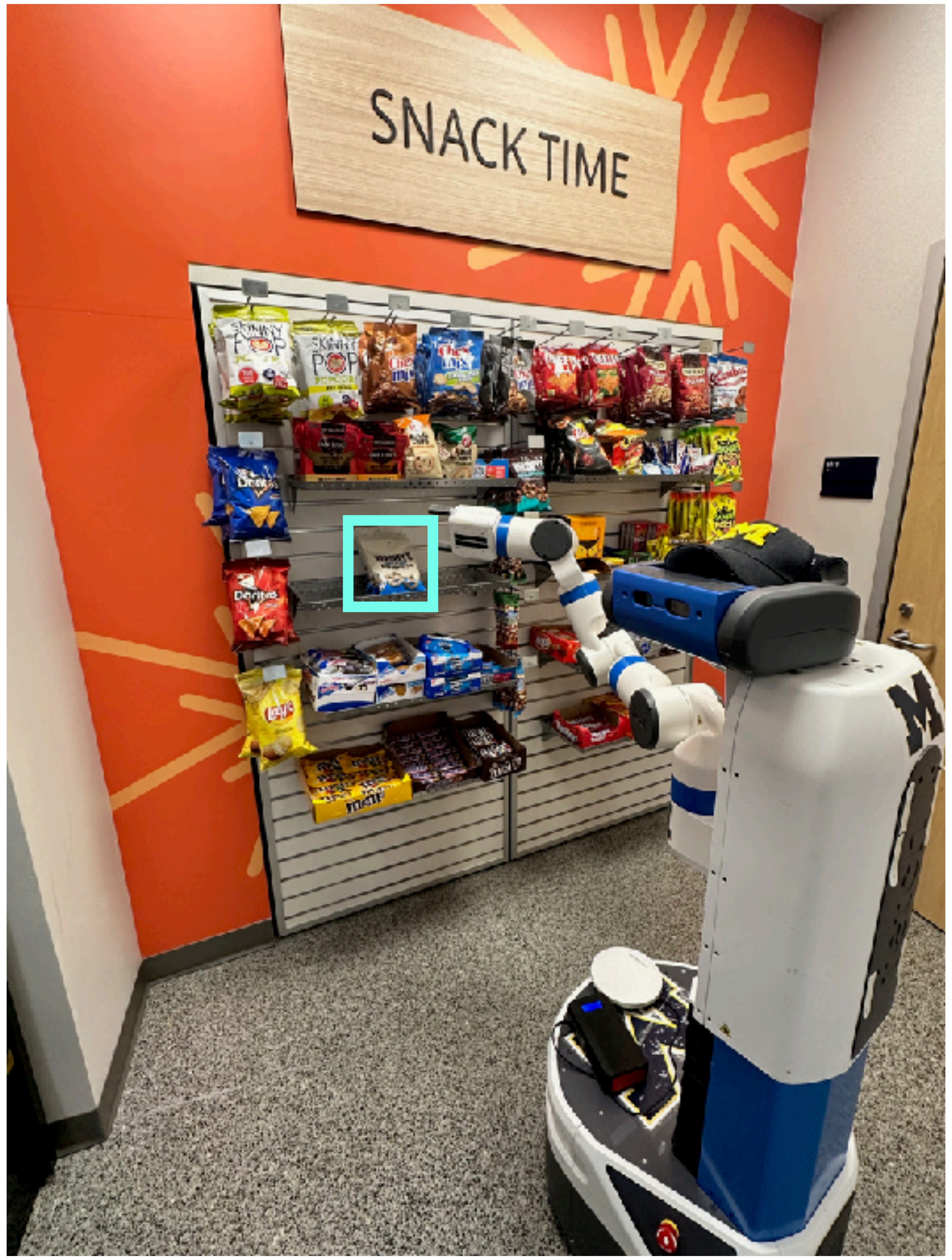
Snacks

Image Classification—Building Block for Other Tasks



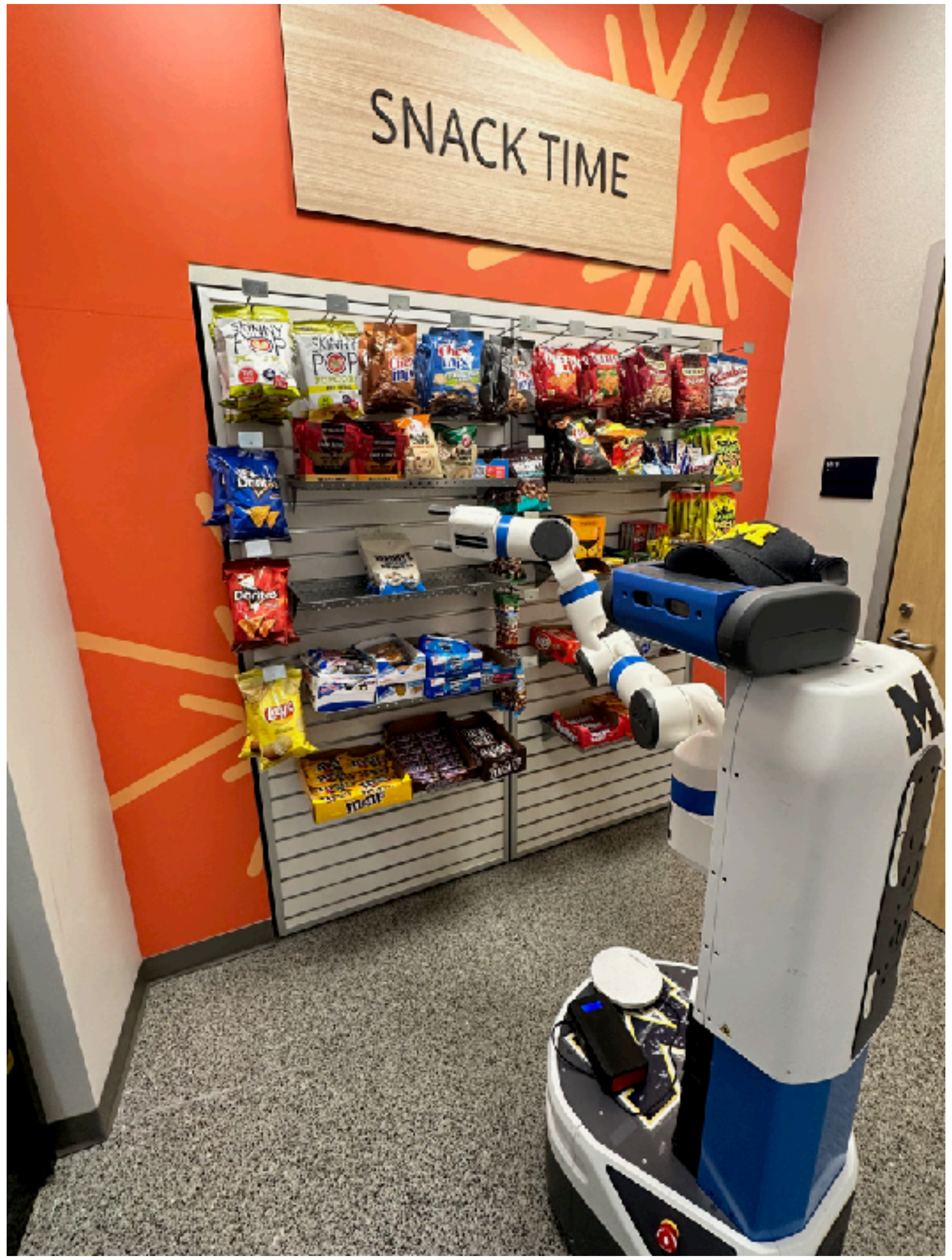
Example: Pose Estimation

Image Classification—Building Block for Other Tasks



Example: Pose Estimation

Image Classification—Building Block for Other Tasks



Example: Pose Estimation

An Image Classifier

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

An Image Classifier

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

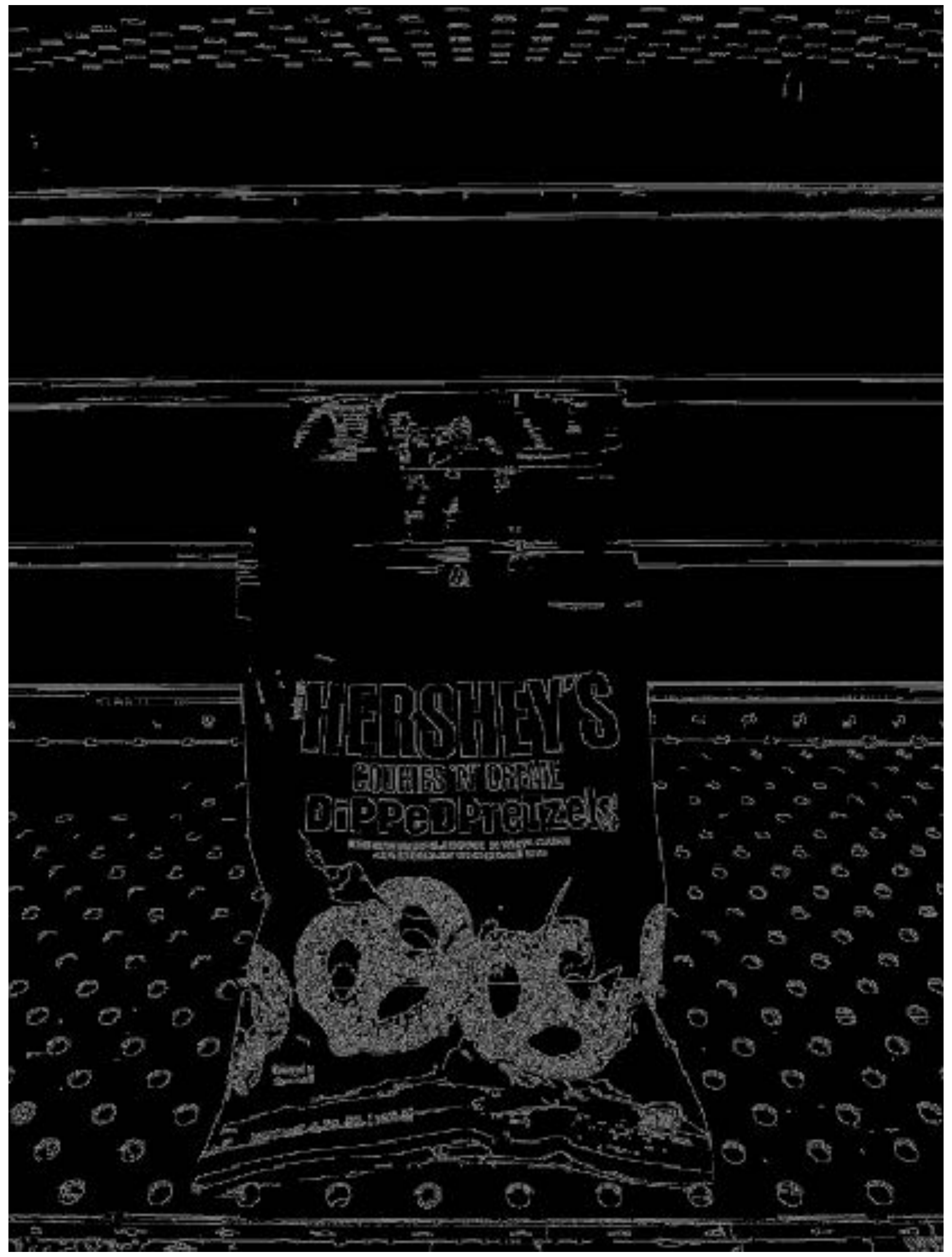
Unlike well defined programming (e.g. sorting a list)

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

An Image Classifier

Input: image

Detect: Edges



Detect: Corners

???

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

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

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

Example training set

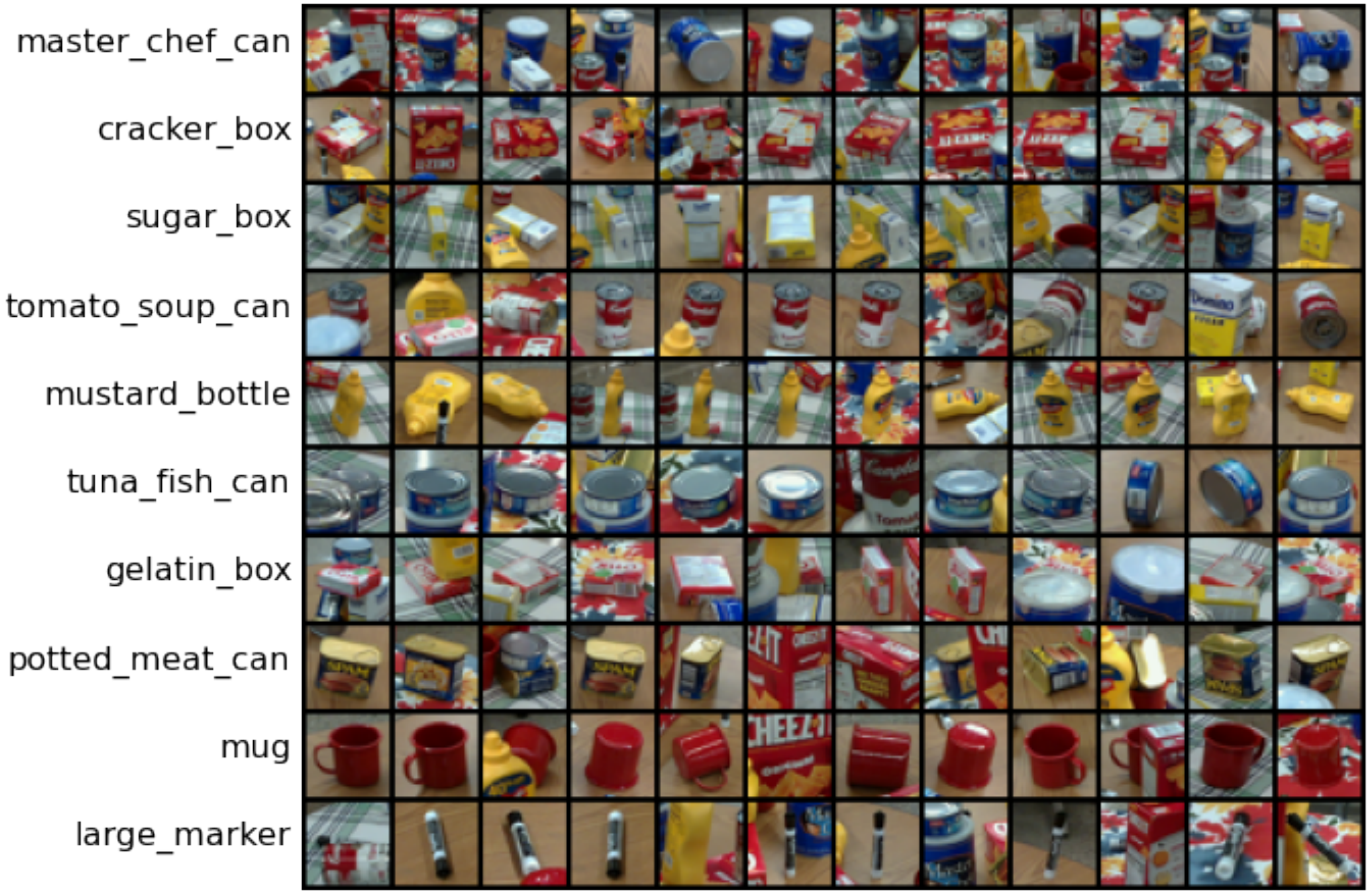


Image Classification Datasets—MNIST

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

Image Classification Datasets—CIFAR10

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

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

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

Image Classification Datasets—CIFAR100

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

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

Trees: maple, oak, palm, pine, willow

Image Classification 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)

Performance metric: **Top 5 accuracy**
Algorithm predicts 5 labels for each image, one must be right

Image Classification 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)
test labels are secret!

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

There is also a 22K category version of ImageNet, but less commonly used

Image Classification Datasets—MIT Places

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

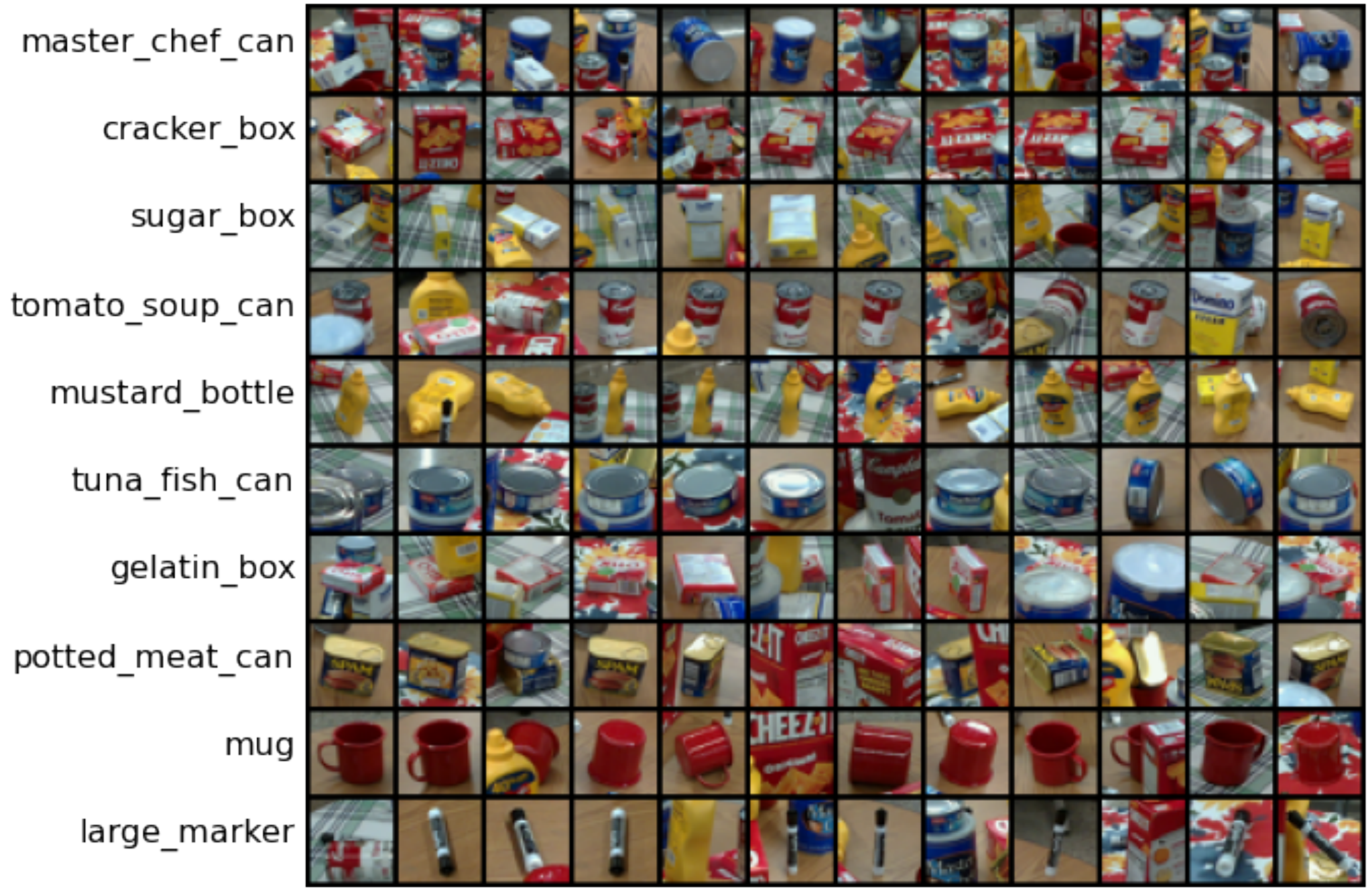
365 classes of different scene types

~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

Image Classification Datasets—PROPS

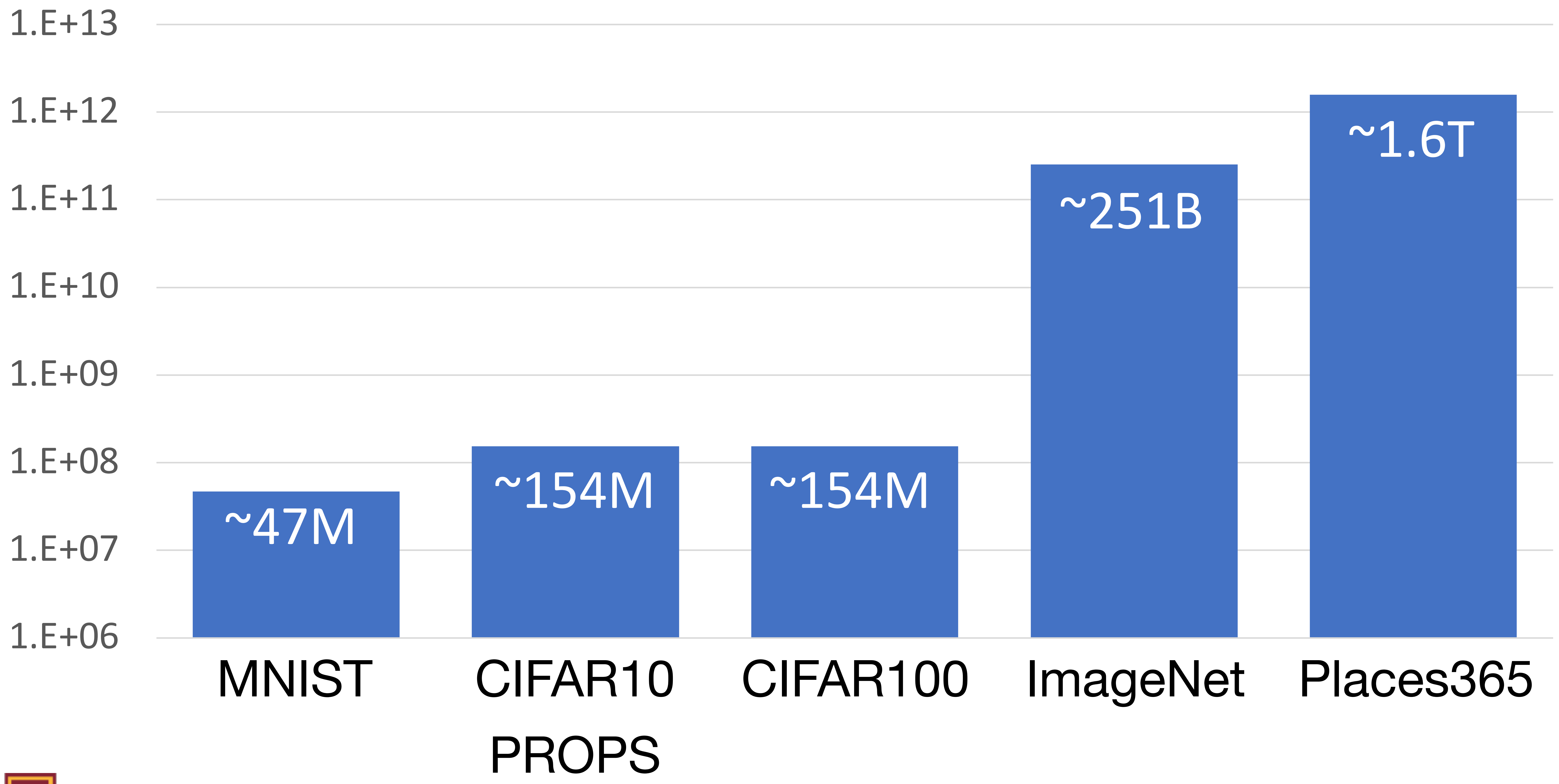
Progress **R**obot **O**bject **P**erception **S**amples **D**ataset



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

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

Classification Datasets—Number of Training Pixels



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

L1 distance: $$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

test image					training image					pixel-wise absolute value differences				
56	32	10	18		10	20	24	17		46	12	14	1	
90	23	128	133		8	10	89	100		82	13	39	33	add
24	26	178	200	-	12	16	178	170	=	12	10	0	30	→ 456
2	0	255	220		4	32	233	112		2	32	22	108	

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
```

Nearest Neighbor Classifier

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    return Ypred
```

Memorize training data

Nearest Neighbor Classifier

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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
```

For each test image:
  Find nearest training image
  Return label of nearest image

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

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Q: With N examples how fast is training?

A: O(1)

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Q: With N examples how fast is testing?

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Q: With N examples how fast is training?

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Q: With N examples how fast is testing?

A: O(N)

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

Nearest Neighbor Classifier

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```
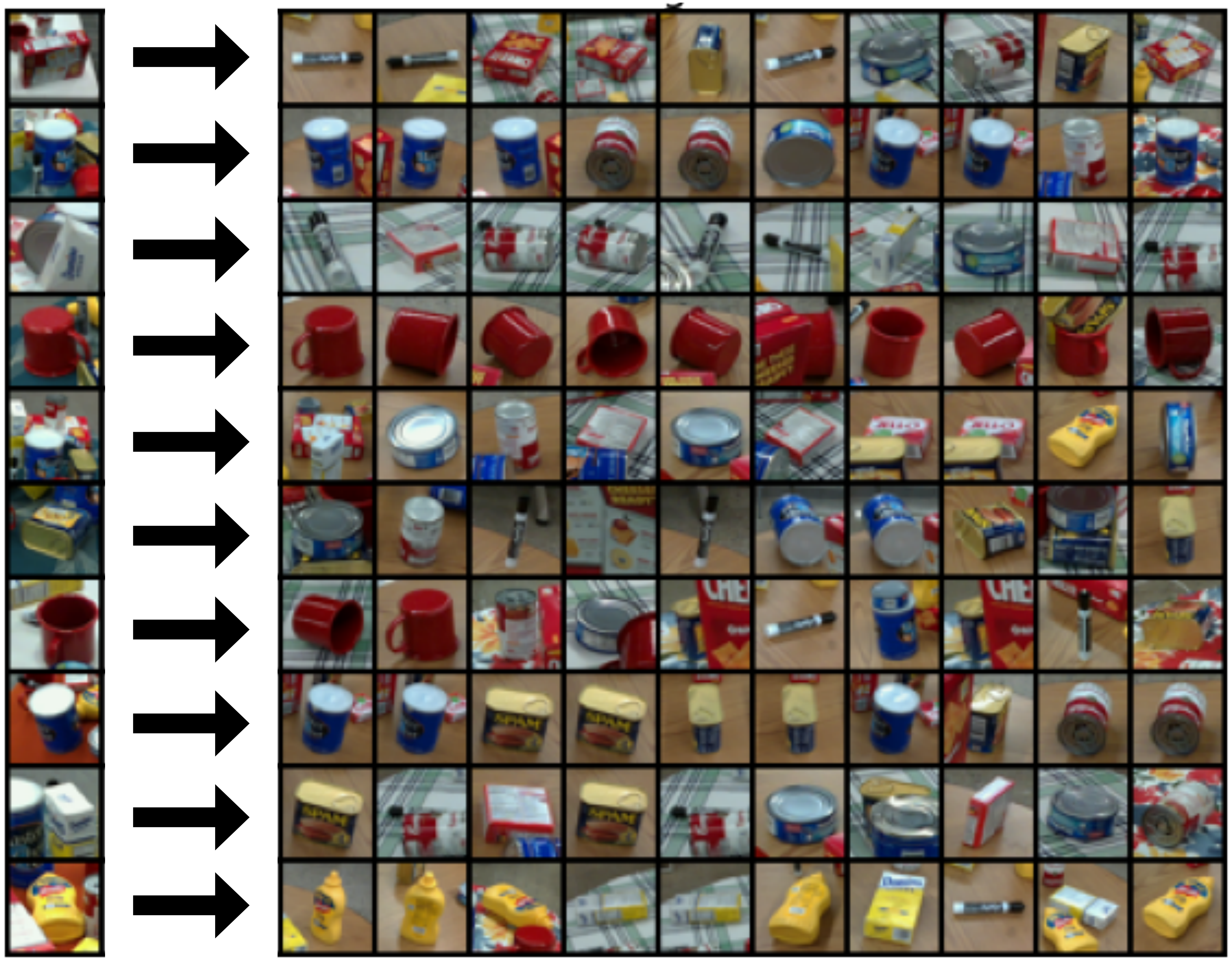

There are many methods for fast / approximate nearest neighbors

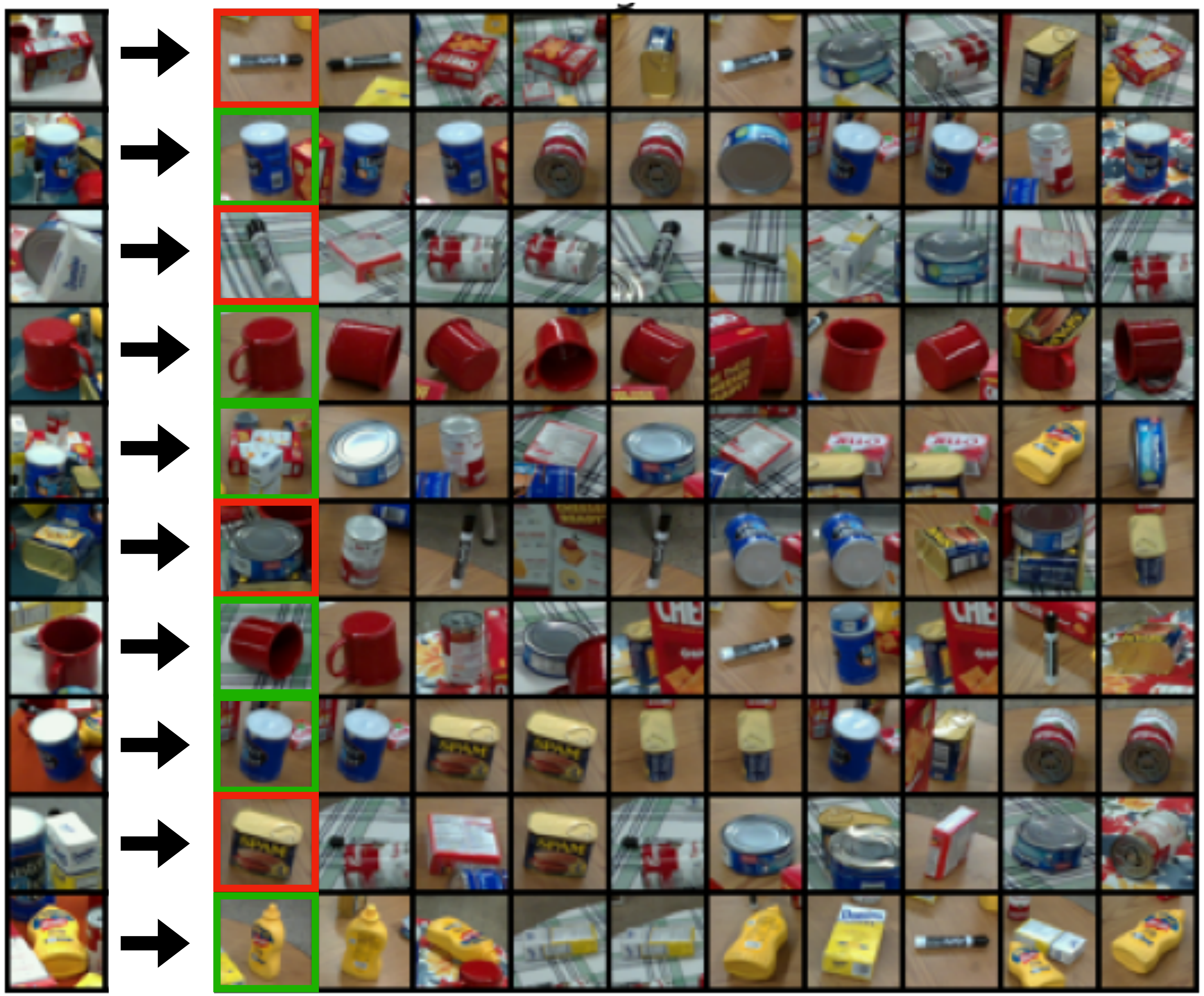
e.g. github.com/facebookresearch/faiss

What does this look like?



What does this look like?

PROPS dataset is instance-level



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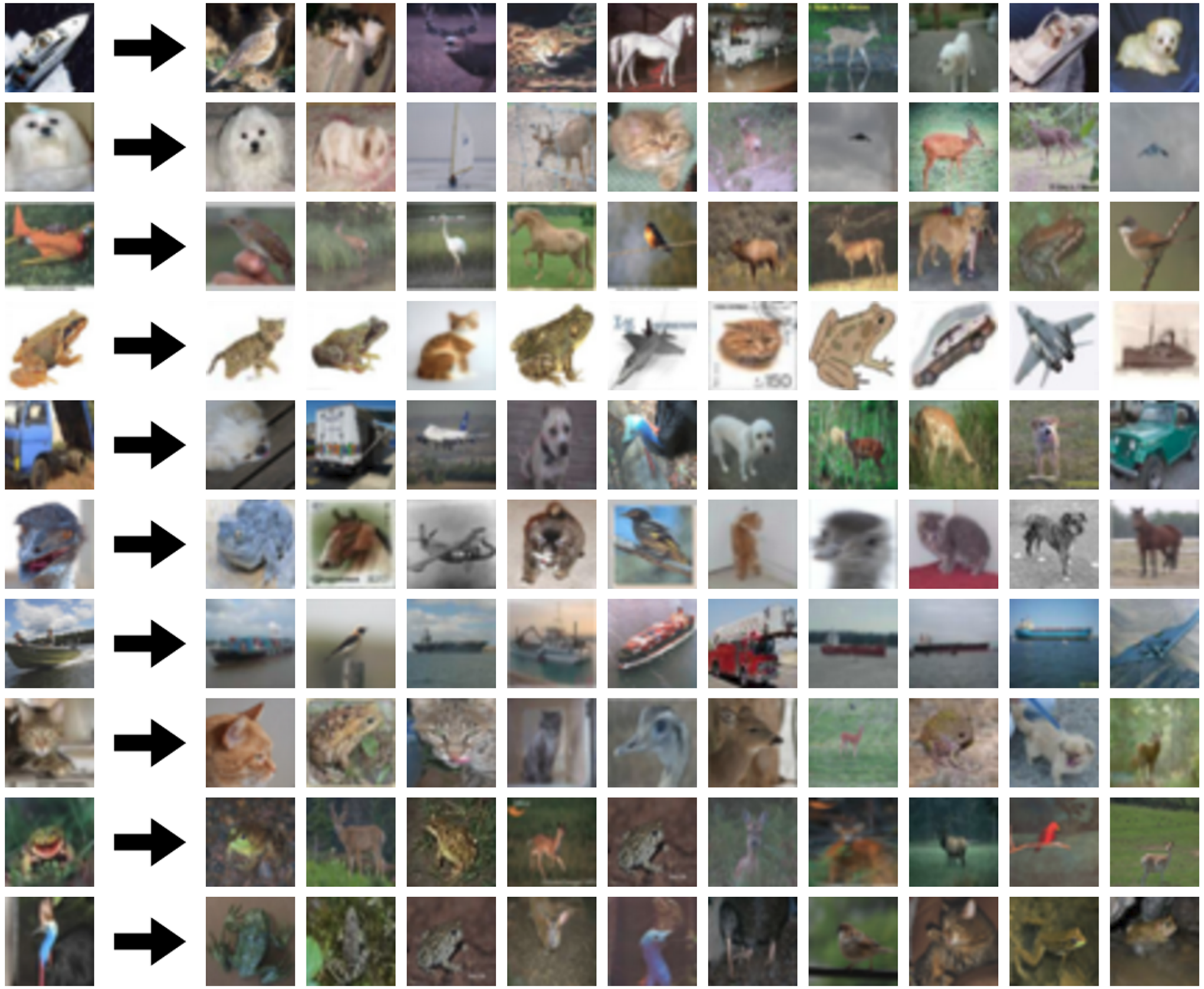
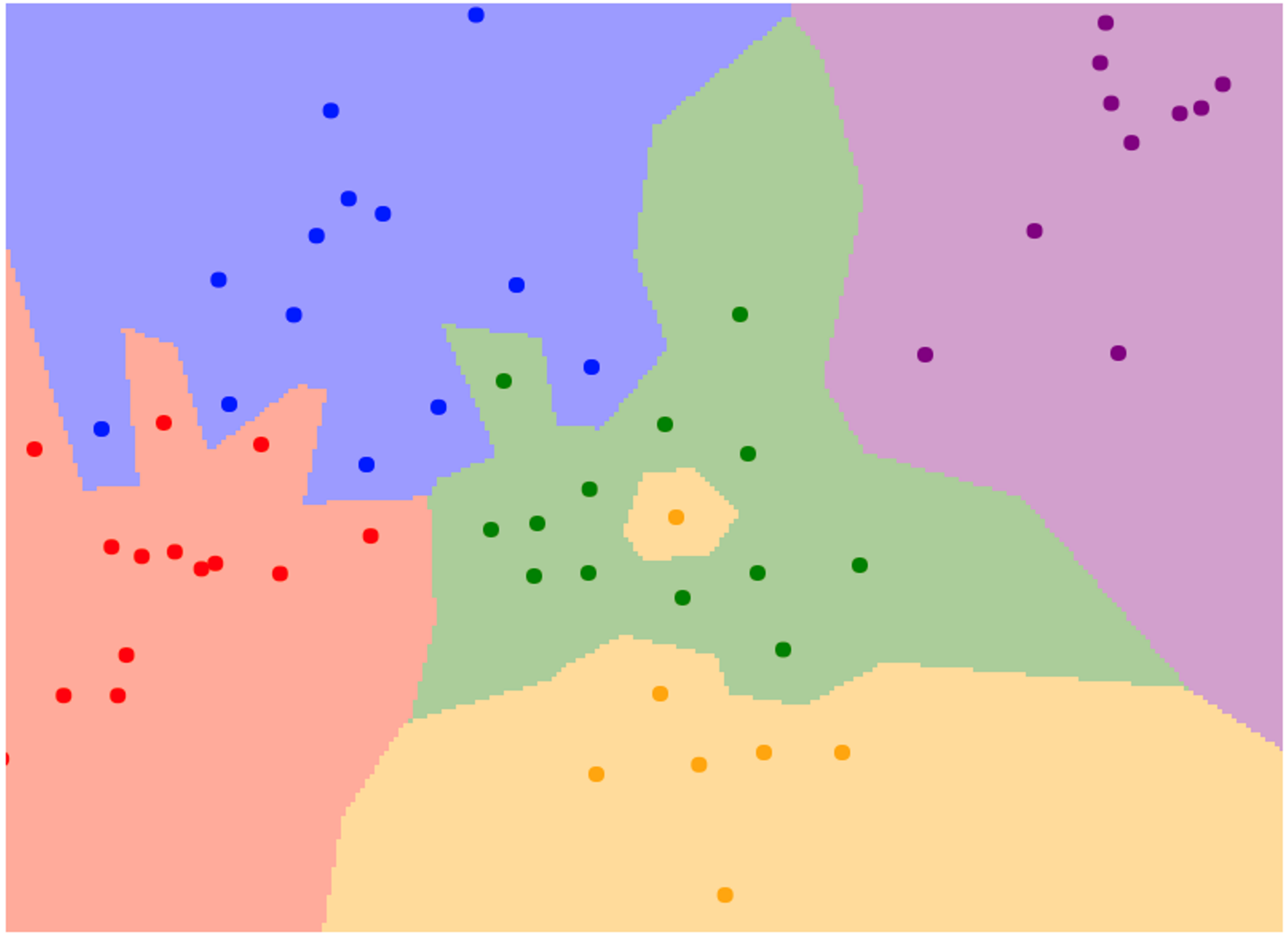


What does this look like?

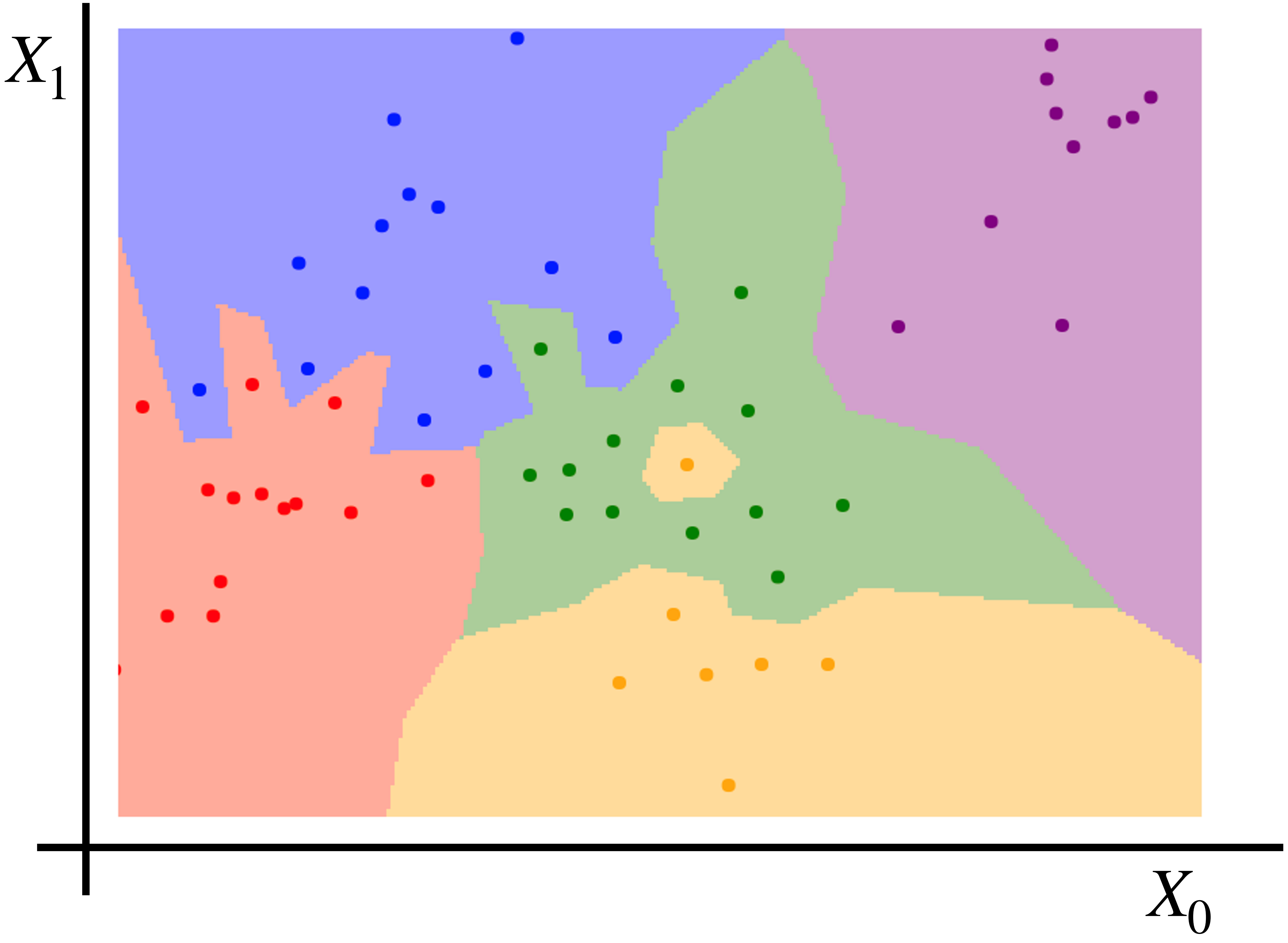
CIFAR10 dataset is category-level

K-Nearest Neighbors Decision Boundaries



K-Nearest Neighbors Decision Boundaries

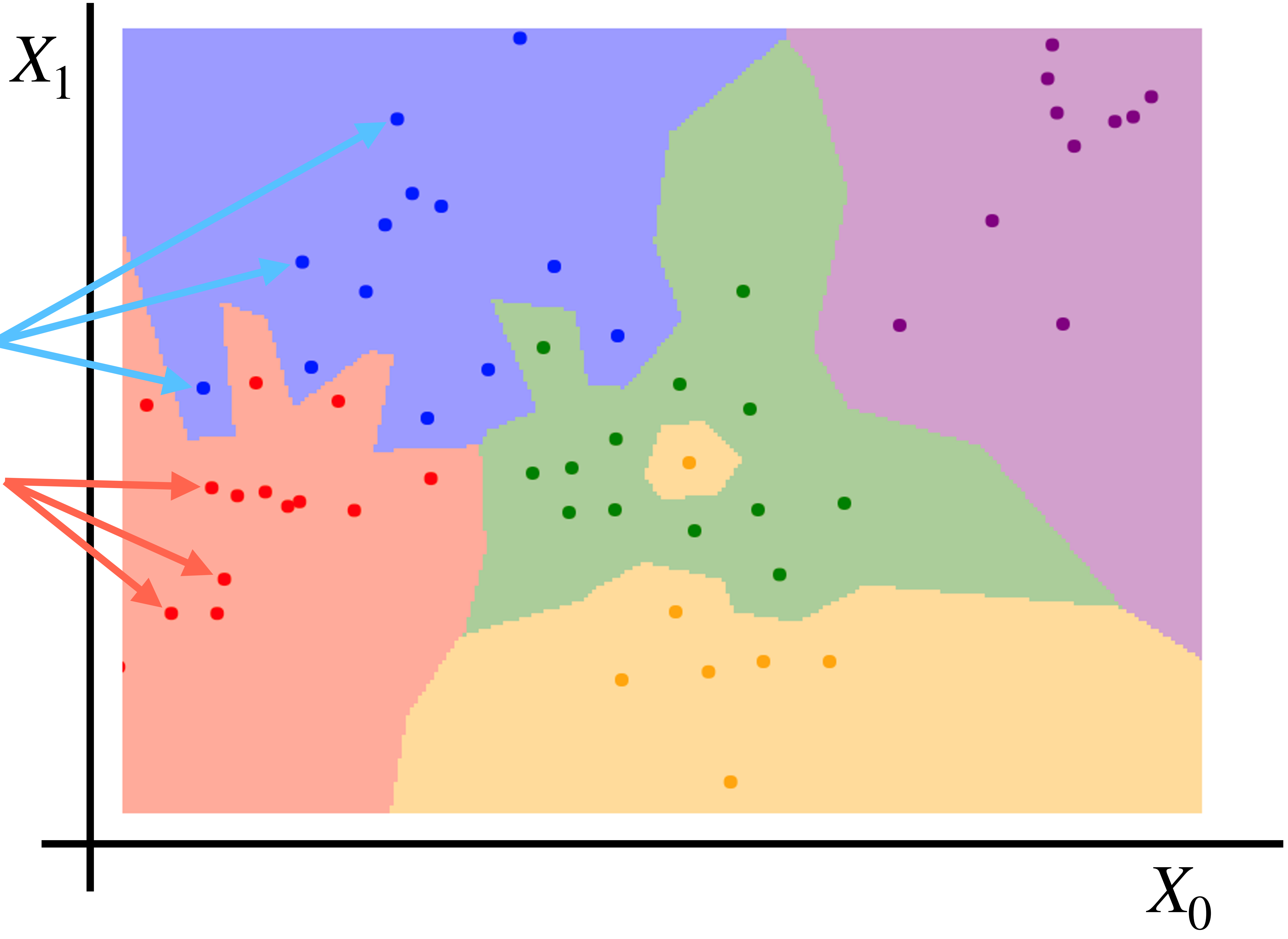
Nearest neighbors
in two dimensions



K-Nearest Neighbors Decision Boundaries

Nearest neighbors in two dimensions

Points are training examples; colors give training labels

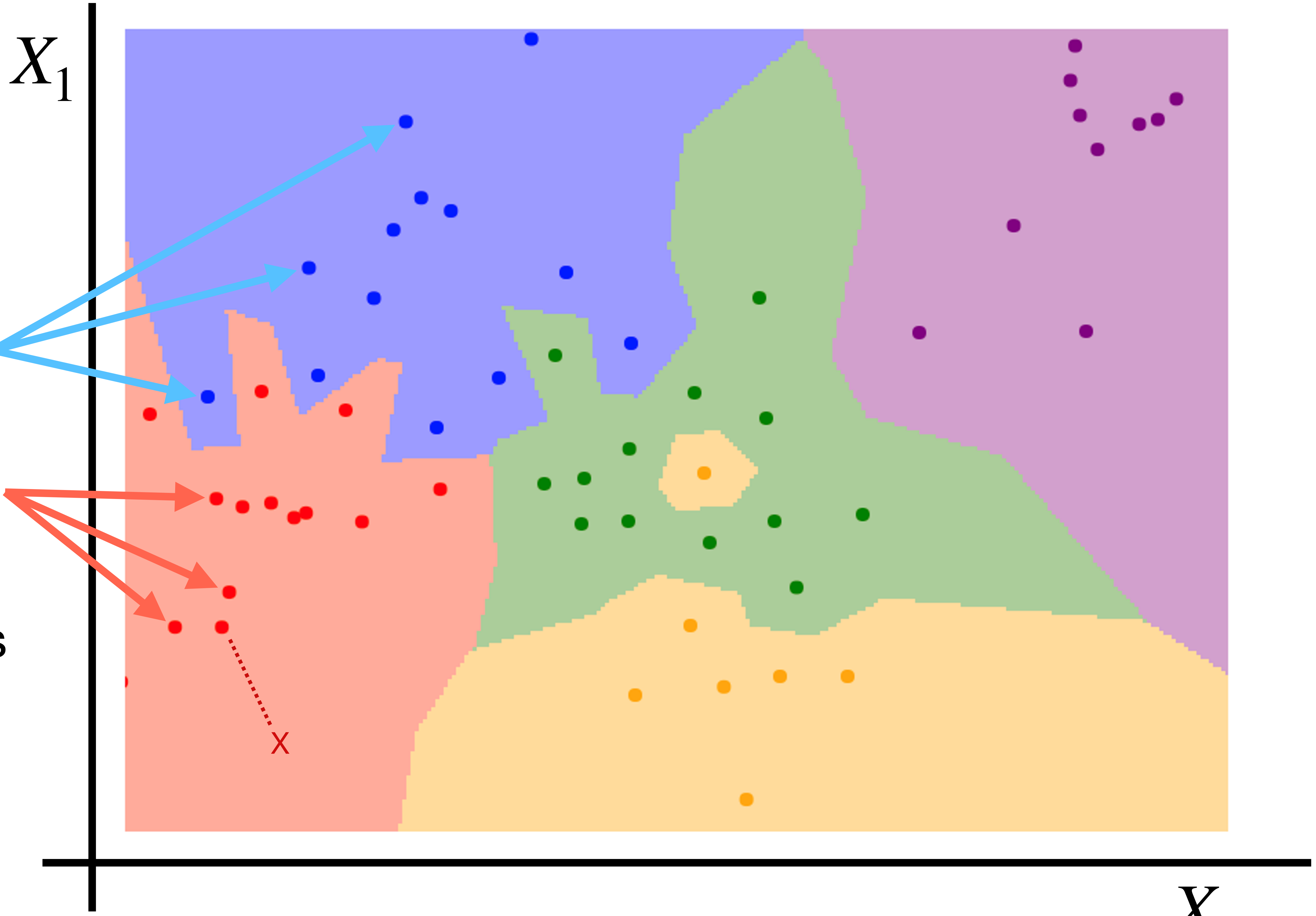


K-Nearest Neighbors Decision Boundaries

Nearest neighbors in two dimensions

Points are training examples; colors give training labels

Background colors give the category a test point would be assigned



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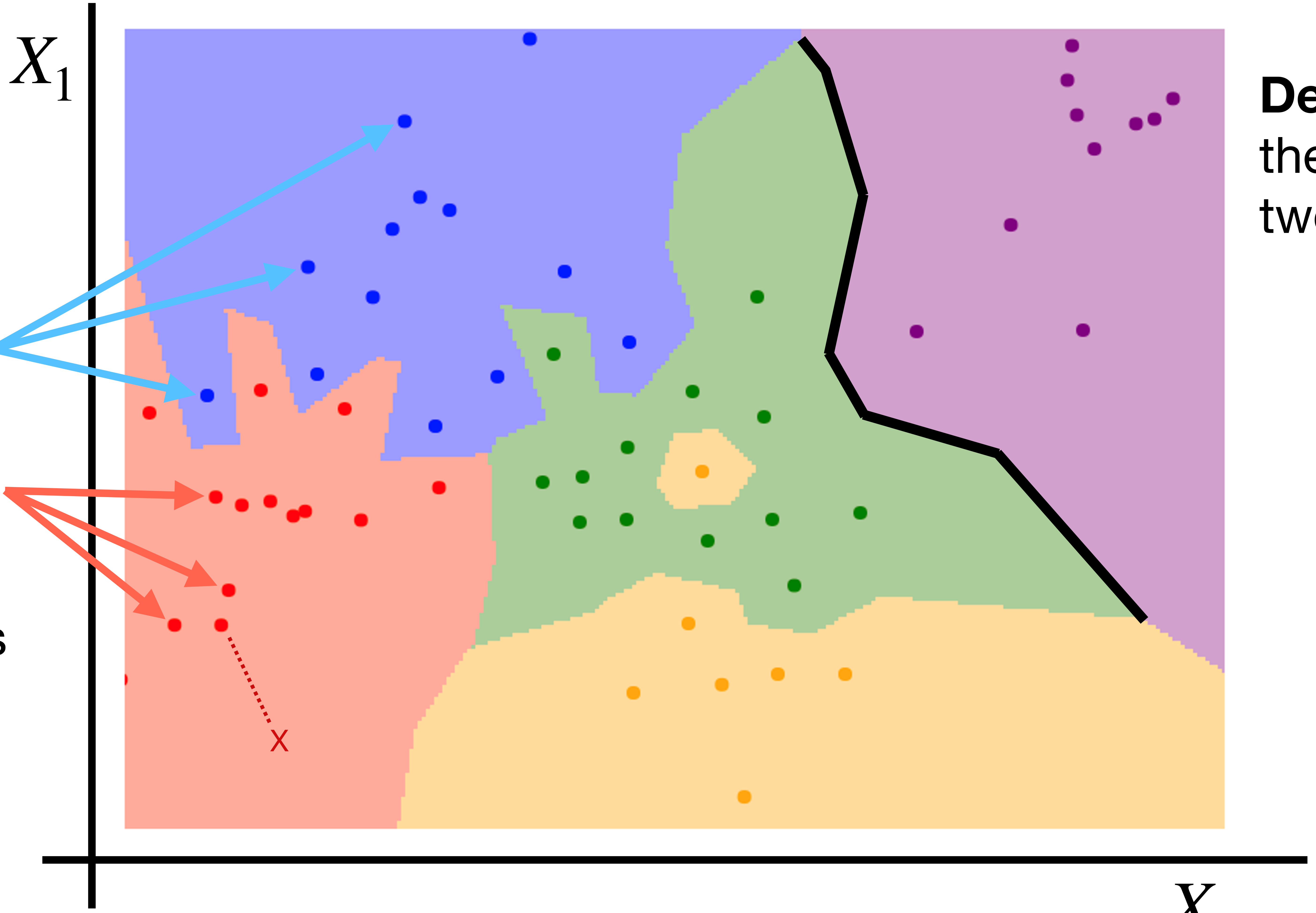

Decision boundary is the boundary between two classification regions

K-Nearest Neighbors Decision Boundaries

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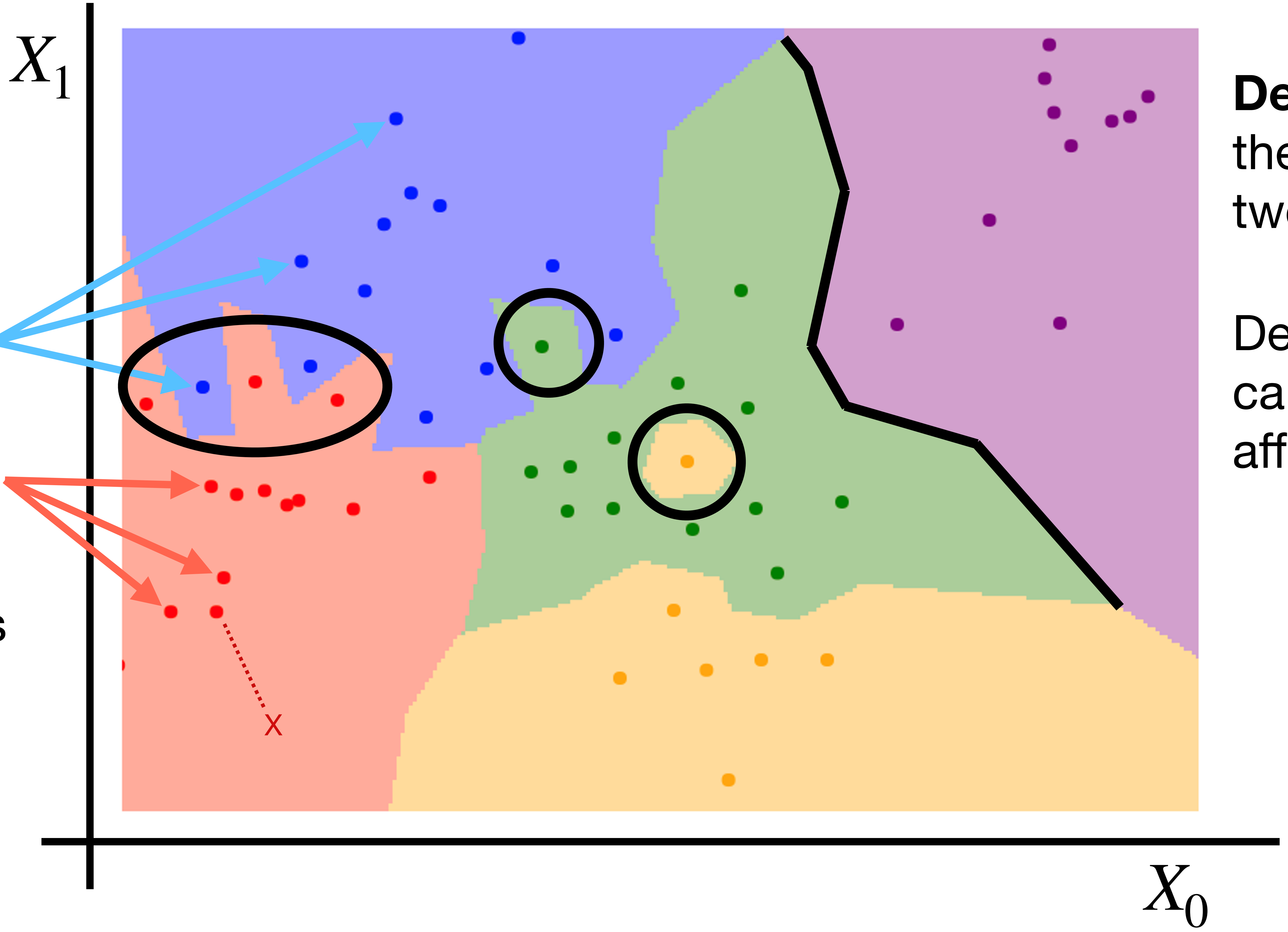

Decision boundary is the boundary between two classification regions

Decision boundaries can be noisy; affected by outliers

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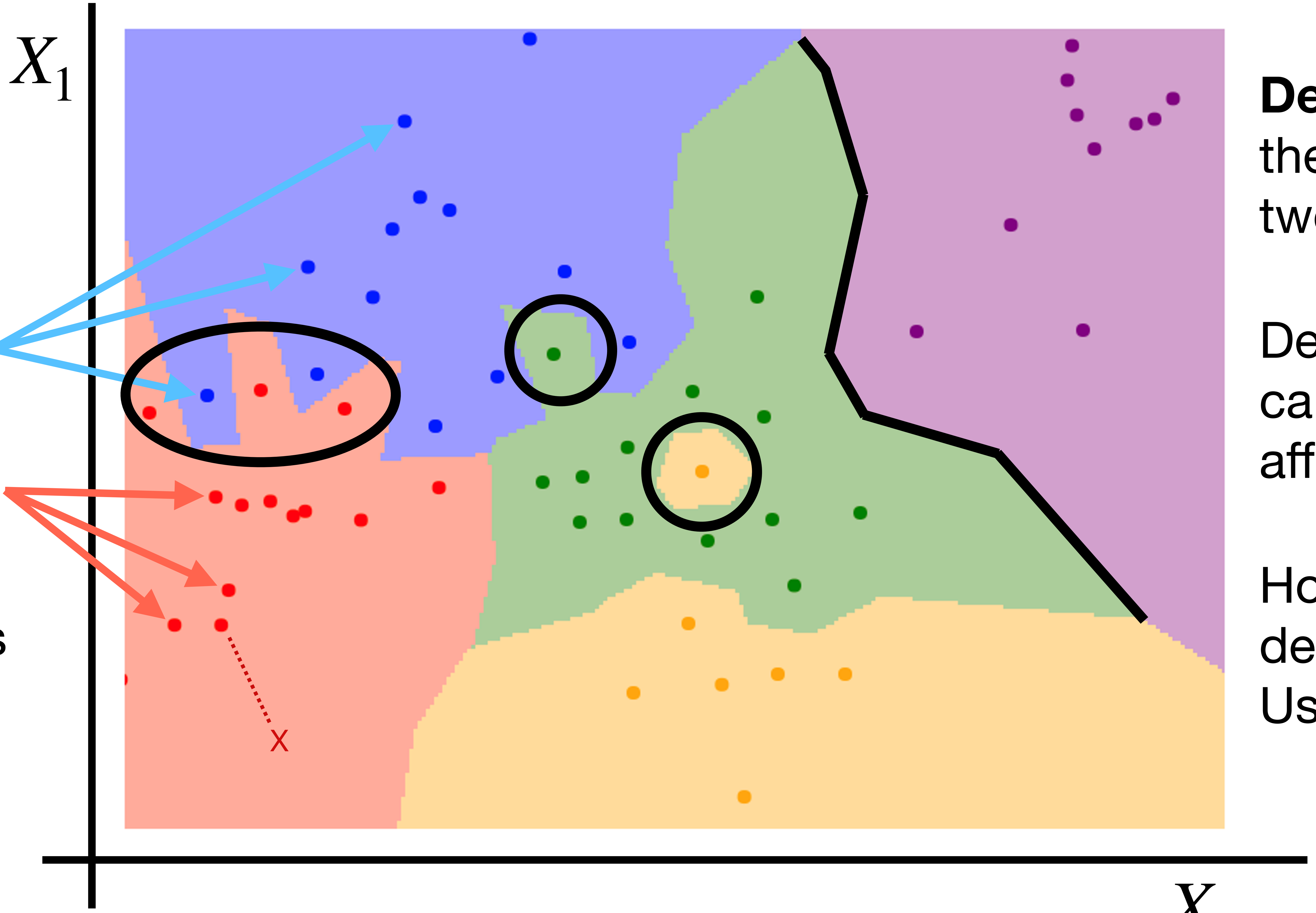


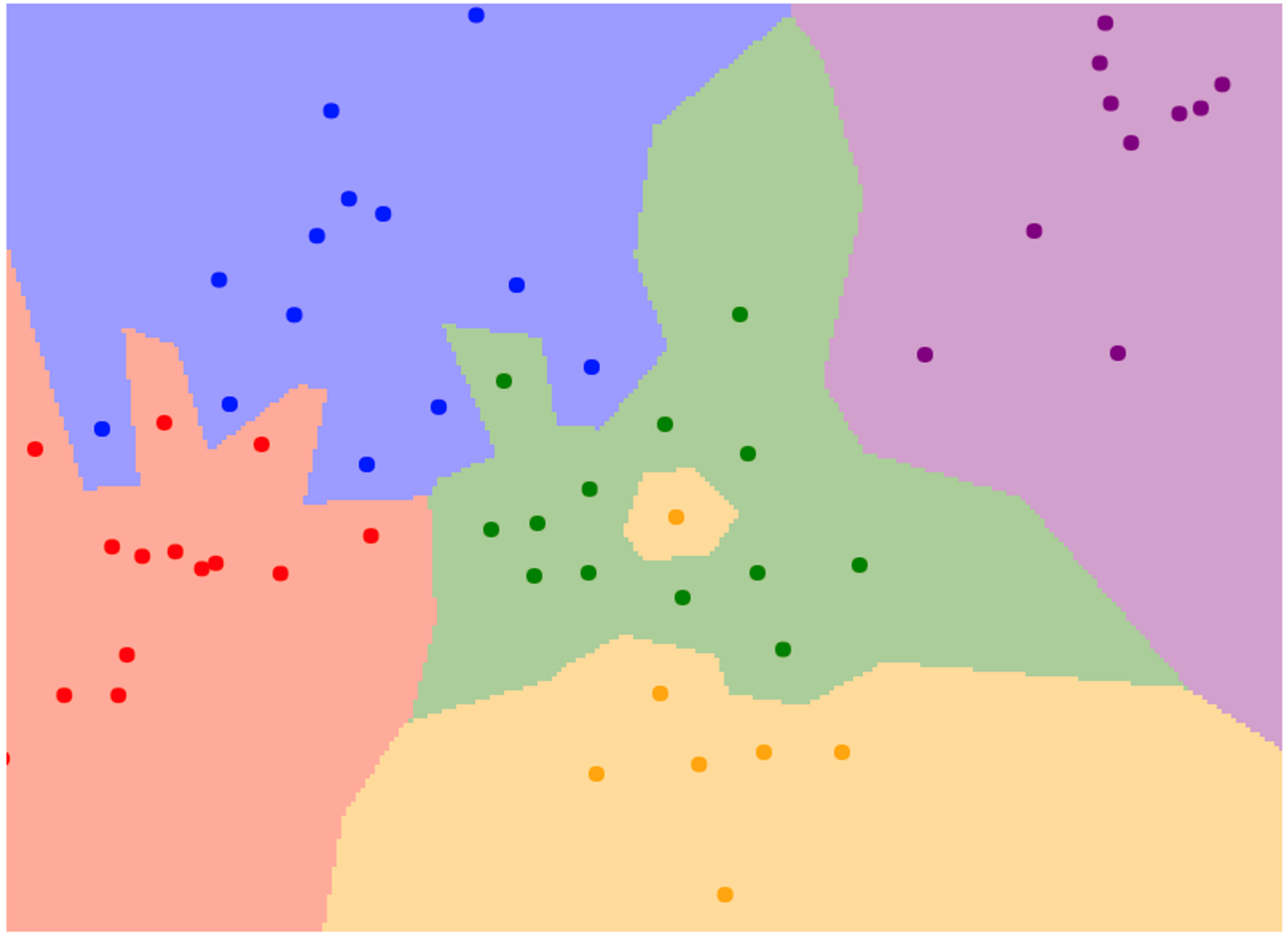
Decision boundary is the boundary between two classification regions

Decision boundaries can be noisy; affected by outliers

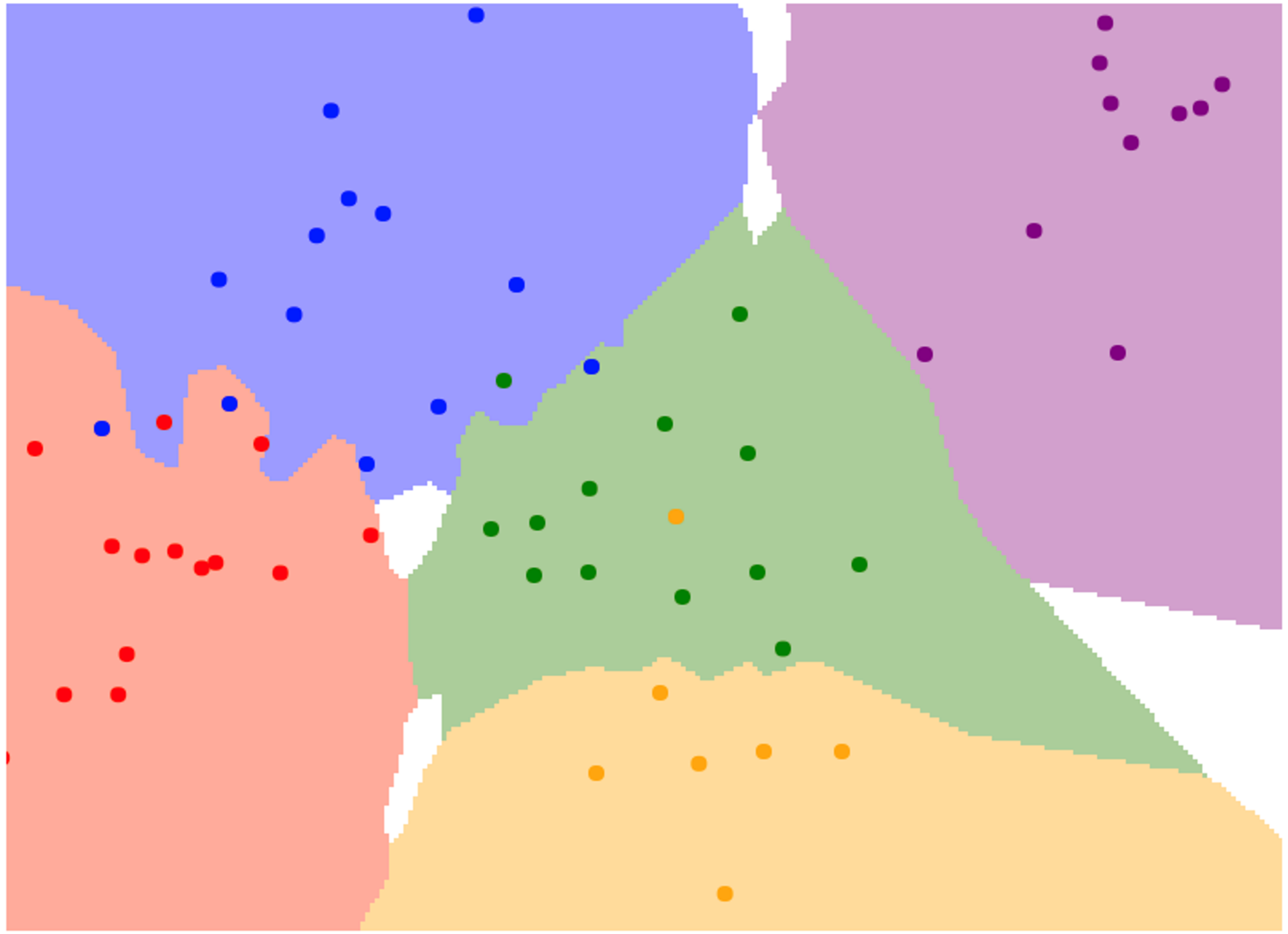
How to smooth the decision boundaries? Use more neighbors!

K-Nearest Neighbors Classification

$K = 1$



$K = 3$



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

K-Nearest Neighbors Classification

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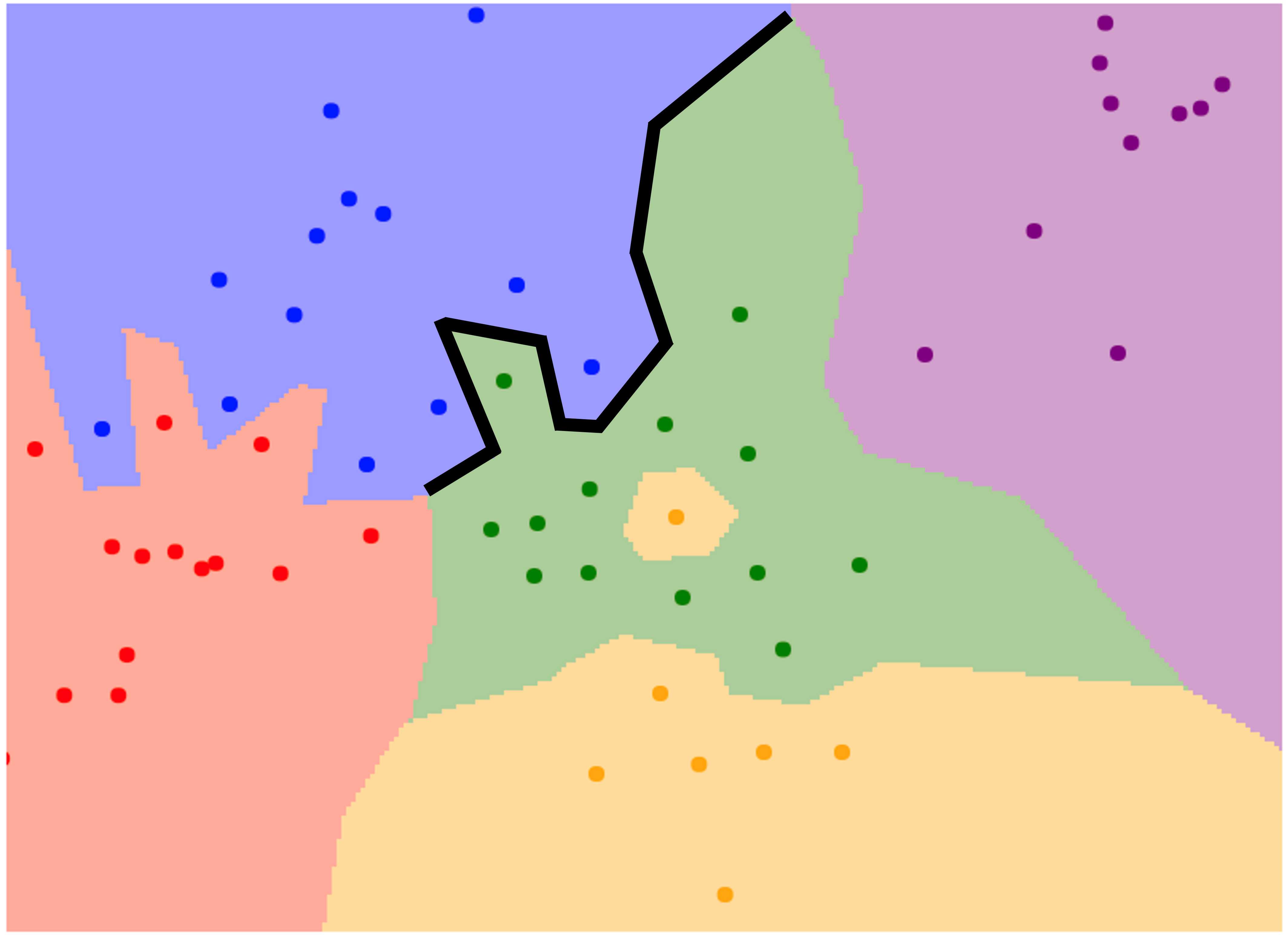

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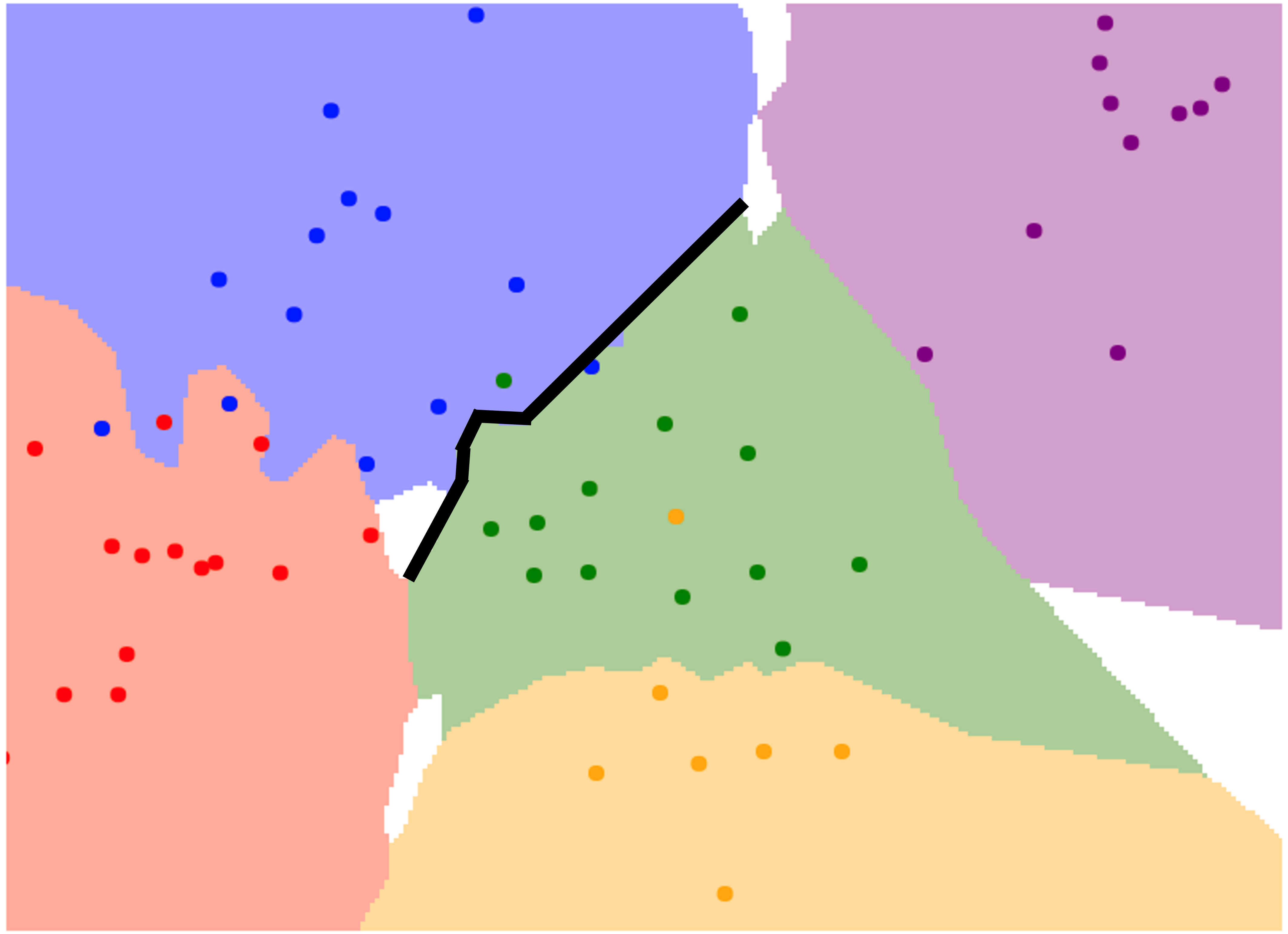

Using more neighbors helps smooth out rough decision boundaries

K-Nearest Neighbors Classification

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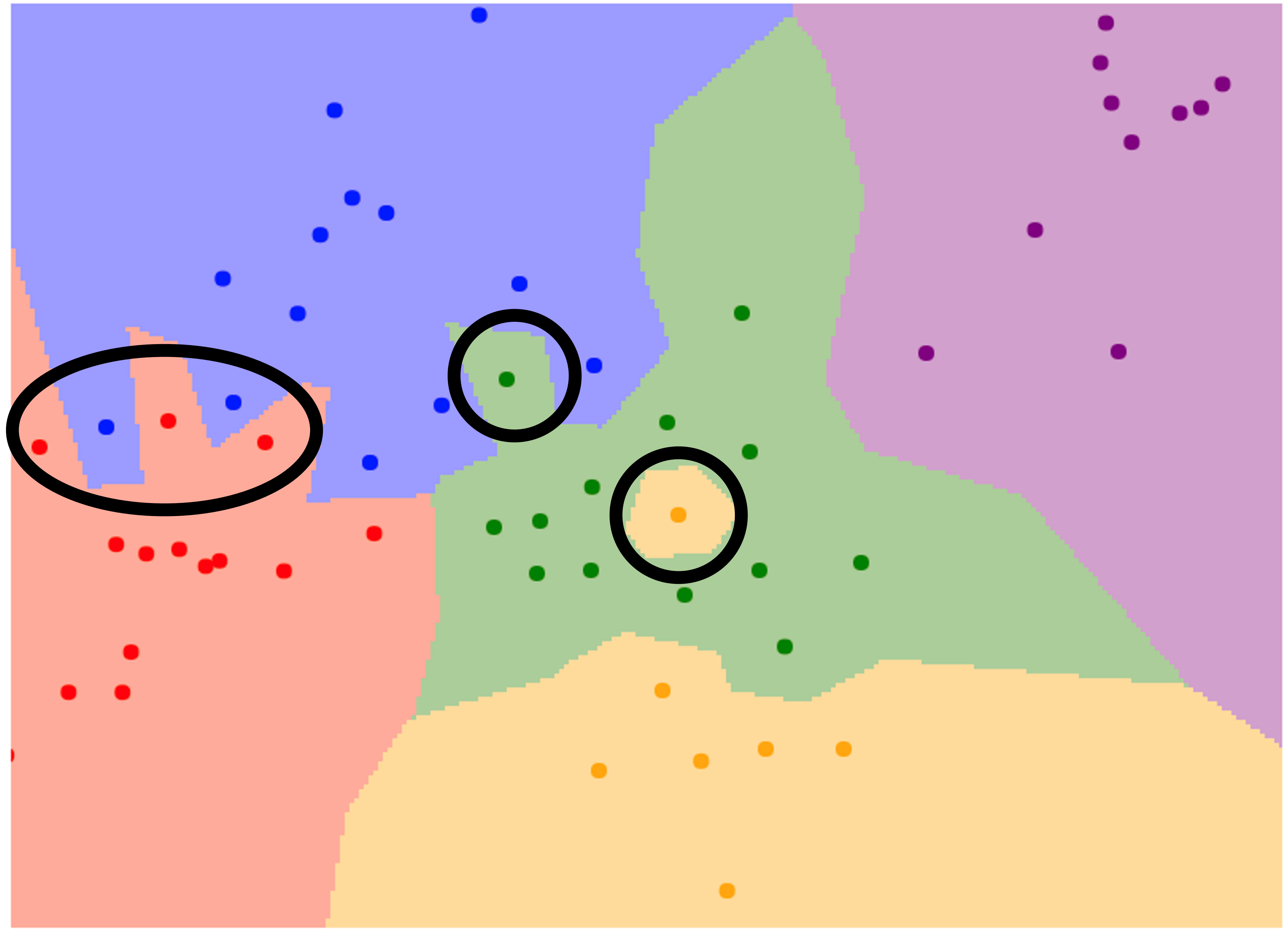

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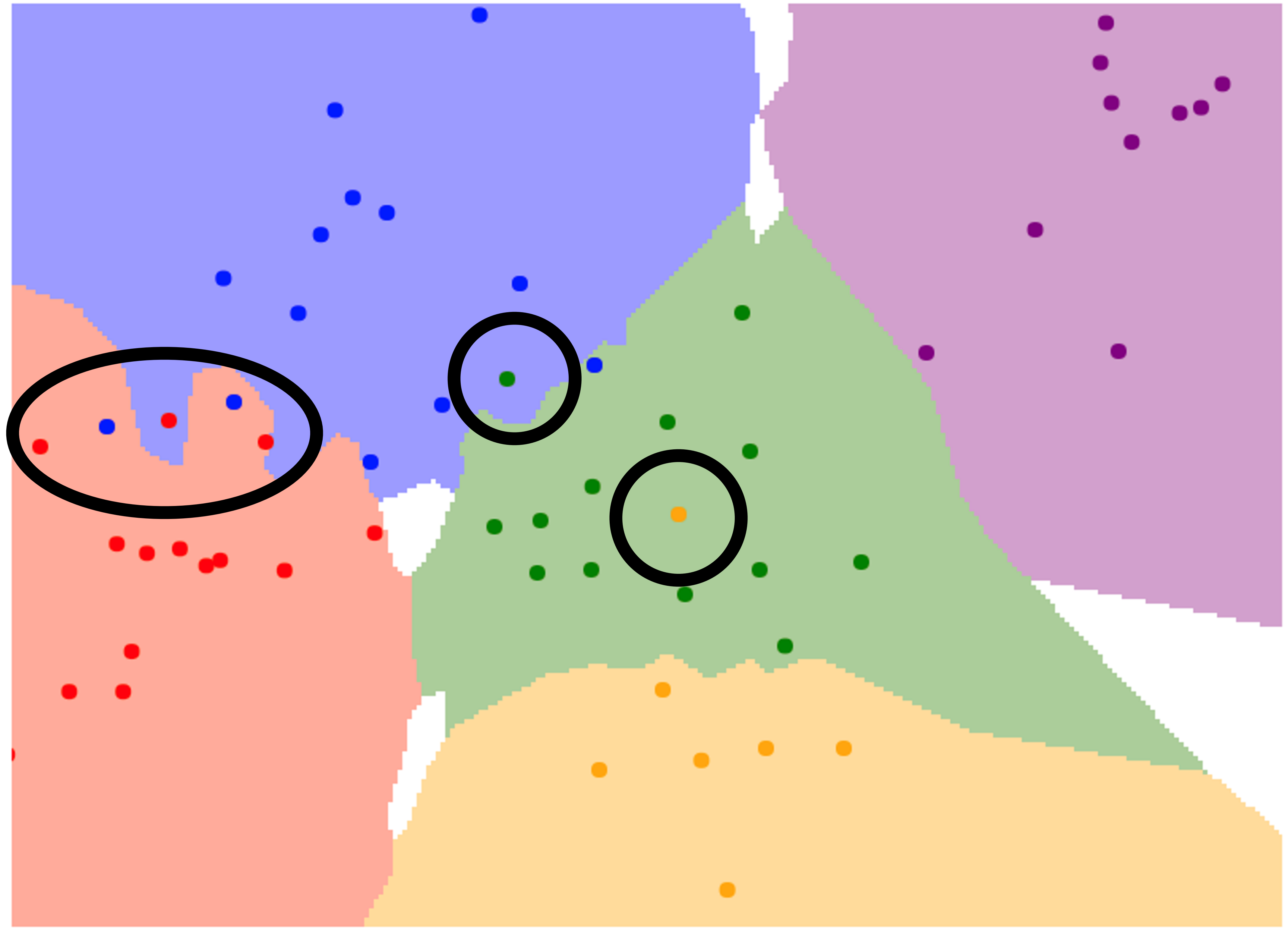
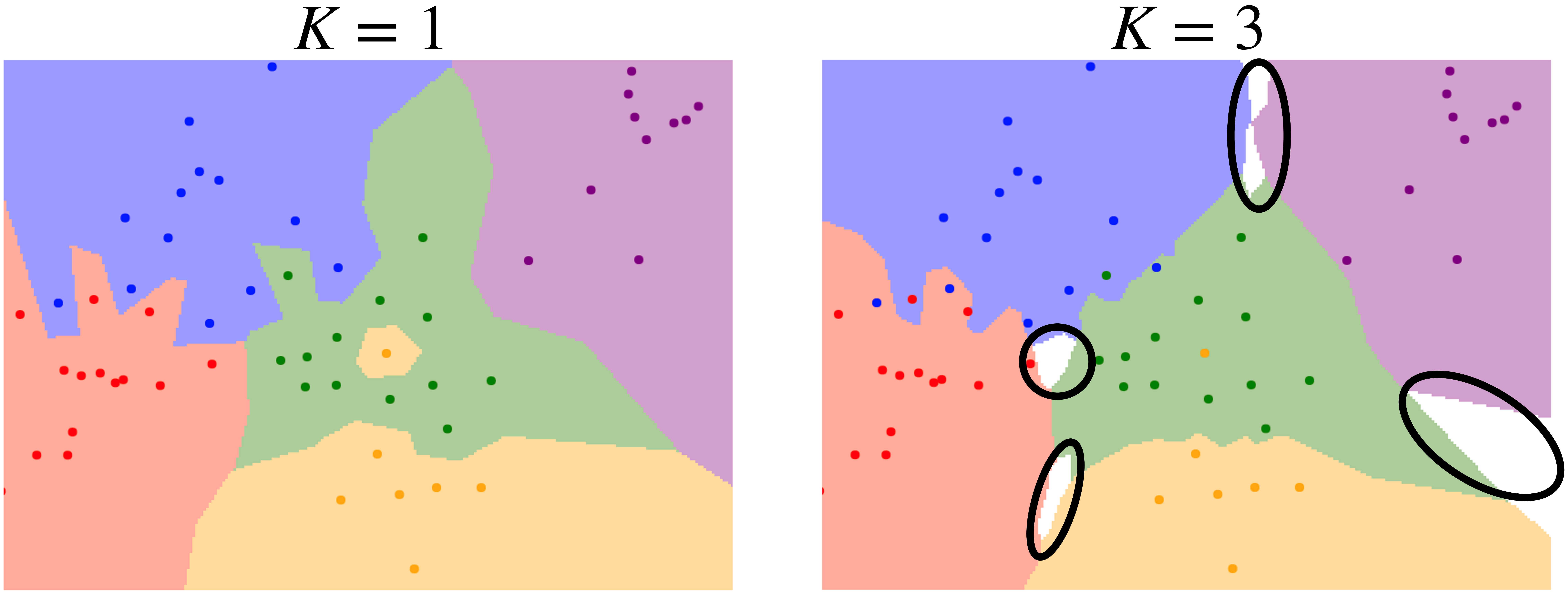


Using more neighbors helps reduce the effect of outliers

K-Nearest Neighbors Classification



When $K > 1$ there can be ties between classes.
Need to break ties somehow!

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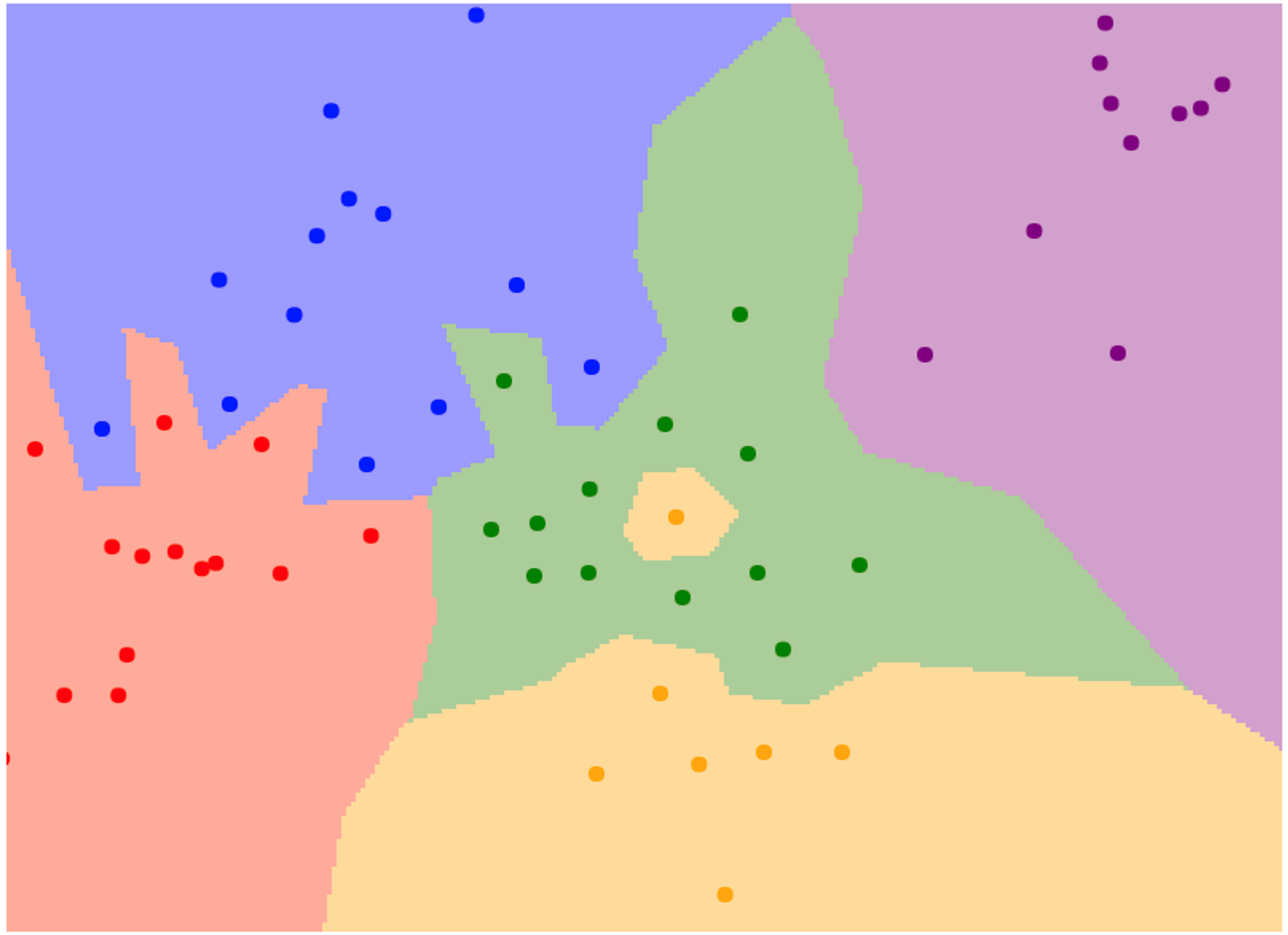

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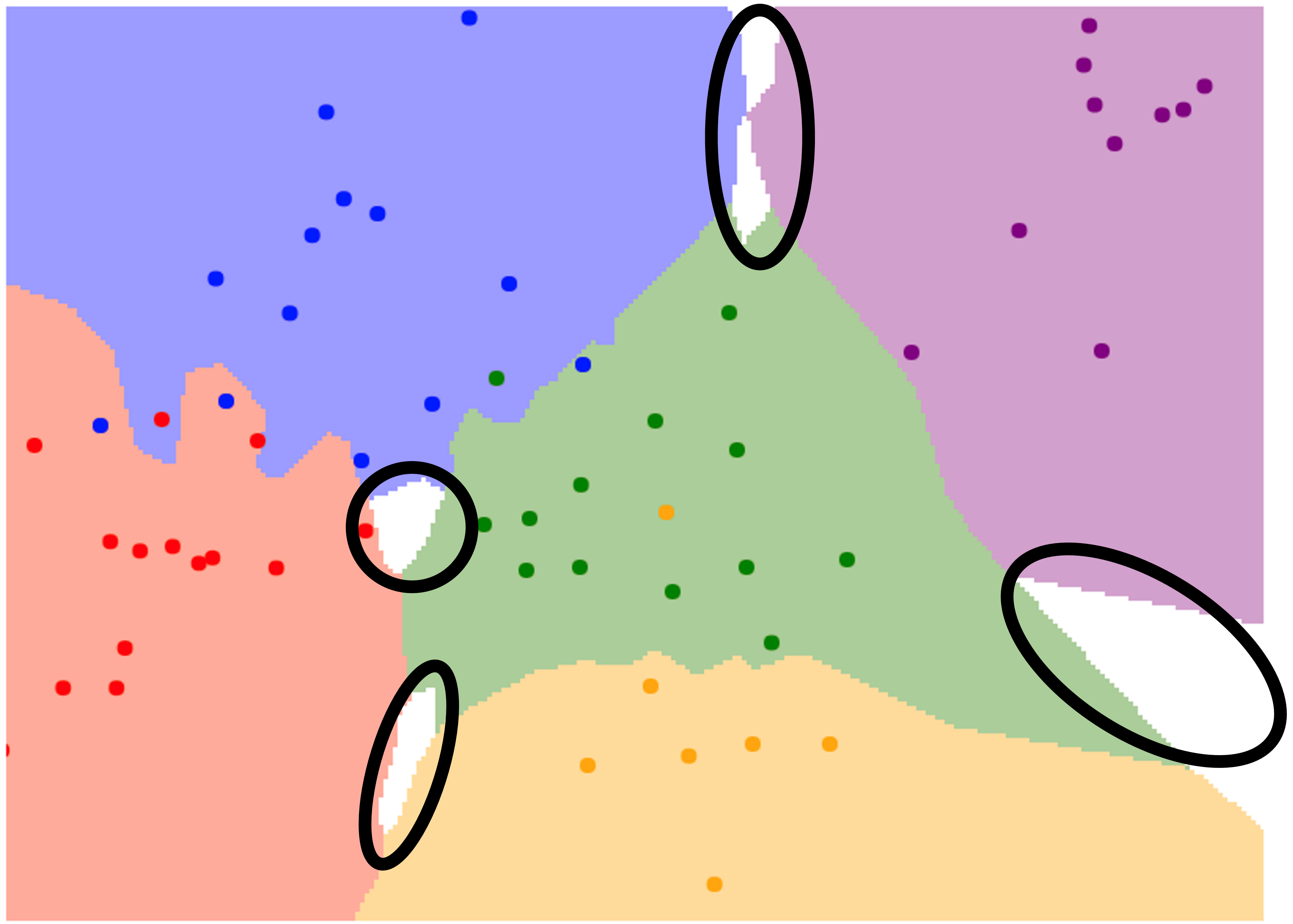

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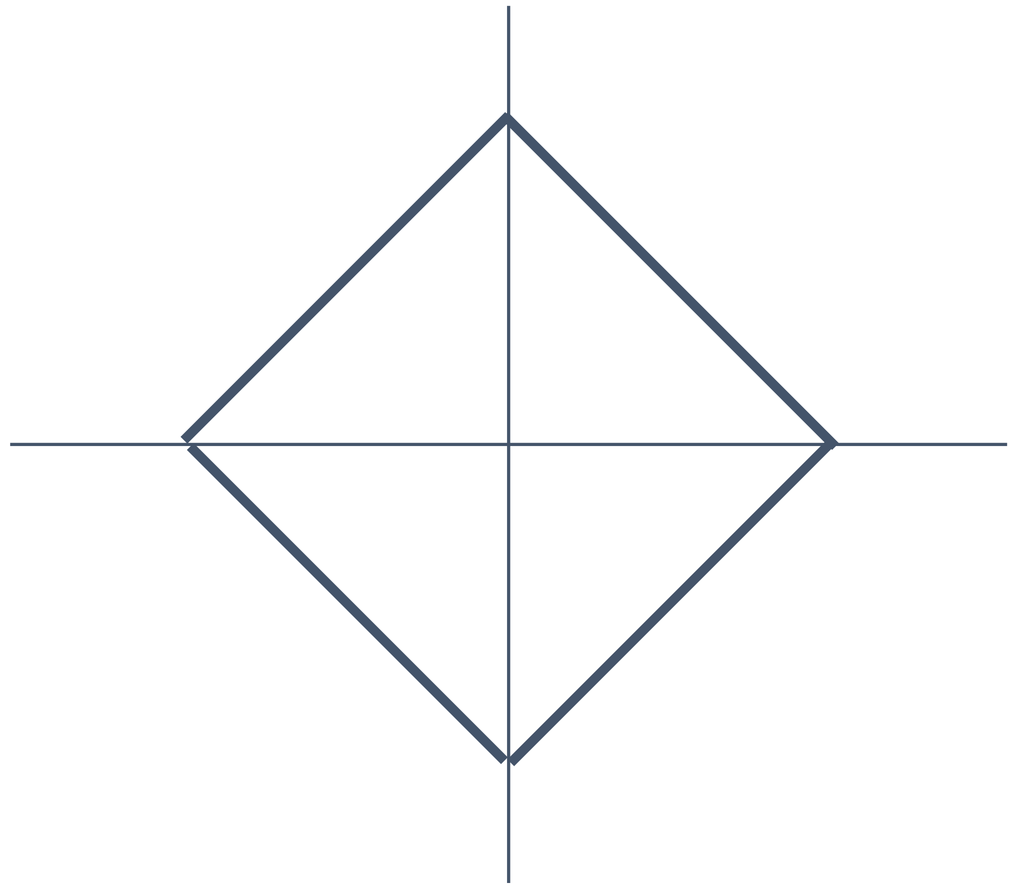
K-Nearest Neighbors—Distance Metric

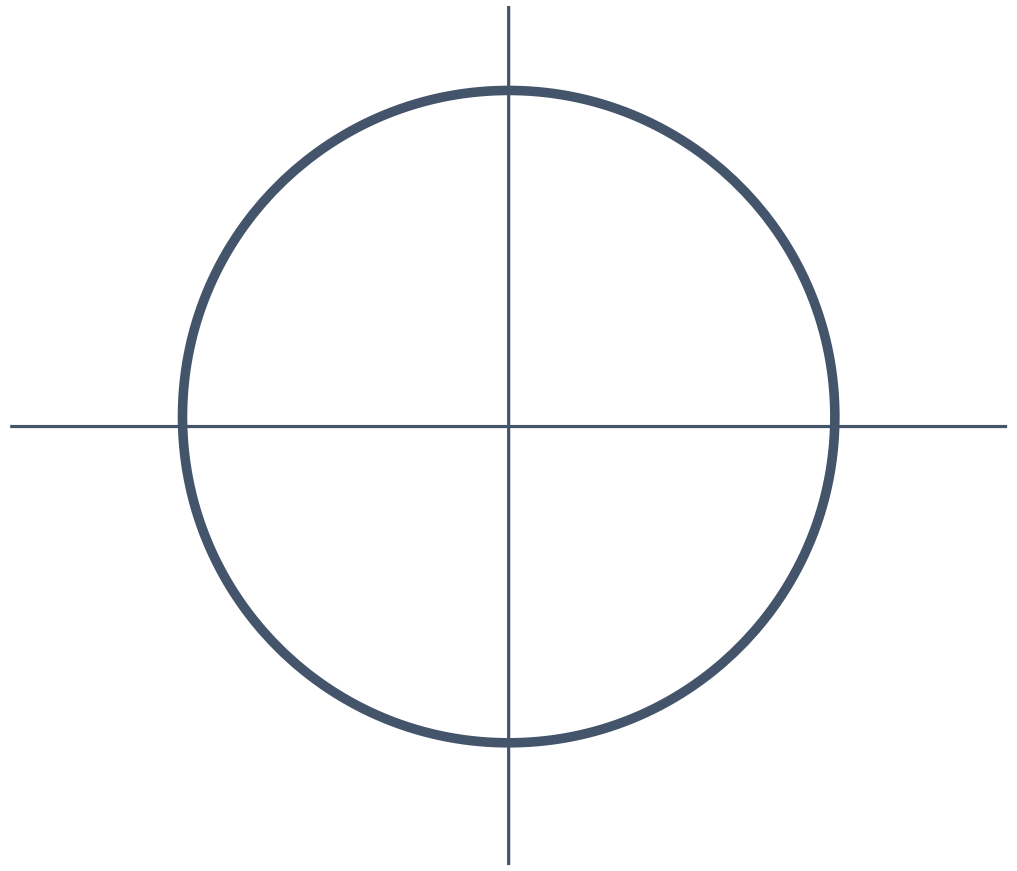
L1 (Manhattan) distance

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



L2 (Euclidean) distance

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



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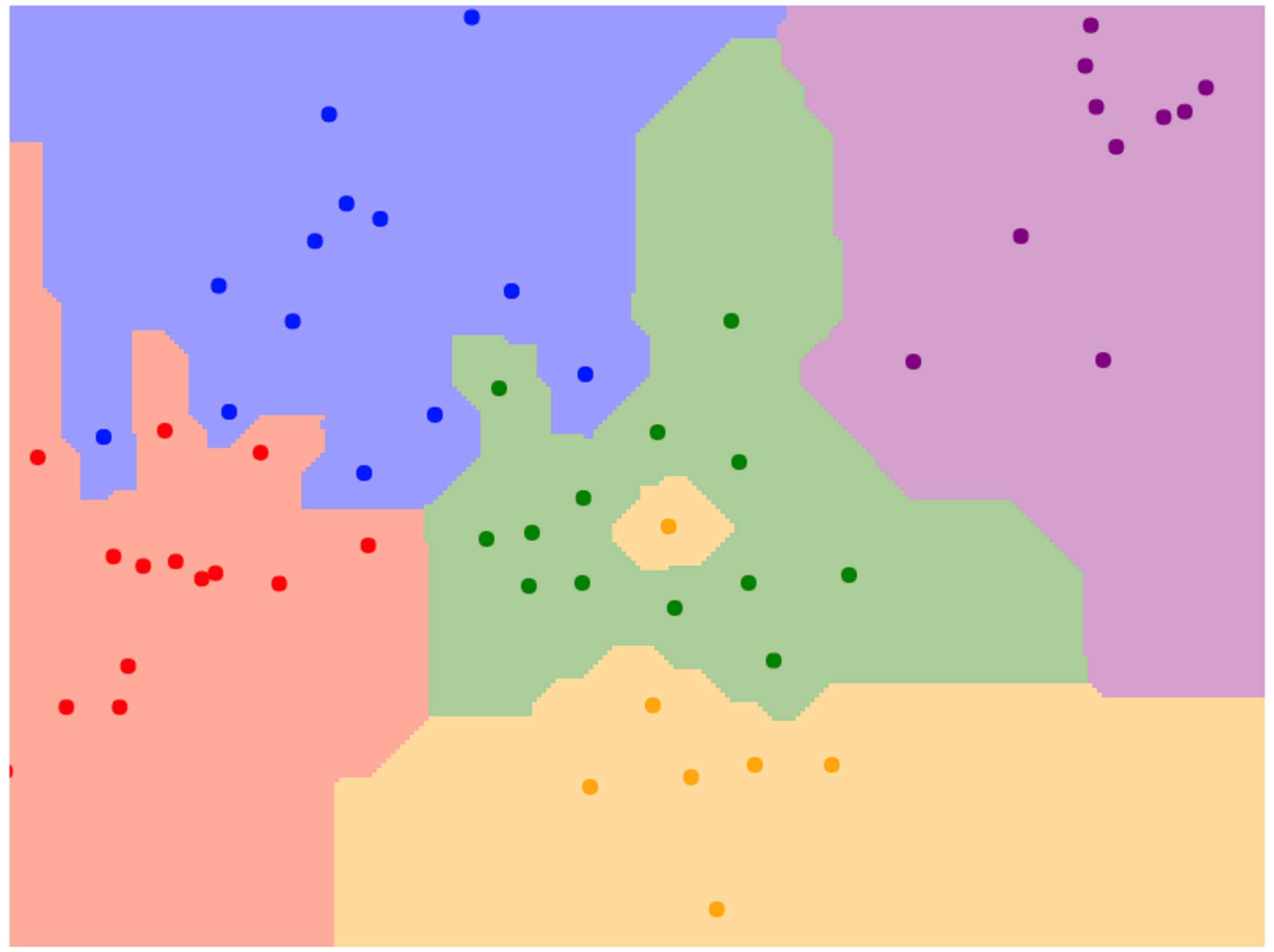

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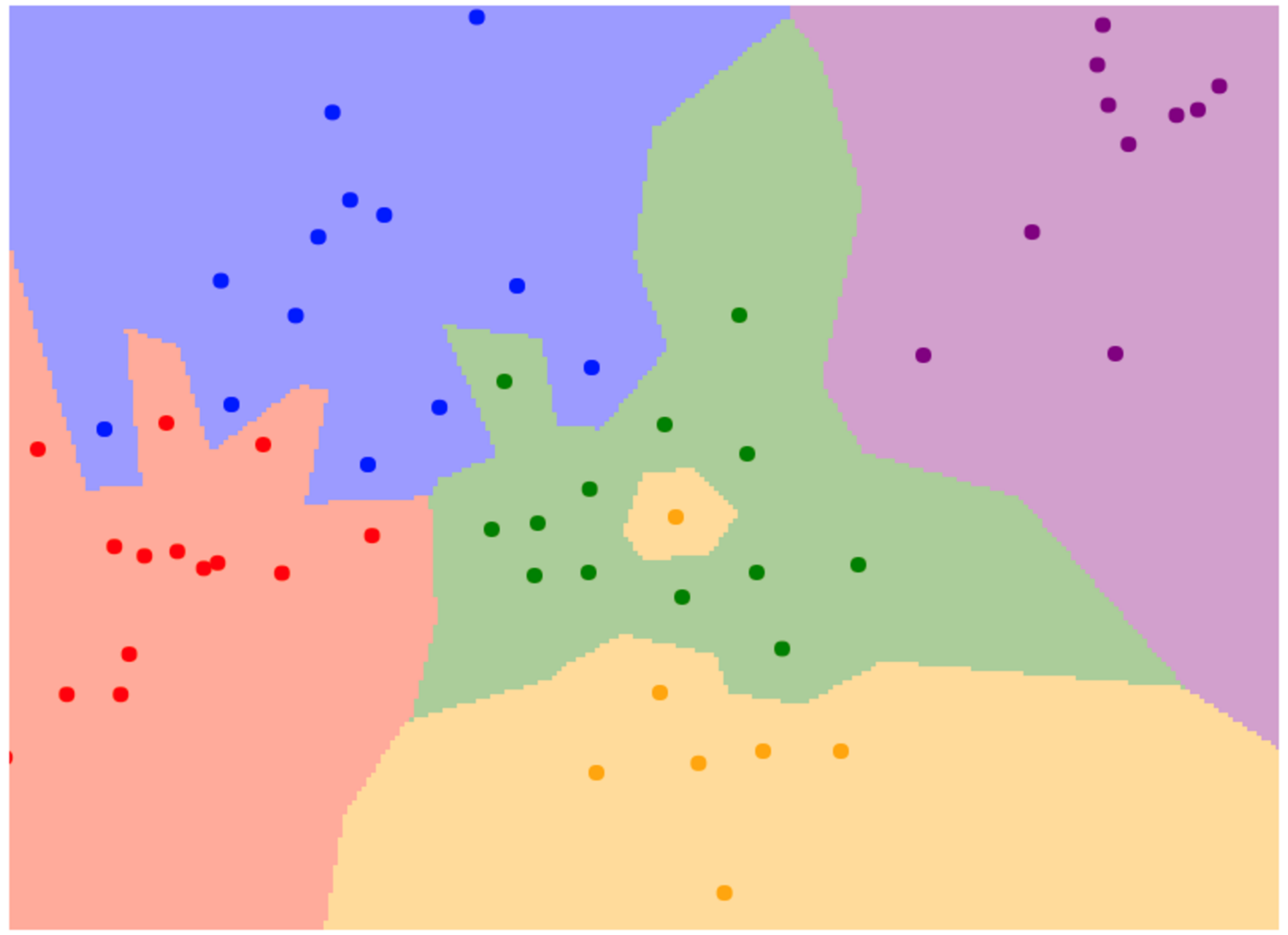


$K = 1$

K-Nearest Neighbors—Distance Metric

With the right choice of distance metric, we can apply K-Nearest Neighbors to any type of data!

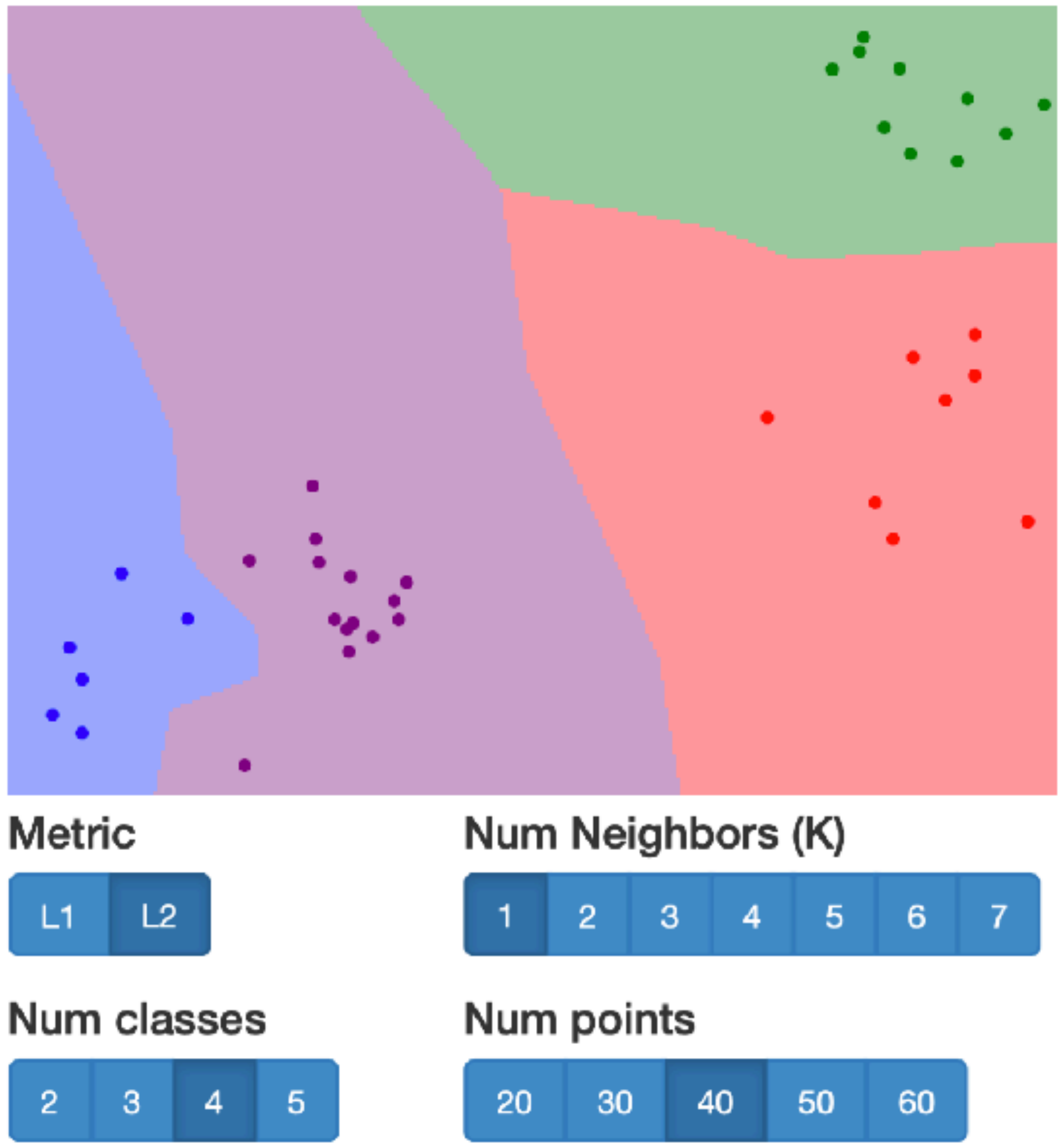
K-Nearest Neighbors—Web Demo

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/



Hyperparameters

What is the best value of K to use?

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

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

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 set them at the start of the learning process

Very problem-dependent.
In general 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

Your Dataset

Setting Hyperparameters

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BAD: K = 1 always works perfectly on training data

Your Dataset

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Your Dataset

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

train	test

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BAD: No idea how algorithm will perform on new data

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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

train	test

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

Better!

train	validation	test

Setting Hyperparameters

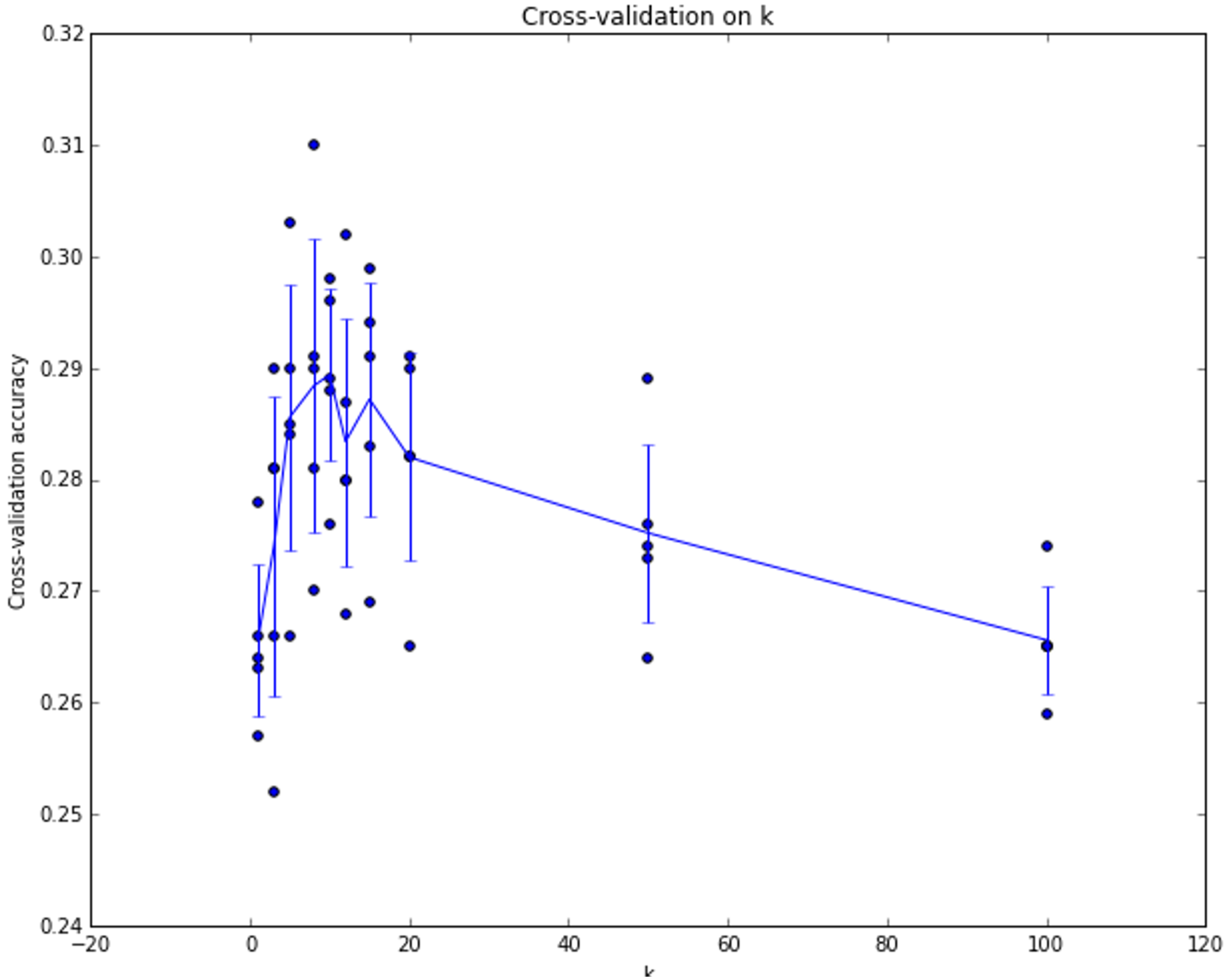
Your Dataset

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



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)

K-Nearest Neighbors—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.

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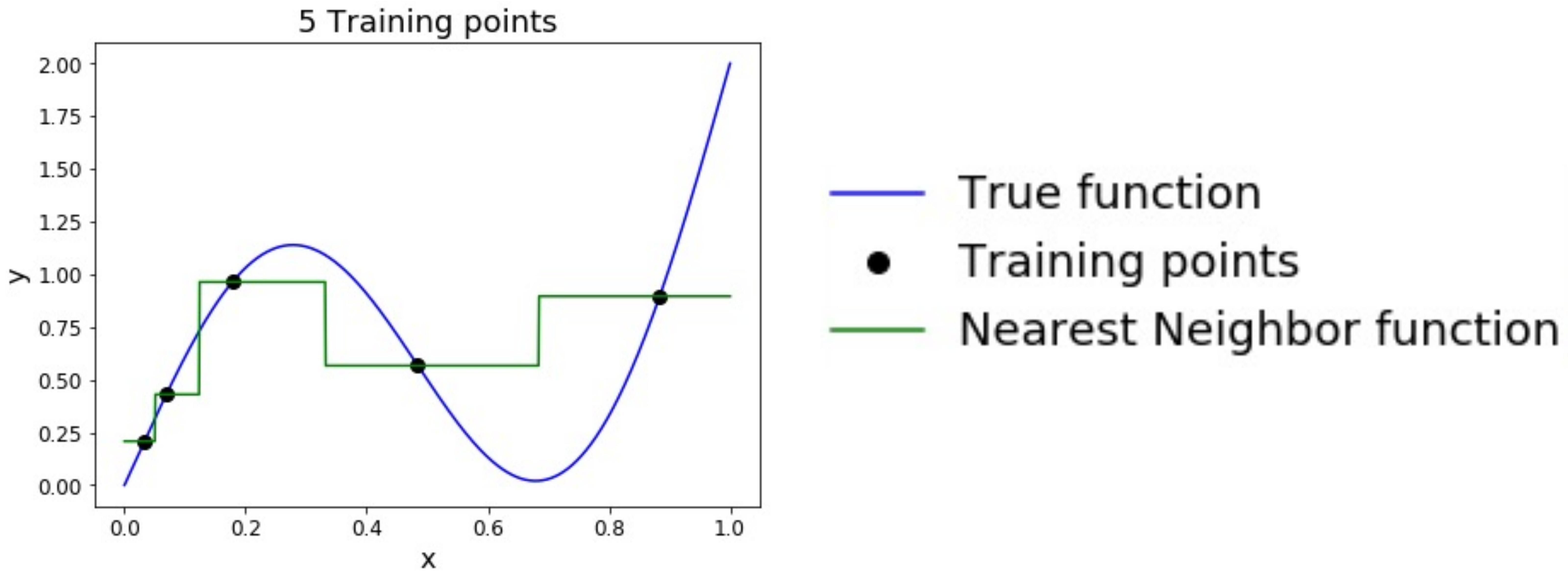

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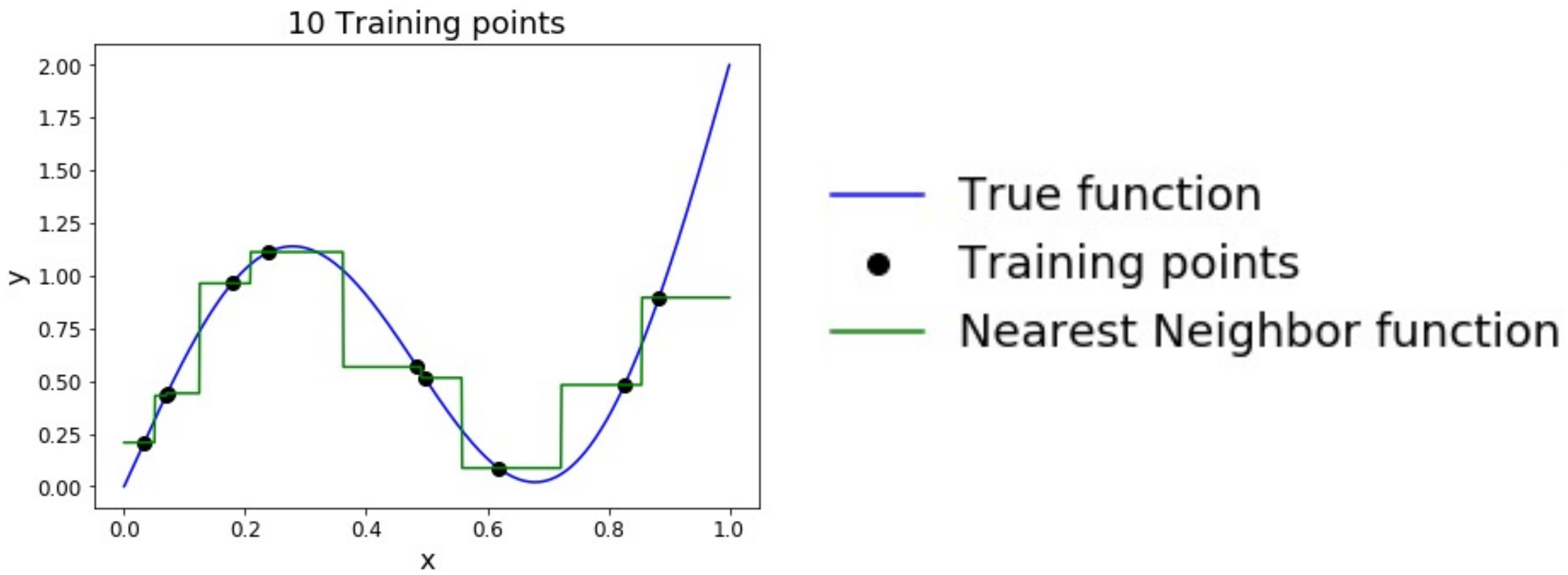

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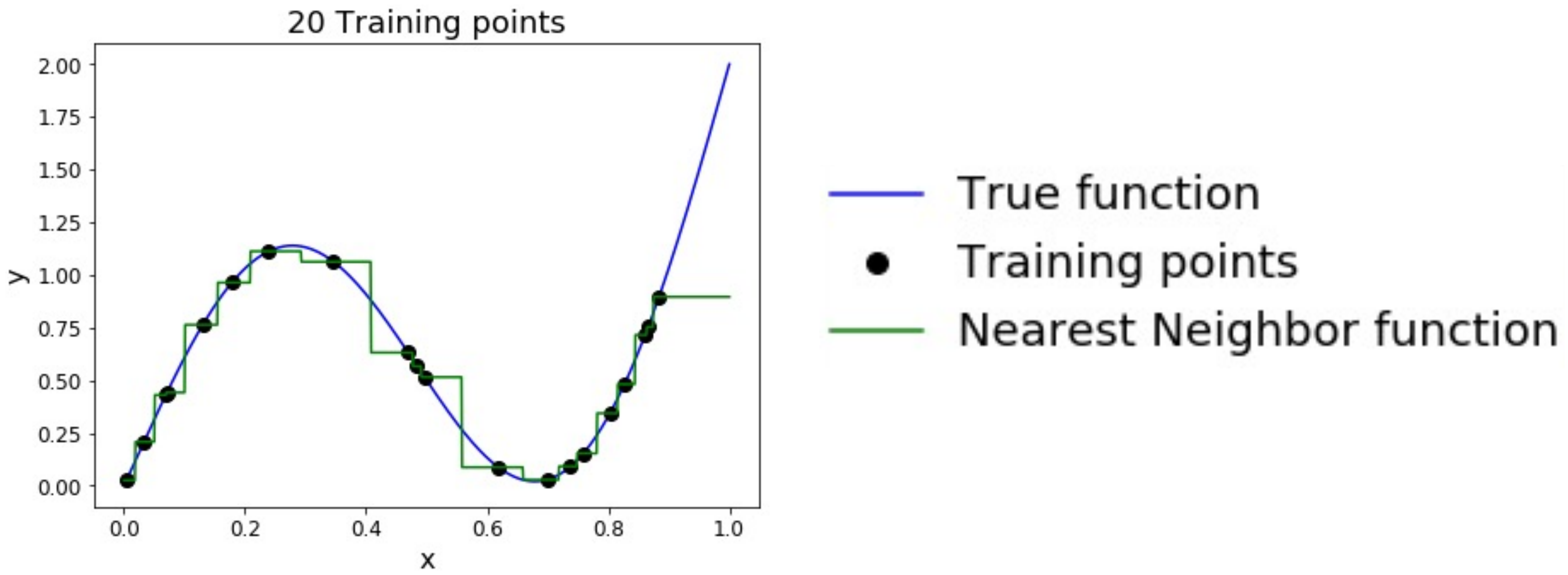

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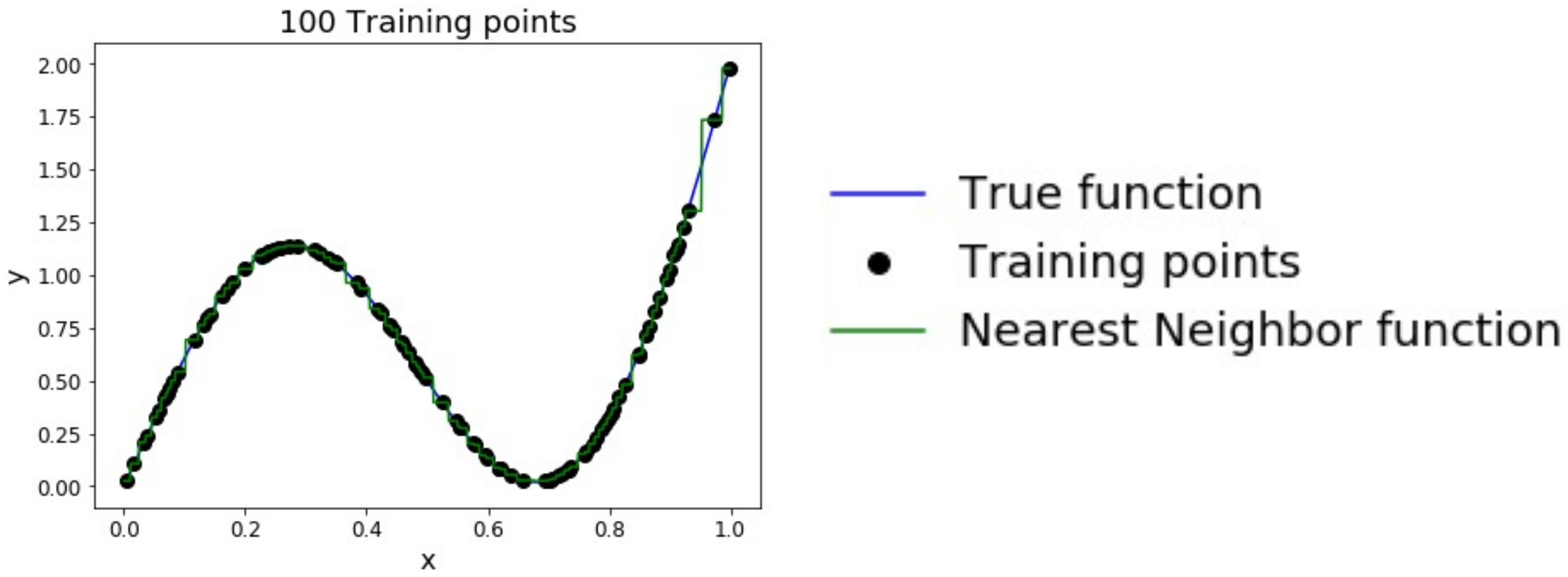

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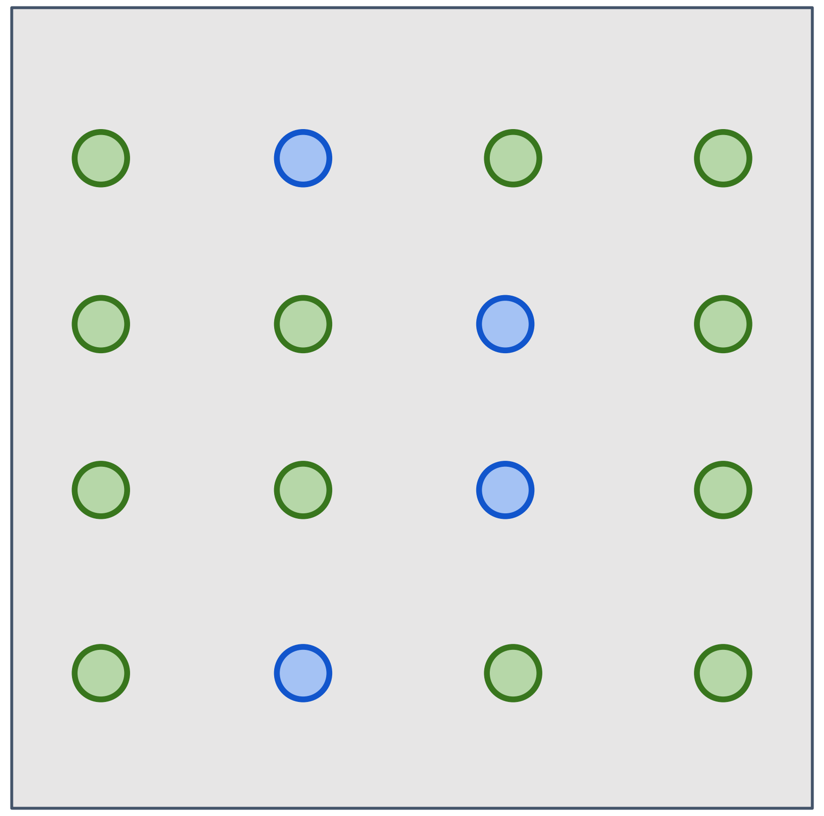
Problem—Curse of Dimensionality

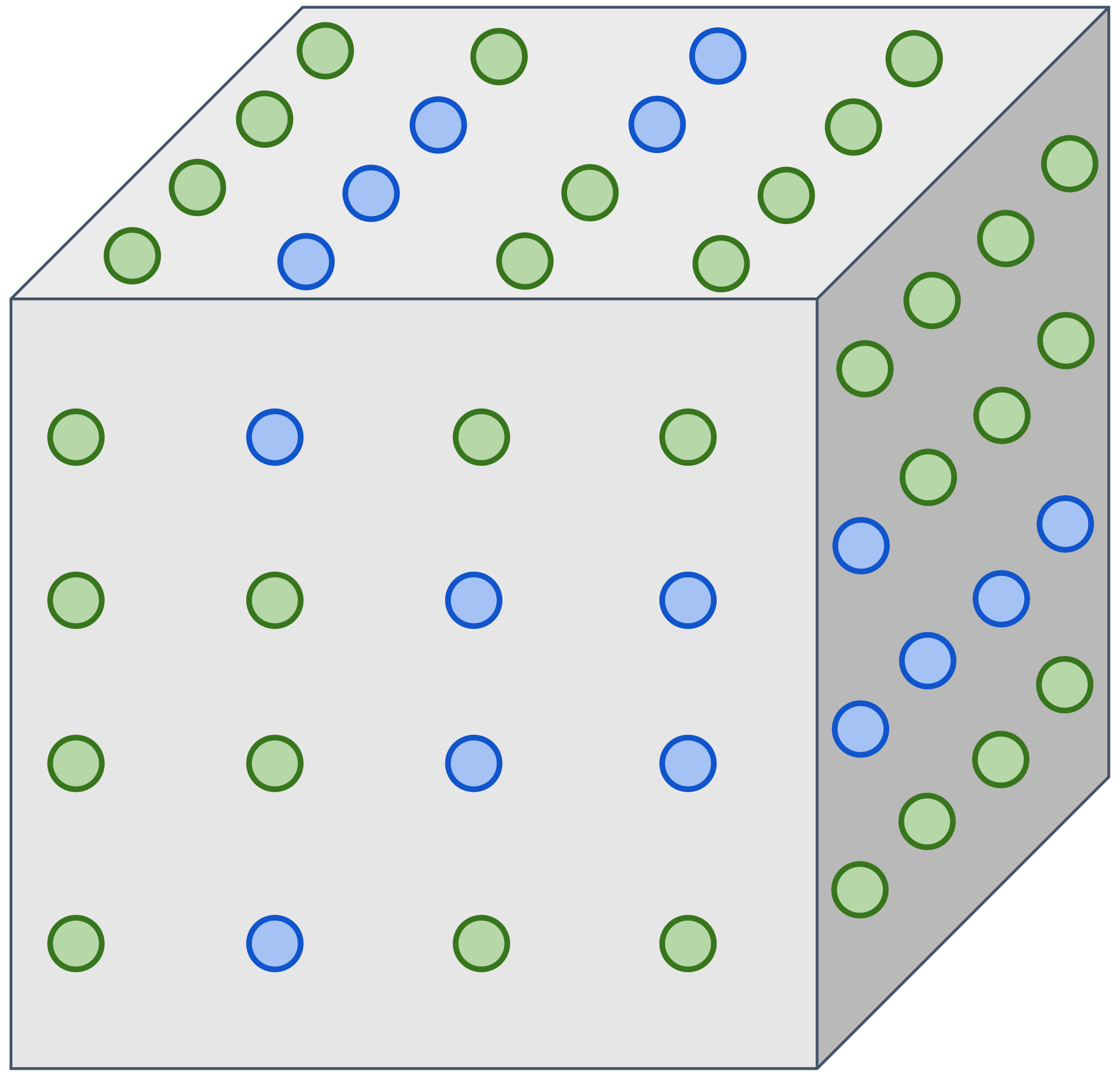
Curse of dimensionality: For uniform coverage of space, number of training points needed grows exponentially with dimension

Dimensions = 1
Points = 4

Dimensions = 2
Points = 4^2



Dimensions = 3
Points = 4^3



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Number of possible
32x32 binary images

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

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Number of possible 32x32 binary images

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

Number of elementary particles in the visible source

$$\approx 10^{97}$$

K-Nearest Neighbors Seldom Used on Raw Pixels

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

Original | Boxed | Shifted | Tinted

All 3 images have same L2 distance to the original

K-Nearest Neighbors with Convent 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.

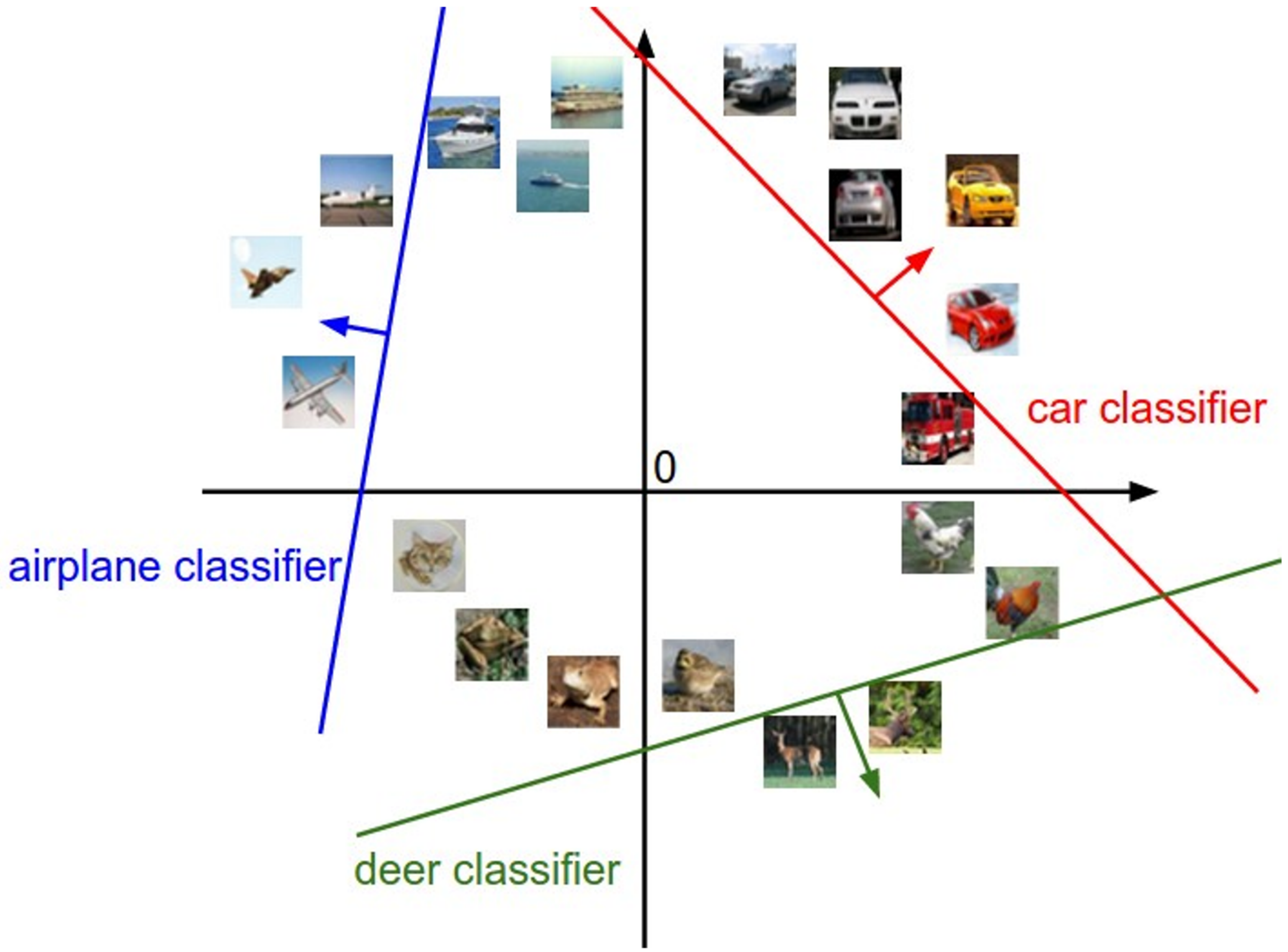
Image classification is a **building block** for other vision tasks

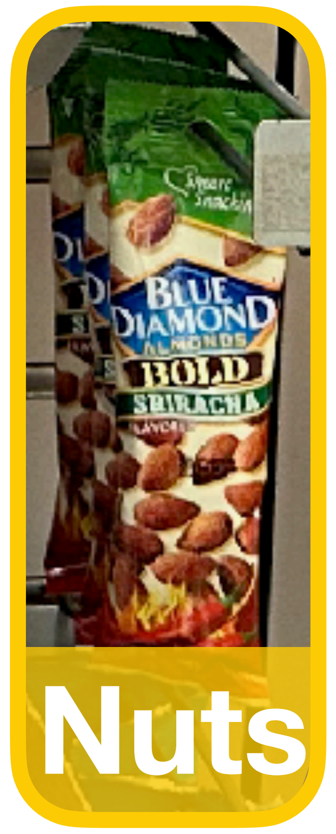
The **K-Nearest Neighbors** classifier predicts labels from nearest training samples

Distance metric and K are **hyperparameters**

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

Next time: Linear Classifiers





DeepRob

Lecture 2
Image Classification
University of Michigan and University of Minnesota