MAI4CAREU Master programmes in Artificial Intelligence 4 Careers in Europe

University of Cyprus

University of Cyprus

MAI645 - Machine Learning for Graphics and Computer Vision

Andreas Aristidou, PhD

Spring Semester 2023

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Image Classification & Object Detection

Notes have been prepared in collaboration with **Ms. Asfa Jamil**

Research Associate at Deep Camera MRG, CYENS CoE

Deep Camera

CYENS CENTRE OF EXCELLENCE

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Image Classification

Image Classification is a fundamental task in computer vision where a model is trained to assign a specific label or class to an input image.

It involves training a model on a large dataset of images, each labeled with a specific class, and then using that model to make predictions on new, unseen images.

The goal is for the model to accurately categorize the images into their respective classes.

Image classification is used in a variety of applications, such as object recognition, scene understanding, and image retrieval.

Classification

CAT

Image Classification

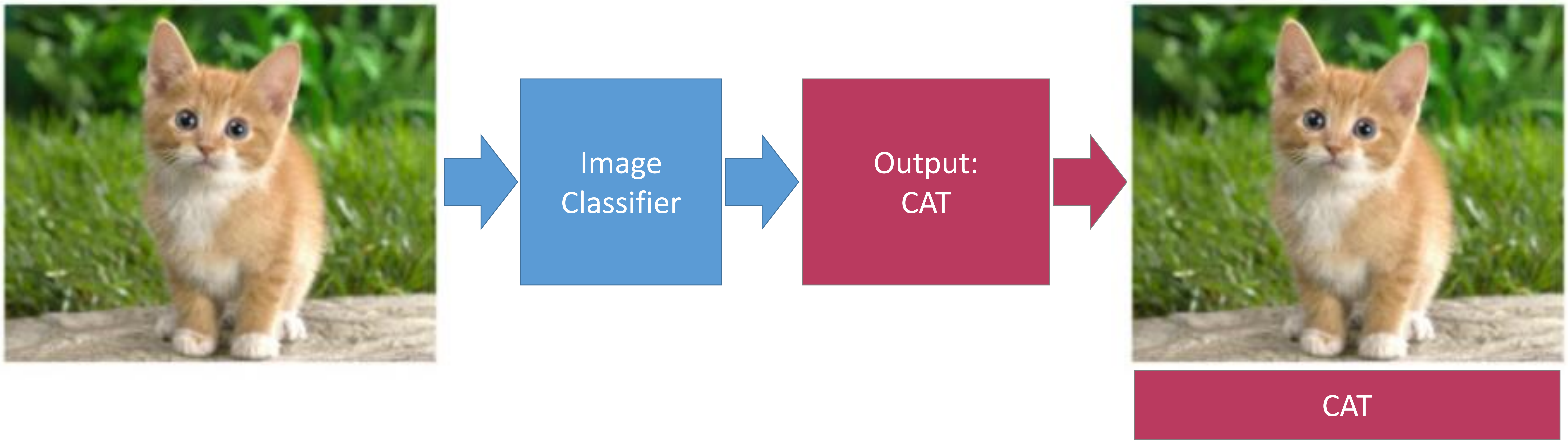


Image Classification

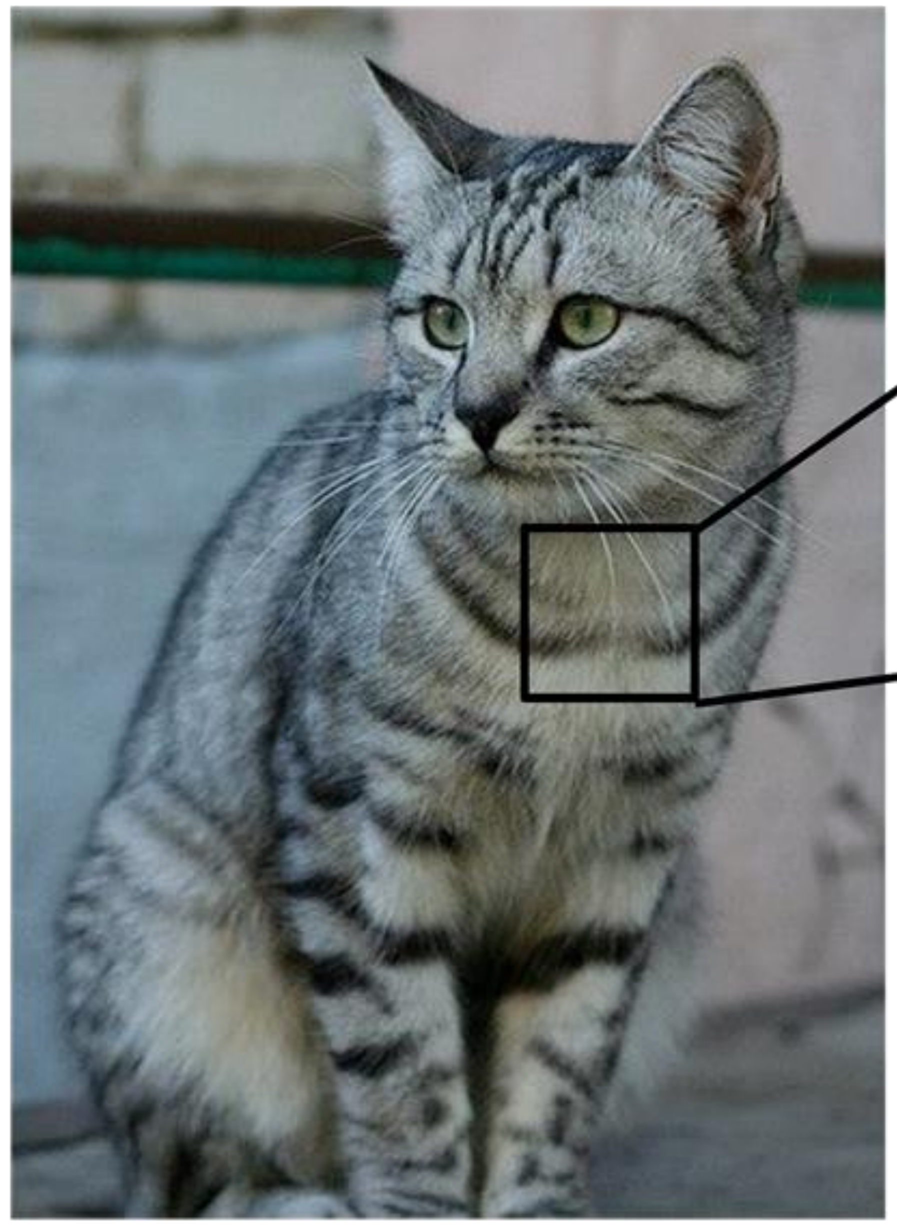
Image Classification: A core task in Computer Vision

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

→ cat

Image Classification

The Problem: Semantic Gap



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```

What the computer sees

An image is a tensor of integers between [0, 255]:

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

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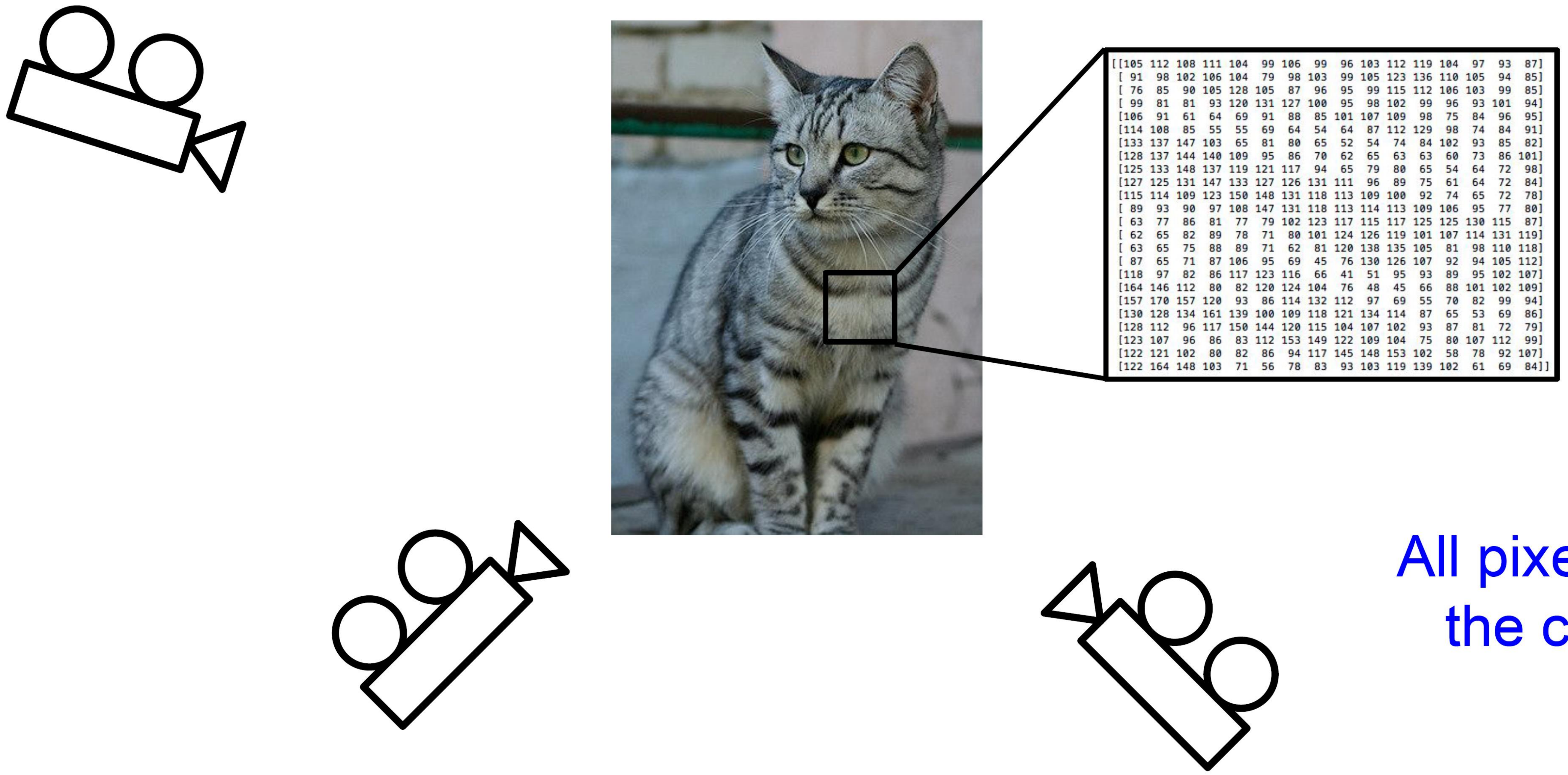
Image Classification

Challenges: Viewpoint variation



All pixels change when
the camera moves!

Image Classification

Challenges: Illumination

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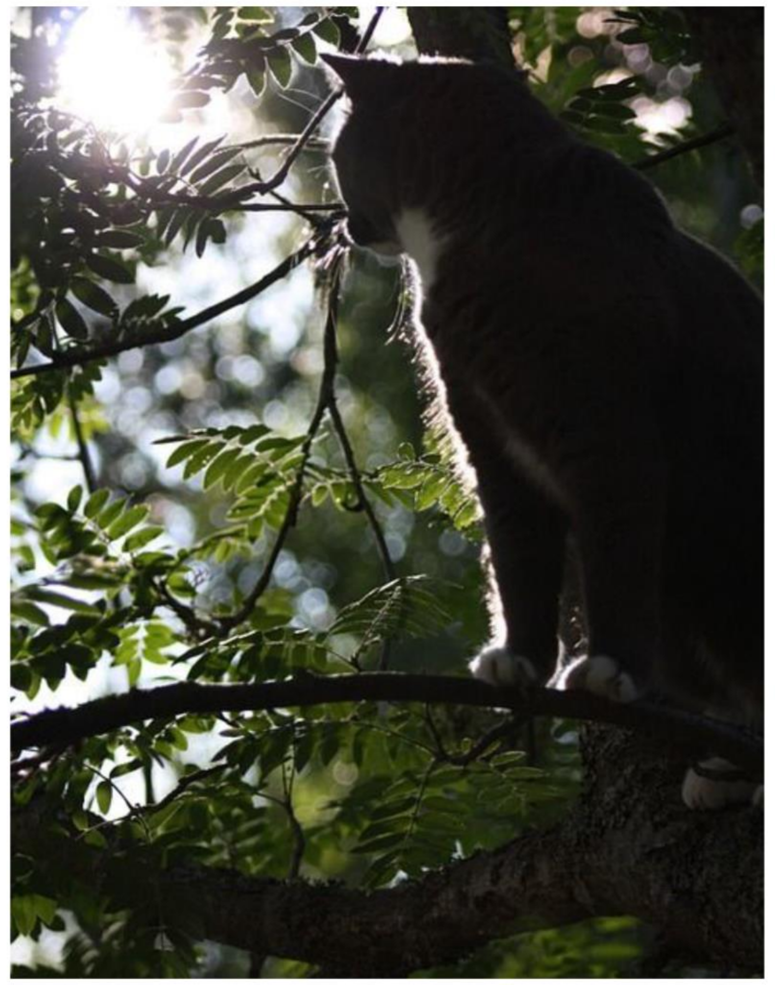

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Image Classification

Challenges: Background Clutter

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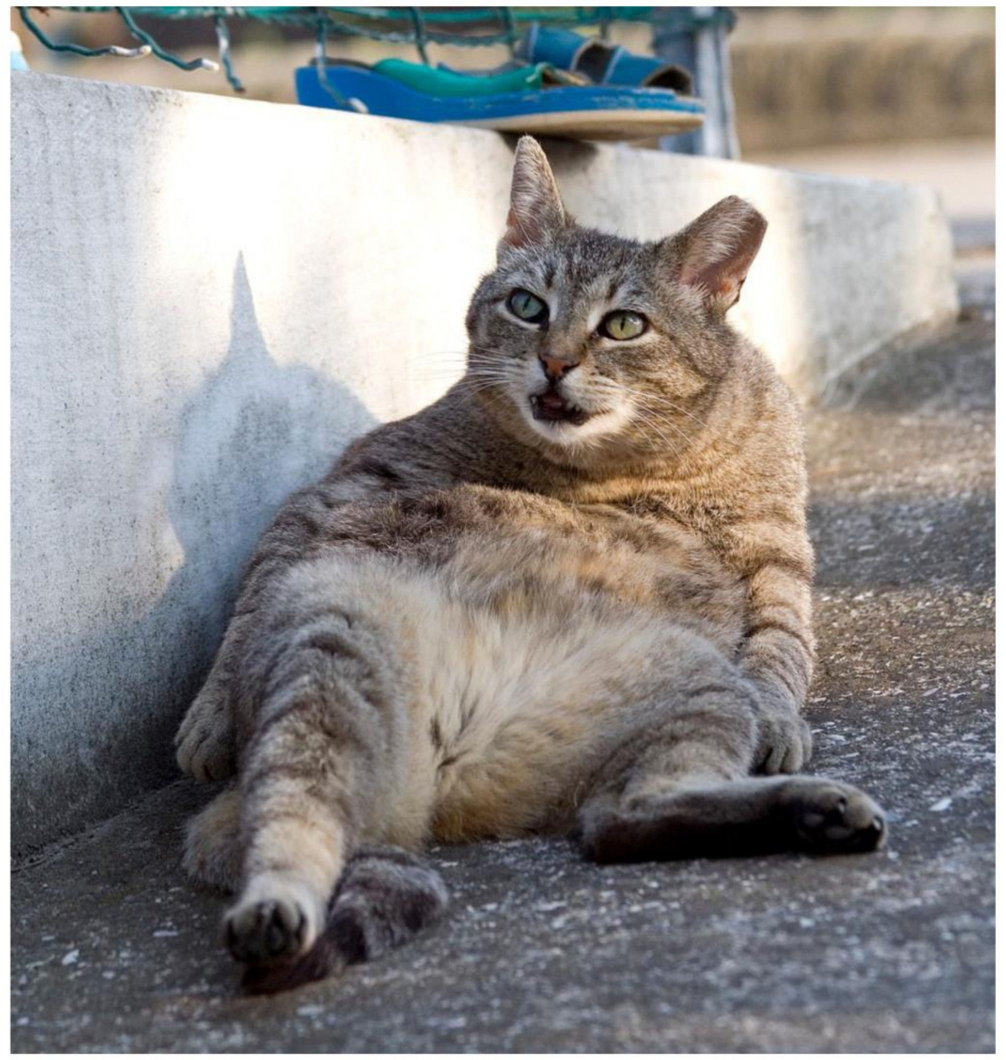
Image Classification

Challenges: Occlusion

Image Classification

Challenges: Deformation



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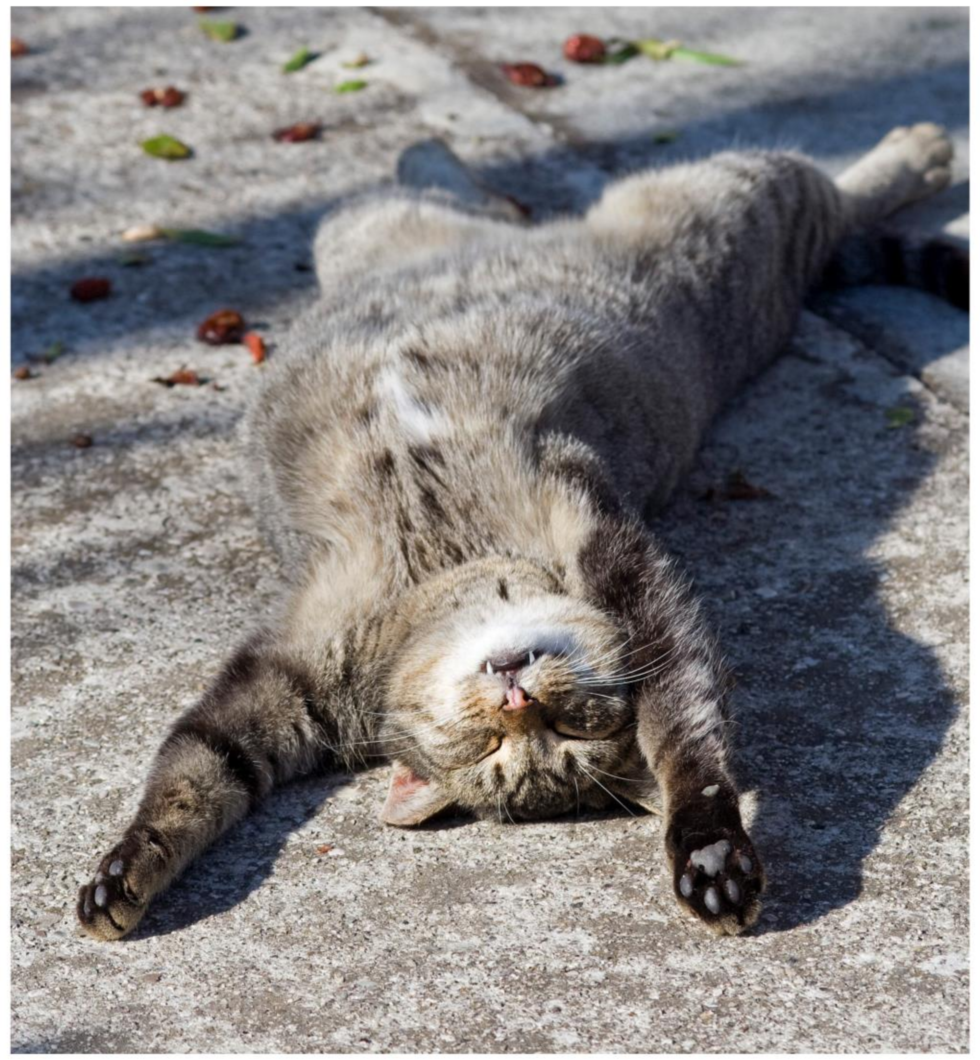

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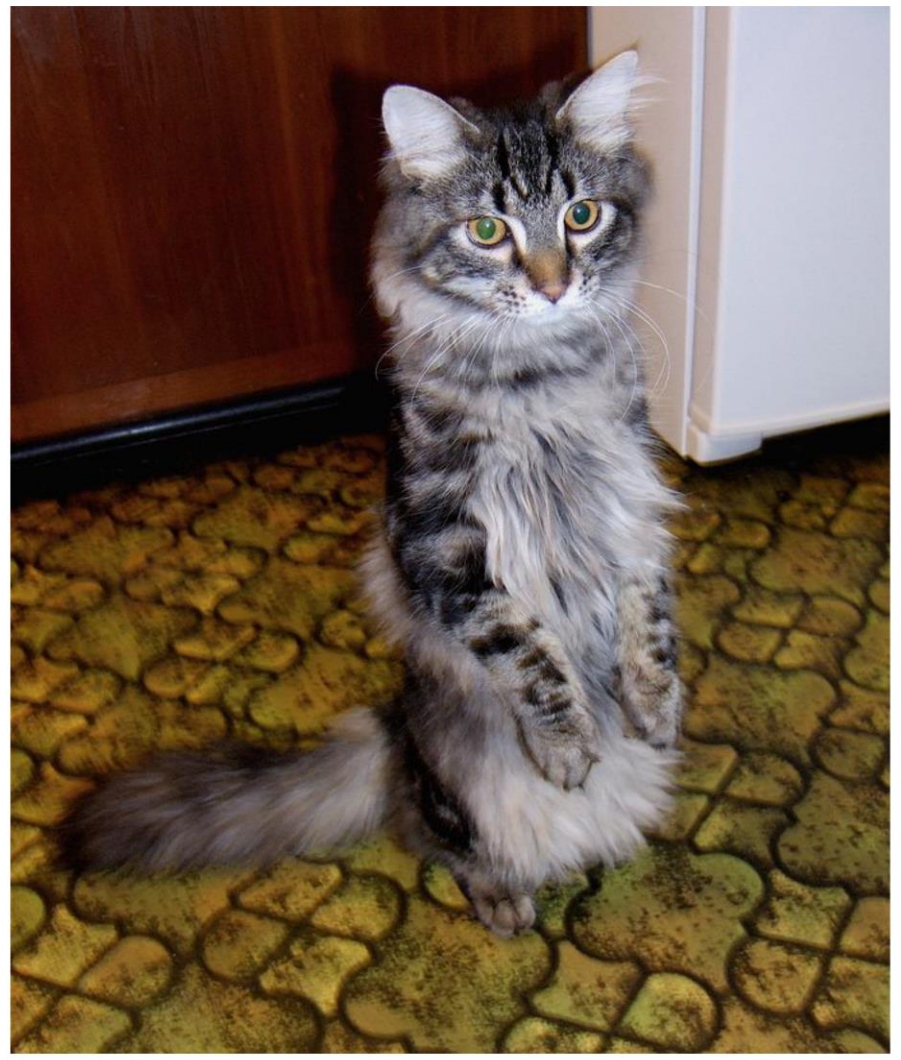

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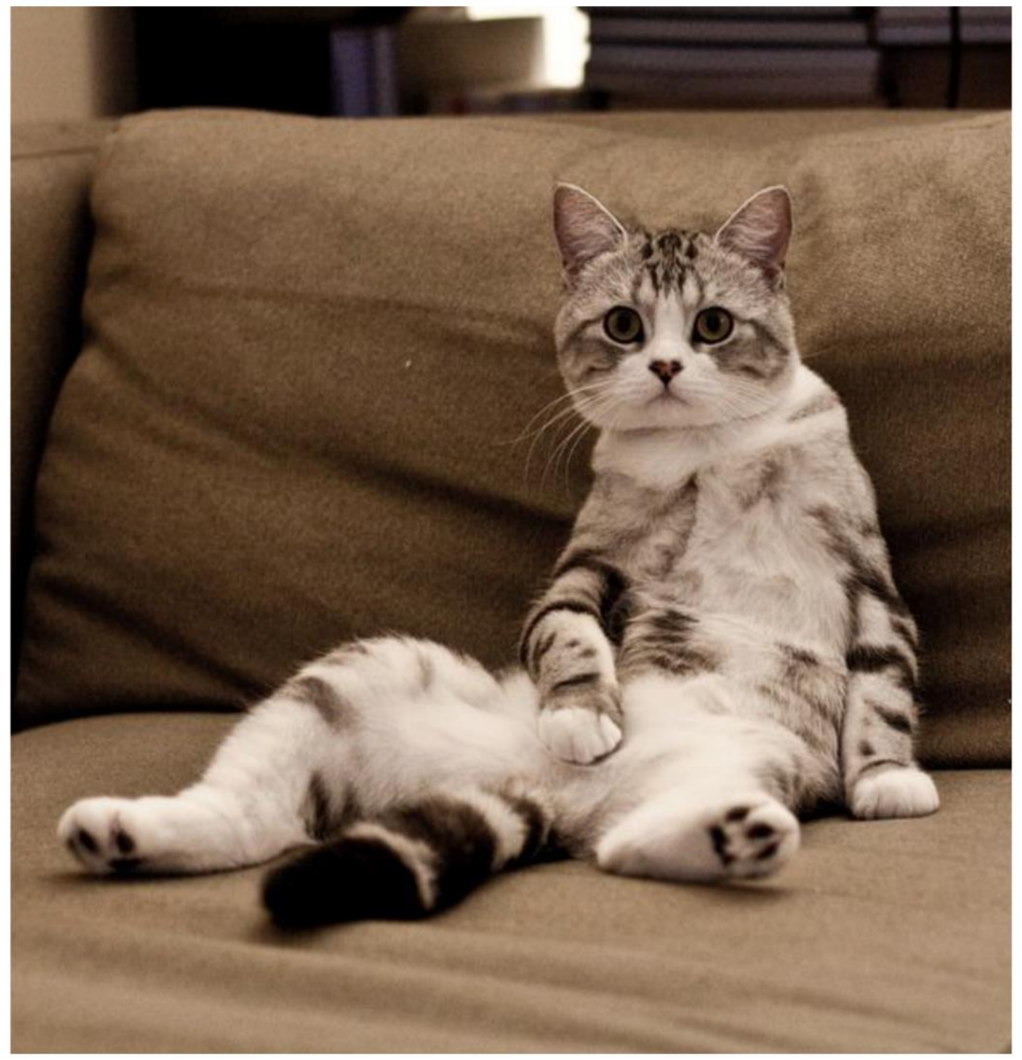

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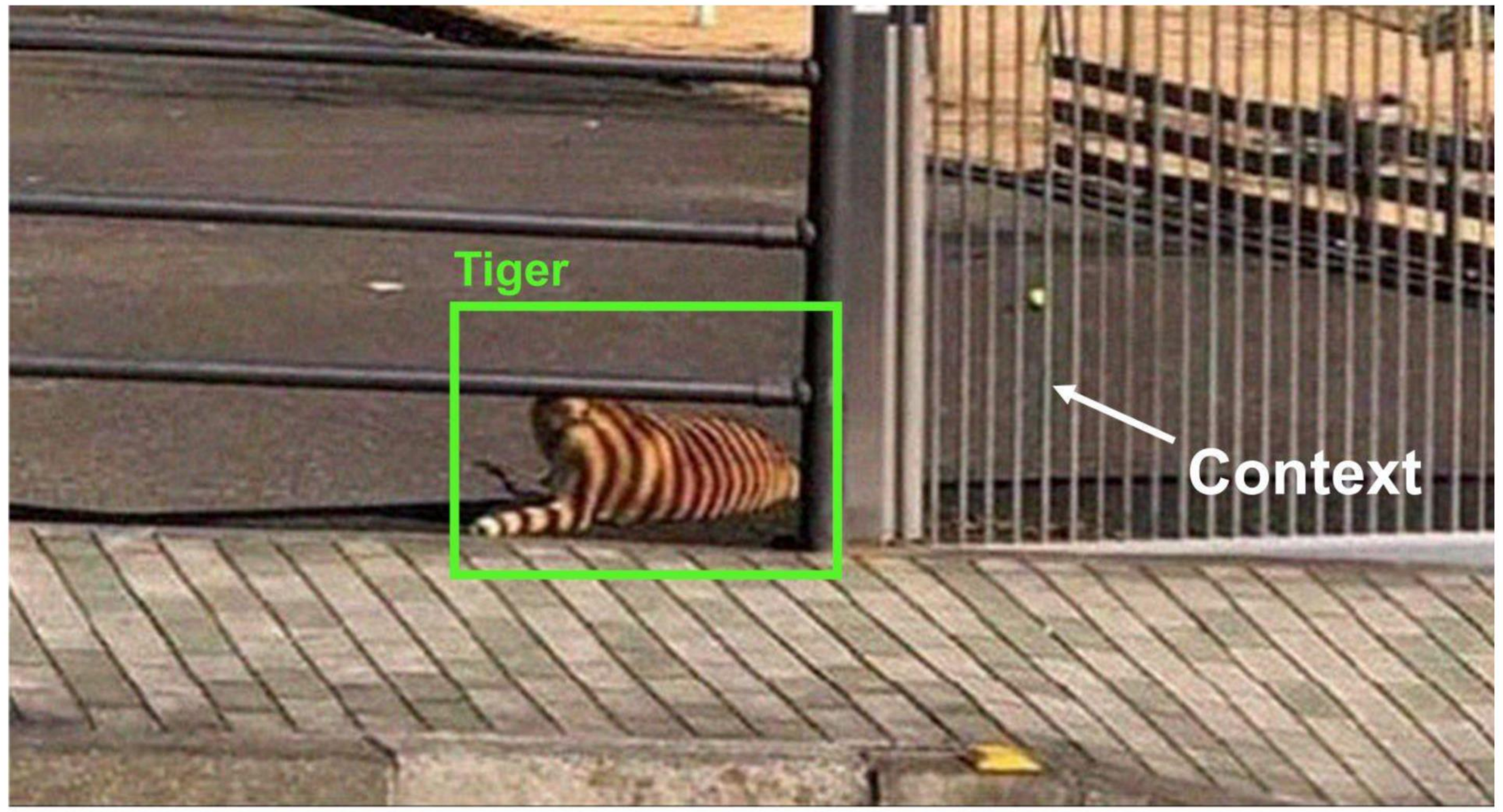
Image Classification

Challenges: Intraclass variation

Image Classification

Challenges: Context



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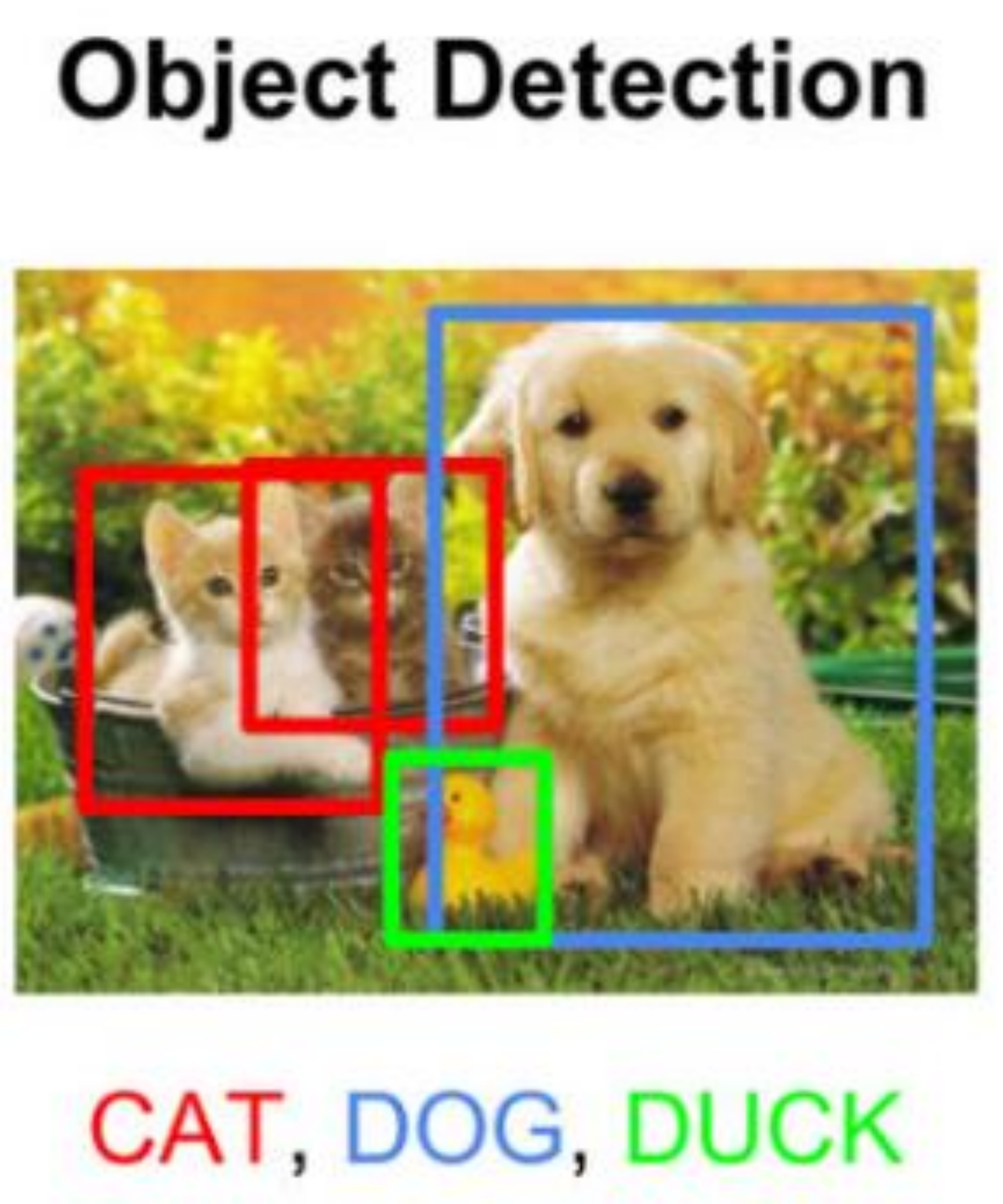
Object detection

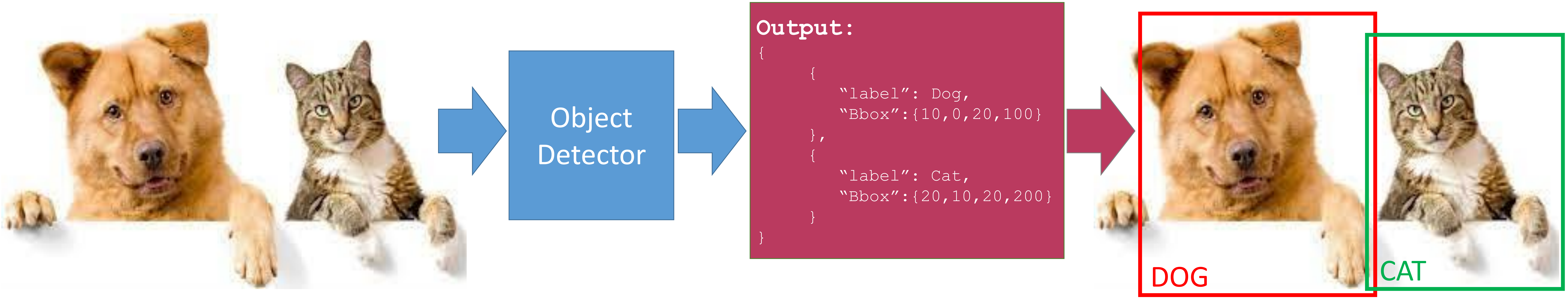
Object detection is a fundamental task in computer vision where the goal is to locate and classify objects within an image or video.

It is a more advanced form of image classification, where instead of just identifying the class of an entire image, they identify multiple instances of multiple classes within an image and locate them with a bounding box; in other words, it deals with more realistic cases in which multiple objects may exist in an image

Object detection algorithms can be used in a variety of applications, such as self-driving cars, security systems, and augmented reality.



Object detection



Differences

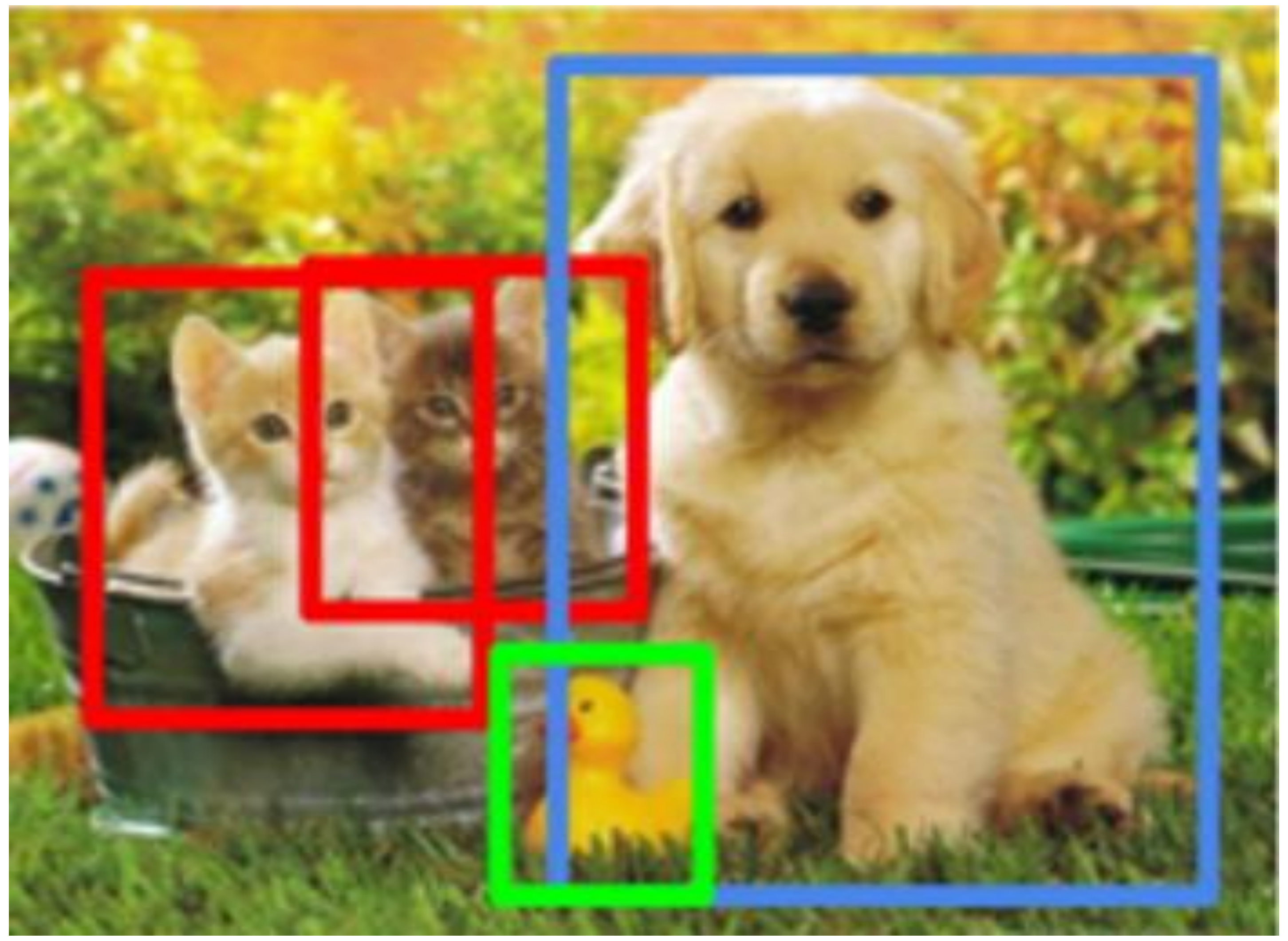
Image Classification

CAT

Localization

CAT

Object Detection



CAT, DUCK, DOG

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Importance

Image classification and object detection are important tasks due to their real-world applications, contributions to the advancement of artificial intelligence, improvements in accuracy and efficiency, and facilitation of human-computer interaction. In particular:

1. **Real-world applications:** Image classification and object detection have numerous real-world applications, including self-driving cars, surveillance systems, and image search engines.
2. **Advancements in artificial intelligence:** These tasks play a significant role in advancing the field of artificial intelligence and computer vision by providing a framework for developing and evaluating new algorithms and models.
3. **Improved accuracy and efficiency:** Image classification and object detection algorithms have been constantly improving in terms of accuracy and efficiency. This enables more robust and reliable systems for various applications.
4. **Facilitation of human-computer interaction:** By automating tasks such as recognizing and locating objects in images, these algorithms make it possible to interact with computers in a more natural and intuitive way.

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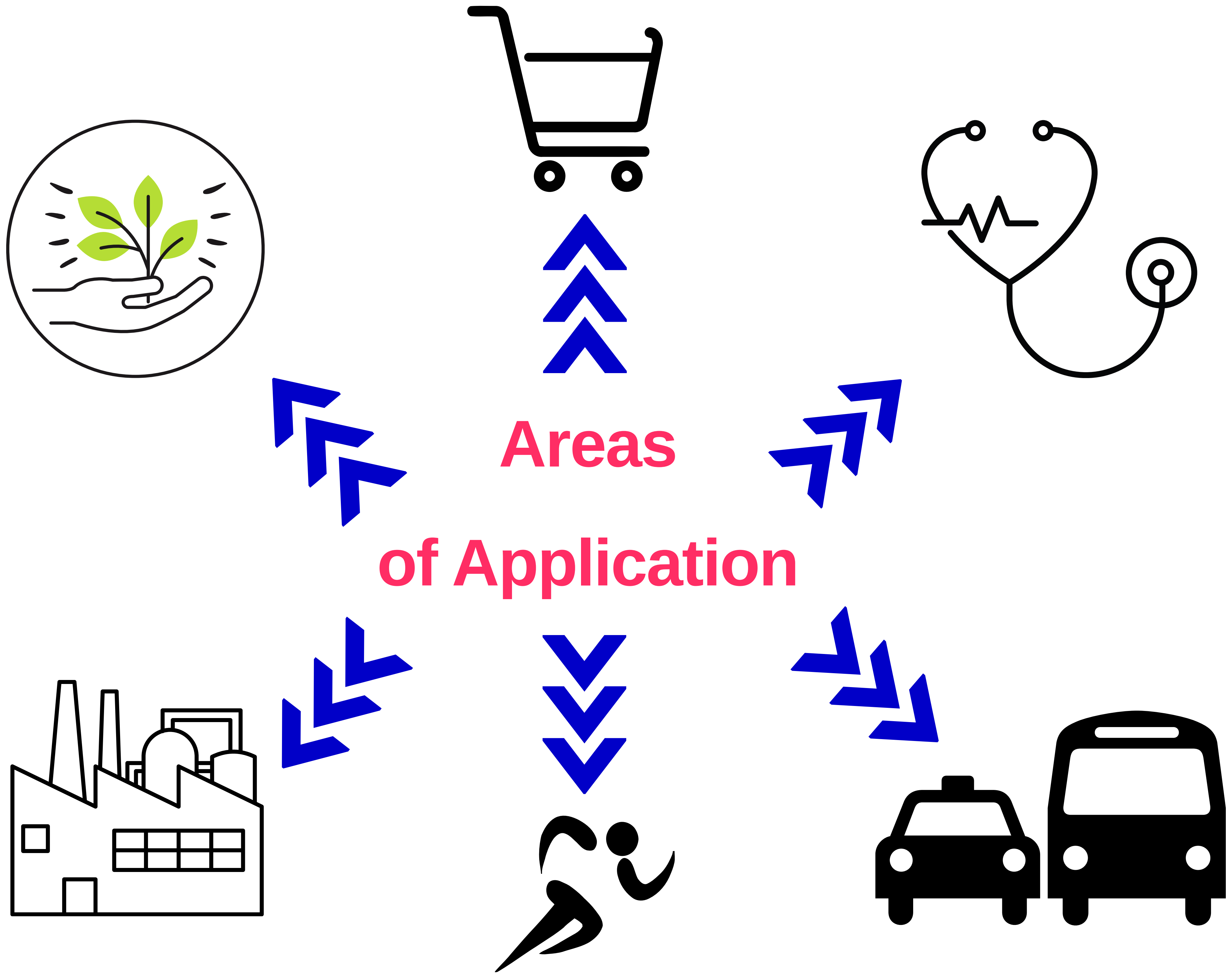
Areas of application of image classification and object detection



Areas of application of image classification and object detection

Image classification and object detection have a wide range of applications in various fields such as:

1. **Computer Vision:** Image classification and object detection are the fundamental tasks in computer vision and are used in various vision-based applications.
2. **Surveillance Systems:** These technologies are used to detect and classify objects in real-time surveillance systems to improve the accuracy of security and monitoring.
3. **Autonomous vehicles:** Object detection is used in autonomous vehicles for tasks such as lane detection, obstacle detection, and traffic sign recognition.
4. **Medical Imaging:** Image classification and object detection techniques are used in medical imaging for tasks such as lesion detection, tumor segmentation, and diagnosis.
5. **Agriculture:** Object detection is used in agriculture for tasks such as crop counting and monitoring crop growth.
6. **Robotics:** Image classification and object detection are used in robotics for tasks such as object recognition and grasping.
7. **E-commerce:** Image classification and object detection are used in e-commerce for product categorization, image-based search, and automatic tagging.

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Areas of application of image classification and object detection

Image classification and object detection have a wide range of applications in various fields such as:

8. **Augmented Reality (AR) and Virtual Reality (VR):** Image classification and object detection are used in AR and VR for tasks such as 3D object recognition and tracking.
9. **Sports:** Object detection is used in sports for tasks such as player tracking and ball detection.
10. **Marketing and Advertising:** Image classification and object detection are used in marketing and advertising for tasks such as image-based recommendations, image-based search, and product categorization.
11. **Wildlife conservation:** Image classification and object detection are used in wildlife conservation for tasks such as animal tracking and species identification.
12. **Retail:** Image classification and object detection are used in retail for tasks such as product recognition, price comparison, and visual search.
13. **Face recognition:** Image classification and object detection are used in face recognition systems for tasks such as facial detection, facial landmarks, and facial verification.
14. **Natural Language Processing (NLP):** Image classification and object detection are used in NLP for tasks such as image captioning, visual question answering, and sentiment analysis.

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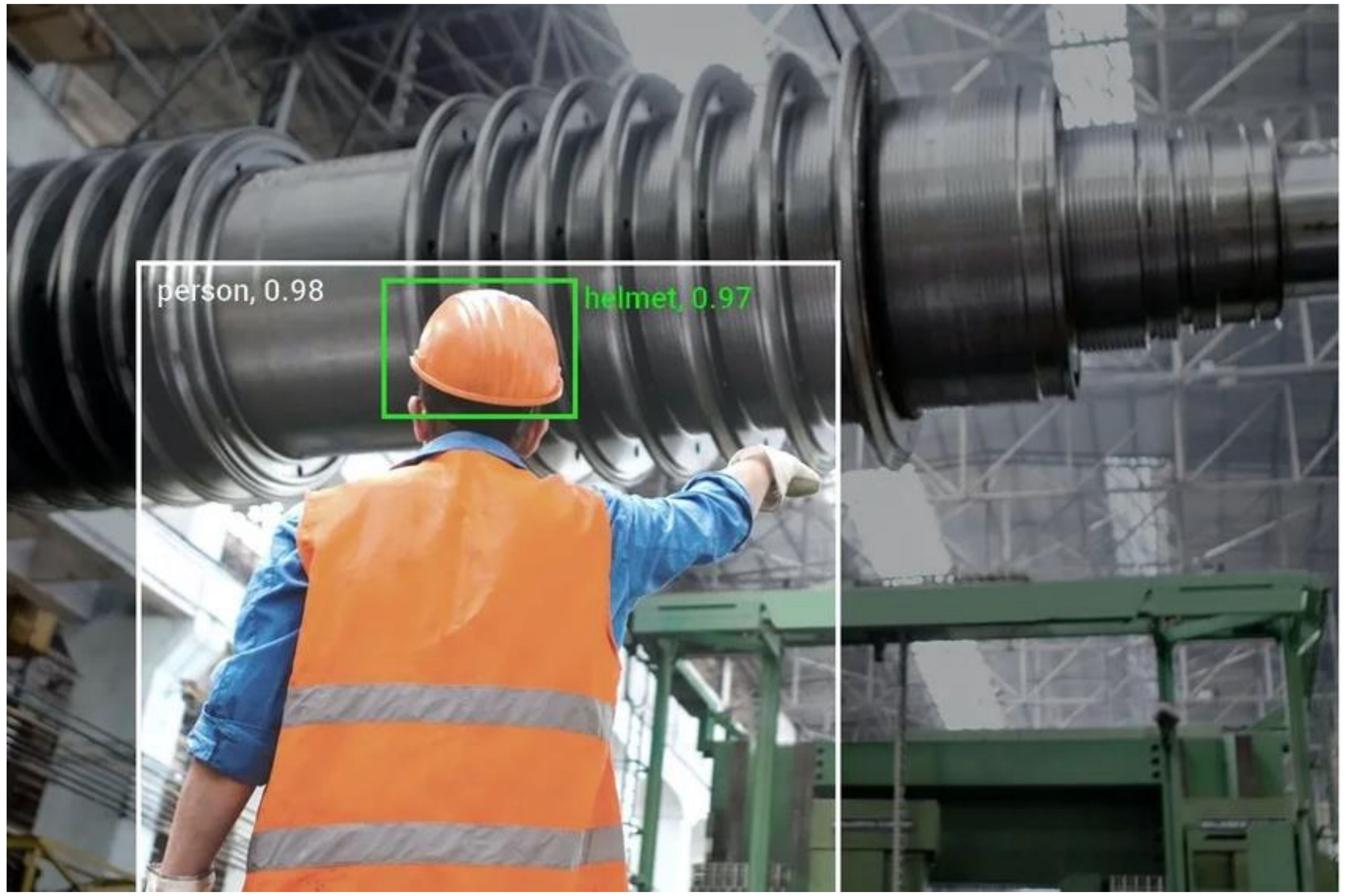
Areas of application of image classification and object detection



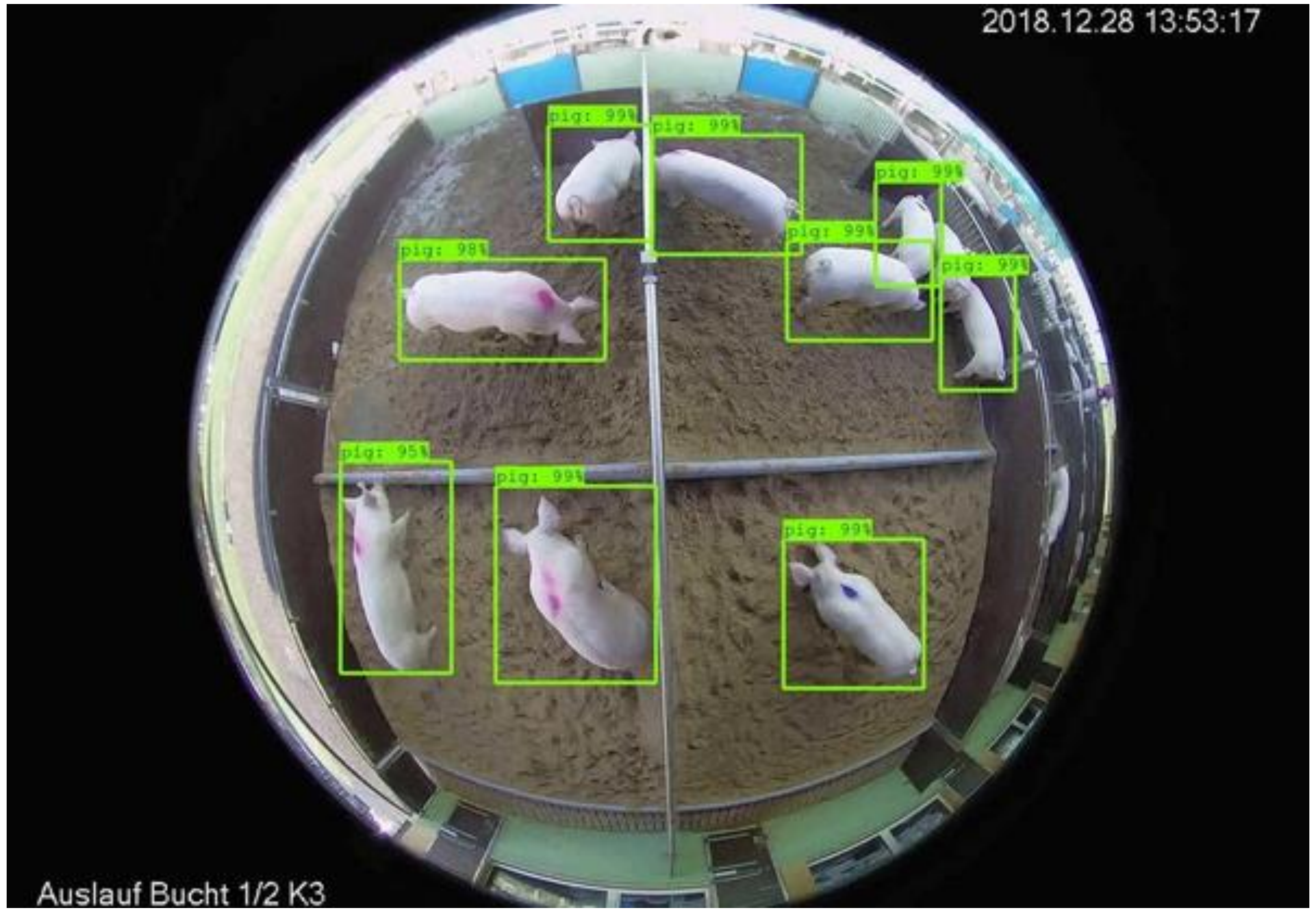
Visual Inspection of Equipment

Areas of application of image classification and object detection

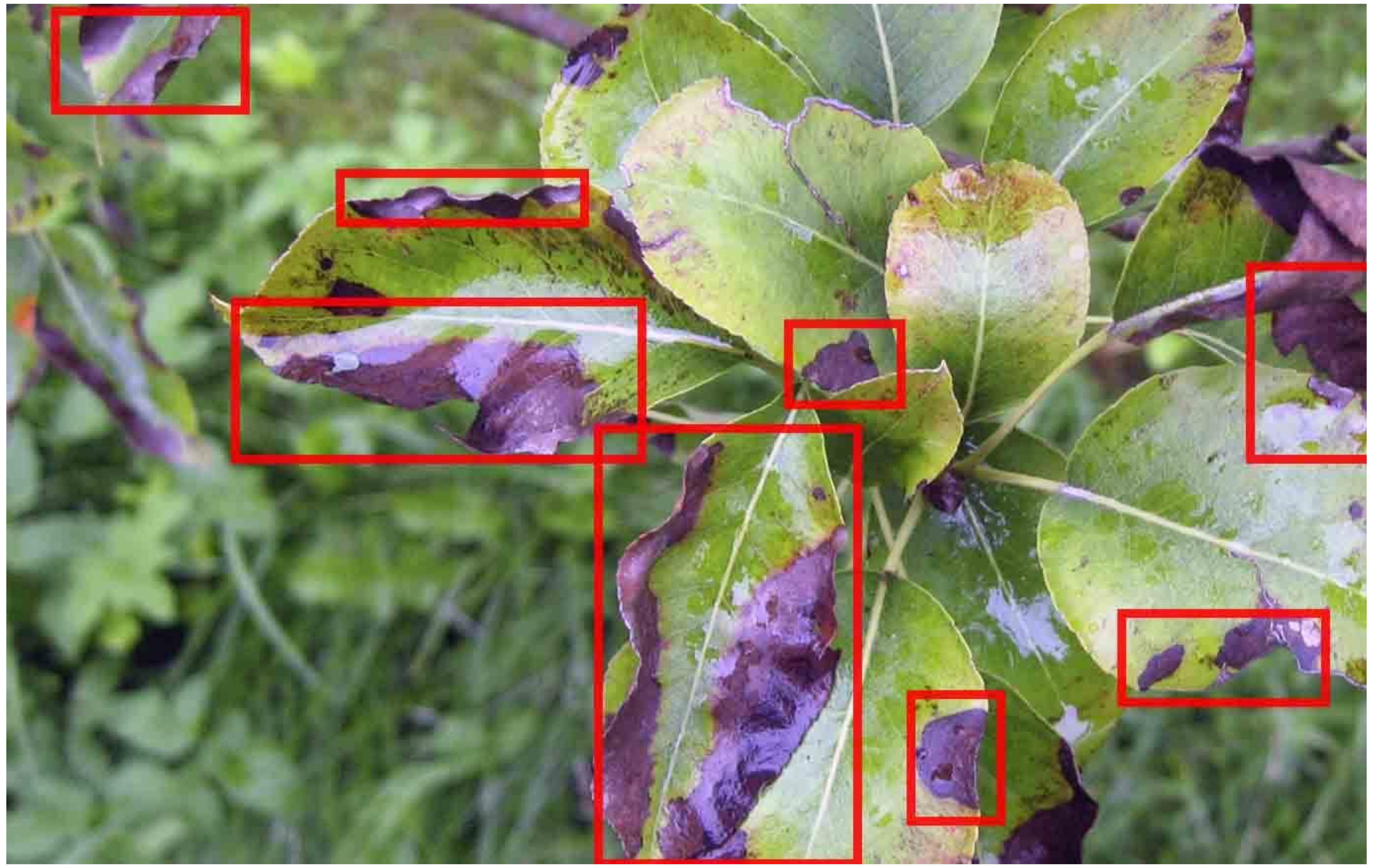
Smart health care: pose detection

Smart health care: mask detection

Areas of application of image classification and object detection

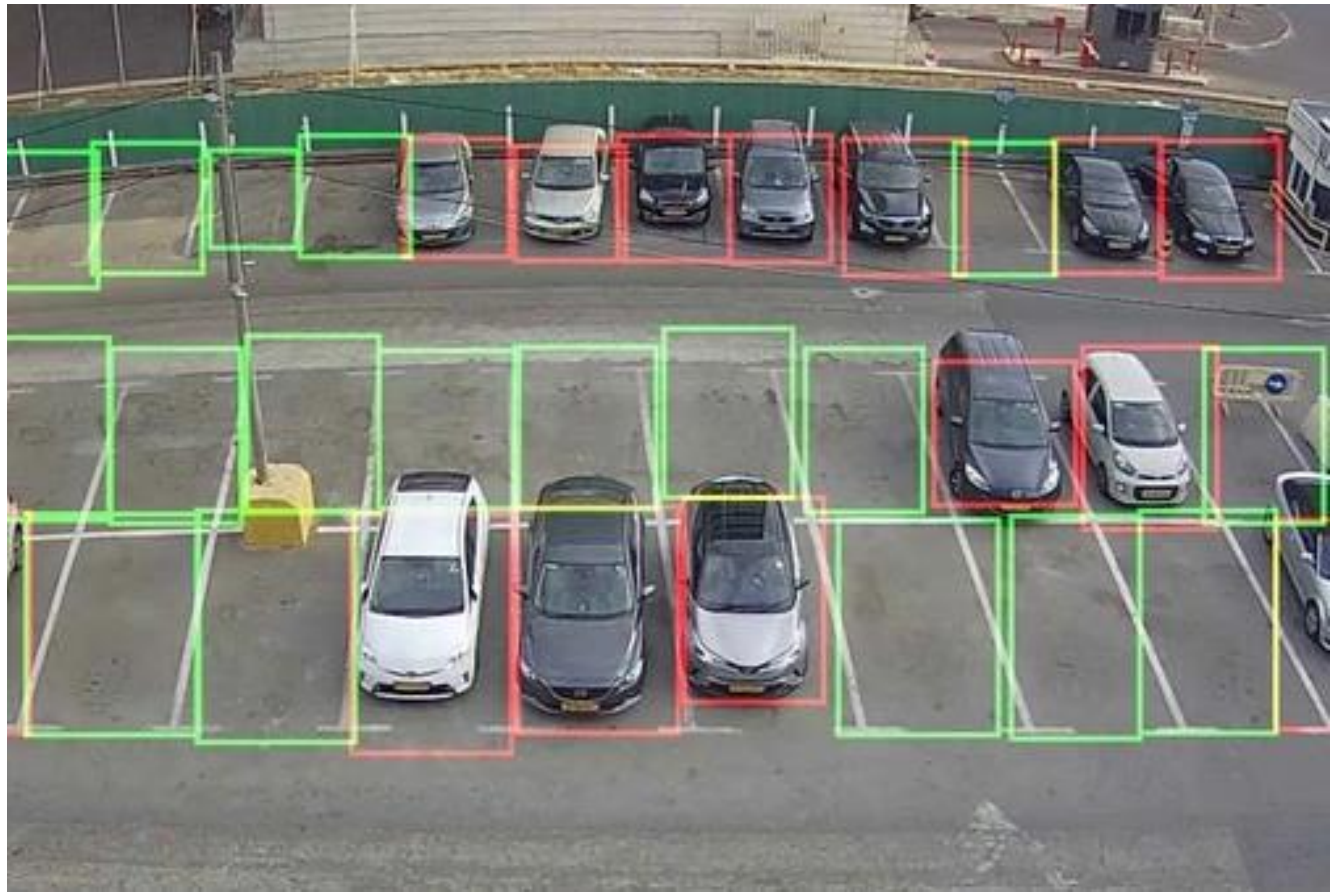


Smart agriculture: animal monitoring

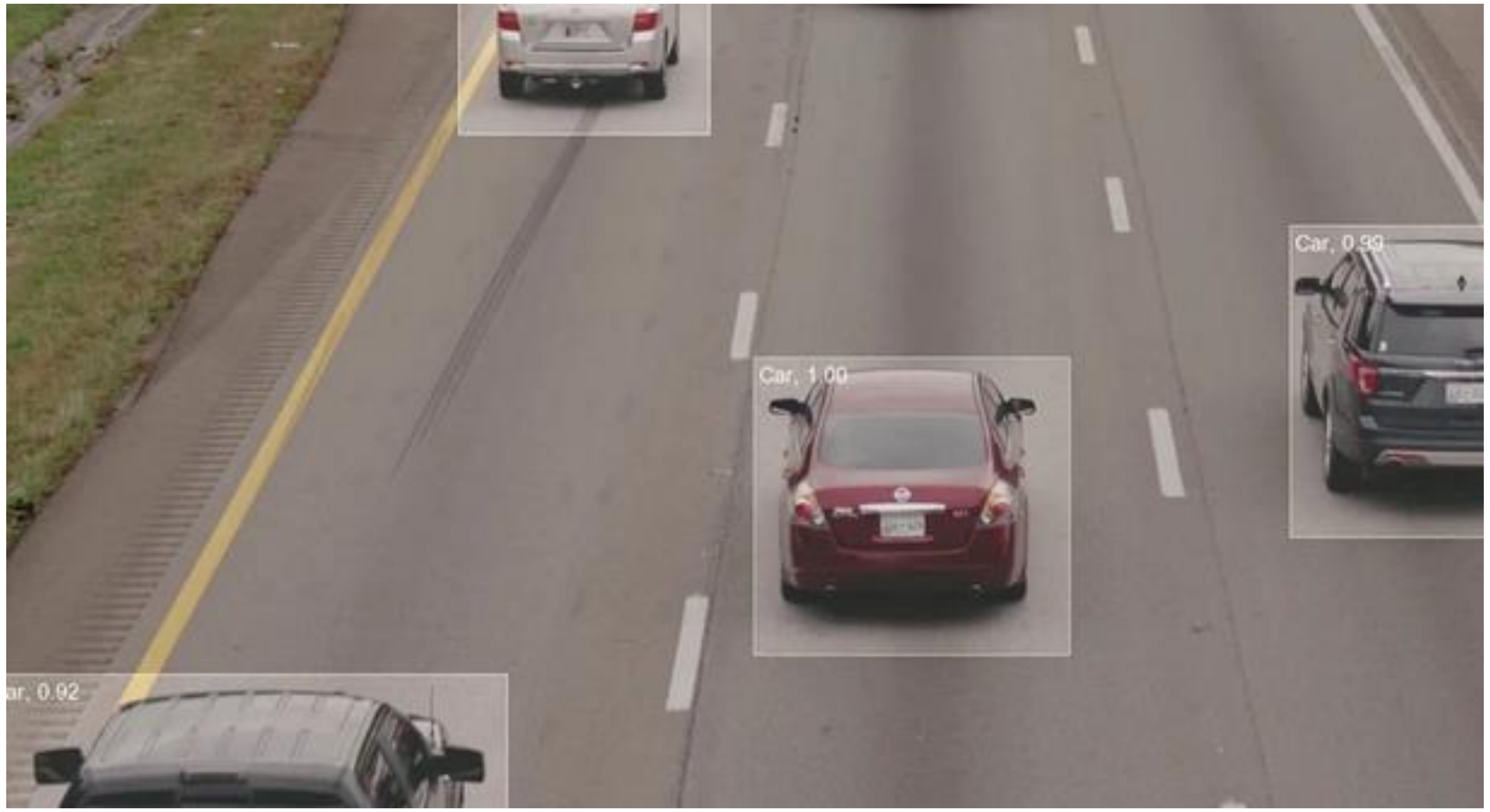


Smart agriculture: Plant Disease Detection

Areas of application of image classification and object detection



Parking Occupancy Detection



Vehicle Classification

Approaches to the problem

Unsupervised

Unsupervised learning is a type of machine learning where the model is trained on an unlabeled dataset, and the algorithm tries to find patterns or relationships within the data without any prior knowledge of the expected outcome. The goal is to group similar data points together or to find lower-dimensional representations of the data. Examples of unsupervised learning algorithms are clustering and dimensionality reduction.

Supervised

Supervised learning, on the other hand, is a type of machine learning where the model is trained on labeled data, where the desired output is already known. The goal is to learn a mapping from inputs to outputs based on the labeled examples. The algorithm uses this mapping to make predictions on new unseen data. Examples of supervised learning algorithms are linear regression, decision trees, and support vector machines.

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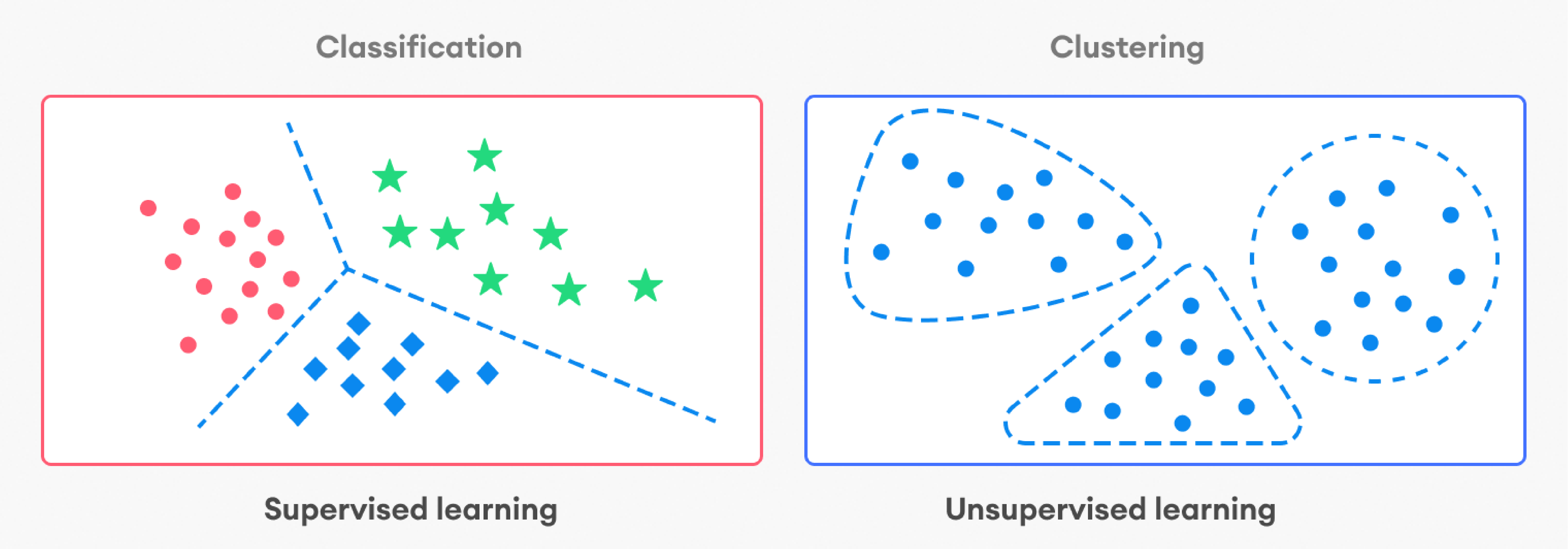
Approaches to the problem

Unsupervised

Supervised



Unsupervised Image Classification

Unsupervised Image Classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes.

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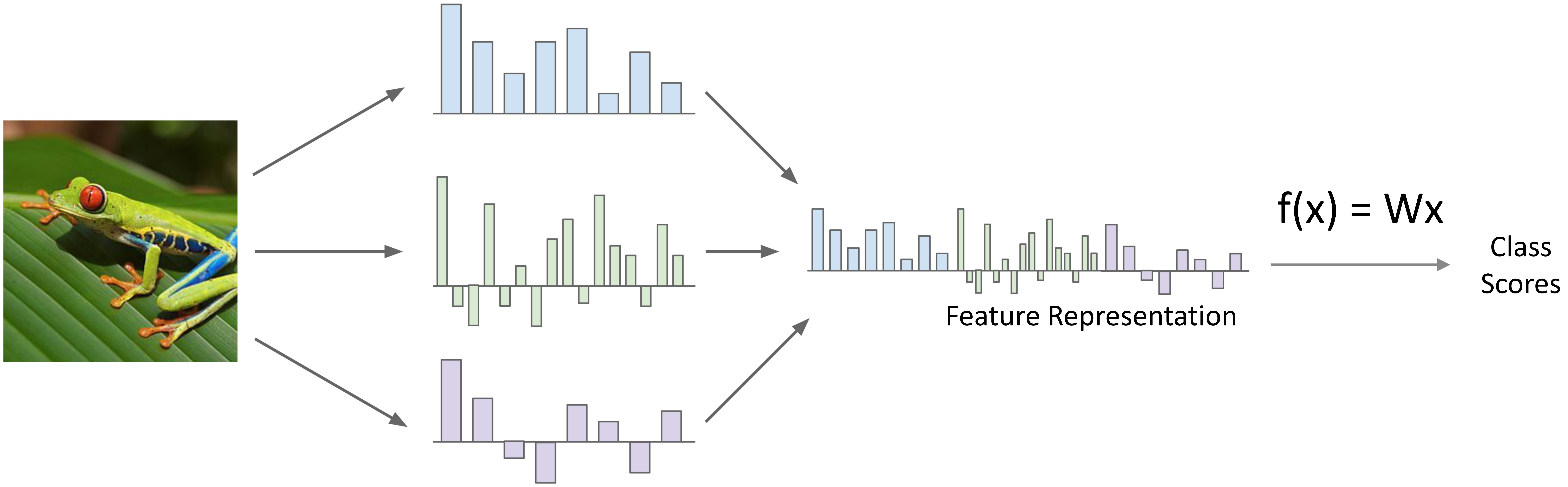
Pixel Space

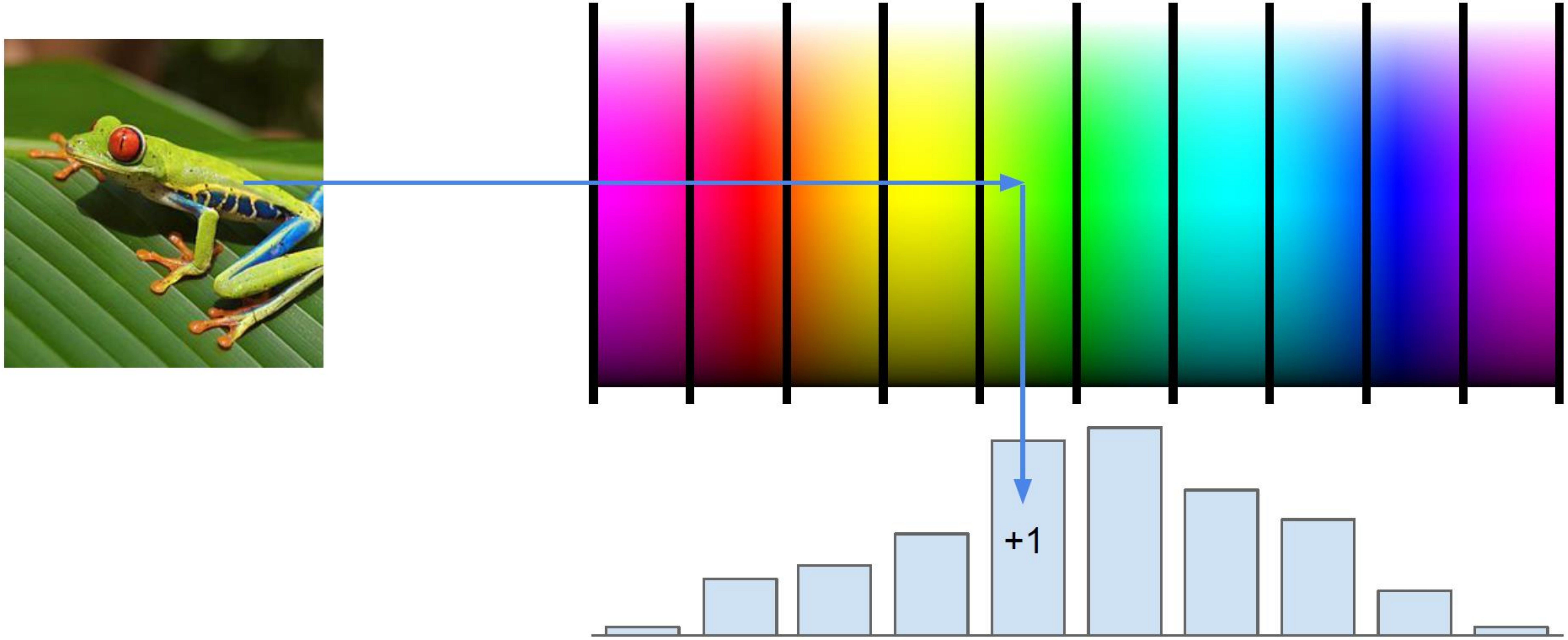
Class scores

$$f(x) = Wx$$

Image Features

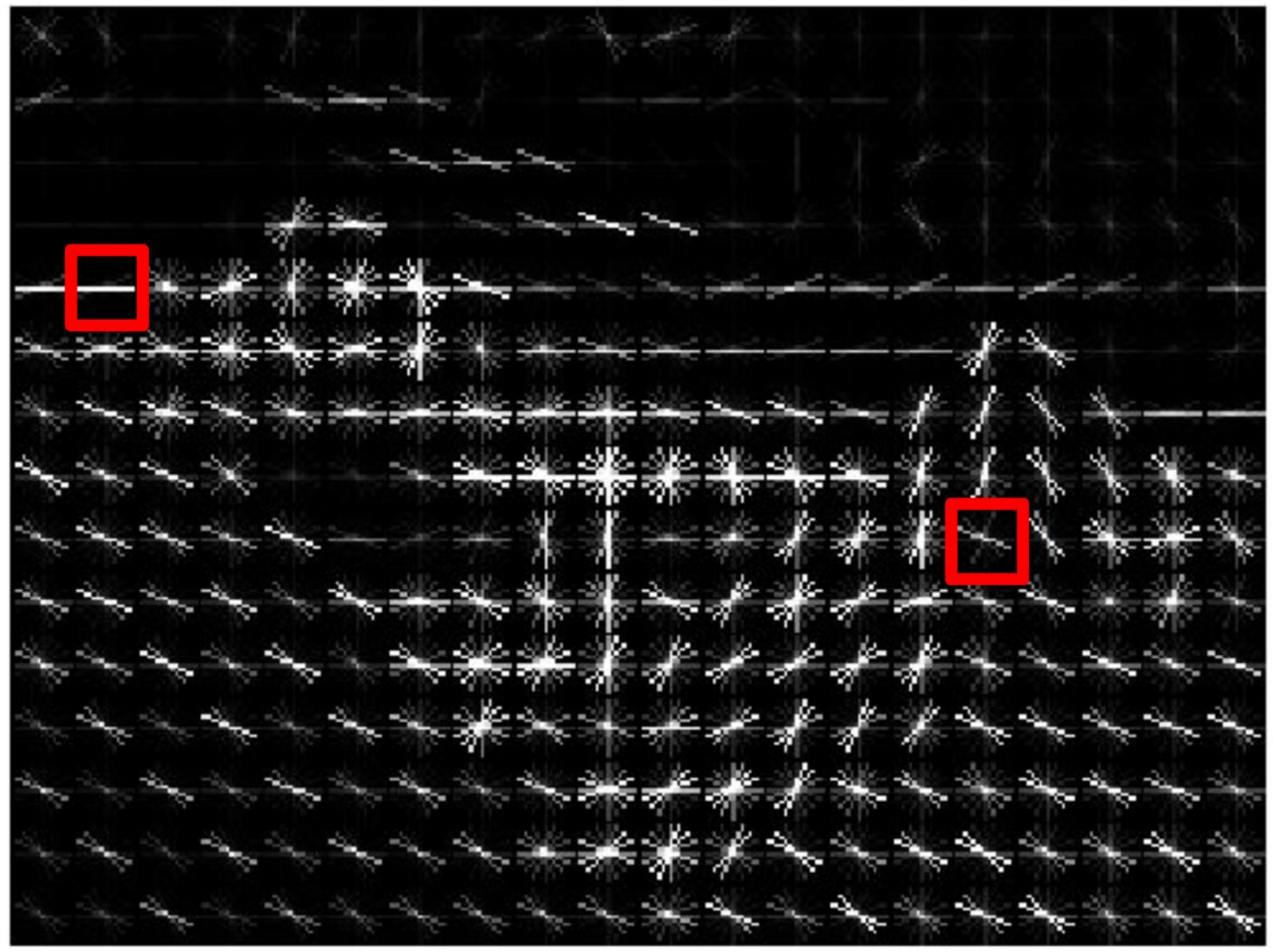


Example: Color Histogram



Example: Histogram of Oriented Gradients (HoG)

Divide image into 8x8 pixel regions
Within each region quantize edge direction into 9 bins



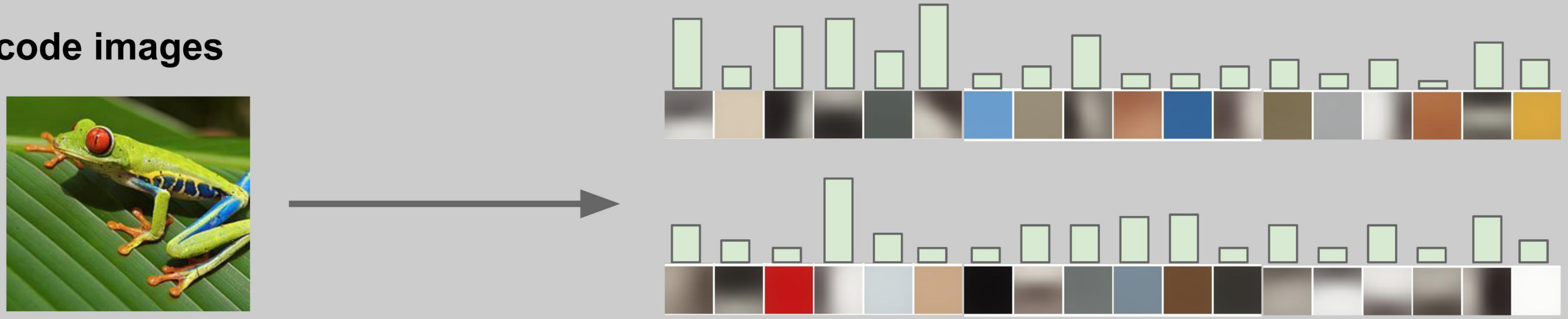
Example: 320x240 image gets divided into 40x30 bins; in each bin there are 9 numbers so feature vector has 30*40*9 = 10,800 numbers

Lowe, "Object recognition from local scale-invariant features", ICCV 1999
Dalal and Triggs, "Histograms of oriented gradients for human detection," CVPR 2005

Unsupervised Image Classification

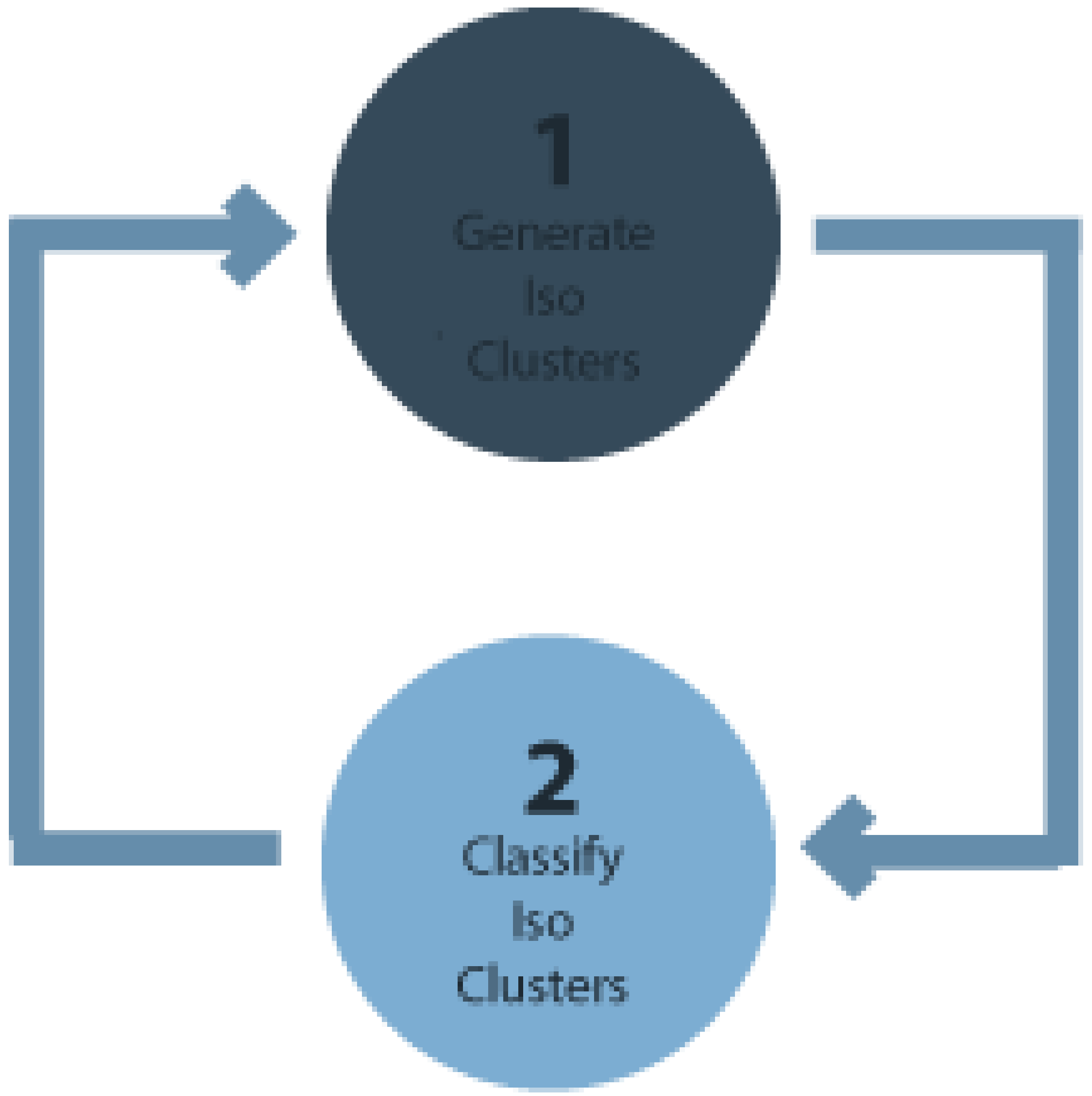
Step 1: Build codebook

Step 2: Encode images



Fei-Fei and Perona, “A bayesian hierarchical model for learning natural scene categories”, CVPR 2005

Unsupervised Image Classification



In unsupervised classification, it first groups pixels into “clusters” based on their properties.

Then, you classify each cluster with a class.

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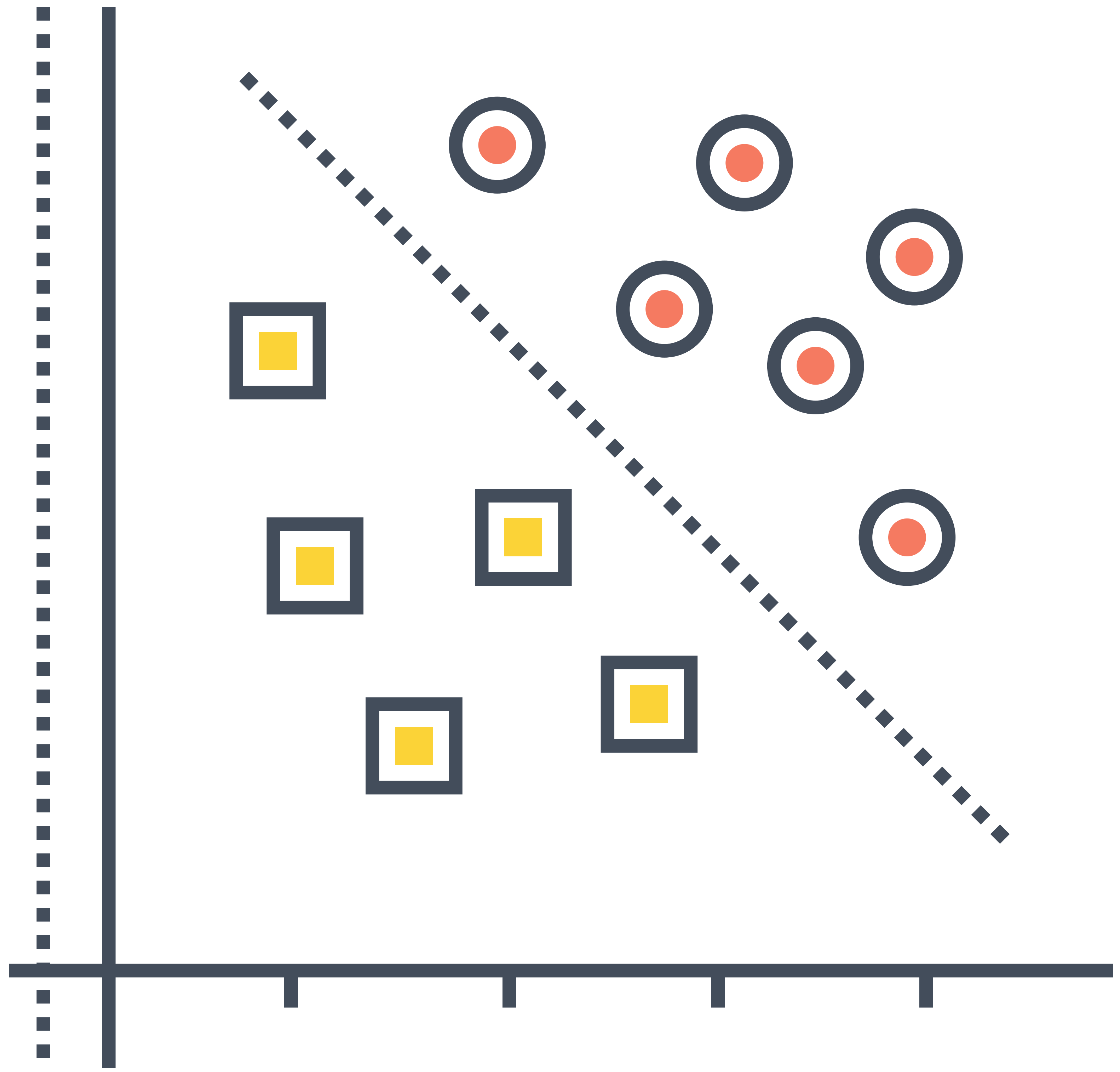
Steps for unsupervised image classification

1. Choose Clustering Algorithm
2. Class Identification
3. Edit\Evaluate Signatures
4. Class Evaluation



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Unsupervised image classification: Clusterization

With unsupervised algorithms, **no pre-existing tags** are given to the system, **only raw data**. The system interprets the data, recognizes patterns, and draws unique conclusions from the data without human interference.

Unsupervised classification makes use of a concept called **clusterization**. Clusterization is the unsupervised, natural locating and grouping (or “clustering”) of data into groups. However, you will not give get a class automatically. You'll only have the different clusters, which you’d need to decide a class for in another way. There are a plethora of different clusterization algorithms e.g., K-Means, Agglomerative Clustering, BIRCH, ISODATA, DBSCAN etc.

There isn’t a single best choice out of these clusterization algorithms. Instead, it is optimal to test various ones until you settle on the one that works best with the specific task at hand.

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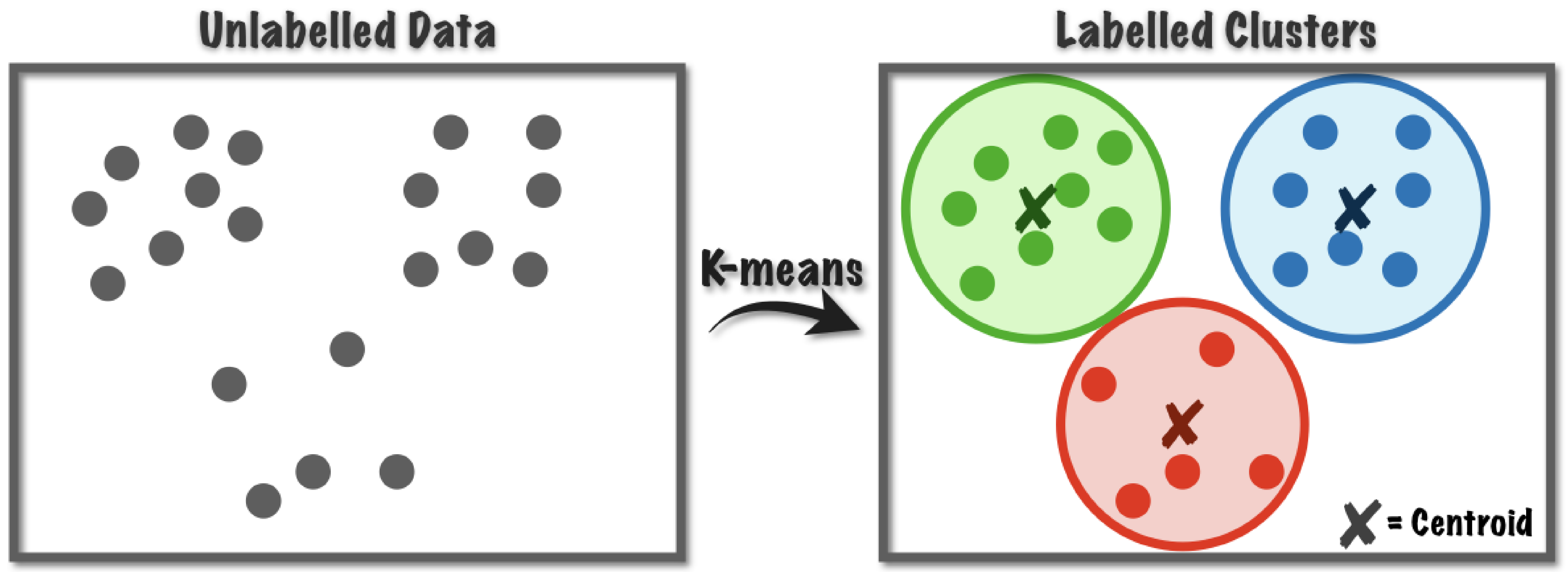
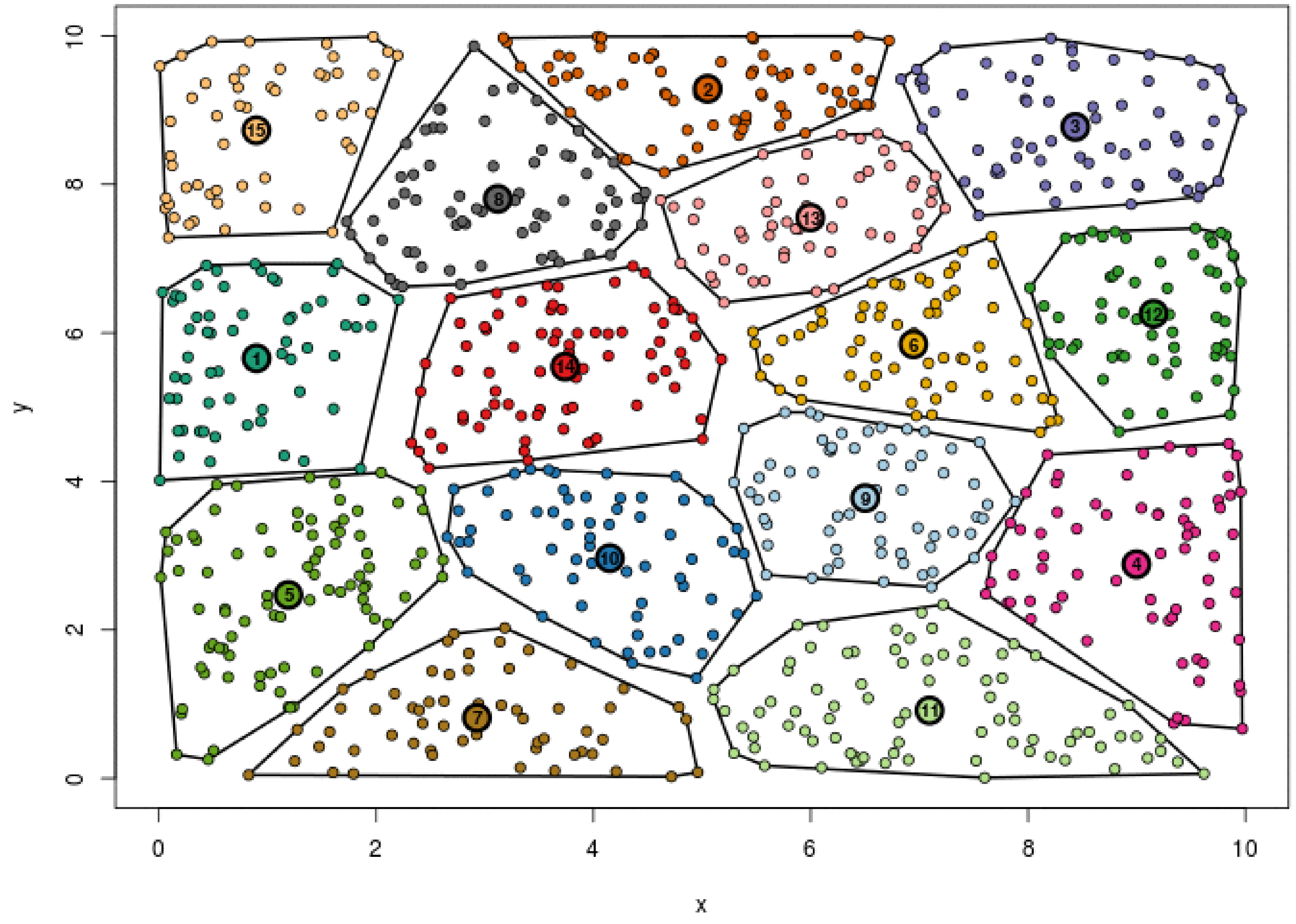
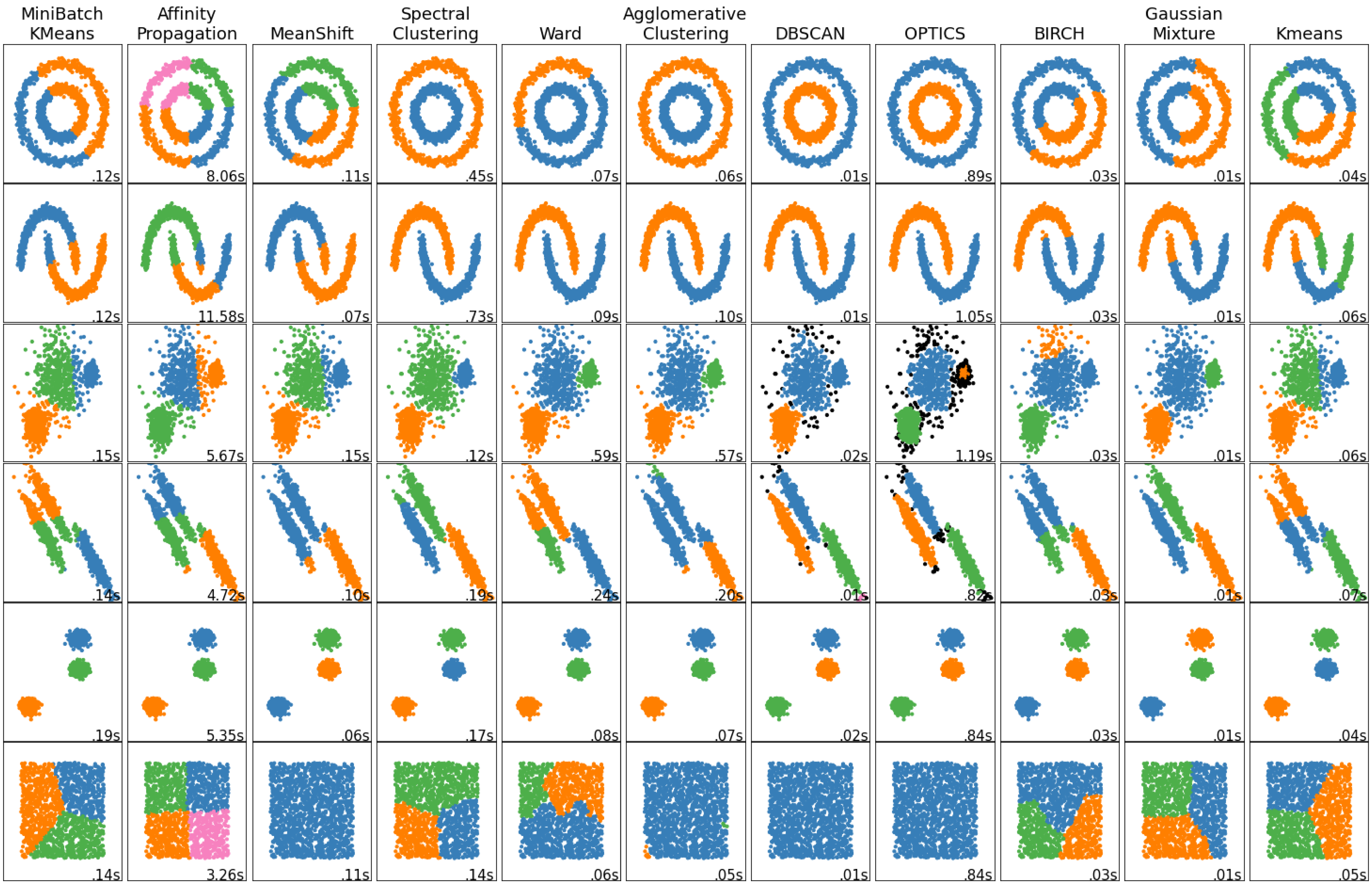
Unsupervised image classification: Clusterization



K-means



ISODATA



MiniBatch KMeans
Affinity Propagation
MeanShift
Spectral Clustering
Ward
Agglomerative Clustering
DBSCAN
OPTICS
BIRCH
Gaussian Mixture
Kmeans
.12s
8.06s
.11s
.45s
.07s
.06s
.01s
.89s
.03s
.01s
.04s
.12s
11.58s
.07s
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.07s
.19s
5.35s
.06s
.17s
.08s
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.84s
.03s
.01s
.04s
.14s
3.26s
.11s
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.06s
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.01s
.84s
.03s
.01s
.05s

Supervised Image Classification

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image.

In supervised classification, you select representative samples for each class. The software then uses these “training sites” and applies them to the entire image.

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Supervised Image Classification

Supervised classification involves **pre-training** the system with a **set of reference data**, allowing it to use the acquired information to classify new visual materials. The algorithm compares the new input with the previously trained data, using the patterns learned from the training data to classify the new images.

Supervised image classification algorithms can be divided into **single-label classification** and **multi-label classification**. Single-label classification refers to a singular label that is assigned to an image as a result of the classification process. While single-label classification assigns an image to a single category, multi-label classification allows an image to be assigned to an unlimited number of categories. Multi-label classification can be particularly useful in cases where an image contains multiple features or attributes. For instance, in medicine, a medical image may reveal multiple diseases or abnormalities in a patient.

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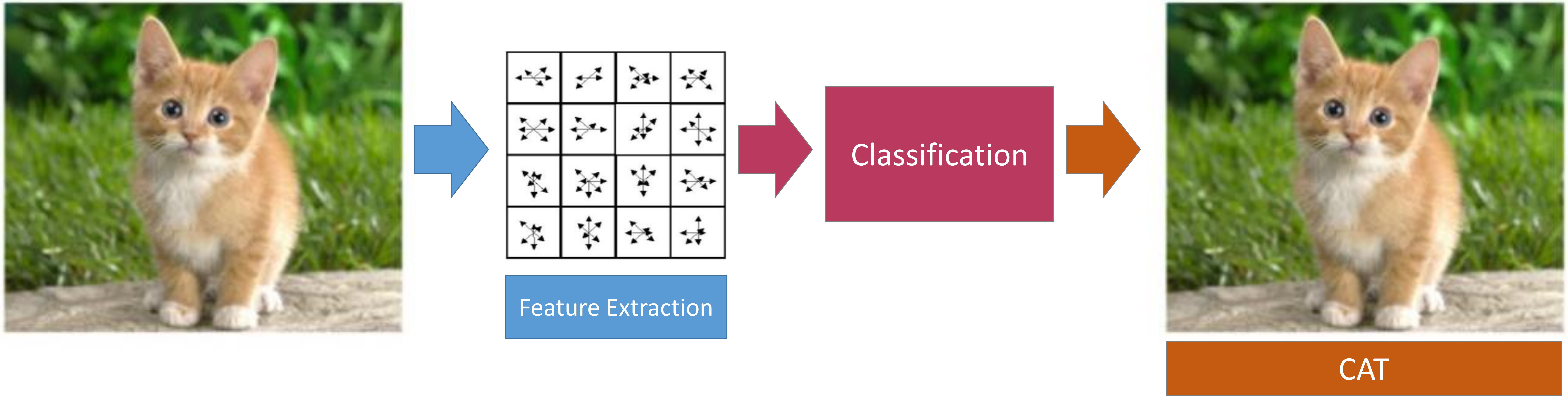
Image Classification Using Traditional Machine learning



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Again, some feature extraction techniques:

- HOG Features
  - Histogram of Oriented Gradients (HOG) is a feature descriptor used in computer vision and image processing. It is used to represent the shape and structure of objects in an image. HOG works by dividing an image into small cells and computing the gradient orientation histogram for each cell.
- Accelerated segment test (AST)
  - The Accelerated Segment Test is a fast and efficient algorithm for detecting changes in the mean of a time-series. It is often used in change point detection problems, where the goal is to identify a point in time when the underlying distribution of the time-series changes.
- Scale Invariant Feature Transform (SIFT)
  - Scale Invariant Feature Transform (SIFT) is an algorithm for detecting and describing local features in images. It is used for tasks such as object recognition, image matching, and texture classification. SIFT works by detecting distinctive, invariant features in an image that are robust to changes in scale, orientation, and illumination.
- Oriented FAST and Rotated BRIEF (ORB)
  - Oriented FAST and Rotated BRIEF (ORB) is a feature detection and description algorithm in computer vision. It is a combination of the FAST (Features from Accelerated Segment Test) corner detector and the BRIEF (Binary Robust Independent Elementary Features) descriptor. FAST is a fast corner detection algorithm that is used to detect features in an image. BRIEF is a binary feature descriptor that describes the local appearance of a feature using a binary string.

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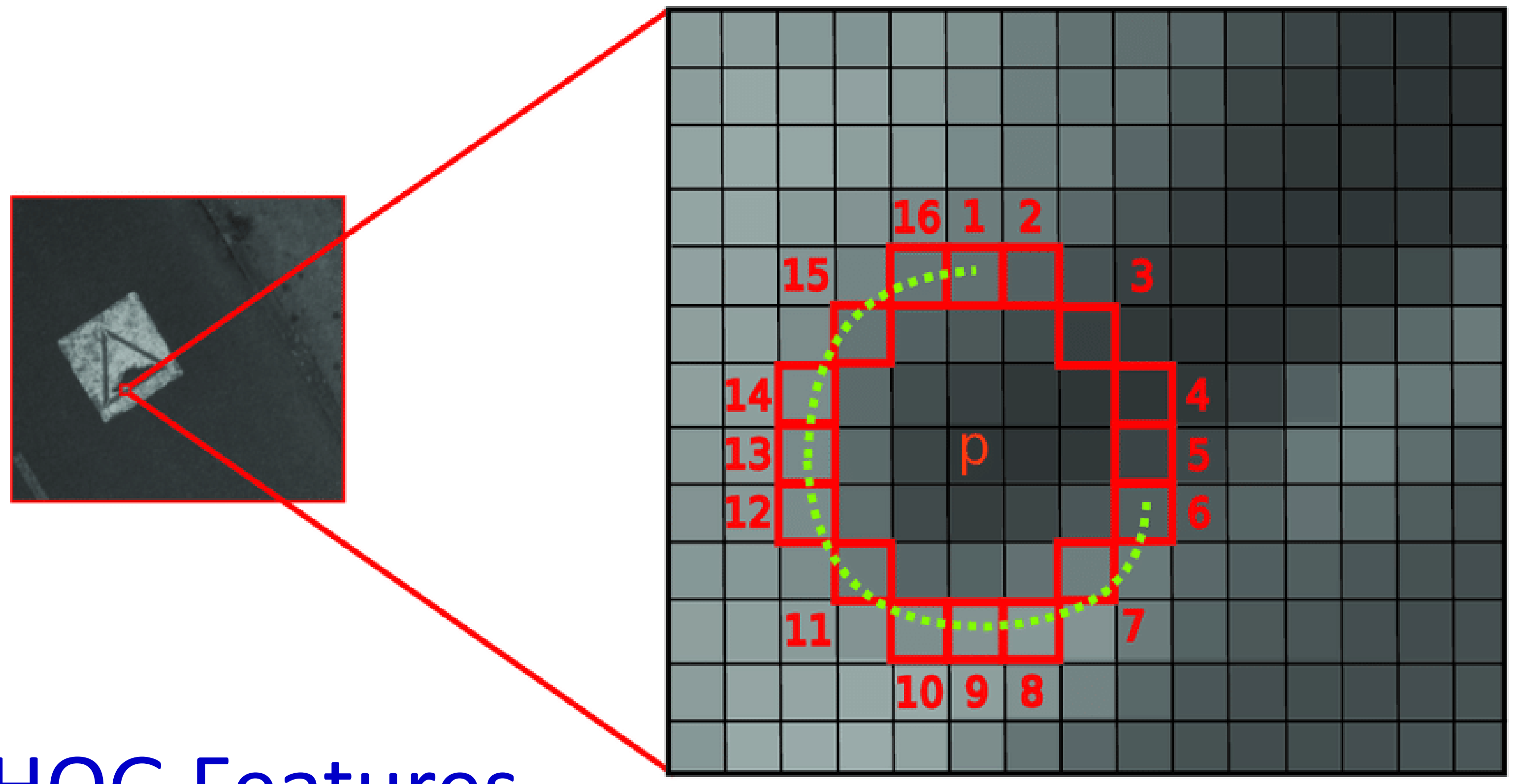
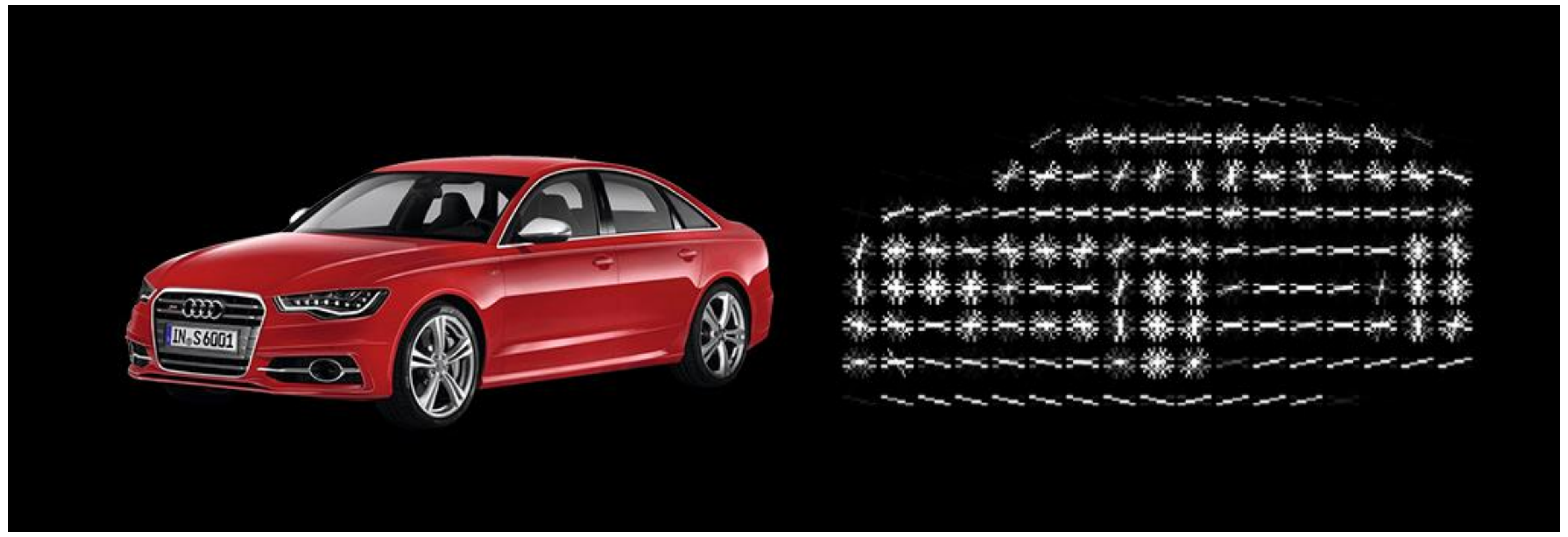
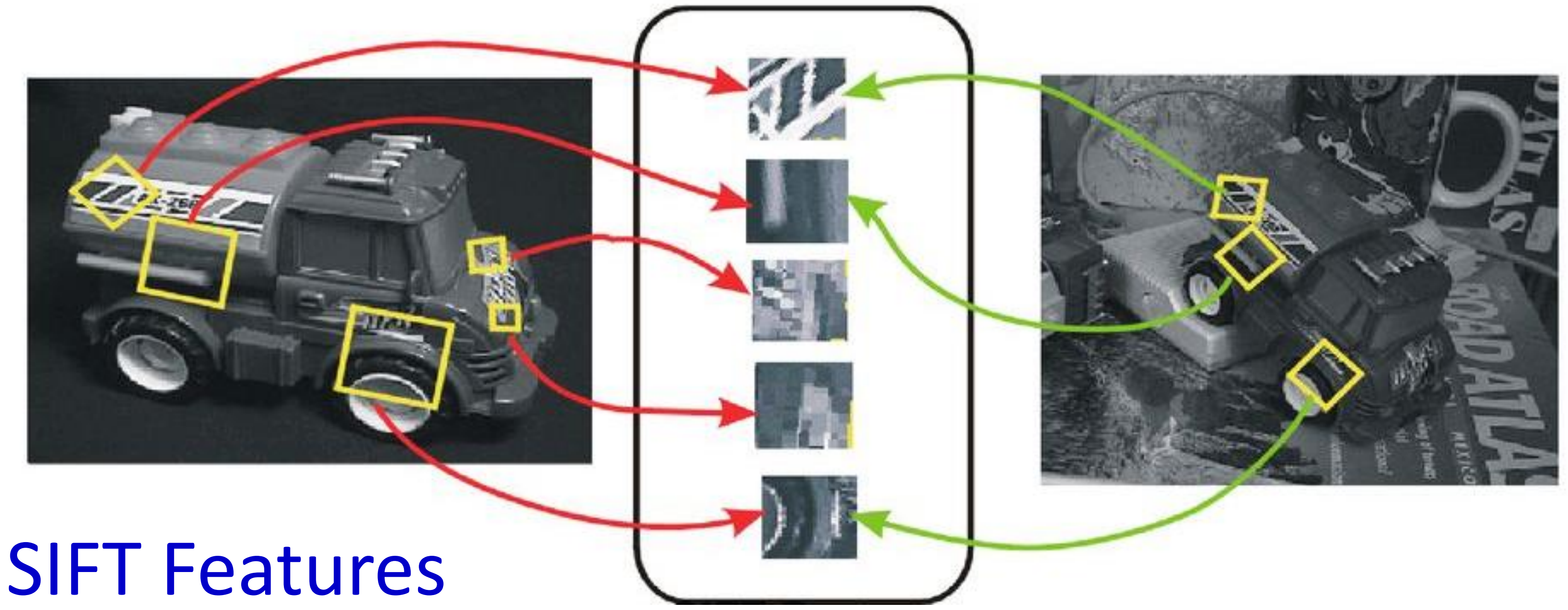
Again, some feature extraction techniques:



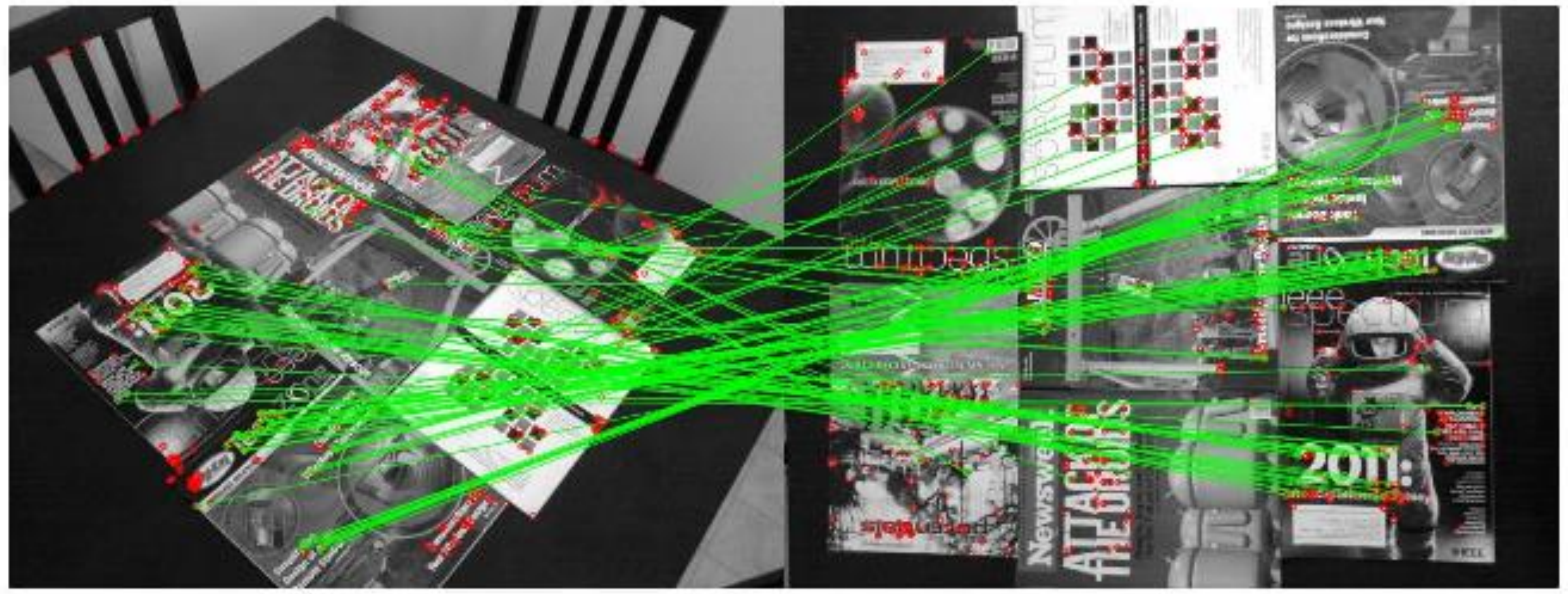
HOG Features



AST Features



SIFT Features



ORB Features

Example of Classifiers

- Decision Tree classifier
  - A Decision Tree classifier is a simple and popular machine learning algorithm used for solving classification problems. It is a type of decision tree algorithm, where the tree is used to make predictions by recursively partitioning the data into smaller subsets based on the values of the input features. Each node in the tree represents a feature, and the branches represent the possible values of that feature. The leaves of the tree represent the class labels, and the path from the root to a leaf represents a decision rule for making predictions. To make a prediction for a new input, the algorithm follows the path through the tree that corresponds to the values of the input features.
- Random Forest Classifier
  - In a Random Forest Classifier, a large number of decision trees are grown, and each tree is trained on a randomly selected subset of the data. When making a prediction for a new input, the Random Forest Classifier aggregates the predictions made by each individual decision tree and outputs the class label that is predicted by the majority of trees.
- Naive Bayes classifier
  - The Naive Bayes classifier is a probabilistic machine learning algorithm used for classification problems. It is based on Bayes' theorem, which states that the probability of a hypothesis (e.g., a class label) given some observed evidence (e.g., input features) can be estimated based on prior probabilities of the hypothesis and the probability of the evidence given the hypothesis.
- Support vector machine
  - Support Vector Machine (SVM) is a type of supervised learning algorithm used for classification and regression analysis. It is a boundary-based algorithm that finds the maximum-margin boundary that separates the classes in the data.

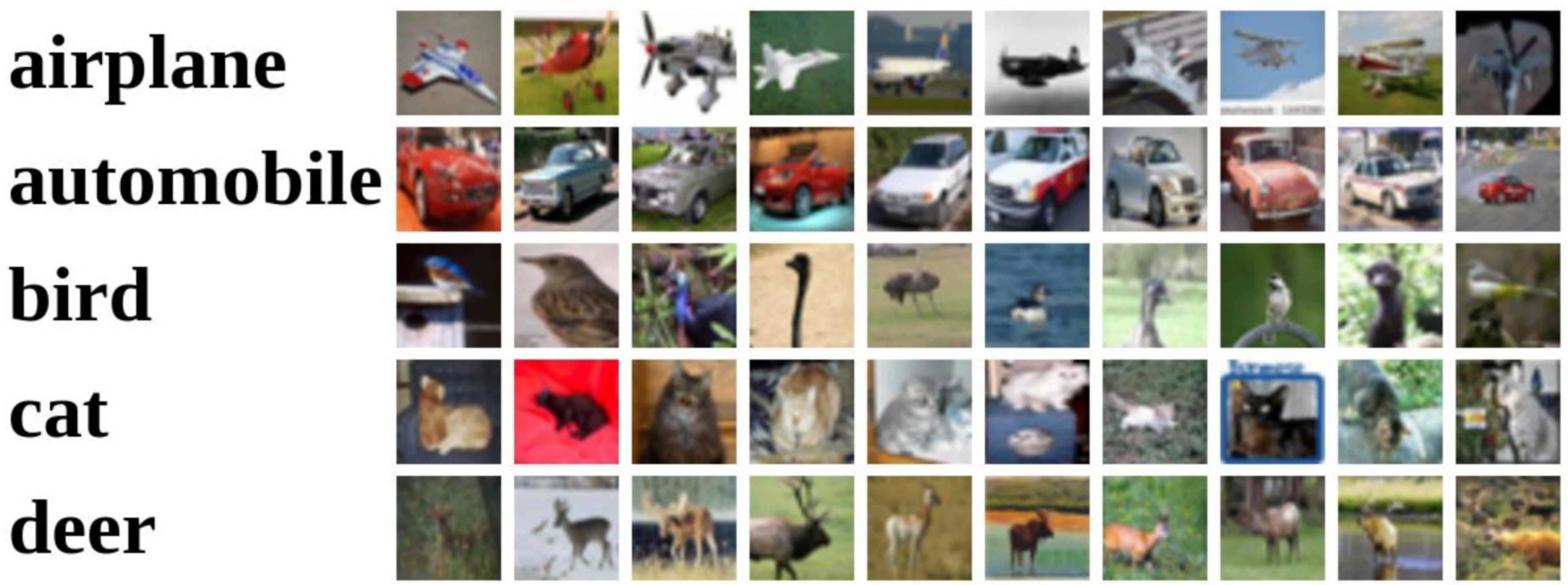
Data-driven approaches

1. Collect a dataset of images and labels
2. Use Machine Learning algorithms 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



First classifier: Nearest Neighbor

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

→ Memorize all data and labels

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

→ Predict the label of the most similar training image

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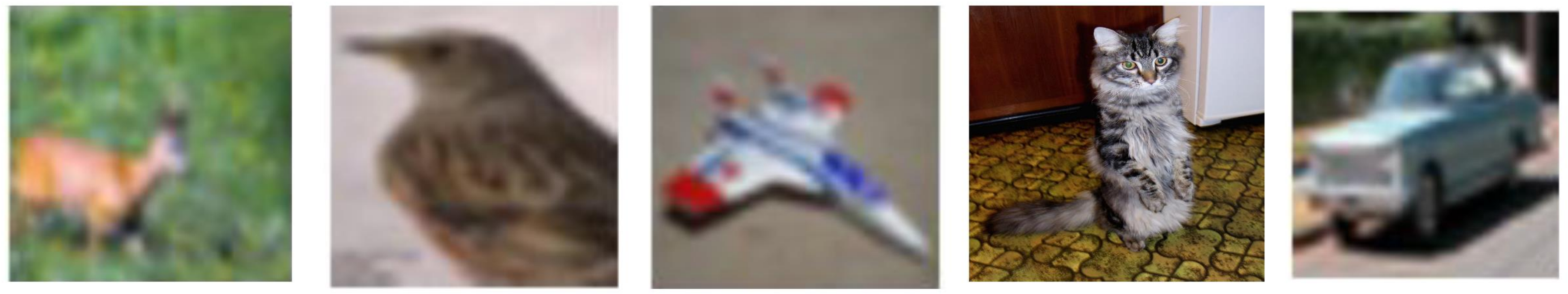
First classifier: Nearest Neighbor

deer bird plane cat car



Training data with labels

?

query data

Distance Metric $\Big|$  ,  $\Big| \rightarrow \mathbb{R}$

First classifier: Nearest Neighbor

Distance Metric to compare 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

$\xrightarrow{\text{add}}$ 456

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A good implementation:
https://github.com/facebookresearch/faiss

First classifier: Nearest Neighbor

```
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

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

Ans: Train O(1), predict O(N)

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

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First classifier: Nearest Neighbor

Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data

train

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First classifier: Nearest Neighbor

Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data

train

Idea #2: choose hyperparameters that work best on **test** data

BAD: No idea how algorithm will perform on new data

train	test

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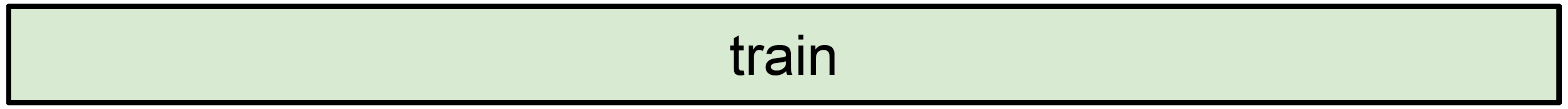
First classifier: Nearest Neighbor

Setting Hyperparameters

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

BAD: K = 1 always works perfectly on training data



Idea #2: choose hyperparameters that work best on **test** data

BAD: No idea how algorithm will perform on new data

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

Correct!!!

First classifier: Nearest Neighbor

Setting Hyperparameters

train

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 not used too frequently in deep learning

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First classifier: Nearest Neighbor

Example Dataset: **CIFAR10**

10 classes
50,000 training images
10,000 testing images

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

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

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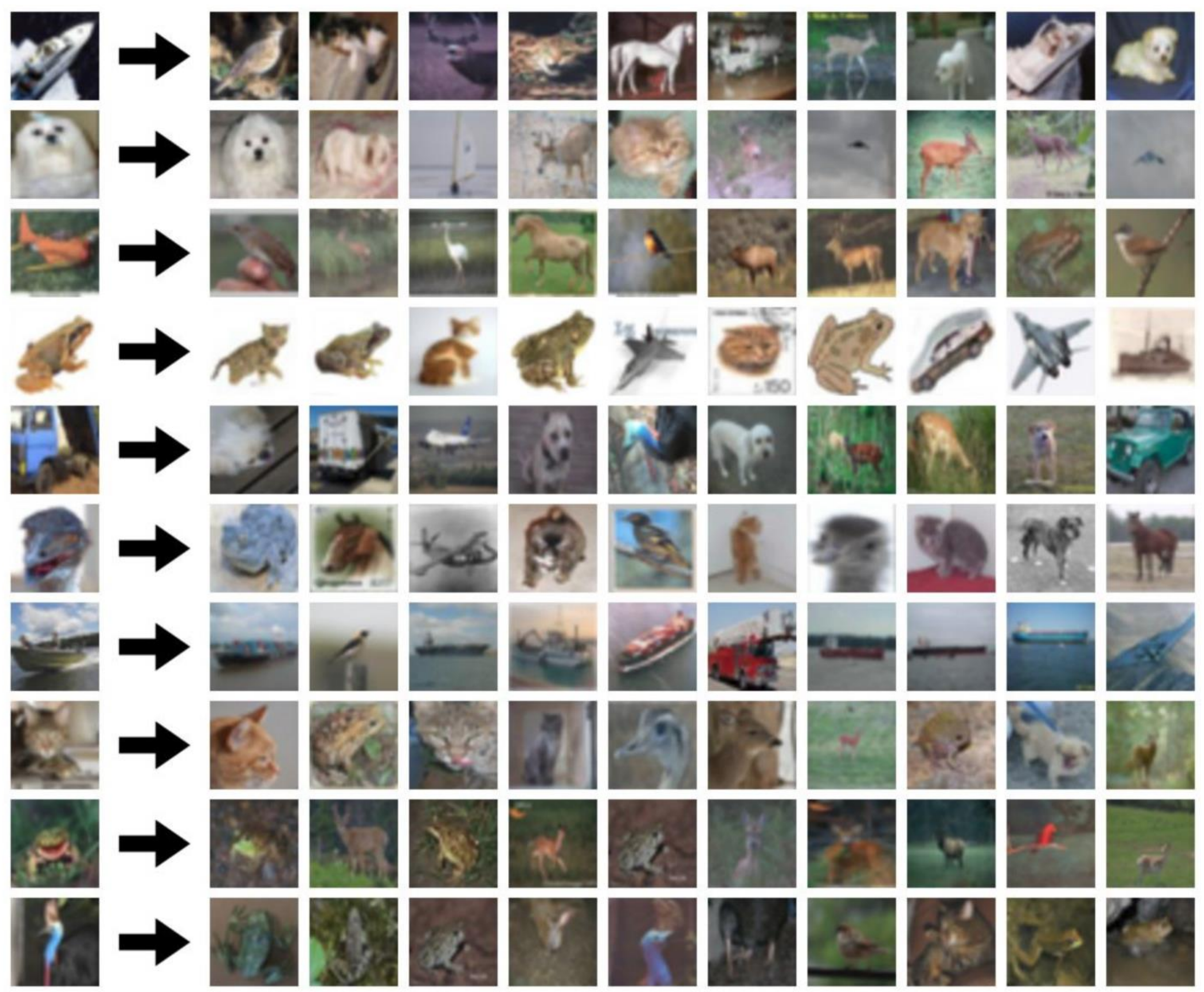
First classifier: Nearest Neighbor

Example Dataset: **CIFAR10**

10 classes
50,000 training images
10,000 testing images

Test images and nearest neighbors



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

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 the K 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!

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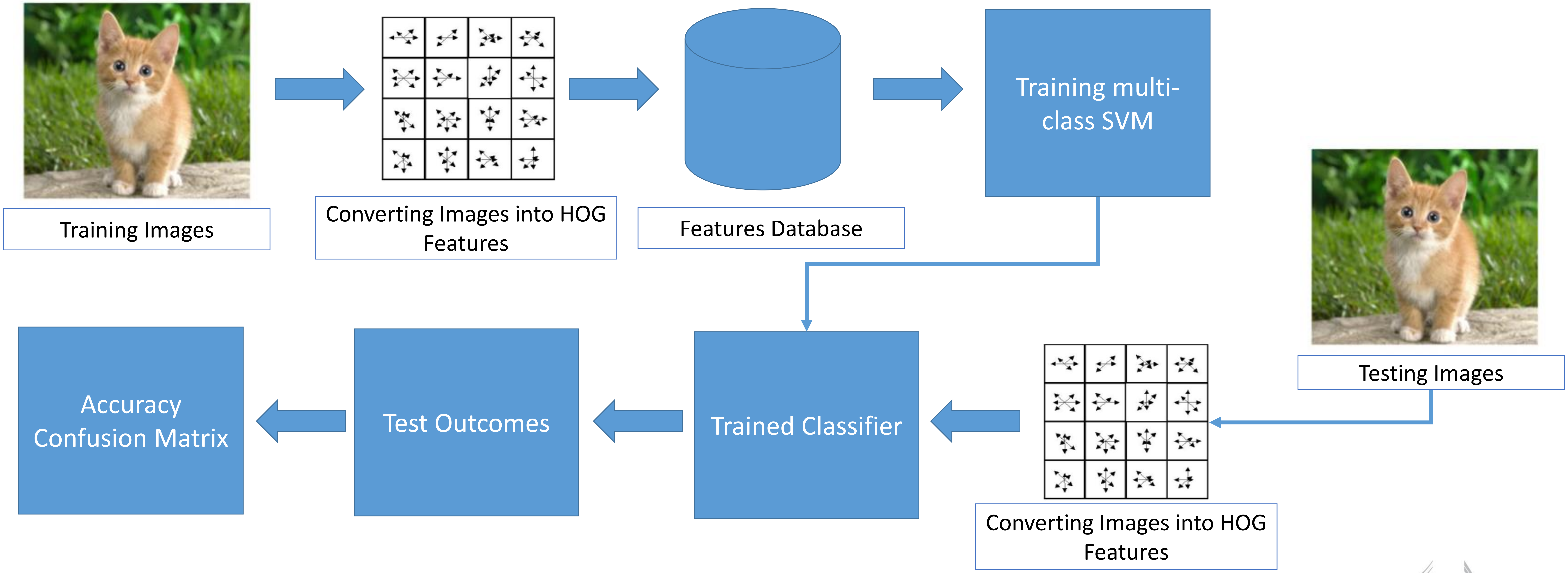
Traditional Image Classification: *Example of using HOG and SVM*



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Linear Classifier: *Parametric Approach*

Image

Array of **32x32x3** numbers (3072 numbers total)

10x1 10x3072

$$\boxed{f(w,X)} = \boxed{W}\boxed{x} + \boxed{b}$$

10x1

3072x1

$$f(x, W)$$

10 numbers giving class scores

W

parameters or weights

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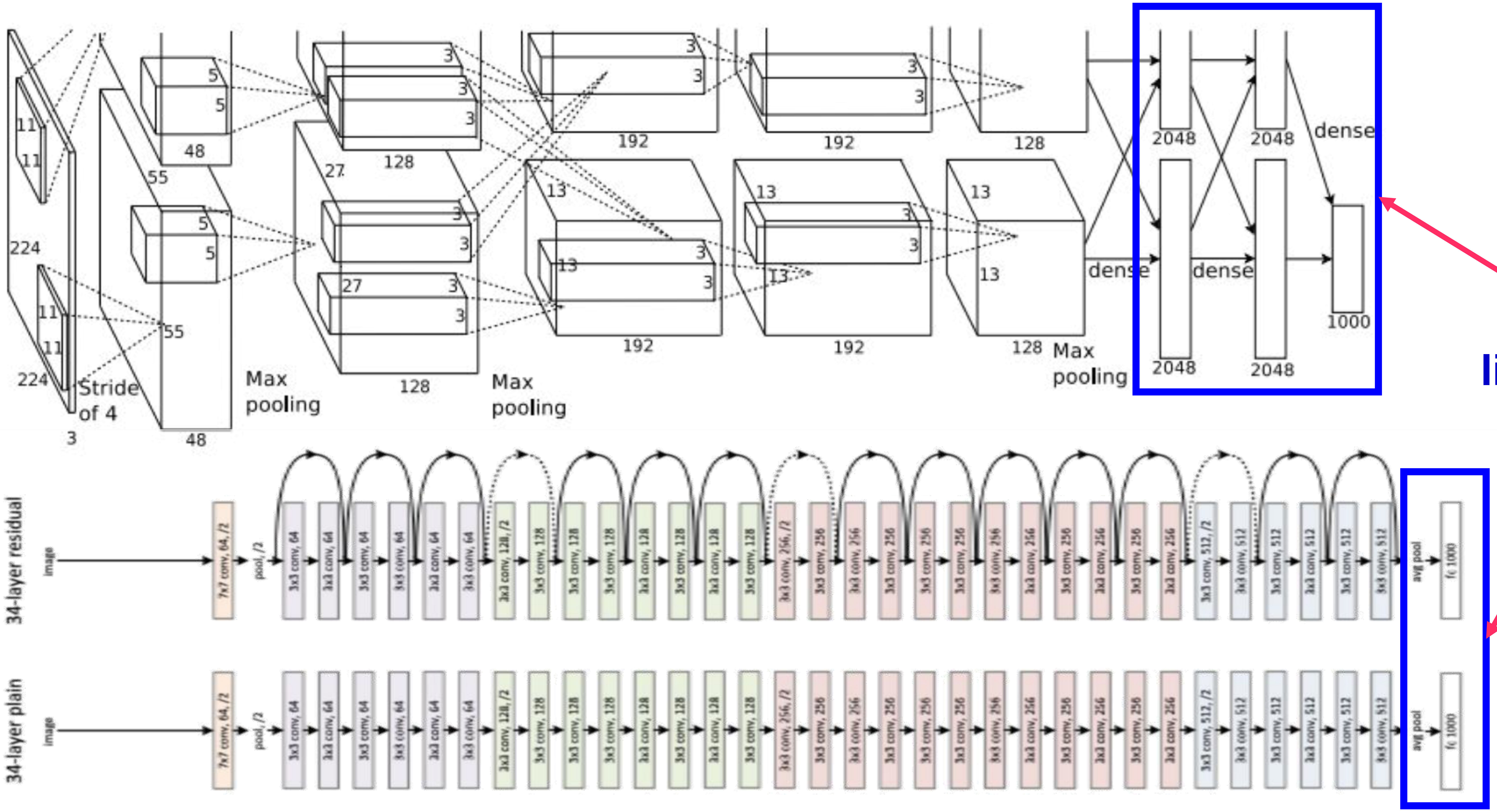
Linear Classifier: *Parametric Approach*

A **neural network** consists of several **linear classifiers**

Linear Classifier: *Parametric Approach*



[Krizhevsky et al. 2012]

linear layers

[He et al. 2015]

Linear Classifier: *Parametric Approach*

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

Flatten tensors into a vector

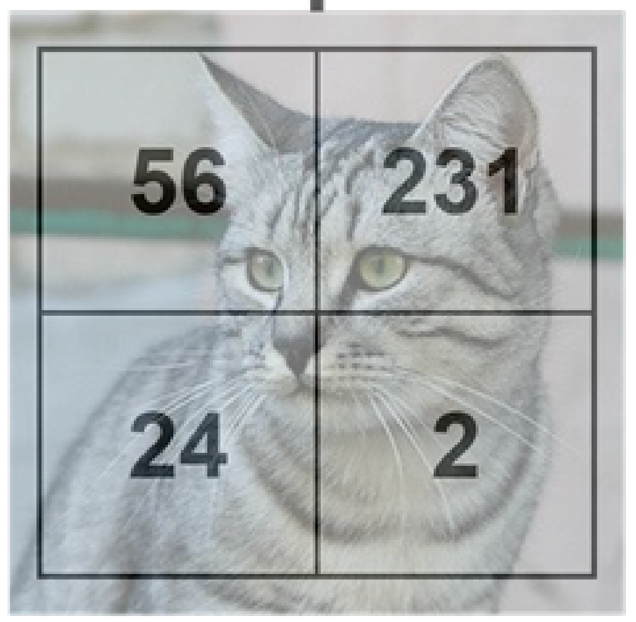
Input image

Linear Classifier: *Parametric Approach*

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

<u>Algebraic Viewpoint</u>

Flatten tensors into a vector



Input image

$$\underbrace{\begin{bmatrix} 0.2 & -0.5 & 0.1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0 & 0.25 & 0.2 & -0.3 \end{bmatrix}}_{W} \begin{bmatrix} 56 \\ 231 \\ 24 \\ 2 \end{bmatrix} + \underbrace{\begin{bmatrix} 1.1 \\ 3.2 \\ -1.2 \end{bmatrix}}_{b} = \begin{array}{cl} \begin{bmatrix} -96.8 \\ 437.9 \\ 61.95 \end{bmatrix} & \begin{array}{l} \text{Cat score} \\ \text{Dog score} \\ \text{Ship score} \end{array} \end{array}$$

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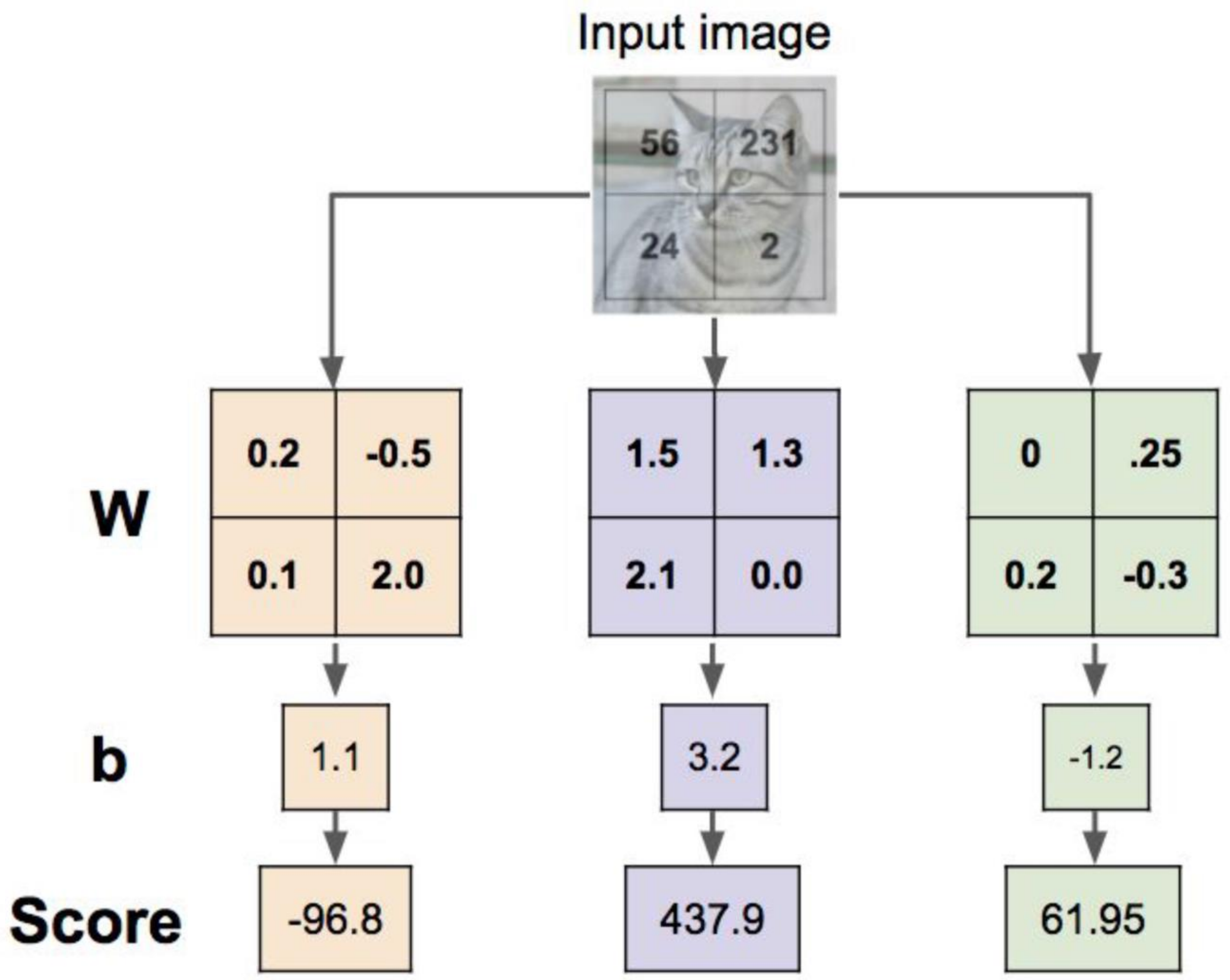
Linear Classifier: *Parametric Approach*

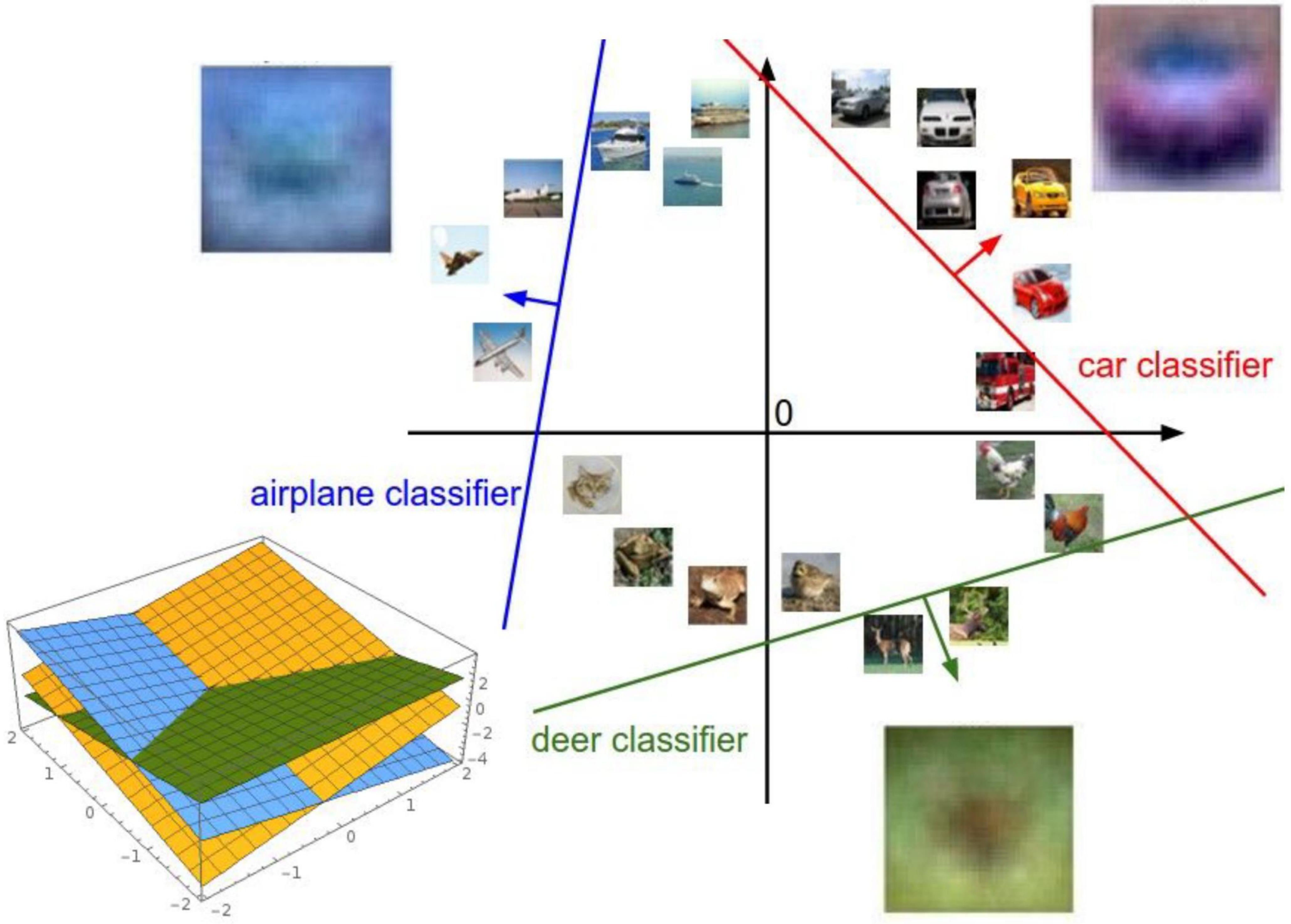
Interpreting a Linear Classifier

Visual Viewpoint



Linear Classifier: *Parametric Approach*

Interpreting a Linear Classifier: Geometric Viewpoint



$$f(x,W) = Wx + b$$

Array of **32x32x3** numbers
(3072 numbers total)

Plot created using Wolfram Cloud

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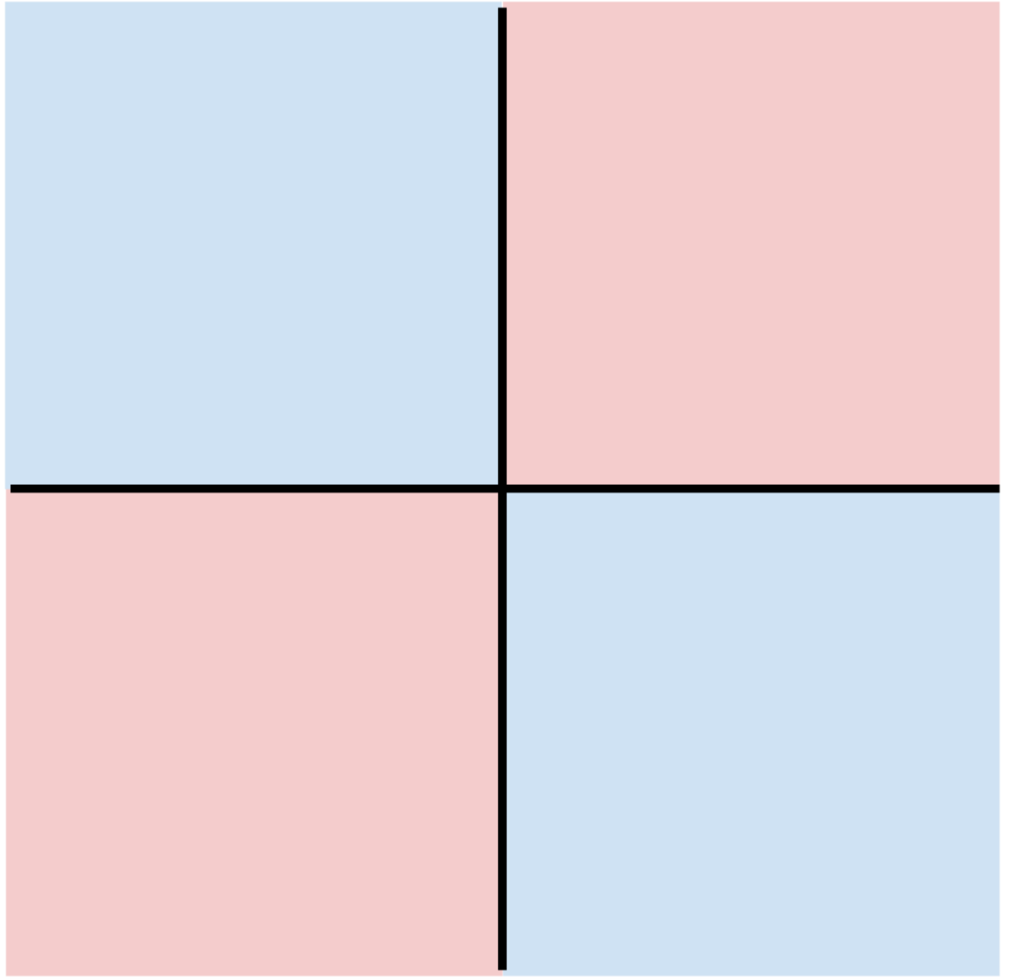
Linear Classifier

Hard cases for a linear classifier

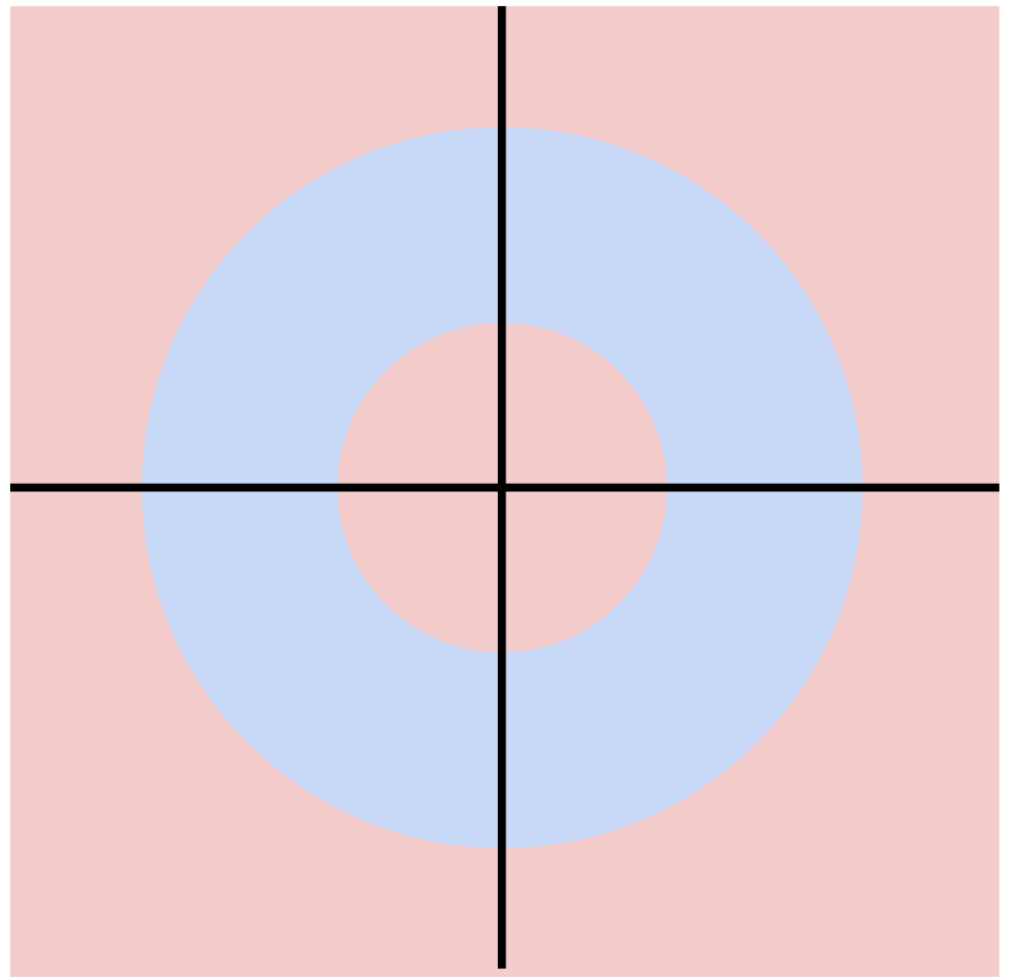
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



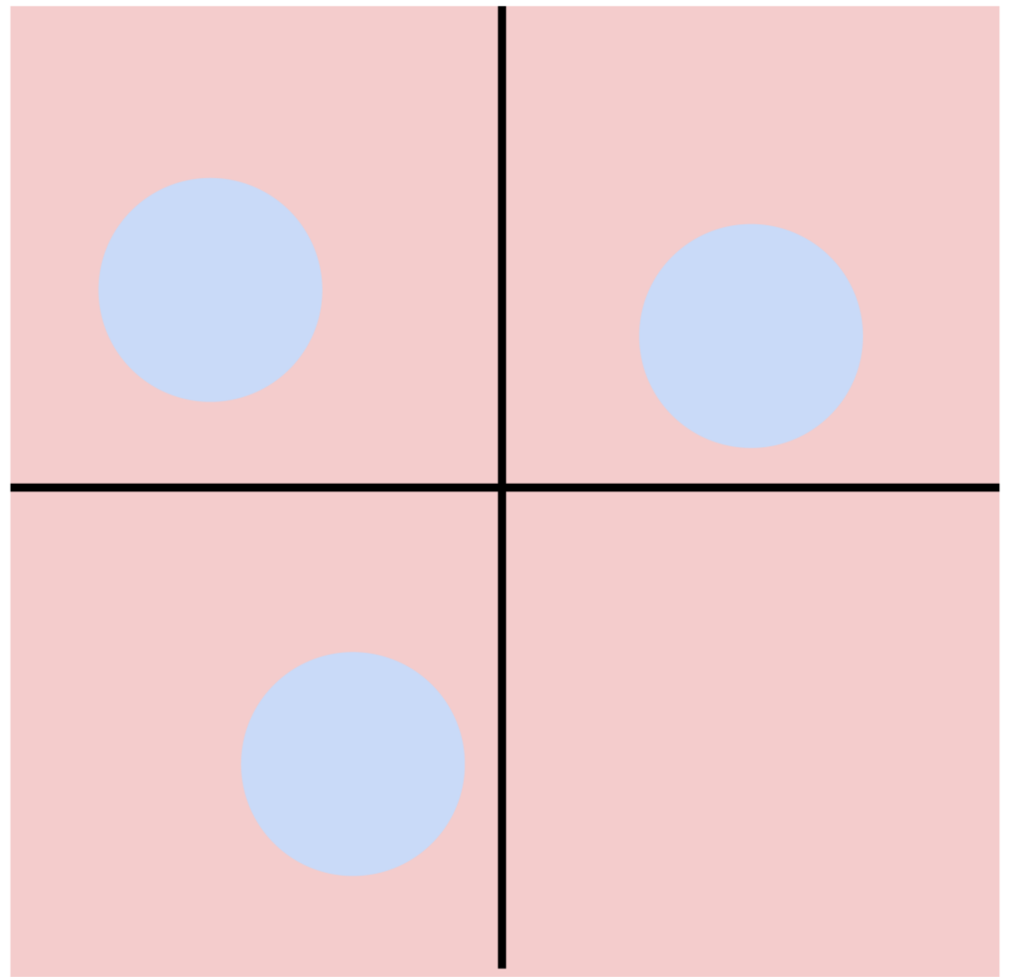
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

Class 2:
Everything else



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Linear Classifier: *SVM*

Linear Classifier – Choose a good W

airplane	-3.45	-0.51	3.42
automobile	-8.87	**6.04**	4.64
bird	0.09	5.31	2.65
cat	**2.9**	-4.22	5.1
deer	4.48	-4.19	2.64
dog	8.02	3.58	5.55
frog	3.78	4.49	**-4.34**
horse	1.06	-4.37	-1.5
ship	-0.36	-2.09	-4.79
truck	-0.72	-2.93	6.14

TODO:

1. Define a **loss function** that quantifies our unhappiness with the scores across the training data.

2. Come up with a way of efficiently finding the parameters that minimize the loss function. **(optimization)**

Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

A **loss function** tells how good our current classifier is

Given a dataset of examples

$$\{(x_i, y_i)\}_{i=1}^{N}$$

Where x_i is image and y_i is (integer) label

Loss over the dataset is a average of loss over examples:

$$L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$$

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Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x,W) = Wx$ are:

cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Multiclass SVM loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$L_i = \sum_{j \neq y_i} \begin{cases} 0 & \text{if } s_{y_i} \geq s_j + 1 \\ s_j - s_{y_i} + 1 & \text{otherwise} \end{cases}$$
$$= \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9		

Multiclass SVM loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

= max(0, 5.1 - 3.2 + 1)
+max(0, -1.7 - 3.2 + 1)
= max(0, 2.9) + max(0, -3.9)
= 2.9 + 0
= 2.9

Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:

cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	

Multiclass SVM loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

= max(0, 1.3 - 4.9 + 1)
+max(0, 2.0 - 4.9 + 1)
= max(0, -2.6) + max(0, -1.9)
= 0 + 0
= 0

Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:

cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Multiclass SVM loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the
scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

= max(0, 2.2 - (-3.1) + 1)
+max(0, 2.5 - (-3.1) + 1)
= max(0, 6.3) + max(0, 6.6)
= 6.3 + 6.6
= 12.9

Linear Classifier: *SVM*

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:

cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Multiclass SVM loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

Loss over full dataset is average:

$$L = \frac{1}{N} \sum_{i=1}^{N} L_i$$

L = (2.9 + 0 + 12.9)/3
= **5.27**

Linear Classifier: *SVM*

Multiclass SVM loss:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

cat	1.3
car	**4.9**
frog	2.0
Losses:	0

Q1: What happens to loss if car scores decrease by 0.5 for this training example?

Q2: What is the min/max possible SVM loss L_i?

Q3: At initialization W is small so all s ≈ 0. What is the loss L_i, assuming N examples and C classes?

Q4: What if the sum was over all classes? (including j = y_i)

Q5: What if we used the mean instead of sum?

Q6: What if we used $L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)^2$

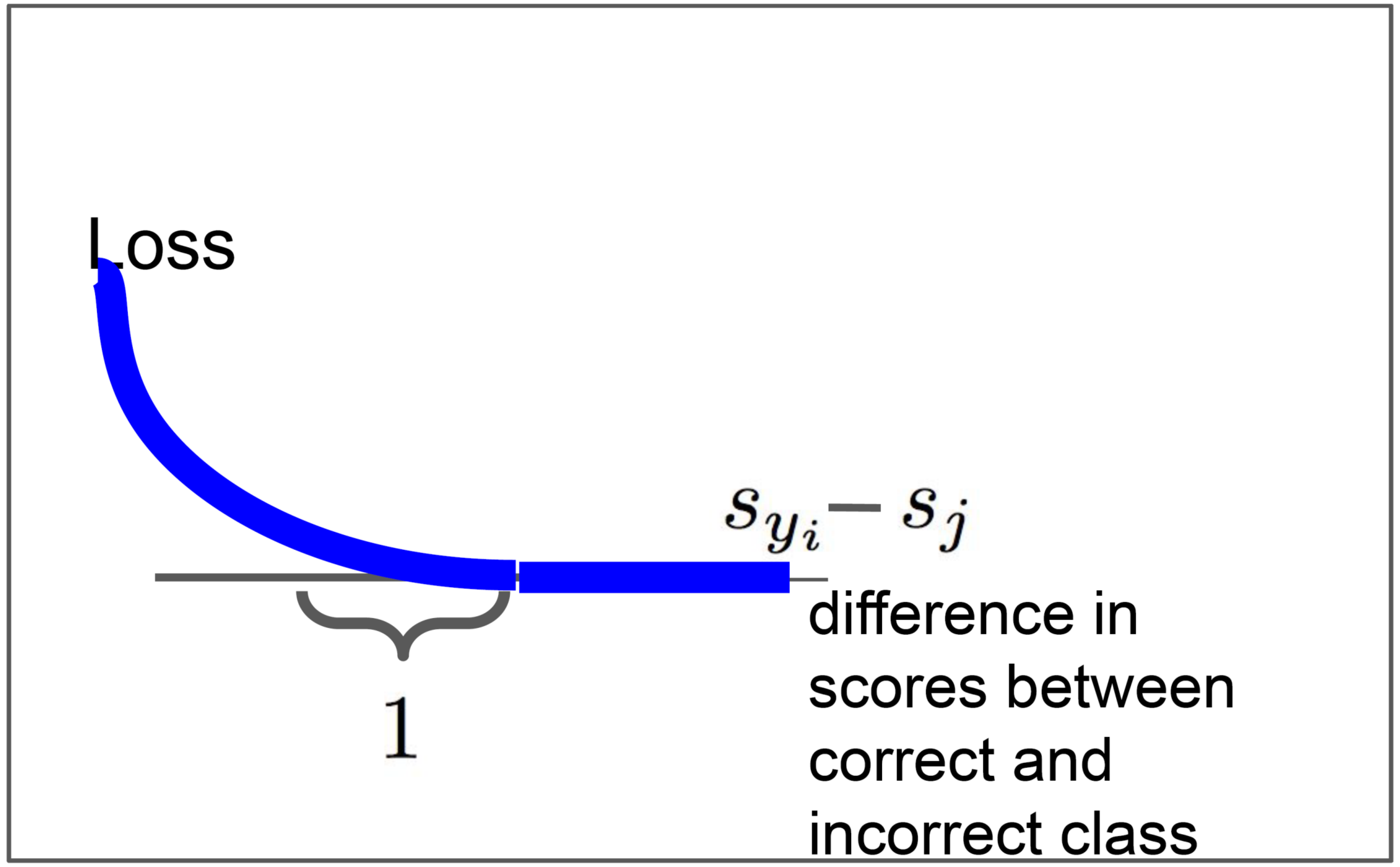
Linear Classifier: *SVM*

Multiclass SVM loss:

$$\boxed{L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)}$$

cat	1.3
car	**4.9**
frog	2.0
Losses:	0

Multiclass SVM loss:



Q6: What if we used $L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)^2$

Linear Classifier: *Softmax*

Softmax Classifier (Multinomial Logistic Regression)

Want to interpret raw classifier scores as **probabilities**

$$s = f(x_i; W)$$

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$ Softmax Function

$$L_i = -\log P(Y = y_i | X = x_i)$$

	Unnormalized log-probabilities / logits		unnormalized probabilities (Probabilities must be >= 0)		probabilities (Probabilities must sum to 1)
cat	**3.2**	exp →	**24.5**	normalize →	$\boxed{\mathbf{0.13}}$
car	5.1		164.0		0.87
frog	-1.7		0.18		0.00

→ $L_i = -\log(0.13)$
$= \mathbf{2.04}$

Maximum Likelihood Estimation
Choose weights to maximize the likelihood of the observed data

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Linear Classifier: *Softmax*

Softmax Classifier (Multinomial Logistic Regression)

Want to interpret raw classifier scores as **probabilities**

$$s = f(x_i; W)$$

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

Softmax Function

Probabilities must be >= 0

Probabilities must sum to 1

	Unnormalized log-probabilities / logits	$\xrightarrow{\text{exp}}$	unnormalized probabilities	$\xrightarrow{\text{normalize}}$	probabilities	→ compare ←	Correct probs
cat	**3.2**		**24.5**		**0.13**		**1.00**
car	5.1		164.0		0.87		0.00
frog	-1.7		0.18		0.00		0.00

Kullback–Leibler divergence

$$D_{KL}(P \| Q) = \sum_y P(y) \log \frac{P(y)}{Q(y)}$$

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Linear Classifier: *Softmax*

Softmax Classifier (Multinomial Logistic Regression)

Want to interpret raw classifier scores as **probabilities**

$$\boxed{s = f(x_i; W)}$$

$$\boxed{P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}}$$

Softmax Function

Probabilities must be >= 0

Probabilities must sum to 1

	Unnormalized log-probabilities / logits	exp → unnormalized probabilities	normalize → probabilities	Correct probs
cat	**3.2**	**24.5**	**0.13**	**1.00**
car	5.1	164.0	0.87	0.00
frog	-1.7	0.18	0.00	0.00

→ compare ←

Cross Entropy

$$H(P, Q) = H(p) + D_{KL}(P \| Q)$$

Linear Classifier: *Softmax*

Softmax Classifier (Multinomial Logistic Regression)

Want to interpret raw classifier scores as **probabilities**

$$\boxed{s = f(x_i; W)}$$

$$\boxed{P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}}$$ Softmax Function

Maximize probability of correct class

$$L_i = -\log P(Y = y_i | X = x_i)$$

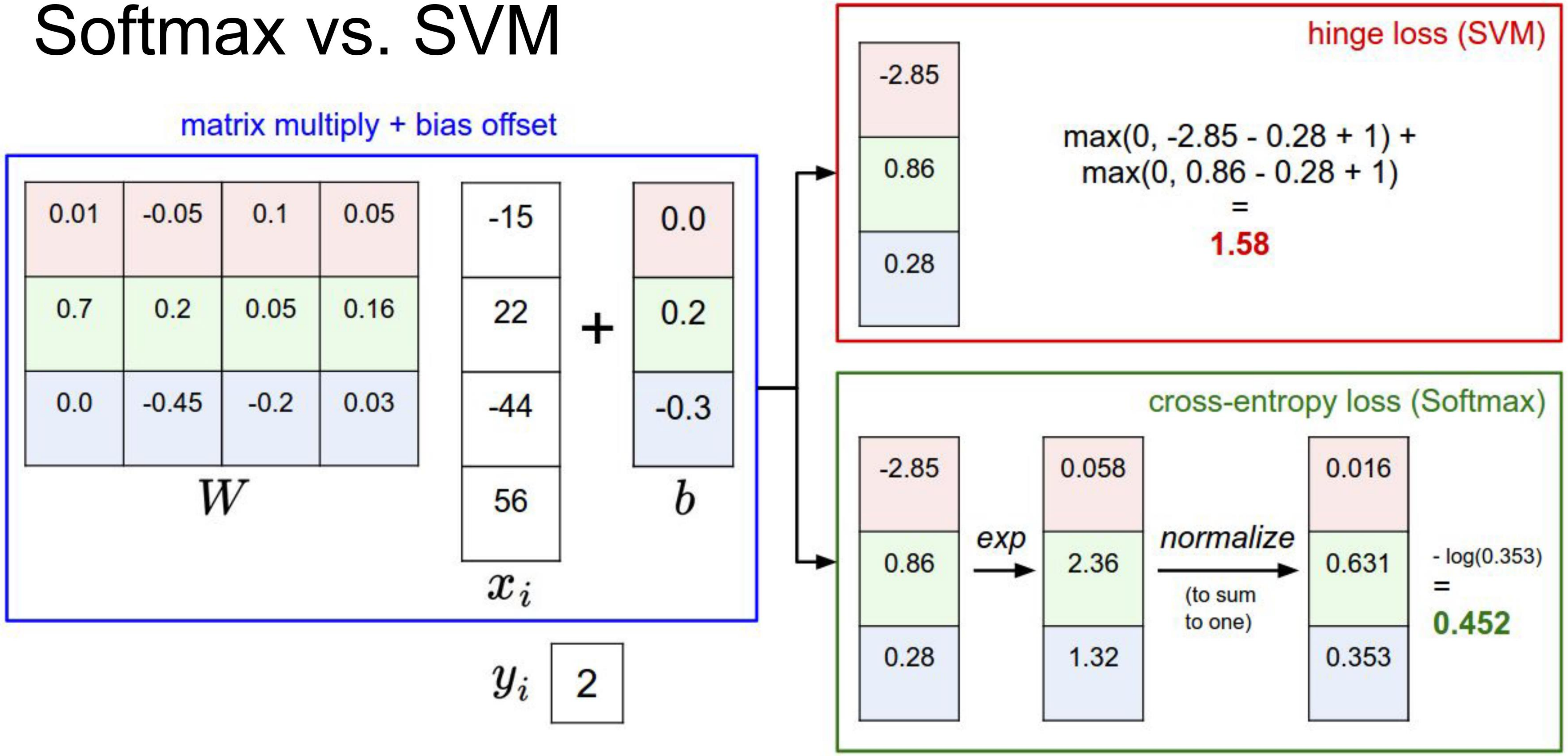
Putting it all together:

$$L_i = -\log\left(\frac{e^{s_{y_i}}}{\sum_j e^{s_j}}\right)$$

cat	**3.2**
car	5.1
frog	-1.7

Linear Classifier: *Softmax*

Softmax vs. SVM



$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$L_i = -\log\left(\frac{e^{s_{y_i}}}{\sum_j e^{s_j}}\right)$$

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Next Courses

- Brief discussion on regularization & optimization techniques
- Image Classification with CNNs
  - Training, Visualizing and Understanding
- Object Detection and Image Classification
  - Recurrent Neural Networks
  - Attention and Transformers

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Research in Deep Camera

Deep Camera

CYENS CENTRE OF EXCELLENCE

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Research Interests:

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Thank you!

See you next week

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