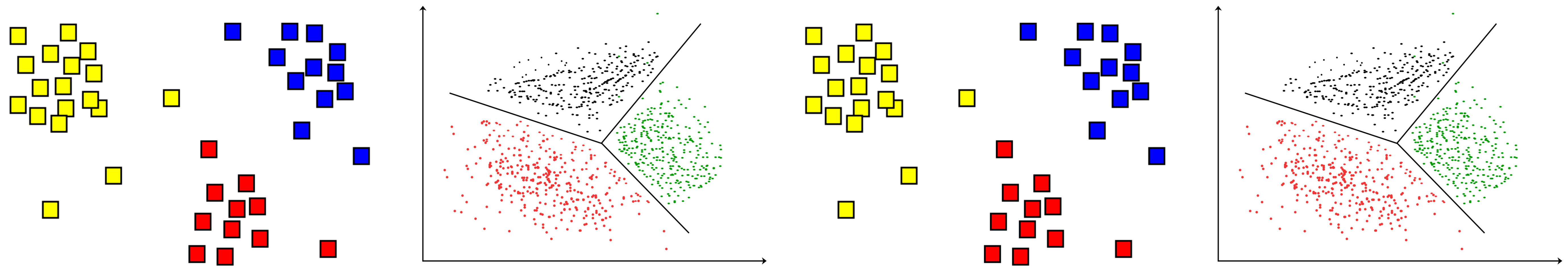
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 26: Classification

Menu for Today (**November 13, 2020**)

Topics:

— Classification (cont)
— kNN, SVMs
— Bag of Words Representation
— Scene Classification

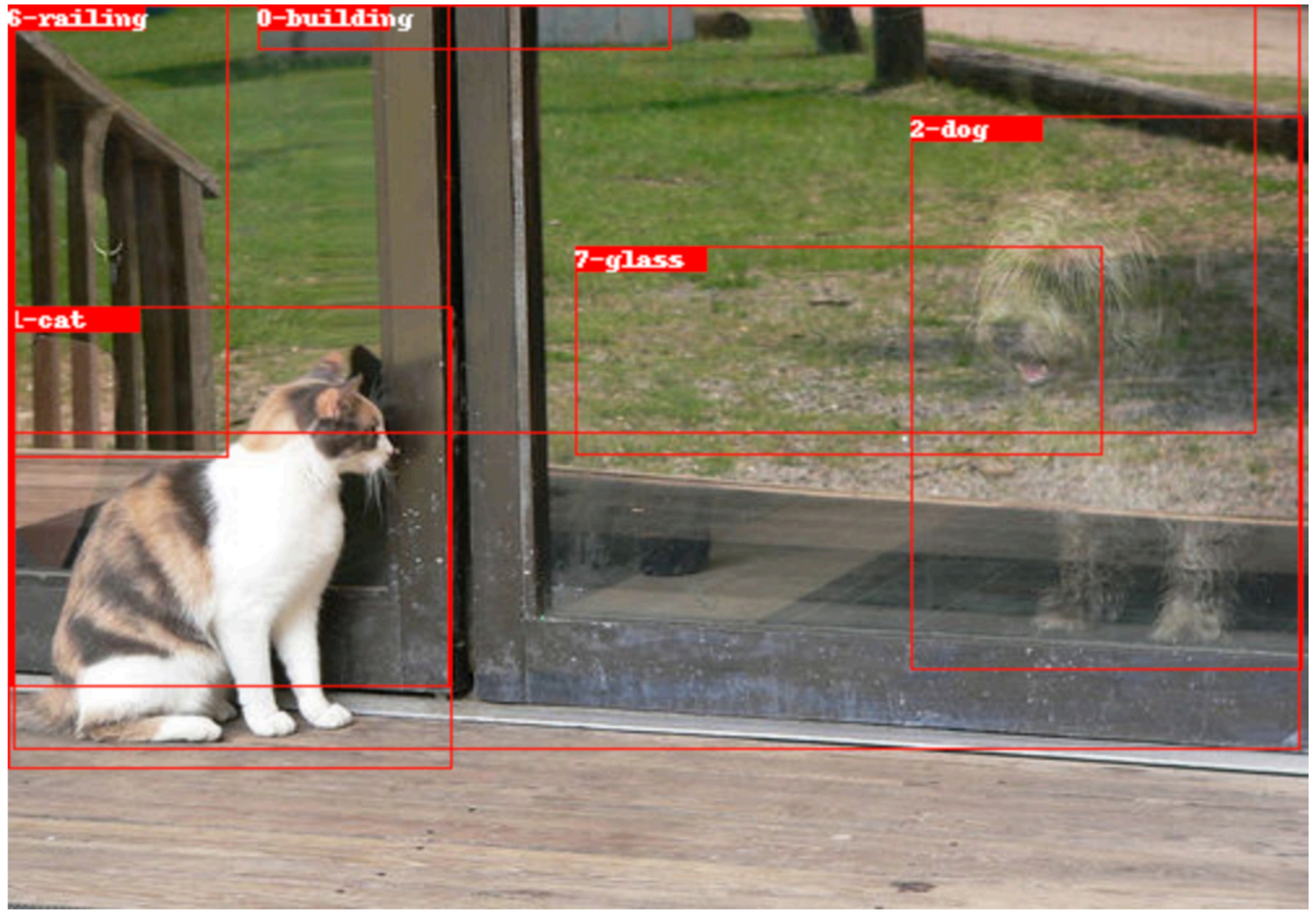
Redings:

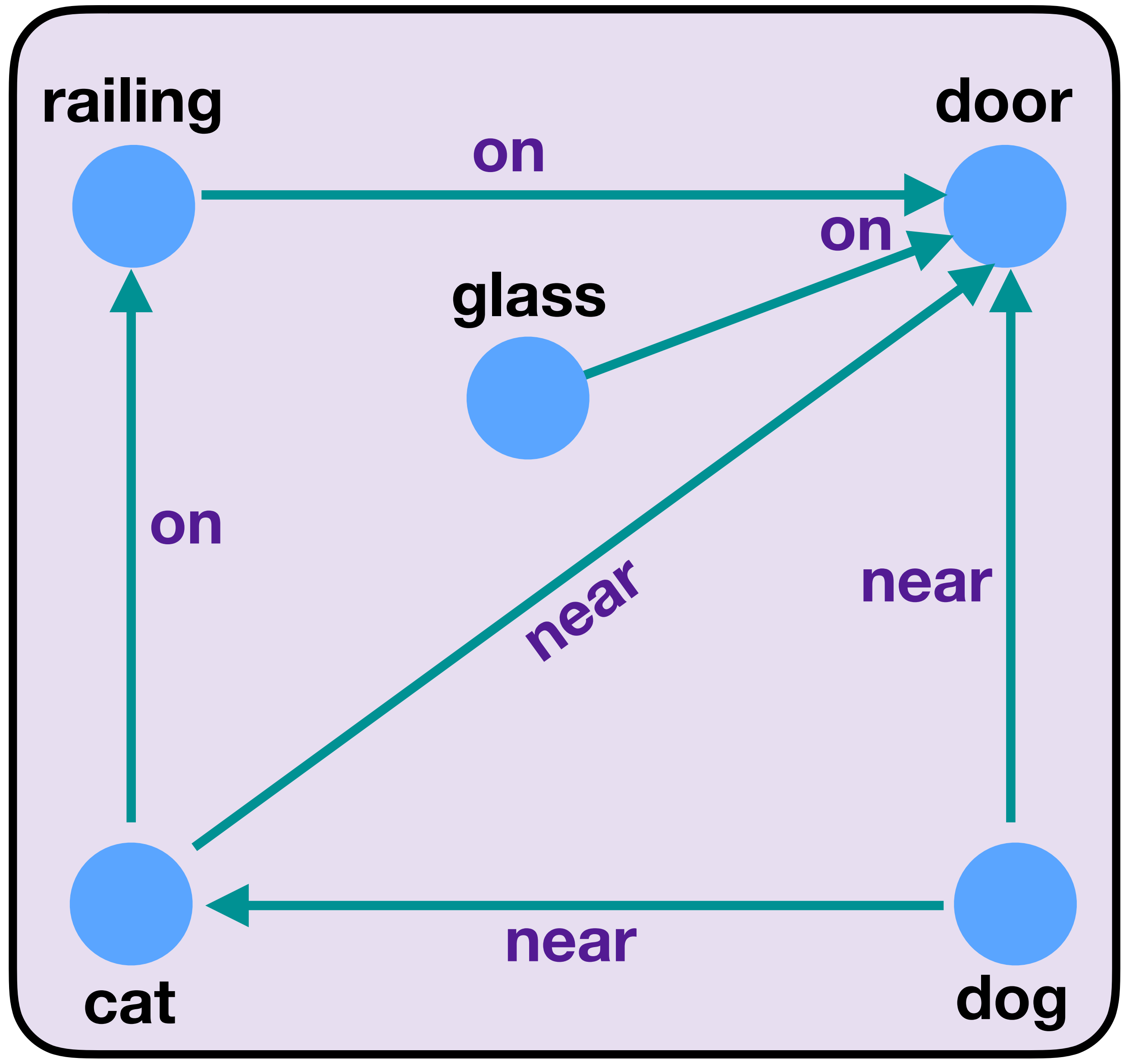
— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 15
— **Next** Lecture: Forsyth & Ponce (2nd ed.) 16.1.3, 16.1.4, 16.1.9

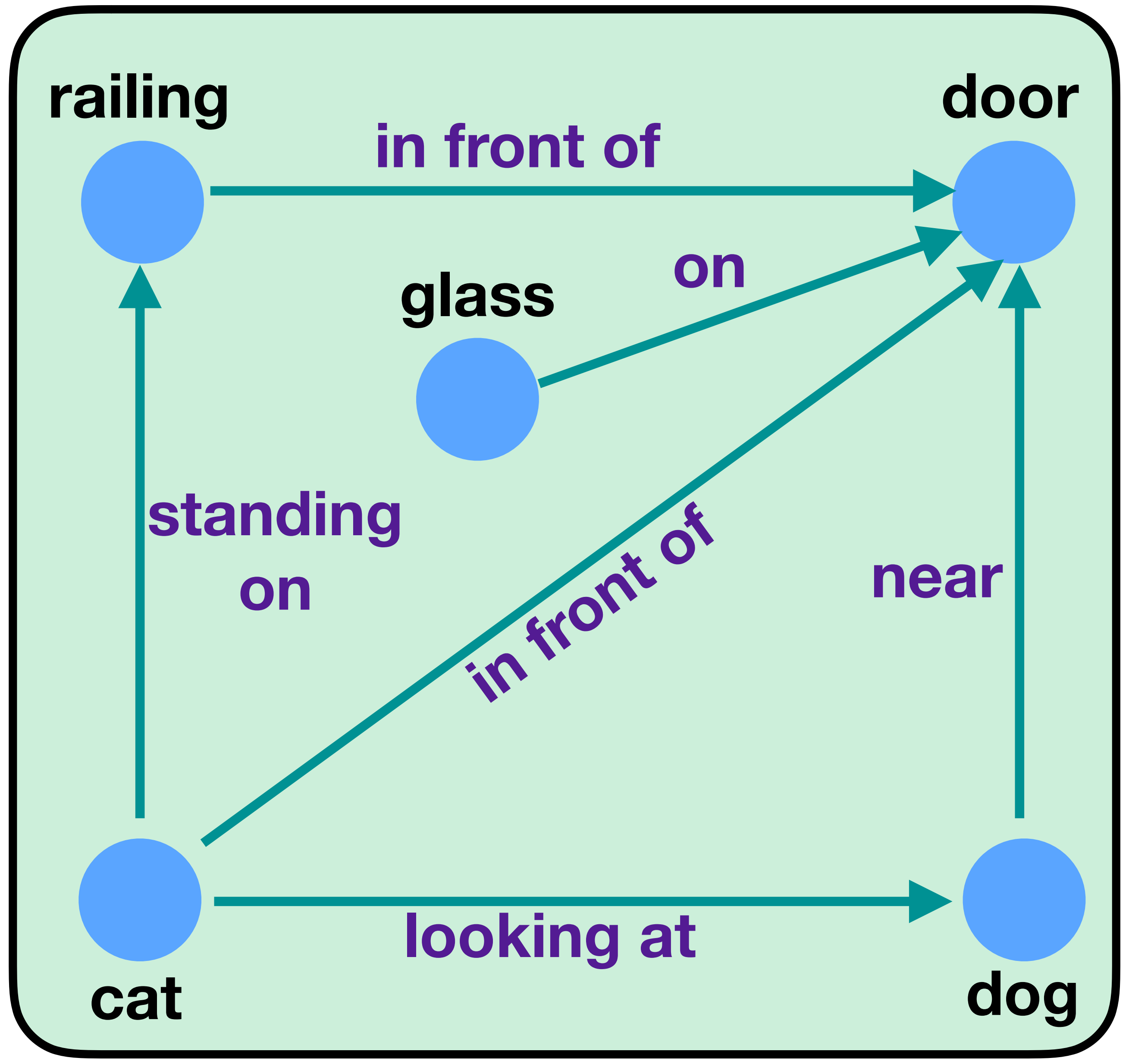
Reminders:

— **Assignment 5**: Scene Recognition with Bag of Words is **out**

Today’s “**fun**” Example: Scene Graph Prediction







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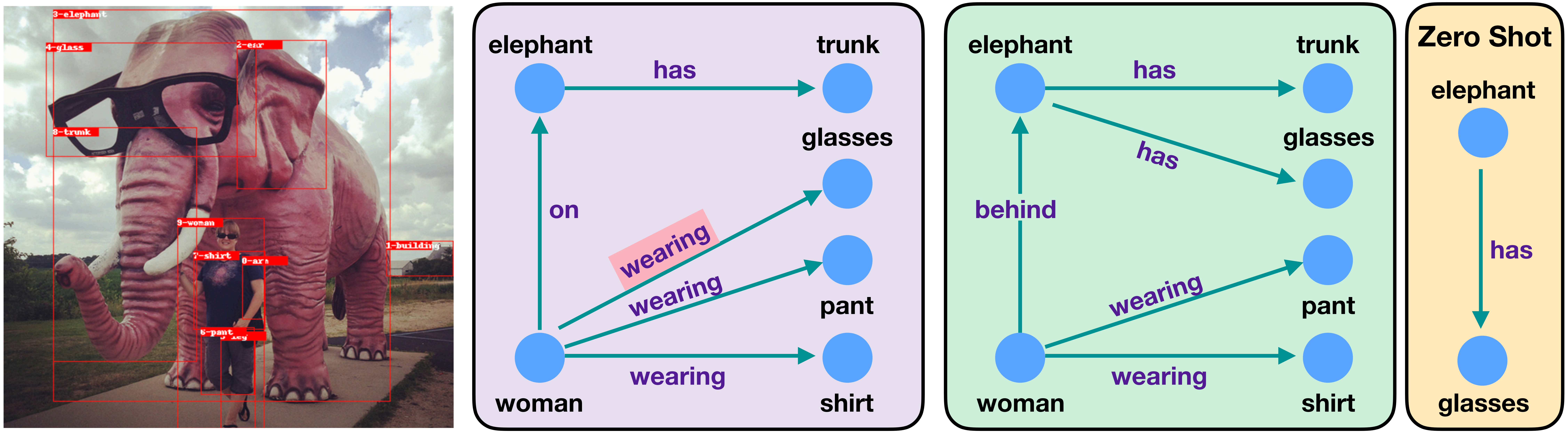
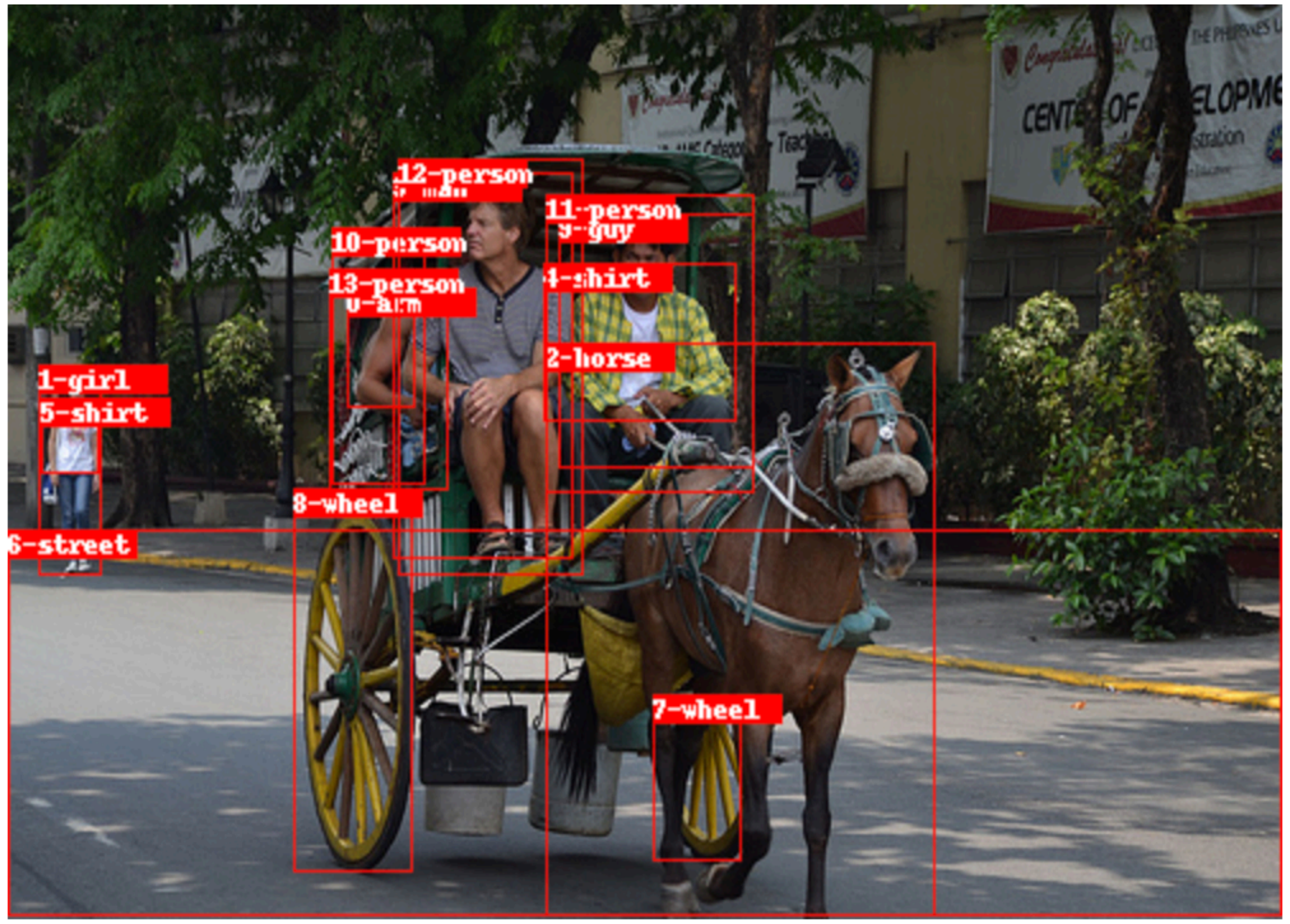
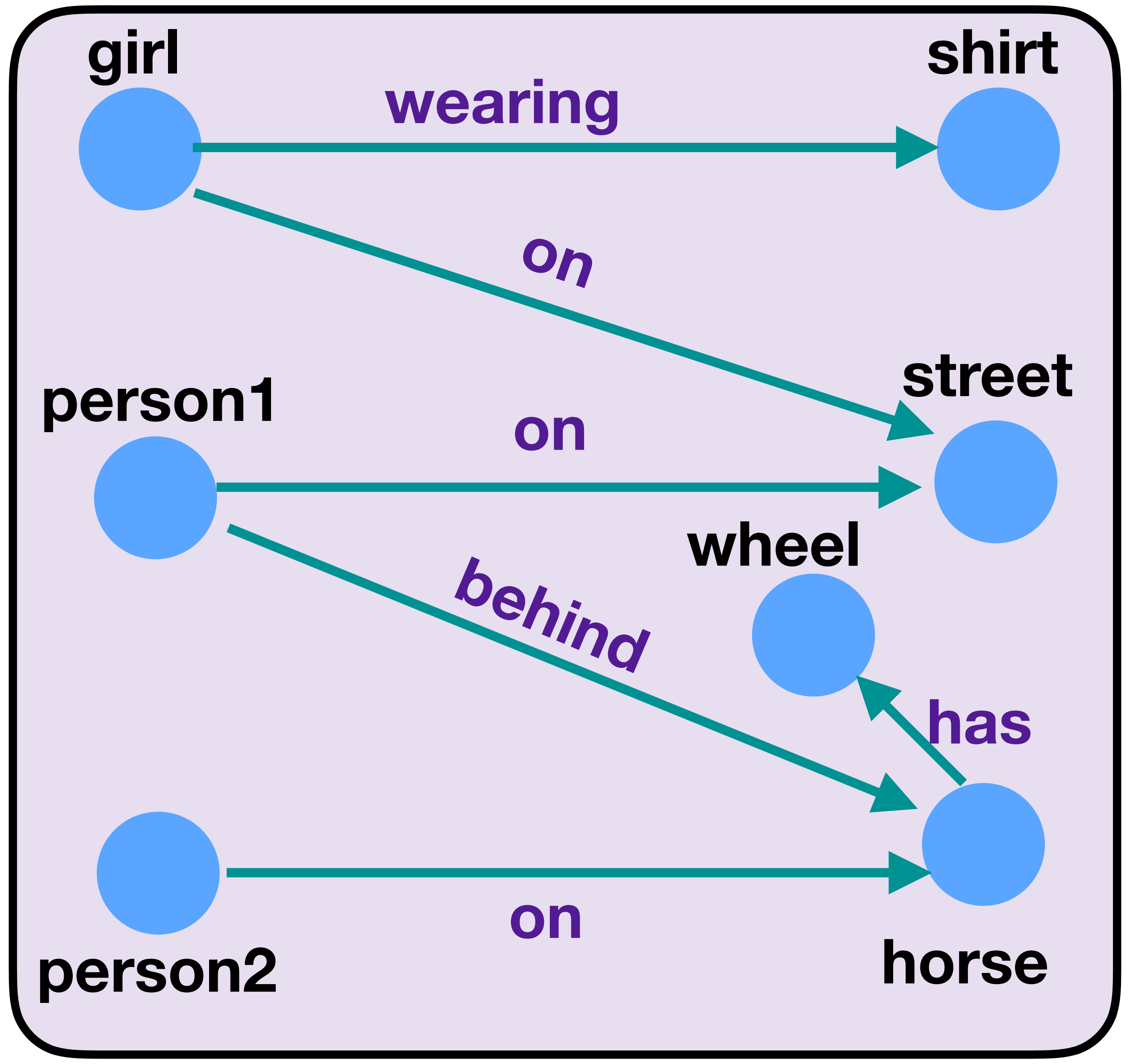
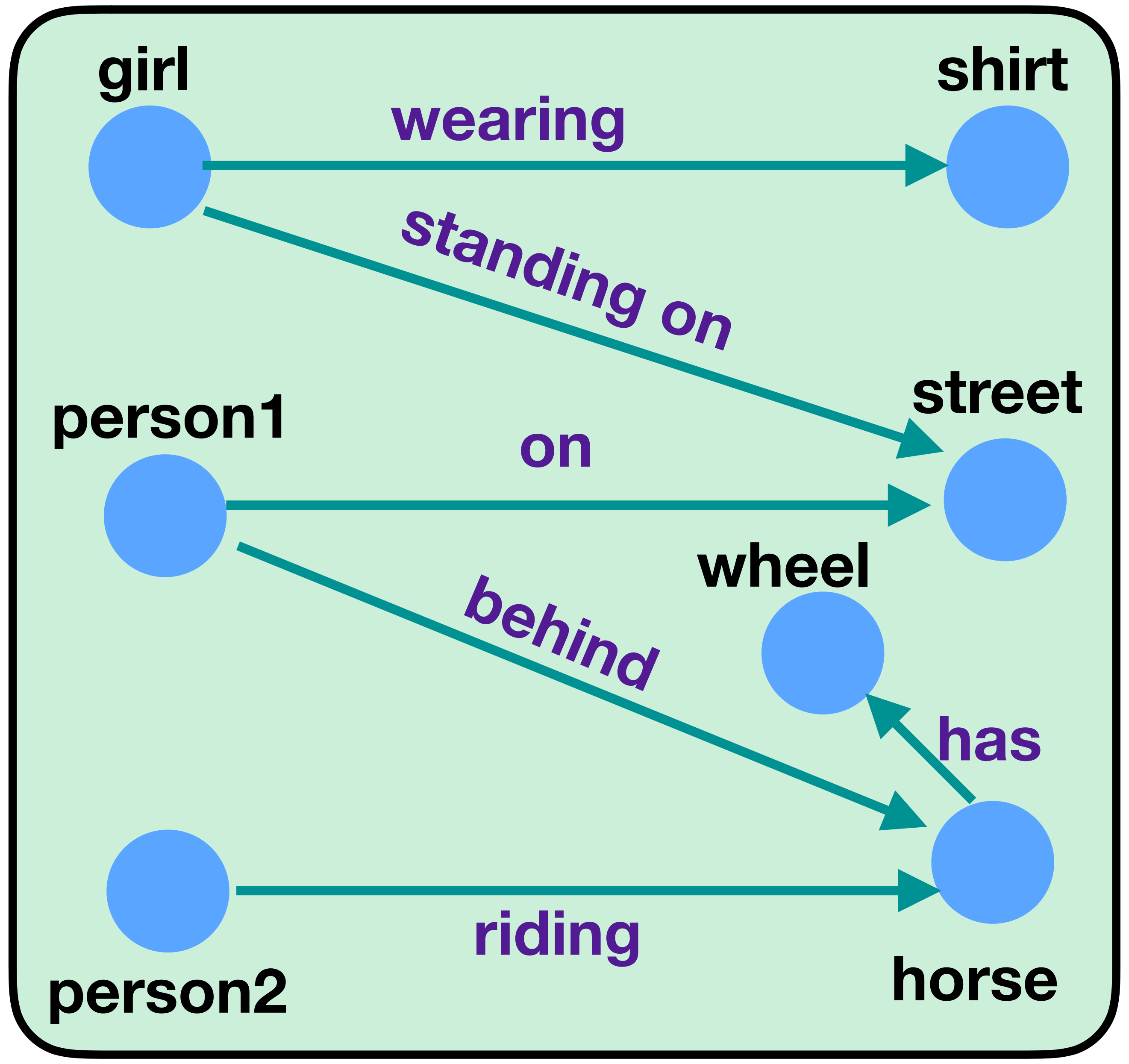


Today’s “**fun**” Example: Scene Graph Prediction





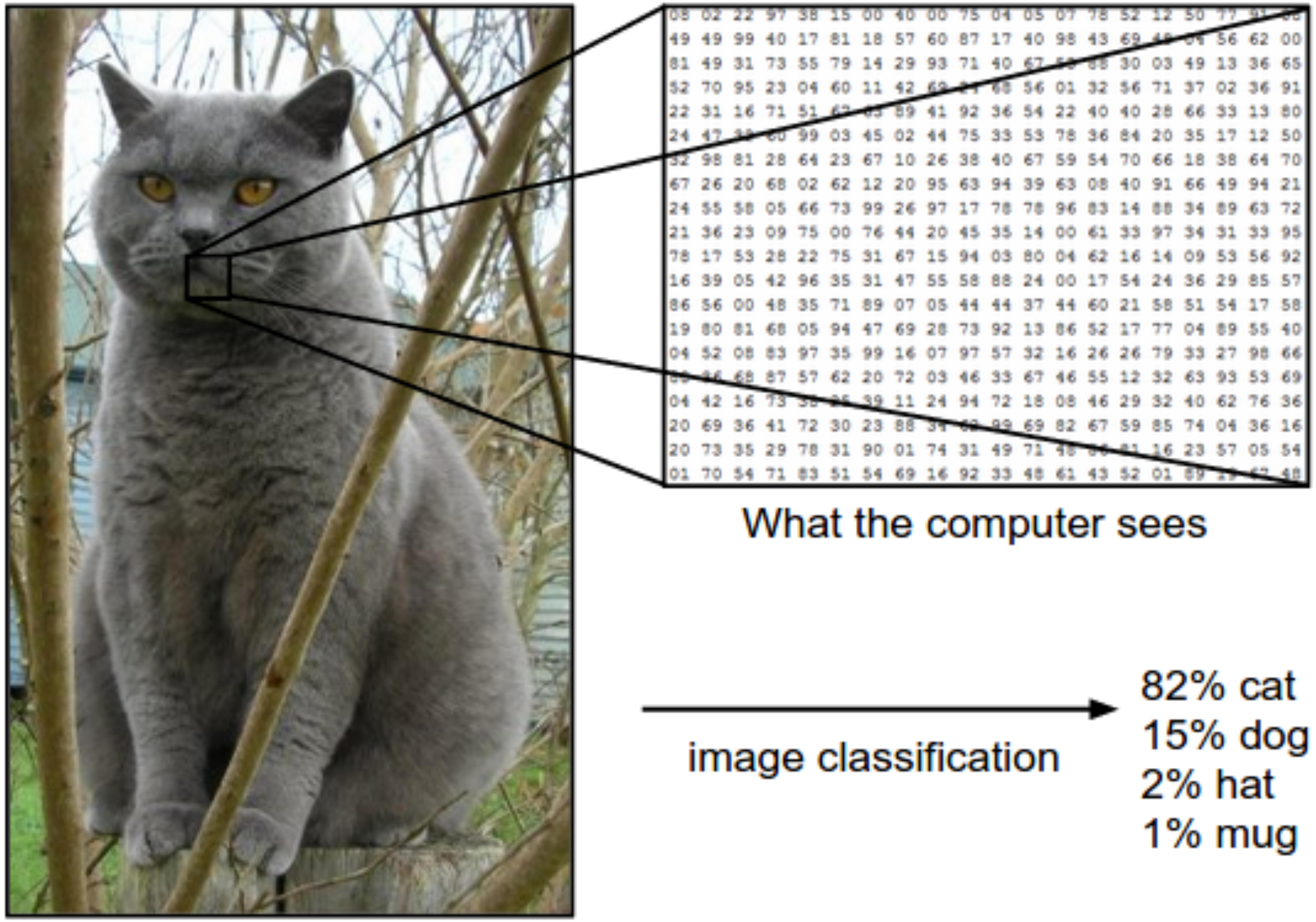


Lecture 25: Classification

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

$\longrightarrow$ cat

Lecture 25: Classification



Lecture 25: Bayes Classifier

Let c be the **class label** and let x be the **measurement** (i.e., evidence)

class–conditional probability
(a.k.a. likelihood)

prior probability

$$P(c|x) = \frac{P(x|c)p(c)}{P(x)}$$

posterior probability

unconditional probability
(a.k.a. marginal likelihood)

Lecture 25: Forms of Classifiers

Classification strategies fall under two broad types: **parametric** and **non-parametric**.

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Parametric classifiers are **model driven**. The parameters of the model are learned from training examples. New data points are classified by the learned model.

— fast, compact

— flexibility and accuracy depend on model assumptions

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Non-parametric classifiers are **data driven**. New data points are classified by comparing to the training examples directly. "The data is the model".
— slow

— highly flexible decision boundaries

Nearest Neighbor Classifier

Given a new data point, assign the label of nearest training example in feature space.

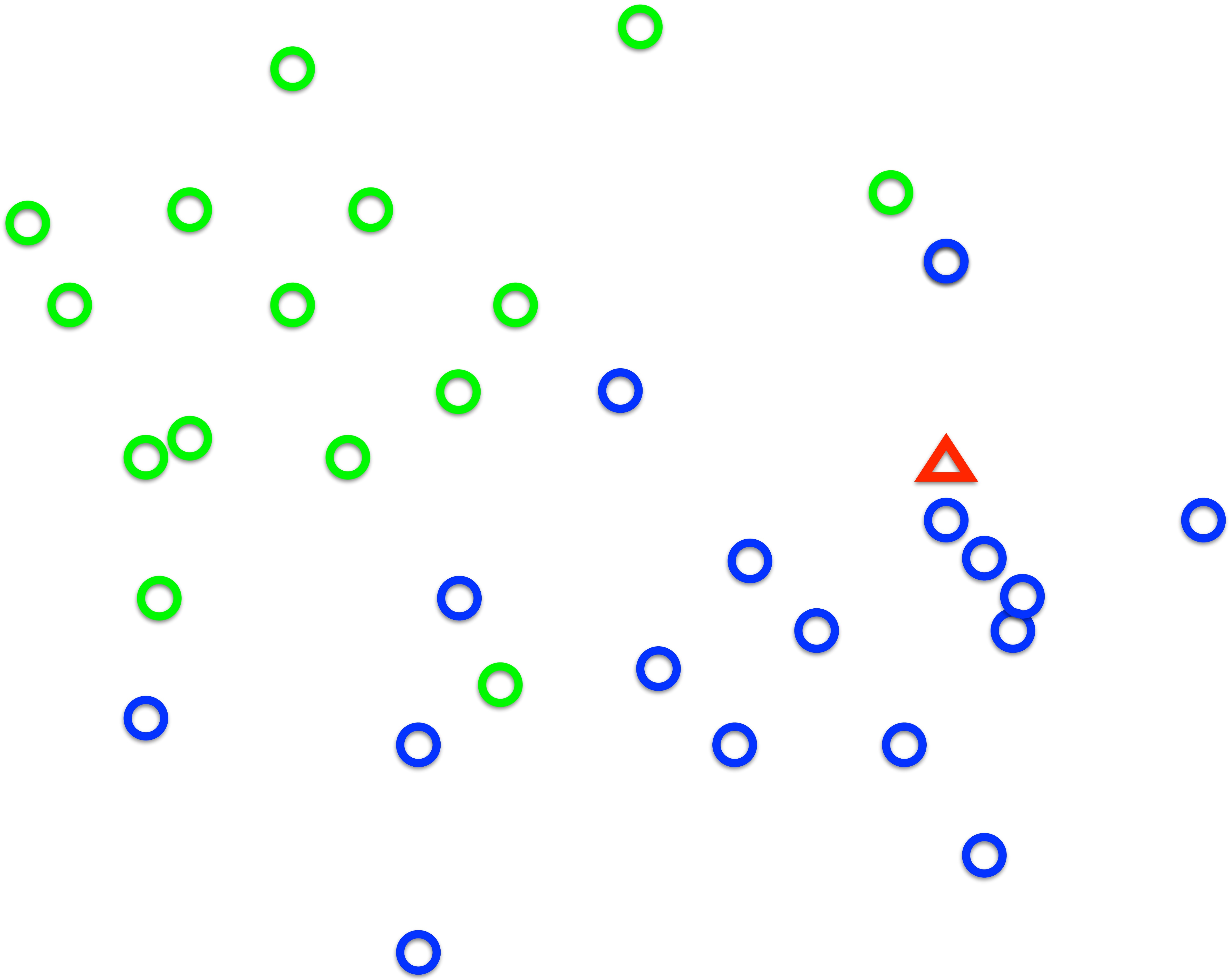

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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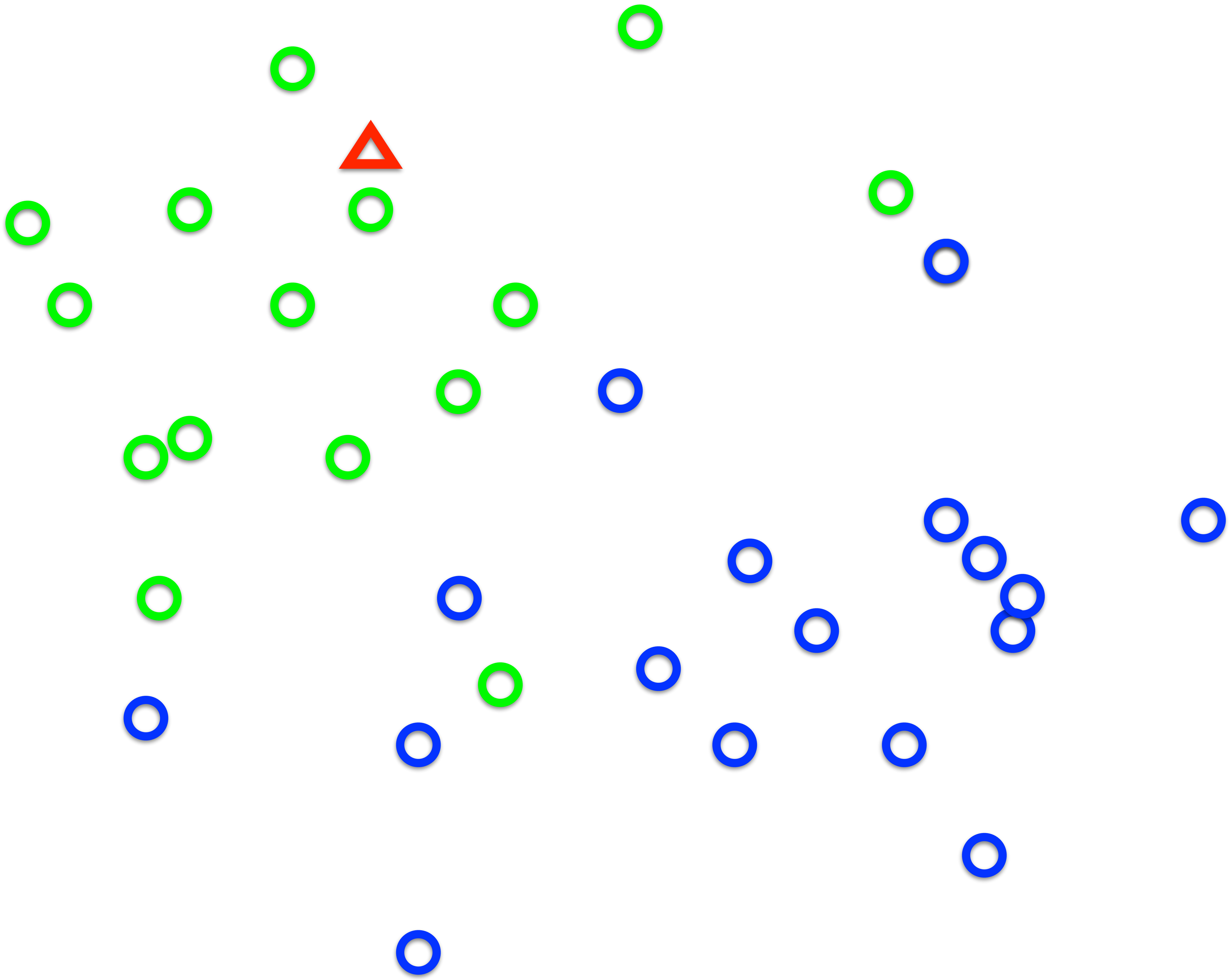


Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

k-**Nearest Neighbor** (kNN) Classifier

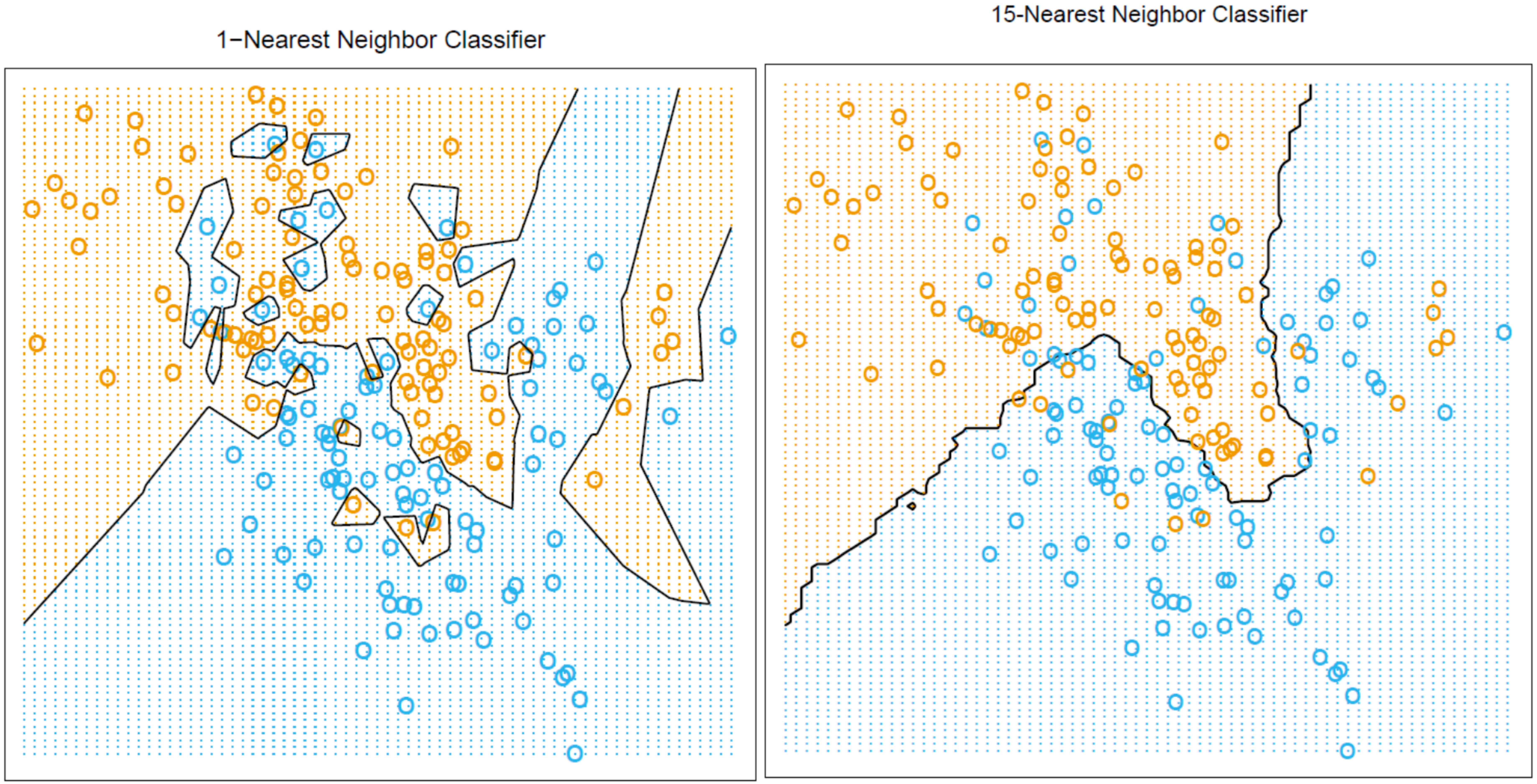
We can gain some robustness to noise by voting over **multiple** neighbours.

Given a **new** data point, find the k nearest training examples. Assign the label by **majority vote**.

Simple method that works well if the **distance measure** correctly weights the various dimensions

For **large data sets**, as k increases kNN approaches optimality in terms of minimizing probability of error

k-**Nearest Neighbor** (kNN) Classifier



kNN decision boundaries respond to local clusters where one class dominates

Figure credit: Hastie, Tibshirani & Friedman (2nd ed.)

Classifier Strategies

Classification strategies fall under two broad types: **parametric** and **non-parametric**.

Parametric classifiers are **model driven**. The parameters of the model are learned from training examples. New data points are classified by the learned model.
— fast, compact
— flexibility and accuracy depend on model assumptions

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— slow
— highly flexible decision boundaries

Support Vector Machines (SVM)

Idea: Try to obtain the decision boundary directly

The decision boundary is parameterized as a **separating hyperplane** in feature space.
— e.g. a separating line in 2D

We choose the hyperplane that is as far as possible from each class - that maximizes the distance to the closest point from either class.

Linear Classifier

Defines a score function:

$$f(\mathbf{x}_i, \mathbf{W}, \mathbf{b}) = \mathbf{W}\mathbf{x}_i + \mathbf{b}$$

image features

weights (parameters)

bias vector (parameters)

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Linear Classifier

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

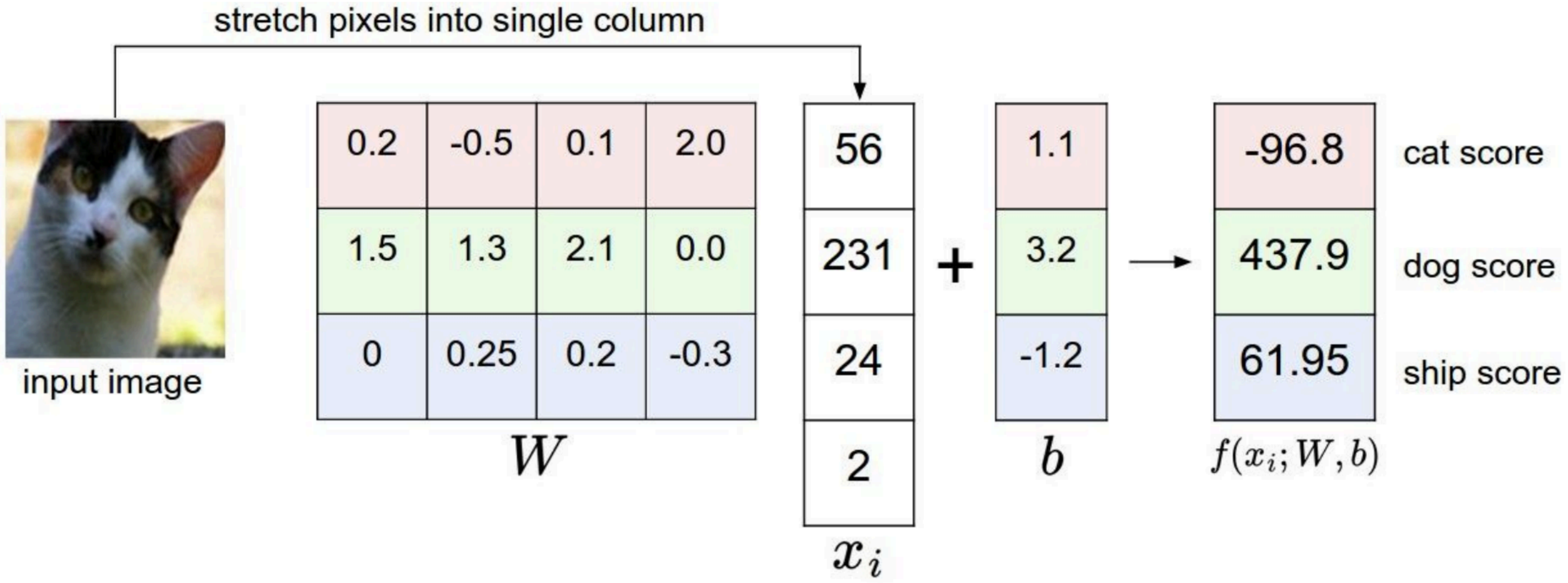

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)

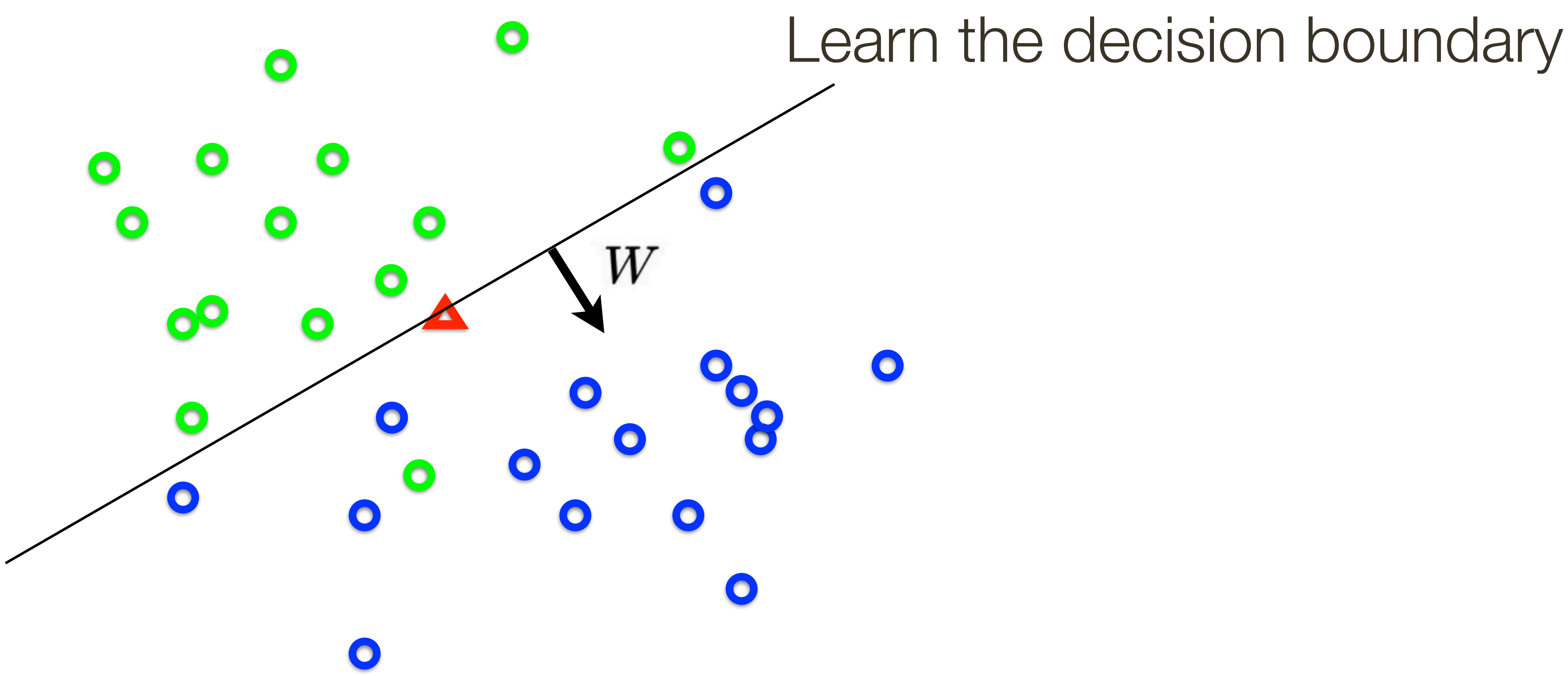

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)

What's the best **w** ?

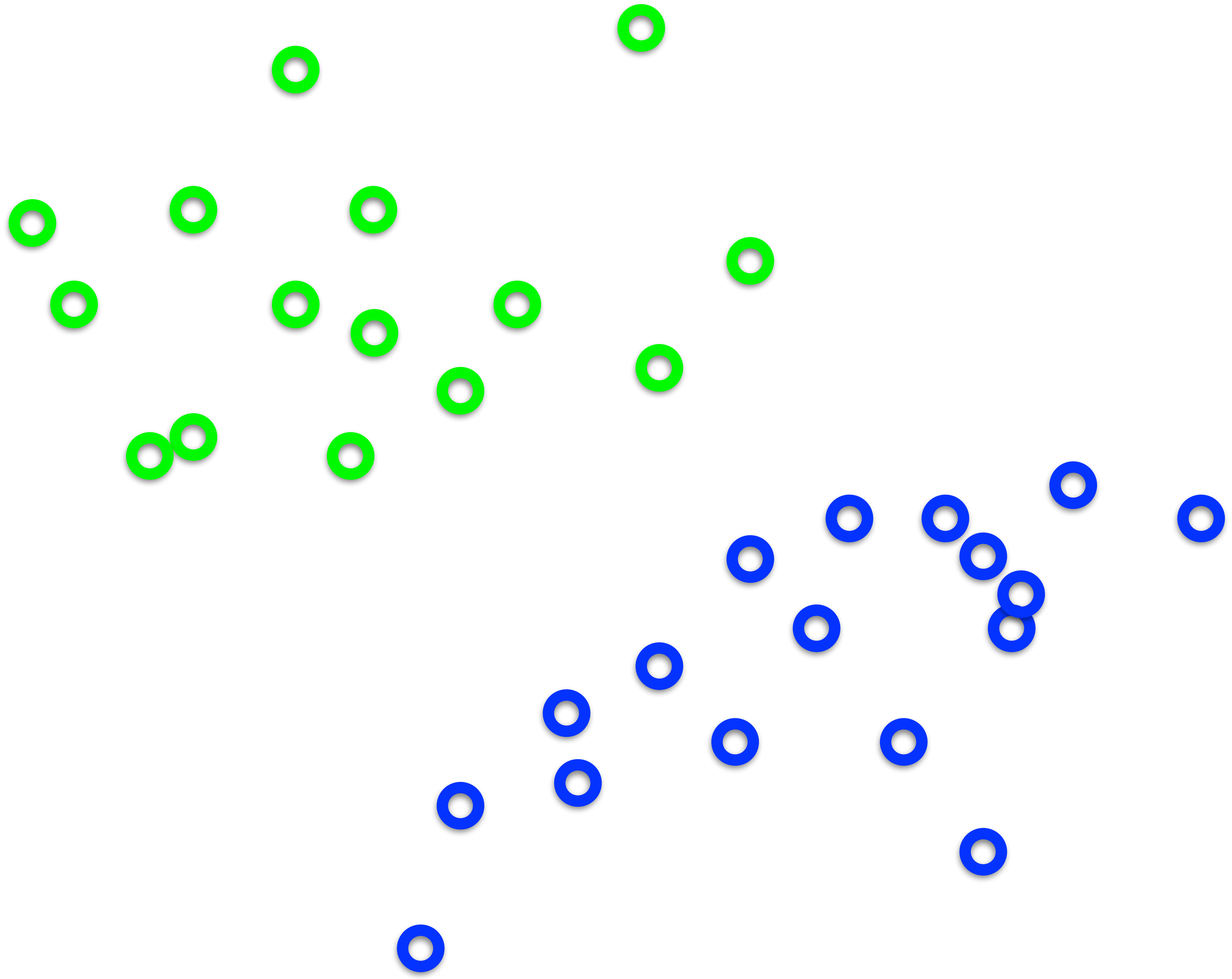

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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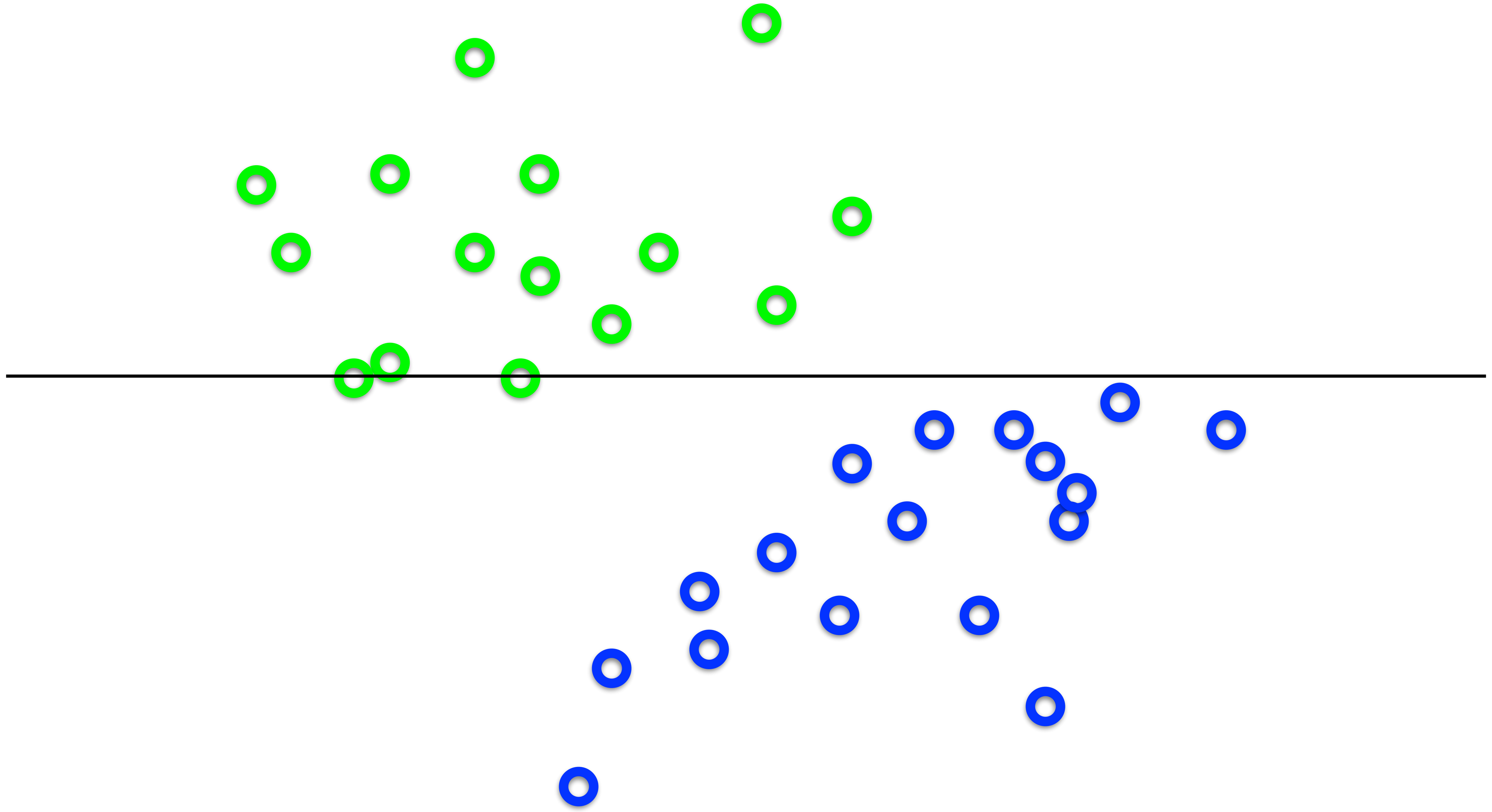

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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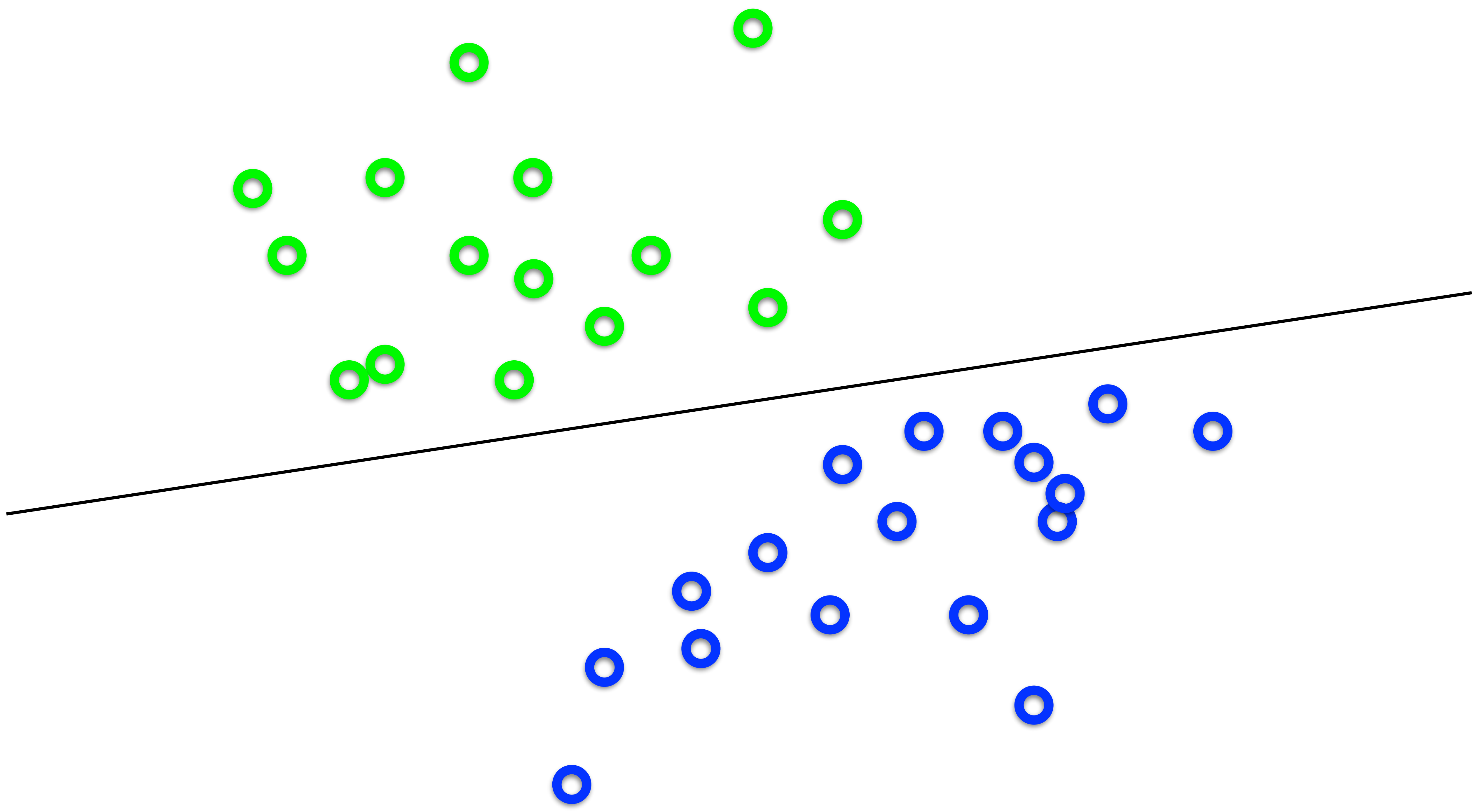

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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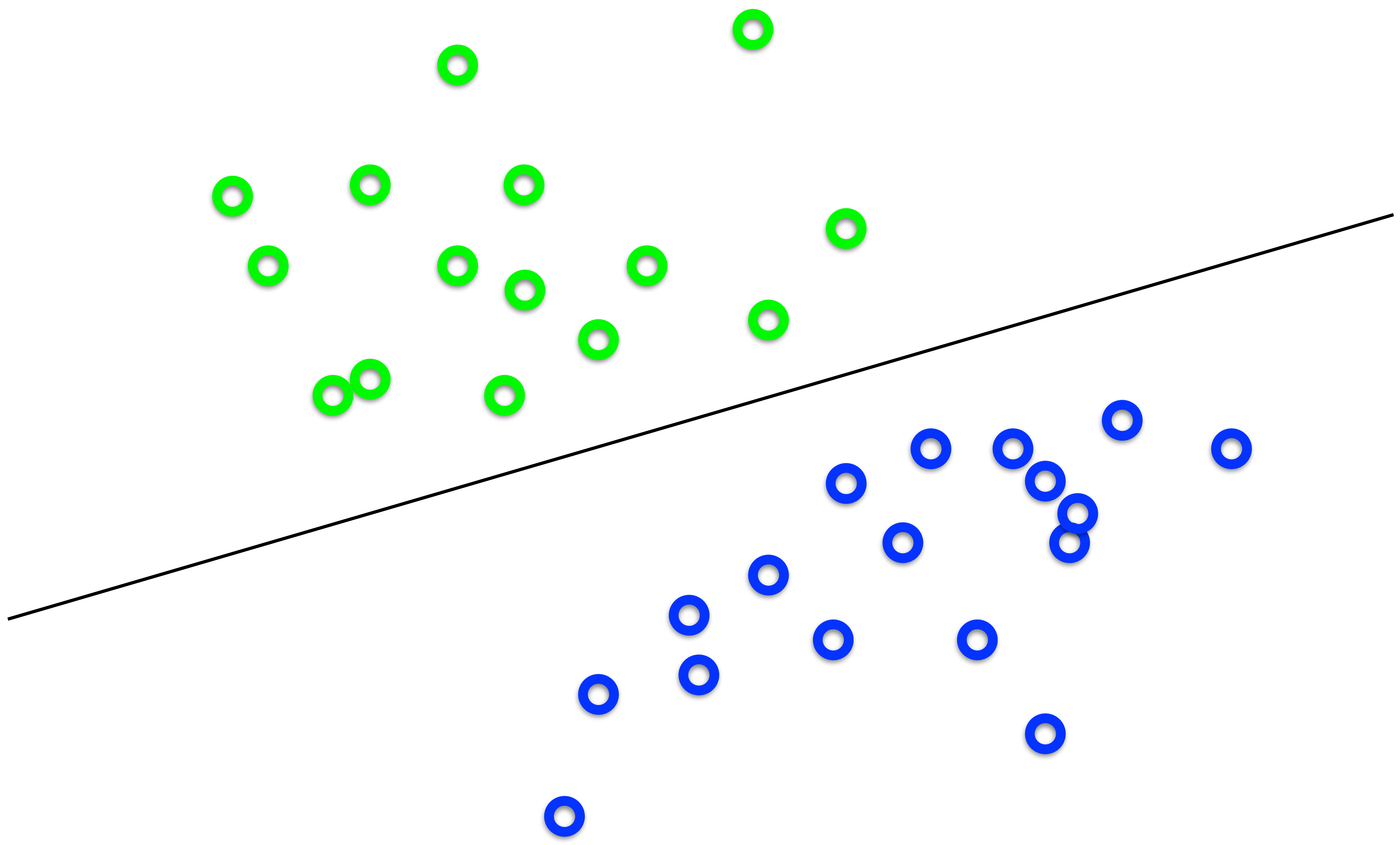

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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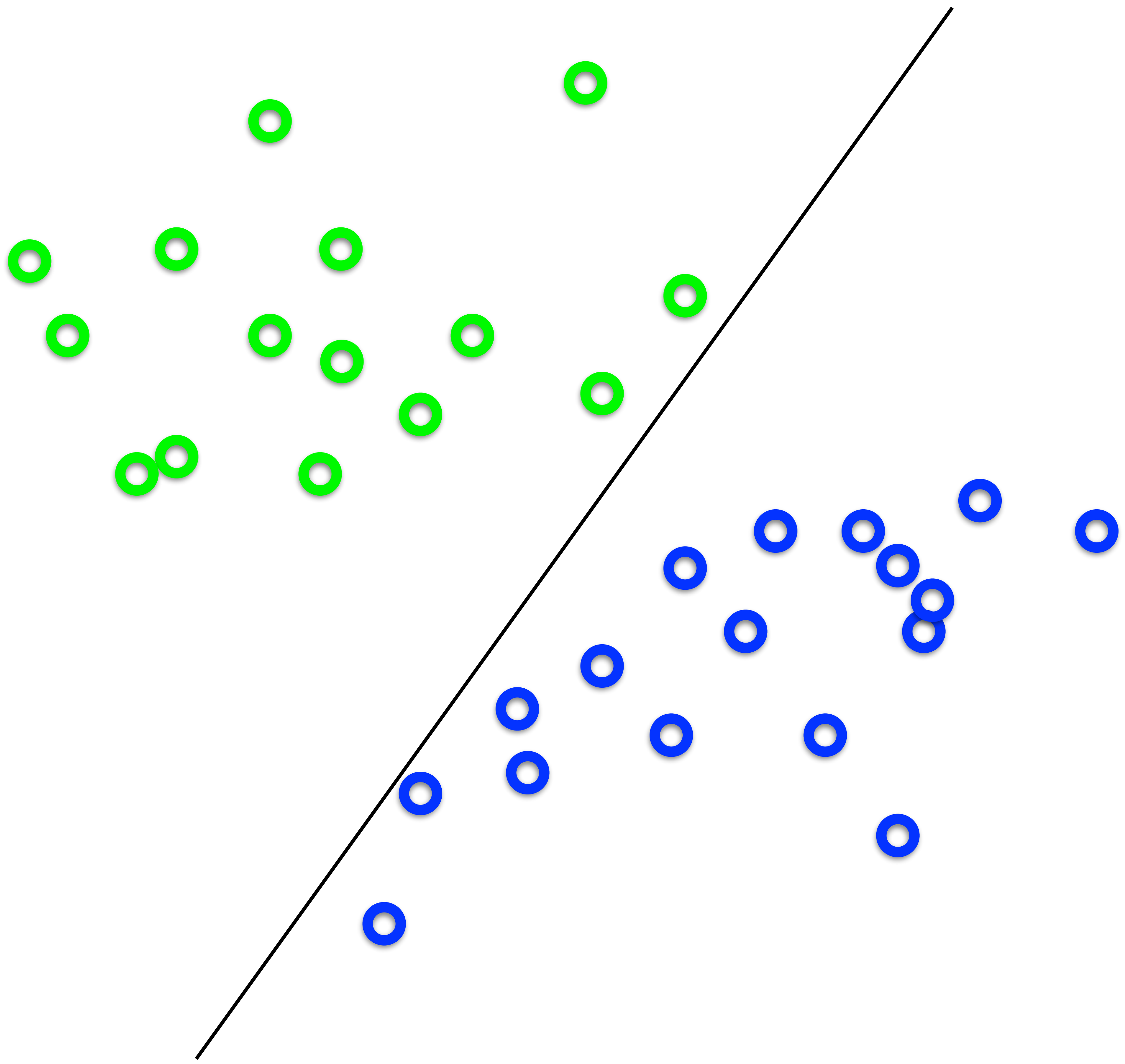

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)

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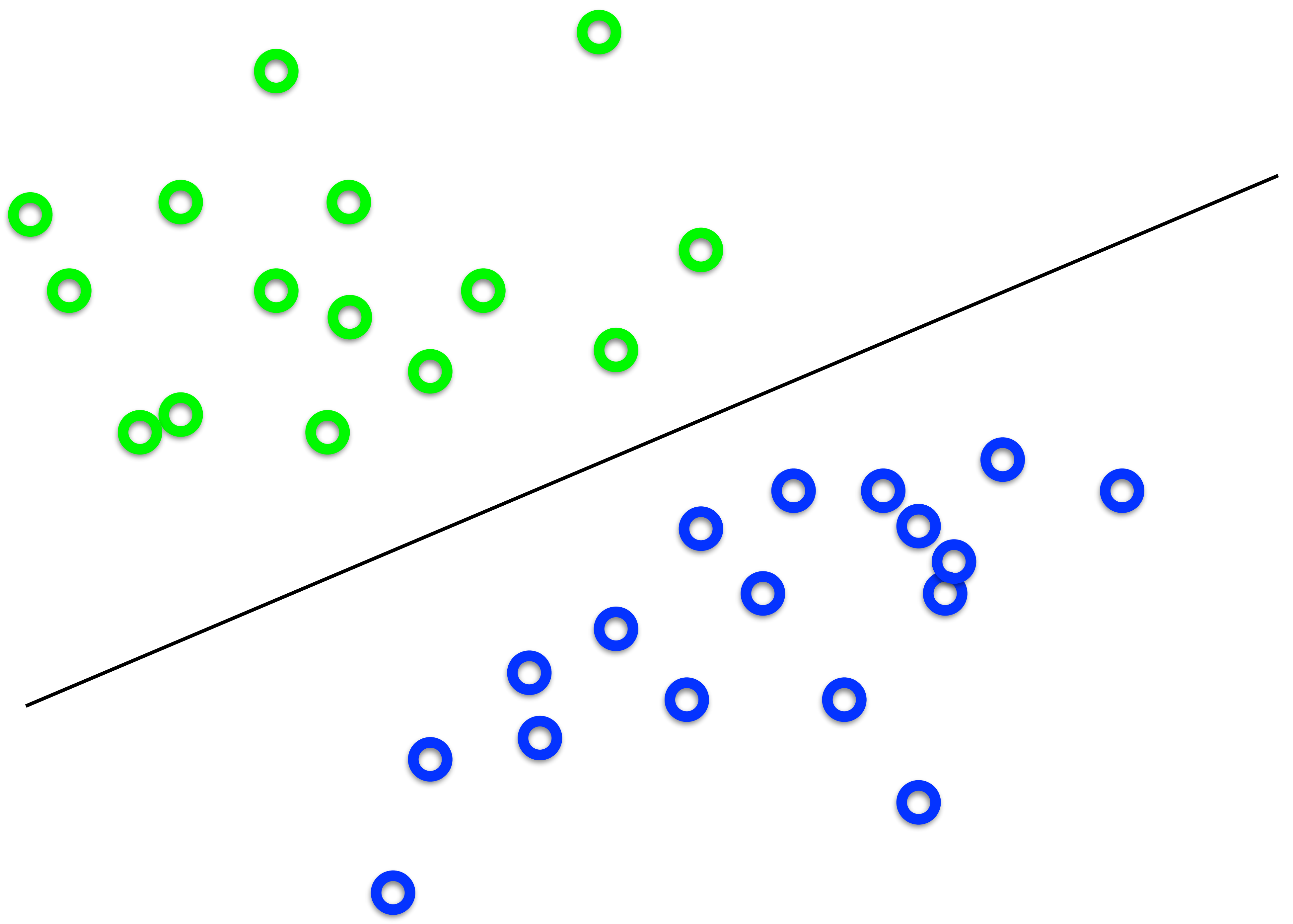
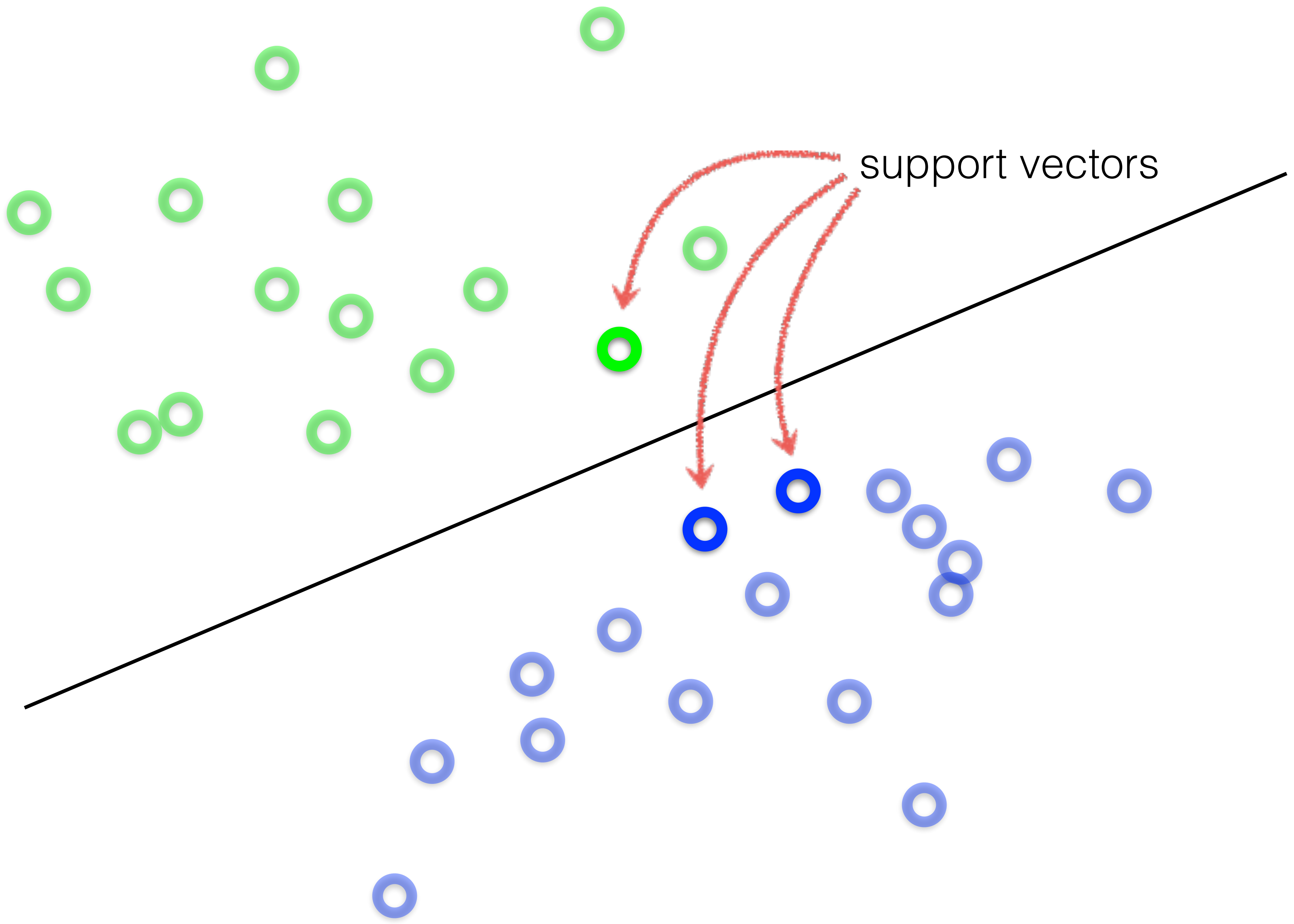


Intuitively, the line that is the farthest from all interior points

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)

What's the best **w** ?

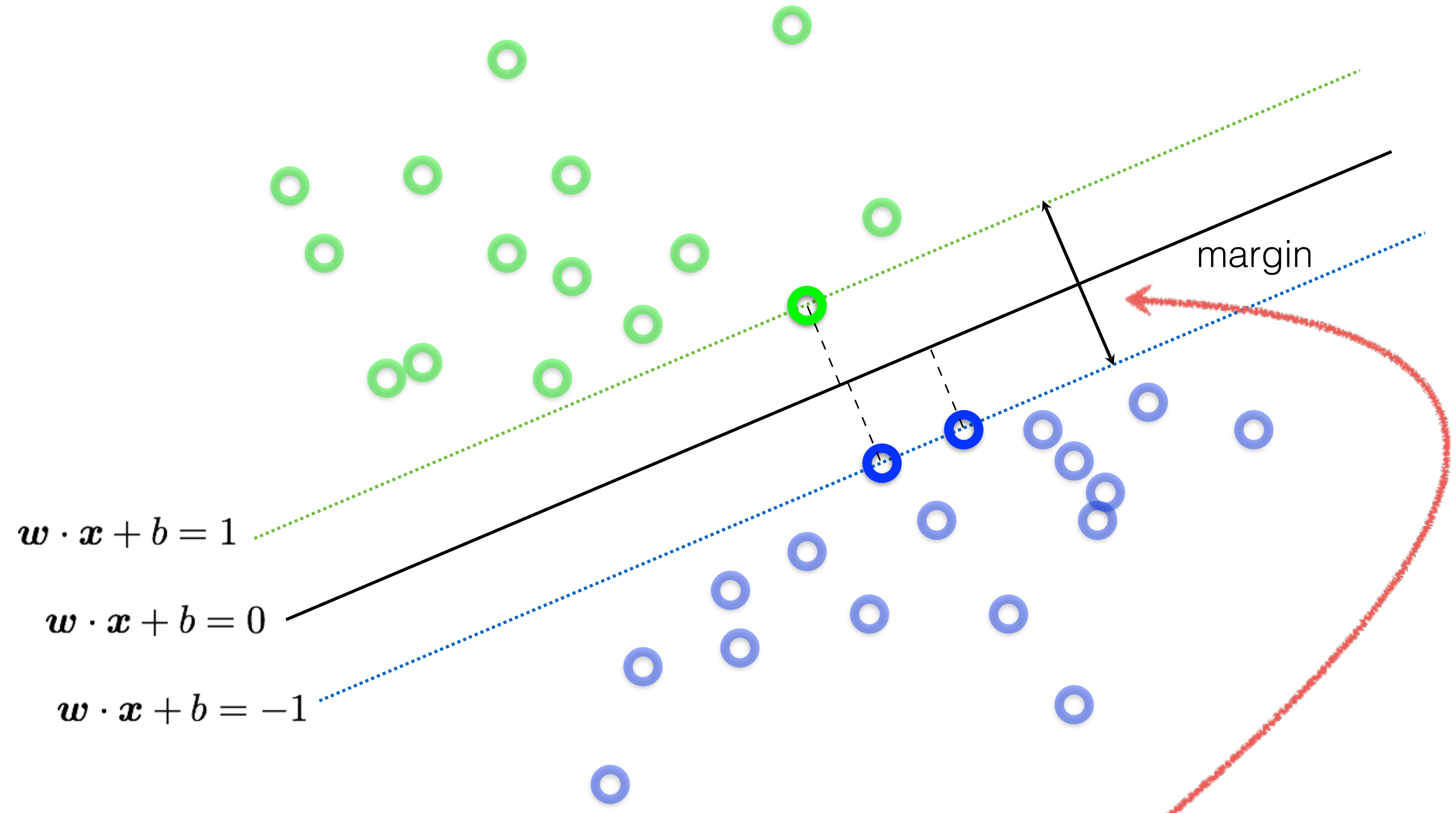


Want a hyperplane that is far away from 'inner points'

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)

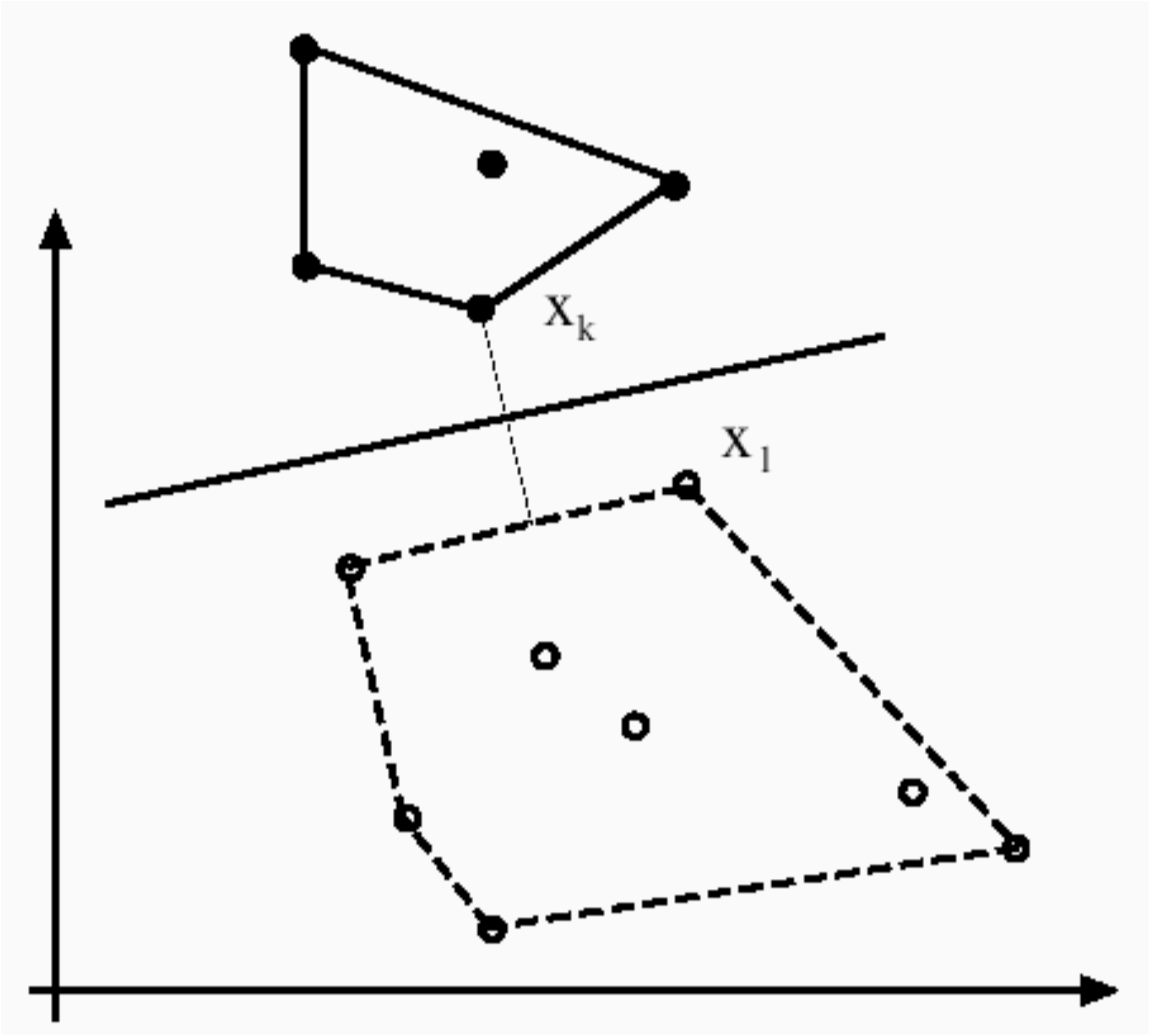
Find hyperplane **w** such that …



the gap between parallel hyperplanes $\frac{2}{\|\boldsymbol{w}\|}$ is maximized

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Support Vector Machines (SVM)



Forsyth & Ponce (2nd ed.) Figure 15.6

Example: Pedestrian Detection with SVM

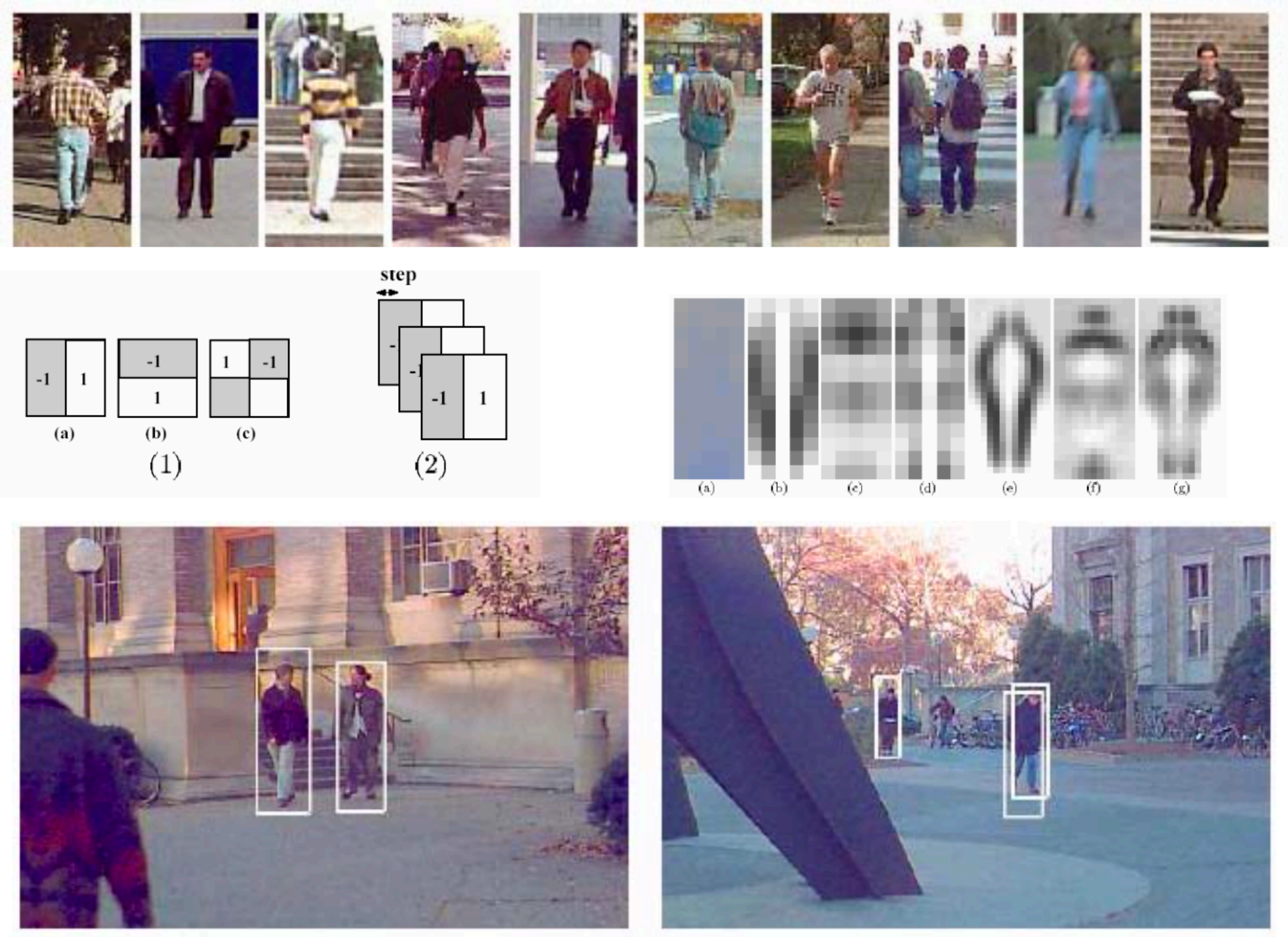


Figure credit: Papageorgiou, Oren, and Poggio, 1998

Summary

A **classifier** accepts as input a set of features and outputs (predicts) a class label

Classifiers need to take into account "**loss**" associated with each kind of classification error

A Receiver Operating Characteristic (**ROC**) curve plots the trade-off between false negatives and false positives

Parametric classifiers are model driven. The parameters of the model are learned from training examples
— e.g. support vector machine, decision tree

Non-parametric classifiers are data driven. New data points are classified by comparing to the training examples directly
— e.g. k-nearest neighbour

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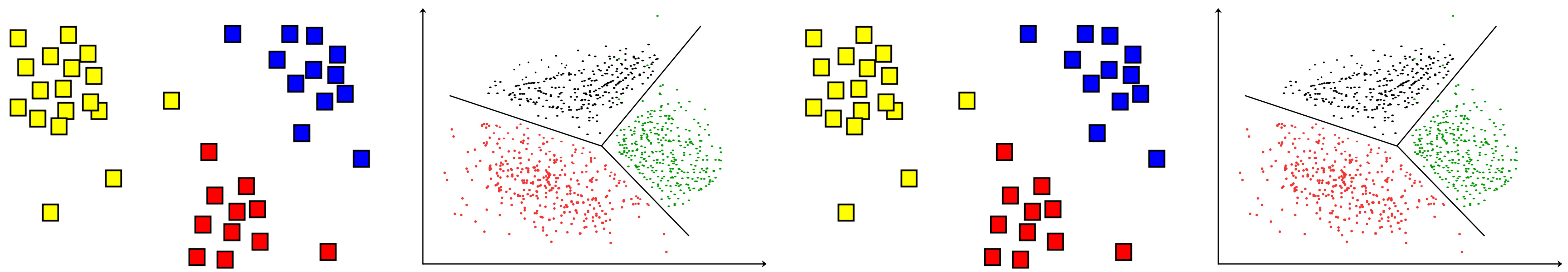
CPSC 425: Computer Vision



Lecture 25: Image Classification

Image Classification

We next discuss **image classification**, where we pass a whole image into a classifier and obtain a class label as output.

What Makes Image Classification **Hard**?

Intra-class variation, viewpoint, illumination, clutter, and occlusion (among others!)

Figure source: Jianxiong Xiao. Original credit: ?

Image Classification

In addition to images containing single **objects**, the same techniques can be applied to classify natural **scenes** (e.g. beach, forest, harbour, library).

Why might classifying scenes be useful?

Image Classification

In addition to images containing single **objects**, the same techniques can be applied to classify natural **scenes** (e.g. beach, forest, harbour, library).

Why might classifying scenes be useful?

Visual perception is influenced by expectation. Our expectations are often conditioned on the **context**.

What is This **Object**?

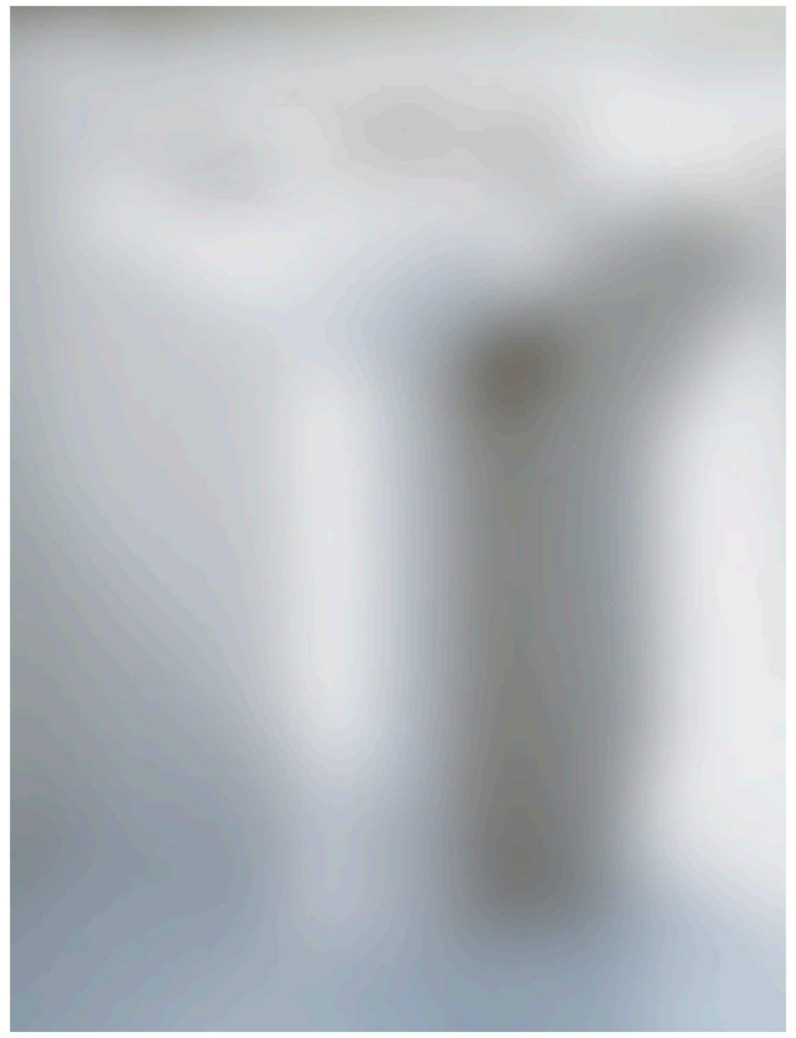


Figure source: Jianxiong Xiao

What is This **Object**?

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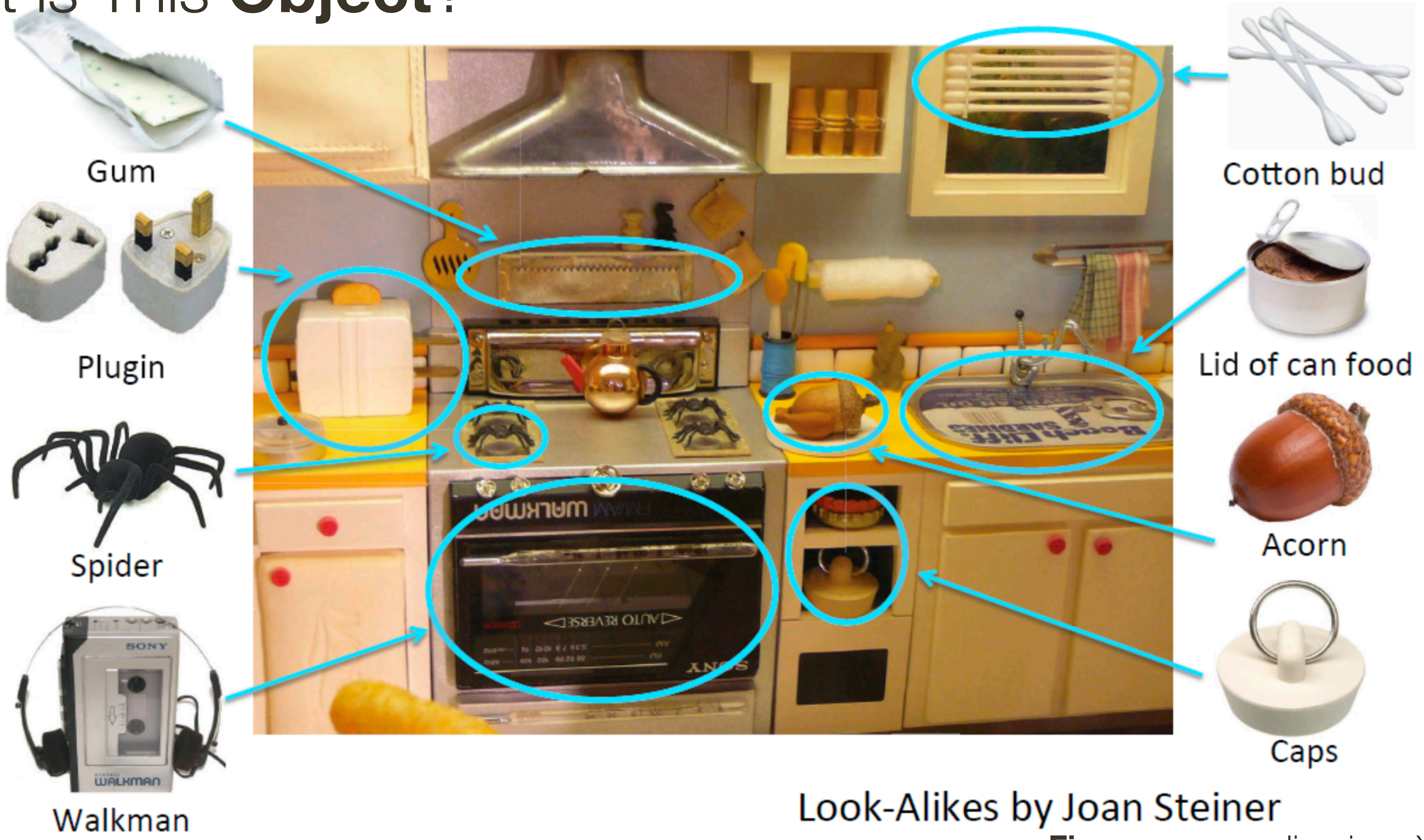


Look-Alikes by Joan Steiner

Figure source: Jianxiong Xiao

Visual **Words**

Many algorithms for image classification accumulate evidence on the basis of **visual words**.

To classify a text document (e.g. as an article on sports, entertainment, business, politics) we might find patterns in the occurrences of certain words.

Vector Space Model

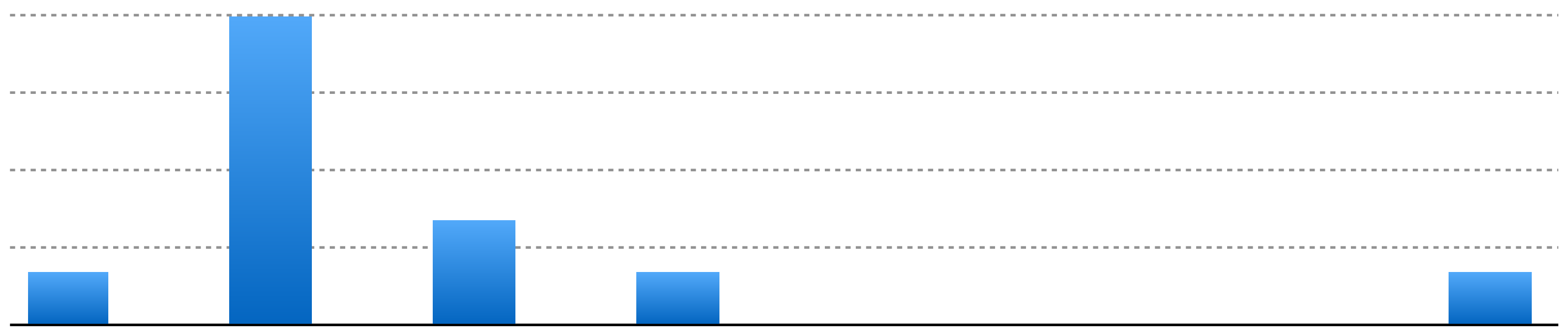
G. Salton. ‘Mathematics and Information Retrieval’ Journal of Documentation,1979

The Newspa

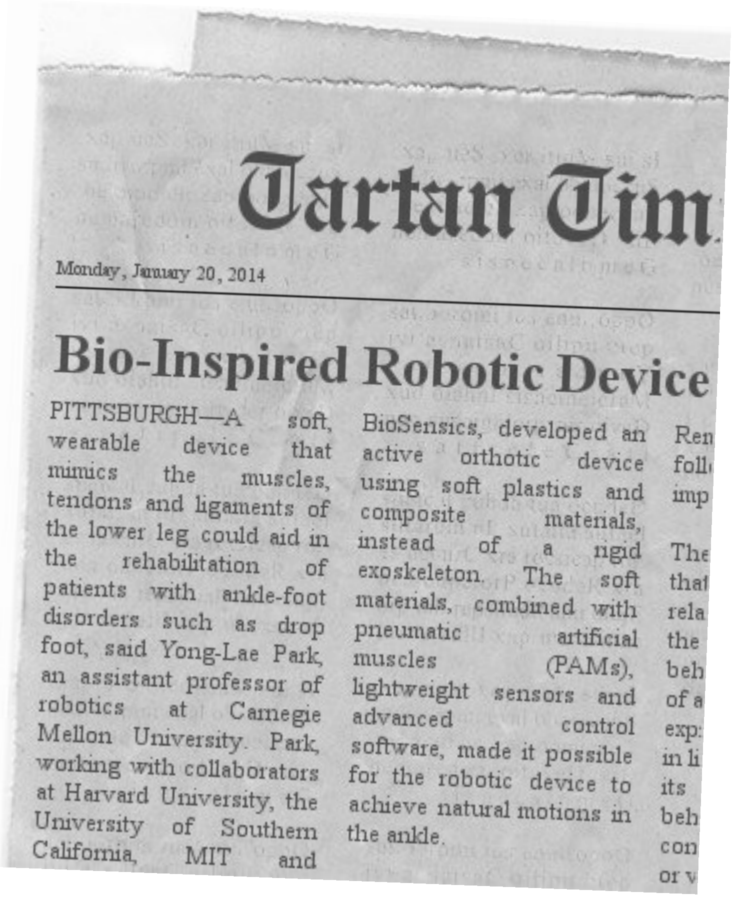
Sunday, December 22, 2013

DARPA Selects Carnegie Me

The Tartan Rescue Team from Carnegie Mellon University's National Robotics Engineering Center ranked third among teams competing in the Defense Advanced Research Projects Agency (DARPA) Robotics Challenge Trials this weekend in Homestead, Fla., and was selected by the agency as one of eight teams eligible for DARPA funding to prepare for next December's finals. The team's four-limbed CMU Highly Intelligent Mobile Platform, or CHIMP, robot scored 18 out of a possible 32 points during the two-day trials. It demonstrated its ability to perform such tasks as removing debris, cutting a hole through a wall and closing a series of valves.



1	6	2	1	0	0	0	1
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor

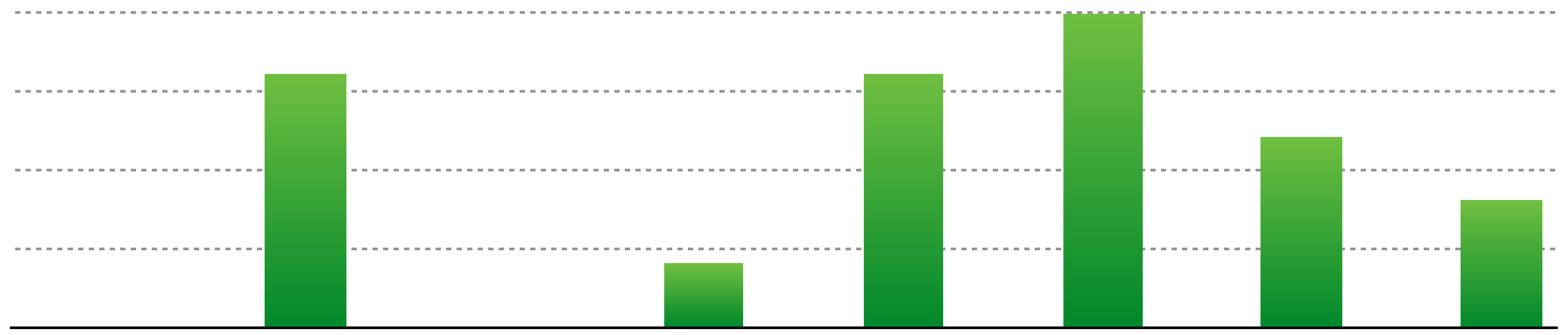


Tartan Tim

Monday, January 20, 2014

Bio-Inspired Robotic Device

PITTSBURGH—A soft, wearable device that mimics the muscles, tendons and ligaments of the lower leg could aid in the rehabilitation of patients with ankle-foot disorders such as drop foot, said Yong-Lae Park, an assistant professor of robotics at Carnegie Mellon University. Park, working with collaborators at Harvard University, the University of Southern California, MIT and BioSensics, developed an active orthotic device using soft plastics and composite materials, instead of a rigid exoskeleton. The soft materials, combined with pneumatic artificial muscles (PAMs), lightweight sensors and advanced control software, made it possible for the robotic device to achieve natural motions in the ankle.



0	4	0	1	4	5	3	2
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor

http://www.fodey.com/generators/newspaper/snippet.asp

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Vector Space Model

A document (datapoint) is a vector of counts over each word (feature)

$$\boldsymbol{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_{T,d})]$$

$n(\cdot)$ counts the number of occurrences

just a histogram over words

What is the similarity between two documents?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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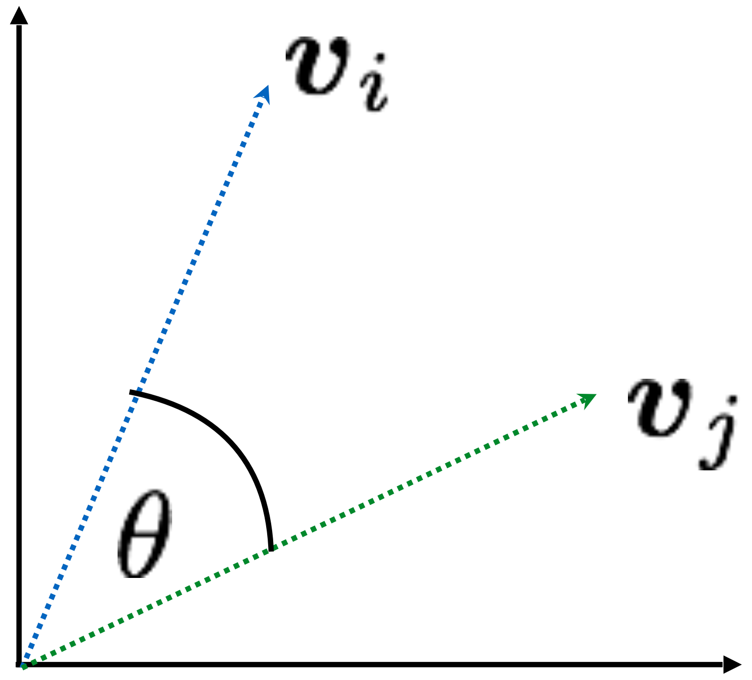
just a histogram over words

What is the similarity between two documents?

Use any distance you want but the cosine distance is fast and well designed for high-dimensional vector spaces:

$$d(\boldsymbol{v}_i, \boldsymbol{v}_j) = \cos\theta = \frac{\boldsymbol{v}_i \cdot \boldsymbol{v}_j}{\|\boldsymbol{v}_i\|\|\boldsymbol{v}_j\|}$$



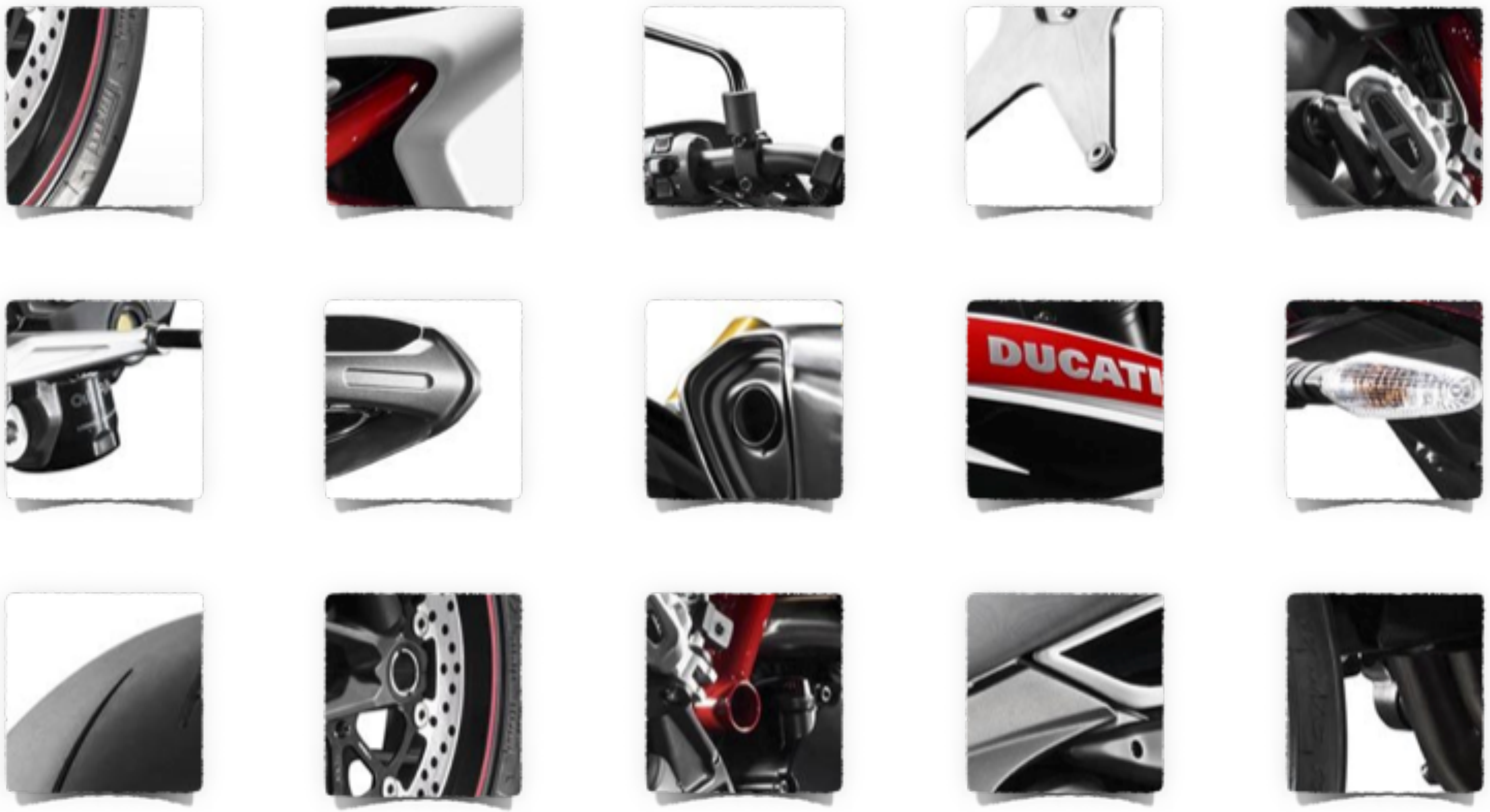
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Visual **Words**

In images, the equivalent of a word is a local image patch. The local image patch is described using a descriptor such as SIFT.

We construct a **vocabulary** or **codebook** of local descriptors, containing representative local descriptors.

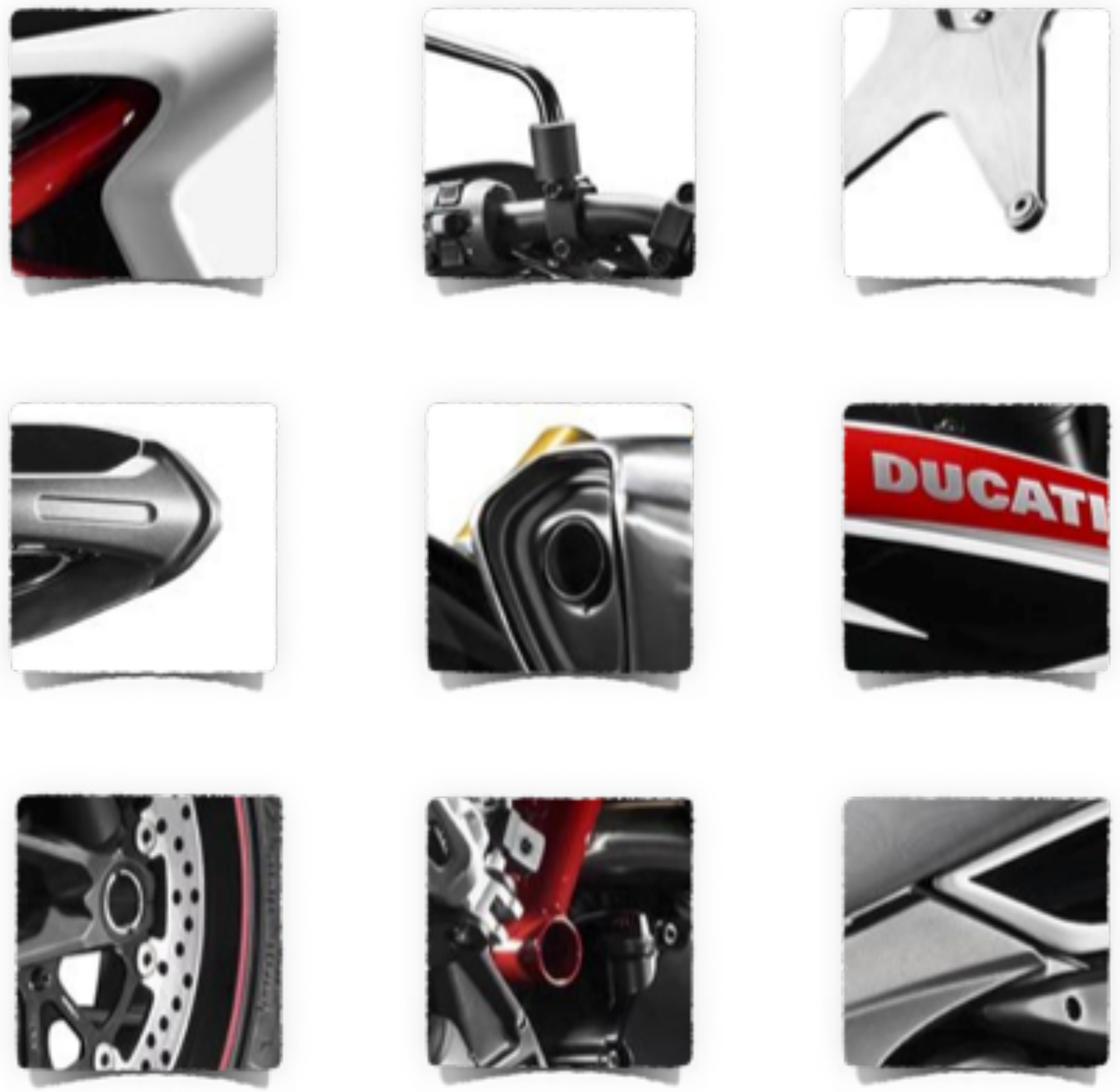
What **Objects** do These Parts Belong To?



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Some local feature are very informative

An object as



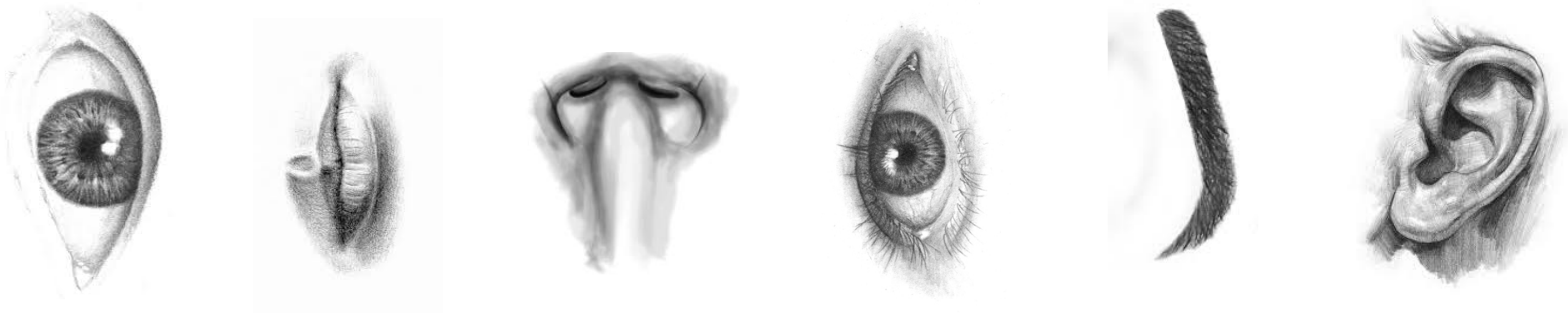
a collection of local features

(bag-of-features)

- deals well with occlusion
- scale invariant
- rotation invariant

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

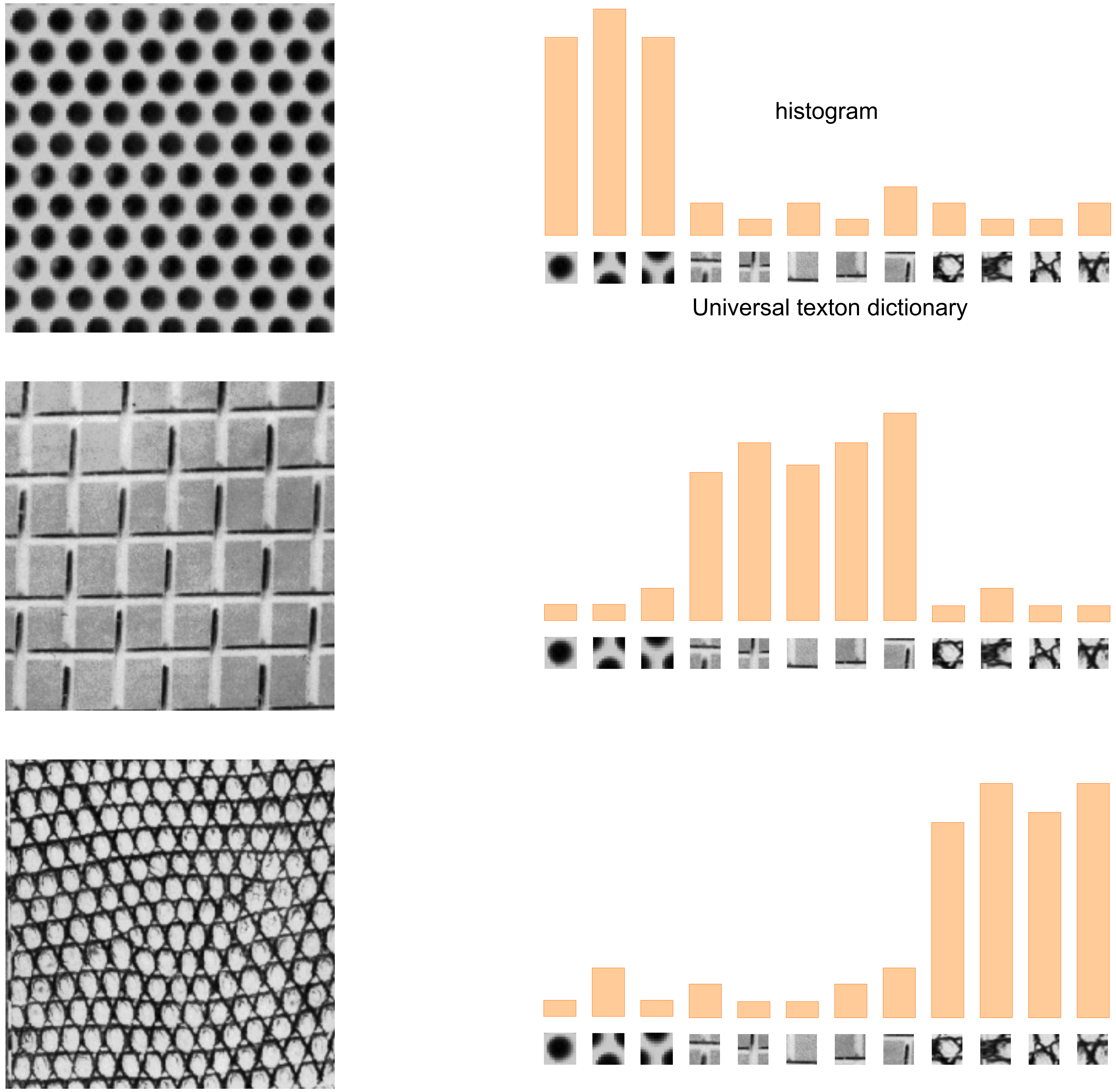
(**not so**) Crazy Assumption



spatial information of local features
can be ignored for object recognition (i.e., verification)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Recall: Texture Representation



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Visual **Words**

In images, the equivalent of a word is a local image patch. The local image patch is described using a descriptor such as SIFT.

We construct a **vocabulary** or **codebook** of local descriptors, containing representative local descriptors.

Question: How might we construct such a codebook? Given a large sample of SIFT descriptors, say 1 million, how can we choose a small number of ‘representative’ SIFT codewords, say 1000?

Standard **Bag-of-Words** Pipeline (for image classification)

Dictionary Learning:
Learn Visual Words using clustering

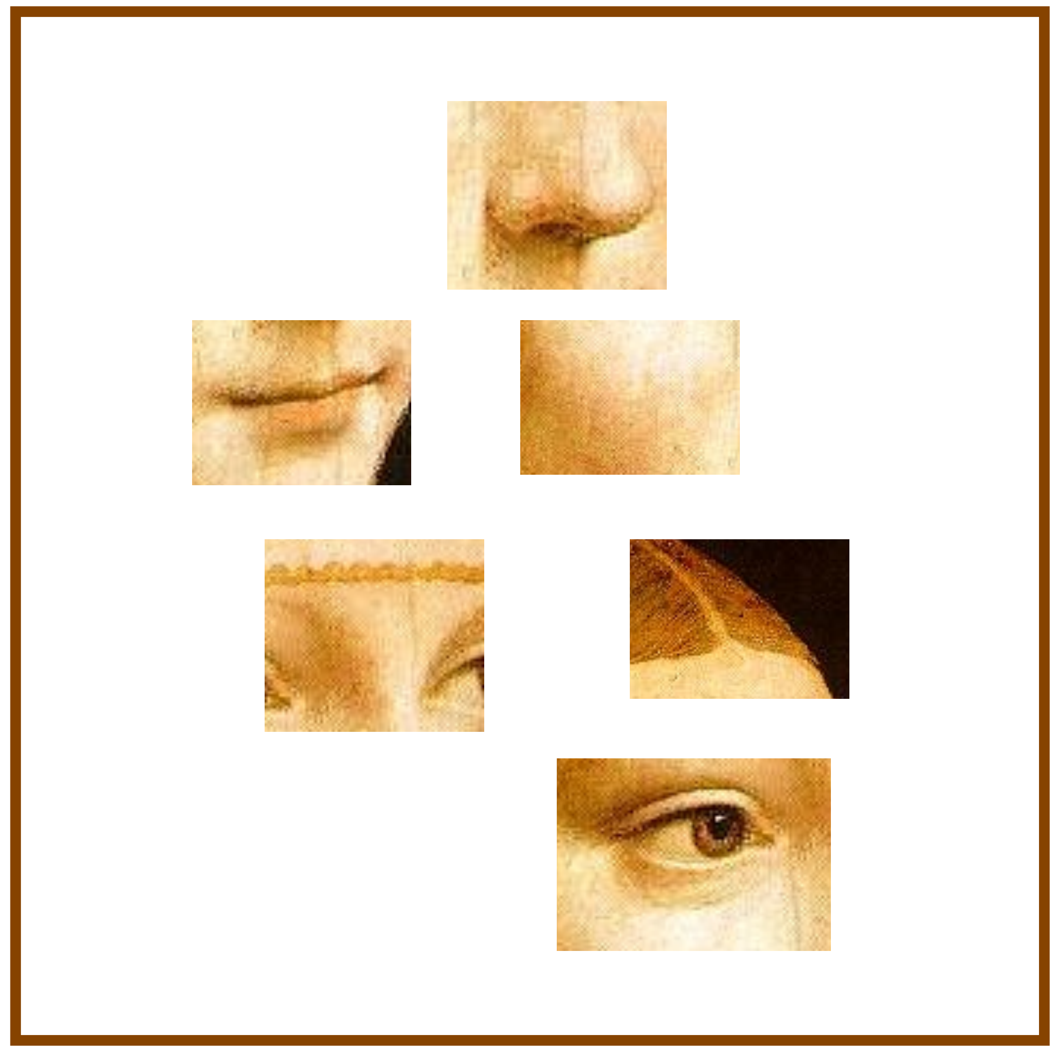
Encode:
build Bags-of-Words (BOW) vectors
for each image

Classify:
Train and test data using BOWs

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

1. **Dictionary Learning**: Learn Visual Words using Clustering

1. **extract features** (e.g., SIFT) from images



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

1. **Dictionary Learning**: Learn Visual Words using Clustering

2. **Learn visual dictionary** (e.g., K-means clustering)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

What **Features** Should We Extract?

— Regular grid

Vogel & Schiele, 2003

Fei-Fei & Perona, 2005

— Interest point detector

Csurka et al. 2004

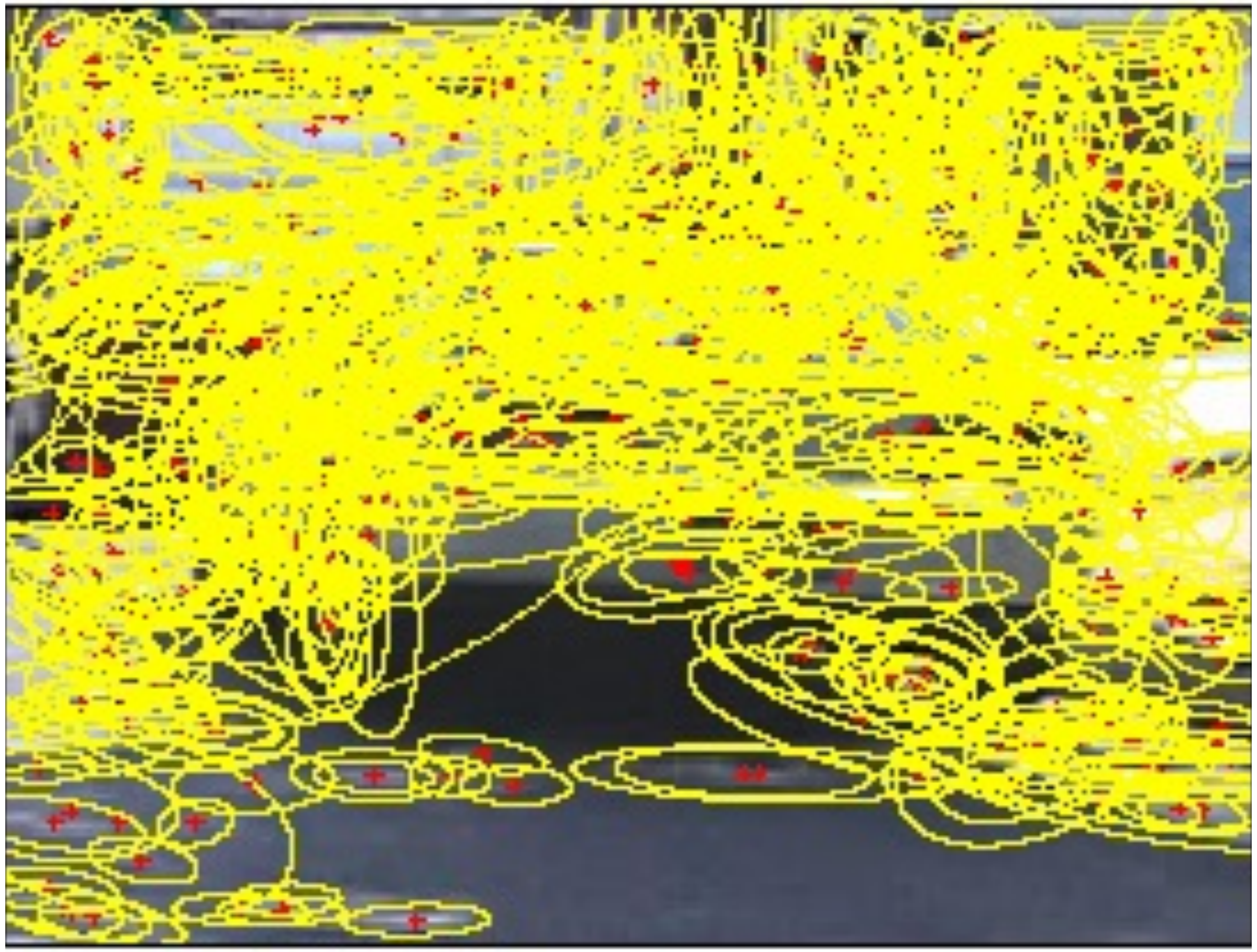
Fei-Fei & Perona, 2005

Sivic et al. 2005

— Other methods

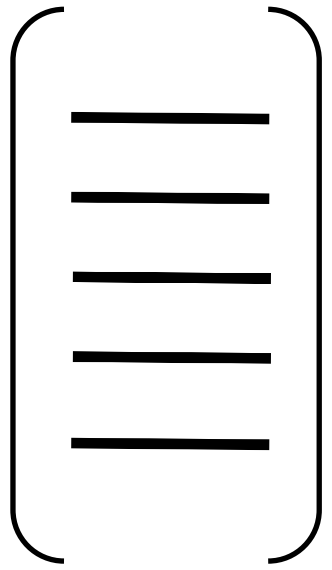
Random sampling (Vidal-Naquet & Ullman, 2002)

Segmentation-based patches (Barnard et al. 2003)



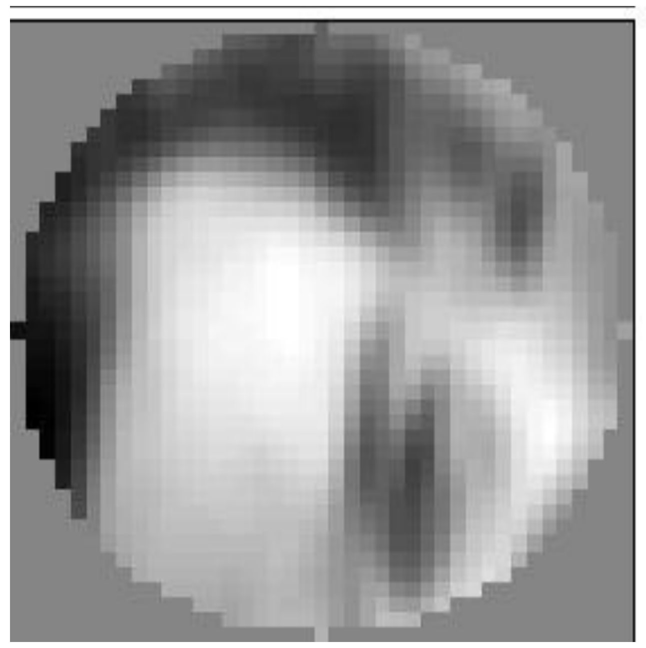
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Extracting **SIFT** Patches

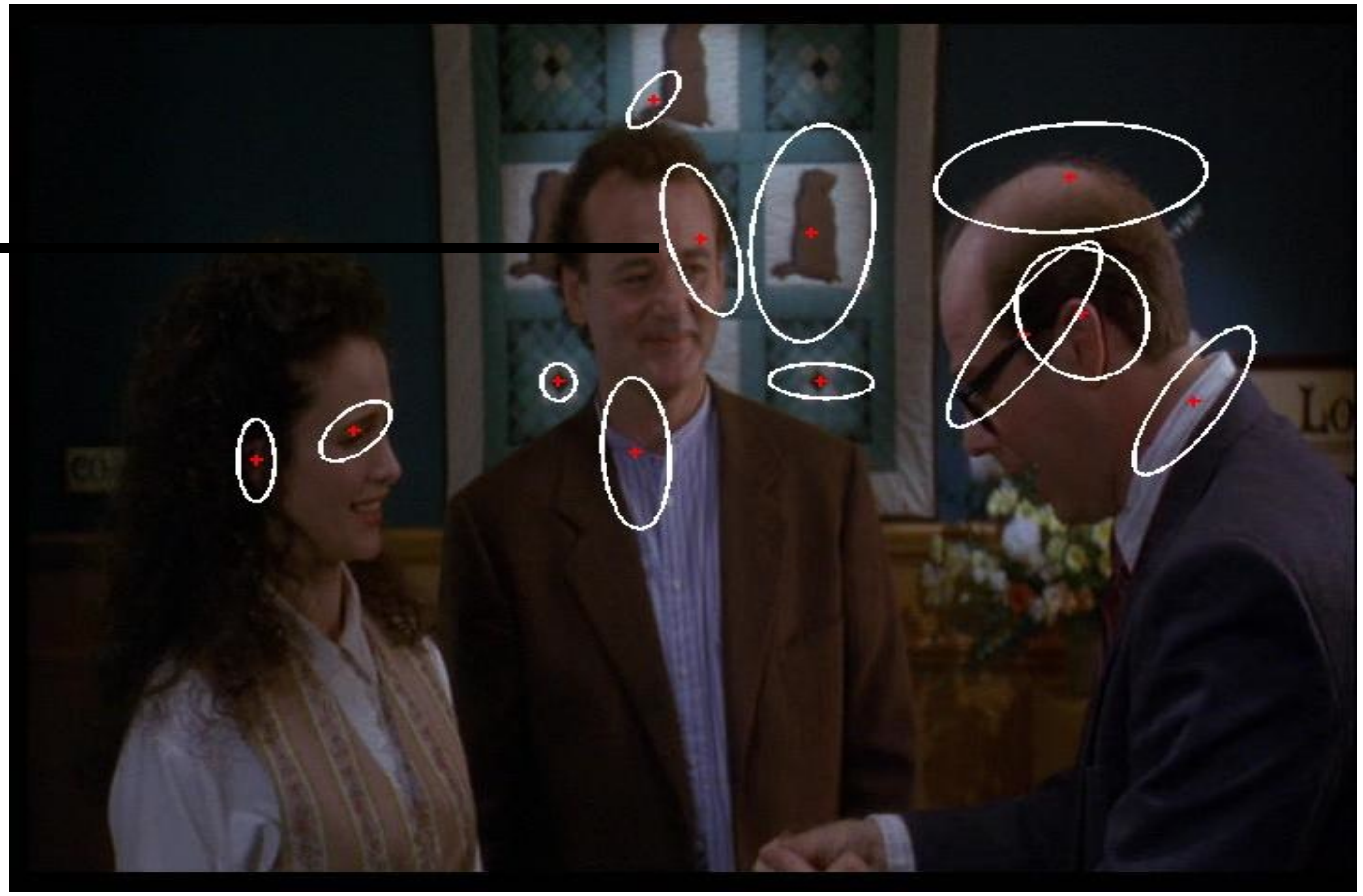


Compute SIFT descriptor

[Lowe'99]



Normalize patch



Detect patches

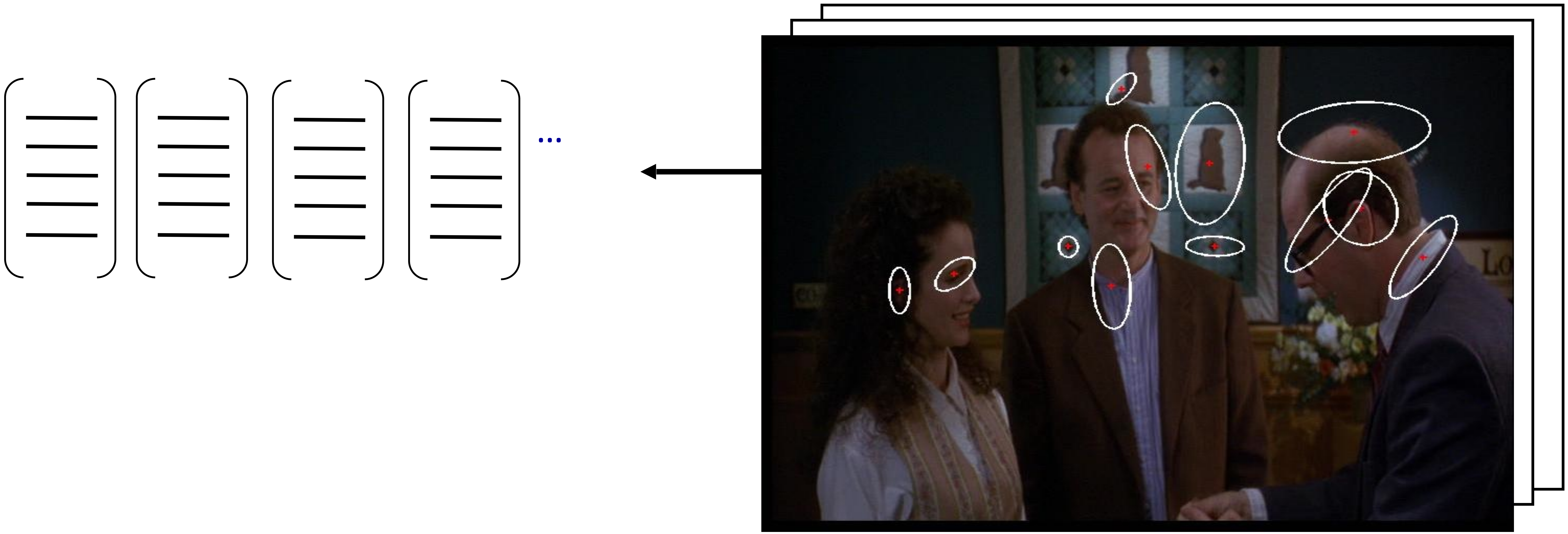
[Mikojaczyk and Schmid '02]

[Mata, Chum, Urban & Pajdla, '02]

[Sivic & Zisserman, '03]

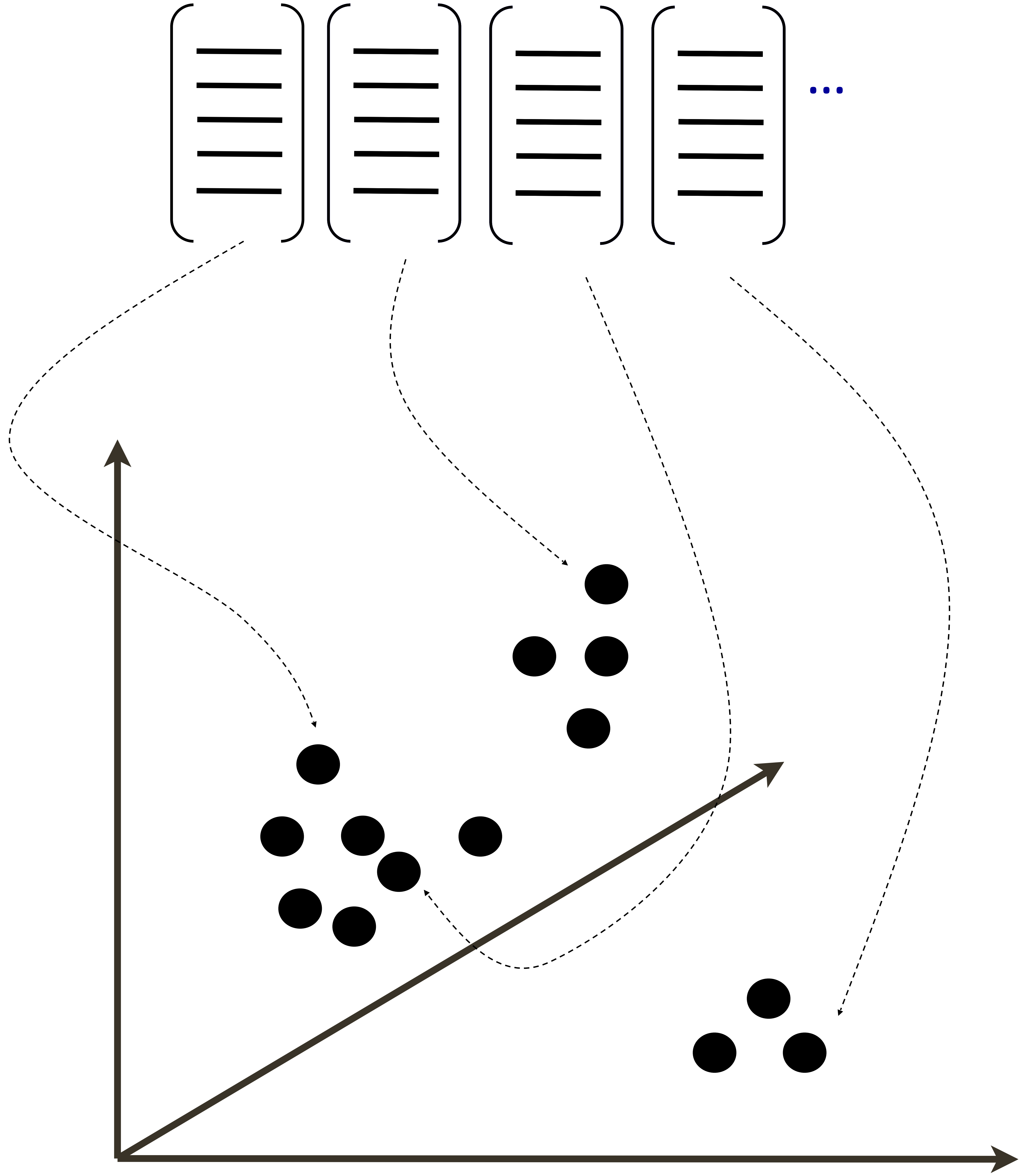
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Extracting **SIFT** Patches



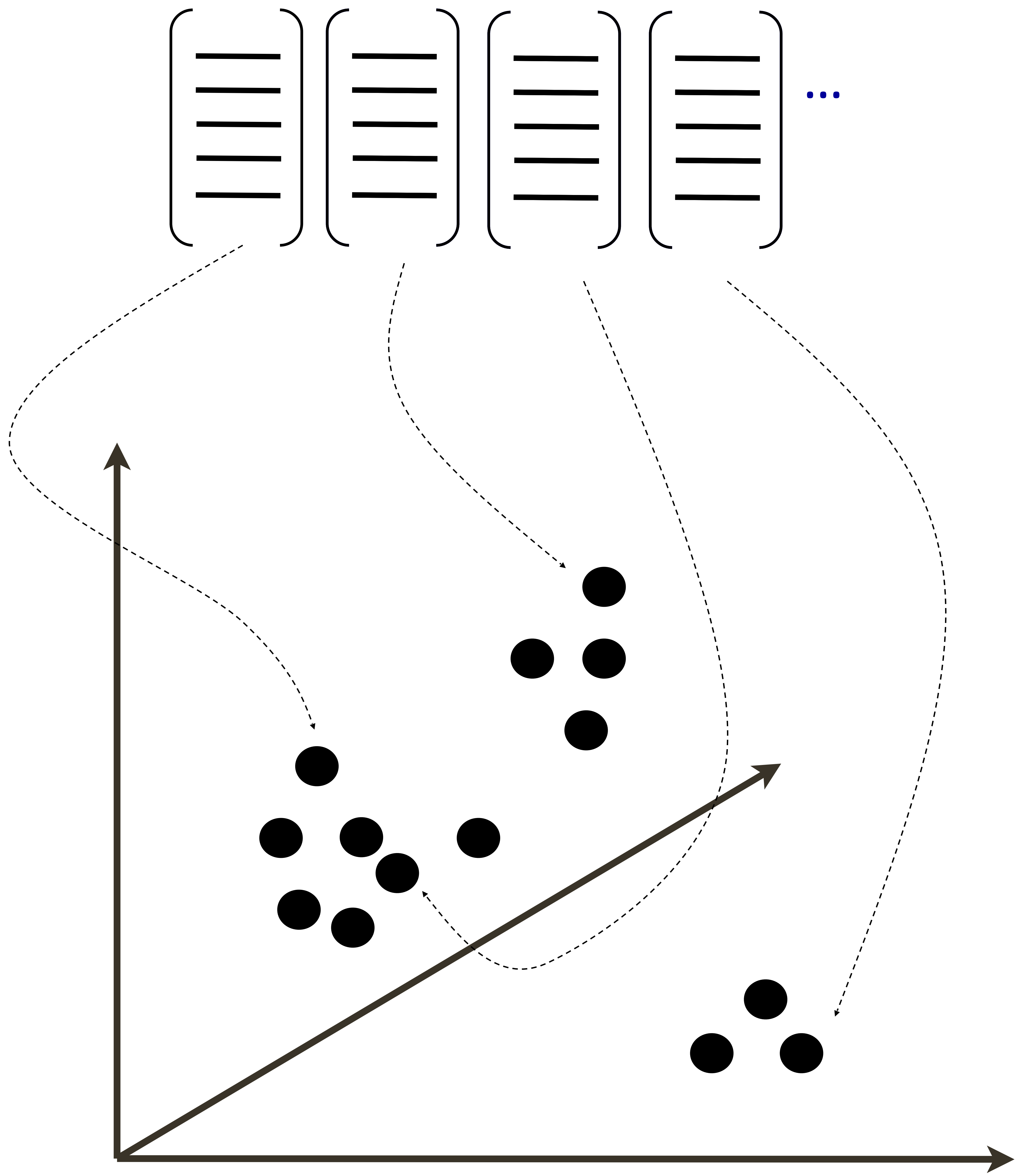
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

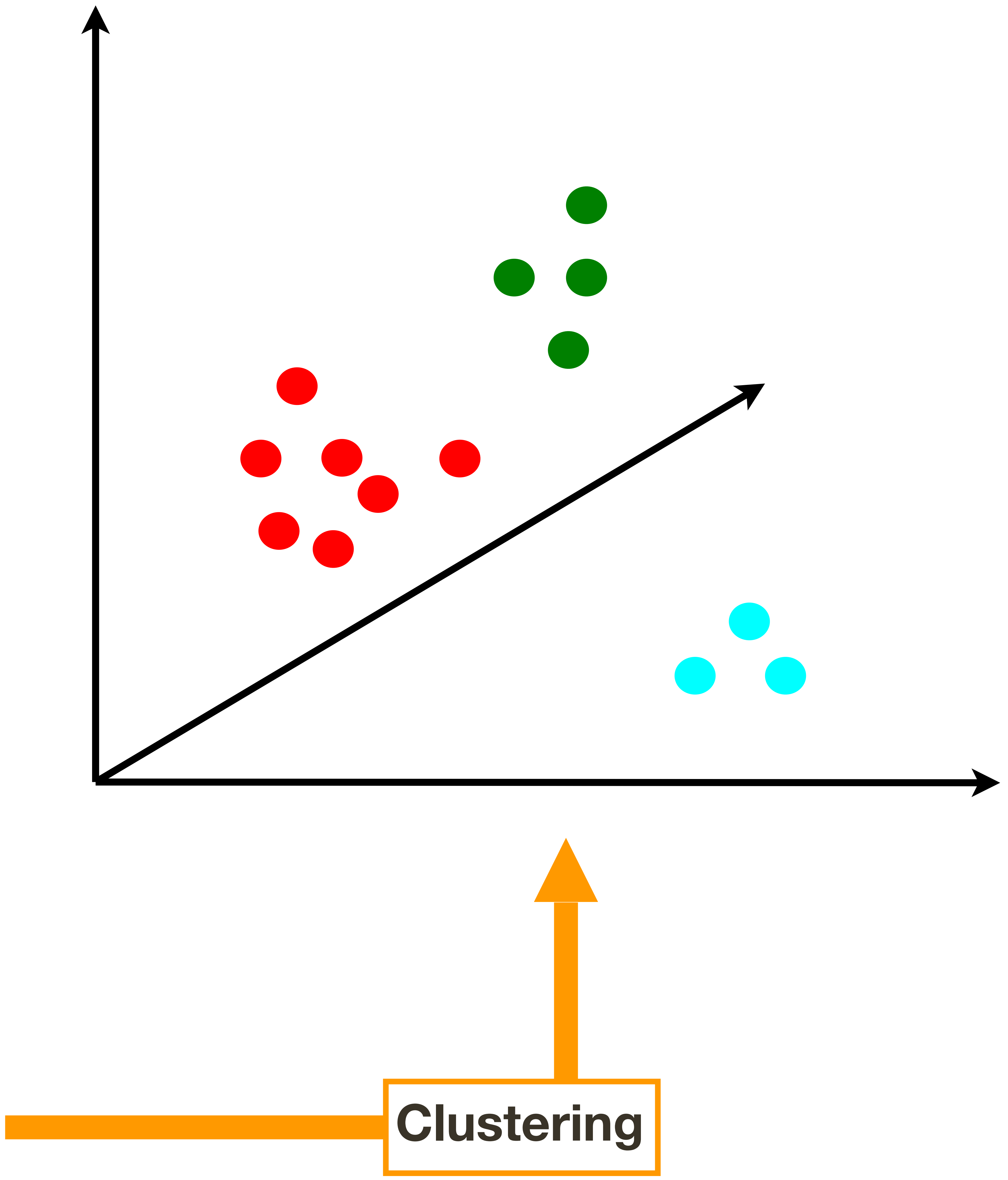
Creating **Dictionary**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

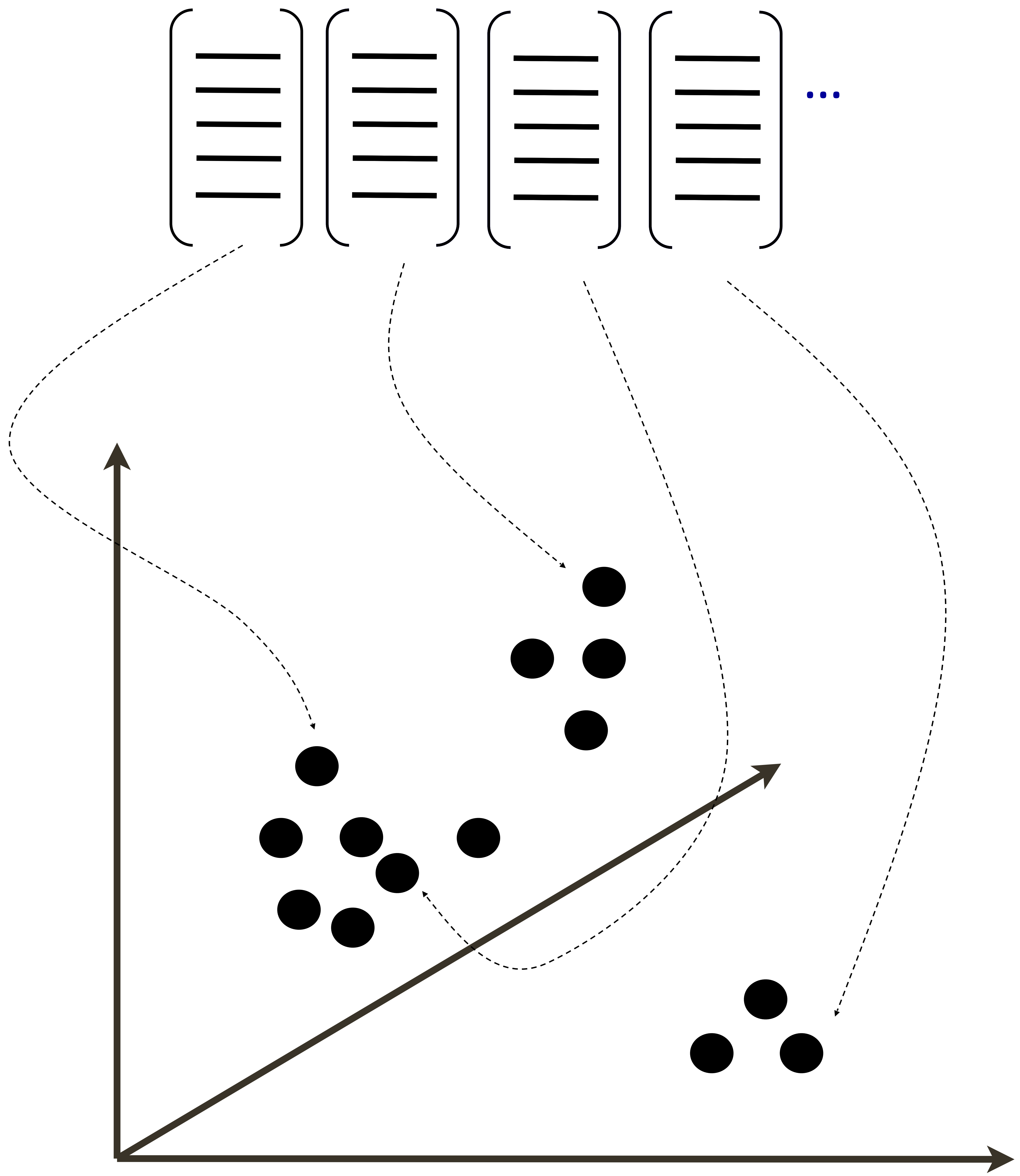
Creating **Dictionary**

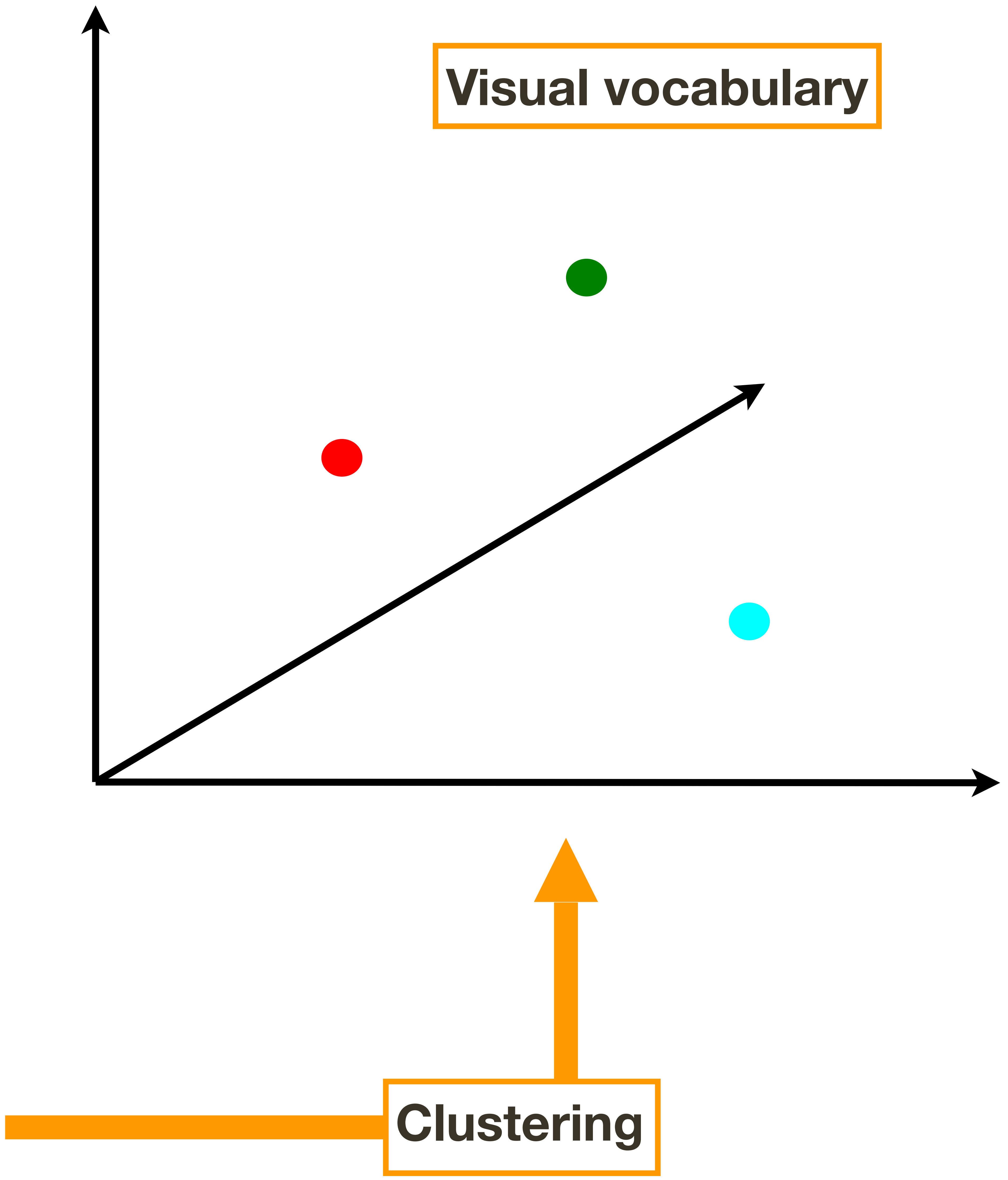




Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Creating **Dictionary**





Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

K-means clustering

K-means Clustering

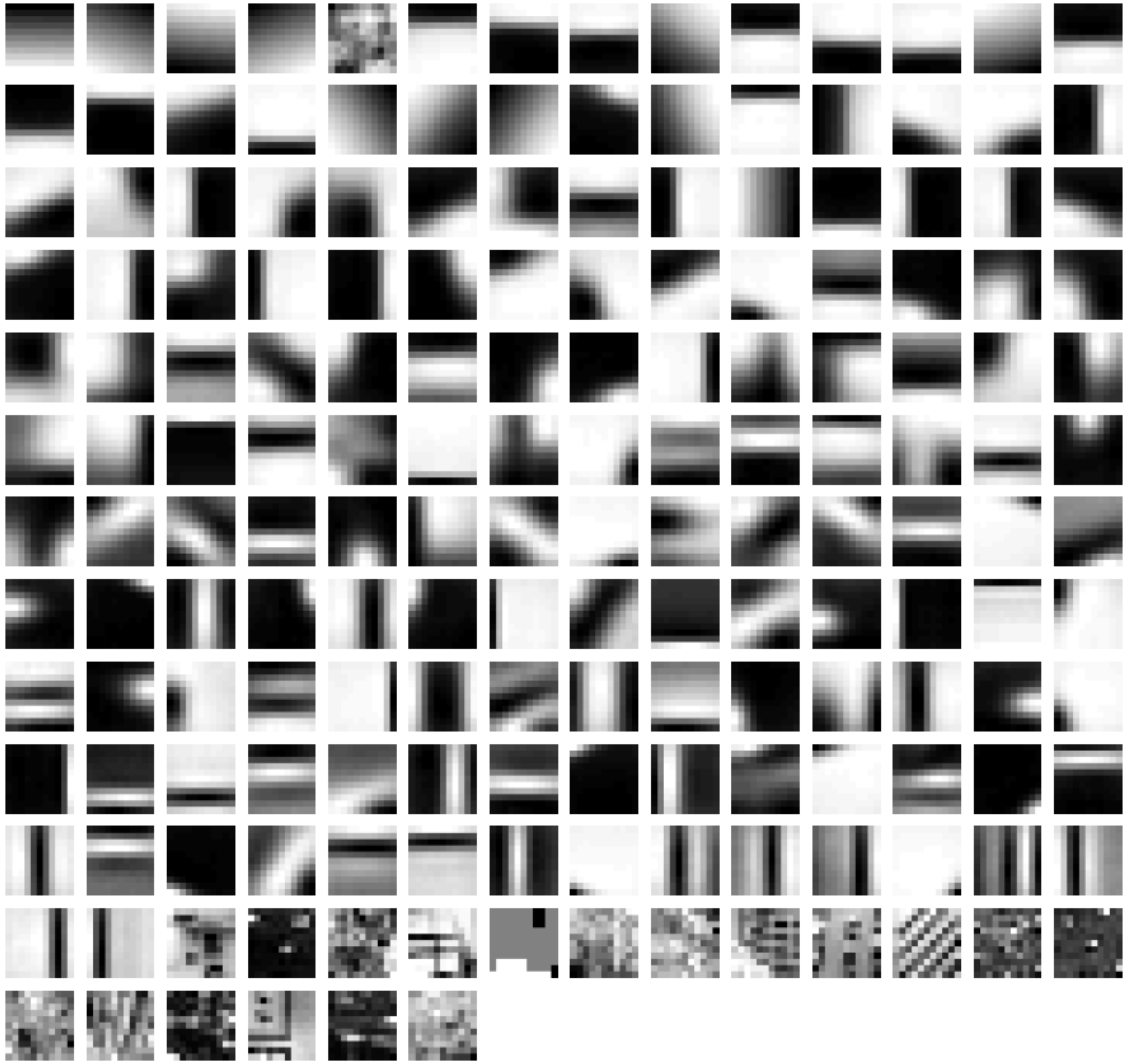
K-means is a clustering technique that iterates between

1. Assume the cluster centers are known. Assign each point to the closest cluster center.

2. Assume the assignment of points to clusters is known. Compute the best cluster center for each cluster (as the mean).

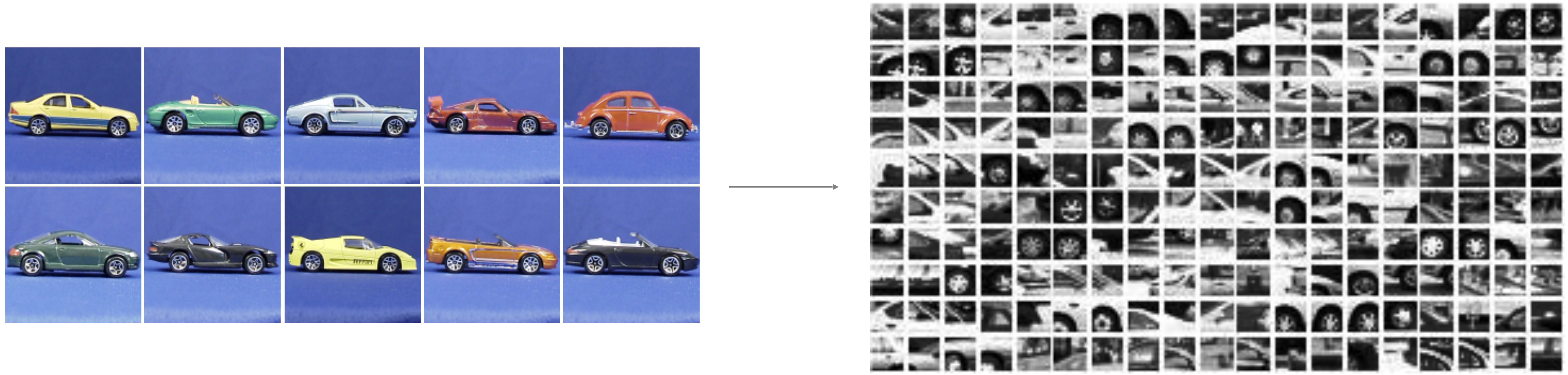
K-means clustering is initialization dependent and converges to a local minimum

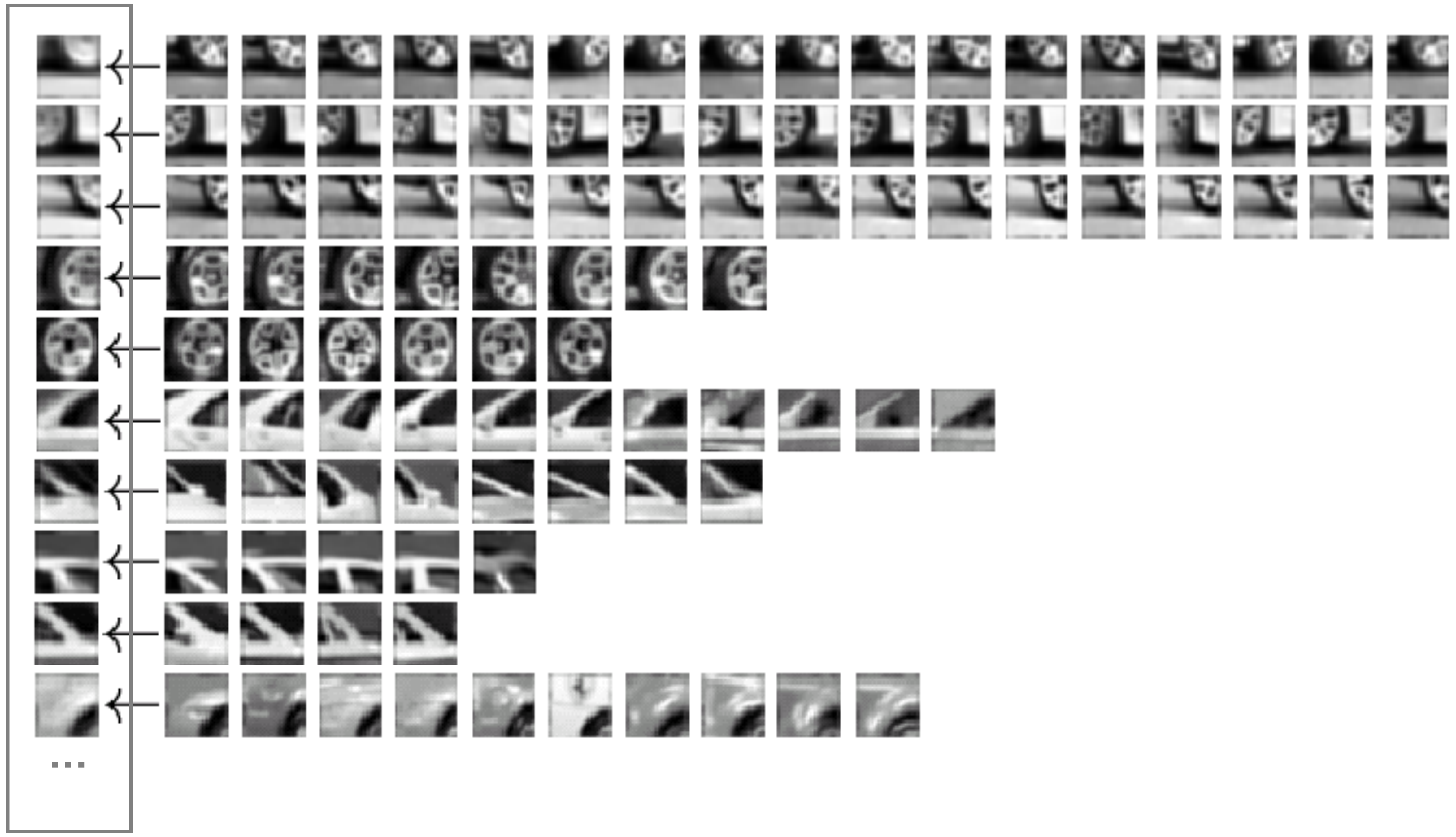
Example **Visual Dictionary**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

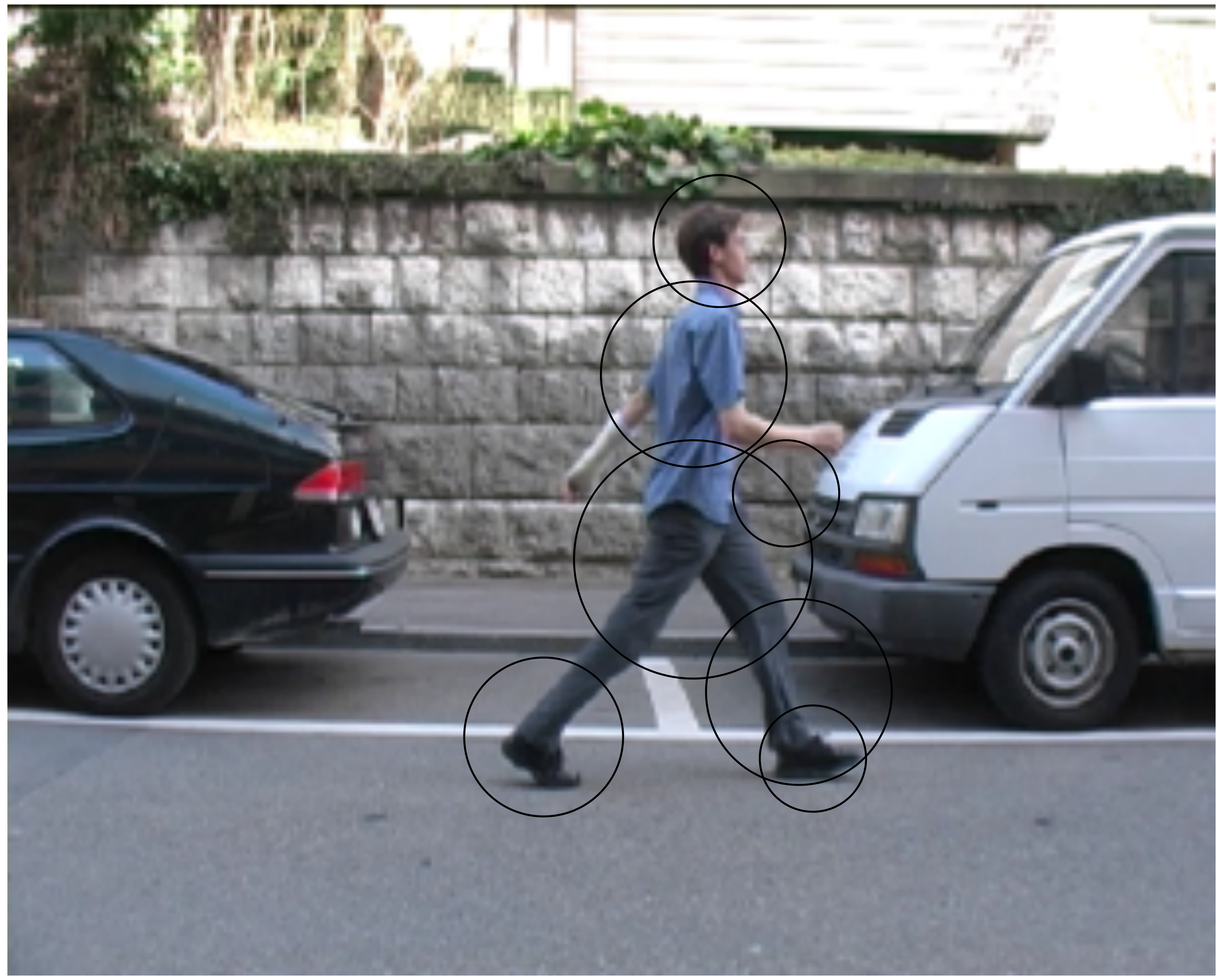
Example **Visual Dictionary**

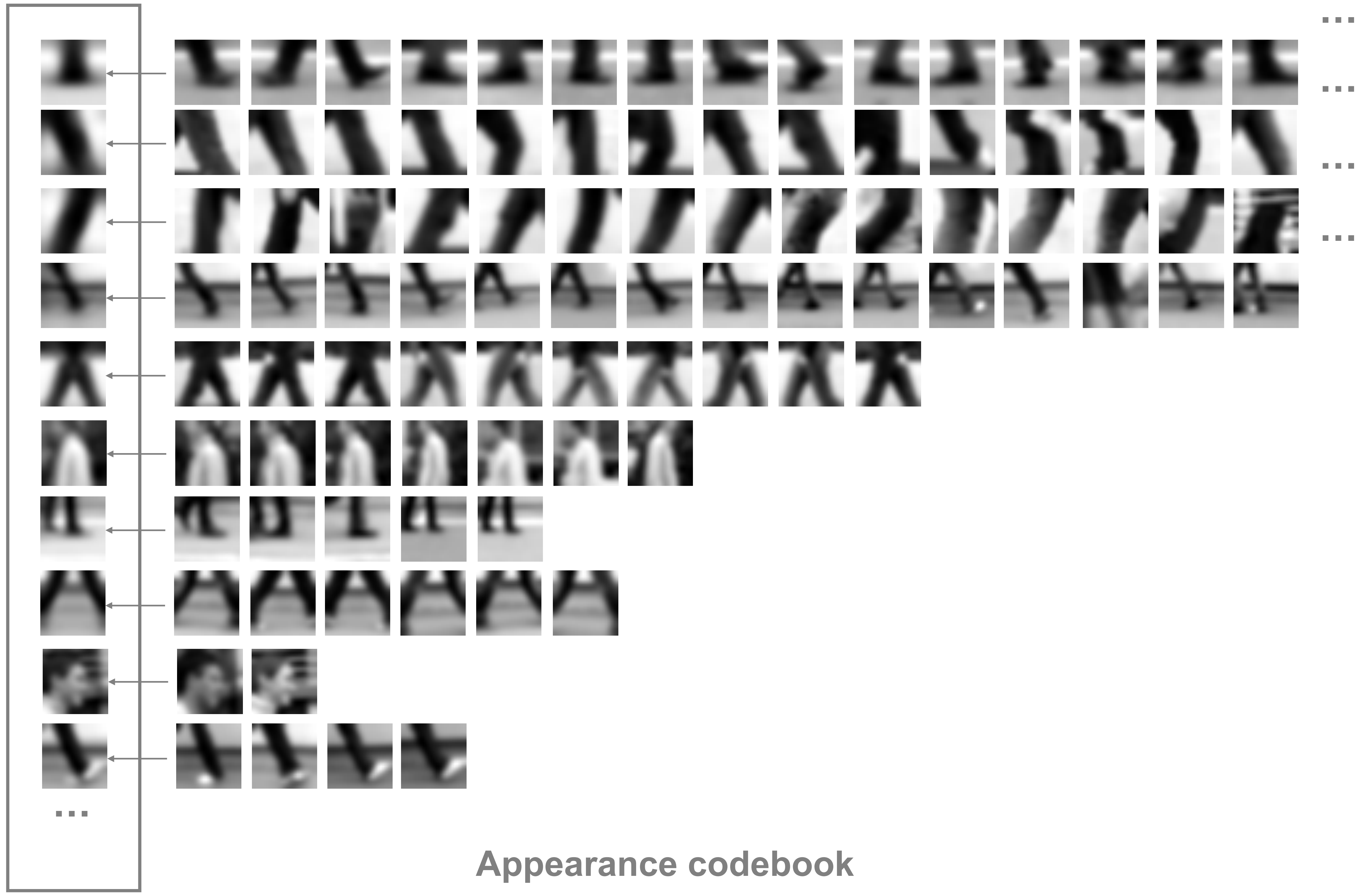




Source: B. Leibe

Example **Visual Dictionary**





Appearance codebook

Source: B. Leibe

Standard **Bag-of-Words** Pipeline (for image classification)

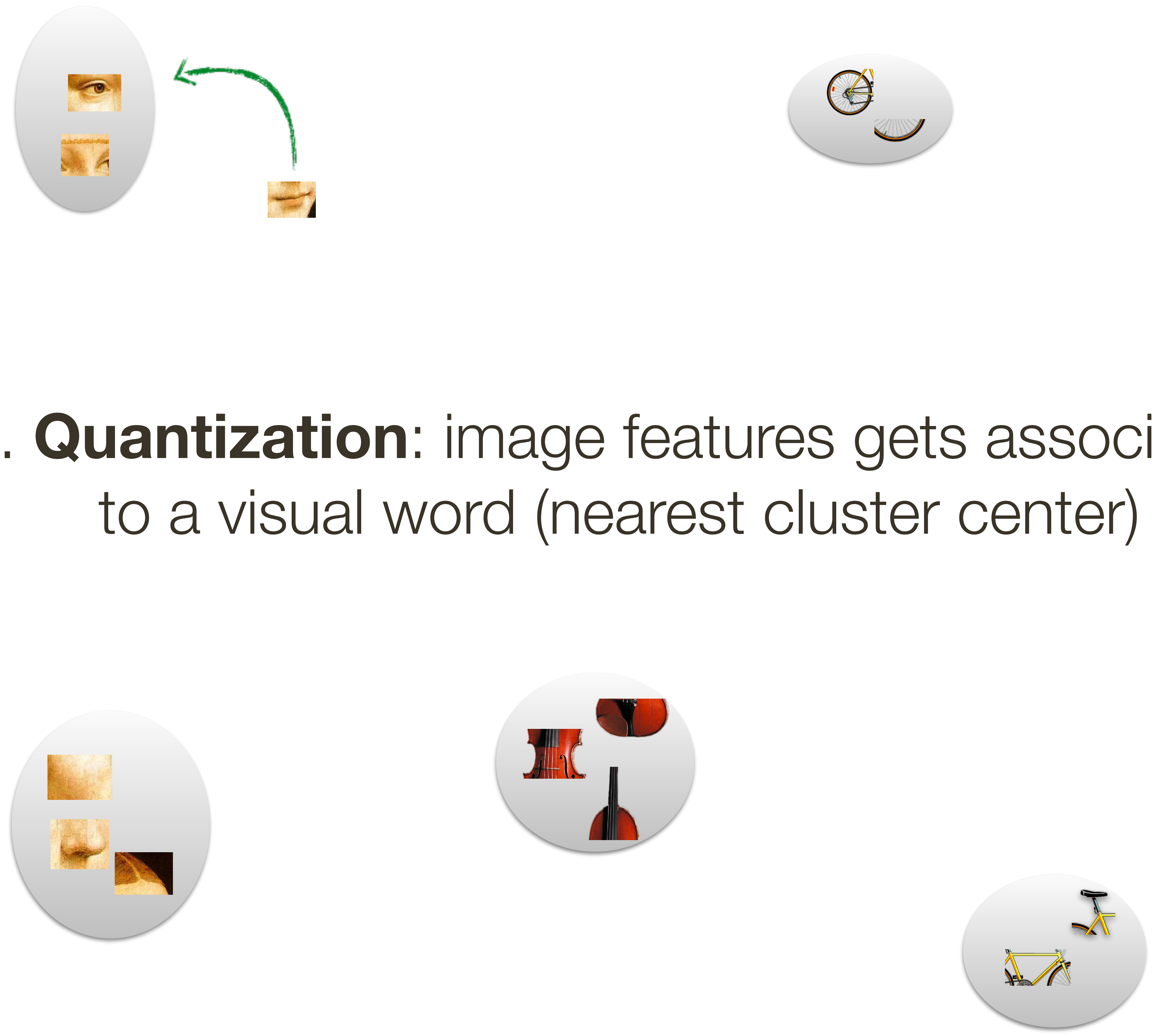
Dictionary Learning:
Learn Visual Words using clustering

Encode:
build Bags-of-Words (BOW) vectors
for each image

Classify:
Train and test data using BOWs

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

2. **Encode:** build Bag-of-Words (BOW) vectors for each image

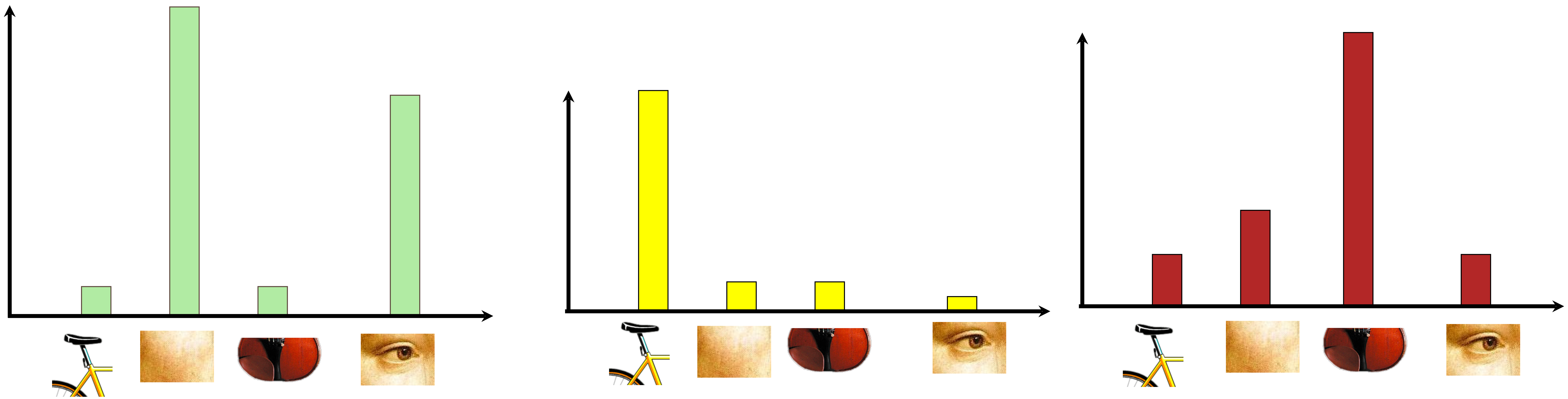


1. **Quantization**: image features gets associated to a visual word (nearest cluster center)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

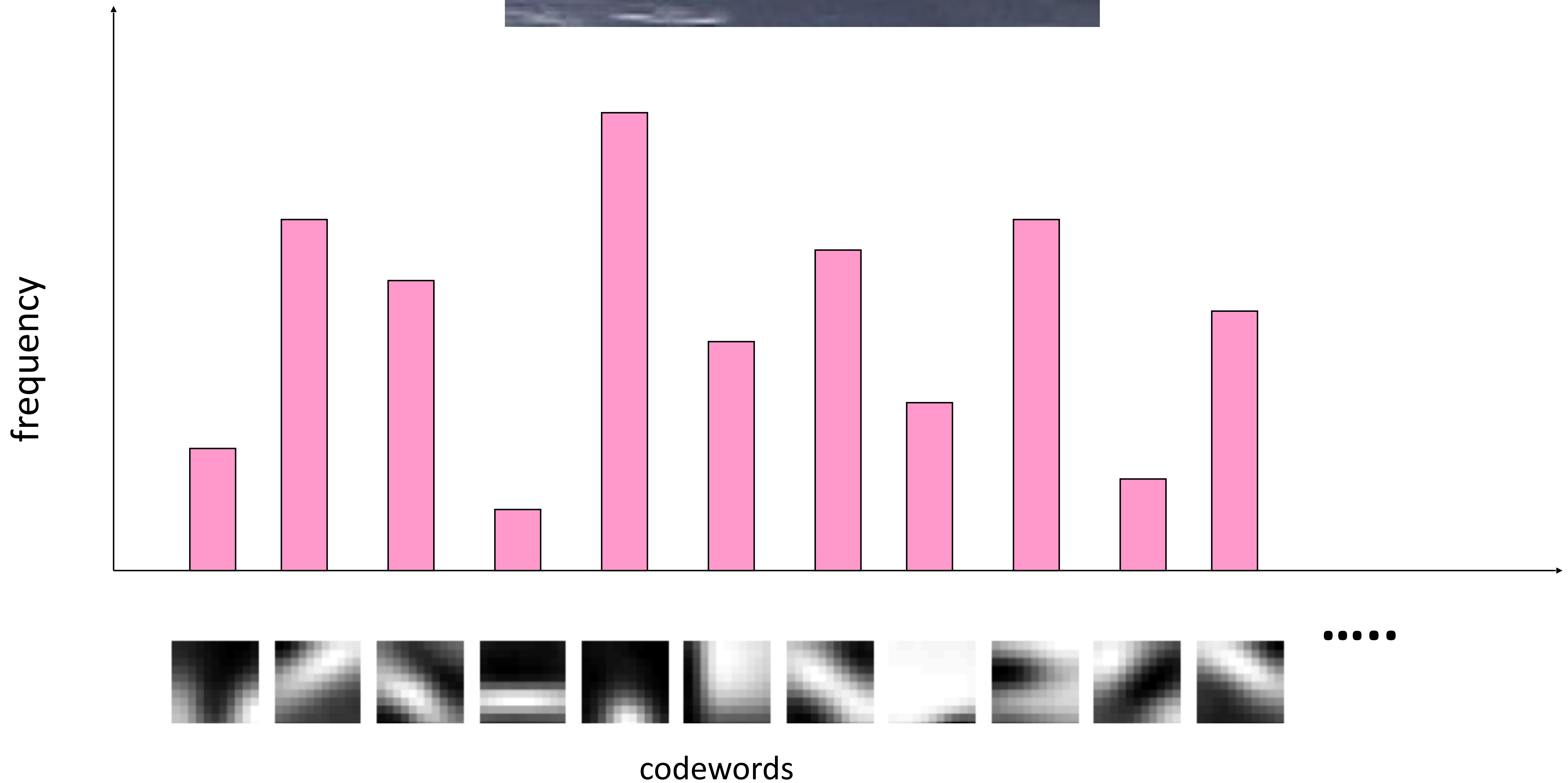
2. Encode: build Bag-of-Words (BOW) vectors for each image

2. **Histogram**: count the number of visual word occurrences



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

2. **Encode:** build Bag-of-Words (BOW) vectors for each image



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Standard **Bag-of-Words** Pipeline (for image classification)

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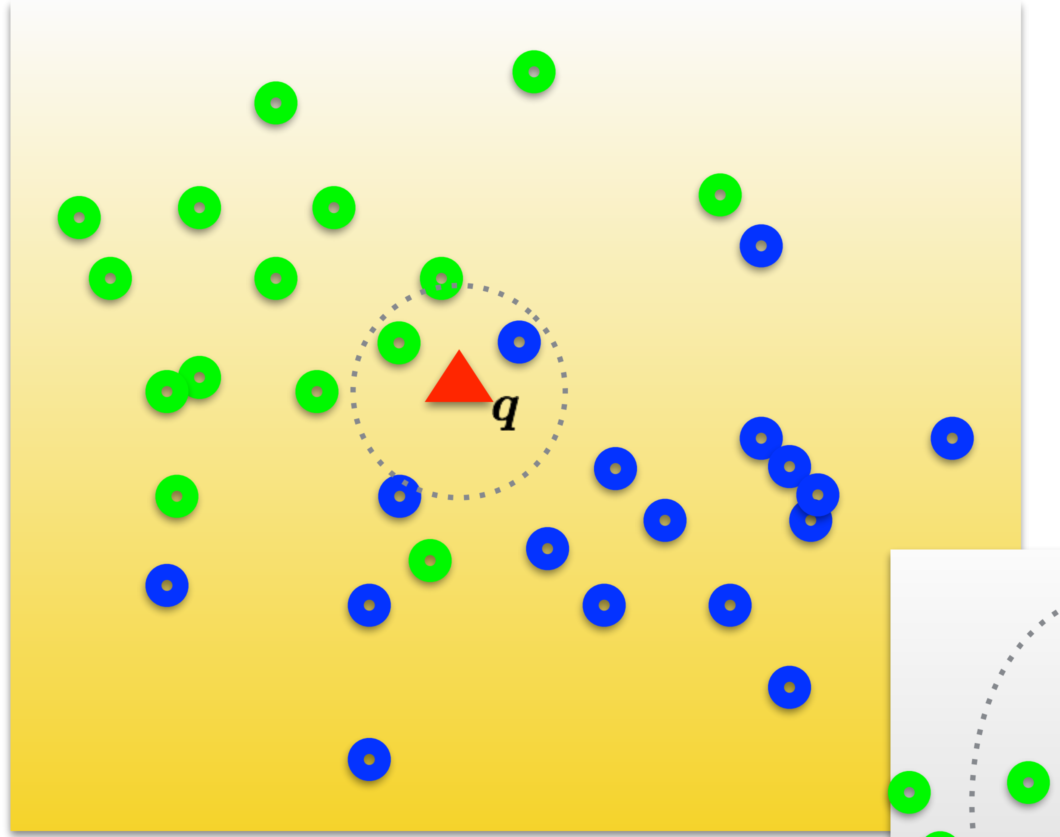
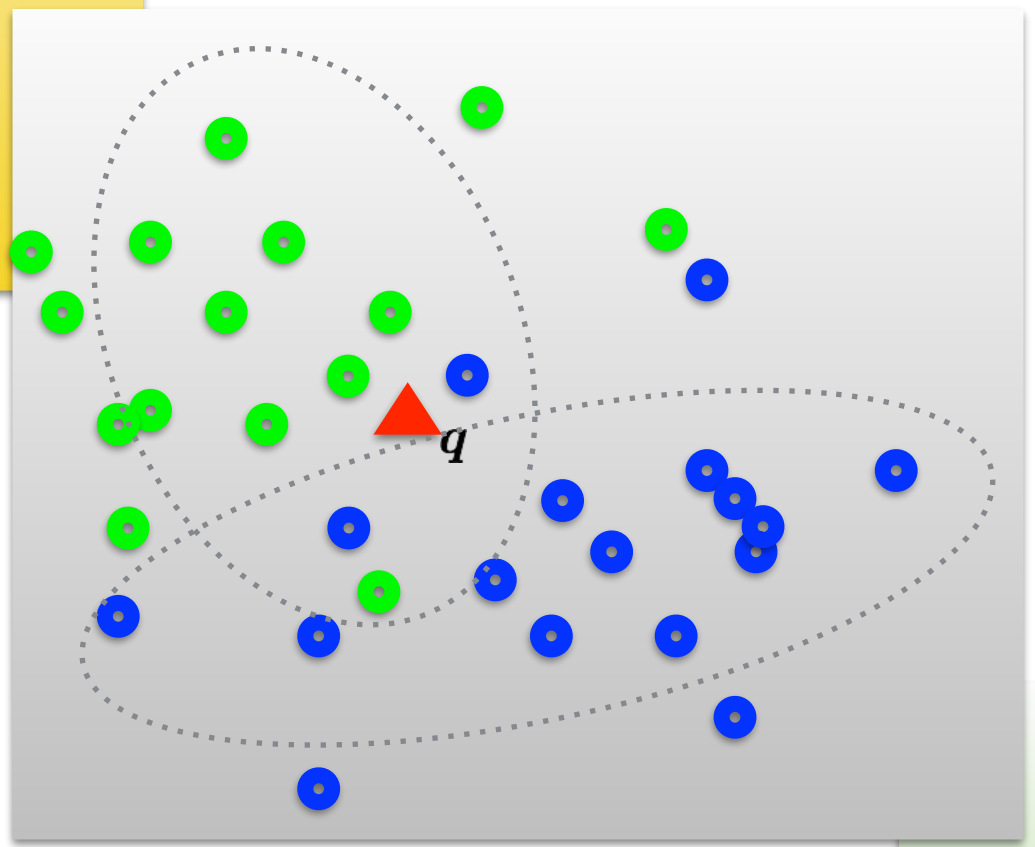
Train and test data using BOWs

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

3. Classify: Train and text classifier using BOWs

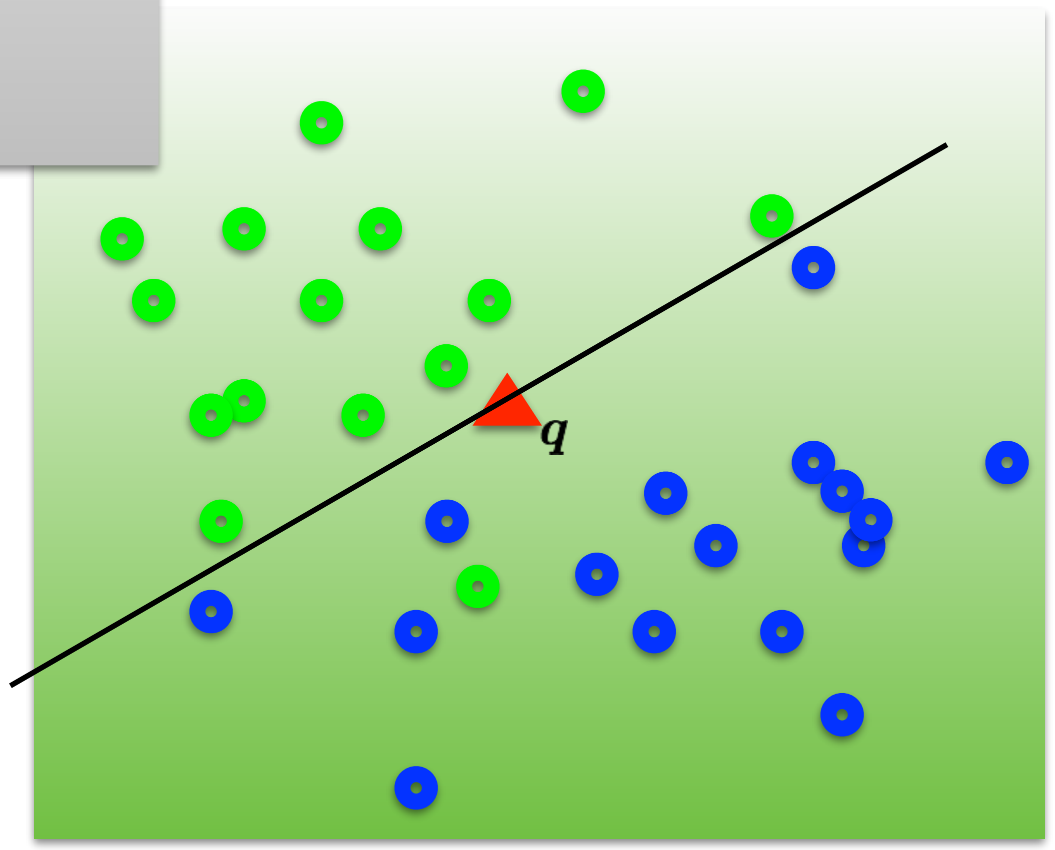


K nearest neighbors



Naïve Bayes

Support Vector Machine



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Bag-of-Words Representation

Algorithm:

Initialize an empty K -bin histogram, where K is the number of codewords
Extract local descriptors (e.g. SIFT) from the image
For each local descriptor **x**

Map (Quantize) **x** to its closest codeword → **c**(**x**)

Increment the histogram bin for **c**(**x**)

Return histogram

We can then classify the histogram using a trained classifier, e.g. a support vector machine or k-Nearest Neighbor classifier

Spatial Pyramid

The bag of words representation does not preserve any spatial information

The **spatial pyramid** is one way to incorporate spatial information into the image descriptor.

A spatial pyramid partitions the image and counts codewords within each grid box; this is performed at multiple levels

Spatial Pyramid

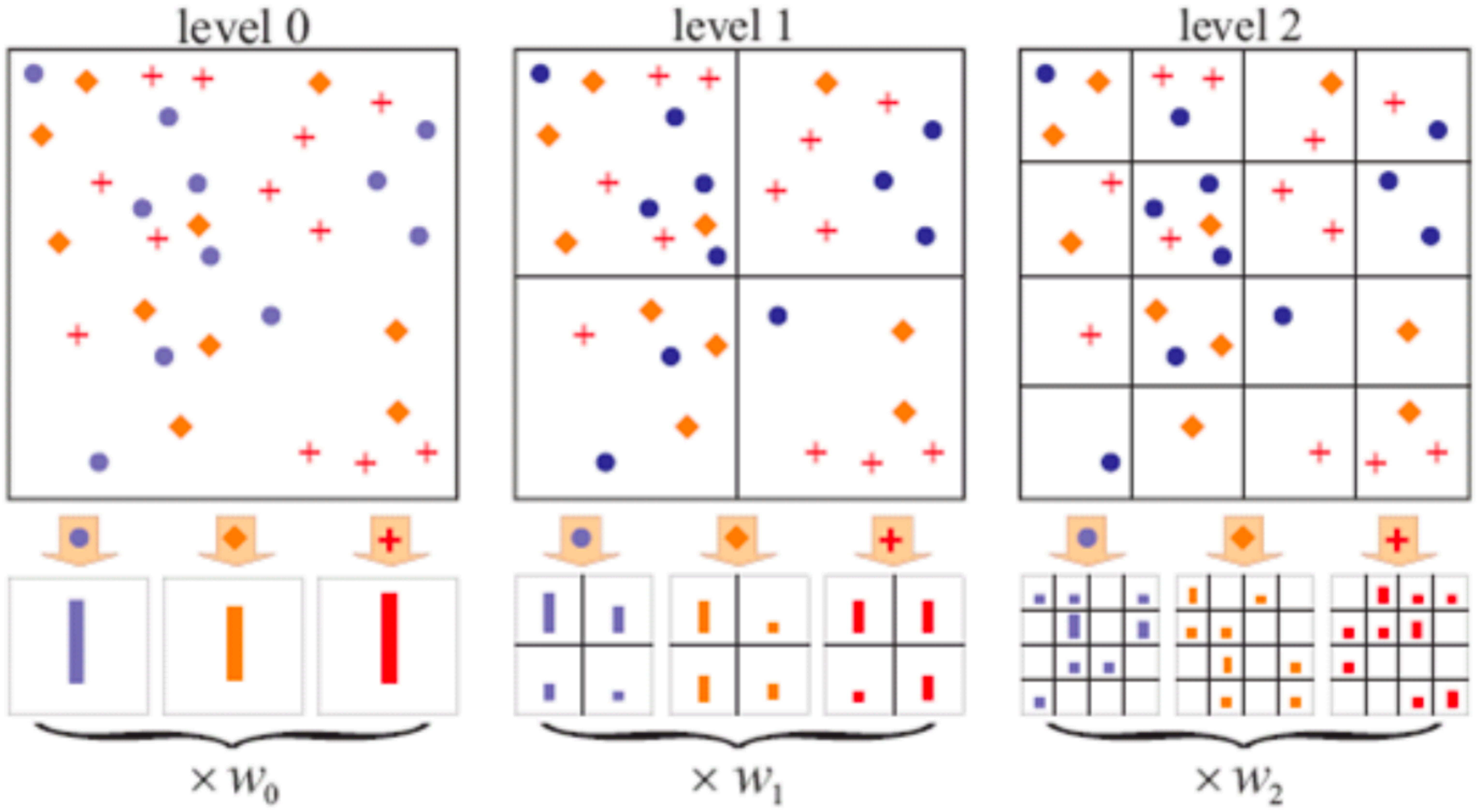


Fig. 16.8 in Forsyth & Ponce (2nd ed.).
Original credit: Lazebnik et al., 2006

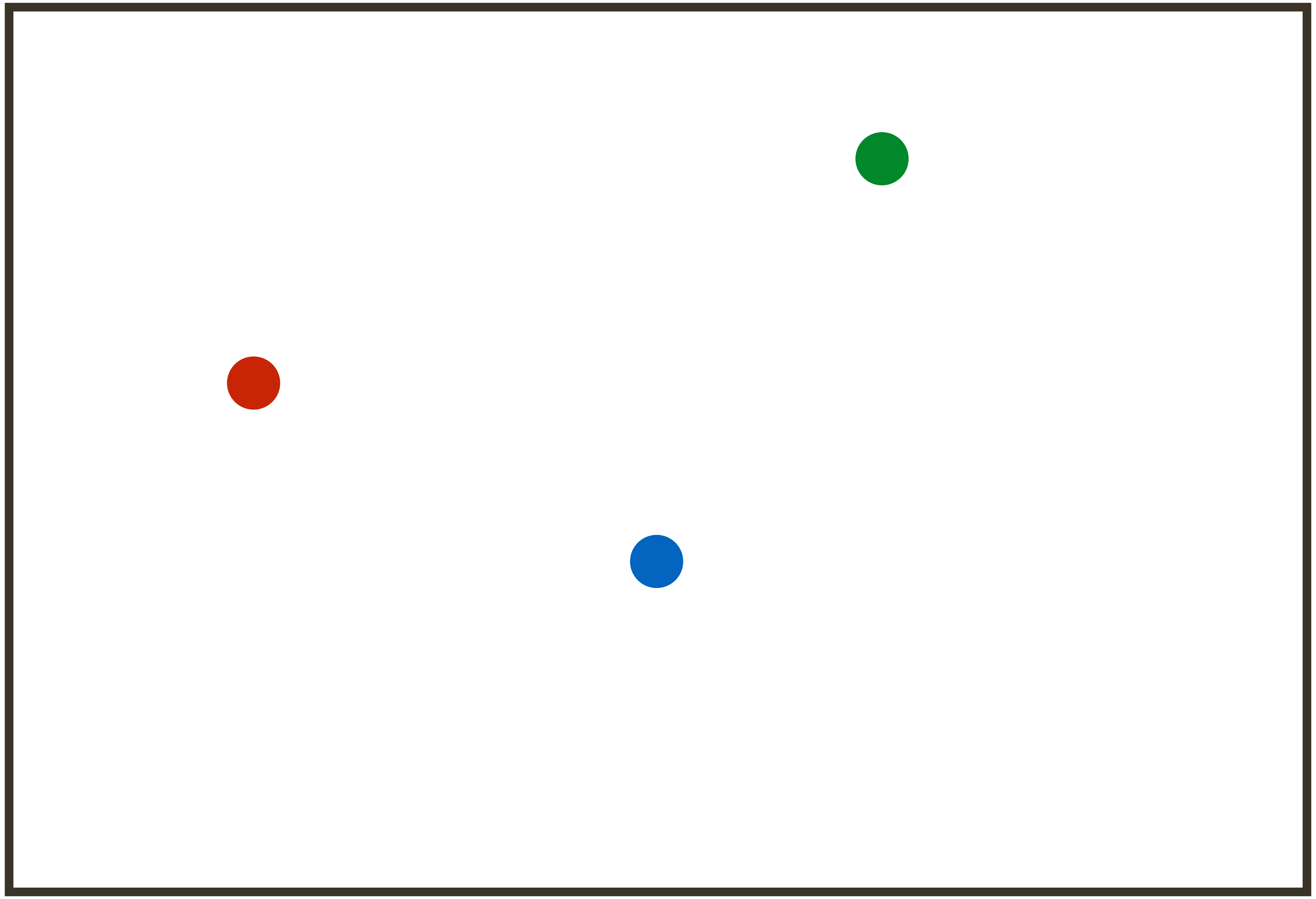
VLAD (Vector of Locally Aggregated Descriptors)

There are more advanced ways to ‘count’ visual words than incrementing its histogram bin

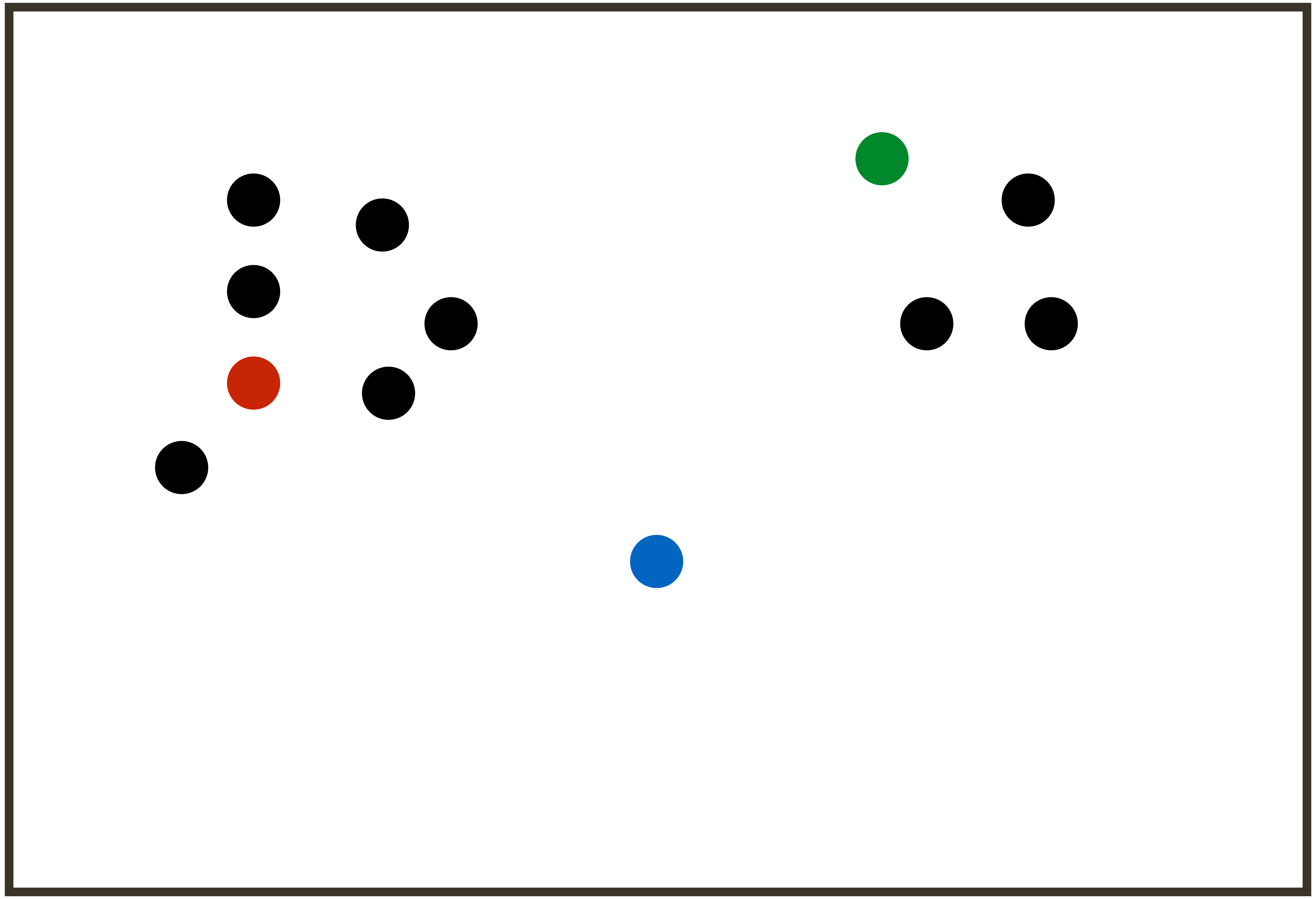
For example, it might be useful to describe how local descriptors are quantized to their visual words

In the VLAD representation, instead of incrementing the histogram bin by one, we increment it by the **residual** vector ***x – c(x)***

Example: VLAD

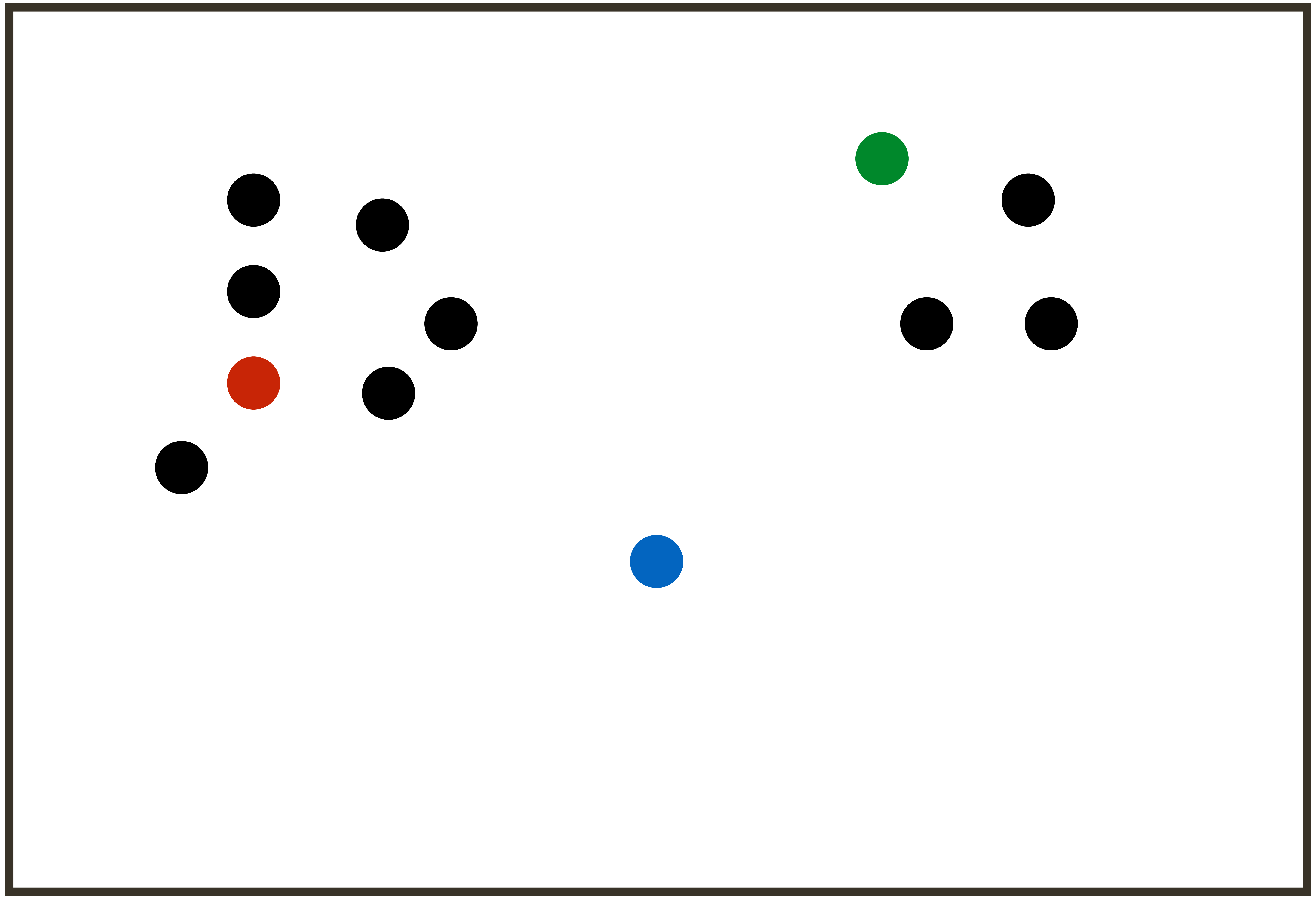


Example: VLAD

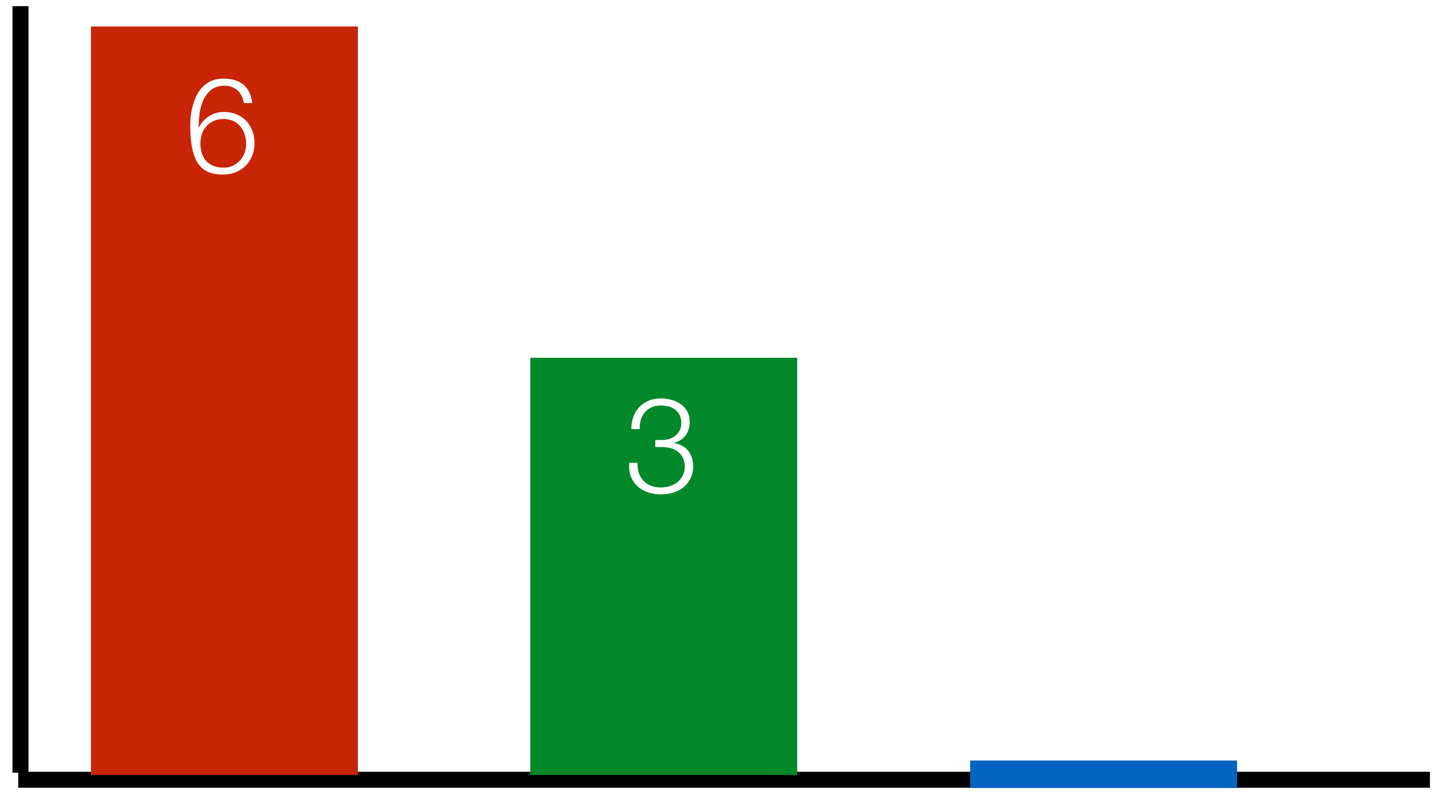


Bag of Word

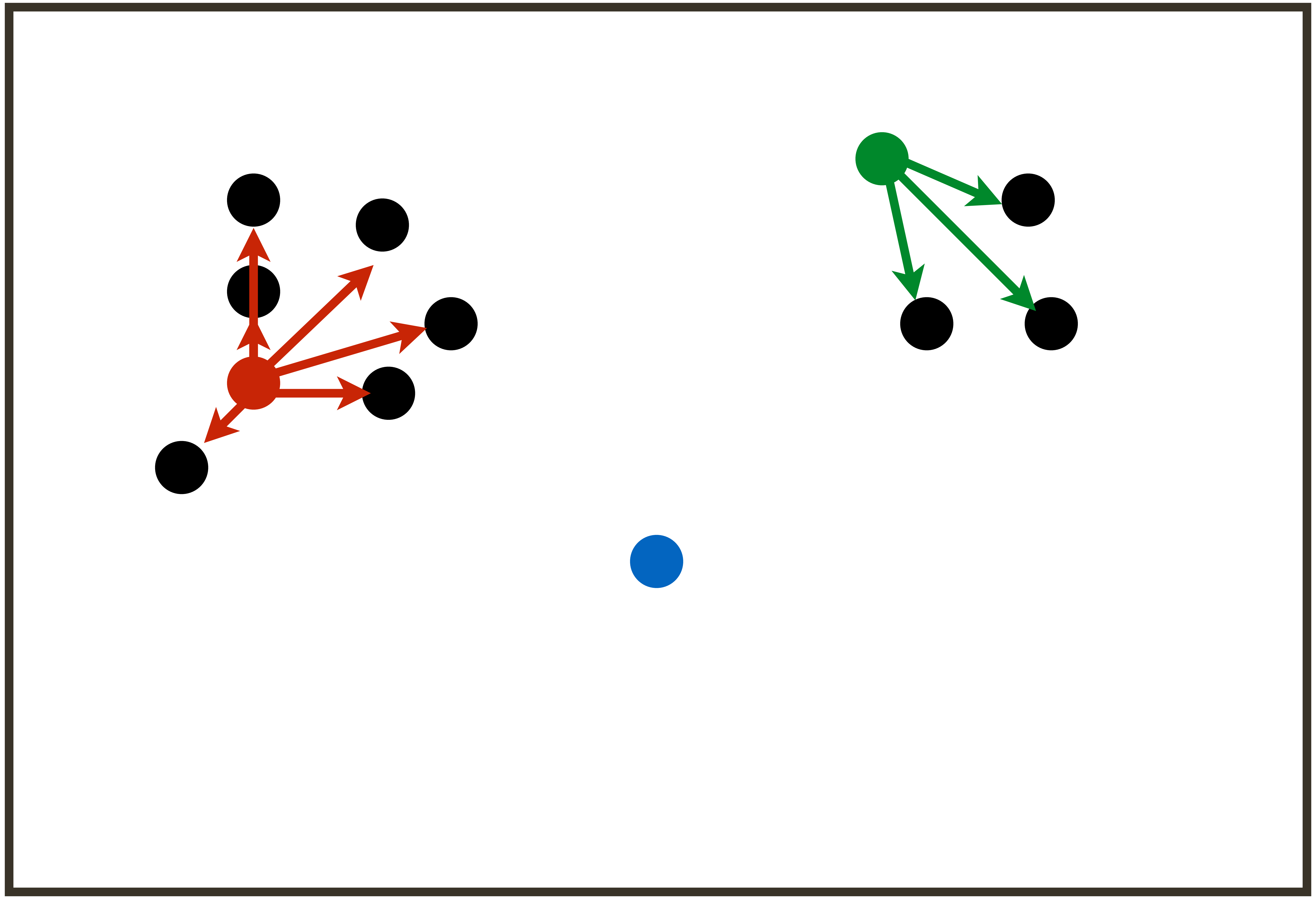
Example: VLAD

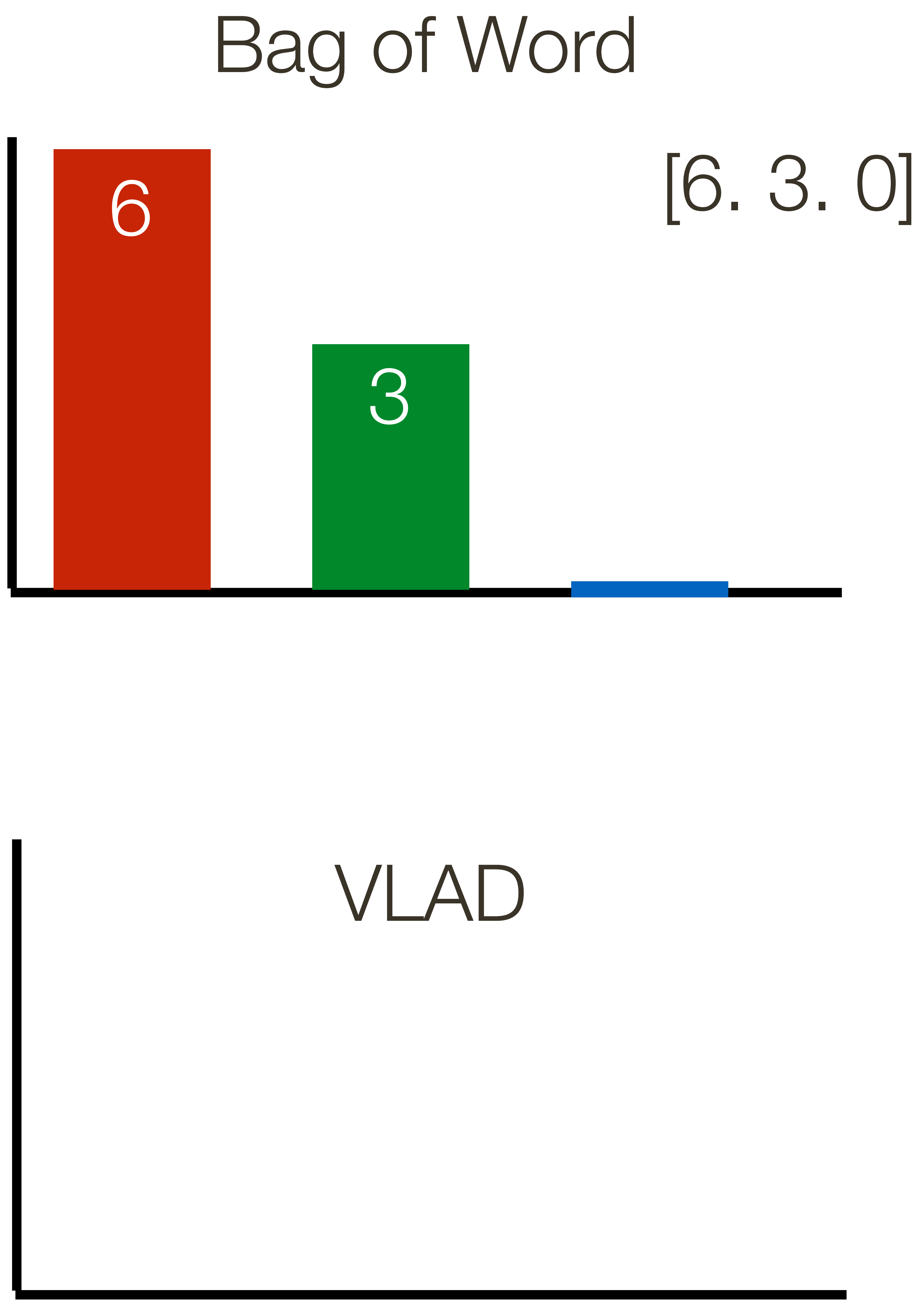


Bag of Word

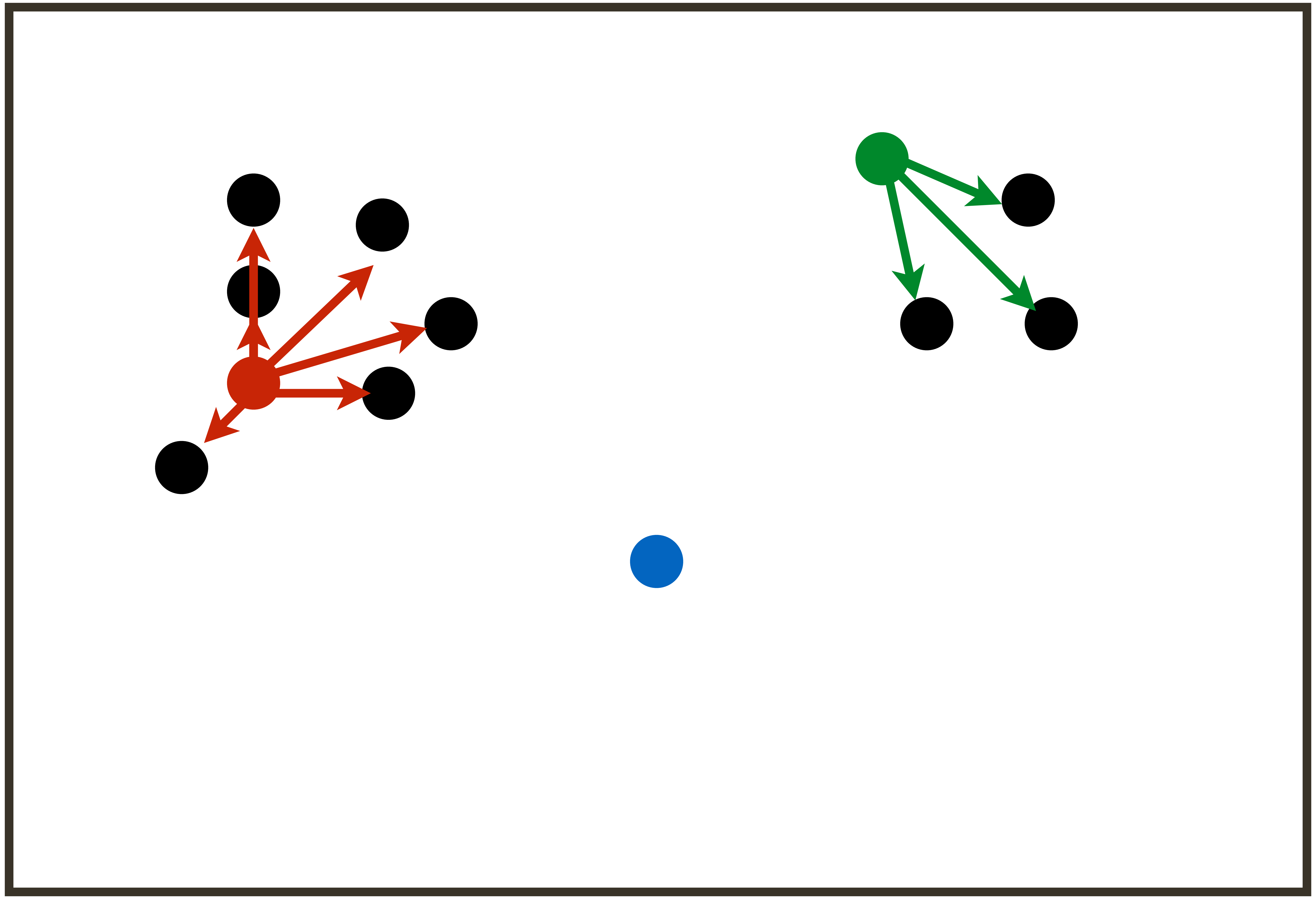


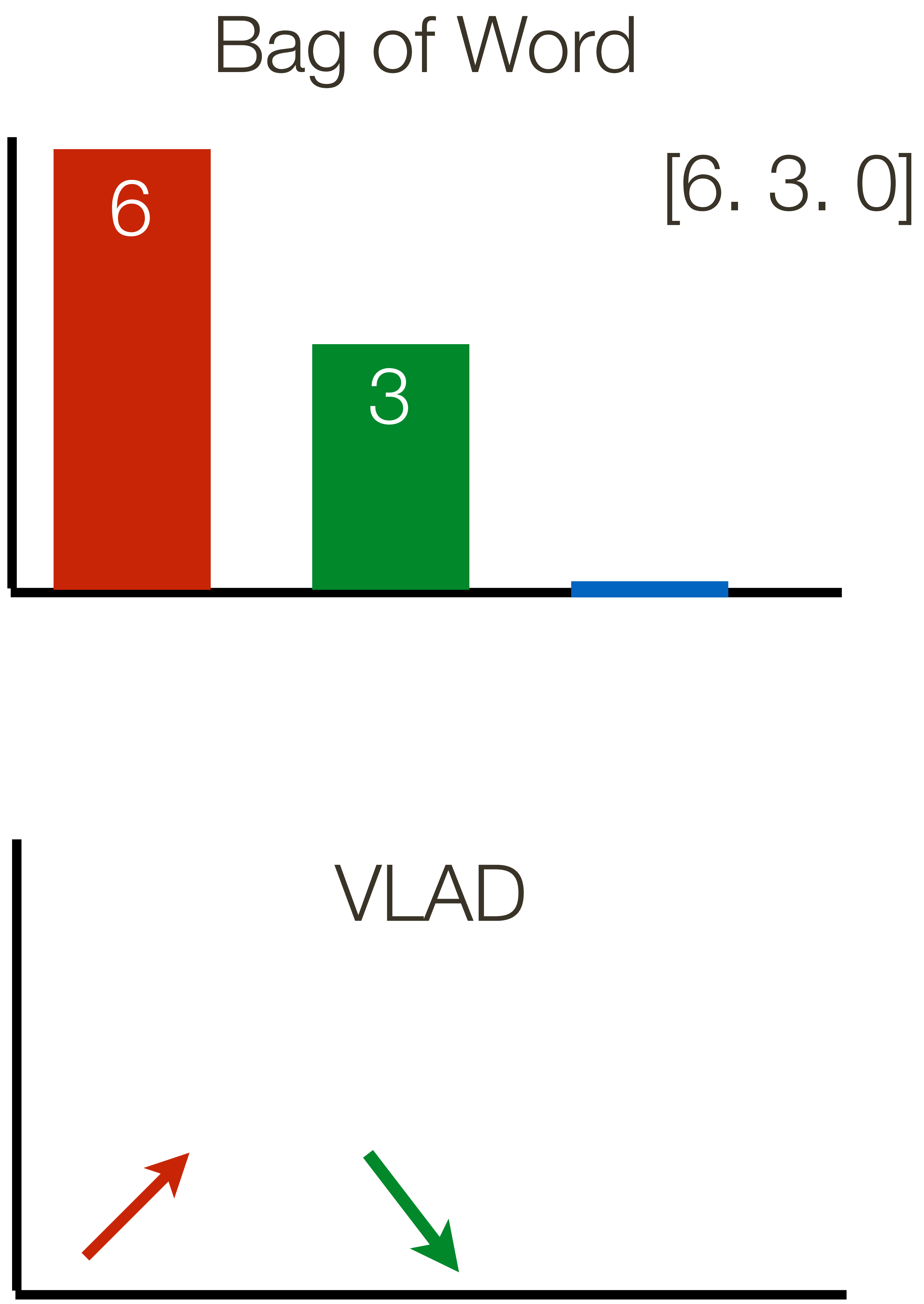
Example: VLAD





Example: VLAD





VLAD (Vector of Locally Aggregated Descriptors)

The dimensionality of a **VLAD** descriptor is Kd

— K : number of codewords

— d : dimensionality of the local descriptor

VLAD characterizes the distribution of local descriptors with respect to the codewords

Summary

Factors that make image classification hard
— intra-class variation, viewpoint, illumination, clutter, occlusion...

A codebook of **visual words** contains representative local patch descriptors
— can be constructed by clustering local descriptors (e.g. SIFT) in training images

The **bag of words** model accumulates a histogram of occurrences of each visual word

The **spatial pyramid** partitions the image and counts visual words within each grid box; this is repeated at multiple levels