

File Name: T-ICML-I\_M0\_L1\_introduction

Format: Presenter in Studio

Presenter: Evan Jones



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## Image Classification Models

Evan Jones

# Specialization

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End-to-End Lab on Structured  
Data

Production ML Systems

**Image Classification Models**

Sequence Models

Recommendation Systems

# Agenda

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## Introduction

Linear and DNN models

Convolutional neural networks

Dealing with Data Scarcity

Going Deeper Faster

Pre-built models

# Agenda

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File Name: Qwiklabs-onboard-lab-M0-overview\_V2

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File Name: T-ICML-O\_M0\_I3\_introduction

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# Learn how to...

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Recognize the applications for modern image classification models

Breakdown images as visual data (height, width, and depth)

Understand the limitations of comparing image data with traditional methods

# Advances in Computer Vision



# Sensors are now commonplace



Visual data growing  
at an incredible rate



**High demand for**  
interpreting the  
meaning of images  
at scale



Clouds or snow-capped mountains?





Good or bad  
diced potatoes?



# Empty or Full?





# Diagnosing Diabetic Retinopathy

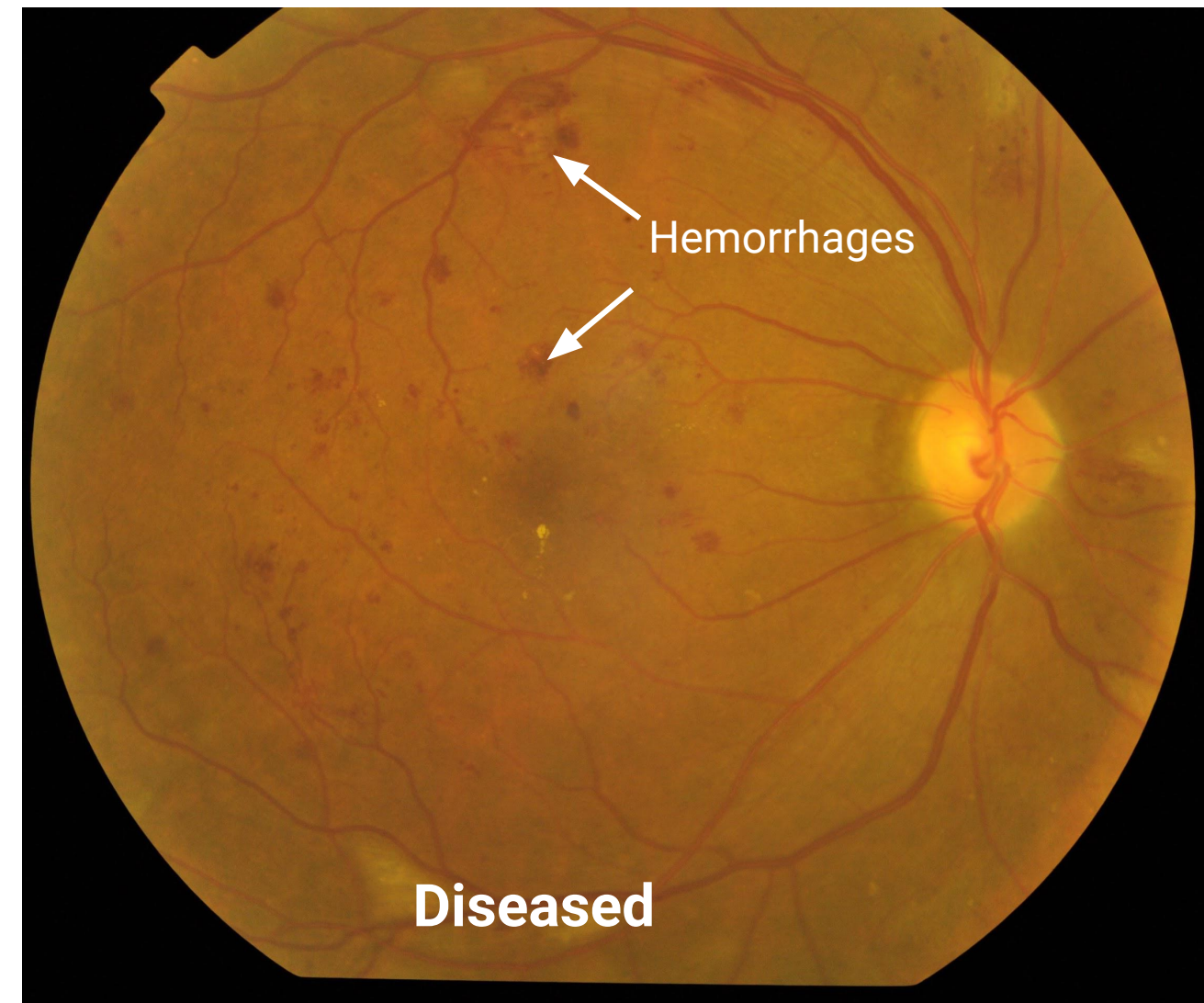
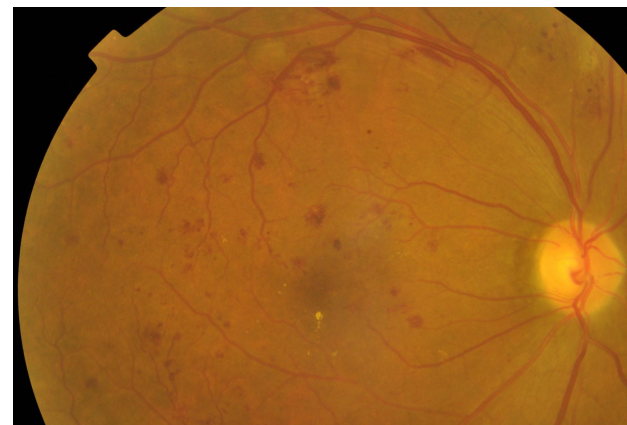


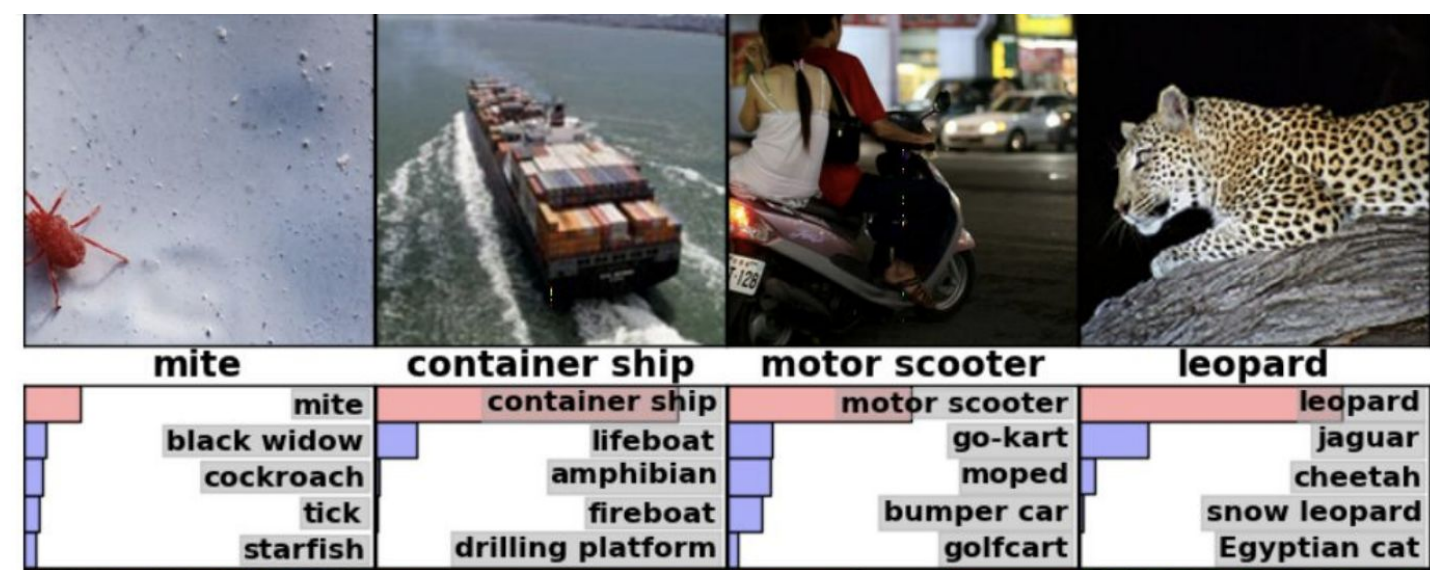




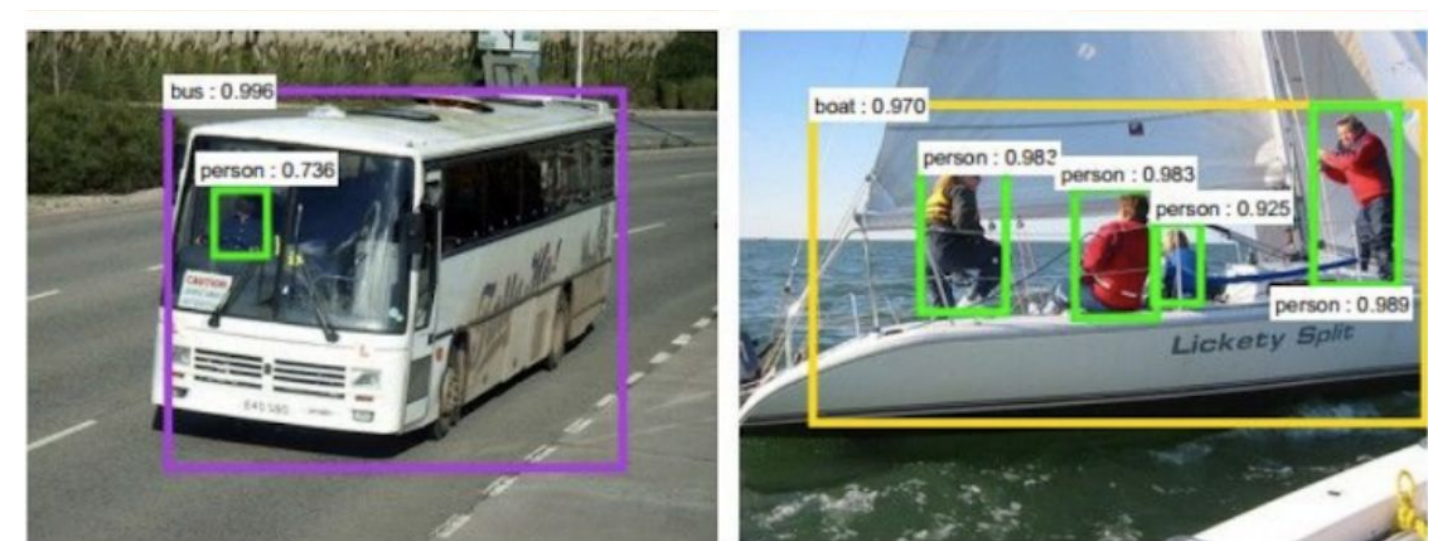
Image classification  
**automates tasks** that are easy  
(and not easy) for humans



# Labeling



# Object Detection





Describes without errors	Describes with minor errors	Somewhat related to the image	Unrelated to the image
 <p>A person riding a motorcycle on a dirt road.</p>	 <p>Two dogs play in the grass.</p>	 <p>A skateboarder does a trick on a ramp.</p>	 <p>A dog is jumping to catch a frisbee.</p>
 <p>A group of young people playing a game of frisbee.</p>	 <p>Two hockey players are fighting over the puck.</p>	 <p>A little girl in a pink hat is blowing bubbles.</p>	 <p>A refrigerator filled with lots of food and drinks.</p>
 <p>A herd of elephants walking across a dry grass field.</p>	 <p>A close up of a cat laying on a couch.</p>	 <p>A red motorcycle parked on the side of the road.</p>	 <p>A yellow school bus parked in a parking lot.</p>

Show and Tell: A Neural Image Caption Generator Vinyals et al 2015:  
<https://arxiv.org/abs/1411.4555>



# Pose Detection



[g.co/movemirror](https://g.co/movemirror)



File Name: T-ICML-O\_M0\_I4\_structured\_vs\_unstructured\_data

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## **Review: Structured Data represented as a vector**

Cat's height and weight

[9.4, 7.9]

# Image Data is multi-dimensional

← 256px Width →

← 256px Height →

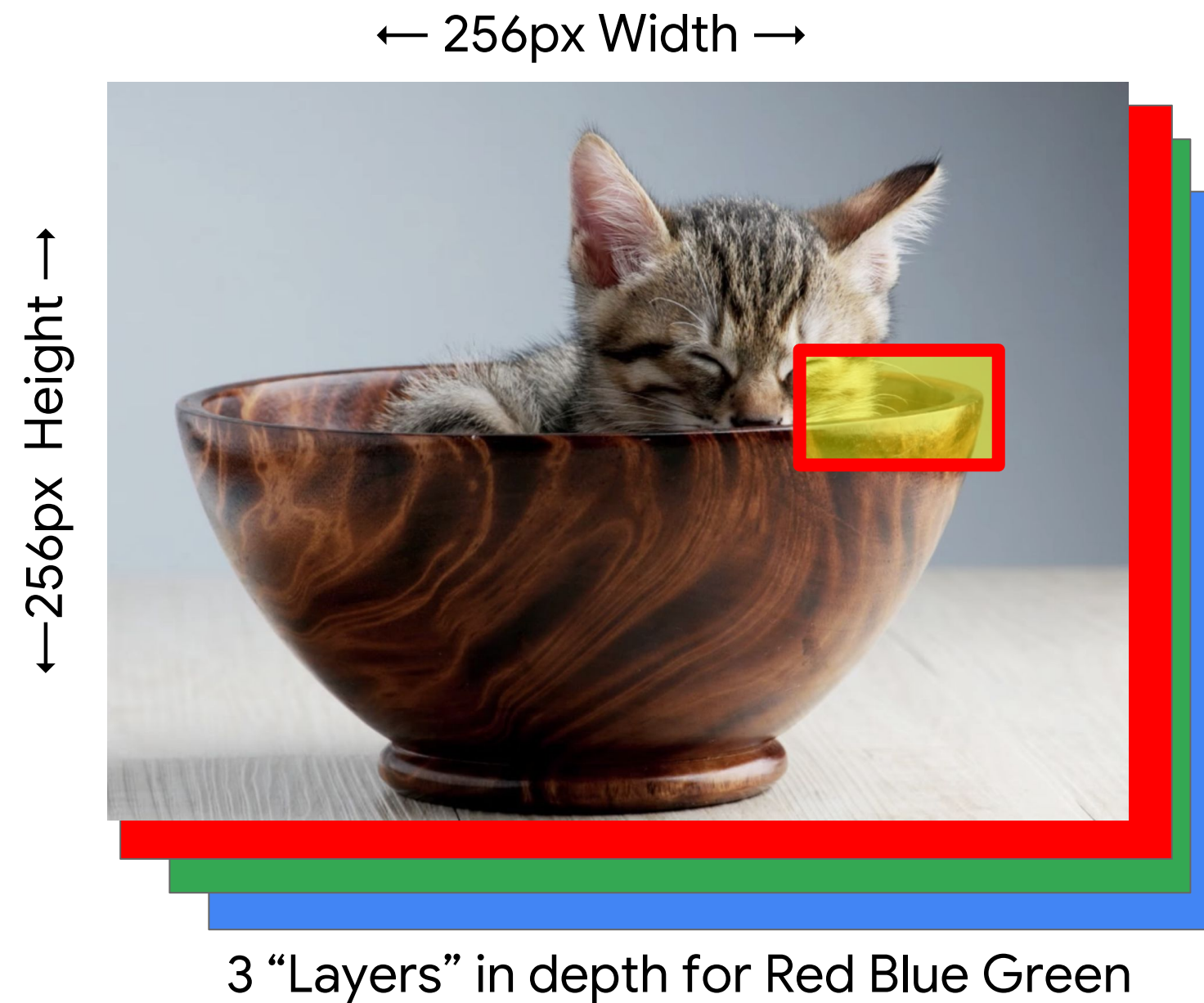


# Image Data has depth which represents color intensity





# Image Data has depth which represents color intensity



**A single high-res image can represent  
millions of weights to learn**



**8 Megapixel resolution**

$3264 \text{ (w)} \times 2448 \text{ (h)} \times 3 \text{ (RGB)} =$

**23,970,816 per image\***

\* ML training time impacted



# Traditional ML methods do not handle translations well

← 256px Width →



← 256px Width →

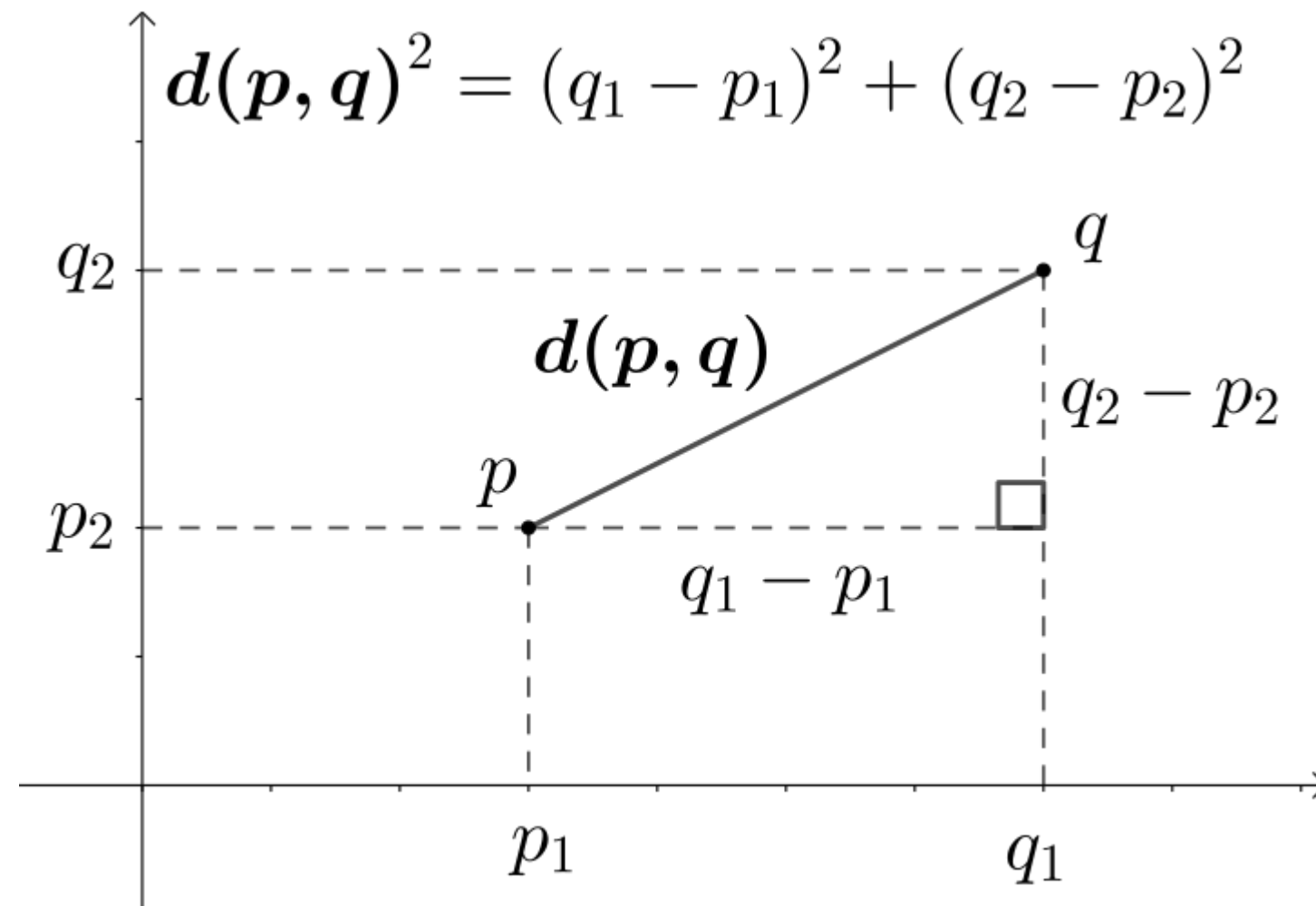


**Comparing pixel for pixel the image has significantly changed**

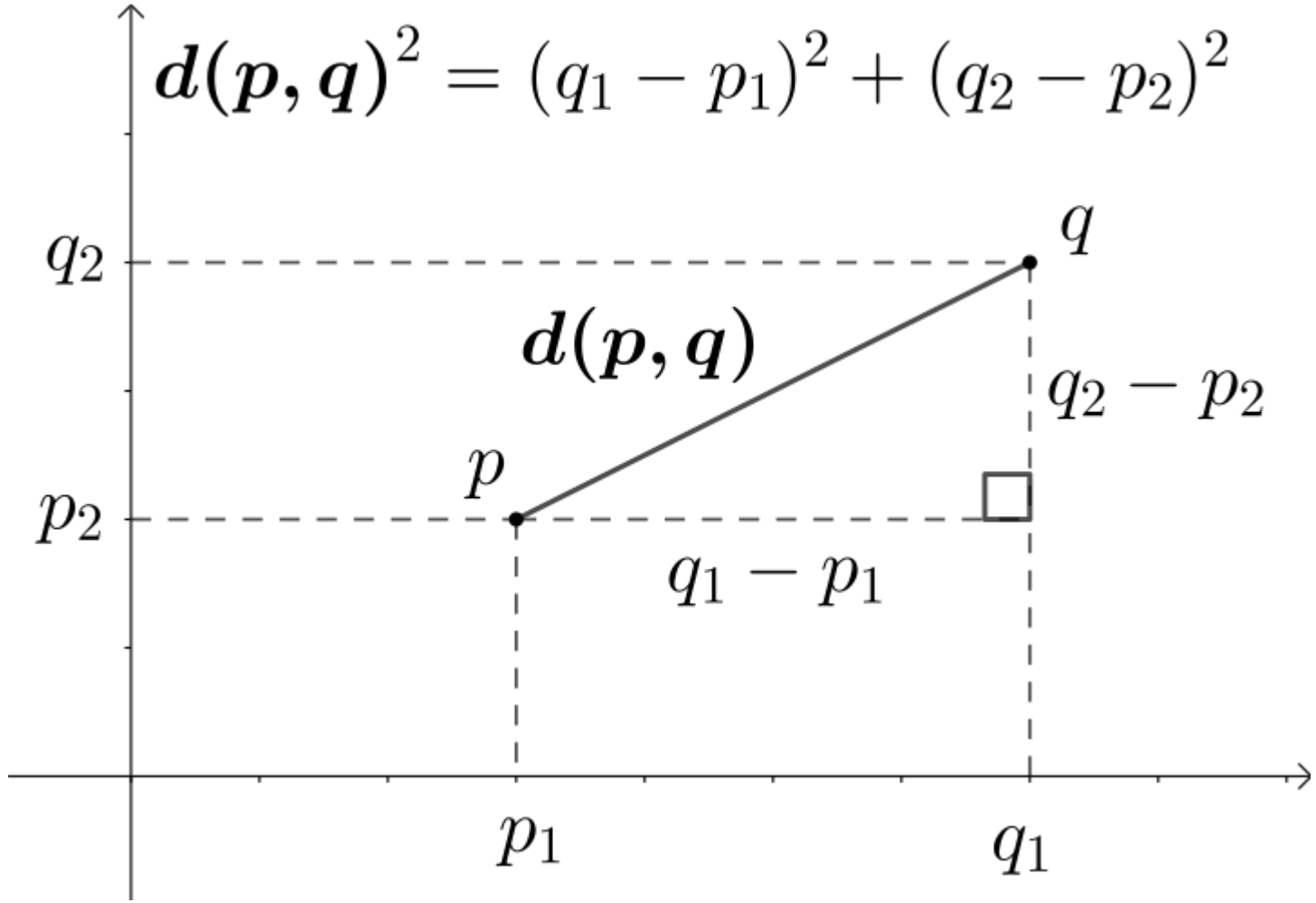




## Comparing feature vectors with straight-line distance



Comparing feature vectors with straight-line distance  
works well for structured data



	Cat Height (in)	Cat Weight (lbs)
1	9.4	7.9
2	9.7	9.9
3	42	320

# Comparing feature vectors with straight-line distance works well for structured data

## Compare distance

between two house cats  
 $(9.4 - 9.7)^2 + (7.9 - 9.9)^2 =$   
 $\sqrt{4.09} = \mathbf{2.02}$

between a cat and tiger  
 $(9.4 - 42)^2 + (7.9 - 320)^2 =$   
 $\sqrt{98,469} = \mathbf{313.79}$

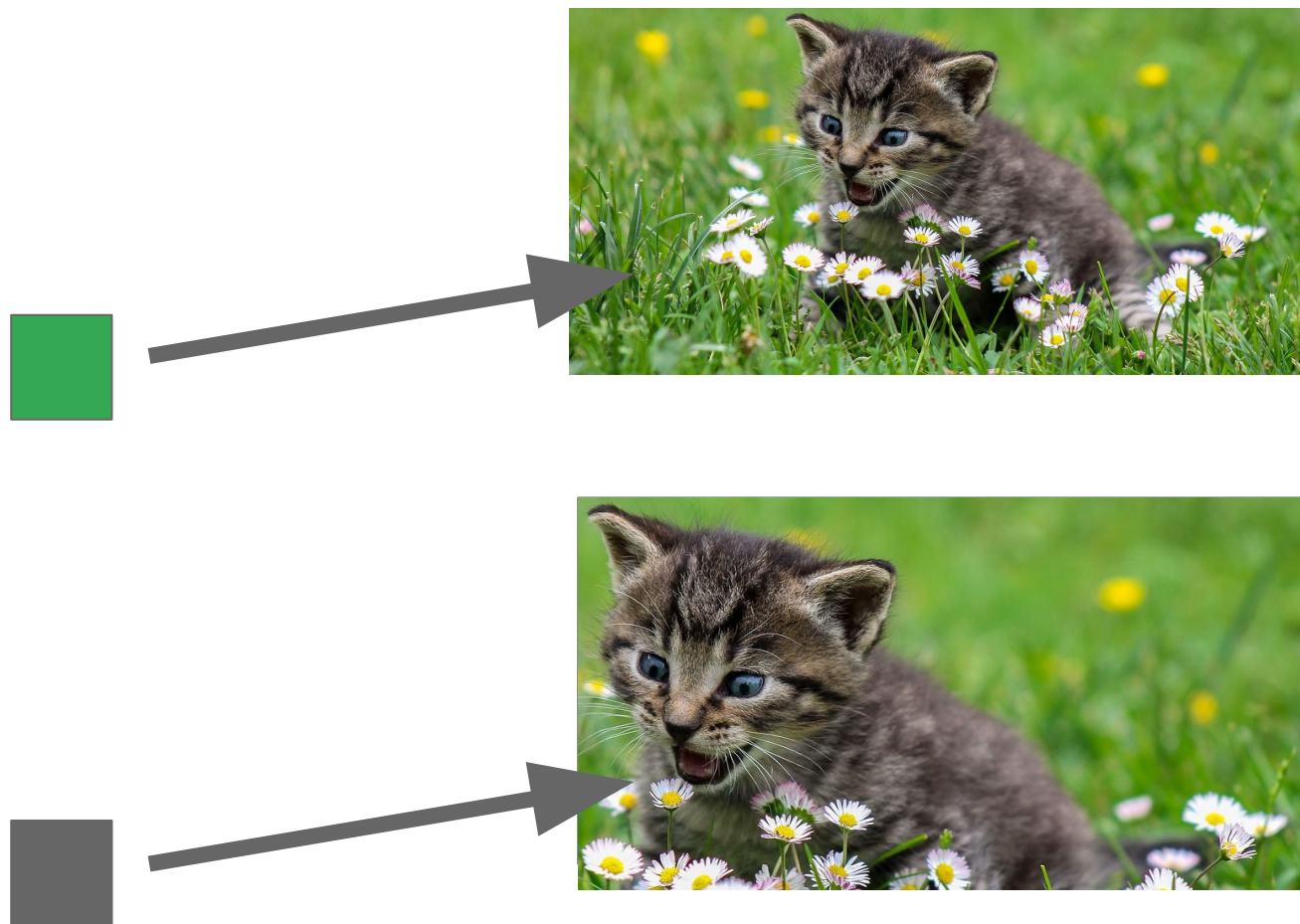


	Cat Height (in)	Cat Weight (lbs)
1	9.4	7.9
2	9.7	9.9
3	42	320

**Comparing feature vectors  
with straight-line distance  
does not work well for  
unstructured data**



Comparing feature vectors  
with straight-line distance  
does not work well for  
unstructured data



**Humans can “see” the same  
image regardless of  
translation**





**Humans can “see” the same  
image regardless of  
translation**



**Humans can “see” the same  
image regardless of  
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**Humans can “see” the same  
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**Humans can “see” the same  
image regardless of  
translation**



**The ideal decision boundary  
of cat vs non-cat**



**is defined by the relationship  
between the pixels**

**How can you model the  
relationship between pixels?**

**??**