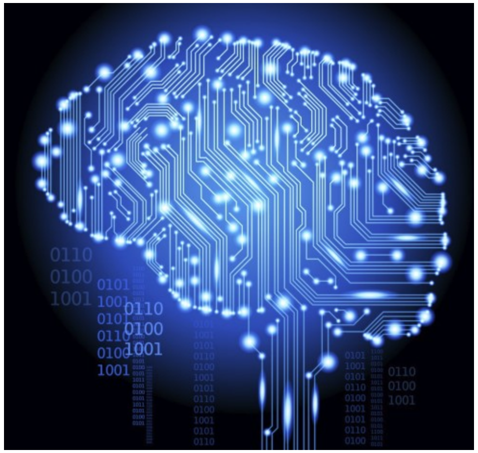
Machine Learning

Artificial Intelligence

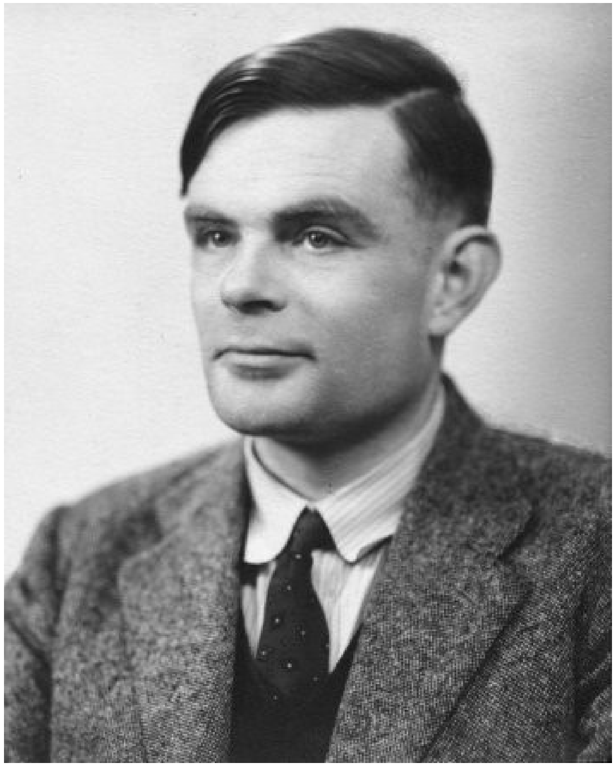
Artificial Intelligence

- Intelligence demonstrated by machines or software, and the study of how to make them that way.
- Reasoning, knowledge, planning, learning, natural language processing, perception.
- What does it mean to “act intelligent”?



The Turing Test

- Operational definition of intelligence
- Proposed by Alan Turing in 1950
- Test of a computers ability to exhibit intelligent behavior equivalent to that of a human.



Alan Turing

Turing test

During the Turing test, the human questioner asks a series of questions to both respondents. After the specified time, the questioner tries to decide which terminal is operated by the human respondent and which terminal is operated by the computer.

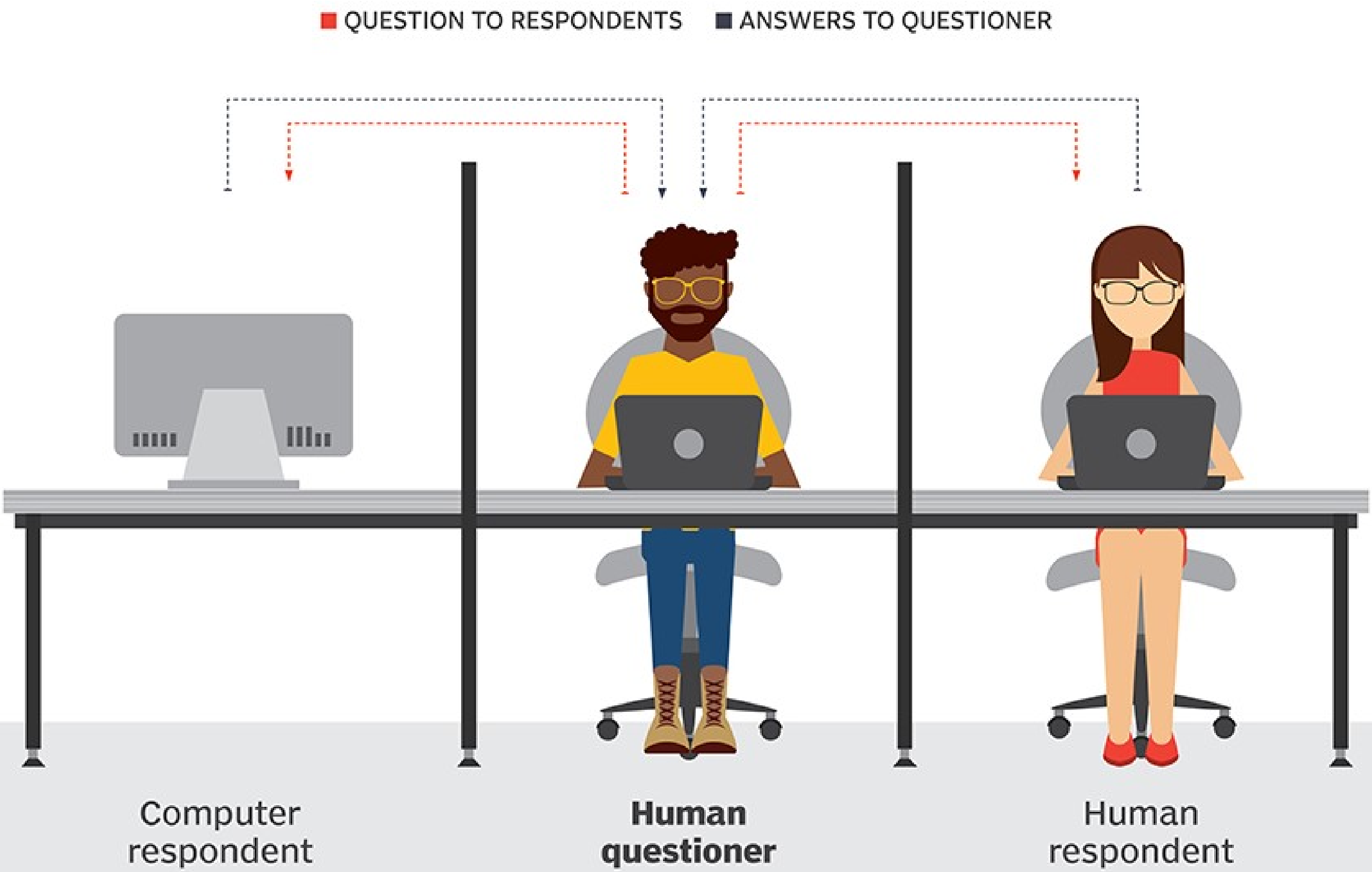
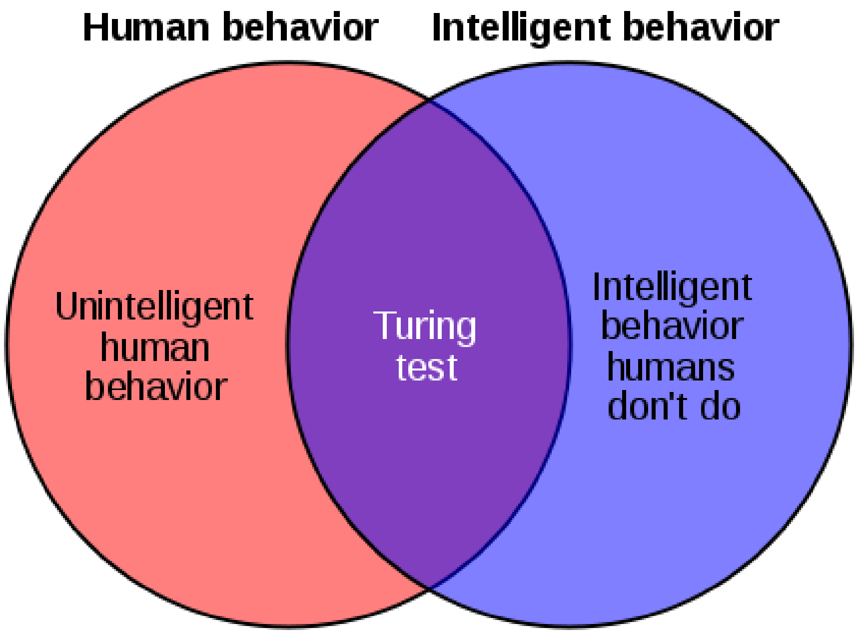


Image from: http://whatis.techtarget.com/definition/Turing-Test

The Turing Test: Problems

Human intelligence vs intelligence in general

Turing Test evaluates if a computer behaves like a human. Not necessarily the same as being intelligent.



The Turing Test: Problems

Consciousness vs. the simulation of consciousness

- Is the computer "thinking" or just following hard coded directions (simulating thought)
- Turing test only evaluates external behaviour, may not be possible to differentiate between consciousness and simulated consciousness based solely on external behaviour.

The Turing Test: Problems

Dependence on Human Questioner

- A naïve questioner may be easily fooled.
- Numerous cases of unsuspecting questioners being fooled by chatterbots.
- Humans tend to consider non-human objects as human (anthropomorphism).

The Turing Test: Now

- Considered impractical and irrelevant by most mainstream AI researchers.
- Better to test to use less subjective tests based on the goal of the research: object recognition, natural language comprehension, automation, etc.

A Brief History of AI

Birth 1950-1956:

- Isaac Asimov's "I, Robot", rudimentary game AI, Turing test, term "artificial intelligence" coined.

Golden Years 1957-1974:

- MIT AI lab setup, assembly line robots, natural language programs, chatbots, first autonomous vehicle.

1st AI Winter 1974-1980:

- Limited computing power, reduced funding, lack of public interest.

A Brief History of AI

Boom 1980-1987:

- Expert systems, knowledge-based, 5th gen project

2nd AI Winter 1987-1993:

- Funding cuts, rise of PCs vs special hardware, robotics

Modern Era 1993-present:

- Increased computer power, specialized for problems, statistical methods, intelligent agents, modern machine learning approaches.

A Brief History of AI

Recent Accomplishments:

1997 IBM Deep Blue [Chess]

2005 Stanley robot [DARPA]

2011 Watson [Jeopardy]

2016 Google AlphaGo [Go]

Optional Reading: The History of Artificial Intelligence
https://en.wikipedia.org/wiki/History_of_artificial_intelligence

Optional Reading: Alibaba's AI Outguns Humans in Reading Test
https://www.bloomberg.com/news/articles/2018-01-15/alibaba-s-ai-outgunned-humans-in-key-stanford-reading-test

Machine Learning

- Branch of AI
- Systems that can learn from data
- Train with data
- Given some examples, generalize to categories.
- **Examples:**
  - **Spam detection:** Classify e-mail as spam vs non spam
  - **Object recognition:** Does this video/image contain a face? cat? car? etc.
  - **Facial recognition:** Identifying some by a picture of their face.
  - **Handwriting recognition**
  - **Speech recognition**

Machine Learning

Traditional Solutions

- Rule-based systems – no learning
- **Example:** Sentiment analysis based on a simple heuristic (>0 positive, =0 neutral, <0 negative)

Machine Learning

- Find patterns based on **features** of data
- Adapt to new and unforeseen situations
- Learn from mistakes
- Draw new conclusions

Classification

Classification is the process of assigning a class to something according to shared qualities or characteristics (**features**).

Classification Methods:

- **Decision Trees**
- *k*-Nearest Neighbors
- Support Vector Machines (SVM)
- Neural networks

The Classification Problem

Have a population that may be partitioned into classes.

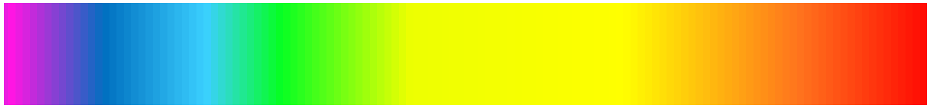
E.g. spam vs non-spam; handwritten digits 0,1,…9

Have a number of classified instances (examples), each of which has a number of attributes (**features**).

Look at the examples and come up with a method to classify things that have not yet been seen.

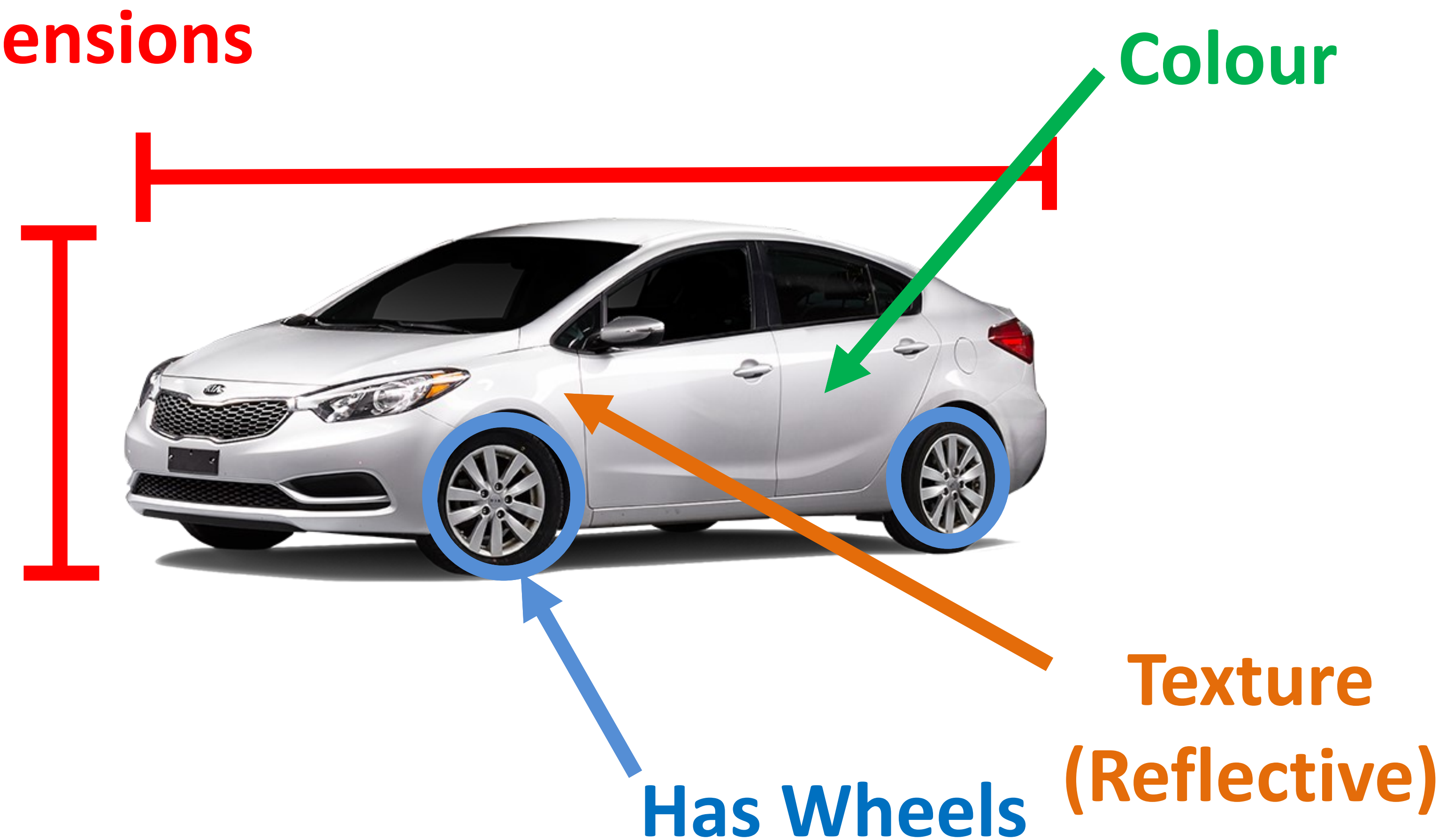
Features

- Individual measurable property or characteristic of object being observed.

- May be represented by many different values:
  - Boolean {Yes, No} or {True, False}
  - Labels {Car, Boat, Plane, Duck, Cat}
  - A color {  }
  - Integers {0, 1, 2, …}
  - Real numbers {1.34, 7.45, …}
  - Percentage (between 0 and 1, e.g. 0.123)
  - Distance, area, time, velocity, etc.

Features

Examples



Features

How do you select the appropriate set of **features** for classification?

We need to have some knowledge of what **features** make good predictors of **class** membership for the **classes** we are trying to distinguish.

For example, having wheels distinguishes people from cars, but doesn't distinguish cars from trains.

Supervised vs. Unsupervised

Two Approaches

Supervised Learning:

- Learn by example.
- Provide training examples that include both the inputs (the data) and the correct outputs (the classifications).

Unsupervised Learning:

- Learn solely based on the structure of the data.
- Provide only the inputs (the data) and try to derive the underlying structure and relationships between features of the data.

Toy Problem

Classify a picture as a **rubber duck** or **not a rubber duck**.

Classes:

- **Rubber duck.**
- **Not a rubber duck.**

Features: ?

What features do you think might be useful for this problem?

Toy Problem: Features

Images contain many features we could choose from.

Toy Problem: Features

Color

Average Color

Red = 241
Green = 207
Blue = 103

Toy Problem: Features

Color

Most Common Colors

Color	Color Code	Percentage
	#ffffff	0.288382
	#f0c000	0.194902
	#d8a800	0.140980
	#ffd800	0.080245
	#c09000	0.040490
	#f06018	0.036667
	#ffd818	0.036029
	#f0d818	0.030245
	#f06000	0.030098
	#fffff0	0.027843

Toy Problem: Features

Shape

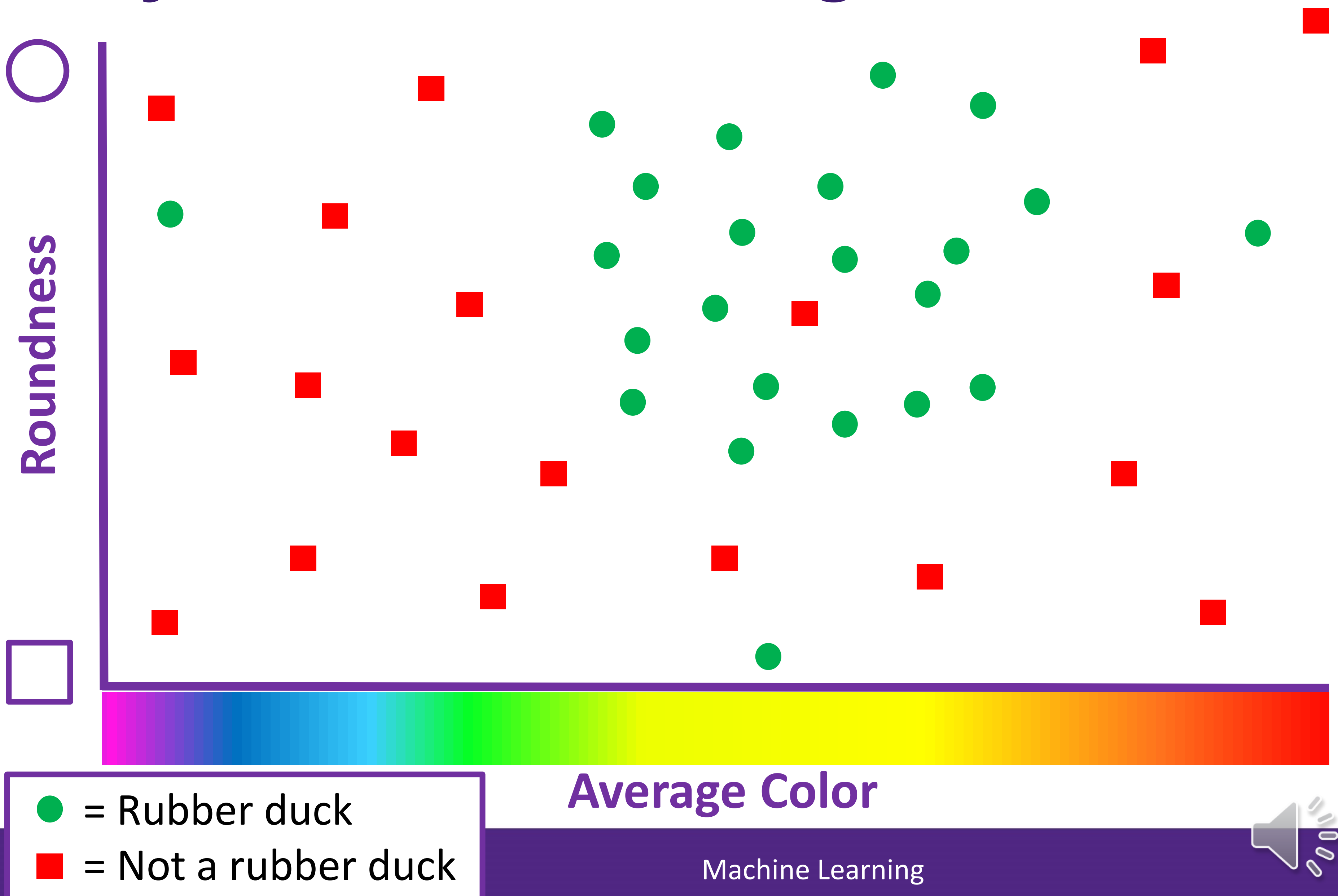
Roundness of Silhouette

0.75

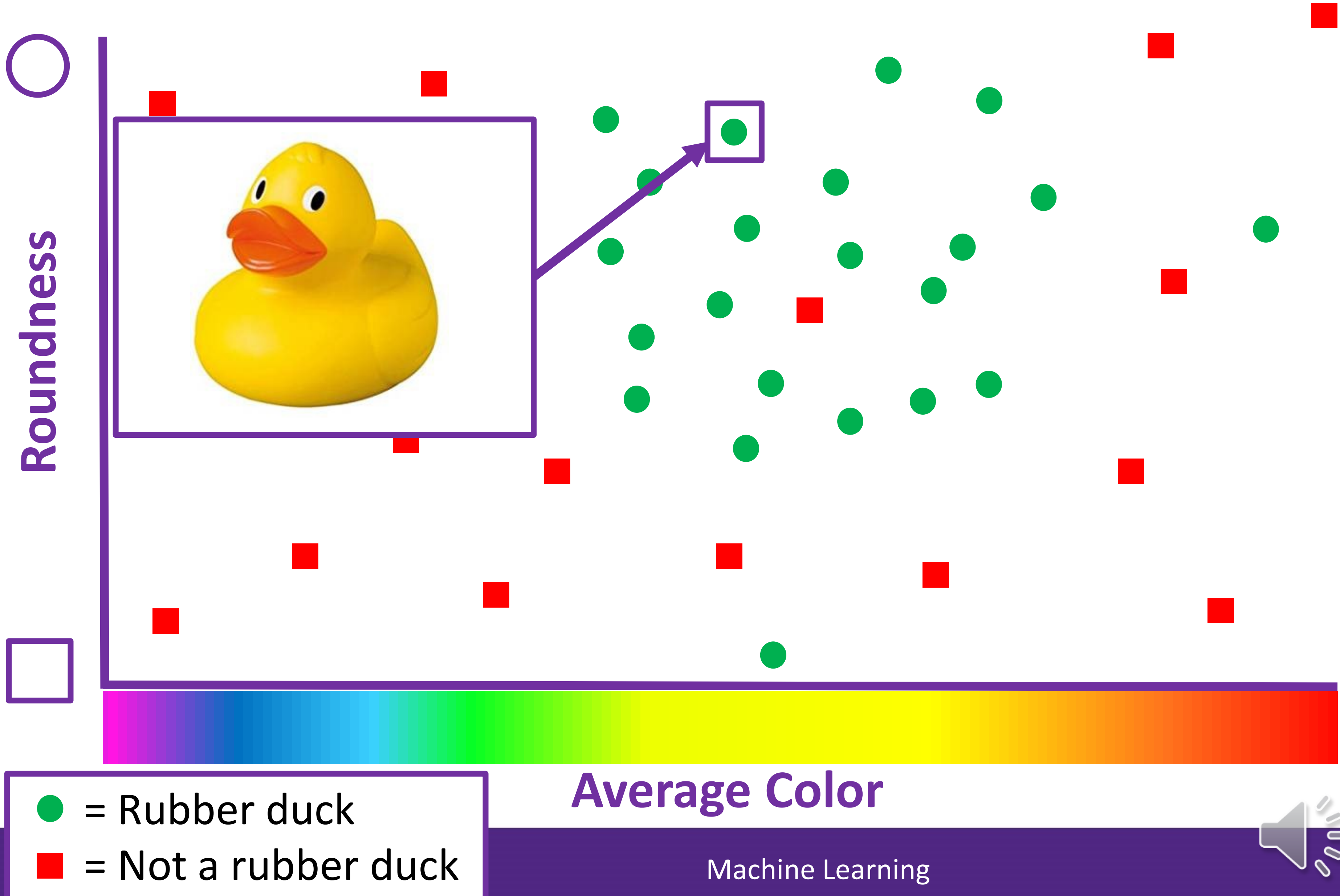
Toy Problem: Features

Thousands of possibilities but we will keep it simple for this example and just use **average color** and **"roundness"**.

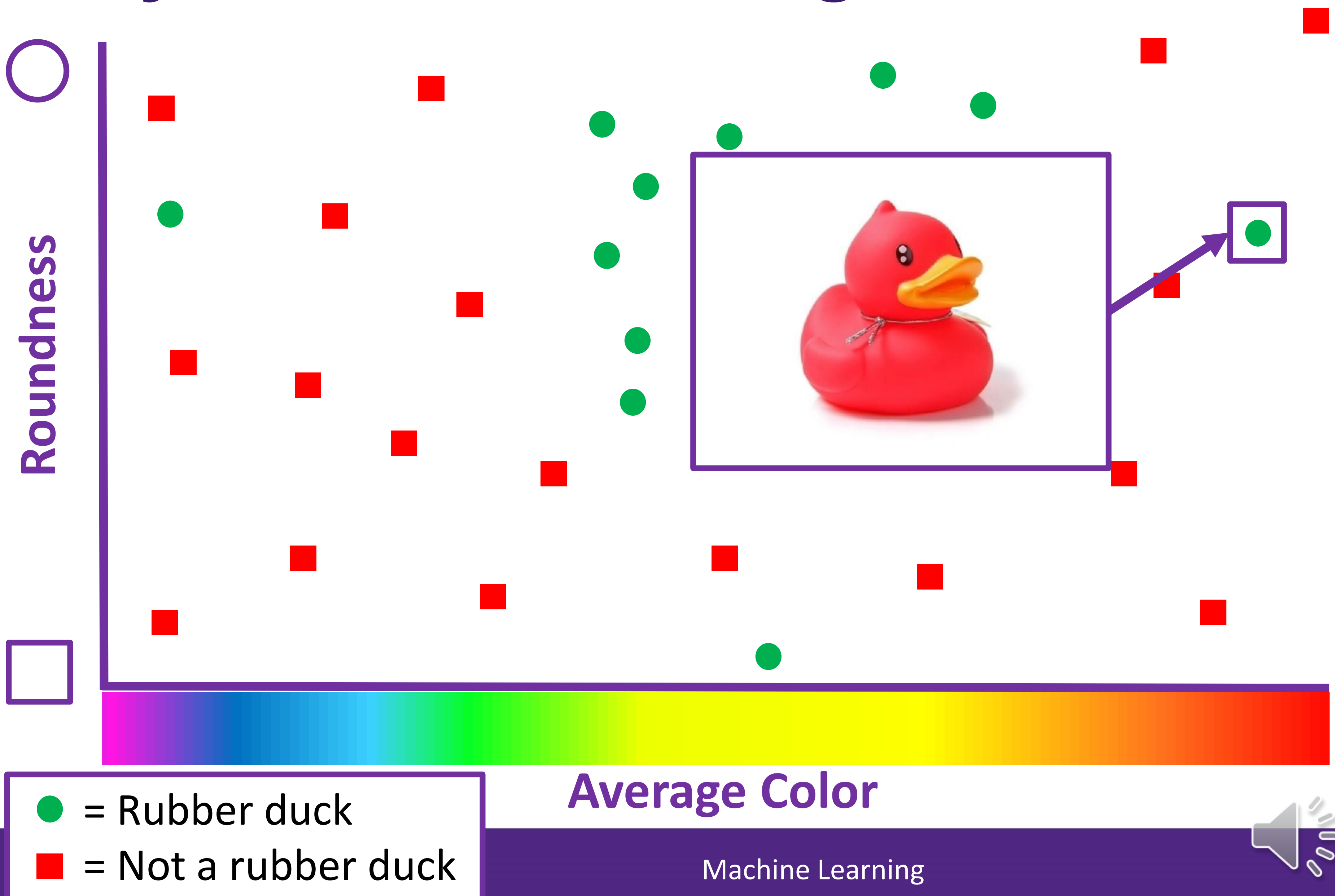
Toy Problem: Training Set



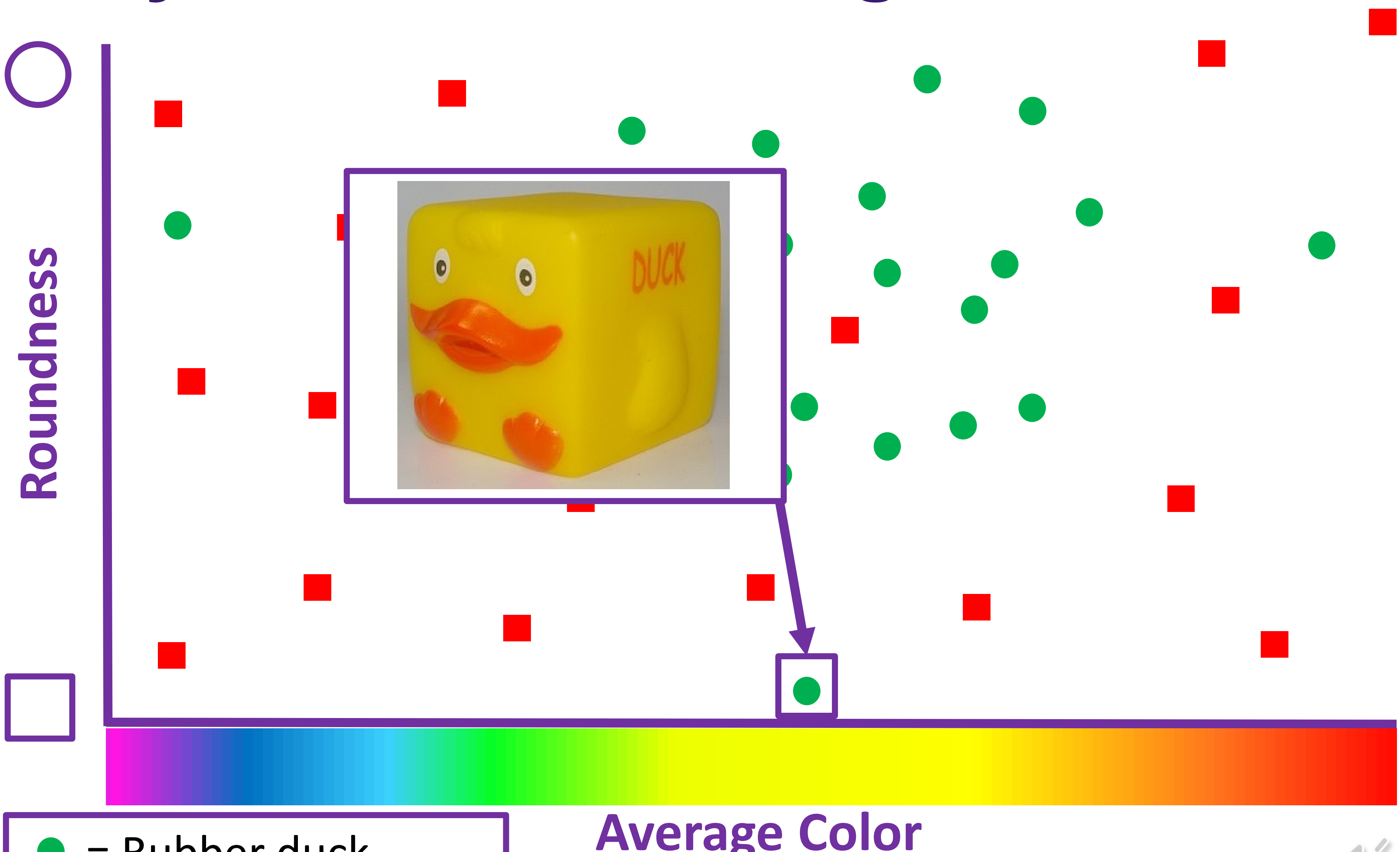
Toy Problem: Training Set



Toy Problem: Training Set

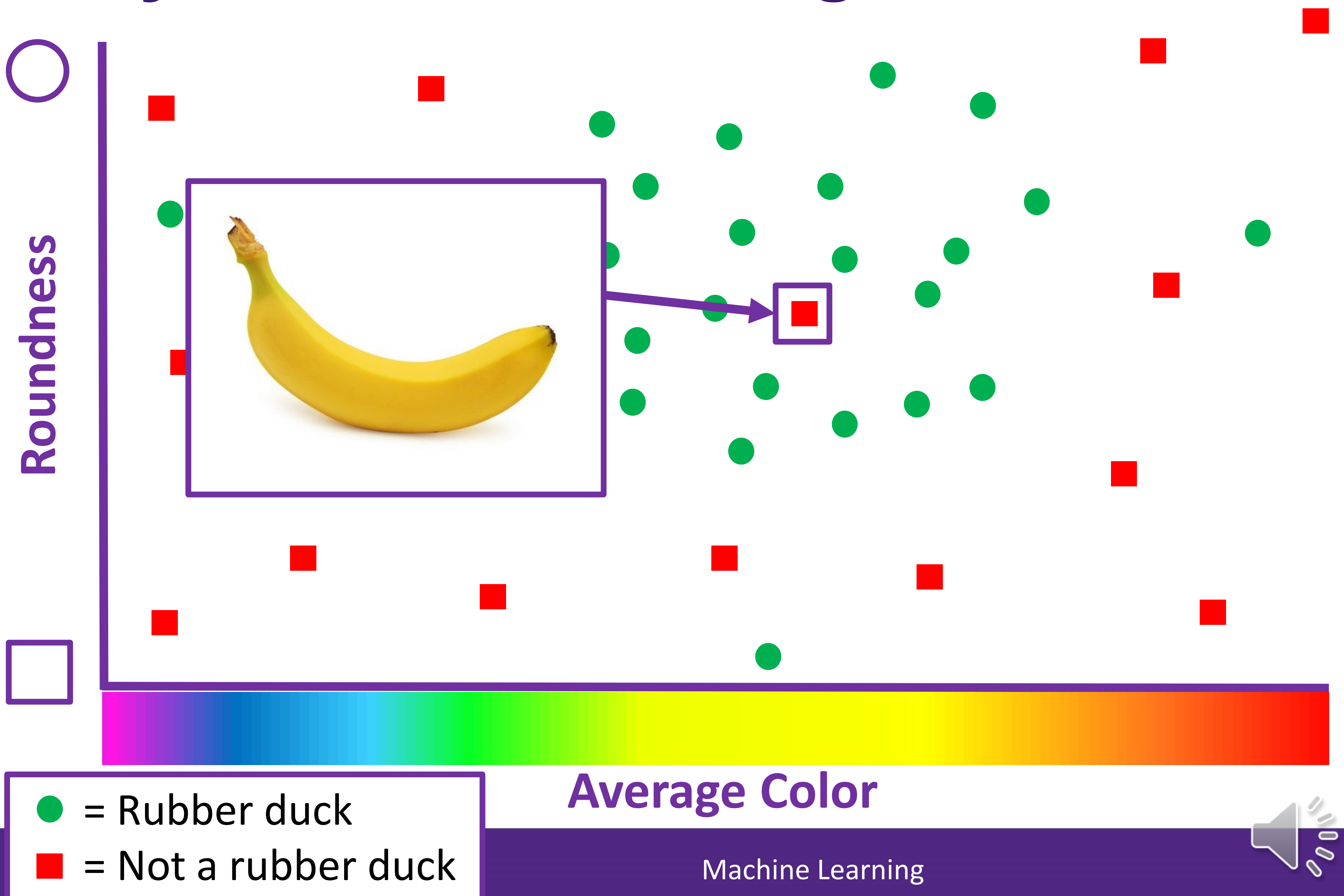


Toy Problem: Training Set

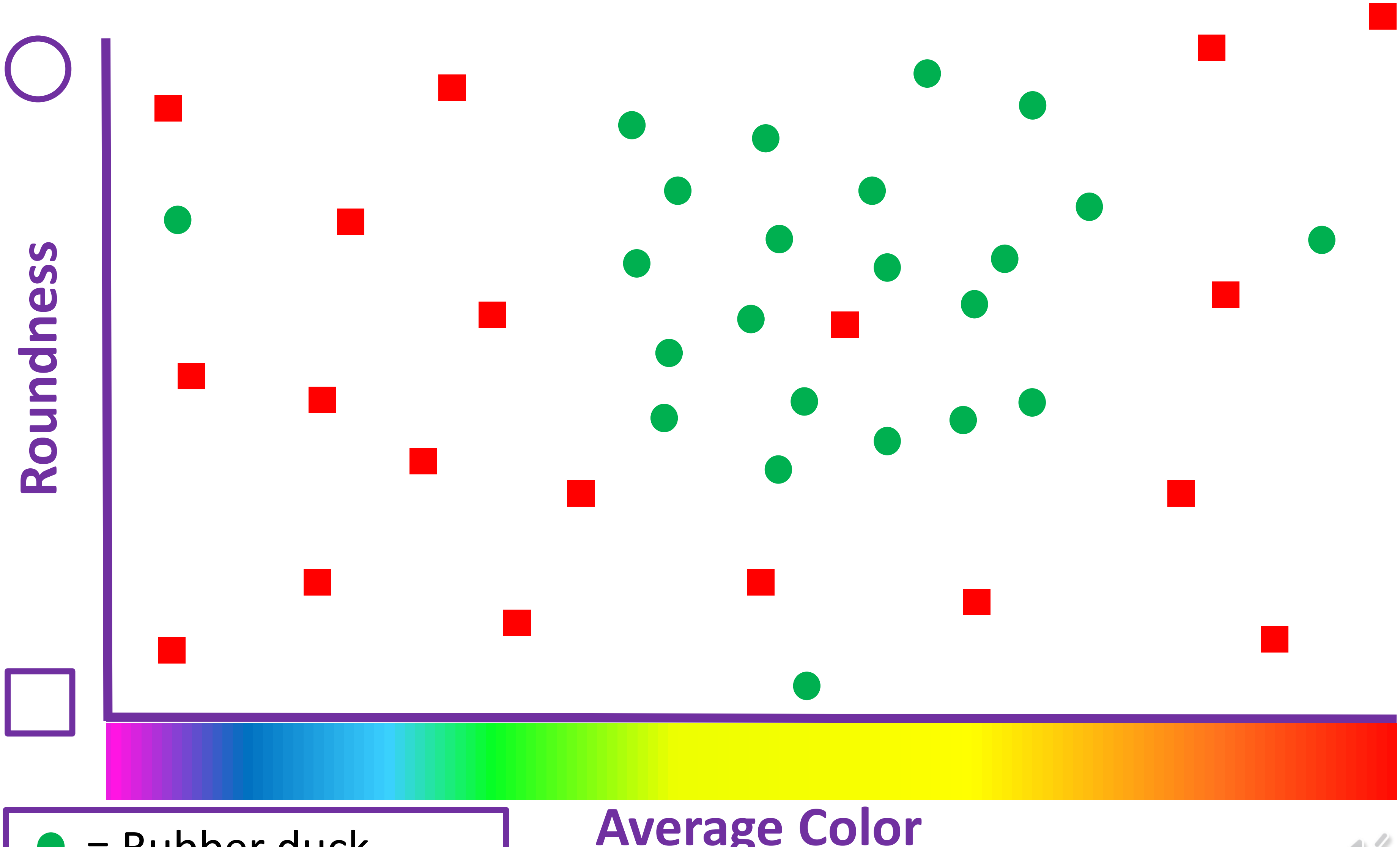


● = Rubber duck
■ = Not a rubber duck

Toy Problem: Training Set



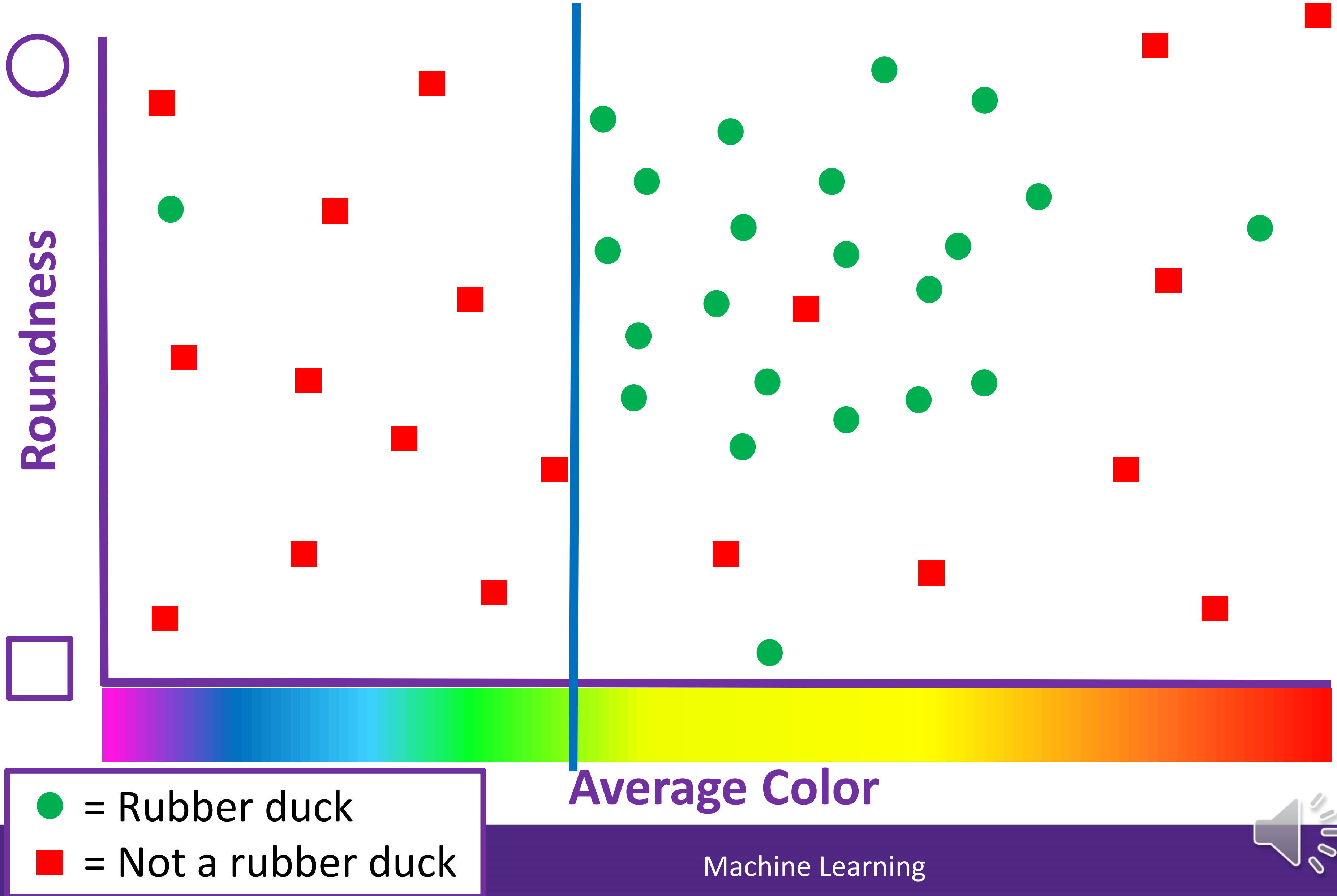
Toy Problem: Linear Classifier



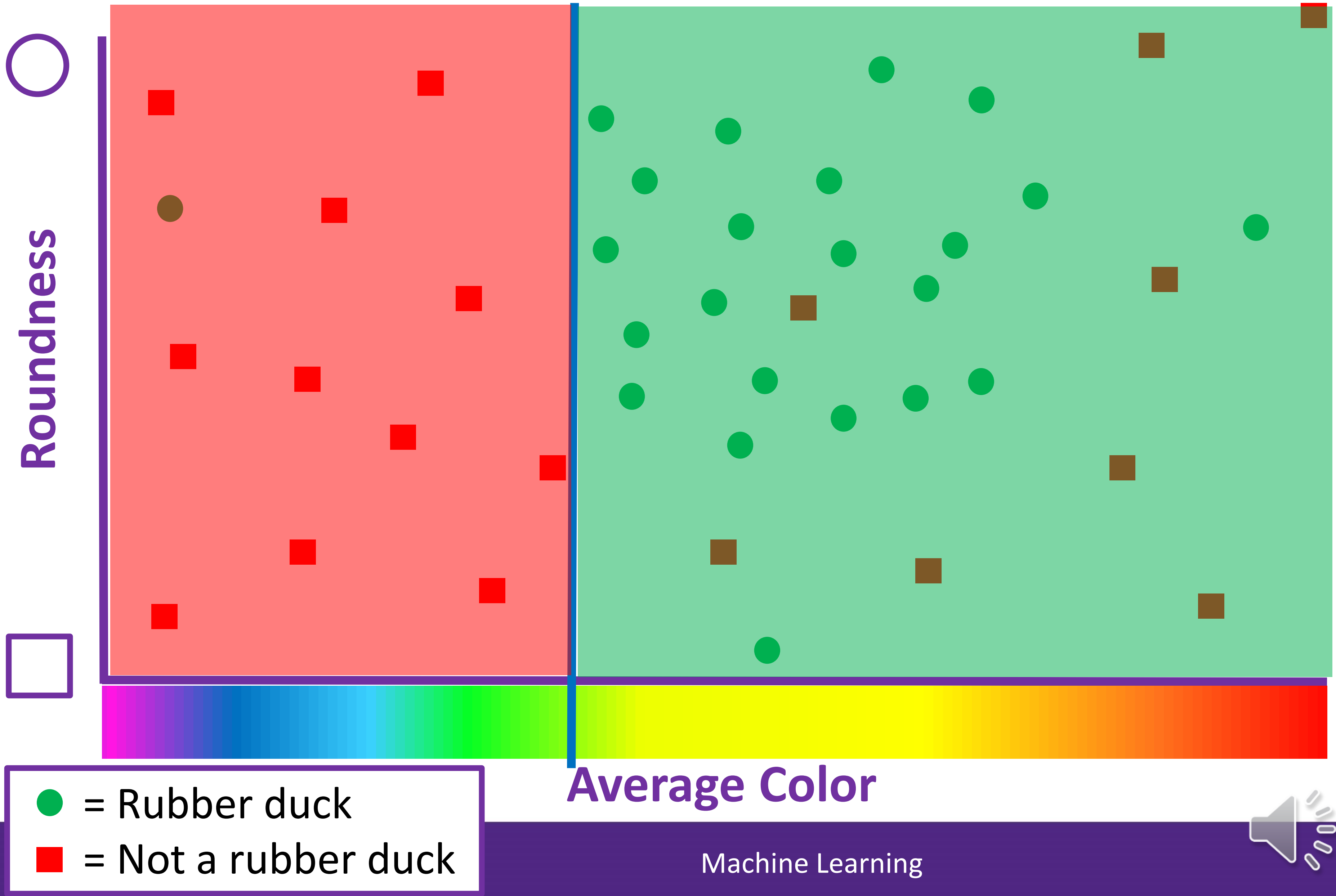
= Rubber duck

= Not a rubber duck

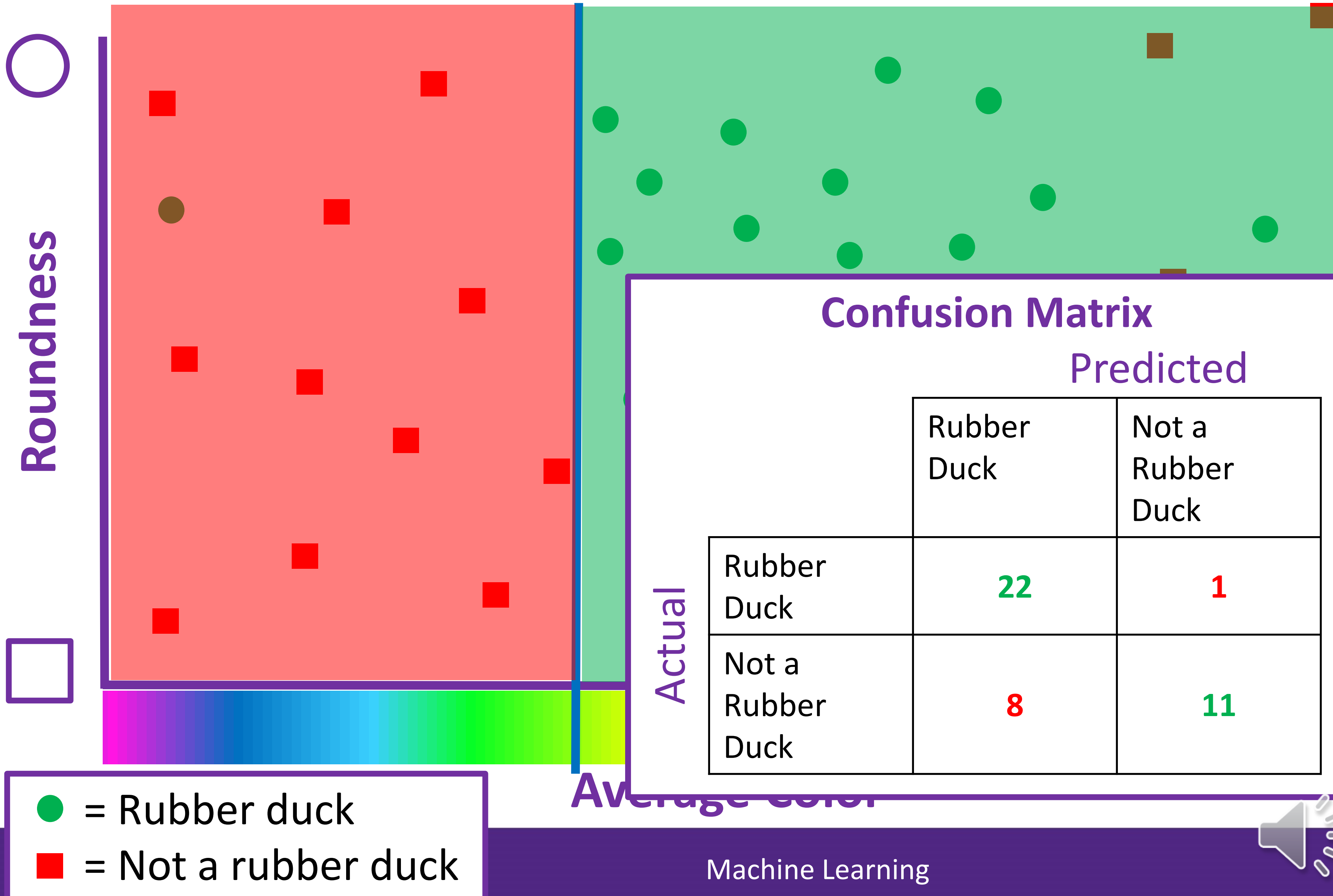
Toy Problem: Linear Classifier



Toy Problem: Linear Classifier



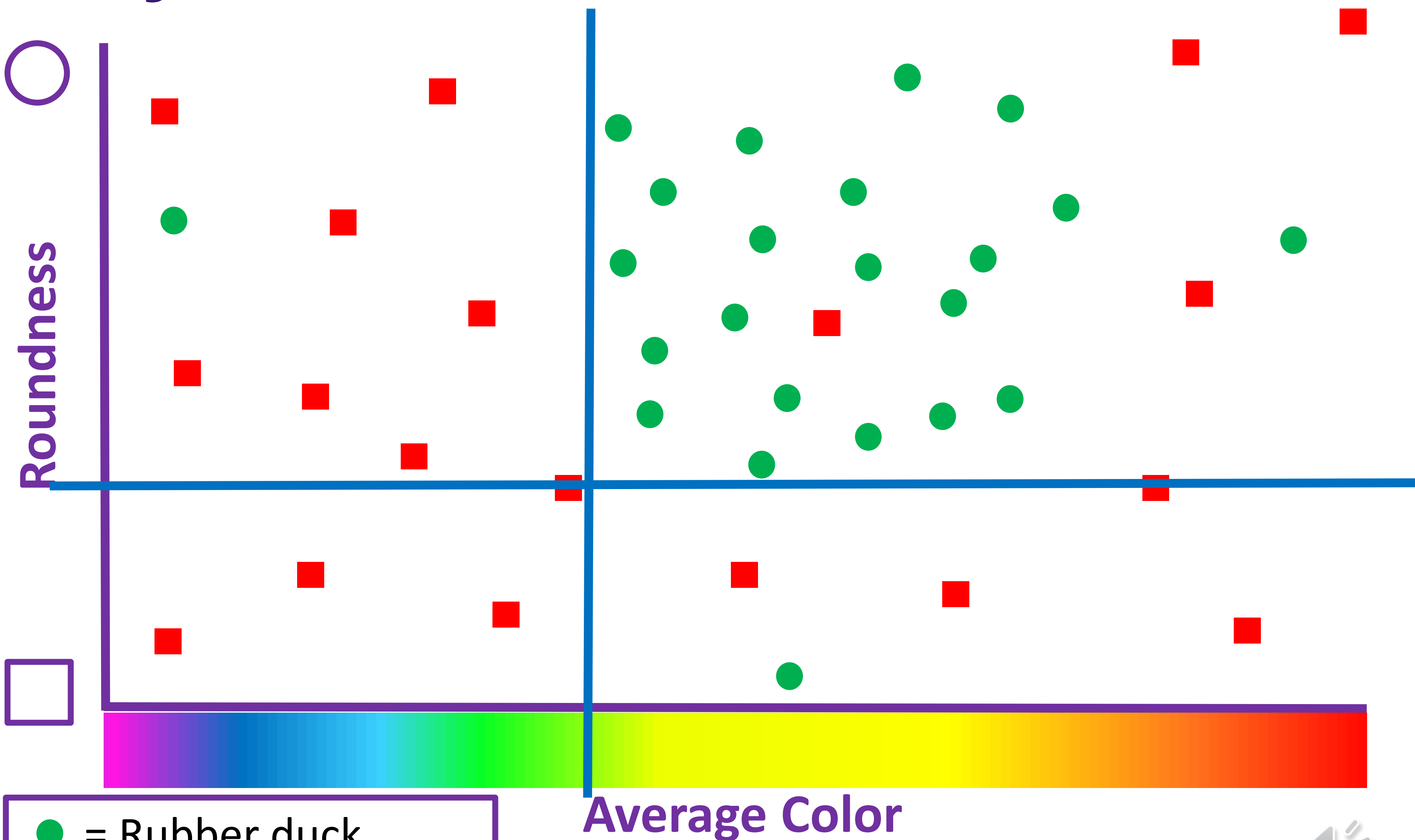
Toy Problem: Linear Classifier



Confusion Matrix

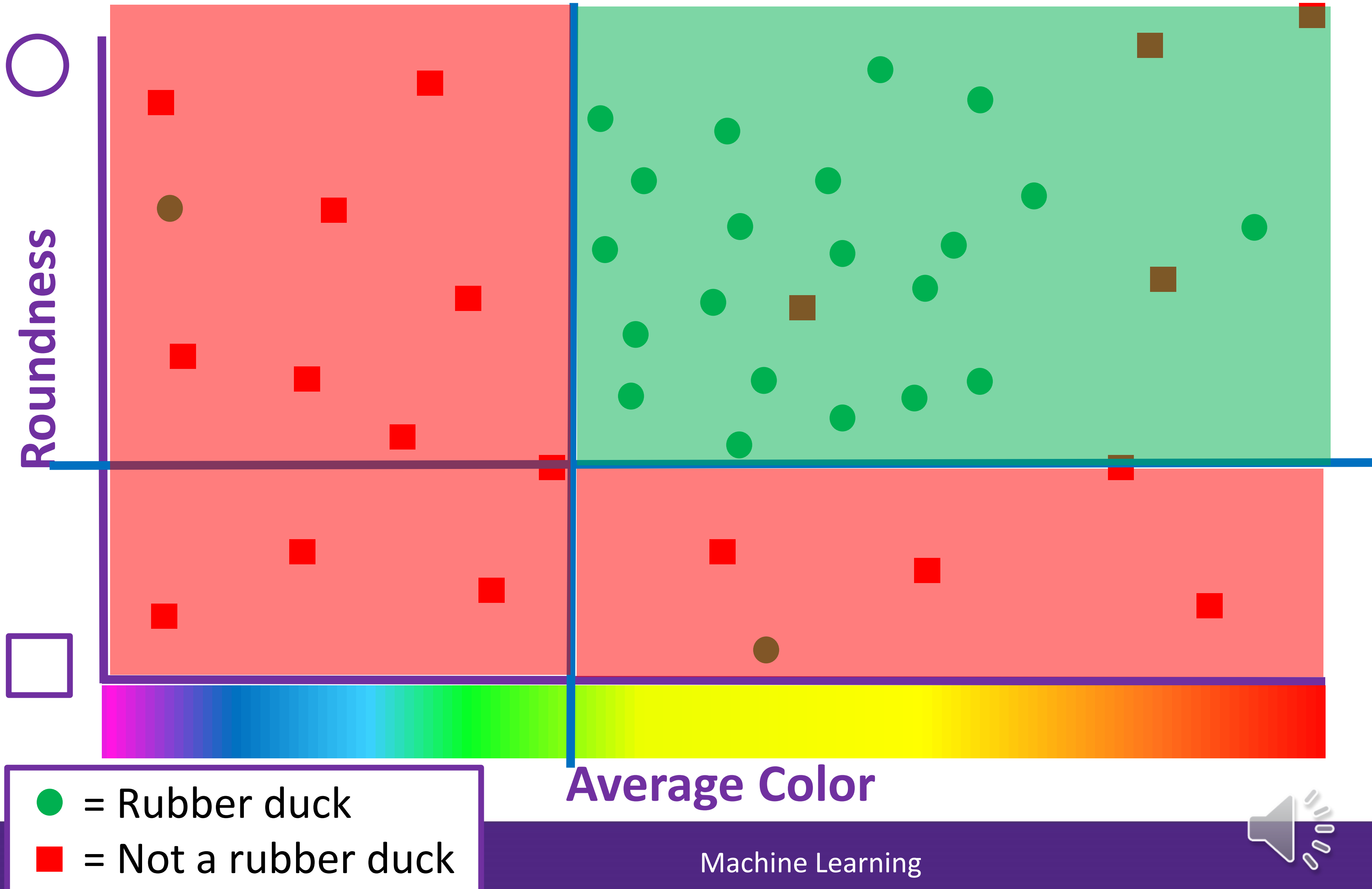
		Predicted	
		Rubber Duck	Not a Rubber Duck
Actual	Rubber Duck	22	1
	Not a Rubber Duck	8	11

Toy Problem: Linear Classifier

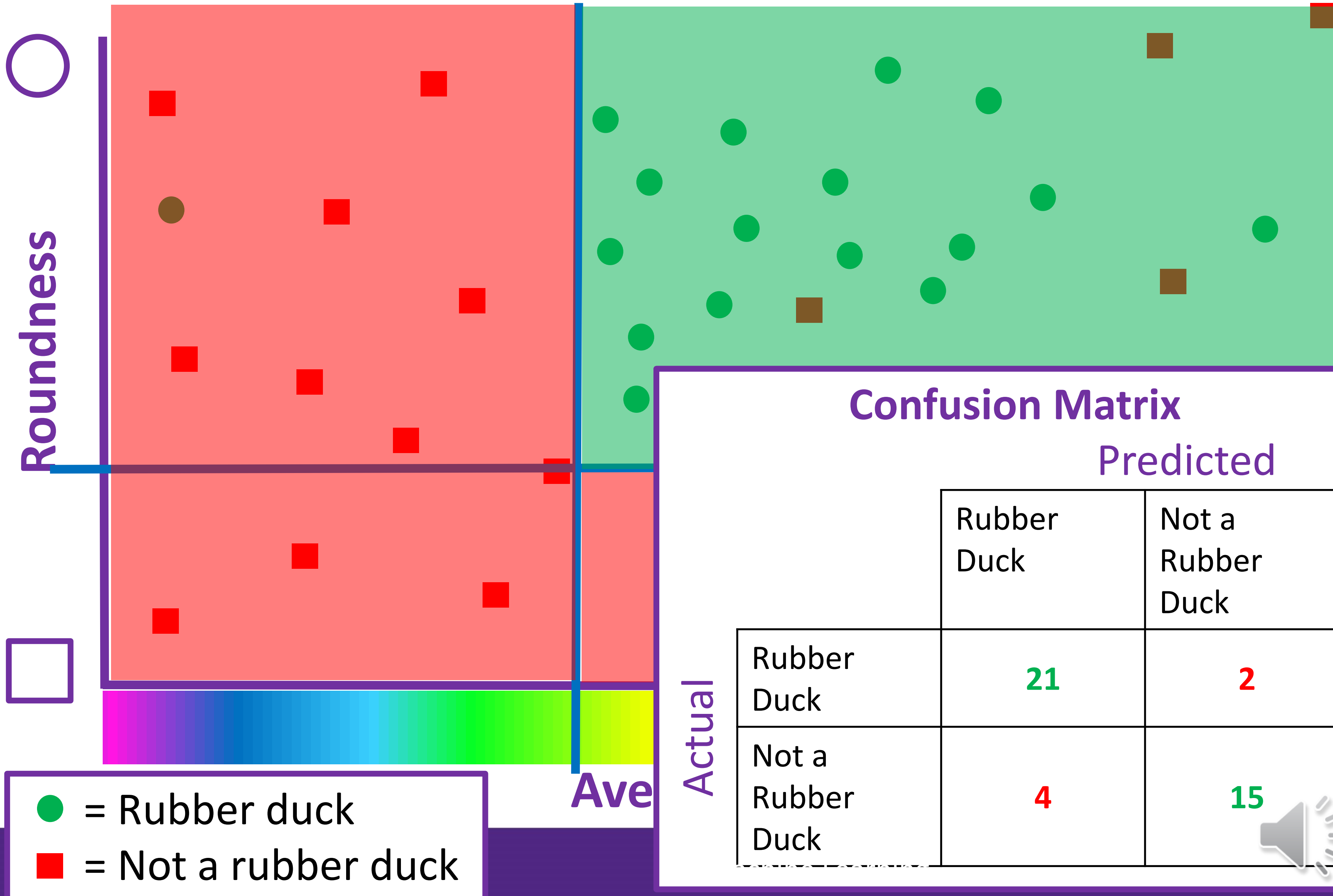


= Rubber duck
= Not a rubber duck

Toy Problem: Linear Classifier



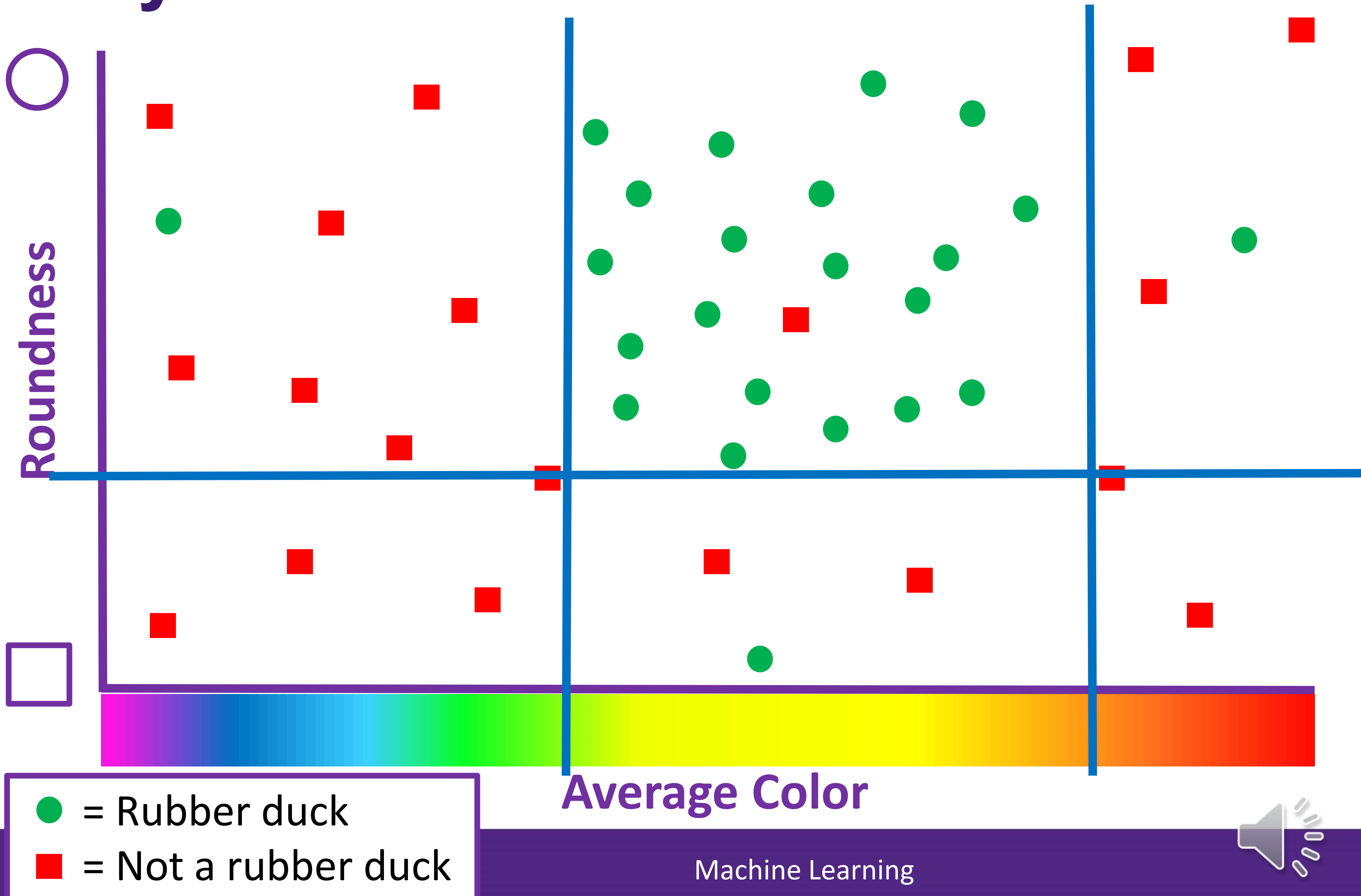
Toy Problem: Linear Classifier



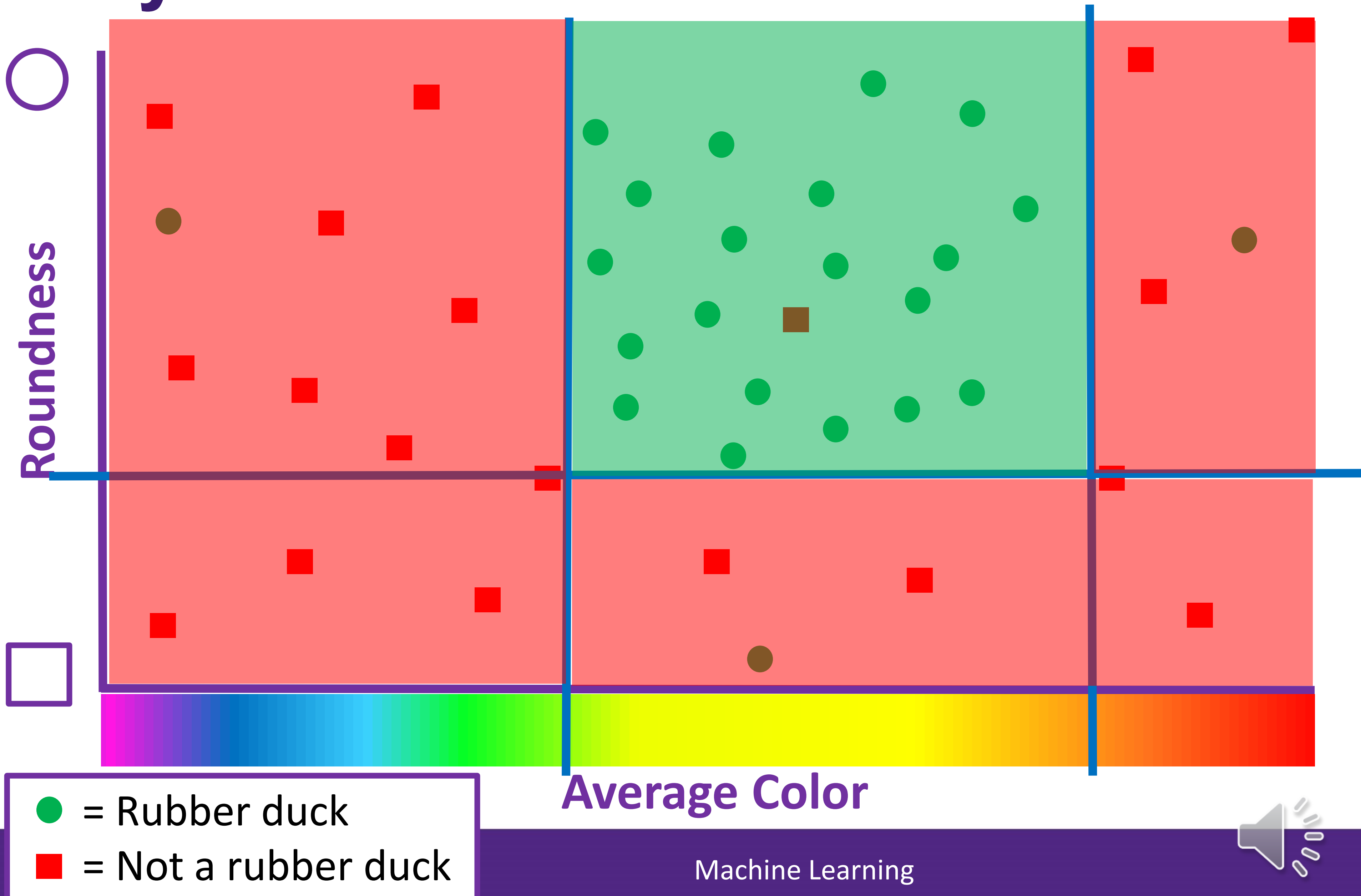
Confusion Matrix

		Predicted	
		Rubber Duck	Not a Rubber Duck
Actual	Rubber Duck	21	2
	Not a Rubber Duck	4	15

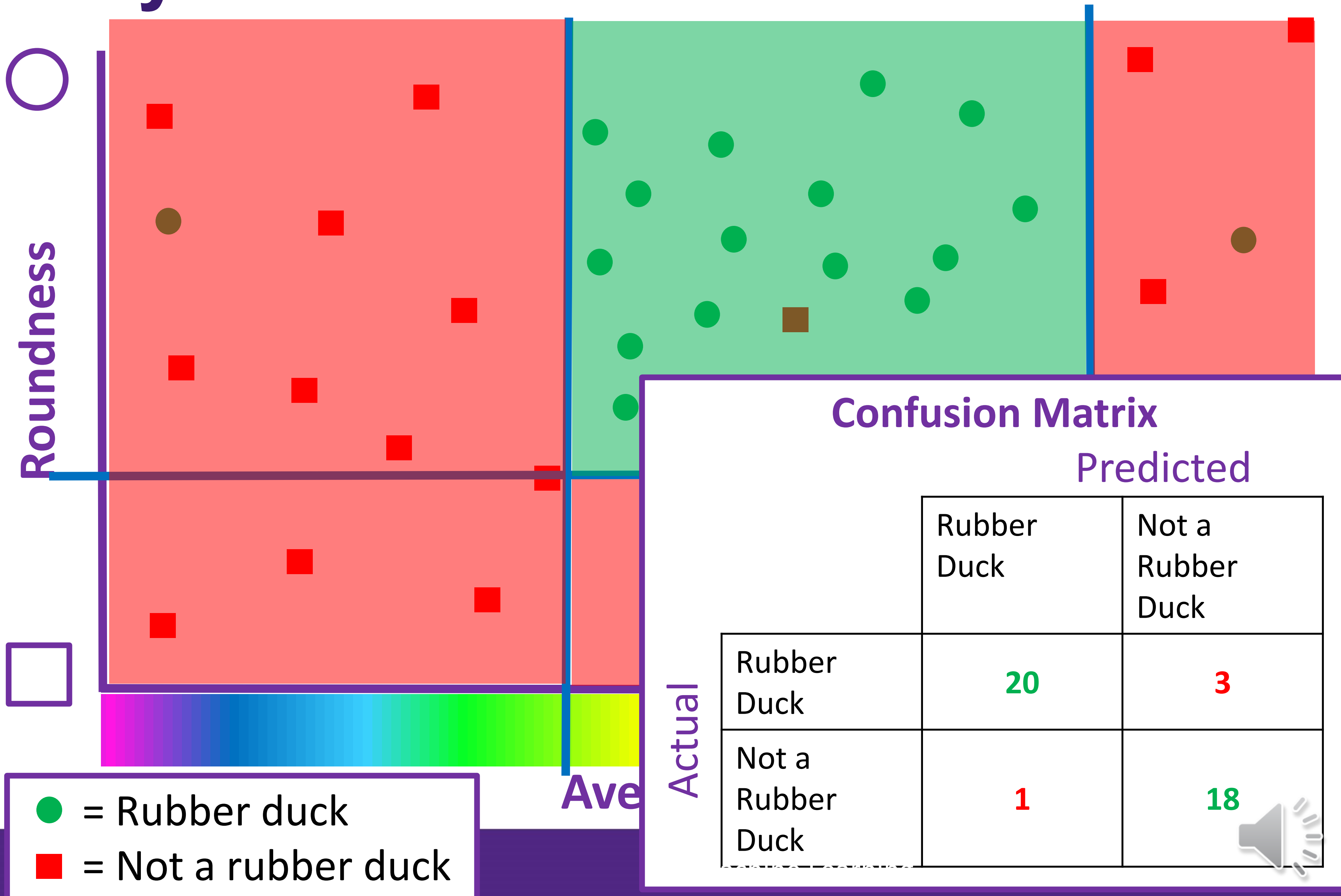
Toy Problem: Linear Classifier



Toy Problem: Linear Classifier



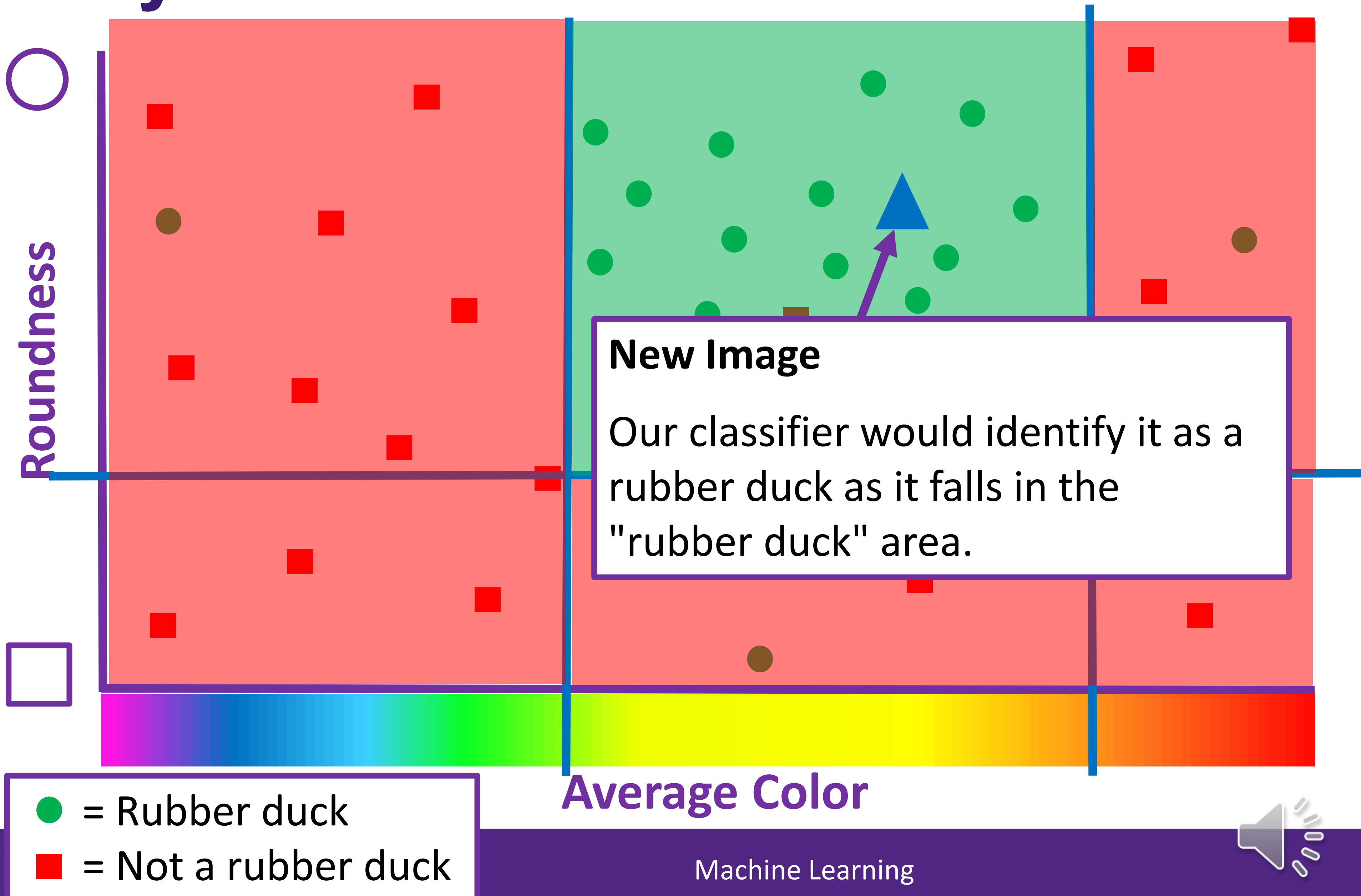
Toy Problem: Linear Classifier



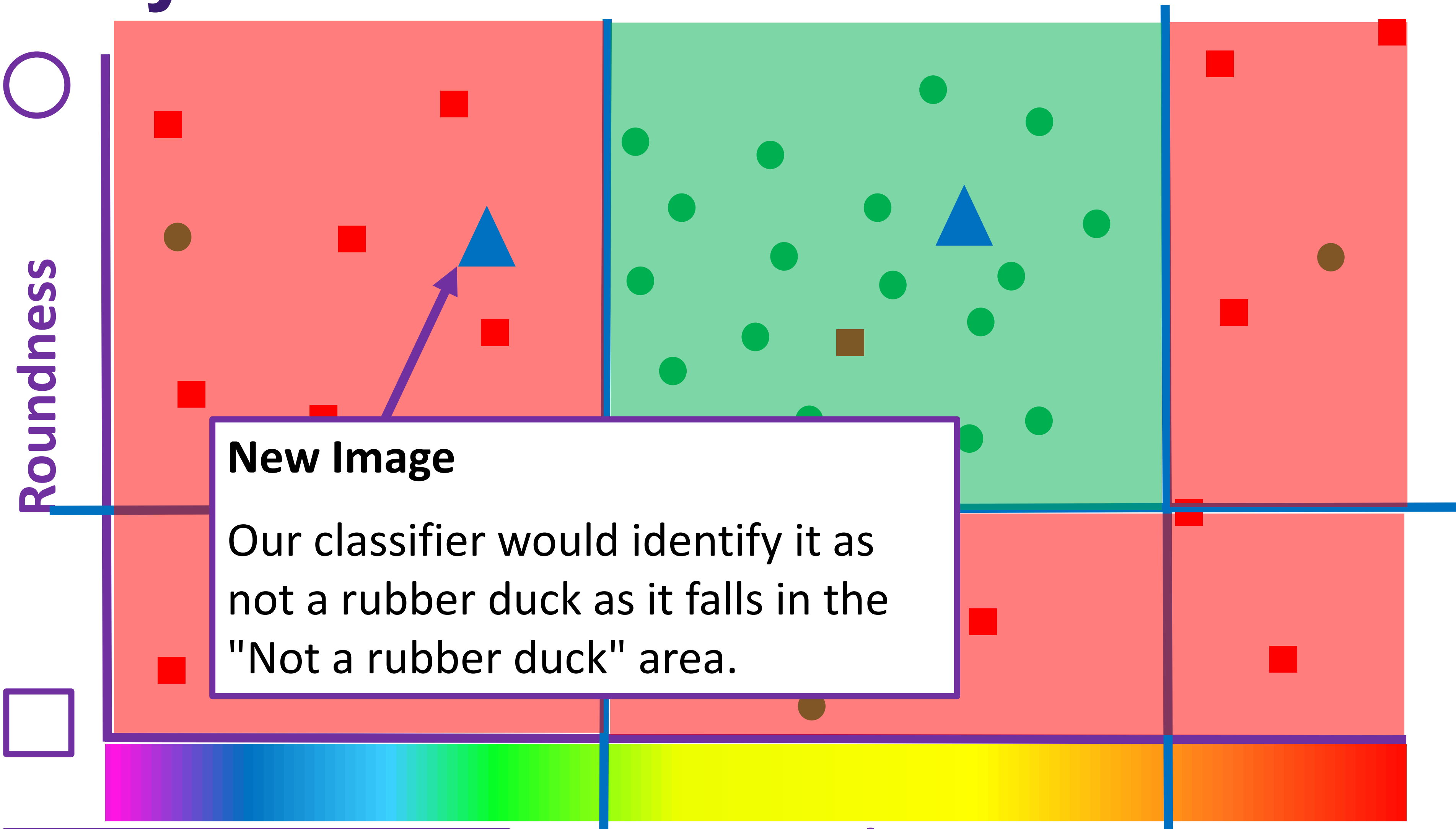
Confusion Matrix

		Predicted: Rubber Duck	Predicted: Not a Rubber Duck
Actual	Rubber Duck	20	3
	Not a Rubber Duck	1	18

Toy Problem: Linear Classifier



Toy Problem: Linear Classifier

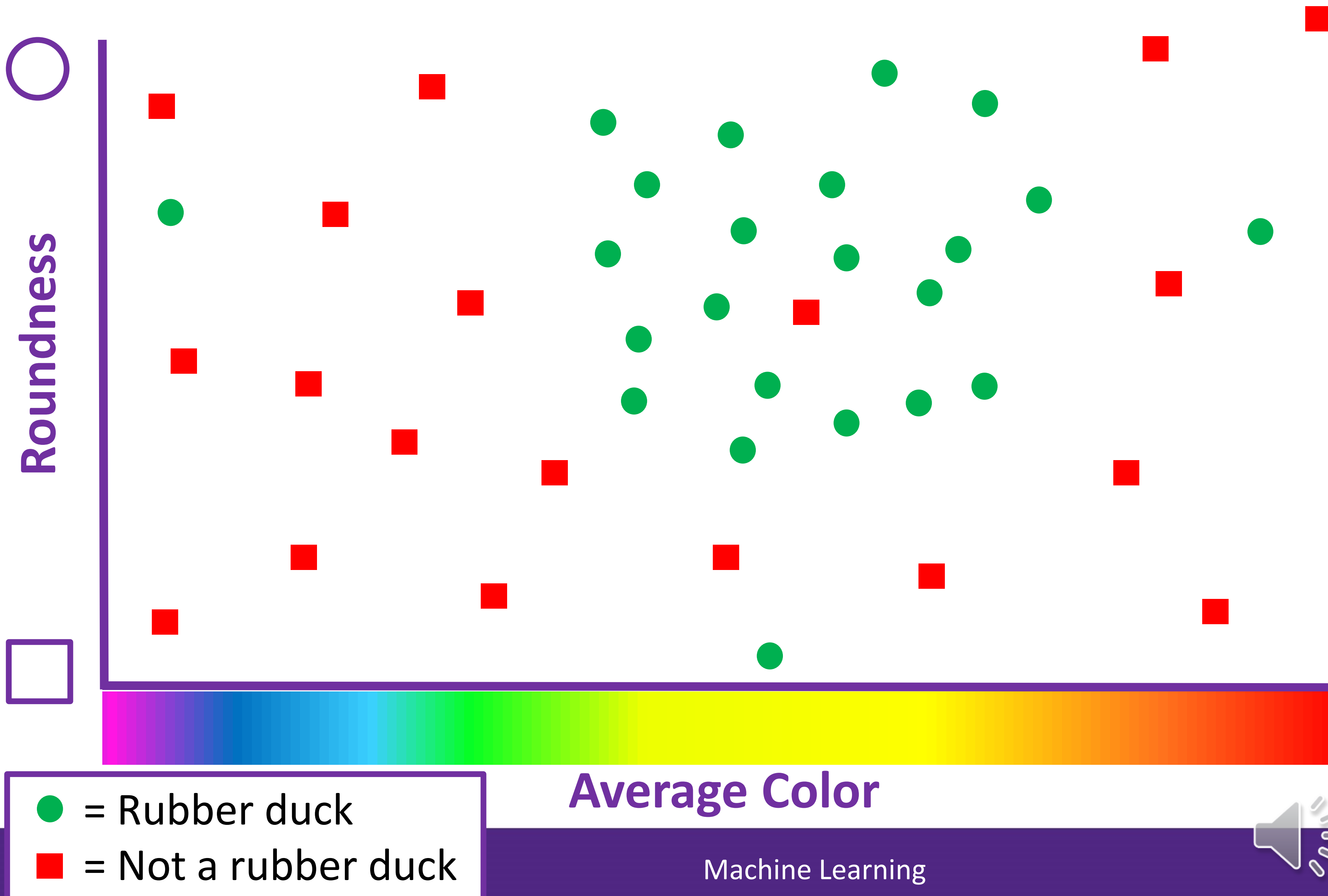


New Image

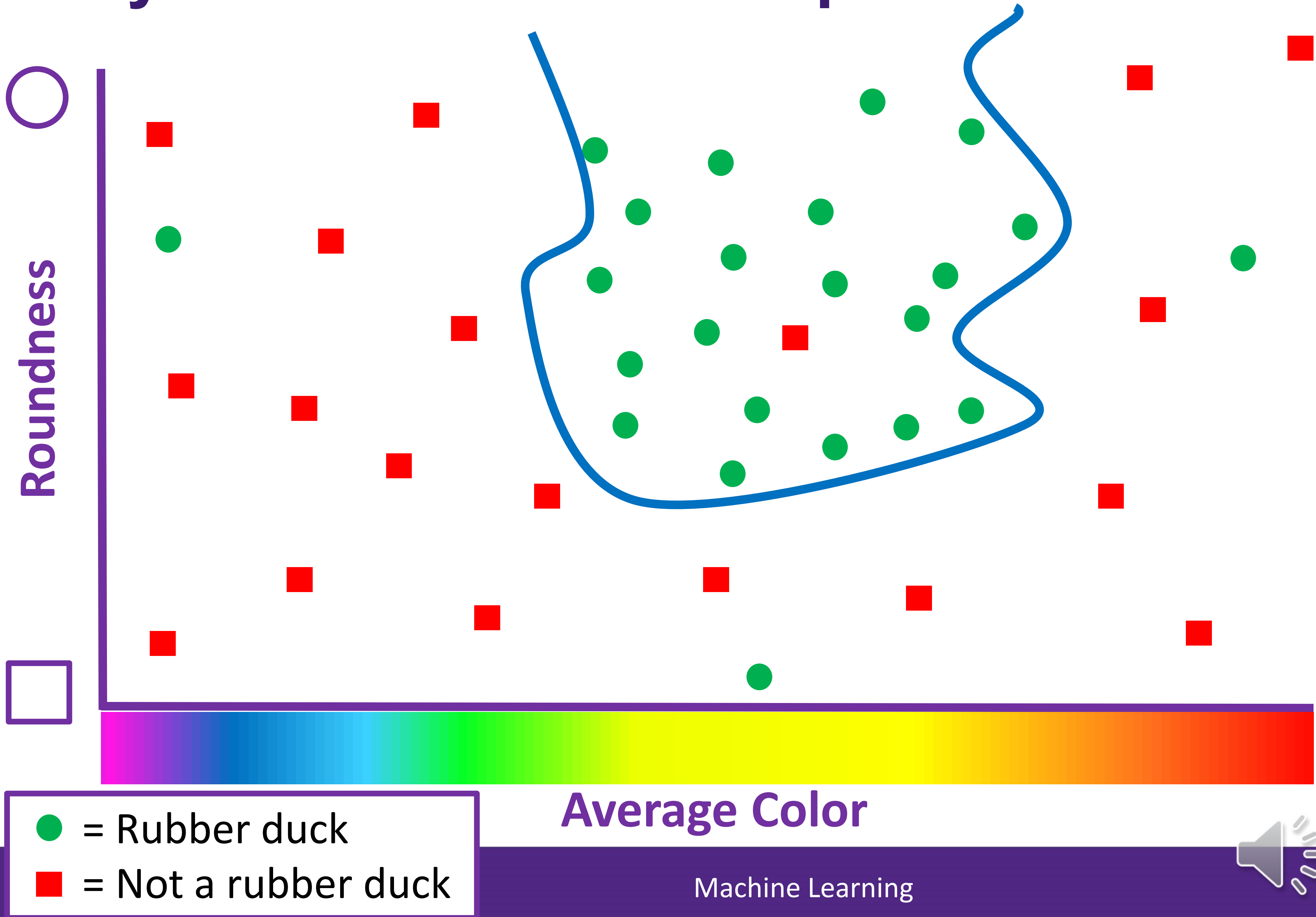
Our classifier would identify it as not a rubber duck as it falls in the "Not a rubber duck" area.

= Rubber duck
= Not a rubber duck

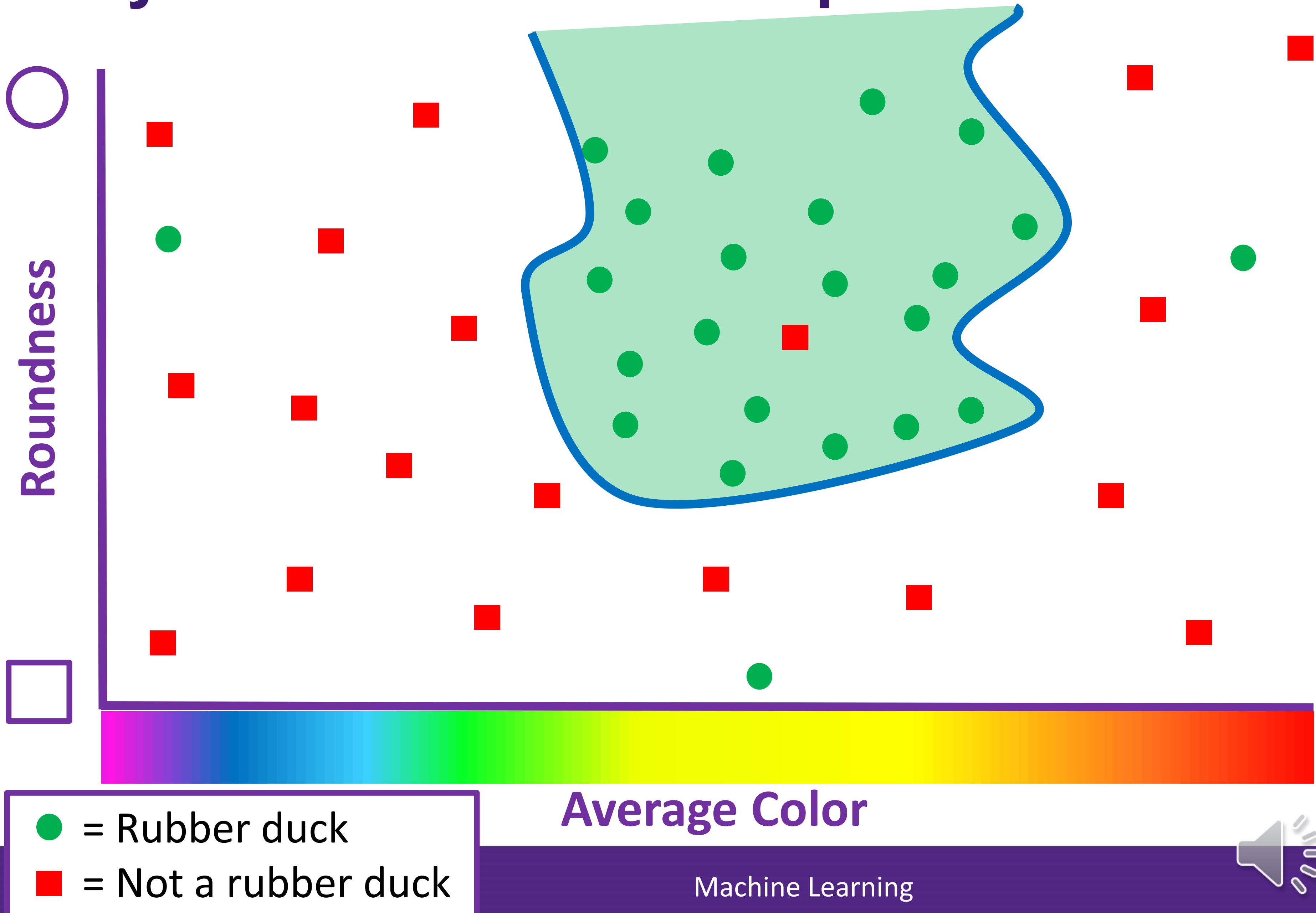
Toy Problem: More Complex Classifiers



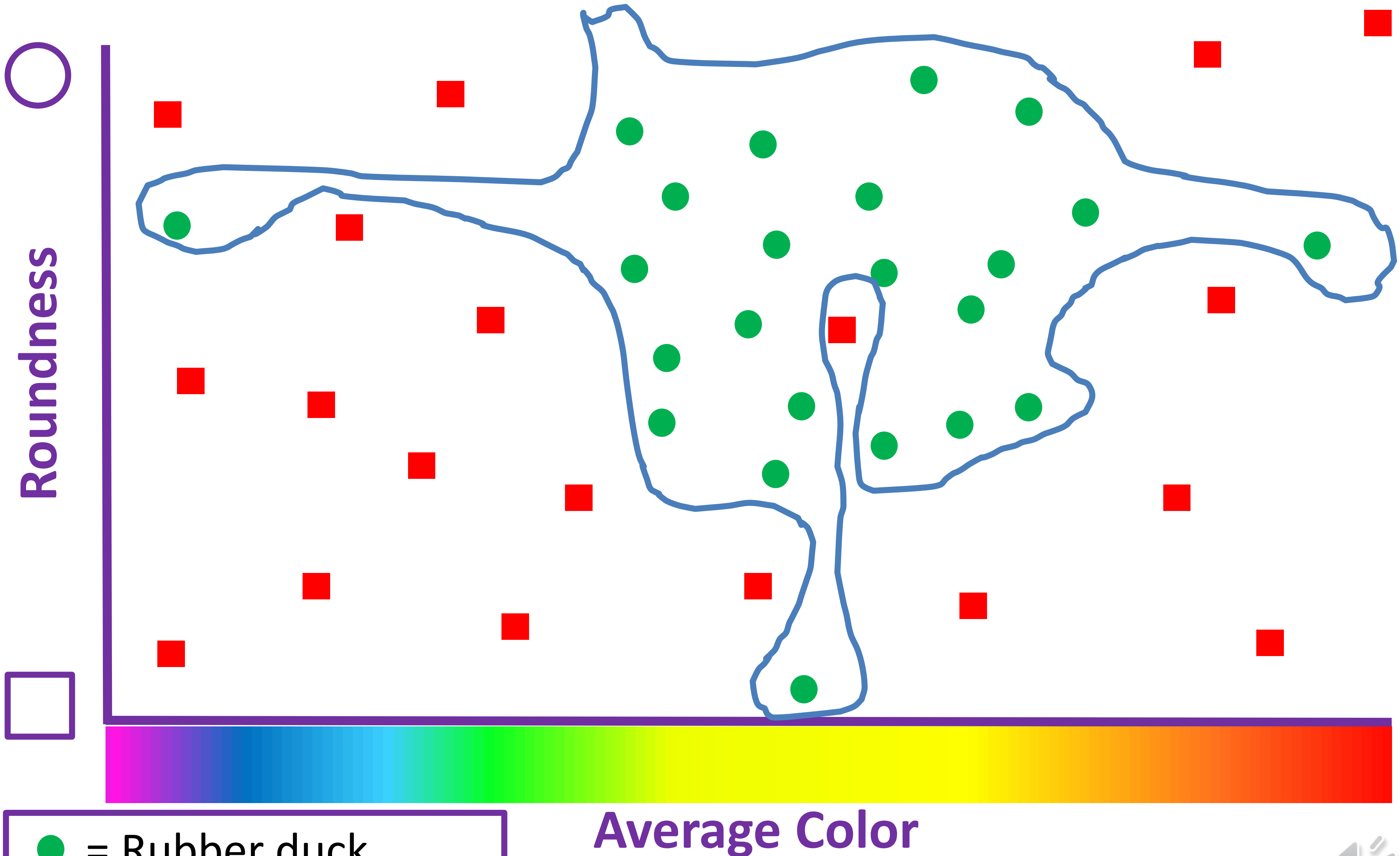
Toy Problem: More Complex Classifiers



Toy Problem: More Complex Classifiers



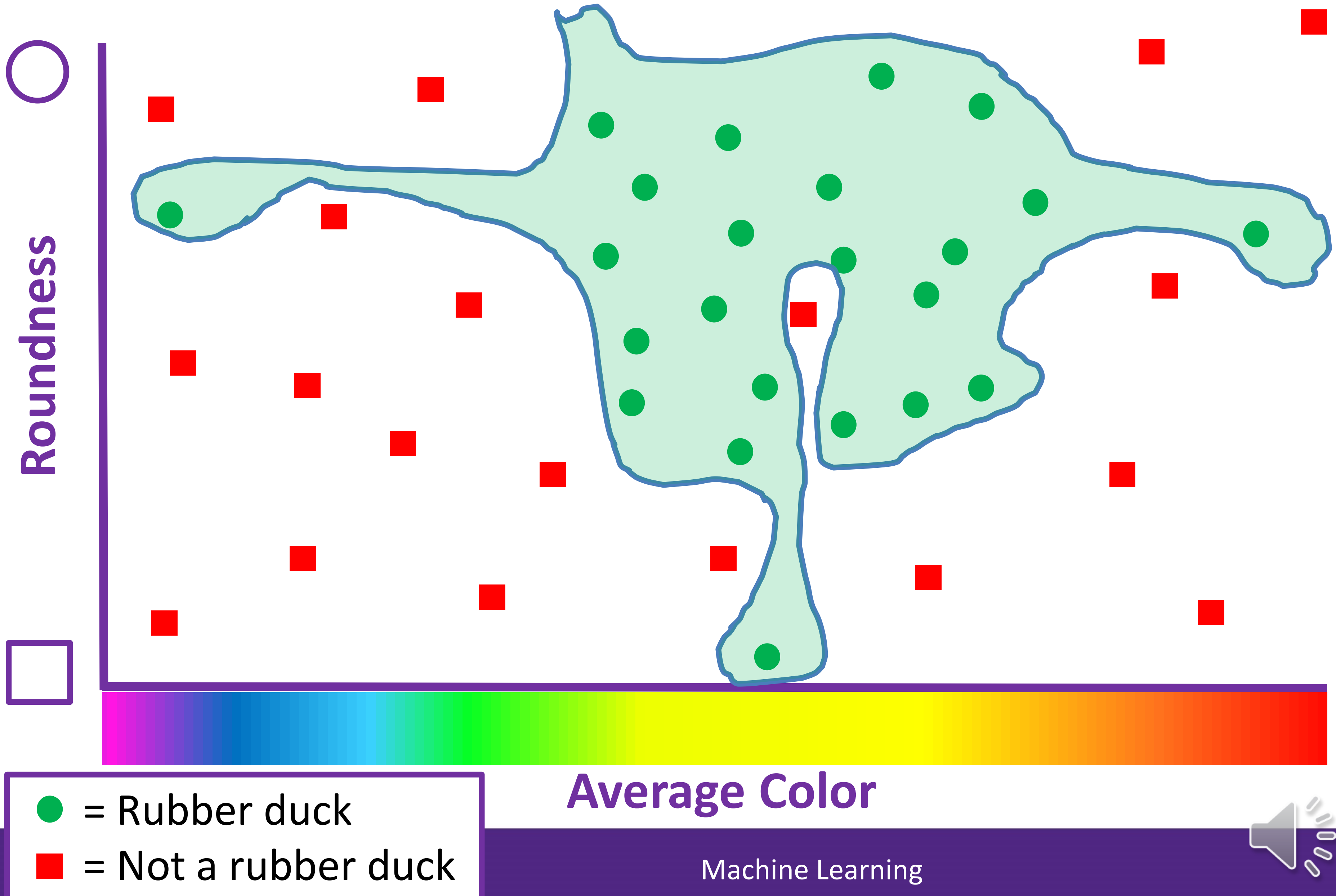
Toy Problem: Overfitting



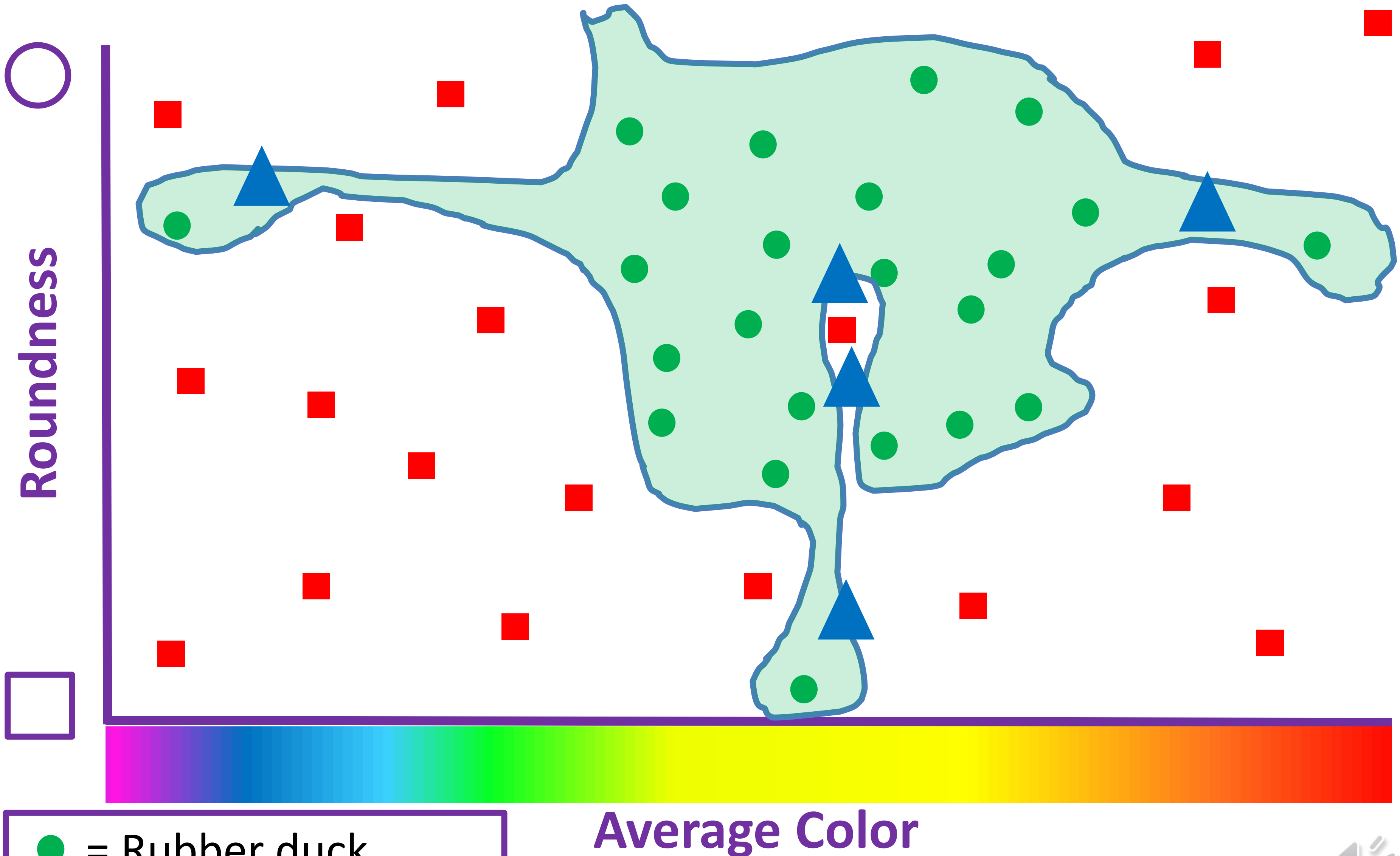
= Rubber duck

= Not a rubber duck

Toy Problem: Overfitting

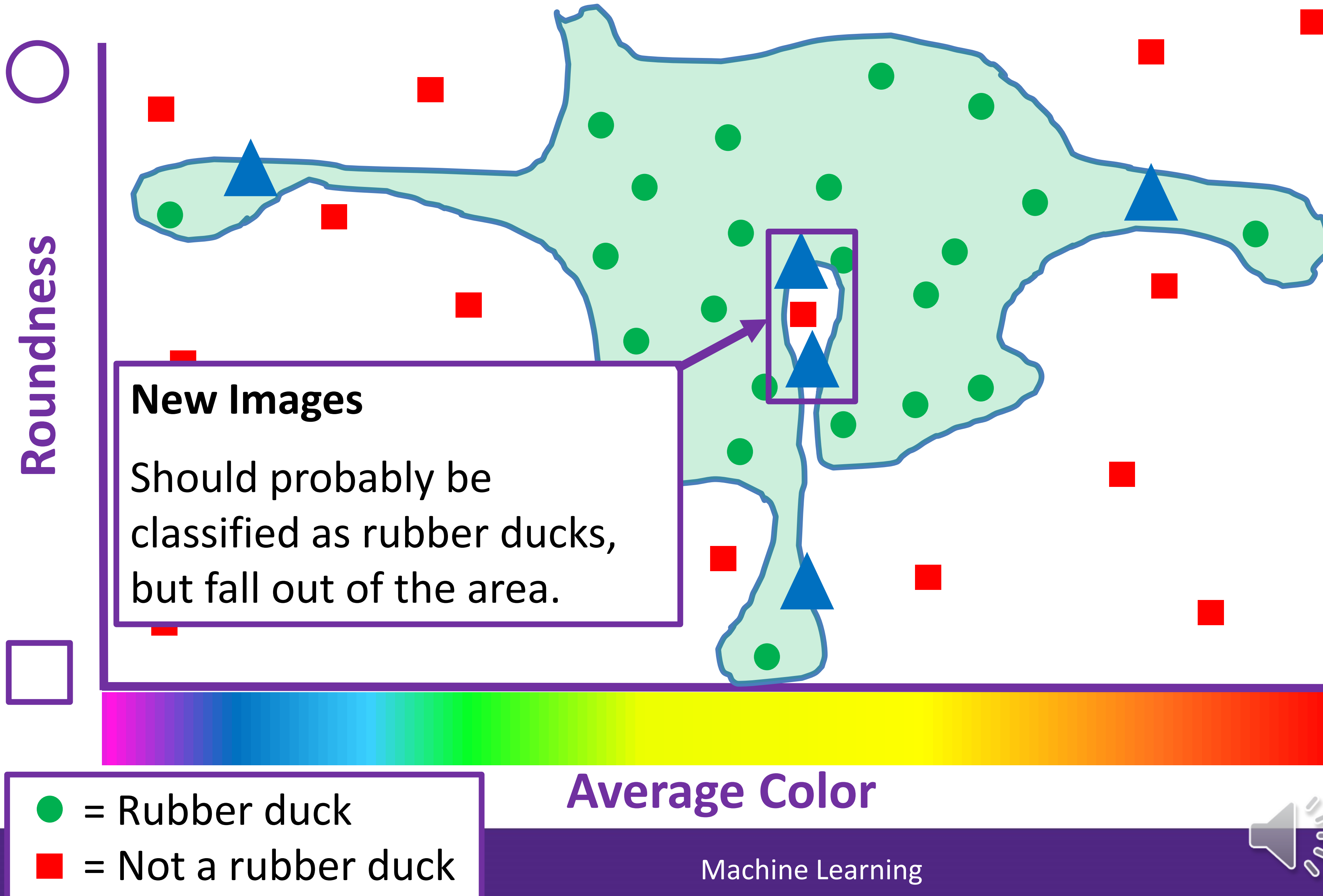


Toy Problem: Overfitting

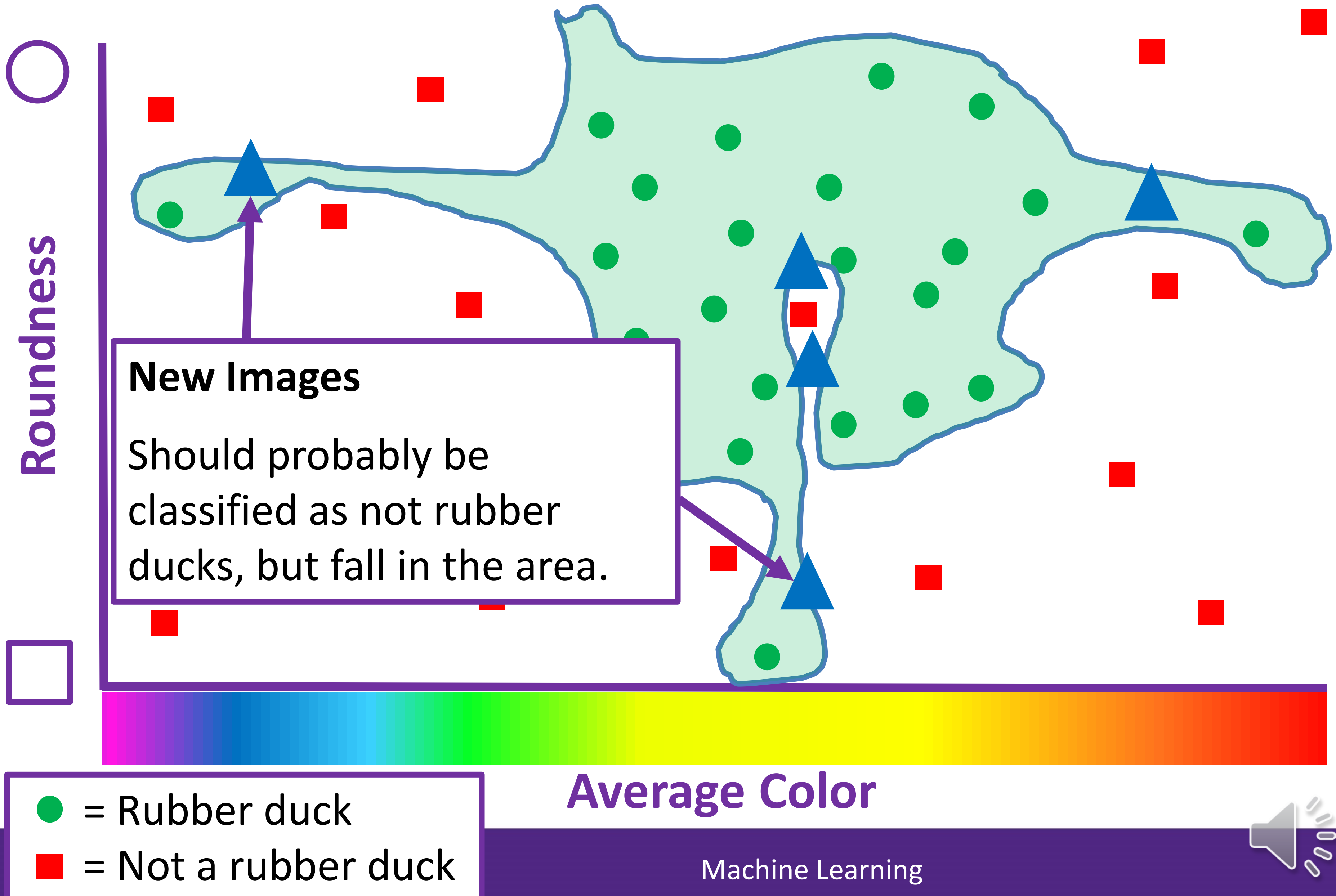


= Rubber duck
= Not a rubber duck

Toy Problem: Overfitting



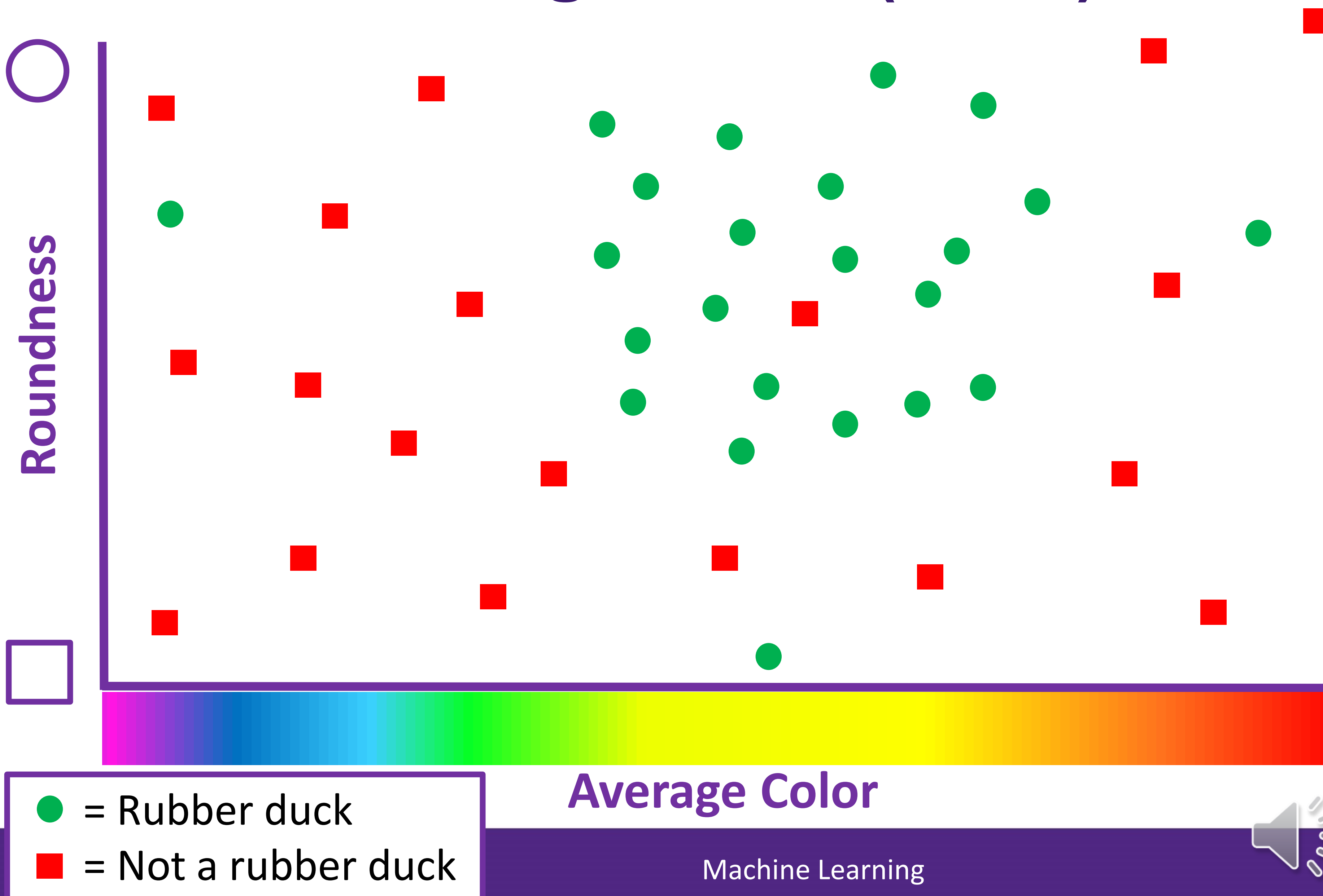
Toy Problem: Overfitting



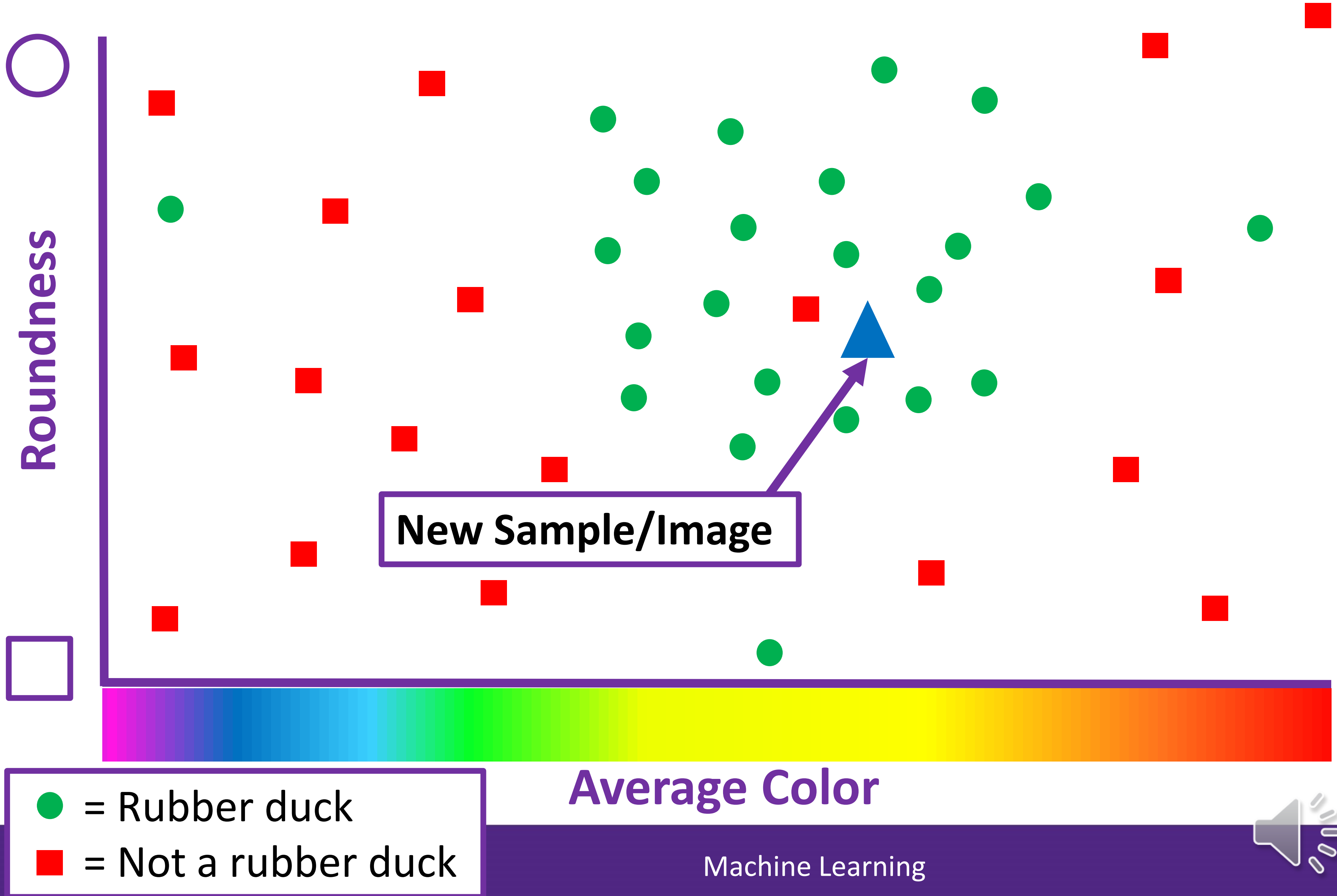
k-Nearest Neighbours (k-NN)

- Another classification method that works when there is a notion of distance in the feature space.
- Bases classification on the k closest neighbors in the training samples to a new sample in the feature space.
- Computationally simple and efficient.
  - Easy to implement
  - Fast results
  - No training time
- Lazy learning
  - Can be powerful in some cases but has limitations
  - Irrelevant features degrade results
  - Classes with more samples dominate

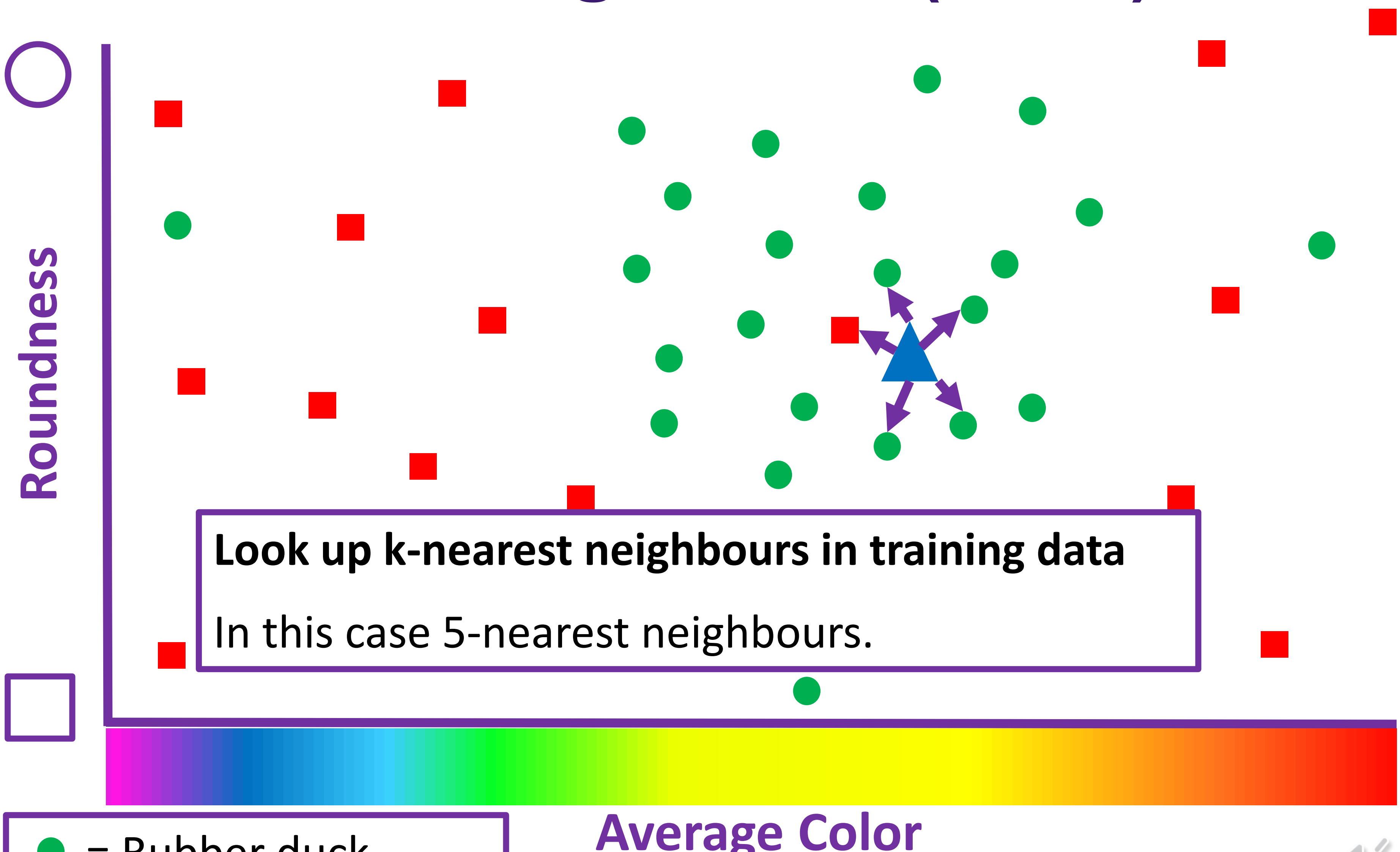
k-Nearest Neighbours (k-NN)



k-Nearest Neighbours (k-NN)



k-Nearest Neighbours (k-NN)

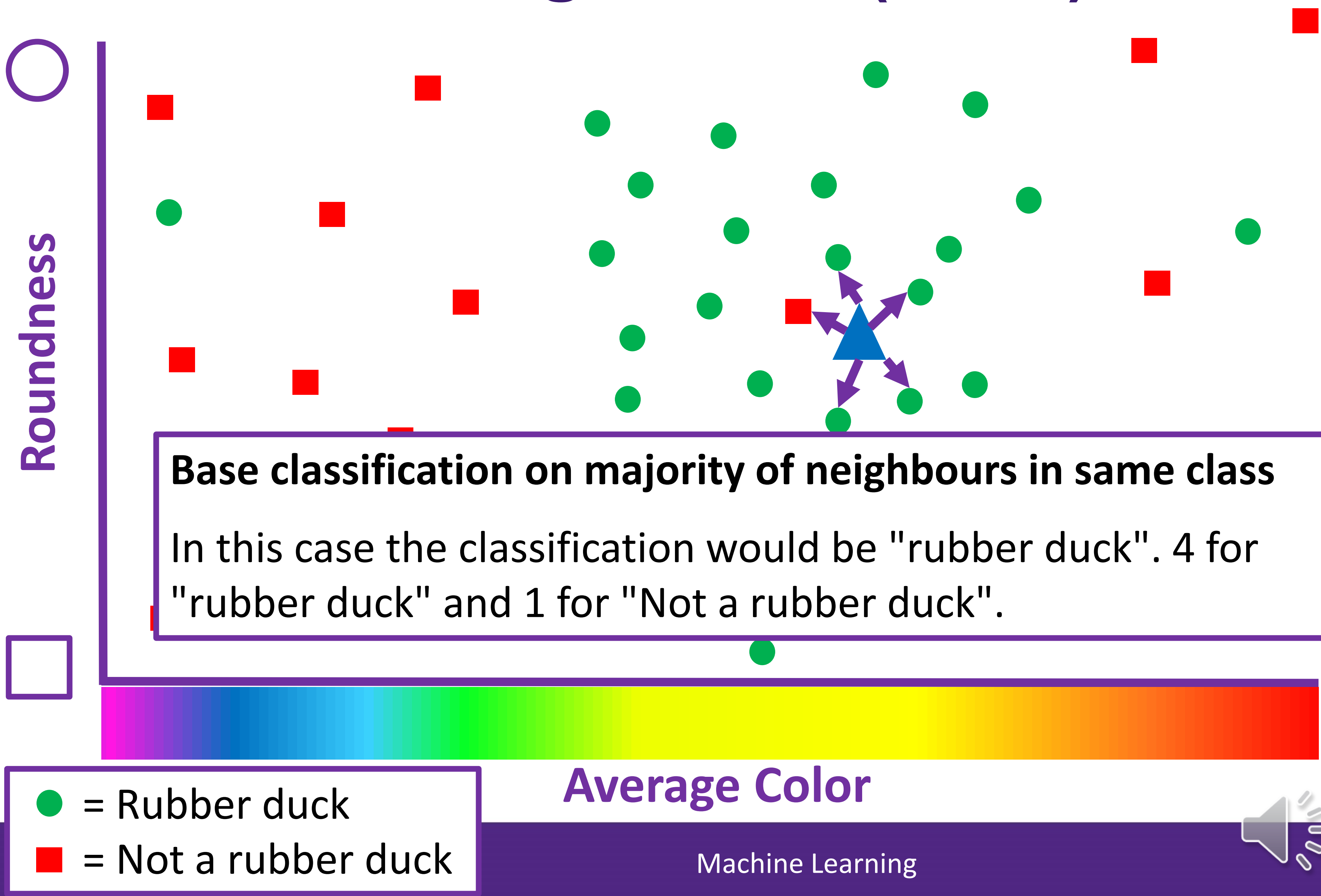


Look up k-nearest neighbours in training data

In this case 5-nearest neighbours.

● = Rubber duck
■ = Not a rubber duck

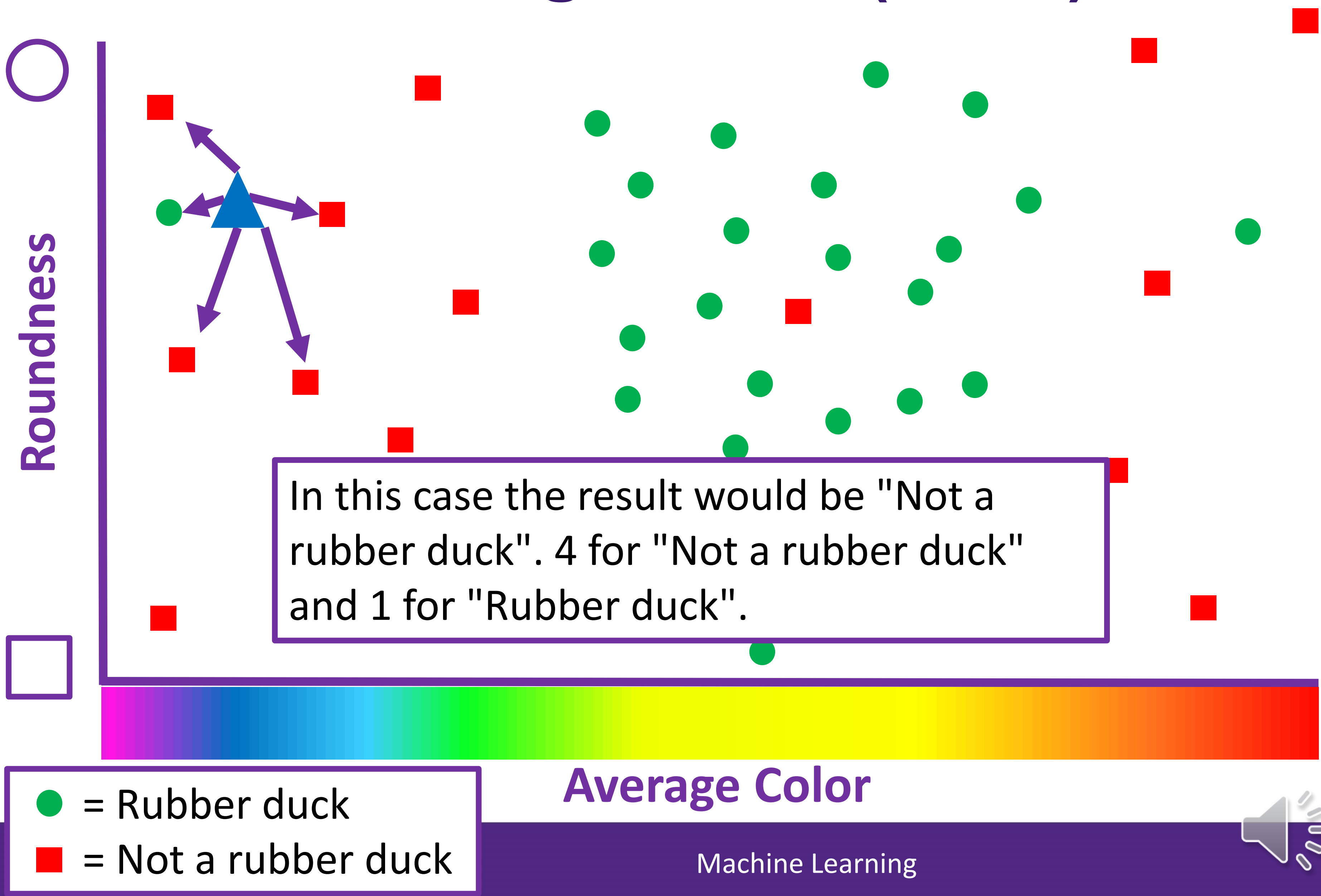
k-Nearest Neighbours (k-NN)



Base classification on majority of neighbours in same class

In this case the classification would be "rubber duck". 4 for "rubber duck" and 1 for "Not a rubber duck".

k-Nearest Neighbours (k-NN)



In this case the result would be "Not a rubber duck". 4 for "Not a rubber duck" and 1 for "Rubber duck".

Decision Tree Learning

- Widely used method for getting a general idea from specific examples.
- Robust to noisy data.
- **Method:**
  - Find the unused feature that gives the most information and consider that feature first.
  - Repeat until done.
- **Concepts:**
  - Information theory
  - Entropy
  - Information gain

Decision Tree Learning

- Widely used method for getting a general idea from specific examples.
- Robust to noisy data.
- **Method:**
  - Find the unused feature that gives the most information and consider that feature first.
  - Repeat until done.
- **Concepts:**
  - Information theory
  - Entropy
  - Information gain

Building a Decision Tree

- Will use the concepts of **entropy** and **information gain**.
- **Entropy** is:
  - A measure of how mixed a collection is.
  - A measure of impurity.
- **Information gain** measures how well a choice separates examples.
  - Measures change in entropy.

Decision Tree Learning: Example

(from “Machine Learning” by Tom Mitchell, McGraw Hill 1997 and notes by J. Forgette)

- Given this information:
  - Outlook is sunny
  - Temperature is hot
  - Humidity is high
  - Wind is strong

- Should we play tennis?
  - Yes
  - No

Decision Tree Learning: Example

(from "Machine Learning" by Tom Mitchell, McGraw Hill 1997 and notes by J. Forgette)

- Given this information:
  - Outlook is sunny
  - Temperature is hot
  - Humidity is high
  - Wind is strong

- Should we play tennis?
  - Yes
  - No

Features (aka Attributes)
- Outlook
- Temperature
- Humidity
- Wind

Decision Tree Learning: Example

(from “Machine Learning” by Tom Mitchell, McGraw Hill 1997 and notes by J. Forgette)

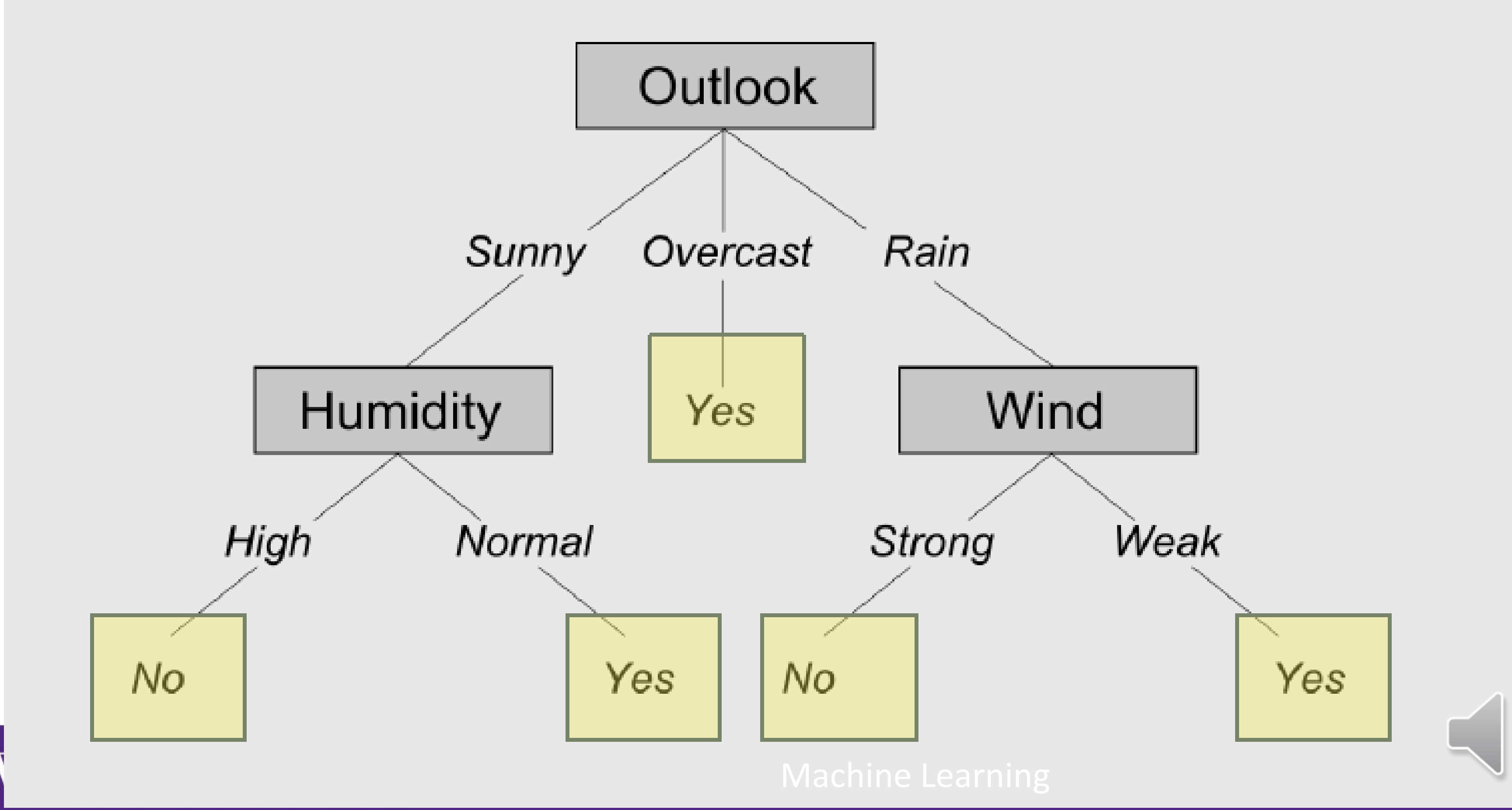
- Given this information:
  - Outlook is sunny
  - Temperature is hot
  - Humidity is high
  - Wind is strong

- Should we play tennis?
  - Yes
  - No

Classes
Yes or No

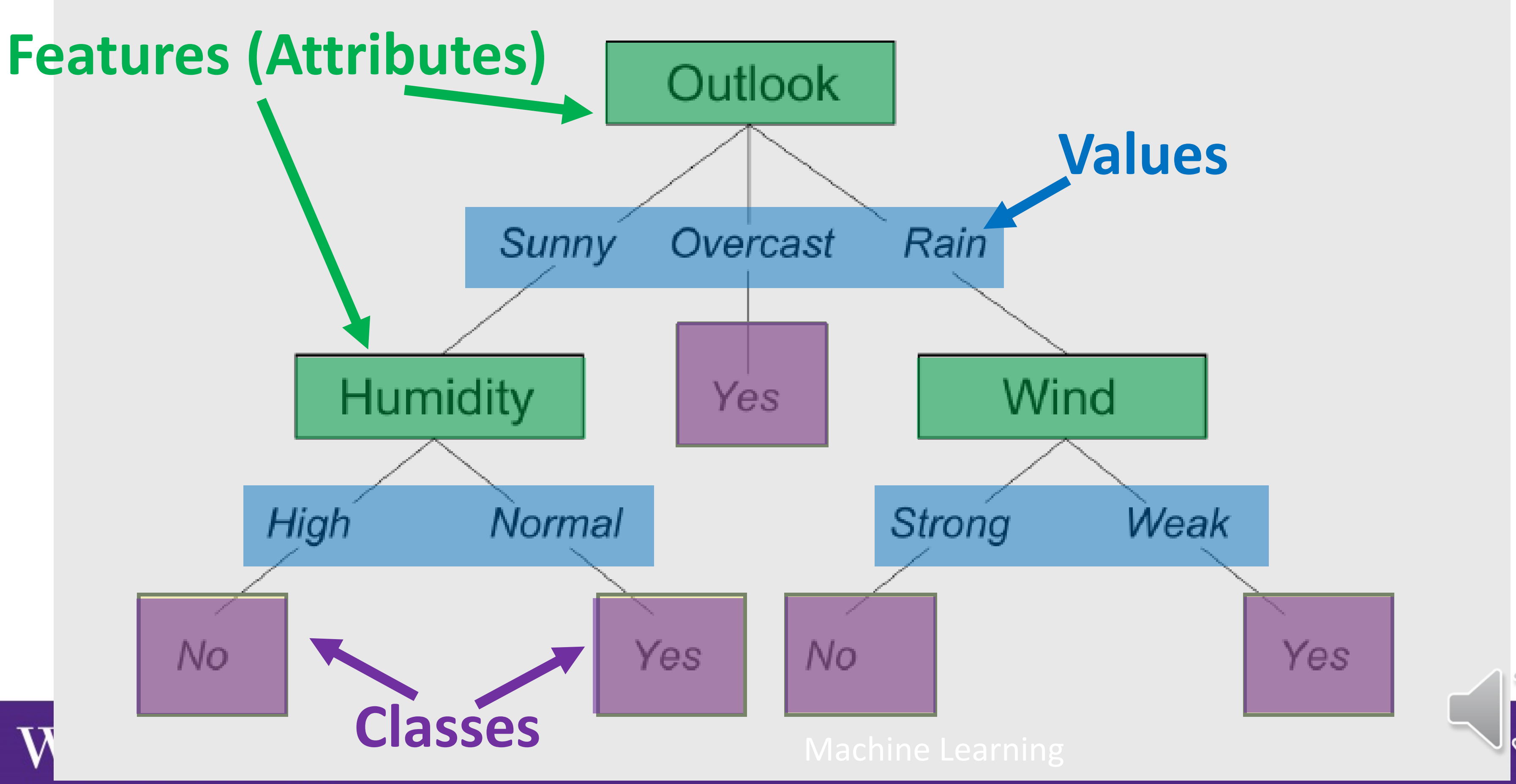
Decision Tree Learning: Example

Goal: Create a decision tree that classifies a set of weather related features (Outlook, Temp, Wind, Humidity) into two classes, play tennis (yes) or do not play tennis (no).



Decision Tree Learning: Example

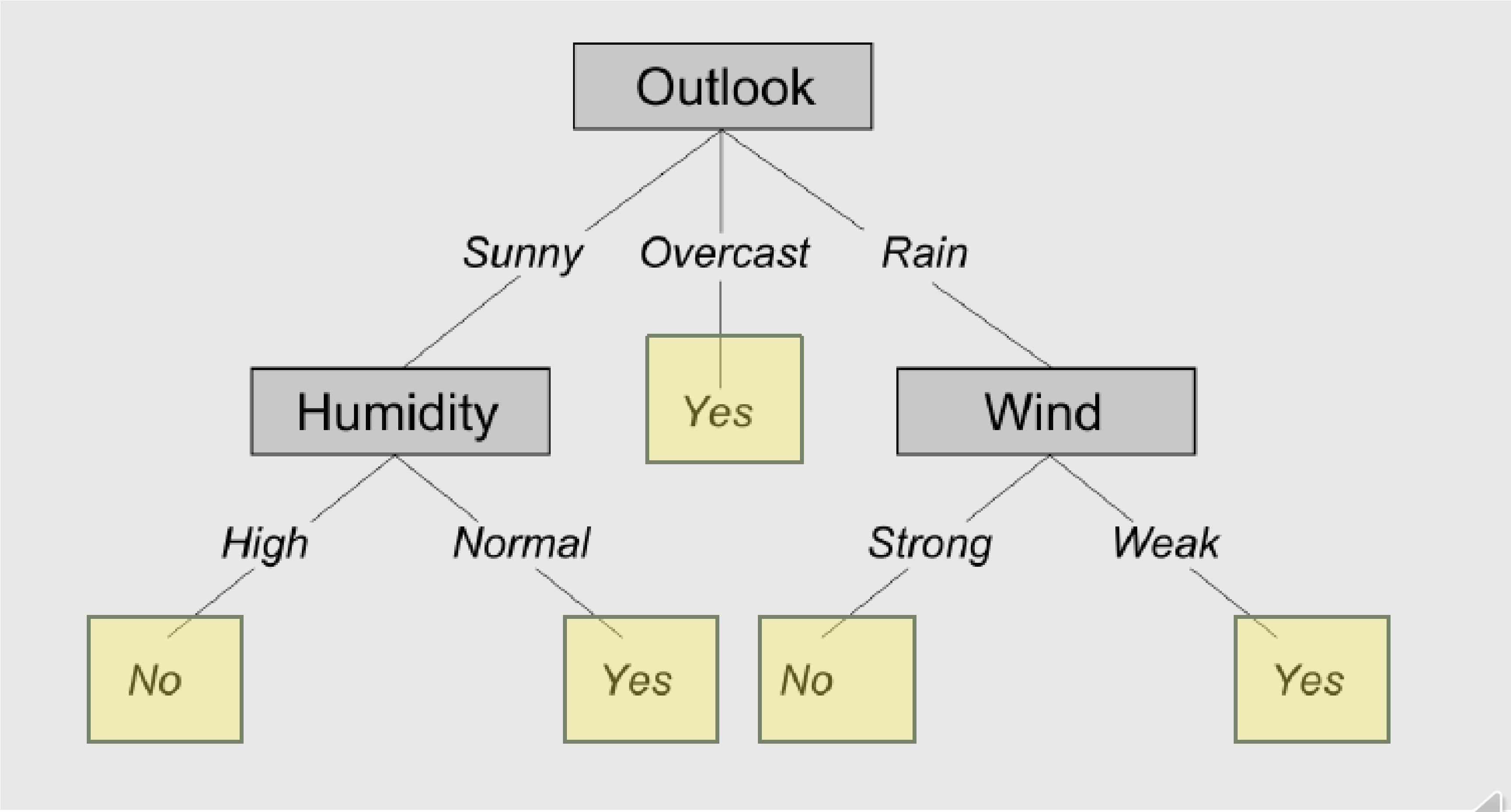
Goal: Create a decision tree that classifies a set of weather related features (Outlook, Temp, Wind, Humidity) into two classes, play tennis (yes) or do not play tennis (no).



Decision Tree Learning: Example

Example Input 1:

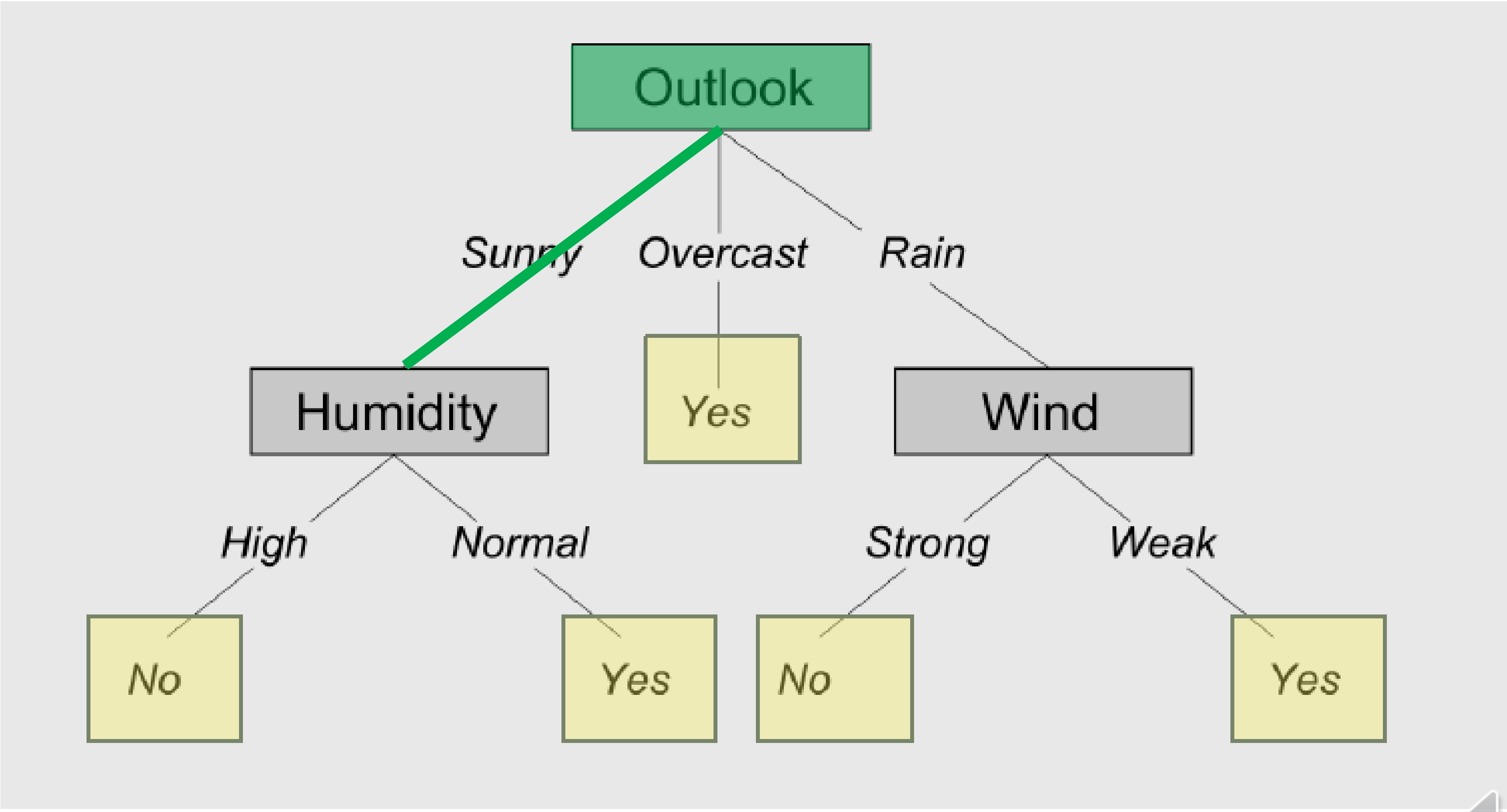
Outlook = Sunny, **Humidity** = Normal, **Wind** = Strong, **Temp** = Hot



Decision Tree Learning: Example

Example Input 1:

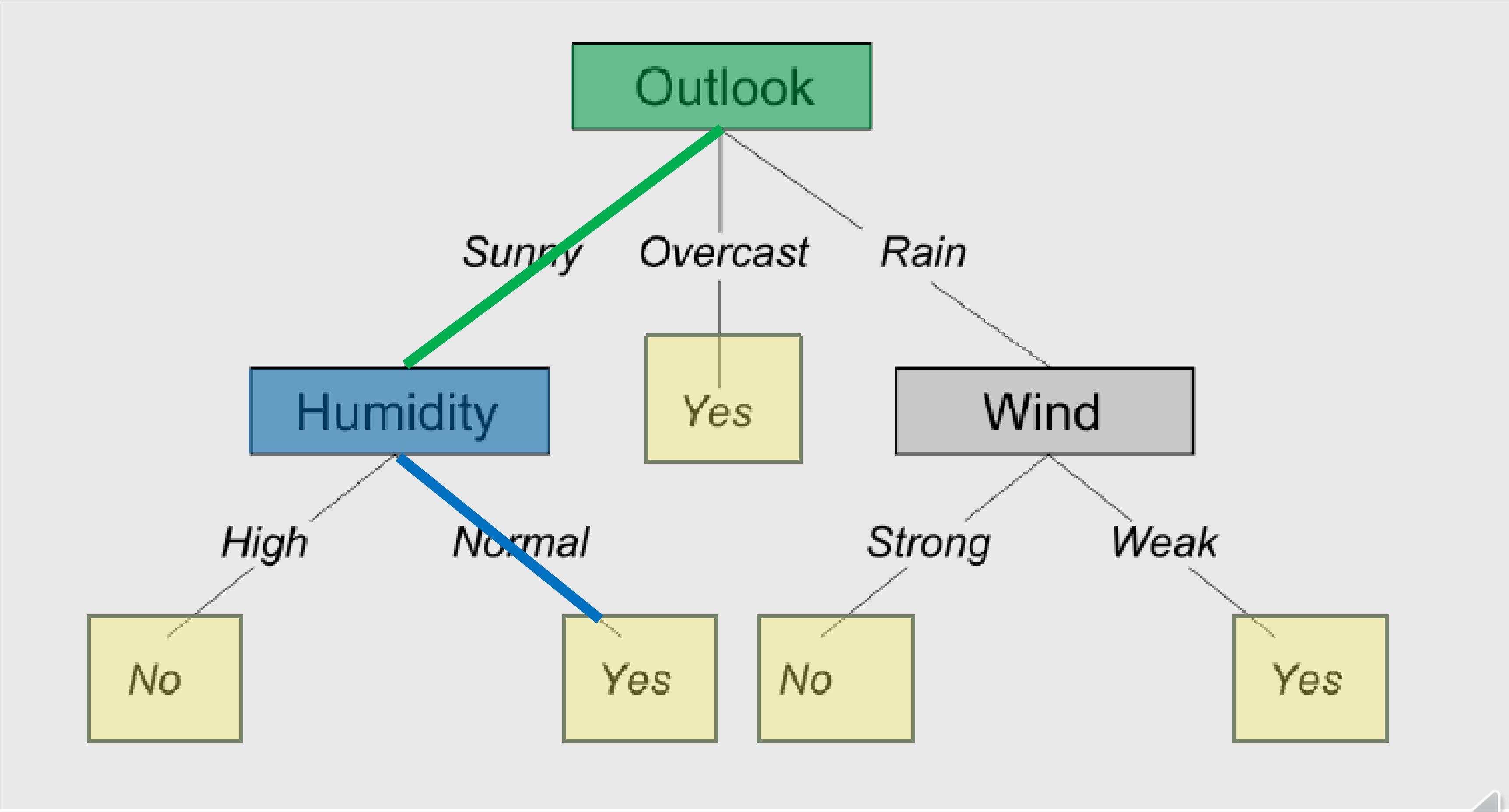
Outlook = Sunny, **Humidity** = Normal, **Wind** = Strong, **Temp** = Hot



Decision Tree Learning: Example

Example Input 1:

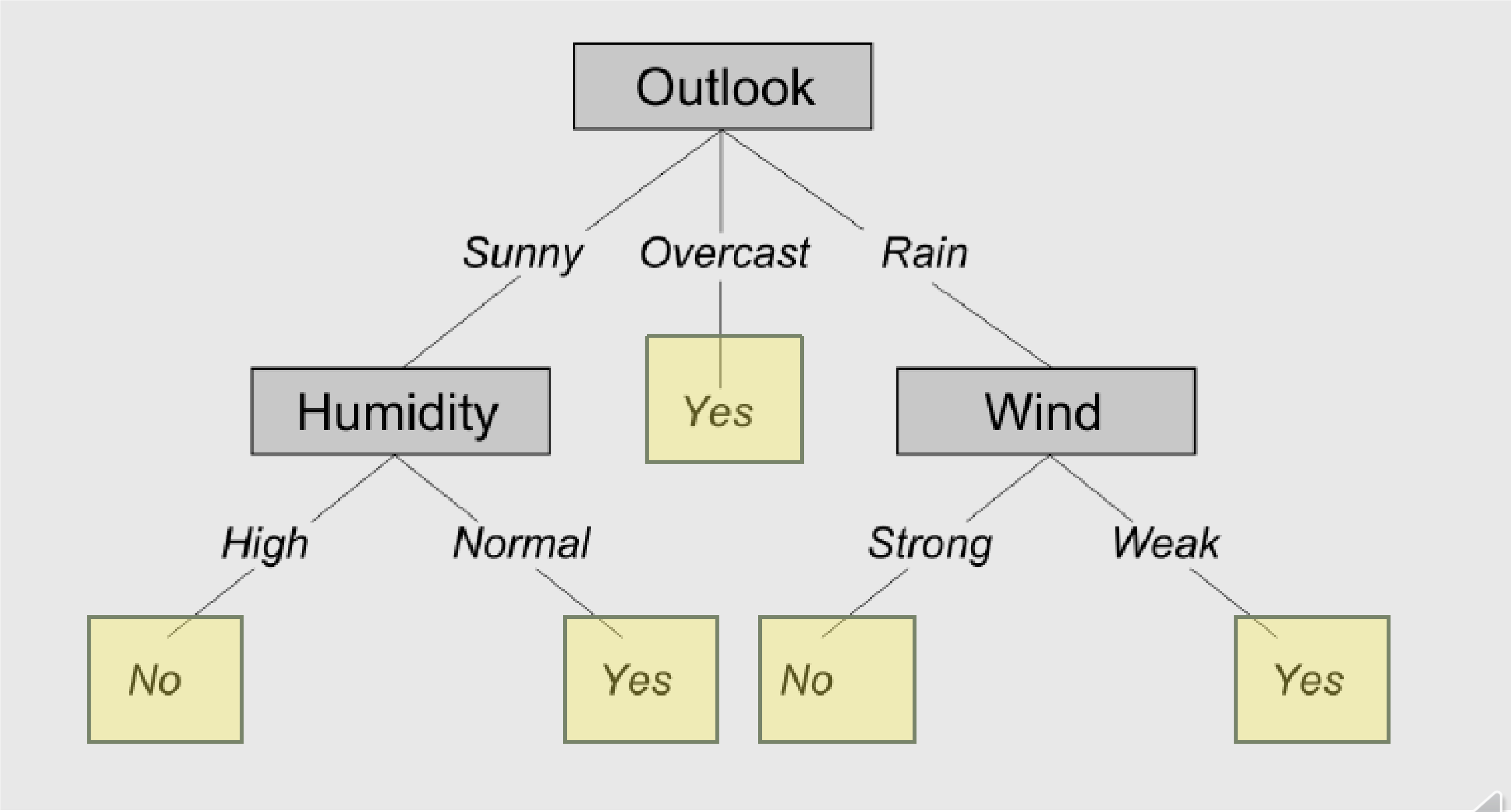
Outlook = Sunny, **Humidity** = Normal, **Wind** = Strong, **Temp** = Hot



Decision Tree Learning: Example

Example Input 2:

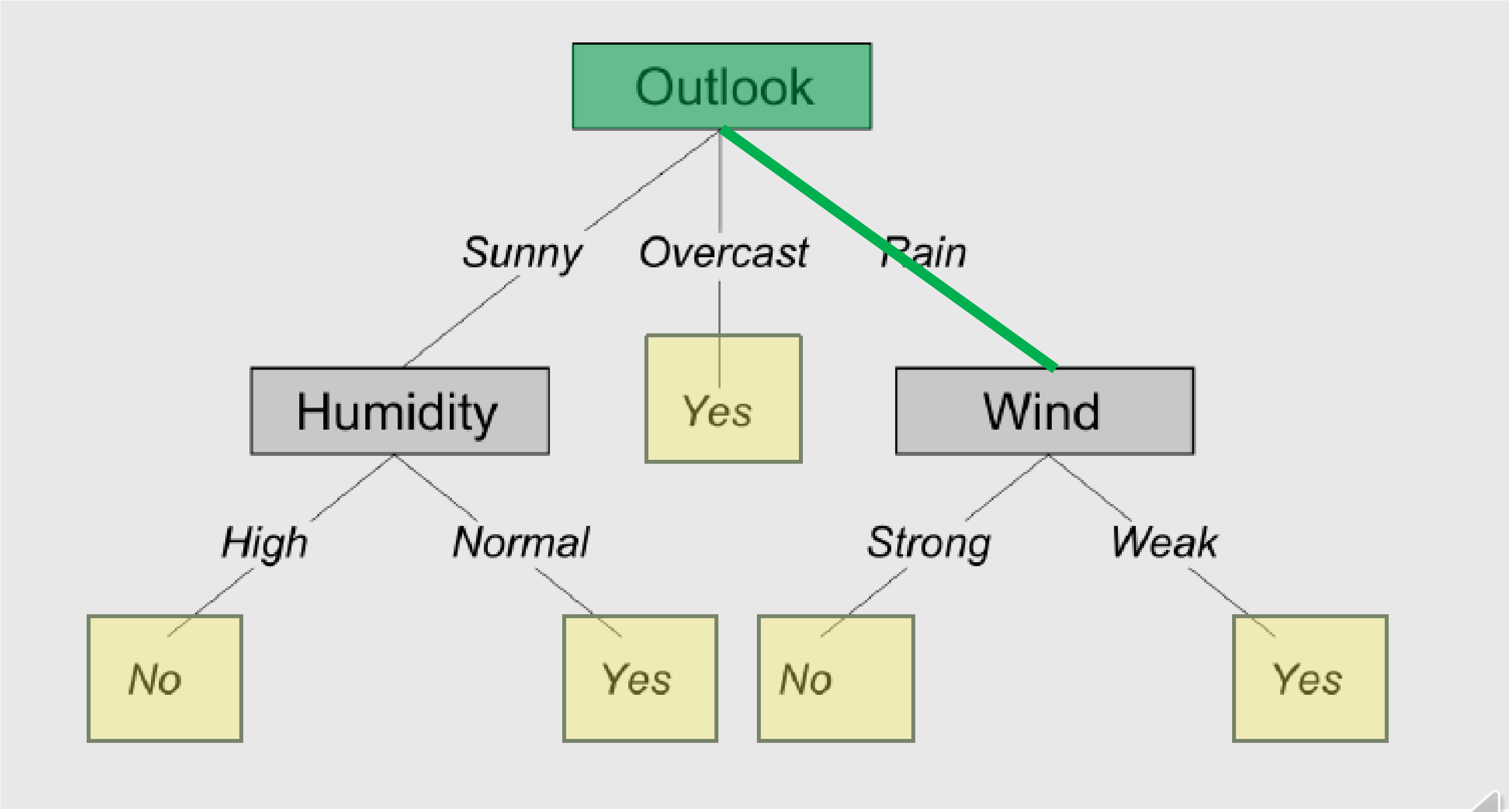
Outlook = Rain, **Humidity** = High, **Wind** = Strong, **Temp** = Cold



Decision Tree Learning: Example

Example Input 2:

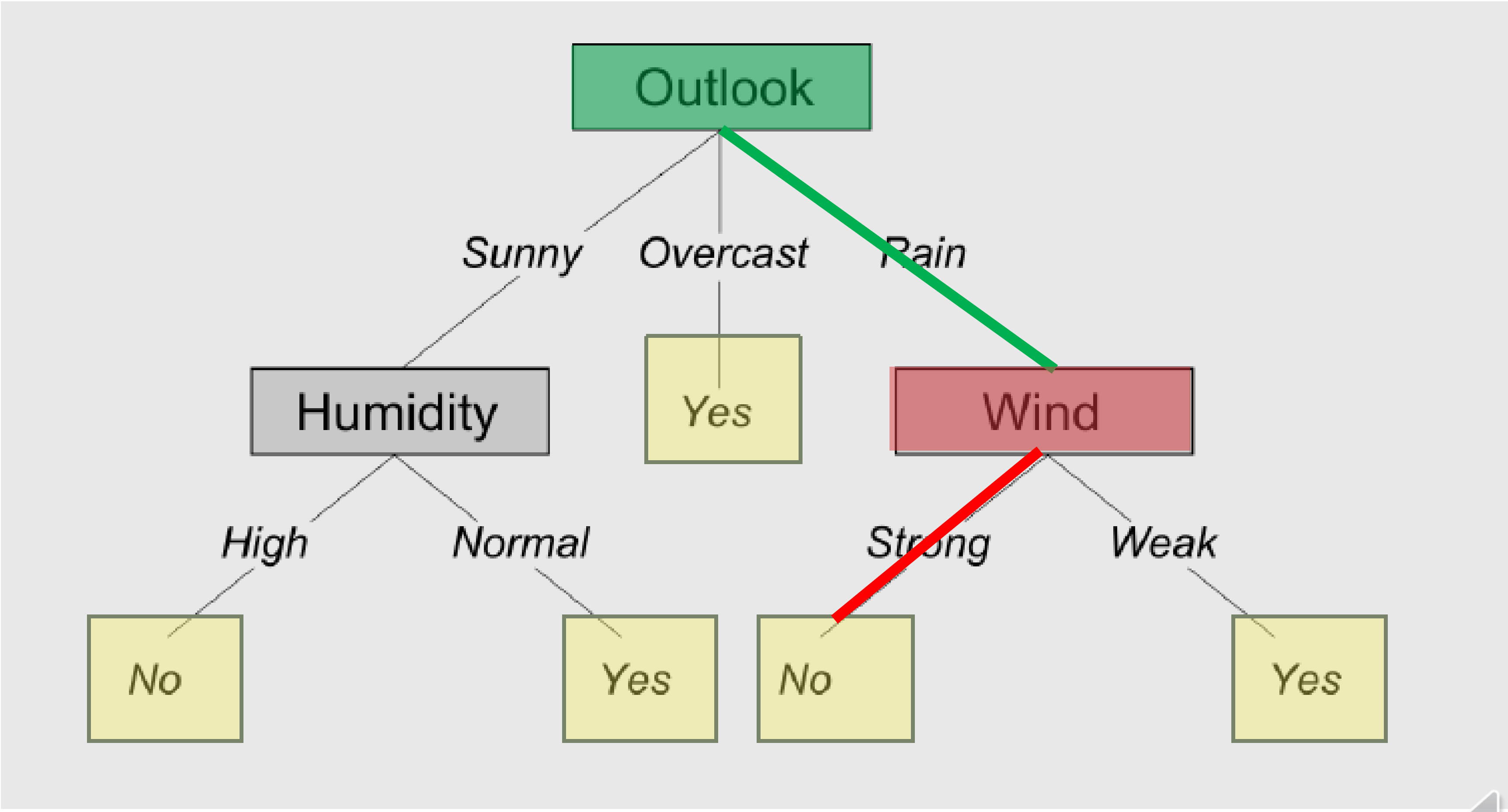
Outlook = Rain, **Humidity** = High, **Wind** = Strong, **Temp** = Cold



Decision Tree Learning: Example

Example Input 2:

Outlook = Rain, **Humidity** = High, **Wind** = Strong, **Temp** = Cold



Decision Trees

- Tree is constructed from training examples.
- Once tree is constructed, use it to classify new instances (that were not in the examples).
- The effectiveness of the tree is determined by the correctness of the classification of new instances.

Other Methods/Classifiers

- Many other methods/classifiers exist
  - Support Vector Machines (SVM)
  - Neural Networks
  - Cluster analysis
  - Genetic algorithms
  - Etc.