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Machine Learning in Action: Exploring Examples in Multiple Domains

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Machine Learning in Action: Exploring Examples in Multiple Domains

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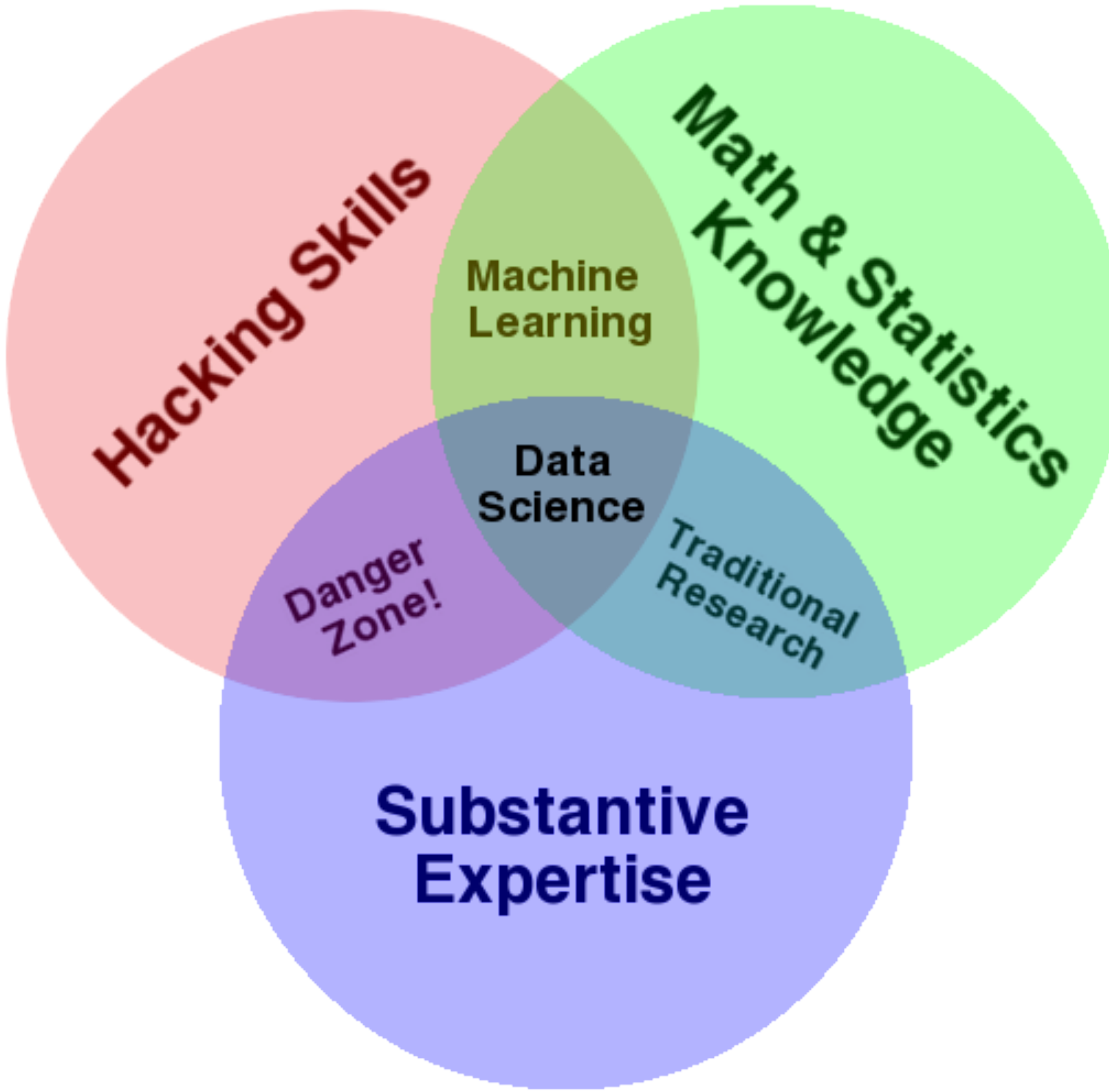

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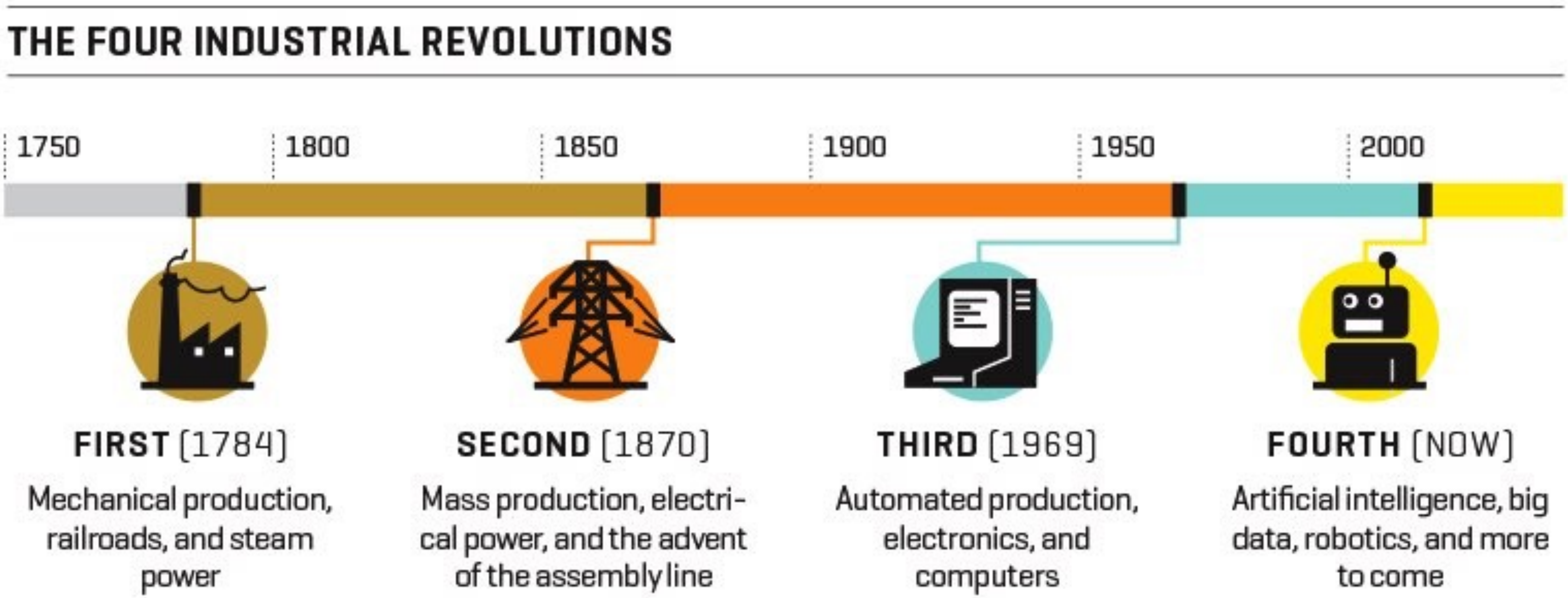

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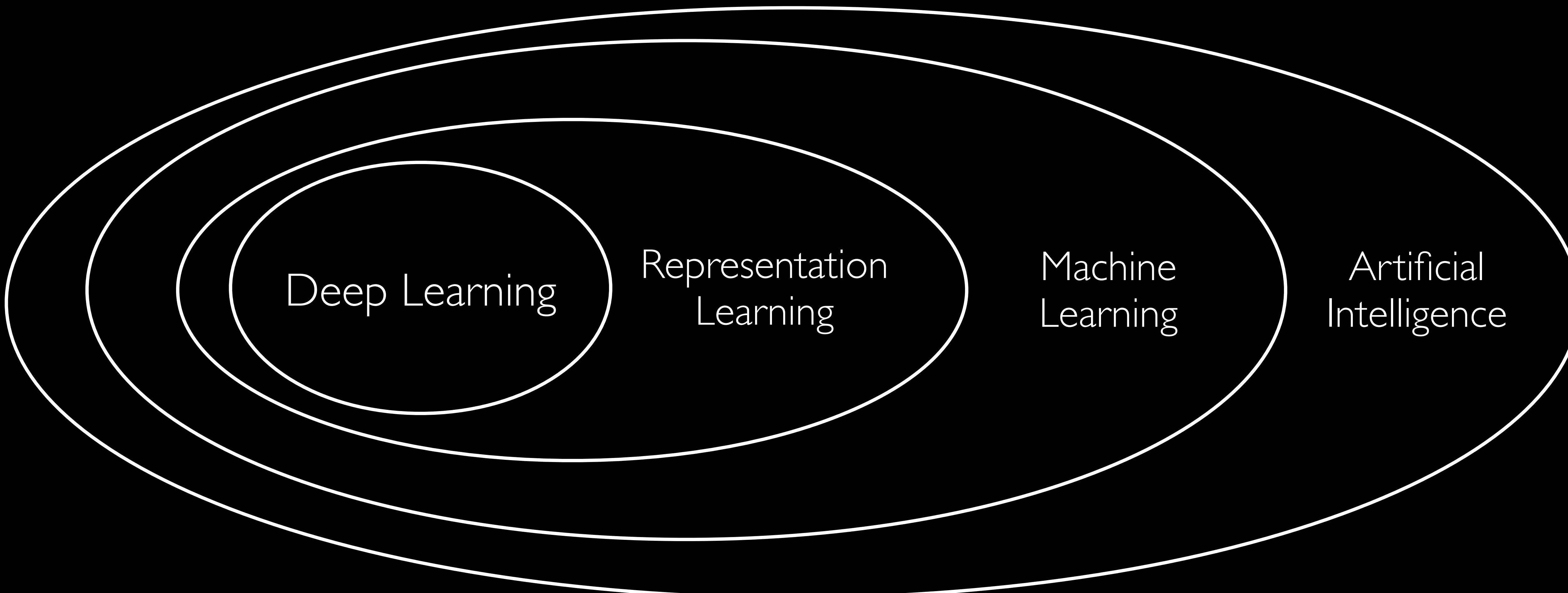

Goodfellow, I., Bengio, Y. y Courville, A. (2016). *Deep learning*. MIT Press.


MACHINE LEARNING

“Learning is any process by which a system improves performance from experience.”

— Herbert Simon

Definition by Tom Mitchell (1998):

Machine Learning is the study of **algorithms** that

improve their performance *P*

at some task *T*

with experience *E*.

A well-defined **learning task** is given by <*P*, *T*, *E*>.

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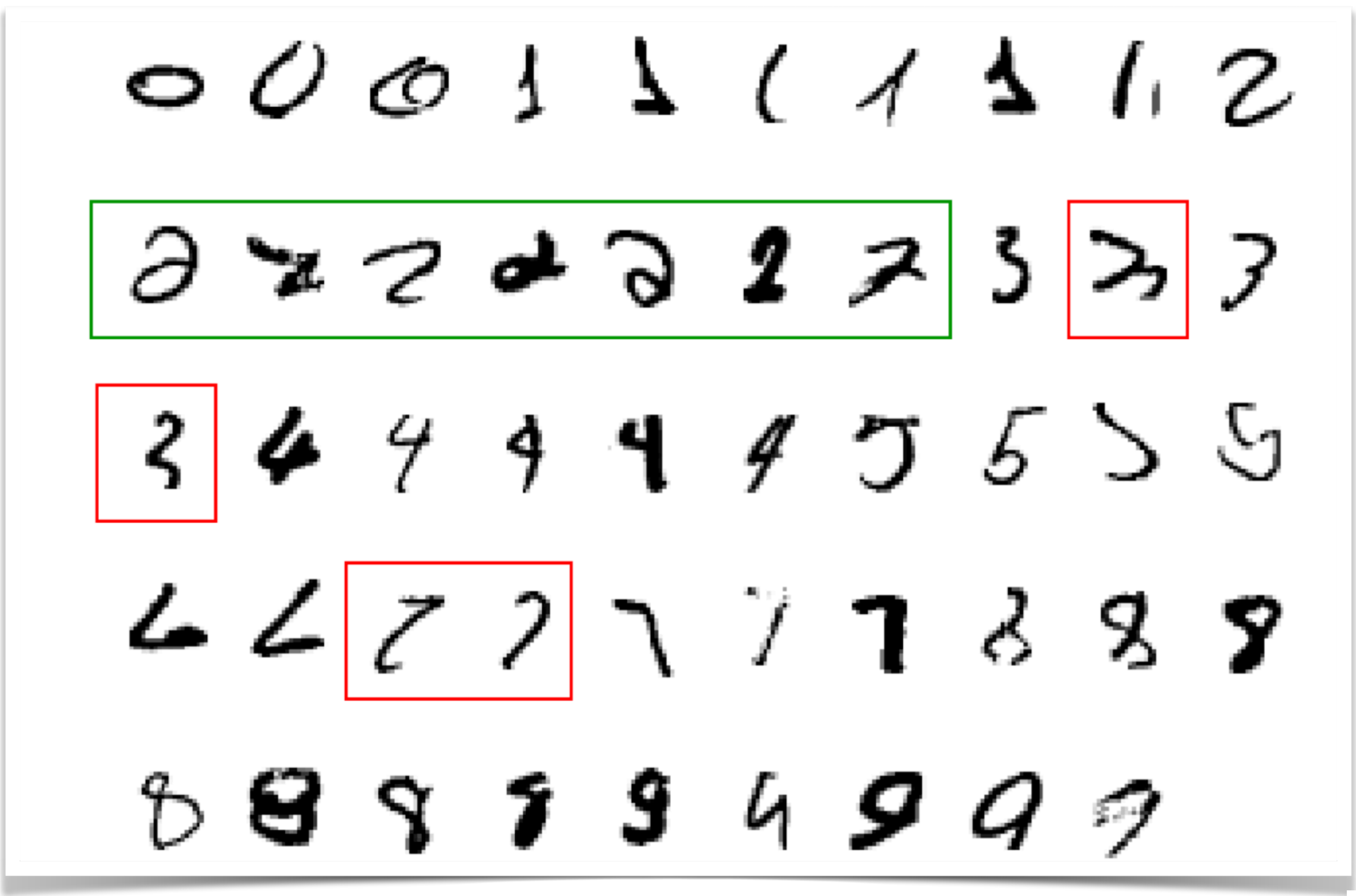
A classic example of a task that requires machine learning: It is very hard to say what makes a 2



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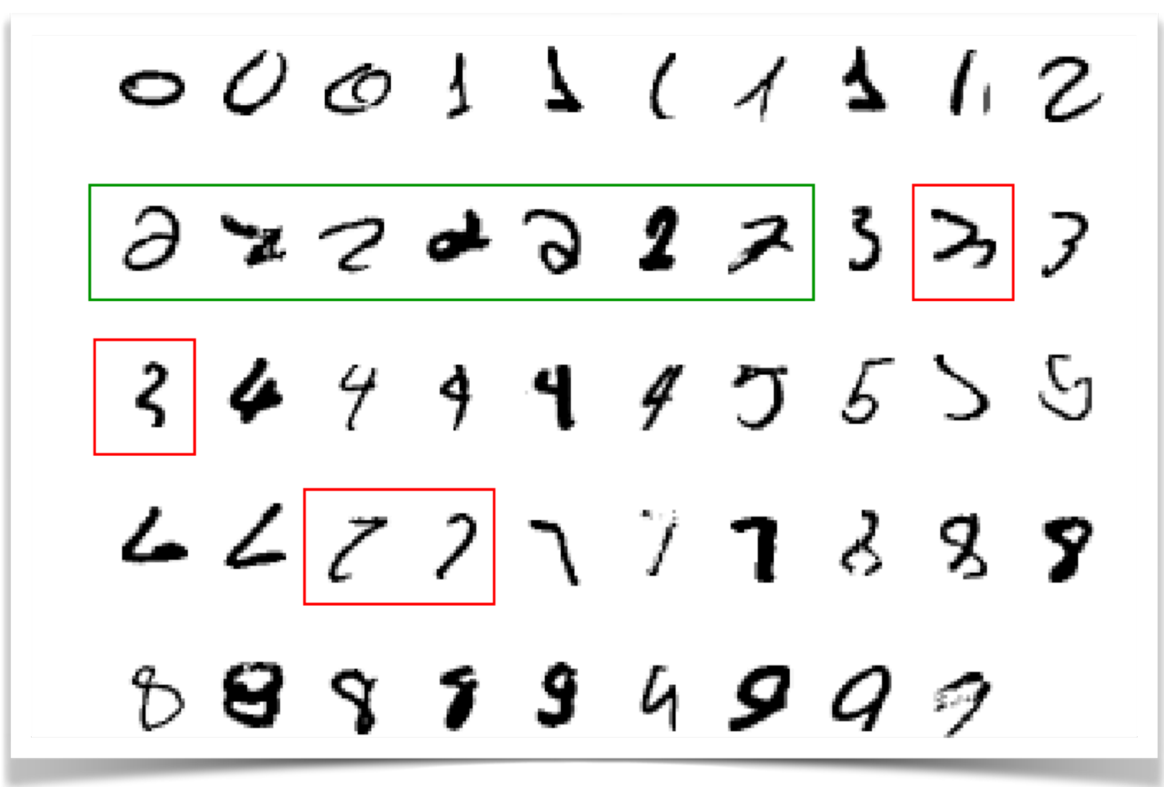
Improve on task T, with respect to performance metric P, based on experience E

T: Recognizing hand-written numbers
P: Percentage of numbers correctly classified
E: Database of human-labeled images of handwritten numbers



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"Machine Learning: Field of study that gives computers the ability to **learn** without being **explicitly programmed**."

— Arthur Samuel (1959)

input → function → output

5 10 → 5 + 10 → 15

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input → function → output

machine learning

number 1 = 0.00012

number 2 = 0.91000

number 3 = 0.00025

. . .

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Machine learning is not statistics

	Statistics	Machine Learning
Approach	Hypothesis-driven development	Creating systems that learn from data
Goal	Relationships between variables	Optimization; prediction accuracy
Assumptions	Some knowledge about population is usually required	None
Data Complexity	Usually applied to low-dimensional data	Usually applied to high-dimensional data; ML learns from data

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Types of machine learning

Supervised (inductive) learning

– Given: training data + desired outputs (labels)

Unsupervised learning

– Given: training data (without desired outputs)

Semi-supervised learning

– Given: training data + a few desired outputs

Reinforcement learning

– Rewards from sequence of actions

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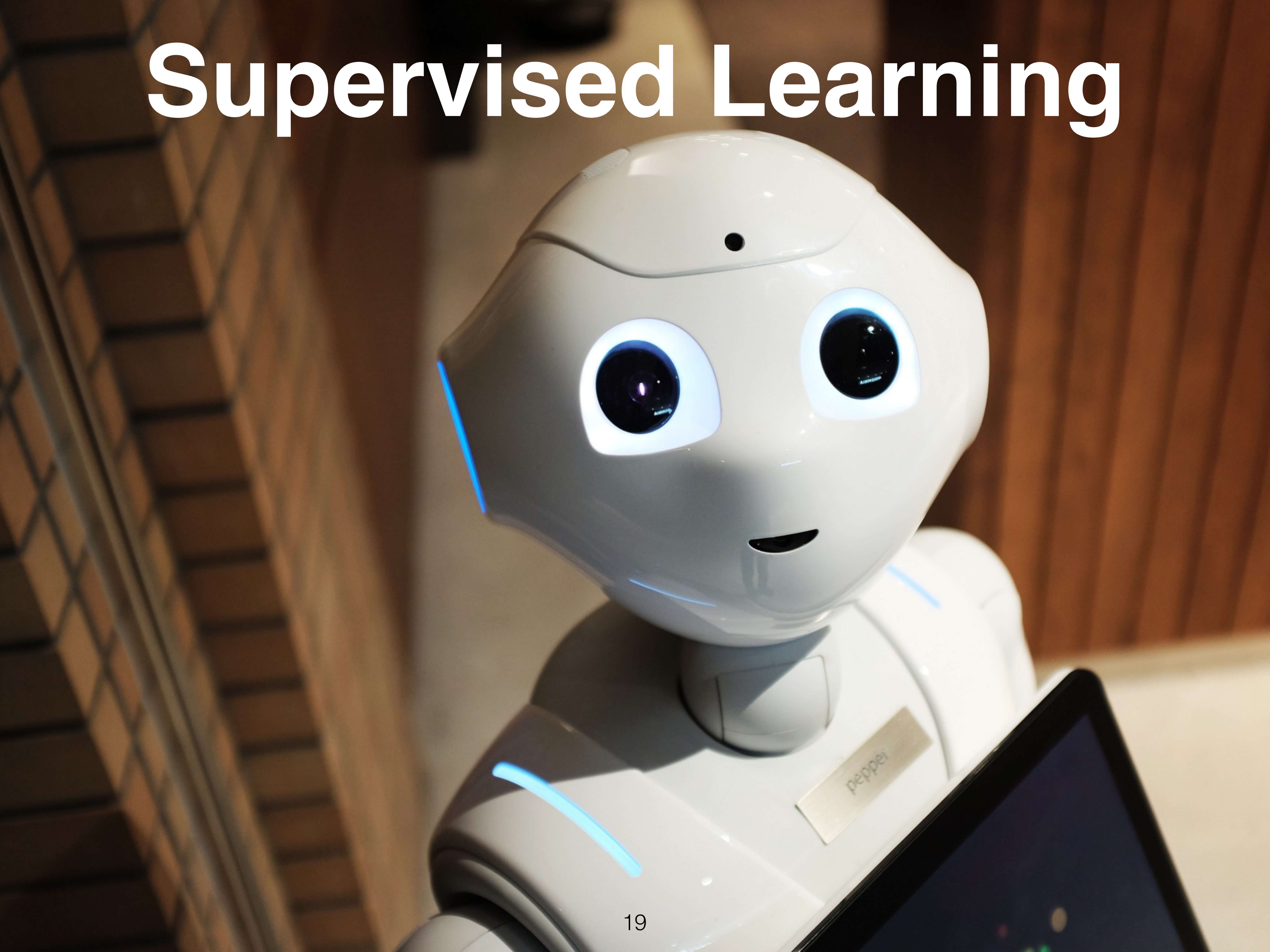
Supervised Learning



If you're trying to predict a target value, then you need to look into **supervised learning**.

– Given: training data + desired outputs (labels)

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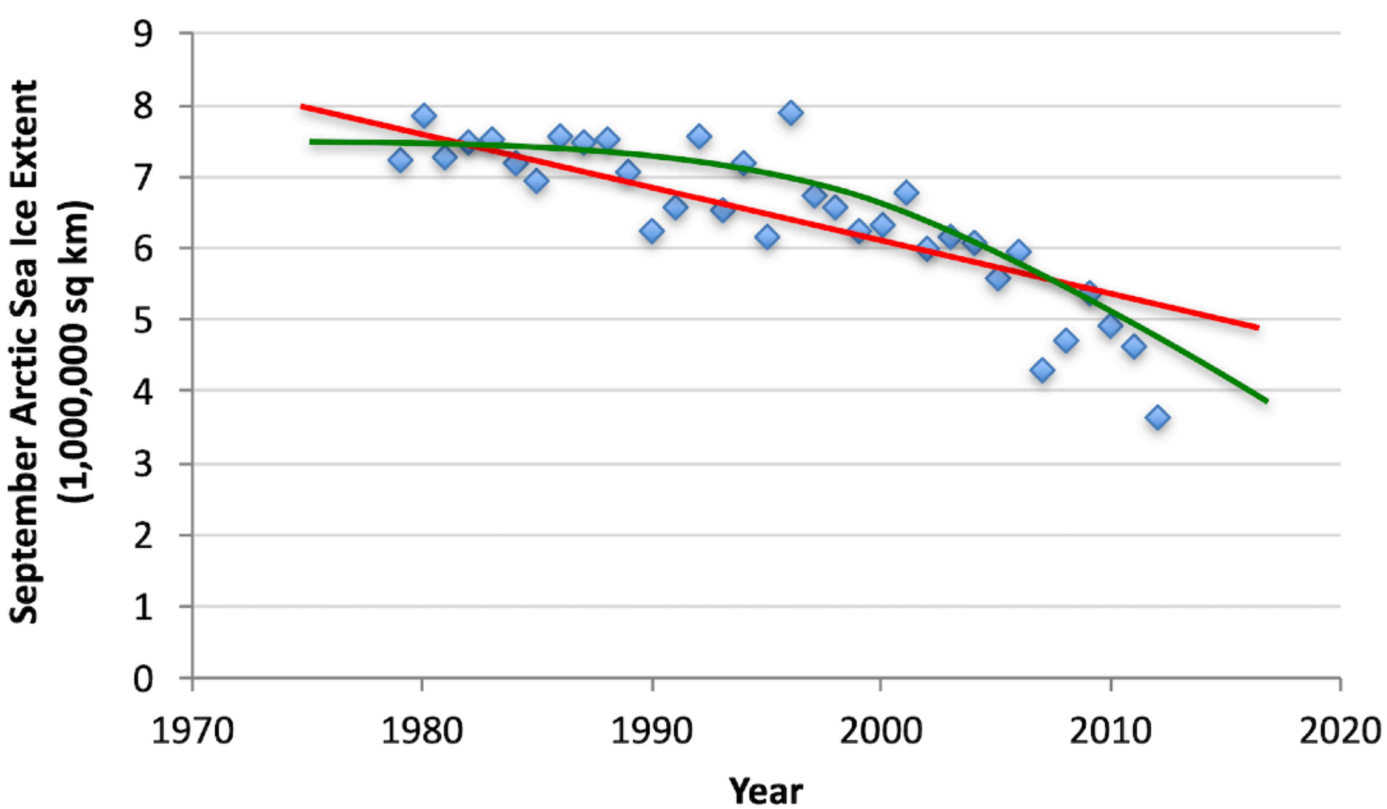
Supervised learning: regression

- Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- Learn a function $f(x)$ to predict y given x
    - y is **real-value** == regression



Data from G. Witt. Journal of Statistics Education, Volume 21, Number 1 (2013)

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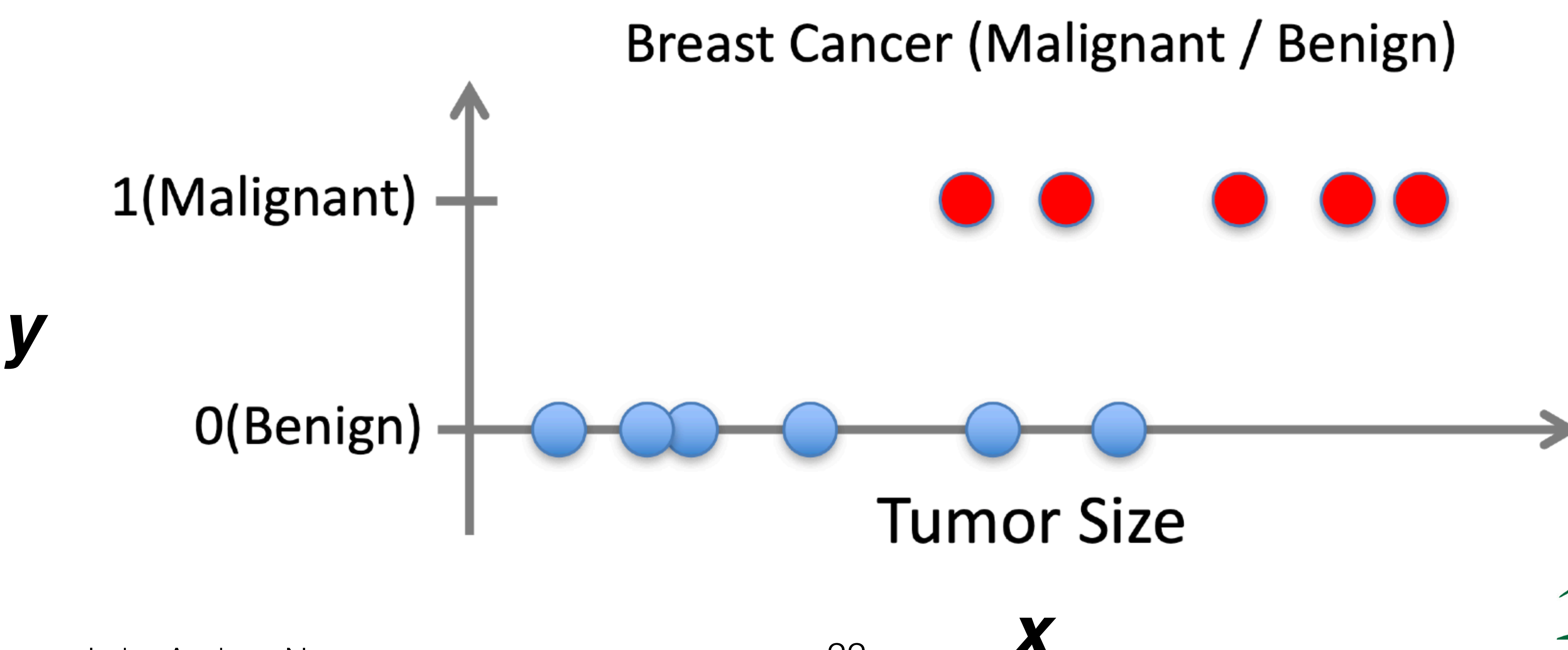
Supervised learning: classification

- Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- Learn a function $f(x)$ to predict y given x
  - y is **categorical** == classification



Based on example by Andrew Ng

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Supervised learning: classification

- Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
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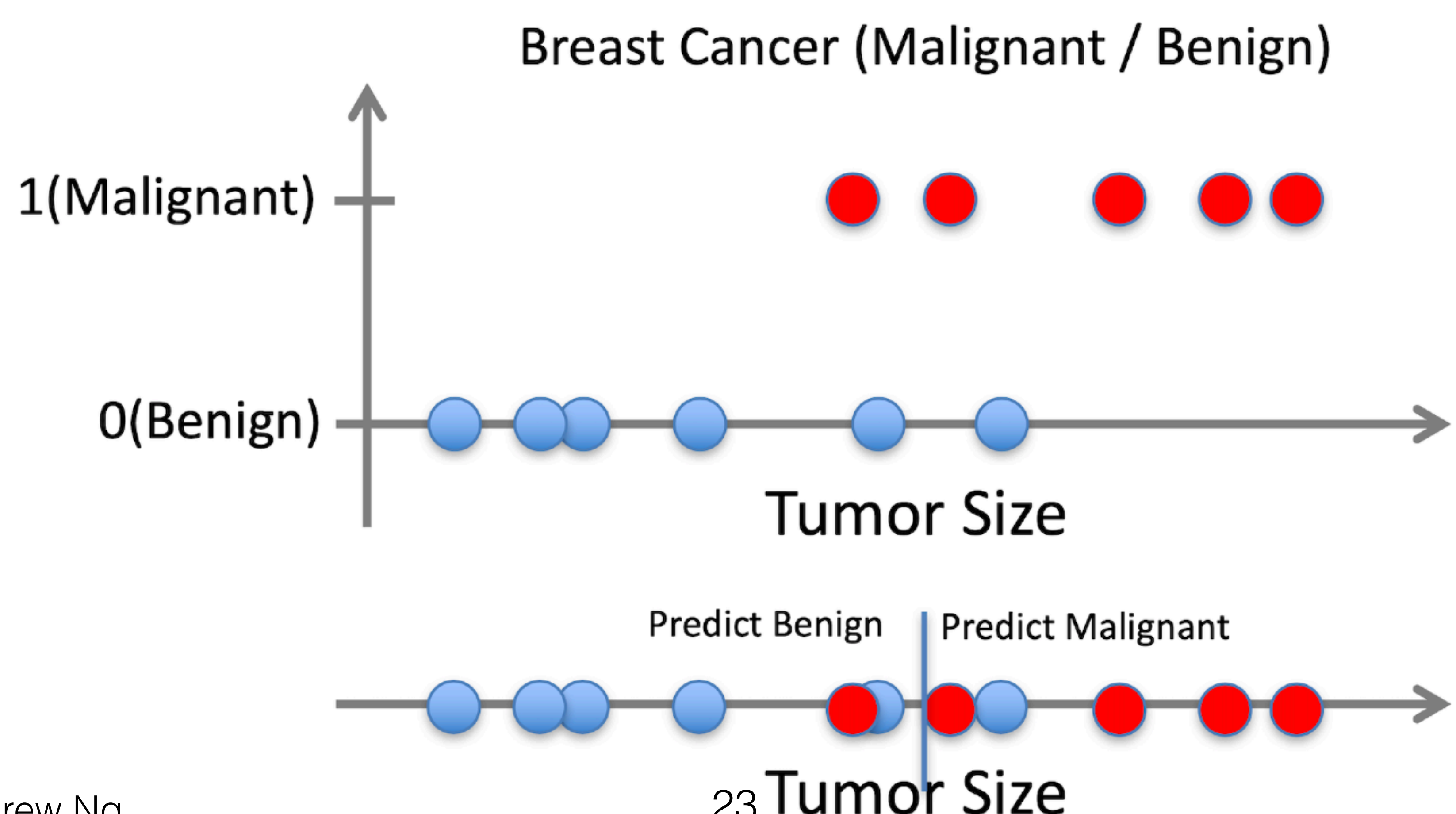
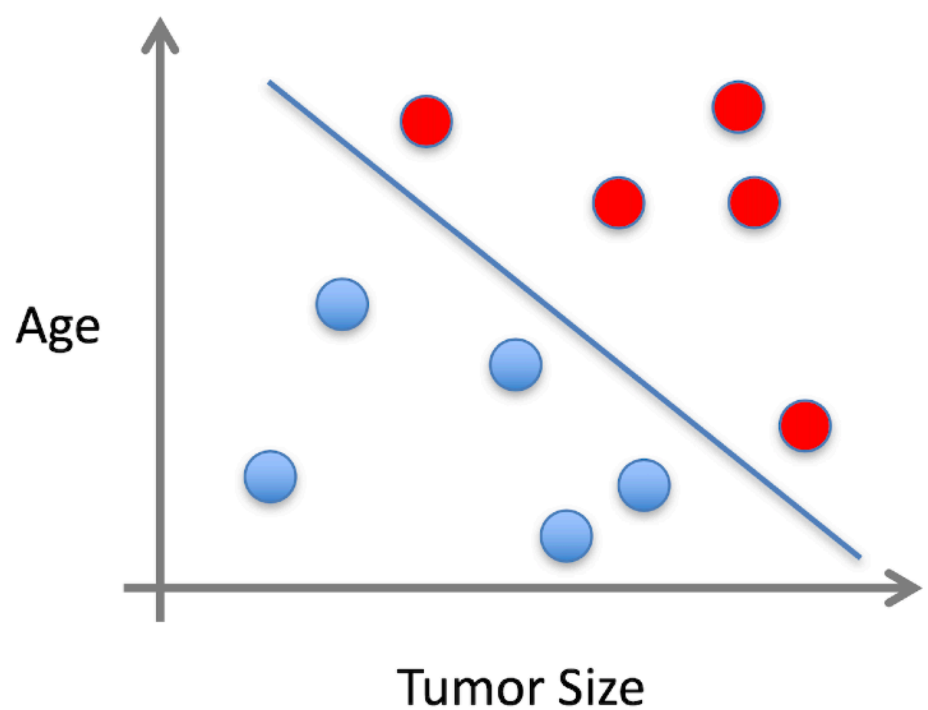


Based on example by Andrew Ng

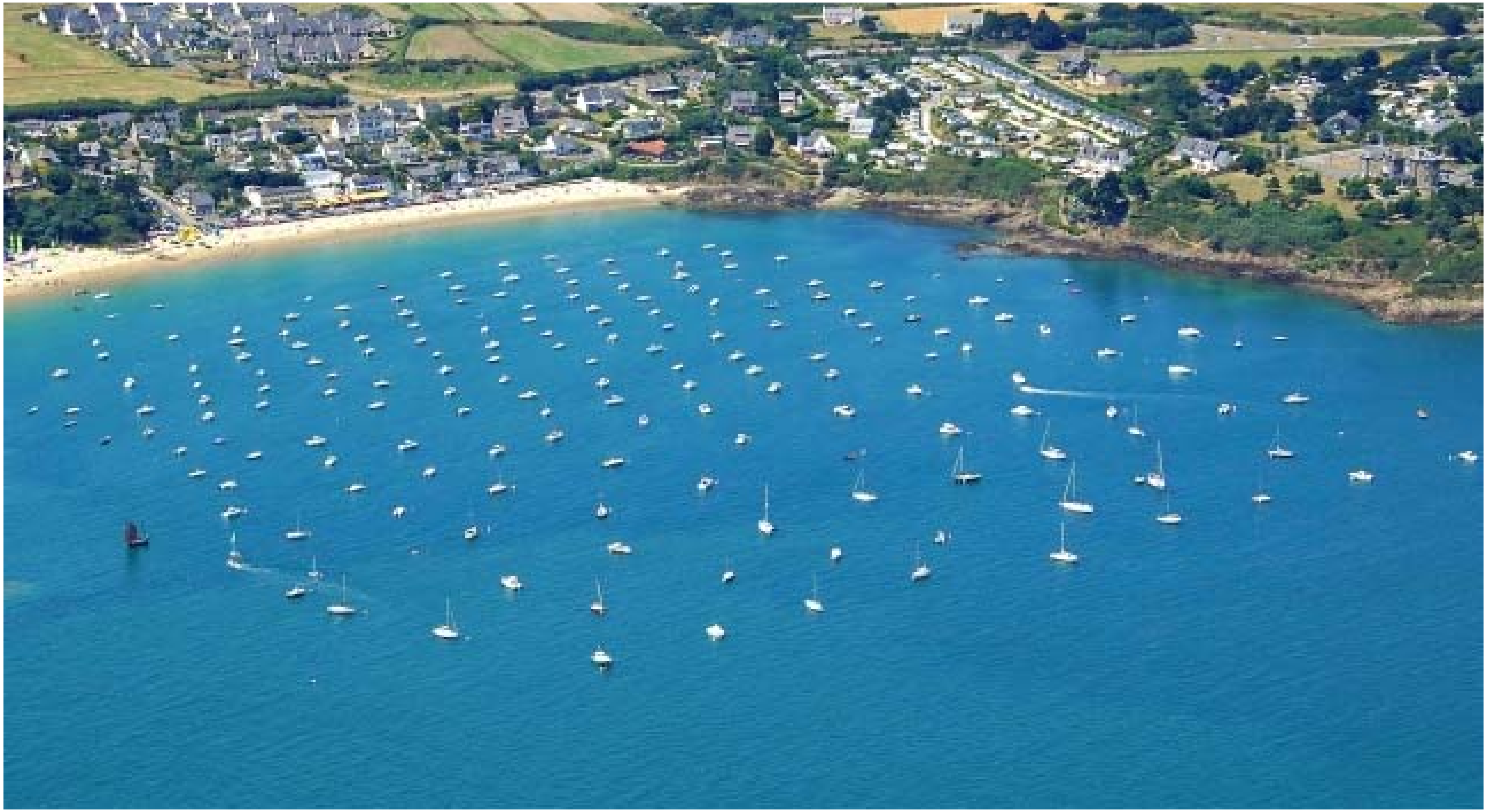
Supervised learning

- x can be multi-dimensional
    - Each dimension corresponds to an attribute



- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

Basic principles of classification



- Want to classify objects as boats and houses.

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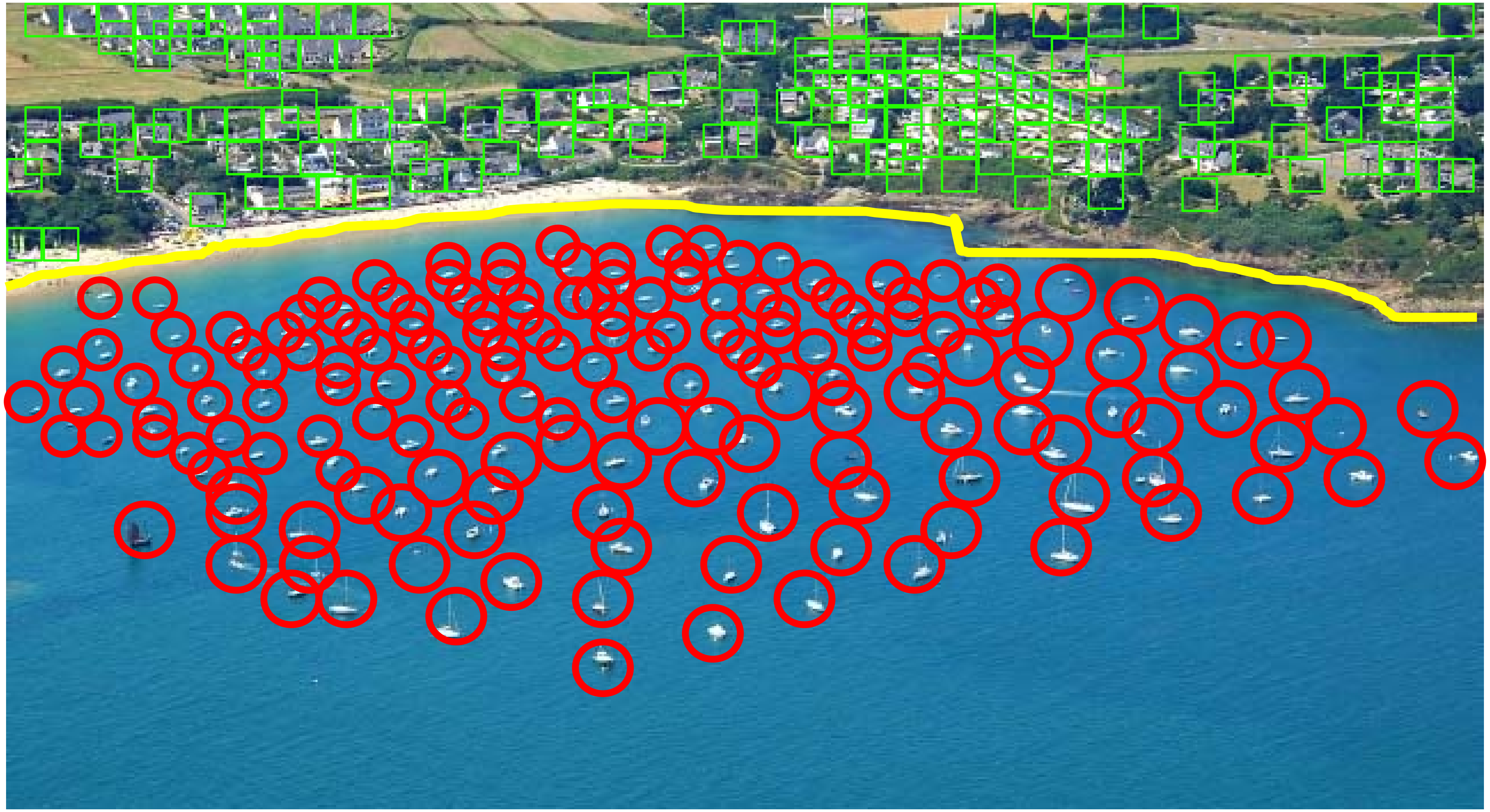
Basic principles of classification



- All objects before the coast line are boats and all objects after the coast line are houses.
- Coast line serves as a *decision surface* that separates two classes.

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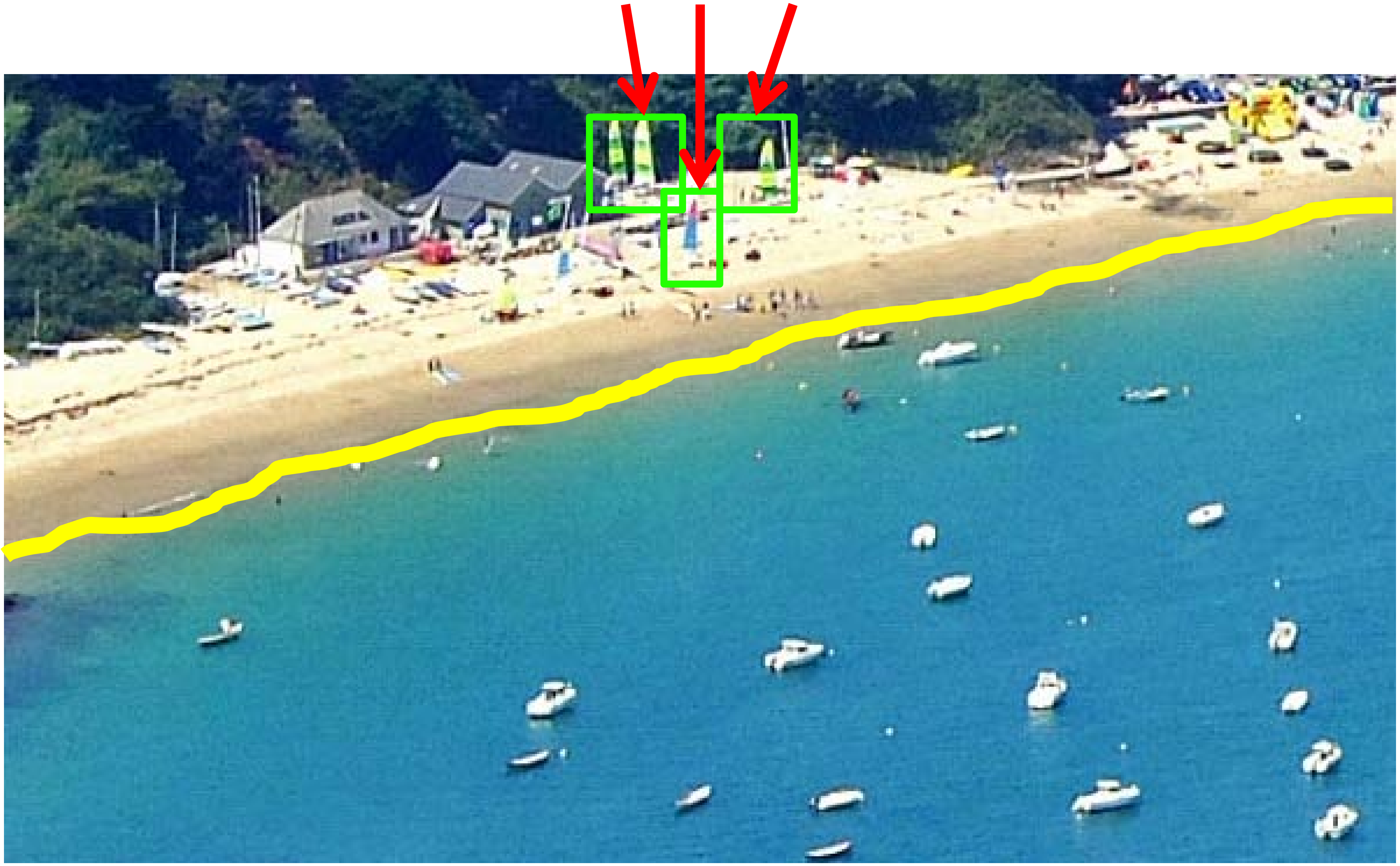
Basic principles of classification

These boats will be misclassified as houses



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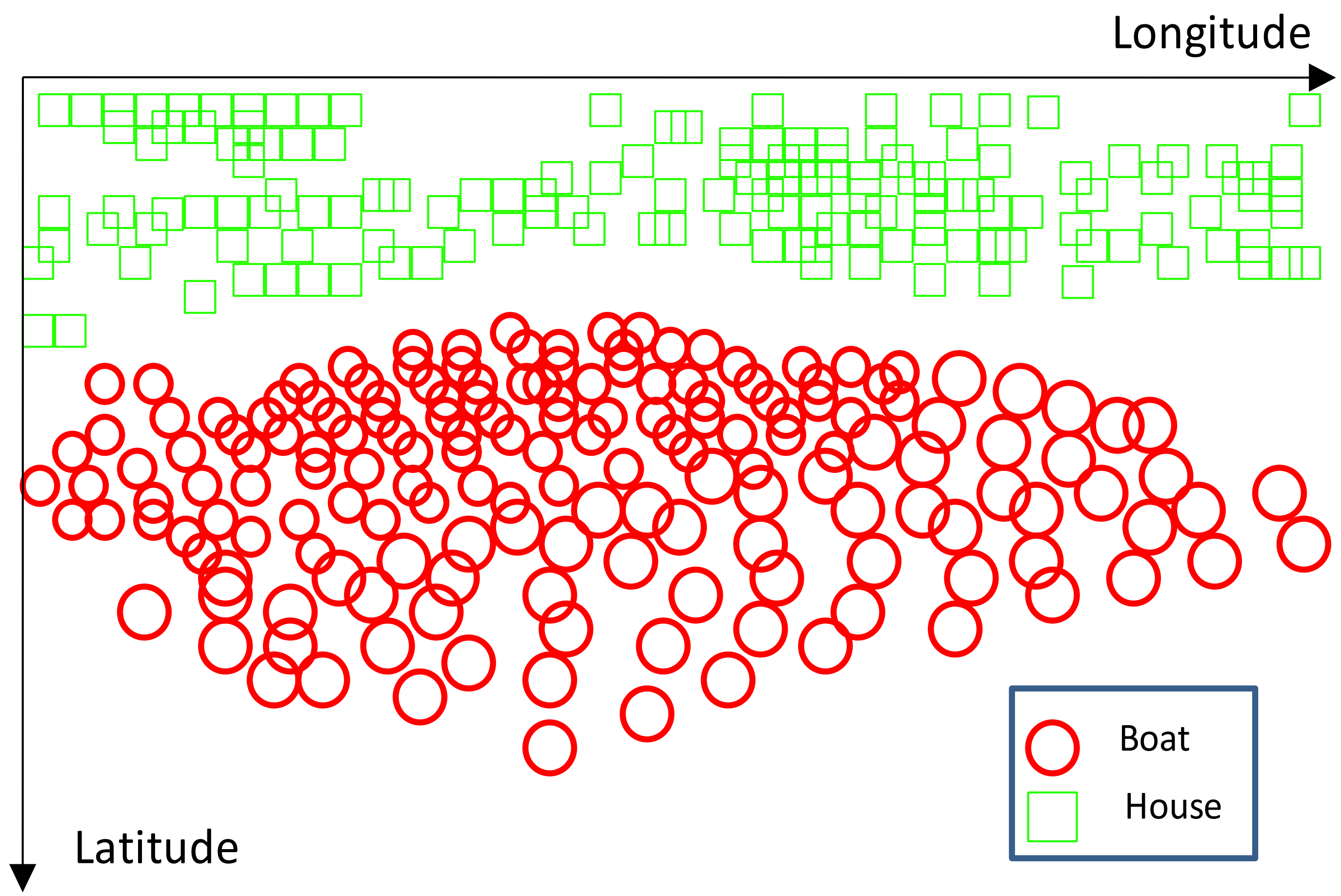
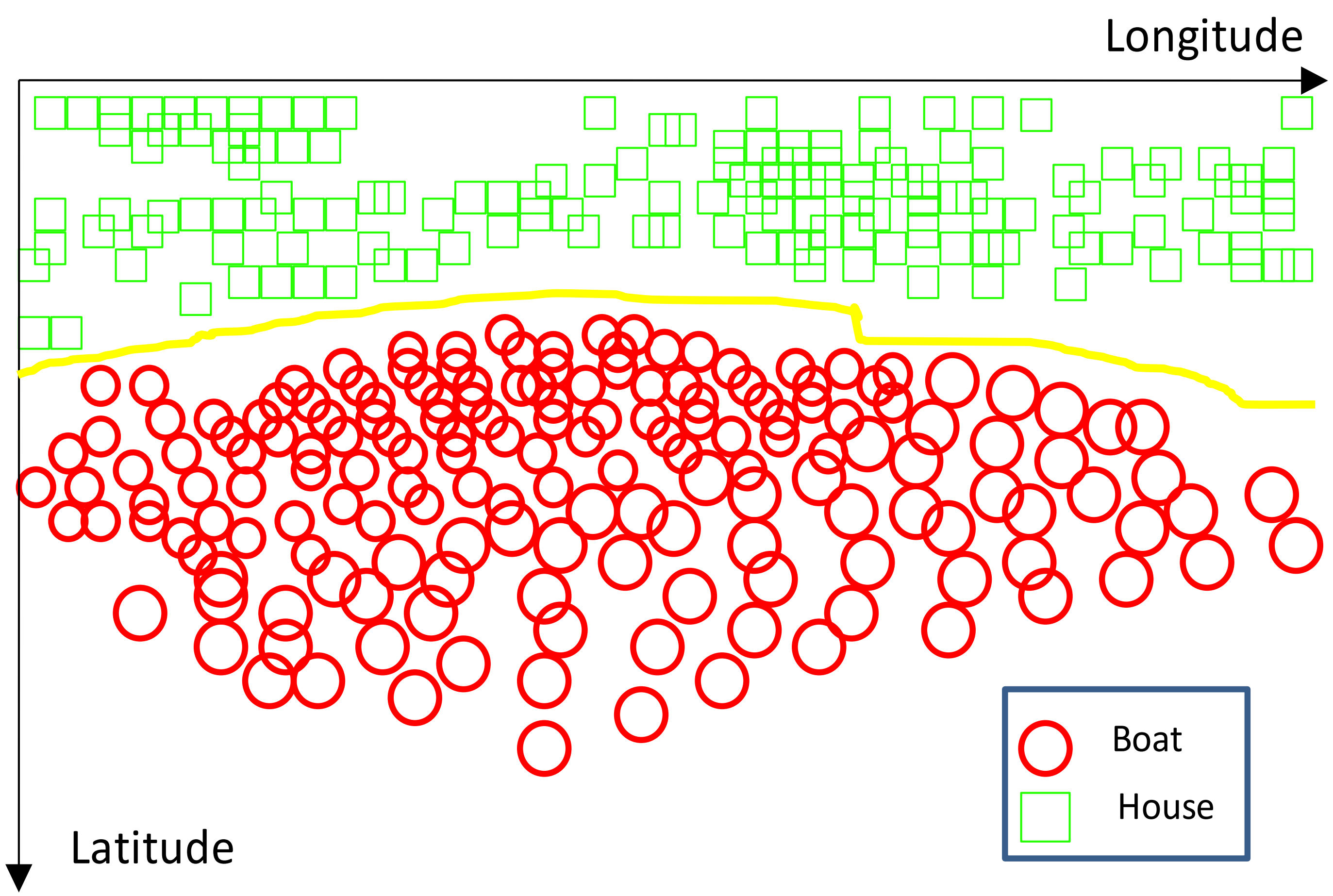
Basic principles of classification



- The methods that build classification models (i.e., "*classification algorithms*") operate very similarly to the previous example.
- First all objects are represented geometrically.

Basic principles of classification



Then the algorithm seeks to find a decision surface that separates classes of objects

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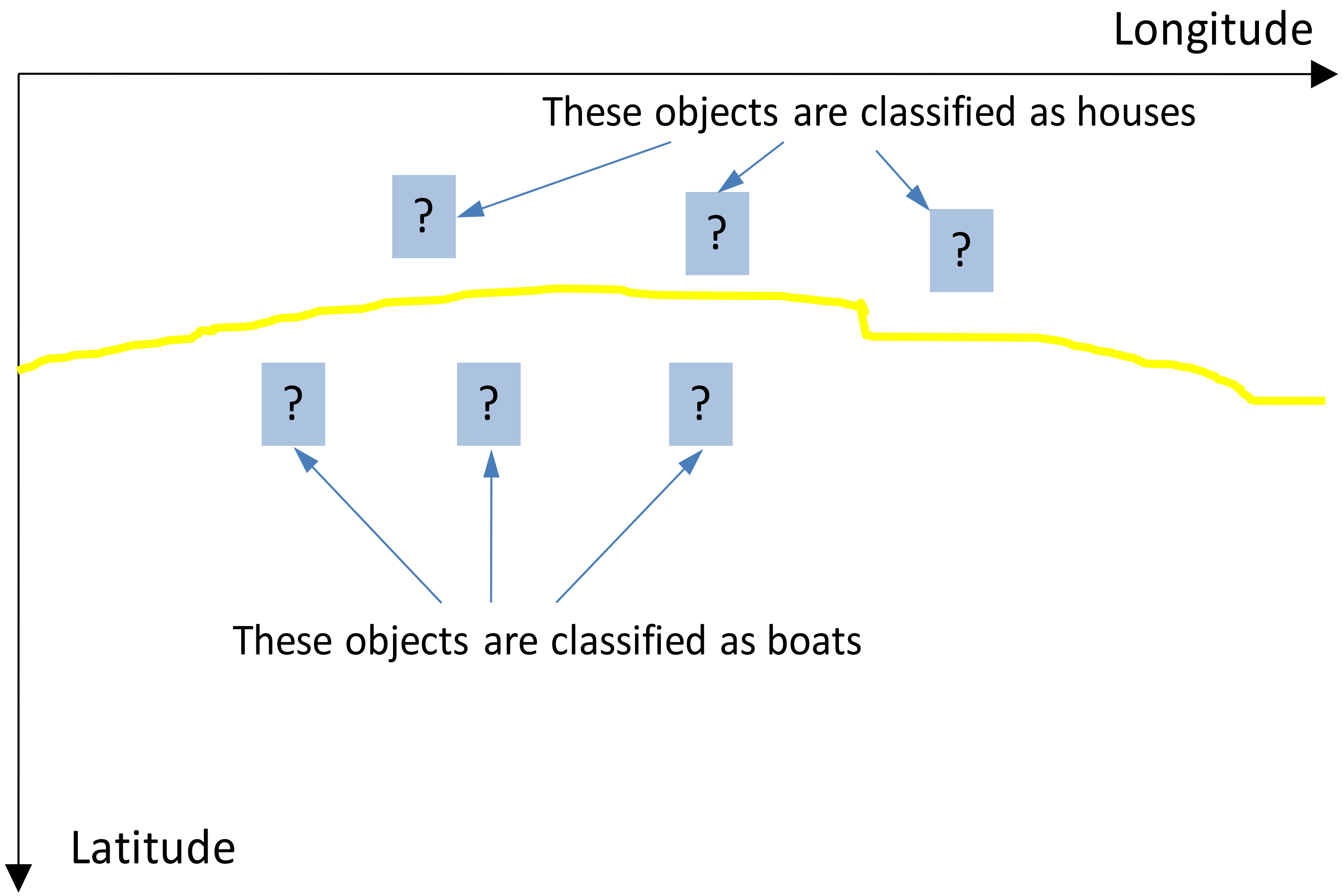
Basic principles of classification



Unseen (new) objects are classified as “boats” if they fall below the decision surface and as “houses” if the fall above it

SVM

- **Support vector machines** are considered by some people to be the **best stock classifier**.
  - Support vector machines make **good decisions** for **data points** that are **outside** the **training set**.

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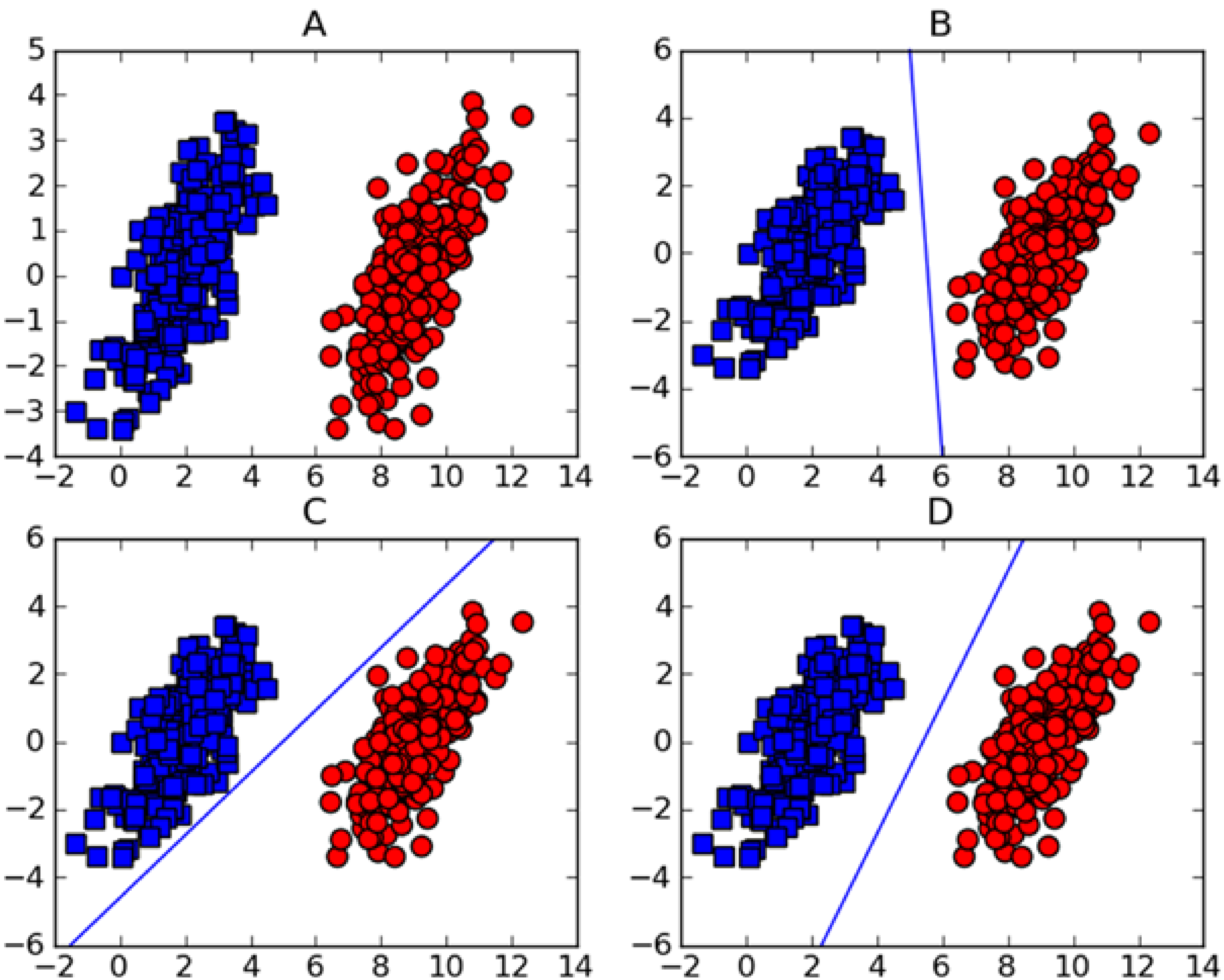
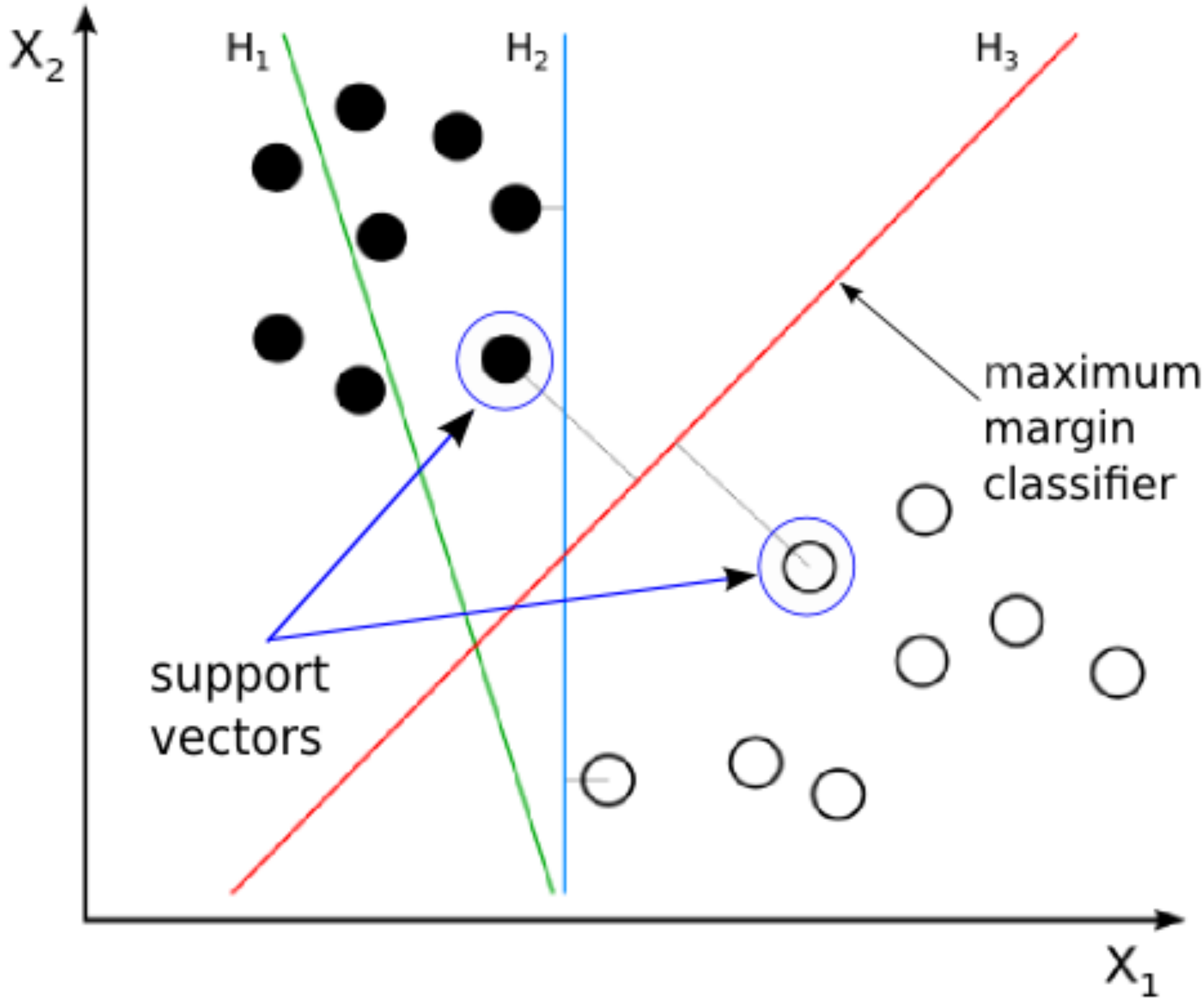

A
B
C
D
5 4 3 2 1 0 −1 −2 −3 −4
6 4 2 0 −2 −4 −6
−2 0 2 4 6 8 10 12 14



The point closest to the separating hyperplane and make sure this is as far away from the separating line as possible.

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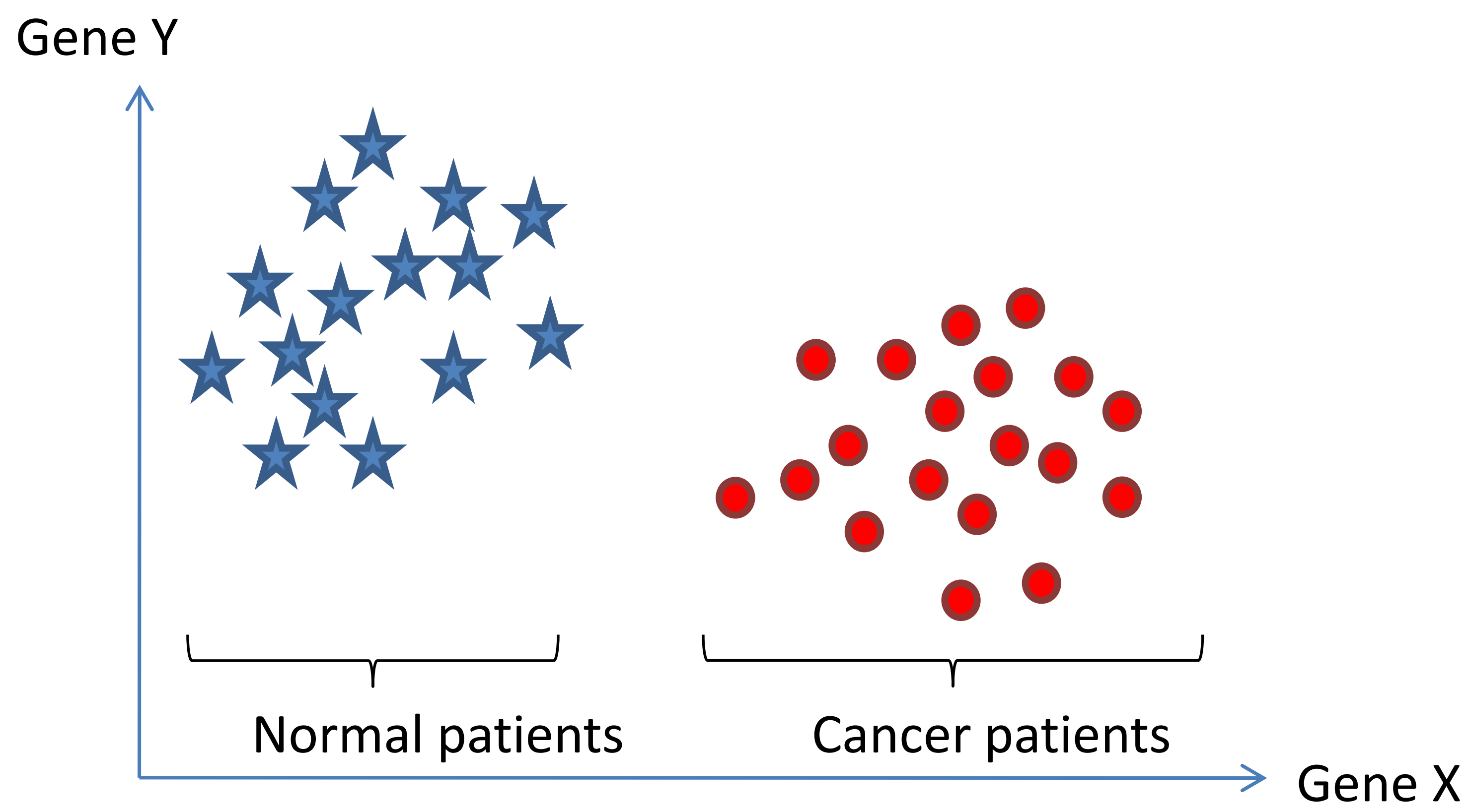
Main ideas of SVMs



- Consider example dataset described by 2 genes, gene X and gene Y
- Represent patients geometrically (by "vectors")

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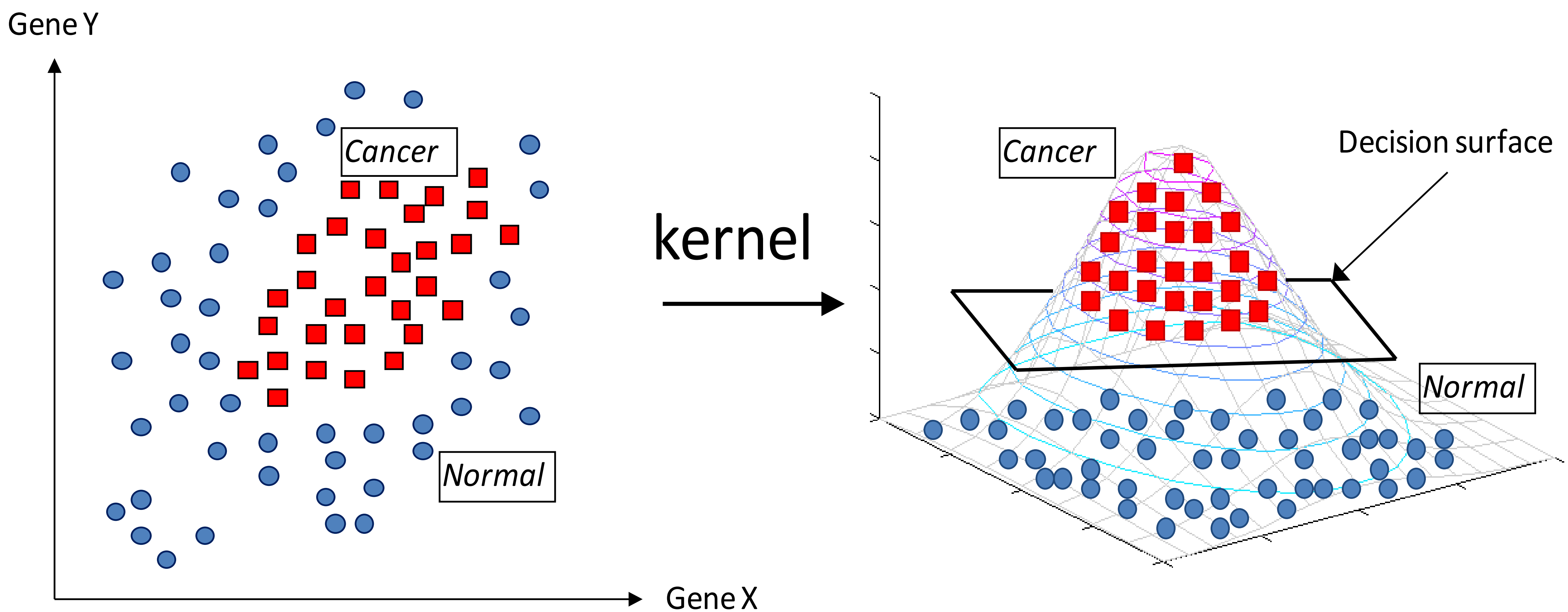
Main ideas of SVMs



- If such linear decision surface does not exist, the data is mapped into a much higher dimensional space ("feature space") where the separating decision surface is found;
- The feature space is constructed via very clever mathematical projection ("kernel trick").

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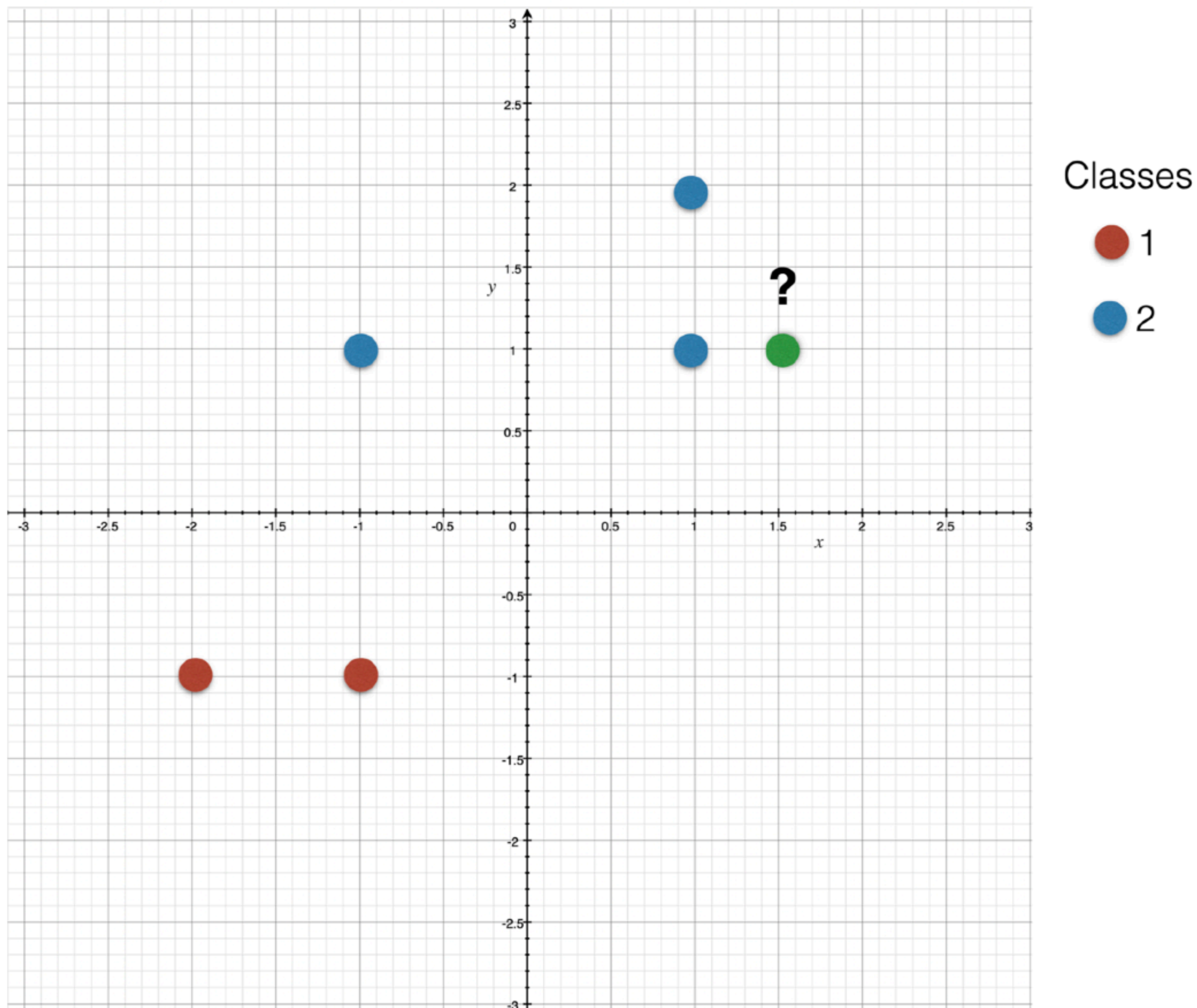
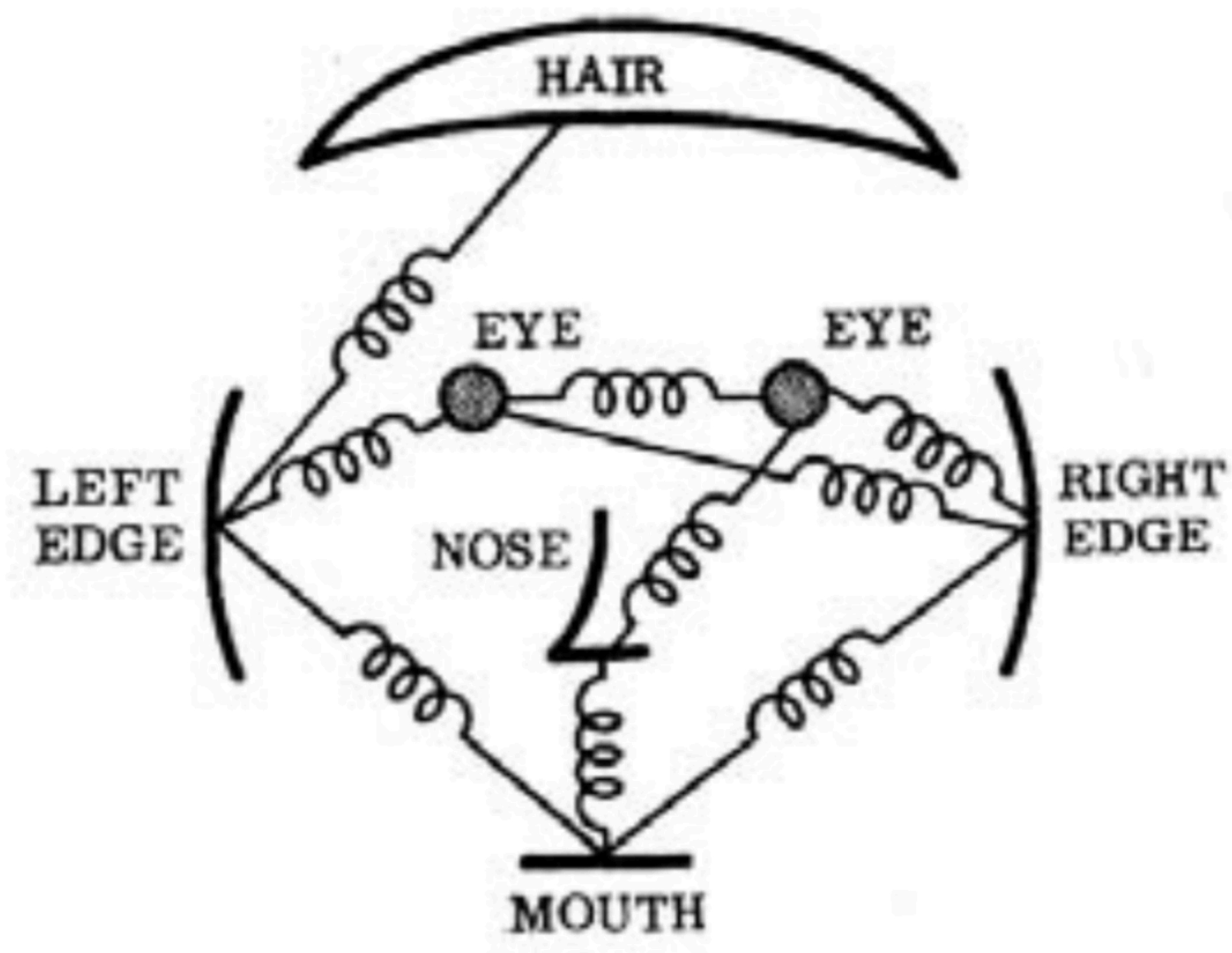
```python
import numpy as np
features = np.array([[-1, -1], [-2, -1], [1, 2], [-1, 1], [1, 1]])
labels = np.array([1, 1, 2, 2, 2])
from sklearn.svm import SVC
clf = SVC()
clf.fit(features, labels)
print(clf.predict([[1.5, 1]]))
```

```
[2]
```



Supervised Learning through

Deep Learning



Pictorial structures (Fischler and Elschlager, 1973)

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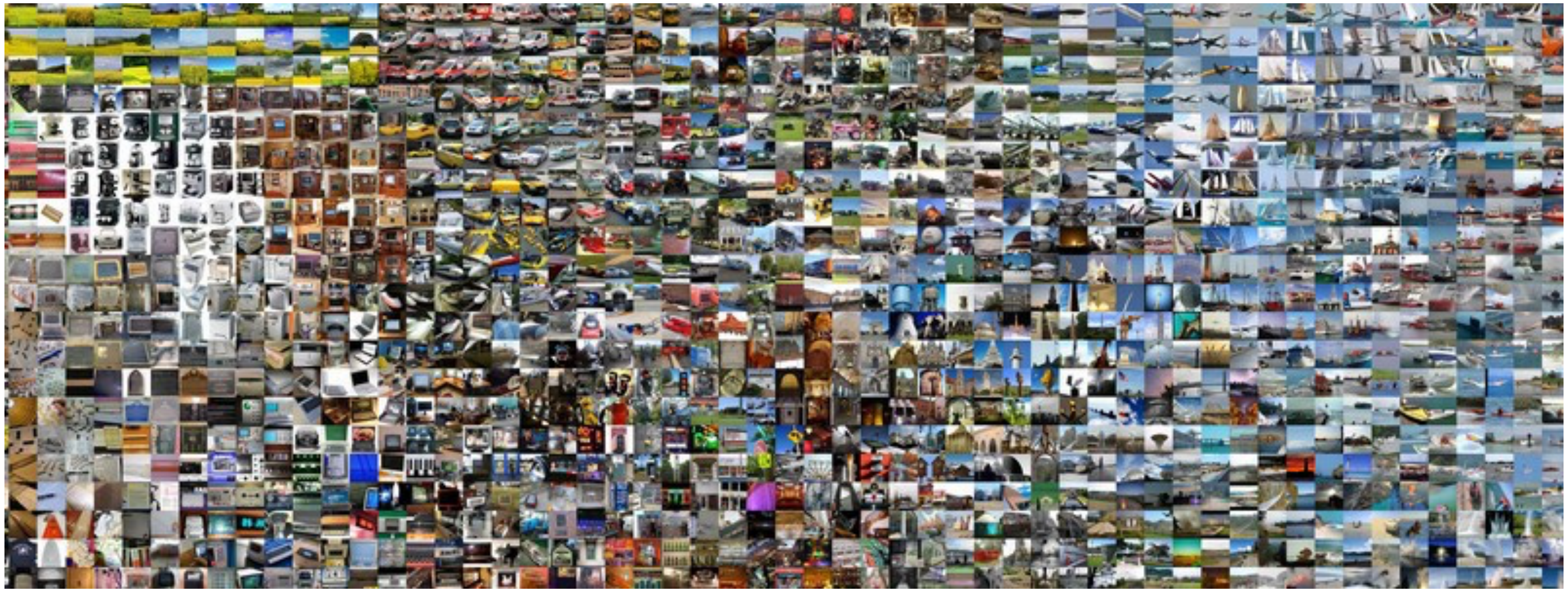
Why is Everyone So Excited about Deep Learning?

- Computer vision
  - ImageNet (1 million labeled images)
    - Yearly contest: train a classifier with the smallest possible error rate
    - Since 2012 - deep learning has been the winner!



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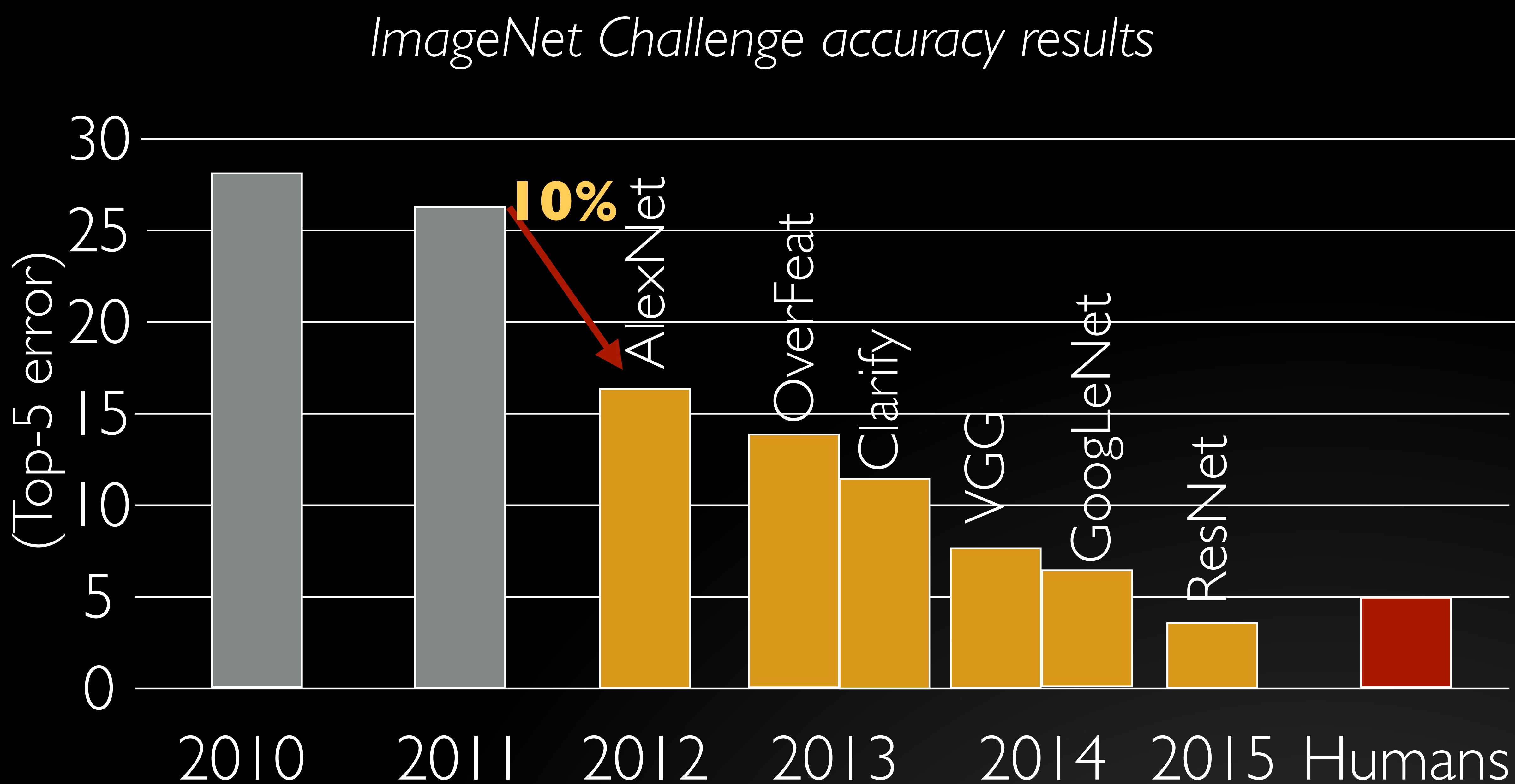

Sze, V., Chen, Y.-H. y Yang, T.-J. (2017). Efficient processing of deep neural networks: a tutorial survey. *Proceedings of the IEEE*, 105. https://doi.org/10.1109/JPROC.2017.2761740

Deep Learning

- Deep learning = layering
- **Goal:** build complex, hierarchical representations from simple building blocks.
- Traditional artificial neural networks = few layers
- Deep artificial neural networks = several layers (6 - 8, similar to the visual cortex)

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input → function → output

fundus of the eye picture

machine learning

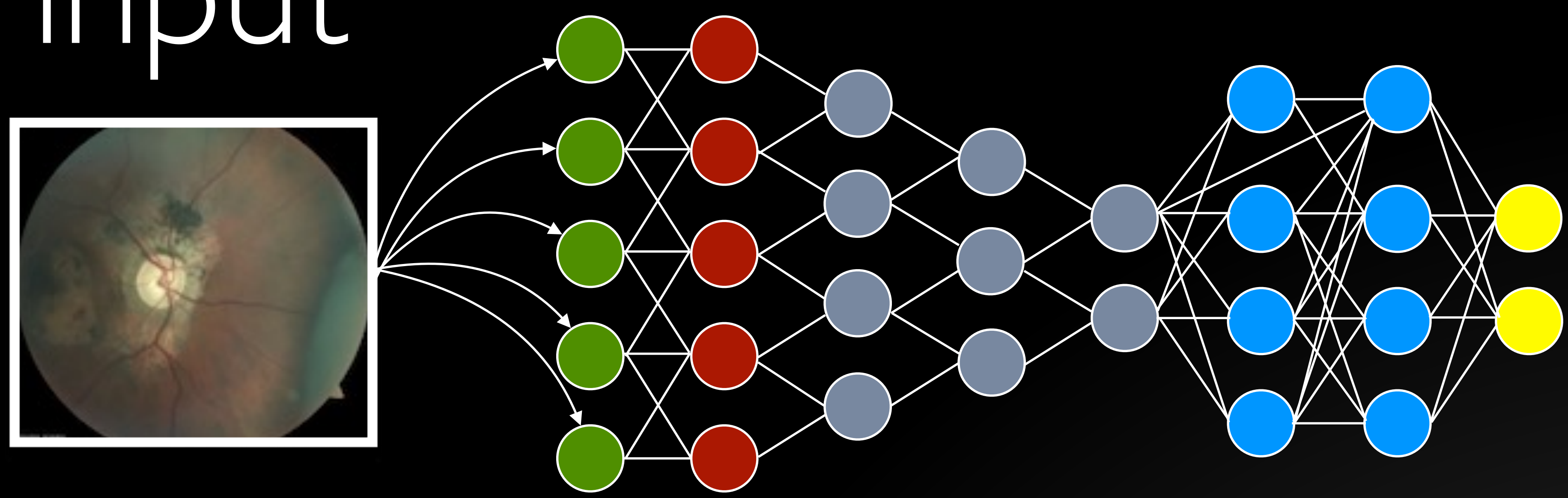
probability of classes

glaucoma = 0.99624

no glaucoma = 0.00869

input

output



glaucoma = 0.99624

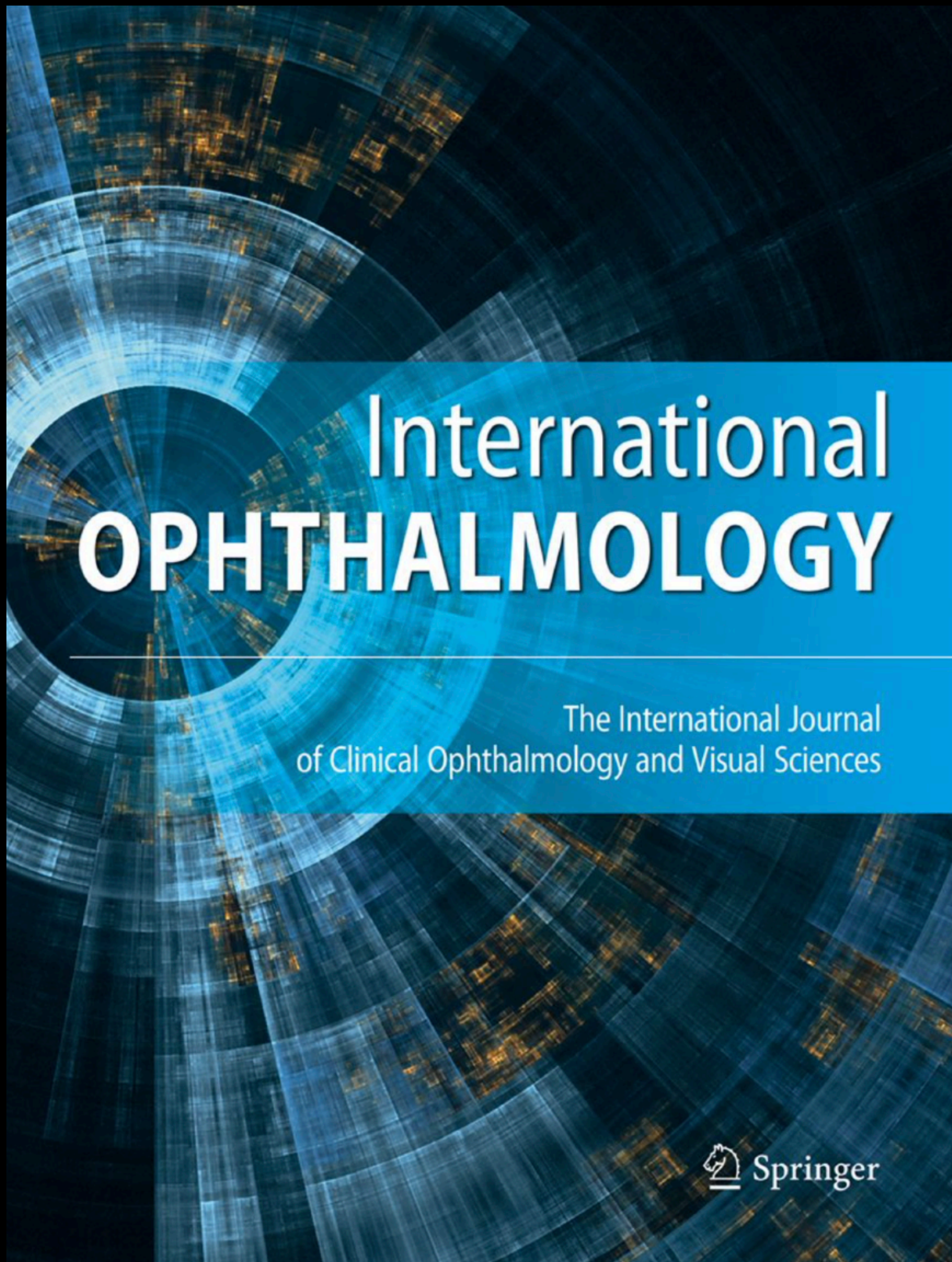
no glaucoma = 0.00869

fundus of the eye picture

Imágenes de pacientes **sin glaucoma**	Clasificación automática: **no glaucoma**
	0.99762
	0.99444
	0.9948

Imágenes de pacientes **con glaucoma**	Clasificación automática: **glaucoma**
	0.99754
	0.99989
	0.99624

Espinoza, M., Alférez, G.H. y Castillo, J. (2018). Prediction of glaucoma through convolutional neural networks. En H. R. Arabnia, L. Deligiannidis, G. Jandieri, A. M. G., F. G. Tinetti y Q.-N. Tran (Eds.), *International Conference on Health Informatics and Medical Systems: The 2018 WorldComp International Conference Proceedings* (p. 90-95). CSREA Press.



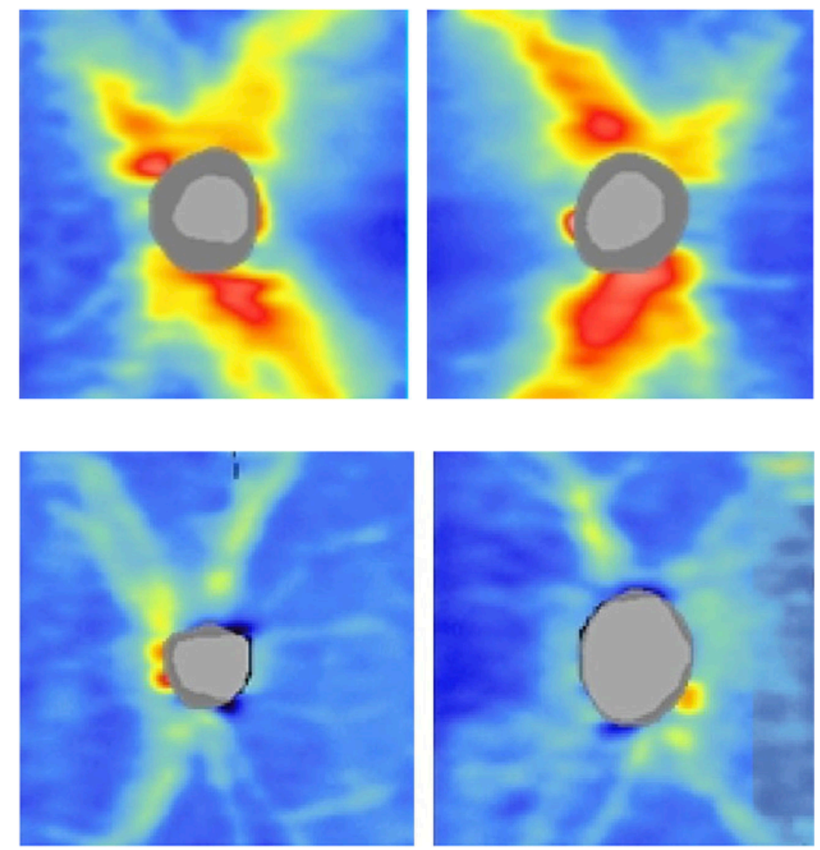


Fig. 3 Non-glaucomatous left and right eyes, respectively

Fig. 4 Glaucomatous left and right eyes, respectively

Olivas, L.G., Alférez, G.H., & Castillo, J. (2021). Glaucoma detection in Latino population through OCT's RNFL thickness map using transfer learning. International Ophthalmology. https://doi.org/10.1007/s10792-021-01931-w

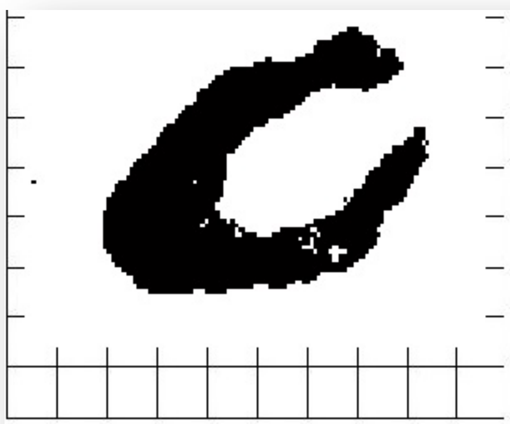
“Misdiagnosis in the United States is disconcertingly common. A review of three very large studies concluded that there are about 12 million significant misdiagnoses a year.”

— Eric Topol. “Deep Medicine.”

1

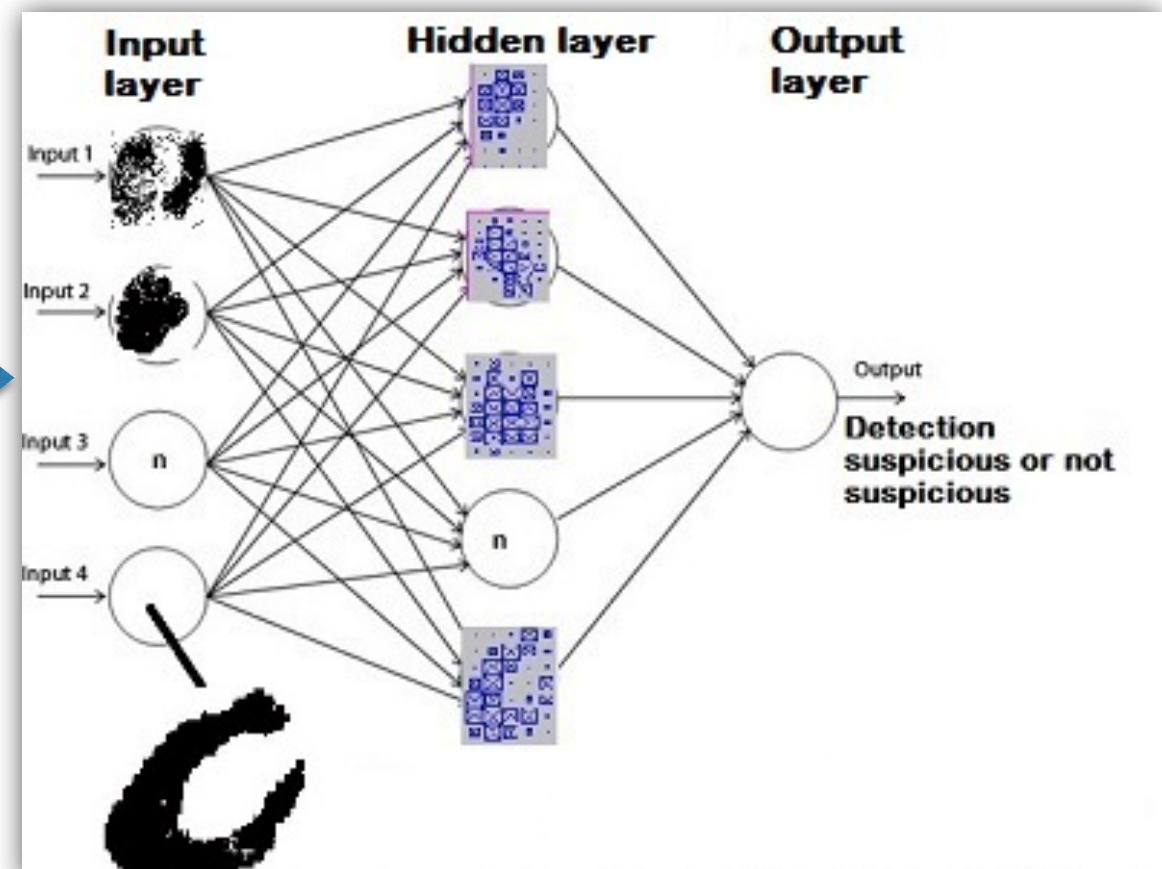
2

3



0	0	0	1	1	0	0	0	0	0
0	0	0	1	1	0	0	0	0	0
0	0	1	1	1	1	1	0	0	0
0	1	1	0	0	1	1	1	0	0
0	1	1	1	1	1	1	1	1	0
0	1	0	0	0	0	0	1	1	0
0	1	0	0	0	0	0	0	1	1
0	1	0	0	0	0	0	0	1	1

4



Marín, C., Alférez, G.H. Córdova, J. y González, V. (2015). Detection of melanoma through image recognition and artificial neural networks. En D. A. Jaffray (Ed.), *World congress on medical physics and biomedical engineering* (pp. 832–835). Springer.

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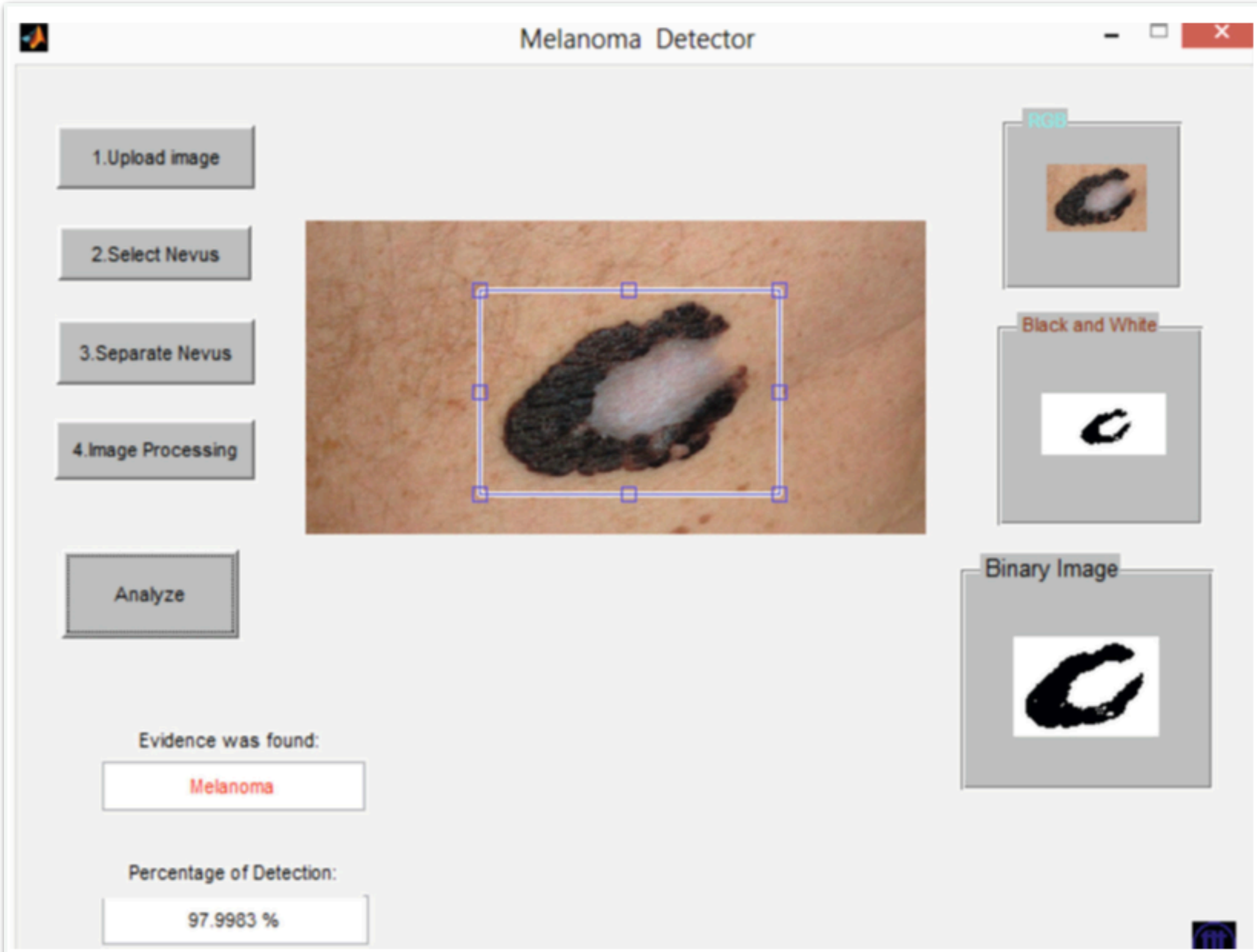

Marín, C., Alférez, G.H. Córdova, J. y González, V. (2015). Detection of melanoma through image recognition and artificial neural networks. En D. A. Jaffray (Ed.), *World congress on medical physics and biomedical engineering* (pp. 832–835). Springer.

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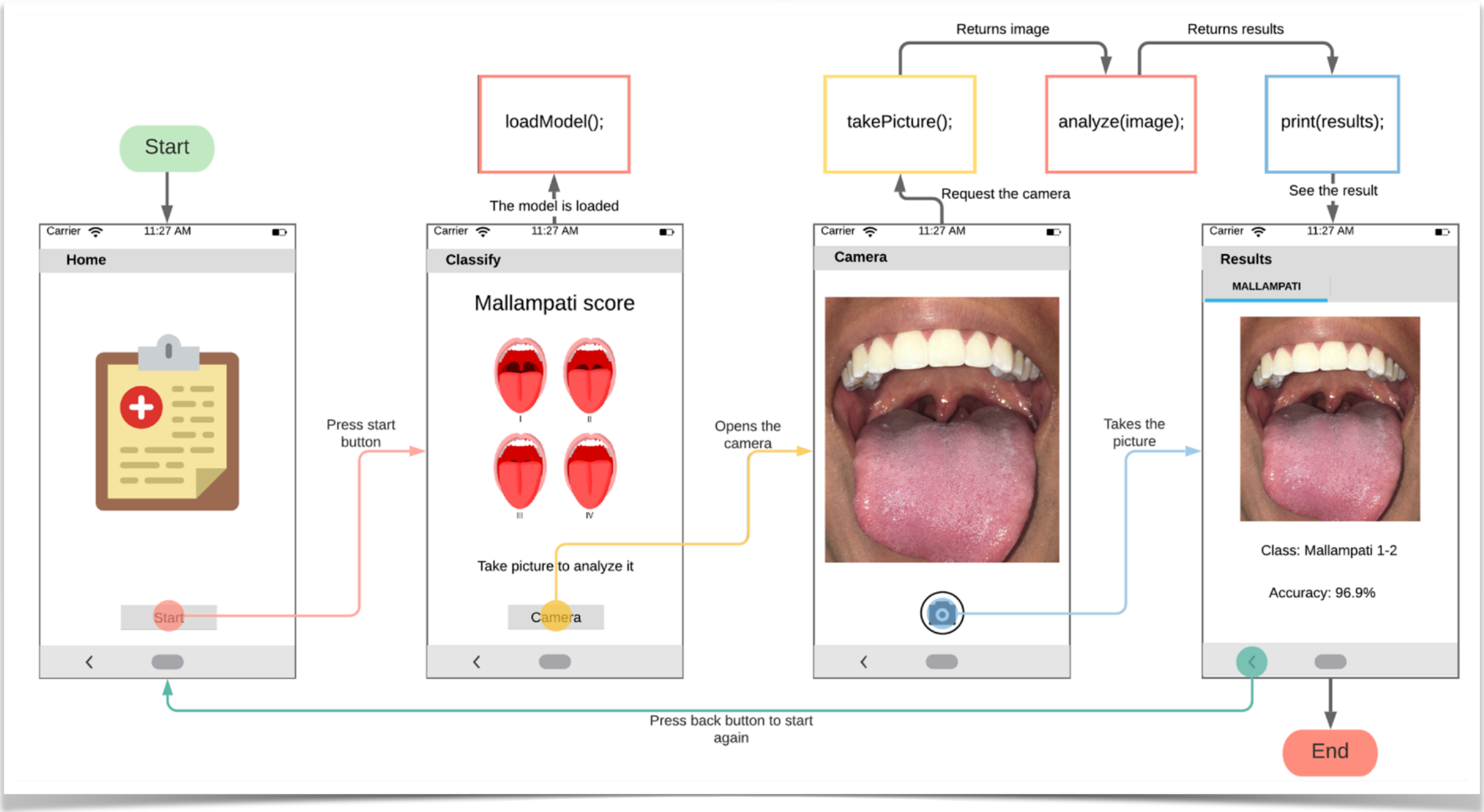

Aguilar, K, Alférez, G.H. y Aguilar, C. (2020). Detection of difficult airway using deep learning. *Machine Vision and Applications*, 31. https://doi.org/10.1007/ s00138-019-01055-3

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Sylnice, J. & Alférez, G.H. (2018). Dynamic Evolution of Simulated Autonomous Cars in the Open World Through Tactics. *Proceedings of the Future Technologies Conference 2018 (FTC 2018)*, Vancouver, Canada.

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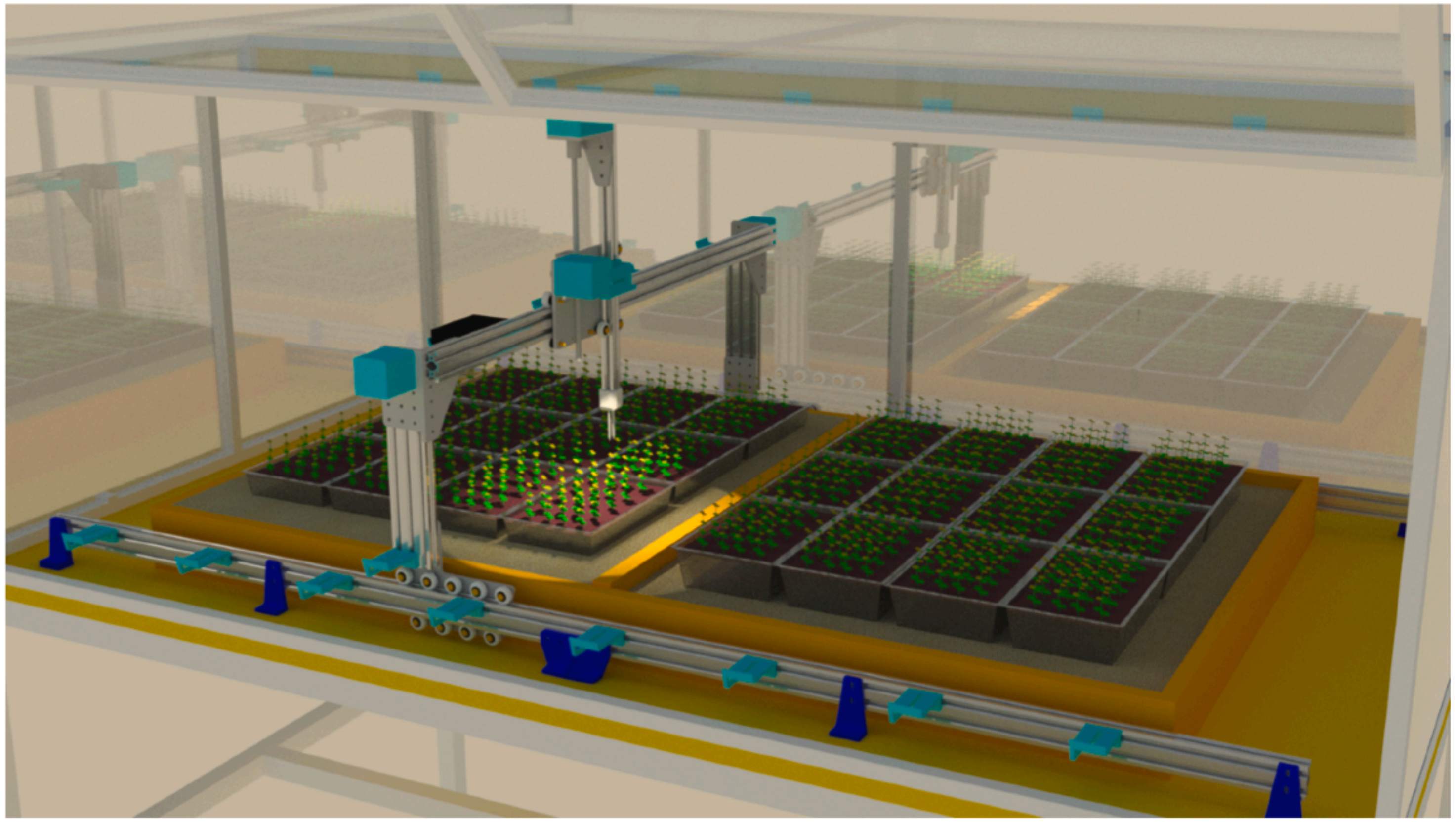

Fig. 1. CNC robotic system.

Fig. 2. Tray with living Legacy blueberry plants.

Fig. 3. Tray without living Legacy blueberry plants.

Fig. 4. No tray.

Quiroz, I. A. y Alférez, G. H. (2020). Image recognition of Legacy blueberries in a Chilean smart farm through deep learning. Computers and Electronics in Agriculture, 168, 105044. https://doi.org/10.1016/ j.compag.2019.105044

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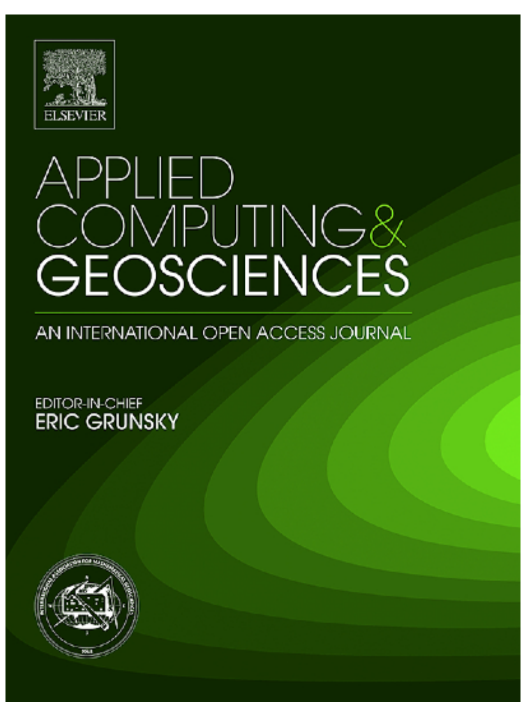
Automatic classification of plutonic rocks with deep learning

Germán H. Alférez, Elías L. Vázquez, Ana María Martínez Ardila, Benjamin Clausen

Applied Computing and Geosciences - Elsevier
https://doi.org/10.1016/j.acags.2021.100061



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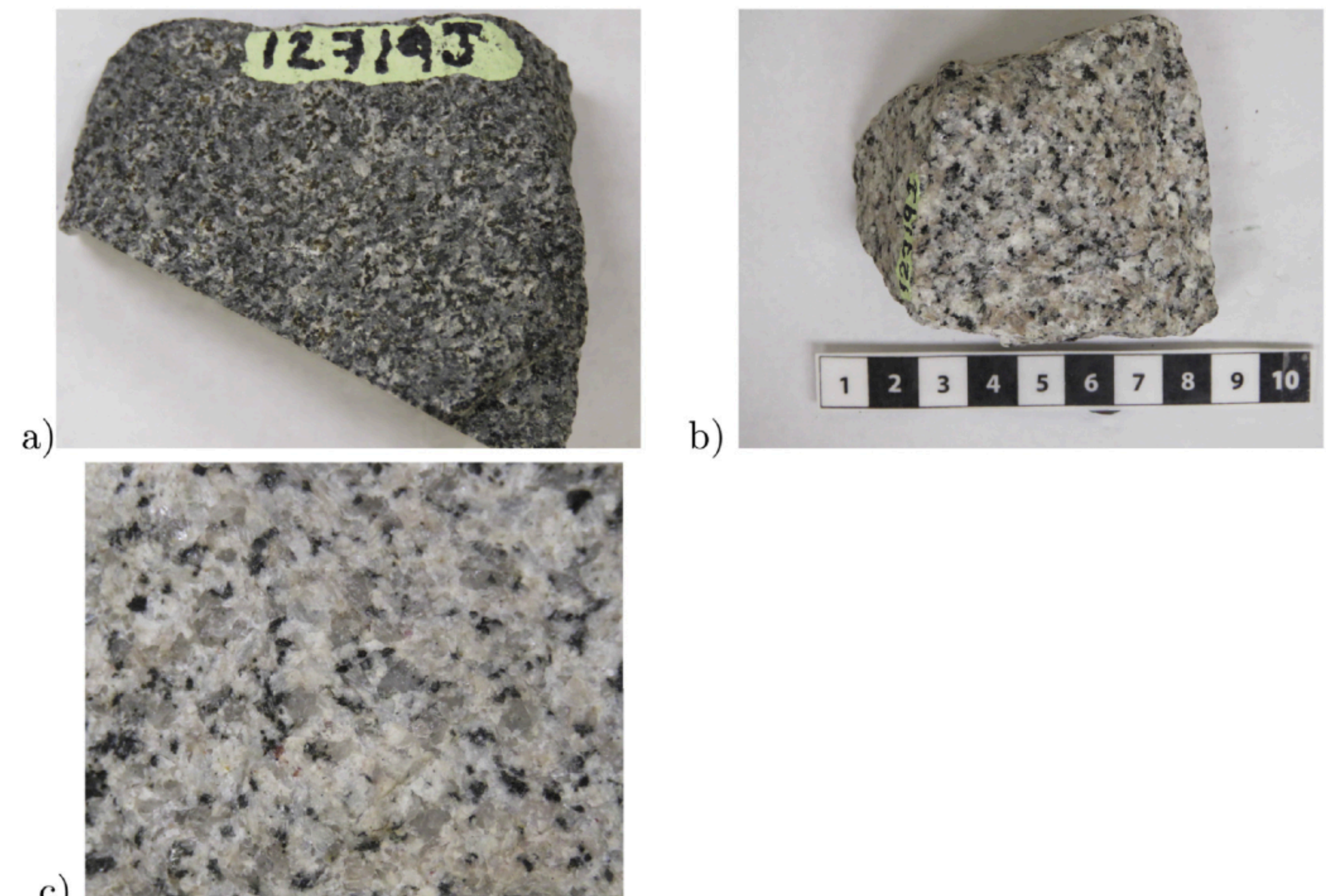


Fig. 2. a) Diorite image taken under white light; b) granite image with a ruler; and c) a cropped granite picture.

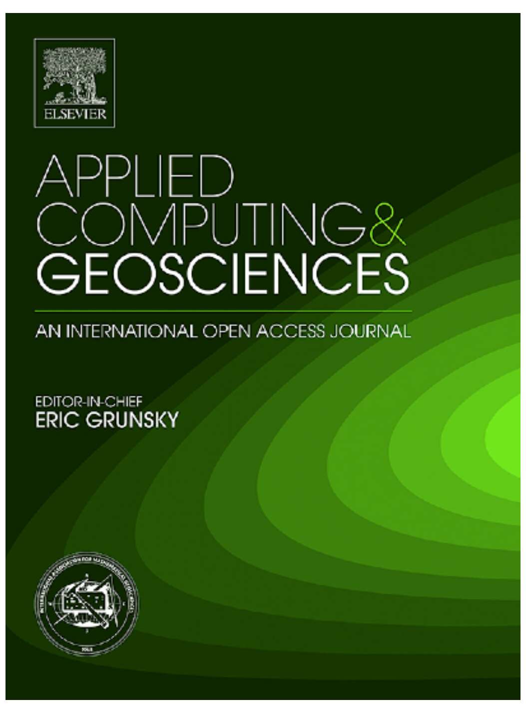
Automatic classification of plutonic rocks with deep learning

Germán H. Alférez, Elías L. Vázquez, Ana María Martínez Ardila, Benjamin Clausen

Applied Computing and Geosciences - Elsevier
https://doi.org/10.1016/j.acags.2021.100061

Rock Classes	Precision	Recall	F_1 Score
gabbro	0.98	0.94	0.96
diorite	1.00	0.94	0.97
granodiorite	0.85	1.00	0.92
granite	1.00	0.94	0.97
Average	***0.96***	***0.95***	***0.95***

Table 5: Validation results per class for the gabbro, diorite, granodiorite, and granite combi
nation with an accuracy of 0.95.



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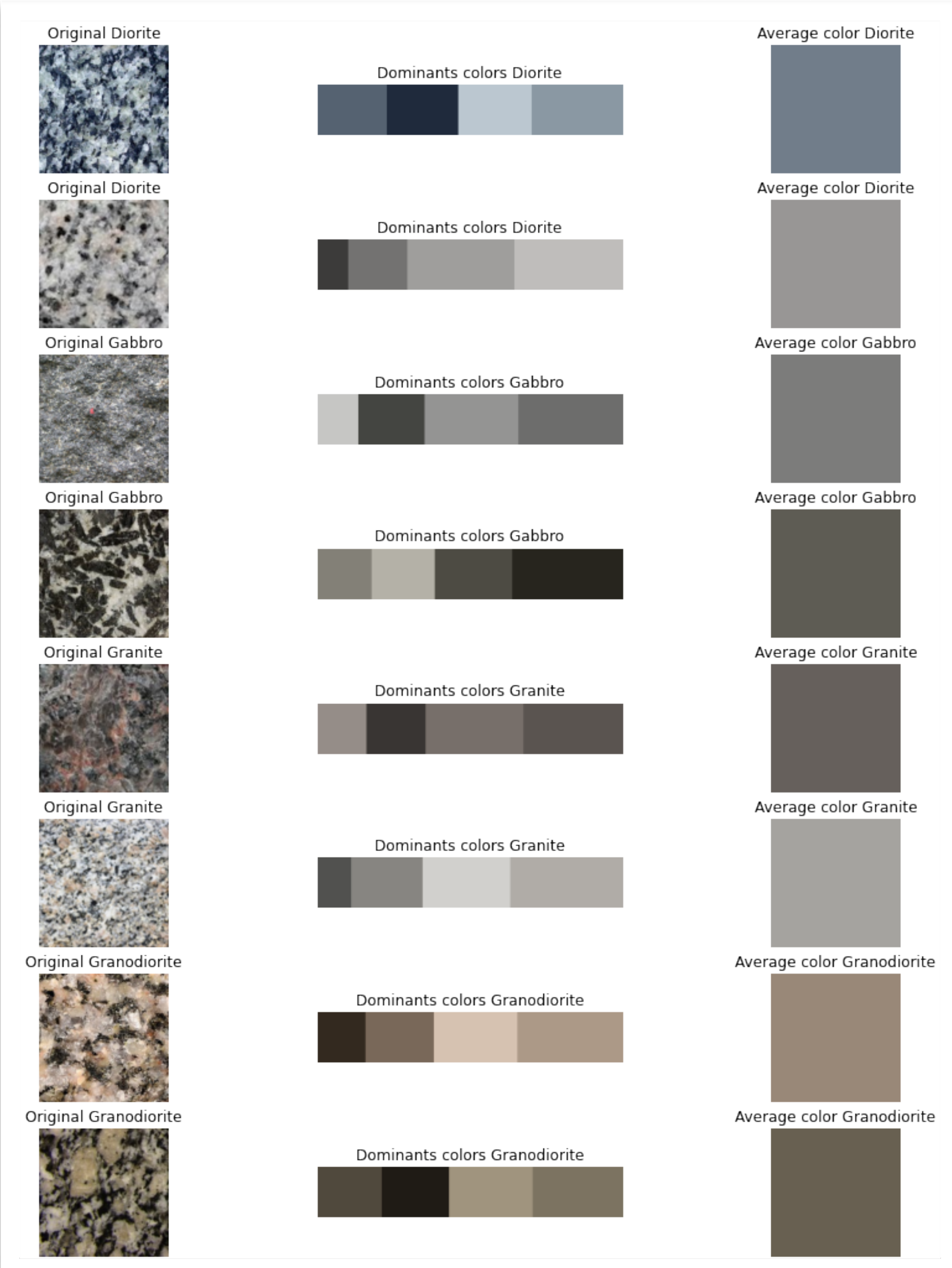

Automatic Classification of Plutonic Rocks with Machine Learning Applied to Extracted Shades and Colors on iOS Devices

Alférez, G.H., Hernández Serrano, S., Martínez Ardila, A.M., & Clausen, B.L. (2021). Automatic Classification of Plutonic Rocks with Machine Learning Applied to Extracted Shades and Colors on iOS Devices.

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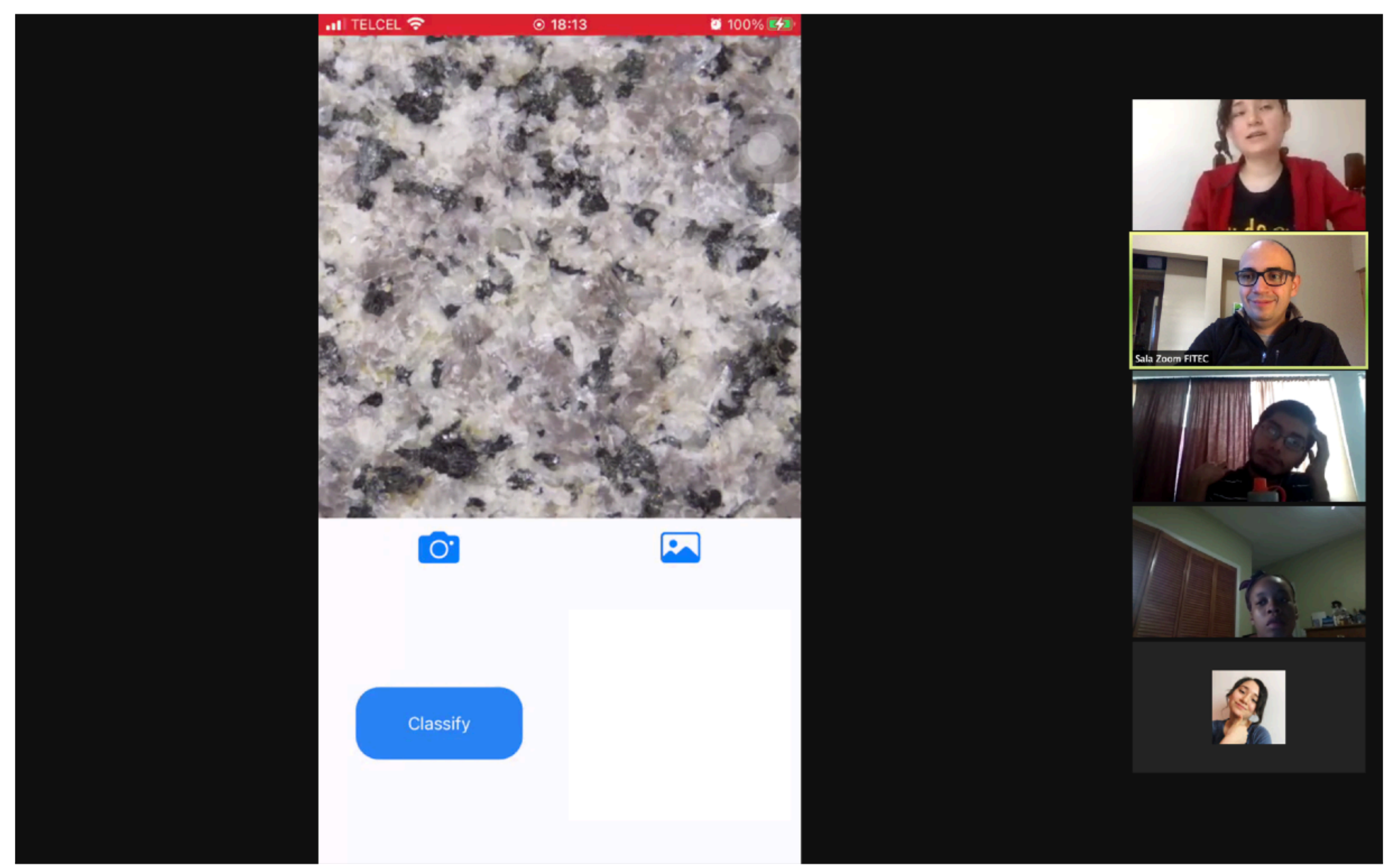

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Automatic Classification of Felsic, Mafic, and Ultramafic Rocks in Satellite Images from Palmira and La Victoria, Colombia

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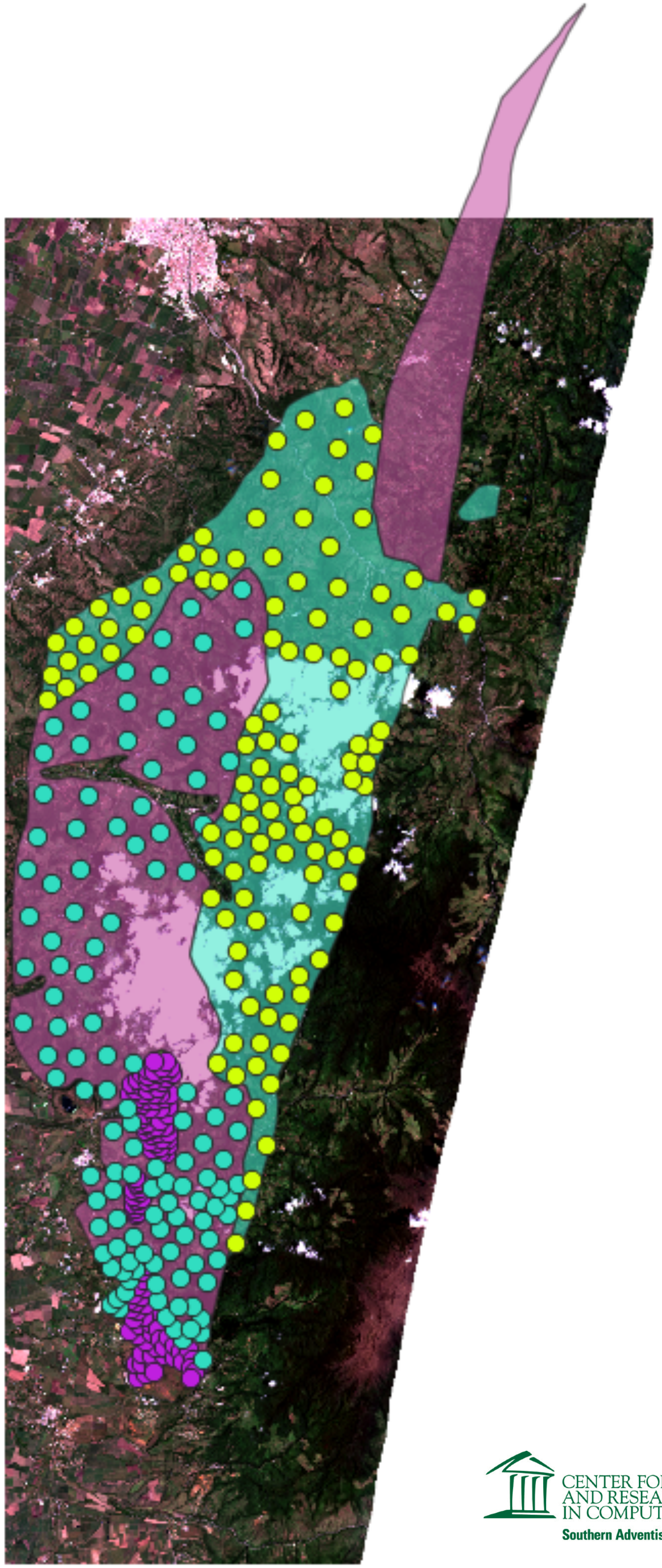

Bosquez, S., Alférez, G.H., Martínez Ardila, A.M., & Clausen B.L. (2022). Automatic Classification of Felsic, Mafic, and Ultramafic Rocks in Satellite Images from Palmira and La Victoria, Colombia. *Proceedings of the Computing Conference 2022*, London, England.

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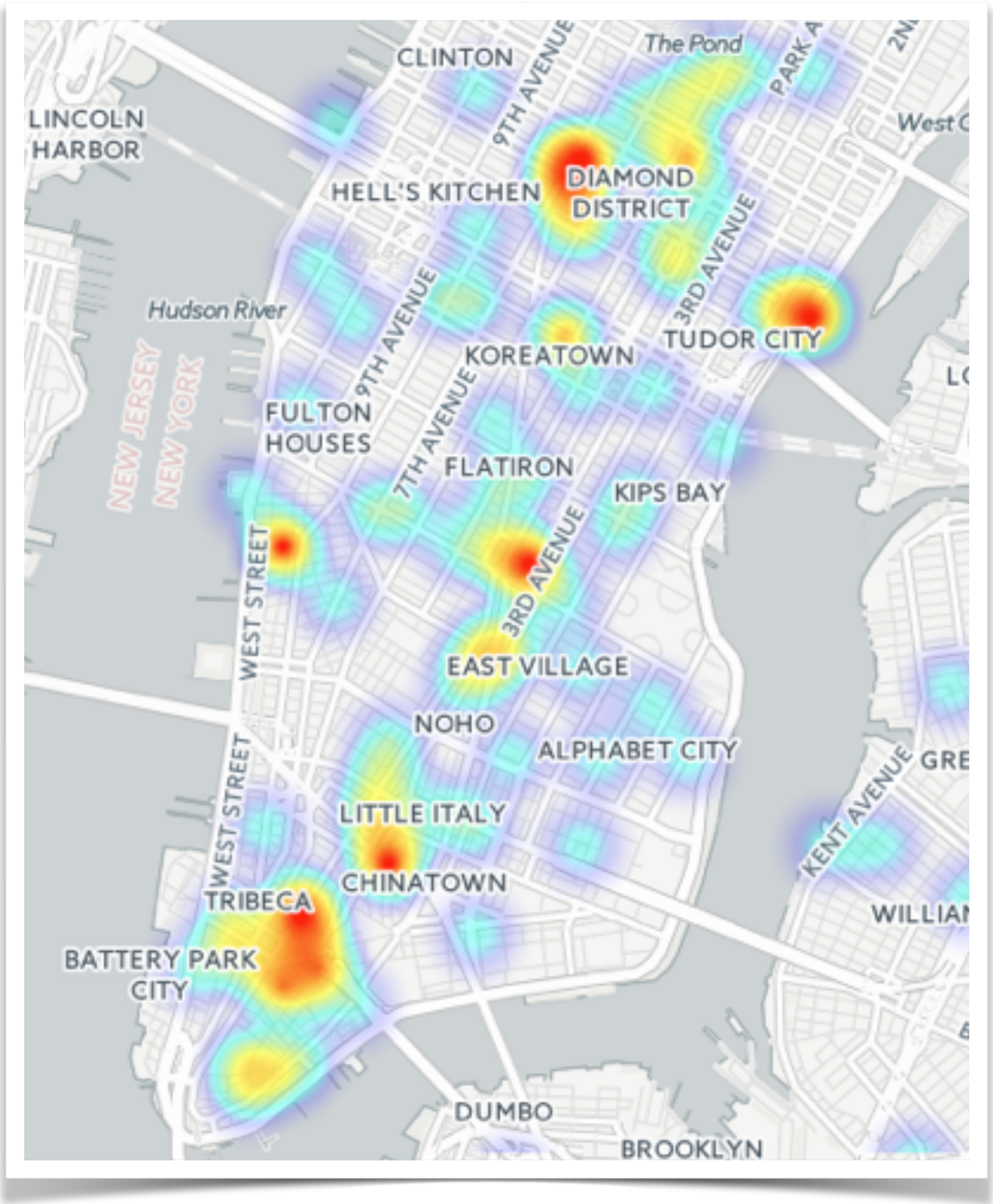

Areas with negative tweets in Manhattan

Alférez, G.H. (2016). Tweeting in New York City - Data Science Can Teach Us to Sympathize. Adventist Review, 193(2), 47-49

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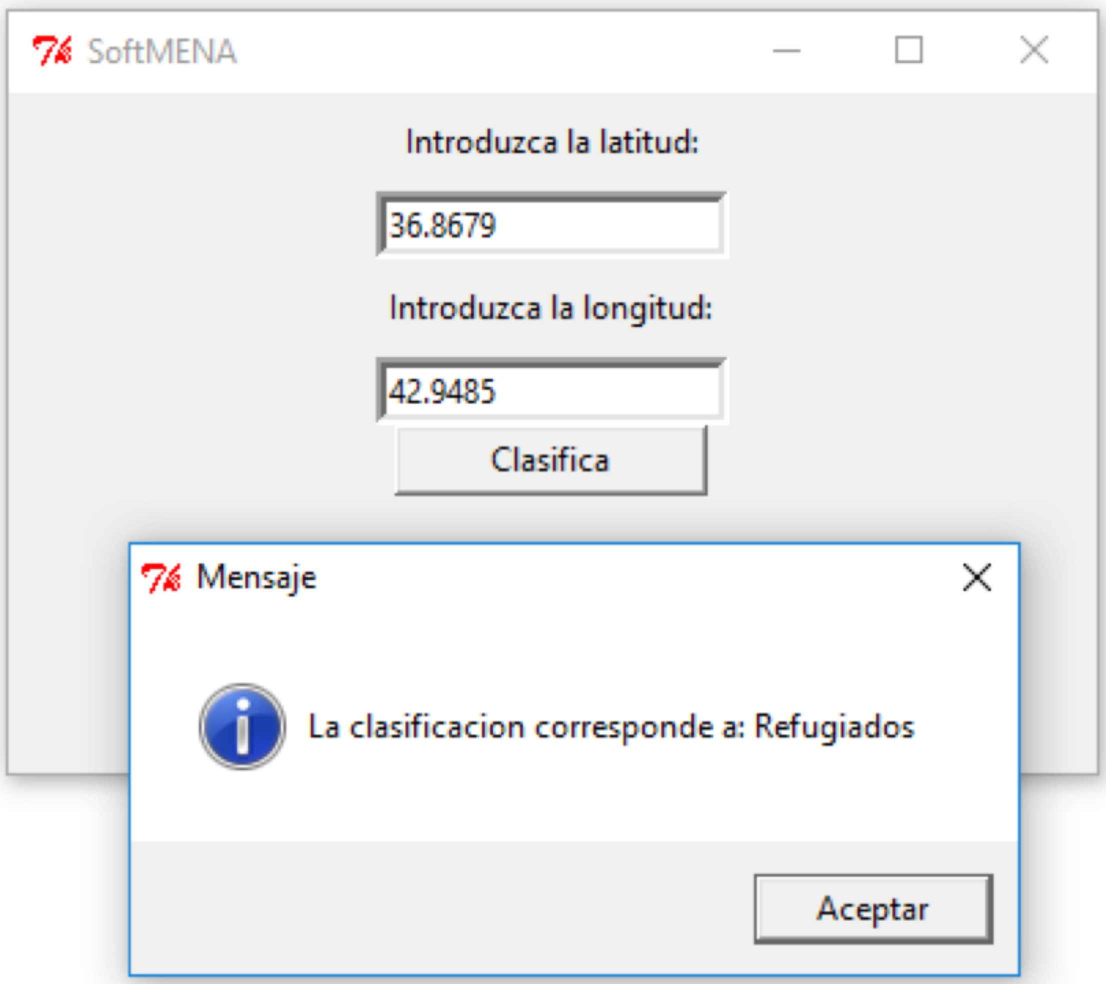

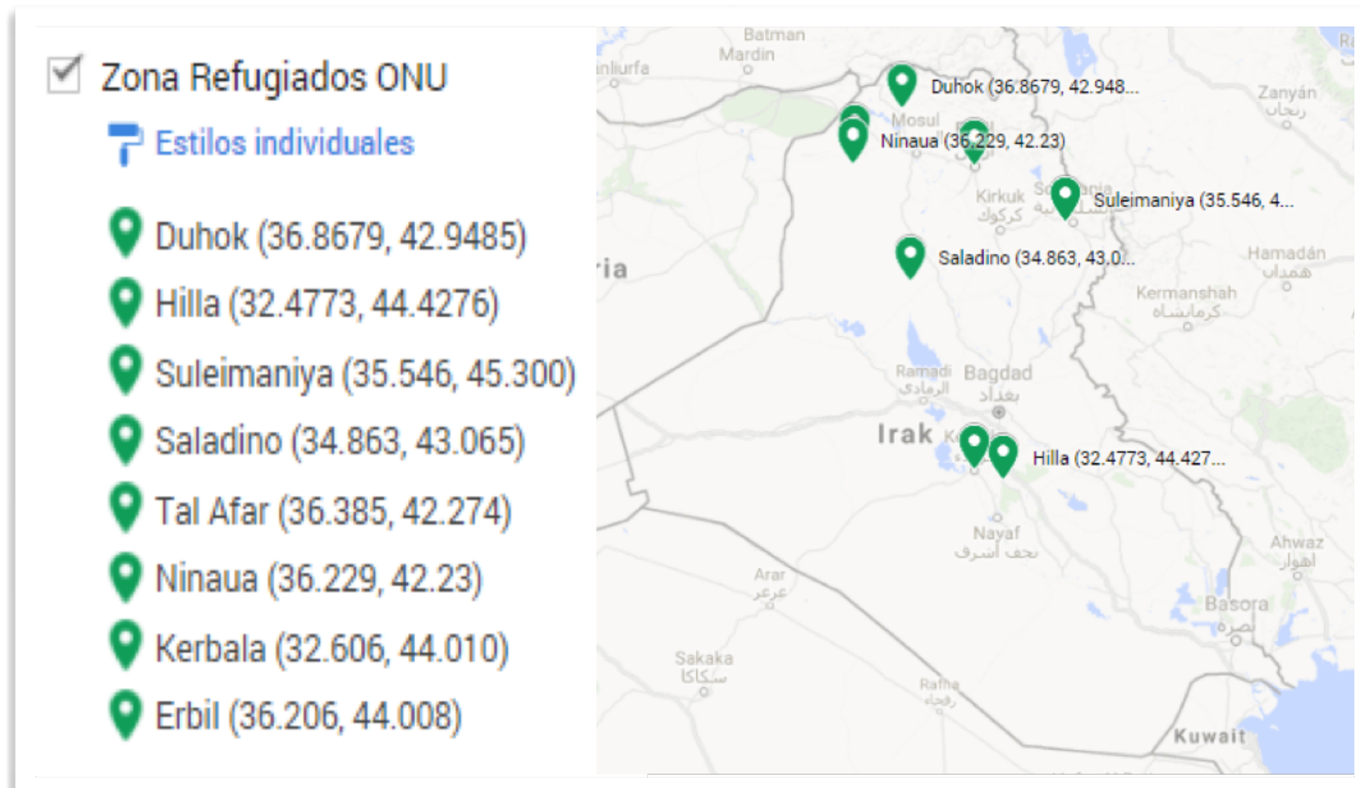

Refugee zones (adapted from UNHigh Commissioner for Refugees, 2017)

Classification Duhok, Iraq

González, M. & Alférez, G.H. (2020). Application of Data Science to Discover Violence-Related Issues in Iraq. arXiv. https://arxiv.org/abs/2006.07980

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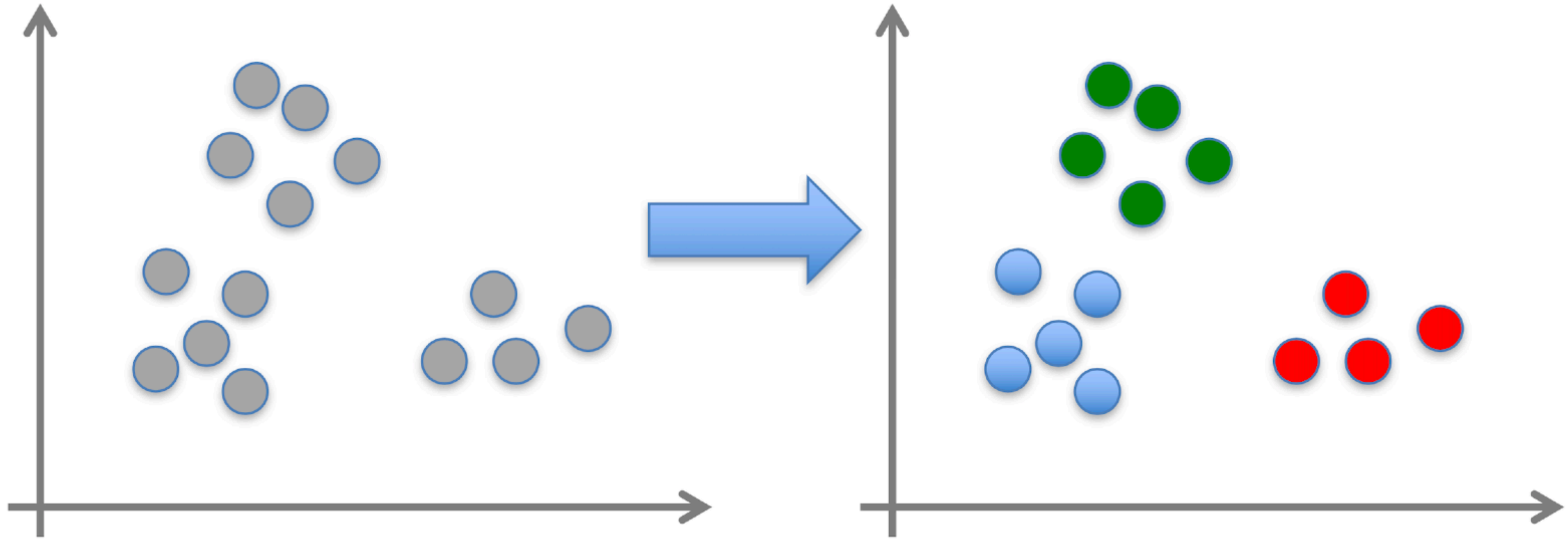
Unsupervised Learning

- If you're not trying to predict a target value, then you need to look into **unsupervised learning**.
    - E.g., **clustering**.

- Given x_1, x_2,…, x_n (without labels)
  - Output hidden structure behind the x's



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Interpreting the Geochemistry of Southern California Granitic Rocks using Machine Learning

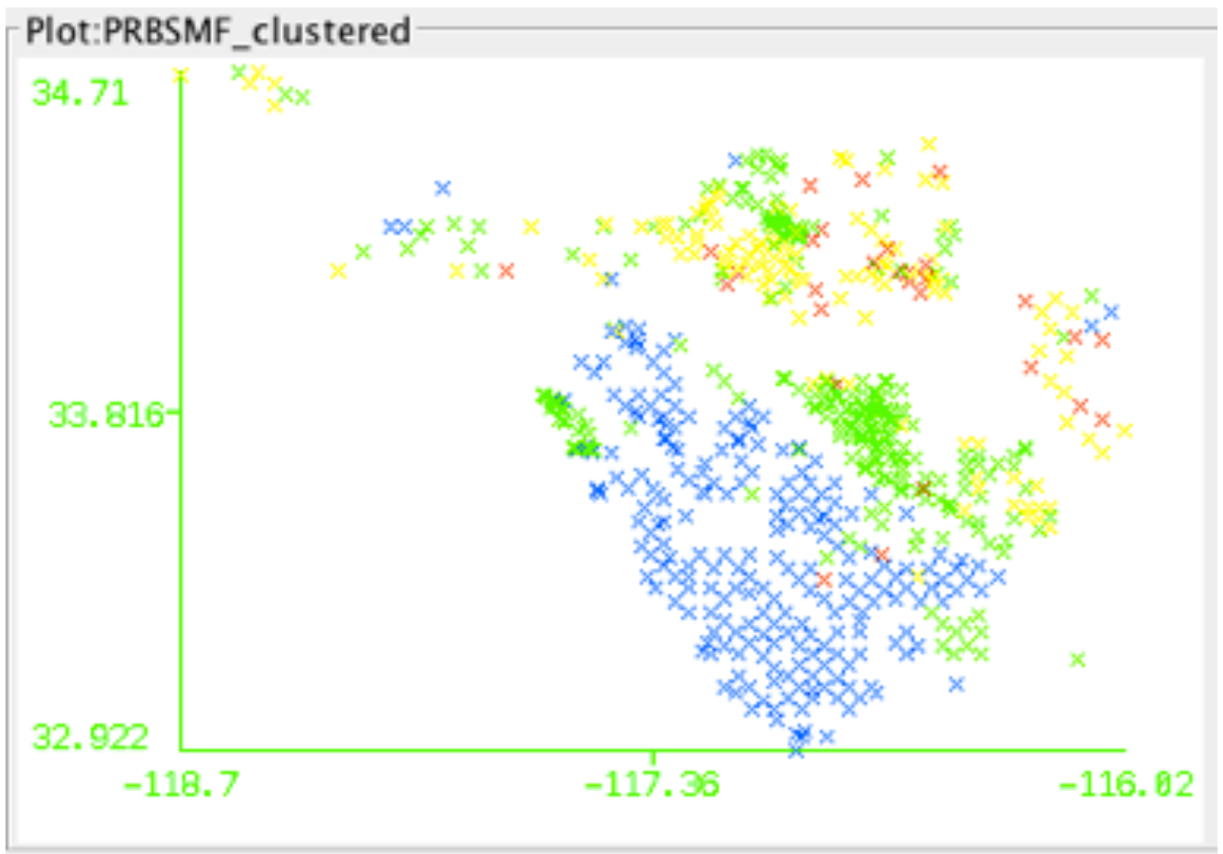

Figure 4. Cluster assignment visualization for Sri.
Cluster 0 is in yellow, **Cluster 1 is in green**, **Cluster 2 is in red**, and **Cluster 3 is in blue**

Sri (Initial $^{87}Sr/^{86}Sr$ ratios) Analysis

Table 2. WEKA results for Sr_i

Cluster #	Number of samples	Isotope ratio
0	135	0.7091
1	358	0.7068
2	31	0.7126
3	243	0.7042

Alférez, G. H., Rodríguez, J., Clausen, B. y Pompe, L. (2015). Interpreting the geochemistry of Southern California granitic rocks using machine learning. En D. de la Fuente, R. Dziegiel, E. B. Kozerenko, P. M. La-Monica, R. A. Liuzzi, J. A. Olivas y T. Waskiewicz (Eds.), Proceedings of the 2015 International Conference on Artificial Intelligence (ICAI) (pp. 592–598). CSREA Press. http://worldcomp-proceedings.com/ proc/p2015/ICA2786.pdf

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Machine learning in practice

- Understand domain, prior knowledge, and goals
- Data integration, selection, cleaning, pre-processing, etc.
- Learn and evaluate models
- Interpret results
- Consolidate and deploy discovered knowledge

Based on a slide by Pedro Domingos

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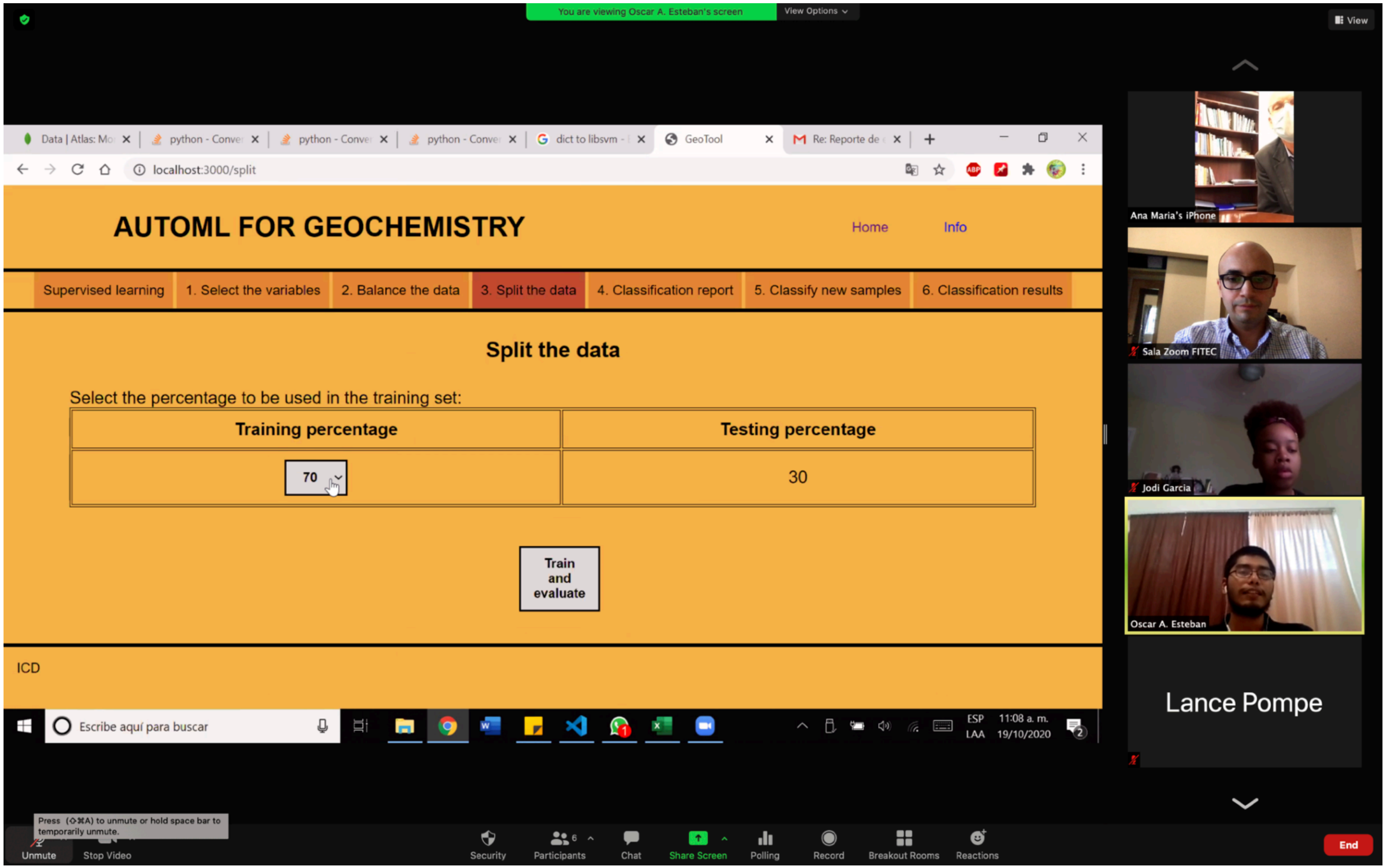
Automated machine learning pipeline for geochemical analysis



THE GEOLOGICAL SOCIETY OF AMERICA

GEOSCIENCE RESEARCH INSTITUTE

Alférez, G.H., Esteban, O.A., Clausen, B.L., & Martínez Ardila, A.M. (2022). Automated machine learning pipeline for geochemical analysis. Earth Science Informatics. https://doi.org/10.1007/s12145-022-00821-8

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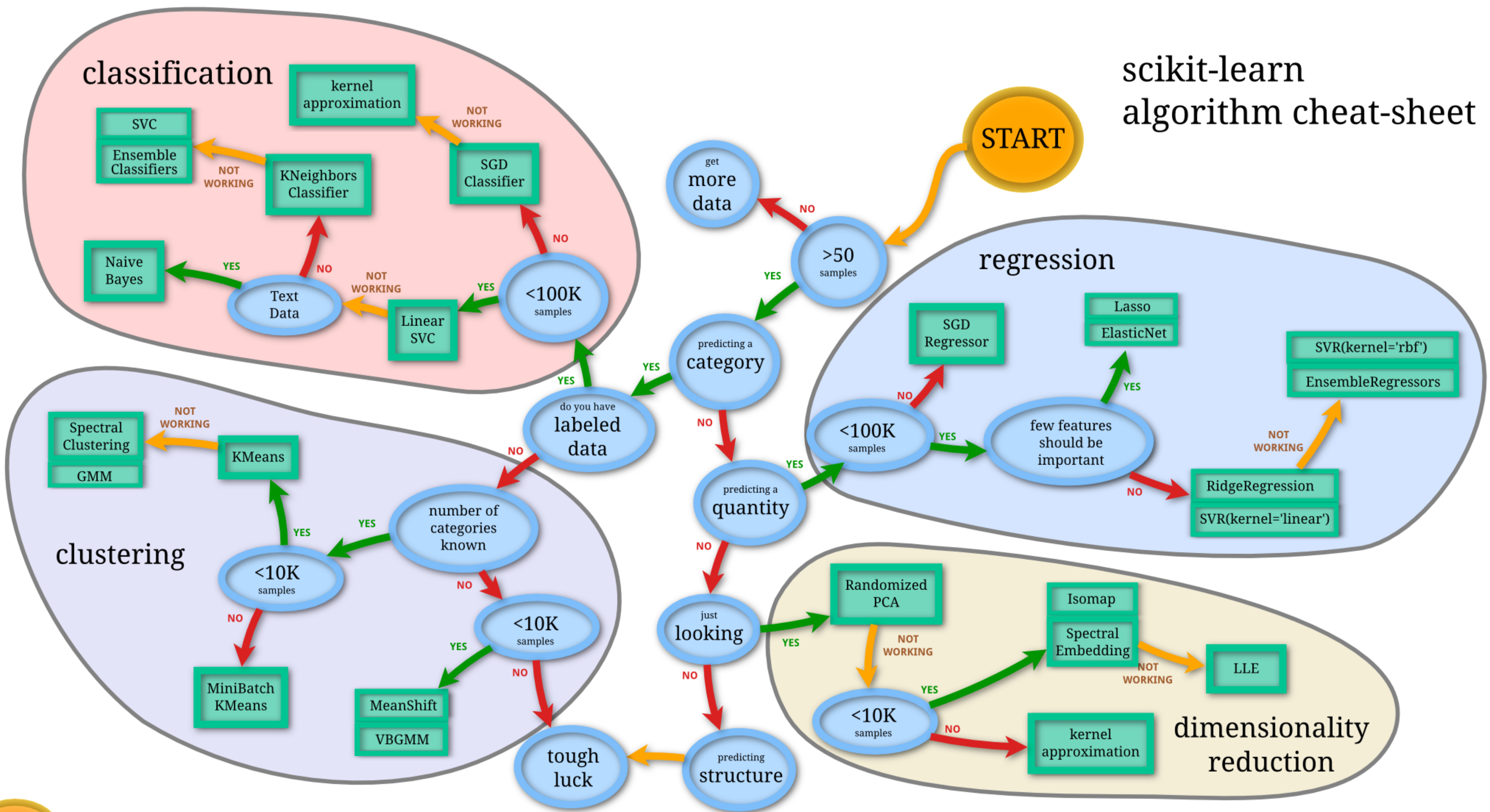
Technologies



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Why TensorFlow?

- Developed by Google
- Python API
- Portability: deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API
- Large community

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Companies Using TensorFlow

- Google
- OpenAI
- DeepMind
- Snapchat
- Uber
- Airbus
- eBay
- Dropbox
- A bunch of startups

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The possibilities are endless!

Machine Learning in Action: Exploring Examples in Multiple Domains

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