

# Machine Learning

## 1.1. Introduction

Teeradaj Racharak (ເອັກຊ້)  
[r.teeradaj@gmail.com](mailto:r.teeradaj@gmail.com)



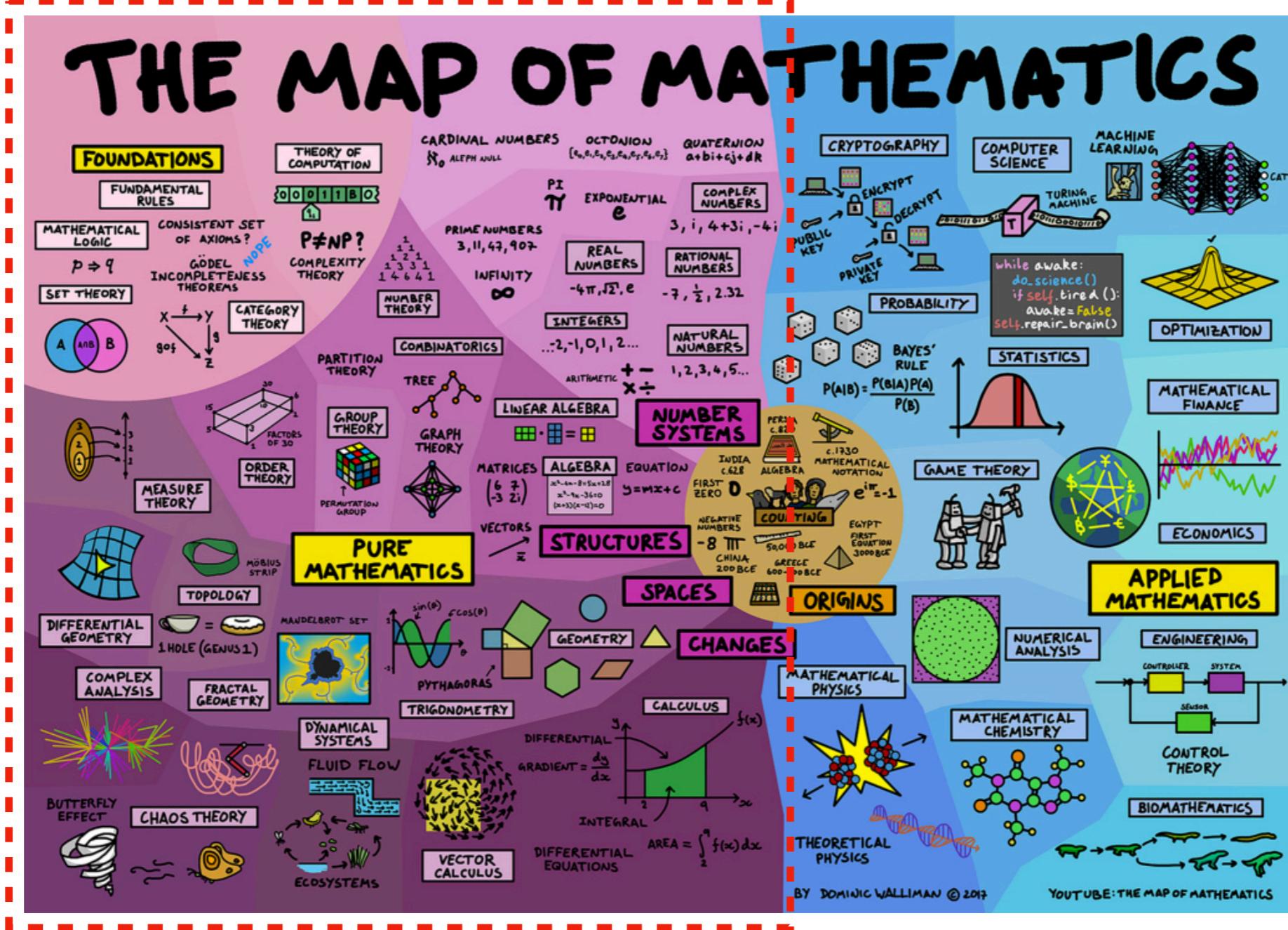
# Readings

Readings for these lecture notes:

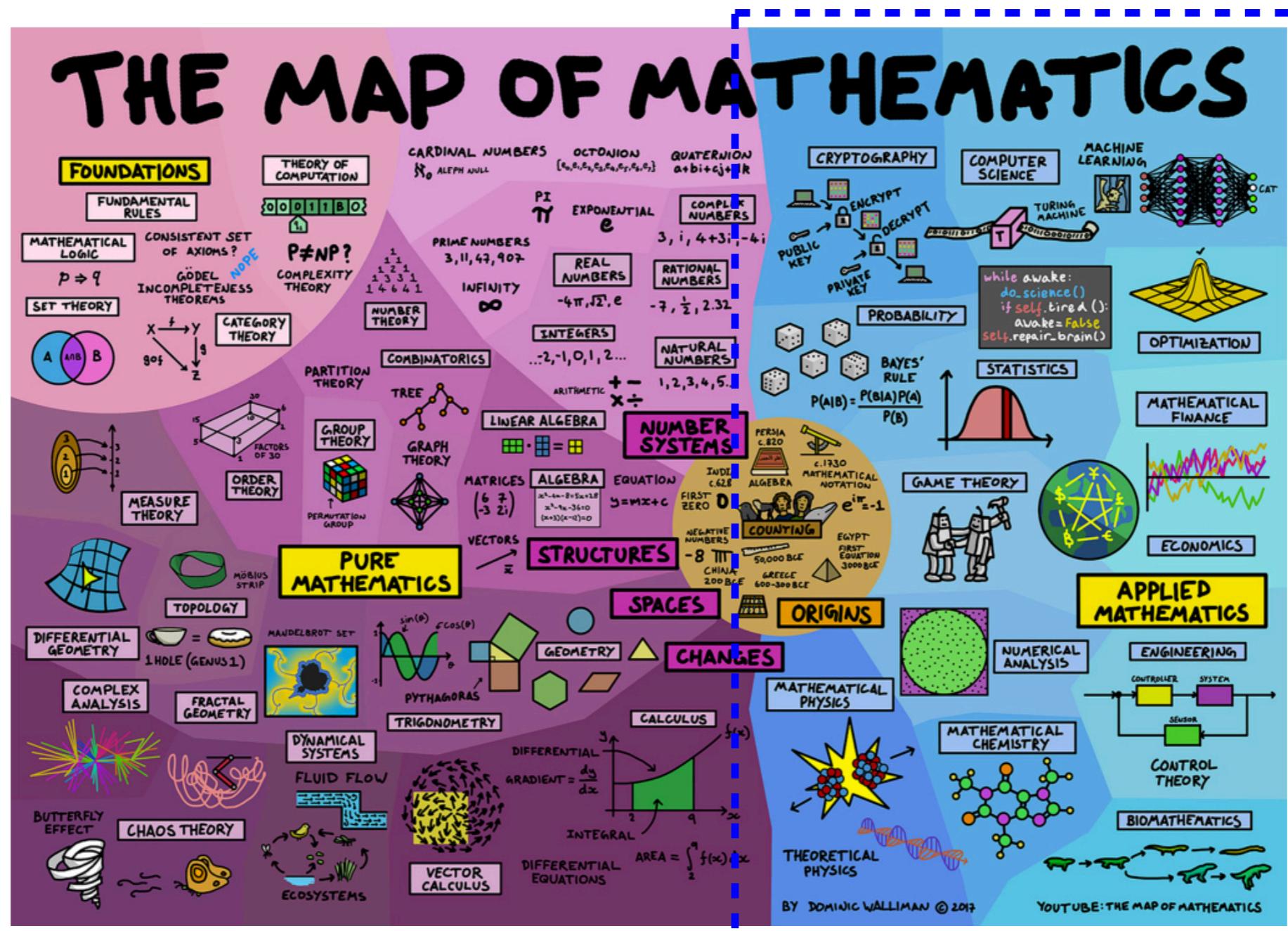
- Bishop, C. (2006), *Pattern Recognition and Machine Learning*, Springer, Chapters 3, 4, 6, 7.
- Hastie, T., Timshirari, R., and Friedman, J. (2016), *Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer, Chapters 2, 3, 4, 12.
- Bonnin, R. (2016), *Building Machine Learning Projects with TensorFlow*, Packt Publishing.
- Ng, A. (2017), *Machine Learning*, Stanford University.
- Dailey, M. (2018), *Machine Learning*, Asian Institute of Technology

These notes contains materials from Bishop (2016), Hastie *et al.* (2016), Ng (2017), and Dailey (2018)

# Recap



# Today Onward



# Introduction

- Machine learning is now near the top of the list of skills U.S. companies want to see in the people they hire.
- Many tasks we want computers to do are difficult to program directly.
- A set of tools that let us specify the computer's behavior by giving examples of how it should respond in given situations, without specifying the computation necessary to formulate that response.
- Essential idea: we want to create a model from data that can later be queried when new situation arises.

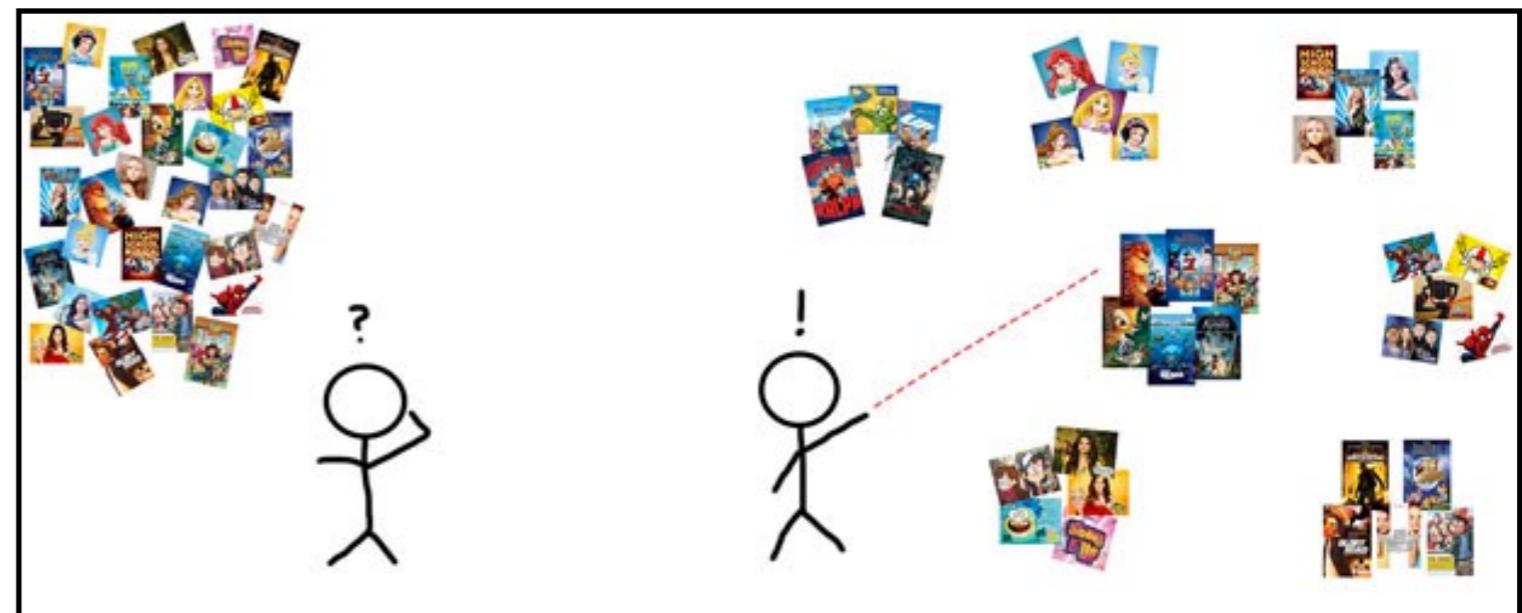
# Examples of ML in real life

We are using machine learning every time that we:

- use a credit card
- get a recommendation from Netflix or Amazon
- Ask Google for directions by voice
- Take a ride in our Tesla !

Let's brainstorm about things closer to home that might be using machine learning already or might benefit from it in the near future.

# How many ways to learn?

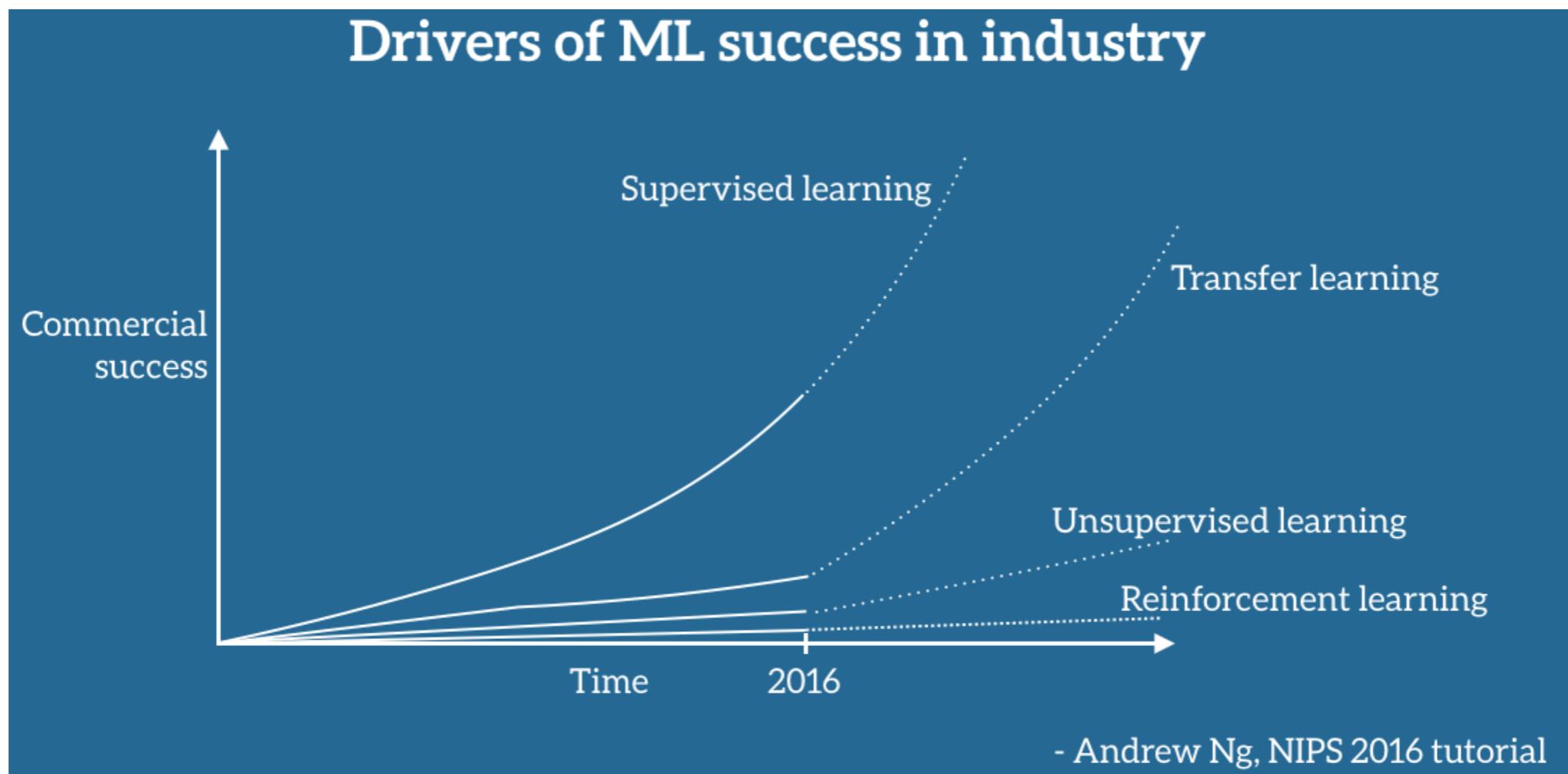


# Types of Learning

1. **Supervised learning:** ‘right’ answers are given
2. **Unsupervised learning:** ‘right’ answers are ‘not’ given
3. **Reinforcement learning:** derives a policy that enables an agent to behave optimally in an uncertain environment using feedback on the goodness of the outcome over time.
4. **Miscellaneous (e.g. transfer learning):** storing knowledge gained solving one problem and applying it to a different but related problem.



# ML's success in industry



# Further readings



**Qiang Yang**

New Bright Chair Professor of Engineering, Hong Kong Univ. of Sci. and Tech.  
Verified email at cse.ust.hk - [Homepage](#)

Artificial Intelligence Transfer Learning Machine Learning and Data...

## TITLE

### A survey on transfer learning

SJ Pan, Q Yang  
IEEE Transactions on knowledge and data engineering 22 (10), 1345-1359

### Top 10 algorithms in data mining

X Wu, V Kumar, JR Quinlan, J Ghosh, Q Yang, H Motoda, GJ McLachlan, ...  
Knowledge and information systems 14 (1), 1-37

### Graph embedding and extensions: A general framework for dimensionality reduction

S Yan, D Xu, B Zhang, HJ Zhang, Q Yang, S Lin  
IEEE transactions on pattern analysis and machine intelligence 29 (1), 40-51

### Boosting for Transfer Learning

W Dai, Q Yang, GR Xue, Y Yu  
Proceedings of the 24th Annual International Conference on Machine Learning ...

- Check publications of Prof. Qiang Yang.
- Blog of Sebastian Ruder, who is currently working on NLP with deep learning:  
<http://ruder.io/transfer-learning/index.html>

# Definitions of ML

- Arthur Samuel (1959).
  - ▶ Machine learning (ML) is a field of study that ‘gives’ computers the ability to learn without being explicitly programmed.
- Tom Mitchell (1998).
  - ▶ A computer program is said to ‘learn’ from experience  $E$  w.r.t. some task  $T$  and some performance measure  $P$ , if its performance on  $T$ , as measured by  $P$ , improves with experience  $E$ .

# Question

- Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is the task  $T$  in this setting?
  - i. Classify emails as spam or not spam
  - ii. Watching you label emails as spam or not spam
  - iii. The number (or fraction) of emails correctly classified as spam / not spam
  - iv. None of the above — this is not a machine learning problem

# Question

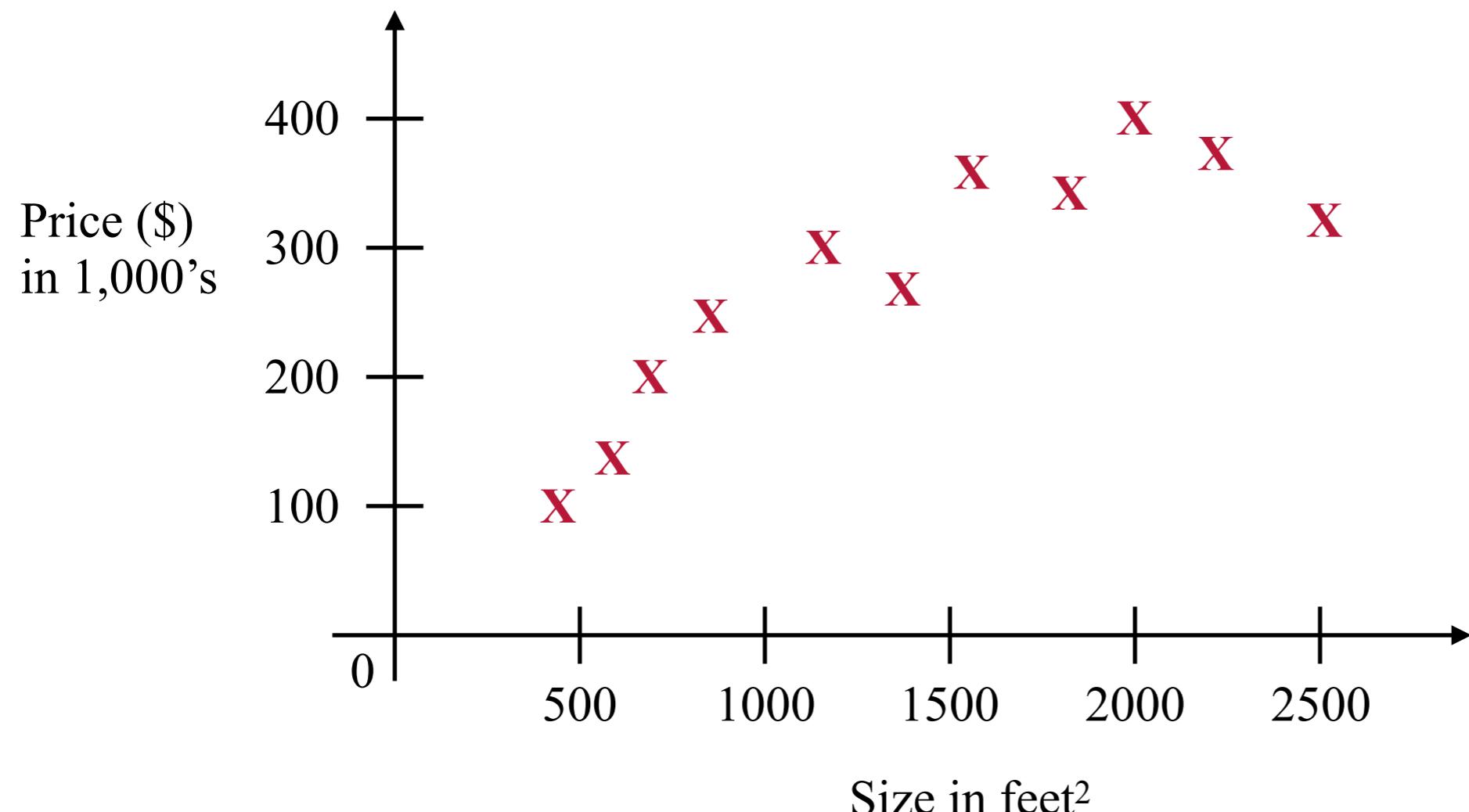
- Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is the task  $T$  in this setting?
  - i. Classify emails as spam or not spam **T**
  - ii. Watching you label emails as spam or not spam **E**
  - iii. The number (or fraction) of emails correctly classified as **P** spam / not spam
  - iv. None of the above — this is not a machine learning problem

Now, let's talk about the intuition  
of each basic problem in ML

# 1. Supervised Learning

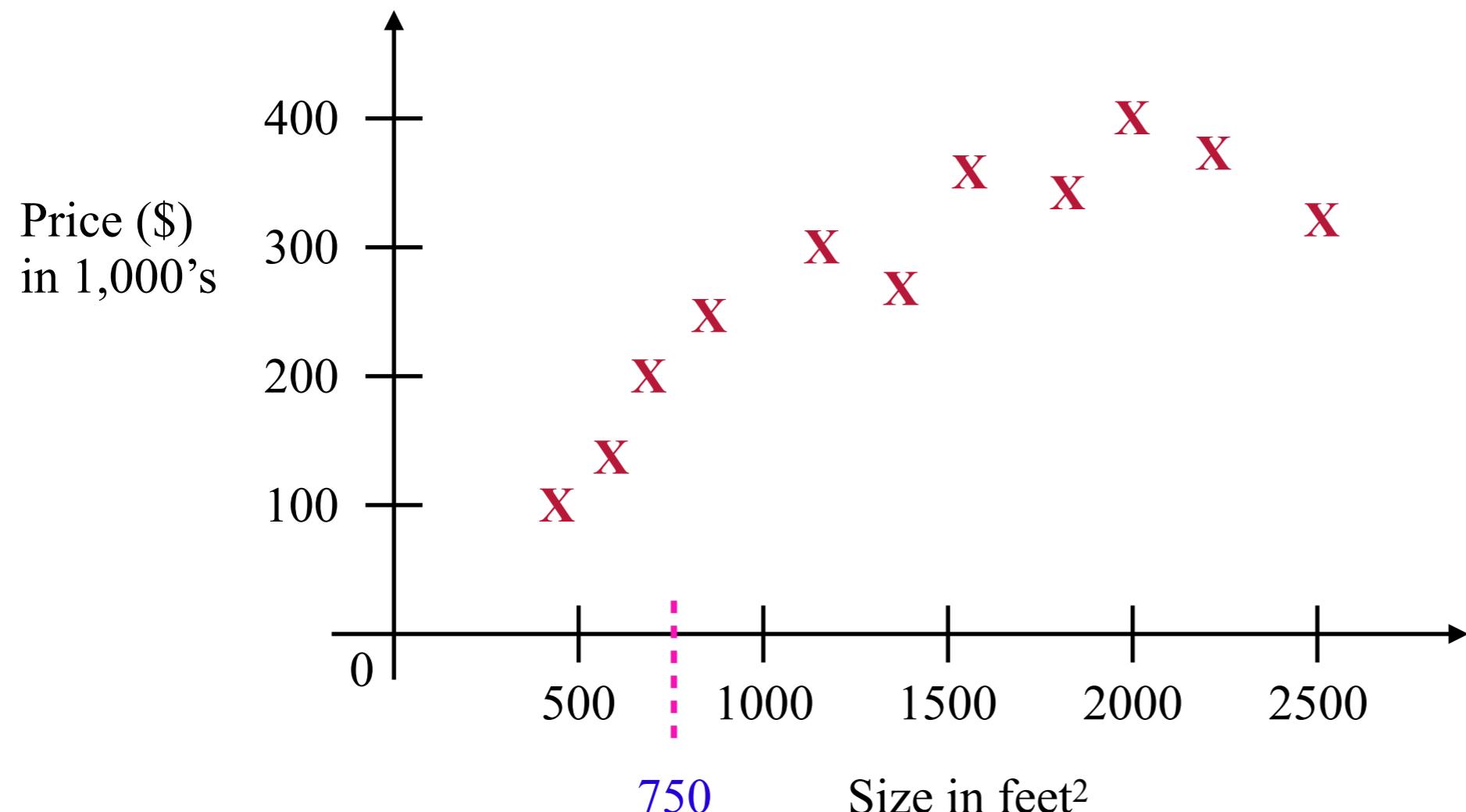
# Intuition (Regression)

Housing price prediction



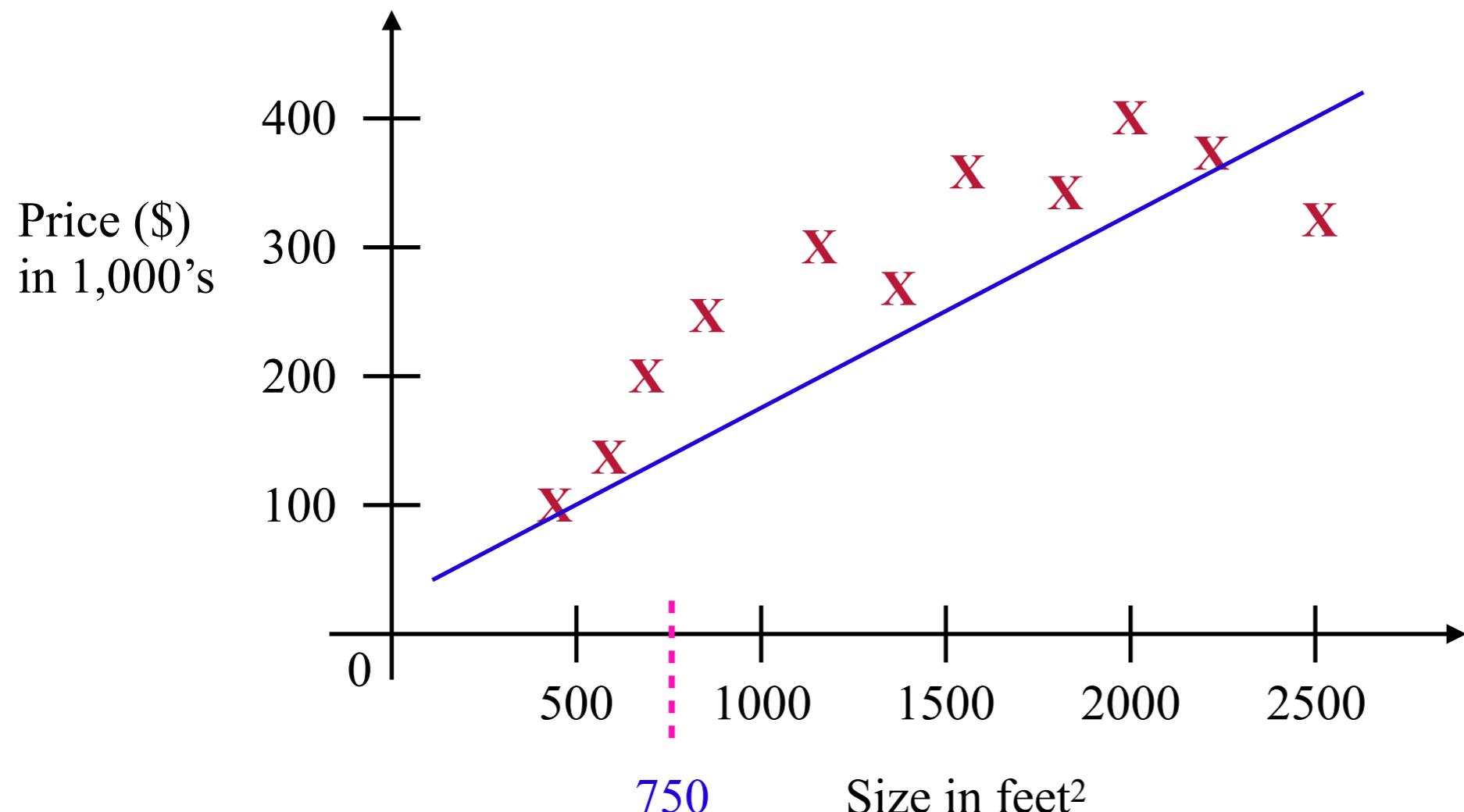
# Intuition (Regression)

Housing price prediction



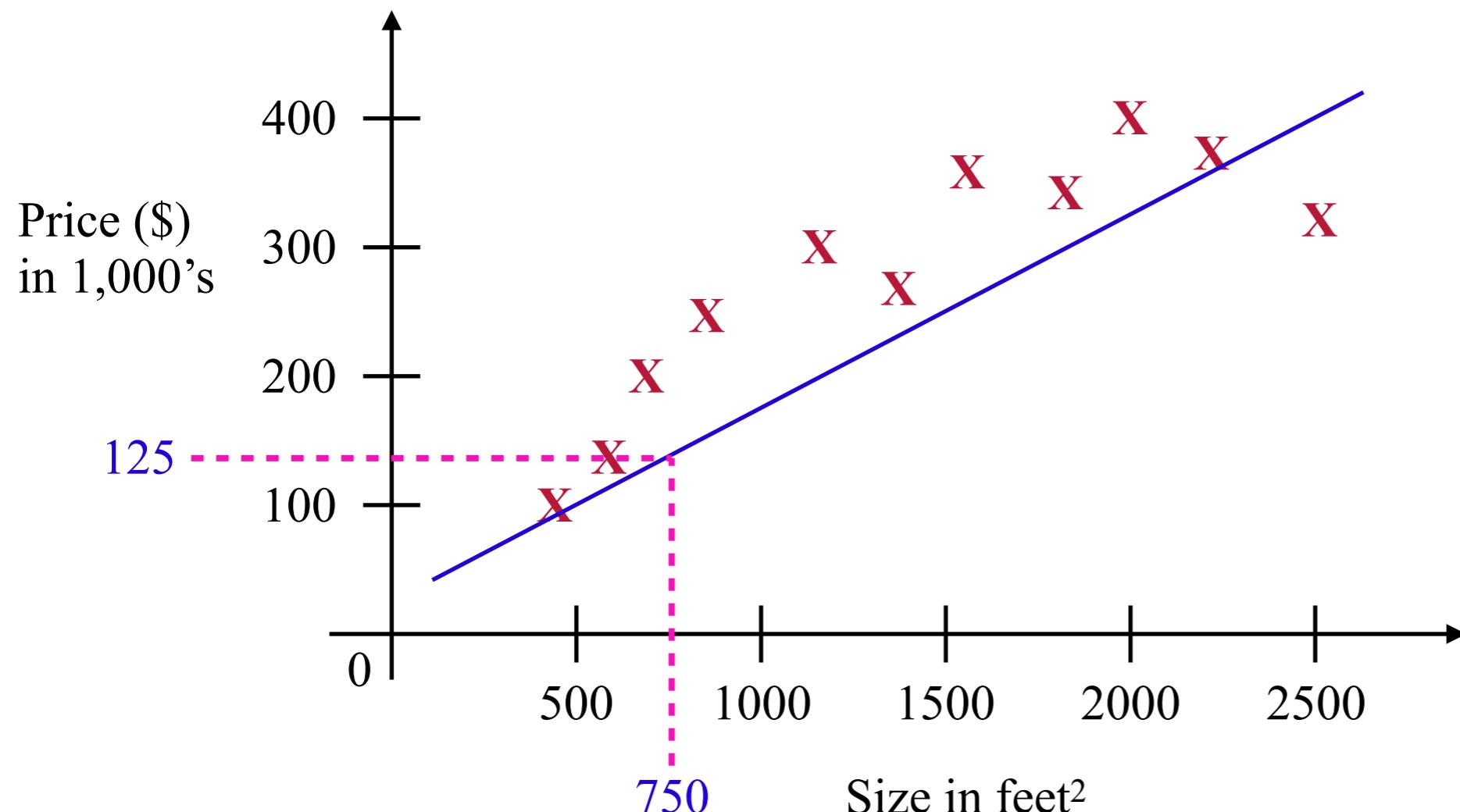
# Intuition (Regression)

Housing price prediction



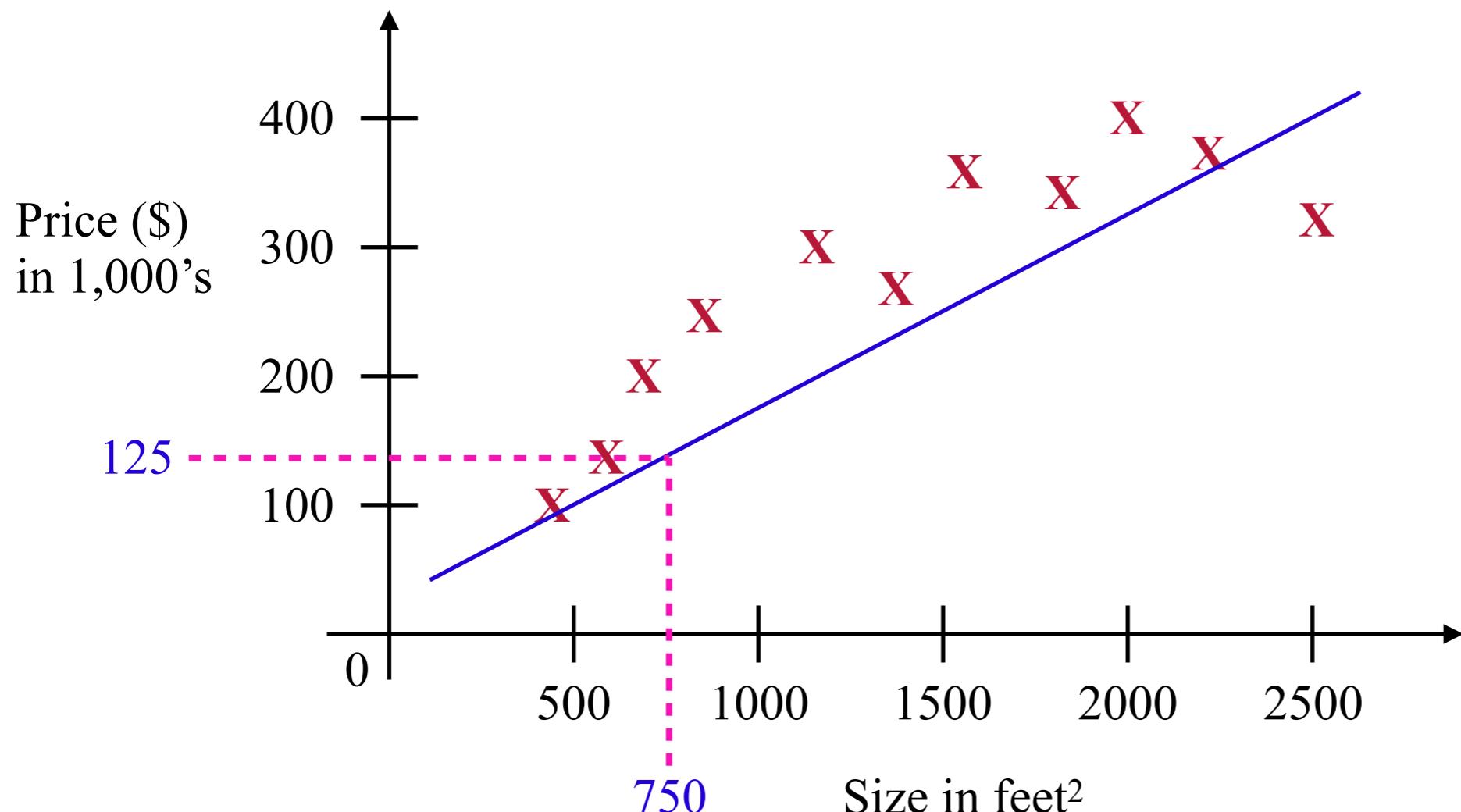
# Intuition (Regression)

Housing price prediction



# Intuition (Regression)

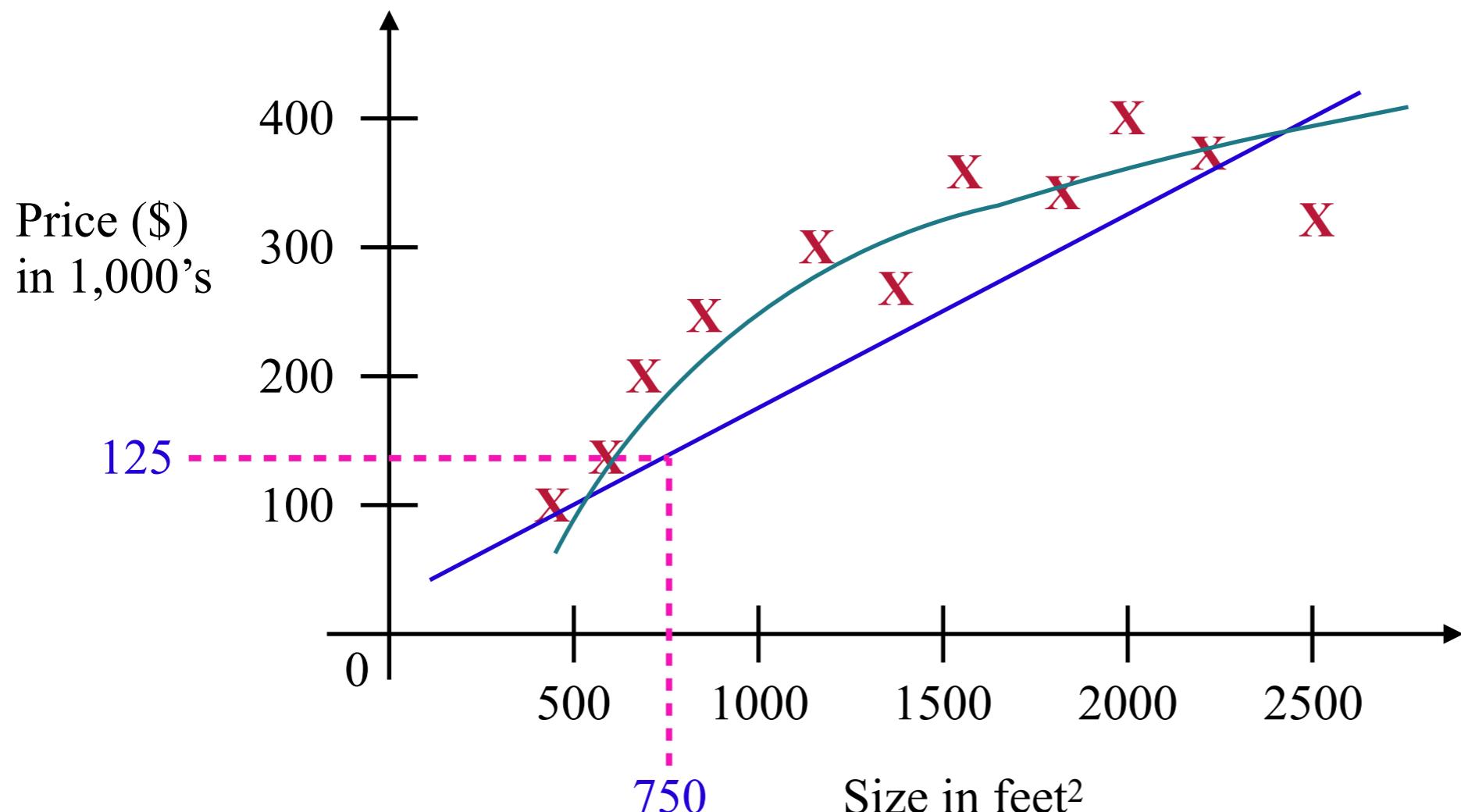
Housing price prediction



Is this the only learning algorithm that we can use?

# Intuition (Regression)

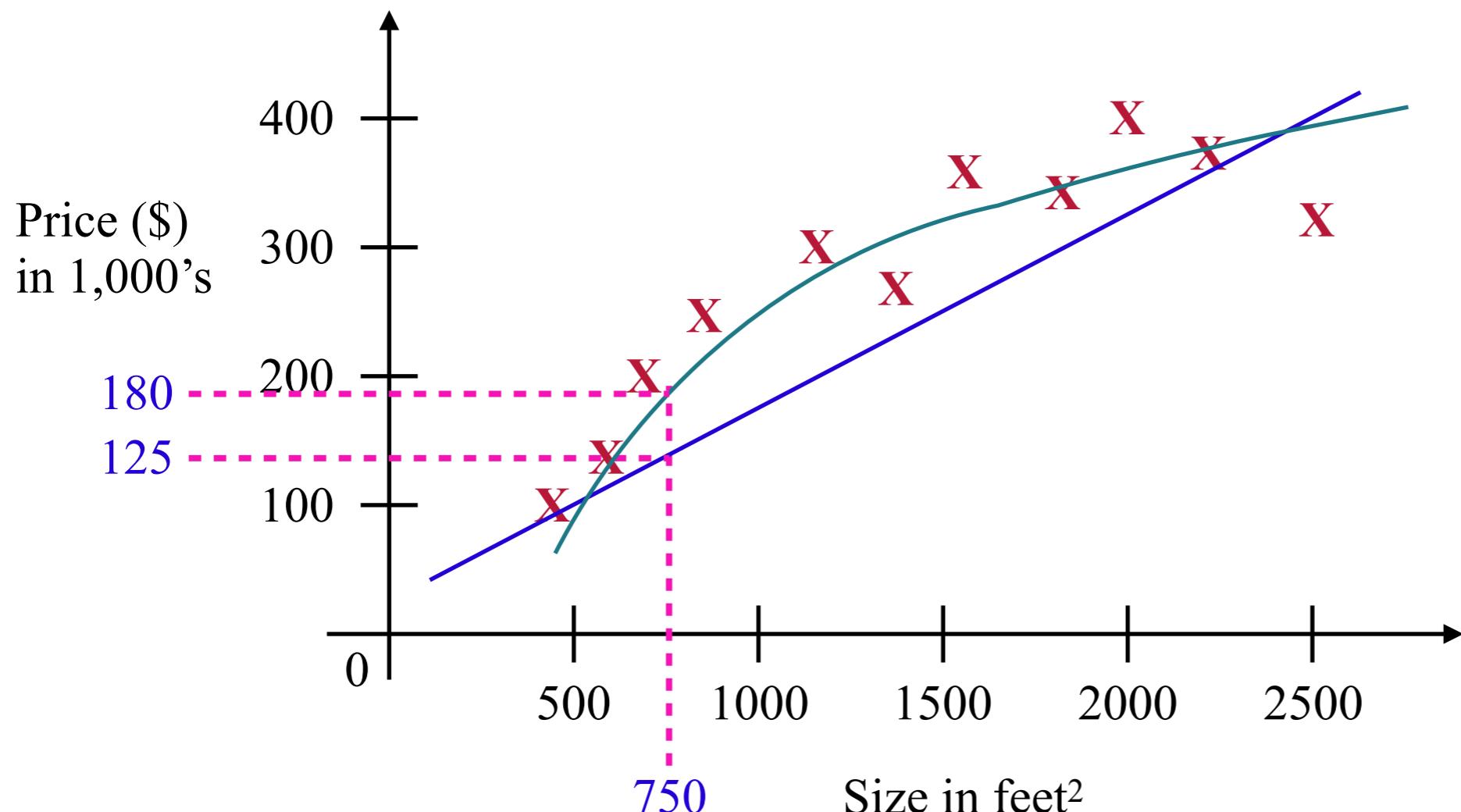
Housing price prediction



Is this the only learning algorithm that we can use?

# Intuition (Regression)

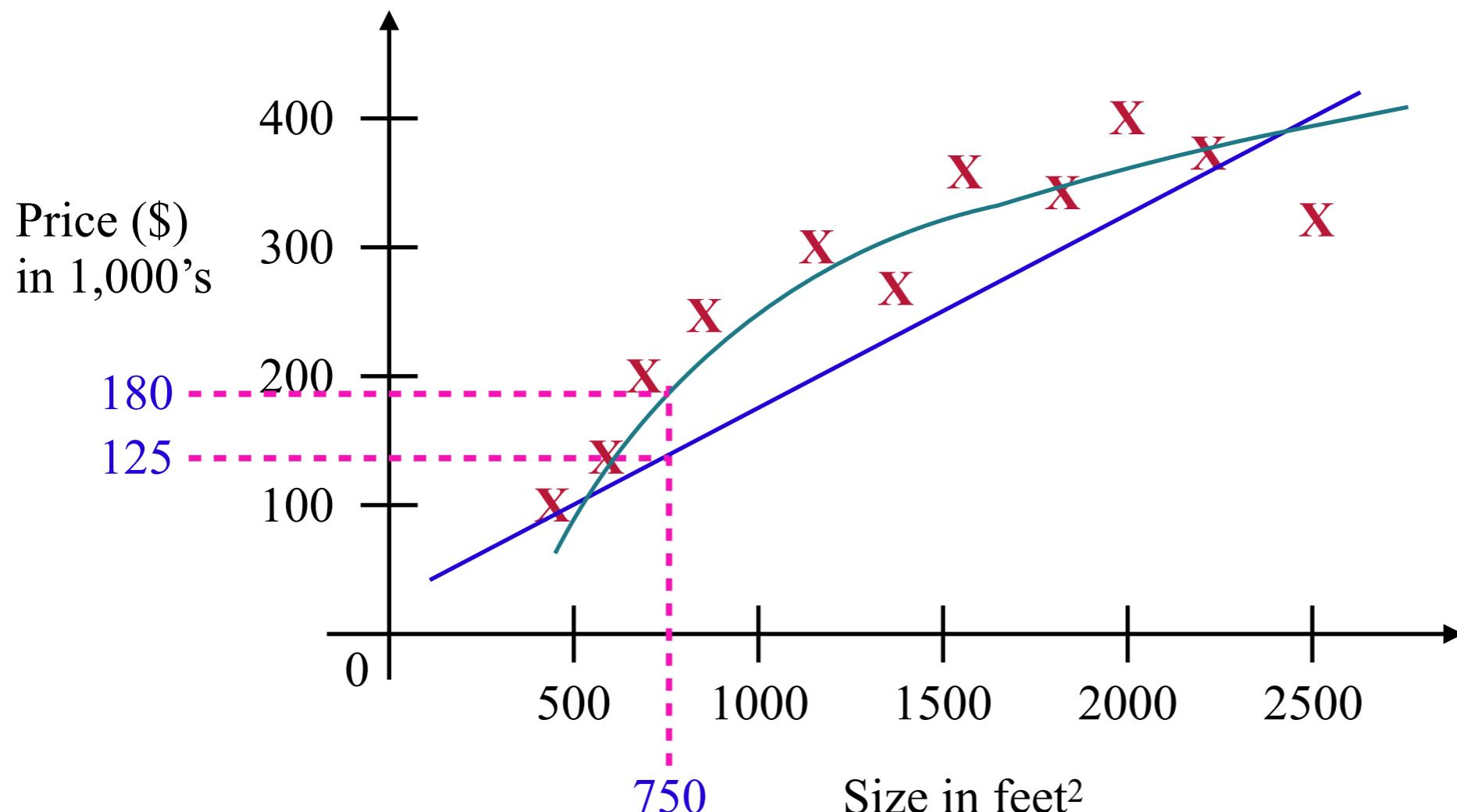
Housing price prediction



Is this the only learning algorithm that we can use?

# Intuition (Regression)

Housing price prediction

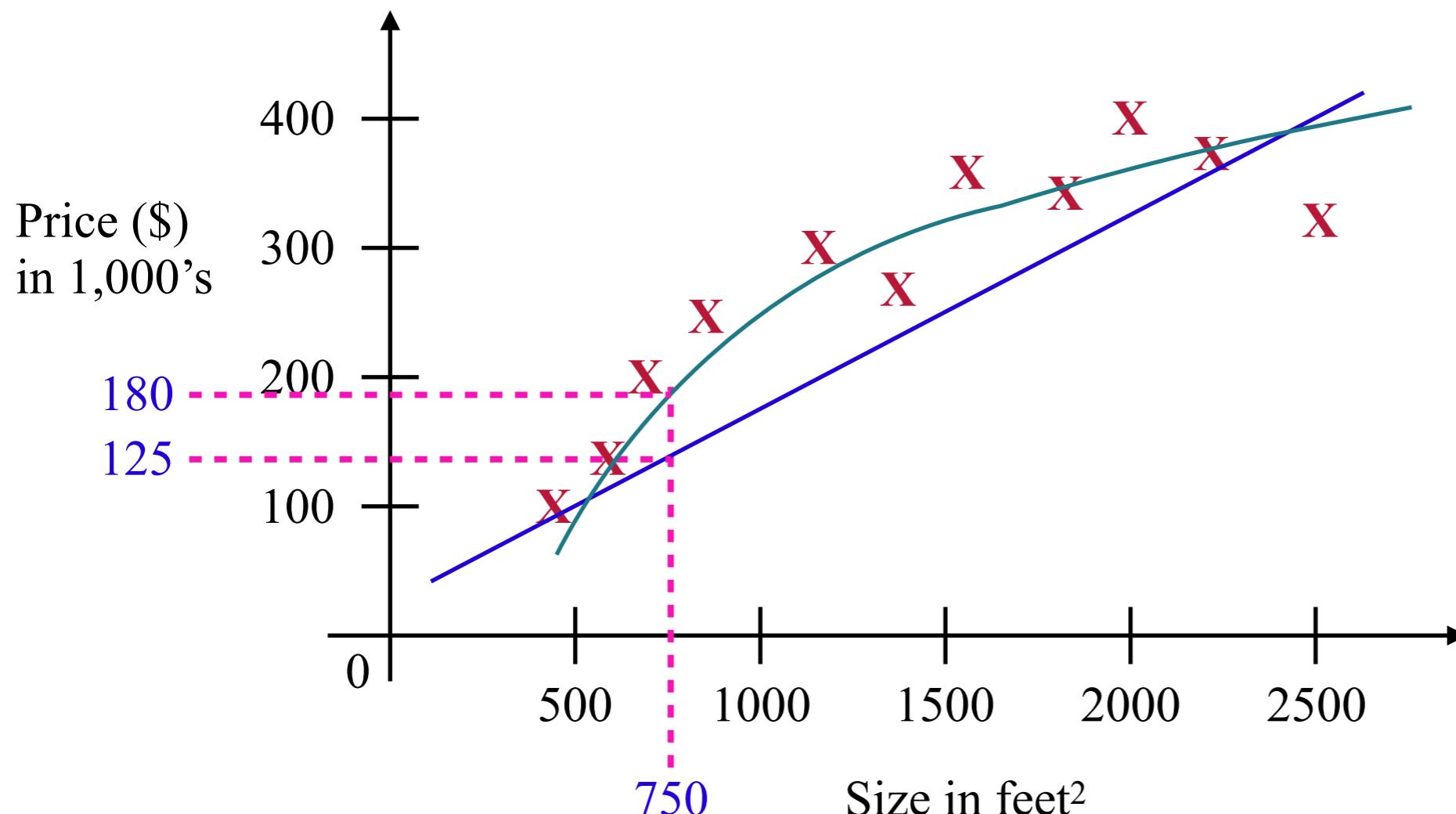


Is this the only learning algorithm that we can use?

Supervised Learning  
“right answer” is given

# Intuition (Regression)

## Housing price prediction



Is this the only learning algorithm that we can use?

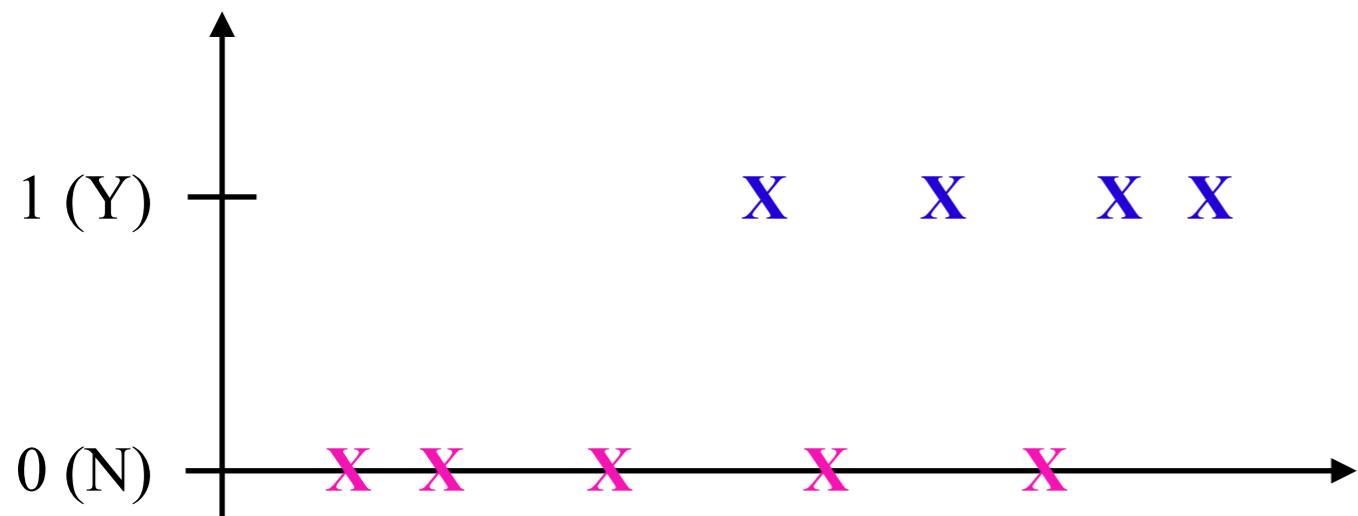
Supervised Learning  
“right answer” is given

Regression  
Predict continuous valued output (price)

# Intuition (Classification)

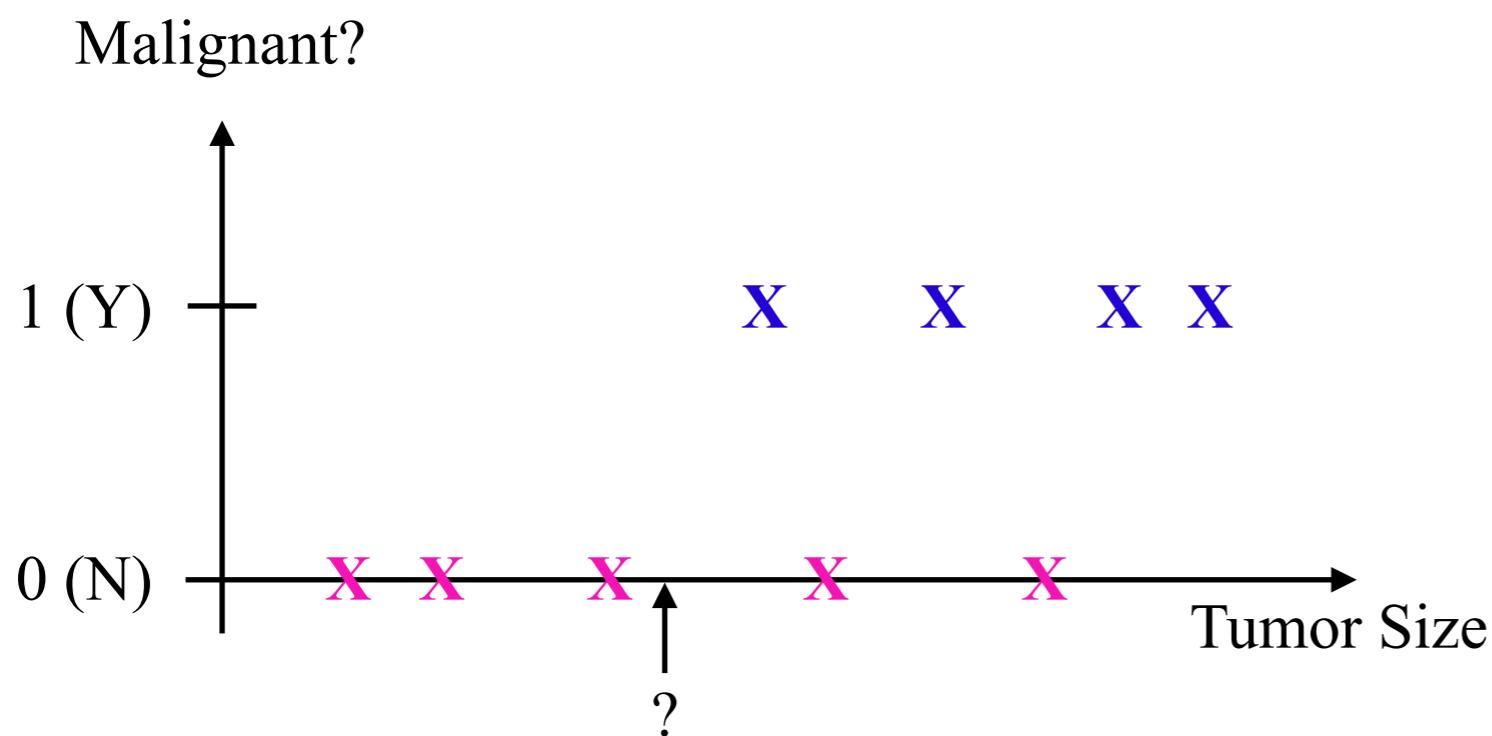
Breast cancer (malignant, benign)

Malignant?



# Intuition (Classification)

Breast cancer (malignant, benign)

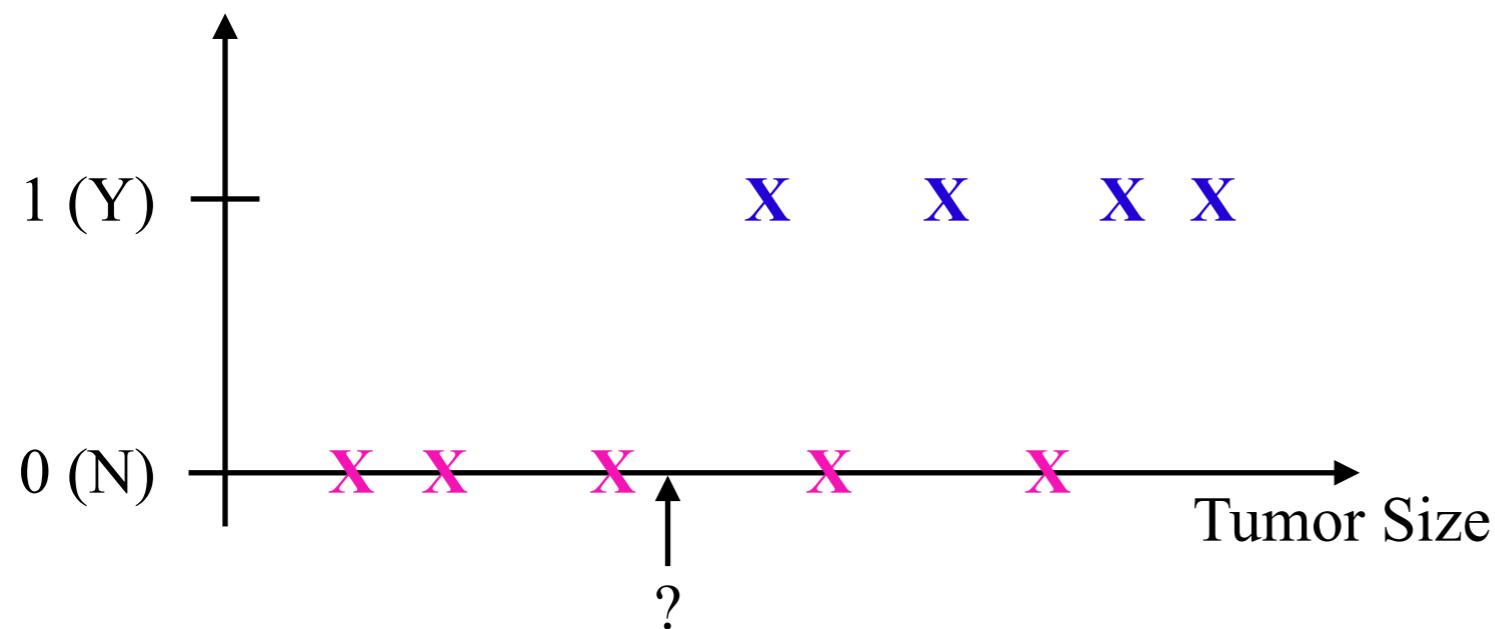


Classification  
Discrete valued  
output (0 or 1)

# Intuition (Classification)

Breast cancer (malignant, benign)

Malignant?



Classification

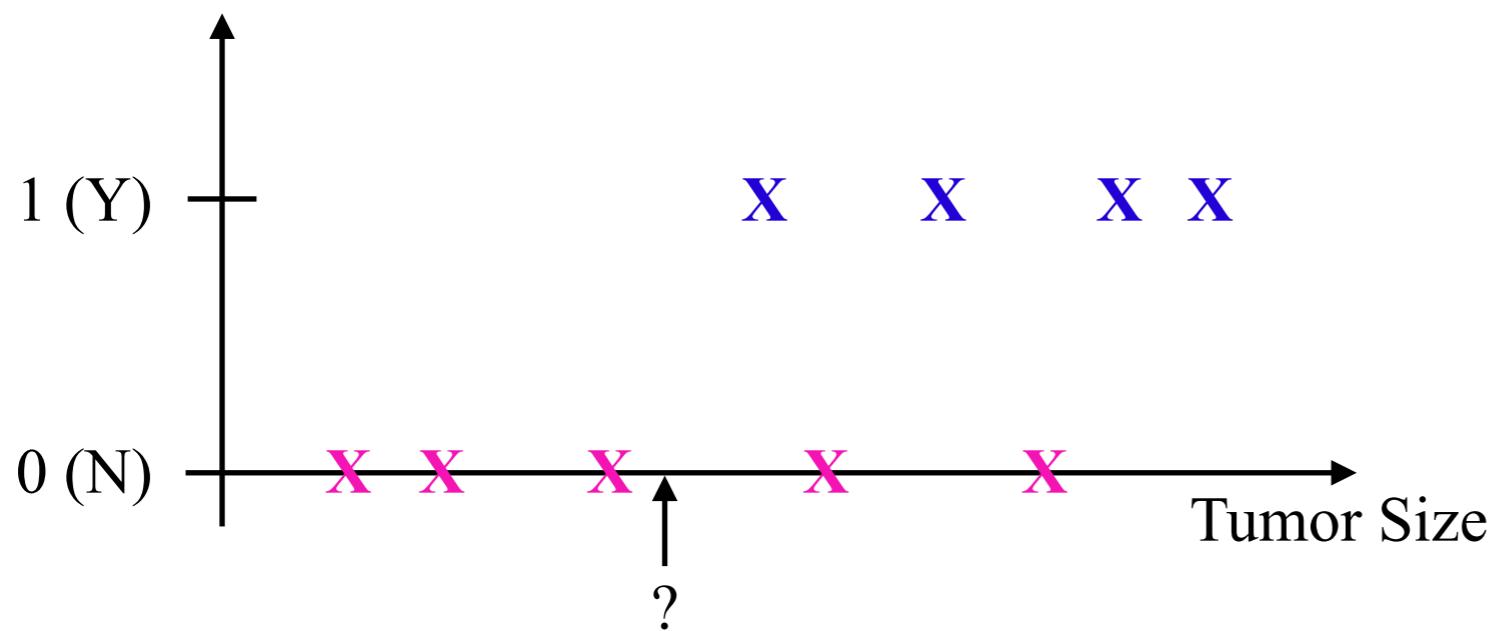
Discrete valued  
output (0 or 1)

Discrete value may be  $\geq 2$   
*e.g. 0, 1, 2, 3*

# Intuition (Classification)

Breast cancer (malignant, benign)

Malignant?



Classification

Discrete valued output (0 or 1)

Discrete value may be  $\geq 2$

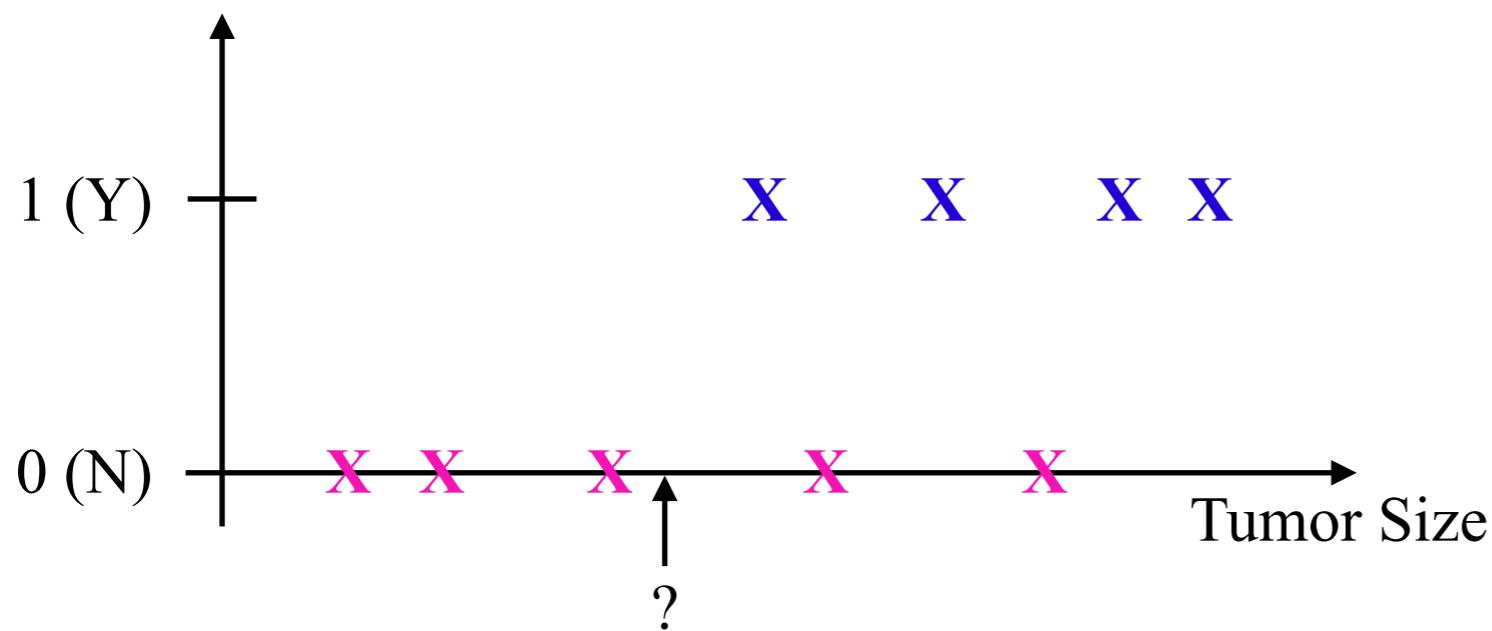
e.g. 0, 1, 2, 3

- 0 : Benign
- 1 : Cancer type#1
- 2 : Cancer type#2
- 3 : Cancer type#3

# Intuition (Classification)

Breast cancer (malignant, benign)

Malignant?



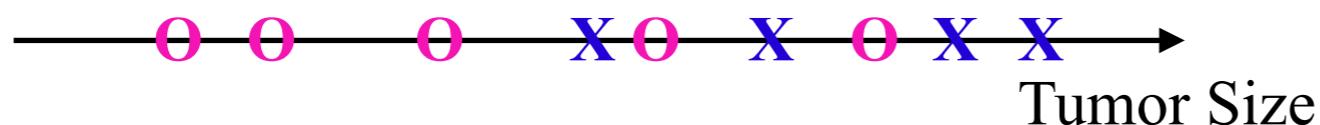
Classification

Discrete valued output (0 or 1)

Discrete value may be  $\geq 2$

e.g. 0, 1, 2, 3

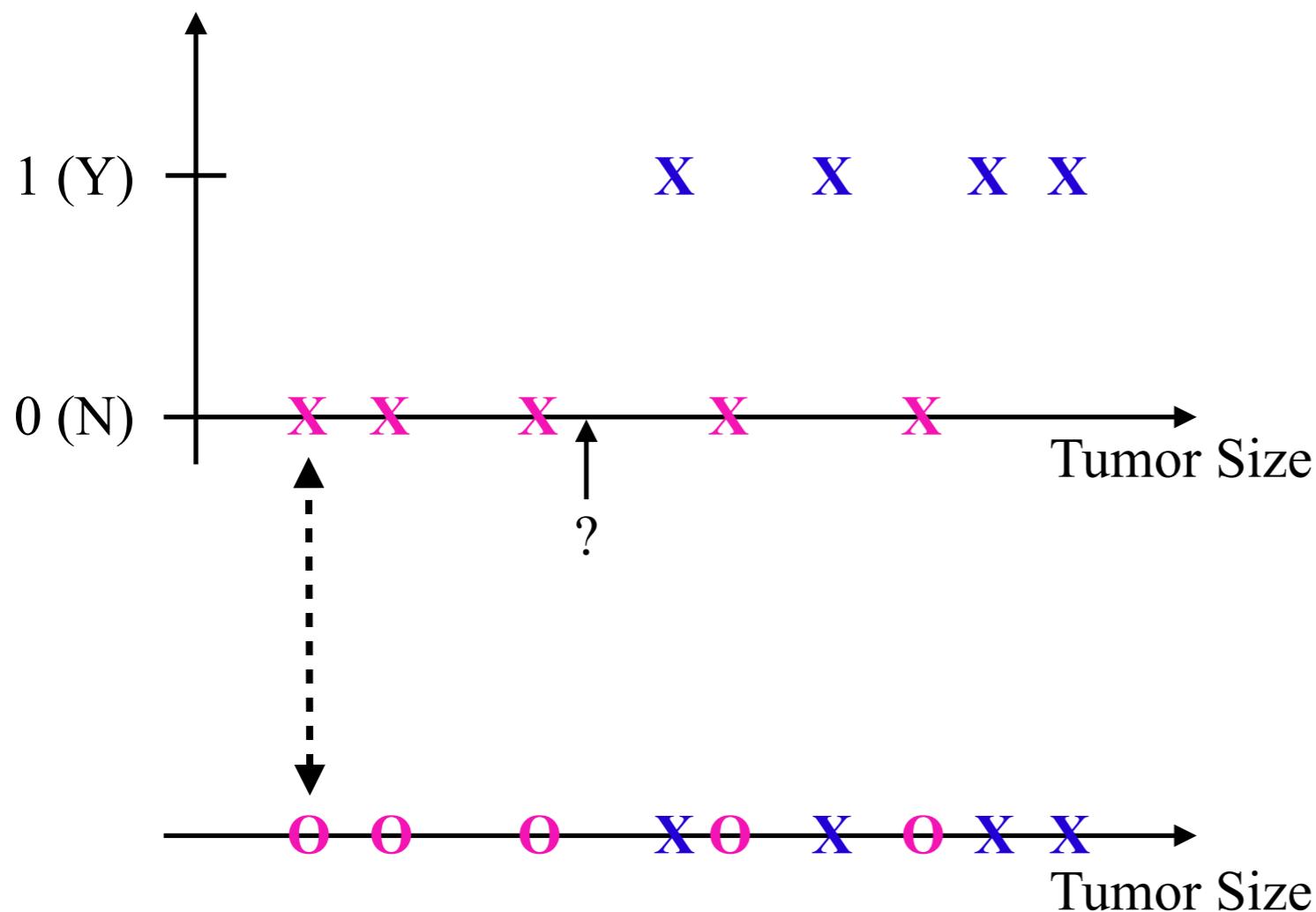
- 0 : Benign
- 1 : Cancer type#1
- 2 : Cancer type#2
- 3 : Cancer type#3



# Intuition (Classification)

Breast cancer (malignant, benign)

Malignant?



Classification

Discrete valued output (0 or 1)

Discrete value may be  $\geq 2$

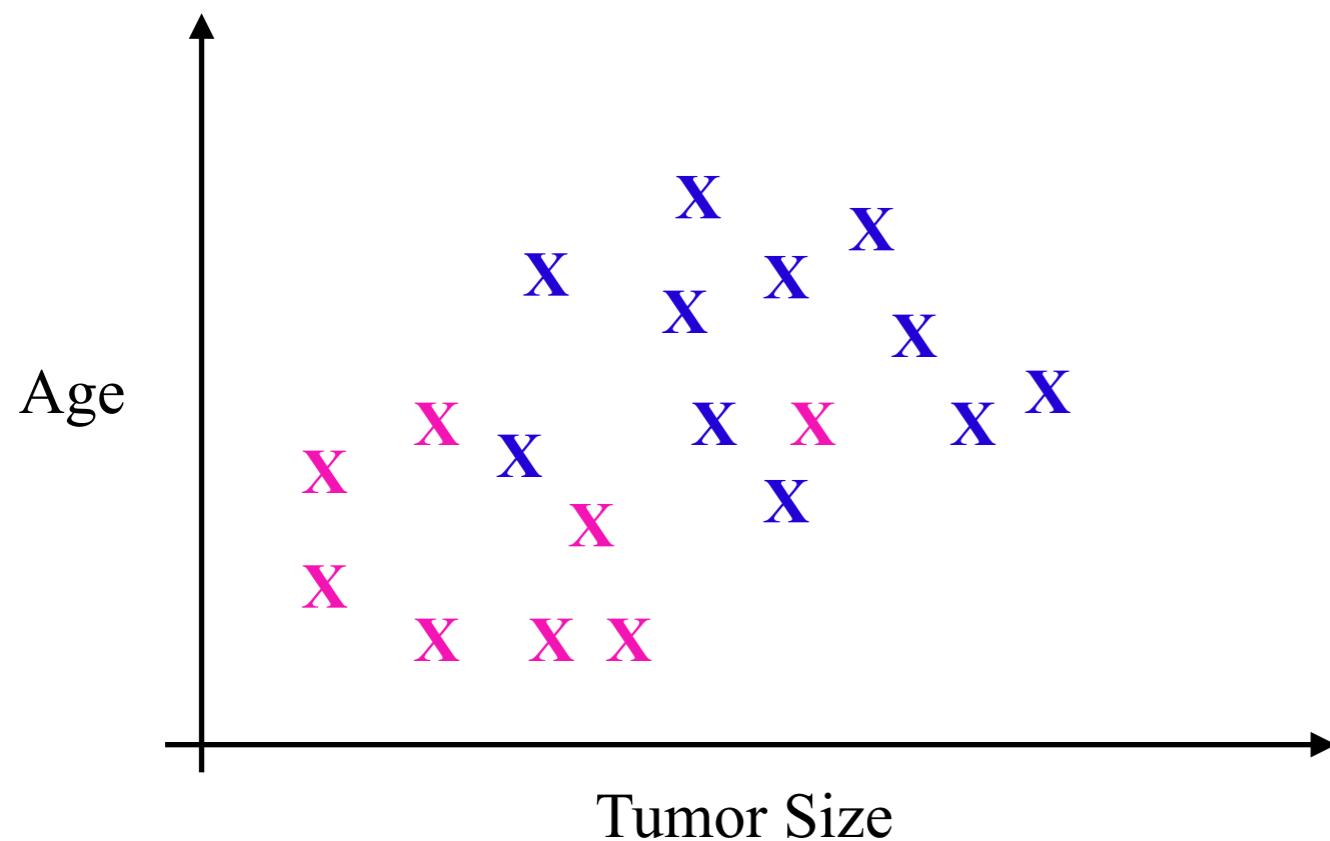
e.g. 0, 1, 2, 3

- 0 : Benign
- 1 : Cancer type#1
- 2 : Cancer type#2
- 3 : Cancer type#3

1 feature (attribute)

# Intuition (Classification)

Breast cancer (malignant, benign)

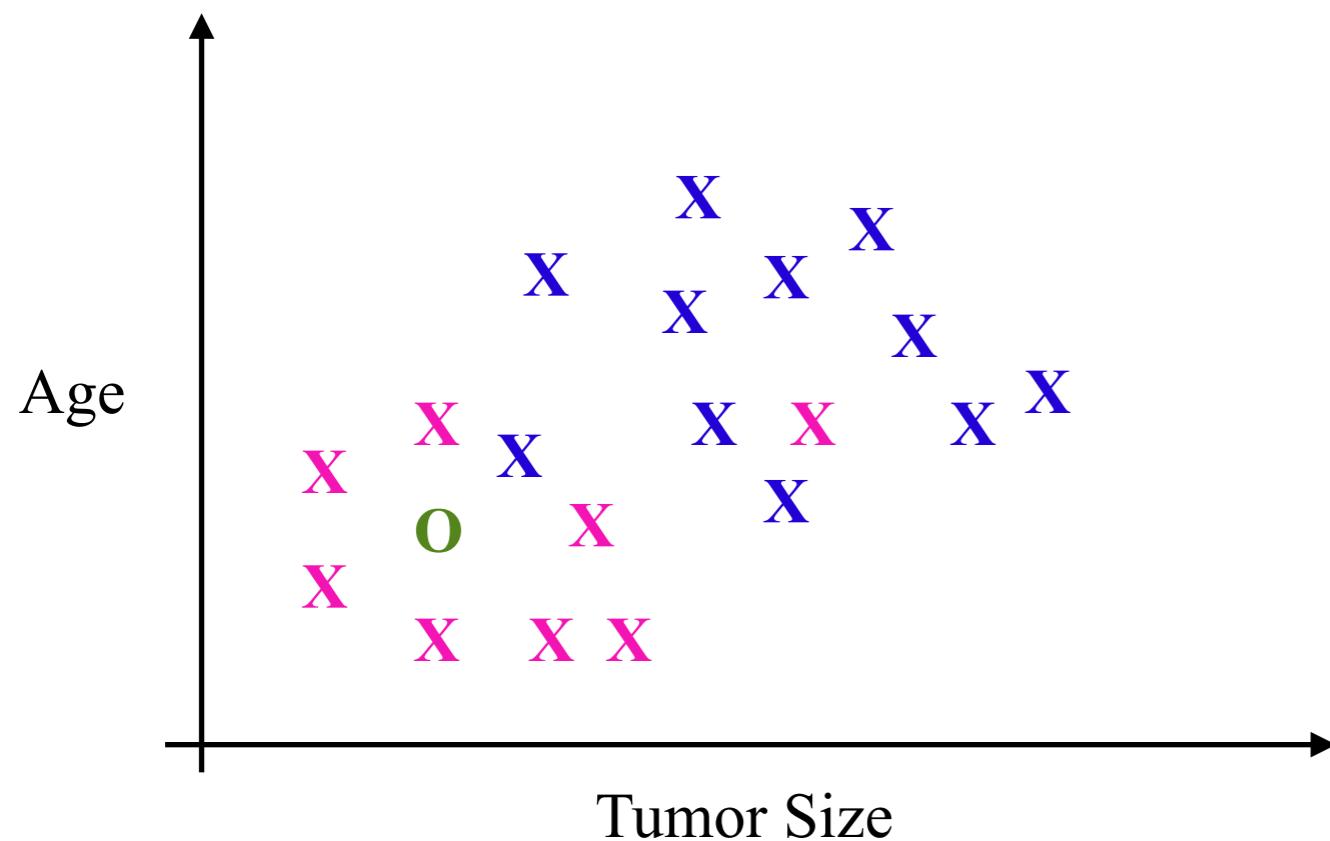


**X** : Malignant

**X** : Benign

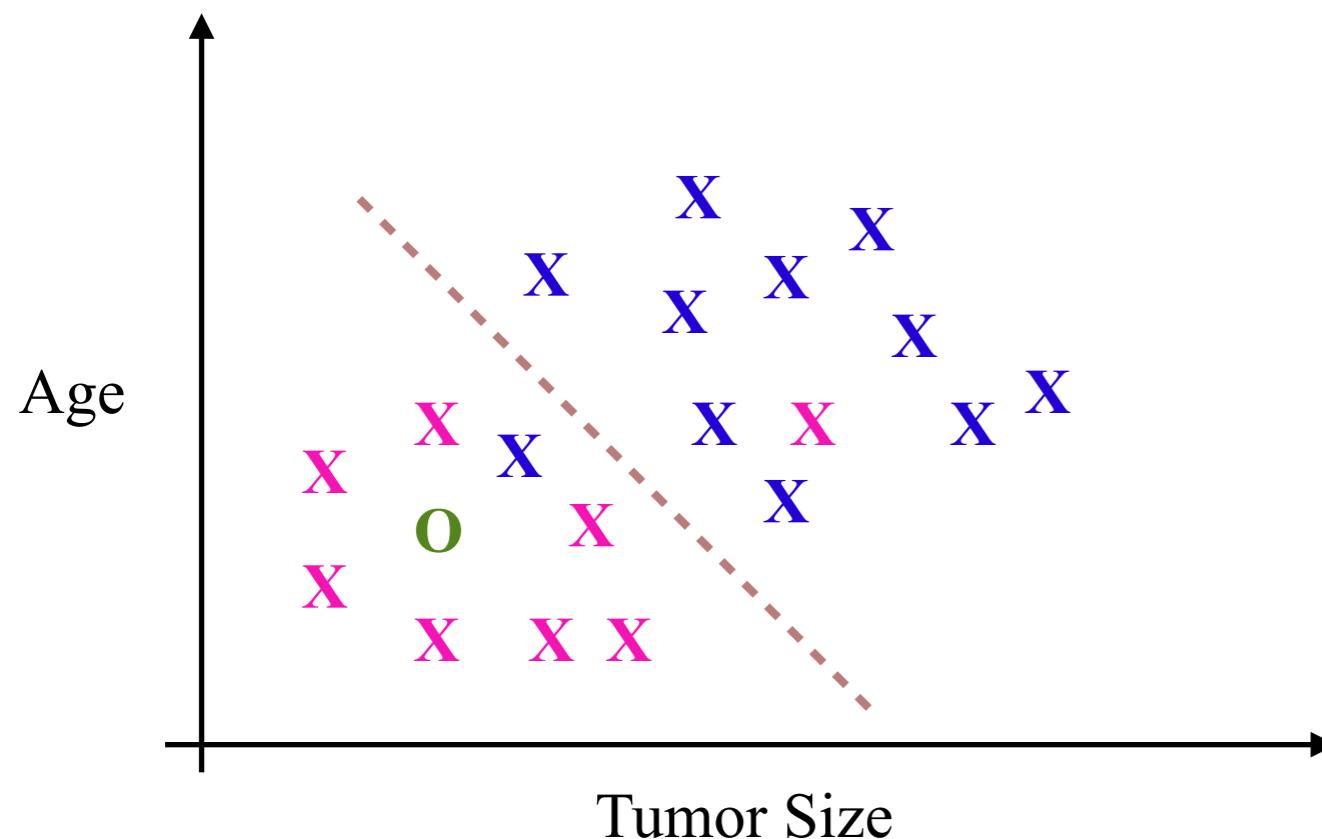
# Intuition (Classification)

Breast cancer (malignant, benign)



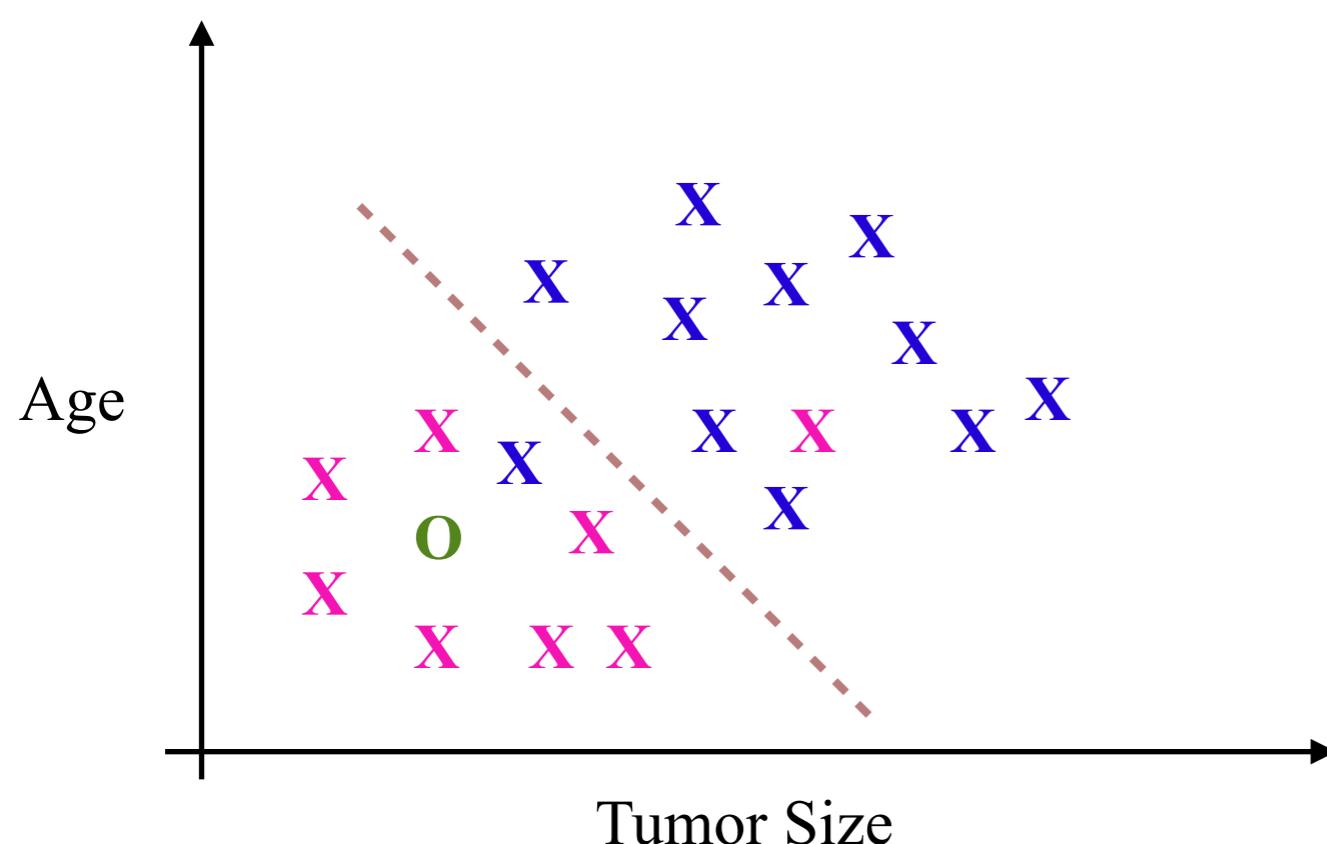
# Intuition (Classification)

Breast cancer (malignant, benign)



# Intuition (Classification)

Breast cancer (malignant, benign)



**X** : Malignant

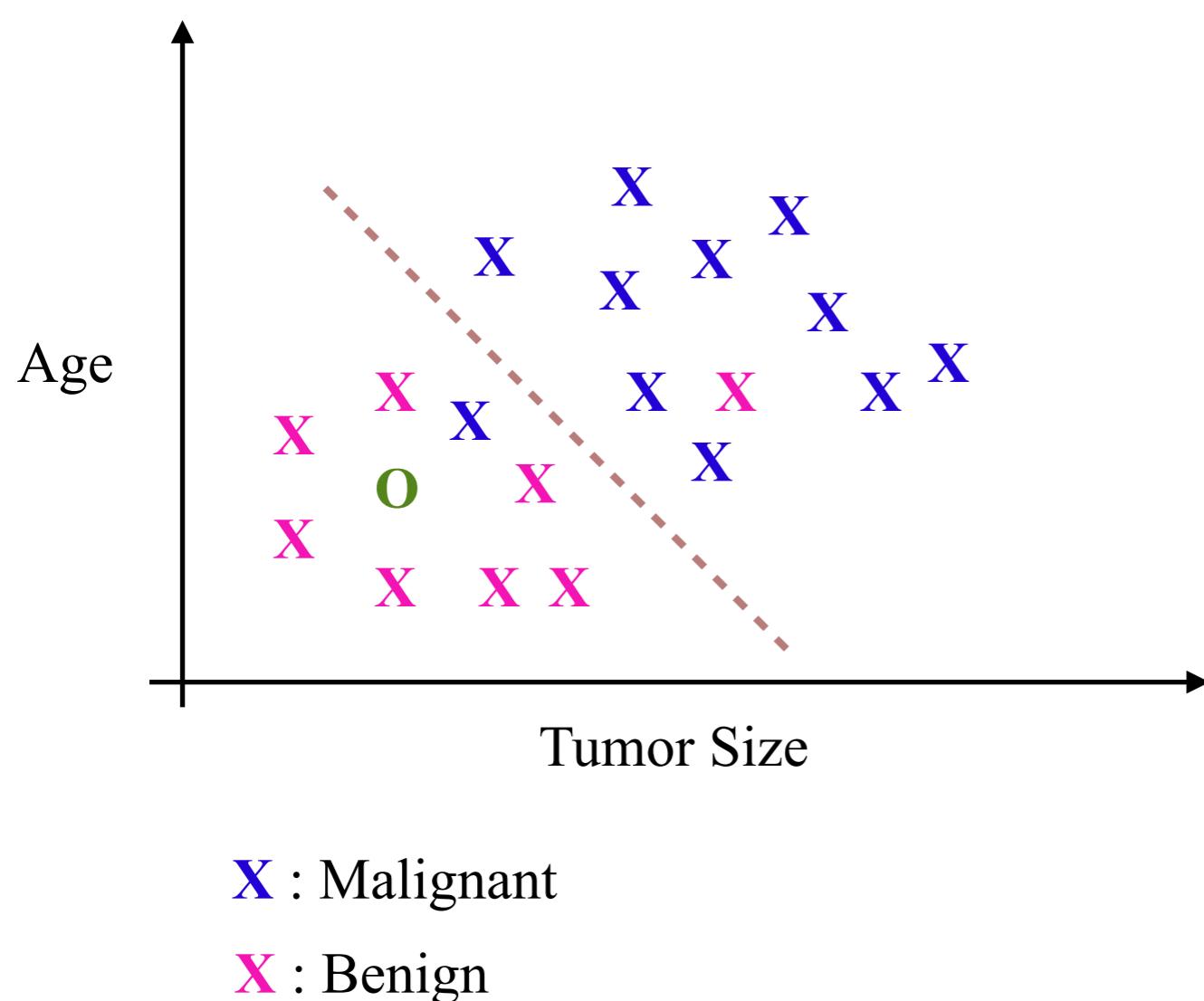
**X** : Benign

Possible to have  $\geq 2$  features e.g.

- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape
- *etc.*

# Intuition (Classification)

## Breast cancer (malignant, benign)



Possible to have  $\geq 2$  features e.g.

- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape
- *etc.*

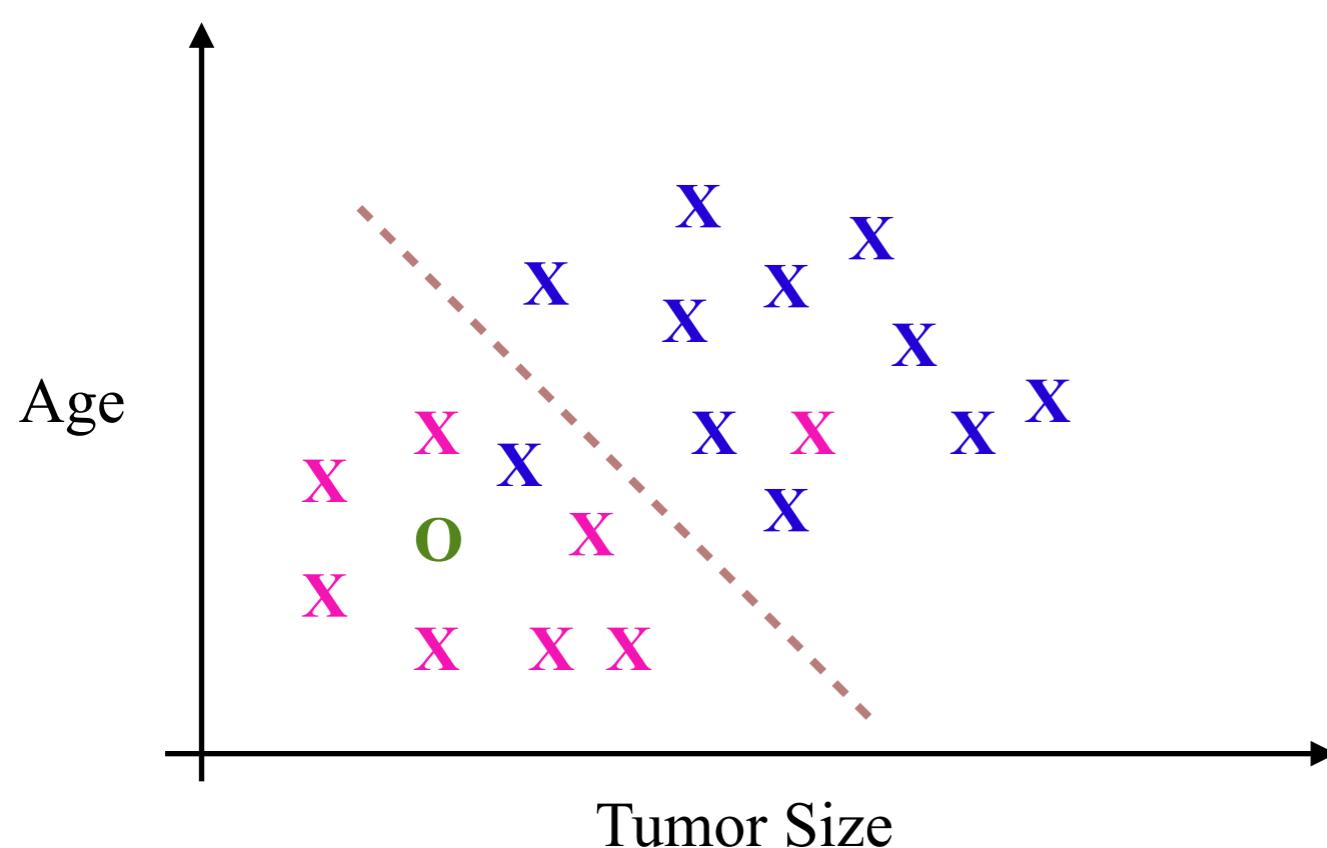
In fact, real problems may involve many features.

Challenges:

How to deal with this situation if a computer is going to run out of memory?

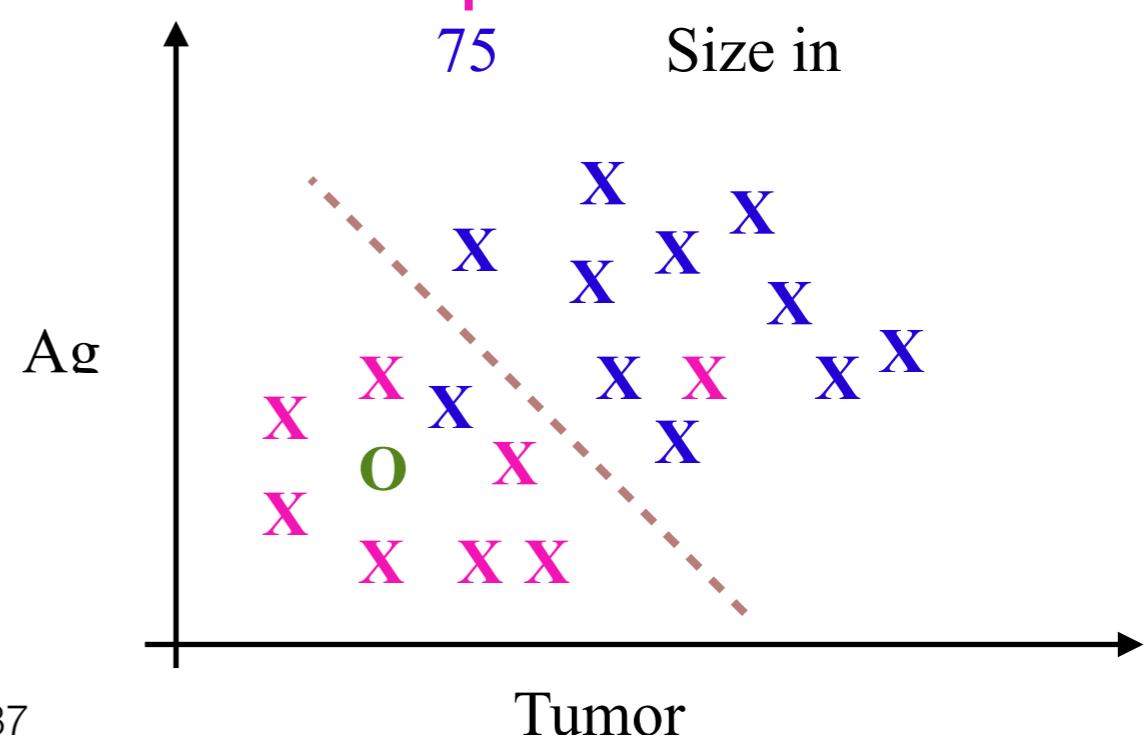
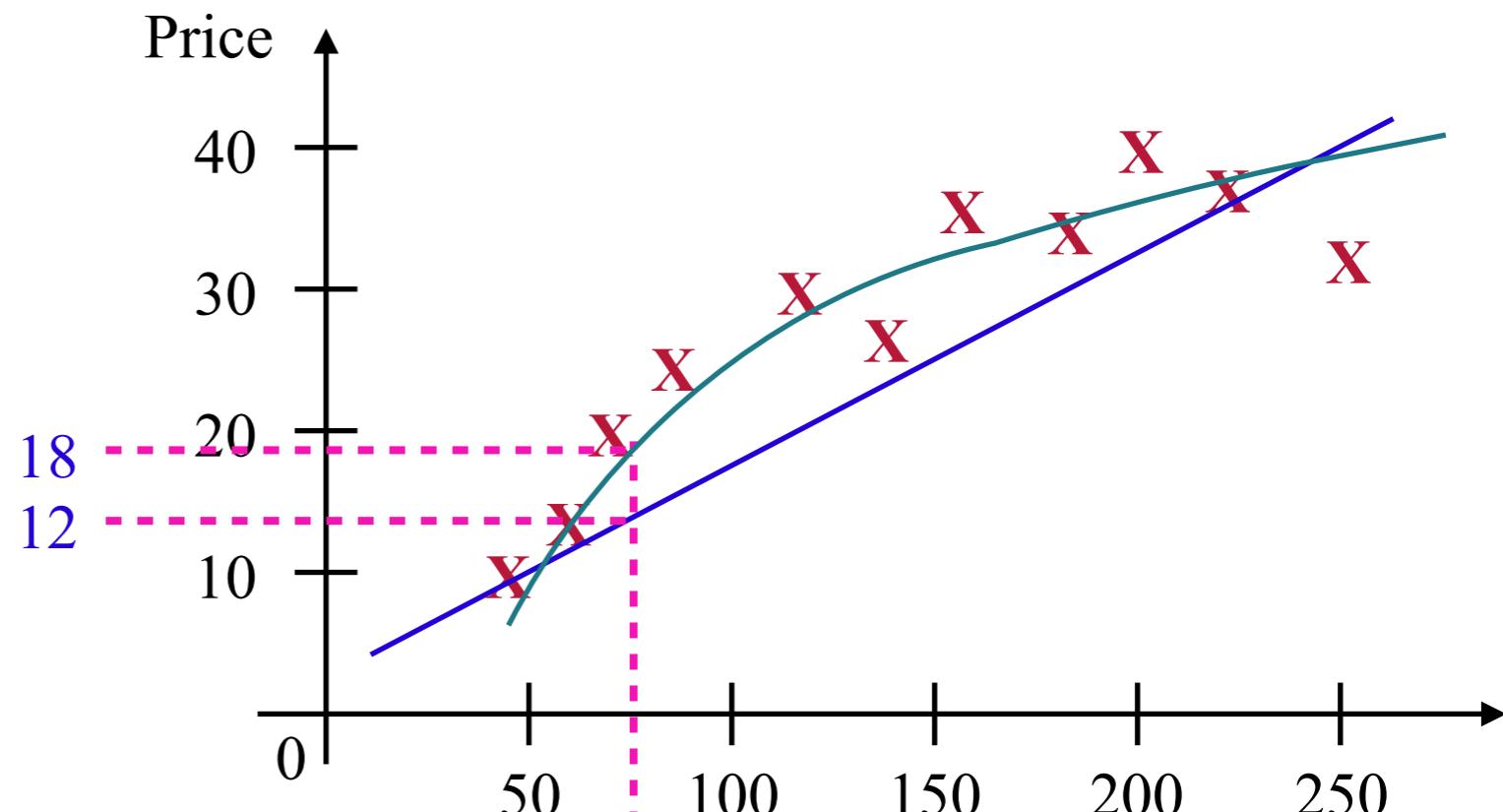
# Intuition (Classification)

Breast cancer (malignant, benign)



# Recap

- Supervised learning
  - ▶ “right answers” are given
- Regression
  - ▶ Predicts a continuous value output
- Classification
  - ▶ Predicts a discrete value output



# Question

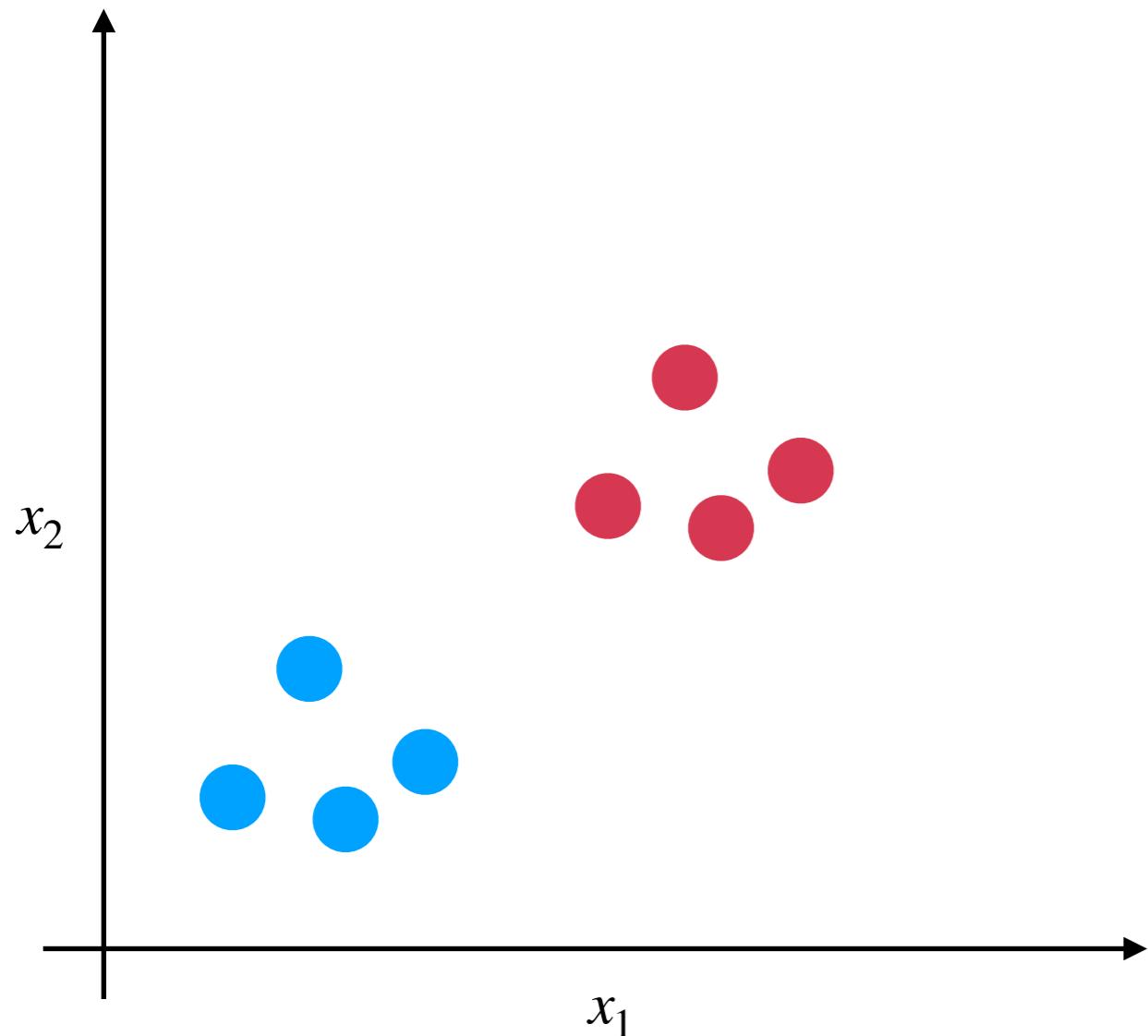
- You are running a company, and you want to employ learning algorithms to address each of the following problems.
  1. You have a large inventory of identical items. You want to predict how many of these items will sell over the next 3 months.
  2. You want to have a software to examine individual customer accounts; and for each account, you want to decide if it has been hacked / compromised.
    - i. Treat both as classification problems
    - ii. Treat problem#1 as a classification problem and problem#2 as a regression problem
    - iii. Treat problem#1 as a regression problem and problem#2 as a classification problem
    - iv. Treat both as regression problems

# Question

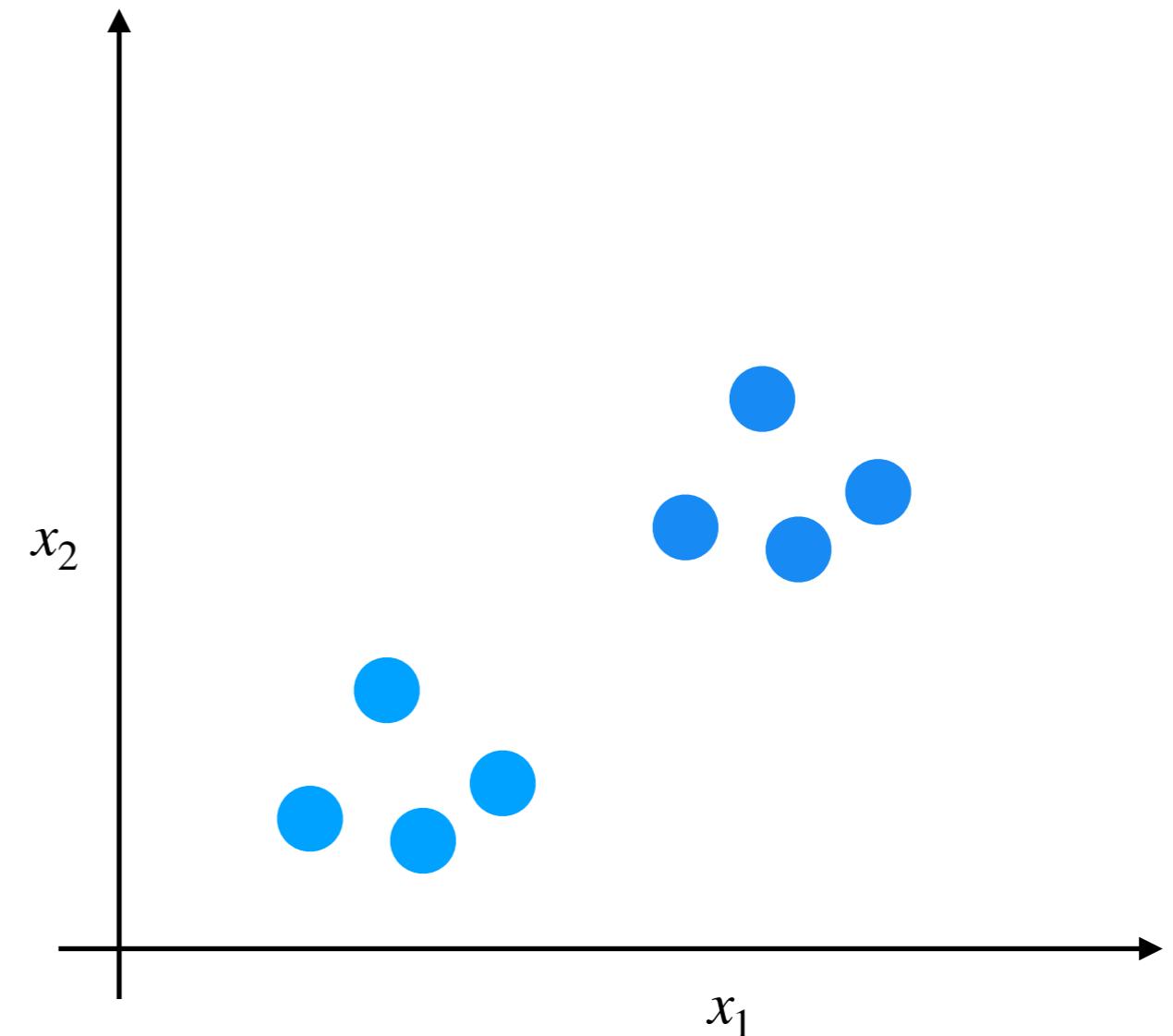
- You are running a company, and you want to employ learning algorithms to address each of the following problems.
  1. You have a large inventory of identical items. You want to predict how many of these items will sell over the next 3 months.
  2. You want to have a software to examine individual customer accounts; and for each account, you want to decide if it has been hacked / compromised.
- i. Treat both as classification problems
- ii. Treat problem#1 as a classification problem and problem#2 as a regression problem
- iii. Treat problem#1 as a regression problem and problem#2 as a classification problem
- iv. Treat both as regression problems

# 2. Unsupervised Learning

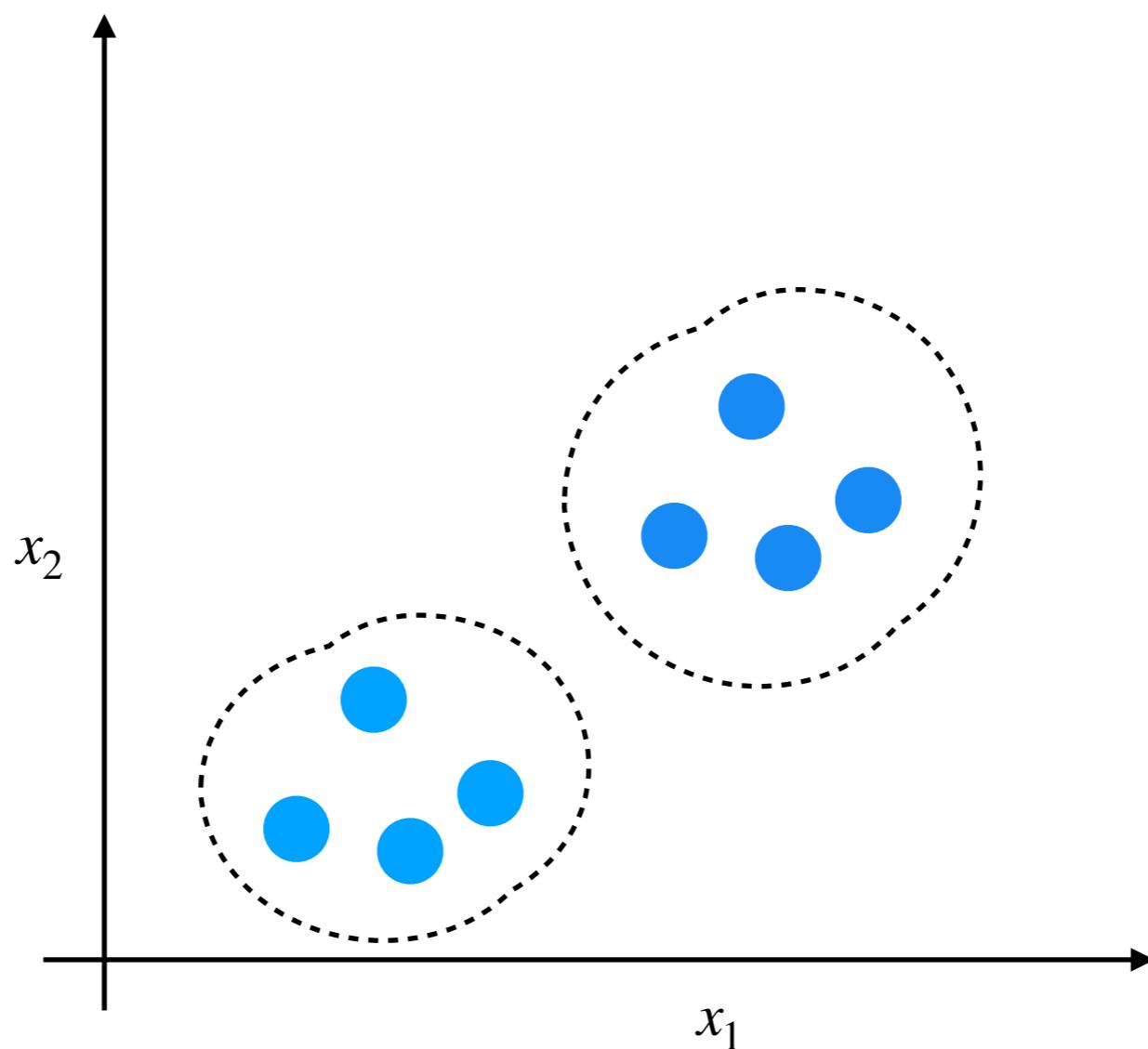
Supervised Learning



Unsupervised Learning



# Intuition (Clustering)

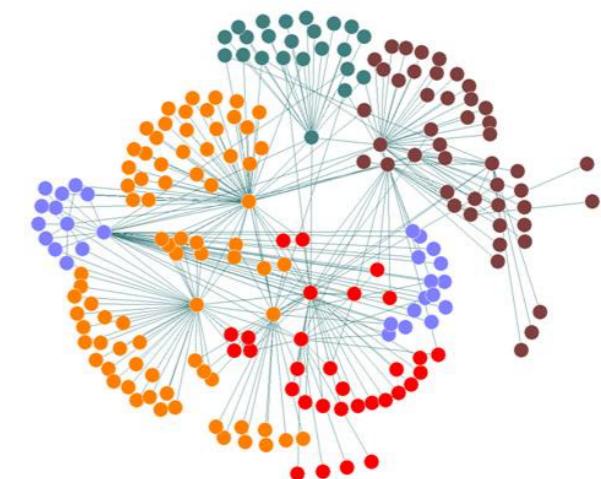


# Intuition (Clustering)

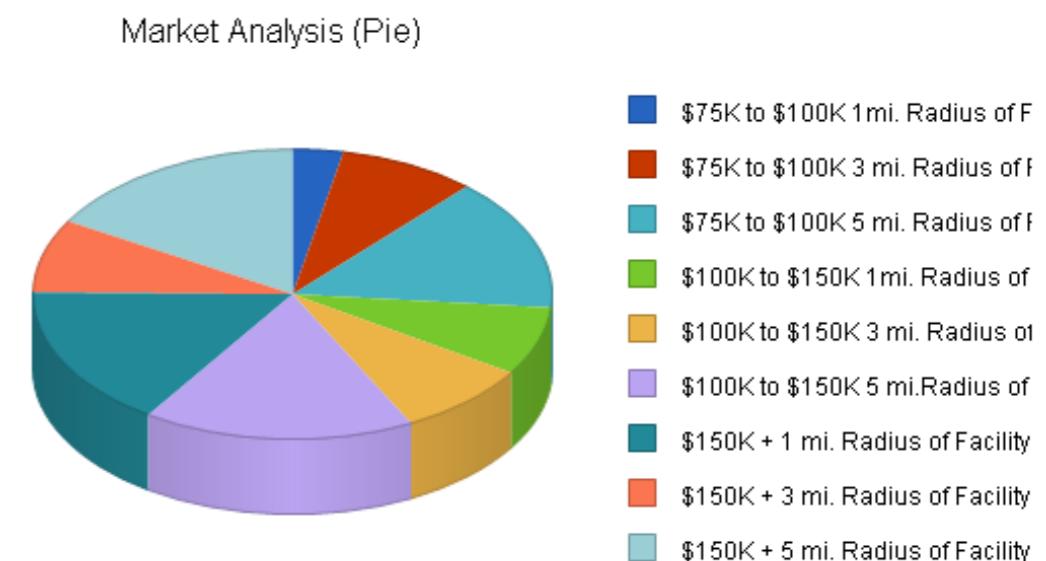
The screenshot shows the Google News homepage at news.google.com. At the top, there's a search bar with the placeholder "Search for topics, locations & sources". Below the search bar, the word "Headlines" is displayed in bold black text. To the right of "Headlines" is a blue link "More Headlines". The main content area displays a list of news items:

- Turkey's president expected to deliver speech describing how Khashoggi was killed**  
The Washington Post • one hour ago  
• Saudi operative dressed as Khashoggi, Turkish source says  
    CNN • today
- Paul to Saudi foreign minister: 'It takes a lot of damn gall' to lecture the US  
    CNN • today
- Steve Hilton: Mr. Trump, you've promised 'severe punishment' over Jamal Khashoggi's death. How about this?  
    Fox News • yesterday • Opinion
- This is the first step to recalibrating U.S.-Saudi relations  
    The Washington Post • today • Opinion

At the bottom left is a link "View full coverage" with a small icon. A small upward arrow is located at the bottom right of the main content area.



Social Network Analysis



Market Segmentation Analysis

# Question

- Of the following examples, which would you address using an unsupervised learning algorithm? (Circle all that apply)
  - i. Given email labeled as spam / not spam, learn a spam filter.
  - ii. Given a set of news articles found on the web, group them into sets of articles about the same stories.
  - iii. Given a database of customer data, automatically discover market segments and group customers into different market segments.
  - iv. Given a dataset of patients diagnosed as either having diabetes or not, learn to classify new patients as having diabetes or not.

# Question

- Of the following examples, which would you address using an unsupervised learning algorithm? (Circle all that apply)
  - i. Given email labeled as spam / not spam, learn a spam filter.
  - ii. Given a set of news articles found on the web, group them into sets of articles about the same stories.
  - iii. Given a database of customer data, automatically discover market segments and group customers into different market segments.
  - iv. Given a dataset of patients diagnosed as either having diabetes or not, learn to classify new patients as having diabetes or not.