Introduction to Machine Learning

KASHTANOVA VICTORIYA

INRIA, EPIONE

UNIVERSITÉ CÔTE D'AZUR

Inria
INVENTEURS DU MONDE NUMÉRIQUE

Plan of the lectures

1. Introduction to Machine Learning (2h)
2. **Practical work (PW)** on Data Analysis and Representation (2h)
3. Supervised Learning : Classification, Regression etc (2h)
4. **PW** on Supervised Learning (2h)
5. ML model evaluation + **PW** (2h)

6. **Project session** (4h)
7. Unsupervised Learning : Clustering + **PW** (4h)
8. Introduction to Deep Learning + **PW** (4h)

Plan of the lectures

1. Introduction to Machine Learning (2h)
2. **Practical work (PW)** on Data Analysis and Representation (2h)
3. Supervised Learning : Classification, Regression etc (2h)
4. **PW** on Supervised Learning (2h)
5. ML model evaluation + **PW** (2h)

6. **Project session** (4h)
7. Unsupervised Learning : Clustering + **PW** (4h)
8. Introduction to Deep Learning + **PW** (4h)

Exam is in early December

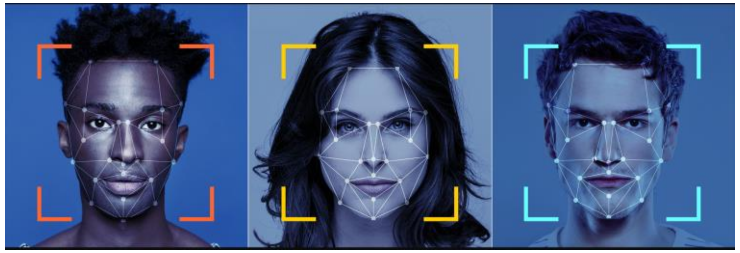
What/Where is Machine Learning ?

Where is Machine Learning ?

AlphaGo

Recommendation systems

Voice assistants



Face recognition

Self-driving cars

Photo filters

What is Machine Learning ?

Using the example of a simple code for playing chess :

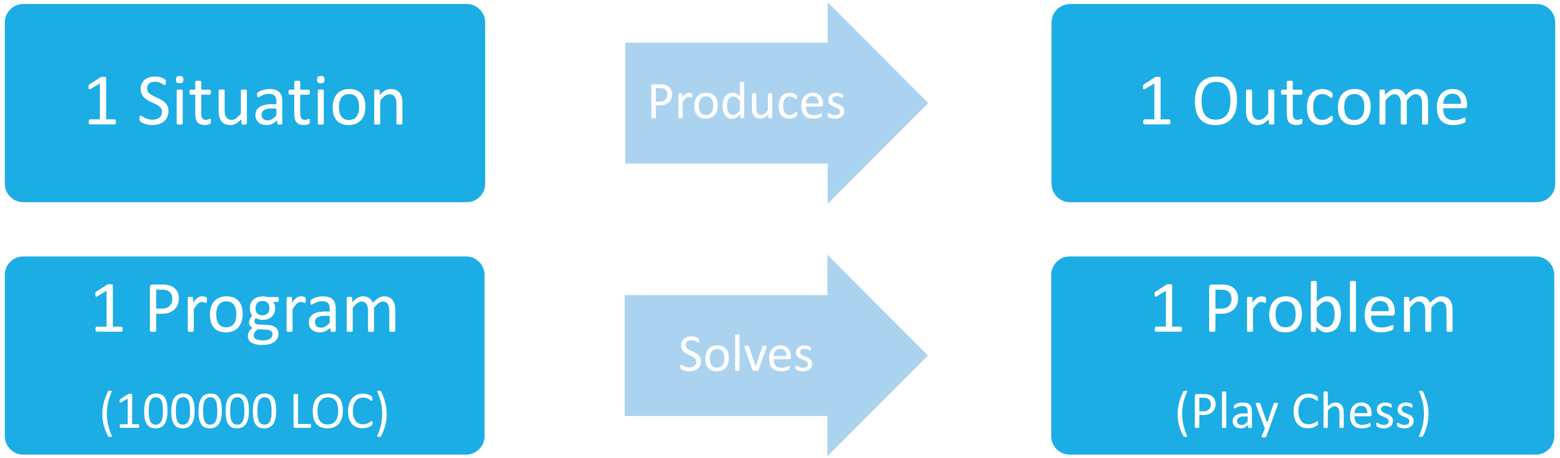
1 Situation → Produses → 1 Outcome

```
if B diagonal from K AND no P around :
    if K can move :
        Move K
    else :
        Game Over
```

Code for ONLY ONE possible outcome

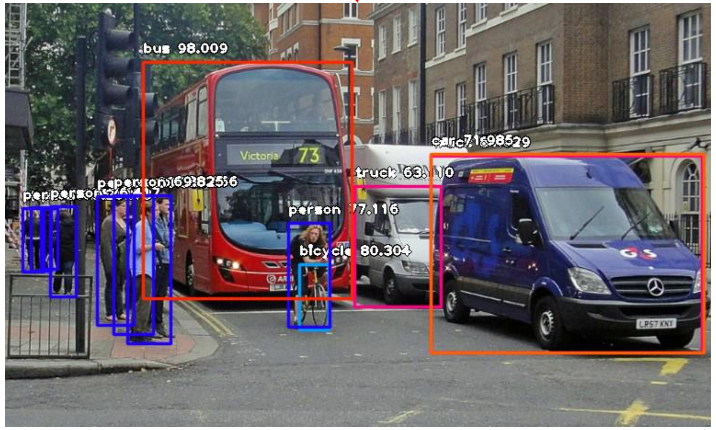
What is Machine Learning ?

Using the example of a simple code for playing chess :



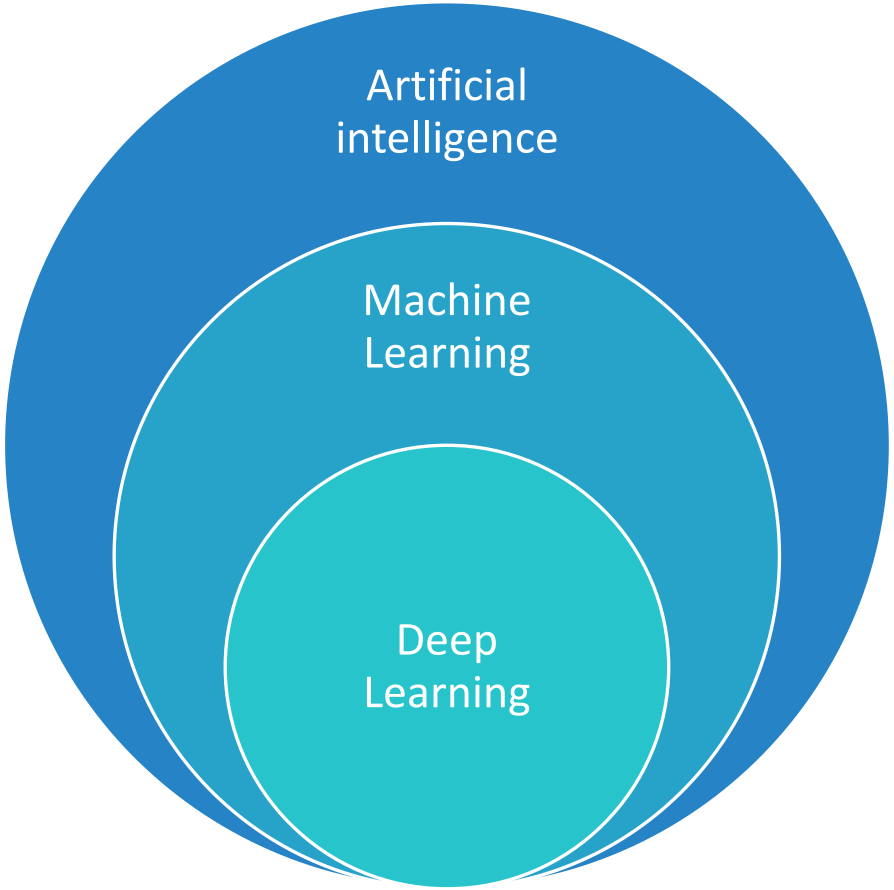
What is Machine Learning ?

1 Program → Solves → **N** Problem (just change input)



What is Machine Learning ?

Machine learning (**ML**) is the study of computer algorithms that improve automatically through experience (Wikipedia)



How are the things learned ?

- Memorization
  - Accumulation of individual facts
  - Limited by :
    - Time to observe facts
    - Memory to store facts

Declarative knowledge

How are the things learned ?

- Memorization
  - Accumulation of individual facts
  - Limited by :
    - Time to observe facts
    - Memory to store facts

- Generalization
  - Deduce new facts from old facts
  - Limited by accuracy of deduction process
    - Essentially a predictive activity
    - Assumes that the past predict the future

Declarative knowledge

Imperative knowledge

How are the things learned ?

- Memorization
  - Accumulation of individual facts
  - Limited by :
    - Time to observe facts
    - Memory to store facts

Declarative knowledge

- Generalization
  - Deduce new facts from old facts
  - Limited by accuracy of deduction process
    - Essentially a predictive activity
    - Assumes that the past predict the future

Imperative knowledge

- Interested in extending to programs that can infer useful information from implicit patterns in data

Basic paradigm of ML

- Observe set of examples : training data
- Infer something about process that generated that data
- Use inference to make predictions about previously unseen data : test data
- Variations on paradigm
    - Supervised : given a set feature/label pairs, find a rule that predicts the label associated with a previously unseen input
    - Unsupervised : given a set of feature vectors (without labels) group them into “natural clusters (or create labels for groups)

Basic paradigm of ML

- Observe set of examples : training data

Benign and Malignant neoplasms with information of neoplasms size and cell density

- Infer something about process that generated that data

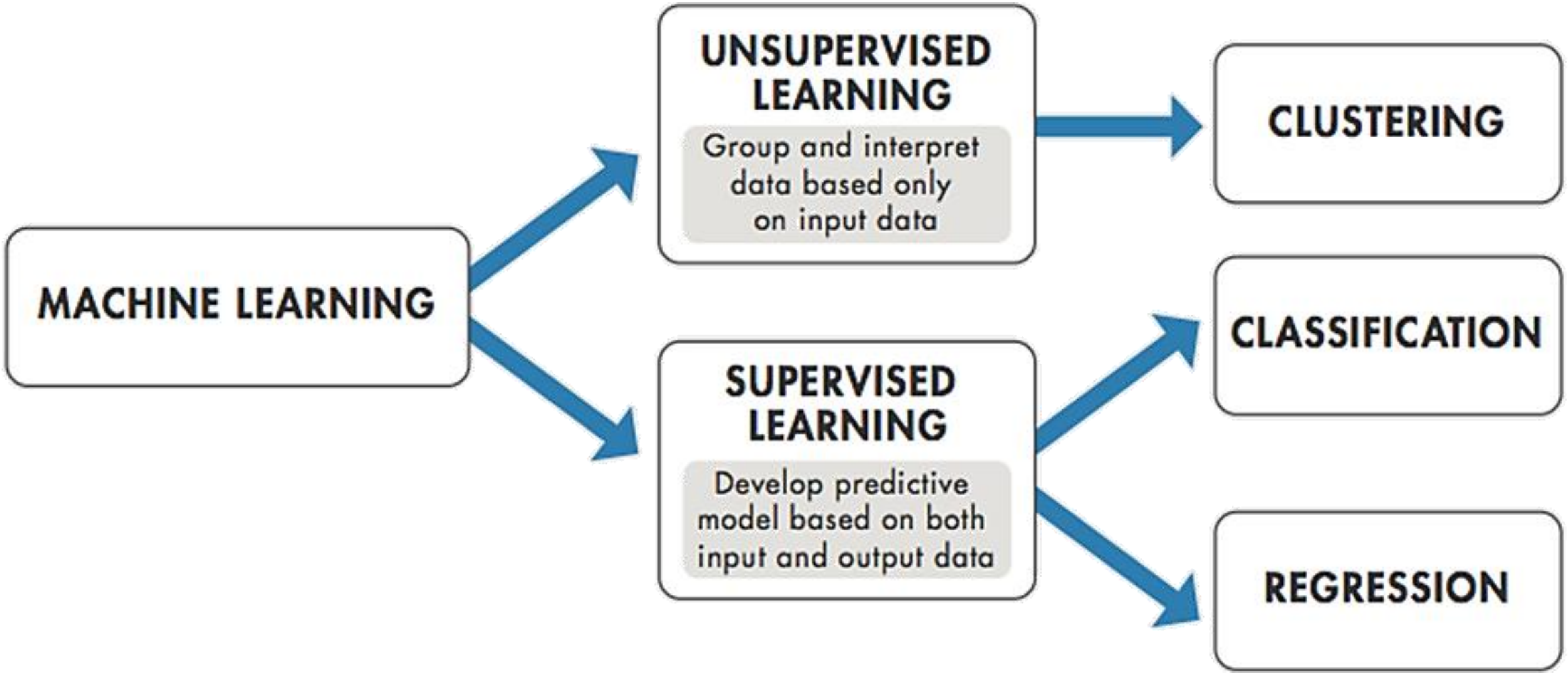
Find canonical model of neoplasms type, by statistics

- Use inference to make predictions about previously unseen data : test data

Predict type of new neoplasms

- Variations on paradigm
    - Supervised : given a set feature/label pairs, find a rule that predicts the label associated with a previously unseen input
    - Unsupervised : given a set of feature vectors (without labels) group them into “natural clusters (or create labels for groups)

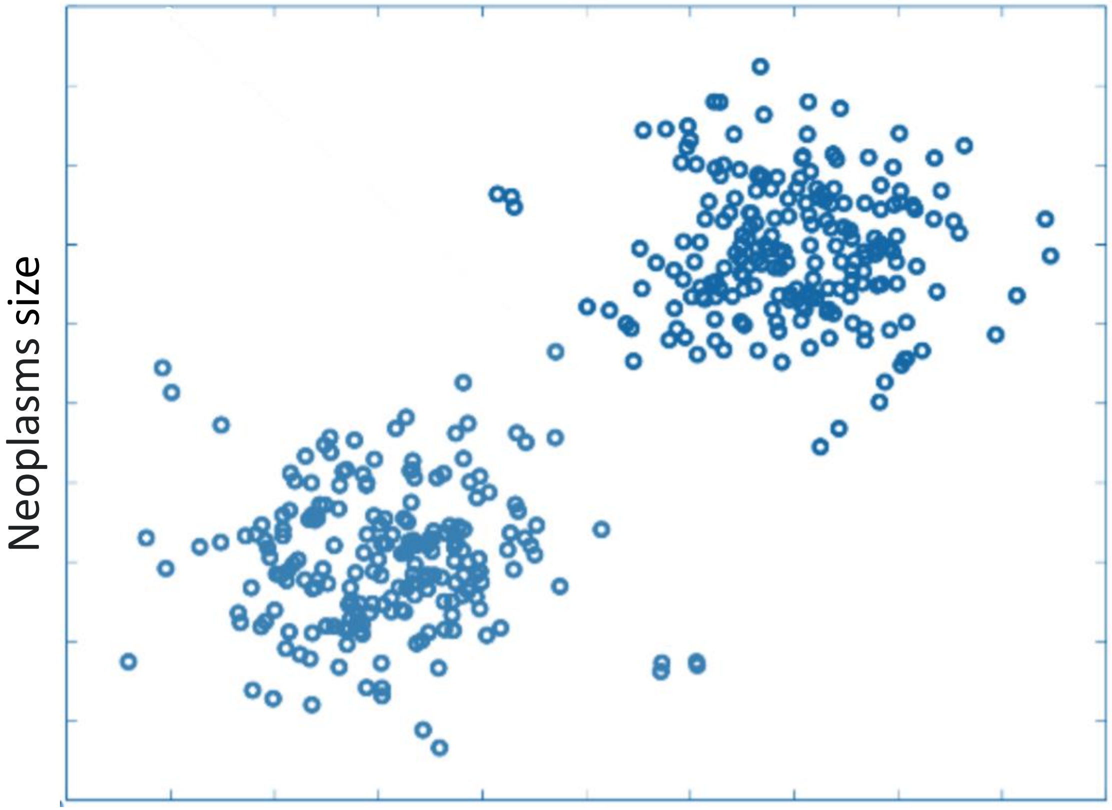
Machine learning methods



Some examples of Classifying and Clustering

Unlabeled data : Breast cancer

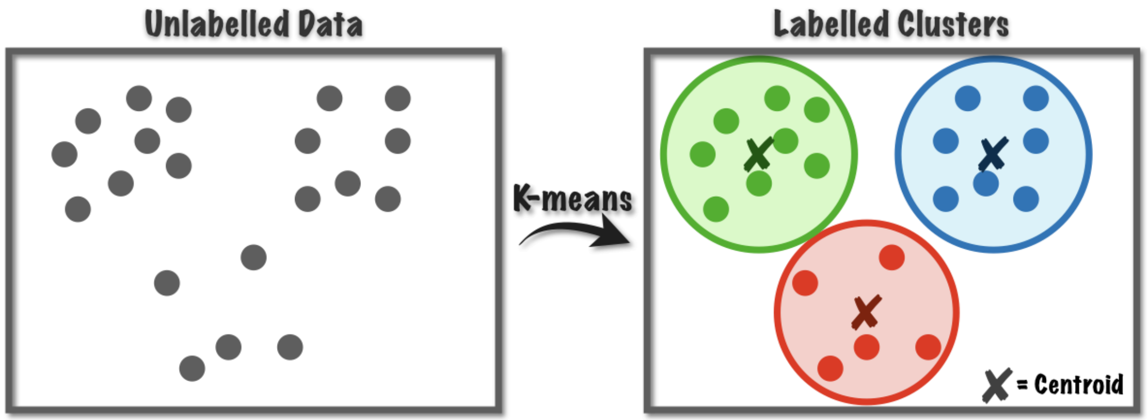
Distribution of neoplasm size vs. cell density



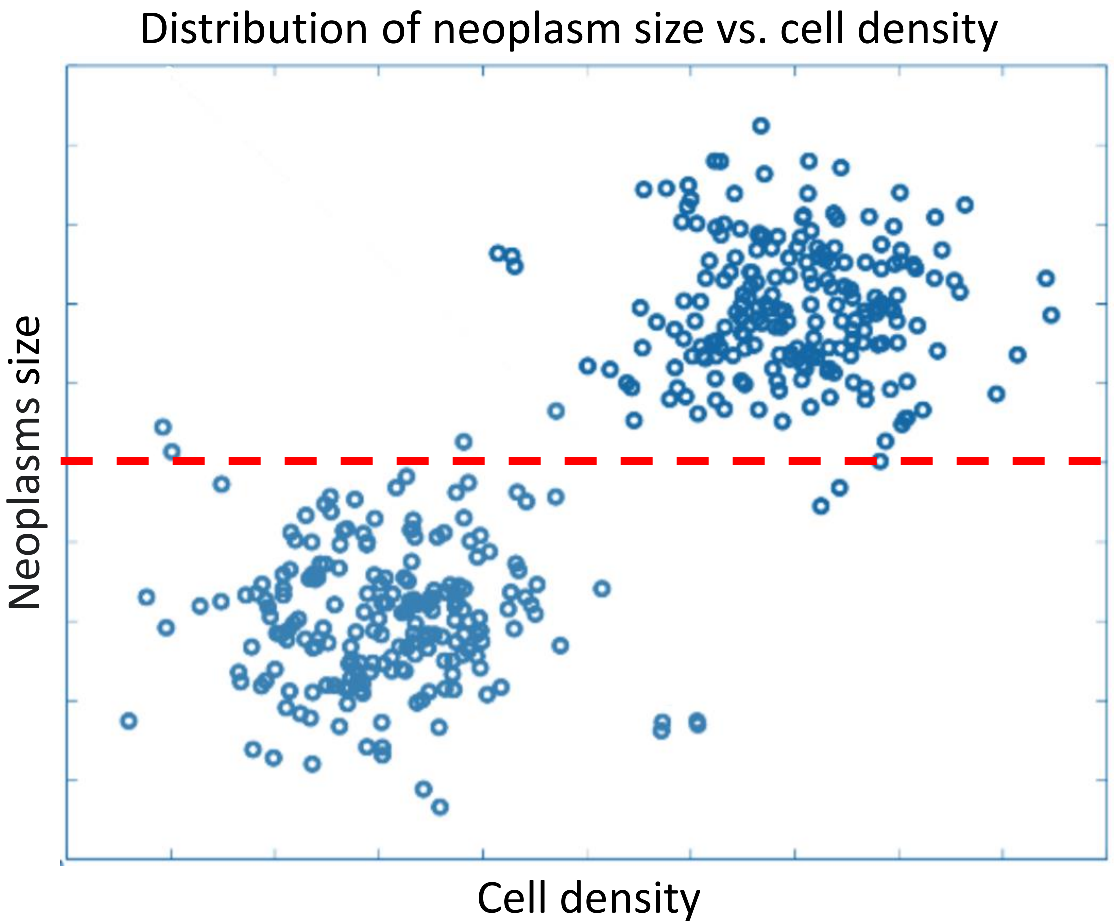
Suppose : There are two types of neoplasms (Benign and Malignant)

Task : Clustering examples into groups

- Want to decide on “similarity” of example, with goal of separating into distinct, “natural” groups
  - Similarity is a distance measure
- Suppose we know that there are K different groups in our training data, but don’t know labels (here K=2)
  - Construct the groups by minimizing of distance between samples in same cluster (objective function)

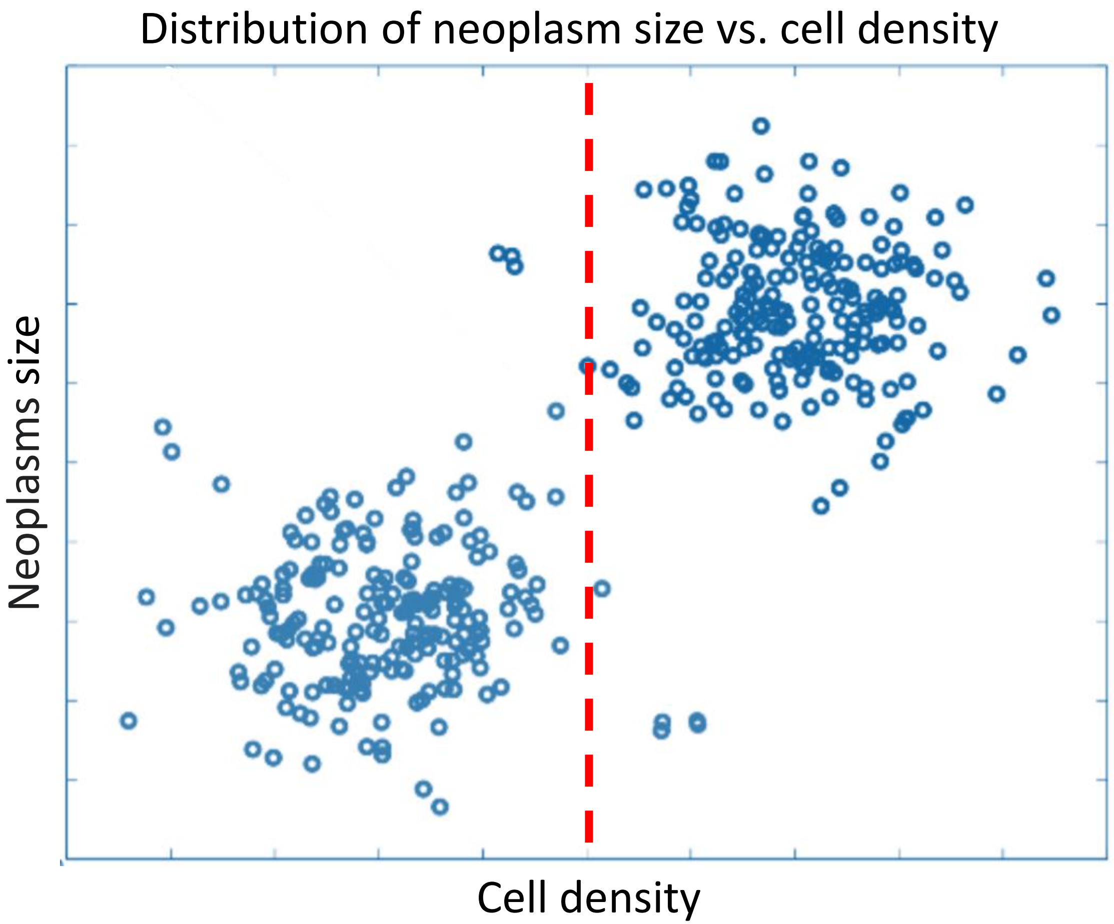


Similarity based on Neoplasm size



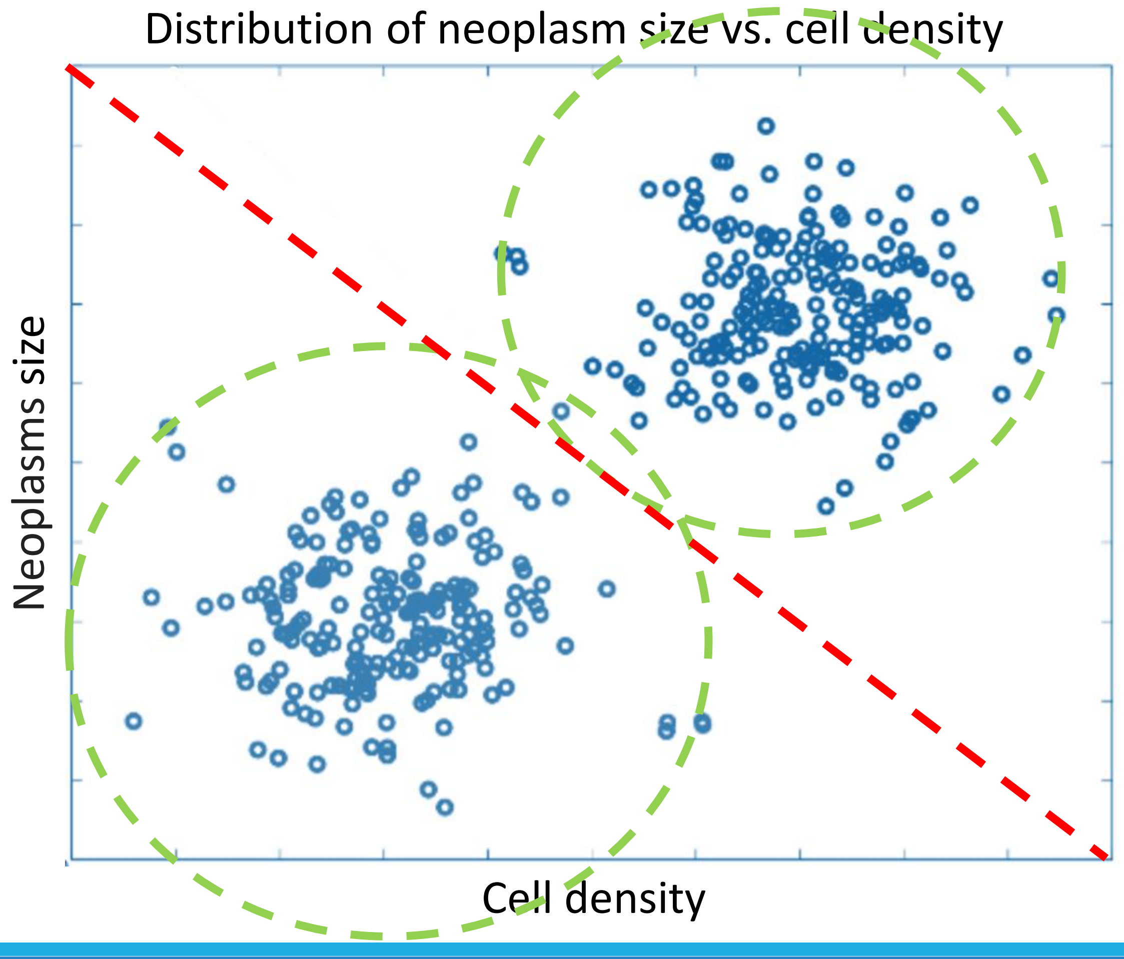
Suppose : There are two types of neoplasms (Benign and Malignant)

Similarity based on Cell density



Suppose : There are two types of neoplasms (Benign and Malignant)

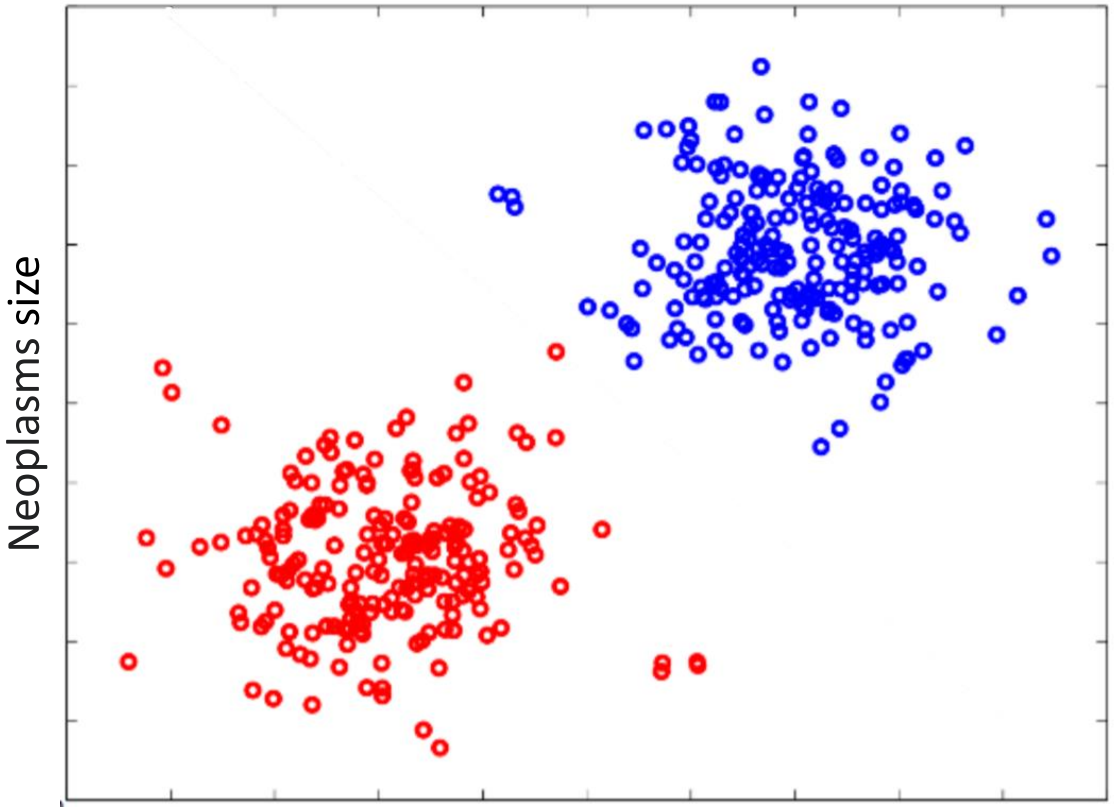
Cluster into two groups using both attributes



Suppose : There are two types of neoplasms (Benign and Malignant)

Suppose data was labeled

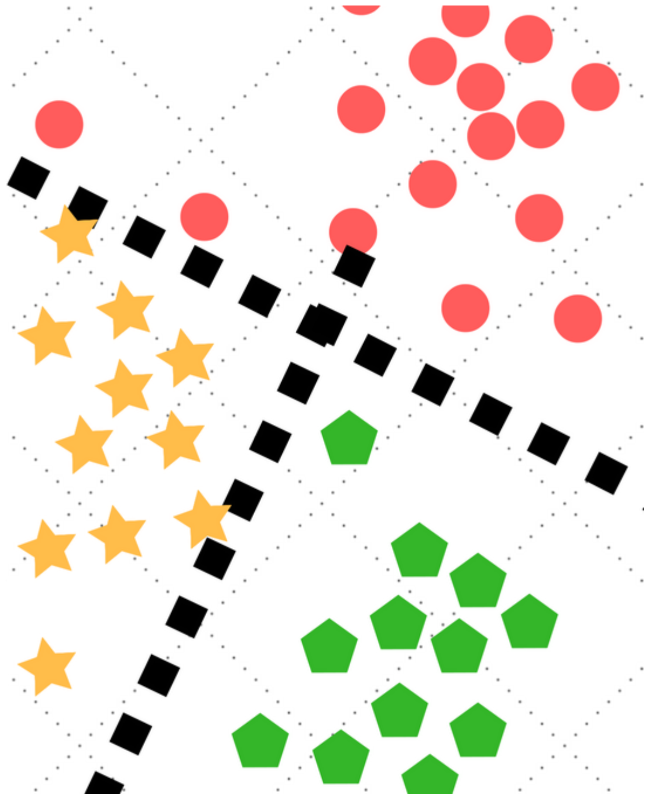
Distribution of neoplasm size vs. cell density



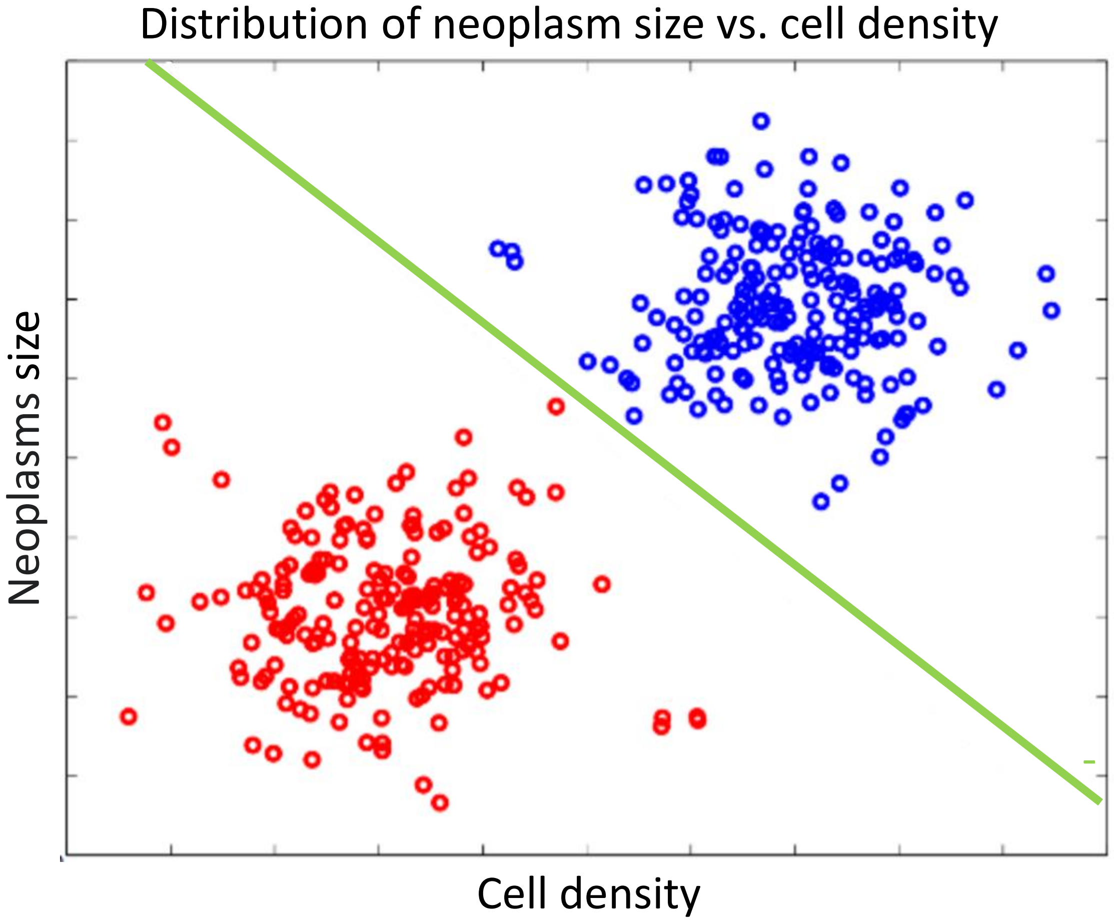
Know : There are two types of neoplasms (Benign and Malignant)

Task : Finding classifier surfaces

- Given labeled groups in feature space, want to find subsurface in that space that separates the groups
  - Subject to constraints on complexity of subsurface
- In this example, have 2D space, so find line (or connected set of line segments) that best separates the two groups
  - When examples well separated this is straightforward
  - When examples in labelled groups overlap, may have to trade off false-positives and false-negatives



Suppose data was labeled



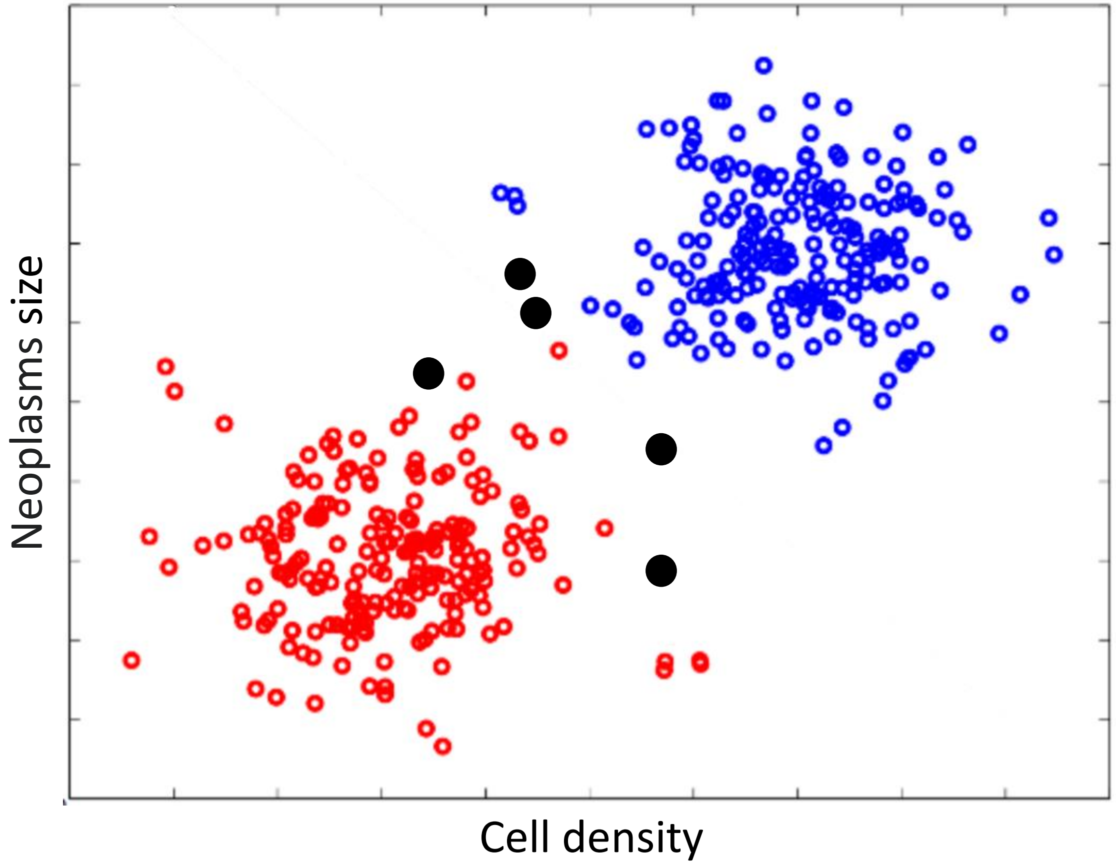
<u>Know :</u> There are two types of neoplasms (Benign and Malignant)

Obvious separator of two groups

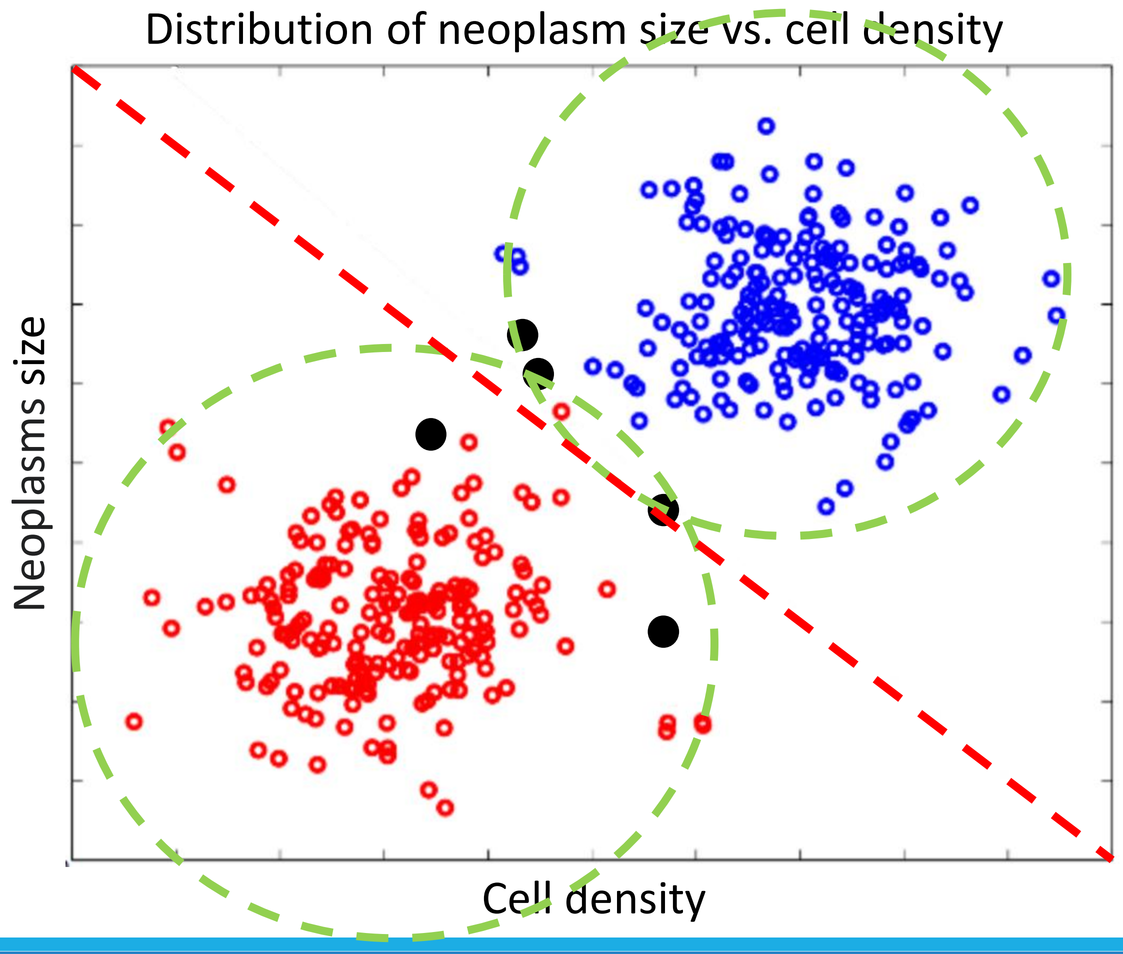
Adding some new data

- Suppose we have learned to separate the Benign and Malignant neoplasms
- Now we are given some new data points and want to use model to decide : **what type do they belong to?**

Distribution of neoplasm size vs. cell density



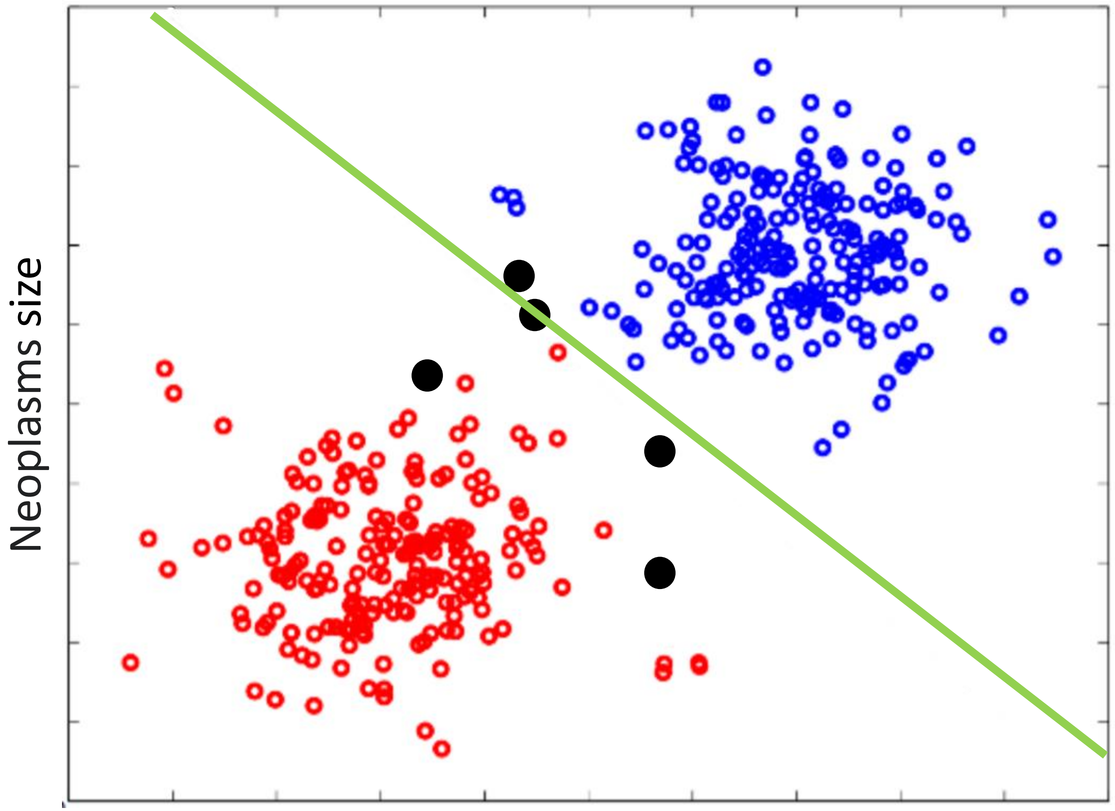
Clustering using unlabeled data



Know : There are two types of neoplasms (Benign and Malignant)

Classified using labeled data

Distribution of neoplasm size vs. cell density



<u>Know :</u> There are two types of neoplasms (Benign and Malignant)

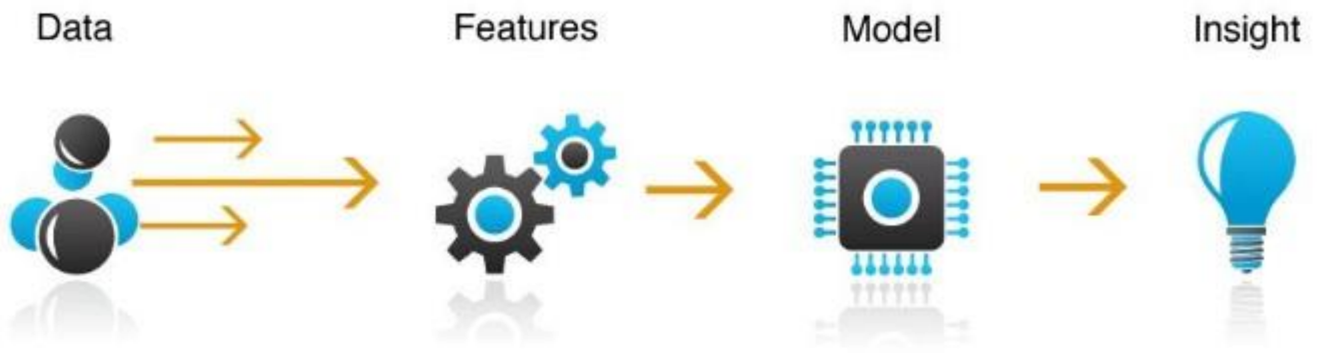
All ML methods require :

- Choosing training data and evaluation method
- Representation of the features
- Distance metric for feature vectors
- Objective function and constraints
- Optimization method for learning the model

Feature Representation

Feature engineering

- Represent examples by feature vectors that will facilitate generalization
- Choose wisely the useful features to avoid an overfitting
- Maximize ratio of useful input to irrelevant input



Reptile classification example

	Features					Label
Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes

Initial model :

- Not enough information to generalize

Reptile classification example

	Features					Label
Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes

Initial model :

- Egg laying
- Has scales
- Is poisonous
- Cold blooded
- No legs

Reptile classification example

	Features					Label
Name	**Egg-laying**	**Scales**	**Poisonous**	**Cold-blooded**	**# legs**	**Reptile**
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes

Current model :

- Has scales
- Cold blooded
- No legs

Boa doesn't fit model, is labeled as reptile
=> Need to refine model

Reptile classification example

		Features				Label
Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes
Chicken	True	True	False	False	2	No

Current model :

- Has scales
- Cold blooded
- No legs

Reptile classification example

		Features				Label
Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes
Chicken	True	True	False	False	2	No
Alligator	True	True	False	True	4	Yes

Current model :

- Has scales
- Cold blooded
- Has 0 or 4 legs

Alligator doesn't fit model, but is labeled as reptile => Need to refine model

Reptile classification example

Features Label

Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes
Chicken	True	True	False	False	2	No
Alligator	True	True	False	True	4	Yes
Dart frog	True	False	True	False	4	No

Current model :

- Has scales
- Cold blooded
- Has 0 or 4 legs

Reptile classification example

Features **Label**

Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes
Chicken	True	True	False	False	2	No
Alligator	True	True	False	True	4	Yes
Dart frog	True	False	True	False	4	No
Salmon	True	True	False	True	0	No
Python	True	True	False	True	0	Yes

Current model :
- Has scales
- Cold blooded
- Has 0 or 4 legs

No easy way to add to rule that will correctly classify (since identical feature values)

Reptile classification example

Current model :
- Has scales
- Cold blooded

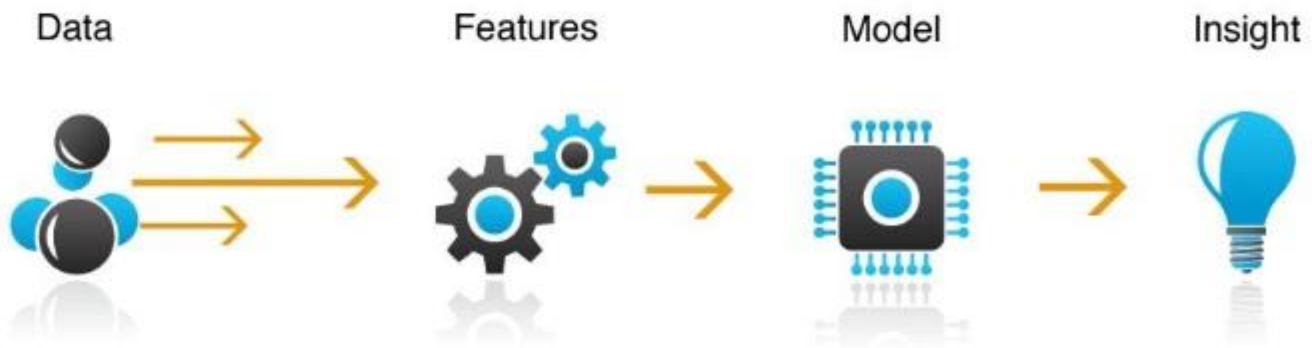
Not perfect, but no false negatives (anything classified as not reptile is correctly labelled); some false positives (may incorrectly label some animals as reptile)

Features **Label**

Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile
Cobra	True	True	True	True	0	Yes
Rattlesnake	True	True	True	True	0	Yes
Boa constrictor	False	True	False	True	0	Yes
Chicken	True	True	False	False	2	No
Alligator	True	True	False	True	4	Yes
Dart frog	True	False	True	False	4	No
Salmon	True	True	False	True	0	No
Python	True	True	False	True	0	Yes

Feature engineering

- Deciding which features to include and which are merely adding noise to classifier
- Defining how to **measure distances between training examples** (and ultimately between classifiers and new instances)
- Deciding how to weight relative importance of different dimensions of feature vector, which impacts definition of distance



Measuring distance between animals

Name	Egg-laying	Scales	Poisonous	Cold-blooded	# legs	Reptile

Binary features

Integer feature

- One way to learn to separate reptiles from non-reptiles is to measure the distance between pairs of examples, and use that :
  - To cluster nearby examples into a common class (unlabeled data), or
  - To find a classifier surface in space of examples that optimally separates different (labelled) collections of examples from other collections

Rattlesnake = (1,1,1,1,0)
Boa constrictor = (0,1,0,1,0)
Dart frog = (1,0,1,0,4)

Can convert examples into feature vectors

Minkowski metric

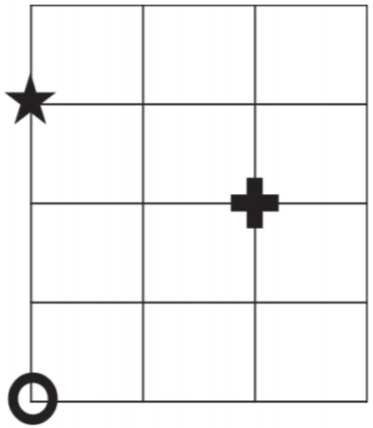
$$dist(X1,X2,p) = \left(\sum_{k=1}^{len} abs(X1_k - X2_k)^p\right)^{1/p}$$

Need to measure distances between feature vectors

p = 1: Manhattan Distance
p = 2: Euclidean Distance

Is circle closer to star or cross ?

- Euclidean distance :
  - Cross - 2.8
  - Star – 3
- Manhattan distance :
  - Cross – 4
  - Star - 3



Typically use Euclidean metric; Manhattan may be appropriate if different dimensions are not comparable

Reptile classification example

```
rattlesnake = [1,1,1,1,0]
boa constrictor = [0,1,0,1,0]
dartFrog = [1,0,1,0,4]
```

Reptile classification example

```
rattlesnake = [1,1,1,1,0]
boa constrictor = [0,1,0,1,0]
dartFrog = [1,0,1,0,4]
```

	rattlesnake	boa constrictor	dart frog
rattlesnake	--	1.414	4.243
boa constrictor	1.414	--	4.472
dart frog	4.243	4.472	--

Using Euclidian distance, rattlesnake and boa constrictor are much closer to each other, then they are to the dart frog

Add an alligator

```
▪alligator = Animal('alligator', [1,1,0,1,4])
▪animals.append(alligator)
▪compareAnimals(animals, 3)
```

Add an alligator

```
▪alligator = Animal('alligator', [1,1,0,1,4])
▪animals.append(alligator)
▪compareAnimals(animals, 3)
```

	rattlesnake	boa constrictor	dart frog	alligator
rattlesnake	--	1.414	4.243	4.123
boa constrictor	1.414	--	4.472	4.123
dart frog	4.243	4.472	--	1.732
alligator	4.123	4.123	1.732	--

Alligator is closer to dart frog than to snakes – why ?

- Alligator differs from frog in 3 features, from boa in only 2 features
- But scale on “legs” is from 0 to 4, on other features is 0 to 1
- **“Legs” dimension is disproportionately large**

Using binary features

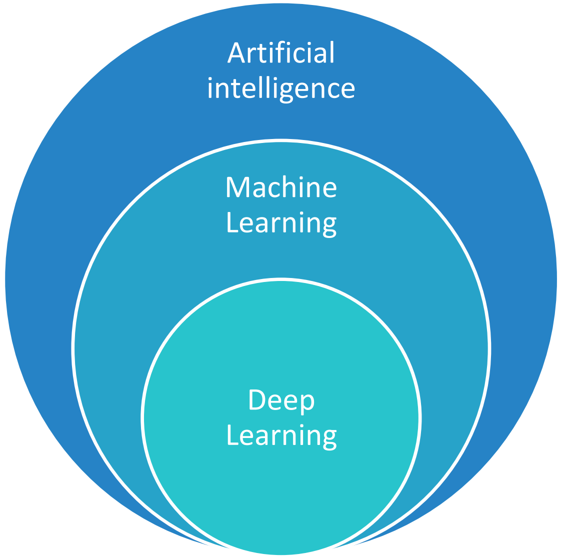
```
rattlesnake = [1,1,1,1,0]
boa constrictor = [0,1,0,1,0]
dartFrog = [1,0,1,0,1]
Alligator = [1,1,0,1,1]
```

	rattlesnake	boa constrictor	dart frog	alligator
rattlesnake	--	1.414	1.732	1.414
boa constrictor	1.414	--	2.236	1.414
dart frog	1.732	2.236	--	1.732
alligator	1.414	1.414	1.732	--

Now alligator is closer to snakes than it is to dart frog =>
Feature Engineering Matters

Summary

- Machine Learning methods provide a way of building models of processes from data sets
  - Supervised learning uses labelled data, and creates classifiers that optimally separate data into known classes
  - Unsupervised learning tries to infer latent variables by clustering training examples into nearby groups
- Choice of features influences results
- Choice of distance measurement between examples influence results
- We will see some examples of clustering methods
- We will see some examples of classifiers
- We will see some advanced techniques such as Deep Learning



Sources

- MIT course “Introduction to Computational Thinking and Data Science” (Prof. Eric Grimson, Prof. John Guttag)
- Open Machine Learning Course (by Yury Kashnitsky, mlcourse.ai)
- YouTube lections “Algorithms and Concepts” (by CodeEmporium)