#### Al Games course

Certificate 2, session 1
Introduction to Machine Learning



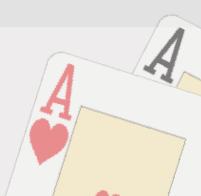




#### Part 1. A few words about learning







#### What is learning?

- Mitchell: learning is improving with experience at some task T according to a performance measure M;
- systems are not explicitly programmed to carry out T; they are programmed how to learn to carry out T;
- learning usually means learning from data.









#### Example: choosing a film for a user

#### **IMDb**

- Do you like *The Matrix*?
- Do you like *Gladiator*?
- Do you like Forest Gump?
- Do you like Sherlock Holmes?
- Do you like Fight Club?

















Yes

No

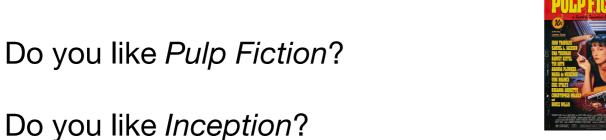
Yes

No

Yes

Yes!

Yes!!









collect a set of data instances

emails, pictures, user profiles, tweets etc.

 represent them in a machine-readable format, as vectors of features

[1, 0, 0, 0.85, -3, 4, 0, 0, 0, 0, 0, 2, 0, 0, 0, 275]

• provide correct labels for every data instance

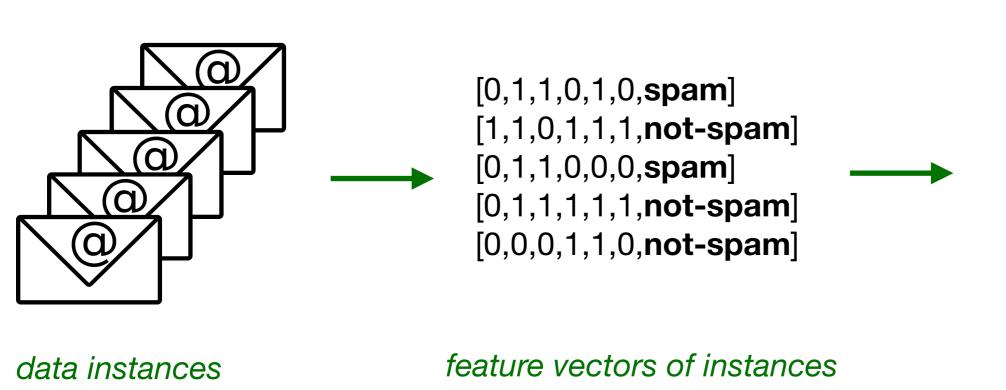
"spam" - "not spam", age, "solvent" - "insolvent", topic etc.

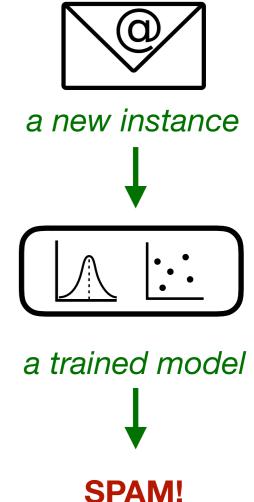
train a model to assign correct labels to instances (potentially unseen)







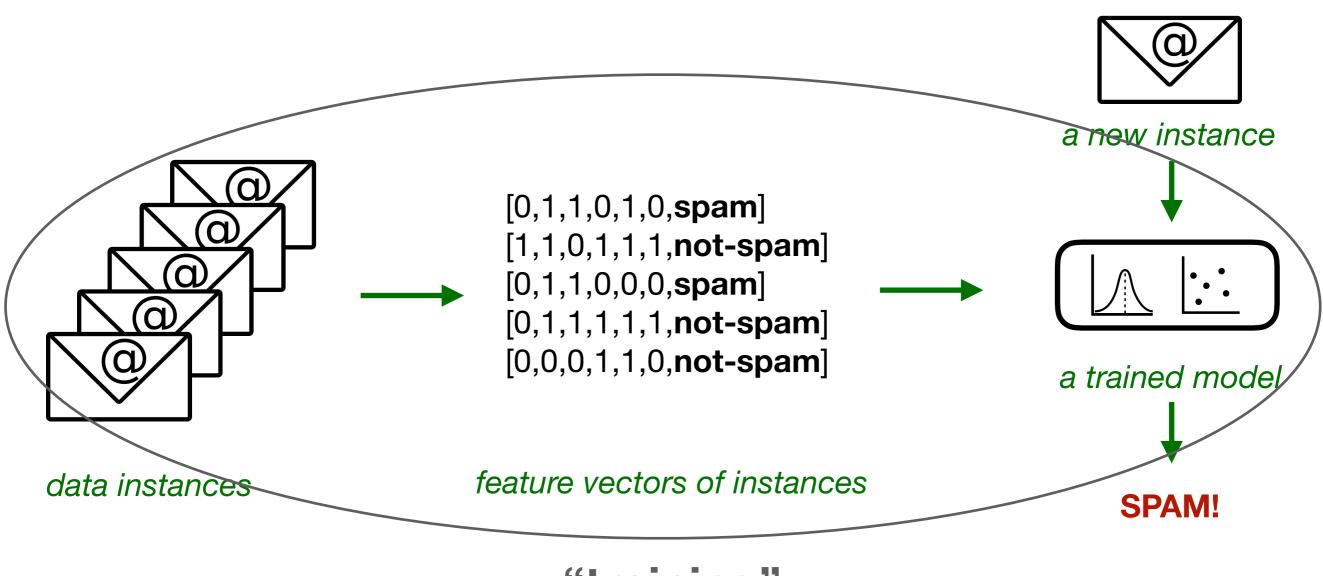










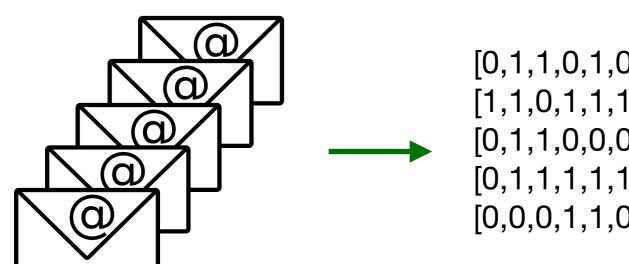


"training"



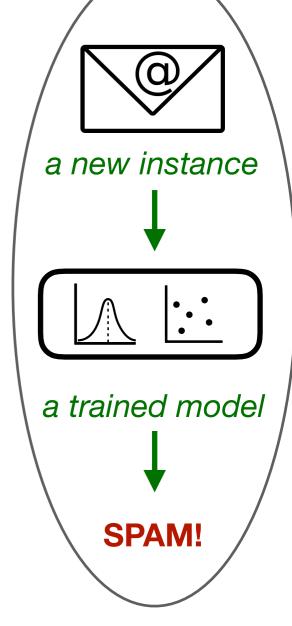






[0,1,1,0,1,0,spam] [1,1,0,1,1,1,not-spam] [0,1,1,0,0,0,spam] [0,1,1,1,1,1,not-spam] [0,0,0,1,1,0,not-spam]

feature vectors of instances



"testing"



data instances





#### Types of learning-1

Supervised learning: we know correct labels

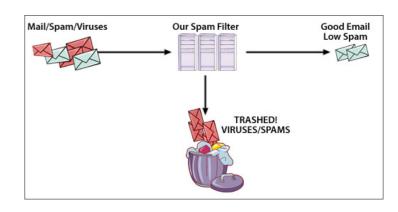
Ex: an email is either "spam" or "not spam"

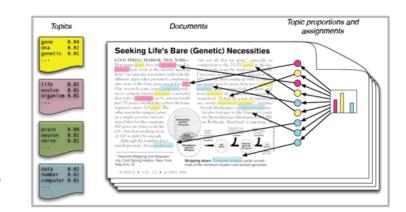
Unsupervised learning: no labels given

Ex: a set of articles you need to group by topics, but you do not know their topic labels

 Semi-supervised learning: we know labels for a fraction of data (usually small)

Ex: same set of articles, but for some of them you do know the topic label











# Types of learning-2

Classification: labels are categories

Ex1: an email is either "spam" or "not spam"

Ex2: bank clients have a known credit rating category



Regression: labels are real numbers

Ex: every bank client has a known numeric credit rating score



 Clustering: instances are divided into groups (number and type of groups unknown)

Ex: new patients have medical profiles and need to be grouped wrt health issues







#### Part 2. Classification example







#### Bankruptcy prediction

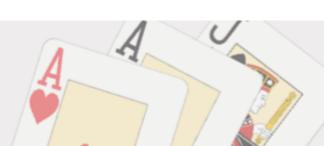
 analytics data on 250 companies: http://archive.ics.uci.edu/ml/datasets/ Qualitative\_Bankruptcy



- based on the data, we need to decide whether or not a company goes bankrupt,
- i.e., classify every instance as bankrupt or not bankrupt.





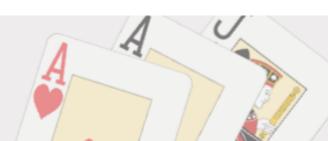




- for each company there is information on:
  - industrial risk: degree of competition, growth of market demand etc.
  - management risk: management stability, HR management, business planning etc.
  - financial flexibility: direct and indirect financing
  - credibility: credit history, relations with financial institutions etc.
  - competitiveness: market position, differentiated strategies etc.
  - operating risk: production efficiency, effectiveness of sale network etc.
- all attributes can have values positive (1), average (0), negative(-1)
- every company is labeled as bankrupt (B) or not bankrupt (NB)

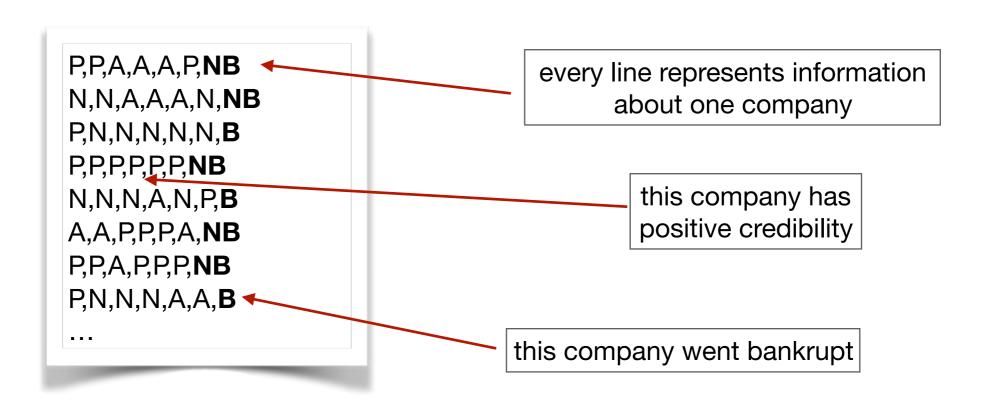






#### Bankruptcy dataset

 such a complicated qualitative analysis is captured in a simple, concise, machine-readable form:



download bankruptcy\_dataset.txt







#### Step 1: preprocessing

```
import numpy as np
import re
# parsing input file into an array
file = open('bankruptcy_dataset.txt', 'r')
input = file.read()
input = input.replace('NB', '1')
input = input.replace('P', '2')
input = input.replace('A', '1')
input = input.replace('N', '0')
input = input.replace('B', '2')
instance strings = input.splitlines()
print(len(instance strings)) # 250 instances
np.random.shuffle(instance_strings) # important for train-test
instances = []
for s in instance_strings:
    instance = re.split(r",", s)
    instances.append(instance)
print(len(instances))
```





#### Step 1: creating a dataset

```
# creating a dataset
data = []
targets = []
for i in instances:
    instance data = i[:6]
    data.append(instance_data)
    target = i[6]
    targets.append(target)
print(len(targets))
print(len(data))
target_names = ['bankrupt', 'not-bankrupt']
dataset = {
    u'data': data,
    u'targets':targets,
    u'target names':target names
```







#### Step 3: training a model

```
dataset_X = dataset.get('data')
dataset_Y = dataset.get('targets')
print(np.unique(dataset_Y))

dataset_X_train = dataset_X[:225] # 90% for training
dataset_Y_train = dataset_Y[:225]
dataset_X_test = dataset_X[225:] # 10% for testing
dataset_Y_test = dataset_Y[225:]

# train a model
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
model.fit(dataset_X_train, dataset_Y_train)
```







#### Step 4: Testing the model

```
#test
predictions = model.predict(dataset_X_test)

print(predictions)
print(dataset_Y_test)
```

#### Output:

```
# predictions
```

[1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 2, 1, 1, 2, 2, 1, 2, 1, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 1, 2, 2, 1, 2, 2, 1, 2, 2, 1, 2, 1, 1]
# answers







#### Playing with the model

Try modifying some of the parameters of the pipeline and see what happens:

- change the train-test ratio (80-20, 70-30 etc.)
- remove some of the features
- change the learning algorithm:
  - logistic regression: <a href="http://scikit-learn.org/stable/modules/">http://scikit-learn.org/stable/modules/</a>
     linear model.html#logistic-regression
  - Support Vector Machines: <a href="http://scikit-learn.org/stable/modules/svm.html">http://scikit-learn.org/stable/modules/svm.html</a>
  - Decision Problems: <a href="http://scikit-learn.org/stable/modules/tree.html">http://scikit-learn.org/stable/modules/tree.html</a>





