COMP30120

# Introduction to Machine Learning

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School of Computer Science and Informatics

Autumn 2015

# Overview

- Module Outline
- Practical Details
- Machine Learning
  - Common Applications
  - Supervised v Unsupervised Learning
  - Representing Data as Features

# Module Outline: Topics Covered

- Introduction and Basics
- Classification Algorithms
  - Nearest neighbour, Decision trees, Naive Bayes
- Unsupervised Learning Algorithms
  - k-Means, Hierarchical clustering
- Working with Data
  - Dimensionality reduction, feature selection
- Evaluation and Methodologies
  - Statistical testing
  - Evaluating performance of ML systems
- Further Topics: Ensemble learning, Social network analysis, Recommender systems

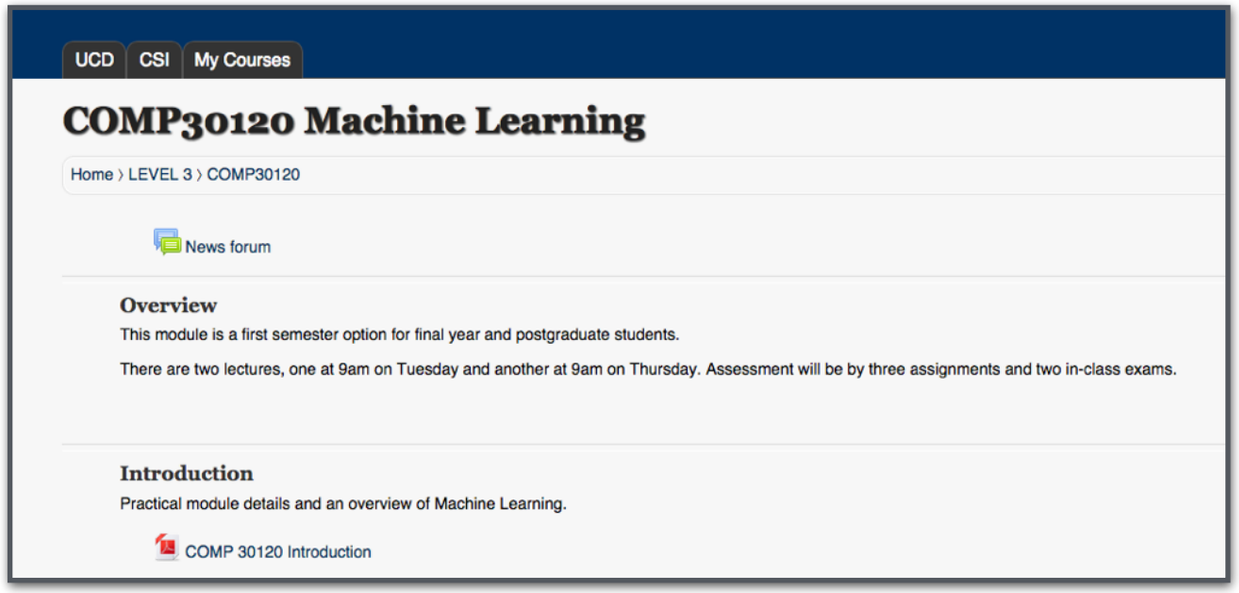
# Practical Details

Lectures/Tutorials: Tuesdays & Thursdays 9-10am B004 CSI

Notes, assignments, and additional material will be available on CS Moodle page for COMP30120 (https://csimoodle.ucd.ie)

Moodle is currently open for registration via self-enrolment.
Password: **ml2015**

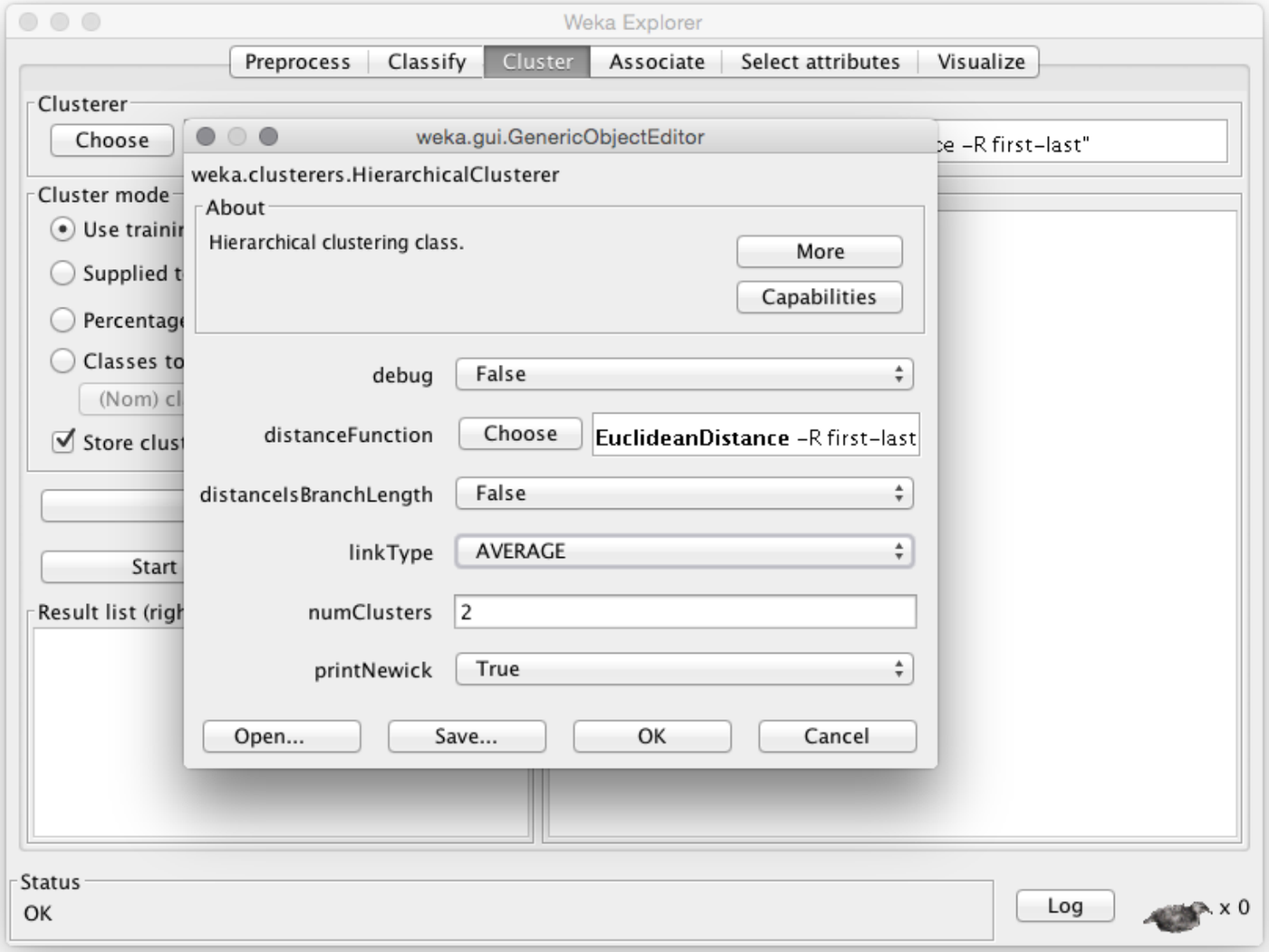
Check that your surname, firstname and student ID number are all correct.




For all module queries contact derek.greene@ucd.ie

# Practical Details

Tutorials require laptop with Java *Weka Toolkit (Stable 3.6.12)*




http://www.cs.waikato.ac.nz/ml/weka

# Practical Details

Module marks based on assignment + in-class exams:

| | |
|---|---|
| 15% | Assignment 1: Weka + Report |
| 15% | Assignment 2: Weka + Report |
| 15% | Assignment 3: Weka + Report |
| 20% | Week 9<br>In-class practical exam, with Weka + laptops. |
| 35% | Week 12<br>In-class theory exam, no laptops etc. |

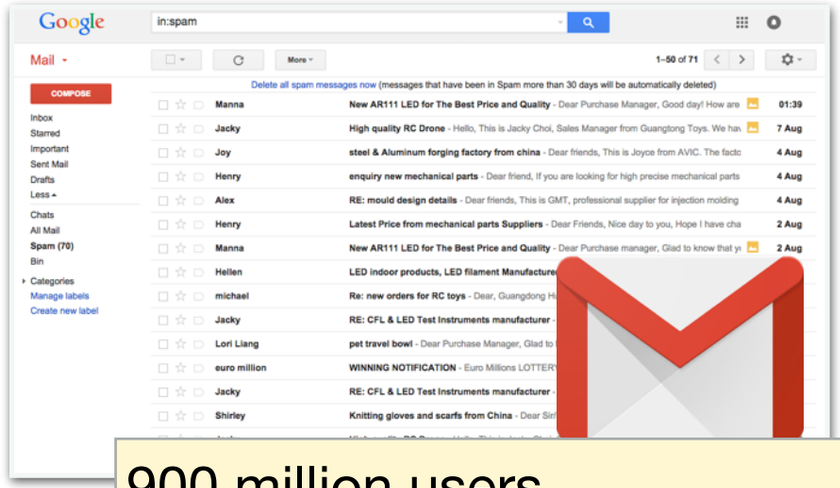
**Please note:**

- ! All assignment deadlines are hard deadlines.
- ! Plagiarism will be treated seriously. Any evidence of plagiarism in an assignment or exam will result in a 0 mark.

# Why Study Machine Learning?

- Explosion in rich, complex data to analyse - online and offline.
- Significant recent progress in algorithms and theory.
- Computational power is now available.
- Industry demand - Data scientists, Data engineers…
- New applications in many disciplines - Medicine, engineering, humanities…

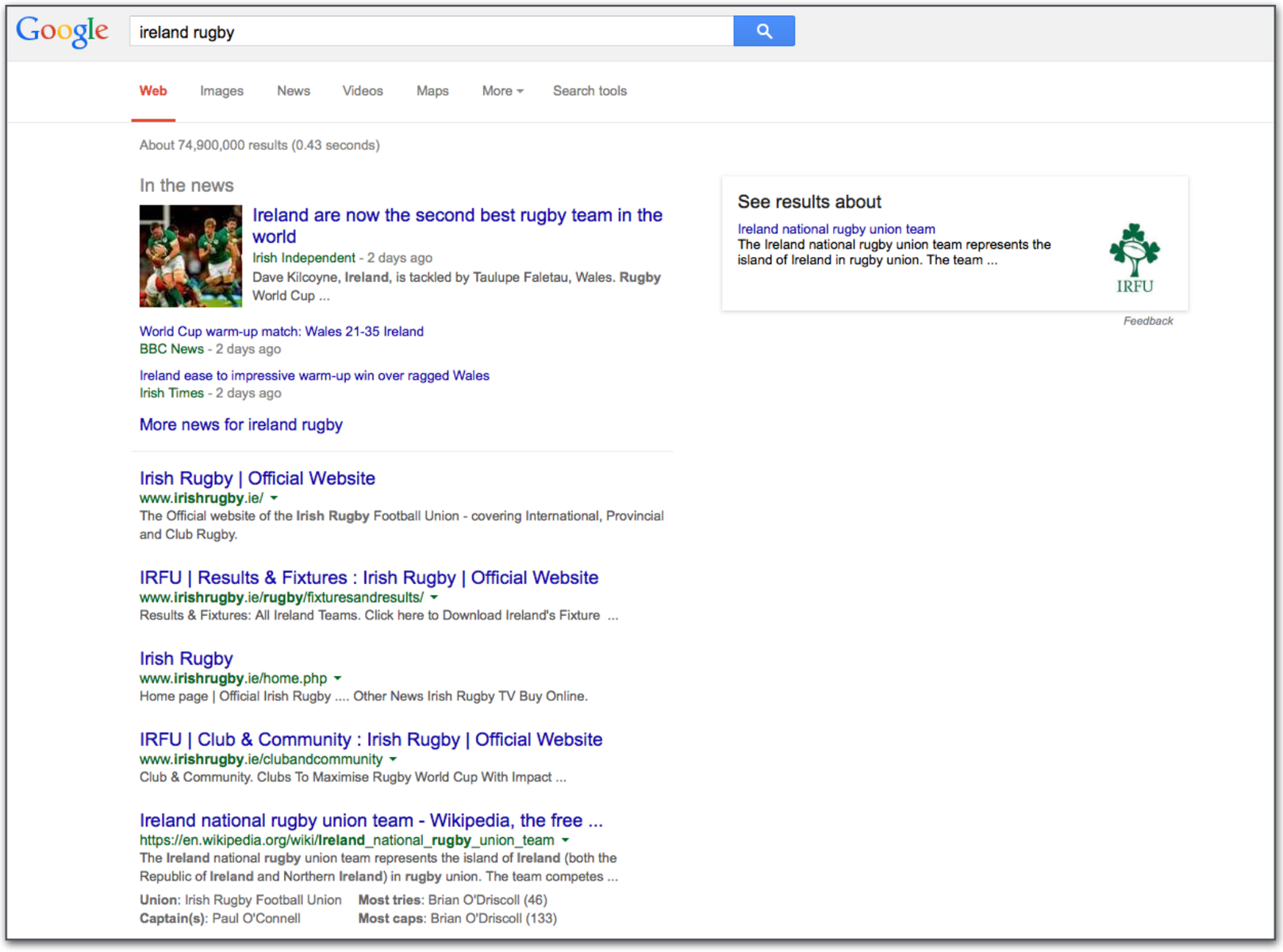

316 million monthly active users
500 million tweets per day
5 billion user sessions per day




900 million users
Handles 2+ trillion mails per year

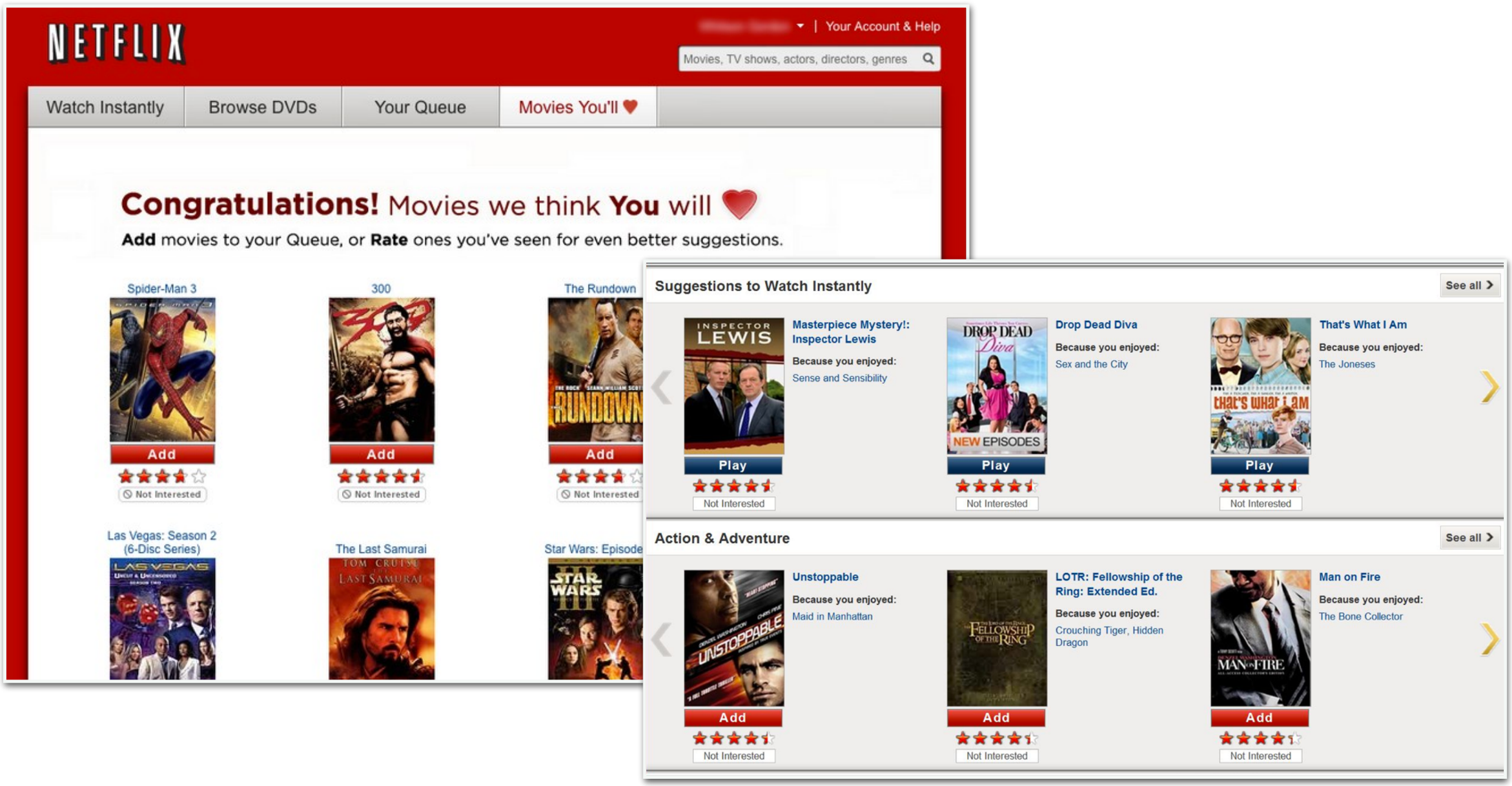
# Application: Web Search

Submit a query to a search engine, it finds pages relevant to the query, and returns them ranked by relevance.



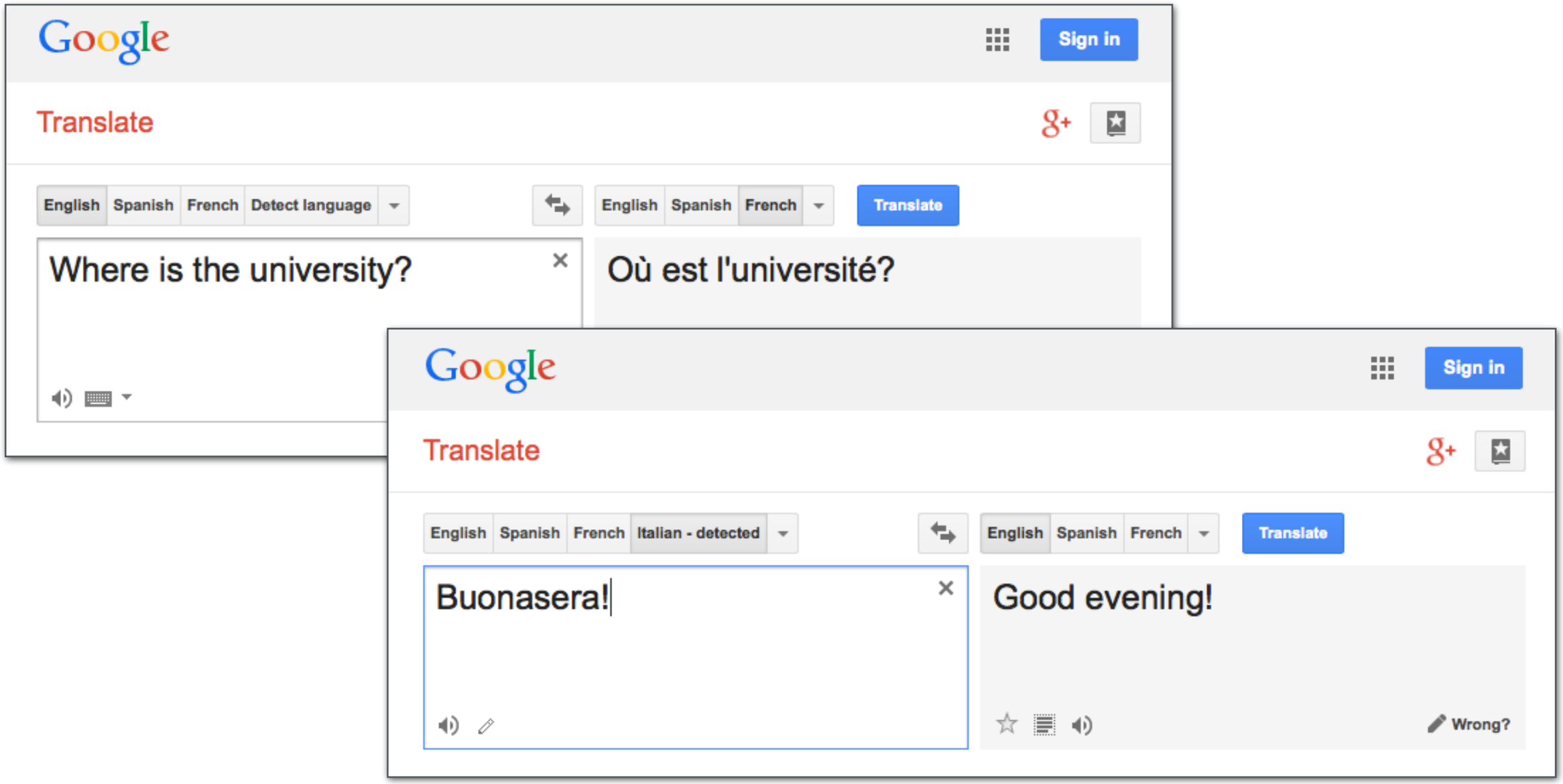
# Application: Movie Recommendation

Netflix provides personalised recommendations for movies you might like, based on previous user ratings.



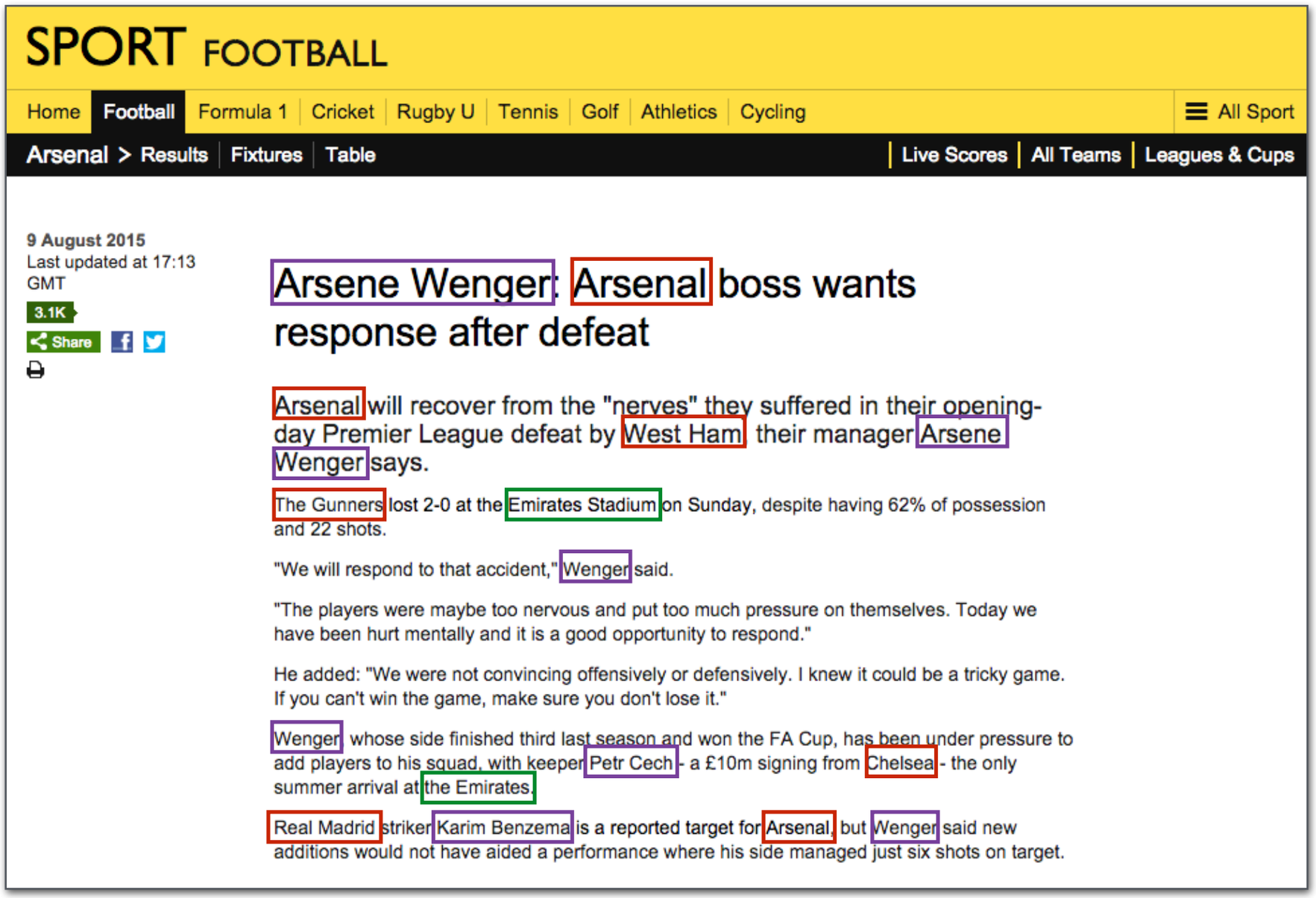
# Application: Machine Translation

Use examples of translated documents to learn how to translate between the two languages.



# Application: Entity Recognition

Automatically extracted named entities (e.g. people, places, organisations) from text documents (e.g. news articles).



SPORT FOOTBALL

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Arsenal > Results | Fixtures | Table | Live Scores | All Teams | Leagues & Cups

9 August 2015
Last updated at 17:13 GMT

3.1K Share

Arsene Wenger: Arsenal boss wants response after defeat

Arsenal will recover from the "nerves" they suffered in their opening-day Premier League defeat by West Ham, their manager Arsene Wenger says.

The Gunners lost 2-0 at the Emirates Stadium on Sunday, despite having 62% of possession and 22 shots.

"We will respond to that accident," Wenger said.

"The players were maybe too nervous and put too much pressure on themselves. Today we have been hurt mentally and it is a good opportunity to respond."

He added: "We were not convincing offensively or defensively. I knew it could be a tricky game. If you can't win the game, make sure you don't lose it."

Wenger, whose side finished third last season and won the FA Cup, has been under pressure to add players to his squad, with keeper Petr Cech - a £10m signing from Chelsea - the only summer arrival at the Emirates.

Real Madrid striker Karim Benzema is a reported target for Arsenal, but Wenger said new additions would not have aided a performance where his side managed just six shots on target.

**Tag colours:**

Person

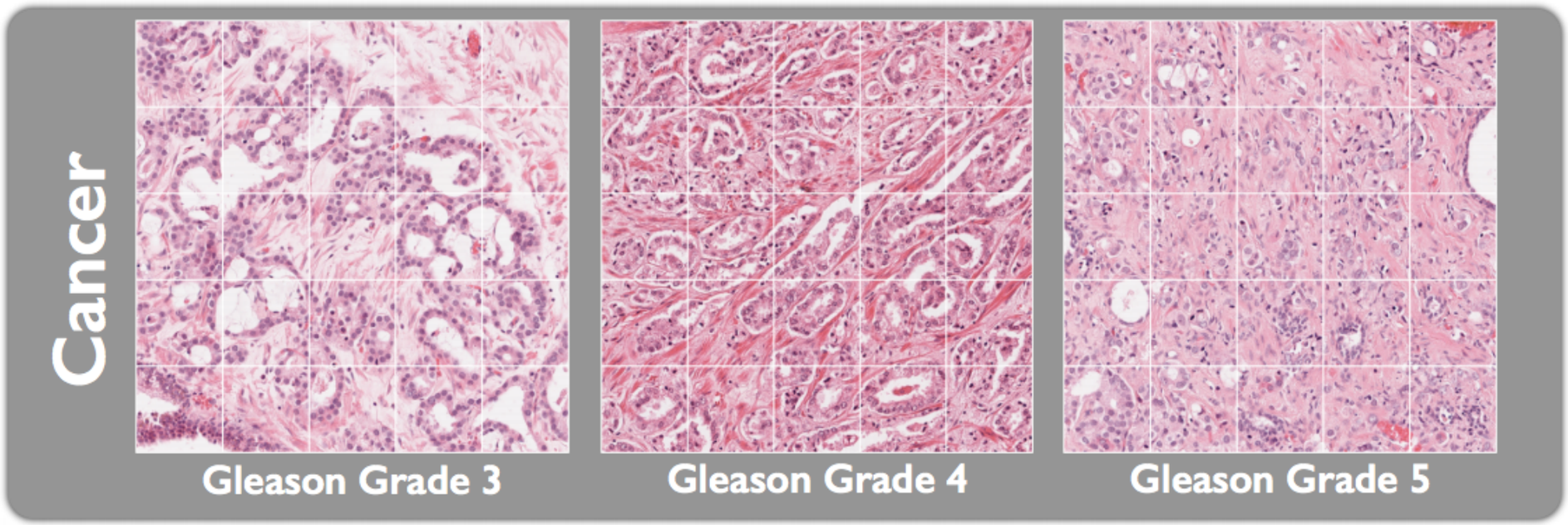
Location

Organisation

# Applications in Medicine

Machine Learning provides tools and support solving diagnostic and prognostic tasks in a variety of medical domains, including…

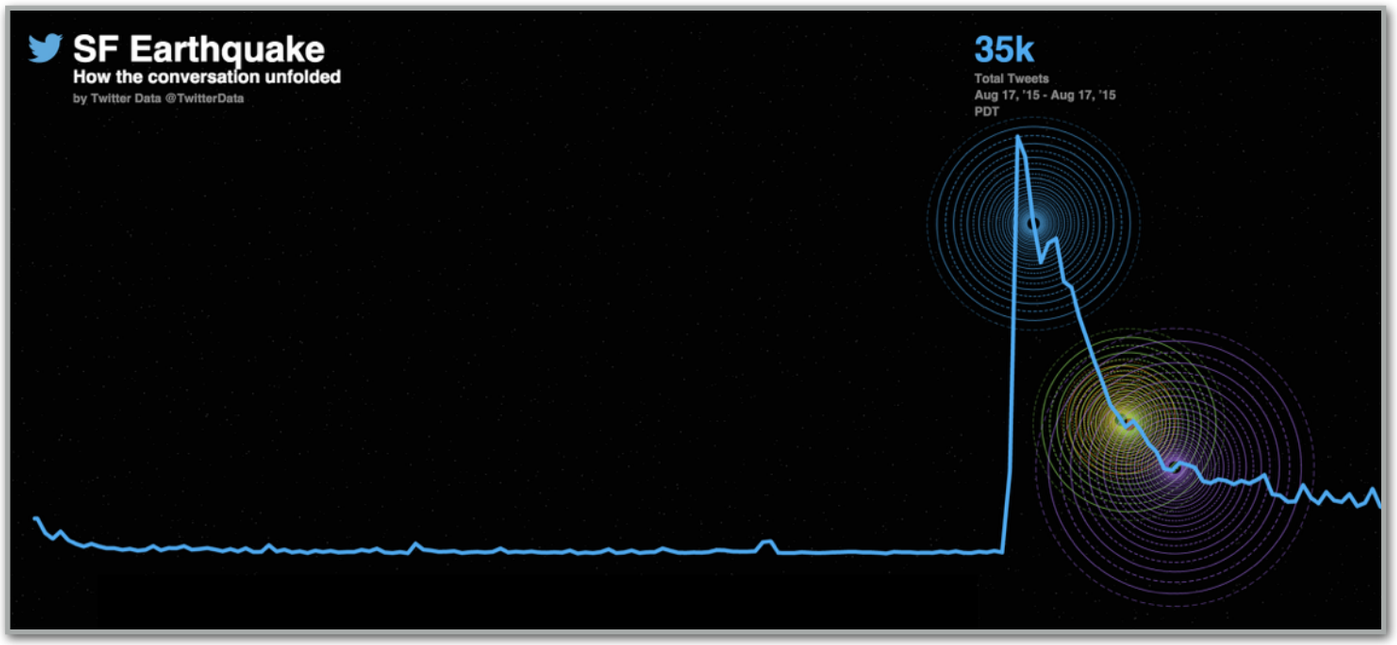
- Disease diagnosis based on previous correct cases
- Prediction of disease progression
- Medical image analysis and understanding
- Hospital information systems



# Application: Anomaly Detection

Algorithms to find patterns in data that do not conform to a model of “normal” behaviour in a system. In some systems, these are rare events. In other systems, these are unexpected bursts of activity.

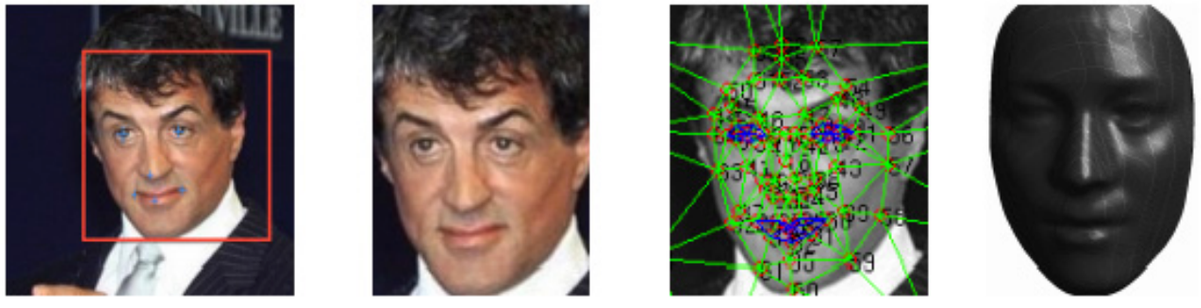
- *Cybersecurity*: Spike in number of false login attempts.
- *Payment systems*: Unusual number of failed or incomplete payments made.
- *Fraud detection*: Unexpected transactions in financial networks.
- *Event detection*: Sudden spike in volume of social media posts.



# Application: Face Recognition

Facebook tags photos by comparing them to profile pictures.

"We currently use facial recognition software that uses an algorithm to calculate a unique template based on someone's facial features, like the distance between the eyes, nose and ears. This template is based on your profile pictures and photos you've been tagged in on Facebook."



In 2013, Facebook revealed its users have uploaded > 250 billion photos, and are uploading 350 million new photos each day.

Using other cues (e.g. hair style, clothing), allows Facebook to accurately identify people, even when their face is obscured.

http://www.fastcolabs.com/3028414/how-facebooks-machines-got-so-good-at-recognizing-your-face

http://arstechnica.com/?p=695873

# Application: Autonomous Vehicles

- Car manufacturers and researchers are exploring the potential of self-driving cars. Involves analysis of large volumes of sensor data, categorised using ML approaches combined with human labelling.

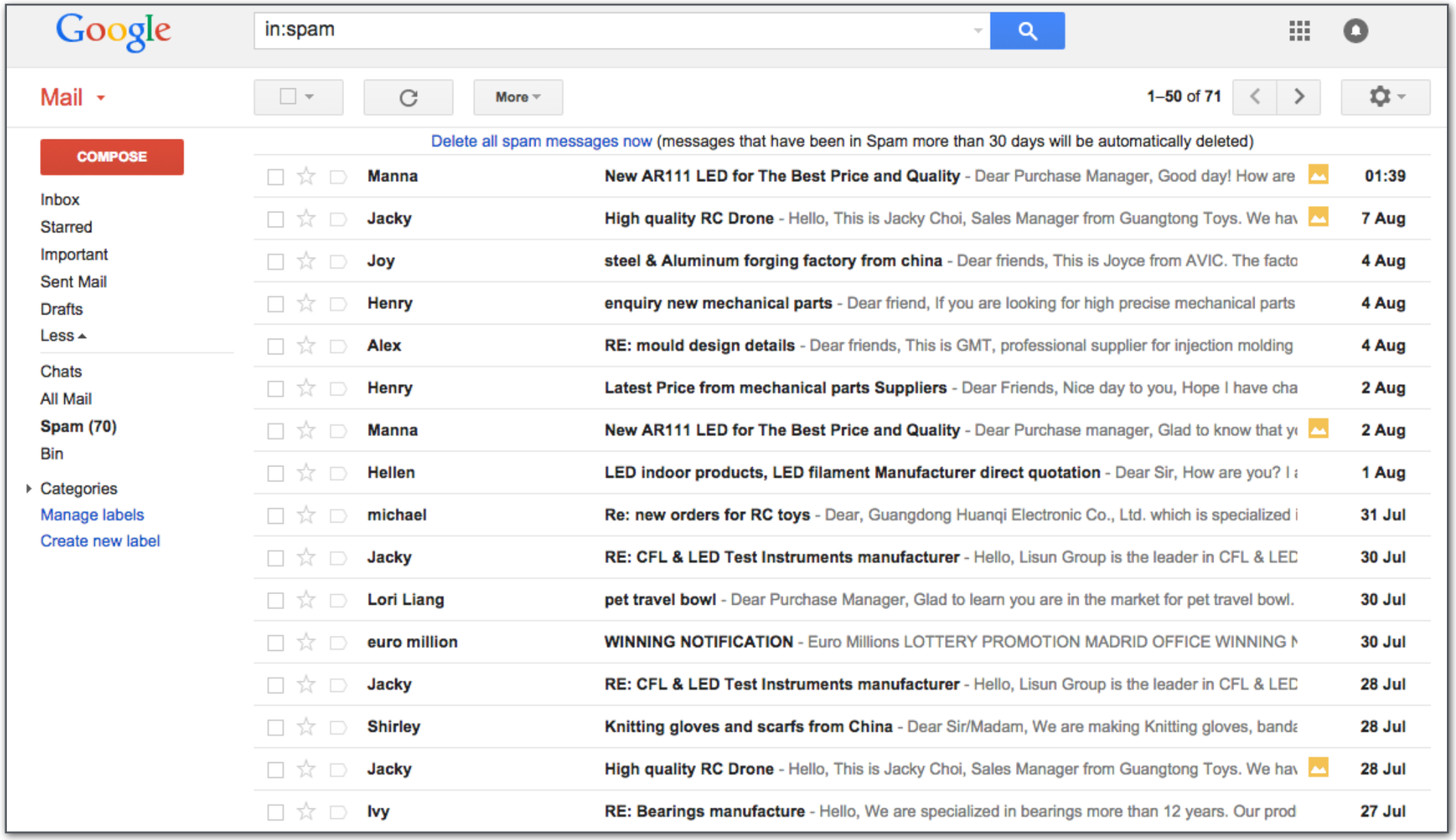
- 2004: Autonomous cars tried to navigate a 150 mile desert DARPA race. None of the 21 teams finished.
- 2015: Google driverless test vehicles have driven nearly 1 million miles, with no accidents caused by a self-driving car. Prototypes launched on public roads.

http://googleblog.blogspot.ie/2015/05/self-driving-vehicle-prototypes-on-road.html

http://www.nature.com/news/autonomous-vehicles-no-drivers-required-1.16832

# Application: Spam Classification

Apply a learning algorithm to automatically classify incoming emails into *spam* or *non-spam*, based on previous examples of legitimate and spam email.



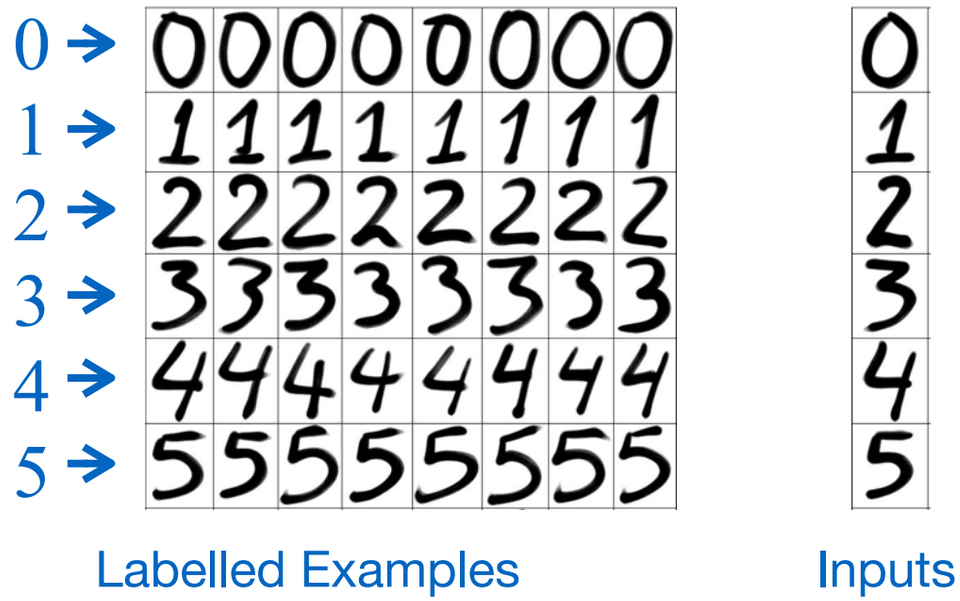
# Supervised v Unsupervised Learning

- Supervised Learning:
  An algorithm that learns a function from examples of its inputs and outputs. It requires manually-labelled example data to learn the correct answer for a given query input.
  - e.g. Classification, Regression algorithms

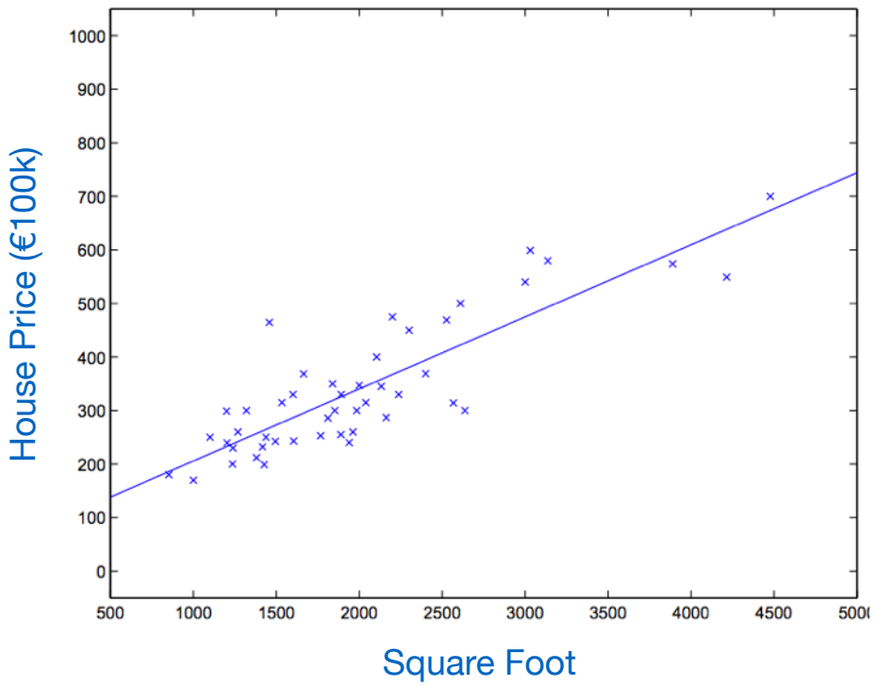
- Unsupervised Learning:
  An algorithm that finds patterns in data when no manually labelled examples are available as inputs. More focused on data exploration and knowledge discovery.
  - e.g. Clustering, Graph partitioning algorithms

# Supervised Learning

- Classification:
  Examples represented by a set of features, which help decide the *class* to which a new query input belongs (i.e. output is a label)



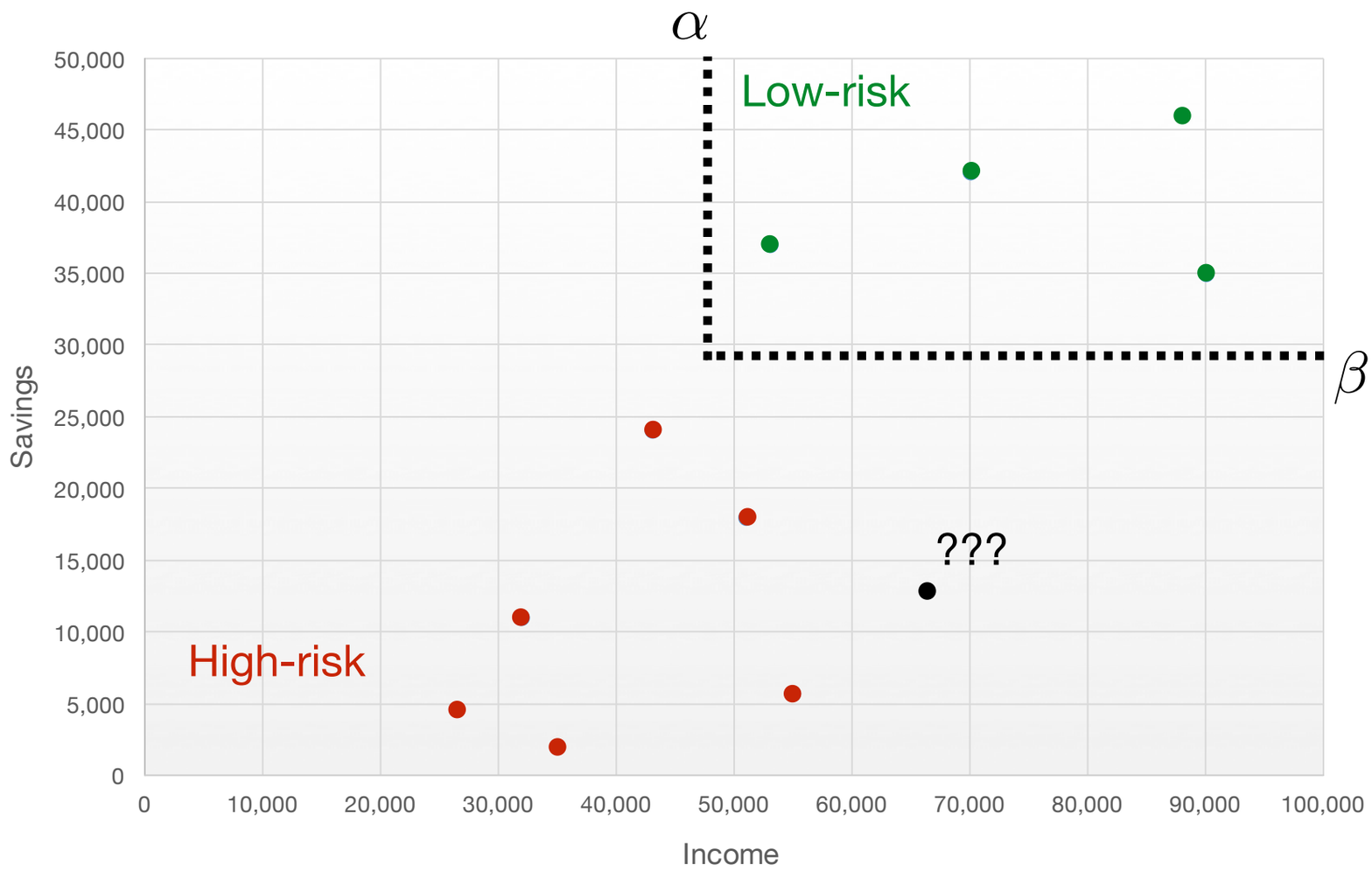

- Regression:
  Examples characterised by a set of features, which help decide the value of a continuous output variable (i.e. output is a number)



# Typical Classification Task

**Example:**
**Credit Scoring**

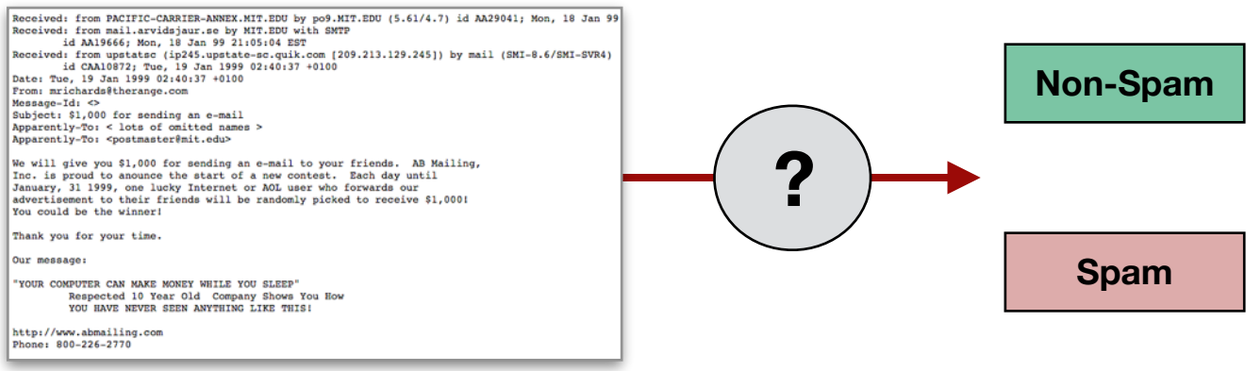
Manually classify customers into two categories (low-risk and high-risk) based on savings and income data.




Q. Can we train an algorithm to learn to automatically classify new customers as either low-risk or high-risk?
i.e. can we learn $\alpha$ and $\beta$?

# Classification Tasks

- Binary Classification:
  Assign an input to one of two possible target class labels.




- Multiclass Classification:
  Assign an input to one of *M* different target class labels.

# Classification Tasks

- **Evaluation:** Standard approach for classification tasks is to split the set of examples into a *training set* and the *test set.*
- Training set: Examples provided to the classifier to build a model of the data. Each example has been manually assigned a class label.
- Test set: Examples held back from the classifier, which are used to evaluate the accuracy of the classifier. Test examples are completely separate from the training set.
- Why not just train on all the data?
  - The test set is used to evaluate how well the model built by the classifier will generalise to new input examples.
  - Using the training data will give us over-optimistic results!

# Classification Algorithms

- Many different learning algorithms exist for classification (e.g. k-nearest neighbour, decision tree, neural network, support vector machine).
- Problem dimensions will often determine which classification algorithm will be practically applicable, due to processing, memory, and storage constraints.

1. Number of input examples *N*.
   → Sometimes millions of input examples.
2. Number of feature (dimensions) *D* representing each input example.
   → Often 10-1000, but sometimes far higher.
3. Number of target classes *M*.
   → Often small (binary), but sometimes far higher.

# Representing Data

- Examples are represented by one or more features, which can be distinguished by the type and number of values they can take.
  - Binary: Takes only two values - a boolean True/False decision
    e.g. married={True,False}, test_result={Pass,Fail}
  - Categorical (Nominal): A feature that takes values from two or more categories, with no intrinsic ordering to the categories.
    e.g. blood_group={A,B,AB,O}, nationality={French,Irish,Italian}
  - Ordinal: Similar to a categorical variable, but there is a clear ordering of the variables.
    e.g. grade={A,B,C,D,E,F}, dosage={Low,Medium,High}
  - Continuous: Numeric measurements, with or without a fixed range for the values.
    e.g. temperature, weight, height, latitude, longitude etc.

# Typical Classification Task

- Training set with N=10 examples (customers). Each is described by D=5 features: 3 continuous, 2 categorical
- Each example has one of two class labels = {High-risk,Low-risk}

| *Example* | *Income* | *Savings* | *Married* | *Gender* | *Age* | *Class* |
|---|---|---|---|---|---|---|
| **1** | 35,000 | 2,000 | Y | M | 32 | High-risk |
| **2** | 51,000 | 18,000 | N | M | 34 | High-risk |
| **3** | 70,000 | 42,000 | Y | F | 41 | Low-risk |
| **4** | 26,500 | 4,500 | N | M | 22 | High-risk |
| **5** | 32,000 | 11,000 | N | F | 25 | High-risk |
| **6** | 53,000 | 37,000 | N | F | 39 | Low-risk |
| **7** | 88,000 | 46,000 | Y | M | 48 | Low-risk |
| **8** | 55,000 | 5,700 | N | M | 55 | High-risk |
| **9** | 90,000 | 35,000 | Y | F | 61 | Low-risk |
| **10** | 43,000 | 24,000 | Y | M | 33 | High-risk |

Q. To which class does this new customer belong?

| *Example* | *Income* | *Savings* | *Married* | *Gender* | *Age* | *Class* |
|---|---|---|---|---|---|---|
| **X** | 66,000 | 13,000 | Y | M | 44 | ??? |

# Typical Classification Task

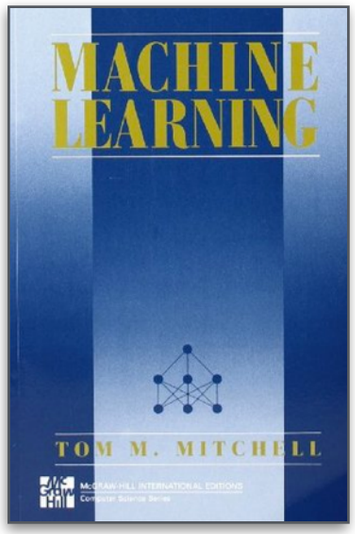
- Training set with N=10 examples (fruit). Each is described by D=4 features: 3 continuous, 1 categorical
- Each has one of three class labels = {Apple,Pear,Orange}

| *Example* | *Height* | *Width* | *Taste* | *Weight* | *Class* |
|---|---|---|---|---|---|
| **1** | 60 | 62 | Sweet | 186 | Apple |
| **2** | 70 | 53 | Sweet | 180 | Pear |
| **3** | 55 | 50 | Tart | 152 | Apple |
| **4** | 76 | 40 | Sweet | 152 | Pear |
| **5** | 68 | 71 | Tart | 207 | Orange |
| **6** | 65 | 68 | Sour | 221 | Apple |
| **7** | 63 | 45 | Sweet | 140 | Pear |
| **8** | 55 | 56 | Sweet | 154 | Apple |
| **9** | 76 | 78 | Tart | 211 | Orange |
| **10** | 60 | 58 | Sour | 175 | Apple |

Q. To which class does this new fruit belong?

| *Example* | *Height* | *Width* | *Taste* | *Weight* | *Class* |
|---|---|---|---|---|---|
| **X** | 63 | 68 | Sweet | 168 | ??? |

# Additional Reading

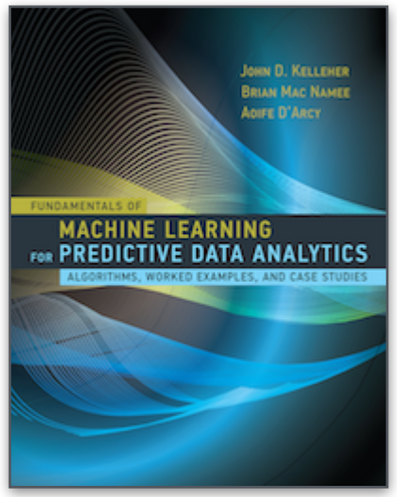


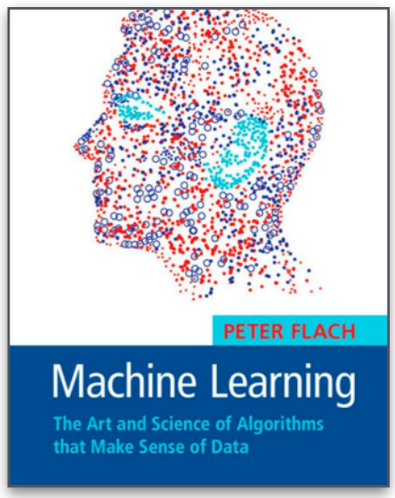

*Machine Learning*
*McGraw-Hill 1997*

Tom M. Mitchell

*Fundamentals of Machine Learning for Predictive Data Analytics*

John D. Kelleher, Brian Mac Namee, Aoife D'Arcy




*Machine Learning: The Art and Science of Algorithms that Make Sense of Data*

Peter Flach

*Data Mining: Practical Machine Learning Tools and Techniques, 3rd Ed*

Ian H. Witten, Eibe Frank, Mark A. Hall