Machine Learning for social sciences

Natural Language Processing : Session 1

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Introduction

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- Value prediction
- Multi-label classification
- Similarity measurement
- and even more...

But what if we want to regroup data into groups without supervising the definition of these groups ?

Supervized vs. unsupervized learning

Supervised Learning

- Learns from labeled data to make predictions or classify data.
- **Key Characteristics :**
  - Data includes input-output pairs.
  - Goal : Minimize error by matching predictions to known outputs.

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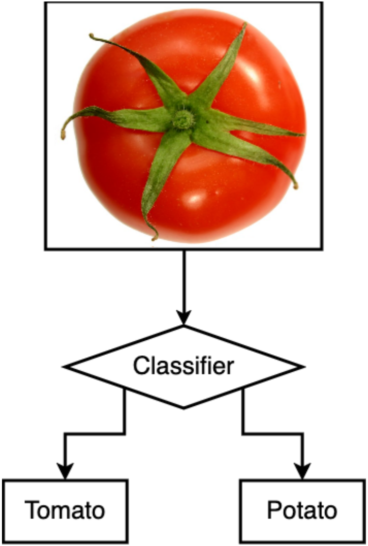

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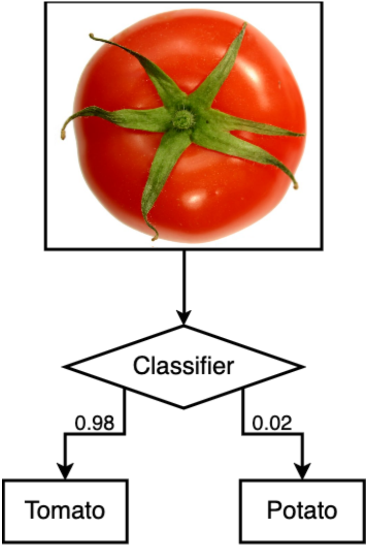

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- **Examples :**
  - Customer segmentation
  - Dimensionality reduction
  - Anomaly detection

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Unsupervised Learning : the example of semantic textual similarity

Objective : Quantifying the degree of similarity between two texts based on their meaning rather than their vocabulary.

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Example :

- **Sentence 1 :** This NLP class is fantastic 😍
- **Sentence 2 :** I really like this natural language processing course
- **Similarity :** 0.703

. Results obtained using `sentence-transformers/all-mpnet-base-v2`

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Unsupervised Learning : the example of semantic textual similarity

Objective : Quantifying the degree of similarity between two texts based on their meaning rather than their vocabulary.

Example :

- **Sentence 1 :** This NLP class is fantastic 😍
- **Sentence 2 :** This class is extremely boring 😴
- **Similarity :** 0.491

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Unsupervised Learning : the example of semantic textual similarity

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Example :

- **Sentence 1 :** This NLP class is fantastic 😍
- **Sentence 2 :** I would like a falafel sandwich with Algerian sauce and a drink please.
- **Similarity :** 0.081

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Clustering

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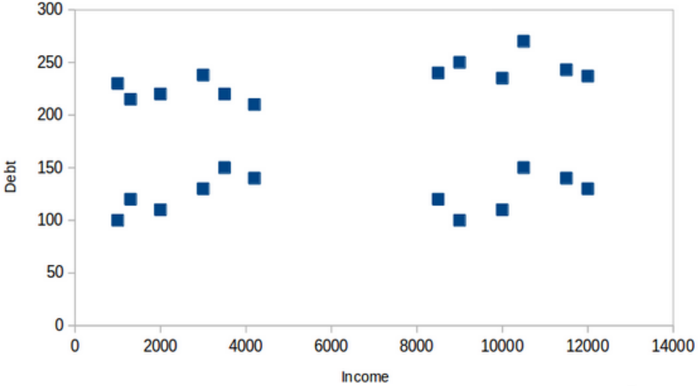
- K-Means Clustering
- Louvain Clustering
- DBSCAN (Density-Based Spatial Clustering)

Clustering

Example : K-Means clustering of people based on their debt and annual income (with $K = 4$)



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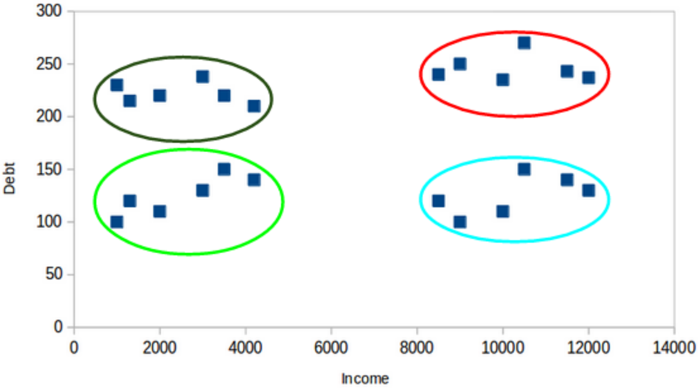

Problem

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But we are in an NLP class, can we cluster texts ? Like, based on topics ? 🤨

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Applications :

- Document categorization
- Information retrieval
- Recommender systems
- Social media analysis

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Assume a collection of documents about topics like sports, politics, and technology.

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LDA uncovers :

- Topic 1 (Sports) : *game, team, player, score, match*.
- Topic 2 (Politics) : *election, policy, government, vote*.
- Topic 3 (Technology) : *software, AI, computer, NLP*.

LDA

Lab 1 : Exploration of an online participatory process using LDA

Let's dive into it 🤓

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So how can we solve (some of) these issues ?

BERTopic

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Combines the strength of **transformer-based embeddings** (e.g., BERT) with techniques like UMAP for dimensionality reduction.

BERTopic

How does it work ?

- **Text Embedding** : Text is converted into embeddings (i.e., vectors) using models like BERT or SBERT.

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- **Dimensionality Reduction** : UMAP reduces embedding dimensions for efficient clustering.
- **Clustering** : HDBSCAN groups similar data points into clusters.
- **Topic Representation** : Key terms are extracted from clusters to represent topics.

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Let's see what we can do with it 🤓