Guessing Students Gender by their Course Plan

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EPFL

A Network Tour of Data Science

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Project Overview

- Project Goals:
  - Understand the gender distribution of EPFL students
  - Predict Student's gender given his/her course plan

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  - Understand the gender distribution of EPFL students
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- Roadmap:
  - Extract Students features (courses), gender and section
  - Reduce dataset dimension while keeping relevant information
  - Observe gender distribution
  - Classify and predict students gender based on courses

Dataset

1. Parse the EPFL public and private access to students lists

Name	Class token	Study field	Gender	Nationality

Dataset

1. Parse the EPFL public and private access to students lists

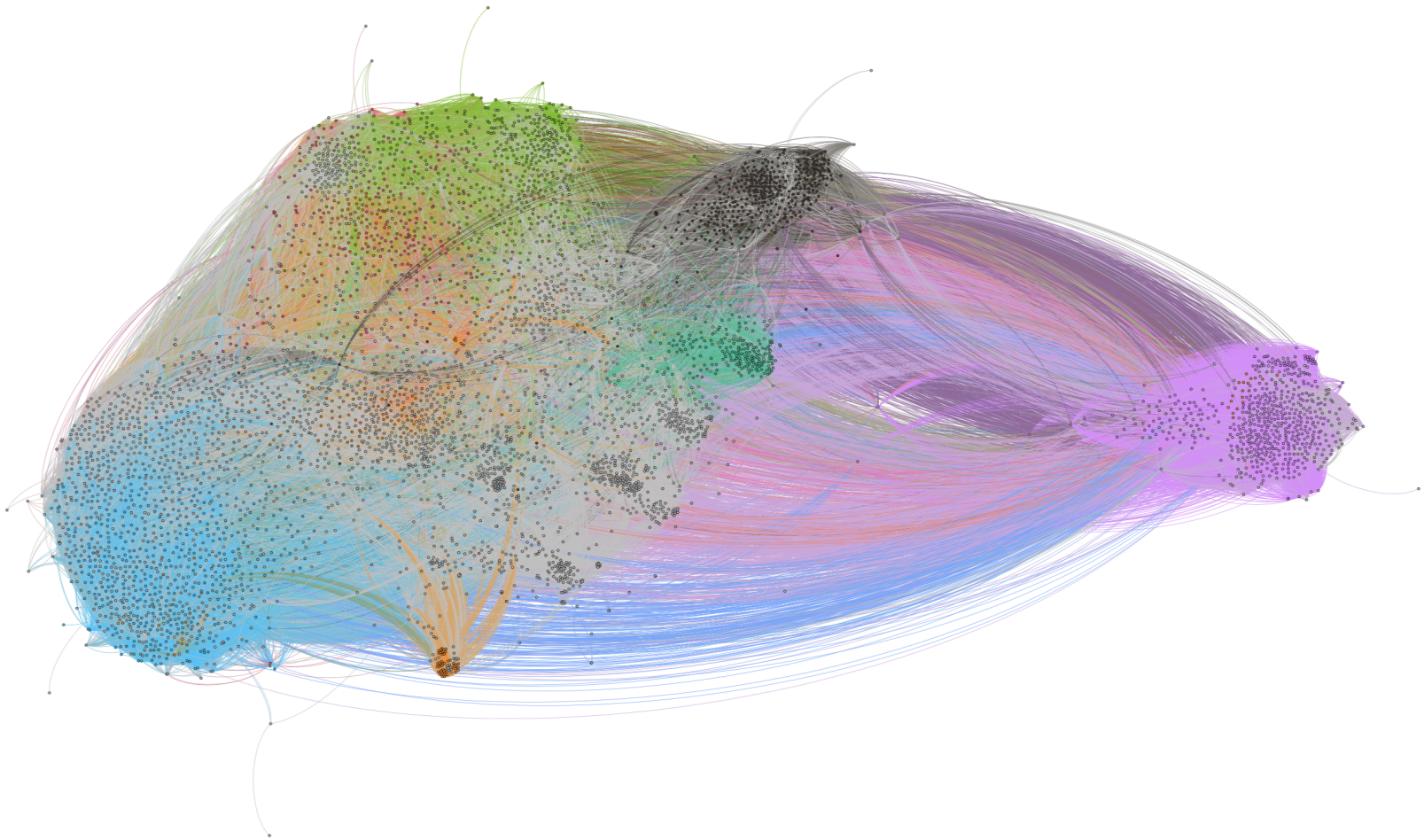
Name	Class token	Study field	Gender	Nationality

2. Clean and filter data:
   - select only master students
   - filter classes with low participants

student_id	course_1	$\cdots$	course_n	Study field	Gender

Student Social Graph

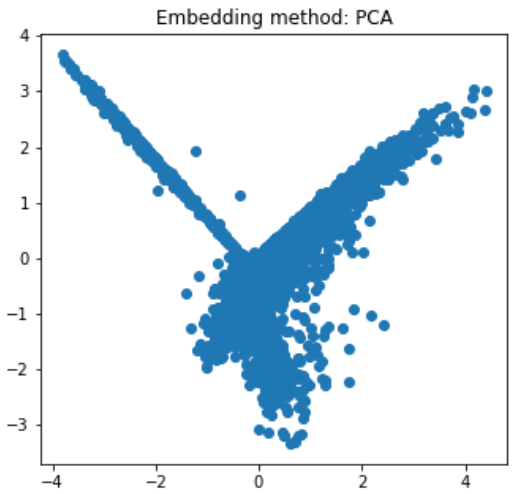
- Each node represents a student
- Students are connected based on the number of common courses

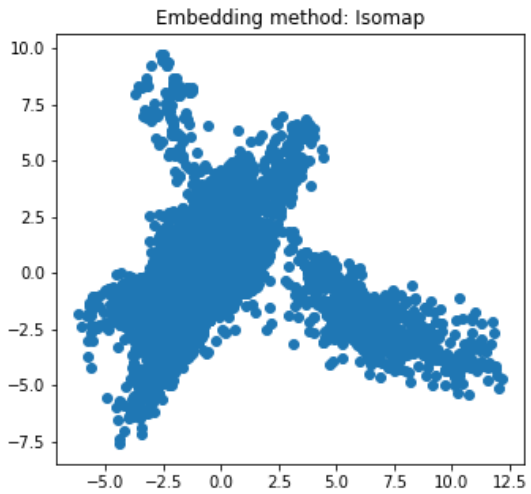


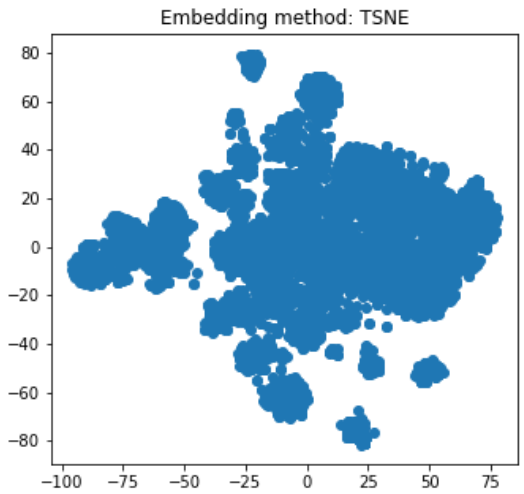
Dimensionality Reduction

Why ?

- to visualize data and for more efficient processing





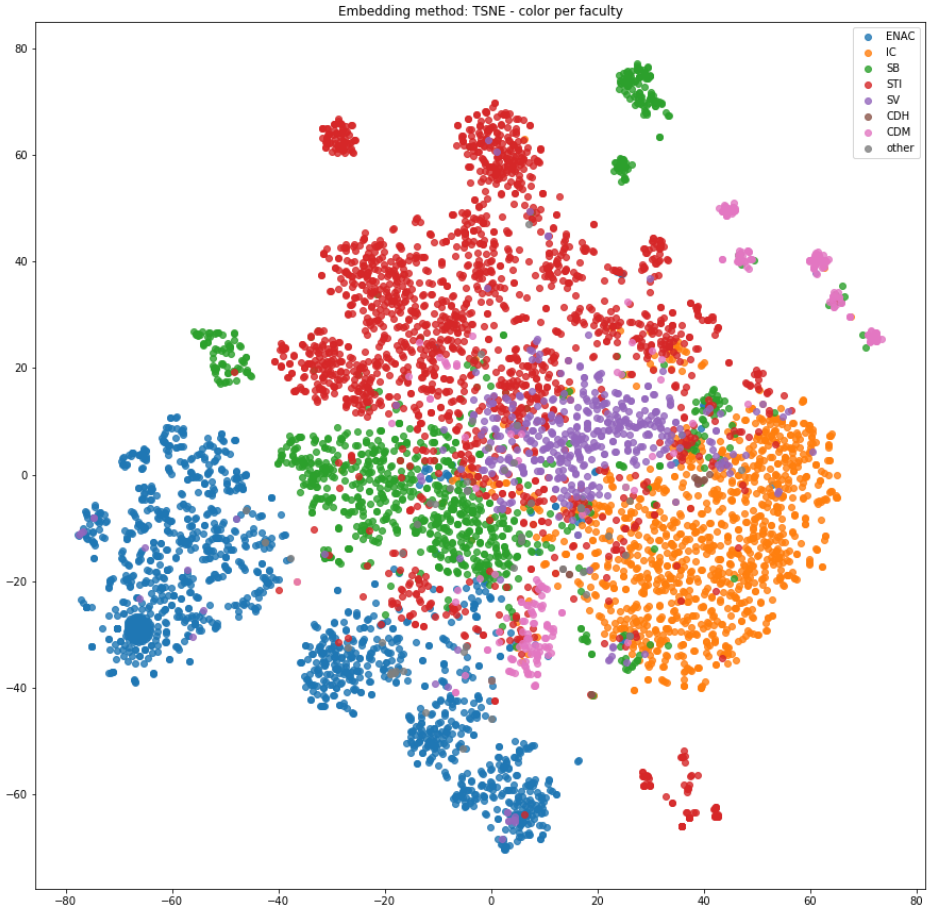


Best method: **t-SNE**

- dataset contains many clusters and is crowded

Dimensionality Reduction

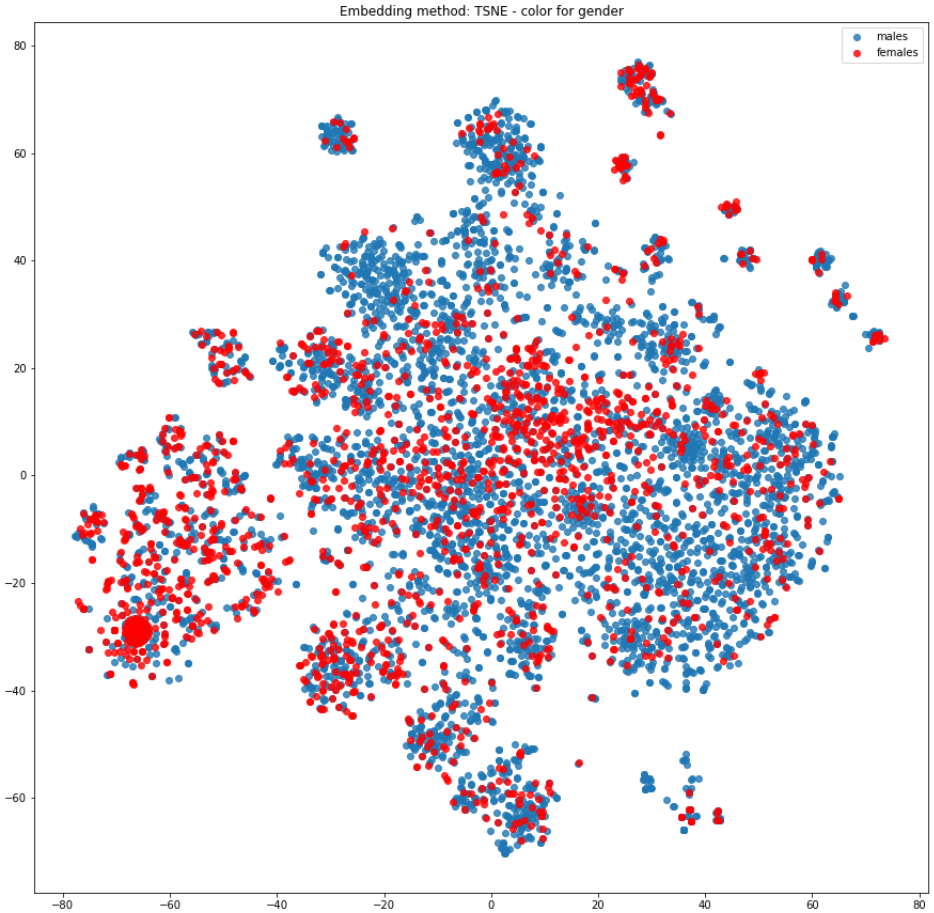
t-SNE embedding with faculty labels



clear relevant clusters

Dimensionality Reduction

t-SNE embedding with gender labels



there are males and females everywhere (but no indication on quantity)

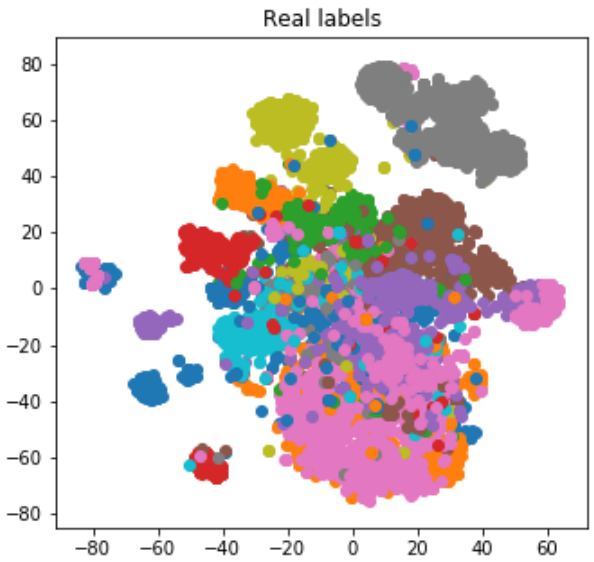
Epsilon-Similarity Graph

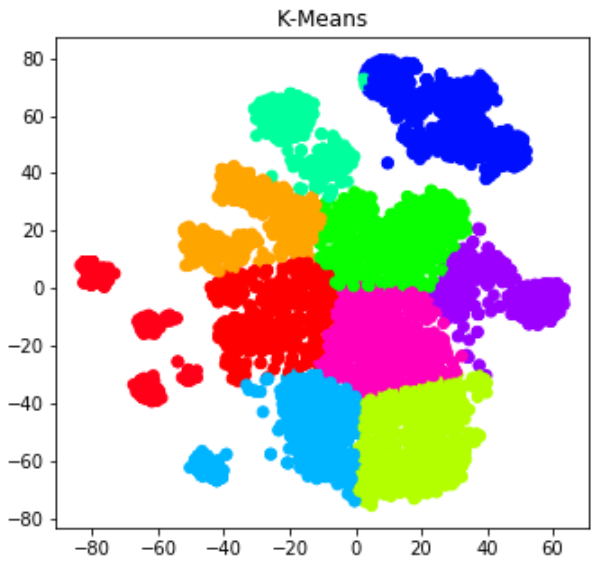
- Built using the dataset of reduced dimension

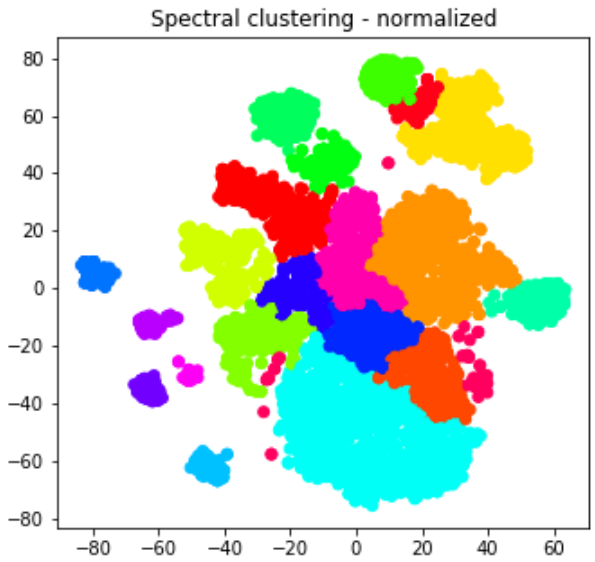
- Graph Construction:
  1. compute euclidean distances
  2. apply RBF Kernel
  3. sparsify using the 3rd quantile

Clustering

Done on Epsilon-Similarity Graph







Gender Classification and Prediction

Classification with Logistic Regression :

Why ?

- Most common method
- Easy to implement

Result : 67.29 %

Gender Classification and Prediction

Classification with SVM :

Why ?

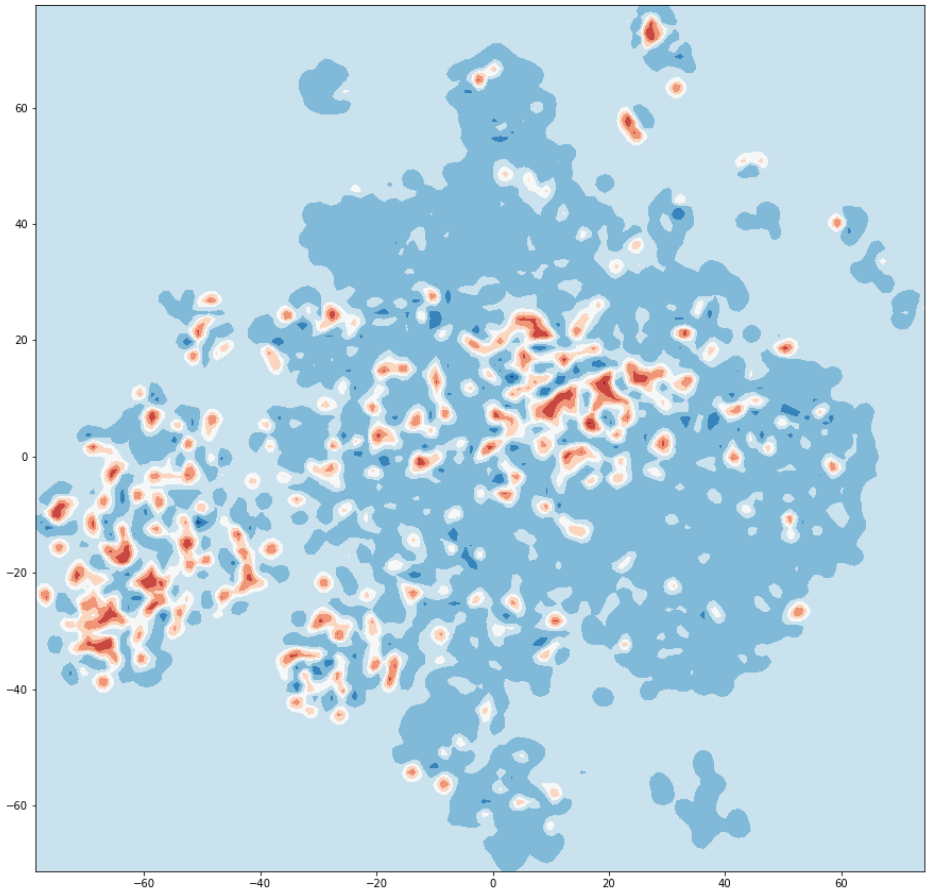
- Convex problem $\Rightarrow$ solved efficiently
- Works well on high dimension data

How ?

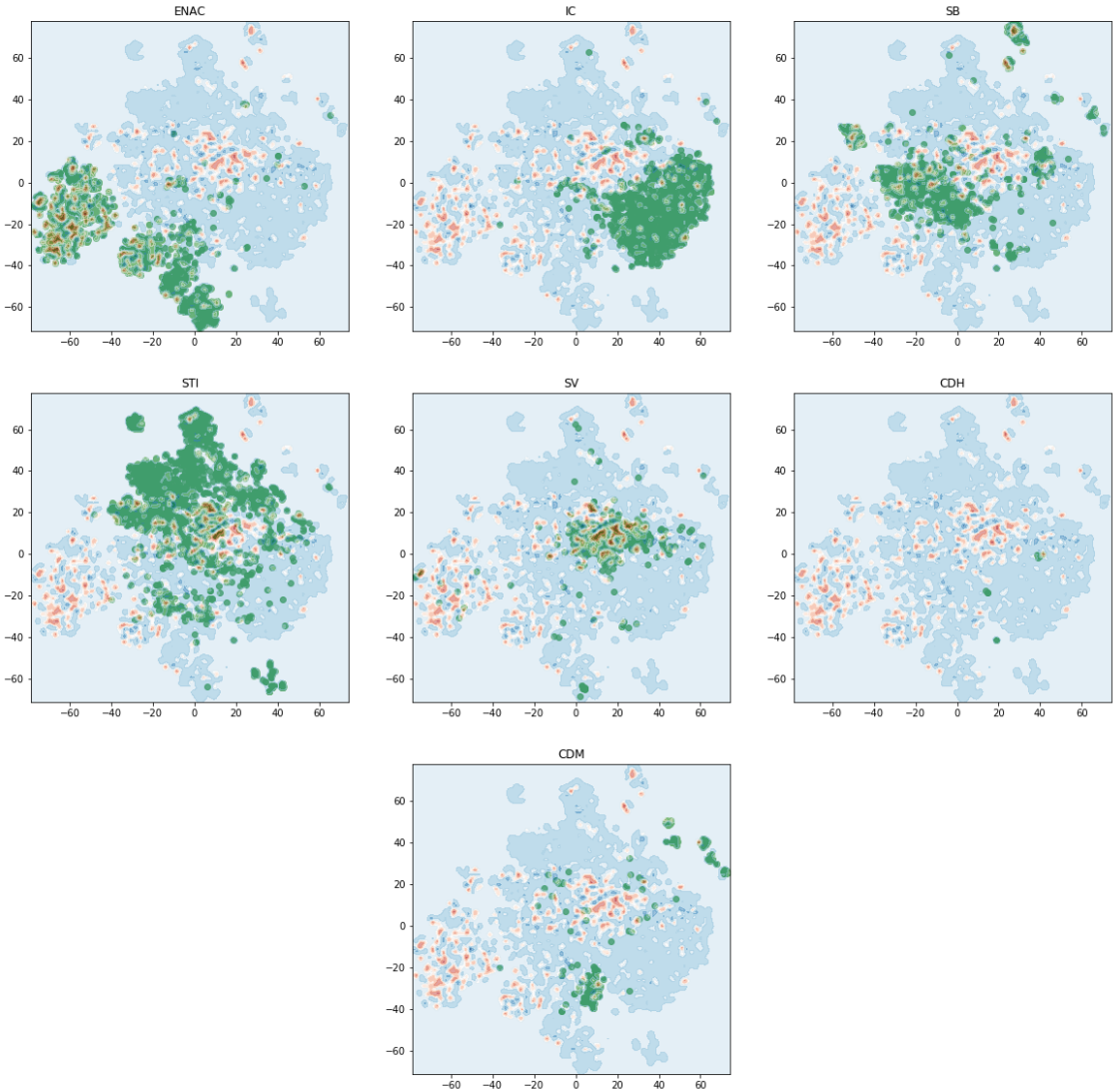
- Linear SVM on high dimension data (no visual)
- RBF SVM on 2D data, assumed as equivalent to previous SVM (visualizable)

Gender Classification and Prediction

Classification with SVM, visualization :



Gender Classification and Prediction



Gender Classification and Prediction

Gender Prediction with SVM, results :

Method	**Score**
Linear SVM in high dimension	67.29 %
RBF SVM in two dimensions	69.51 %

Gender Classification and Prediction

Classification with Graph Convolutional Network :

Why ?

- capture the structural relations among data
- gives more insight than analyzing data in isolation

How ?

- Approximate GFT with a polynomial of degree 3
- Learn on 1000 epochs

Results :

Graph	**score**
social students graph	68.27 %
epsilon similarity graph	73.13 %

Conclusion on Gender Distribution

- Females minority among master students
  - less critical in SV and AR sections[1]
- The distribution is explained by the psychological differences between males and females regarding STEM [2]:
  - females tends towards organic STEM and arts
  - males favor mathematics, mechanics and engineering
  - differences are amplified in societies where individuals are free to choose their field of career.
- Conclusion: there is no apparent bias on the relation between gender and choice of major in the scope of EPFL.

[1] confirmed by EPFL statistics [1]

Conclusion on Gender Prediction

- SVM prediction is not bad but cannot be used as a reliable result
- Graph Convolutional Networks is almost equal
- Conclusion: our gender prediction accuracy is limited
  - predicting a female in a male dominated section is difficult
  - wrong prediction of females as males
- Improvements: for better minority detection:
  - use different weights for features based on the locally dominant gender of a course
  - the "cluster membership" information is useful for this purpose

References

[1] EPFL internal statistics (GASPAR required), https://tableau.epfl.ch/#/home

[2] David Geary (2018), "Sex Differences in Science, Tech, Engineering, and Math", www.psychologytoday.com/us/blog/male-female/201911/sex-differences-in-science-tech-engineering-and-math

Thank You

True labels by class