Assignments of JEL codes via Adaptive Weights Clustering

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Outline

- Publication industry offers a rich portfolio of research work
- The mass of textual data requires pre-structuring
  - Abstracts are a condensed information of full documents
  - Economic papers require manually specify the JEL codes (project areas, topics)
- Clustering can be a solution to identify the research directions and activity of economic research on certain topics.

Motivation

- Analyze Discussion paper abstracts from School of Business and Economics at Humbold-Universität zu Berlin
- Find a **cluster structure** using Adaptive Weights Clustering
- Examine its correlation with paper's *JEL codes*

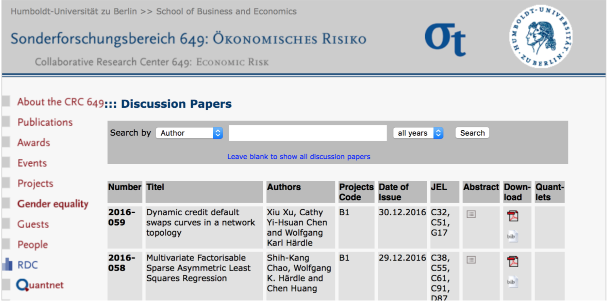


Abbildung: Papers on SFB website

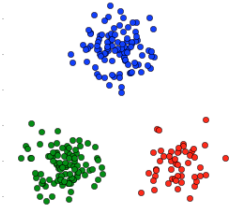
What is clustering?

Data: $X_1, \ldots, X_n \in \mathbb{R}^d$.

Aim: split into homogeneous groups (clusters).

Number and structure/shape of clusters usually unknown.

Ideal picture:



- Scrape SFB webpage with discussion papers and extract:
  - Abstracts
  - JEL Codes
- Preprocess abstracts:
  - Tokenize
  - Transfer all letters to small ones
  - Remove punctuation, numbers, stopwords, special characters
  - Lemmatize/stemming
  - Remove words which occur only once

Term-Document Matrix (TDM)

- Rows correspond to the documents
- Columns correspond to the terms
- Each cell represents frequency of a word in a document

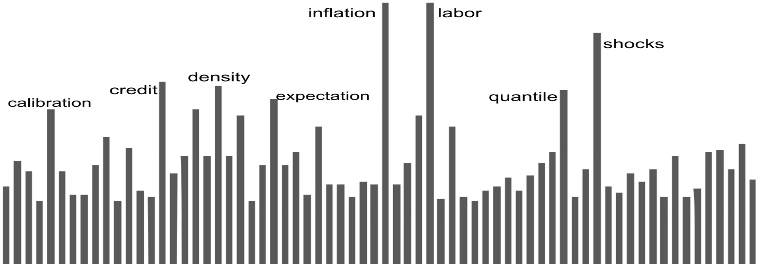


Abbildung: Most frequent terms from abstracts on SFB website

- A weighting factor
- Reflects how important a word is to a document in a collection
- i-th document is presented as vector $X_i = \{x_{ij}\}_{j=1}^{d}$, where

$$x_{ij} = tf_{ij} \times idf_j, \qquad idf_j = \log \frac{1+n}{1+n_j} + 1.$$

tf_{ij} : frequency of term j in the document i

idf_j : inverse document frequency

n : number of documents

n_j : number of documents which contain the term j.

Outline

Aim: an efficient procedure which adapts to unknown cluster structure.

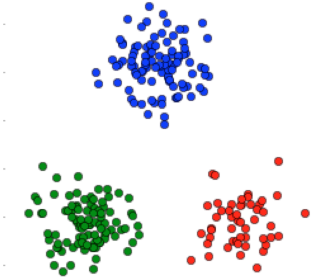
Approach: Describe the cluster structure by an adjacency matrix $W = (w_{ij})$, where

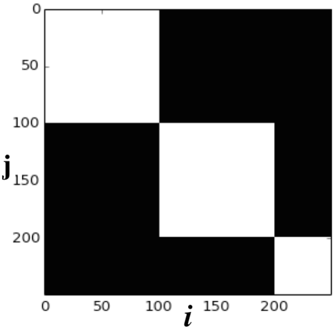
$$w_{ij} = \begin{cases} 1 & i,j \text{ from the same cluster,} \\ 0, & \text{otherwise} \end{cases}$$

The matrix W is recovered from the data by an iterative procedure.

Let $\{X_1, \ldots, X_n\} \subset \mathbb{R}^d$ be the set of all samples X_i.

Example: 250 points, 3 normal clusters (100 + 100 + 50) and the corresponding matrix of weights W.





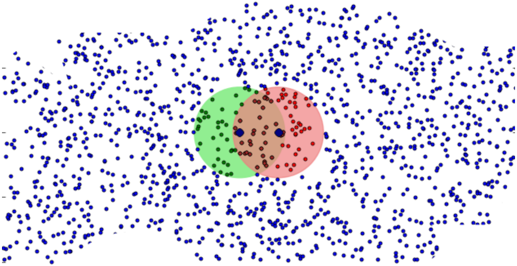
$$W = (w_{ij})_{i,j=1,\ldots,n} \ , \ w_{ij} \in [0,1] \, .$$

AWC Procedure

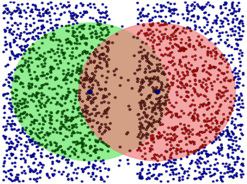
- Initialize with one cluster $\mathscr{C}_i^{(0)}$ per point X_i ;
- At each step, increase the locality parameter h_k and recompute the local weights $w_{ij}^{(k)}$ using a statistical test of no gap between two local clusters $\mathscr{C}_i^{(k-1)}$ and $\mathscr{C}_j^{(k-1)}$.
- Stop when the bandwidth h_k reaches the global value.

Test of "no gap between local clusters"

Homogeneous case:



"Gap" case:



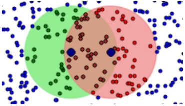
After $k-1$ steps, for each $i \le n$, the cluster $\mathscr{C}_i^{(k-1)}$ is given via weights $w_{ij}^{(k-1)}$, $j \le n$.

At step k, suppose the locality parameter h_k to be fixed and consider any pair (X_i, X_j) with $\|X_i - X_j\| \le h_k$.

Problem: For two local clusters $\mathscr{C}_i^{(k-1)}$ and $\mathscr{C}_j^{(k-1)}$ with $\|X_i - X_j\| \le h_k$, compute the value $w_{ij}^{(k)}$ reflecting the gap between $\mathscr{C}_i^{(k-1)}$ and $\mathscr{C}_j^{(k-1)}$.

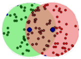
Principal idea: check the data density in the overlap $\mathscr{C}_i^{(k-1)} \cap \mathscr{C}_j^{(k-1)}$.

Test of "no gap between local clusters". Cont

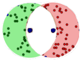


Mass of the overlap $N^{(k)}_{i\cap j}$,  :

$$N^{(k)}_{i\cap j} \stackrel{\text{def}}{=} \sum_{l\neq i,j} w^{(k-1)}_{il} w^{(k-1)}_{jl} \approx \#\text{ points in } \mathcal{B}(X_i, h_{k-1}) \cap \mathcal{B}(X_j, h_{k-1})$$

Mass of the union $N^{(k)}_{i\cup j}$  :

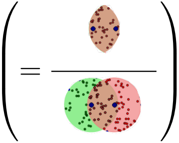
$$N^{(k)}_{i\cup j} \stackrel{\text{def}}{=} N^{(k)}_{i\cap j} + N^{(k)}_{i\triangle j} \approx \#\text{ points in } \mathcal{B}(X_i, h_{k-1}) \cup \mathcal{B}(X_j, h_{k-1})$$

where $N^{(k)}_{i\triangle j}$ is the mass of the complementary parts  :

$$N^{(k)}_{i\triangle j} \stackrel{\text{def}}{=} \sum_{l\neq i,j:\{\|X_i - X_l\| \le h_{k-1}\} \triangle \{\|X_j - X_l\| \le h_{k-1}\}} \left(w^{(k-1)}_{il} + w^{(k-1)}_{jl} \right).$$

Estimated relative density in the overlap:

$$\widetilde{\theta}^{(k)}_{i\cap j} = \frac{N^{(k)}_{i\cap j}}{N^{(k)}_{i\cup j}}$$



Local homogeneous case corresponds to the nearly uniform distribution:

$$\widetilde{\theta}^{(k)}_{i\cap j} \approx q^{(k)}_{ij} \stackrel{\text{def}}{=} \frac{\mathrm{Vol}_{\cap}(\rho_{ij}, h_{k-1})}{2\,\mathrm{Vol}(h_{k-1}) - \mathrm{Vol}_{\cap}(\rho_{ij}, h_{k-1})} = q\left(\frac{\rho_{ij}}{h_{k-1}}\right),$$

where $\mathrm{Vol}(h)$ is the volume of a ball with radius h and $\mathrm{Vol}_{\cap}(\rho, h)$ is the volume of the intersection of two balls with radii h and the distance ρ between centers, $\rho_{ij} = \|X_i - X_j\|$.

Null (no gap): $\theta^{(k)}_{i\cap j} > q^{(k)}_{ij}$ vs alternative (a gap) $\theta^{(k)}_{i\cap j} < q^{(k)}_{ij}$.

Outline

1 Motivation

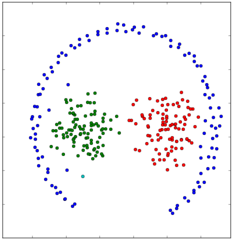
2 Data Preparation

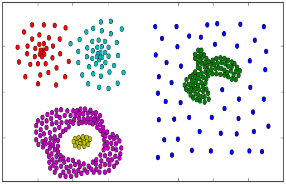
3 Adaptive Weights Clustering

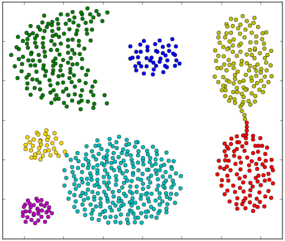
4 **AWC Results**

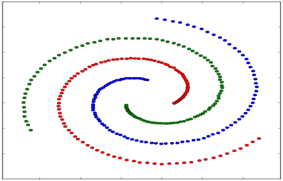
5 AWC on SFB Abstracts

Artificial Examples









AWC

More examples

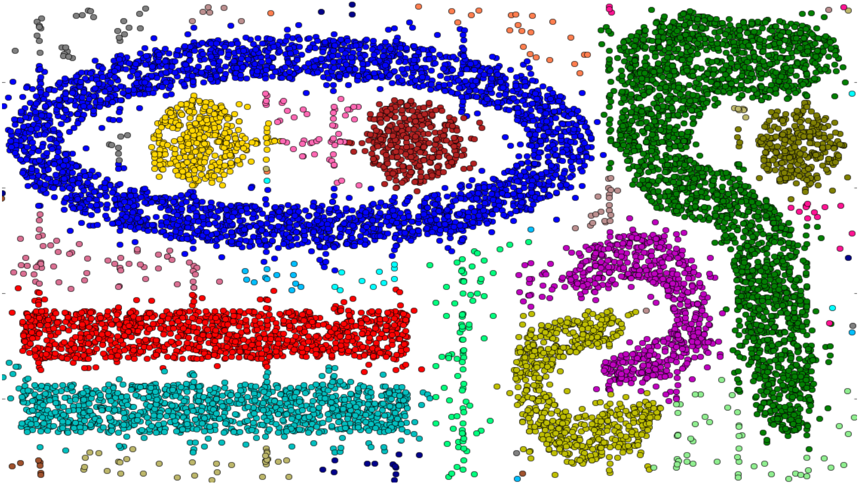
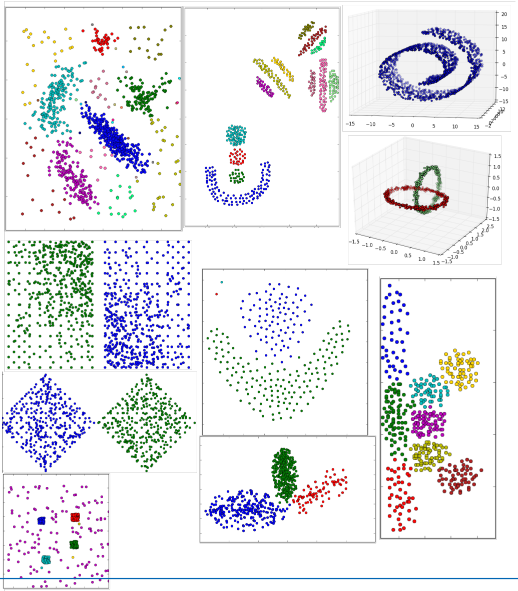


Abbildung: $DS4$, $n = 10000$ points

More examples



Outline

AWC Result

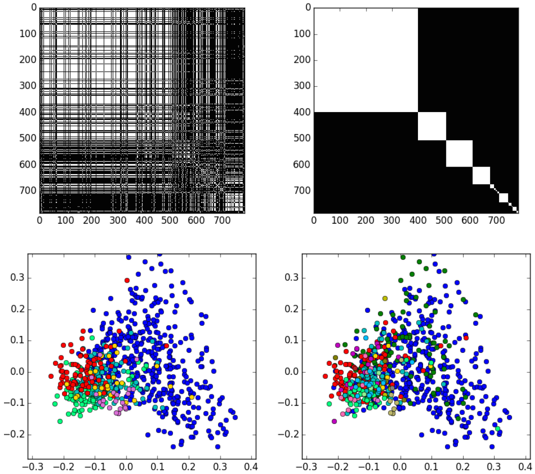


Abbildung: Clustering Structure found by AWC vs Original

- 46% contain *G*: 'Financial economics'
- 81% contain *C*: 'Mathematical and quantitative methods'
- Contains 86% of pairs {C, G}

Abbildung: size = word frequency, darker color – higher idf

Cluster 2 found by AWC

- 77% contain J: 'Labor economics'

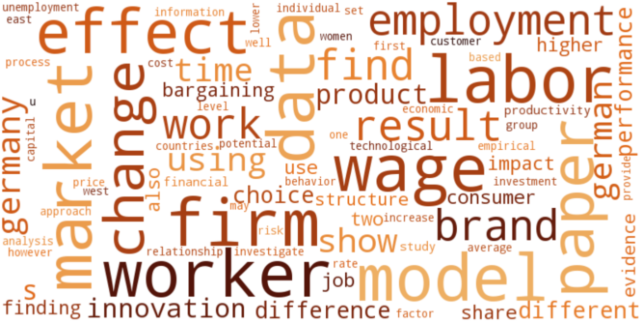


Abbildung: size = word frequency, darker color – higher idf

Cluster 3 found by AWC

- 51% contain *D*: 'Microeconomics'
- 54% contain *C*: 'Mathematical and quantitative methods'

Abbildung: size = word frequency, darker color – higher idf

Cluster 4 found by AWC

- 73% contain *E*: ’Macroeconomics and monetary economics’

Abbildung: size = word frequency, darker color – higher idf

Cluster 5 found by AWC

- 32% contain *R*: 'Urban, rural, and regional economic'
- 24% contain *Q*: 'natural resource economics'
- 40% contain *C*: 'Mathematical and quantitative methods'

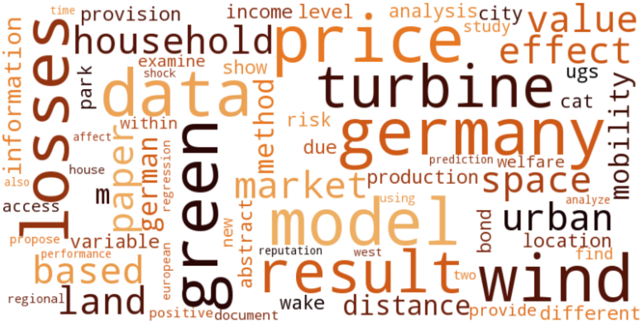


Abbildung: size = word frequency, darker color – higher idf

Cluster 6 found by AWC

- 54% contain *I*: 'Health, education, and welfare'
- 80% contain *C*: 'Mathematical and quantitative methods'
- 50% contain pairs {*I*, *C*}

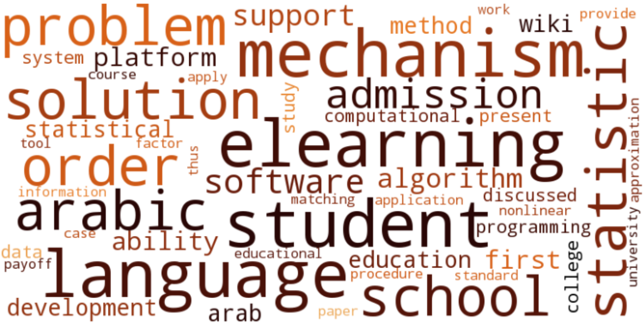


Abbildung: size = word frequency, darker color – higher idf

- Clustering as a specification of research directions of the papers
- Clustering using adaptive weights:
  - numerically feasible and applicable for large data sets
  - fully adaptive to unknown clustering structure including the number and shape of clusters and the separation distance
  - State-of-the-art performance of a wide range of artificial and real life examples
- Clustering procedure automatically assigns the JEL codes to submitted papers.

Thank you!

Test of “no gap between local clusters”. Formal definition

We need to test if $\theta_{i\cap j}^{(k)} > q_{ij}^{(k)}$. Following to Polzehl and Spokoiny (2006), define the test statistic $T_{ij}^{(k)}$

$$T_{ij}^{(k)} = N_{i\cup j}^{(k)} \mathcal{K}(\widetilde{\theta}_{i\cap j}^{(k)}, q_{ij}^{(k)})(-1)^{\mathbf{I}(\widetilde{\theta}_{i\cap j}^{(k)} > q_{ij}^{(k)})},$$

where $\mathcal{K}(\theta, q)$ is the Kullback-Leibler divergence:

$$\mathcal{K}(\theta, q) = \theta \log \frac{\theta}{q} + (1-\theta) \log \frac{1-\theta}{1-q}.$$

Algorithm steps:

- Initialization of weights w_{ij}
  - each point is connected with its n_0 closest neighbors
  - default choice of $n_0 = 2d+1$
- Fix a sequence of radii h_k:
  - The average number of screened neighbors for each X_i at step *k* grows at most exponentially.
- Iterative update of the weights:
  - At step k for all pairs of points X_i and X_j with distance $\|X_i - X_j\| \le h_k$ compute

$$w_{ij}^{(k)} = \mathbb{1}\left(\|X_i - X_j\| \le h_k\right) \mathbb{1}\left(T_{ij}^{(k)} \le \lambda\right)$$

- Cluster extraction from matrix of weights

- Take the point X_i with maximal local cluster $\mathscr{C}(X_i) = (X_j : w_{ij} > 0)$.
- Consider it as a separated cluster if majority of points X_j in $\mathscr{C}(X_i)$ have almost the same number of neighbors as X_i.
- Delete this cluster $\mathscr{C}(X_i)$ and repeat the procedure for remaining points until we delete all points.

Run the procedure with different λ and select one by checking an increase of the sum of weights $\sum_{i,j} w_{ij}^{(K)}$.

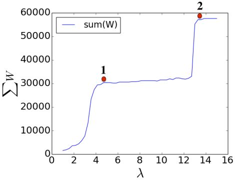


Abbildung: $\sum_{i,j} w_{ij}^{(K)}(\lambda)$

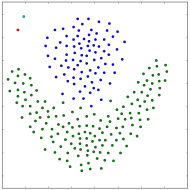


Abbildung: AWC for 1