Sparsity-sensitive Diagonal Co-clustering Algorithms for the Effective Handling of Text Data

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Prix de Thèse EGC'2018

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January 26, 2018

Outline

1. Introduction
    - Context
    - Co-clustering
    - Motivations
2. Graph-based Co-clustering
    - Graph Modularity
    - Modularity for Co-clustering
    - Experiments
3. Model-based Co-clustering
    - Sparse Poisson Latent Block Model (SPLBM)
    - Soft SPLBM-based Co-clustering Algorithm
    - Hard SPLBM-based Co-clustering Algorithm
    - Experiments
4. Using Co-clustering in Biomedical Text Mining Framework
    - The Biomedical Framework
    - Results and Discussions
5. Conclusion and Perspectives

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- Exponential growth of textual documents on the web, e.g. the PUBMED database contains more than 20 millions of biomedical articles
- It is become more laborious to access what we are looking for
- We need automated Text Mining tools to help us understand, interpret and organize this vast amount of information

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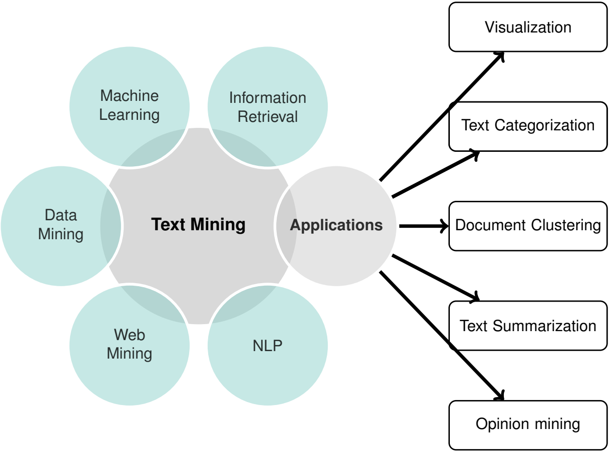
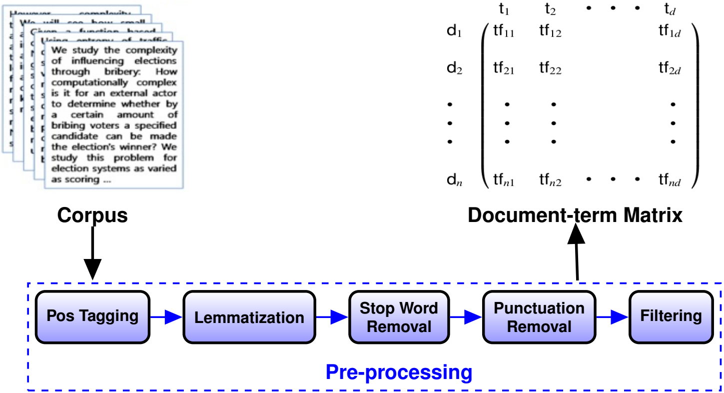


Data Representation



Document Representation

- Vector space model
- tf_{ij}=Frequency of term j in document i

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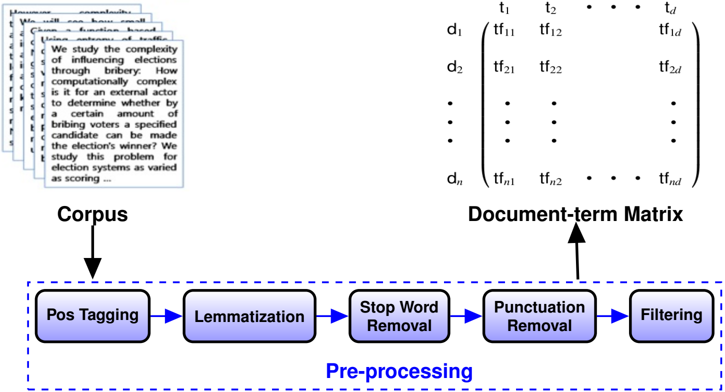

$$
\begin{array}{c|cccc}
 & t_1 & t_2 & \cdots & t_d \\
\hline
d_1 & tf_{11} & tf_{12} & & tf_{1d} \\
d_2 & tf_{21} & tf_{22} & & tf_{2d} \\
\vdots & \vdots & \vdots & & \vdots \\
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Weighting scheme

- TF-IDF weighting scheme

$$w_{ij} = tf_{ij} \times \log \frac{N}{d_j}$$

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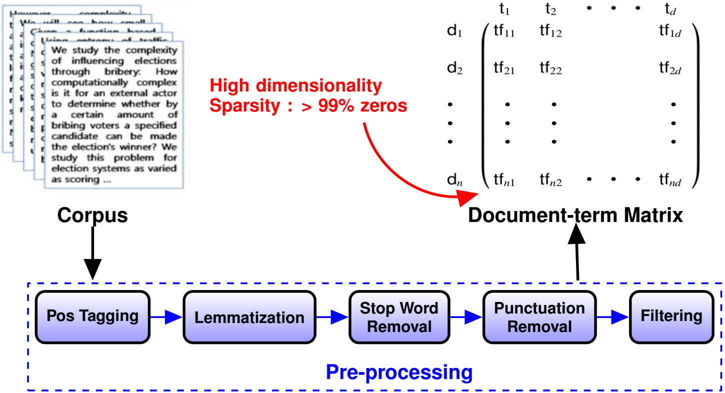

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- A widely used unsupervised learning technique, to group together similar documents based on their content
- Documents within a cluster are semantically coherent or deal with the same topics

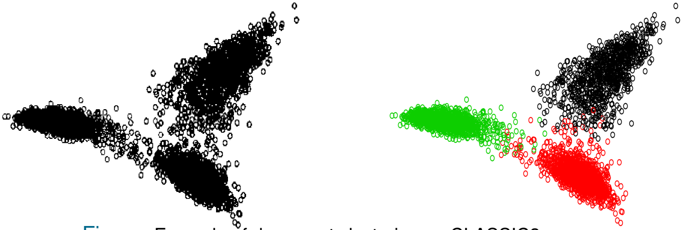

Figure: Example of document clustering on CLASSIC3 corpus

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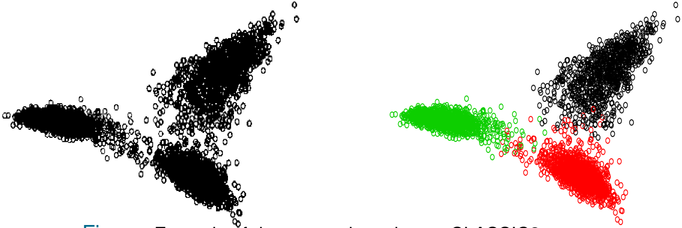

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Advantages :

- Organization of documents, efficient browsing and navigation of huge text corpora, speed up search engines, etc.

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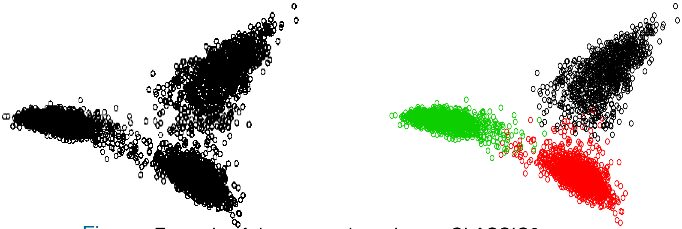

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Challenges :

- High dimensionality
- Sparsity

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Co-clustering

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	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8	Term 9	Term 10	Term 11	Term 12
Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 2	1	0	0	1	0	1	1	1	0	1	1	0
Doc 3	1	0	1	1	0	1	1	1	1	1	1	0
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
Doc 7	1	0	1	1	0	1	1	1	0	1	1	0
Doc 8	0	1	0	0	1	0	0	0	1	0	0	1
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0

(a) Original Data

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Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 2	1	0	0	1	0	1	1	1	0	1	1	0
Doc 3	1	0	1	1	0	1	1	1	1	1	1	0
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
Doc 7	1	0	1	1	0	1	1	1	0	1	1	0
Doc 8	0	1	0	0	1	0	0	0	1	0	0	1
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0

(a) Original Data

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Doc 7	1	0	1	1	0	1	1	1	0	1	1	0
Doc 3	1	0	1	1	0	1	1	1	1	1	1	0
Doc 2	1	0	0	1	0	1	1	1	0	1	1	0
Doc 8	0	1	0	0	1	0	0	0	1	0	0	1
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0

(b) Clustering

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	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8	Term 9	Term 10	Term 11	Term 12
Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 2	1	0	0	1	0	1	1	1	0	1	1	0
Doc 3	1	0	1	1	0	1	1	1	1	1	1	0
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
Doc 7	1	0	1	1	0	1	1	1	0	1	1	0
Doc 8	0	1	0	0	1	0	0	0	1	0	0	1
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0

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Doc 8	0	1	0	0	1	0	0	0	1	0	0	1
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0

(b) Clustering

	Term 4	Term 10	Term 3	Term 6	Term 12	Term 2	Term 9	Term 5	Term 11	Term 7	Term 1	Term 8
Doc 1	1	1	1	1	0	0	0	0	1	1	1	1
Doc 2	1	1	1	1	0	0	1	0	1	1	1	1
Doc 3	1	1	0	1	0	0	0	0	1	1	1	1
Doc 4	0	0	0	0	1	1	1	1	0	0	0	0
Doc 5	0	0	0	0	1	1	1	0	0	0	1	0
Doc 6	0	0	0	0	1	1	1	1	0	0	0	0
Doc 7	0	0	0	0	0	0	0	0	1	1	1	1
Doc 8	0	0	0	0	0	0	0	0	1	1	1	1
Doc 9	0	0	0	0	0	1	0	0	1	1	1	1

(c) Co-clustering

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Doc 1	0	1	0	0	1	0	0	0	1	0	0	1
Doc 2	1	0	0	1	0	1	1	1	0	1	1	0
Doc 3	1	0	1	1	0	1	1	1	1	1	1	0
Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0
Doc 6	1	1	0	0	0	0	0	0	1	0	0	1
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Doc 4	1	0	0	0	0	0	1	1	0	0	1	0
Doc 9	1	0	0	0	0	0	1	1	0	0	1	0
Doc 5	1	1	0	0	0	0	1	1	0	0	1	0

(b) Clustering

	Term 4	Term 10	Term 3	Term 6	Term 12	Term 2	Term 9	Term 5	Term 11	Term 7	Term 1	Term 8
Doc 1	1	1	1	1	0	0	0	0	1	1	1	1
Doc 2	1	1	1	1	0	0	1	0	1	1	1	1
Doc 3	1	1	0	1	0	0	0	0	1	1	1	1
Doc 4	0	0	0	0	1	1	1	1	0	0	0	0
Doc 5	0	0	0	0	1	1	1	0	0	0	1	0
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Doc 8	0	0	0	0	0	0	0	0	1	1	1	1
Doc 9	0	0	0	0	0	1	0	0	1	1	1	1

(c) Co-clustering

Why Co-clustering?

- Exploit the duality between object space and attribute space
- Cluster Characterization
- Technique for dimensionality reduction
- Reduce Computation time

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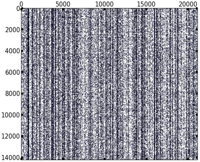

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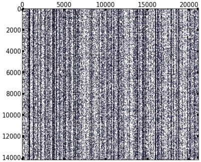

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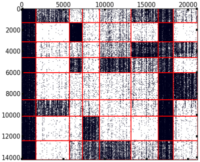
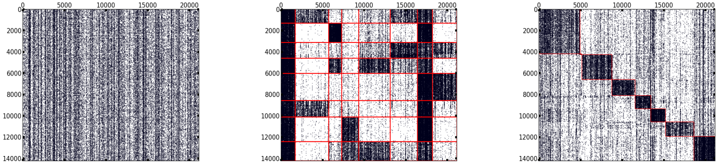


(b) General co-clustering

Motivations

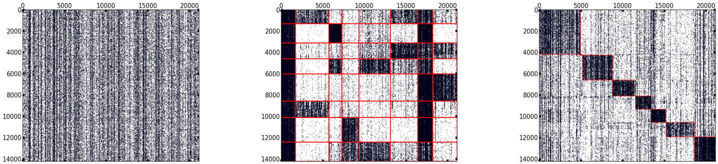
- When dealing with high dimensional sparse data, several co-clusters are primarily composed of zeros.
- Seeking homogeneous blocks is not sufficient to produce meaningful results.



(a) Original Data (b) General co-clustering (c) Diagonal co-clustering

Motivations

- When dealing with high dimensional sparse data, several co-clusters are primarily composed of zeros.
- Seeking homogeneous blocks is not sufficient to produce meaningful results.
- Seeking diagonal structure turns out to be more beneficial.
  - In good agreement with sparsity
  - Produces directly the most relevant co-clusters and ignore noisy ones
  - Cluster hypothesis
  - Allows a direct interpretation of co-clusters
  - Parsimonious



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Contributions

- Graph-based block diagonal clustering
- Model-based block diagonal clustering

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  - Find minimum cut using spectral relaxation (Dhillon, 2001)
  - Find maximum Modularity using spectral relaxation (Labiod and Nadif, 2011)
- Eigen vector computation may be prohibitive when dealing with high dimensional matrices

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Contributions

- We propose a new block-diagonal clustering algorithm (Coclus) (Ailem, Role, and Nadif, 2015; Ailem, Role, and Nadif, 2016)
- Coclus is based on the direct maximization of graph modularity
- Use an iterative alternating optimization procedure

M. Ailem, F. Role, and M. Nadif (2015). "Co-clustering Document-term Matrices by Direct Maximization of Graph Modularity". In: *CIKM'2015*. ACM, pp. 1807–1810.

M. Ailem, F. Role, and M. Nadif (2016). "Graph modularity maximization as an effective method for co-clustering text data". In: *Knowledge-Based Systems Journal* 109, pp. 160–173.

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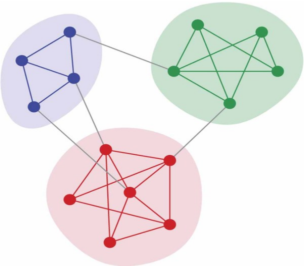
Graph Modularity



- Introduced by Newman and Girvan (2004)
- Identify community structure in graphs
- Measure the strength of the community structure of a graph
- Maximize the difference between the original graph and its corresponding random version
- Q=(number of intra-cluster edges) - (expected number of edges)

Given the graph $G(V,E)$ and its corresponding adjacency matrix A :

$$Q(\mathbf{A},\mathbf{C}) = \frac{1}{2|E|}\sum_{i=1}^{n}\sum_{i'=1}^{n}(a_{ii'} - \frac{a_{i.}a_{i'.}}{2|E|})c_{ii'}, \quad (1)$$

- where $|E|$ represents the number of edges
- $a_{ii'} = 1$ if there is an edge between nodes i and i'
- $a_{i.}$ and $a_{i'.}$ the degree of nodes i and i' respectively, and $\frac{a_{i.}a_{i'.}}{2|E|}$ represents the expected number of edges between nodes i and i'
- $c_{ii'} = \sum_k z_{ik}z_{i'k}$ is equal to 1 if i and i' belong to the same community k

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Modularity for Co-clustering

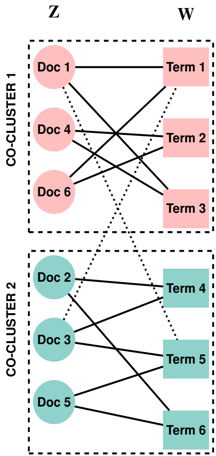
Given a rectangular positive matrix $\mathbf{A}$, modularity can be reformulated as follows in the co-clustering context:

$$Q(\mathbf{A},\mathbf{C}) = \frac{1}{a_{..}} \sum_{i=1}^{n} \sum_{j=1}^{d} (a_{ij} - \frac{a_{i.}a_{.j}}{a_{..}}) c_{ij}, \qquad (2)$$

$$Q(\mathbf{A},\mathbf{Z}\mathbf{W}^t) = \frac{1}{a_{..}} \sum_{i=1}^{n} \sum_{j=1}^{d} \sum_{k=1}^{g} (a_{ij} - \frac{a_{i.}a_{.j}}{a_{..}}) z_{ik} w_{jk}, \qquad (3)$$

where $a_{..} = \sum_{i,j} a_{ij} = |E|$ is the number of edges (or edge weights for weighted graphs) and $c_{ij} = \sum_k z_{ik} w_{jk} = 1$ if nodes i and j belong to the same co-cluster k and 0 otherwise

$$Q(\mathbf{A},\mathbf{C}) = \frac{1}{a_{..}} Trace[(\mathbf{A} - \boldsymbol{\delta})^t \mathbf{Z}\mathbf{W}^t] = Q(\mathbf{A},\mathbf{Z}\mathbf{W}^t). \qquad (4)$$



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Doc 4	0	1	2	0	0	0
Doc 6	1	1	0	0	0	0
Doc 2	0	0	0	1	0	1
Doc 3	1	0	0	3	1	0
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Alternated Maximization of Modularity

Proposition

Let $\mathbf{A}$ be a $(n \times d)$ positive data matrix and $\mathbf{C}$ be a $(n \times d)$ matrix defining a block seriation, the modularity measure $Q(\mathbf{A}, \mathbf{C})$ can be rewritten as

$$1) \quad Q(\mathbf{A},\mathbf{C}) = \frac{1}{a_{..}} \sum_{i=1}^{n} \sum_{k=1}^{g} (a_{ik}^{\mathbf{W}} - \frac{a_{i.} a_{.k}^{\mathbf{W}}}{a_{..}}) z_{ik} = \frac{1}{a_{..}} Trace[(\mathbf{A}^{\mathbf{W}} - \boldsymbol{\delta}^{\mathbf{W}})^t \mathbf{Z}] = Q(\mathbf{A}^{\mathbf{W}}, \mathbf{Z})$$

where $\boldsymbol{\delta}^{\mathbf{W}} := \{\delta_{ik}^{\mathbf{W}} = \frac{a_{i.} a_{.k}^{\mathbf{W}}}{a_{..}}; i = 1, \ldots, n; k = 1, \ldots, g\}$ with $a_{.k}^{\mathbf{W}} = \sum_{j=1}^{d} w_{jk} a_{.j}$

$$2) \quad Q(\mathbf{A},\mathbf{C}) = \frac{1}{a_{..}} \sum_{j=1}^{d} \sum_{k=1}^{g} (a_{kj}^{\mathbf{Z}} - \frac{a_{.j} a_{k.}^{\mathbf{Z}}}{a_{..}}) w_{jk} = \frac{1}{a_{..}} Trace[(\mathbf{A}^{\mathbf{Z}} - \boldsymbol{\delta}^{\mathbf{Z}}) W] = Q(\mathbf{A}^{\mathbf{Z}}, \mathbf{W})$$

where $\boldsymbol{\delta}^{\mathbf{Z}} := \{\delta_{kj}^{\mathbf{Z}} = \frac{a_{.j} a_{k.}^{\mathbf{Z}}}{a_{..}}; j = 1, \ldots, d; k = 1, \ldots, g\}$ with $a_{k.}^{\mathbf{Z}} = \sum_{i=1}^{n} z_{ik} a_{i.}$

`Coclus` Algorithm

Algorithm 1: `Coclus`

Input : positive data matrix $\mathbf{A}$, number of co-clusters g
Step 1. Initialization of $\mathbf{W}$
repeat

- **Step 2.** Compute $\mathbf{A}^{\mathbf{W}} = \mathbf{AW}$
- **Step 3.** Compute $\mathbf{Z}$ maximizing $Q(\mathbf{A}^{\mathbf{W}}, \mathbf{Z})$ by

$$z_{ik} = \arg\max_{1 \leq \ell \leq g} \left(a^{\mathbf{W}}_{i\ell} - \frac{a_{i.} a^{\mathbf{W}}_{.\ell}}{a_{..}} \right) \forall i = 1, \ldots, n; k = 1, \ldots, g$$

- **Step 4.** Compute $\mathbf{A}^{\mathbf{Z}} = \mathbf{Z}^t \mathbf{A}$
- **Step 5.** Compute $\mathbf{W}$ maximizing $Q(\mathbf{A}^{\mathbf{Z}}, \mathbf{W})$ by

$$w_{jk} = \arg\max_{1 \leq \ell \leq g} \left(a^{\mathbf{Z}}_{\ell j} - \frac{a^{\mathbf{Z}}_{\ell .} a_{.j}}{a_{..}} \right) \forall j = 1, \ldots, d; k = 1, \ldots, g$$

- **Step 6.** Compute $Q(\mathbf{A}, \mathbf{ZW}^t)$

until *Convergence*;
Output : partition matrices $\mathbf{Z}$ and $\mathbf{W}$, and modularity value $\mathbf{Q}$

Complexity : $O(nz \cdot it \cdot g)$

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Datasets	Characteristics				
	#Documents	#Words	#Clusters	Sparsity (%)	Balance
CLASSIC4	7095	5896	4	99.41	0.323
NG20	19949	43586	20	99.99	0.991
SPORTS	8580	14870	7	99.99	0.036
REVIEWS	4069	18483	5	99.99	0.098

- Evaluation measure : Accuracy (Acc) and Normalized mutual information (NMI) (Strehl and Ghosh, 2003)
- Data Types : binary, contingency and TF-IDF

Method	**Data Type**	**References**	**Co-clustering**	**Type of implementation**
Spec	Positive data	(I. Dhillon, 2001)	Diagonal	Scickit Learn
Block	Binary	(Li, 2005)	Diagonal	Our python implementation
ITCC	Positive data	(I. S. Dhillon, Mallela, and D. S. Modha, 2003)	Non-diagonal	C++ implementation
SpecCo	Positive data	(Labiod and Nadif, 2011)	Diagonal	Our python implementation
χ-*Sim*	Positive data	(Bisson and Hussain, 2008)	Non-diagonal	MATLAB implementation of the authors
FNMTF	Positive data	(Wang et al., 2011)	Non-diagonal	MATLAB implementation of the authors

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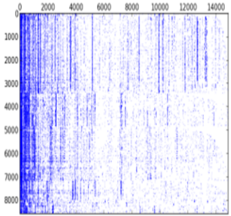
		Binary							**Contingency**						**TF-IDF**					
datasets	per.	Spec	ITCC	Block	SpecCo	χ-Sim	FNMTF	CoClus	Spec	ITCC	SpecCo	χ-Sim	FNMTF	CoClus	Spec	ITCC	SpecCo	χ-Sim	FNMTF	CoClus
CLASSIC4	Acc	0.34	0.65	0.52	0.45	0.31	0.50	**0.90**	0.53	0.87	0.58	0.31	0.56	**0.90**	0.44	0.60	0.45	0.35	0.76	**0.88**
	NMI	0.14	0.51	0.16	0.02	0.15	0.30	**0.72**	0.45	0.67	0.48	0.15	0.30	**0.73**	0.02	0.55	0.009	0.13	0.58	**0.70**
NG20	Acc	0.14	**0.43**	0.20	0.19	0.26	0.13	0.40	0.05	**0.45**	0.30	0.30	0.09	0.37	0.19	**0.41**	0.15	0.29	0.40	0.37
	NMI	0.29	**0.55**	0.22	0.42	0.33	0.03	**0.55**	0.02	**0.52**	0.49	0.37	0.07	**0.52**	0.32	0.44	0.38	0.41	0.40	**0.52**
SPORTS	Acc	0.56	0.45	0.47	0.59	0.57	0.28	**0.70**	0.44	0.56	0.68	0.53	0.36	**0.75**	0.45	0.54	0.61	0.67	0.57	**0.68**
	NMI	0.47	0.49	0.38	0.45	0.48	0.15	**0.54**	0.38	0.58	0.59	0.48	0.19	**0.62**	0.43	0.58	0.45	0.55	0.54	**0.59**
REVIEWS	Acc	0.56	0.58	0.53	0.59	0.46	0.34	**0.65**	0.50	0.71	0.45	0.41	0.38	**0.72**	0.35	0.63	0.46	0.44	0.43	**0.65**
	NMI	0.36	0.46	0.42	0.39	0.31	0.18	**0.54**	0.40	0.57	0.34	0.23	0.17	**0.58**	0.03	0.51	0.35	0.28	0.27	**0.52**

- Results obtained after running each algorithm 100 times with random initialization
- We retained the solution optimizing the associated criterion (maximizing the modularity for *CoClus*)
- Superiority of Coclus in almost all situations
- Robustness w.r.t the type of data (binary tables, contingency tables and TF-IDF weighted tables)

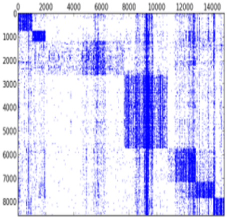
Assessing the Number of Co-clusters

- Most previous co-clustering algorithms require the number of co-clusters as an input parameter
- The modularity measure can be used to predict the right number of co-clusters
- Run *Coclus* algorithm with different values of g (number of co-clusters)
- For each number of co-cluster the modularity is computed
- Retain the number of co-clusters for which the modularity measure reaches it's maximum value

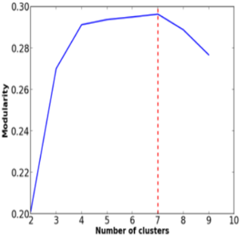
Assessing the Number of Co-clusters



Original matrix (document x term)



Reorganized matrix (after Co-clustering)



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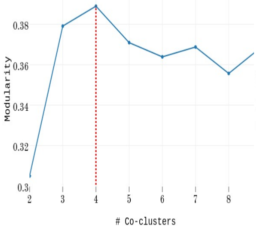
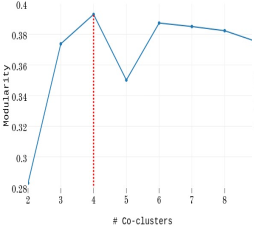
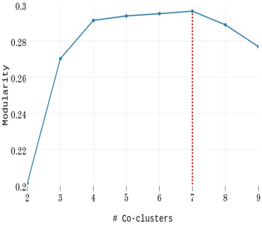
Assessing the right number of co-clusters



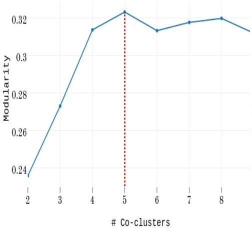
(a) CSTR (real : **4**, predicted : **4**)



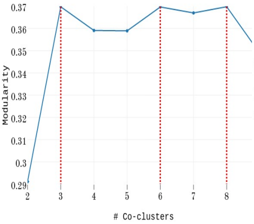
(b) CL4 (real : **4**, predicted : **4**)



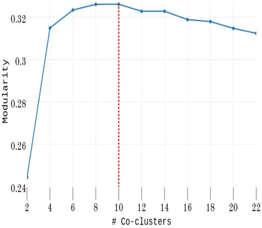
(c) SPORTS (real : **7**, predicted : **7**)



(d) Reviews (real : **5**, predicted : **5**)



(e) CL3 (real : **3**, predicted : **3**,6,8)



(f) NG20 (real : **20**, predicted : 10)

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Motivation

- Investigate probabilistic mixture models allowing to make precise assumptions about the anatomy of diagonal co-clusters
- Flexibility
- Give rise to both soft and hard co-clustering

Motivation

- Investigate probabilistic mixture models allowing to make precise assumptions about the anatomy of diagonal co-clusters
- Flexibility
- Give rise to both soft and hard co-clustering

Contribution

- We present a sparse generative mixture model for co-clustering text data
- This model is based on the Poisson distribution, which arises naturally for contingency tables, such as document-term matrices
- The proposed model takes into account the sparsity in its formulation

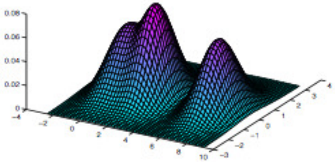
Model-based clustering - Finite mixture model

The matrix is assumed to be an i.i.d sample $\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_n)$ where $\mathbf{x}_i = (x_{i1}, \ldots x_{id}) \in \mathbb{R}^d$ is generated from a probability density function (pdf) with density :

$$f(\mathbf{x}_i, \theta) = \sum_{k=1}^{g} \pi_k f_k(\mathbf{x}_i, \alpha_k),$$

The likelihood of data $\mathbf{X}$ can be written as :

$$f(\mathbf{X}, \theta) = \prod_i \sum_{k=1}^{g} \pi_k f_k(\mathbf{x}_i, \alpha_k),$$

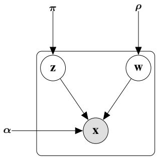


where

- $f_k(., \alpha_k)$ is the density of an observation $\mathbf{x}_i$ from the k-th component
- $\alpha_k' s$ are the corresponding class parameters
- π_k represents the proportions of each cluster.
- Each component k of the mixture represents a cluster.

Model-based co-clustering - Latent block model (LBM)

For each block $k\ell$, the values x_{ij} are generated according to a probability density function (pdf) $f(x_{ij};\alpha_{k\ell})$ (Govaert and Nadif, 2003)



Likelihood function

Denoting by $\mathcal{Z}$ and $\mathcal{W}$ the sets of all possible partitions, the likelihood function of a data matrix $\mathbf{X}$ of size $n \times d$ can be written

$$f(\mathbf{X};\boldsymbol{\theta}) = \sum_{(\mathbf{Z},\mathbf{W})\in\mathcal{Z}\times\mathcal{W}} \prod_{i,k} \pi_k^{z_{ik}} \prod_{j,\ell} \rho_\ell^{w_{j\ell}} \prod_{i,j,k,\ell} f(x_{ij};\alpha_{k\ell})^{z_{ik}w_{j\ell}},$$

Where

- $\boldsymbol{\theta} = (\boldsymbol{\pi},\boldsymbol{\rho},\boldsymbol{\alpha})$, is the parameters of the latent block model.
- $\boldsymbol{\pi}$ and $\boldsymbol{\rho}$ are the mixing proportions.
- $\boldsymbol{\alpha} = (\alpha_{k\ell}; k = 1,\ldots g, \ell = 1,\ldots,m)$ is the matrix of parameters of each block (k,ℓ).
- g (resp. m) represents the number of row (resp. column) clusters.

Latent block model (LBM)

Algorithm 2: Generative Process of LBM

Input : $n, d, g, m, \boldsymbol{\theta} = (\boldsymbol{\pi}, \boldsymbol{\rho}, \boldsymbol{\alpha})$

Output: data matrix $\mathbf{X}$, vector of row labellings $\mathbf{z} = (z_1, \ldots, z_n)$ and vector of column labellings $\mathbf{w} = (w_1, \ldots, w_d)$

for $i = 1$ **to** n **do**
- Generate the row label z_i according to the multinomial distribution $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_g)$

end

for $j = 1$ **to** d **do**
- Generate the column label w_j according to the multinomial distribution $\boldsymbol{\rho} = (\rho_1, \ldots, \rho_g)$

end

for $i = 1$ **to** n **do**
  for $j = 1$ **to** d **do**
  - Generate a value x_{ij} according to the distribution $f(.; \alpha_{z_i, w_j})$

  end

end

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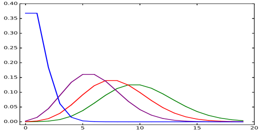
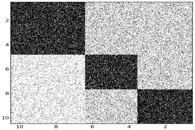


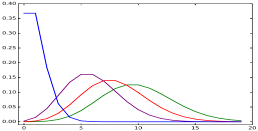


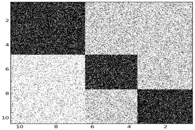
Intuition

- For each diagonal block kk the values x_{ij} are distributed according to the Poisson distribution $\mathcal{P}(\lambda_{ij})$ where the parameter λ_{ij} takes the following form :
$$\lambda_{ij} = x_{i.}x_{.j}\sum_k z_{ik}w_{jk}\gamma_{kk}.$$
- For each off-diagonal block $k\ell$ with $k \neq \ell$ the values x_{ij} are distributed according to the Poisson distribution $\mathcal{P}(\lambda_{ij})$ where the parameter λ_{ij} takes the following form :
$$\lambda_{ij} = x_{i.}x_{.j}\sum_{k,\ell\neq k} z_{ik}w_{j\ell}\gamma.$$
- Assuming $\forall \ell \neq k \quad \gamma_{k\ell} = \gamma$ leads to suppose that all blocks outside the diagonal share the same parameter.

Likelihood function

$$f(\mathbf{X};\boldsymbol{\theta}) = \sum_{(\mathbf{z},\mathbf{w})\in\mathcal{Z}\times\mathcal{W}} \prod_{i,k} \pi_k^{z_{ik}} \prod_{j,k} \rho_\ell^{w_{jk}} \times \prod_{i,j,k} (f(x_{ij};\alpha_{kk}))^{z_{ik}w_{jk}} \times \prod_{i,j,k,\ell\neq k} (f(x_{ij};\alpha_{k\ell}))^{z_{ik}w_{j\ell}}$$





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Likelihood function

$$\begin{aligned} f(\mathbf{X};\boldsymbol{\theta}) &= \sum_{(\mathbf{z},\mathbf{w})\in\mathcal{Z}\times\mathcal{W}} \prod_{i,k}\pi_k^{z_{ik}}\prod_{j,k}\rho_\ell^{w_{jk}} \\ &\times \prod_{i,j,k}(f(x_{ij};\alpha_{kk}))^{z_{ik}w_{jk}} \times \prod_{i,j,k,\ell\neq k}(f(x_{ij};\alpha_{k\ell}))^{z_{ik}w_{j\ell}} \end{aligned}$$

Sparse Poisson Latent Block Model (SPLBM)

Complete Data Likelihood

$$f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \prod_{i,k} \pi_k^{z_{ik}} \prod_{j,k} \rho_k^{w_{jk}} \times \prod_{i,j,k} \left(\frac{e^{-x_{i.}x_{.j}\gamma_{kk}} (x_{i.}x_{.j}\gamma_{kk})^{x_{ij}}}{x_{ij}!} \right)^{z_{ik}w_{jk}}$$
$$\times \prod_{i,j,k,\ell \neq k} \left(\frac{e^{-x_{i.}x_{.j}\gamma} (x_{i.}x_{.j}\gamma)^{x_{ij}}}{x_{ij}!} \right)^{z_{ik}w_{j\ell}}$$

Complete Data Log-likelihood

$$L_C(\mathbf{Z},\mathbf{W},\boldsymbol{\theta}) = \log f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \sum_{k=1}^{g} \mathcal{L}_C^k$$

$$\mathcal{L}_C^k = z_{.k}\log\pi_k + w_{.k}\log\rho_k + x_{kk}^{\mathbf{ZW}}\log\left(\frac{\gamma_{kk}}{\gamma}\right) - x_{k.}^{\mathbf{Z}}x_{.k}^{\mathbf{W}}(\gamma_{kk}-\gamma) + \frac{N}{g}(\log(\gamma) - \gamma N)$$

where $x_{kk}^{\mathbf{ZW}} = \sum_{ij} z_{ik}w_{jk}x_{ij}$, $z_{.k} = \sum_i z_{ik}$ and $w_{.k} = \sum_j w_{jk}$, $x_{k.}^{\mathbf{Z}} = \sum_i z_{ik}x_{i.}$ and $x_{.k}^{\mathbf{W}} = \sum_j w_{jk}x_{.j}$

Sparse Poisson Latent Block Model (SPLBM)

Complete Data Likelihood

$$f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \prod_{i,k}\pi_k^{z_{ik}}\prod_{j,k}\rho_k^{w_{jk}} \quad\times\quad \prod_{i,j,k}\left(\frac{e^{-x_{i.}x_{.j}\gamma_{kk}}(x_{i.}x_{.j}\gamma_{kk})^{x_{ij}}}{x_{ij}!}\right)^{z_{ik}w_{jk}}$$

$$\times\quad \prod_{i,j,k,\ell\neq k}\left(\frac{e^{-x_{i.}x_{.j}\gamma}(x_{i.}x_{.j}\gamma)^{x_{ij}}}{x_{ij}!}\right)^{z_{ik}w_{j\ell}}$$

Complete Data Log-likelihood

$$\mathrm{L}_{\mathrm{C}}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta}) = \log f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \sum_{k=1}^{g}\mathcal{L}_C^k$$

$$\mathcal{L}_C^k = z_{.k}\log\pi_k + w_{.k}\log\rho_k + x_{kk}^{\mathbf{ZW}}\log\left(\frac{\gamma_{kk}}{\gamma}\right) - x_{k.}^{\mathbf{Z}}x_{.k}^{\mathbf{W}}(\gamma_{kk}-\gamma) + \frac{N}{g}(\log(\gamma) - \gamma N)$$

where $x_{kk}^{\mathbf{ZW}} = \sum_{ij} z_{ik}w_{jk}x_{ij}$, $z_{.k} = \sum_i z_{ik}$ and $w_{.k} = \sum_j w_{jk}$, $x_{k.}^{\mathbf{Z}} = \sum_i z_{ik}x_{i.}$ and $x_{.k}^{\mathbf{W}} = \sum_j w_{jk}x_{.j}$

Sparse Poisson Latent Block Model (SPLBM)

Complete Data Likelihood

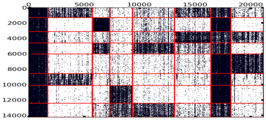
$$f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \prod_{i,k} \pi_k^{z_{ik}} \prod_{j,k} \rho_k^{w_{jk}} \times \prod_{i,j,k} \left(\frac{e^{-x_{i.}x_{.j}\gamma_{kk}} (x_{i.}x_{.j}\gamma_{kk})^{x_{ij}}}{x_{ij}!} \right)^{z_{ik}w_{jk}} \times \prod_{i,j,k,\ell \neq k} \left(\frac{e^{-x_{i.}x_{.j}\gamma} (x_{i.}x_{.j}\gamma)^{x_{ij}}}{x_{ij}!} \right)^{z_{ik}w_{j\ell}}$$

Complete Data Log-likelihood

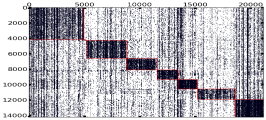
$$\mathrm{L_C}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta}) = \log f(\mathbf{X},\mathbf{Z},\mathbf{W};\boldsymbol{\theta}) = \sum_{k=1}^{g} \mathcal{L}_C^k$$

$$\mathcal{L}_C^k = z_{.k}\log\pi_k + w_{.k}\log\rho_k + x_{kk}^{\mathbf{ZW}}\log\left(\frac{\gamma_{kk}}{\gamma}\right) - x_{k.}^{\mathbf{Z}}x_{.k}^{\mathbf{W}}(\gamma_{kk}-\gamma) + \frac{N}{g}(\log(\gamma) - \gamma N)$$

where $x_{kk}^{\mathbf{ZW}} = \sum_{ij} z_{ik}w_{jk}x_{ij}$, $z_{.k} = \sum_i z_{ik}$ and $w_{.k} = \sum_j w_{jk}$, $x_{k.}^{\mathbf{Z}} = \sum_i z_{ik}x_{i.}$ and $x_{.k}^{\mathbf{W}} = \sum_j w_{jk}x_{.j}$



(a) Traditional LBM - **64 parameters**



(b) Sparse PLBM - **9 parameters**

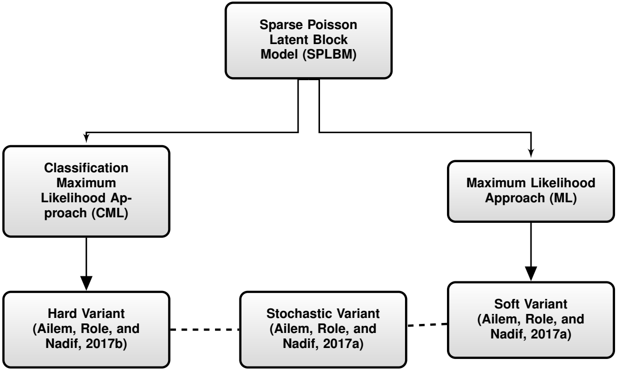


Figure: **SPLBM-based co-clustering algorithms**

M. Ailem, F. Role, and M. Nadif (2017b). "Sparse Poisson Latent Block Model for Document Clustering". In: *IEEE TKDE journal* 29.7, p. 1563.

M. Ailem, F. Role, and M. Nadif (2017a). "Model-based co-clustering for the effective handling of sparse data". In: *Pattern Recognition* 72, pp. 108–122.

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Soft SPLBM-based Co-clustering Algorithm

- Estimate the model's parameters $\boldsymbol{\theta}$, $\widetilde{\mathbf{Z}}$ and $\widetilde{\mathbf{W}}$
- We rely on the Expectation-Maximization (EM) algorithm that consists in maximizing the expectation of the complete data likelihood $\mathrm{L_C}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta})$ given by :

$$\begin{aligned}\mathbb{E}\left(\mathrm{L_C}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta})|\boldsymbol{\theta}^{(t)},\mathbf{X}\right) &= \sum_{i,k}\tilde{z}_{ik}^{(t)}\log\pi_k+\sum_{j,k}\tilde{w}_{jk}^{(t)}\log\rho_k\\ &+ \sum_{i,j,k}\tilde{e}_{ijk}^{(t)}\left(x_{ij}\log(\gamma_{kk})-x_{i.}x_{.j}\gamma_{kk}\right)\\ &+ \sum_{i,j,k,\ell\neq k}\tilde{e}_{ikj\ell}^{(t)}\left(x_{ij}\log(\gamma)-x_{i.}x_{.j}\gamma\right),\end{aligned}$$

where $\tilde{z}_{ik}^{(t)}=\mathbb{E}(z_{ik}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$, $\tilde{w}_{j\ell}=\mathbb{E}(w_{j\ell}^{(t)}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$,
$\tilde{e}_{ikj\ell}^{(t)}=\mathbb{E}(e_{ikj\ell}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})=\mathbb{E}(z_{ik}w_{j\ell}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$ and $\tilde{e}_{ijk}^{(t)}=\mathbb{E}(z_{ik}w_{jk}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$.

Soft SPLBM-based Co-clustering Algorithm

- Estimate the model's parameters $\boldsymbol{\theta}$, $\widetilde{\mathbf{Z}}$ and $\widetilde{\mathbf{W}}$
- We rely on the Expectation-Maximization (EM) algorithm that consists in maximizing the expectation of the complete data likelihood $\mathrm{L_C}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta})$ given by :

$$\begin{aligned}\mathbb{E}\left(\mathrm{L_C}(\mathbf{Z},\mathbf{W},\boldsymbol{\theta})|\boldsymbol{\theta}^{(t)},\mathbf{X}\right) &= \sum_{i,k}\tilde{z}_{ik}^{(t)}\log\pi_k+\sum_{j,k}\tilde{w}_{jk}^{(t)}\log\rho_k\\ &+ \sum_{i,j,k}\tilde{e}_{ijk}^{(t)}(x_{ij}\log(\gamma_{kk})-x_{i.}x_{.j}\gamma_{kk})\\ &+ \sum_{i,j,k,\ell\neq k}\tilde{e}_{ikj\ell}^{(t)}(x_{ij}\log(\gamma)-x_{i.}x_{.j}\gamma),\end{aligned}$$

where $\tilde{z}_{ik}^{(t)}=\mathbb{E}(z_{ik}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$, $\tilde{w}_{j\ell}=\mathbb{E}(w_{j\ell}^{(t)}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$,
$\tilde{e}_{ikj\ell}^{(t)}=\mathbb{E}(e_{ikj\ell}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})=\mathbb{E}(z_{ik}w_{j\ell}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$ and $\tilde{e}_{ijk}^{(t)}=\mathbb{E}(z_{ik}w_{jk}=1|\mathbf{X},\boldsymbol{\theta}^{(t)})$.
The coupling of $\mathbf{Z}$ and $\mathbf{W}$ in e makes the direct application of the EM algorithm difficult, due to the determination of $\tilde{e}_{ijk}$ and $\tilde{e}_{ikj\ell}$

Model Fitting Using the Variational EM Algorithm

- Solution : Use a mean-field variational EM (VEM) algorithm for inferences
- The VEM algorithm is equivalent to maximizing the following soft co-clustering criteria:

$$F_C(\widetilde{\mathbf{Z}},\widetilde{\mathbf{W}},\boldsymbol{\theta}) = L_C(\widetilde{\mathbf{Z}},\widetilde{\mathbf{W}},\boldsymbol{\theta}) + H(\widetilde{\mathbf{Z}}) + H(\widetilde{\mathbf{W}}),$$

- where $H(\widetilde{\mathbf{Z}}) = -\sum_{i,k}\widetilde{z}_{ik}\log\widetilde{z}_{ik}$ and $H(\widetilde{\mathbf{W}}) = -\sum_{j,k}\widetilde{w}_{jk}\log\widetilde{w}_{jk}$ are respectively the entropy of the missing variables $\widetilde{\mathbf{Z}}$ and $\widetilde{\mathbf{W}}$
- $L_C(\widetilde{\mathbf{Z}},\widetilde{\mathbf{W}},\boldsymbol{\theta})$ is the soft complete data likelihood defined as follows :

$$\begin{aligned} L_C(\widetilde{\mathbf{Z}},\widetilde{\mathbf{W}},\boldsymbol{\theta}) &= \sum_{i,k}\widetilde{z}_{ik}\log\pi_k + \sum_{j,k}\widetilde{w}_{jk}\log\rho_k + \sum_{i,j,k}\widetilde{z}_{ik}\widetilde{w}_{jk}x_{ij}\log(\frac{\gamma_{kk}}{\gamma}) \\ &- \sum_k x_{k.}^{\widetilde{\mathbf{Z}}}x_{.k}^{\widetilde{\mathbf{W}}}\gamma_{kk} + \gamma\sum_k x_{k.}^{\widetilde{\mathbf{Z}}}x_{.k}^{\widetilde{\mathbf{W}}} + N(\log(\gamma) - \gamma N) \end{aligned}$$

- The SPLBvem algorithm consists of the expectation and maximization steps

Model Fitting Using the Variational EM Algorithm

M-step

- **Computation of $\hat{\gamma}_{kk}$ for all k.** It is easy to show that $\forall k$ the $\hat{\gamma}_{kk}$'s maximizing $\mathrm{F_C}$ can be computed separately for each k.

$$\hat{\gamma}_{kk} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}.$$

- **Computation of $\hat{\gamma}$ maximizing $\mathrm{F_C}$.** It is easy to show that $\hat{\gamma}$ is given by:

$$\hat{\gamma} = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}.$$

- **Computation of $\hat{\pi}_k$, $\hat{\rho}_k$ for all k.** Under the constraints $\sum_k \pi_k = \sum_k \rho_k = 1$, it is easy to show that each $\hat{\pi}_k$ and $\hat{\rho}_k$ maximizing $\mathrm{F_C}$ are respectively given by $\pi_k = \frac{\widetilde{\mathbf{Z}}_{.k}}{n}$ and $\rho_k = \frac{\widetilde{\mathbf{W}}_{.k}}{d}$.

Model Fitting Using the Variational EM Algorithm

E-step

- The E-step consists in computing the posterior probabilities $\widetilde{z}_{ik}$ and $\widetilde{w}_{jk}$ maximizing $\mathrm{F_C}$
- Plugging the estimation of γ_{kk}'s and γ (explicitly in some terms of $\mathrm{F_C}$) we obtain

$$\begin{aligned}\mathrm{F_C}(\widetilde{\mathbf{Z}},\widetilde{\mathbf{W}},\hat{\boldsymbol{\theta}}) &= \sum_{i,k}\widetilde{z}_{ik}\log\hat{\pi}_k + \sum_{j,k}\widetilde{\mathrm{w}}_{jk}\log\hat{\rho}_k + \sum_{i,j,k}\widetilde{z}_{ik}\widetilde{\mathrm{w}}_{jk}x_{ij}\log(\frac{\hat{\gamma}_{kk}}{\hat{\gamma}}) \\ &+ N(\log(\hat{\gamma})-1) - \sum_{i,k}\widetilde{z}_{ik}\log\widetilde{z}_{ik} - \sum_{j,k}\widetilde{w}_{jk}\log\widetilde{w}_{jk}.\end{aligned}$$

- Taking $x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{\mathrm{w}}_{jk}x_{ij}$ and $x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik}x_{ij}$ it is easy to show that under the constraints:
  - $\sum_k \tilde{z}_{ik} = 1$
  - $\sum_k \tilde{w}_{jk} = 1$

$$\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}}\log\frac{\gamma_{kk}}{\gamma}).$$

$$\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}}\log\frac{\gamma_{kk}}{\gamma}).$$

The `SPLBvem` Algorithm

Algorithm 3: `SPLBvem`

Input : $\mathbf{X}$, g

Initialization : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k, γ_{kk}, γ

repeat

$x^{\widetilde{\mathbf{W}}}_{ik} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x^{\widetilde{\mathbf{W}}}_{ik} \log \frac{\gamma_{kk}}{\gamma})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x^{\widetilde{\mathbf{W}}}_{ik}}{x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}} = \frac{x^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}_{kk}}{x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}}$ $\quad, \gamma = \frac{N - \sum_k x^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}_{kk}}{N^2 - \sum_k x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}}$

$x^{\widetilde{\mathbf{Z}}}_{kj} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x^{\widetilde{\mathbf{Z}}}_{kj} \log \frac{\gamma_{kk}}{\gamma})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x^{\widetilde{\mathbf{Z}}}_{kj}}{x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}} = \frac{x^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}_{kk}}{x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}}$ $\quad, \gamma = \frac{N - \sum_k x^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}_{kk}}{N^2 - \sum_k x^{\widetilde{\mathbf{Z}}}_{k.} x^{\widetilde{\mathbf{W}}}_{.k}}$

until *Convergence*;

Output : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k, γ_{kk}, γ

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The hard SPLBM-based co-clustering algorithm (SPLBcem)

Intuition

- It consists in maximizing the classification likelihood instead of its expectation
- This is done by incorporating a classification step (C-step) between the E and M steps of the SPLBvem

Algorithm 4: `SPLBcem`

Input : $\mathbf{X}$, g
Initialization : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k,γ_{kk}, γ
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. $z_{ik} = \arg\max_k \widetilde{z}_{ik}$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. $w_{jk} = \arg\max_k \widetilde{w}_{jk}$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

Advantages

- SPLBcem is considerably faster and scalable than SPLBvem
- It allows us to avoid numerical difficulties, related to the computation of the posterior probabilities $\widetilde{z}_{ik}$ and $\widetilde{w}_{jk}$

The hard SPLBM-based co-clustering algorithm (SPLBcem)

Intuition

- It consists in maximizing the classification likelihood instead of its expectation
- This is done by incorporating a classification step (C-step) between the E and M steps of the SPLBvem

Algorithm 4: `SPLBcem`

Input : $\mathbf{X}$, g
Initialization : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k,γ_{kk}, γ
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. $z_{ik} = \arg\max_k \tilde{z}_{ik}$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. $w_{jk} = \arg\max_k \tilde{w}_{jk}$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

Advantages

- SPLBcem is considerably faster and scalable than SPLBvem
- It allows us to avoid numerical difficulties, related to the computation of the posterior probabilities $\tilde{z}_{ik}$ and $\tilde{w}_{jk}$

The stochastic SPLBM-based co-clustering algorithm (SPLBsem)

`SPLBvem` and `SPLBcem` are very dependant on their starting points!

Algorithm 5: `SPLBsem`

Input : $\mathbf{X}, g$
Initialization : $\widetilde{\mathbf{Z}}, \widetilde{\mathbf{W}}, \pi_k, \rho_k, \gamma_{kk}, \gamma$
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. simulation of z_i according to $\mathcal{M}(\widetilde{z}_{i1}, \ldots, \widetilde{z}_{ig})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}, \gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}, \gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. simulation of w_j according to $\mathcal{M}(\widetilde{w}_{j1}, \ldots, \widetilde{w}_{jg})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}, \gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}, \gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}, \mathbf{W}, \pi_k, \rho_k, \gamma_{kk}, \gamma$

The stochastic SPLBM-based co-clustering algorithm (SPLBsem)

Algorithm 5: `SPLBsem`

Input : $\mathbf{X}$, g
Initialization : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k,γ_{kk}, γ
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. simulation of z_i according to $\mathcal{M}(\widetilde{z}_{i1}, \ldots, \widetilde{z}_{ig})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. simulation of w_j according to $\mathcal{M}(\widetilde{w}_{j1}, \ldots, \widetilde{w}_{jg})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

The stochastic SPLBM-based co-clustering algorithm (SPLBsem)

Algorithm 5: `SPLBsem`

Input : $\mathbf{X}$, g
Initialization : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k, γ_{kk}, γ
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. simulation of z_i according to $\mathcal{M}(\widetilde{z}_{i1}, \ldots, \widetilde{z}_{ig})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. simulation of w_j according to $\mathcal{M}(\widetilde{w}_{j1}, \ldots, \widetilde{w}_{jg})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

Advantages : It does not stop at the first stationary point of the likelihood function, which makes it possible to avoid bad local maxima due to the initial position

The stochastic SPLBM-based co-clustering algorithm (SPLBsem)

Algorithm 5: `SPLBsem`

Input : $\mathbf{X}$, g
Initialization : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k,γ_{kk}, γ
repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. simulation of z_i according to $\mathcal{M}(\widetilde{z}_{i1}, \ldots, \widetilde{z}_{ig})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. simulation of w_j according to $\mathcal{M}(\widetilde{w}_{j1}, \ldots, \widetilde{w}_{jg})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;
Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

Advantages : It does not stop at the first stationary point of the likelihood function, which makes it possible to avoid bad local maxima due to the initial position
Weakness : `SPLBsem` does not share the convergence properties of `SPLBvem` and `SPLBcem` and may require a large number of iterations to reach a steady state

The stochastic SPLBM-based co-clustering algorithm (SPLBsem)

Algorithm 5: `SPLBsem`

Input : $\mathbf{X}$, g

Initialization : $\widetilde{\mathbf{Z}}$, $\widetilde{\mathbf{W}}$, π_k, ρ_k,γ_{kk}, γ

repeat

$x_{ik}^{\widetilde{\mathbf{W}}} = \sum_j \widetilde{w}_{jk} x_{ij}$

step 1. $\widetilde{z}_{ik} \propto \pi_k \exp(x_{ik}^{\widetilde{\mathbf{W}}} \log \frac{\gamma_{kk}}{\gamma})$

step 1'. simulation of z_i according to $\mathcal{M}(\widetilde{z}_{i1}, \ldots, \widetilde{z}_{ig})$

step 2. $\pi_k = \frac{\widetilde{z}_{.k}}{n}$, $\gamma_{kk} = \frac{\sum_i \widetilde{z}_{ik} x_{ik}^{\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

$x_{kj}^{\widetilde{\mathbf{Z}}} = \sum_i \widetilde{z}_{ik} x_{ij}$

step 3. $\widetilde{w}_{jk} \propto \rho_k \exp(x_{kj}^{\widetilde{\mathbf{Z}}} \log \frac{\gamma_{kk}}{\gamma})$

step 3'. simulation of w_j according to $\mathcal{M}(\widetilde{w}_{j1}, \ldots, \widetilde{w}_{jg})$

step 4. $\rho_k = \frac{\widetilde{w}_{.k}}{d}$, $\gamma_{kk} = \frac{\sum_j \widetilde{w}_{jk} x_{kj}^{\widetilde{\mathbf{Z}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}} = \frac{x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$, $\gamma = \frac{N - \sum_k x_{kk}^{\widetilde{\mathbf{Z}}\widetilde{\mathbf{W}}}}{N^2 - \sum_k x_{k.}^{\widetilde{\mathbf{Z}}} x_{.k}^{\widetilde{\mathbf{W}}}}$

until *Convergence*;

Output : $\mathbf{Z}$, $\mathbf{W}$, π_k, ρ_k, γ_{kk}, γ

Advantages : It does not stop at the first stationary point of the likelihood function, which makes it possible to avoid bad local maxima due to the initial position

Weakness : `SPLBsem` does not share the convergence properties of `SPLBvem` and `SPLBcem` and may require a large number of iterations to reach a steady state

- Solution ⇒ initialize `SPLBvem` with the parameters resulting from `SPLBsem` ⇒ `SPLBsvem`

Outline

1 Introduction
- Context
- Co-clustering
- Motivations

2 Graph-based Co-clustering
- Graph Modularity
- Modularity for Co-clustering
- Experiments

3 Model-based Co-clustering
- Sparse Poisson Latent Block Model (SPLBM)
- Soft SPLBM-based Co-clustering Algorithm
- Hard SPLBM-based Co-clustering Algorithm
- Experiments

4 Using Co-clustering in Biomedical Text Mining Framework
- The Biomedical Framework
- Results and Discussions

5 Conclusion and Perspectives

Global Performance Comparison - Document Clustering

Datasets	Characteristics				
	#Documents	#Words	#Clusters	Sparsity (%)	Balance
SPORTS	8580	14870	7	99.14	0.036
TDT2	9394	36771	30	99.64	0.028
Yahoo_K1B	2340	21839	6	99.41	0.043
Reuters40	8203	18914	40	99.75	0.003

- Data : contingency tables
- Evaluation measures : Acc, NMI (Strehl and Ghosh, 2003) and ARI (Rand, 1971)

Comparative study

- Proposed diagonal co-clustering : Coclus, SPLBcem, SPLBvem, SPLBsem, SPLBsvem
- Non-diagonal co-clustering : ITCC (I. S. Dhillon, Mallela, and D. S. Modha, 2003), PLBvem (Govaert and Nadif, 2010) and LDA (Blei, Ng, and Jordan, 2003)
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datasets	per.	Skmeans	ITCC	LDA	PLBvem	CoClus	SPLBcem	SPLBvem	SPLBsem	SPLBsvem
SPORTS	Acc	0.49	0.53	0.53	0.47	0.75	0.85	0.85	**0.86**	0.81
	NMI	0.50	0.60	0.54	0.64	0.62	0.69	0.70	**0.71**	0.67
	ARI	0.30	0.44	0.33	0.49	0.55	0.76	0.75	**0.77**	0.69
TDT2	Acc	0.57	0.59	0.60	0.59	**0.87**	0.83	0.84	0.84	0.85
	NMI	0.76	0.78	0.73	0.76	**0.84**	0.81	0.82	**0.84**	**0.84**
	ARI	0.46	0.52	0.49	0.51	**0.85**	0.81	0.80	**0.85**	**0.85**
Yahoo_K1B	Acc	0.57	0.61	0.62	0.58	0.60	0.79	0.84	0.86	**0.88**
	NMI	0.64	0.58	0.58	0.62	0.54	0.66	0.69	0.72	**0.75**
	ARI	0.39	0.40	0.37	0.38	0.31	0.60	0.72	0.76	**0.79**
REUTERS40	Acc	0.26	0.27	0.47	0.25	0.61	0.73	0.74	0.73	**0.77**
	NMI	0.50	0.52	0.51	0.52	0.54	0.57	0.58	0.57	**0.62**
	ARI	0.11	0.18	0.42	0.15	0.51	0.71	0.75	0.73	**0.76**

- Diagonal co-clustering are better in almost all situations
- In particular the SPLBsvem which leverages the benefits of both soft and stochastic variants

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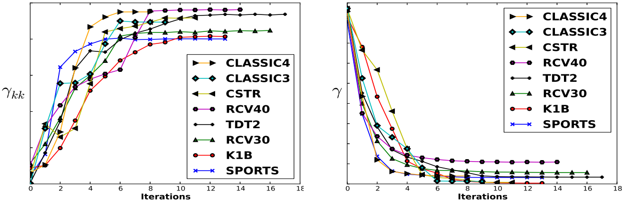

Figure: Behaviour of the γ_{kk}'s (left) and γ (right) parameters at each iteration.

- The proposed diagonal approaches deal well with unbalanced datasets

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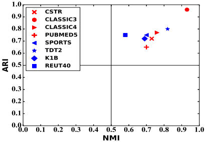
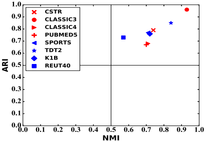
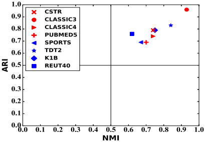
- ARI, unlike NMI, is more sensitive to cluster merging/splitting



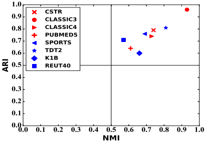
(a) **SPLBvem**



(b) **SPLBsem**



(c) **SPLBsvem**



(d) **SPLBcem**

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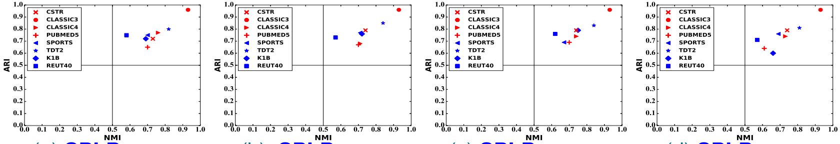
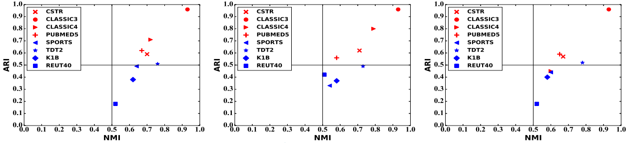


(a) **SPLBvem** (b) **SPLBsem** (c) **SPLBsvem** (d) **SPLBcem**



(e) `PLBvem` (f) `LDA` (g) `ITCC`

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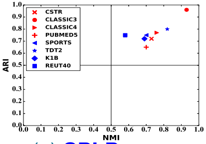

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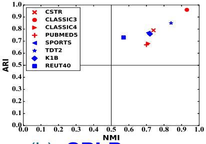
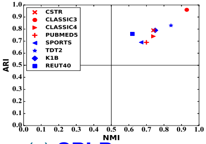
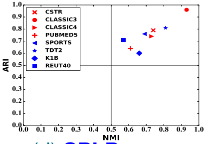


(b) **SPLBsem**



(c) **SPLBsvem**



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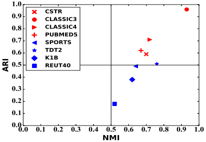
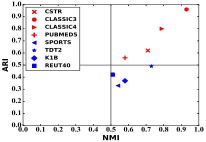
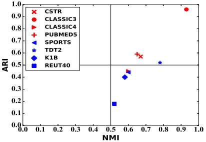


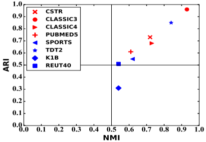
(e) `PLBvem`



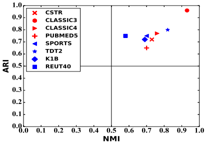
(f) `LDA`



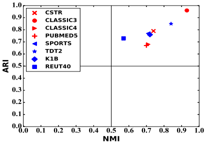
(g) `ITCC`



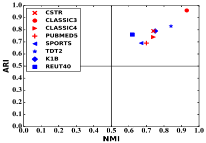
(h) **CoClus**



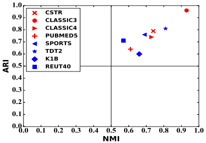
(a) **SPLBvem**



(b) **SPLBsem**



(c) **SPLBsvem**



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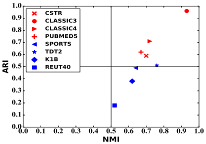
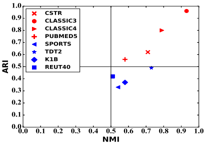
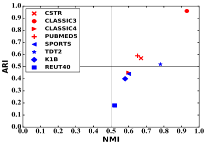


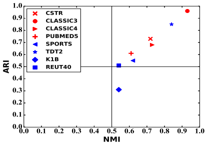
(e) `PLBvem`



(f) `LDA`



(g) `ITCC`



(h) **CoClus**

- Comparison of the standard deviation in cluster size (SDCS) of clusters obtained by each method
  SDCS = $\left(\frac{1}{g-1}\sum_{k=1}^{g}(z_{.k} - \frac{n}{g})^2\right)^{0.5}$
- The SDCS values of the clusters obtained with `SPLBcem` are the closest to the real SDCS of the datasets

Data	Clustering	Co-clustering				Real SDCS
		Non-diagonal			Diagonal	
	`Skmeans`	`ITCC`	`LDA`	`PLBcem`	`SPLBcem`	
REUTERS40	112.638	144.195	362.102	201.162	**642.839**	**654.556**
REUTERS30	161.797	238.353	414.568	261.291	**752.129**	**747.879**
K1B	154.3684	198.828	261.765	189.849	**336.555**	**513.303**
TDT2	154.143	216.152	189.609	235.698	**516.685**	**481.830**
SPORTS	760.099	346.066	482.714	393.510	**1359.321**	**1253.011**

Assessing the Quality of Term Clusters

- Lack of benchmark datasets providing the true cluster labels of both the objects and attributes.
- Most studies evaluate the co-clustering algorithms based on the object (document) clustering only.
- We propose two different approaches to evaluate term clusters :
  - Visual assessment of term cluster coherence
  - Quantitative evaluation of term cluster quality
- We use a biomedical document-term matrix, namely the PUBMED5 dataset.
- PUBMED5 dataset is a document-term matrix of size 12648×19518 that contains documents about 5 different diseases.

Disease	Number of documents
Migraine	3703
Age-related Macular Degeneration	3283
Otitis	2596
Kidney Calculi	1549
Hay Fever	1517

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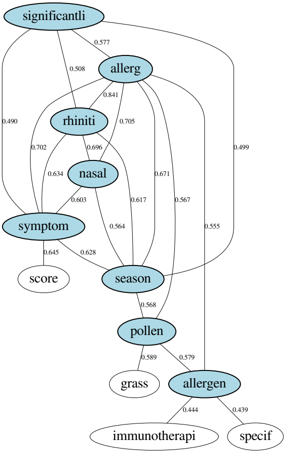
Visual assessment of term cluster coherence

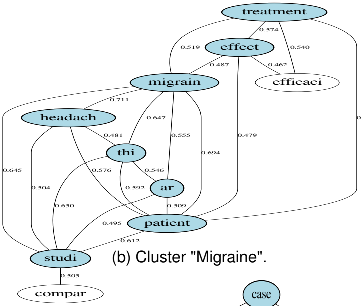
Assess if the top terms present in a co-cluster are densely interconnected and form a semantically coherent set.

Principle

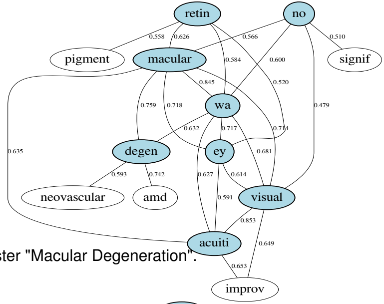
1. Co-clustering with `SPLBcem` on the PUBMED5 dataset into $g = 5$ blocks
2. For each diagonal block c, we extract the corresponding matrix X_c
3. Build a term-term cosine similarity matrix $S_c = X_c^{norm\prime} X_c^{norm}$ for each diagonal block
4. Place the $n = 8$ top terms of c in a graph
5. Connect each top word their $k = 5$ most similar neighbors according to the cosine similarity recorded in S_c



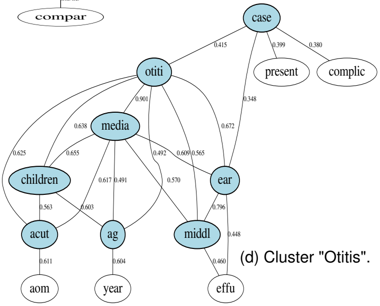
(a) Cluster "Hay fever".



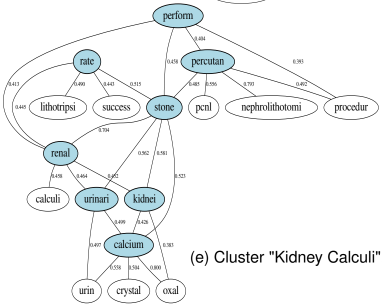
(b) Cluster "Migraine".



(c) Cluster "Macular Degeneration".



(d) Cluster "Otitis".



(e) Cluster "Kidney Calculi".

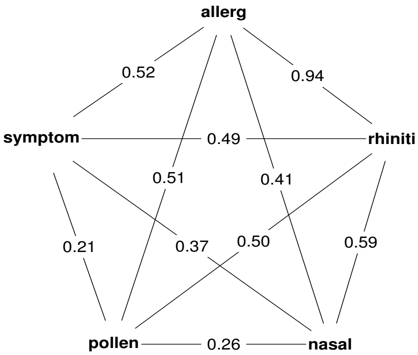
Quantitative evaluation of term cluster quality

Principle

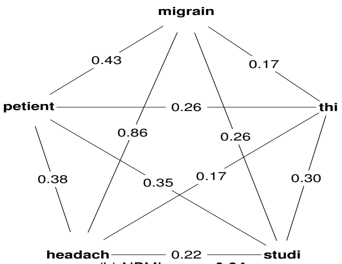
- Use the Point-wise Mutual Information (PMI) to measure the degree of association between word pairs

$$\text{PMI}(w_i, w_j) = \log \frac{p(w_i, w_j)}{p(w_i)p(w_j)}$$

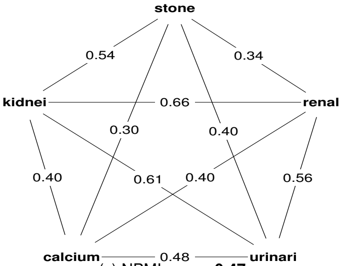
- PMI can be estimated using an external corpus
- Use the whole English WIKIPEDIA corpus that consists of approximately 4 millions of documents and 2 billions of words
- The $\text{NPMI}(w_i, w_j) = \frac{\text{PMI}(w_i, w_j)}{-\log(p(w_i, w_j))}$ ranges between -1 and +1, the higher the NPMI, the greater the correlation between words w_i and w_j



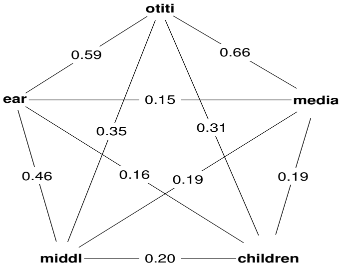
(a) NPMI score: **0.48**.



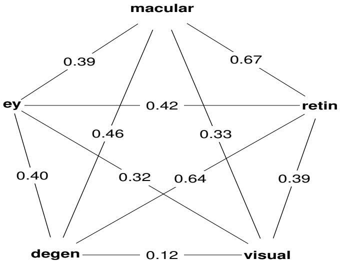
(b) NPMI score: **0.34**.



(c) NPMI score: **0.47**.



(d) NPMI score: **0.33**.



(e) NPMI score: **0.41**.

Concluding remarks

- Diagonal co-clustering algorithm (Coclus) by direct maximization of graph modularity
- Coclus is able to effectively co-cluster different kind of positive document-term matrices
- Sparse Poisson Latent Block Model (SPLBM)
- SPLBM is also very parsimonious
- SPLBM has been designed from the ground up to deal with data sparsity problems
- From this model, three co-clustering algorithms have been inferred
  - A hard variant SPLBcem
  - A soft variant SPLBvem
  - A stochastic variant SPLBsem
- Extensive numerical experiments show that
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Context

- Exponential growth of biomedical text data (PUBMED, GO, . . .)
- There is a genuine need for text mining techniques to analyse and interpret these large amounts of information
- Help researchers to characterize relationships between biomedical entities (genes, diseases, . . .) quickly and efficiently

Motivations

- Genome-wide association studies (GWAS) : examination of many genetic variants (SNPs) in different individuals to study their correlations with phenotypic traits
- GWAS allow to identify groups of genes associated with a common phenotype
- GWAS do not provide information about associations in these gene groups

Contributions

- A biomedical text mining framework (Ailem et al., 2016) to augment the results of GWAS
- Benefits of co-clustering in biomedical text mining application
- Illustration on GWAS of asthma disease (Moffatt et al., 2010), which reported 10 genes associated with asthma
- Assess the strength of association between these genes and infer new candidate genes likely associated with asthma

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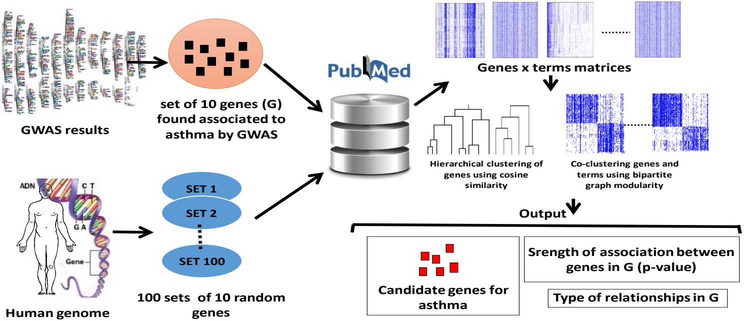

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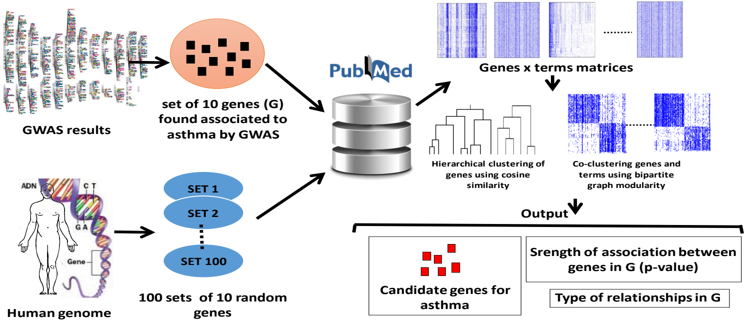

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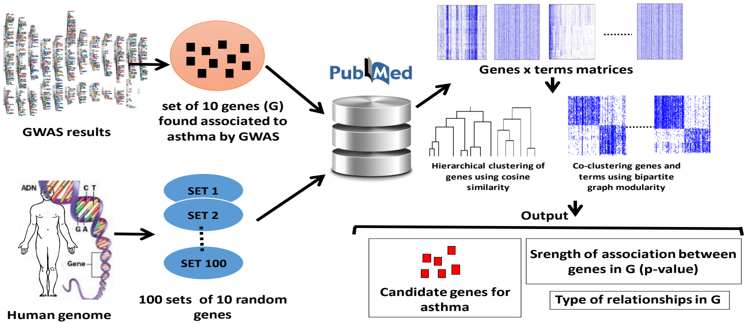

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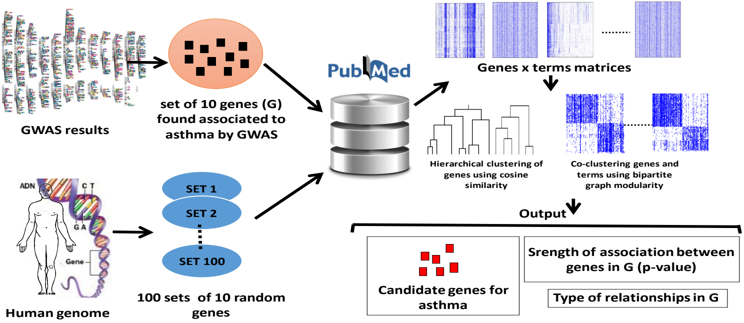

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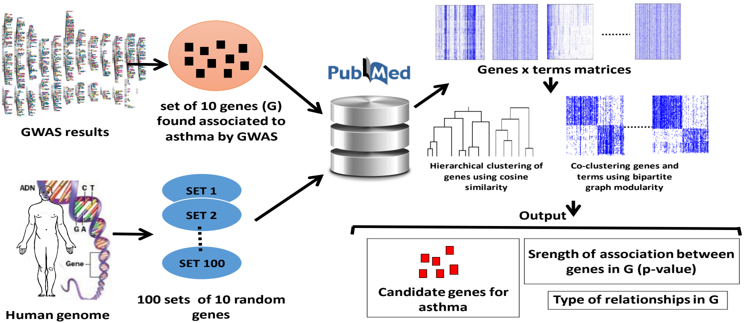

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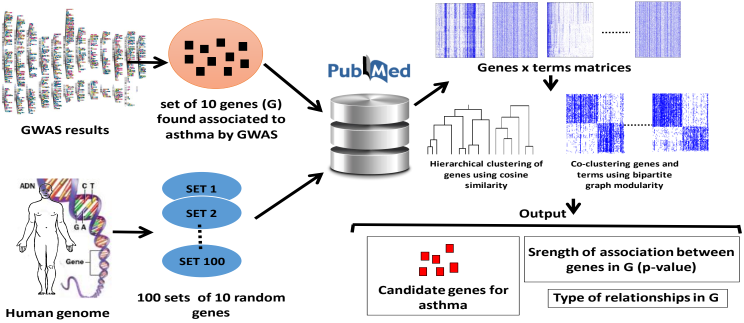

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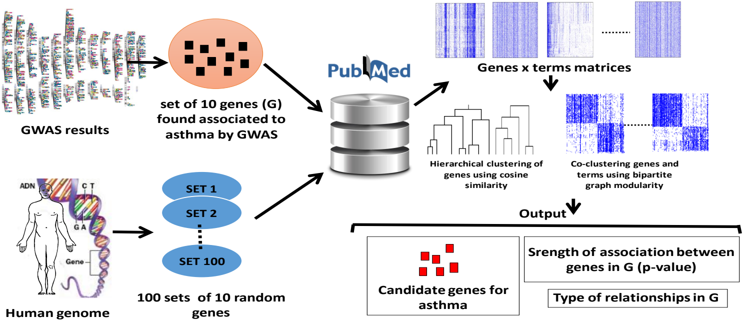

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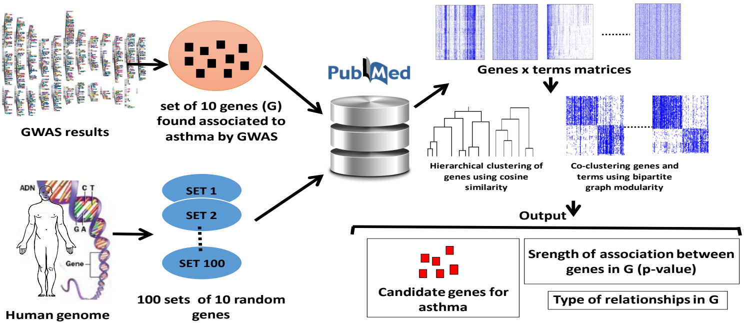

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- Application of clustering and co-clustering to 100 sets of 20 genes that each included the 10 asthma genes plus 10 random genes, returned an average purity of 89%
- 20 Top terms of asthma genes co-cluster

Smoking	diabetes	th2	environmental
immune-mediated	chronic	enterotoxin	proinflammatory
child	microenvironment	cytokine	autoimmune
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- Moreover, 104 random genes were grouped with the 10 asthma associated-genes and, therefore, might be new candidates for asthma
- We ranked these candidate genes according to their cosine similarity with the group of asthma genes ($\mathbf{G}$)
- Study the Top 20 genes
- Use the biomedical literature and experts to validate the results

IL1RL1	*RAG1*	*CLEC1B*	***IL23R***
STAT6	*EFNA3*	*S1PR5*	*TGFBR1*
FCMR	***CXCL8/IL8***	*CHRNB4*	***NFKB1***
TNFRSF1A	*TMED1*	***NOD2***	***TSLP***
NLRP10	*POMP*	***SPINK1***	***PTGES***

- **Reported associated with asthma or allergy**
- **Reported associated with auto-immune diseases**
- **Encode proteins that are involved in immune-related mechanisms**

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- Three main contributions
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  3. Using Co-clustering for Biomedical Text Mining
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- Methods for assessing term clusters
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  1. Graph-based Diagonal co-clustering approach
  2. Model-based Diagonal co-clustering approach
  3. Using Co-clustering for Biomedical Text Mining
- Assessing the right number of co-clusters
- Methods for assessing term clusters
- Soft, hard and stochastic assignments
- Extensive experiments on real world text datasets
- Availability : Coclust python module (https://pypi.python.org/pypi/coclust)

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Toward Semantic (co)-clustering

Motivation

- Existing (co)-clustering methods ignore the semantic relationships between words, which may result in a significant loss of semantics since documents that are about the same topic may not necessarily use exactly the same vocabulary.

Contribution

- We propose a new (co)-clustering models which goes beyond the bag of word representation so as to preserve more semantics.
- We achieve our objective by successfully integrating `word2vec` into a (co)-clustering framework.
- The proposed models substantially outperforms existing (co)-clustering models in terms of document clustering, cluster interpretability as well as document/word embedding.

M. Ailem, A. Salah, and M. Nadif (2017). "Non-negative Matrix Factorization Meets Word Embedding". In: *SIGIR*. ACM, pp. 1081–1084.

A. Salah, M. Ailem, and M. Nadif (2017). "A Way to Boost Semi-NMF for Document Clustering". In: *CIKM*. ACM, pp. 2275–2278.

A. Salah, M. Ailem, and M. Nadif (2018). "Word Co-occurrence Regularized Non-Negative MatrixTri-Factorization for Text Data Co-clustering". In: *AAAI'2018*.

Perspectives

- Investigate an overlapping version of the Coclus algorithm
- Study the theoretical link between graph-based and model-based approaches
- Assessing the number of (co-)clusters for model-based approaches using information criteria such as BIC, AIC, ICL ...
- Investigate Bayesian non-parametric formulations of SPLBM, which would allows us to overcome the problem of the number of clusters as well as handle evolving data

Thank you for your attention!

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