

UNIFYING DEPENDENT CLUSTERING AND DISPARATE CLUSTERING FOR NON-HOMOGENEOUS DATA

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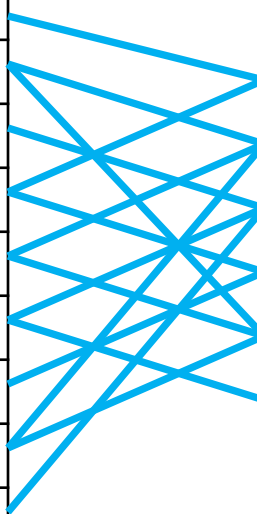
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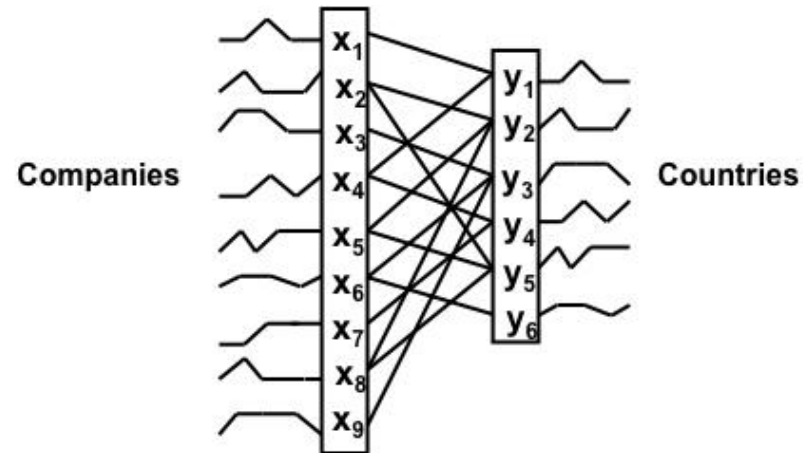
Problem Setting

Companies	Avg. salary of Employees	Stock values	Profit margins
x_1	1.0 K	25.11	11%
x_2	1.1 K	21.32	20%
x_3	1.2 K	28.81	12%
x_4	1.2 K	31.85	22%
x_5	1.1 K	85.32	5%
x_6	1.2 K	10.71	32%
x_7	0.9 K	11.61	18%
x_8	1.1 K	35.81	12%
x_9	1.2 K	20.81	4%

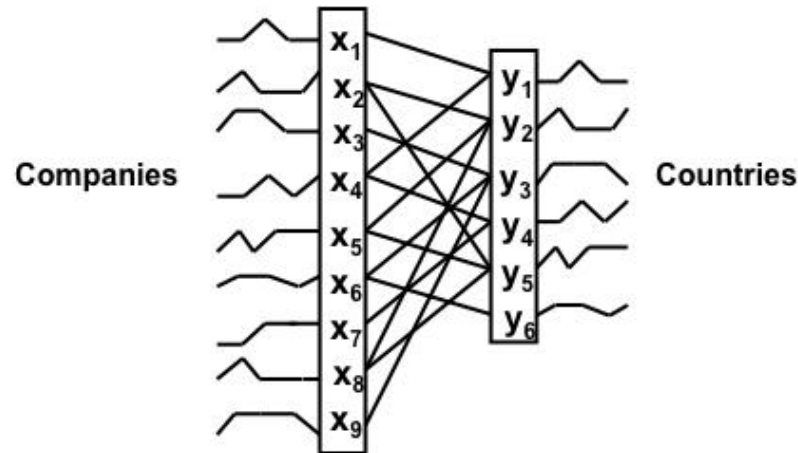


Countries	GDP	GNP	Inflation
y_1	\$11832 B	\$12970 B	-0.4%
y_2	\$8219 B	\$8153 B	2.0%
y_3	\$6732 B	\$7812 B	-0.3%
y_4	\$1761 B	\$2852 B	1.8%
y_5	\$5022 B	\$4391 B	0.0%
y_6	\$7224 B	\$8312 B	1.1%

Objective

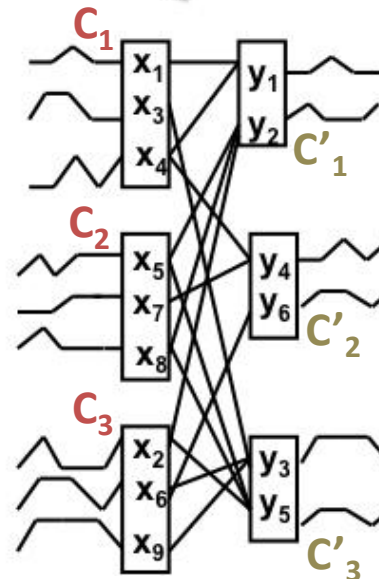
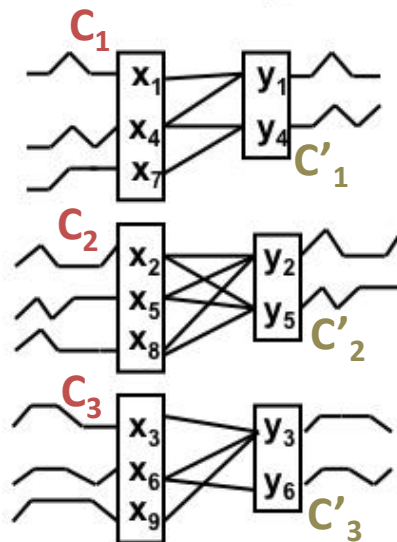


Objective



dependent clustering

disparate clustering

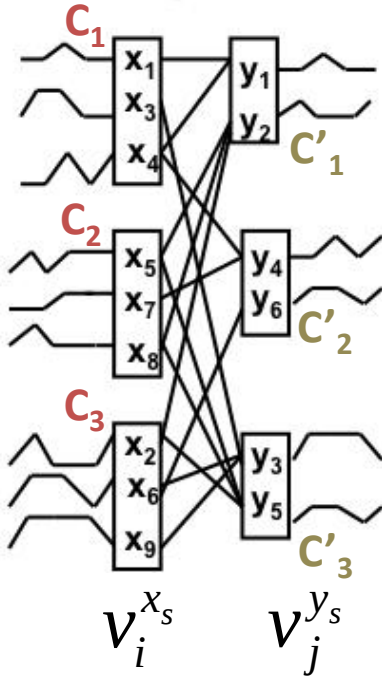


Performances of companies may not necessarily be tied to the economies of the countries.

		Countries		
		C'_1	C'_2	C'_3
Companies	C_1	4	0	0
	C_2	0	6	0
	C_3	0	0	4

		Countries		
		C'_1	C'_2	C'_3
Companies	C_1	2	1	1
	C_2	2	1	2
	C_3	1	1	3

Objective Function

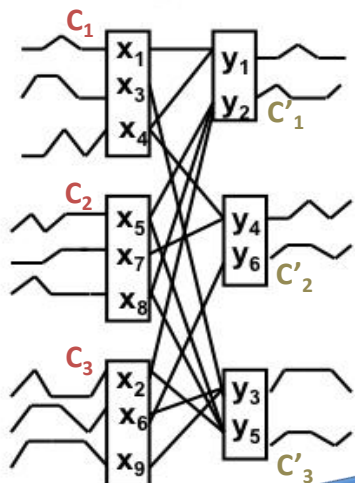


	C'_1	C'_2	C'_3
C_1	2	1	1
C_2	2	1	2
C_3	1	1	3

$$\begin{aligned}
 \text{Obj} &= \mathcal{F}(\text{Contingency table}) \\
 &= \mathcal{F}(n(\text{Clustering1, Clustering2, Relation})) \\
 &= \mathcal{F}(n(v(\text{Dataset1, Prototypes1}), \\
 &\quad v(\text{Dataset2, Prototypes2}), \\
 &\quad \text{Relation}))
 \end{aligned}$$

- Optimize $\mathcal{F}$
 - Disparate clustering:
 - minimize: $\mathcal{F}$
 - Dependent clustering:
 - maximize: $\mathcal{F}$ or
 - minimize: $-\mathcal{F}$
- Quasi Newton Trust Region Algorithm

Formulations



	C'_1	C'_2	C'_3
C_1	2	1	1
C_2	2	1	2
C_3	1	1	3

w

	C'_1	C'_2	C'_3
C_1	0.33	0.33	0.33
C_2	0.33	0.33	0.33
C_3	0.33	0.33	0.33

U

	C'_1	C'_2	C'_3
C_1	0.5	0.25	0.25
C_2	0.4	0.2	0.4
C_3	0.2	0.2	0.6

α
Row distributions

	C'_1	C'_2	C'_3
C_1	0.4	0.33	0.17
C_2	0.4	0.33	0.33
C_3	0.2	0.33	0.5

β
Col. distributions

Membership Probability

$$v_i^{(\mathbf{x}_s)} = \frac{\exp(-\frac{\rho}{D} \|\mathbf{x}_s - \mathbf{m}_{i,\mathcal{X}}\|^2)}{\sum_{i'=1}^{k_x} \exp(-\frac{\rho}{D} \|\mathbf{x}_s - \mathbf{m}_{i',\mathcal{X}}\|^2)}$$

Contingency Table Counts

$$w_{ij} = \sum_{s=1}^{n_x} \sum_{t=1}^{n_y} B(s, t) v_i^{(\mathbf{x}_s)} v_j^{(\mathbf{y}_t)}$$

Probability Distributions
(row and column)

$$p(\alpha_i = j) = p(C_{(y)} = j | C_{(x)} = i) = \frac{w_{ij}}{w_{i.}}$$

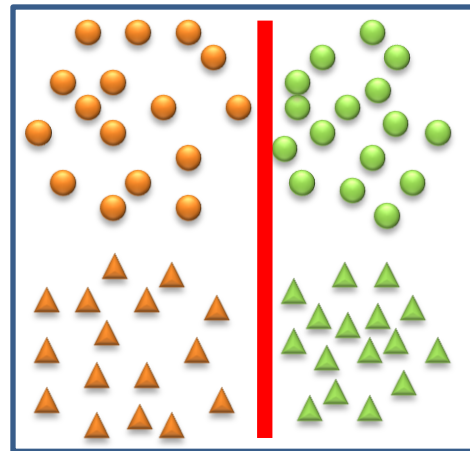
$$p(\beta_j = i) = p(C_{(x)} = i | C_{(y)} = j) = \frac{w_{ij}}{w_{.j}}$$

Objective Function

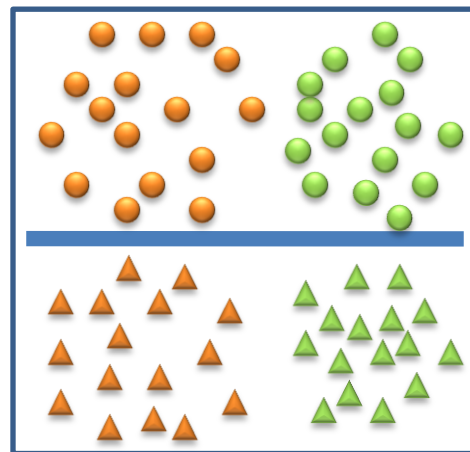
$$\mathcal{F} = \frac{1}{k_x} \sum_{i=1}^{k_x} D_{KL} \left(\alpha_i \parallel U \left(\frac{1}{k_y} \right) \right) + \frac{1}{k_y} \sum_{j=1}^{k_y} D_{KL} \left(\beta_j \parallel U \left(\frac{1}{k_x} \right) \right)$$

Single Dataset Scenarios

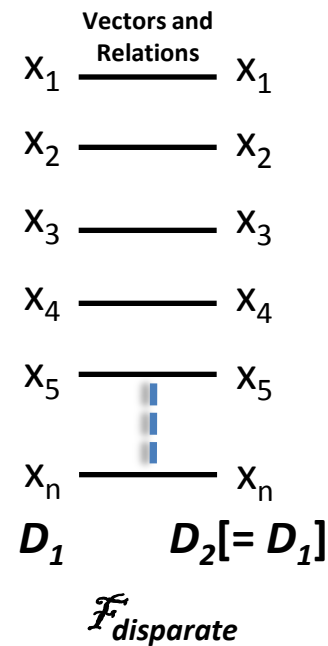
- **ALTERNATIVE CLUSTERING**



D_1



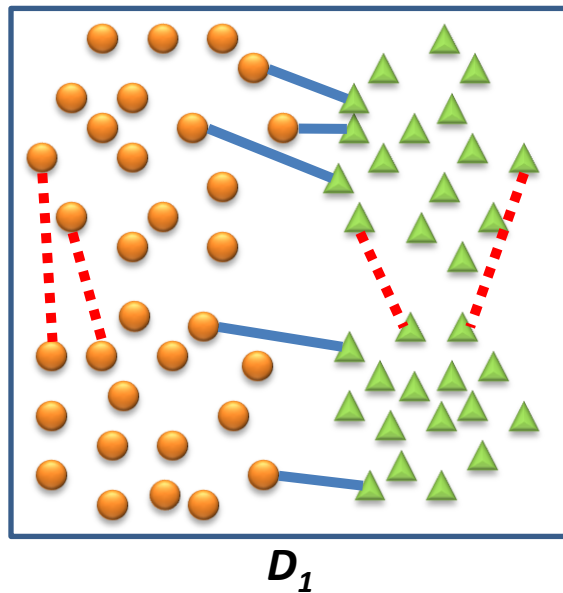
D_2



Single Dataset Scenarios

- **CONSTRAINED CLUSTERING**

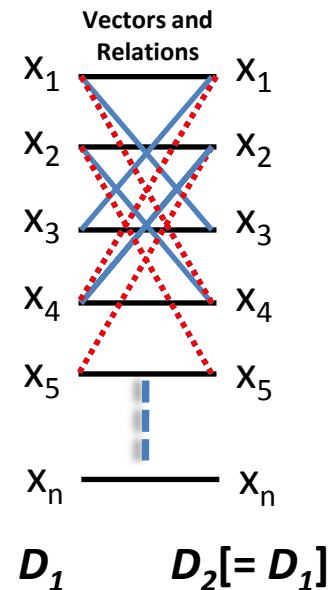
- Instance-level constraints



— Must-Link (ML)

- - - Must-Not-Link (MNL)

- Clustering of D_1 is given.
- The desired constrained clustering is obtained in D_2 .

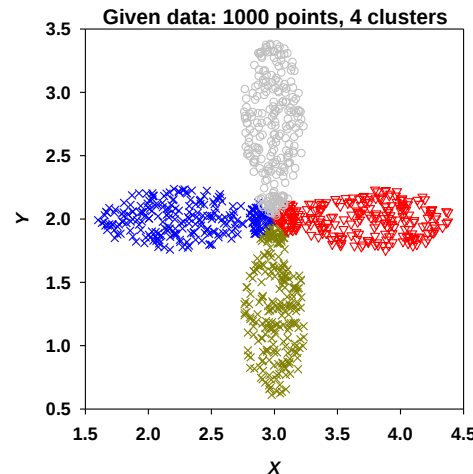
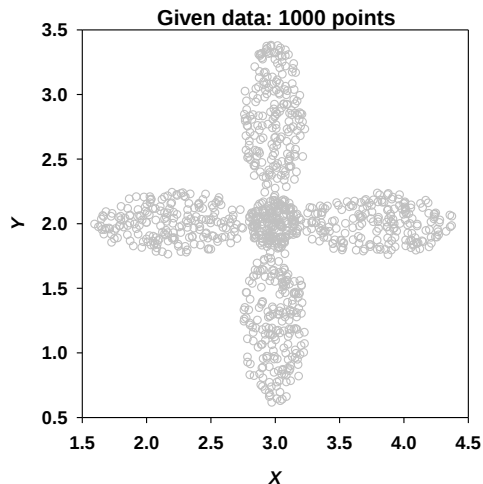


$$\mathcal{F} = \alpha \mathcal{F}_{dep} + (1 - \alpha) \mathcal{F}_{disparate}$$

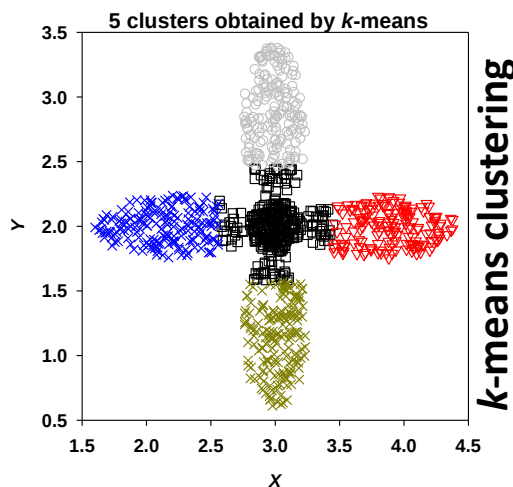
Single Dataset Scenarios

- **CONSTRAINED CLUSTERING**

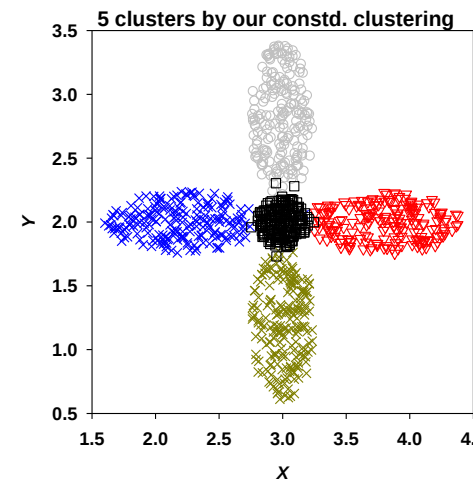
- Cluster-level constraints



Given clustering, D_1

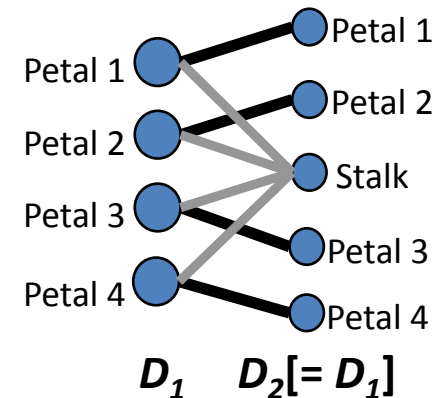


k-means clustering



Obtained clustering, D_2

- Clustering of D_1 is given.
- The desired constrained clustering is obtained in D_2 .



Experimental Results

- **ALTERNATIVE CLUSTERING**

- Portrait Dataset



➤ **3** people each in **3** poses and **36** illuminations (i.e., **324** images.)



➤ **300** features

Prateek Jain et al. 2008

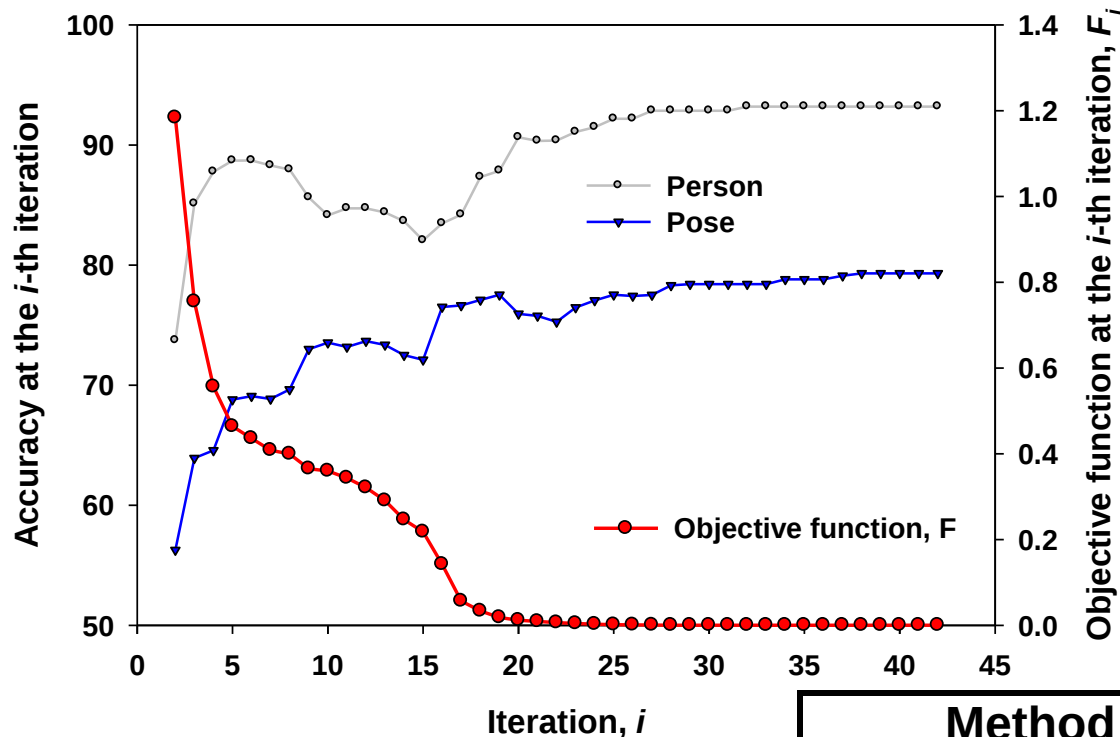
Experimental Results

• ALTERNATIVE CLUSTERING

Portrait dataset, Iterations=42

Accuracy_{person}=93%, Accuracy_{pose}=79%

(Accuracy axis is at left and the axis for objective function is at right)



Vectors for
alternative clustering
 D

X_1

X_5

X_2

X_4

X_3

Vectors and
Relations

X_1

X_1

X_2

X_2

X_3

X_3

X_4

X_4

X_5

X_5

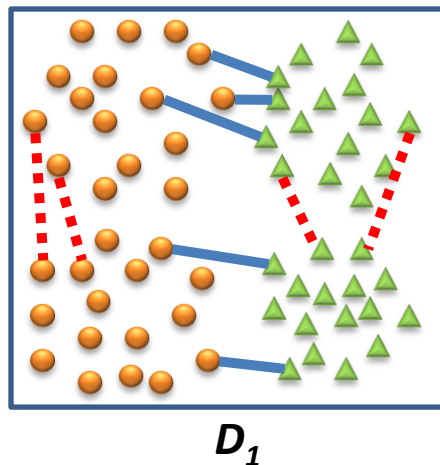
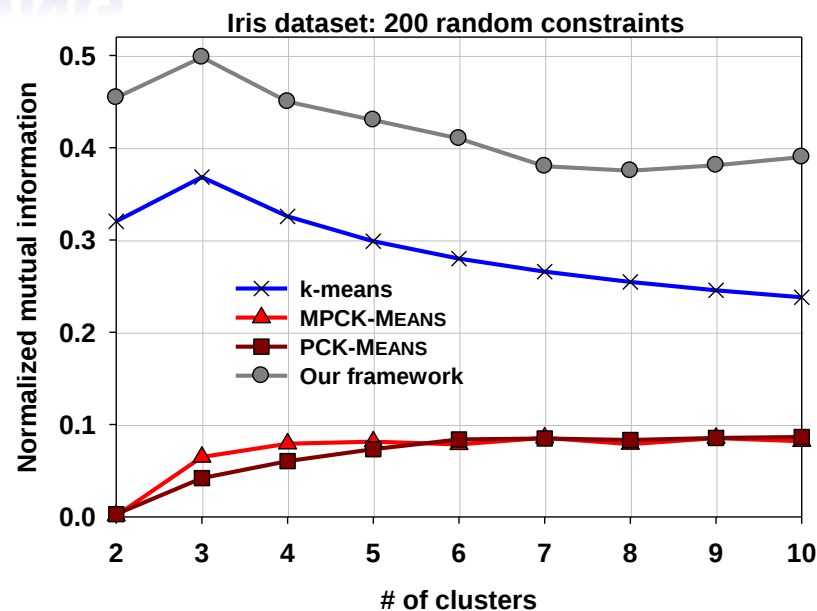
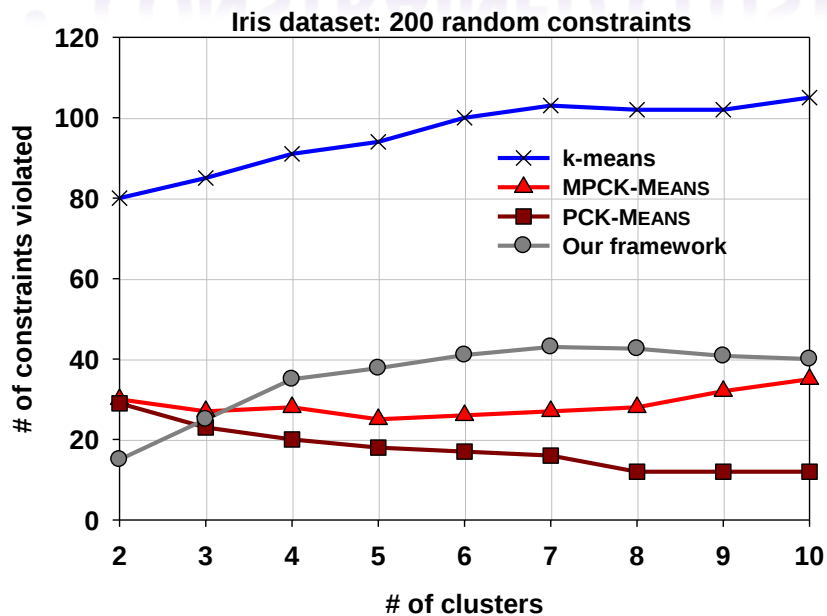
D_1

D_2

Method	Person	Pose
<i>k</i> -means	0.65	0.55
Conv-EM	0.69	0.72
Dec-kmeans	0.84	0.78
Our framework	0.93	0.79

Experimental Results

• CONSTRAINED CLUSTERING

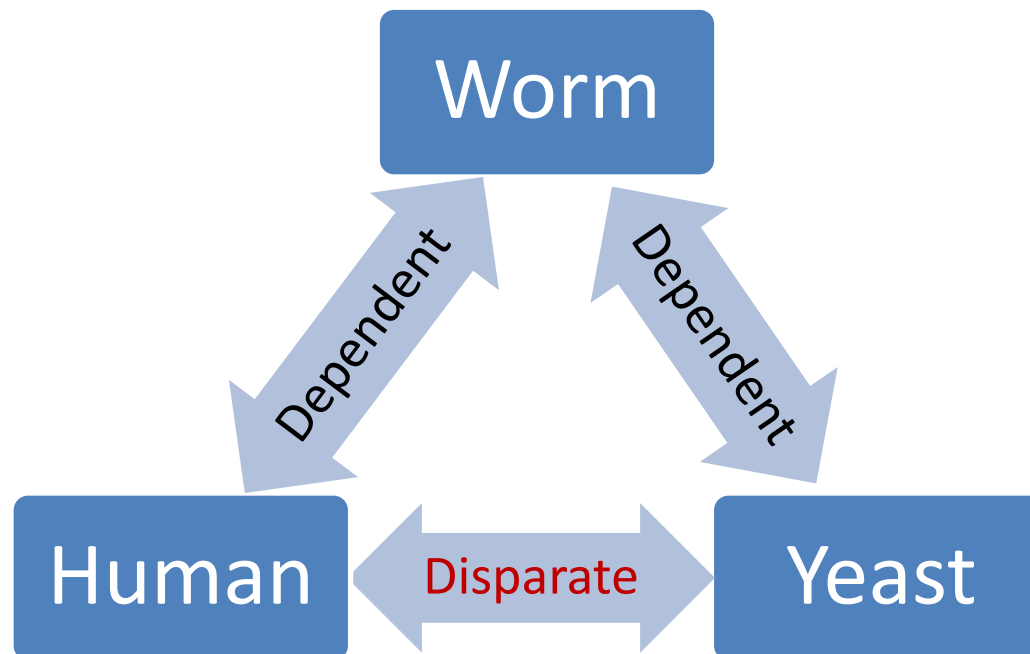


— Must-Link (ML)
- - - Must-Not-Link (MNL)

Experimental Results

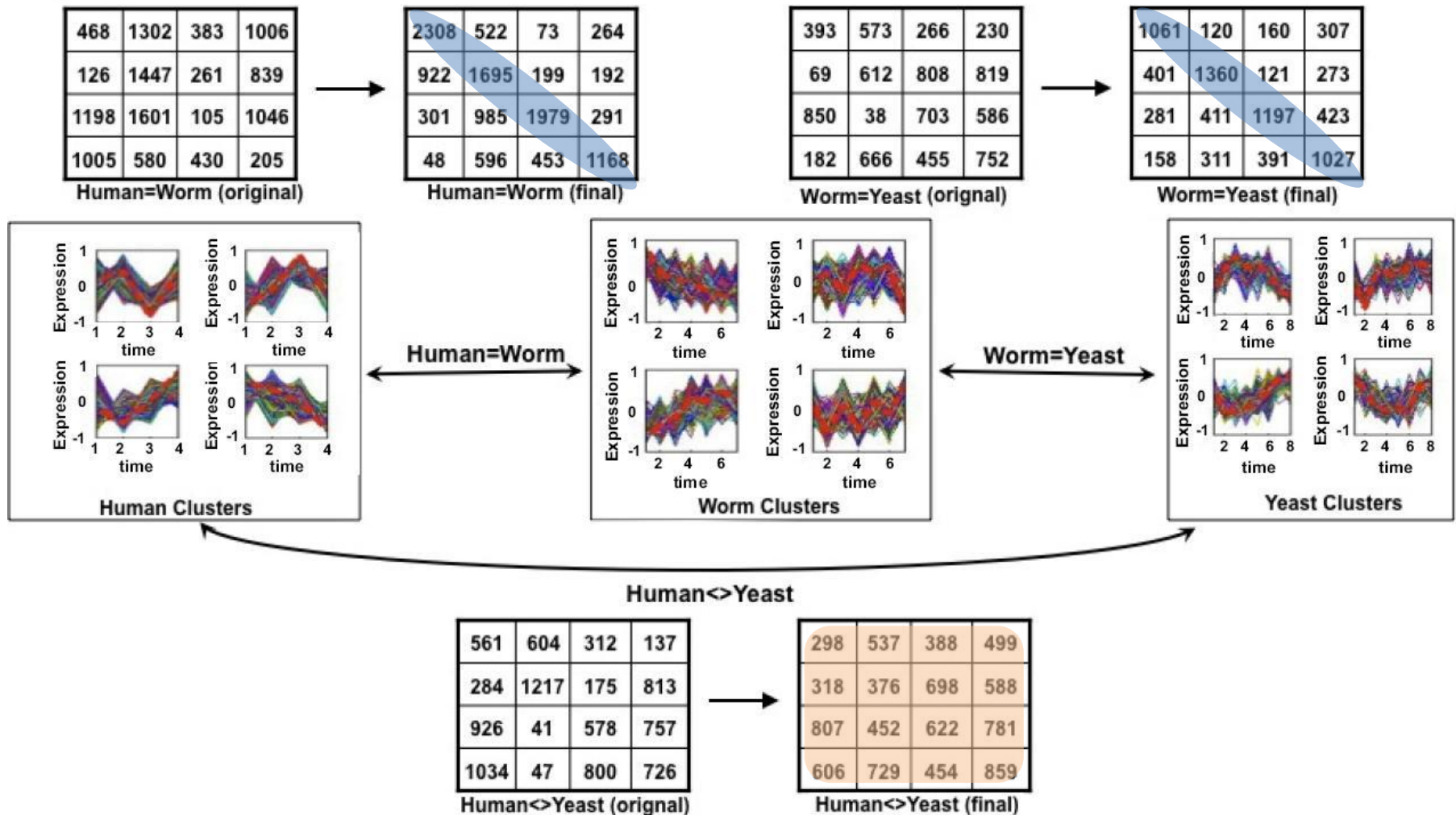
- COMPARING GENE EXPRESSION PROGRAMS

Gene	Count	Pairs	Relationships
Human	9,125	Human-Worm	12,000
Yeast	3,664	Worm-Yeast	8,002
Worm	5,987	Human-Yeast	9,012



Experimental Results

• COMPARING GENE EXPRESSION PROGRAMS



Future Work & Conclusion

- Future directions
 - Capture more expressive relationships
 - Dependent and disparate clustering on same set of relationships
 - Different goal for different types of relationships (one-to-one, ML, MNL, etc.)
 - Clustering dependencies
- Conclusion
 - General, expressive framework for clustering non-homogenous datasets
 - The framework subsumes previously defined formulations
 - MDI (Kullback et al. '78), Disparate Clustering (Jain et al. '08), Clustering over Relation Graphs (Banerjee et al. '07), Multivariate Information Bottleneck (Friedman '01), etc.

Thank you

