



VIS 2015

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The Data Context Map: Fusing Data and Attributes into a Unified Display

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Computer Science Department,
Stony Brook University and SUNY Korea

Data Explosion

12+ TBs
of tweet data
every day



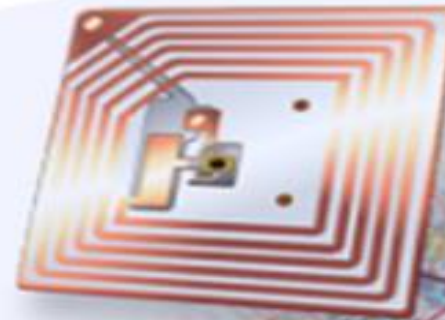
? TBs of
data every day



25+ TBs of
log data every day



30 billion RFID
tags today
(1.3B in 2005)



76 million smart
meters in 2009...
200M by 2014

**4.6
billion**
camera
phones
world wide



**100s of
millions
of GPS
enabled
devices
sold
annually**



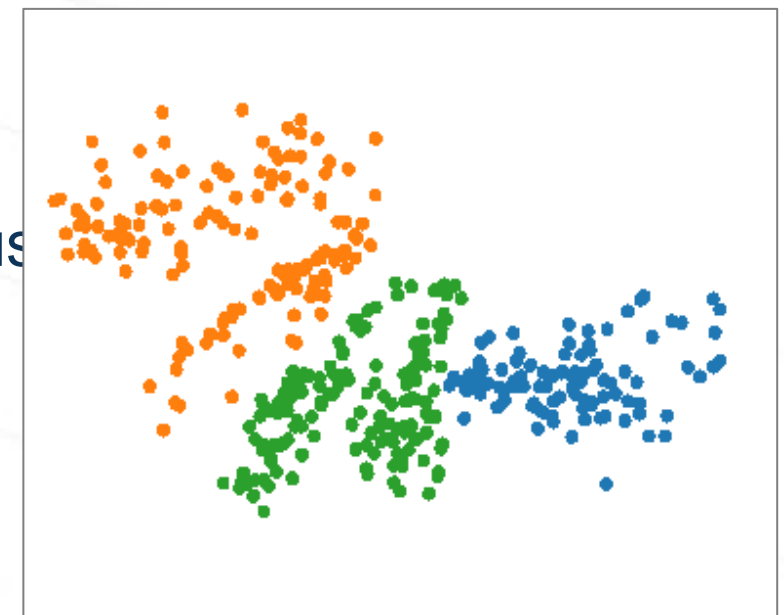
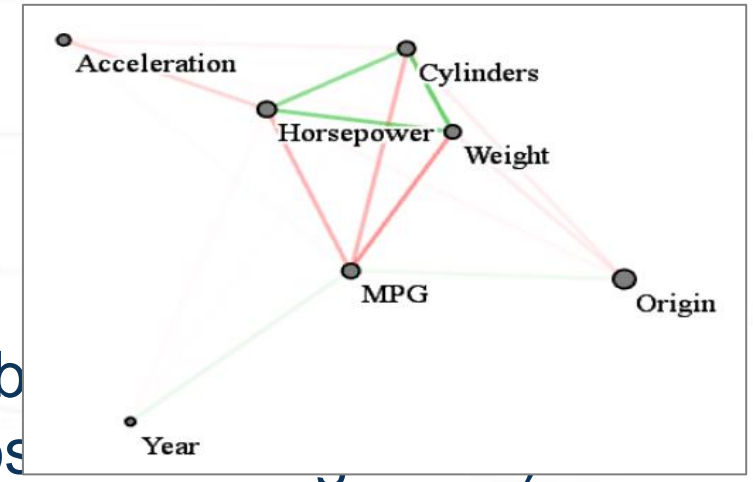
**2+
billion**
people on
the Web
by end
2011



Context Analysis

MPG	CYL	Hpower	Weight	Accel	Year	Origin
18	8	130	3504	12	70	1
15	8	165	3693	11.5	70	1
18	8	150	3436	11	70	1
16	8	150	3433	12	70	1
17	8	140	3449	10.5	70	1
15	8	198	4341	10	70	1
14	8	220	4354	9	70	1
14	8	215	4312	8.5	70	1
14	8	225	4425	10	70	1
15	8	190	3850	8.5	70	1
15	8	170	3563	10	70	1
14	8	160	3609	8	70	1
15	8	150	3761	9.5	70	1
14	8	225	3086	10	70	1
24	4	95	2372	15	70	3
22	6	95	2833	15.5	70	1
18	6	97	2774	15.5	70	1
21	6	85	2587	16	70	1
27	4	88	2130	14.5	70	3
26	4	46	1835	20.5	70	2
25	4	87	2672	17.5	70	2
24	4	90	2430	14.5	70	2
25	4	95	2375	17.5	70	2
26	4	113	2234	12.5	70	2
21	6	90	2648	15	70	1
10	8	215	4615	14	70	1
10	8	200	4376	15	70	1
11	8	210	4382	13.5	70	1
9	8	193	4732	18.5	70	1

- Attributes (Variables) to Attributes Relation (Horsepower and weight? Position?)
- Data to Data Relation (which cars are similar? Clustering?)
- Context: Data to Attributes Relation ? (which cars are latest?)



Fusion

Data Matrix

$$DM = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}$$

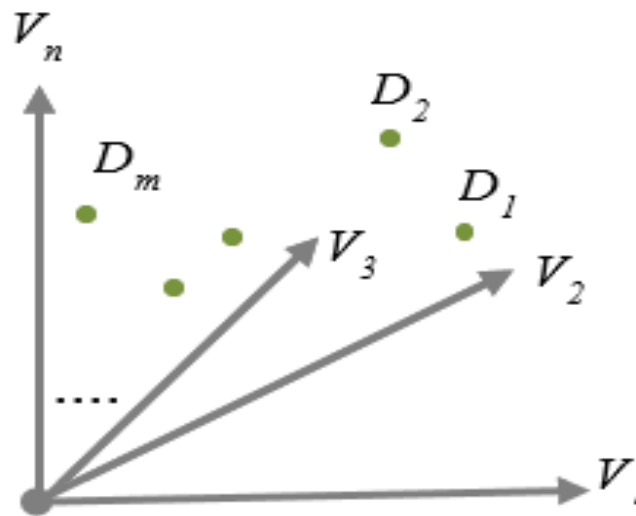
$$D_i = [x_{i1}, x_{i2}, \dots, x_{in}]$$

$$(i = 1, 2, \dots, m)$$

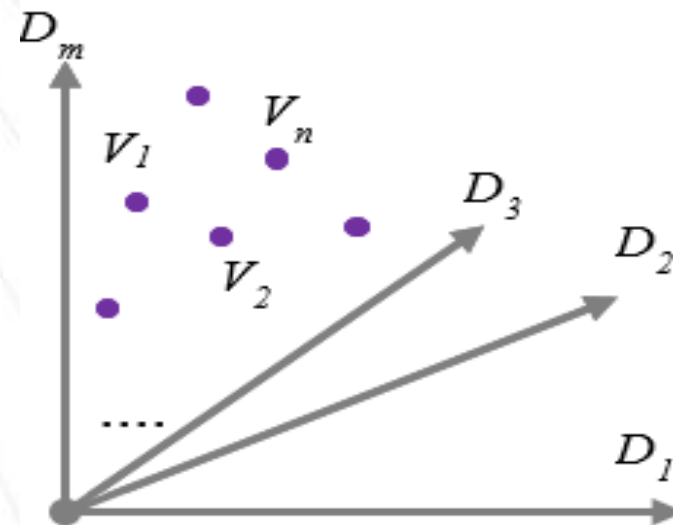
$$V_j = [x_{1j}, x_{2j}, \dots, x_{mj}]'$$

$$(j = 1, 2, \dots, n)$$

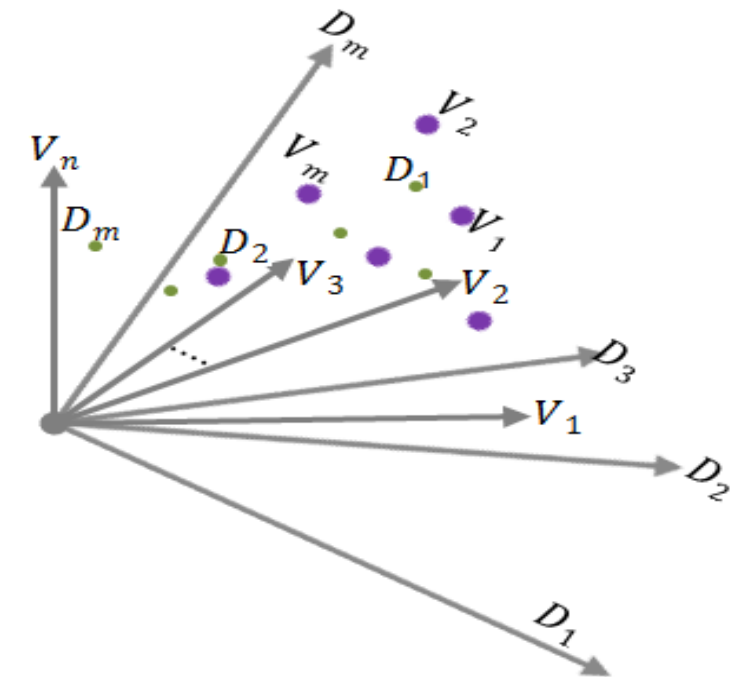
Data Space



Variable Space



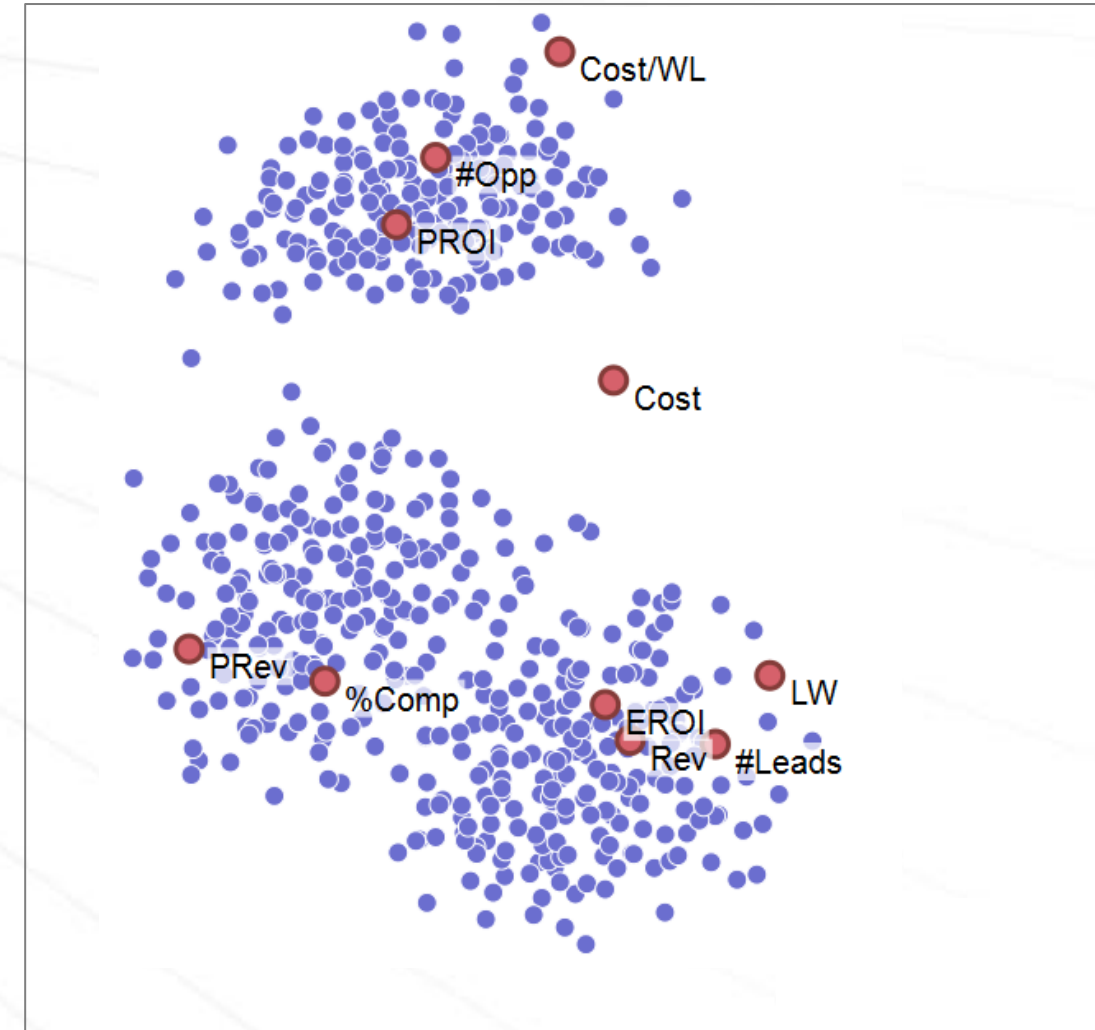
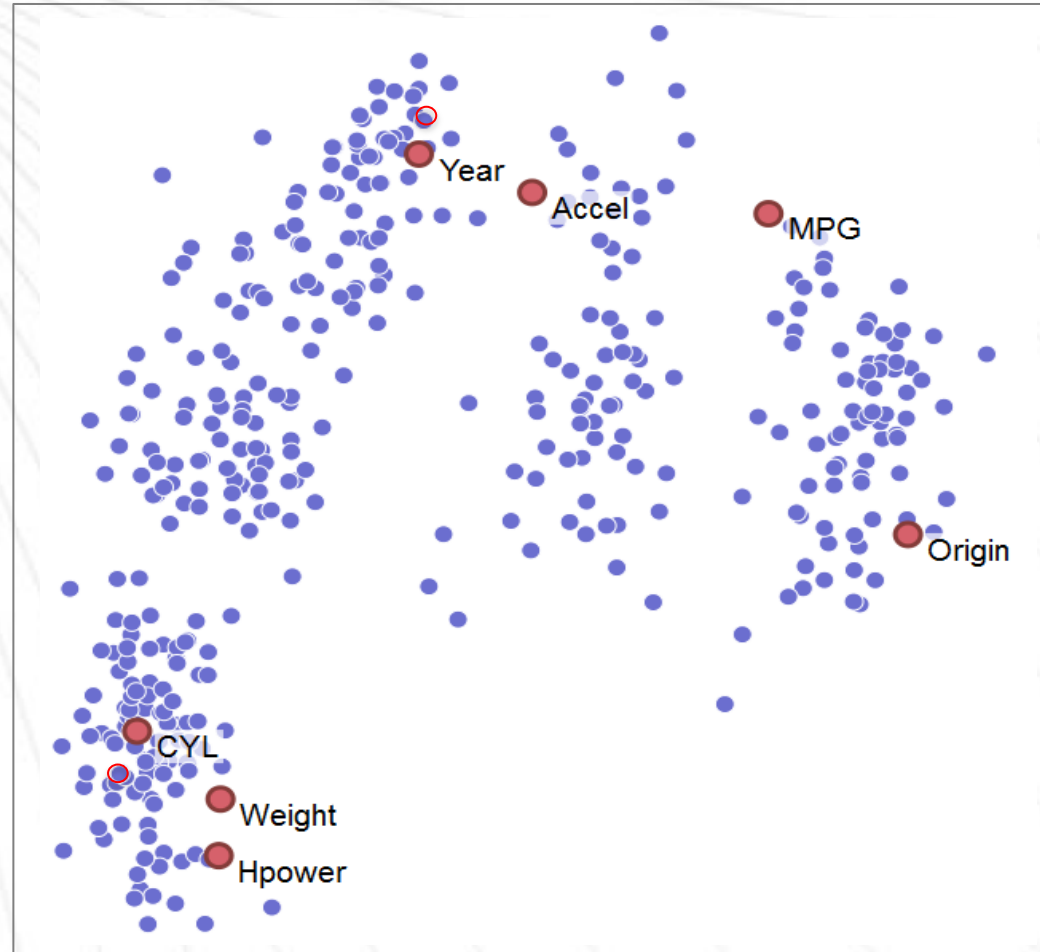
Fusion



Fusion

Chevrolet Cavalier
MPG: 34
CYL: 4
Hpower: 88
Weight: 2395
Accel: 18
Year: 82
Origin: 1

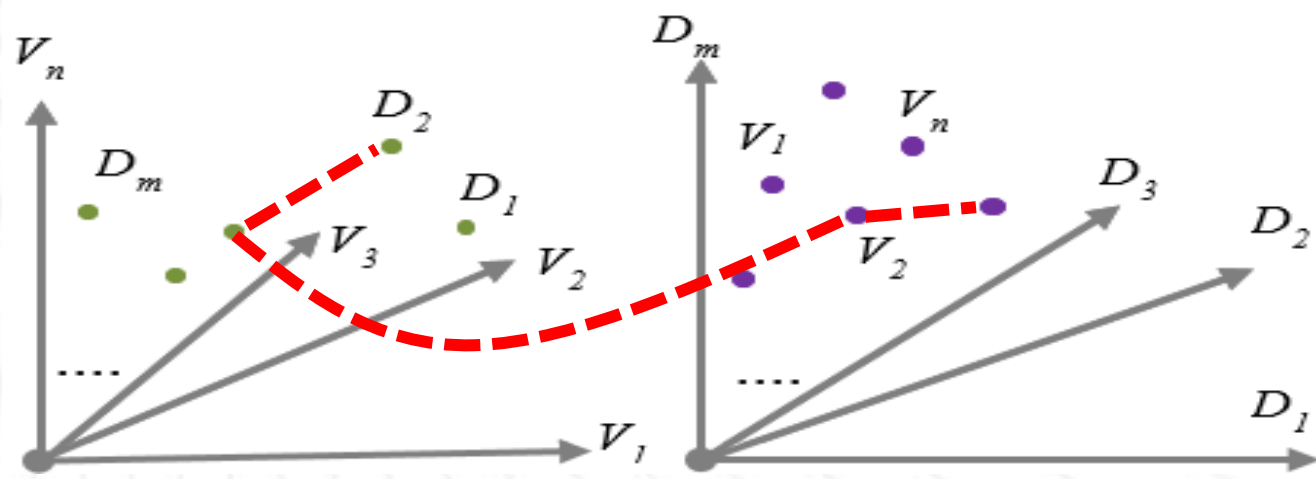
Pontiac Catalina
MPG: 16
CYL: 8
Hpower: 170
Weight: 4668
Accel: 11.5
Year: 75
Origin: 1



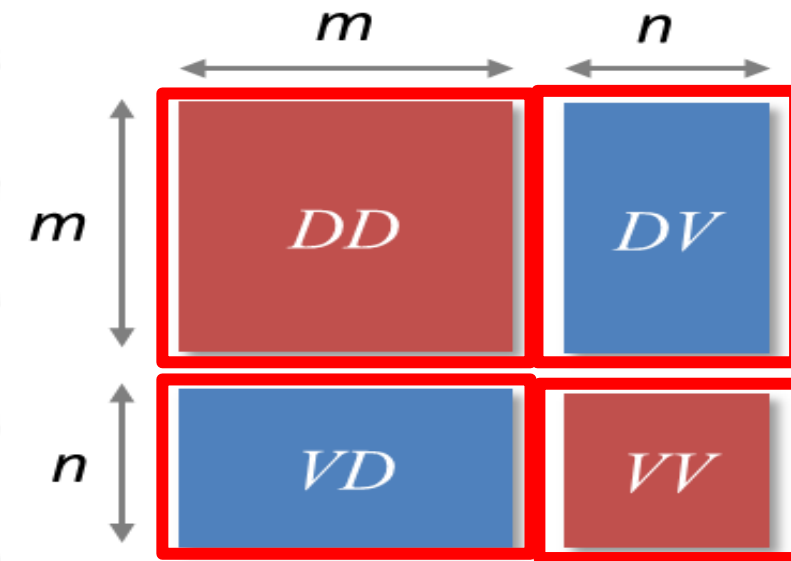
Fusion Pipeline

Data Space

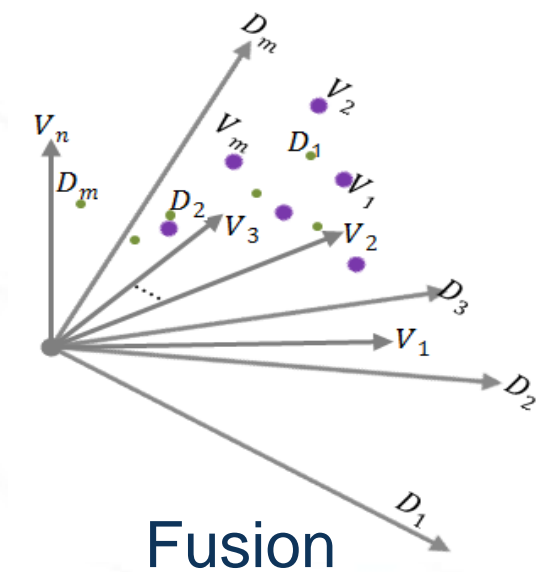
Variable Space



Distance Matrix

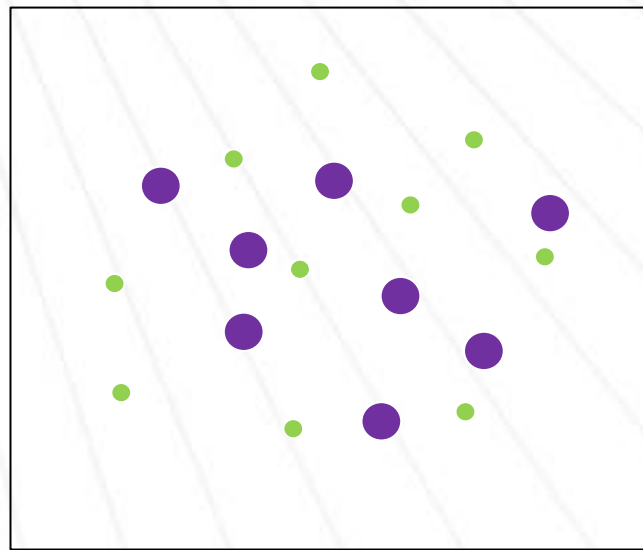


Transformation



Fusion

Glimmer MDS



Mapping

Distance Measurement

MPG	CYL	Hpower	Weight	Accel	Year	Origin
18	8	130	3504	12	70	1
15	8	165	3693	11.5	70	1
18	8	150	3436	11	70	1
16	8	150	3433	12	70	1
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11	8	210	4382	13.5	70	1
9	8	193	4732	18.5	70	1
27	4	88	2130	14.5	71	3
28	4	90	2264	15.5	71	1
25	4	95	2228	14	71	3

Variable to Variable Distance (VV):

$$\text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Distance is opposite meaning !

1- Correlation`

Data to Data Distance (DD): Euclidean Distance

Data to Variable (DV) or Variable to Data (VD) Distance???

Not equal length!

Distance Measurement

n dimensional

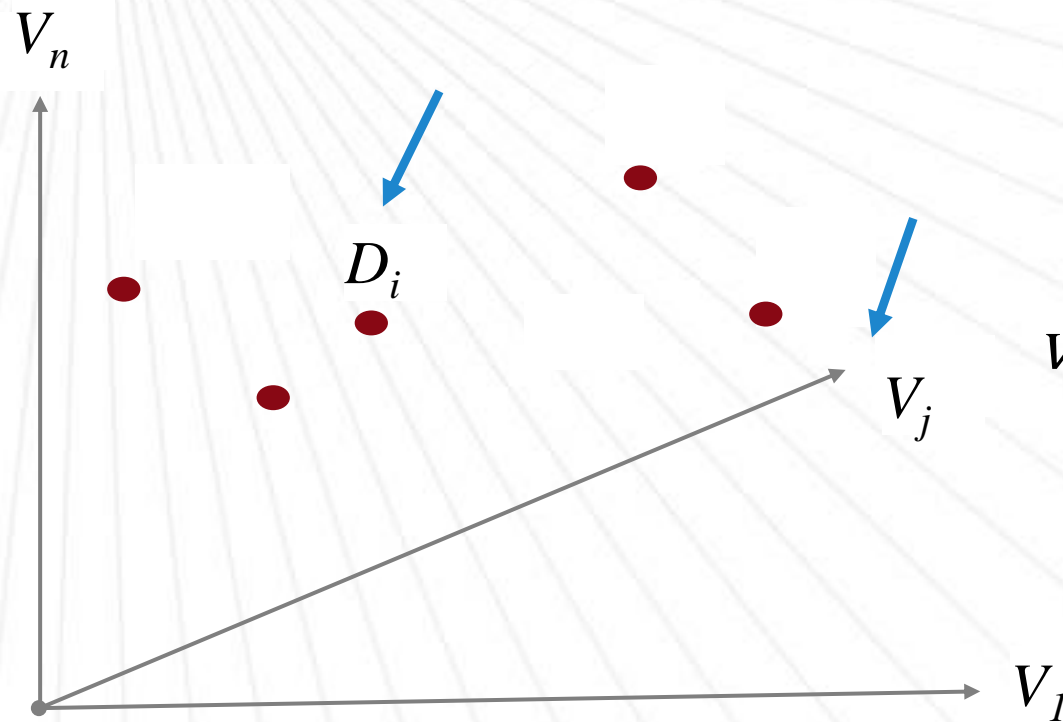
$$D_i = [x_{i1}, x_{i2}, \dots, x_{in}]$$

Project to j th dimension: 1

Project to the other dimensions: 0

n dimensional !

j numbers



$$V_j = [x_{1j}, x_{2j}, \dots, x_{mj}]'$$



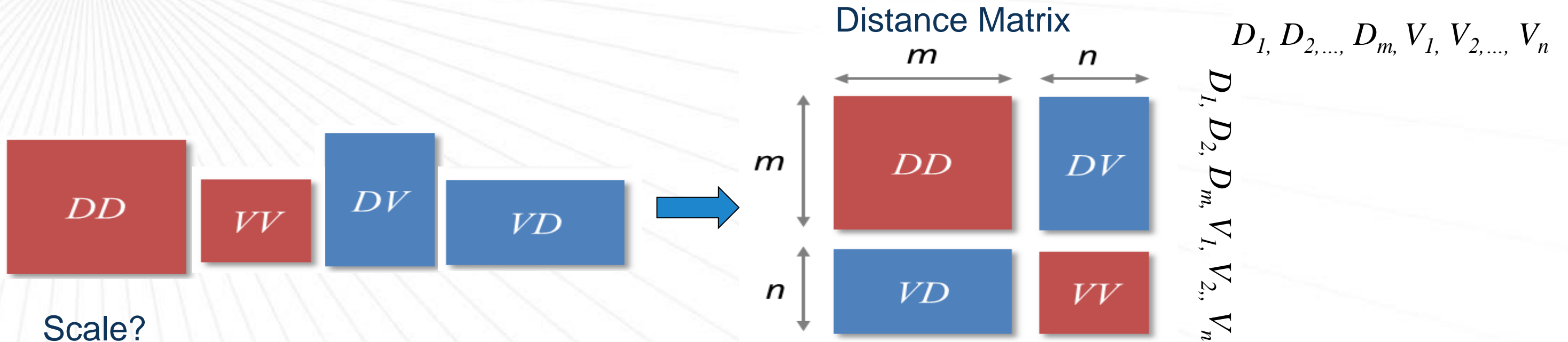
$$\hat{V}_j = [\overbrace{0, 0, \dots, 1}^{j \text{ numbers}}, 0, \dots, 0]^T$$

D_i and V_j are equal length now.

Transpose?

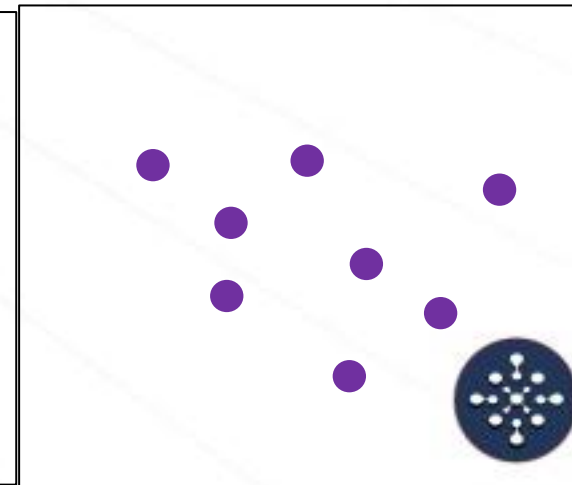
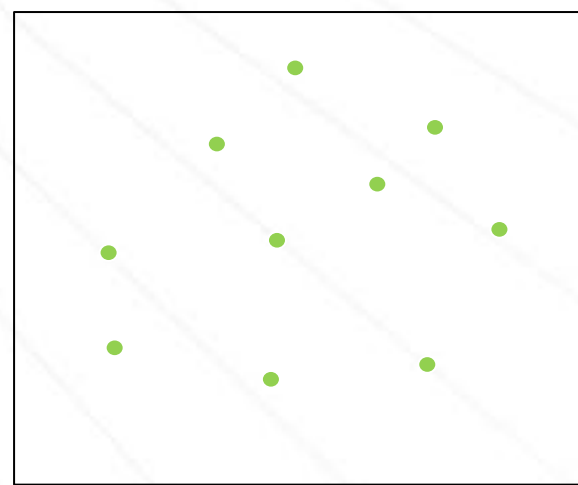
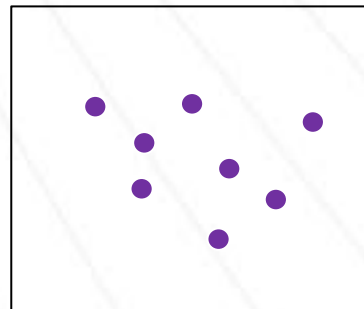
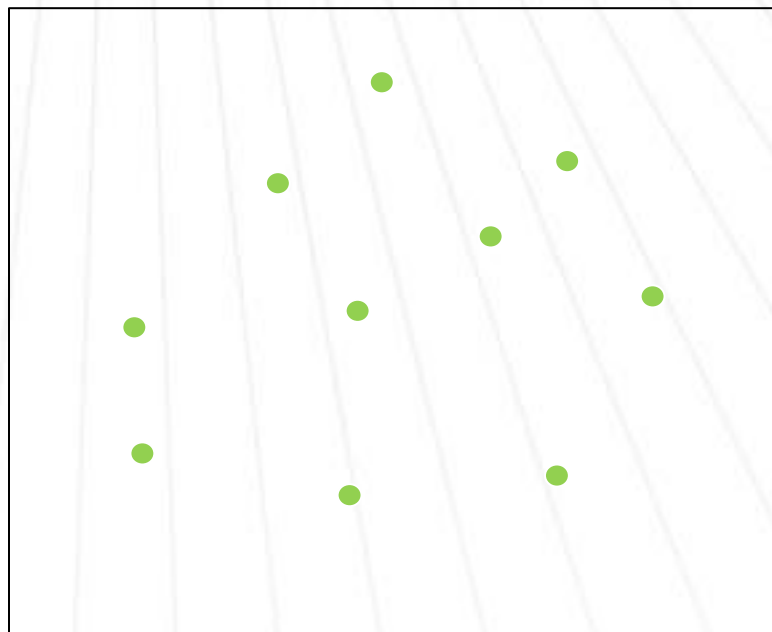
$$DV = VD !$$

Composite Distance Matrix



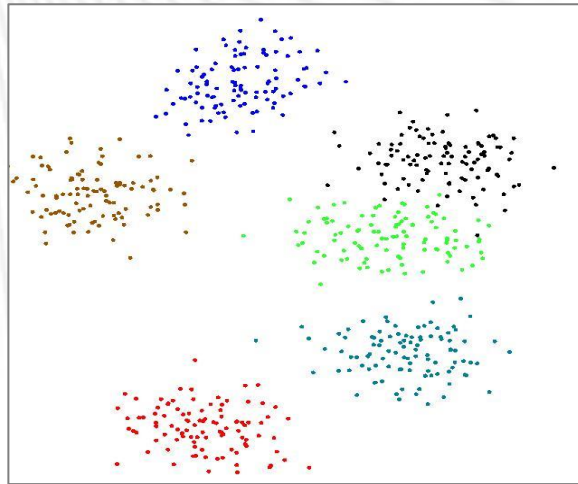
Scale?

$$\overline{DD} = \overline{DV} = \overline{VD} = \overline{VV}$$

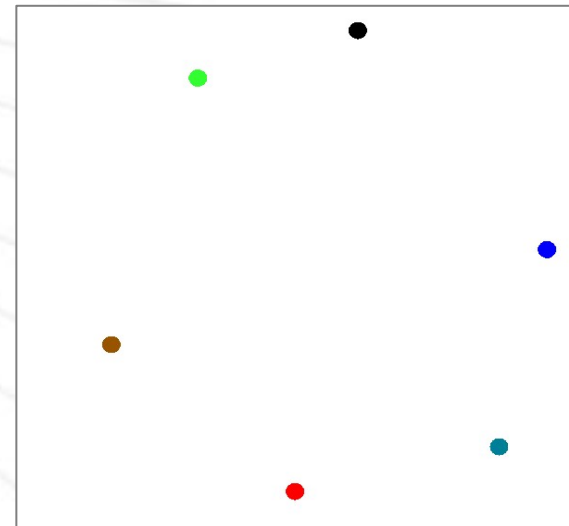


At a Glance

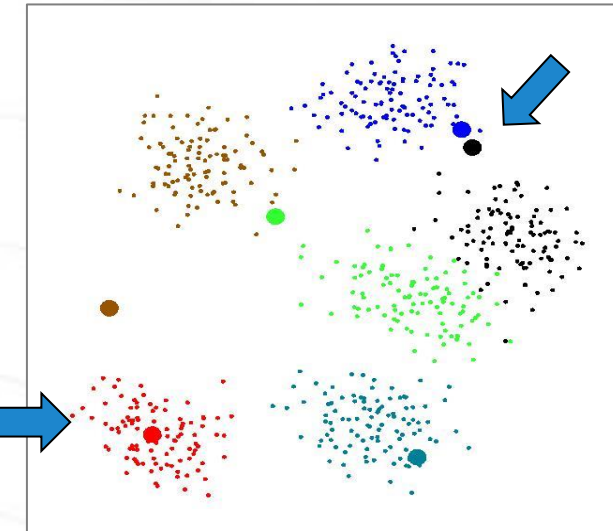
Data to Data



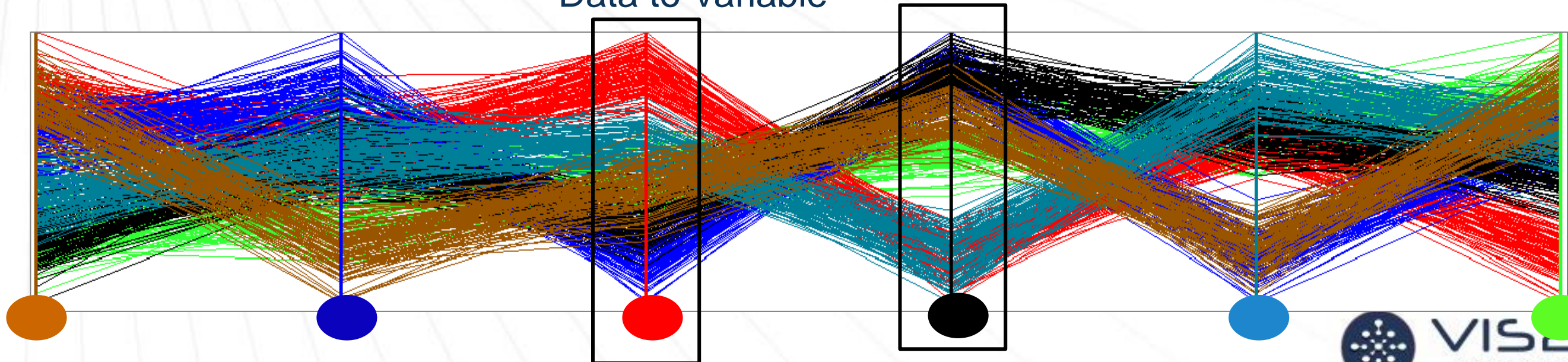
Variable to Variable



Data and Variable

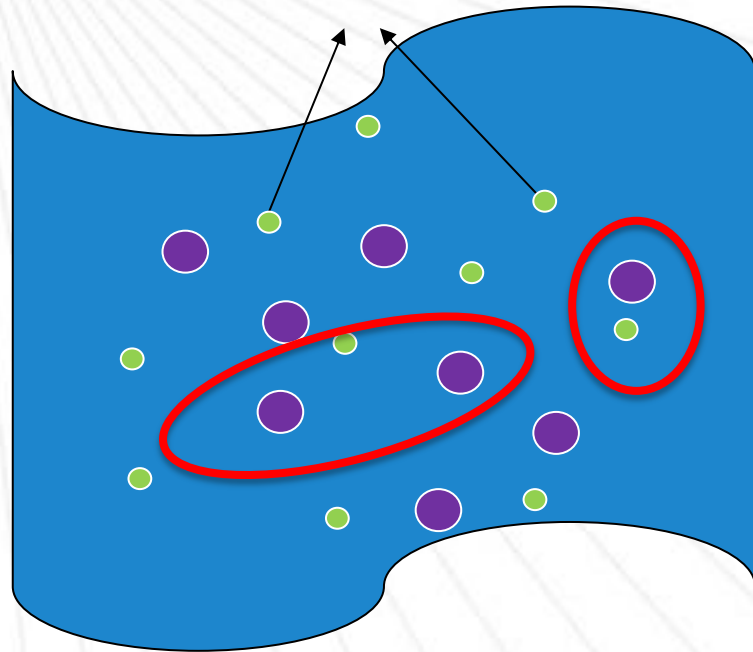


Data to Variable



Layout Schedules

Original Distance

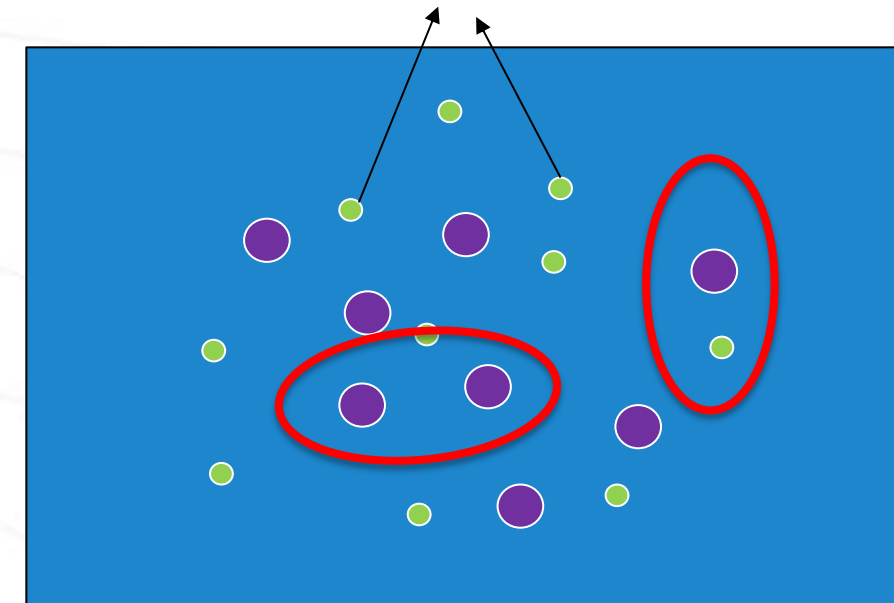


High Dimensional Data Space

Mapping



2D Distance

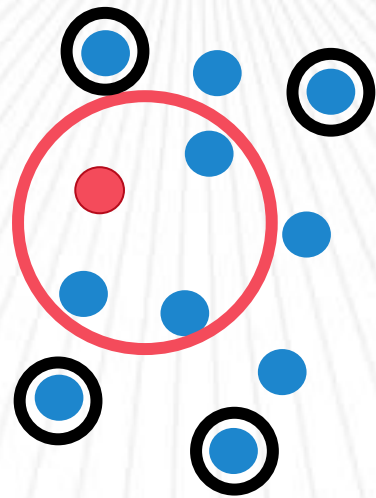


2 Dimensional Data Space

Data or Variable Error?

Layout Schedules

Glimmer MDS



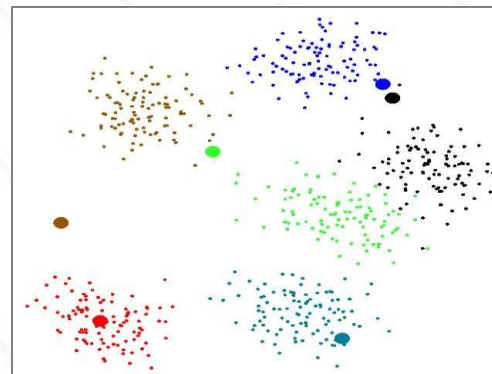
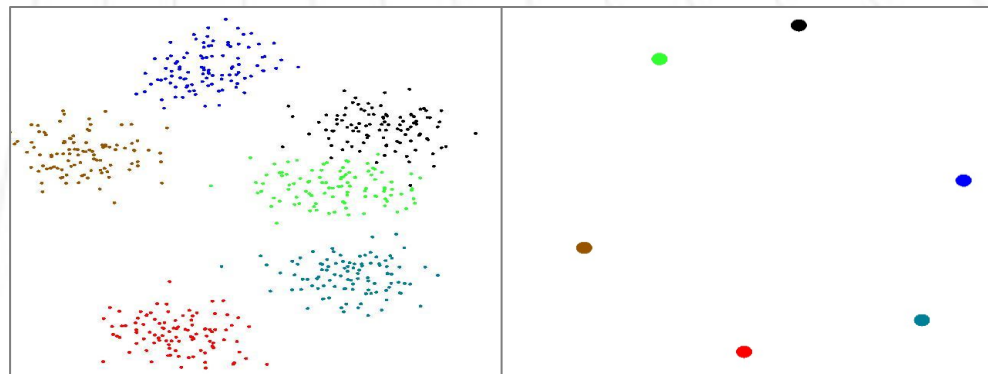
Near Set

Random Set

Data

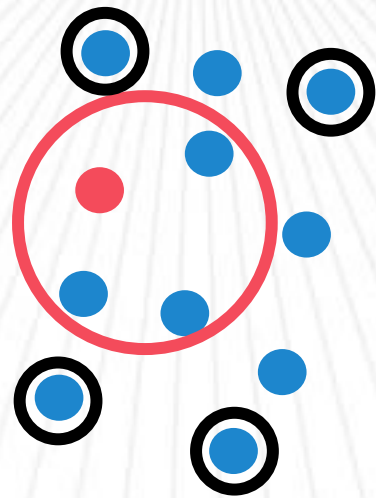
Data Variables

Variables



Layout Schedules

Glimmer MDS



Near Set

Random Set

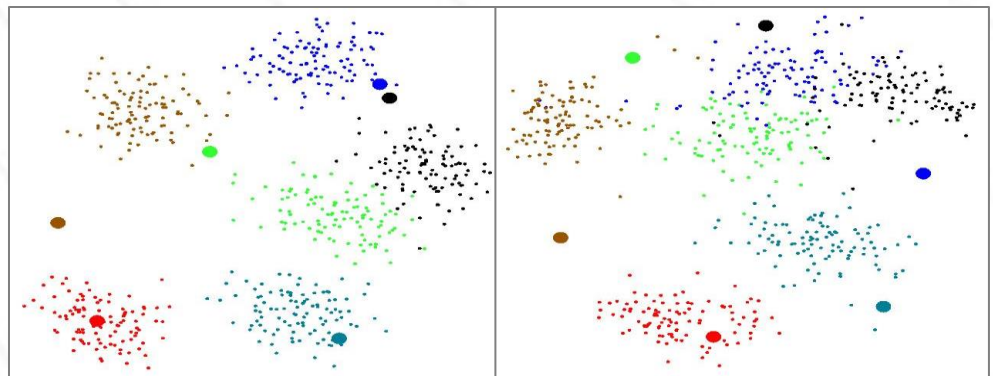
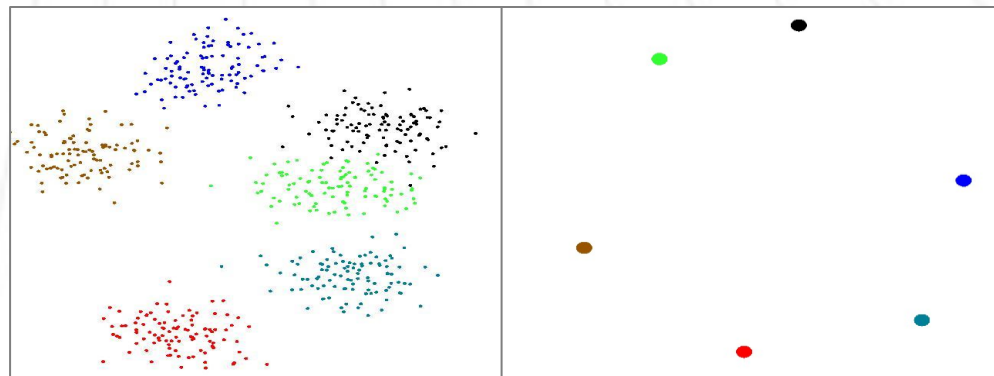
Data

Data Variables

Variables

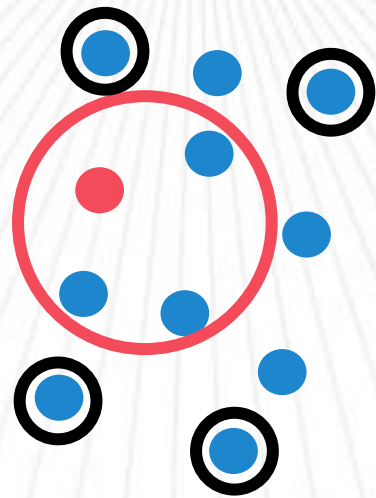
Data Variables

Variables



Layout Schedules

Glimmer MDS



Near Set

Random Set

Data

Data Variables

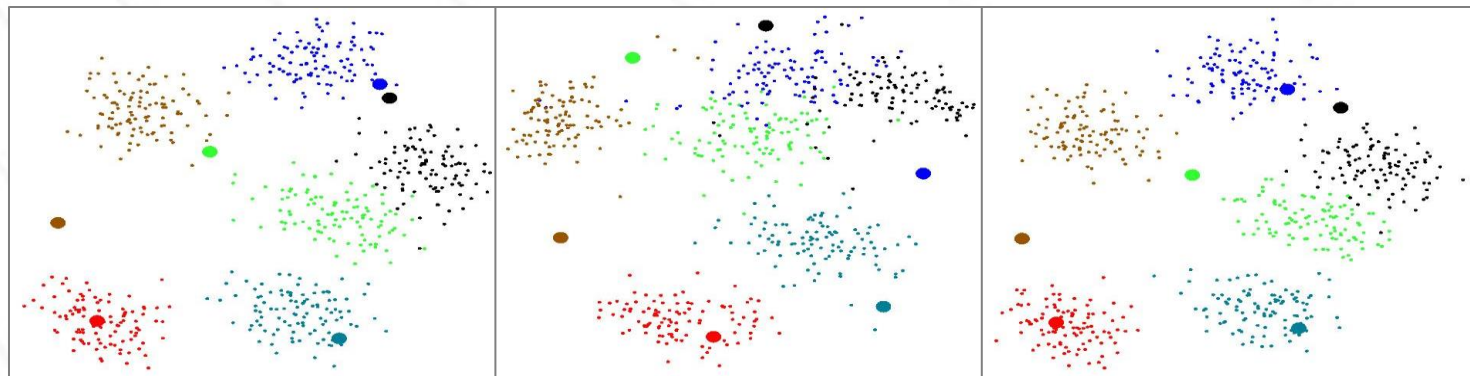
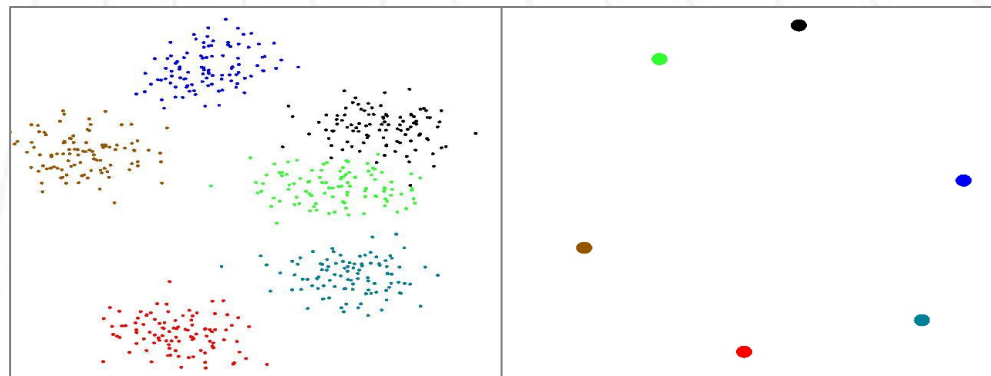
Variables

Data Variables

Data

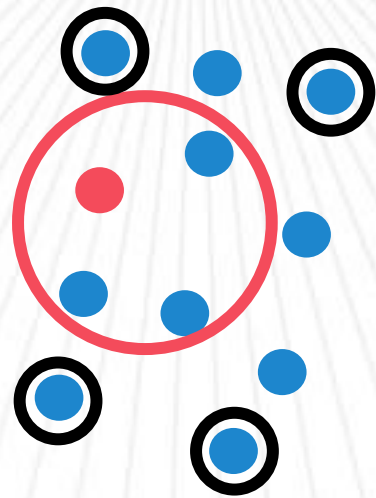
Data Variables

Variables



Layout Schedules

Glimmer MDS



Near Set

Random Set

Data

Data Variables

Variables

Data Variables

Data

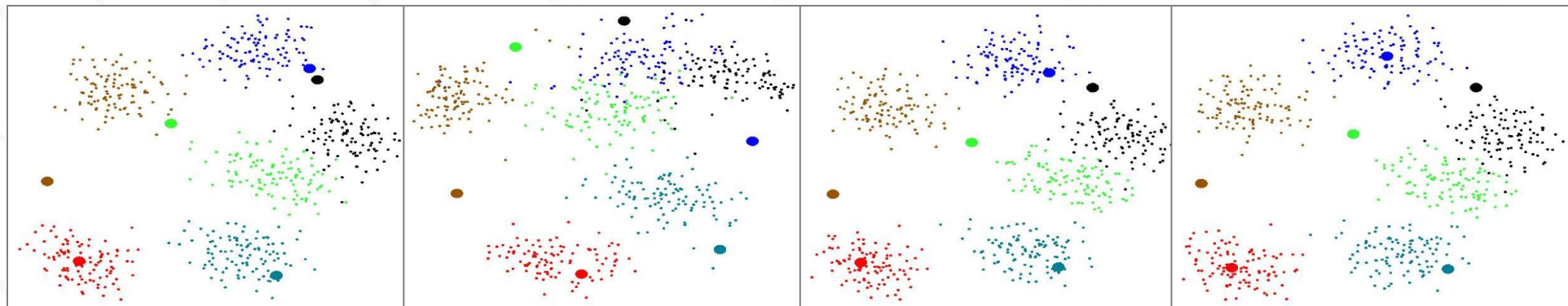
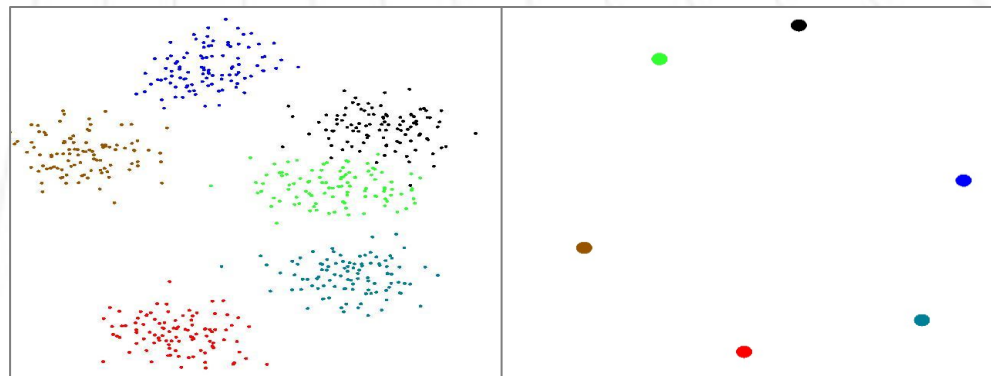
Data Variables

Variables

Variables

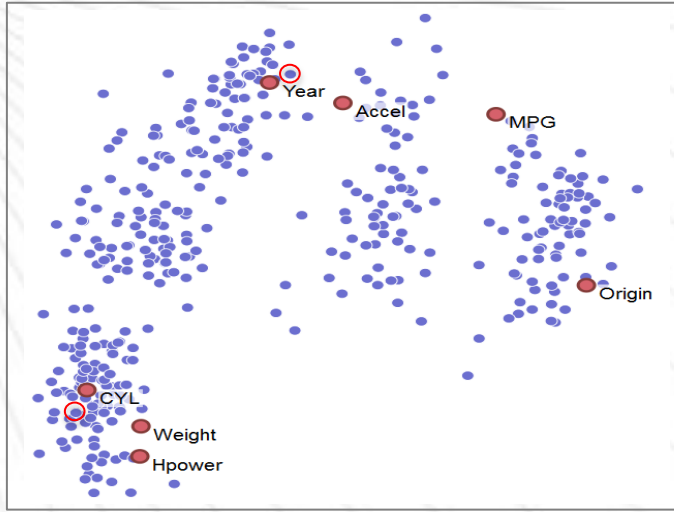
Data

Data Variables



Data Context Map

Chevrolet Cavalier
MPG: 34
CYL: 4
Hpower: 88
Weight: 2395
Accel: 18
Year: 82
Origin: 1



Pontiac Catalina
MPG: 16
CYL: 8
Hpower: 170
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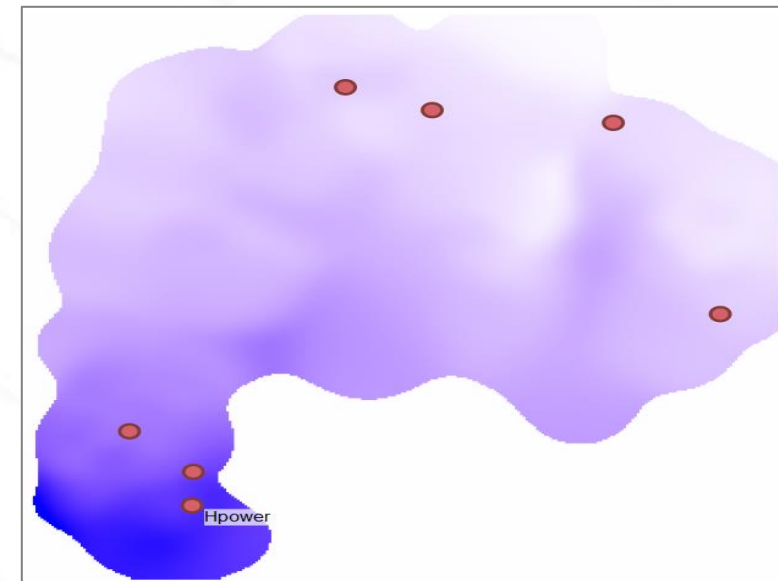
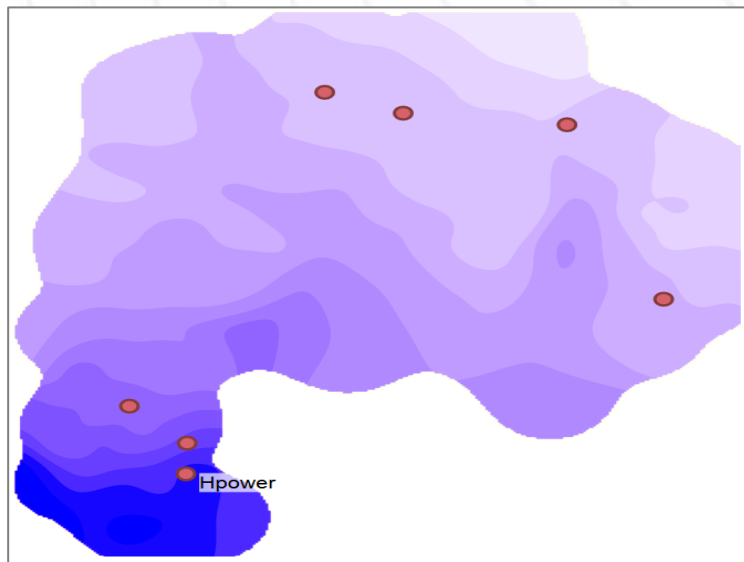
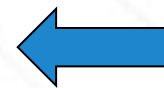
Adaptive Kernel
Density Estimation



Nadaraya-Watson
kernel regression



Contour boundary

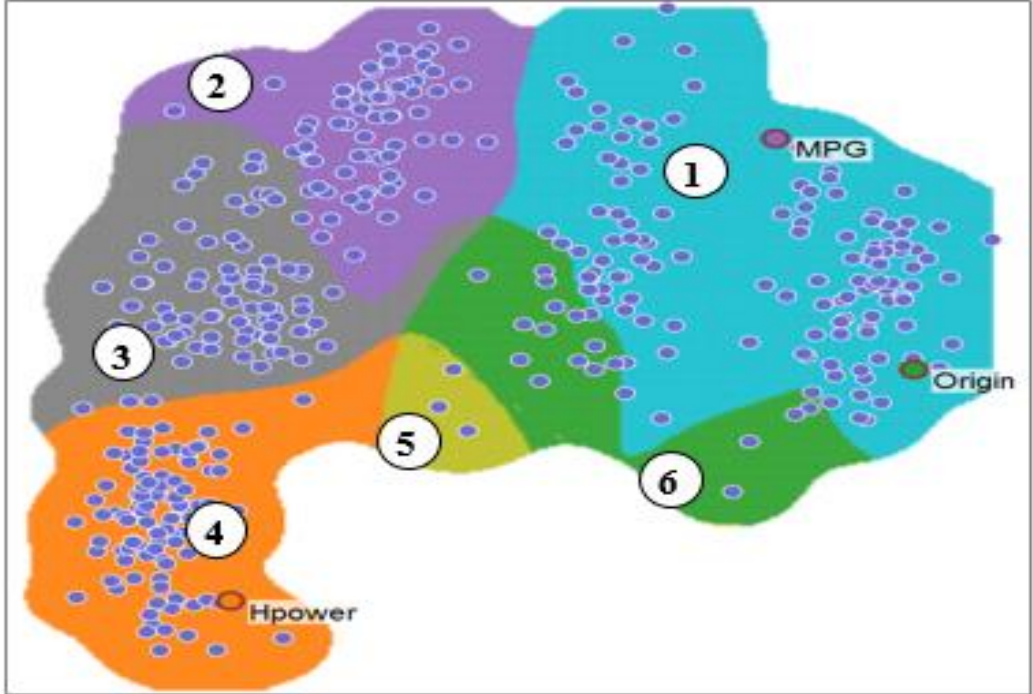
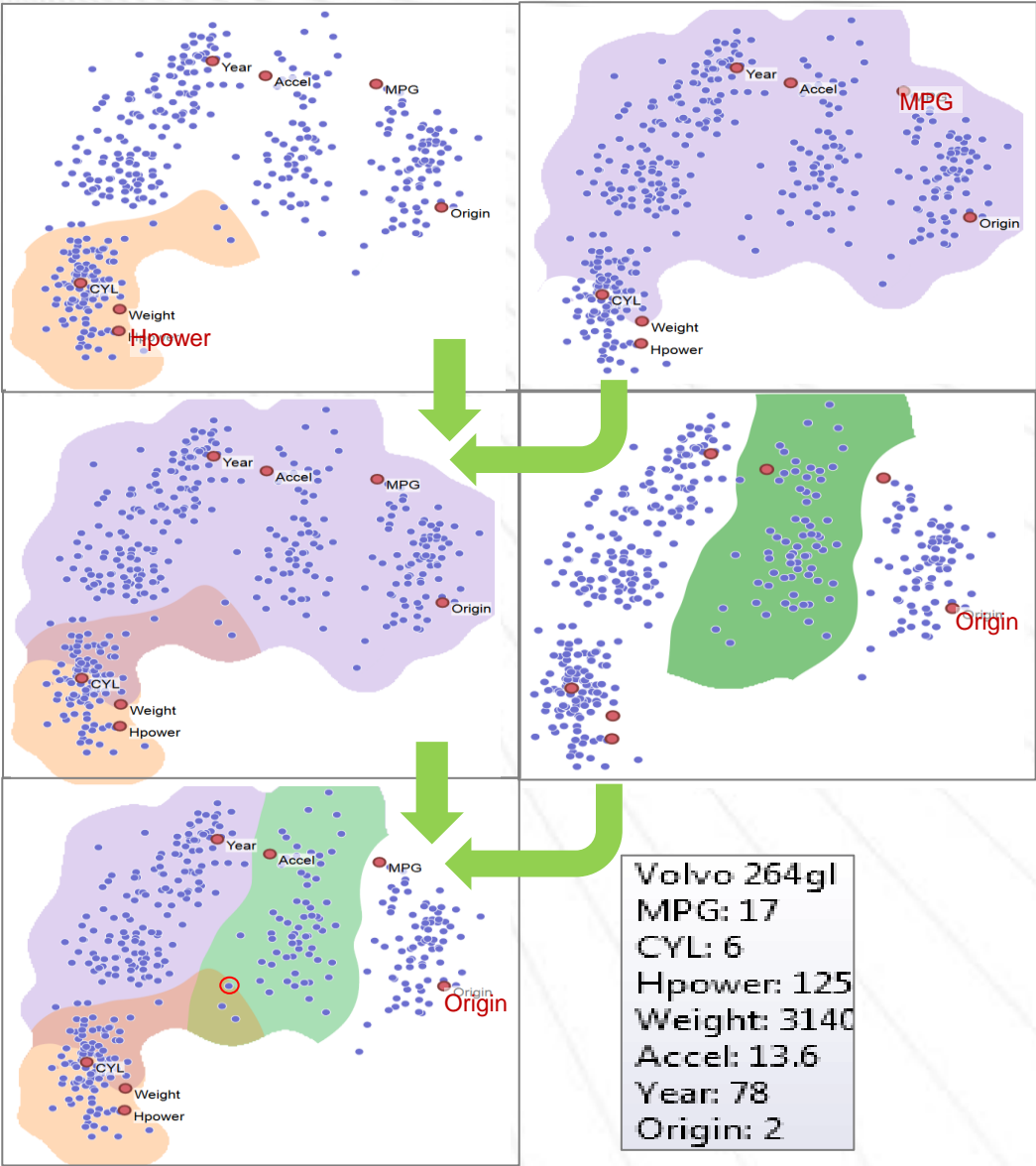


Data Context Map

Horsepower: 116~192

MPG: 16~30

European Car



- Euro-Japanese efficient compact cars
- US efficient compact cars
- US semi-efficient medium-power cars
- US big block gas guzzlers
- Euro-Japanese gas guzzlers
- Euro-Japanese semi-efficient medium-power cars

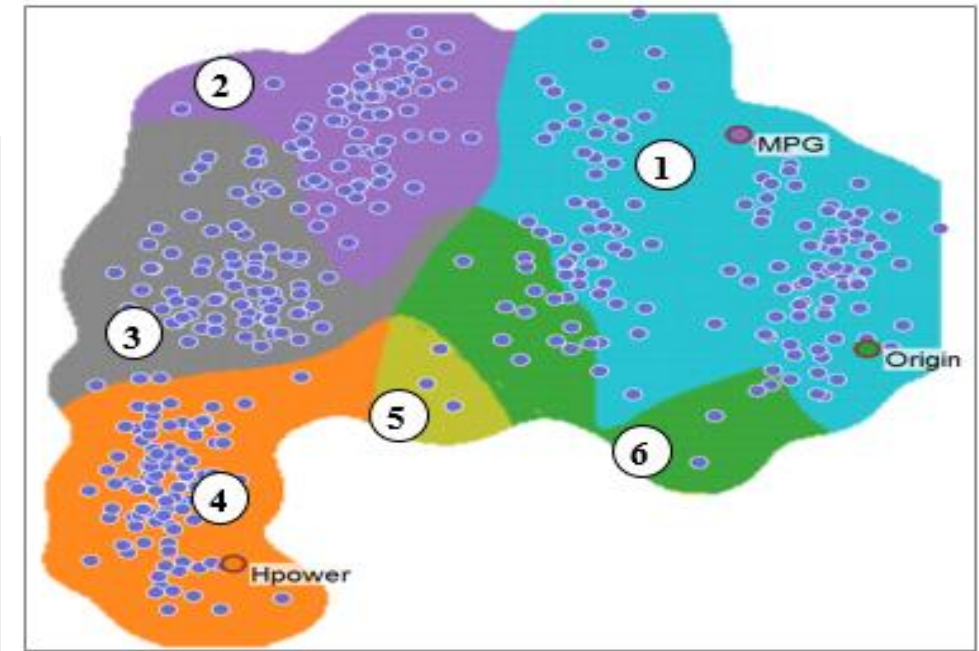
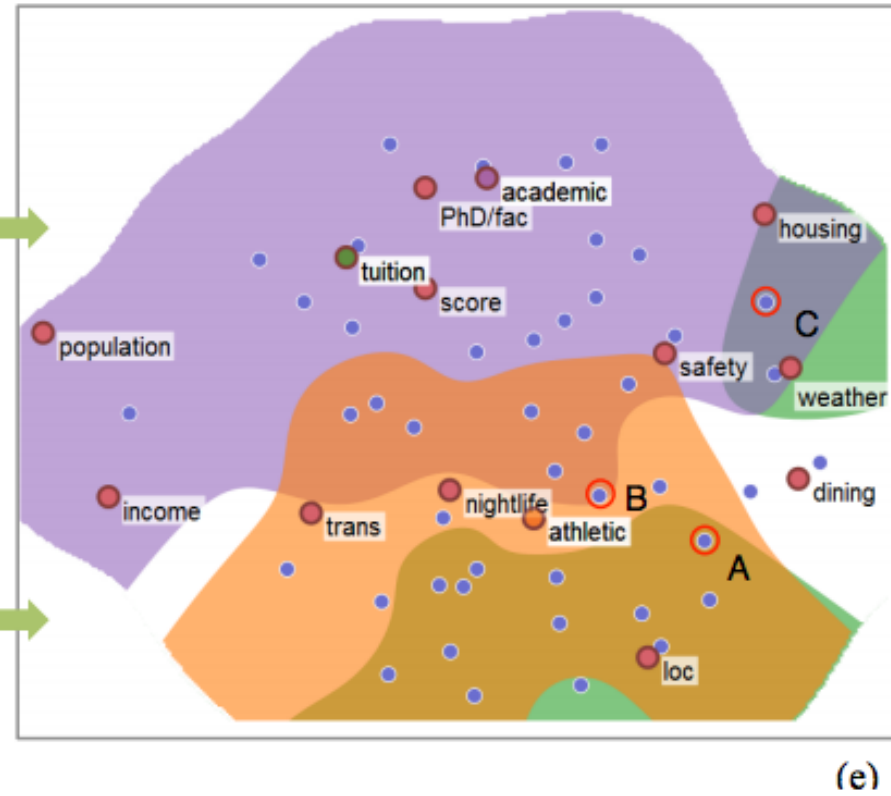
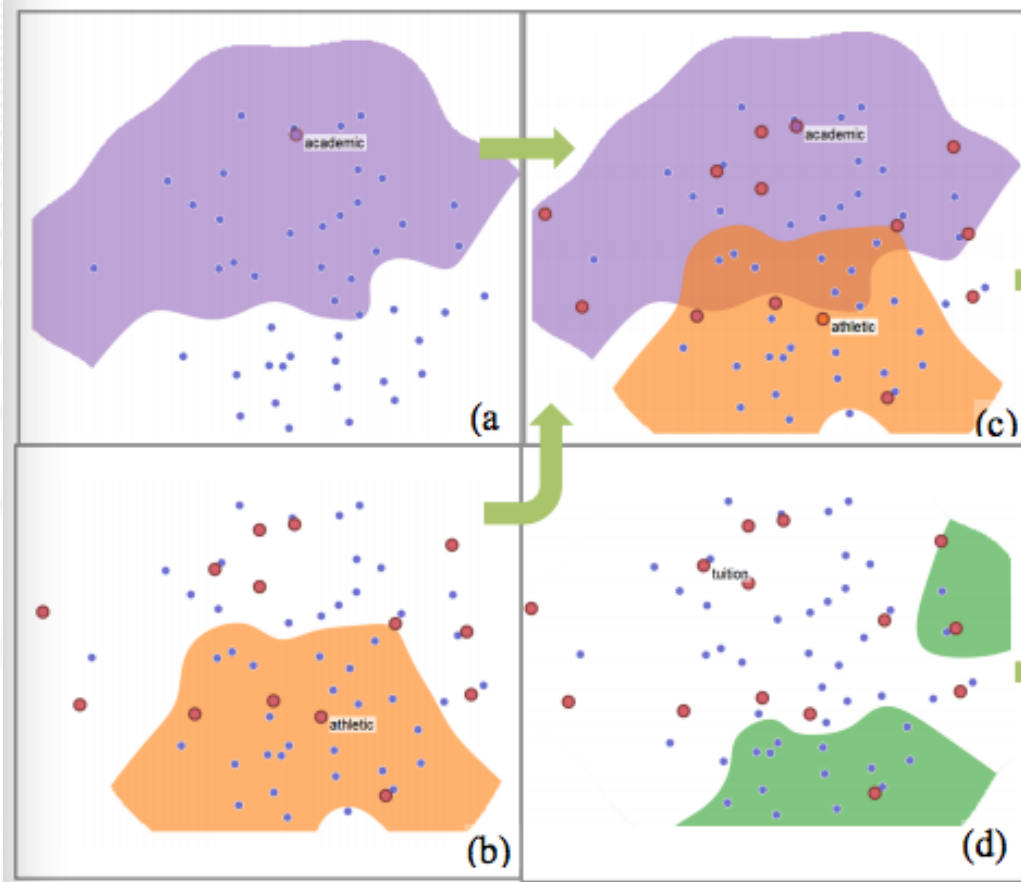
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Reference

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Thank you !

