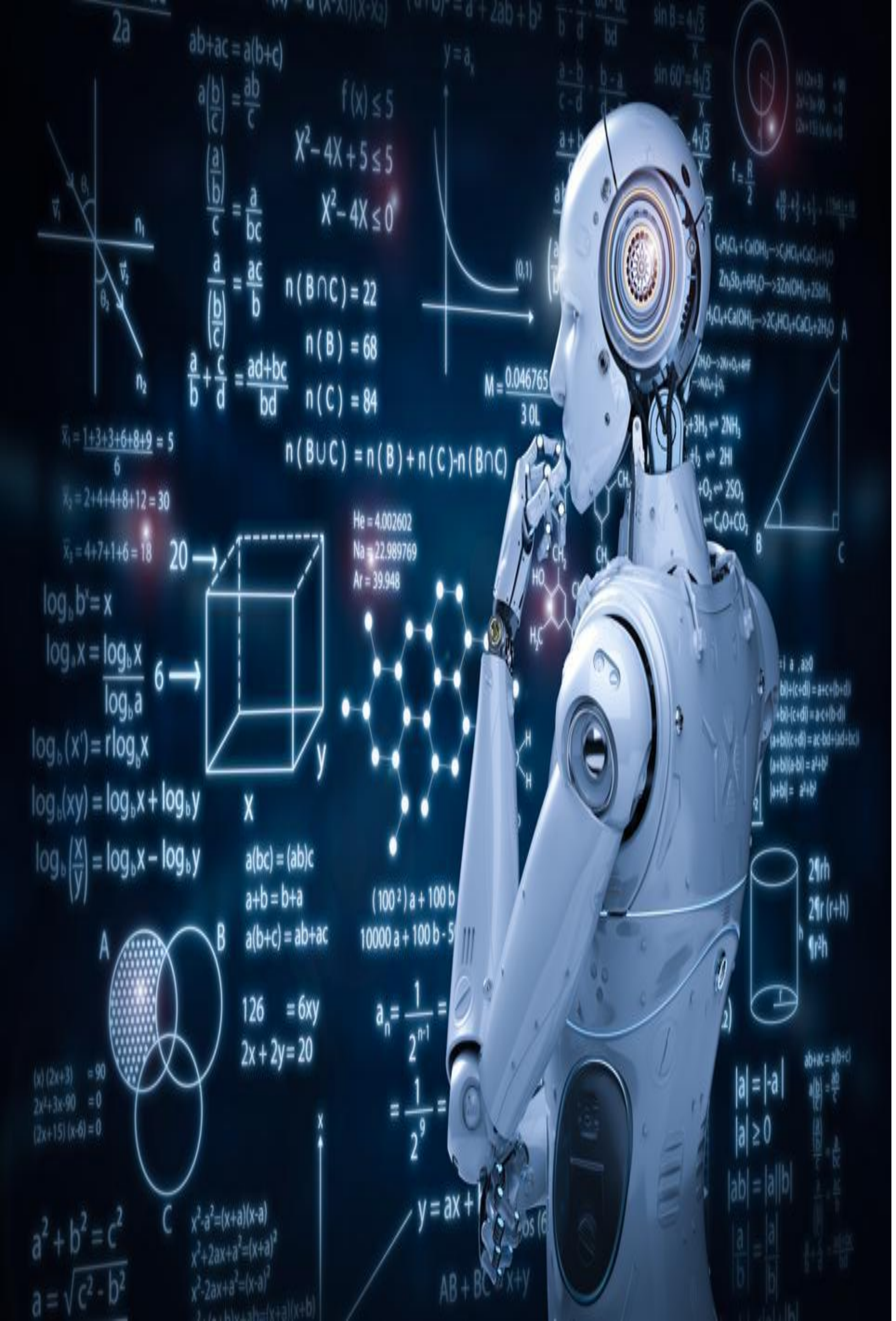


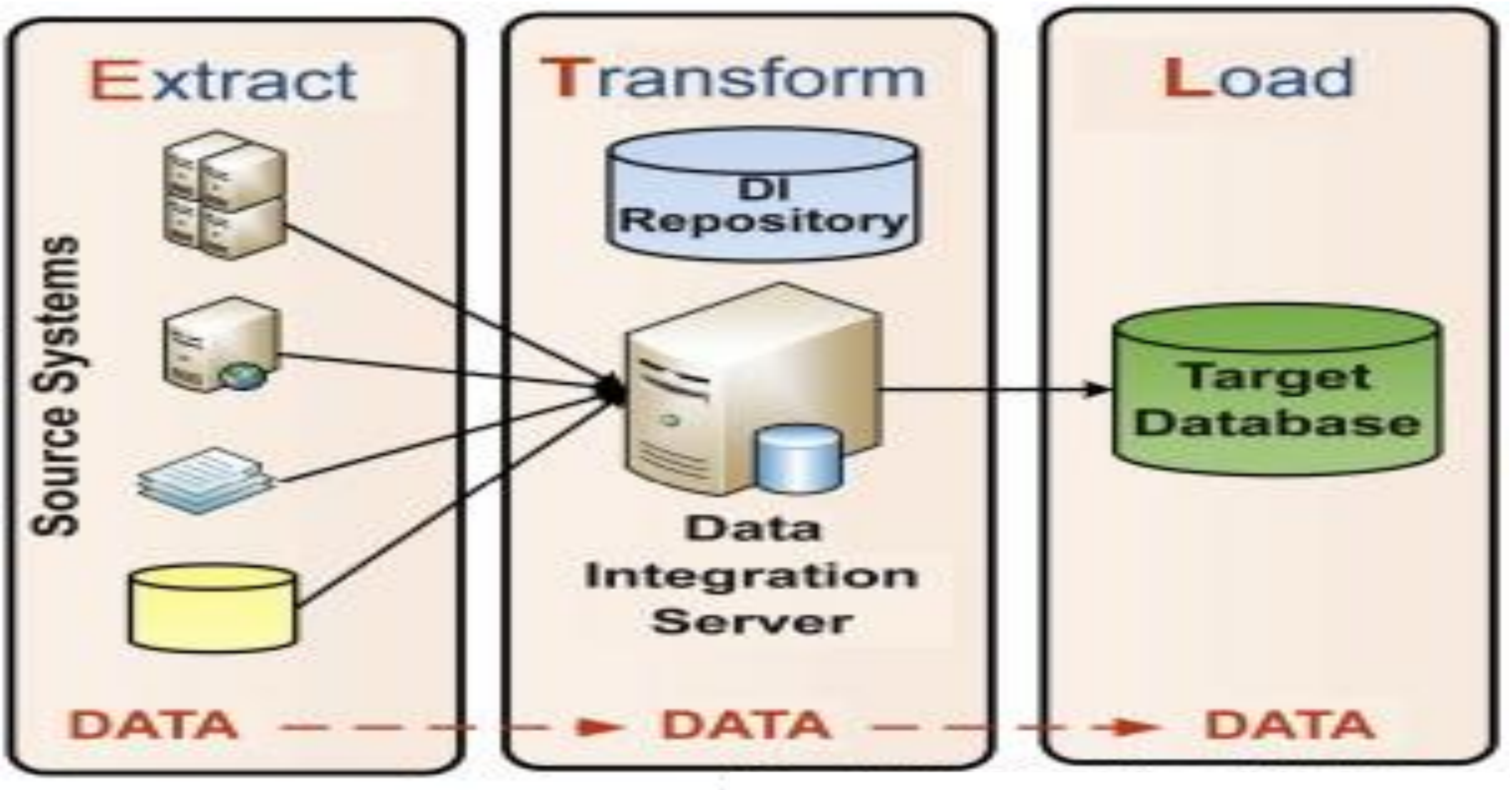
Practical Machine Learning

Day 8: Mar22 DBDA

Kiran Waghmare

Agenda

- Preprocessing Techniques


Extract
Transform
Load
Source Systems
DI
Repository
Data
Integration
Server
Target
Database
DATA
DATA
DATA

Data Integration

- **Data integration:**
- **Combines data from multiple sources into a coherent store**
- **Schema integration**: e.g., A.cust-id ≡ B.cust-#
  - Integrate metadata from different sources
- **Entity identification problem**:
  - Identify real world entities from **multiple data sources**, e.g., Bill Clinton = William Clinton
- **Detecting and resolving data value conflicts**
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - ***Object identification***: The same attribute or object may have different names in different databases
  - ***Derivable data:*** One attribute may be a "derived" attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by ***correlation analysis*** **and** ***covariance analysis***
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Nominal Data)

- **X^2 (chi-square) test**

$$\chi^2 = \sum \frac{(Observed - Expected)^2}{Expected}$$

- The larger the X^2 value, the more likely the variables are related
- The cells that contribute the most to the X^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
  - # of hospitals and # of car-theft in a city are correlated
  - Both are causally linked to the third variable: population

Chi-Square Calculation: An Example

	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- X^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group

Correlation Analysis (Numeric Data)

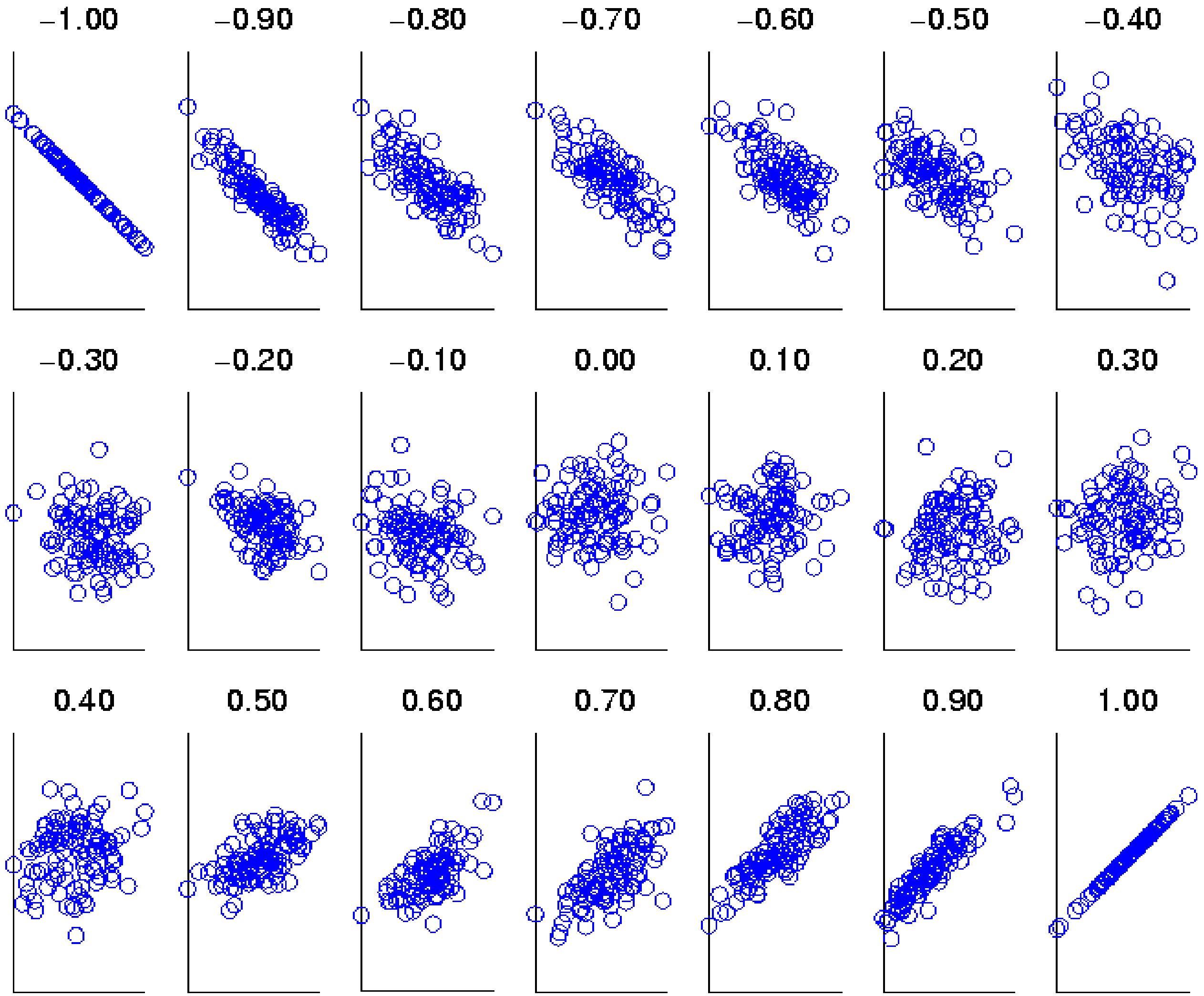
- Correlation coefficient (also called Pearson's product moment coefficient)

$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{(n-1)\sigma_A \sigma_B} = \frac{\sum_{i=1}^{n}(a_i b_i) - n\bar{A}\bar{B}}{(n-1)\sigma_A \sigma_B}$$

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

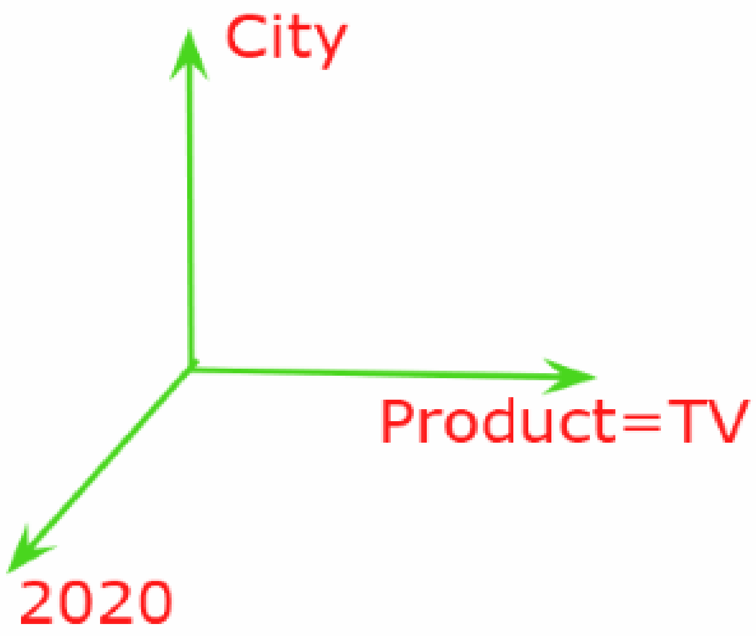
Visually Evaluating Correlation



Scatter plots showing the similarity from –1 to 1.

Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
  - Smoothing: Remove noise from data
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Aggregation: Summarization, data cube construction
  - Normalization: Scaled to fall within a smaller, specified range
    - min-max normalization
    - z-score normalization
    - normalization by decimal scaling
  - Discretization: Concept hierarchy climbing



Normalization

- **Min-max normalization**: to [new_min_A, new_max_A]

$$v' = \frac{\boxed{v} - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

  - Ex. Let income range $12,000 to $98,000 normalized to [0.0, 1.0]. Then $73,000 is mapped to

min max

$$\frac{73{,}600 - 12{,}000}{98{,}000 - 12{,}000}(1.0 - 0) + 0 = 0.716$$

- **Z-score normalization** (μ: mean, σ: standard deviation):

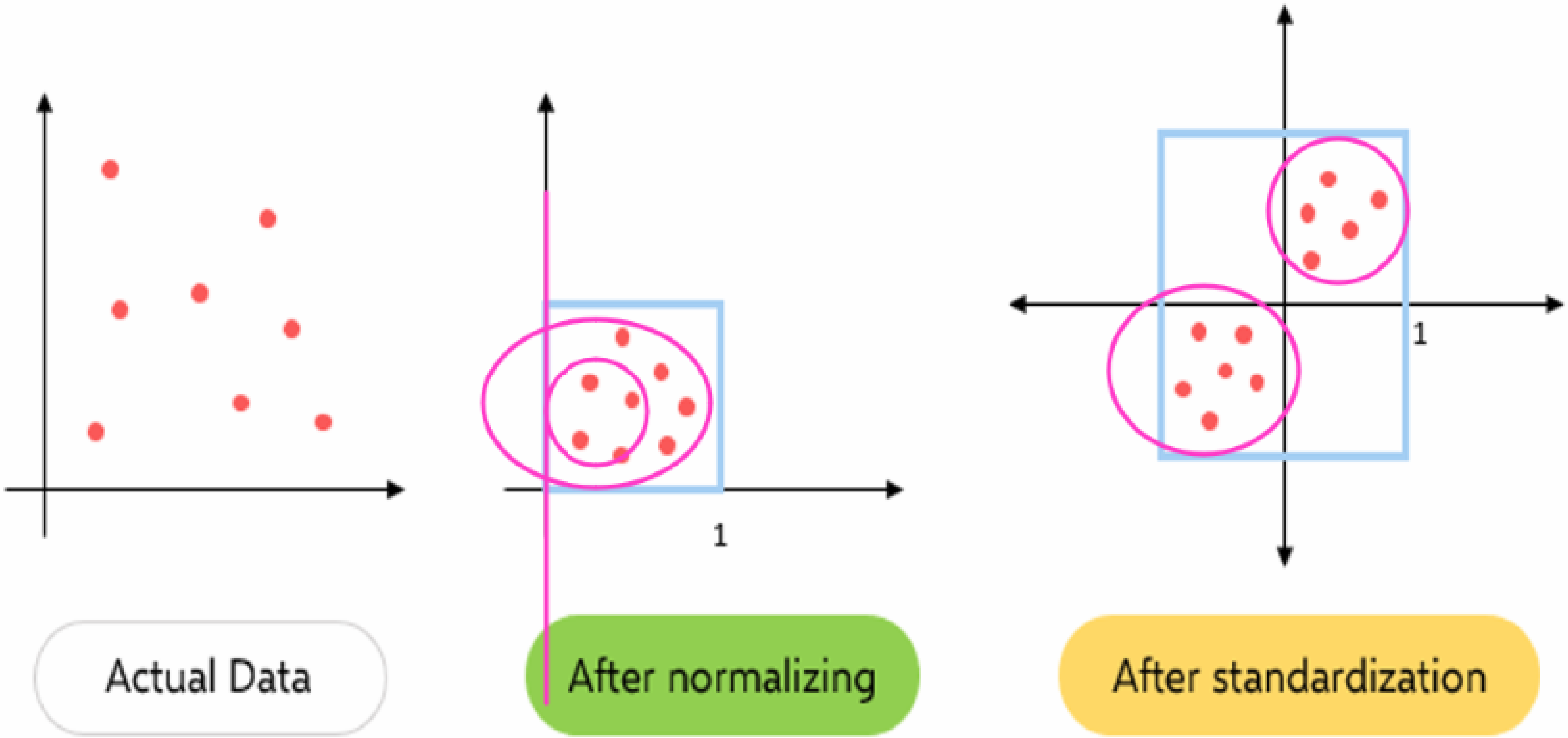
$$v' = \frac{v - \mu_A}{\sigma_A}$$

  - Ex. Let μ = 54,000, σ = 16,000. Then

$$\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$$

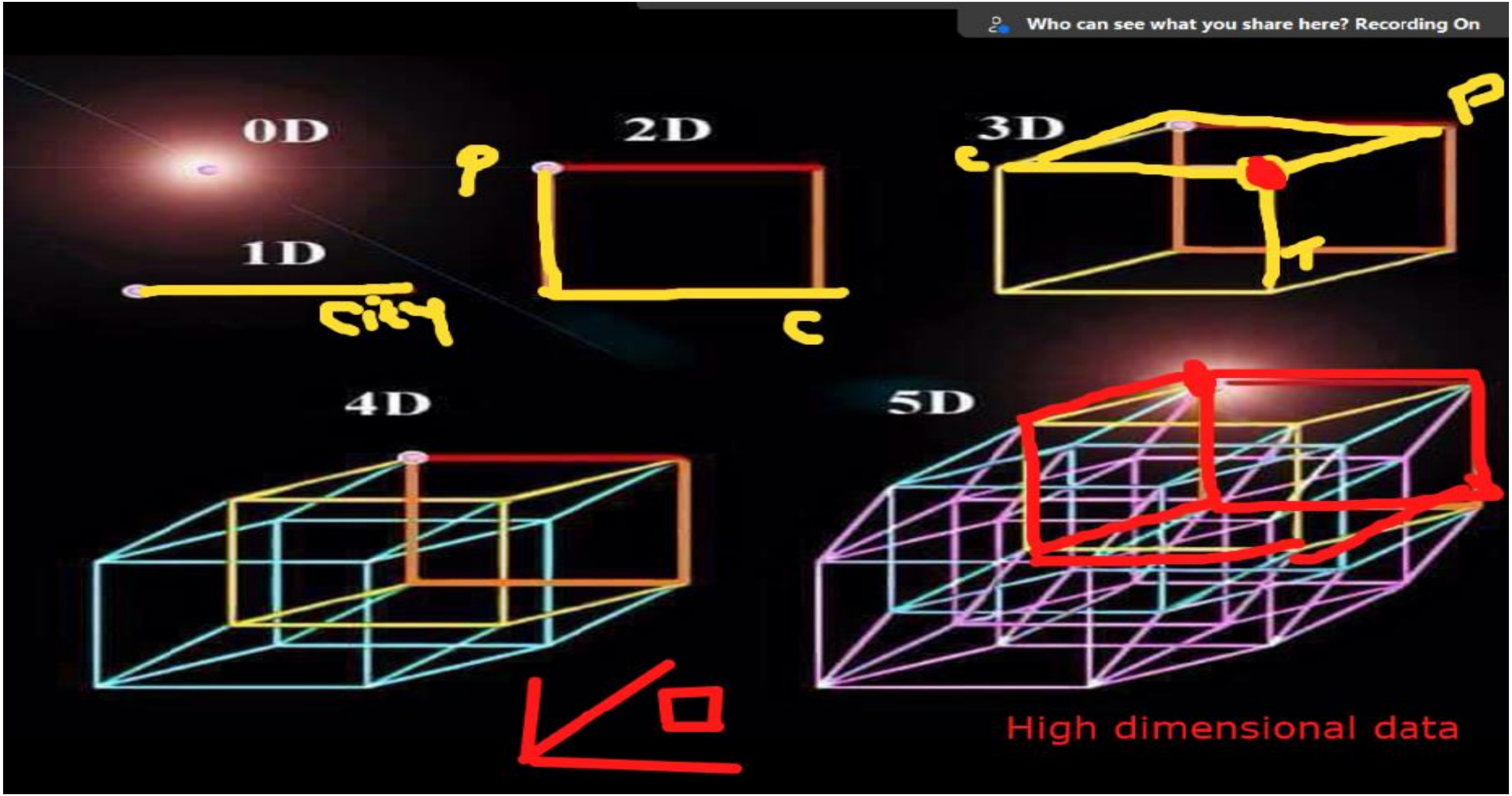
- **Normalization by decimal scaling**

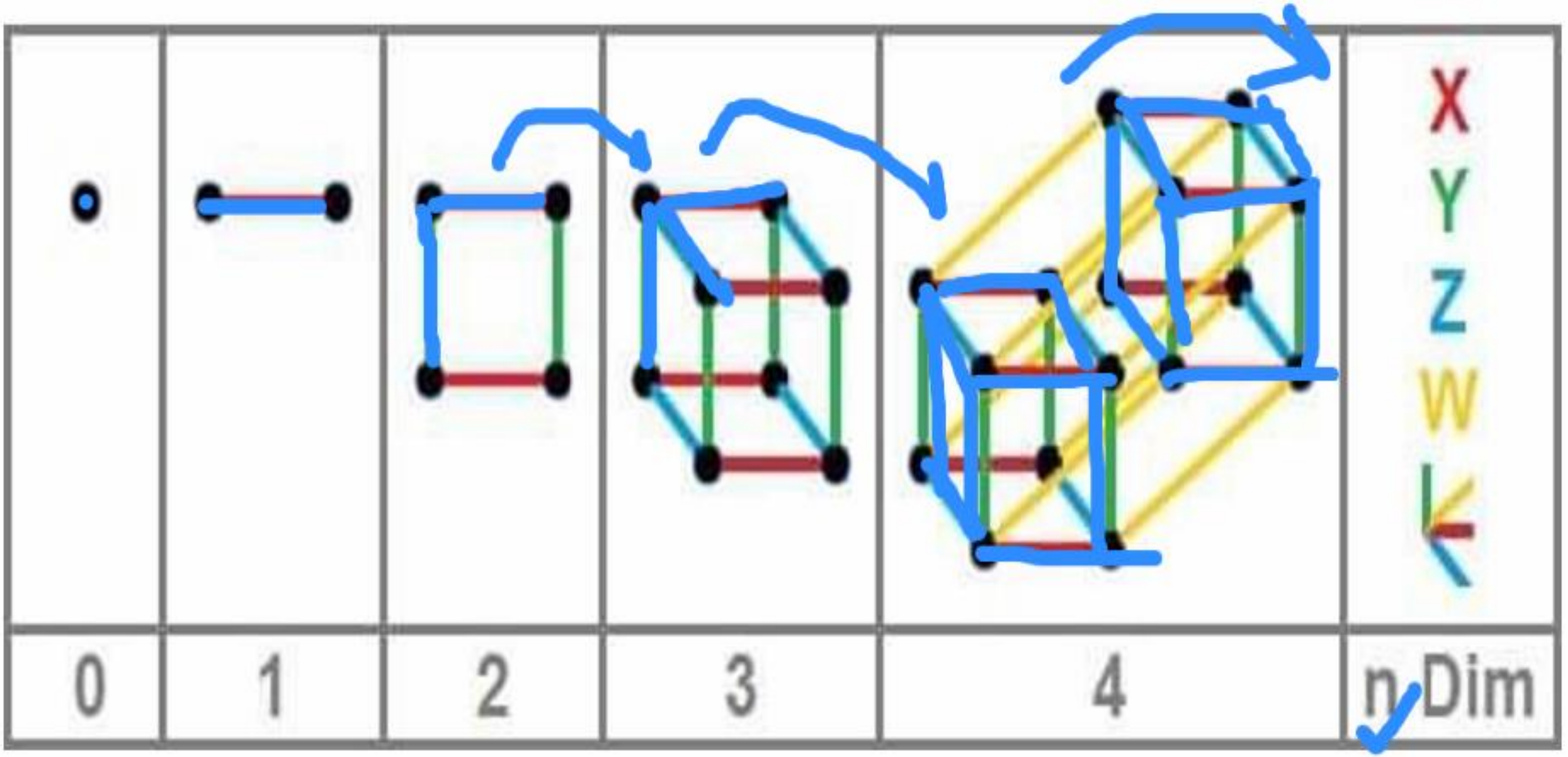
$$v' = \frac{v}{10^j}$$ Where j is the smallest integer such that Max(|ν'|) < 1


1
1
Actual Data
After normalizing
After standardization

Data Reduction Strategies

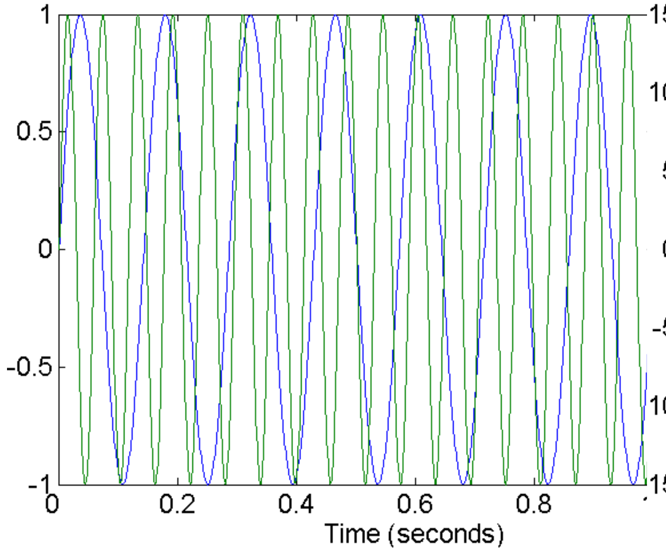
- **Data reduction**: Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
  - **Dimensionality reduction**, e.g., remove unimportant attributes
    - Wavelet transforms
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
  - **Numerosity reduction** (some simply call it: Data Reduction)
    - Regression and Log-Linear Models
    - Histograms, clustering, sampling
    - Data cube aggregation
  - **Data compression**


Who can see what you share here? Recording On
0D
1D
city
2D
p
c
3D
p
c
4D
5D
High dimensional data

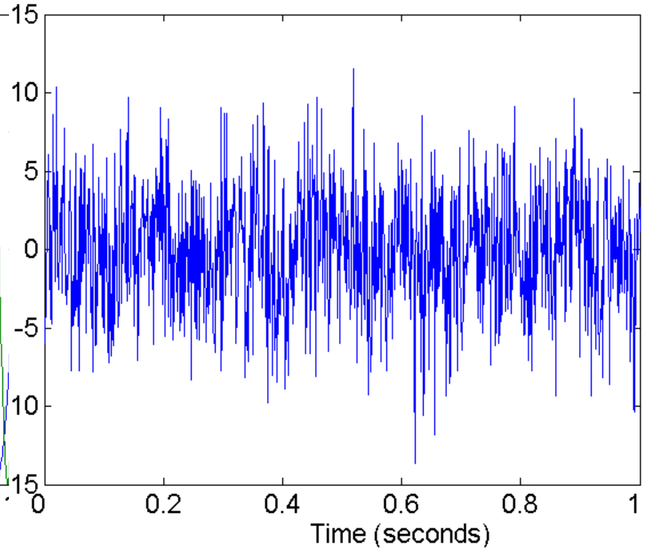

X
Y
Z
W
0
1
2
3
4
n Dim

Mapping Data to a New Space

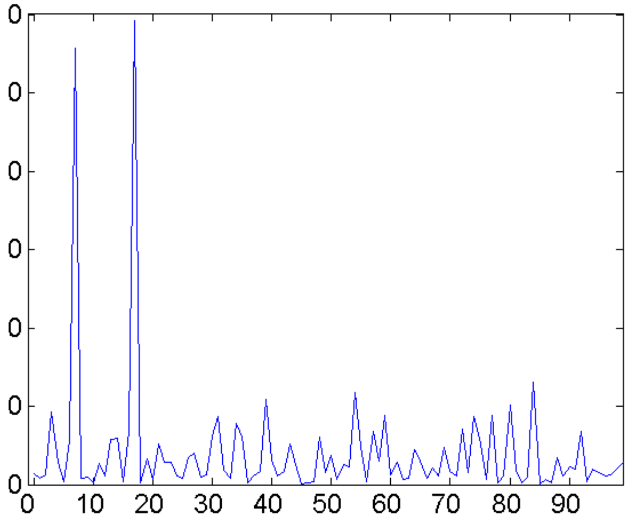
- **Fourier transform**
- **Wavelet transform**



Two Sine Waves



Two Sine Waves + Noise

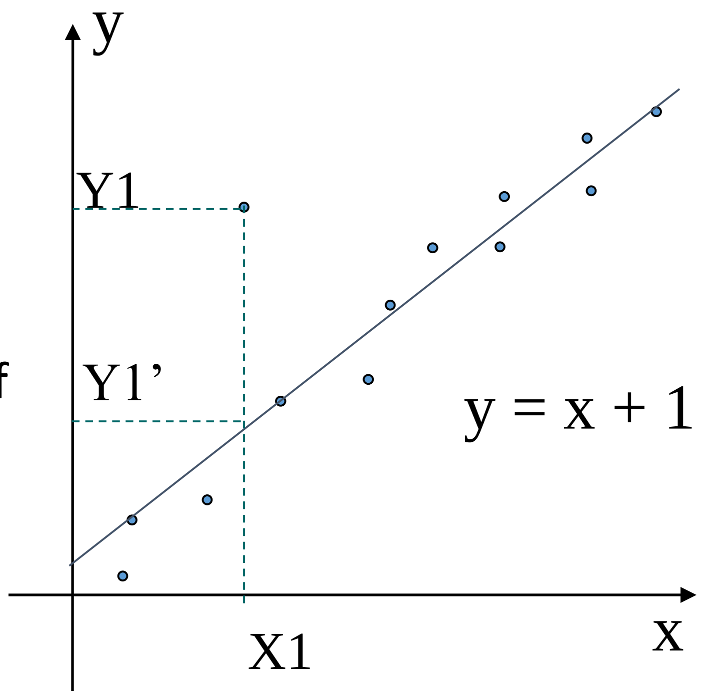


Frequency

Parametric Data Reduction: Regression and Log-Linear Models

- **Linear regression**
  - Data modeled to fit a straight line
  - Often uses the least-square method to fit the line
- **Multiple regression**
  - Allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- **Log-linear model**
  - Approximates discrete multidimensional probability distributions

Regression Analysis

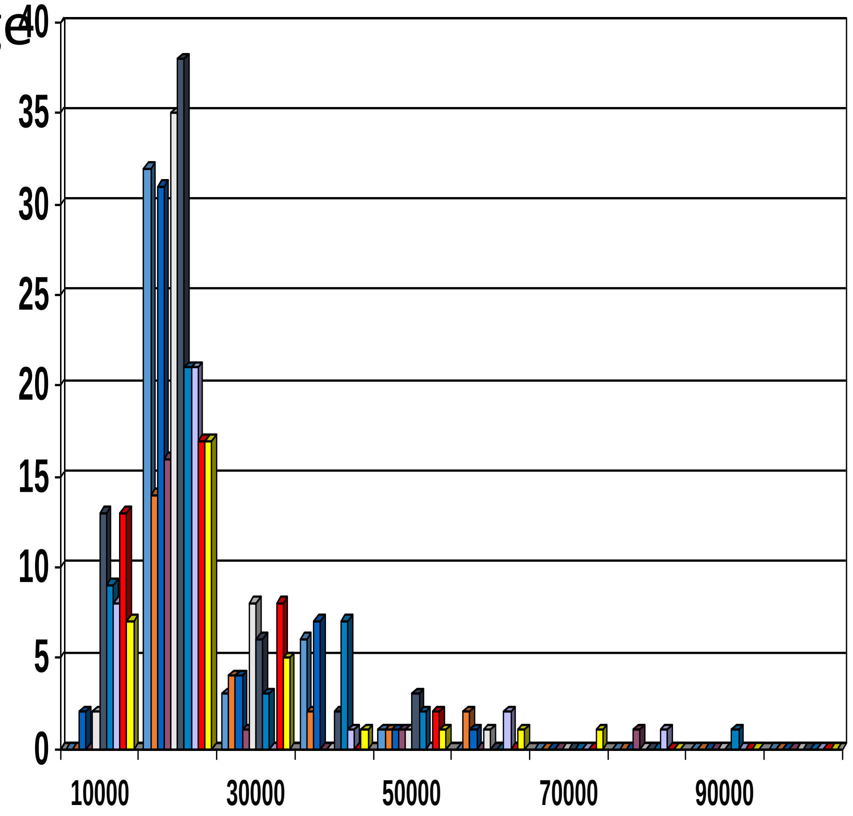


- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a ***dependent variable*** (also called ***response variable*** or *measurement*) and of one or more *independent variables* (aka. ***explanatory variables*** or ***predictors***)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly the best fit is evaluated by using the ***least squares method***, but other criteria have also been used

- Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships

Histogram Analysis

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
    - Equal-width: equal bucket range
    - Equal-frequency (or equal-depth)



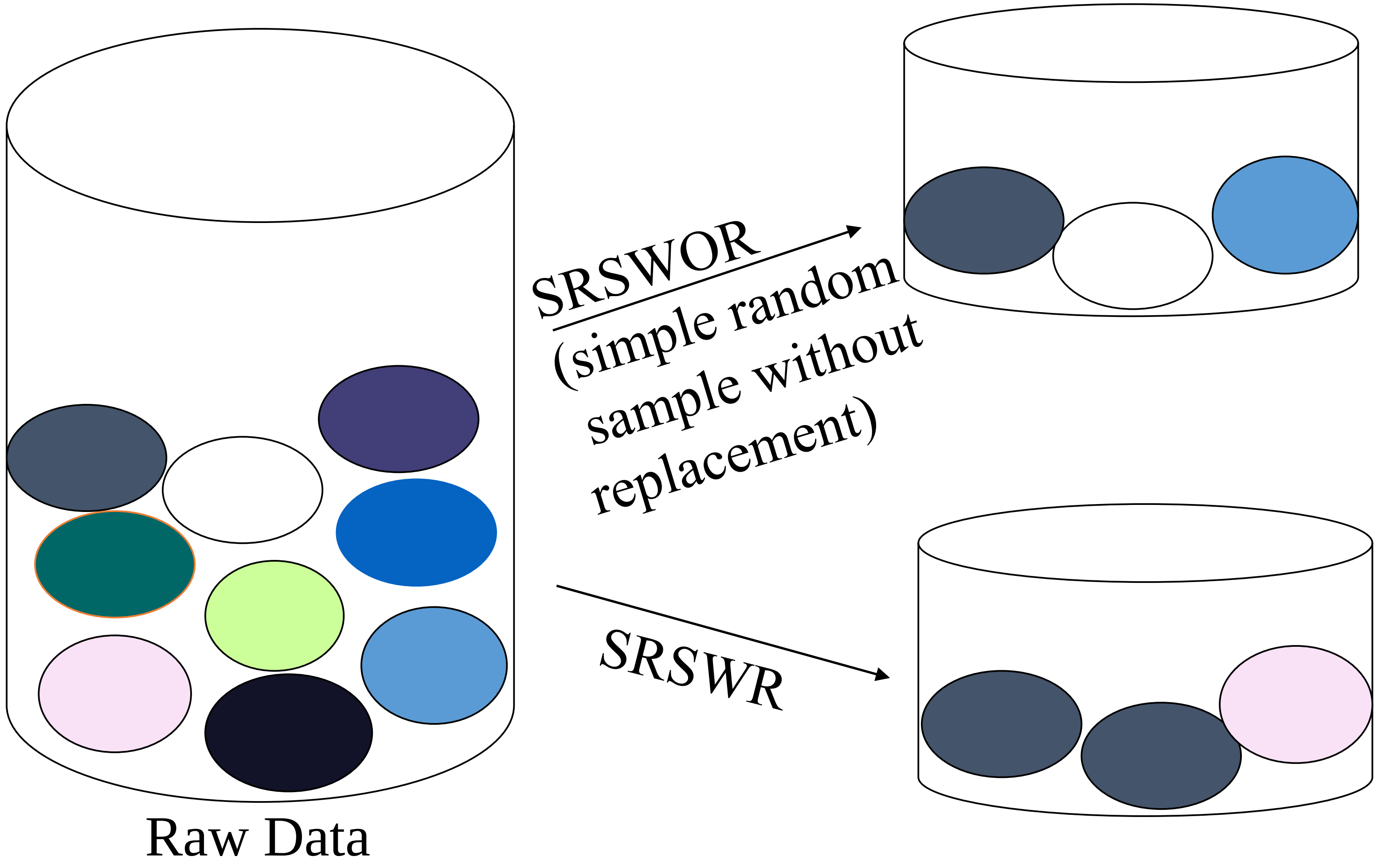
Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is “smeared”
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 10

Sampling

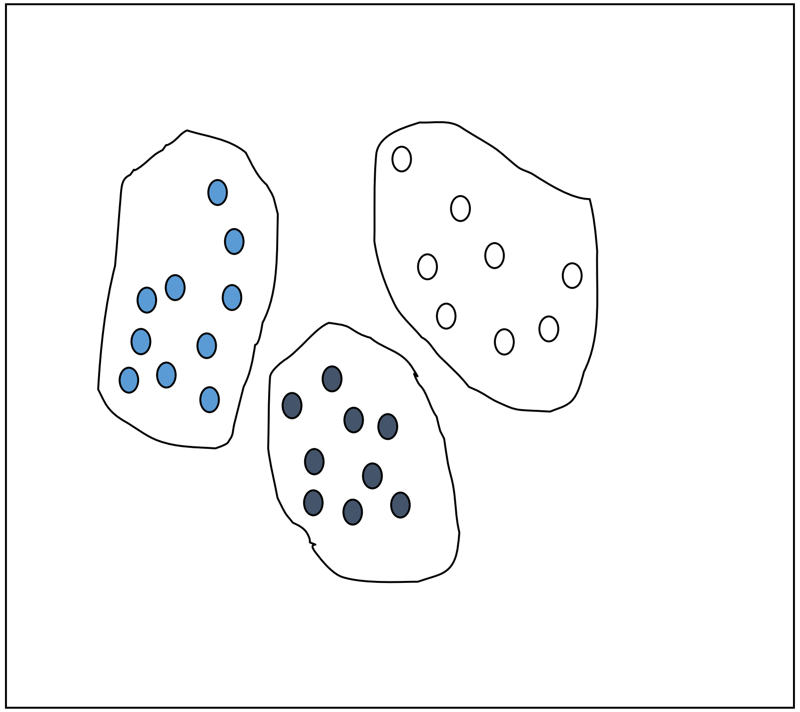
- Sampling: obtaining a small sample *s* to represent the whole data set *N*
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
  - Develop adaptive sampling methods, e.g., stratified sampling:
- Note: Sampling may not reduce database I/Os (page at a time)

Sampling: With or without Replacement

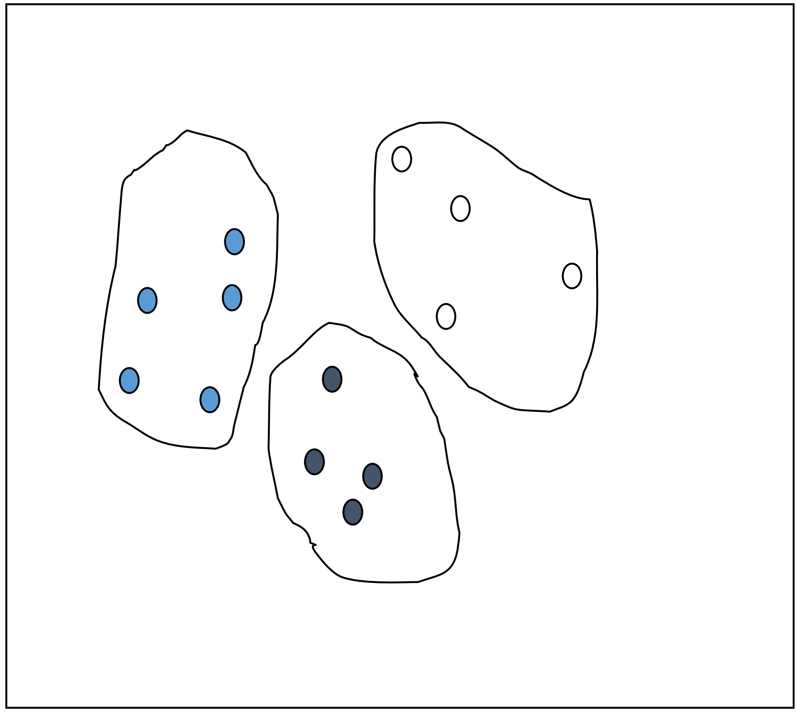


Sampling: Cluster or Stratified Sampling

Raw Data



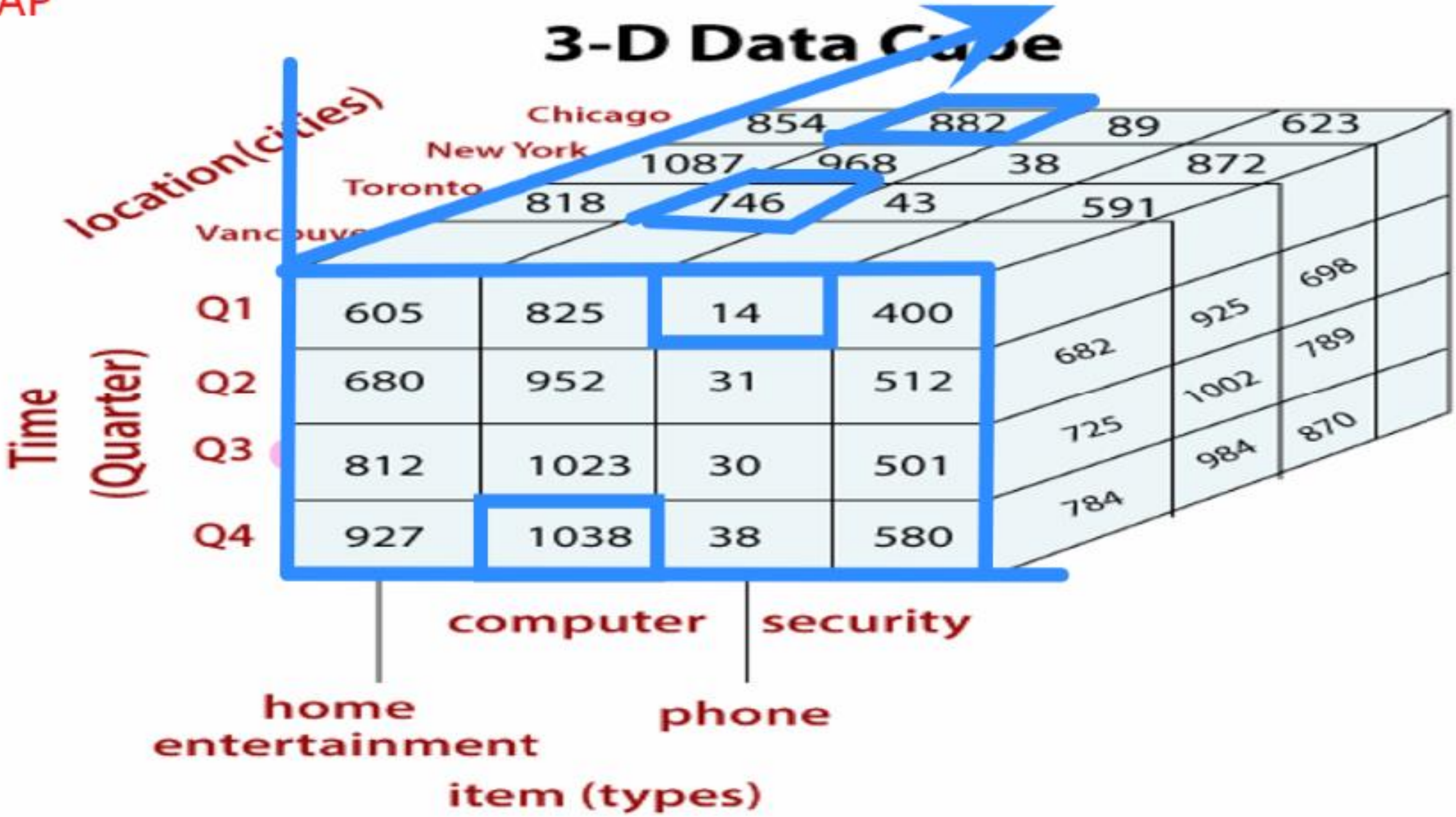
Cluster/Stratified Sample

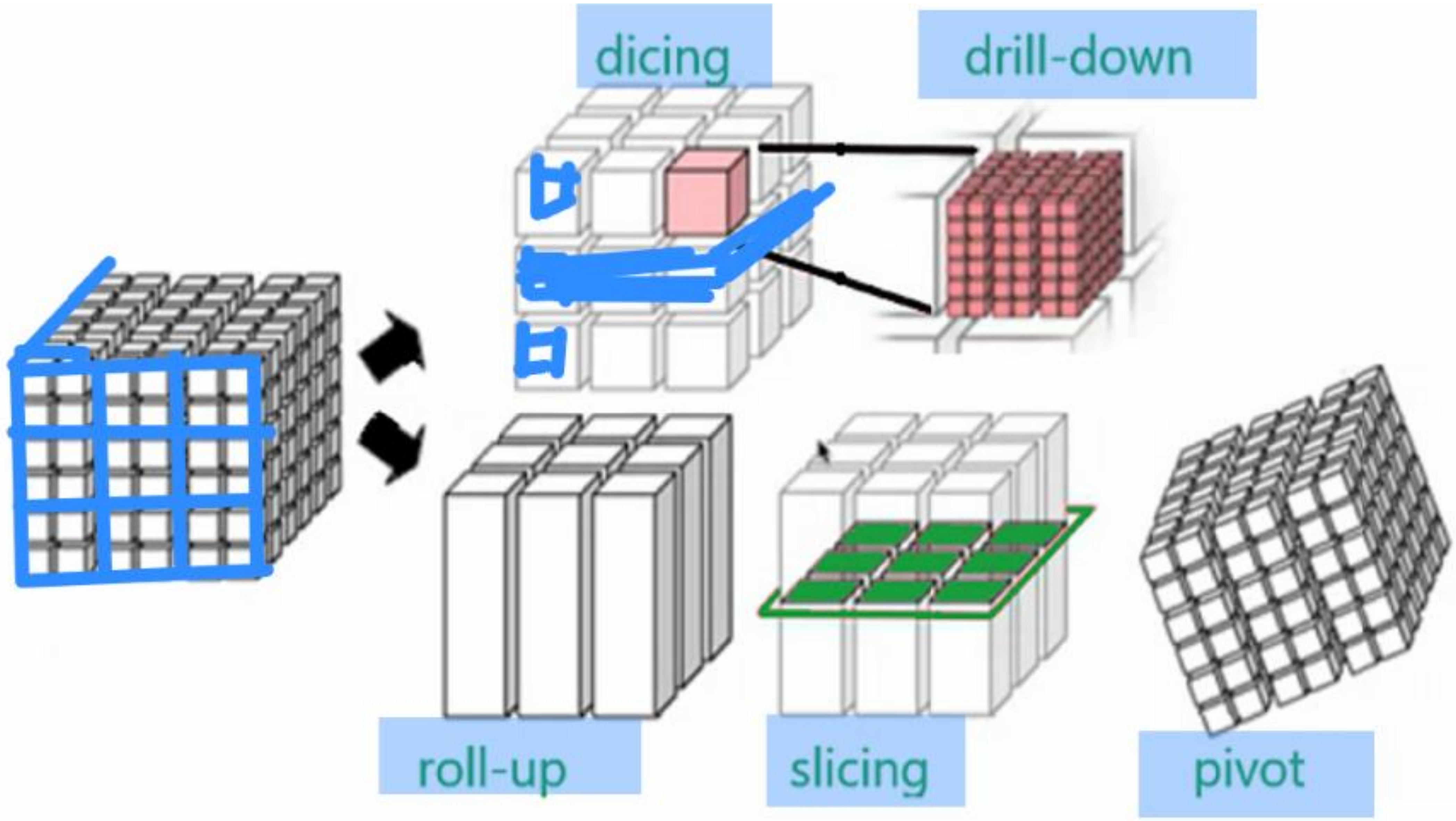


Data Cube Aggregation

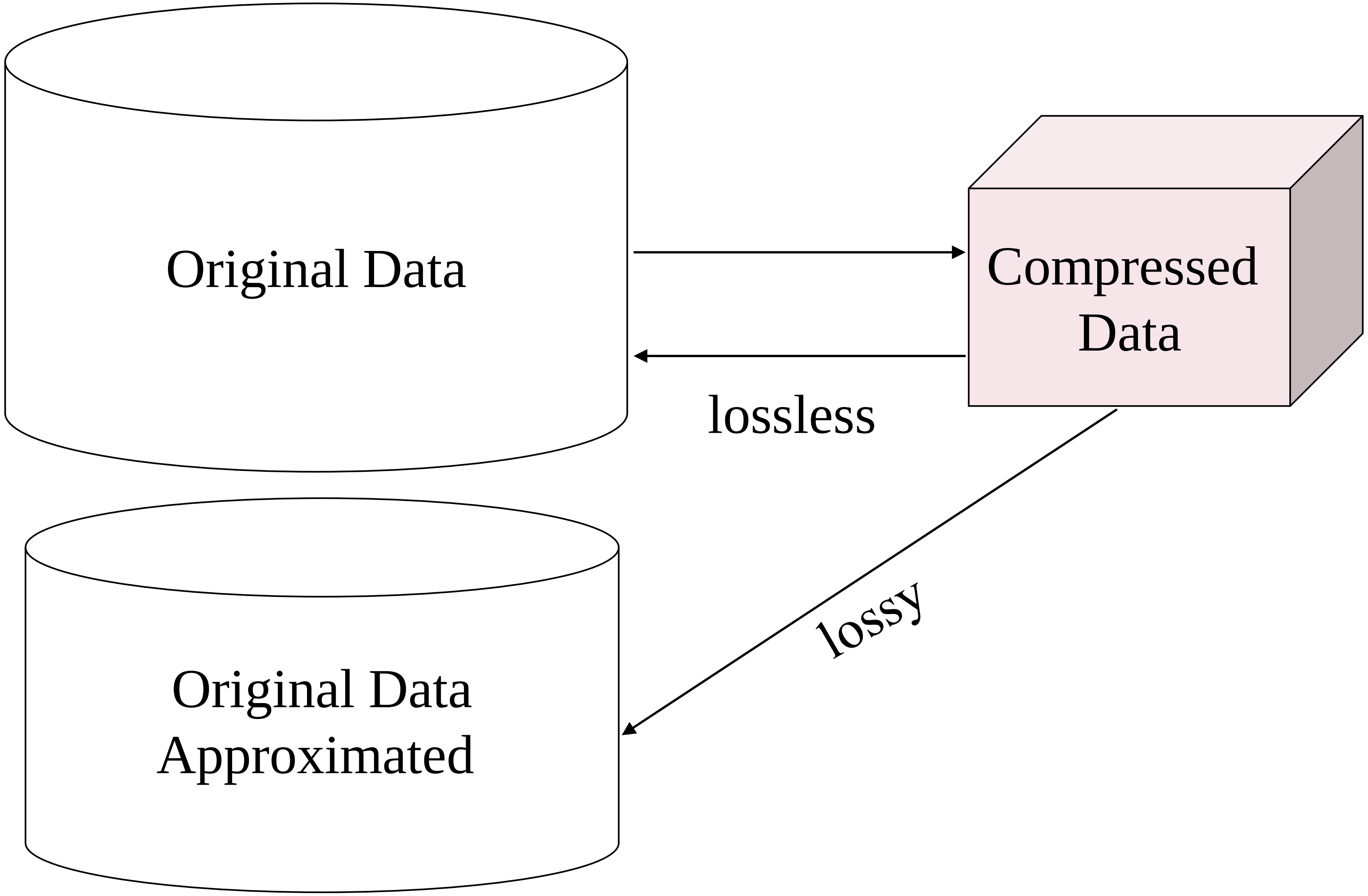
- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

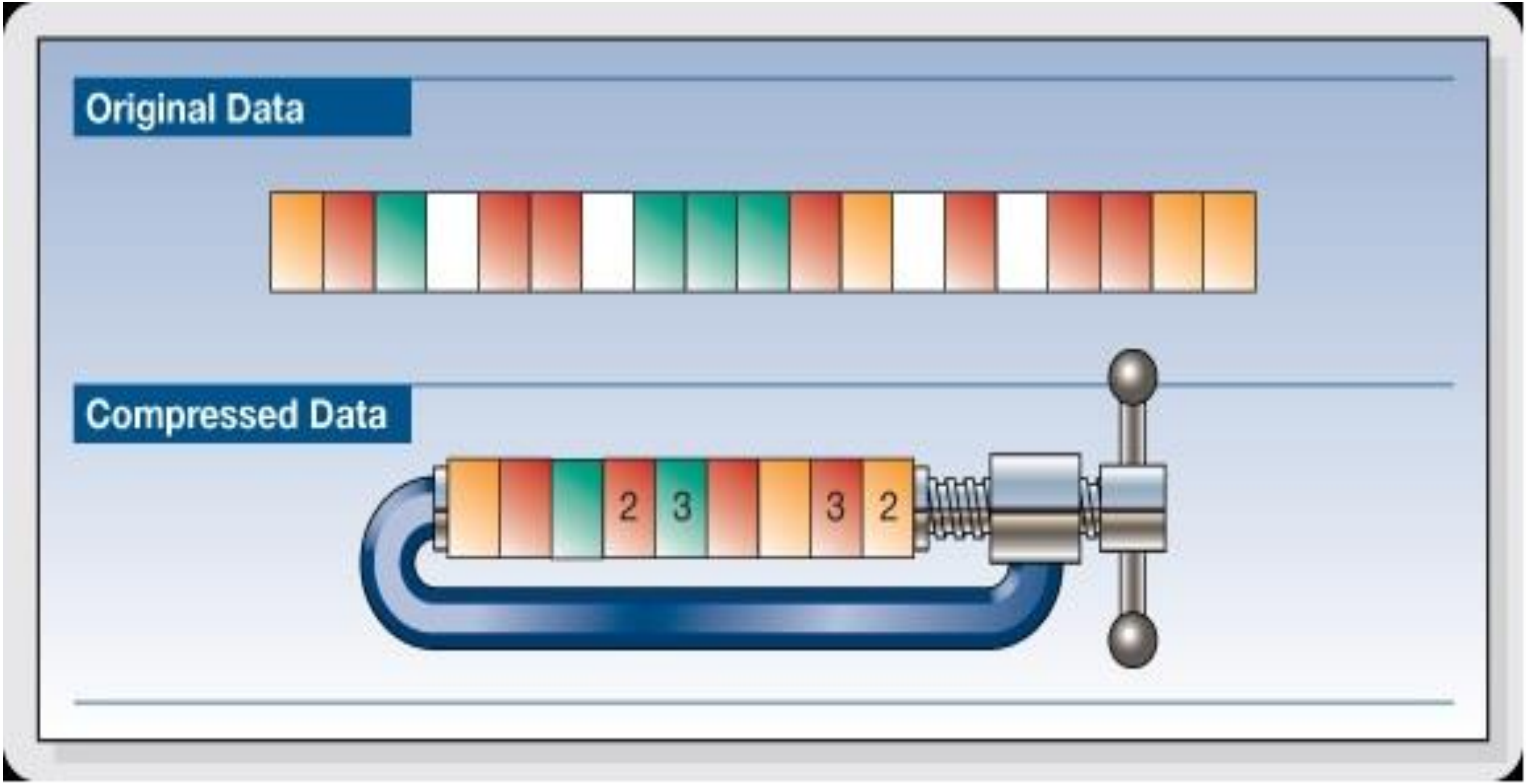
OLAP


3-D Data Cube
location(cities)
Chicago
New York
Toronto
Vancouver
854
882
89
623
1087
968
38
872
818
746
43
591
698
925
789
682
1002
870
725
984
784
Time (Quarter)
Q1
Q2
Q3
Q4
605
825
14
400
680
952
31
512
812
1023
30
501
927
1038
38
580
home entertainment
computer
phone
security
item (types)


dicing
drill-down
roll-up
slicing
pivot

Data Compression




Original Data
Compressed Data
2
3
3
2

Discretization

- Three types of attributes
  - **Nominal**—values from an unordered set, e.g., color, profession
  - **Ordinal**—values from an ordered set, e.g., military or academic rank
  - **Numeric**—real numbers, e.g., integer or real numbers
- **Discretization:** Divide the range of a continuous attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Reduce data size by discretization
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)
  - Discretization can be performed recursively on an attribute
  - Prepare for further analysis, e.g., classification

Binning Methods for Data Smoothing

❑Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (**equi-depth**) bins:

- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

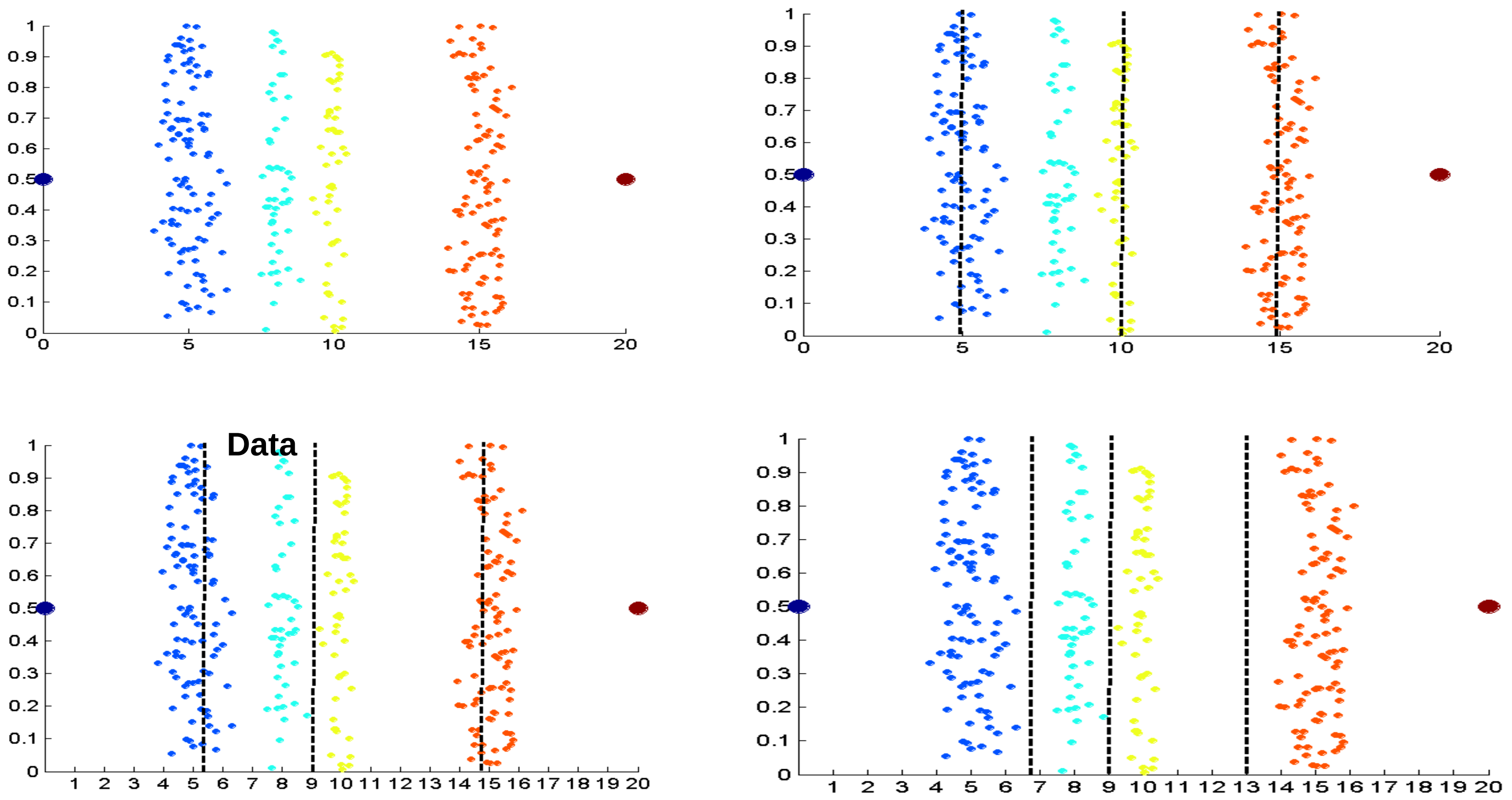
* Smoothing by **bin means**:

- Bin 1: 9, 9, 9, 9
- Bin 2: 23, 23, 23, 23
- Bin 3: 29, 29, 29, 29

* Smoothing by **bin boundaries**:

- Bin 1: 4, 4, 4, 15
- Bin 2: 21, 21, 25, 25
- Bin 3: 26, 26, 26, 34

Discretization Without Using Class Labels (Binning vs. Clustering)

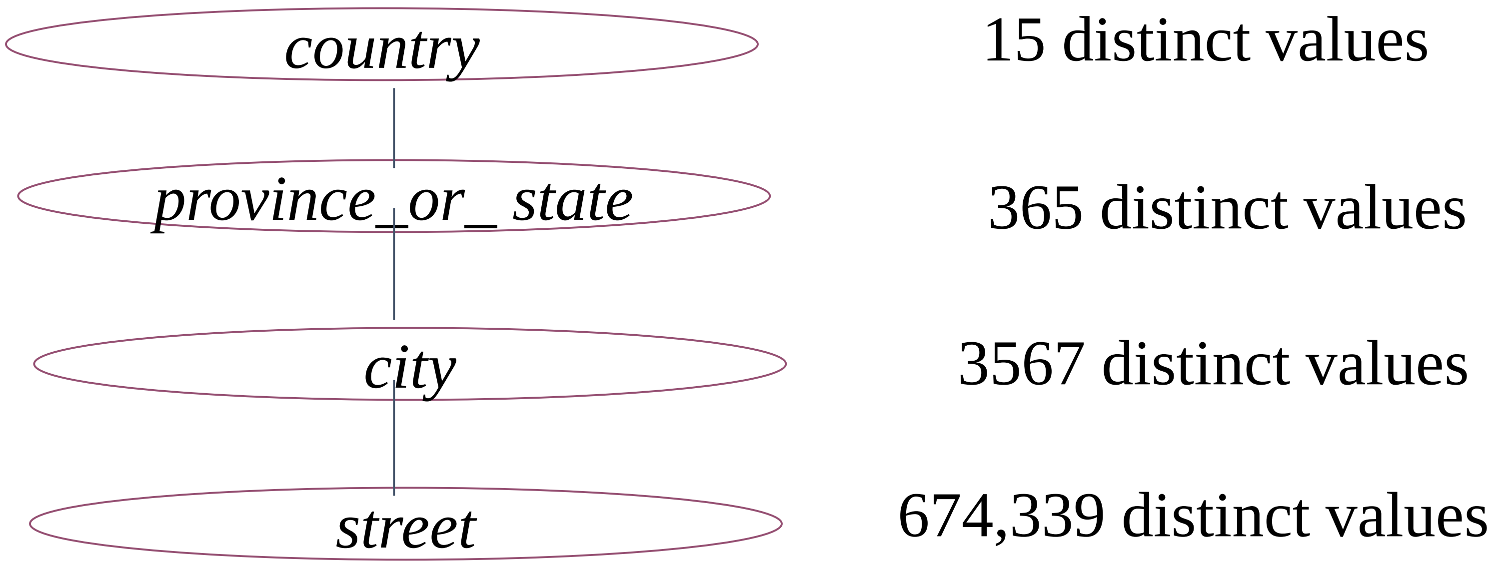


Equal frequency (binning)

K-means clustering leads to better results

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy
  - Exceptions, e.g., weekday, month, quarter, year



Summary

- **Data quality**: accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning**: e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
  - Entity identification problem
  - Remove redundancies
  - Detect inconsistencies
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

In [2]:
```
dataset= pd.read_csv('D:/Test/Data.csv')
```

In [4]:
```
dataset.head()
```

Out[4]

	0 Country	1 Age	2 Salary	3 Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

In [5]:
```
X=dataset.iloc[:,:-1].values
y=dataset.iloc[:,3].values
```

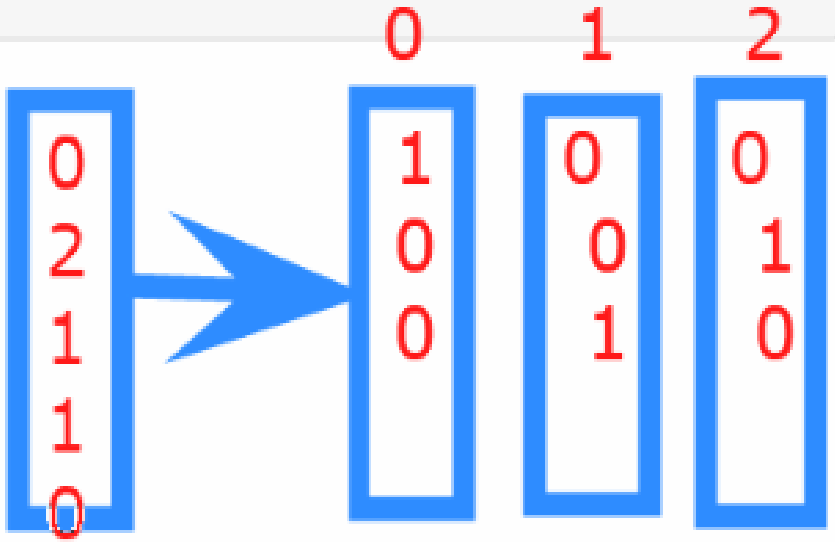
```
In [12]: from sklearn.preprocessing import LabelEncoder, OneHotEncoder
         labelX=LabelEncoder()
         X[:,0]=labelX.fit_transform(X[:,0])

In [13]: X

Out[13]: array([[0, 44.0, 72000.0],
                [2, 27.0, 48000.0],
                [1, 30.0, 54000.0],
                [2, 38.0, 61000.0],
                [1, 40.0, 63777.77777777778],
                [0, 35.0, 58000.0],
                [2, 38.77777777777778, 52000.0],
                [0, 48.0, 79000.0],
                [1, 50.0, 83000.0],
                [0, 37.0, 67000.0]], dtype=object)

In [ ]: from sklearn.preprocessing import OneHotEncoder

In [ ]:
```



```
In [2]: dataset= pd.read_csv('D:/Test/Data.csv')
```

```
In [11]: dataset.head(10)
```

Out[11]:

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

y

Yes ✓

No ✓

Logistic Regression

```
In [5]: X=dataset.iloc[:,:-1].values
        y=dataset.iloc[:,3].values
```