Big Data Analysis and Approximations in Information Systems

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USA

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Outline

- Introduction

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- Overview

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- Rough Set Theory

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- Big Data Analysis

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- Big Data Analysis
- Concluding Remarks

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- A zettabyte is 1,000 000,000,000,000,000,000 bytes 10^{21}

Technology Growth

	90s	00s	10s
Capacity	2.1GB	200GB	3,000GB
Price	$157/GB	$1.05/GB	$0.05/GB
Speed	16.6MB/s	56.5 MB/s	210 MB/s
Time to read whole Disk	126 seconds	58 minutes	4 hours

Figure: Storage capacity has improved so much that collecting data is cheaper than ever

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- The increasing volume and detail of information captured by enterprises, the rise of multimedia, social media, and the Internet of Things will fuel exponential growth in data for the foreseeable

Big Data Trends

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- Rise of metadata catalogs helps people find analysis-worthy big data

Demand of talent

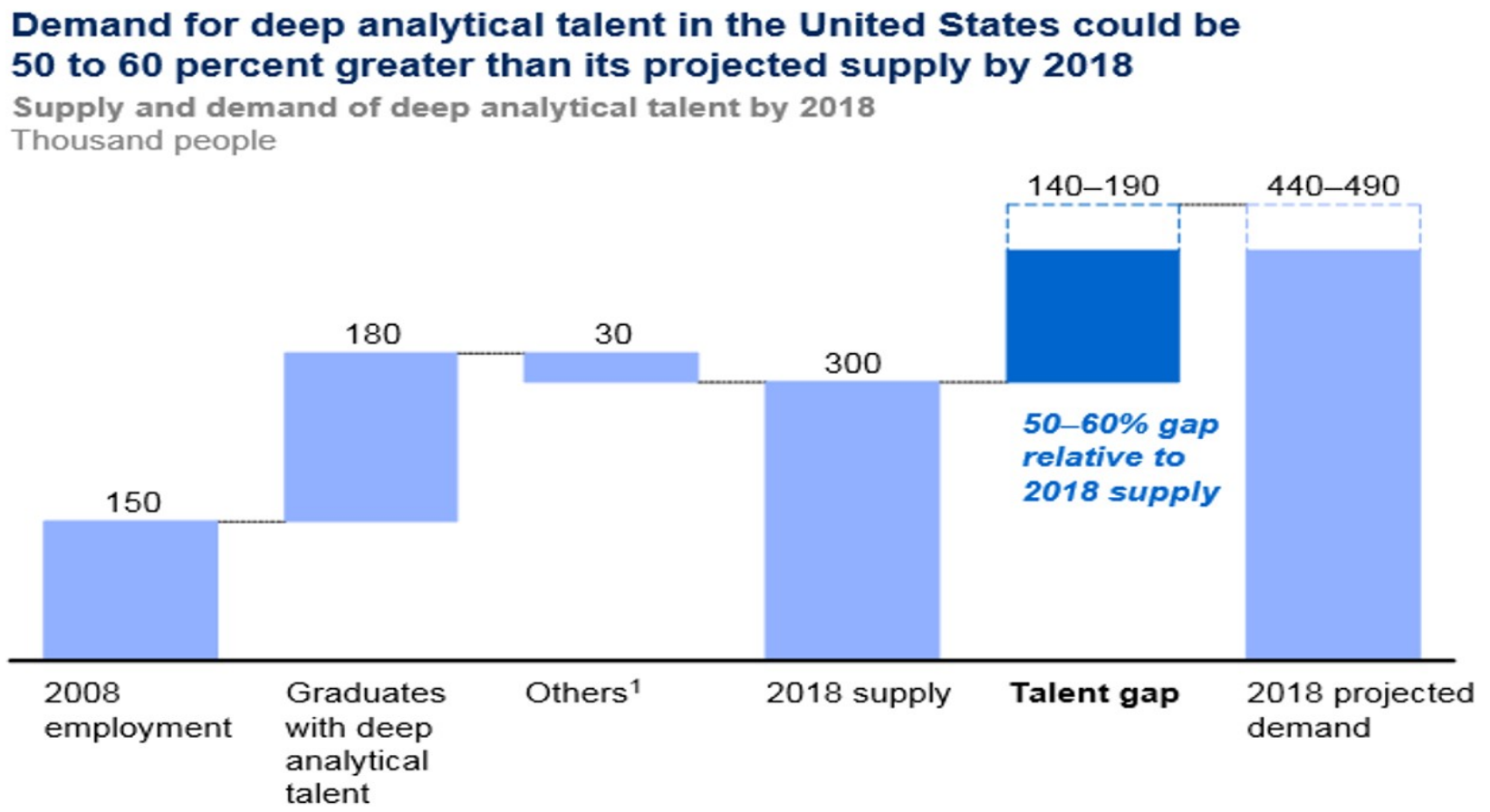


Figure: Supply and demand of deep analytic talent

Intenet of Things

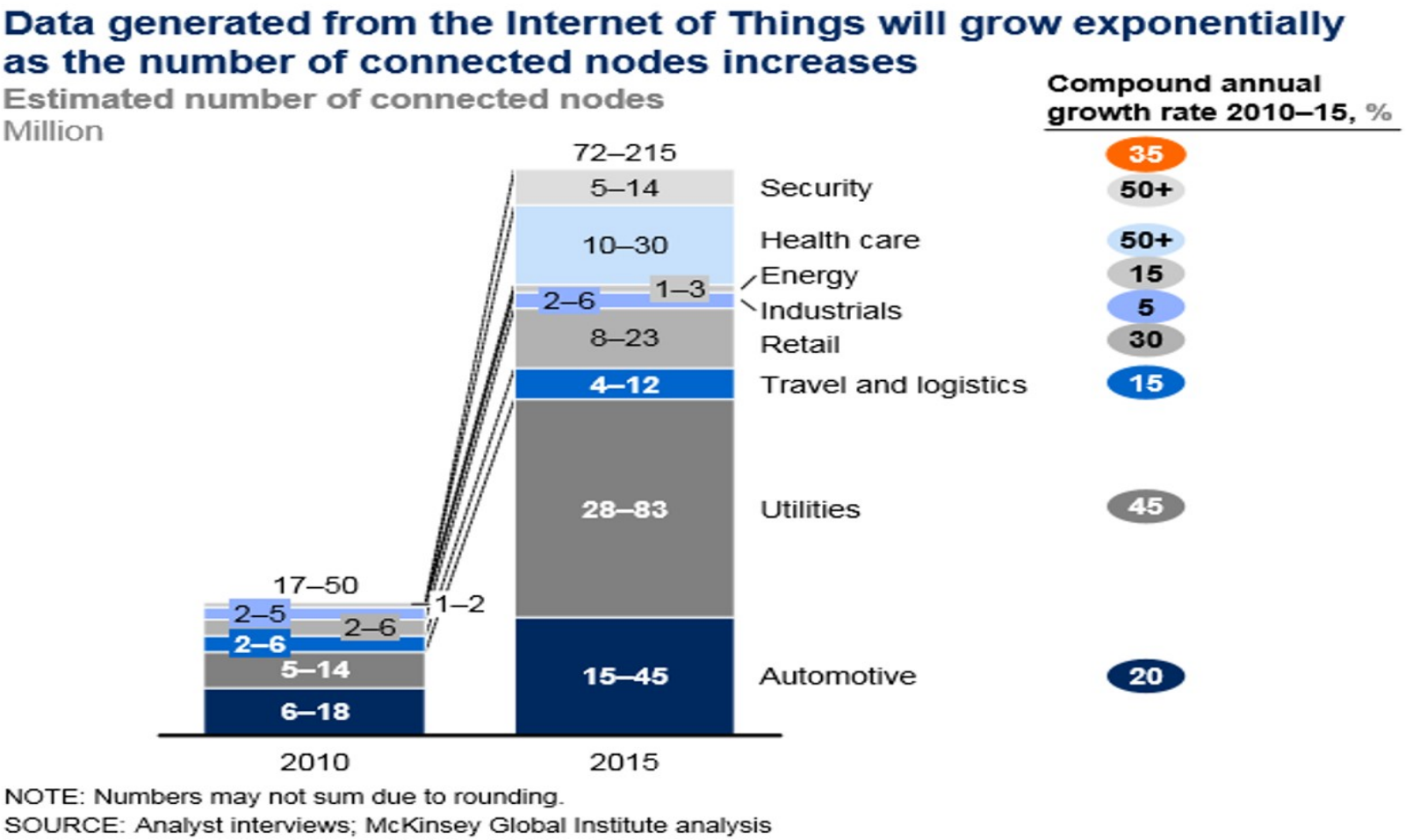


Figure: IOT

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- Growing technological ability to capture, aggregate, and process an ever-greater volume, velocity, variety, value and veracity of data.
- Large, diverse, complex, longitudinal, and/or distributed datasets generated from instruments, sensors, Internet transactions, email, video, click streams, and/or all other digital sources available today and in the future.

Value, Veracity, Viability, Visualization, Vulnerability

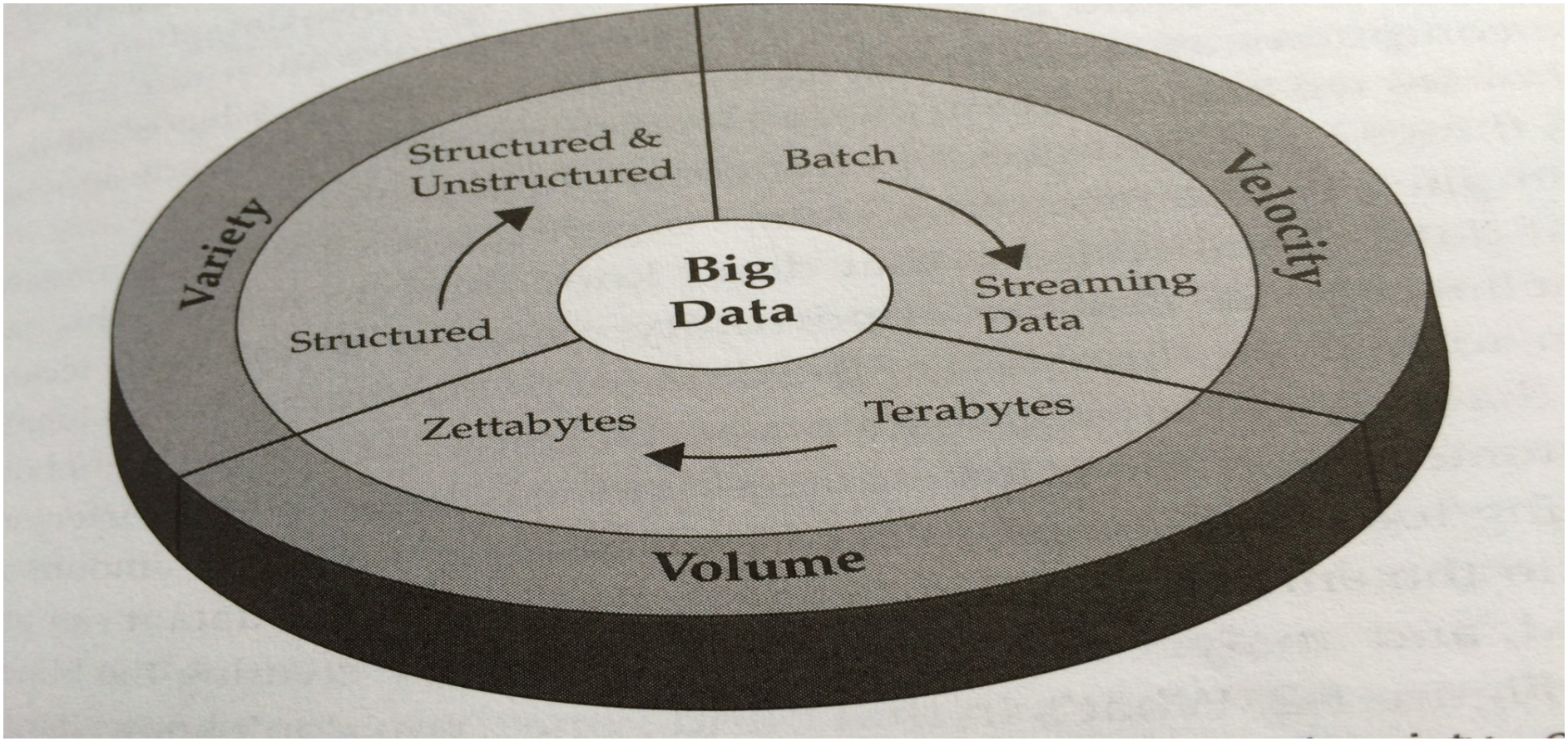


Figure: 8V

Finding new value in Data

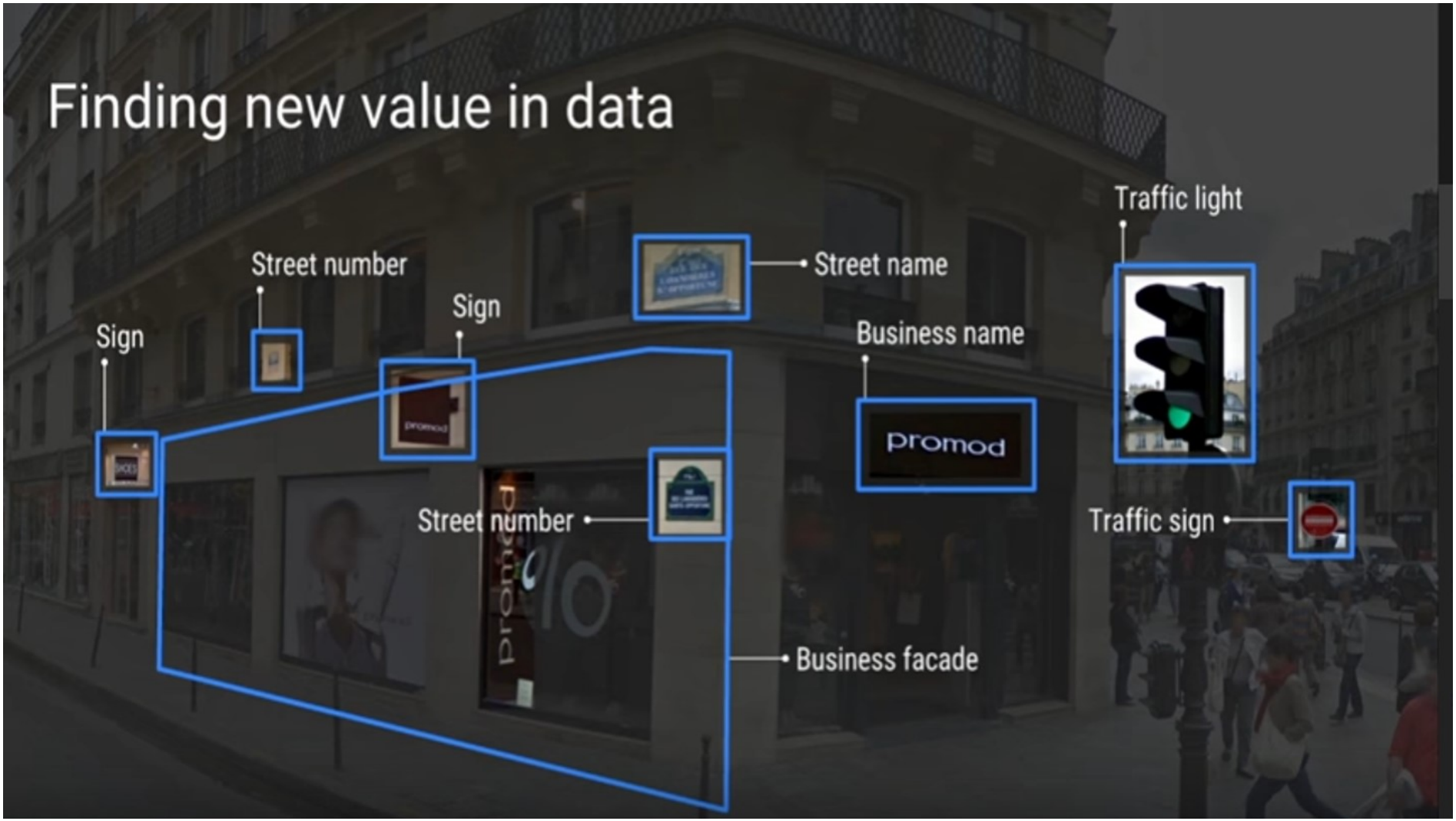


Figure: knowledge discovery

Service

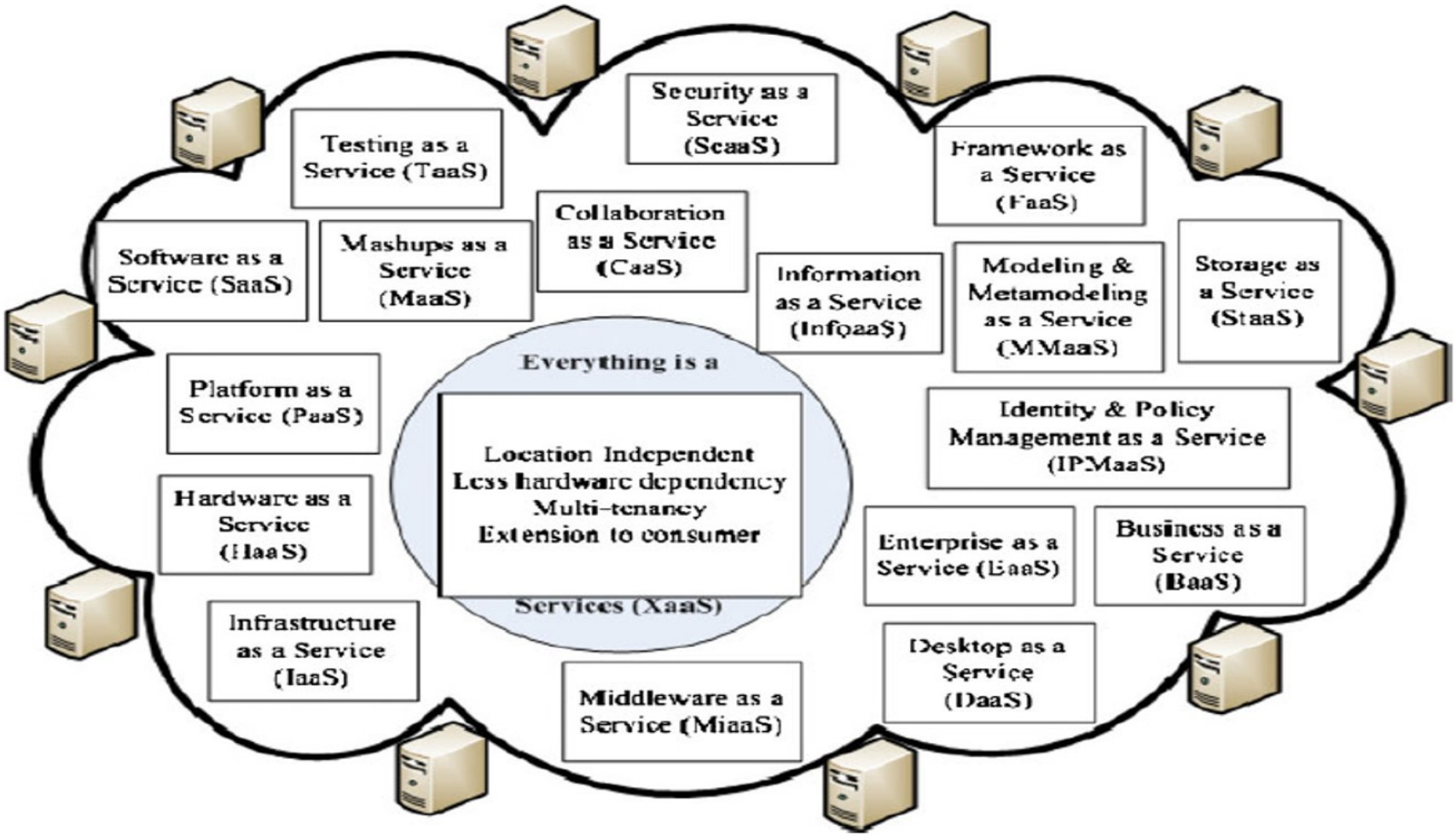


Figure: As a Service

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- HDFS
  - Hadoop Distributed File System
- MapReduce

The flow of data in a simple MapReduce job

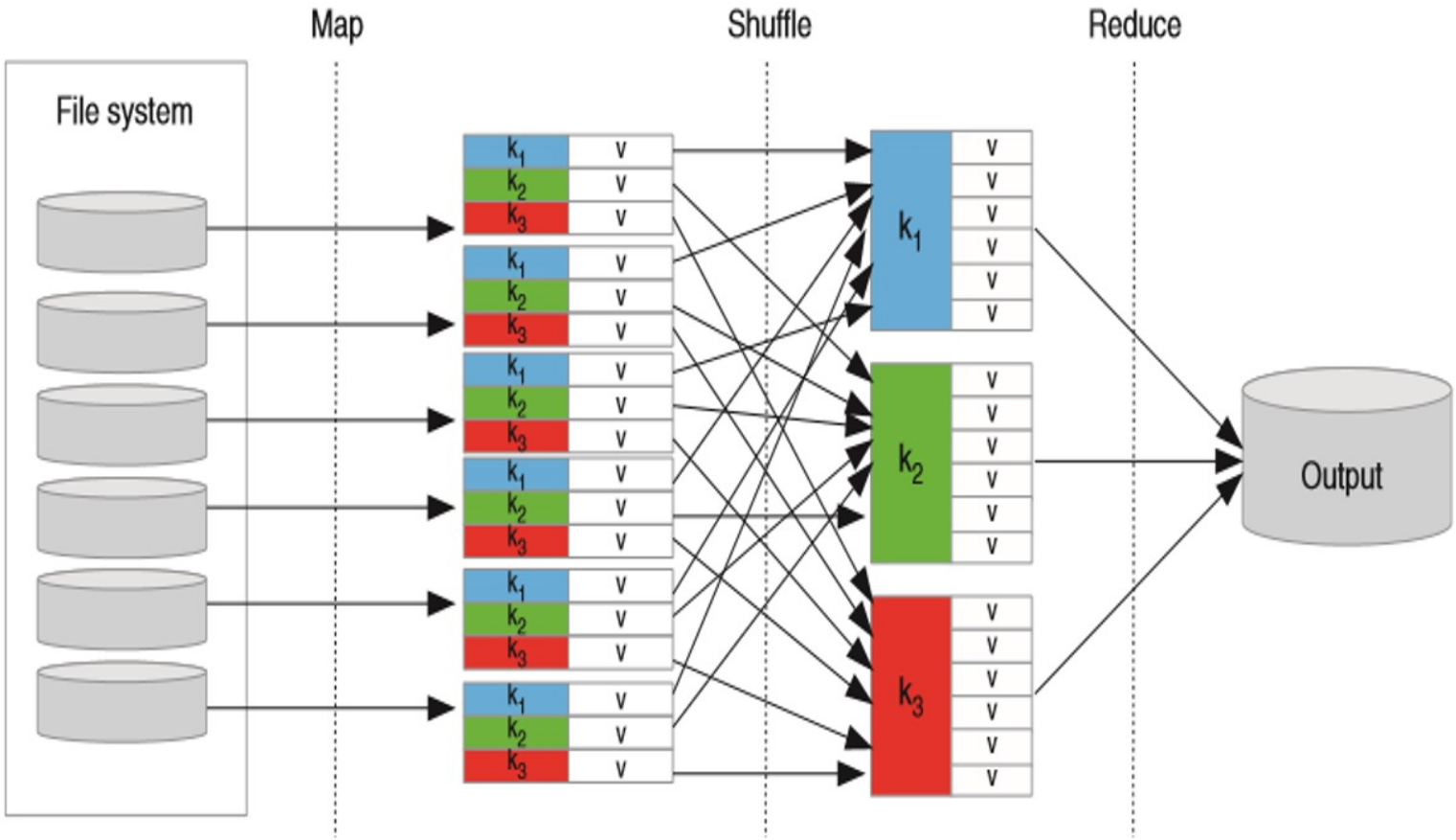


Figure: Map Reduce

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- Both multi-stage and interactive apps require faster data sharing across parallel jobs

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- Compatible with Hadoop's storage APIs
  - Can read/write to any Hadoop-supported system, including HDFS, HBase, SequenceFiles, etc.

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- feature selection, decision making, rule mining, data prediction, , environment, banking, medicine, bioinformatics, pattern recognition, data mining, machine learning and others.

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- a: $U \longmapsto V_a$

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- Transitive Property: if xRy and yRz, then xRz.

There are some identical objects in the following data set. For instance, objects x_1 and x_3 cannot be distinguished.

Table 1

U	a_1	a_2	a_3
x_1	2	1	3
x_2	3	2	1
x_3	2	1	3
x_4	2	2	3
x_5	1	1	4
x_6	1	1	2
x_7	3	2	1
x_8	1	1	4
x_9	2	1	3
x_{10}	3	2	1

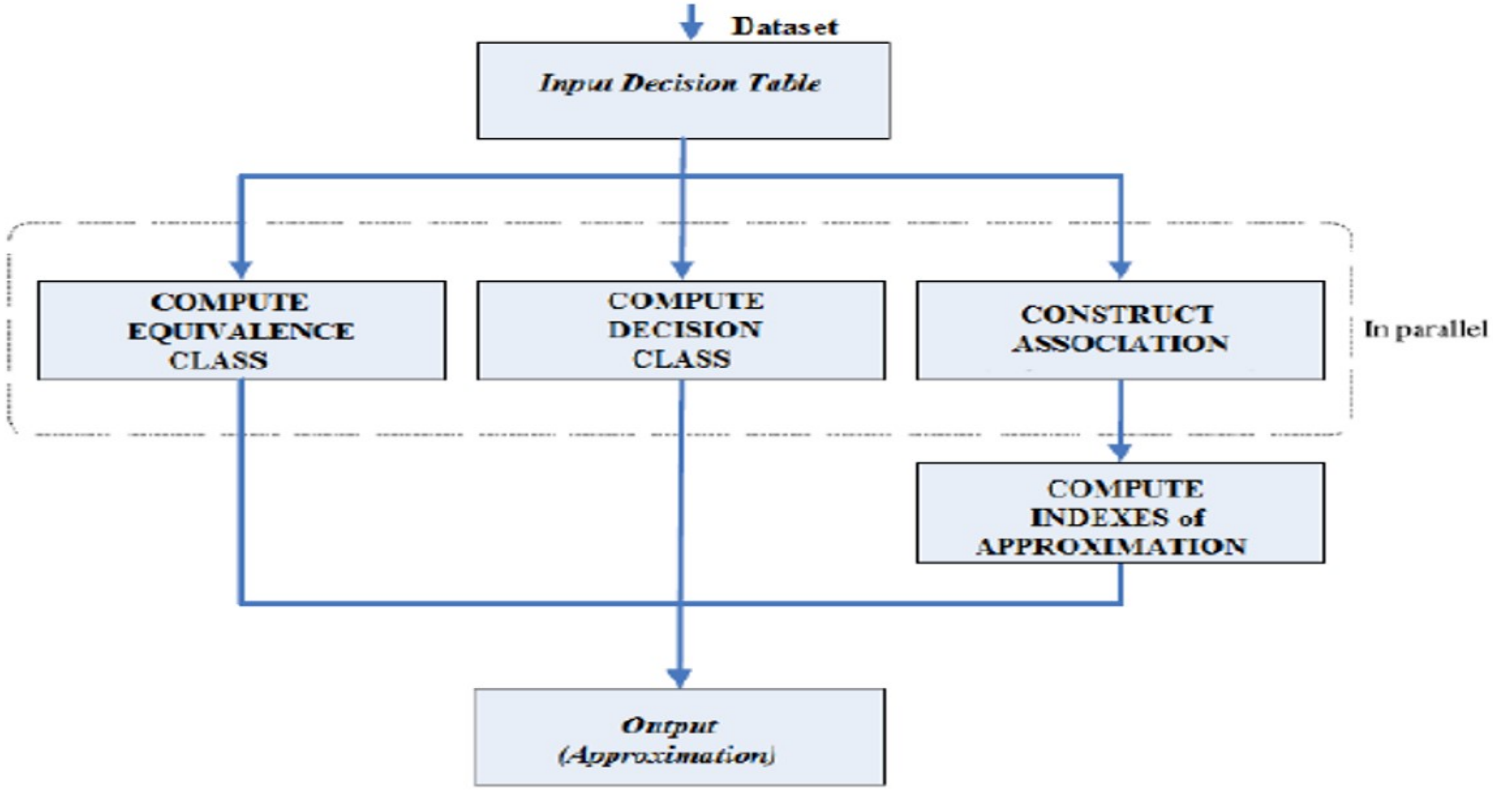
Equivalence classes

Table 2

U/A	a_1	a_2	a_3
$\{x_1, x_3, x_9\}$	2	1	3
$\{x_2, x_7, x_{10}\}$	3	2	1
$\{x_4\}$	2	2	3
$\{x_5, x_8\}$	1	1	4
$\{x_6\}$	1	1	2

Figure: Each class is an elementary set of the universe U associated with A, U/A

Speed up – number of nodes; Scale up – distributed file system; Size up – larger system



Method to Calculate Approximation Based on Map Reduce

Figure: Calculate approximation

Approximation

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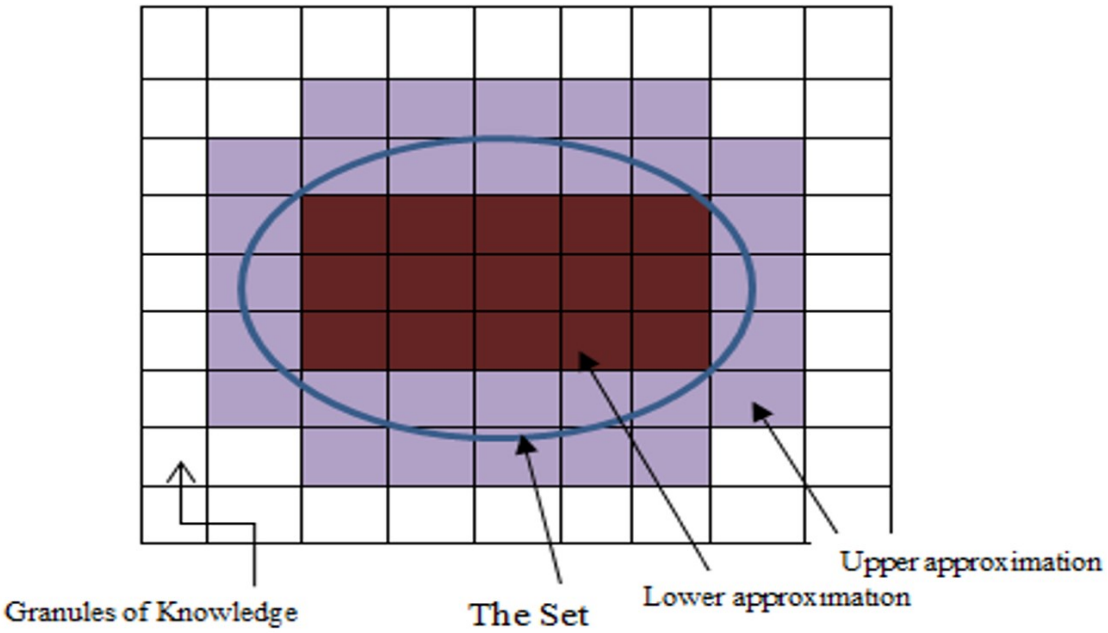


Figure: lower and upper approximations

Inclusion degree

Let U be a finite and nonempty set, known as the universe of discourse. We use the symbol " $\subseteq$ " (" $\subset$ ") to denote set inclusion (strict set inclusion, respectively).

The cardinality of a set $S \subseteq U$, denoted $|S|$, is the number of elements in S.

The power set of U is the collection $2^U = \{S \mid S \subseteq U\}$.

The inclusion degree of a nonempty set $X \subseteq U$ in a set $Y \subseteq U$ is defined as

$$I(X,Y) = \frac{|X \cap Y|}{|X|}. \tag{2.1}$$

Let us define $Pr : 2^U \longrightarrow [0,1]$ as follows:

$$Pr(X) = \frac{|X|}{|U|}, \quad \forall \ X \subseteq U. \tag{2.2}$$

The greatest lower bound (inf or infimum) and least upper bound (sup or supremum) of a subset S of the unit interval $[0,1]$ will be denoted by inf S and sup S, respectively.

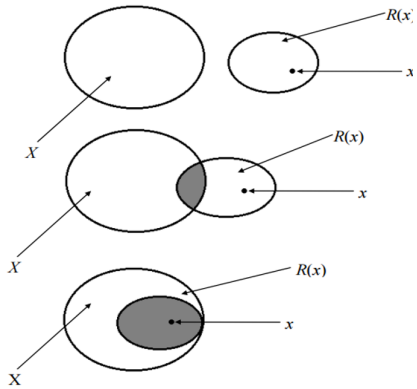
Figure: X and Y

Inclusion degree

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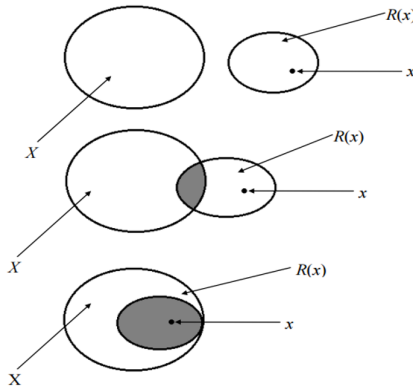
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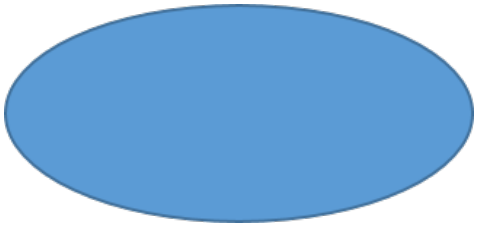
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Decision Table

Fact	Days	Solar energy	Volcanic activity	Residual	Temperature
1	20	Medium	High	Low	High
2	30	High	High	High	High
3	34	Medium	Low	High	Low
4	70	High	High	Medium	High
5	90	Medium	Low	High	High
6	120	Low	Low	Low	Low

Inclusion degree

2.1 VP-models under decision tables

The knowledge representation in the rough set model is often structured in a decision table which is a 4-tuple $(U, Q = C \cup D, V, f)$,

where U is a nonempty finite universe, C is a nonempty finite set of condition attributes, D is a nonempty finite set of decision attributes, $C \cap D = \emptyset$, $V = \bigcup_{q \in Q} V_q$ and V_q is a domain of the attribute q, and

$$f : U \times Q \longrightarrow V$$

is an information function such that $f(x, q) \in V_q$ for every $x \in U$ and $q \in Q$.

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2.1 VP-models under decision tables

The knowledge representation in the rough set model is often structured in a decision table which is a 4-tuple $(U, Q = C \cup D, V, f)$,

where U is a nonempty finite universe, C is a nonempty finite set of condition attributes, D is a nonempty finite set of decision attributes, $C \cap D = \emptyset$, $V = \bigcup_{q \in Q} V_q$ and V_q is a domain of the attribute q, and

$$f : U \times Q \longrightarrow V$$

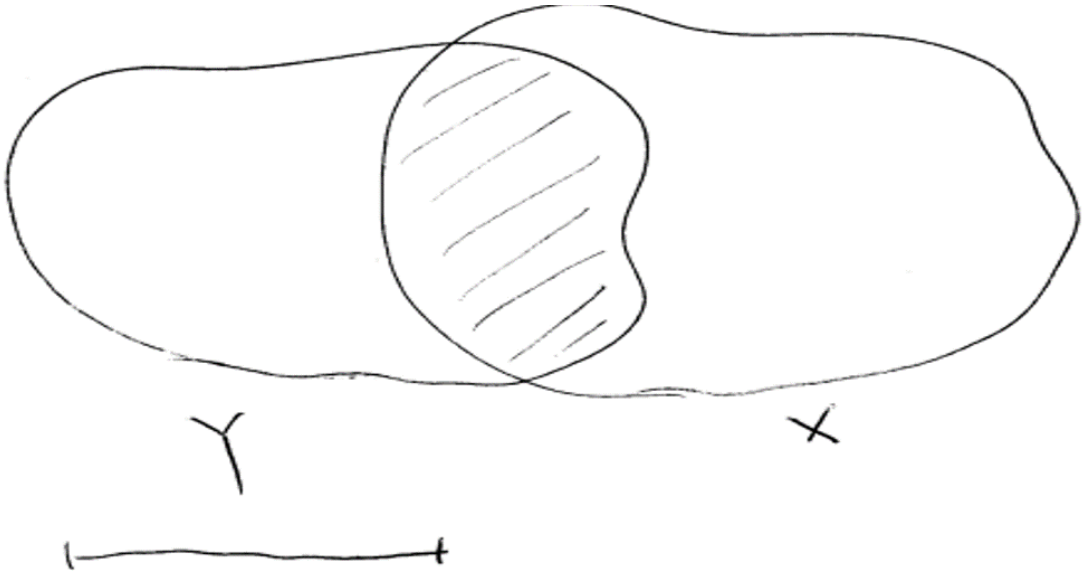
is an information function such that $f(x, q) \in V_q$ for every $x \in U$ and $q \in Q$.

Every nonempty subset P of condition attributes C, or decision attributes D, generates an equivalence relation on U, denoted by $\hat{P}$ and defined as follows [12].

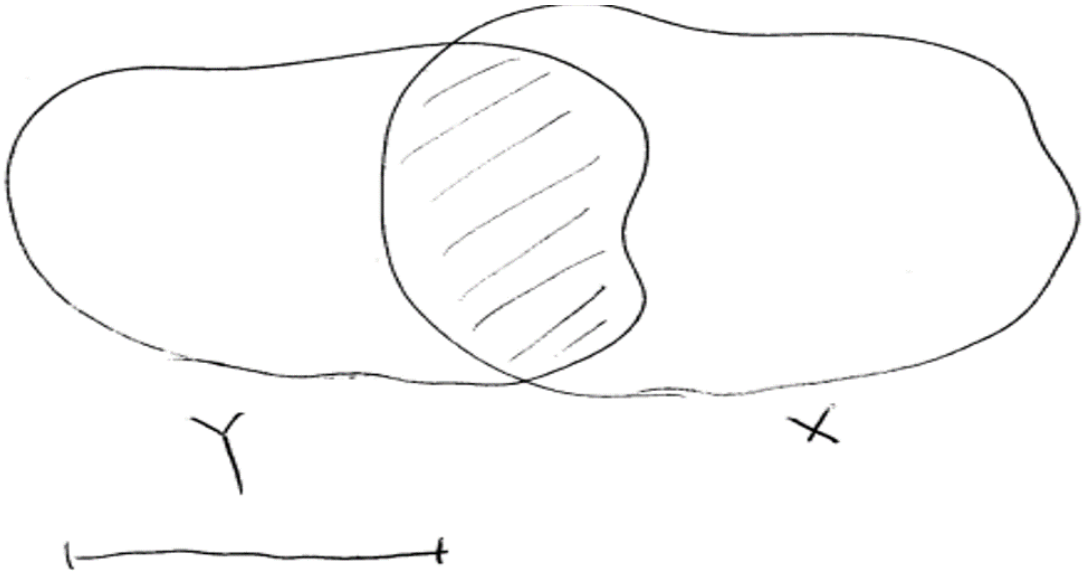
$$\hat{P} = \{(x, y) \in U \times U \mid \forall\, q \in P, f(x, q) = f(y, q)\}. \tag{2.4}$$

Let $P^* = \{P_1, P_2, \cdots, P_{|P^*|}\}$ denote the partition on U induced by equivalence relation $\hat{P}$. Each member of D^* will be called a decision class.

Inclusion degree

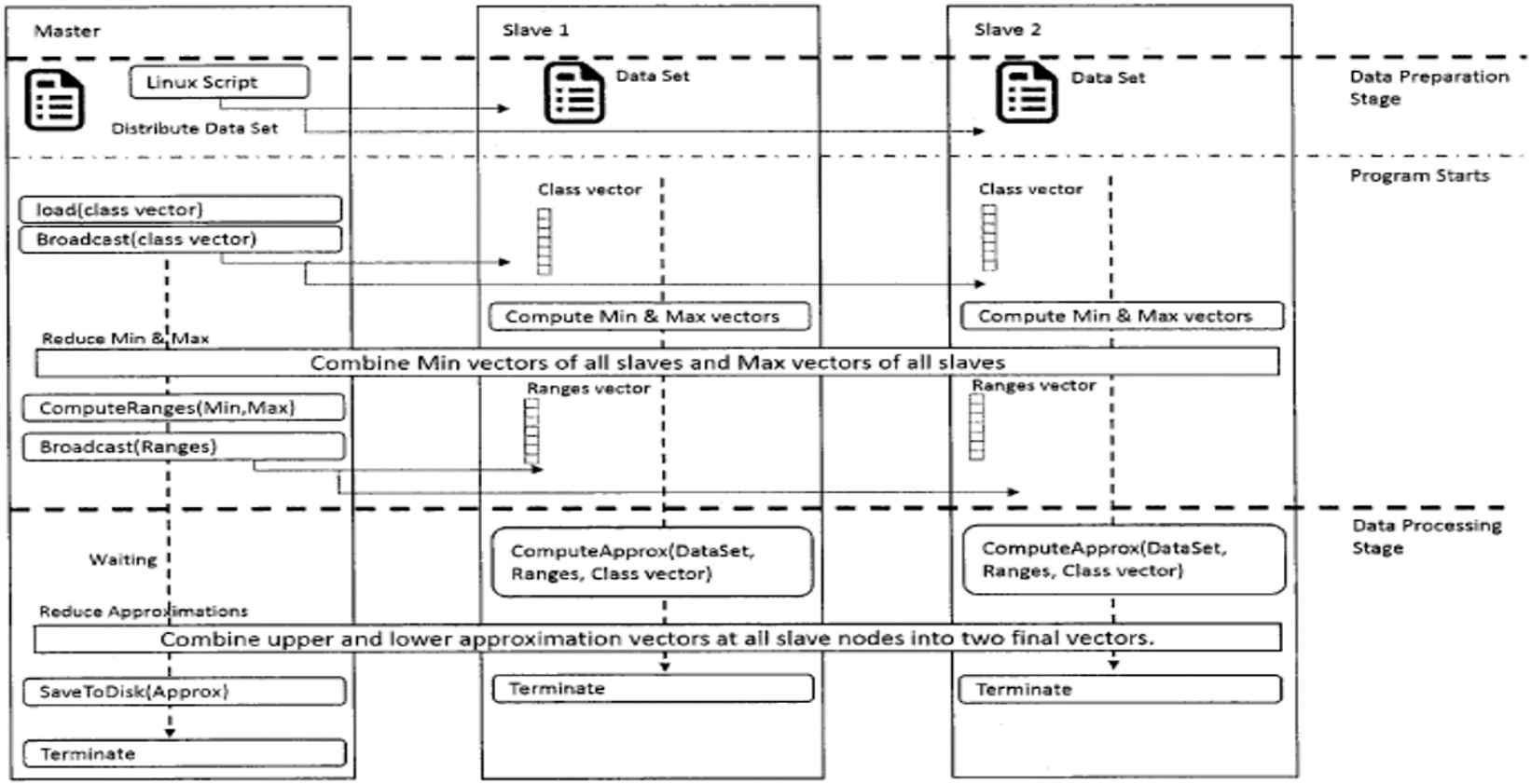


Inclusion degree





Process


Master
Slave 1
Slave 2
Linux Script
Distribute Data Set
Data Set
Data Set
Data Preparation Stage
Program Starts
load(class vector)
Broadcast(class vector)
Class vector
Class vector
Compute Min & Max vectors
Compute Min & Max vectors
Reduce Min & Max
Combine Min vectors of all slaves and Max vectors of all slaves
ComputeRanges(Min,Max)
Broadcast(Ranges)
Ranges vector
Ranges vector
Data Processing Stage
Waiting
ComputeApprox(DataSet, Ranges, Class vector)
ComputeApprox(DataSet, Ranges, Class vector)
Reduce Approximations
Combine upper and lower approximation vectors at all slave nodes into two final vectors.
SaveToDisk(Approx)
Terminate
Terminate
Terminate

Example

Fact	Days	Solar energy	Volcanic activity	Residual	Temperature
1	20	Medium	High	Low	High
2	30	High	High	High	High
3	34	Medium	Low	High	Low
4	70	High	High	Medium	High
5	90	Medium	Low	High	High
6	120	Low	Low	Low	Low

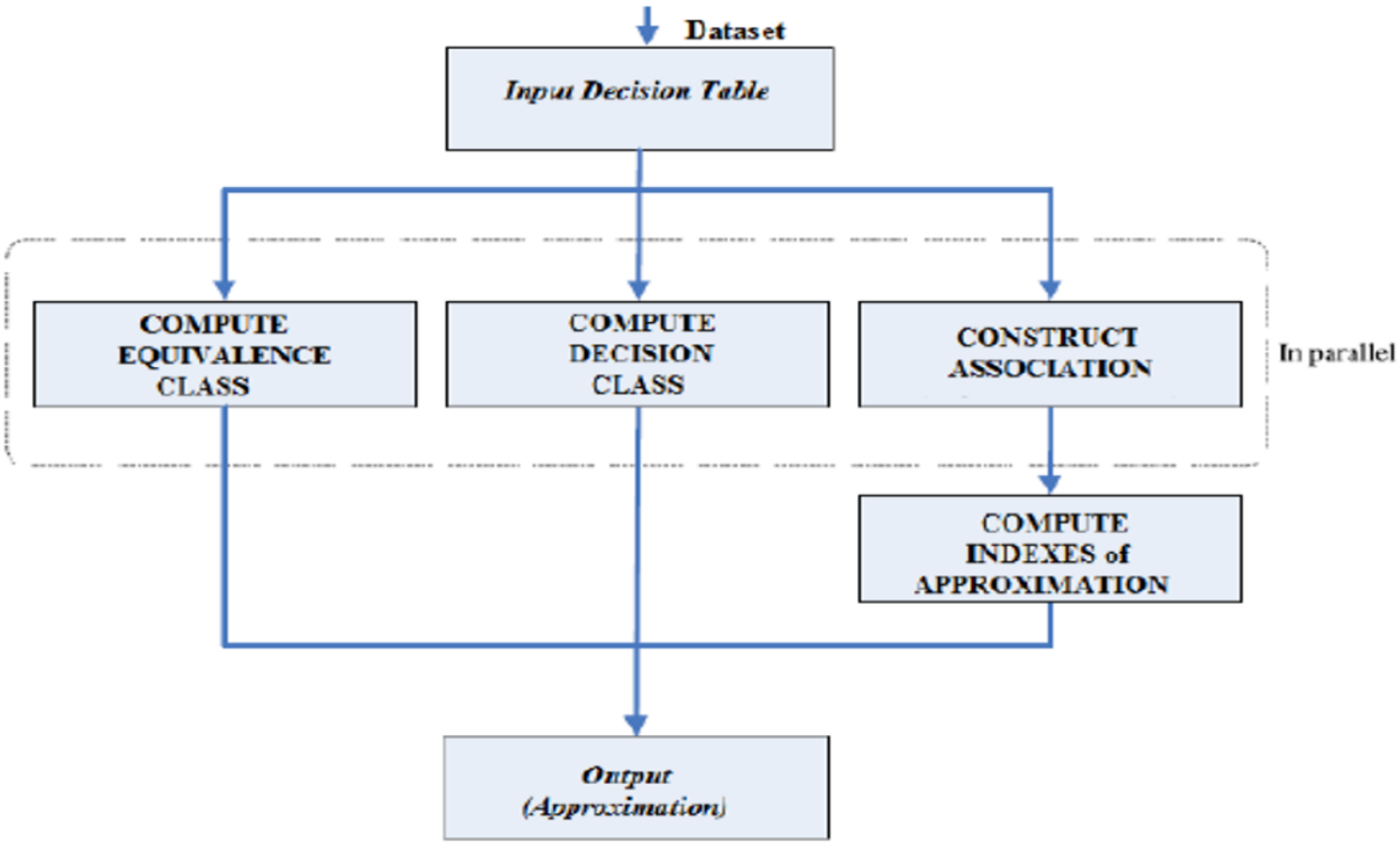
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- Low solar energy certainly causes low temperature;
- Medium solar energy and high volcanic activity or high solar energy certainly causes high temperature.

Map Reduce



Method to Calculate Approximation Based on Map Reduce

Concluding Remarks

- VPGRST

Concluding Remarks

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- VPGRST and its -reduct

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- VPGRST and its -reduct
- FRST

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Concluding Remarks

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- VPGRS-incomplete decision tables

Conclusions

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- There's the supply chain aspect of manufacturing and shipping products. Analytics can be used to monitor fuel efficiency, calculate optimal optimization for delivery fleets, and improve inventory management.
- With data analytics, researchers have the ability to look at more patient characteristics in a shorter amount of time, develop profiles for them, and then use those profiles to find potential trial candidates.

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- "informed improvement", "continuous consideration" , predict student outcomes, should ensure that students have "open futures" .
- Big data transform our lives – optimizing, improving, making more efficient, and capturing benefits.


Cảm ơn bạn
감사합니다
Grazie
Terima Kasih
Merci Beaucoup
谢谢
Shukran
Obrigado
¡Gracias!
Danke
Todah
Thank you!
Dankie
Спасибо
Selamat
Dhanyavaad
शुक्रिया
ขอบคุณ
ありがとう
তোমাকে ধন্যবাদ