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Advanced Incremental Attribute Learning Clustering Algorithm for Medical and Healthcare Applications

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BESTMOD

Outline

Section 1

Introduction

Context

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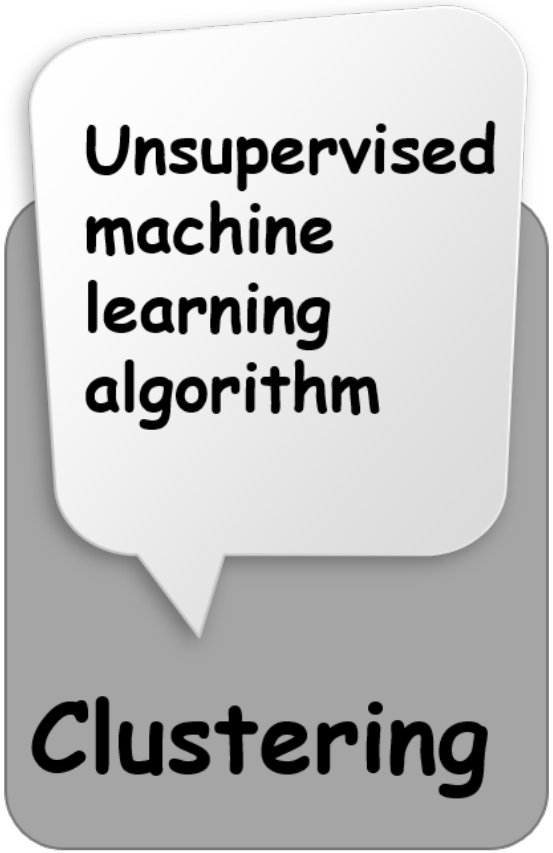

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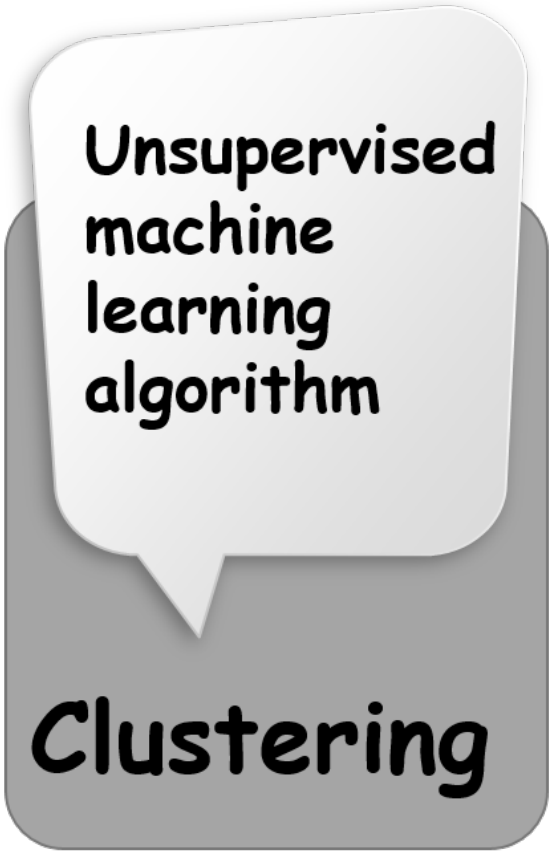


Context

Limits of batch clustering algorithms

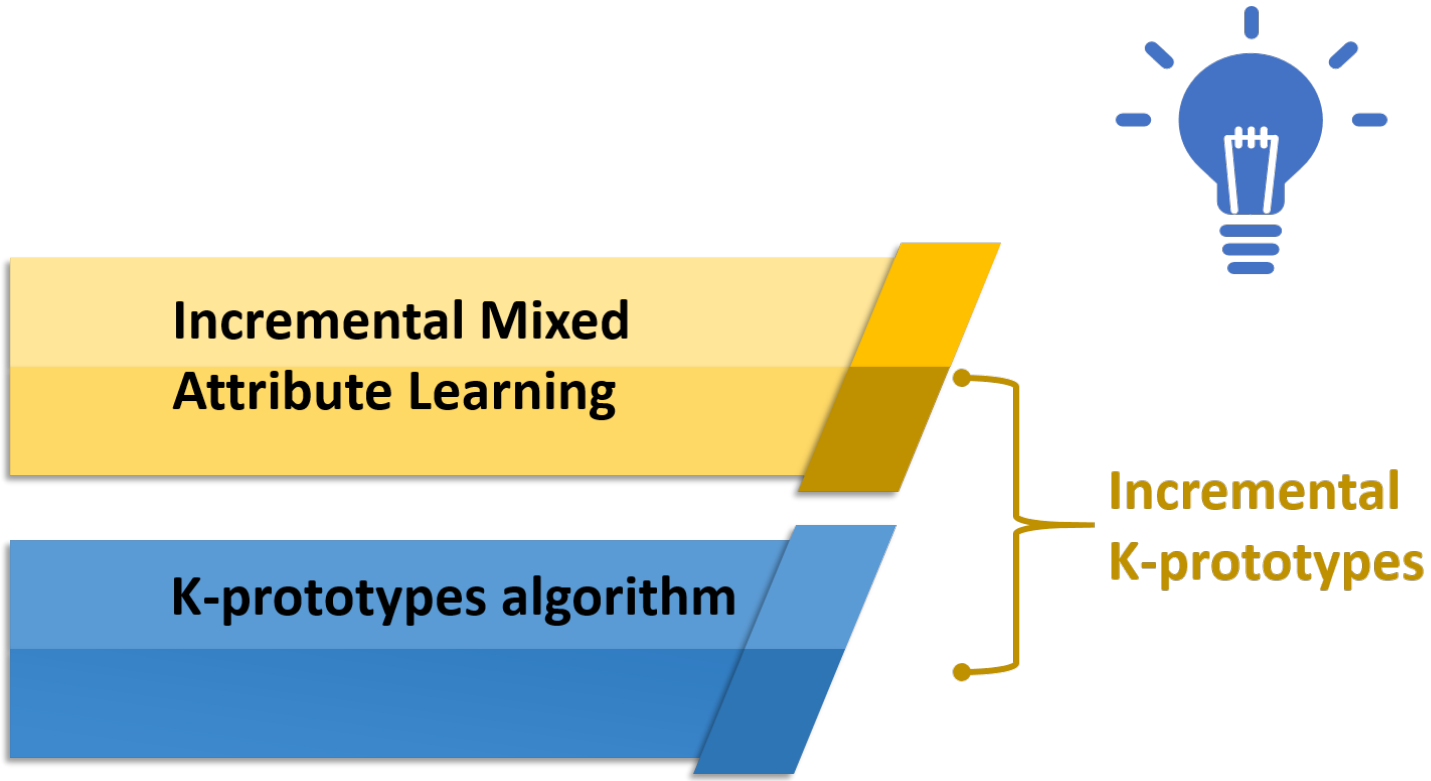
- Generate the best predictor by learning on the **all training data at once**.
- Need the **complete input data** being loaded into memory
  - The requirements of memory space will become **high**.
- Need to **regenerate** their clusters from scratch.
- **Complex** and **slow** analysis.

Context

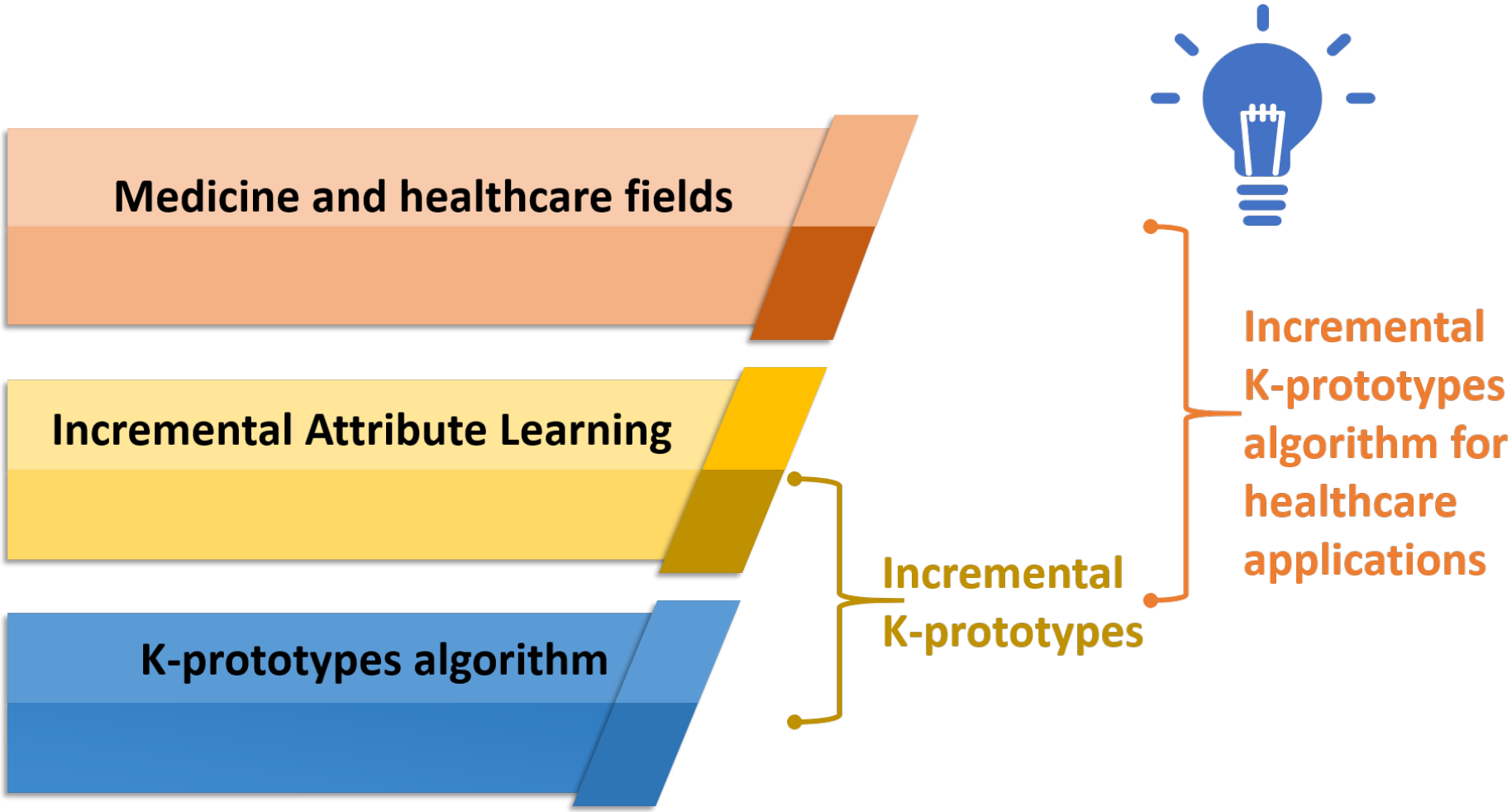
Incremental clustering

- ✓ Handle a bulk of **updates** owing to the training samples which become available one after another **over time**.
- ✓ Mixed data is processed **sequentially** over flexible time windows.

Objectives


Incremental Mixed
Attribute Learning
K-prototypes algorithm
Incremental
K-prototypes

Objectives


Medicine and healthcare fields
Incremental Attribute Learning
K-prototypes algorithm
Incremental K-prototypes
Incremental K-prototypes algorithm for healthcare applications

Section 2

Basic concepts

K-prototypes

Proposed by **Huang** in **1998** as an **extension to the k-means** algorithm to deal with **mixed data**

- Combinig the **k-modes** and **k-means** algorithms.
- Simplicity, scalability and speed of convergence.

✓ Its objective is to group the data set X into k clusters while minimizing the cost function

$$J = \sum_{i=1}^{n} \sum_{j=1}^{k} u_{ij} d(x_i - c_j), \tag{1}$$

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- The first term is the **squared Euclidean distance** measure on the **numeric** attributes.
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- Stores and processes **all the input data** in the **memory**.

  ↷ *High requirements of memory space!*

- Deals only with **object** learning **in batch**.
- **Inability** to handle **incremental attribute learning** task.

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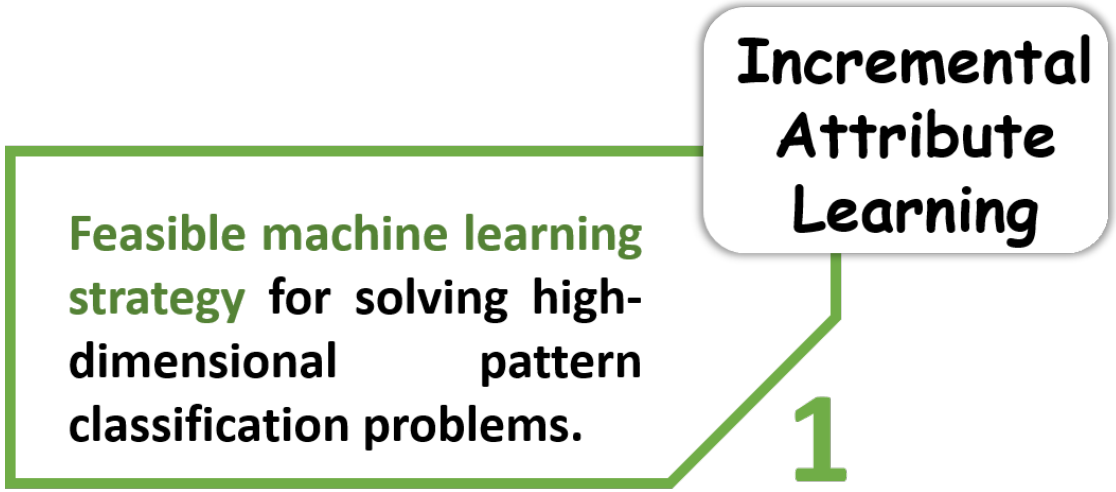
Incremental Attribute Learning



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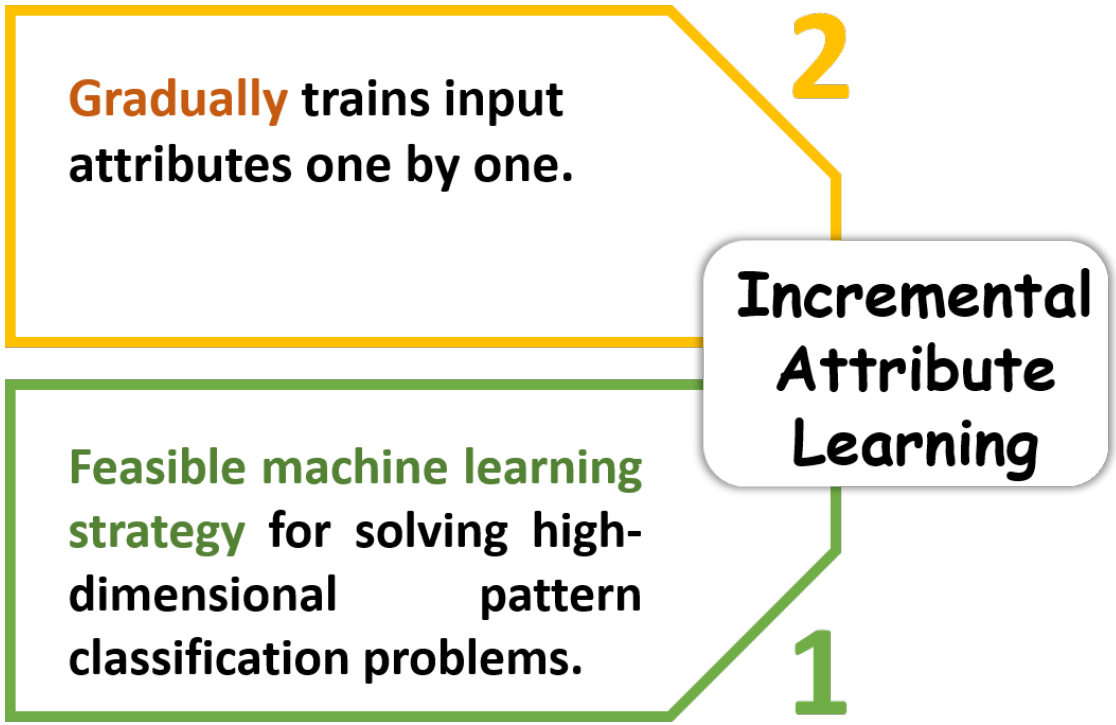

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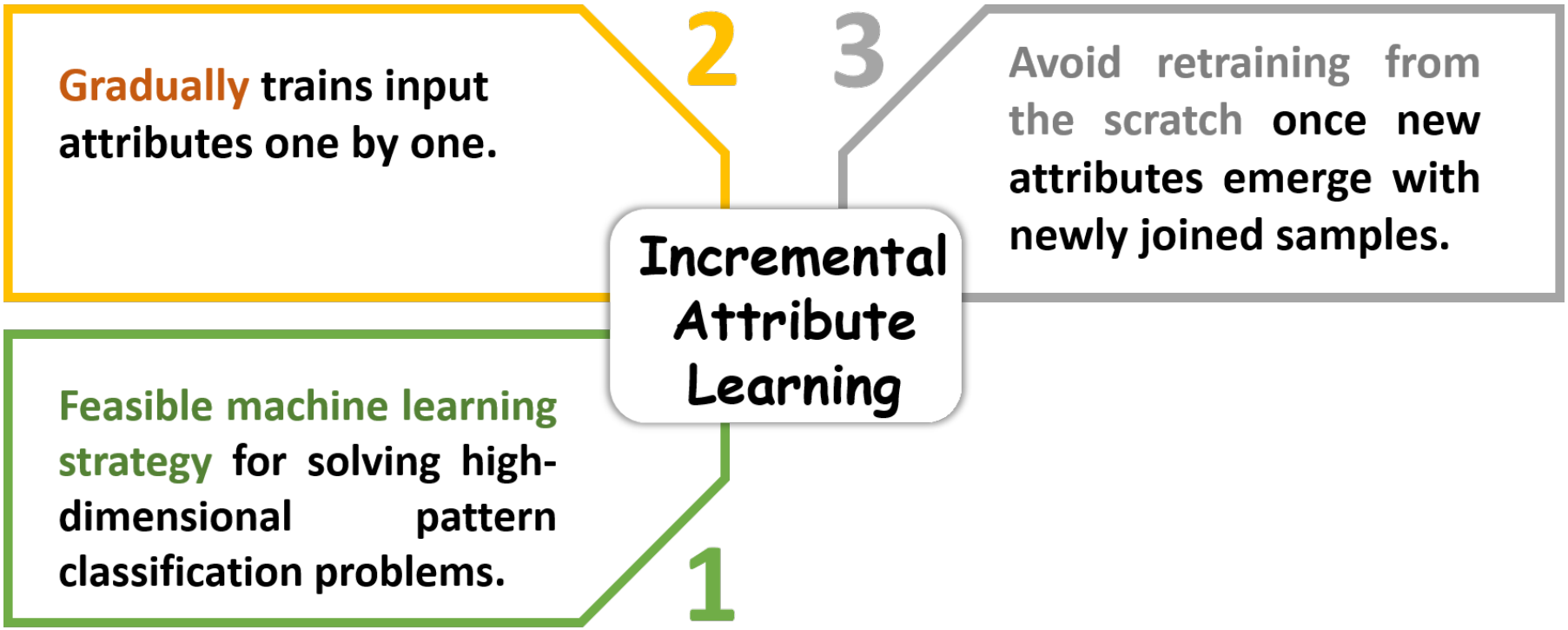

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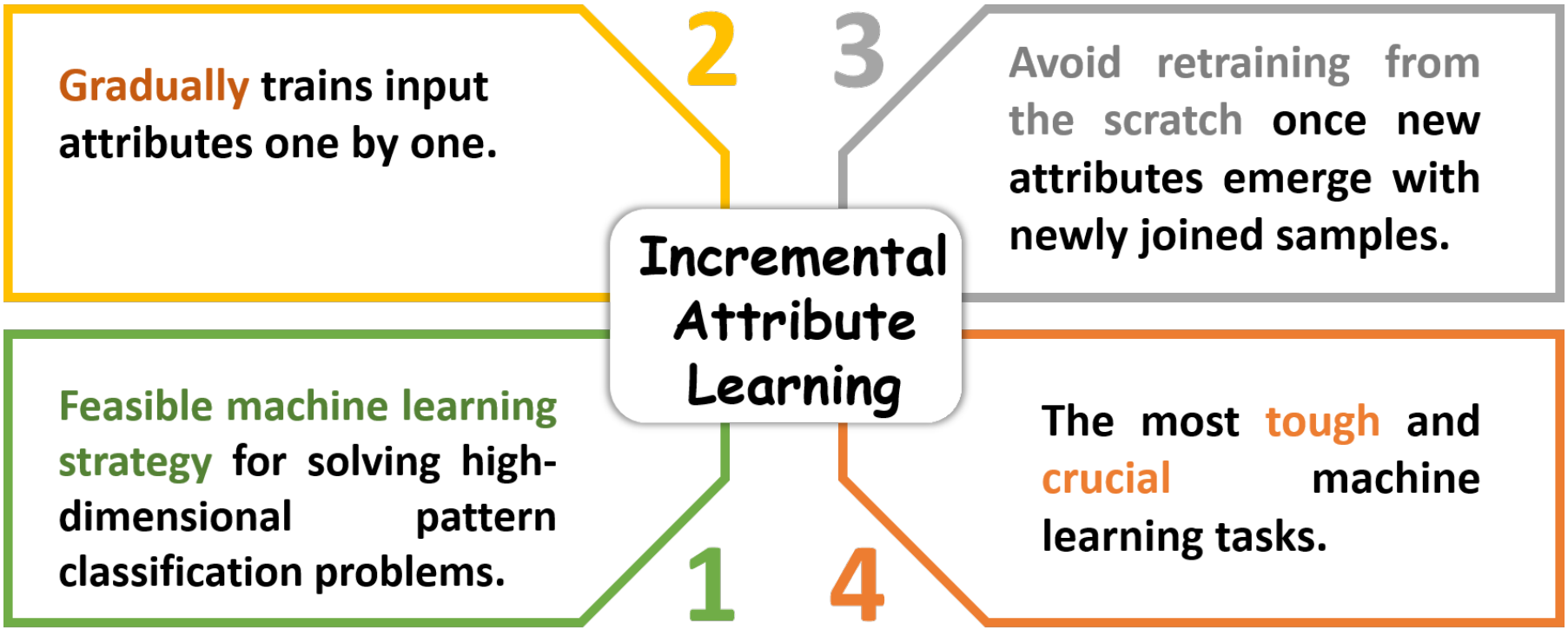

Problematic

1. **Mixed** medical data with **new emerging attributes** has not yet been evaluated.
2. Mining these massive data sets **faster** and **more accurately**.
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Section 3

Proposed Incremental K-prototypes

Definition of IK-prototypes

IK-prototypes

- Big data solution in medicine and healthcare fields, through incremental attribute learning context.
- Proposed towards handling **mixed** large scale data in the form of **continuously** emerging data streams
  - escorted with **new added features**.

⇒ As **data stream** proceeds, **IK-prototypes** tackles both **incremental object** and **attribute** learning at the same deal.

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1. Manage the incremental attribute learning task in medical healthcare field.
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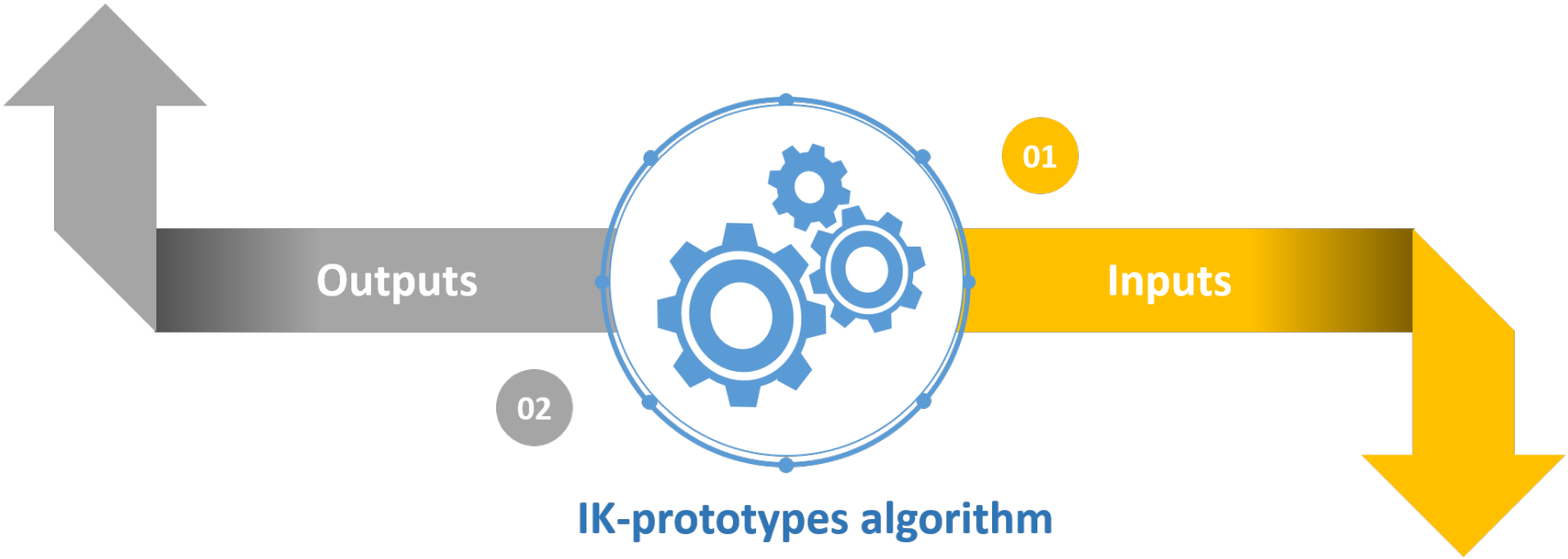
Definition of IK-prototypes

- K clusters with new attributes



- Input mixed data
- Data streams with additive patient's attributes

IK-prototypes steps

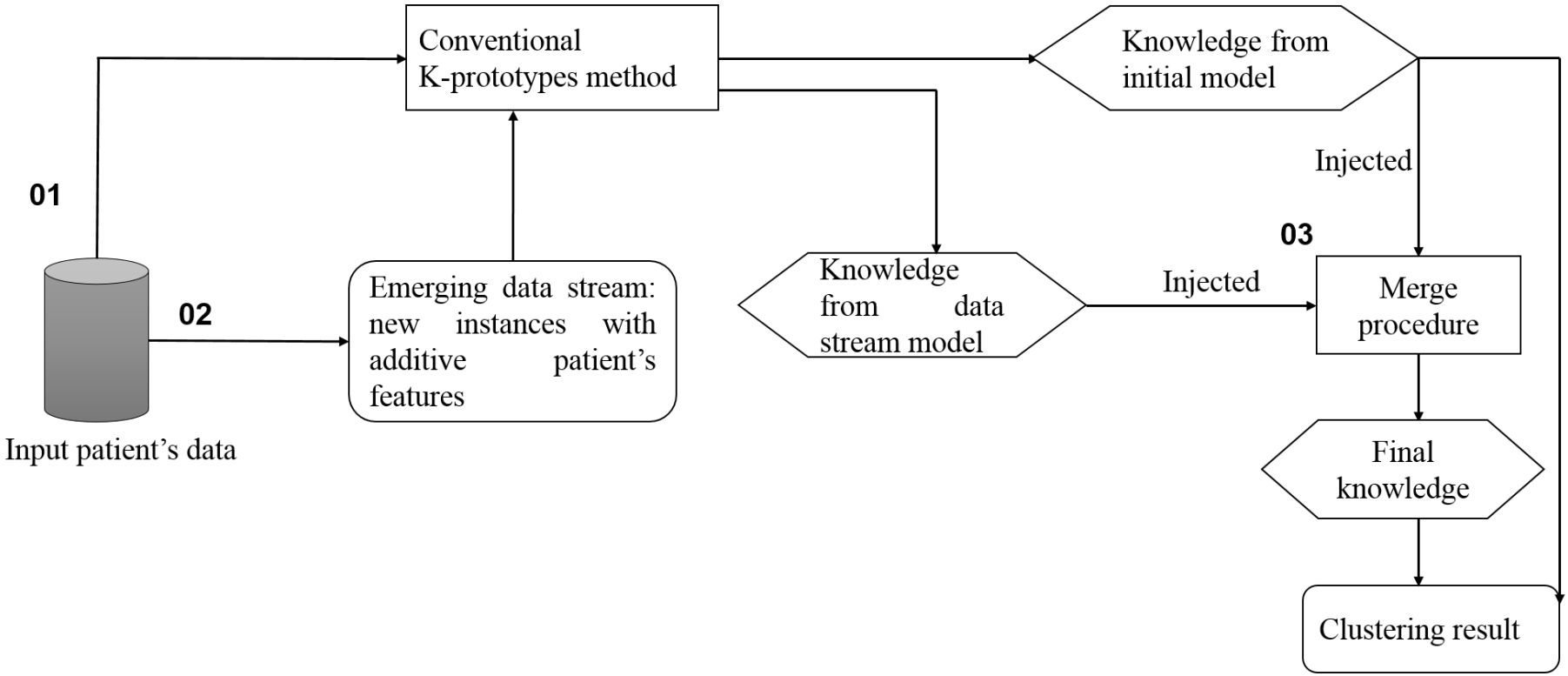


Figure 1: An overview of the proposed Incremental k-prototypes through IAL context

Merge process

- Merge the knowledge coming from both models
  - ↷ each two **similar clusters** are combined together
  - ↷ return to the initial k

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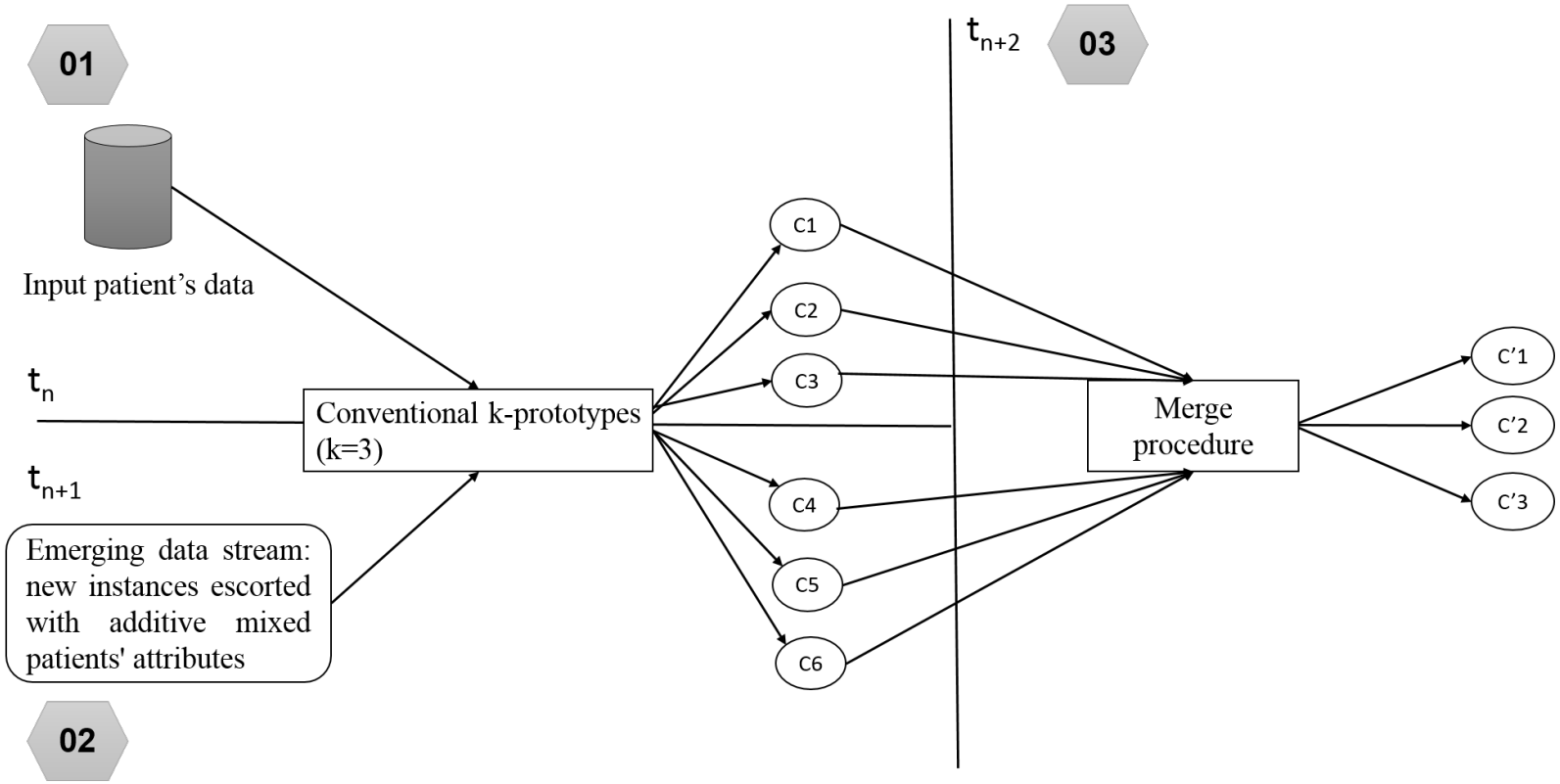

Figure 2: Workflow of the merge process

Merge process

Similarity measure

1. **Davies-Bouldin index (DB)** calculates the average similarity between clusters
   - Similarity based on a comparison between the **distance** between clusters and **the size** of the clusters themselves.
   - The **lower DB** is, the **better** partition of clusters is.
2. **Calinski-Harabasz Index (CH)** is the ratio of the sum of between-clusters dispersion and of inter-cluster dispersion for all clusters.
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- Our algorithm will choose the clusters corresponding to the **highest DB** value, **coinciding** with the **lowest CH** score.

	C1	C2	C3	C4	C5	C6
C1	0.0	****	****	****	****	****
C2	1.431	0. 0	****	****	****	****
C3	0.718	1.051	0.0	****	****	****
C4	**2.196**	1.382	0.796	0.0	****	****
C5	0.938	1.178	1.187	1.144	0.0	****
C6	0.689	0.953	1.597	0.776	1.464	0.0

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C2	102.047	10000	****	****	****	****
C3	450.566	241.2	10000	****	****	****
C4	**33.759**	95.732	316.75	10000	****	****
C5	249.744	180.158	204.4	146.258	10000	****
C6	302.609	176.655	67.716	210.596	77.58	10000

Figure 3: DB index and CH score matrices for each two clusters

✓ Indexes represented in bold refer to the same couple of clusters that will be merged.

⇒ *The **incremental attribute learning** is established without retraining from the scratch.*

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- The **highest DB** index and the **lowest CH** score may not be the best choices for the merge procedure
  - if they result in different combinations of clusters.

⇒ The algorithm will carry on

1. **Merge** both clusters resulting from the two calculated indexes
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Section 4

Experimental results

Real data sets description

Data set	#Instance	#Attribute	Acronym
Stroke Prediction	5110	12	SP
Pharmaceutical Drug Spending	1036	7	PDS
Breast Cancer Wisconsin	569	32	BCW
Personality Scale Analysis	315	8	PSA

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2. **Silhouette Coefficient (SC ↑)** is bounded between **−1** for incorrect clustering and **+1** for highly dense clustering.
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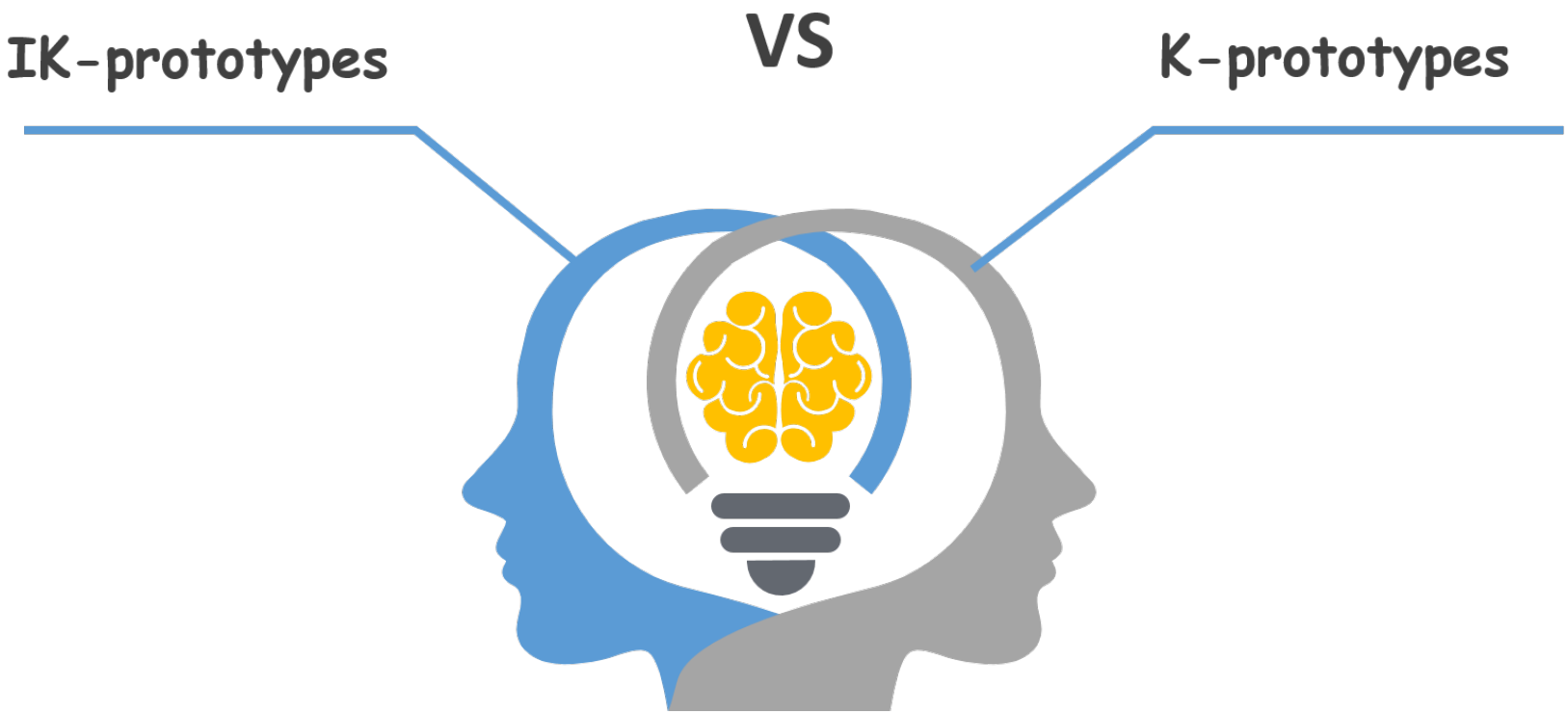

Sum of Squared Errors results

The total SSE is

Data sets	SP	PDS	BCW	PSA
K-prototypes	1.920	1.956	2.130	2.587
IK-prototypes	1.651	1.577	1.547	1.682

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Conclusion and future works

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- ✓ Helping in **early detection of diseases**, **treatment recommendations**, and **clinical services to doctors**.

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Thank you.