# Machine Intuition in Mobile Network Automation

Ph. D. defense of Márton Kajó
Technical University of Munich, Chair of Network Architectures and Services
April 5th, 2023

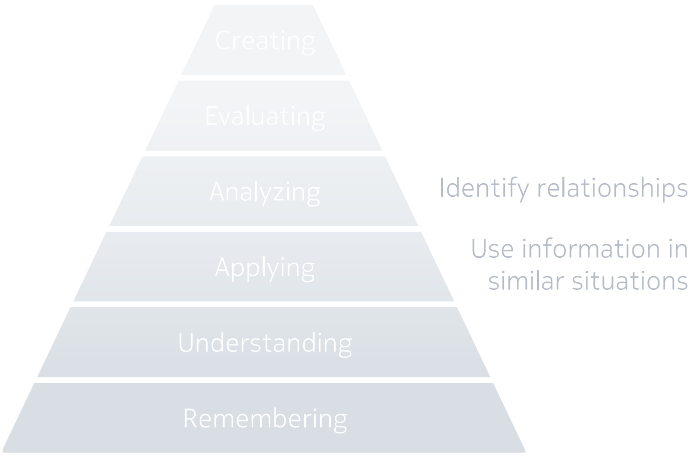
Chairman: Prof. Dr. Debarghya Ghoshdastidar
Examiners: Prof. Dr.-Ing. Georg Carle
Prof. Dr. Rolf Stadler (KTH Royal Institute of Technology, Stockholm, Sweden)

# Machine Intuition
is Unsupervised Deep Learning

1. Mobile network automation targets tasks undertaken by humans.
   - ➢ The human-like logic of **Deep Learning** (DL) models fits these tasks.

2. Labeled data is scarce in mobile networks.
   - ➢ Unsupervised learning is the preferred paradigm.

Learning without the guidance of labels requires a higher cognitive capacity than supervised DL.




Bloom's taxonomy of cognitive learning objectives

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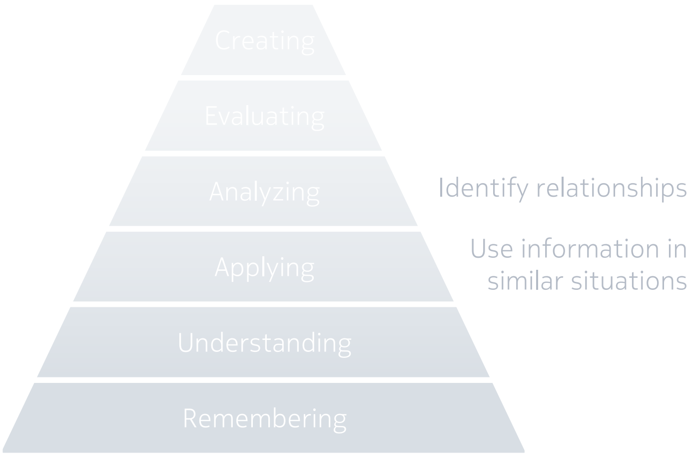


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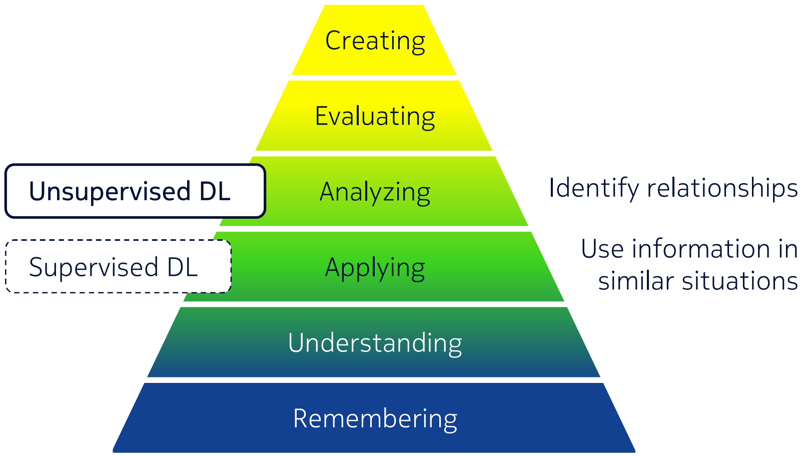


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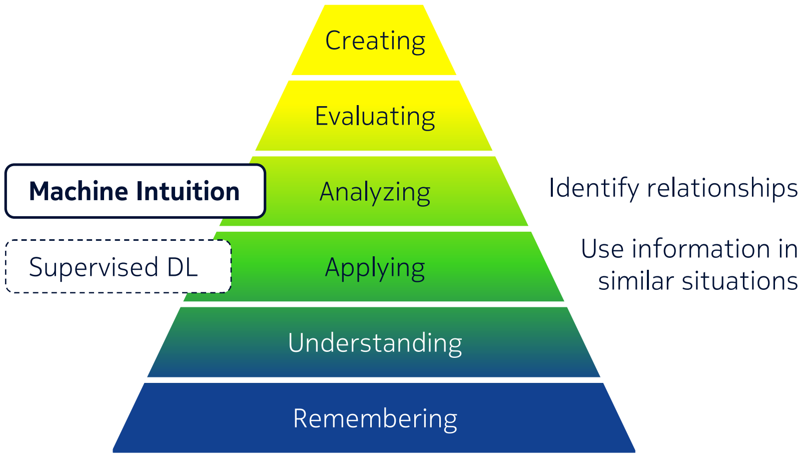


Bloom's taxonomy of cognitive learning objectives

**Mobile network automation requires a sort of machine intuition.**

# Machine Intuition
in Mobile Network Automation

Research questions:

A) Can mobile network automation benefit from machine intuition (feasible/practical/applicable)?

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Unsupervised learning is not applicable to all problems. I have identified 4 areas where machine intuition is applicable in mobile network automation:

**Exemplification** (Part I)

Description of behavior through examples.

- Tool: Quantization

**Prediction** (Part III)

Extrapolation of behavior into the future.

- Tool: Sequence prediction

**Associative Modeling** (Part II)

Finding groups through meaningful similarity.

- Tool: Clustering

**Machine Confidence** (Part IV)

Being critical of inputs and own inference.

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1. Deep clustering of mobile network data:
   - 1.1 Uses of clustering in mobile network automation
   - 1.2. Deep clustering approaches
   - 1.3. Own contribution: the DANCE algorithm
   - 1.4. Evaluation results
2. Communication and utilization of confidence values
   - 2.1. Data corruption in cognitive function chains
   - 2.2. Own contribution: the ICI algorithm
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3. Conclusion and outlook on machine intuition
   - 3.1. Recap of work and answer to research question A)
   - 3.2. Outlook and answer to research question B)

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# Part 1:
# Deep Clustering of Mobile Network Data

Covered in Chapter 7 of the dissertation

Based on the publication:

**Clustering Mobile Network Data with Decorrelating Adversarial Nets**

M. Kajó, J. Schnellbach, S. S. Mwanje and G. Carle

NOMS 2022-2022 IEEE/IFIP Network Operations and Management Symposium, 2022, pp. 1-9

# Deep Clustering of Mobile Network Data

## 1.1 Uses of Clustering in Mobile Network Automation

Clustering is the act of **finding groups** in the data.

Clustering can be used as:

- an unsupervised alternative to classification in DL-based network automation functions, or as
- a data labeling tool: clusters can be formed using a larger unlabeled dataset, and then labeled according to a small set of labelled examples.

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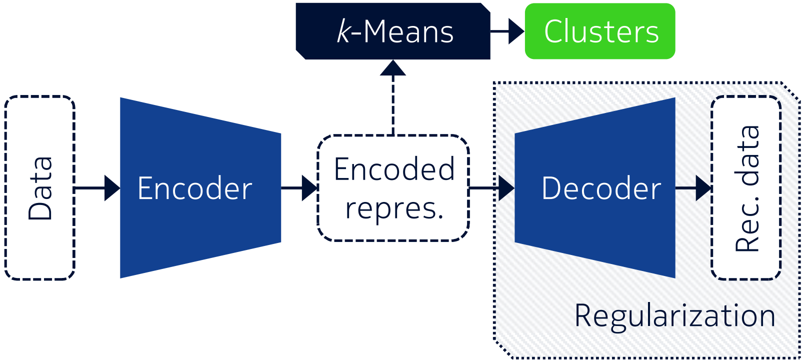
Research goal: designing a high-performance deep clustering method **for mobile network data**.

# Deep Clustering of Mobile Network Data

## 1.2 Deep Clustering Approaches

**Reconstructive deep clustering:**

- Clusters defined from the encoded representation of Autoencoders (AEs).
- Domain-agnostic regularization.




**Discriminative deep clustering:**

- Clusters defined directly from the original representation.
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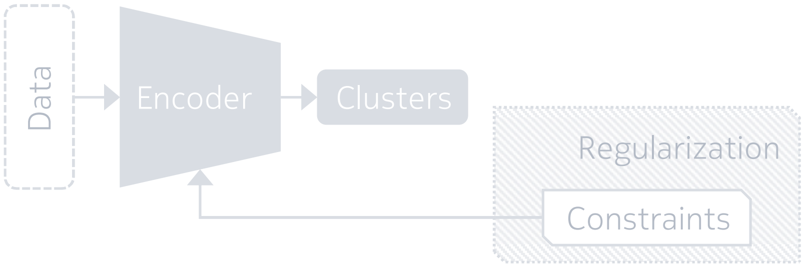

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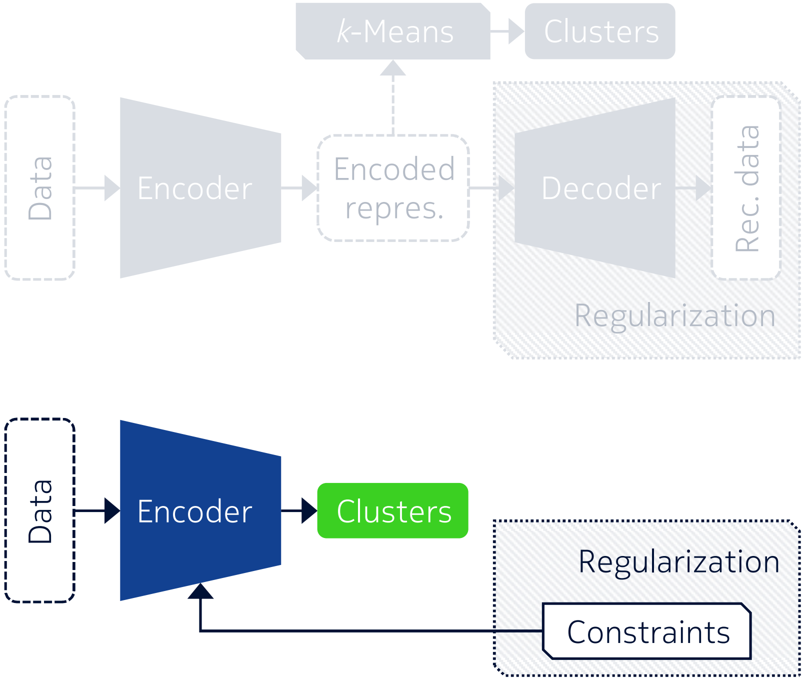

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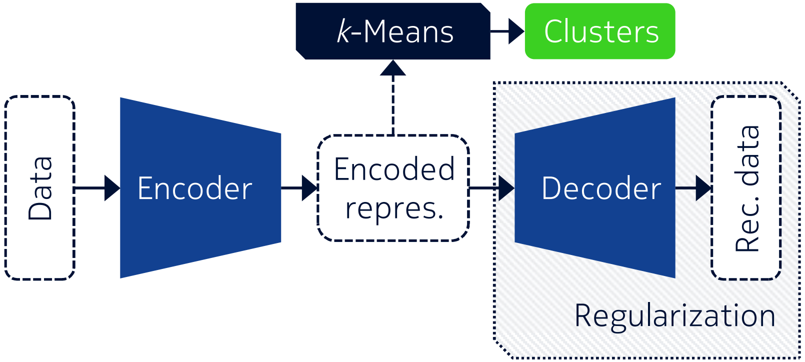


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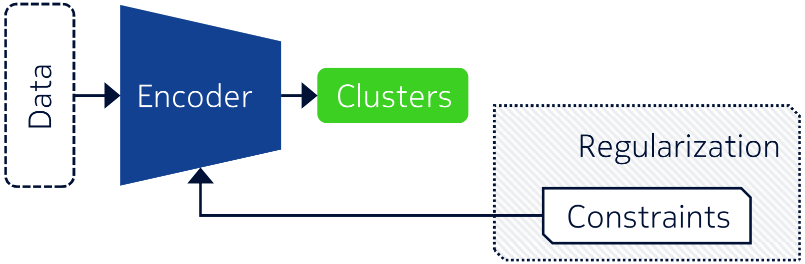

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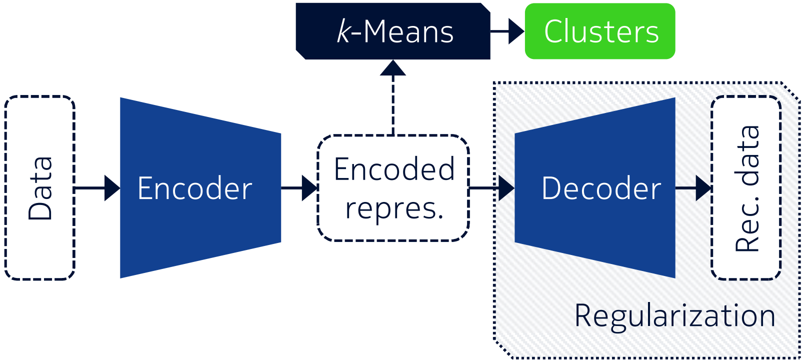


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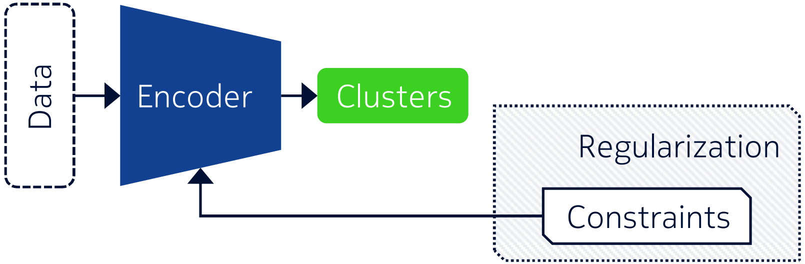



Reconstructive clustering often suffers from **irrelevant information** in the encoded representation.

# Deep Clustering of Mobile Network Data

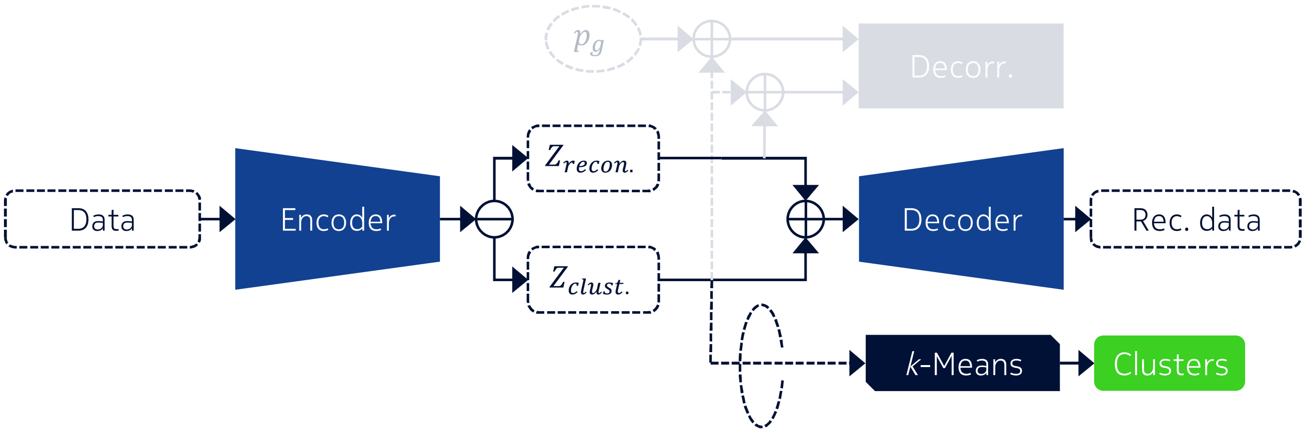
## 1.3 Own contribution: the DANCE algorithm

**Split encoded features** into 2 sets:

- $Z_{recon.}$ with reconstruction-relevant information.
- $Z_{clust.}$ with clustering-relevant information.

The split is achieved with a decorrelator adversarial net:

- $Z_{recon.}$ follows a Gaussian distribution ($p_g$).
- $Z_{clust.}$ is not correlated to $Z_{recon.}$



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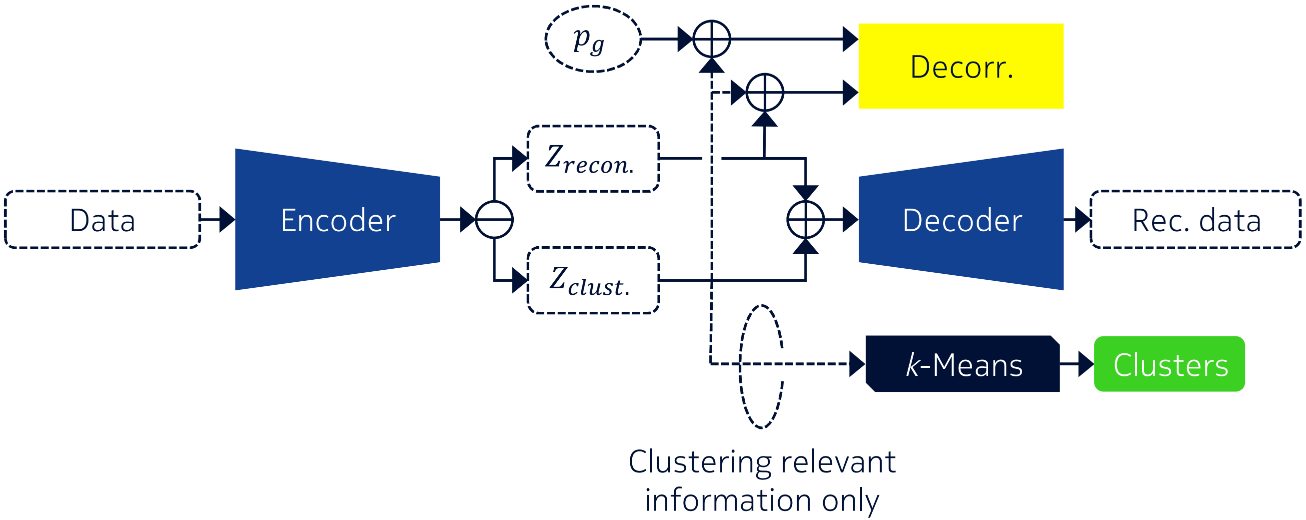

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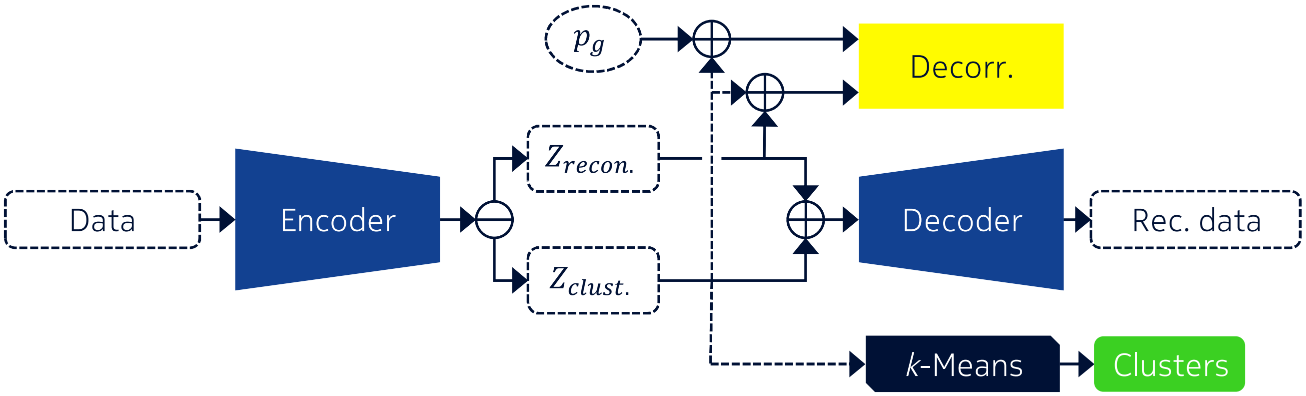


Our contribution: **Decorrelating Adversarial Nets for Clustering-friendly Encodings** (DANCE)

# Deep Clustering of Mobile Network Data

## 1.4 Evaluation Results

Collected simulated mobile network data containing **8 user groups**:

| | Traffic | Speed [km/h] | Occupied area |
|---|---|---|---|
| Stationary FTP | FTP | 0 | Inner & outer |
| Stationary VoIP | VoIP | 0 | Inner & outer |
| Stationary HTTP | HTTP | 0 | Inner & outer |
| Pedestrian FTP | FTP | 4-10 | Inner circle |
| Pedestrian VoIP | VoIP | 4-10 | Inner circle |
| Pedestrian HTTP | HTTP | 4-10 | Inner circle |
| Vehicular FTP | FTP | 10-100 | Outer ring |
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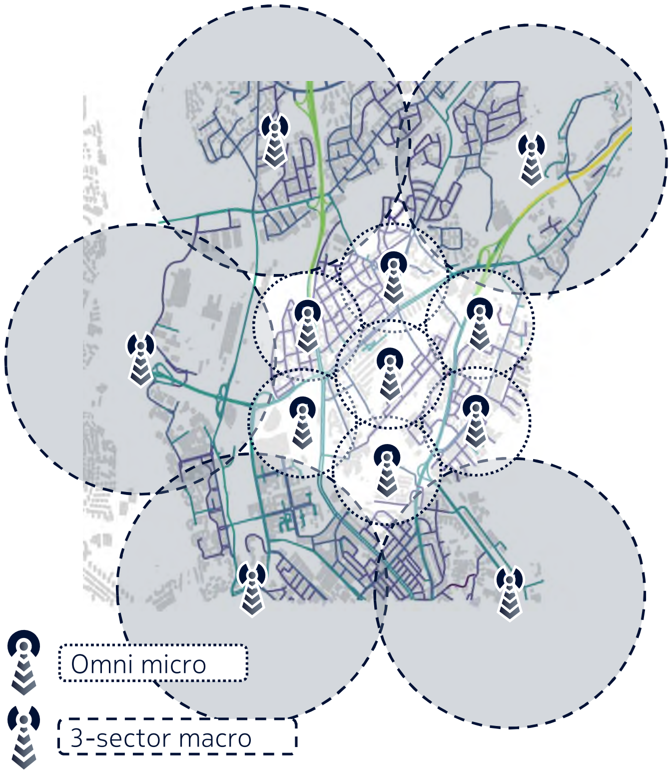
With the ground-truth labels known from the simulation, we can measure clustering accuracy (ACC):

$$ACC = \frac{n_{corretcly\_labeled}}{n_{all\_observations}}$$



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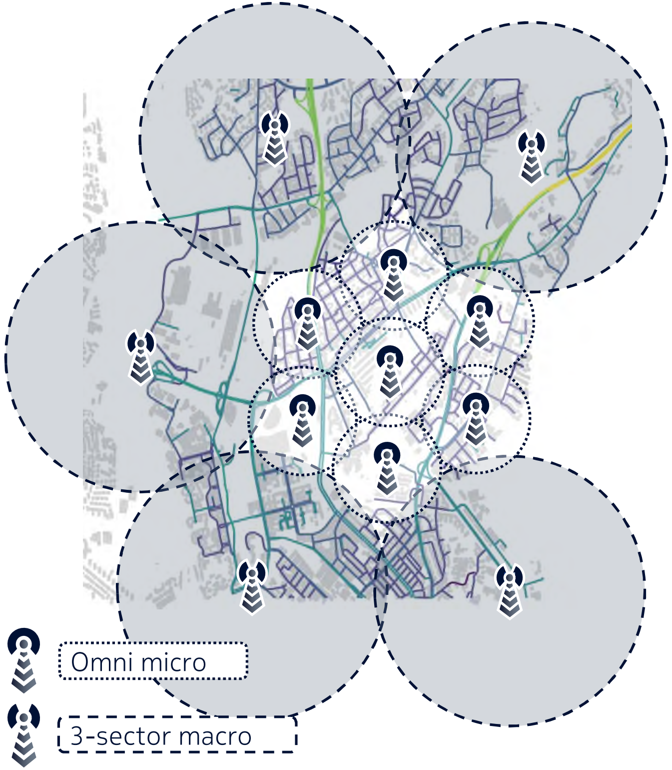

# Deep Clustering of Mobile Network Data

## 1.4 Evaluation Results

| | | Publication | Recon. | Discr. | Feat. split | ACC |
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| **DEC** | Deep Embedded Clustering | [Xie et al., 2016] | ✓ | | | 0.7409 |
| **ACAI** | Adversarially Constrained Autoencoder Interpolation | [Berthelot et al., 2016] | ✓ | | | 0.7629 |
| **IMSAT** | Information Maximizing Self-Augmented Training | [Hu et al., 2017] | | ✓ | | 0.4775 |
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| **DANCE** | Decorrelating Adversarial Nets with Clustering-friendly Encodings | [Kajo et al., 2022] | ✓ | | ✓ | **0.8923** |

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Using reconstructive clustering with feature splitting, DANCE is a **high-performance clustering on network data**.

# Part 2: Communication and Utilization of Confidence Values

Covered in Chapter 12 of the dissertation

Based on the publication:

**Robust Deep Learning against Corrupted Data in Cognitive Autonomous Networks**

M. Kajó, J. Schnellbach, S. S. Mwanje and G. Carle

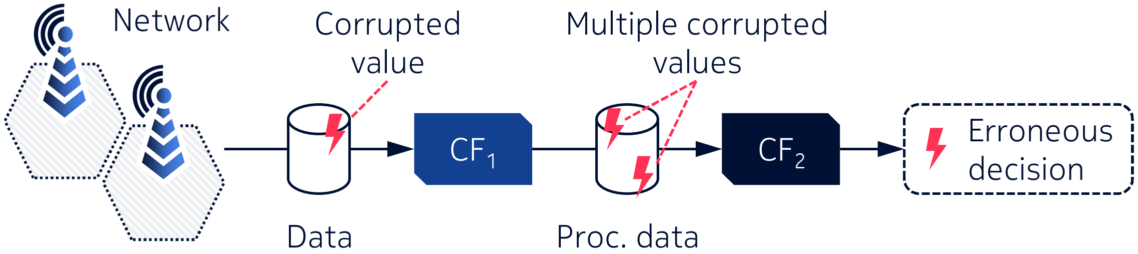
NOMS 2022-2022 IEEE/IFIP Network Operations and Management Symposium, 2022, pp. 1-7

# Communication and Utilization of Confidence Values

## 2.1 Data Corruption in Cognitive Function Chains

DL-based Cognitive Function (CF) chains propagate and possibly multiply **corrupted values**, likely leading to severe impact.

If the corrupted values are signaled through a “mask” attached to communicated data, the task is called imputation.



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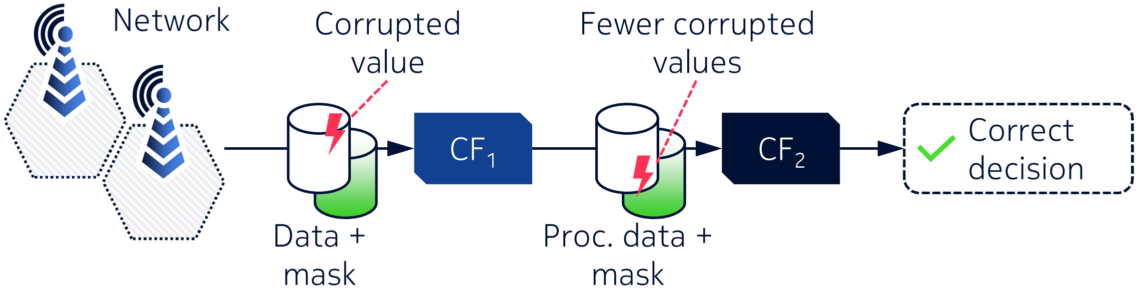

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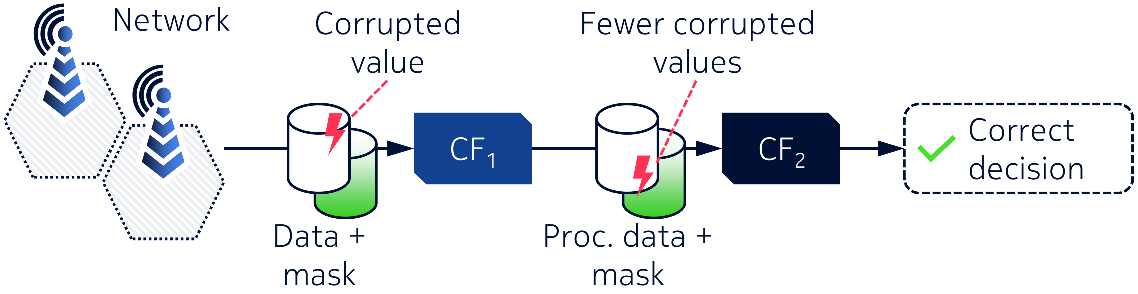


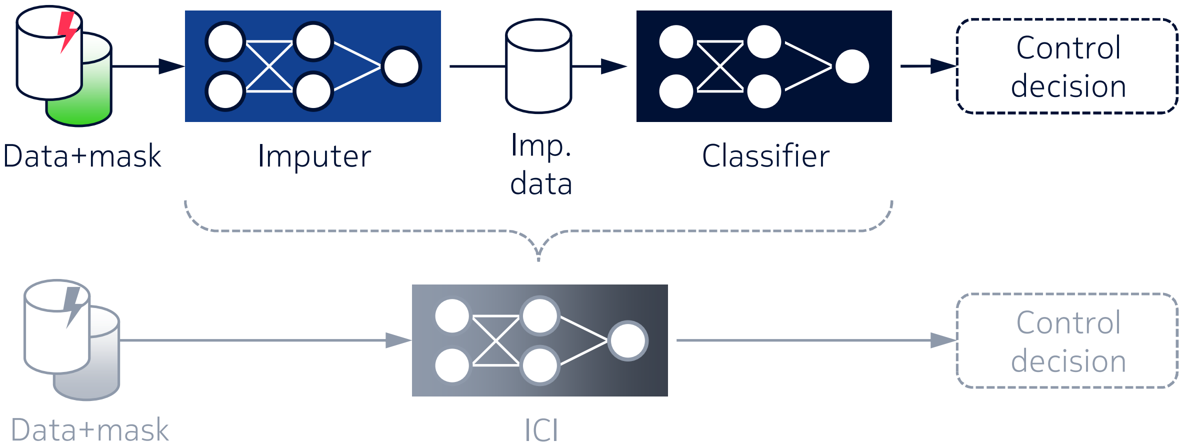

Research goal: designing a high-performance deep imputation **for cognitive functions**.

# Communication and Utilization of Confidence Values

## 2.1 Own Contribution: the ICI Algorithm

As both the imputer and the classifier models the same data, it is likely they will be of roughly the same complexity.

➢ The imputation capability could be integrated into the DL-based CF.



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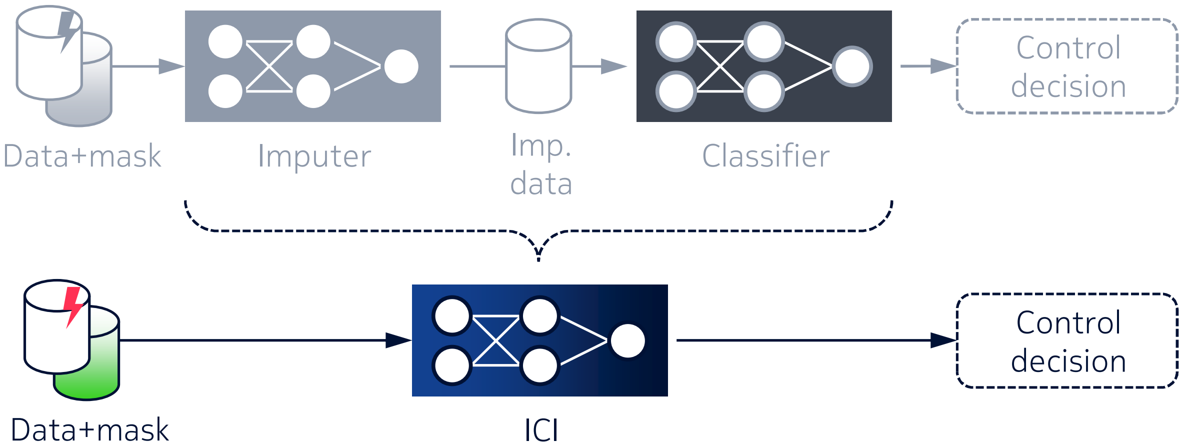

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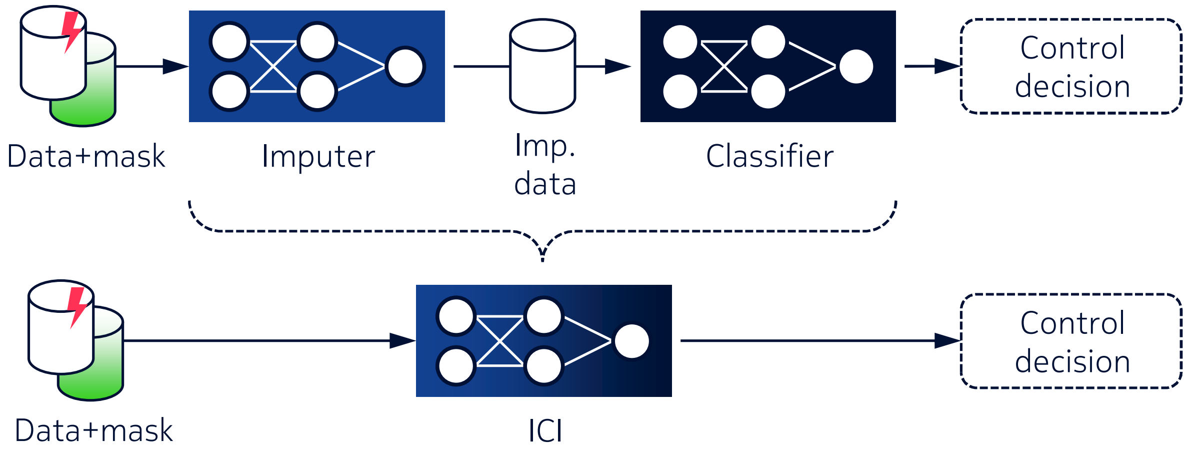



Our contribution: **Integrated Classification with Imputation** (ICI)

# Communication and Utilization of Confidence Values
## 2.3 Evaluation Results

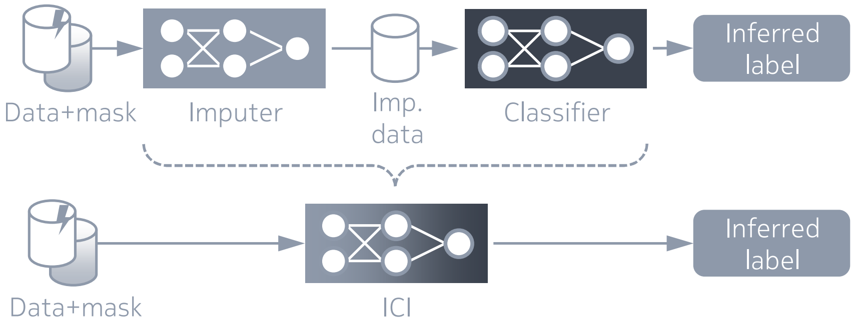
The evaluation dataset is the same as shown before, with **8 user groups** present in the simulation.

Values are randomly corrupted in the dataset, according to a missing rate:

$$missing\_rate = \frac{n_{missing\_observations}}{n_{all\_observations}}$$

Classification accuracy (ACC) is measured after a hypothetical CF utilizes the imputed dataset:

$$ACC = \frac{n_{corretcly\_categorized}}{n_{all\_user\_traces}}$$



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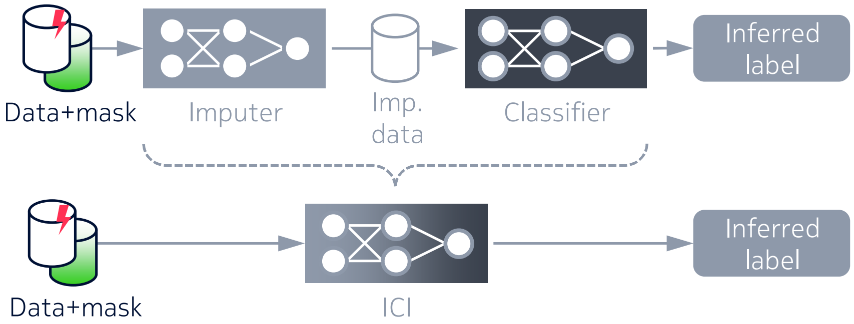

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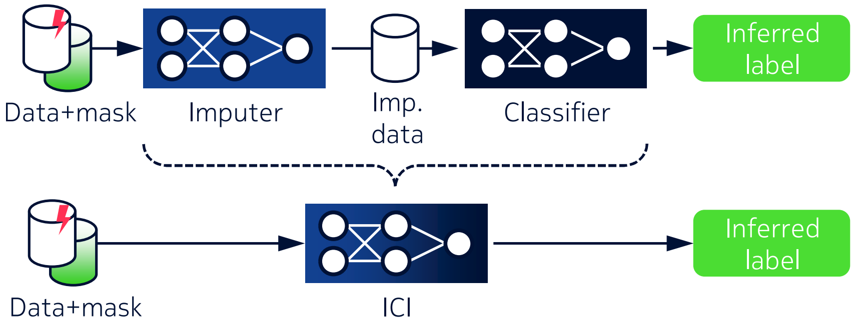

# Communication and Utilization of Confidence Values

## 2.3 Evaluation Results

| | | Publication | ML | DL | Intgr. |
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| **kNN** | *K*-nearest-neighbors | - | | | |
| **mean** | Mean imputation | - | | | |
| **MICE** | Multivariate Imputation By Chained Equations | [Buuren et al., 2011] | ✓ | | |
| **Miss Forest** | Nonparametric Missing Value Imputation using Random Forest | [Stekhoven et al., 2012] | ✓ | | |
| **MIDA** | Multiple Imputation using Denoising Autoencoders | [Gondara et al., 2018] | | ✓ | |
| **GAIN** | Generative Adversarial Imputation Nets | [Yoon et al., 2018] | | ✓ | |
| **WGAIN** | Wasserstein Generative Adversarial Imputation Nets | - | | ✓ | |

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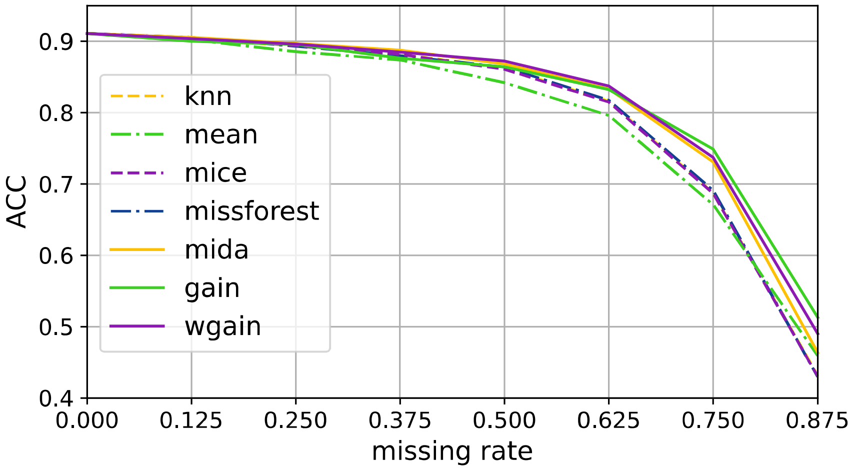

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| **kNN** | *K*-nearest-neighbors | | | |
| **mean** | Mean imputation | | | |
| **MICE** | Multivariate Imputation By Chained Equations | ✓ | | |
| **Miss Forest** | Nonparametric Missing Value Imputation using Random Forest | ✓ | | |
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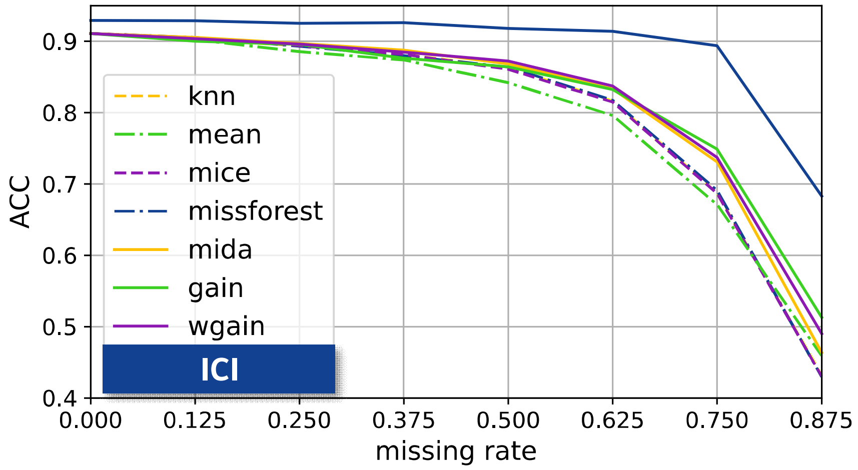

# Communication and Utilization of Confidence Values

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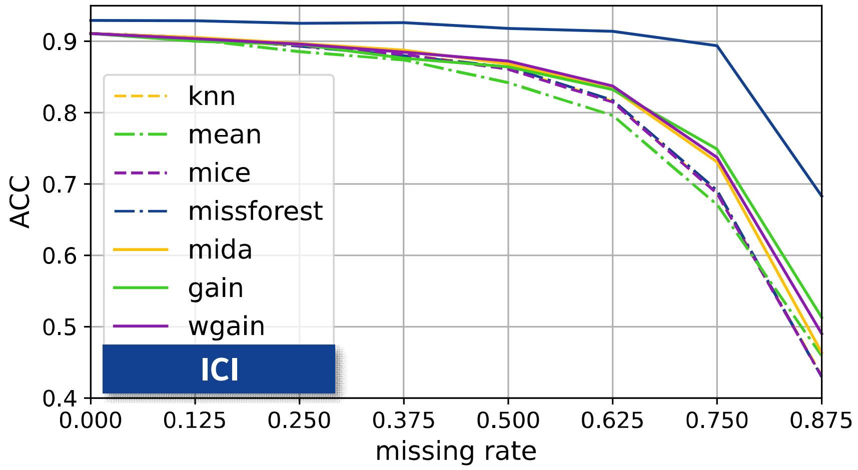


ICI is a **high-performance integrated imputation** with marginal additional cost.

# Part 3:

# Conclusion and Outlook on Machine Intuition

Covered in Chapter 14 of the dissertation

# Conclusion and Outlook on Machine Intuition

## 3.1 Recap of Work and Answers to Research Questions

**Exemplification**

New quantization alg. for facilitating communication between CFs.

**Prediction**

DL-based user movement prediction combined with a digital twin for radio environment prediction.

**Associative Modeling**

New deep clustering algorithm that outperforms SoTA on mobile network data.

**Machine Confidence**

New approach of integrating imputation into DL-based CFs.

- **Equal-Volume Quantization of Mobile Network Data using Bounding Spheres and Boxes**
  M. Kajó, B. Schultz, J. Ali-Tolppa, G. Carle
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  A. Masri, T. Veijalainen, H. Martikainen, S. S. Mwanje, J. Ali-Tolppa, M. Kajó
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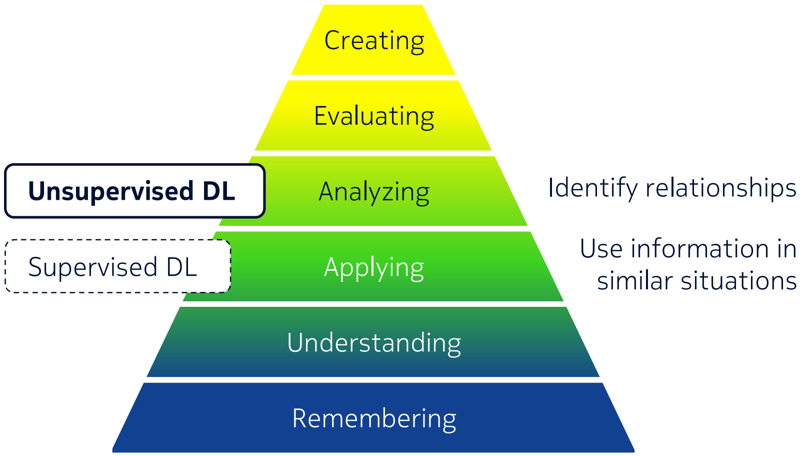
B) Does machine intuition reduce/remove human labor? - **No, it shifts supervision**

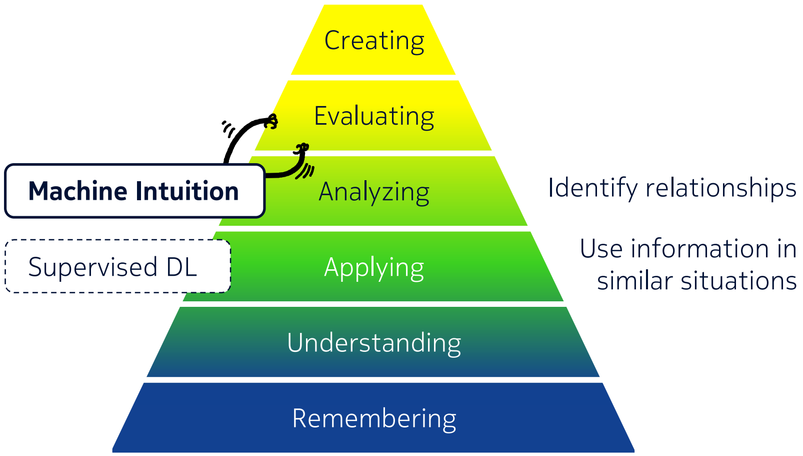
# Conclusion and Outlook on Machine Intuition

## 3.2 Outlook




Bloom's taxonomy of cognitive learning objectives

# Conclusion and Outlook on Machine Intuition
## 3.2 Outlook




Bloom's taxonomy of cognitive learning objectives

True Machine Intuition should eliminate human supervision, which requires further improvement in **cognitive power**.

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# Publications

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  NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium, 2018, pp. 1-9
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  IEEE Network, 2020, vol. 34, no. 6, pp. 8-13
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- **Classic Artificial Intelligence: Tools for Autonomous Reasoning**
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  Towards Cognitive Autonomous Networks: Network Management Automation for 5G and Beyond, 2020, pp. 173-201
- **Machine Learning: Tools for End-to-End Cognition**
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- **Cognitive Autonomy for Network Self-Healing**
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  Towards Cognitive Autonomous Networks: Network Management Automation for 5G and Beyond, 2020, pp. 345-384

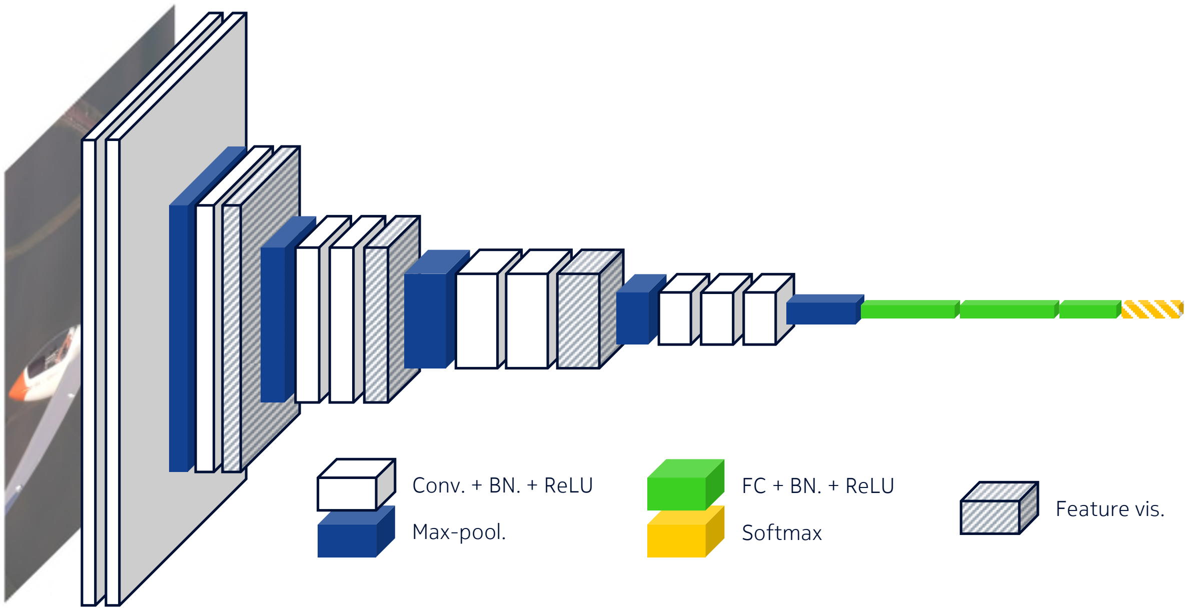
# Backup Slides

# Machine Intuition

## Deep Learning

DL (Deep Learning) algorithms learn to model data through a **hierarchy of rules**.

- Because of their layered architecture, neural nets are a natural choice for this.



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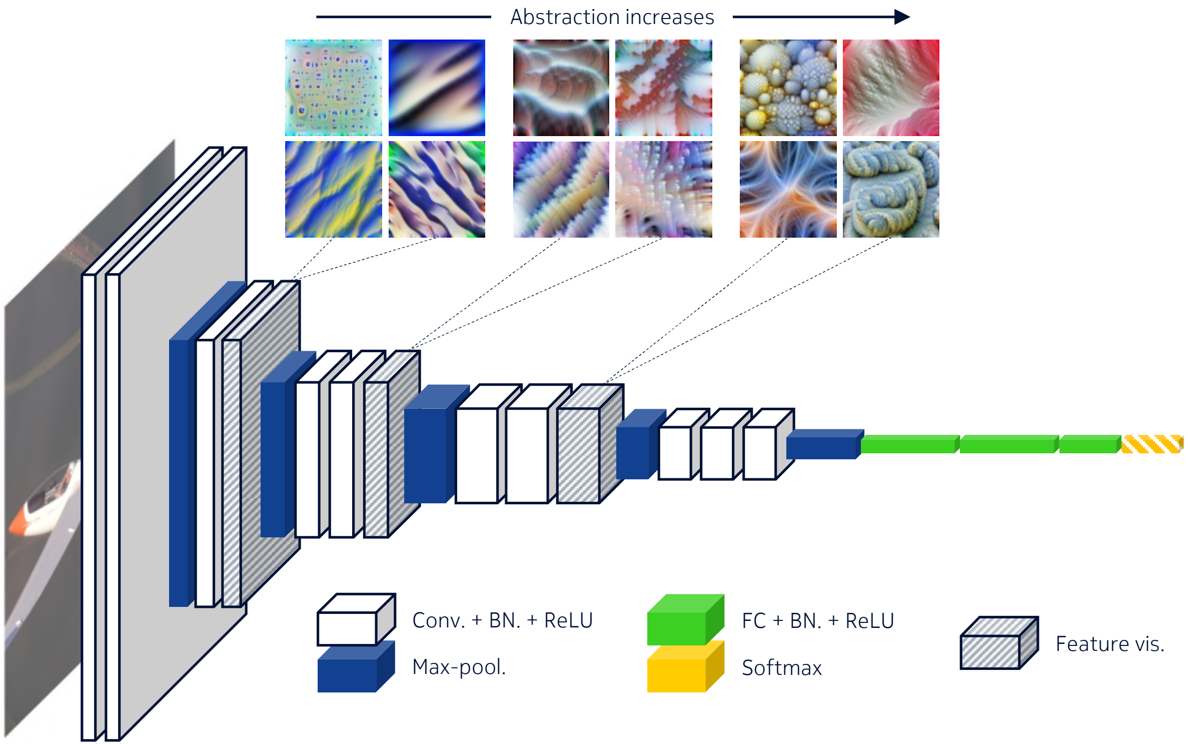

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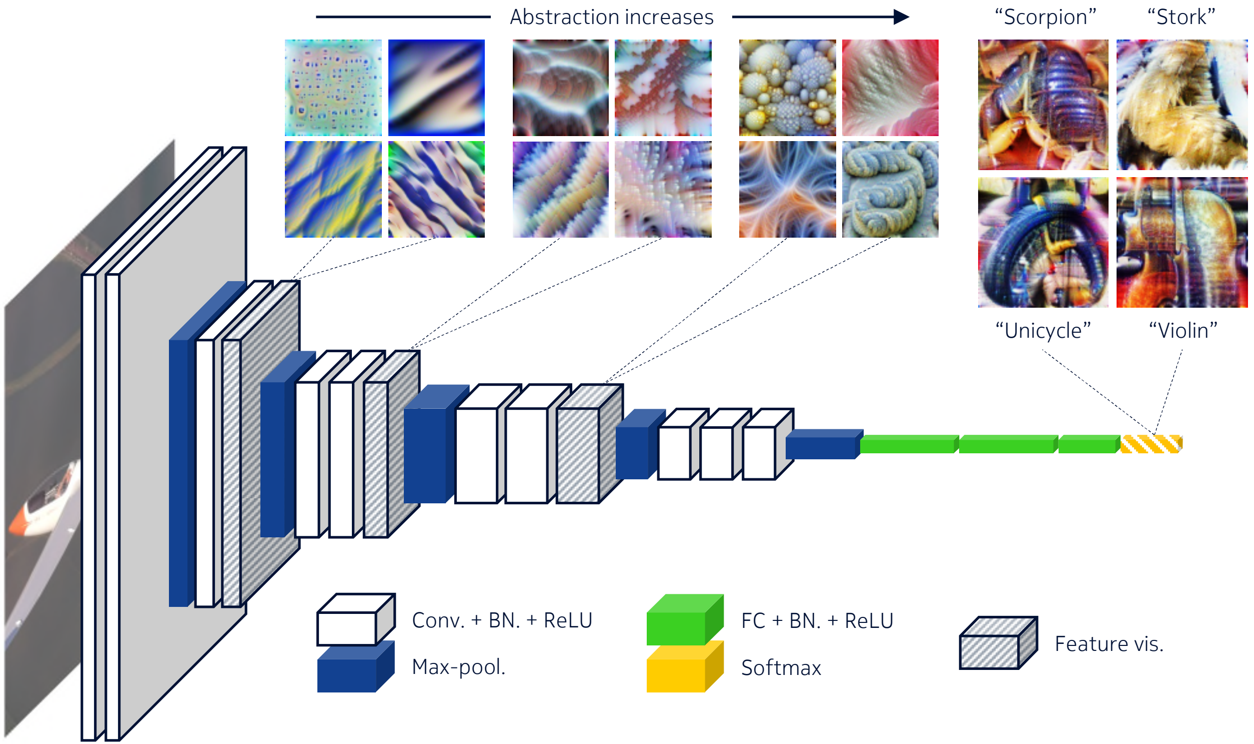


Subsequent abstractions can realize **human-like** logic.

# Machine Intuition

## Machine Learning Paradigms

**Supervised learning**

Substantial human/computational effort in data preparation:

- Manual labeling of anomalies
- Surveys
- Drive tests
- Ray-traced coverage maps

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Experimentation cannot be done directly on real mobile networks*:

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### Reinforcement learning

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Unsupervised learning only requires **light** data preparation.

# Deep Clustering of Mobile Network Data

## Example Use Case in Network Automation

**Quality of Experience (QoE)** estimation tries to quantify user satisfaction:

1. -
2. Map measured Key Performance Indicators (KPIs) to QoE values.

# Deep Clustering of Mobile Network Data
## Example Use Case in Network Automation

Quality of Experience (QoE) estimation tries to quantify user satisfaction:

1. -
2. Map measured Key Performance Indicators (KPIs) to QoE values.

**Problem**

Context greatly influences the QoE:

- Different situations
- Different expectations

# Deep Clustering of Mobile Network Data

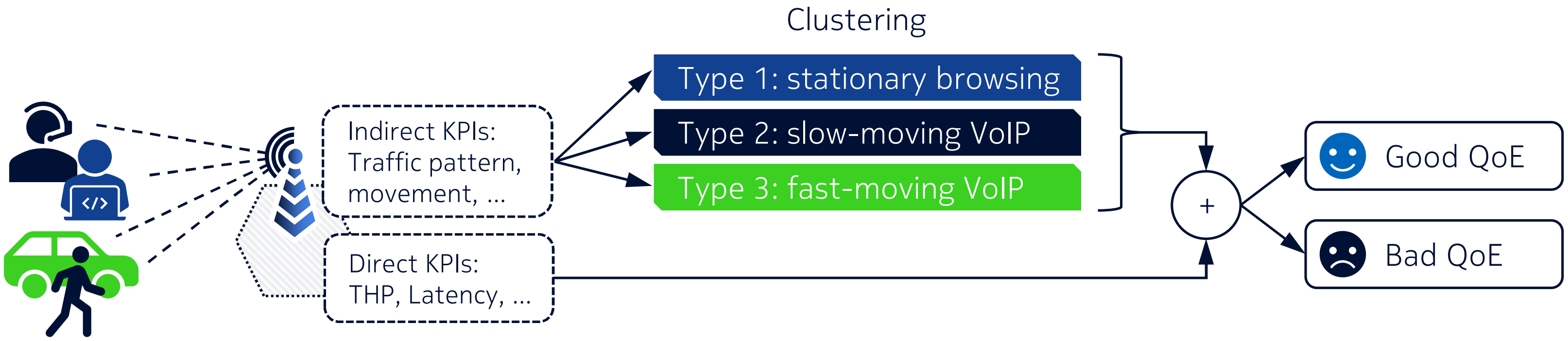
## Example Use Case in Network Automation

Quality of Experience (QoE) estimation tries to quantify user satisfaction:

1. **Cluster** the user contexts into usage types.
2. Map measured Key Performance Indicators (KPIs) to QoE values for each usage type.

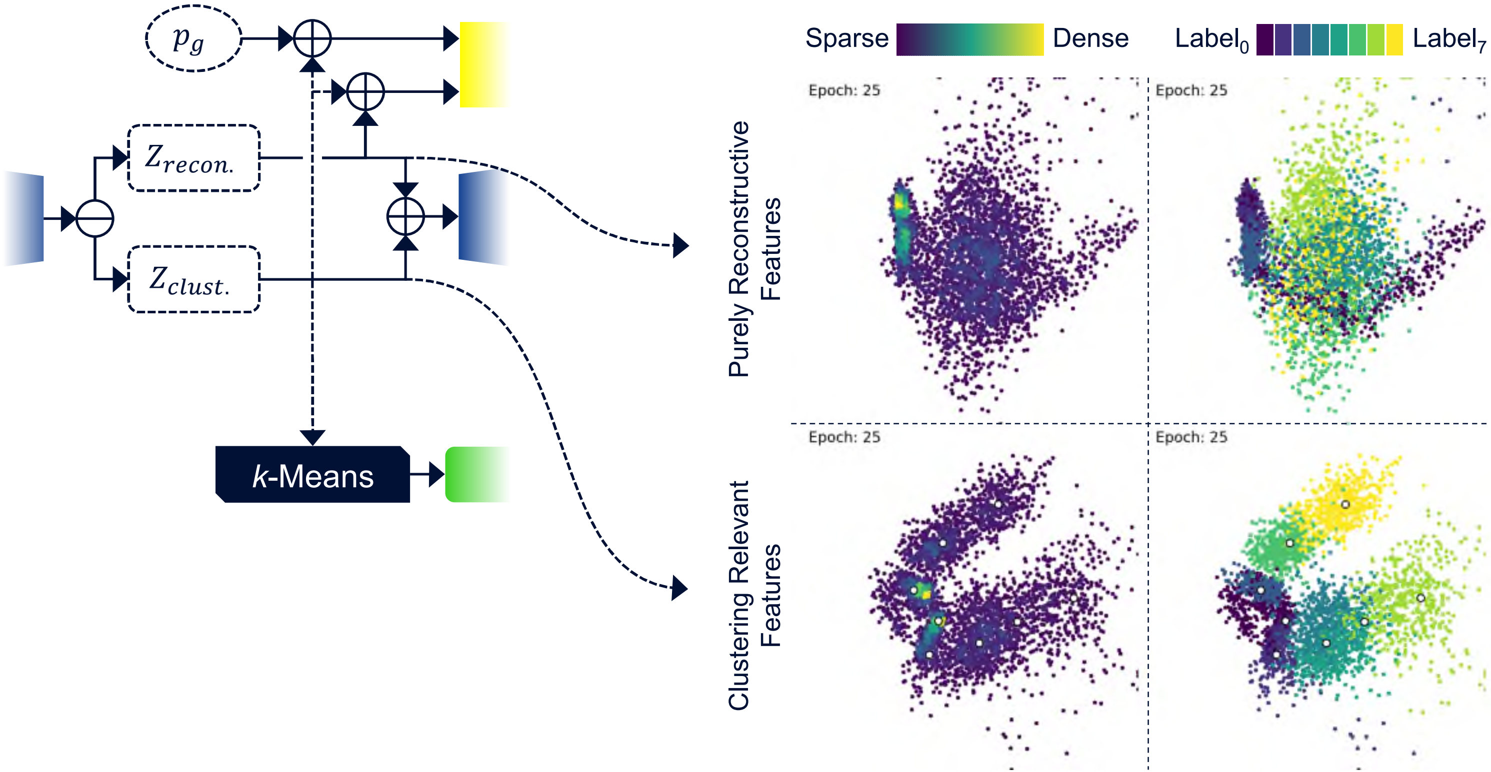
**Solution**

User-context-specific QoE maps.



# Deep Clustering of Mobile Network Data

## DANCE Training



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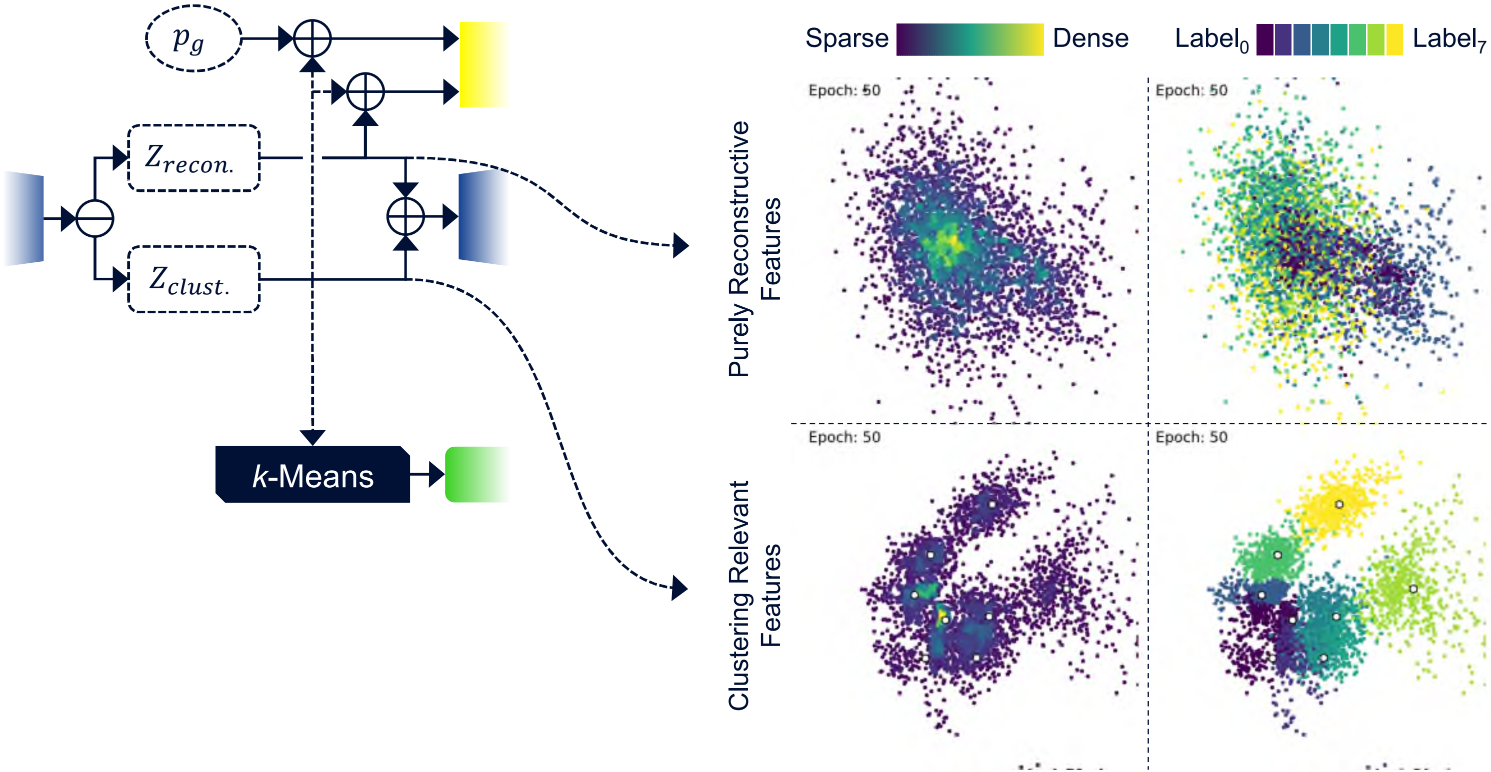

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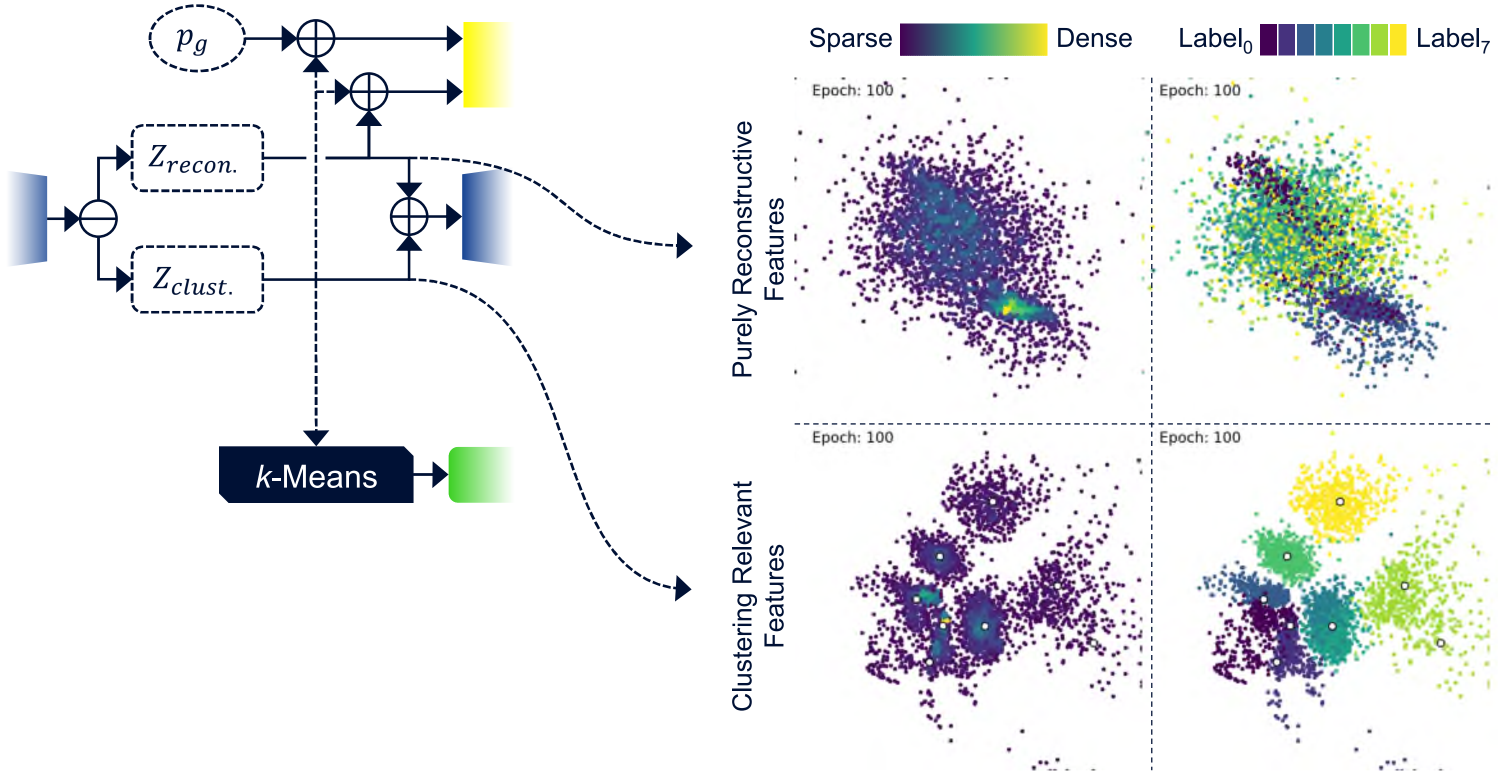

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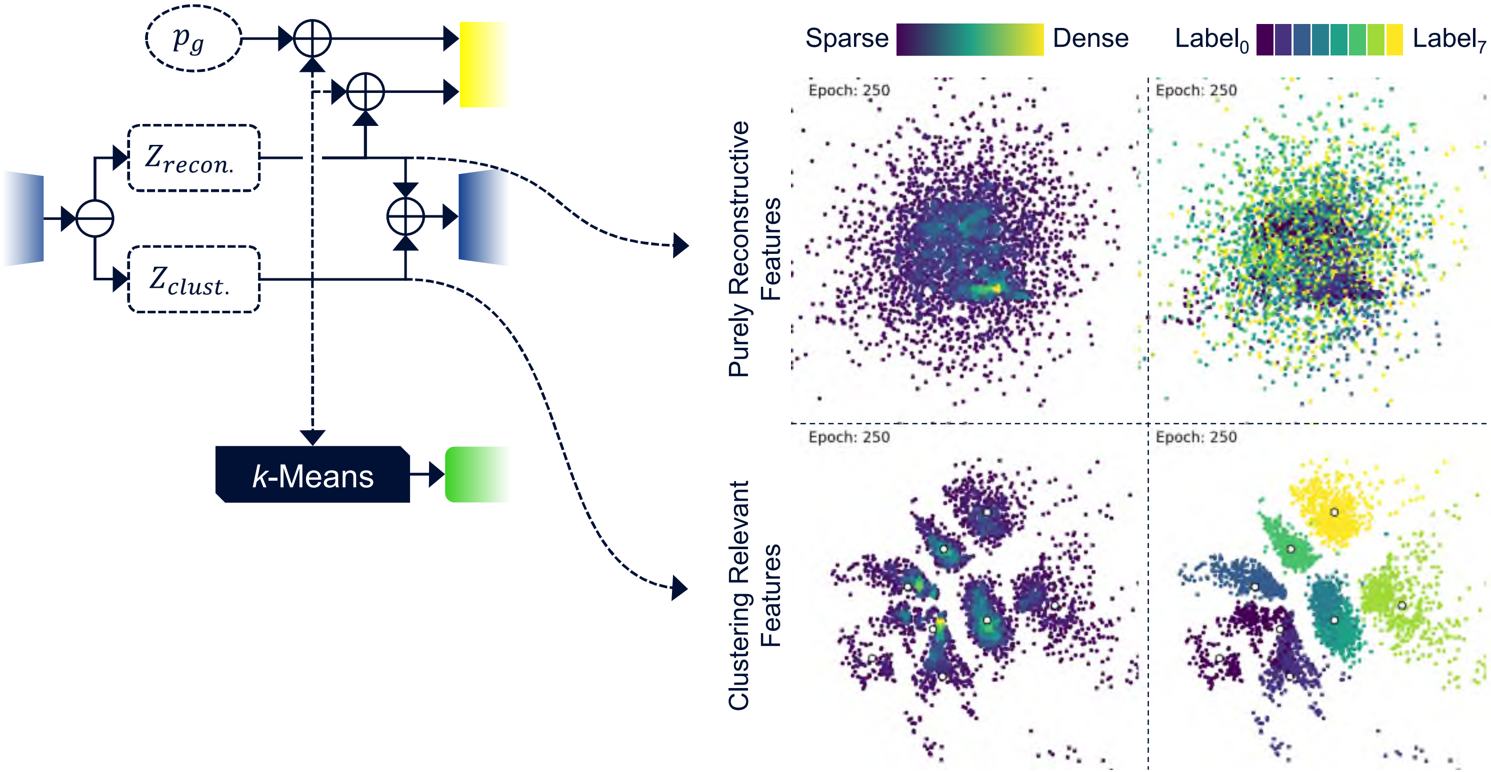

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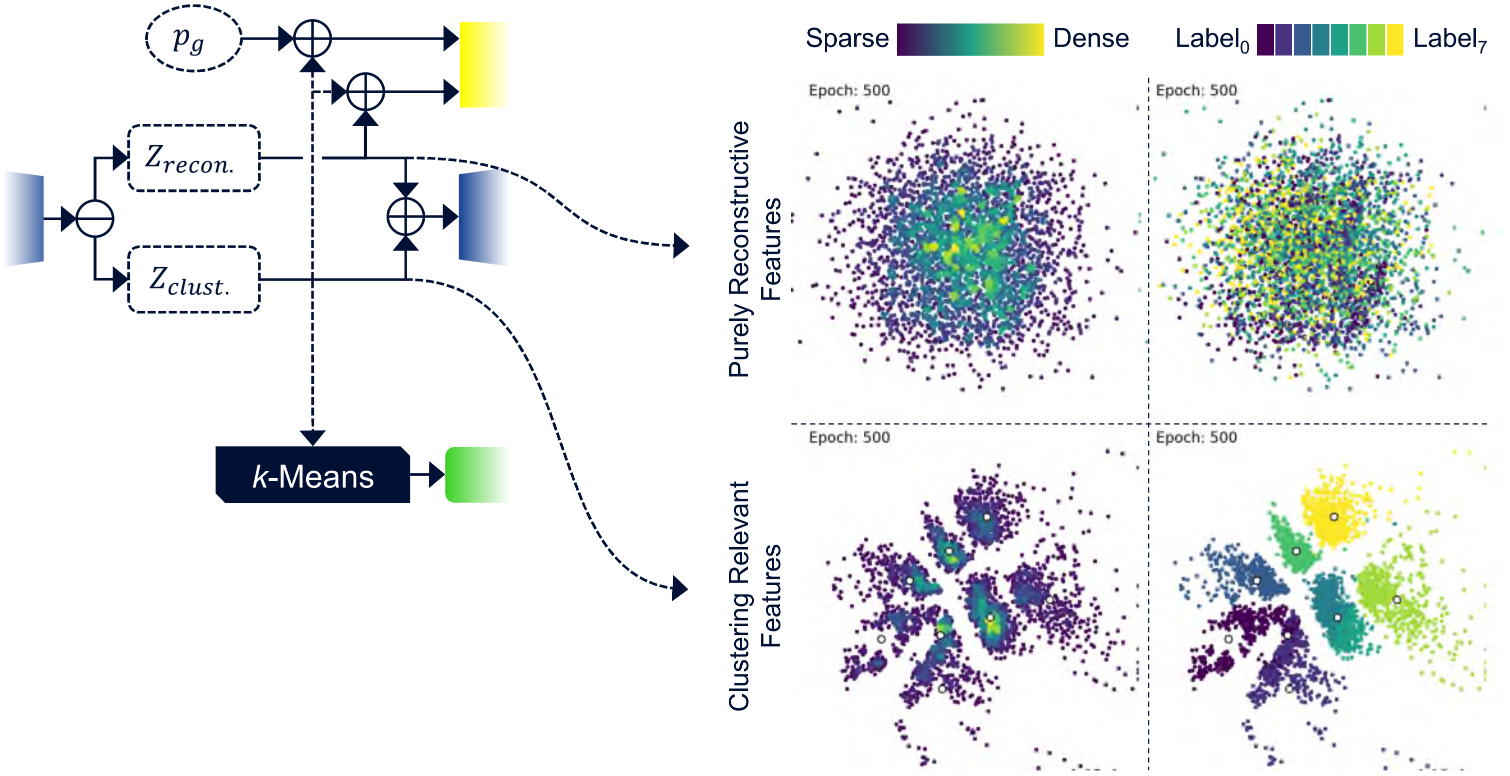

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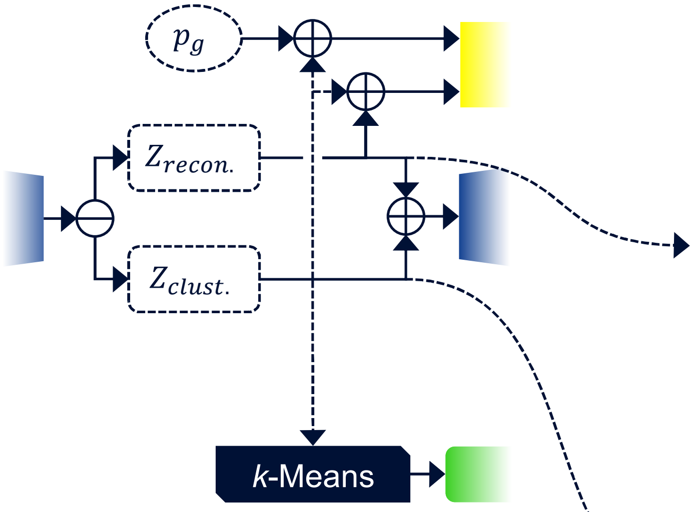


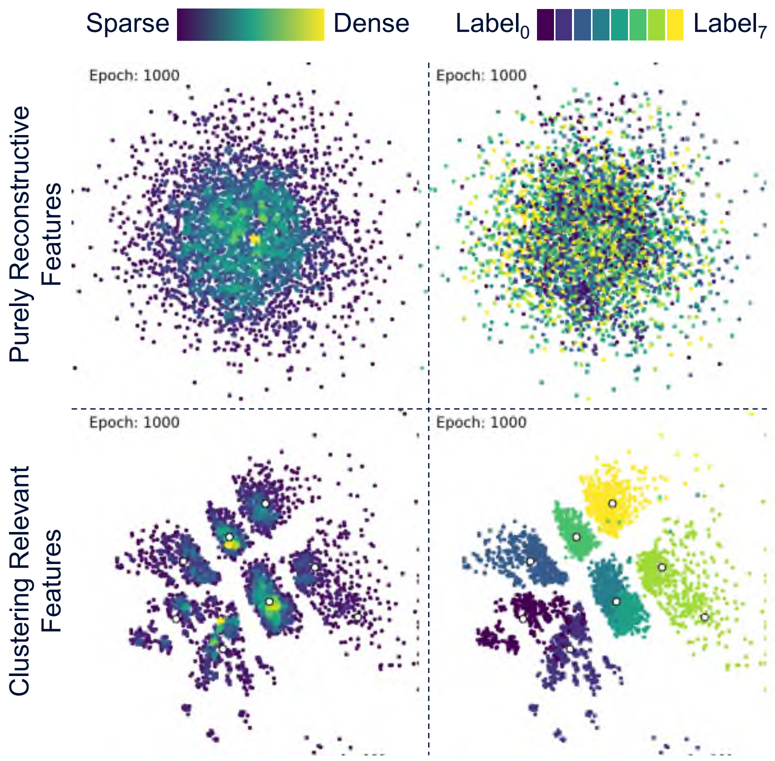

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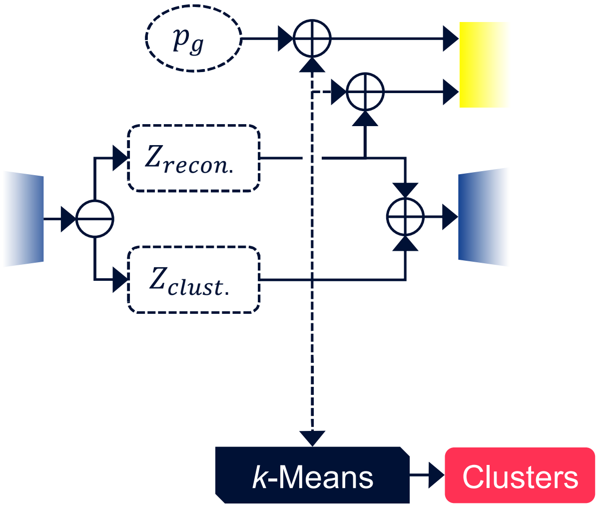
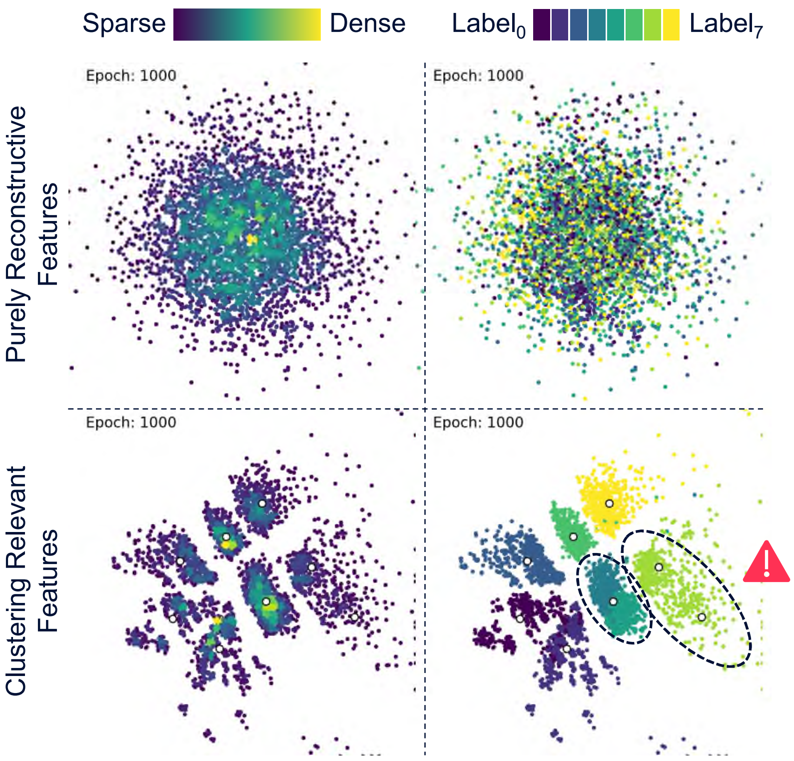
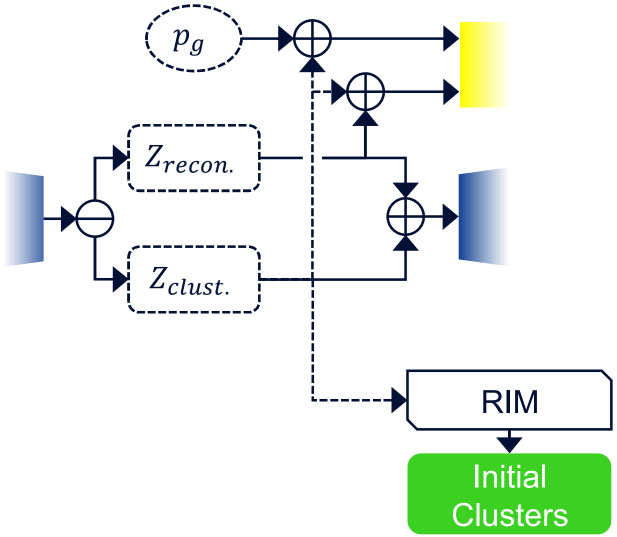
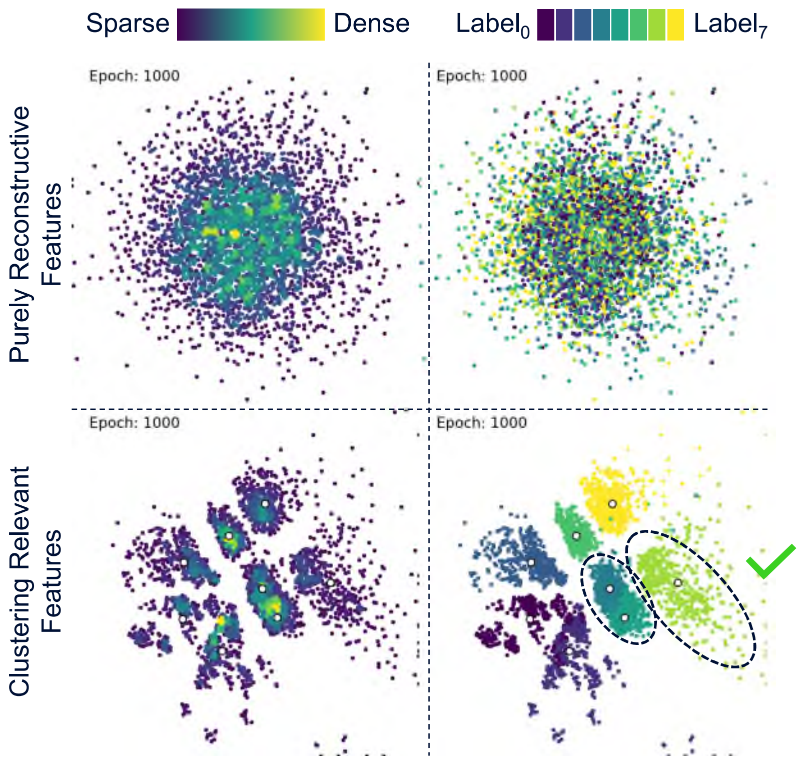



Unfortunately, even with the clustering-relevant features separated, *k*-means is **unreliable** in finding the clusters.



# Deep Clustering of Mobile Network Data
## RIM Initialization in DANCE

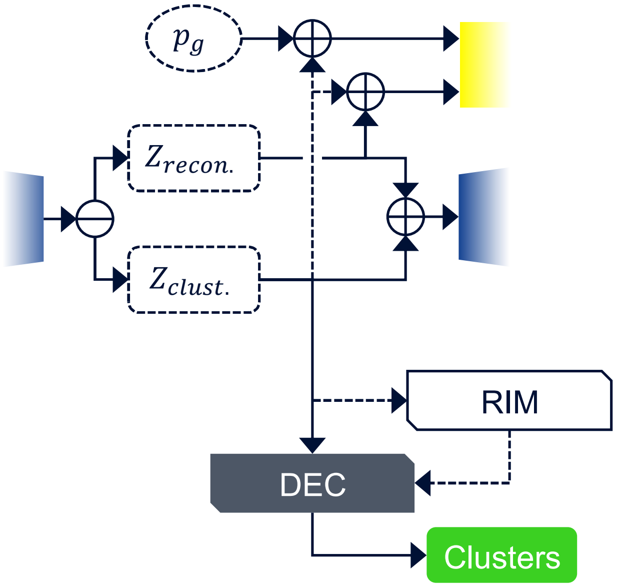


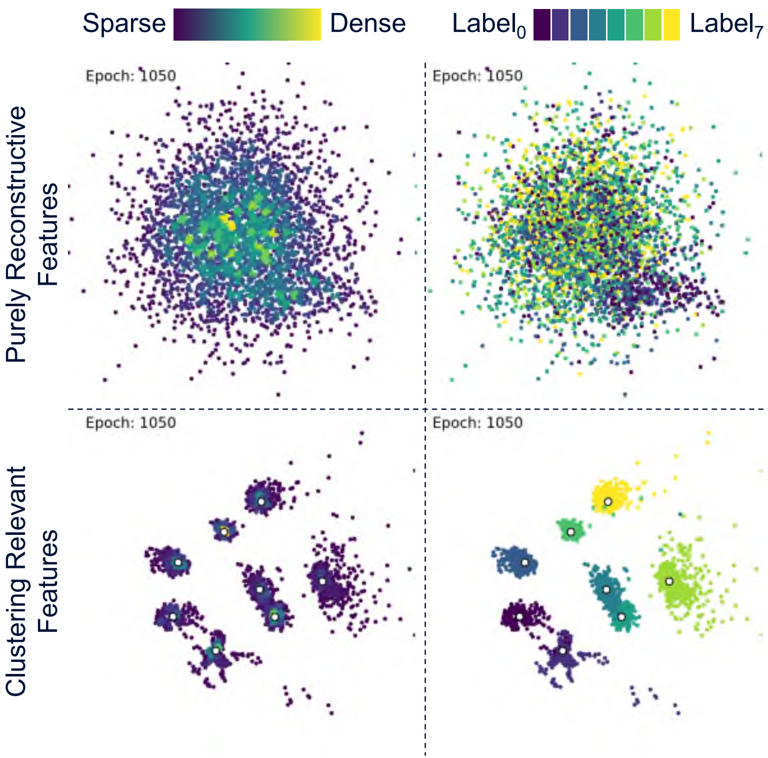

The **Regularized Information Maximization (RIM)** algorithm is capable of reliably finding an initial set of cluster centroids, by looking for sparse separating areas between dense groups of points.

# Deep Clustering of Mobile Network Data

## DEC Refinement in DANCE



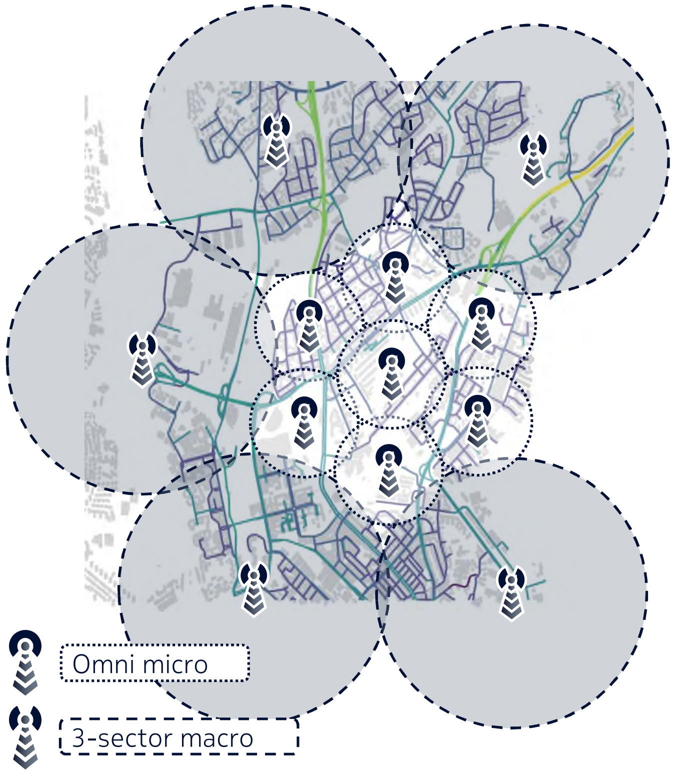

Using the initial clusters provided by RIM, the **Deep Embedded Clustering (DEC)** algorithm can refine and finalize the clustering, by grouping the clusters more tightly together.



# Associative Modeling
## Evaluation Data

Collected **simulated** mobile network data containing 8 user groups:

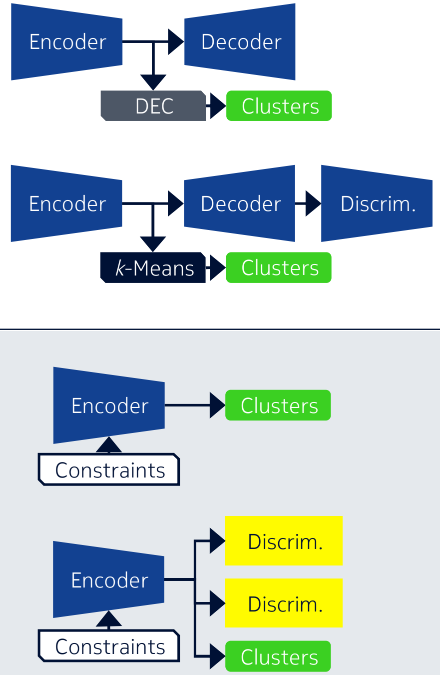
- **Throughput** measured on the application level
- **Radio quality** indicators: RSRP, allocated PRBs, SINR, …
- **Radio Resource Control** (RRC) status flags (connected, Radio Link Failure (RLF), handover signaling, idle etc.)



# Associative Modeling

## Evaluation Results

| | | ACC avg. (± std.) |
|---|---|---|
| **DEC** | (Deep Embedded Clustering) | 0.7409 (±0.021) |
| **ACAI** | (Adversarially Constrained Autoencoder Interpolation) | 0.7629 (±0.040) |
| **IMSAT** | (Information Maximizing Self-Augmented Training) | 0.4775 (±0.072) |
| **DCCS** | (Deep image Clustering with Category-Style representation) | 0.8416 (±0.055) |
| **DANCE** | | **0.8923** (±0.041) |

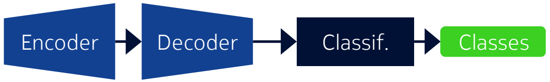


# Machine Confidence
## Evaluation Results

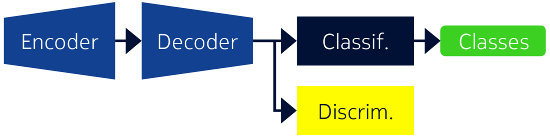
**Non-deep-imputation:**

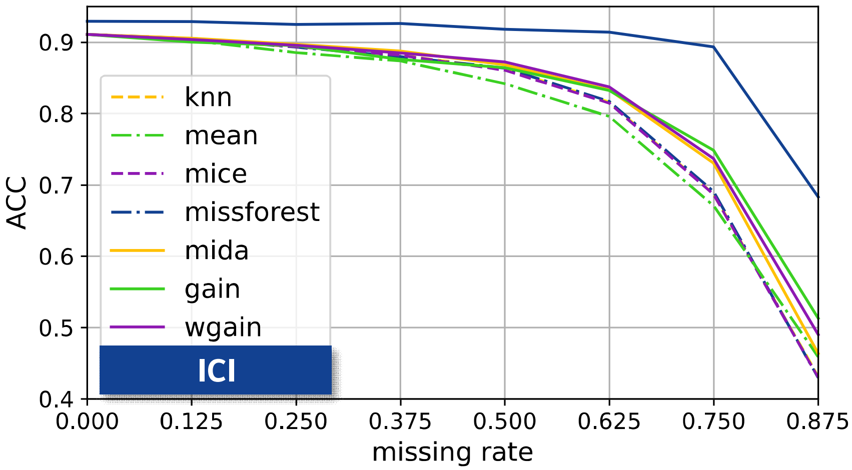
- *K*-nearest-neighbors
- Mean imputation
- MICE
- MissForest

**MIDA** (Multiple Imputation using Denoising Autoencoders)




**(W)GAIN** ((Wasserstein) Generative Adversarial Imputation Nets)



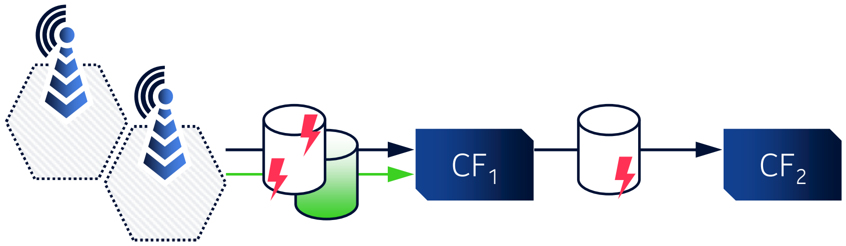



# Robust Deep Learning against Corrupted Data in CANs

## Conclusion

With integrated imputation:

- CFs can potentially withstand a significant amount of corrupted data.
- The processing of missing or corrupted inputs requires no additional processing step.



# Robust Deep Learning against Corrupted Data in CANs

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Continuation of the concept:

- Continuous confidence values in [0, 1].
- **Generating confidence** values in CFs.