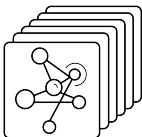




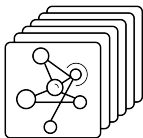




**CHATGPT**



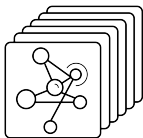
**1** training session



1 training session

500 ton  $CO_2$  emissions





1 training session

500 ton  $CO_2$  emissions



1000 cars driving 1000 km

2000 questions

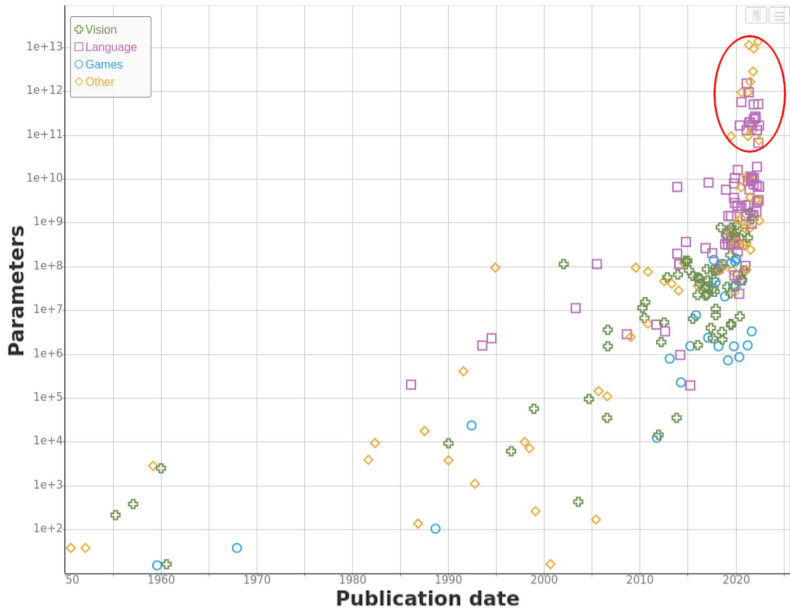


2000 questions



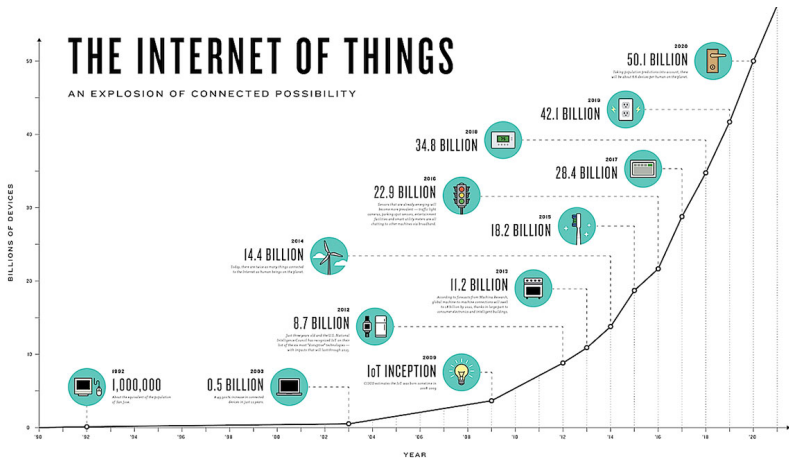
1 household per day





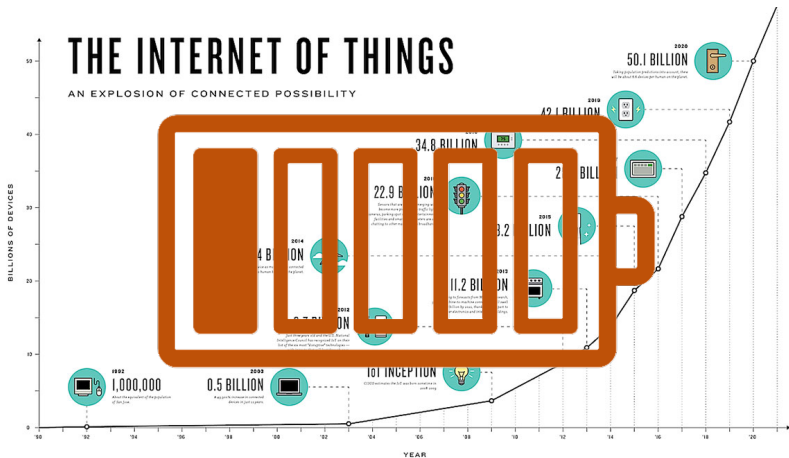
# THE INTERNET OF THINGS

AN EXPLOSION OF CONNECTED POSSIBILITY



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# Energy-efficient algorithms

Laura Smets

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Currently:

- ▶ PhD student at IDLab (UAntwerp - imec) since 2022

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# HyperDimensional Computing

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  - ▶ similarity: compare vectors (e.g., Hamming distance)



- ▶ Brain-inspired



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- ▶ Noise robustness [3, 15, 11]



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HDC has already been used in several applications, such as

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# Training framework

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## 1. MAPPING

MOST BASIC OBJECTS



ATOMIC VECTORS



(CONTINUOUS)  
ITEM MEMORY



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MOST BASIC OBJECTS



ATOMIC VECTORS



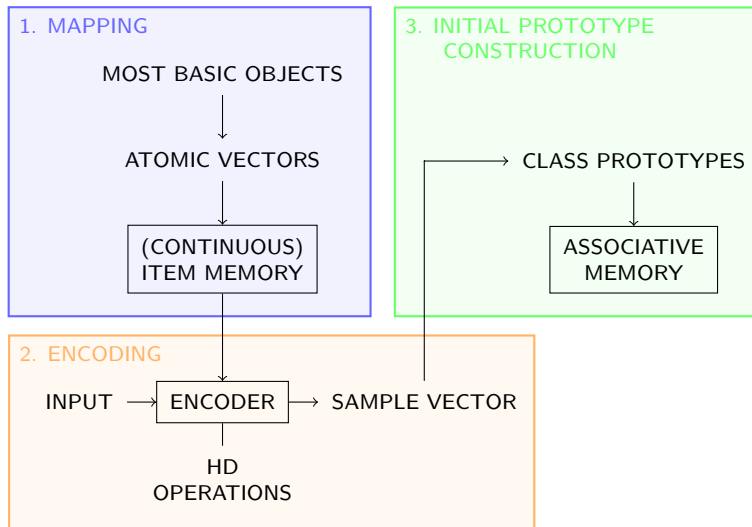
(CONTINUOUS)  
ITEM MEMORY

## 2. ENCODING

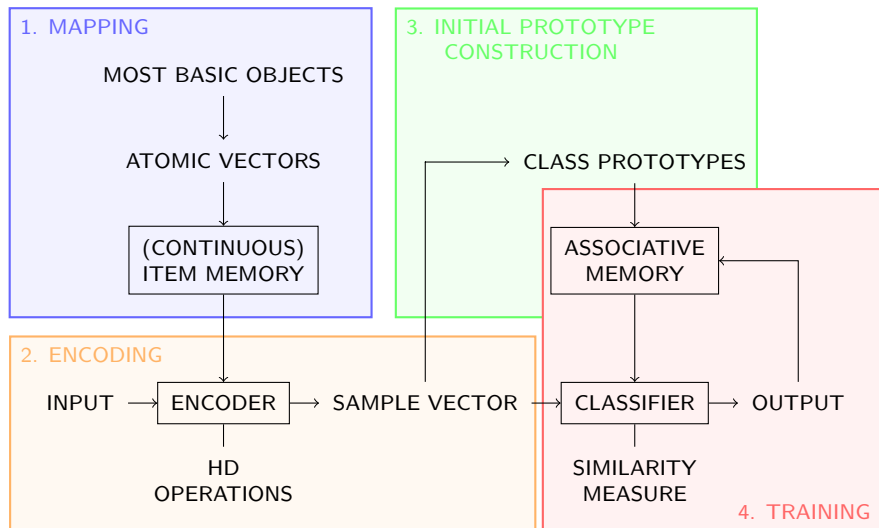
INPUT → ENCODER → SAMPLE VECTOR

HD  
OPERATIONS

# Training framework



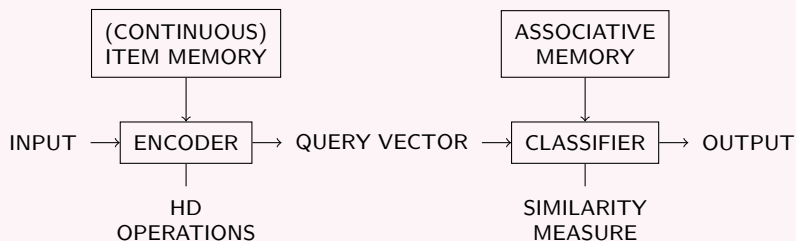
# Training framework



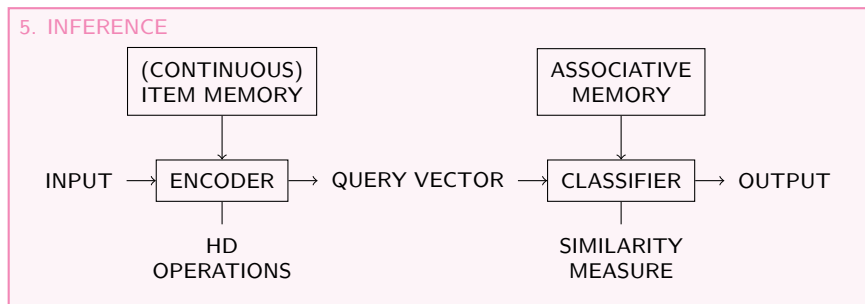
# Inference framework

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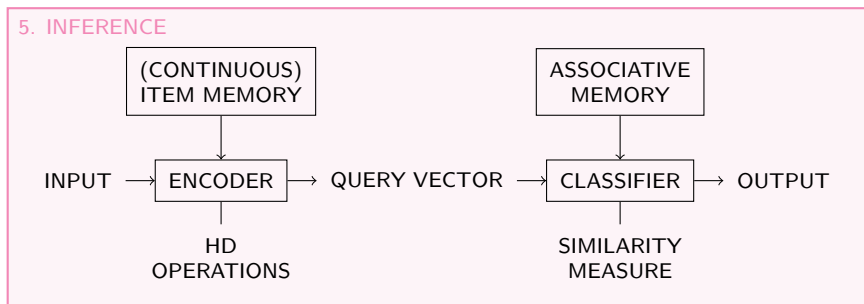
## 5. INFERENCE



# Inference framework



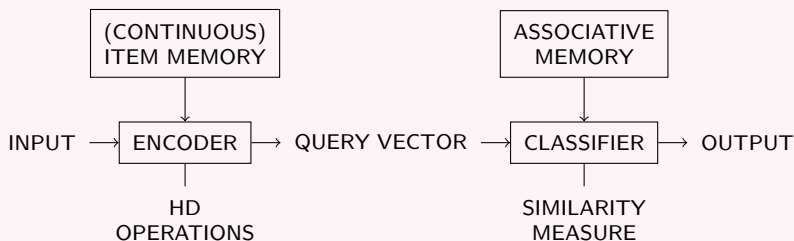
Two main building blocks:



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## 5. INFERENCE



Two main building blocks:

- ▶ Encoder
  - ▶ responsible for mapping input to HD vectors
- ▶ Classifier
  - ▶ creates class prototypes during training
  - ▶ compares query to all class prototypes during inference



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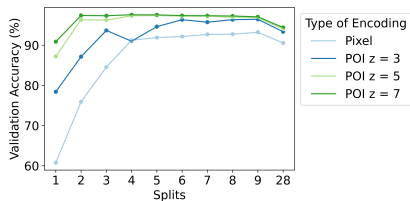
- ▶ text data [10]
- ▶ numeric data [2, 4]
- ▶ time-series data [12]

A uniform framework to encode (binarized) images is still lacking in the literature.

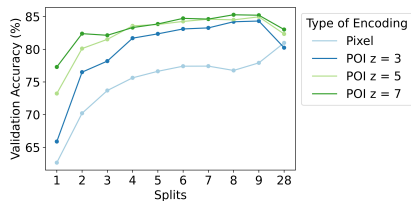
Smets, L., Van Leekwijck, W., Tsang, I.J. & Latré, S. (2024). An Encoding Framework for Binarized Images using Hyperdimensional Computing. Submitted to *Frontiers in Big Data*.



# Encoder

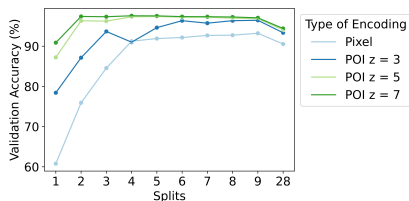


MNIST data set

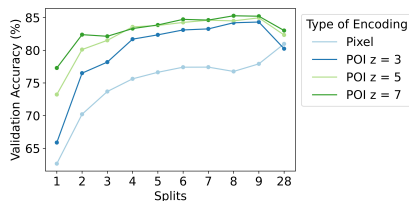


Fashion-MNIST data set

# Encoder



MNIST data set

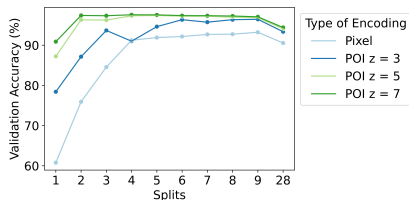


Fashion-MNIST data set

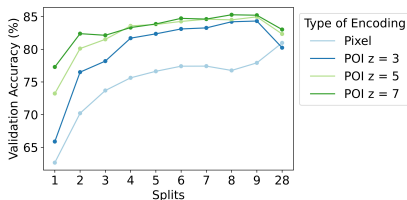
- ▶ Resulted in an accuracy of **97.92%** on the test set for the MNIST data set and **84.62%** for the Fashion-MNIST data set.



# Encoder



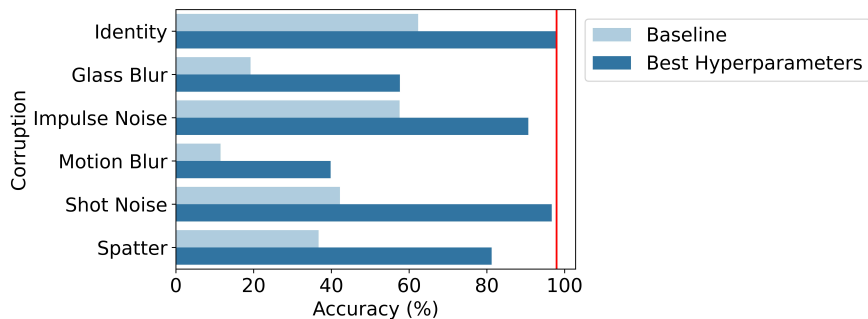
MNIST data set



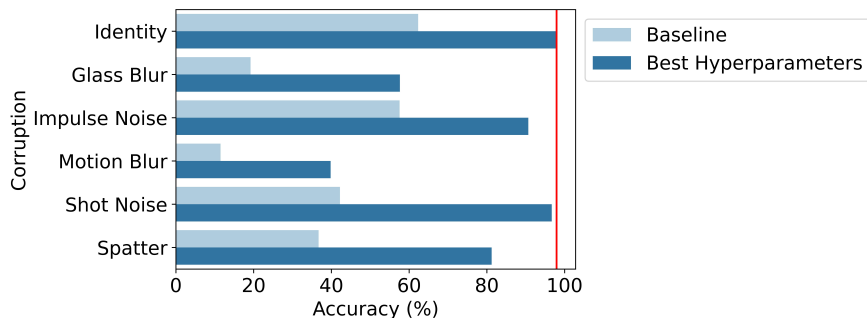
Fashion-MNIST data set

- ▶ Resulted in an accuracy of **97.92%** on the test set for the MNIST data set and **84.62%** for the Fashion-MNIST data set.
- ▶ The obtained results **outperform** other studies using native HDC with different encoding approaches and are **on par** with more complex hybrid HDC models and lightweight binarized neural networks.

# Encoder



MNIST-C data set



MNIST-C data set

- ▶ The proposed encoding approach demonstrates **higher robustness to noise and blur** compared to the baseline encoding.



During training, only **misclassified** samples are used to update class prototypes, i.e., the samples for which highest similarity is not obtained for correct class.

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What if for a **correctly classified sample**, the similarity to the class with the **second highest similarity is only slightly lower** than the similarity to the class with the highest similarity?



Smets, L., Van Leekwijck, W., Tsang, I.J. & Latré, S. (2023). Training a Hyperdimensional Computing Classifier Using a Threshold on its Confidence. *Neural Computation*, 35 (12): 2006–2023.

- ▶ Tested on ISOLET, UCIHAR, CTG and HAND data set



- ▶ Tested on ISOLET, UCIHAR, CTG and HAND data set
- ▶ Resulted in an HDC classifier that is **more accurate** and **more confident** in its predictions.

# Thank you!

Questions?  
Suggestions?  
Remarks?

Find me on LinkedIn:



or contact me via email:  
[laura.smets@uantwerpen.be](mailto:laura.smets@uantwerpen.be)

# References I

Information for introduction retrieved from:

- ▶ ChatGPT logo: <https://jacobsmedia.com/a-radio-conversation-with-chatgpt-part-1-sales/chatgpt-logo-square/>
- ▶ ChatGPT numbers (1): <https://nos.nl/nieuwsuur/artikel/2477186-kunstmatige-intelligentie-vreet-stroom-een-opdracht-hetzelfde-als>
- ▶ ChatGPT numbers (2): <https://innovationorigins.com/nl/de-enorme-hoeveelheid-stroom-die-ai-nodig-heeft-kan-zomaar-eens-het-groot>
- ▶ Graph model parameters: Pablo Villalobos et al. "Machine learning model size and the parameter gap". In: Jul. 2022. URL: <https://arxiv.org/abs/2207.02852>.
- ▶ Graph IoT: <https://www.ncta.com/whats-new/infographic-the-growth-of-the-internet-of-things>

Icons from:

- ▶ ai dataset by Olena Panasovska from <https://thenounproject.com/browse/icons/term/ai-dataset/>
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- ▶ Car by shashank singh from <https://thenounproject.com/browse/icons/term/car/>

# References II

- ▶ Question by Naya Putri from <https://thenounproject.com/browse/icons/term/question/>
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