Quick and Robust Feature Selection

the Strength of Energy-efficient Sparse Training for Autoencoders [1]

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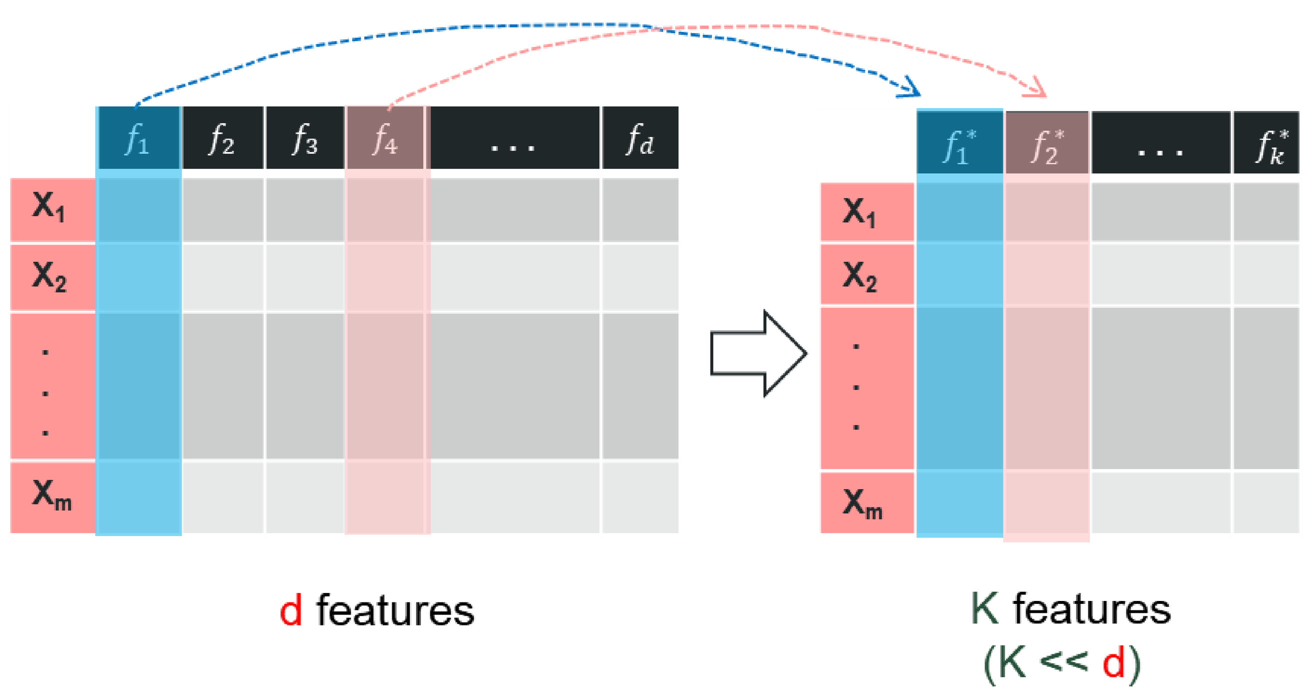
Introduction

- High-dimensional data challenges
  - High computational costs and memory requirements.
- Solution: Feature selection
  - Feature Selection aims to address the above challenges [2].
  - Most existing feature selection methods are computationally inefficient. Inefficient algorithms lead to high energy consumption, which is not desirable for devices with limited computational and energy resources.
- We present a novel feature selection method named **QuickSelection**, which introduces the strength of the neuron in sparse neural networks as a criterion to measure the feature importance. This criterion, blended with sparsely connected denoising autoencoders trained with the sparse evolutionary training procedure, derives the importance of all input features simultaneously.

Feature Selection

Feature Selection identifies the most relevant and informative attributes of a dataset.



Challenges

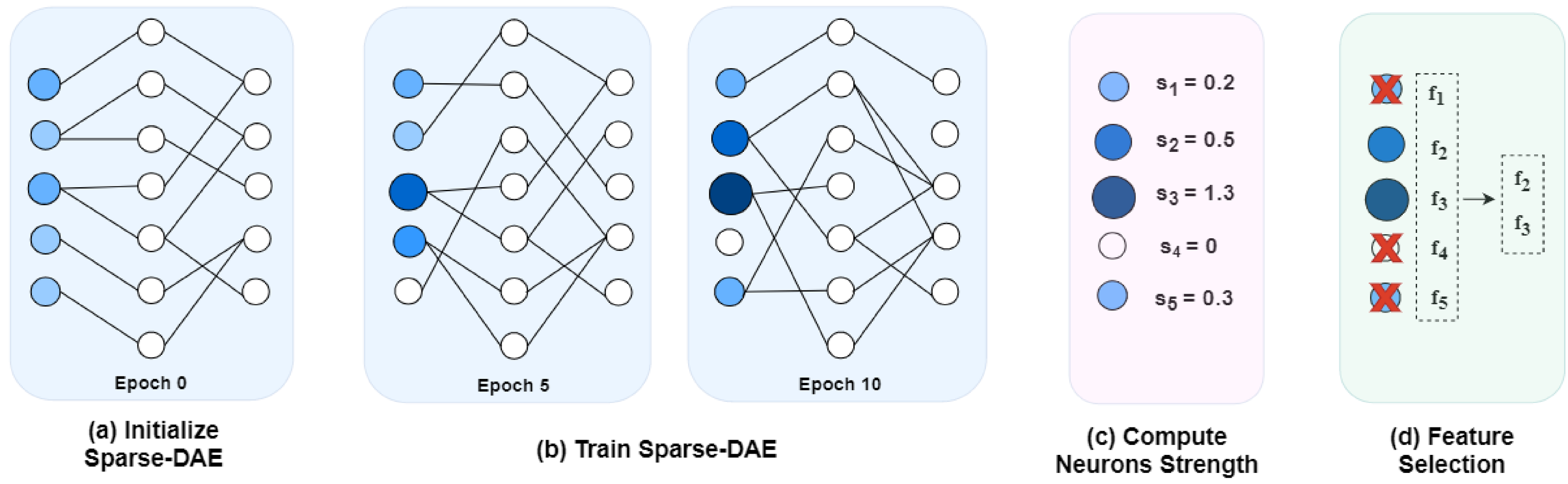
Annotation

Scalability
- Performance degradation
- High resource requirement
- High energy consumption

Research Question

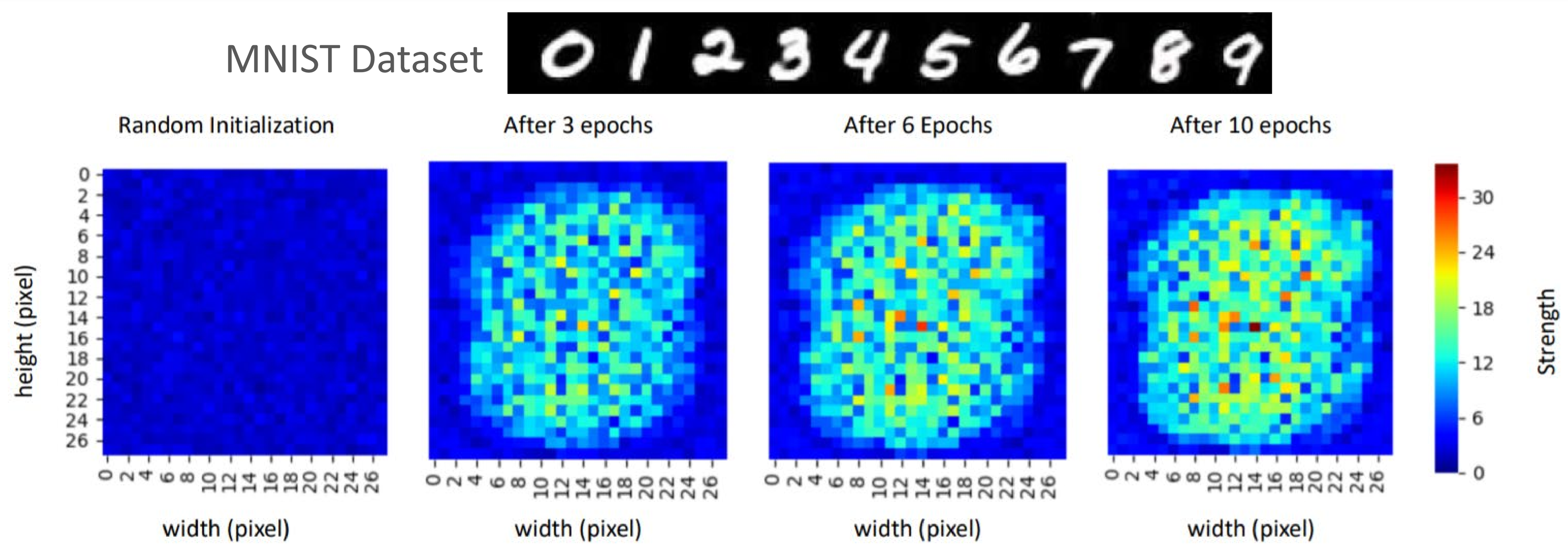
How can we design an energy-efficient unsupervised feature selection algorithm to select an informative subset of the features?

Methodology: QuickSelection



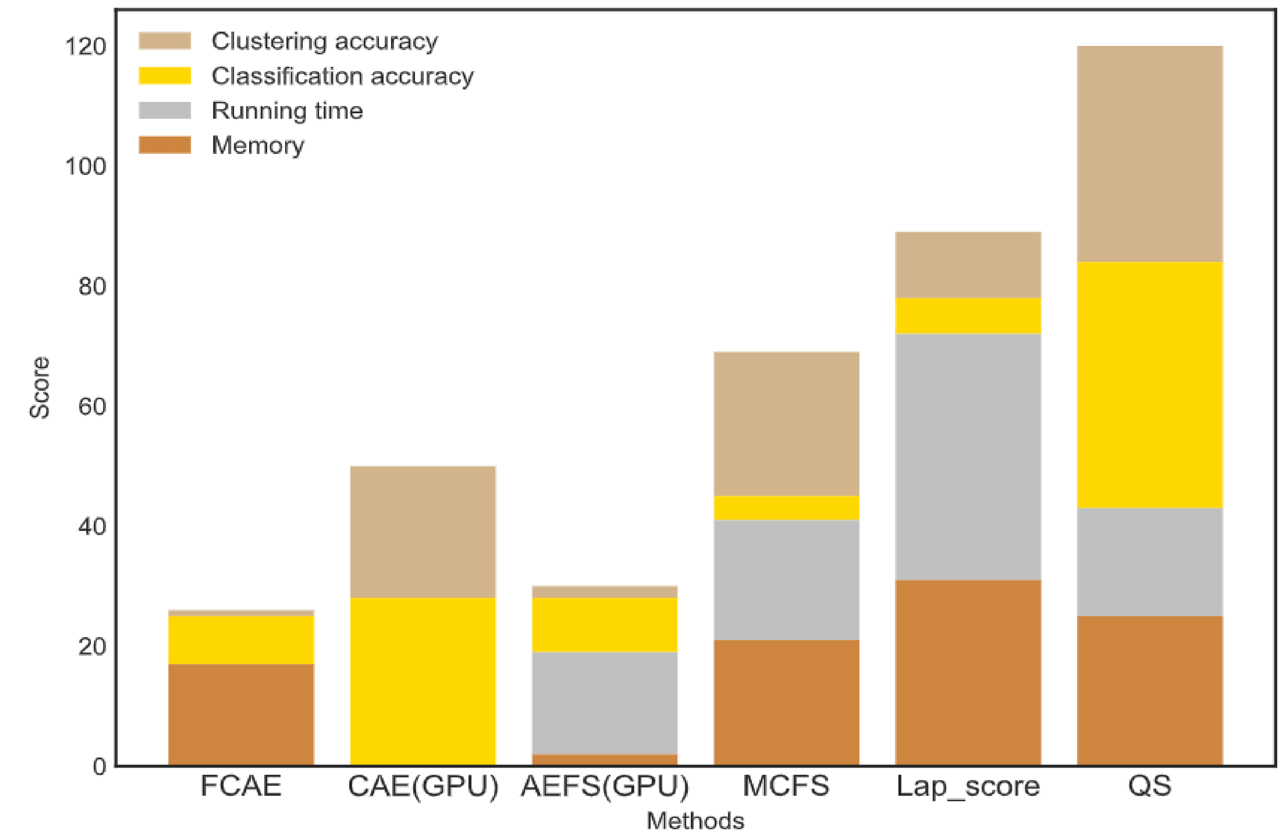
- **Training.** We train a sparse denoising autoencoder (DAE) with sparse evolutionary training (SET) [3].
- **Neuron Strength.** We determine the importance of the neurons based on their strength.
  - We estimate the strength as $S_i = \sum_{j=1}^{n^1} |W_{ij}^1|$, where n^1 is the number of neurons of the first hidden layer, and W_{ij}^1 denotes the weight of connection linking input neuron i to hidden neuron j.
- **Feature Selection.** We select the features corresponding to the neurons with the K largest strength values

Neuron Strength Visualization



Results

- ✓ QuickSelection achieves the best trade-off between classification accuracy, clustering accuracy, memory, and running time among the considered methods.
- ✓ QuickSelection runs on only one CPU core.
- ✓ It derives the importance of all features simultaneously in a single run.



Conclusions

Efficient Feature Selection. We show that feature selection can be performed using neural networks *efficiently* in terms of computational cost and memory requirement.

Reducing Energy Cost. Efficient feature selection can pave the way for reducing the ever-increasing computational costs of deep learning models. This will not only save the *energy costs* of processing high-dimensional data but also will ease the *challenges* of high energy consumption imposed on the *environment*.

References

[1] Atashgahi, Z., Sokar, G., van der Lee, T., Mocanu, E., Mocanu, D. C., Veldhuis, R., & Pechenizkiy, M. (2022). Quick and robust feature selection: the strength of energy-efficient sparse training for autoencoders. *Machine Learning (ECML-PKDD 2022 Journal Track)".*

[2] Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. Computers & Electrical Engineering, 40(1), 16-28.

[3] Mocanu, D. C., Mocanu, E., Stone, P., Nguyen, P. H., Gibescu, M., & Liotta, A. (2018). Scalable training of artificial neural networks with adaptive sparse connectivity inspired by network science. *Nature Communications*, *9*(1), 1-12.