Wrangling with “Unsupervised Space Partitioning for ANN Search”

A Study on Performance Enhancements

Stathis Kotsis Michael Darmanis

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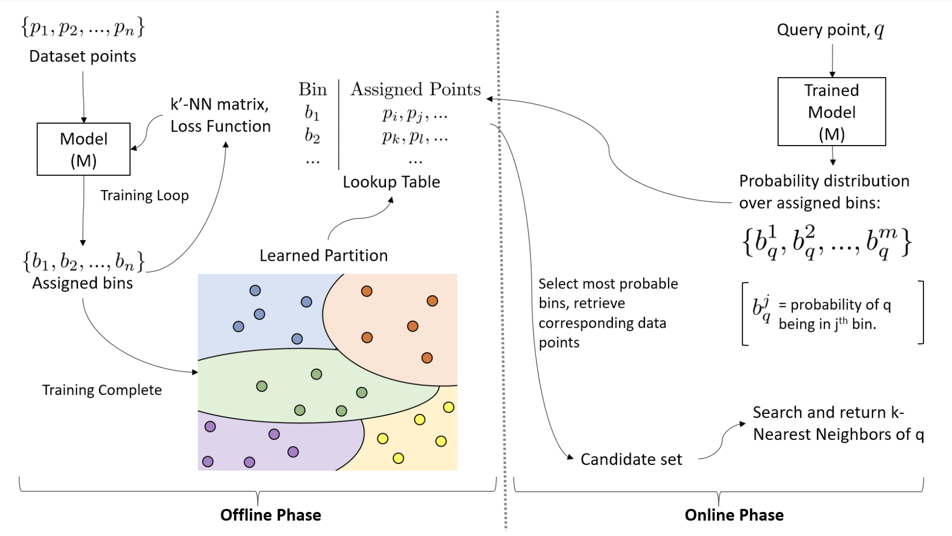
M149 Database Systems, NKUA

Introduction

- Approximate Nearest Neighbour (ANN) search is crucial in handling large datasets.
- Traditional methods may not scale well with high-dimensional data.
- This study investigates extensions to the original approach in ”Unsupervised Space Partitioning for Approximate Nearest Neighbour Search”.

Original ANN Scheme



Implementations and Integrations

Indexing

- Hierarchical Navigable Small Worlds[4] (not fully implemented)
- Product vector quantization pipeline[1] (implemented with slow training time, but significant memory savings)

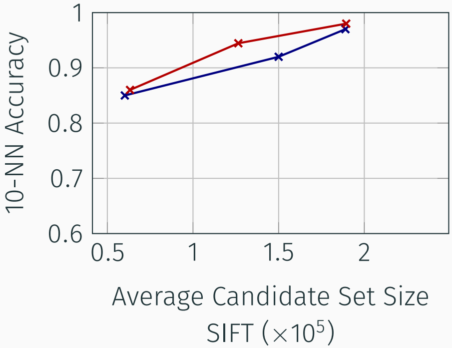
Sketching

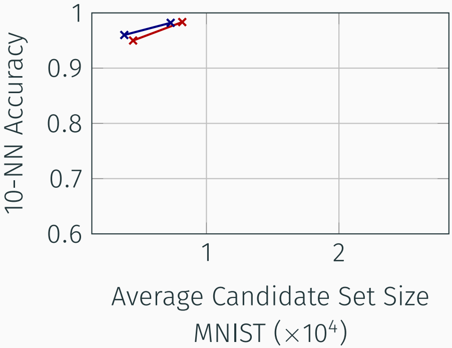
- Principal Component Analysis[5] (PCA)

Model enrichment

- Mahalanobis distance[3]
- Convolutional Neural Networks[2] (CNNs)
- Multi-ensembling paradigm[6]
- Loss function modifications (not fully implemented)

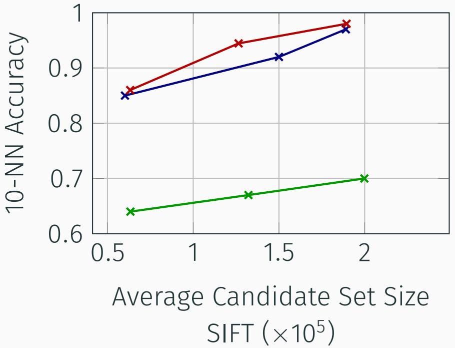
Results: Original, PCA

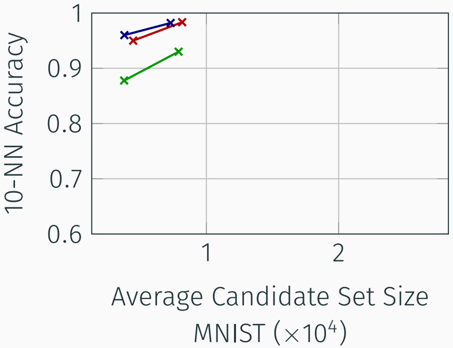




- Achieved 1% accuracy increase at candidate sizes of 190,000-195,000 on SIFT.
- Reduced search time to 0.42 ms on SIFT, a 66% improvement.
- Exhibited similar performance to the original on MNIST.
- Achieved 0.22 ms search time on MNIST, a 70% reduction.

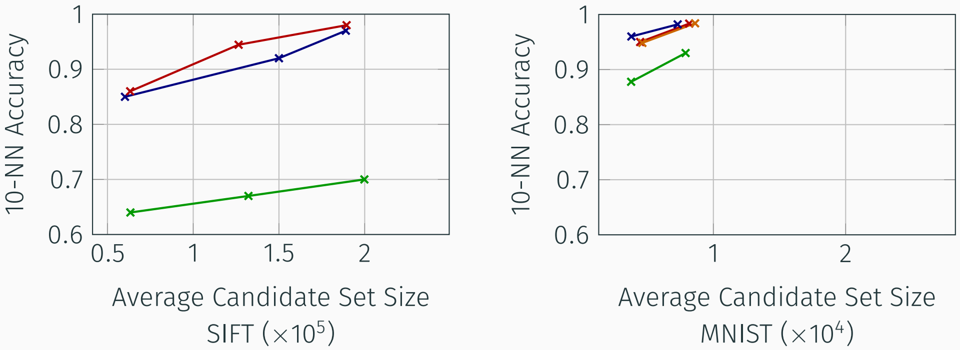
Results: Original, PCA, Mahalanobis





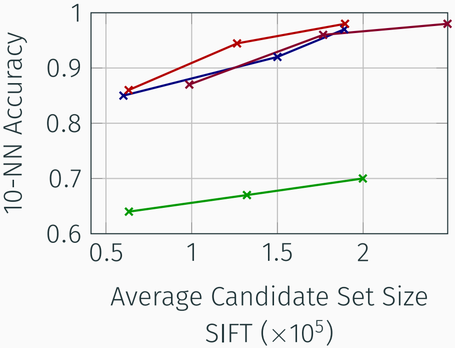
- Matched PCA with 0.42 ms search time on SIFT, a 66% improvement.
- Reduced search time to 0.21 ms on MNIST, a 70% improvement.

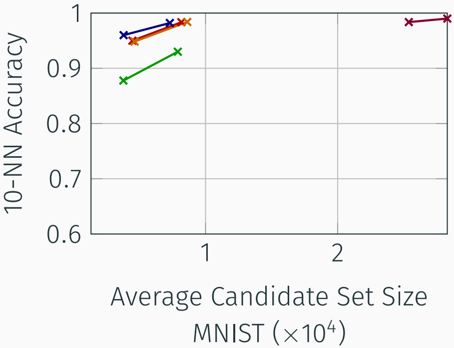
Results: Original, PCA, Mahalanobis, CNN



- Achieved high performance on MNIST with only 4-5 epochs, compared to 40+ epochs for linear models.

Results: Original, PCA, Mahalanobis, CNN, Multi-Ensembling





- Exhibited tendency of creating oversized partitions.
- Demonstrated complexity in integrating different models for high-dimensional data.

Conclusions

- Achieved notable search time reductions with PCA and Mahalanobis; difficulties presented in handling high number of partitions
- Demonstrated CNNs' efficiency; achieved high performance with minimal epochs (original used 90+ with a neural network)
- Revealed multi-ensembling complexities; smarter functions for the combination of models are required (probabilistic, genetic algorithms)
- Proposed future steps in adaptive techniques, alternative loss functions, and hybrid model and unsupervised space partitioning (hnsw and product vector quantisation)

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