Exploiting contemporary architectures for fast Nearest Neighbor classification

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Outline

The Nearest Neighbor algorithm

- Definition of the problem
  - Given a set of samples and an element, find the closest match from the set of samples
- Both a problem and a tool
- Some applications
  - Pattern recognition
  - Statistical classification
  - Data compression
  - DNA sequencing

The Nearest Neighbor algorithm

- Definition of the problem
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- Both a problem and a tool
- Some applications
  - Statistical classification

Input data

- Database
  - M training elements
  - N testing elements
  - D features
- Training set
  - TRAIN, a $M \times D$ matrix
  - $\text{classof}(b)$, the class label of an element b (a row in matrix TRAIN)
- Testing set
  - TEST, a $N \times D$ matrix
  - $\text{classof}(a)$, same as with TRAIN

Analytical model

- Performance measured in Normalized Cycles

$$NC = \frac{\mathrm{CPU\_time\_in\_cycles}}{N \cdot M \cdot D}$$

- NC modeled as

$$NC = NC_{cpu} + NC_{mem}$$

Hardware platform

- Intel Xeon E5520 “Gainestown” (*Nehalem* microarchitecture)
- Two quad-core processors
- Two 4GB memory modules
- NUMA, Quick Path Interconnect
- 256kB per core L2 cache
- 8MB per processor L3 cache
- SSE 4.2

Basic algorithm

for all $a \in \text{TEST}$ **do**
  $min \leftarrow \infty$
  for all $b \in \text{TRAIN}$ **do**
    $dist \leftarrow 0$
    for $i = 0$ **to** D **do**
      $dist \leftarrow dist + (a_i - b_i)^2$
    end for
    if $dist < min$ **then**
      $min \leftarrow dist$
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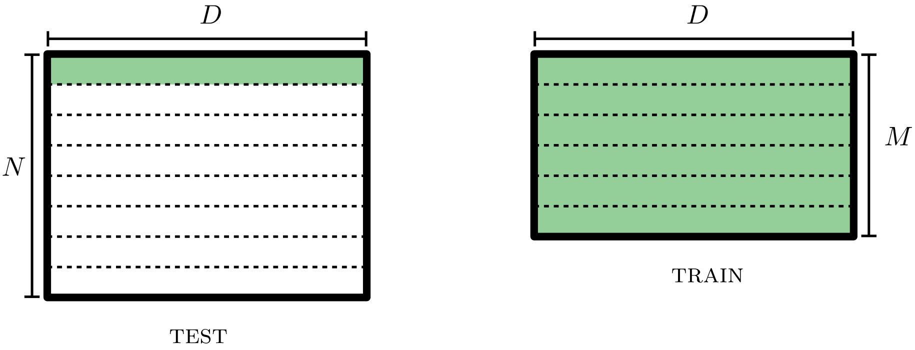
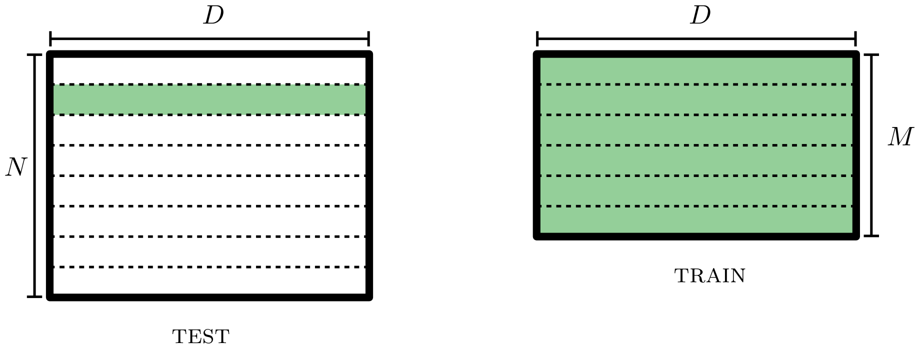
end for

Memory access pattern



Memory access pattern



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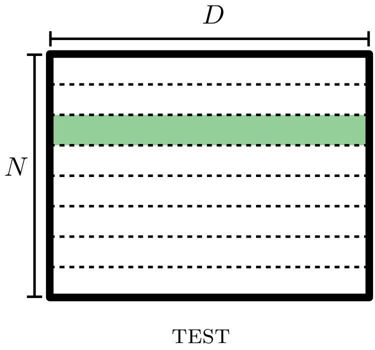

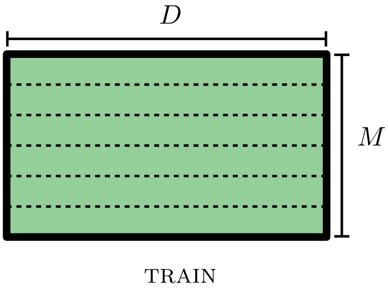

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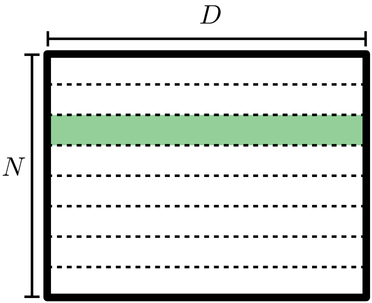
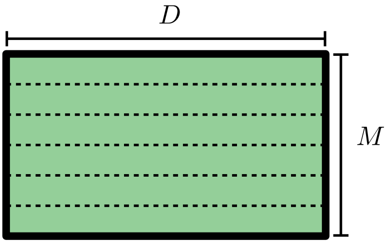


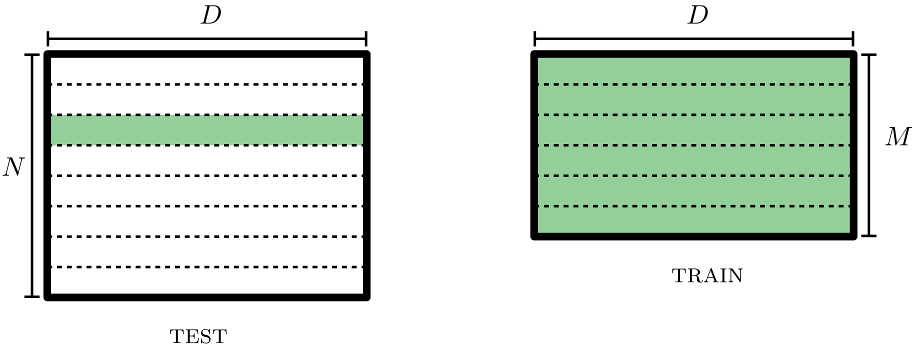
TEST



TRAIN

- D influences NC_{cpu}

Memory access pattern



- D influences NC_{cpu}
- M and N influence NC_{mem}

Outline

Blocking

for all $a \in \text{TEST}$ **do**
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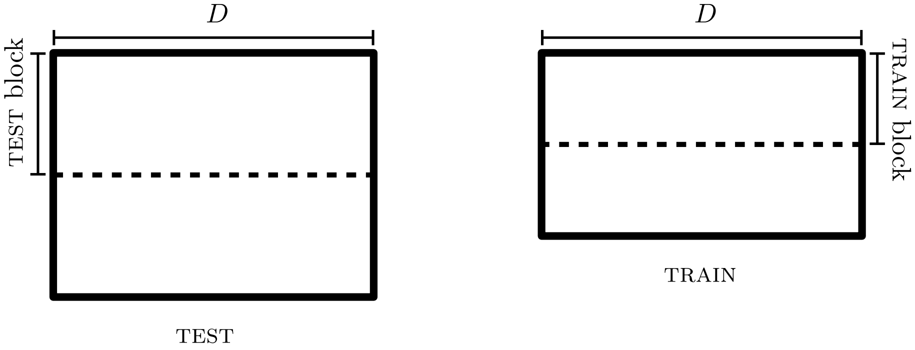
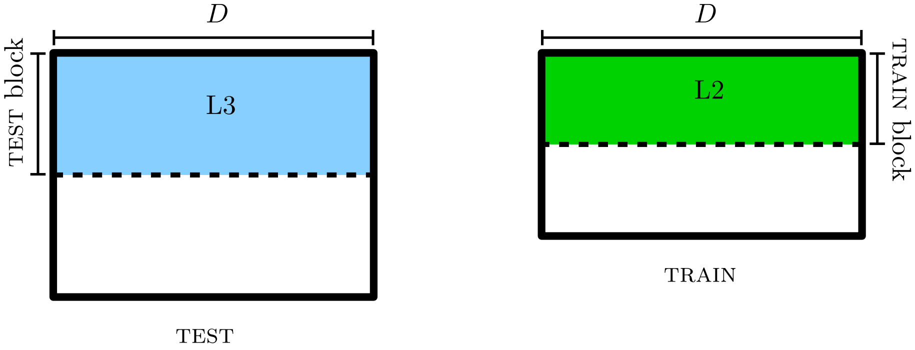
Blocking scheme



Blocking scheme



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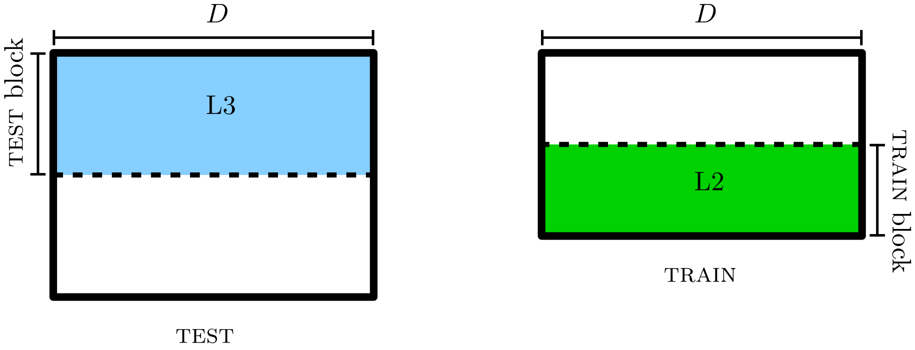

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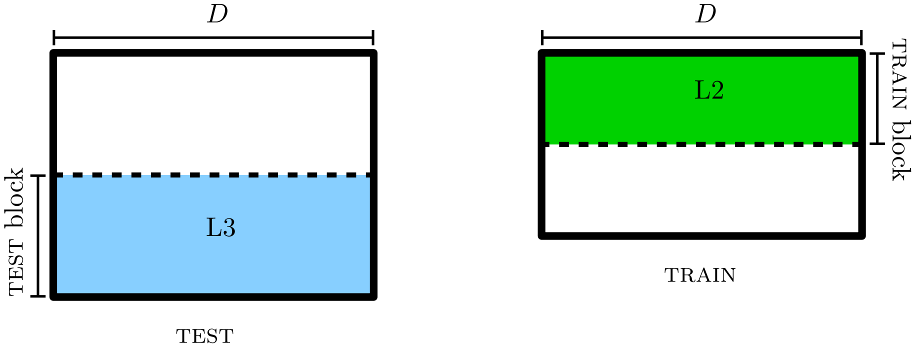

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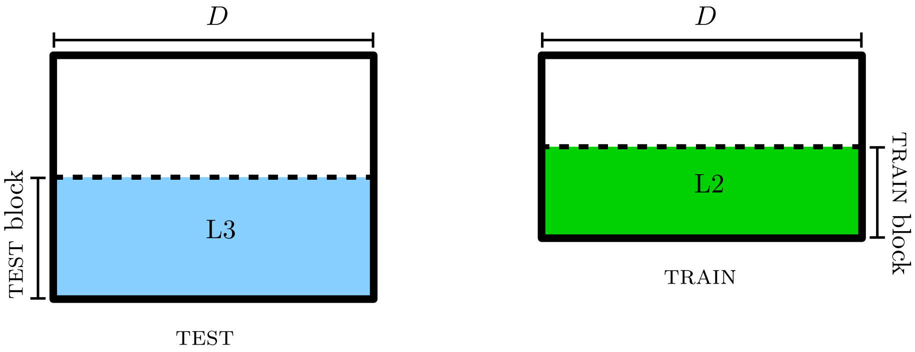
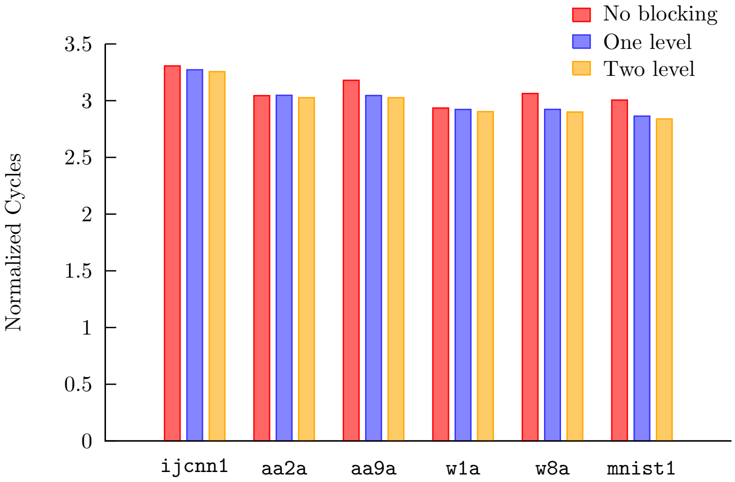


Blocking results



NC_{mem} reduction

Algorithm	NC(Small)	NC(Large)
No blocking	3.03	3.14
One level blocking	3.03	3.04
Two level blocking	3.03	3.03

- Stalls due to cache misses are reduced

NC_{mem} reduction

Algorithm	NC(Small)	NC(Large)
No blocking	3.03	3.14
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Two level blocking	3.03	3.03

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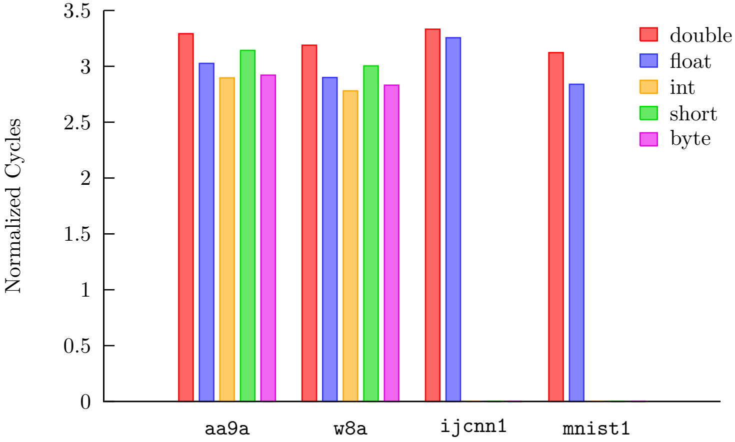
$$NC = NC_{cpu} + NC_{mem}$$

$$NC_{mem} \approx 0$$

$$NC \approx NC_{cpu}$$

Changing data type



Loop unrolling

for all $a \in \text{TEST}$ **do**
    $min \leftarrow \infty$
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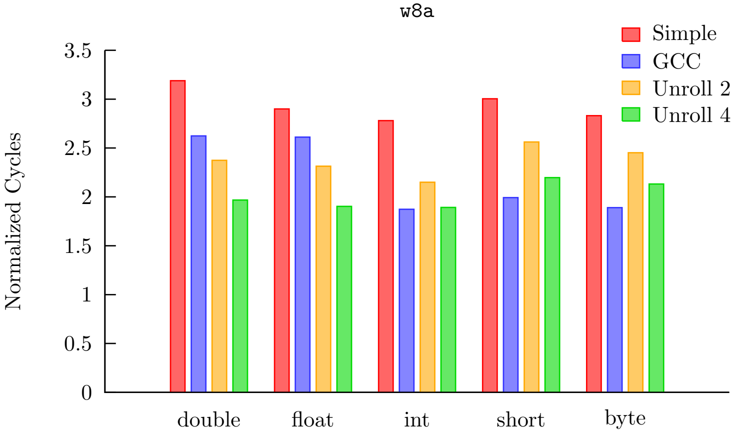
Unrolling results



Vectorization

for all $a \in \text{TEST}$ **do**
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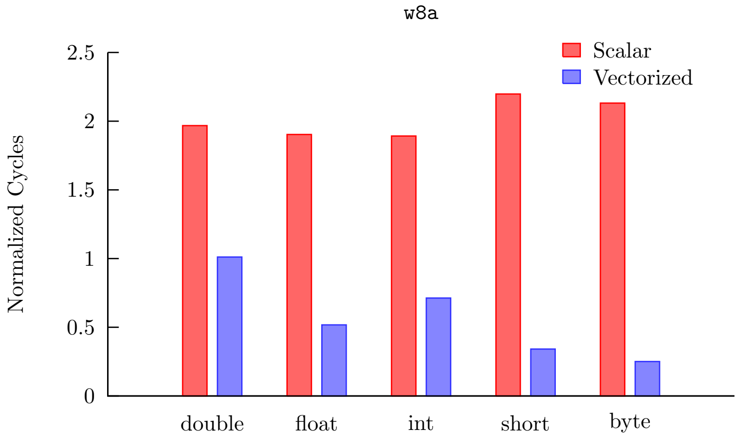
Vectorization results



Parallelization

for all $a \in \text{TEST}$ **do**
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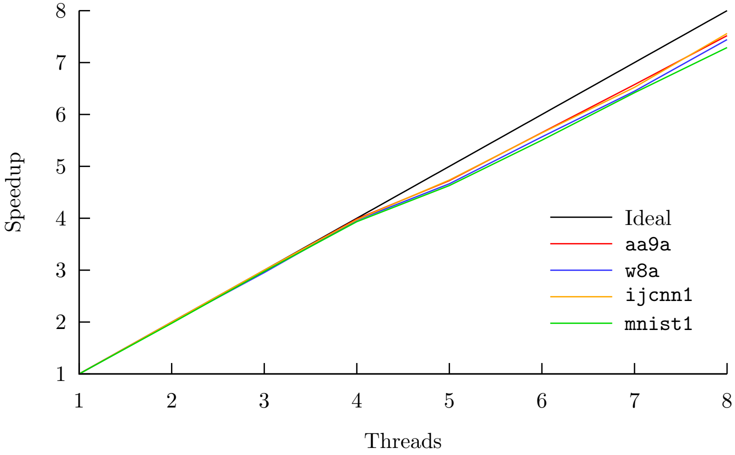
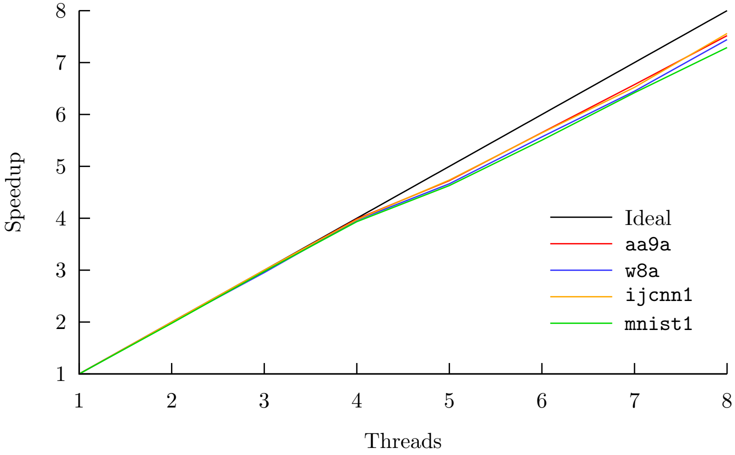
Scalability results

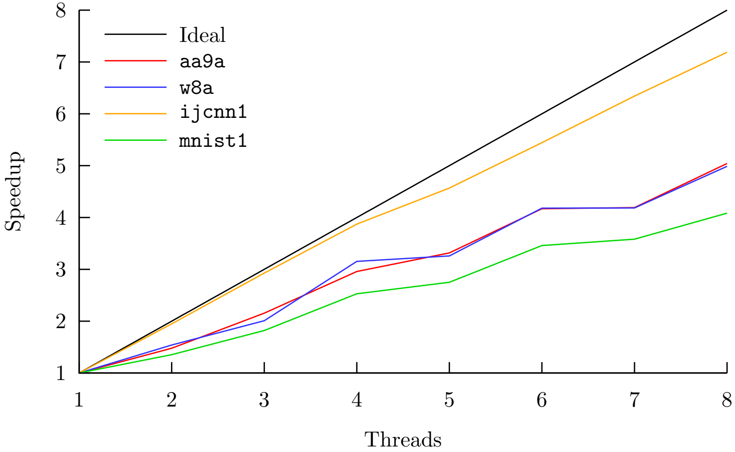


Scalability results



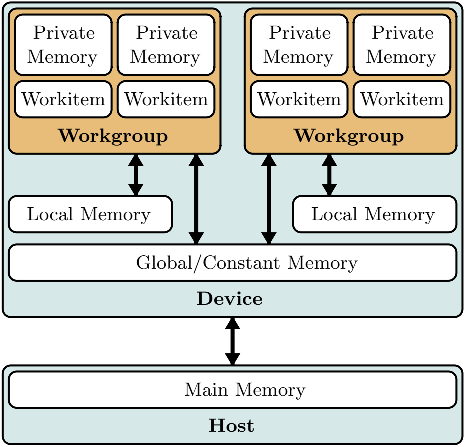
- Good scalability thanks to blocking

Scalability without blocking



Outline

OpenCL overview



Algorithm adaptation

- Inspired by `sgemmnt` from CUBLAS 2.0

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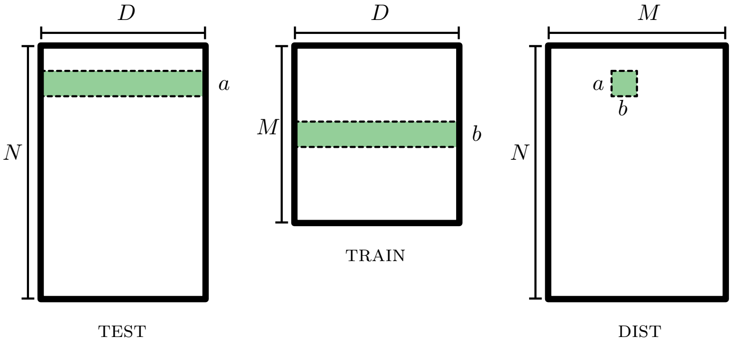
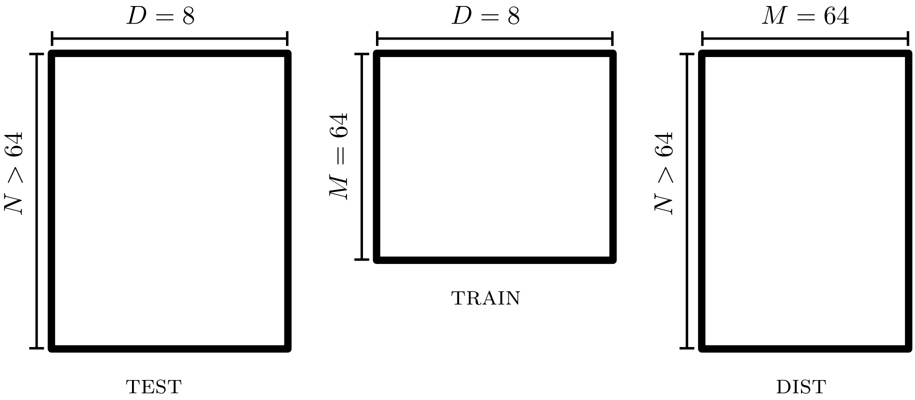


GPU memory access pattern



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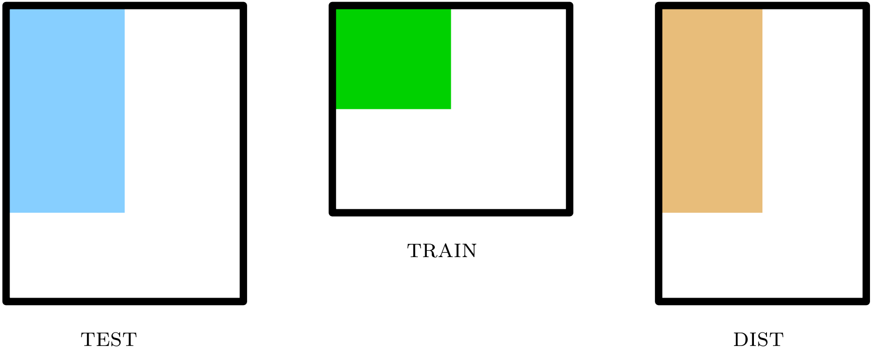

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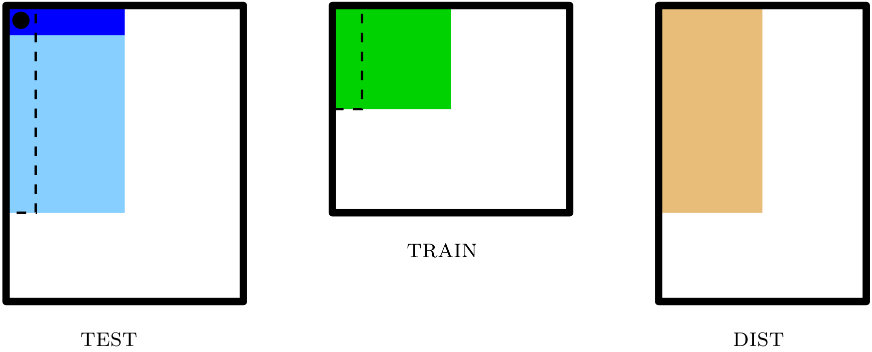

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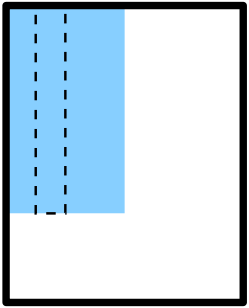
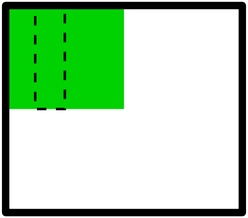
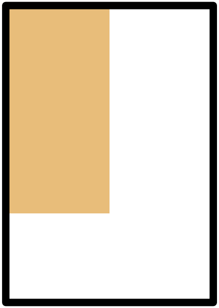


TEST

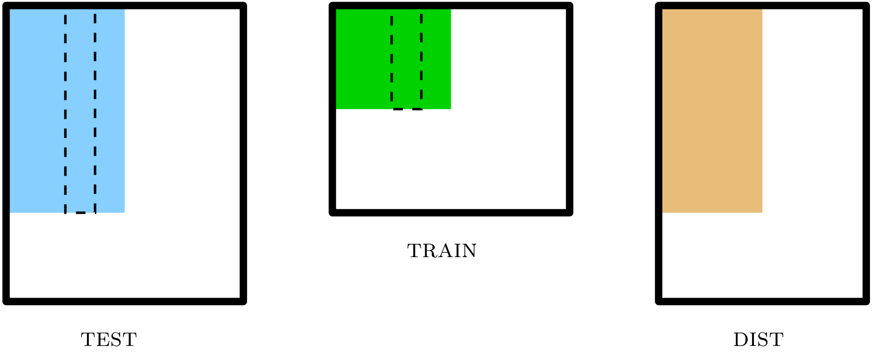


TRAIN



DIST

GPU memory access pattern



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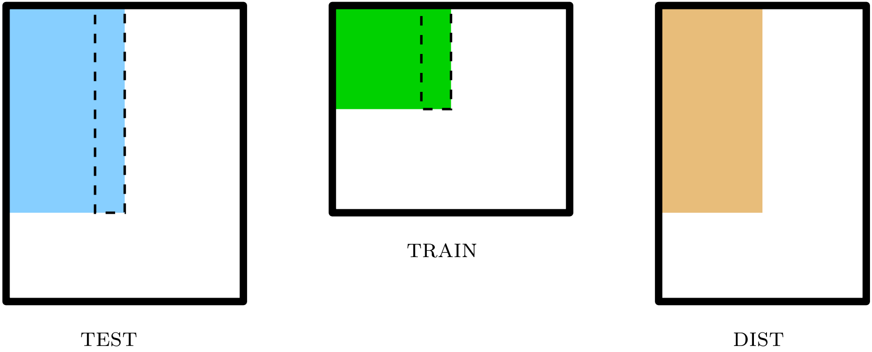

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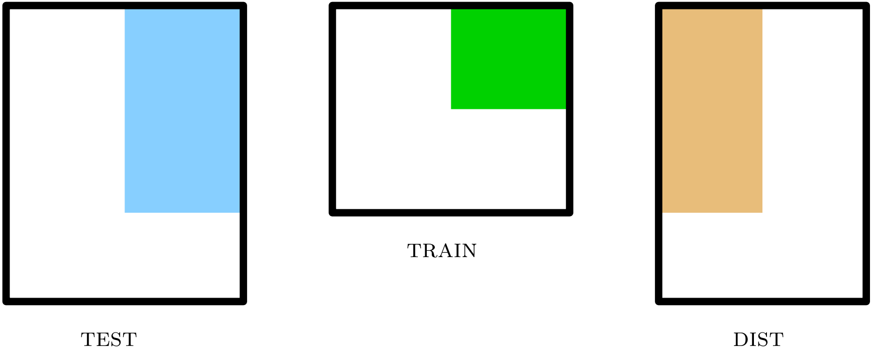

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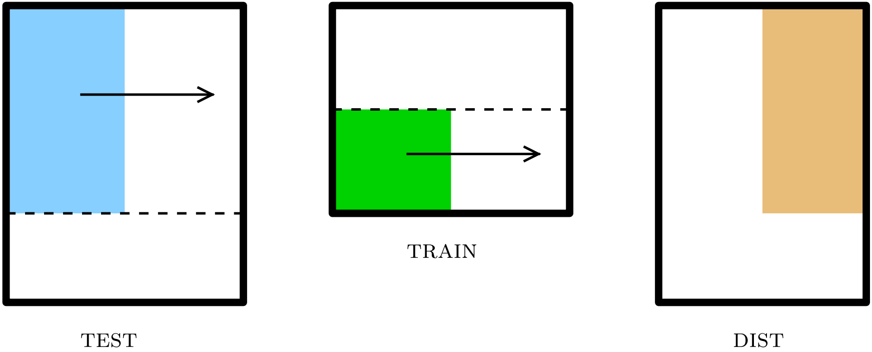
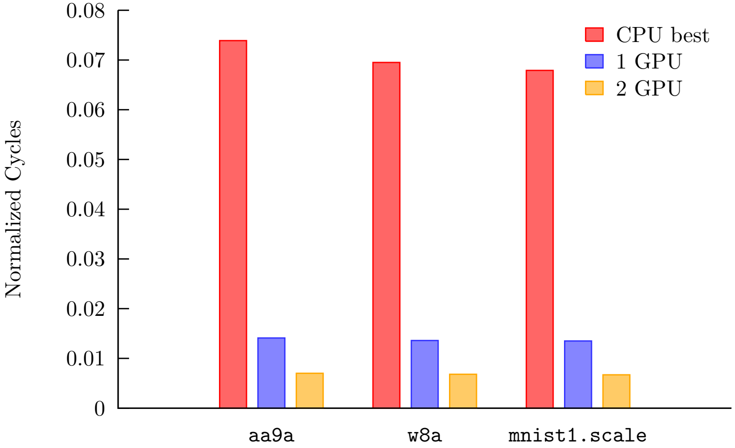


GPU performance



Outline

1. Introduction
2. CPU optimizations
3. GPU port
4. Other classification methods
   - Overview
   - Classification accuracy
   - Performance
5. Conclusions

Overview

- k-Nearest Neighbors
- Support Vector Machines
  - Originally conceived for two class problems
  - LibSVM and LibLINEAR

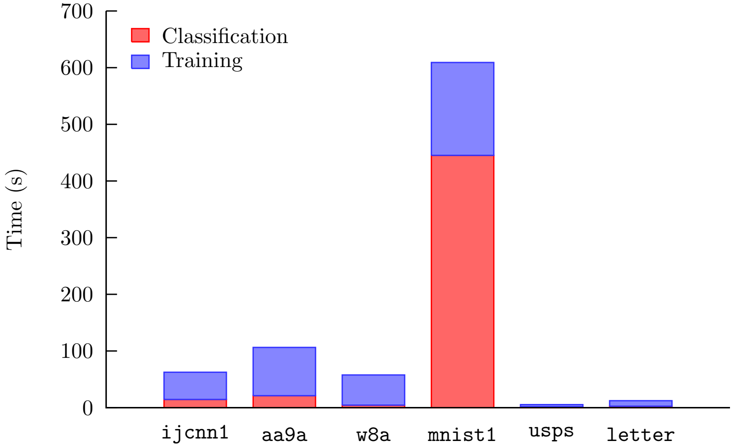
Overview

- k-Nearest Neighbors
- Support Vector Machines
  - Originally conceived for two class problems
  - LibSVM and LibLINEAR
  - Classification procedure:
    1. Find model parameters or cross-validation (optional)
    2. Generate a model from the training set
    3. Use the model to classify elements from the testing set

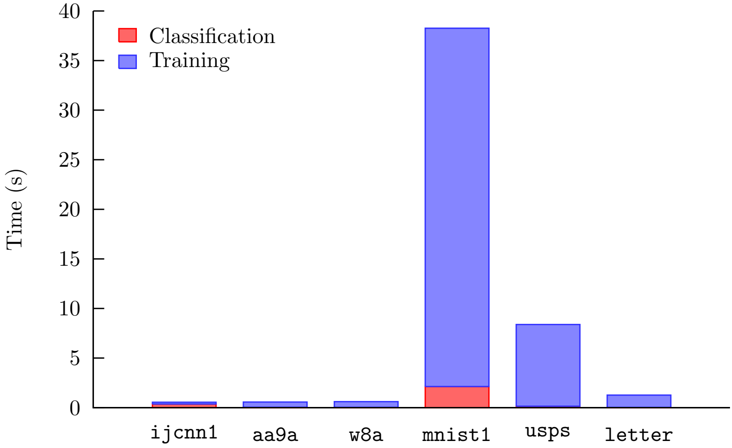
Accuracy comparison

Database	1-NN	3-NN	13-NN	23-NN	LibSVM	LibLINEAR
ijcnn1	97.39%	97.09%	95.63%	94.71%	97.82%	91.79%
aa9a	79.51%	81.73%	83.69%	84.09%	85.03%	84.96%
w8a	97.93%	98.74%	98.36%	94.48%	99.18%	90.54%
mnist1	95.71%	95.93%	95.24%	98.15%	97.70%	90.07%
svmguide3	100%	70.73%	43.90%	43.90%	82.93%	24.39%

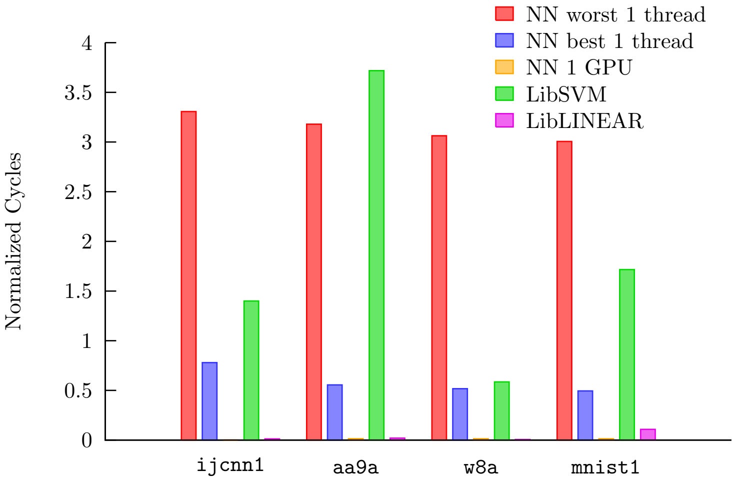
LibSVM times



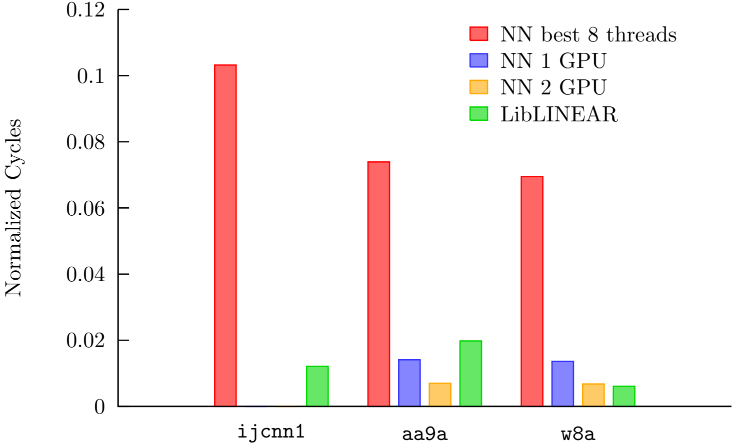
LibLINEAR times



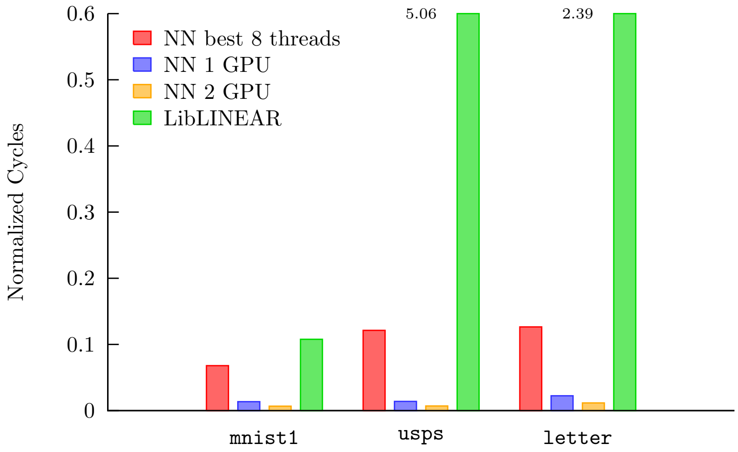
Performance comparison (I)



Performance comparison (II)



Performance comparison (III)



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Conclusions

- Simpler algorithms are easier to optimize
- Parallelism can be exploited in several granularities
- Controlling memory access patterns brings more optimization opportunities
  - Specially when programming with GPGPUs
- There is no single best classification solution
- Performance of optimized NN rivals that of state of the art classifiers

Future work

- Overcome current limitations
  - Support out of core operation
- Compare against other nearest neighbor search algorithms
  - Locality sensitive hashing
  - Space partitioning structures
- Extend the GPU implementation to k-NN
- Find techniques to shrink the training set (i.e. TRAIN matrix)

END