
Random Kernel Perceptron on ATTiny2313 Microcontroller

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Kernel Perceptron

■ Predictor

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^N \alpha_i K(\mathbf{x}, \mathbf{x}_i)\right)$$

■ Costs

- $O(N)$ space
- $O(N)$ update time
- $O(N^2)$ total training time

Inputs : data sequence $((\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N))$

Output : trained Kernel Perceptron $f(\mathbf{x})$

$f(\mathbf{x}) = 0$ at time $t = 0$

while (training set not empty)

{

if ($y_i \cdot f(\mathbf{x}_i) > 0$)

$\alpha_i = 0$

else

$\alpha_i = y_i$

$f(\mathbf{x}) \leftarrow f(\mathbf{x}) + \alpha_i \cdot K(\mathbf{x}_i, \mathbf{x})$

}

Random Budget Kernel Perceptron

Idea

- assign support vector budget T
- when budget is exceeded, remove a random SV
- resulting predictor

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^T \alpha_i K(\mathbf{x}, \mathbf{x}_i)\right)$$

Costs

- $O(1)$ space
- $O(1)$ update time
- $O(N)$ training time

Inputs : data sequence $((\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N))$, budget T

Output : support vector set $SV = \{SV_i, i = 1 \dots I\}$

$I \leftarrow 0; i \leftarrow 1$

$SV = \emptyset$

for $i = 1 : N$

{

if $((y_i \cdot \sum_{j=1}^I y_j \cdot K(\mathbf{x}_i, \mathbf{x}_j)) \leq 0)$

{

if $(I == T)$

$new = \text{random}(I)$

else

{

$I \leftarrow I + 1$

$new \leftarrow I$

}

$SV_{new} = (x_i, y_i)$

}

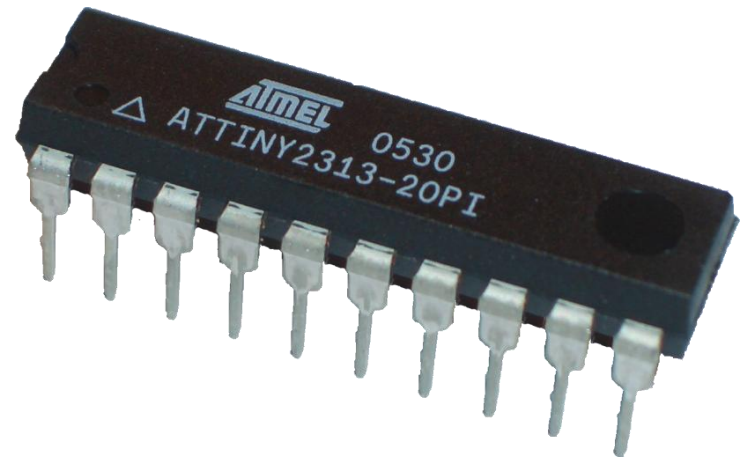
}

Motivation

- Random Kernel Perceptron
 - online algorithm
 - low cost
 - easy to implement
 - can solve nonlinear problems
 - accurate
 - It still **CANNOT** be implemented on the simplest computers
 - it uses floating-point operations
 - model size easily exceeds available memory
 - Goal: Implement Kernel Perceptron on microcontrollers
 - Applications
 - sensor networks
 - low-cost online data mining
 - resource-constrained environments
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Microcontroller

- ATTiny2313
 - one of the most primitive processors
 - very cheap (< \$1)
- Characteristics
 - 128 bytes to store:
 - Kernel Perceptron
 - working variables
 - 2 Kbytes to store program
 - 4 MHz processor speed
 - fixed-point arithmetic (**integers**)

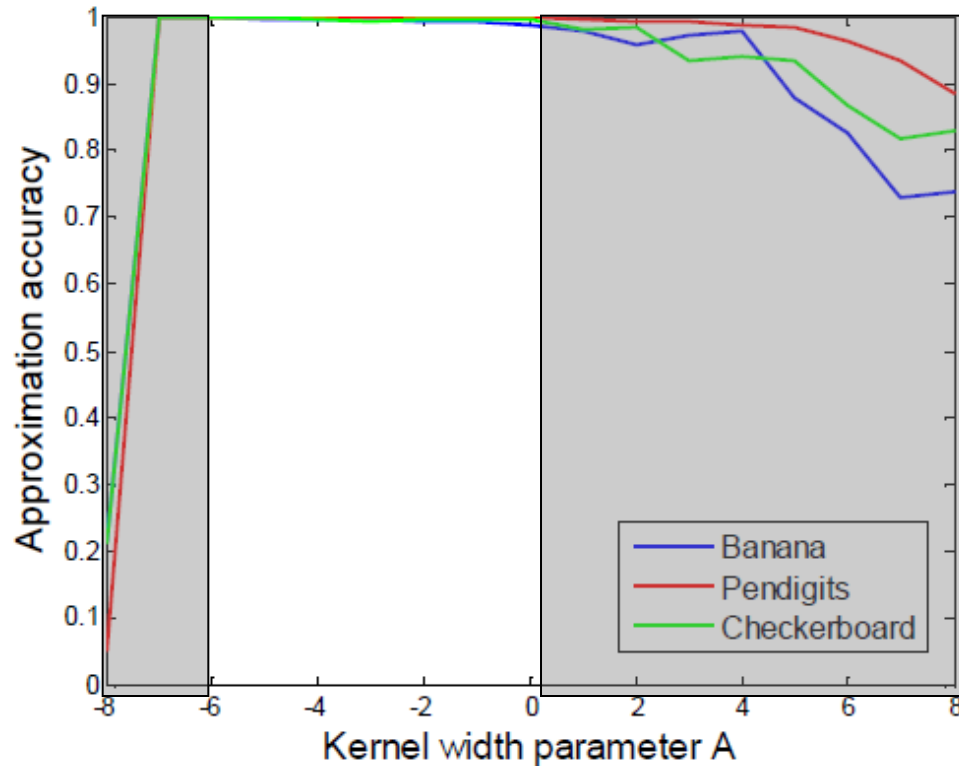


Some details

- Use Gaussian kernel: $K(\mathbf{x}, \mathbf{x}_i) = \exp\left(\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2^A}\right)$
- Resource-saving strategies
 - Quantization of attributes using b bits
 - trade-off between #SV and #bits
 - quantization loss
 - Approximation of kernel function using only integers and integer calculations
 - we devised an iterative procedure that uses look-up table
 - approximation loss

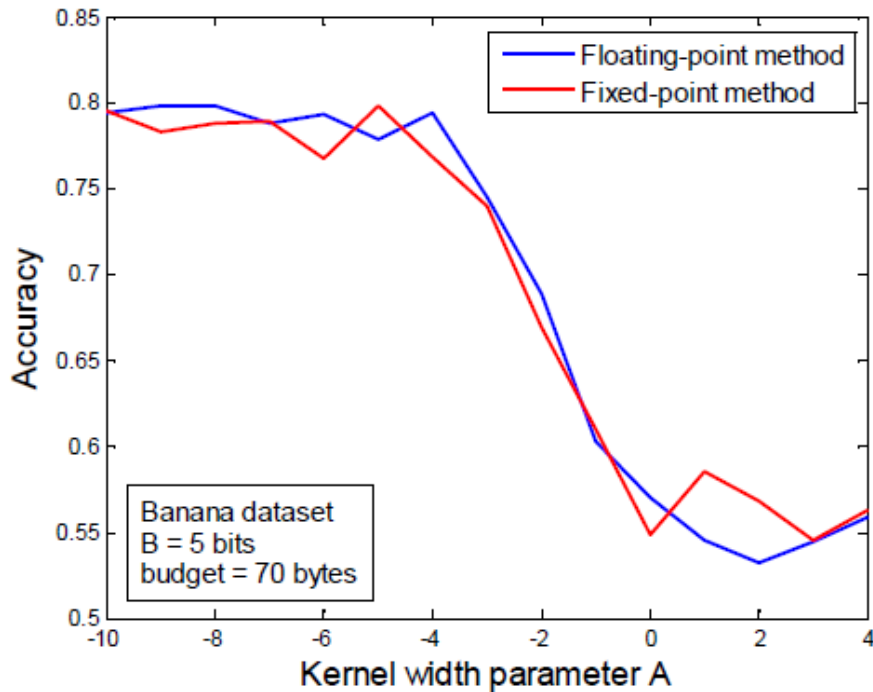
Results

- Fixed-point vs. floating-point method
- Approximation accuracy (kernel width = 2^A)

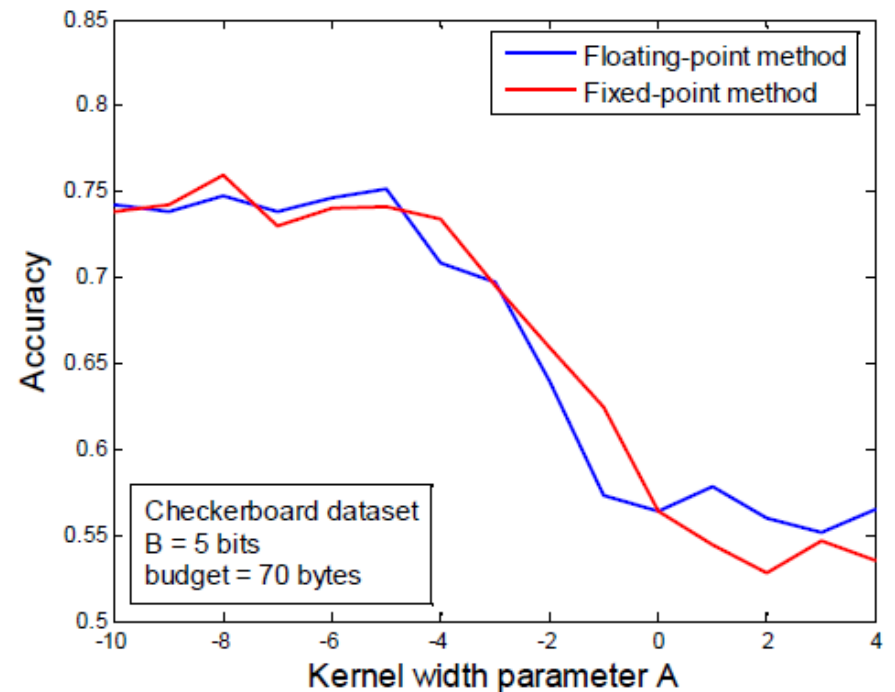


Results

- Accuracy on benchmark datasets



Banana dataset



Checkerboard dataset

Results

- Implementation on microcontroller
- Double-precision Kernel Perceptron: 89.2% accuracy
- Much less memory, faster execution time

| Banana dataset | 4 bits | | 6 bits | |
|--------------------------------|--------------|--------------|--------------|--------------|
| | <i>Fixed</i> | <i>Float</i> | <i>Fixed</i> | <i>Float</i> |
| <i>Data [B] (max 128B)</i> | 128 | 379 | 128 | 379 |
| <i>Program [B] (max 2048B)</i> | 1720 | 6012 | 1720 | 6012 |
| <i>Time [ms]</i> | 1985 | 7505 | 1883 | 7610 |
| <i>Accuracy [%]</i> | 81.00 | 81.08 | 79.36 | 79.60 |
| <i># of SVs</i> | 62 | | 43 | |

| <i>Data memory</i> | <i>After quantization</i> | | <i>Before (Double-precision)</i> | |
|--------------------|---------------------------|--------------------------|----------------------------------|--------------------------|
| | <i>Model</i> | <i>Working variables</i> | <i>Model</i> | <i>Working variables</i> |
| <i>Memory size</i> | <i>70B</i> | <i>58B</i> | <i>> 1KB</i> | <i>> 500B</i> |

Conclusions

- Implemented Kernel Perceptron on ATtiny2313 microcontroller
 - Fixed-point calculations of prediction
 - key for implementation
 - low data and program memory
 - speeds up calculations
 - only slightly decreases accuracy
 - Our results
 - useful in establishing lower bounds on necessary computational resources for online learning
 - open doors for novel application of data mining, such as data mining from sensor data
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Thank you!

- More details in the paper
 - Questions? E-mail to nemanja.djuric@temple.edu
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