

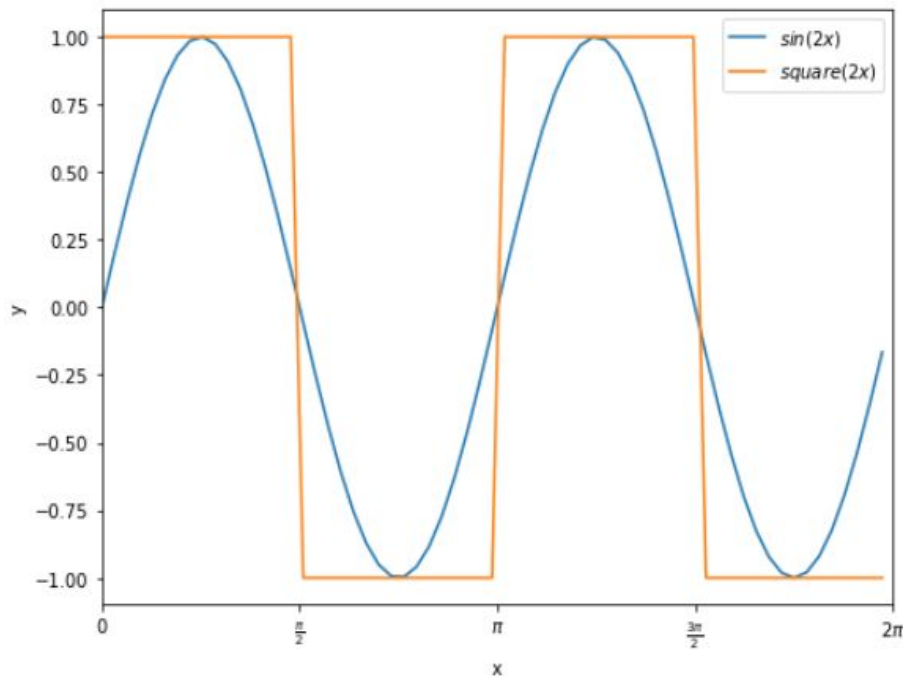
Lab 2

Artificial Neural Networks and Deep Architectures

15 February 2023

Group 12 - Isabella Rositi, Gustav Thorén and Nicolas Wittmann

Function Approximation with RBF Networks



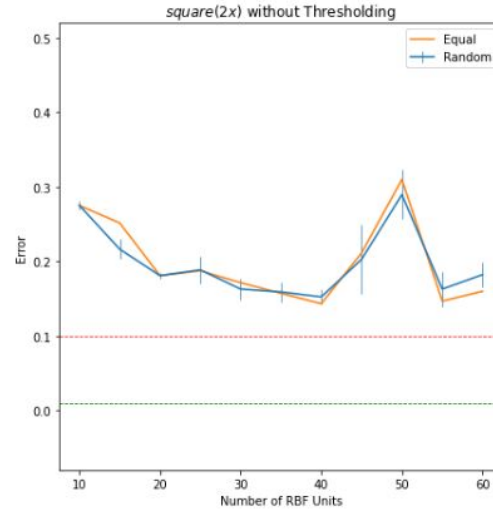
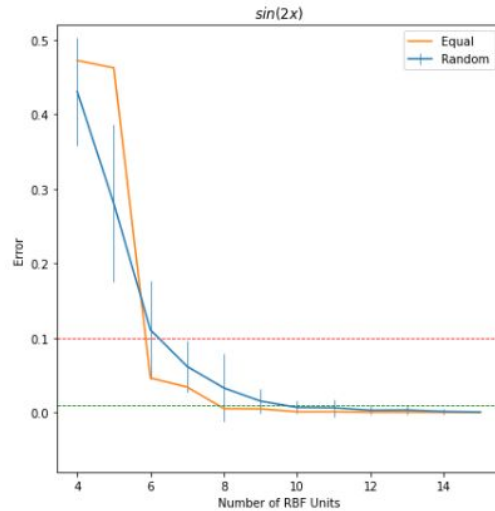
Clean Data

2 functions sampled in the interval $[0, 2\pi]$ divided into two independent training and test sets:

$\sin(2x)$

$\text{square}(2x)$

Absolute Residual Error vs Number of RBF Nodes

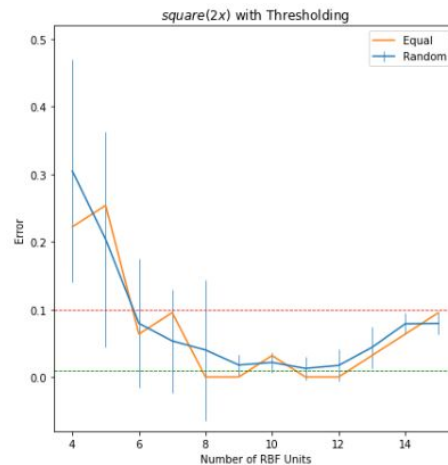
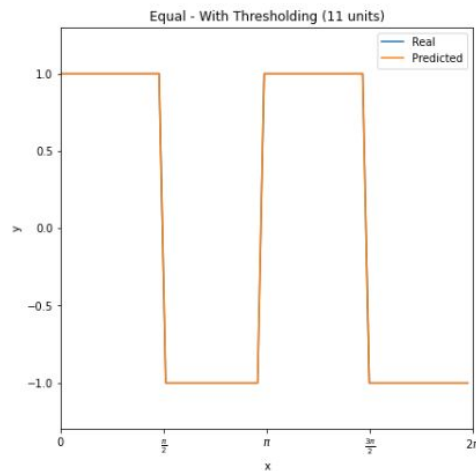
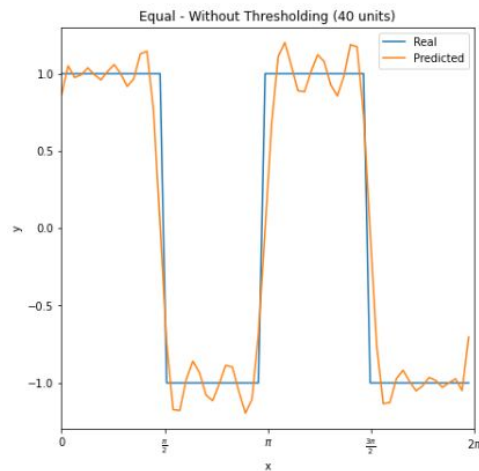


| Below Error | 0.1 | 0.01 | 0.001 |
|-------------|-----|------|-------|
| RBFs | 6 | 8 | 10 |

As the number of units increases, the error decreases

For square(2x) the error is never below 0.1

Thresholding $\text{square}(2x)$



Below Error

0.1

0.0

RBFs

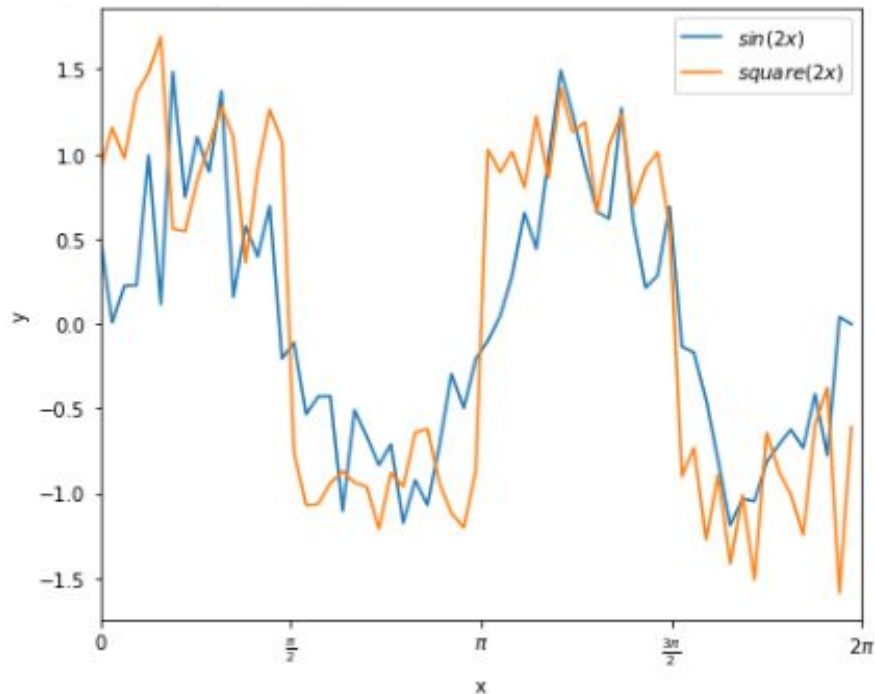
6

8

Thresholded: if $\text{pred} \geq 0$ then $\text{pred}_t = 1$

otherwise $\text{pred}_t = -1$

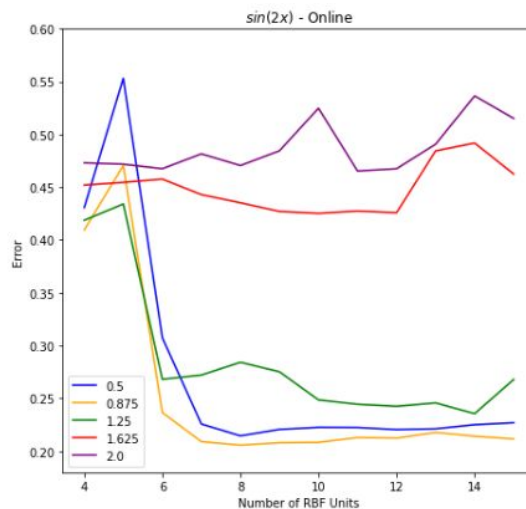
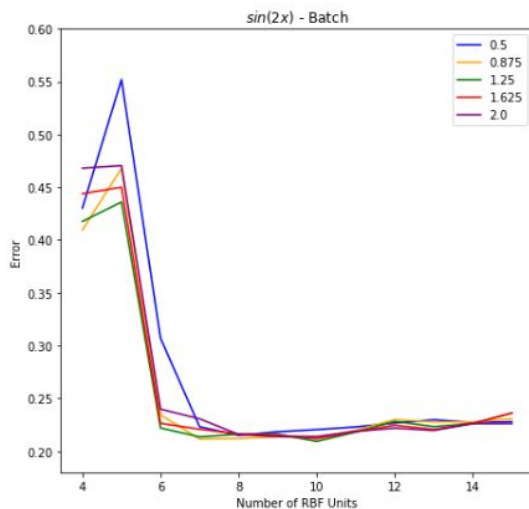
Function Approximation with RBF Networks



Noisy Data

Zero-mean Gaussian noise with the variance of 0.1 added to both functions, to both training and test data independently.

Variance Impact for Batch and Online Learning

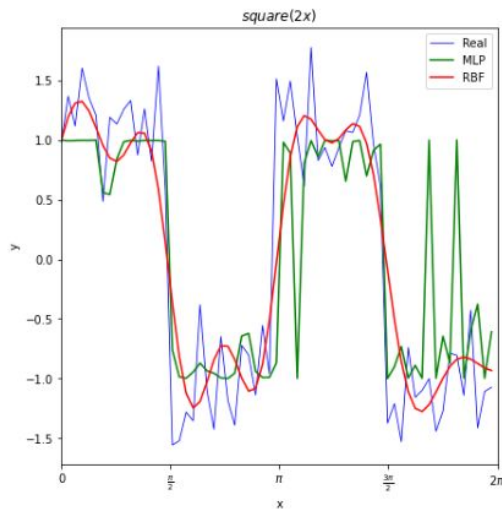
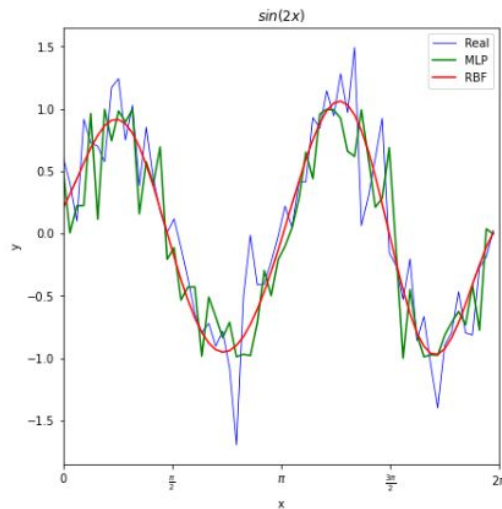


| | Batch | Online |
|----------------|-------|--------|
| Initialization | Equal | Equal |
| Eta | - | 0.05 |

For batch the variance doesn't impact much

For online the highest variances are not able to describe the data even when the number of units increases

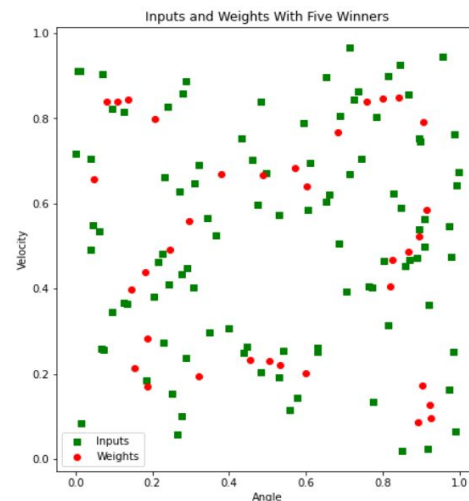
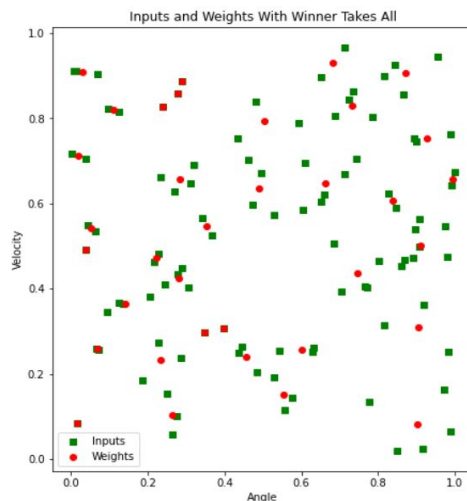
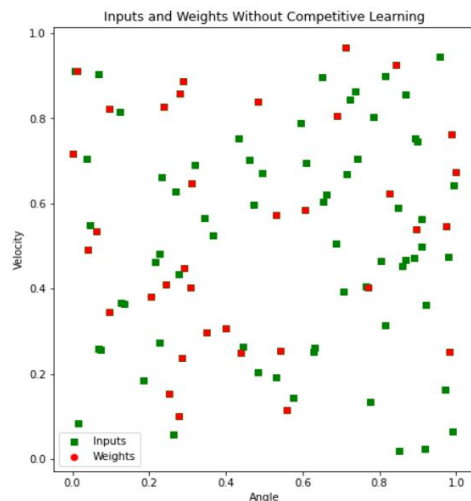
MLP vs RBF



| | $\sin(2x)$ | $\text{square}(2x)$ | time (avg.) |
|------------|------------|---------------------|-------------|
| MLP | 0.303 | 0.436 | 0.167s |
| RBF | 0.209 | 0.361 | 0.027s |

RBF captures less noise than MLP, hence its predictions are smoother and more accurate

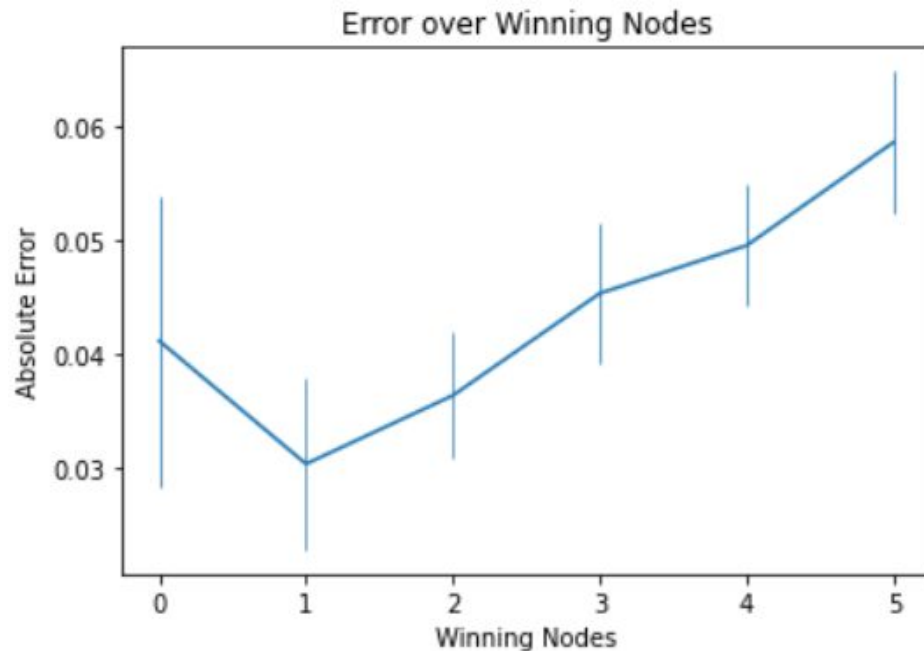
Competitive Learning



| | Random | 1 winner | 5 winners |
|-------|--------|----------|-----------|
| Error | 0.041 | 0.030 | 0.059 |
| std. | 0.013 | 0.008 | 0.006 |

Random initialization fails to efficiently capture the data. The "winner takes all" scheme better captures the data and multiple winners over represents denser clusters.

2D Function Approximation



Best Performance

Winner Takes All

Mean: 0.030

STD: 0.0075

Topological Ordering of Animals with SOMs

| | | | | | | | |
|--------|-------------|-----------|-----------|-----------|-----------|--------|---------|
| beetle | grasshopper | dragonfly | butterfly | moskito | housefly | spider | pelican |
| duck | penguin | ostrich | frog | seaturtle | crocodile | walrus | bear |
| hyena | ape | skunk | dog | lion | cat | rat | bat |
| rabbit | kangaroo | elephant | antelope | horse | camel | pig | giraffe |

Neighbourhood decay

linear from
50 to 0

Learning Rate

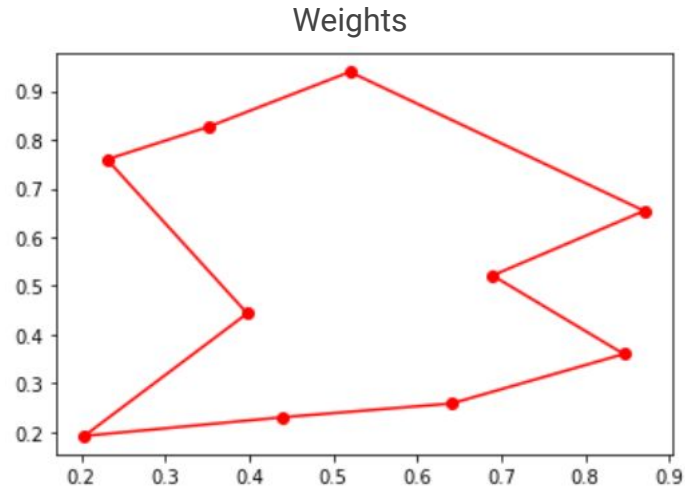
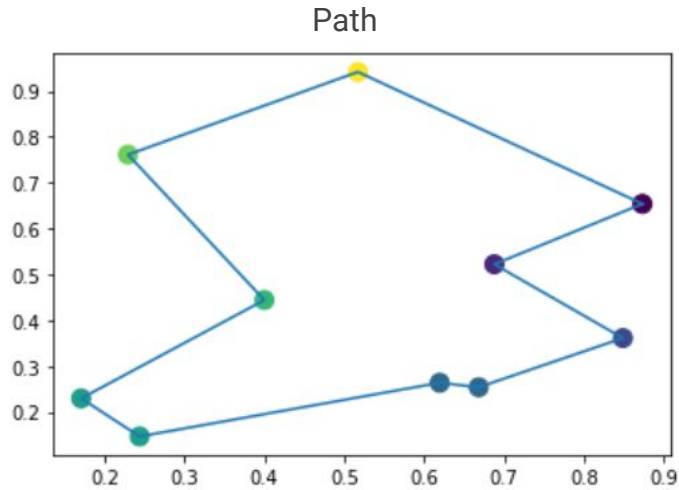
0.2

Epochs

20

The animals gets sorted into a order
where similar animals are placed next
to each other

Cyclic Tour with SOMs

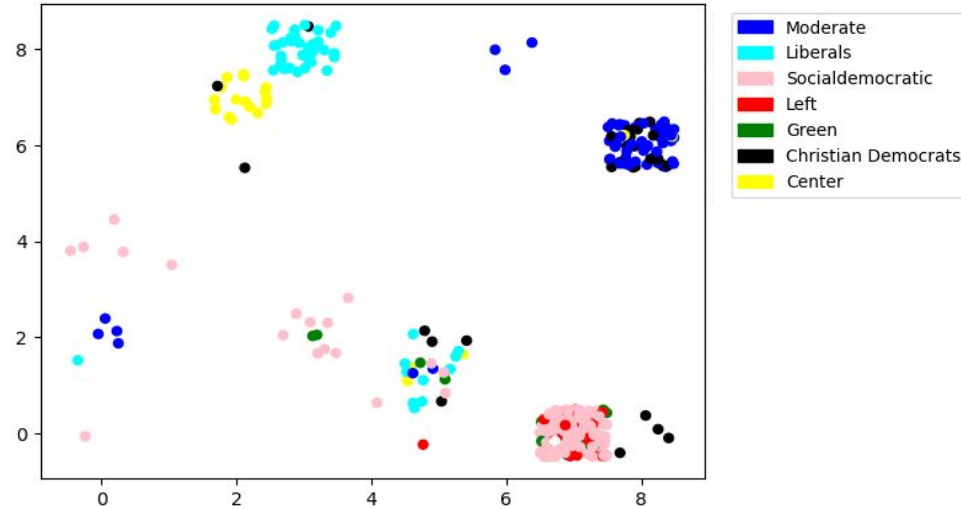


| | |
|----------------------------|-------------------------|
| Learning Rate | 0.2 |
| Neighbourhood Decay | Linear from 2 towards 0 |

Efficient solution found

Weights correspond quite well to the cities

Clustering with SOMs

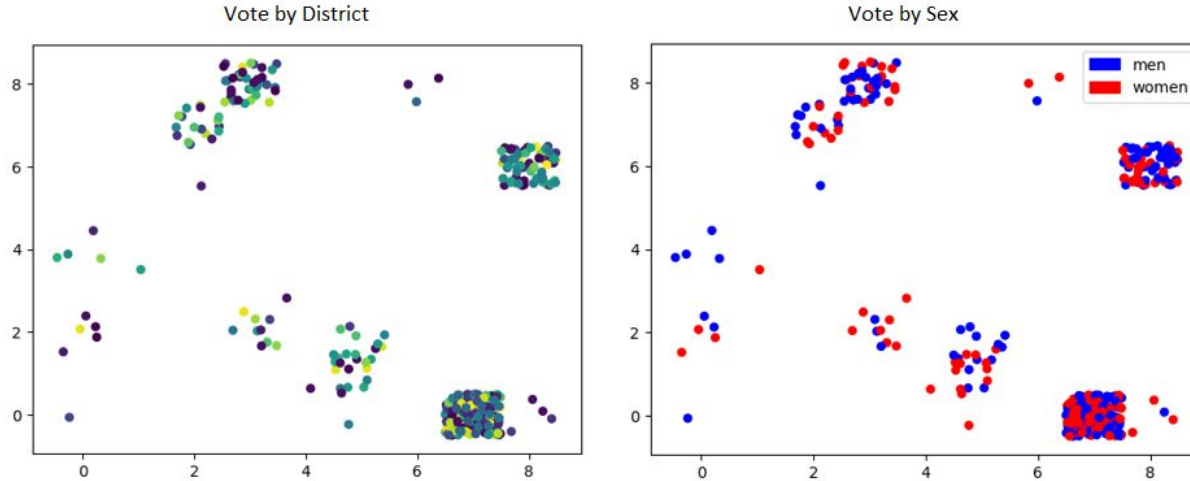


| | |
|----------------------------|--------------------|
| Learning Rate | 0.2 |
| Neighbourhood Decay | Linear from 4 to 0 |

Each politician is sent to their closest node (with a small shift)

Quite strong voting trend among the same party and in between some parties.

Clustering with SOMs



| | |
|----------------------------|--------------------|
| Learning Rate | 0.2 |
| Neighbourhood Decay | Linear from 4 to 0 |

We do not observe such strong trend among genders and districts.

Final Remarks

- RBF Networks combine Supervised and Unsupervised techniques
- “Winner-takes-all” scheme for Competitive Learning seems to perform better than “Multiple Winners” if data is evenly distributed
- SOM can be used in multiple aspects, are sensitive to initialisation and the learning should be monitored so that it captures both large and small scale pattern.

Thank you!