Compulsory Assignment 2 ML

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Question 1

1.1.

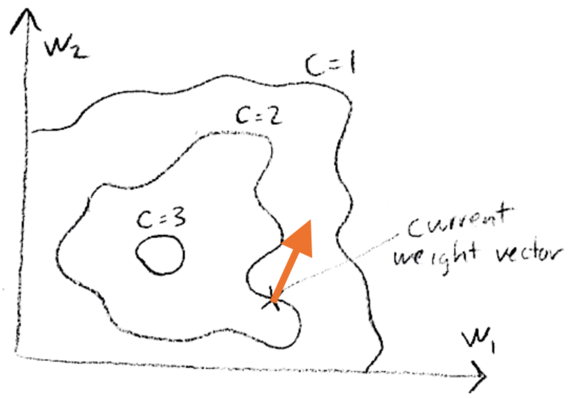
This is a typical sign of overfitting. In that case a model gets too complex and learns in too much detail; thus, performing perfectly on the training data but performing way worse on data it hasn't seen before. In other words, the model learns the data and not the underlying pattern.

1.2.

When using the SGD the model calculates the gradient for each sample and updates the weights accordingly (so n epochs if n is the number of training samples), whereas the Batch GD calculates the average gradient of all sample gradients and updates the weight only once per epoch. Mini batch GD tries to balance the inefficiency and time-consumption of the Batch GD and the fluctuations of the SGD. A mini-batch of sample data is used to calculate the average of that batch and update the weights for that mini batch. When using SGD, the number of arithmetic operations is the same, since every sample is looked at individually. But using mini-batch sizes can still be more efficient, as the parallel performance of todays GPUs and CPUs enables the execution of multiple calculations at the same time. Thereby multiple batches can be served at the same time.

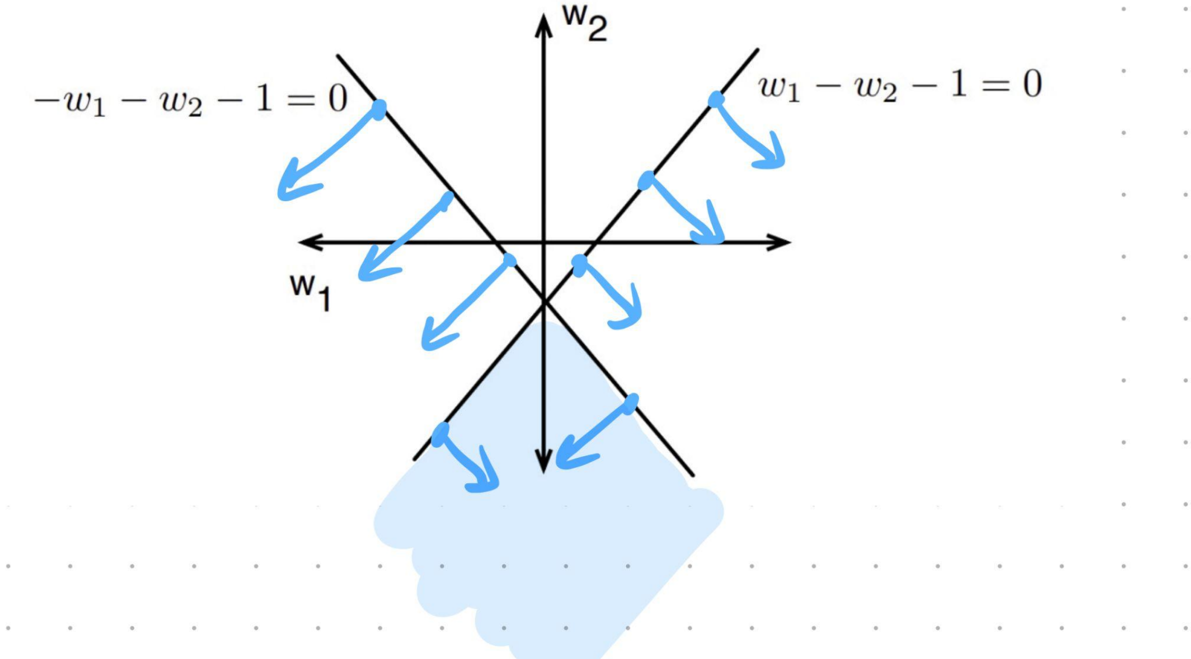
Mini-batch GD: Takes sample of all observations and calculate the GD for the sample (less CPU needed for the reduced number of observations, however; same number of calculations)

1.3.



The arrow is orthogonal to the C2 line hence the steepest way "down" to C1 is the orange arrow.

1.4.



The arrows indicate on which of the decision boundaries the combinations lead to a positive result.

Example

-w1 - w2 - 1 becomes positive for:

-3, 1 => 1

or

1, -3 => 1

w1 - w2 - 1 becomes positive for:

3, 1 => 1

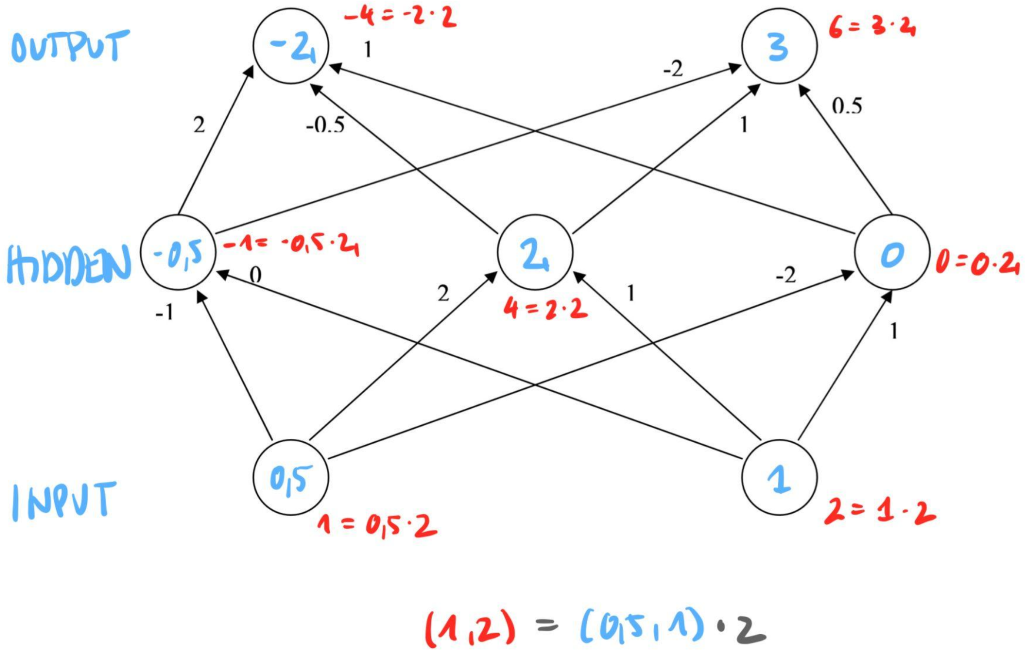
or

-2, -4 => 1

These points are example points for the areas indicated by the arrows. The intersection of the arrows is where both decision boundaries lead to positive results at the same time.

Question 2

2.1



2.2

As the input is exactly twice as high as the previous input the ratio within the calculations in the hidden layers will also be the same. That is why the output will just be twice as high for each linear neuron (in the hidden layer as well as the output layer; see numbers colored in red).

Question 3

See appendix ml_ca2_handin.ipynb

Question 4

Introduction

Machine learning (ML) has had a profound impact on robotics development, pushing the boundaries of what can be achieved in terms of autonomy, functionality, and adaptability. This extended abstract critically considers the role of ML in robotic design by discussing the basic principles and contributions of ML in the state of the art. Additionally, it highlights potential challenges and future opportunities for the field.

Machine Learning Principles

ML, a subset of artificial intelligence (AI), refers to a set of algorithms and techniques that enable machines to learn from data and improve their performance over time. Supervised learning, unsupervised learning, and reinforcement learning are the three primary categories of ML (Bishop, 2006). Supervised learning involves training an algorithm to recognize patterns and relationships between input and output variables, while unsupervised learning identifies patterns without predefined output variables. Reinforcement learning, on the other hand, focuses on agents that learn from interacting with their environment by receiving feedback in the form of rewards or penalties (Sutton & Barto, 2018).

Contributions to Robotics Design

ML has revolutionized robotics design in various ways. First, it has facilitated the development of more advanced perception systems, allowing robots to process sensory data more efficiently and accurately (Guizzo & Ackerman, 2012). For instance, convolutional neural networks (CNNs) have significantly improved image and object recognition, enabling robots to navigate complex environments and interact with objects more effectively (Krizhevsky, Sutskever, & Hinton, 2012).

Second, ML has enhanced the adaptability and autonomy of robots by enabling them to learn from their experiences and make decisions based on their acquired knowledge. Reinforcement learning has been particularly instrumental in this regard, with robots learning to optimize their behavior over time through trial and error (Kober, Bagnell, & Peters, 2013). This adaptability allows robots to function in dynamic and unpredictable environments, enhancing their practical applicability across various domains.

Lastly, ML has facilitated the design of more efficient and effective control systems. Traditional control methods often require extensive domain-specific knowledge and manual tuning, which can be labor-intensive and prone to error. ML-based control systems, such as model predictive control (MPC) and adaptive control, can automatically adjust and optimize their parameters in real-time, leading to improved performance and reliability (Kiumarsi et al., 2018).

Challenges and Future Opportunities

Despite the significant advancements in robotics design brought about by ML, several challenges remain. Data quality and quantity are critical factors in ML performance, and obtaining sufficiently diverse and representative datasets can be challenging, especially in complex or hazardous environments (Yang et al., 2020). Additionally, the generalizability of learned behaviors and models to new situations is not guaranteed, posing potential risks in safety-critical applications.

Moreover, ML models can be computationally expensive, which may limit their applicability in resource-constrained robotics platforms. Optimizing algorithms for real-time operation and low-power consumption is an ongoing challenge that requires further research and development (Tan et al., 2019).

Future opportunities in ML-driven robotics design include the development of more robust and generalizable learning algorithms, as well as the integration of advanced sensing technologies, such as LiDAR and event-based cameras, to enhance perception capabilities. Furthermore, interdisciplinary collaboration between ML and robotics experts can lead to the development of innovative solutions that transcend traditional boundaries, opening up new possibilities for robotics applications.

Conclusion

In conclusion, ML has played a pivotal role in the evolution of robotics design by enabling greater autonomy, adaptability, and efficiency. Despite the challenges faced, the future of ML-driven robotics design is promising, with ample opportunities for further innovation and improvement. As the field continues to advance, the potential applications of ML in robotics will expand, opening up new possibilities for solving complex problems and enhancing human-robot interaction. By addressing the current challenges and leveraging interdisciplinary collaboration, ML has the potential to further revolutionize robotics and transform the way we live and work.

References

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