Practical work 10 - Artificial Neural Networks (ANN)

Students

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Summary of work to include in the report

- Answer questions 1-3 from the *3_delta_rule_points* notebook and present the resulting plot when the option SHOW_VIDEO is set to False.
- Run notebook 5, provide the final plots *MSE vs spread* and comment the difference between results.
- Run notebook 7 and provide the chosen hyperparameters for each of the three dataset types. Test on three dataset types: balanced with clear separation, balanced with mixed classes, and unbalanced. Present the top three experiments per dataset with metrics like confusion matrices and summarize your findings

Notebook 3 : *3_delta_rule_points*

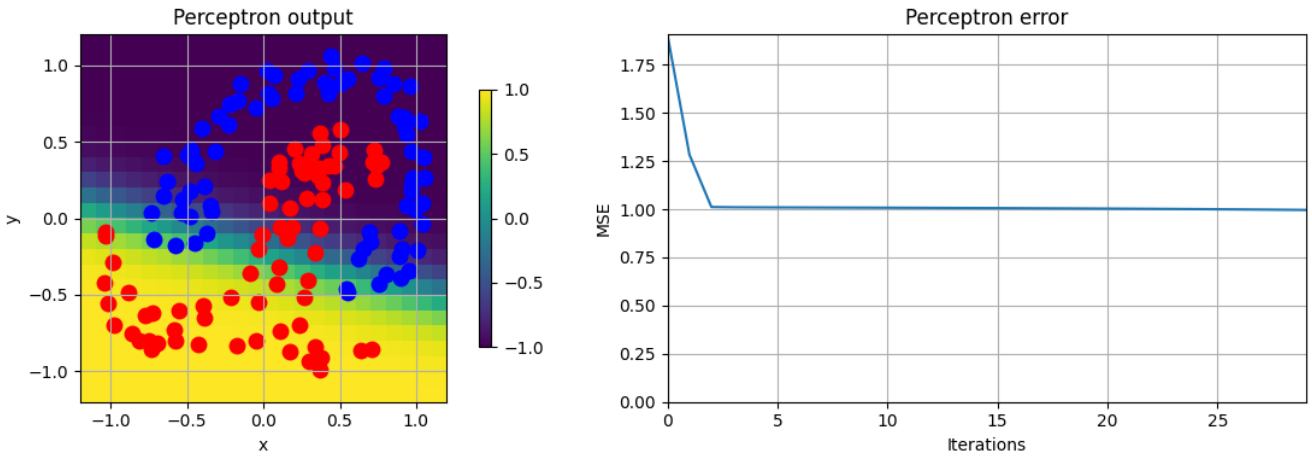
Q1. What happens if the boundaries between both classes are well defined?

In this first case, the perceptron just successfully learn a decision boundary that separates the two classes. We observe that the error rapidly decrease. That means, we have a fast convergence.

Q2. What happens if the classes overlap? What could you say about oscillations in the error signal?

Int this second case, the decision boundary attempts to split the both classes but struggles due to the overlap. Also the error signal shows fluctuations unless there is a perfect separation. We can say that the convergence is slower and the model accuracy is limited by the intrinsic overlap.

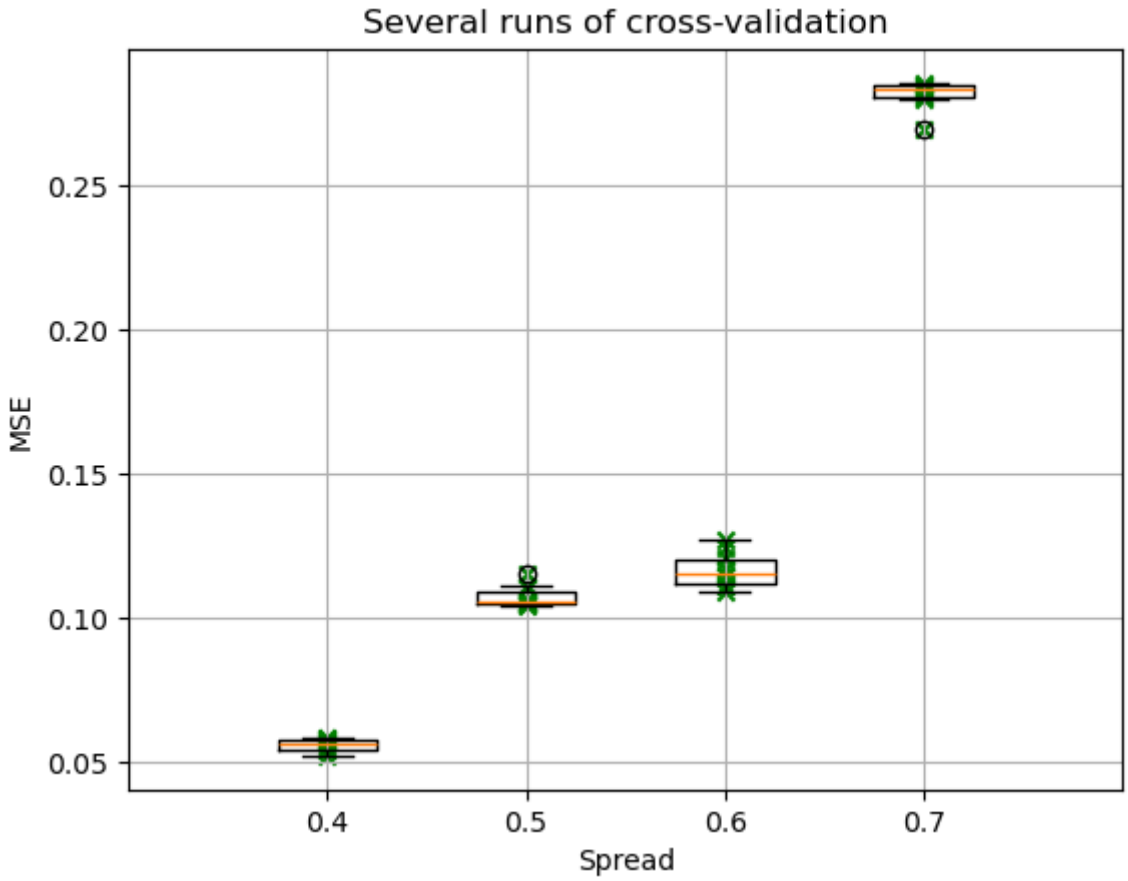
Q3. What happens if it is not possible to separate the classes with a single line? What could you say about local minima?



We can clearly see that the perceptron fails to find a suitable decision boundary with a linear function. The

error signal stagnates around a high value, reflecting the presence of local minima and the inability of the model to minimize error effectively.

Notebook 5 : *5_cross_validation*



Comparaison MSE vs Spread

for MSE smaller than 0.15, the result are quite both. The box are smaller for small values of MSE and Spread, this seem to present Distribution seem symetric for more case (not in spread 0.5) the boxes in spread(0.4;0.6) have not aberrant values (out of minimum or maximum).
Box in spread(0.6) has more maximum than the other and bigger than the minimum of box, this box is the biggest so they have more of data to correspond at.
The spread(0.4) seems havee better result because is the smaller value of MSE and all values are next to the mean. Normaly at this values, it must be simplify to separate.

Notebook 7 : *7_mlp_keras*

Exercise

Please try changing hyperparameters (number of neurons, number of layers, learning rate, momentum, number of epochs...) and observe the impact it has on training and validation loss, convergence, and computation time. For instance, observe if there's overfitting if you put a high number (i.e. 128) of neurons in the hidden layer.

Experiment with 3 Different Datasets: Apply the above parameter tuning on three distinct types of datasets:

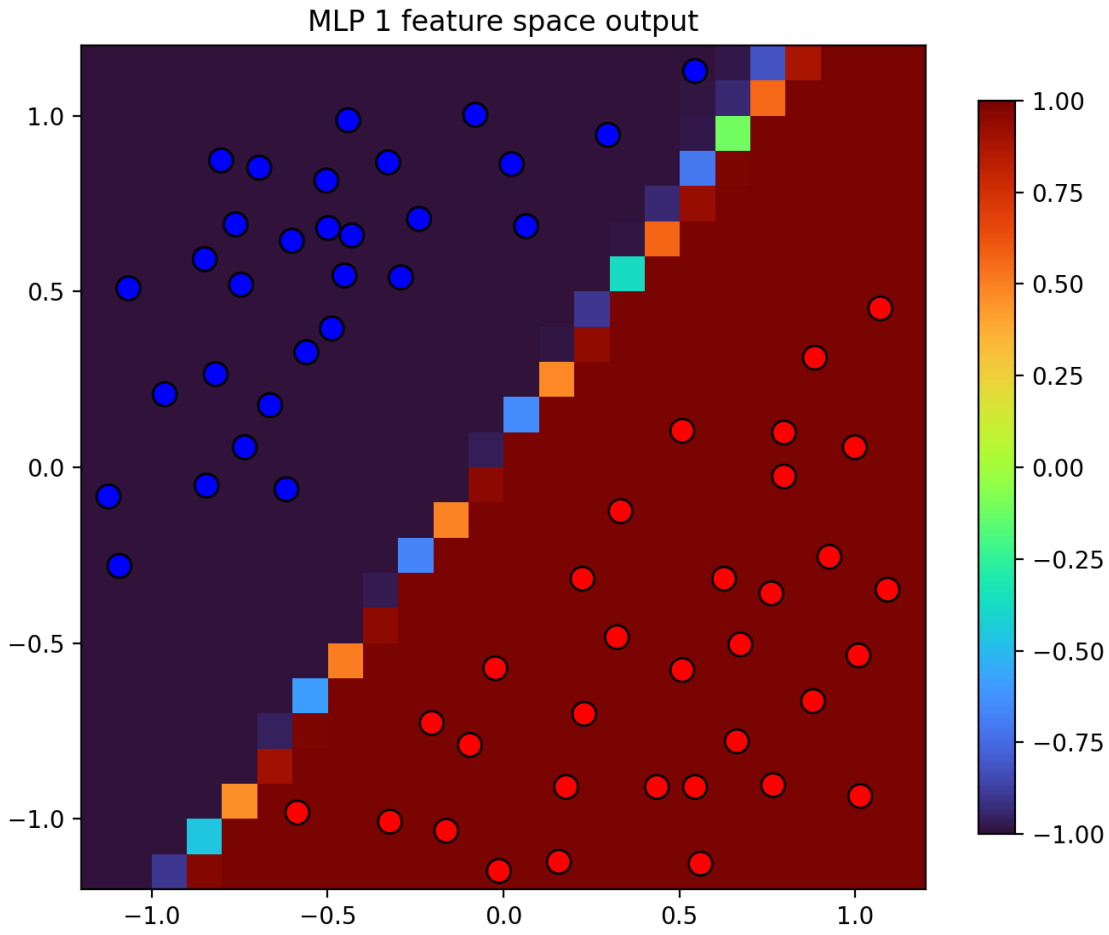
- Balanced dataset with clear separation between classes.

- Balanced dataset with mixed or overlapping classes.
- Unbalanced dataset (e.g., one class significantly larger than the others).

For each dataset type, select and present the three best experiments (with tuned hyperparameters). Provide relevant results such as confusion matrices and other metrics, and analyze the effects on loss, convergence, computation time, and overfitting.

Balanced dataset with clear separation between classes.

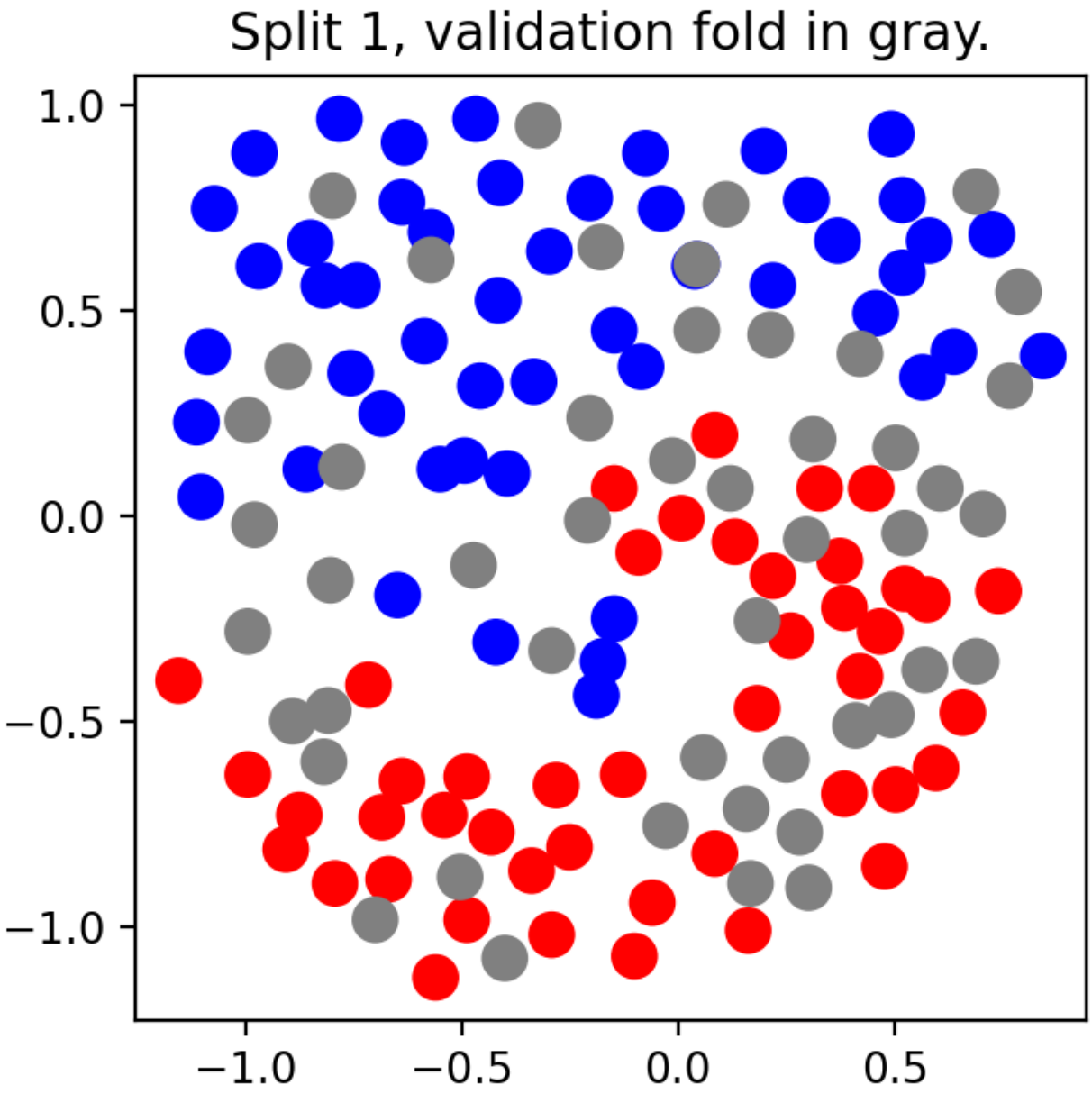
The sepration is easy, it's difficult to see overfitting.



1. `hidden-layer=8` & `learning_rate = 0.9`, `momentum = 0.0001` val
    1. F1-score all : 1.0
2. `hidden-layer=2` & `learning_rate = 0.8`, `momentum = 0.0001` val
    1. F1-score all : 1.0
3. `hidden-layer=1` & `learning_rate = 0.9`, `momentum = 0.0001`val

    1. F1-score all : 1.0

Balanced dataset with mixed or overlapping classes.



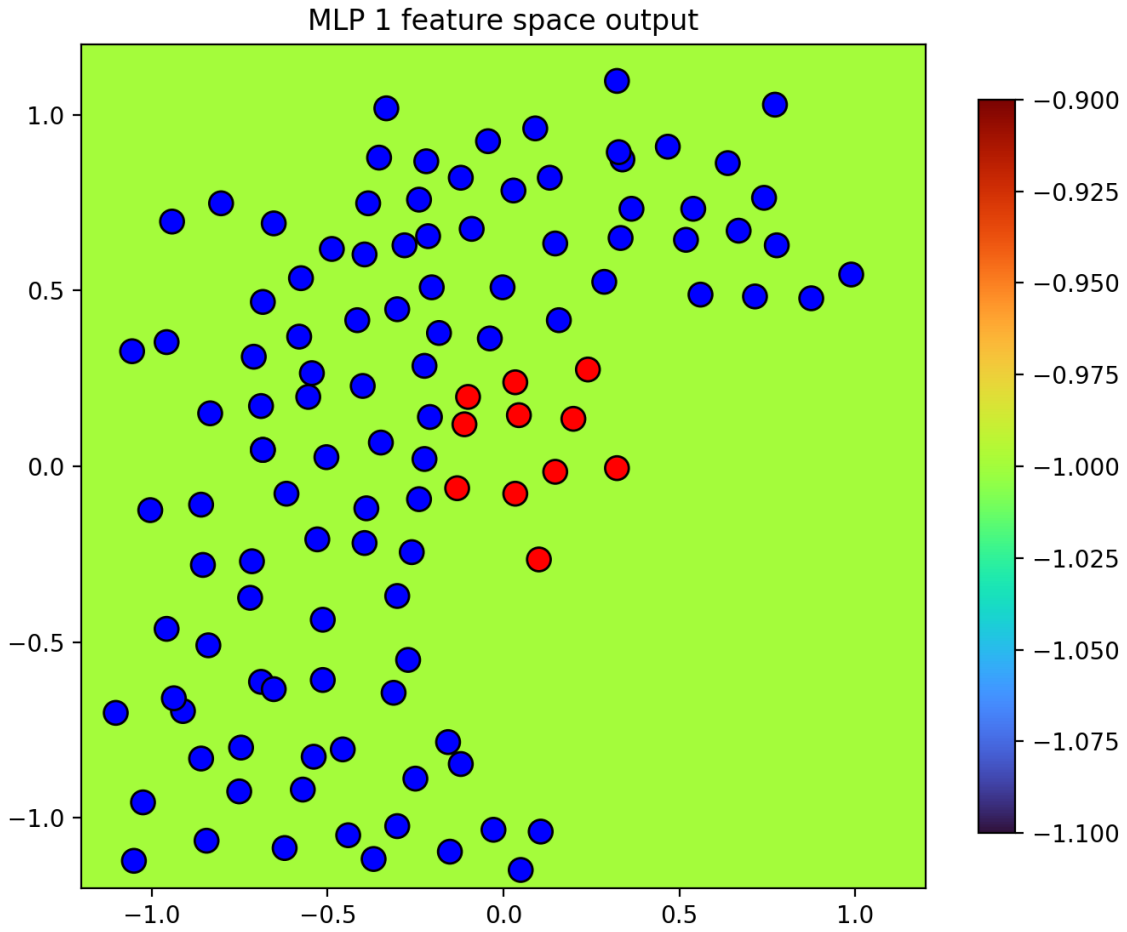
PS: I forgott to take at right moment

1. `hidden-layer=4` & `learning_rate = 0.9`, `momentum = 0.0001` val
    1. F1-score all : 0.9418181818181819
2. `hidden-layer=8` & `learning_rate = 0.8`, `momentum = 0.0001` val
    1. F1-score all : 0.9934640522875817 - 1.0
3. `hidden-layer=8` & `learning_rate = 0.9`, `momentum = 0.0001`val
    1. F1-score all : 0.9629629629629629 $\rightarrow$ overfitting

With 128 hidden layer, the F1-score decrease so they have overfitting (F1-score : 0.9528943652932872)

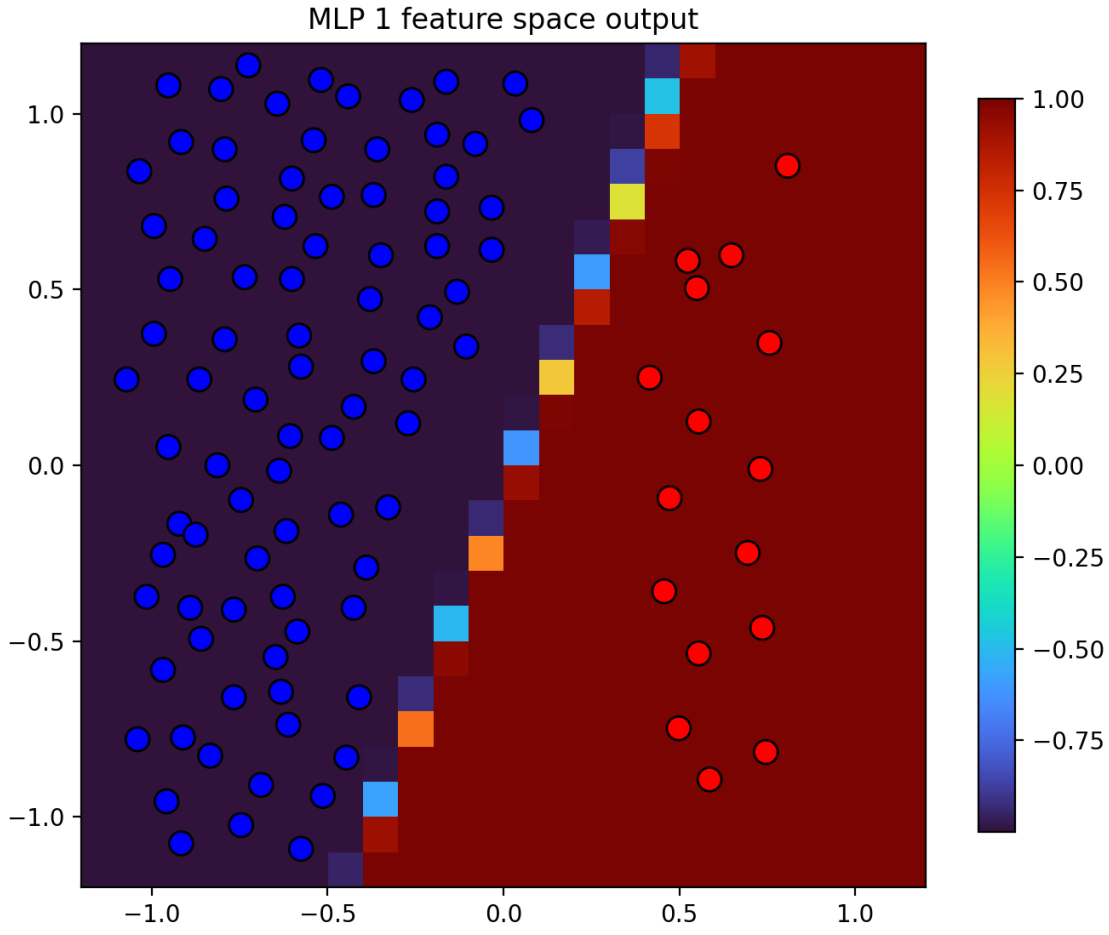
Unbalanced dataset (e.g., one class significantly larger than the others).

Data :



1. `hidden-layer=8` & `learning_rate = 0.8`, `momentum = 0.0001` val
    1. F1-score all : 0.2857142857142857
2. `hidden-layer=8` & `learning_rate = 0.8`, `momentum = 0.0001` val
    1. F1-score all : 0.6190476190476191
3. `hidden-layer=8` & `learning_rate = 0.9`, `momentum = 0.0001`val
    1. F1-score all : 0.0

For same parameters, F1-score could be extremly different, this means the data are to variable because of difference. If the data was more separate (like exemple above) the result could be better.


MLP 1 feature space output
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75