50.039 Theory and Practice of Deep Learning

W2-S3 Neural Networks, Initializers, Optimizers and other Good Practices

Matthieu De Mari

About this week (Week 2)

1. What are the **typical initializers for trainable parameters** in Neural Networks?
2. What is **symmetry** in a Neural Network and why is it essential to **break it** with proper initializers?
3. What is the **exploding gradient** problem?
4. How to **spot and fix an exploding gradient** problem?
5. What is the **vanishing gradient** problem?
6. How to **spot and fix a vanishing gradient** problem?
7. Why are **activation functions** needed in Neural Networks?
8. What is the **universal approximation theorem**?

About this week (Week 2)

9. What are typical **examples** of **activation functions**? Which activations should I be using?
10. What are typical examples of **advanced optimizers**? (Adagrad, RMSProp, Adam, etc.).
11. How to **implement** said **optimizers** manually?
12. What is a **stochastic gradient descent** and what are its **benefits**?
13. How to implement the **stochastic gradient descent** manually?
14. What is a **mini-batch gradient descent** and what are its **benefits**?
15. How to implement the **mini-batch gradient descent** manually?
16. How to **combine all optimizers concepts** into a great optimizer?

About this week (Week 2)

17. What is the **no free lunch theorem**?
18. What is the **train-test-validation split**?
    Why is it **good practice** to use an extra validation set?
19. What is the **early stopping** of optimizer concept?
    Why is it **good practice** to use it?
20. What are **saver** and **loader** functions?
    Why is it **good practice** to use them?
21. What are **other common good practices** when it comes to Neural Networks?

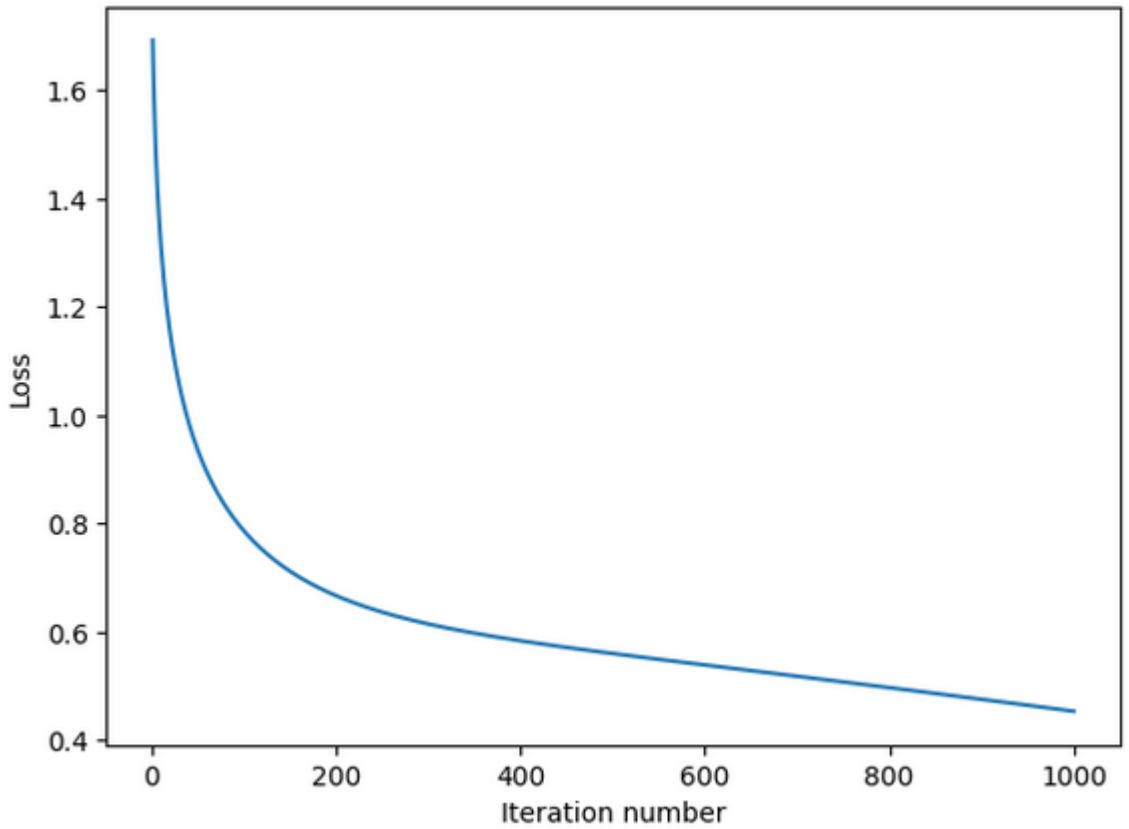
Good Practice #1: using additional performance metrics beyond loss

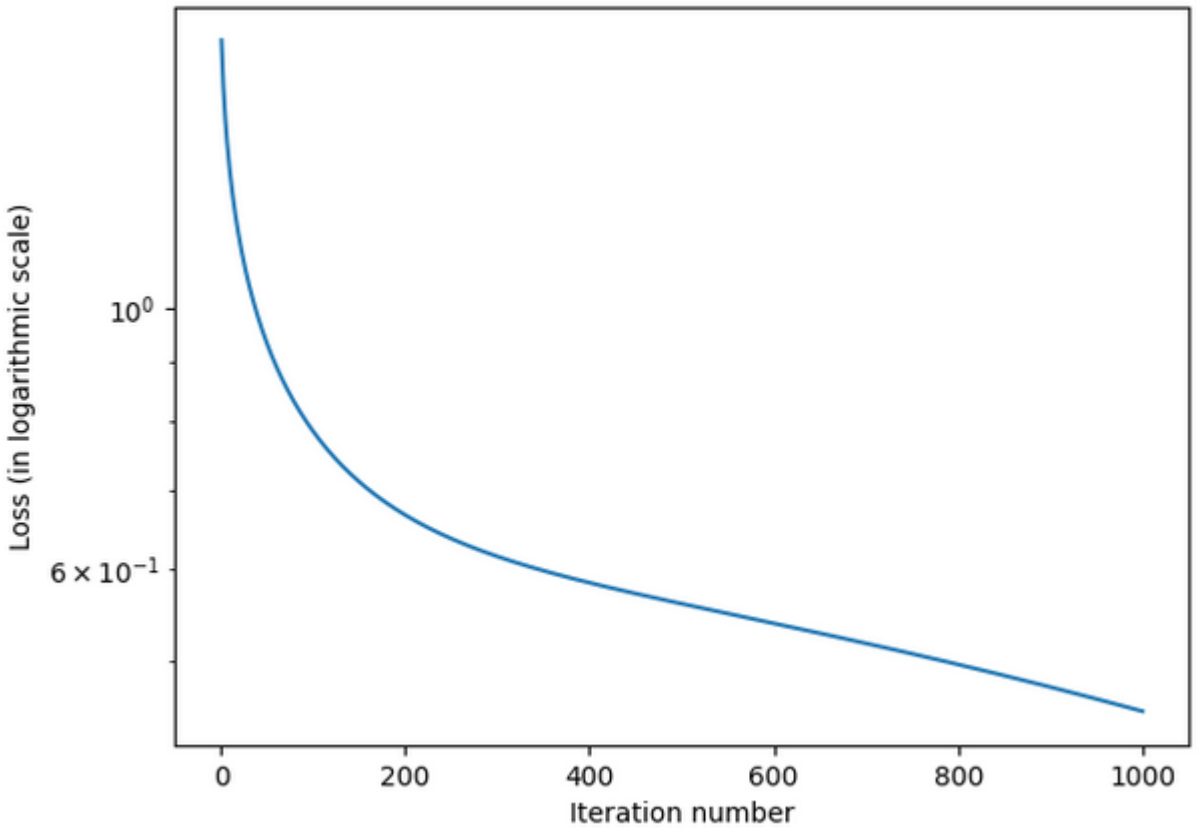
Good practice #1: Using additional performance metrics beyond loss.

- Loss functions are great functions to minimize (for instance MSE is convex, which is a nice property to have).
- But these loss functions do not always carry a meaning that is easily interpretable.
- **For instance, the cross-entropy loss function we have used in binary classification does not tell us much about the actual performance of the model.**
- Recall notebook 4, when we had no activation functions.

Good Practice #1: using additional performance metrics beyond loss

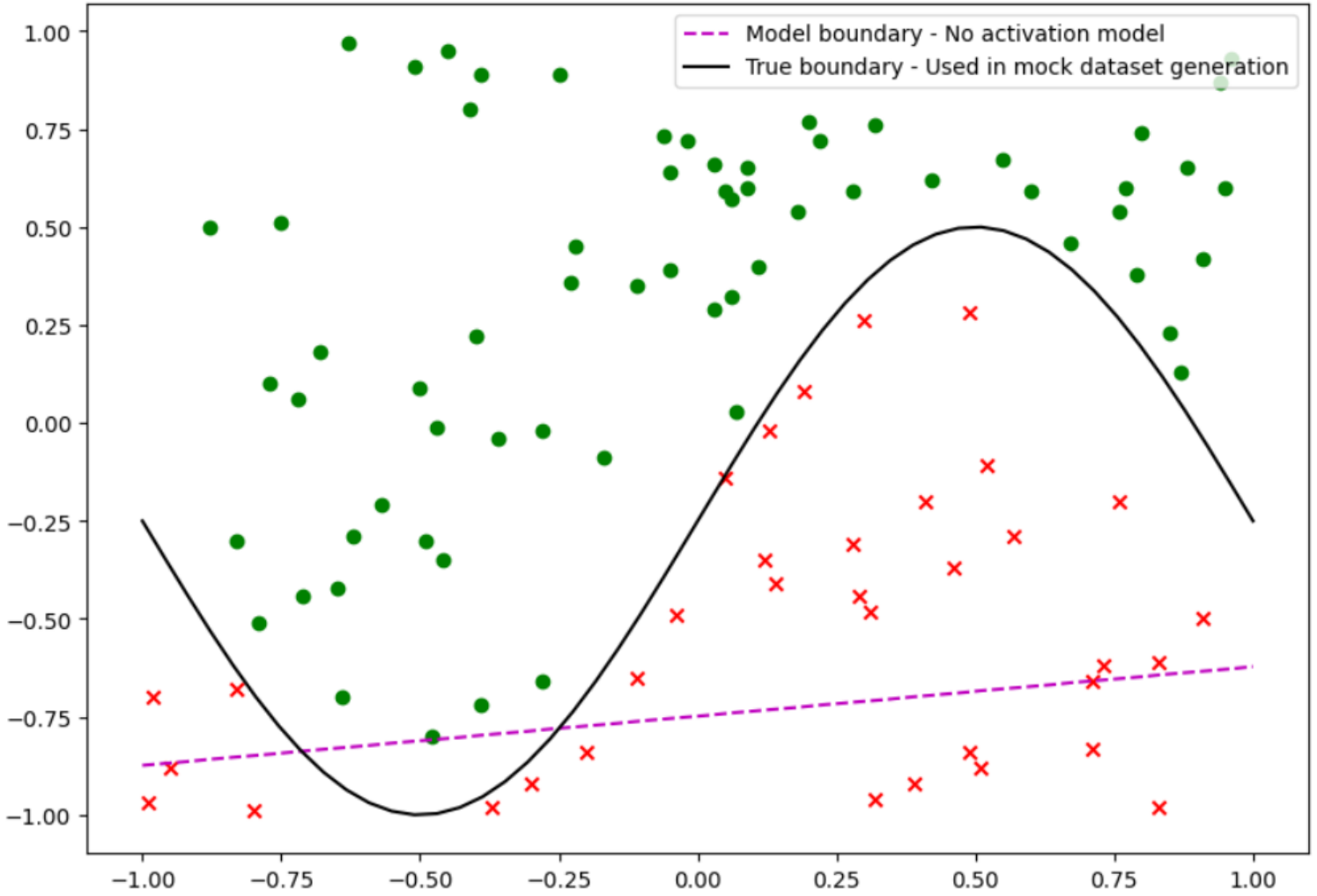
We were able to train, if we consider the loss evolution curves.





Good Practice #1: using additional performance metrics beyond loss

If we consider the **accuracy** of the model, however, then it is fairly obvious to say that the model fails at the given task.



Good Practice #1: using additional performance metrics beyond loss

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- As such, it would be a good idea to have a more interpretable performance metric, such as the accuracy for instance, to display along with the loss function during training.
- This could confirm that the model succeeds at the task (or not).

1. Let us start by adding an accuracy method to our model.

```
43      def accuracy(self, inputs, outputs):
44          # Calculate accuracy for given inputs and ouputs
45          pred = [int(val >= 0.5) for val in self.forward(inputs)]
46          acc = sum([int(val1 == val2[0]) for val1, val2 in zip(pred, outputs)])/outputs.shape[0]
47          return acc
```

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- As such, it would be a good idea to have a more interpretable performance metric, such as the accuracy for instance, to display along with the loss function during training.
- This could confirm that the model succeeds at the task (or not).

2. We can then add another list for tracking accuracies, along with losses during training.

```
104     def train(self, inputs, outputs, N_max = 1000, alpha = 1e-5, beta1 = 0.9, beta2 = 0.999, \
105               delta = 1e-5, batch_size = 100, display = True):
106         # Get number of samples
107         M = inputs.shape[0]
108 
109         # List of losses, starts with the current loss
110         self.losses_list = [self.CE_loss(inputs, outputs)]
111         self.accuracies_list = [self.accuracy(inputs, outputs)]
```

Good Practice #1: using additional performance metrics beyond loss

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- As such, it would be a good idea to have a more interpretable performance metric, such as the accuracy for instance, to display along with the loss function during training.
- This could confirm that the model succeeds at the task (or not).

3. During training we will update the accuracy of the model, appending to list, and displaying them during training along with loss.

```
134             # Update accuracies
135             acc = self.accuracy(inputs, outputs)
136             self.accuracies_list.append(acc)
137 
138             # Display
139             if(display and iteration_number % (N_max*0.05) == 1):
140                 print("Iteration {} - Loss = {} - Acc = {}".format(iteration_number, self.loss, acc))
```

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- As such, it would be a good idea to have a more interpretable performance metric, such as the accuracy for instance, to display along with the loss function during training.
- This could confirm that the model succeeds at the task (or not).

4. Finally, amend our performance curves to show evolution of accuracy over the training iterations.

```
164         axs[2].plot(list(range(len(self.accuracies_list))), self.accuracies_list)
165         axs[2].set_xlabel("Iteration number")
166         axs[2].set_ylabel("Accuracy")
167         # Display
168         plt.show()
```

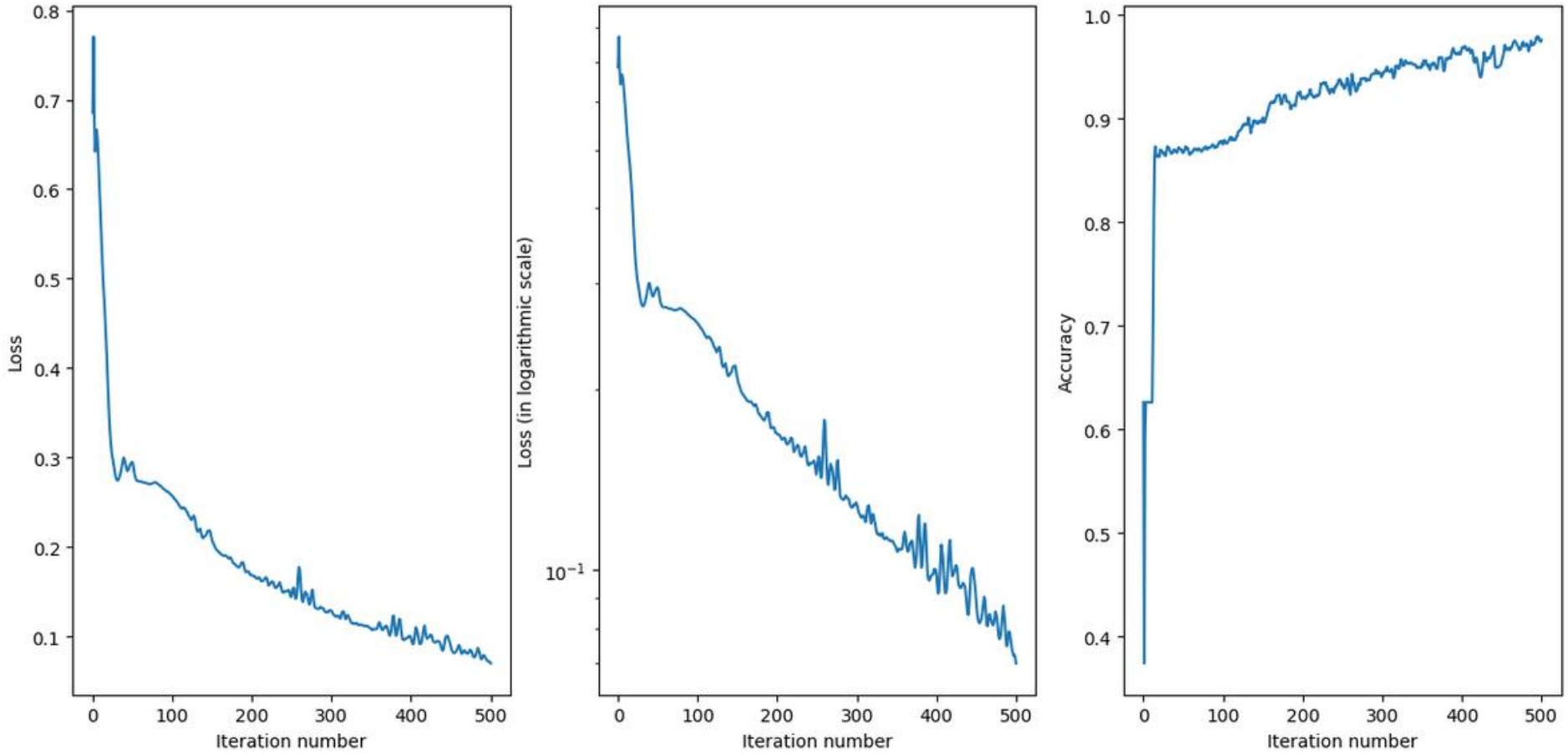
Good Practice #1: using additional performance metrics beyond loss

When the model, with activation functions, is trained, we can see the evolution of the accuracy performance, which is interpretable.

```
Iteration 1 - Loss = 0.7704676641856629 - Acc = 0.374
Iteration 26 - Loss = 0.29408041996849577 - Acc = 0.867
Iteration 51 - Loss = 0.2907713475859916 - Acc = 0.868
Iteration 76 - Loss = 0.2714162997128199 - Acc = 0.871
Iteration 101 - Loss = 0.25587504504663494 - Acc = 0.879
Iteration 126 - Loss = 0.23378145473572498 - Acc = 0.893
Iteration 151 - Loss = 0.2045784244297011 - Acc = 0.897
Iteration 176 - Loss = 0.18302469671030092 - Acc = 0.922
Iteration 201 - Loss = 0.167838515123934 - Acc = 0.921
Iteration 226 - Loss = 0.16116229703195345 - Acc = 0.934
Iteration 251 - Loss = 0.1512993470399631 - Acc = 0.931
Iteration 276 - Loss = 0.15216076879868856 - Acc = 0.938
Iteration 301 - Loss = 0.12705500255256222 - Acc = 0.944
Iteration 326 - Loss = 0.11463009619046385 - Acc = 0.951
Iteration 351 - Loss = 0.10719722692507941 - Acc = 0.951
Iteration 376 - Loss = 0.113238740132263 - Acc = 0.953
Iteration 401 - Loss = 0.09424265876829825 - Acc = 0.969
Iteration 426 - Loss = 0.10069262359991561 - Acc = 0.949
Iteration 451 - Loss = 0.08506155393228489 - Acc = 0.958
Iteration 476 - Loss = 0.08332931024313735 - Acc = 0.973
Stopping - Maximal number of iterations reached.
0.06991123688339018
```

Good Practice #1: using additional performance metrics beyond loss

And of course, training curves.



Good Practice #2: using a train-test-valid split

Good practice #2: Using a train-test-validation split.

If you allow the model to train, you will most likely realize that the accuracy reaches 100% (or close to 100% after a few iterations).

The loss however requires a few more iterations to converge.

This raises a few questions:

- Should we have stopped when the accuracy was already 100%?

- Are we starting to overfit by pursuing the training in an attempt to minimize the loss even more, even though it will not improve the accuracy further?

Good Practice #2: using a train-test-valid split

Good practice #2: Using a train-test-validation split.

While it is true we are using the minimization of the loss function to decide on model parameters...

Our objective is NOT to minimize the training loss function (or maximize the accuracy we obtain on training samples).

Our objective is and always has been **generalization**, that is, training a model that will **generalize well to unseen data**.

This was the reason for using a **train-test split** earlier.

Good Practice #2: using a train-test-valid split

Good practice #2: Using a train-test-validation split.

We introduced the concept of **generalization** and discussed how it is common practice **not to evaluate the performance of the model on the same samples that have been used for training**.

This led us to define two sets, called train and test sets, and we would:

- use the train samples in the backpropagation/training procedure,
- and use the test samples to evaluate the model and assess if it is able to generalize well or not.

We will push it one step further, by introducing the concept of **train, test and validation samples**.

Good Practice #2: using a train-test-valid split

Good practice #2: Using a train-test-validation split.

During the data preparation procedure, we will split the data in three sets:

- **Training** samples
- **Validation** samples
- **Test** samples.

- The **training set** is used to train the machine learning model.
- The model is presented with many examples from the training set, and the model "learns" to make predictions based on those examples.
- For the training procedure to be efficient, **most samples from the dataset should go into the training set**.

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During the data preparation procedure, we will split the data in three sets:

- **Training** samples
- **Validation** samples
- **Test** samples.

- After each iteration of training, the model is tested on the **validation set** to **assess the performance of the model** and see **how well it generalizes to unseen data**.
- The **validation set** also helps to **tune the hyperparameters** of the model.
- The **validation set** requires less samples than the **training set**.

Good Practice #2: using a train-test-valid split

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During the data preparation procedure, we will split the data in three sets:

- **Training** samples
- **Validation** samples
- **Test** samples.

- The **test set** is a set of data that **the model has not seen during the training or validation** process, and is used to **evaluate the final performance** of the model after training is complete, hence providing an estimate of **how well the model will perform on unseen data**.
- The **testing set** is usually set to have as many samples as the **validation set**.

Good Practice #2: using a train-test-valid split

Question: What is considered a good repartition for the train-test-validation split?

The core idea is that:

1. **We want as many samples as possible in the training set. Helps speed up the training of the model.**
2. **We want enough samples in validation/test sets, to ensure diversity and that the law of large numbers applies.**

Definition (law of large numbers): When approximating a mean/average metric, like MSE, we need enough samples so that the empirical approximation matches closely the theoretical value.

Good Practice #2: using a train-test-valid split

<u>Question:</u> What is considered a good repartition for the train-test-validation split?

Following the two ideas from earlier.

Scenario 1: you have more than ~10000 samples (large dataset).

Scenario 2: you have less than ~10000 samples (small dataset).

Scenario 1: you have more than ~10000 samples (large dataset).

- Put **1000 samples** in the **validation set**. And put another **1000 samples** in the **test set**.
- (Having 1000 samples should be enough for law of large numbers to apply).
- Put **the rest** in **training set**.

Good Practice #2: using a train-test-valid split

Question: What is considered a good repartition for the train-test-validation split?

Following the two ideas from earlier.

Scenario 1: you have more than ~10000 samples (large dataset).

Scenario 2: you have less than ~10000 samples (small dataset).

Scenario 2: you have less than ~10000 samples (small dataset).

- Put **10% of samples** in the **validation set**. And put another **10%** in the **test set**.
- (We might not have enough samples to ensure the law of large numbers applies, but we try our best).
- Put **the remaining 80%** in **training set**.

Good Practice #2: using a train-test-valid split

Here we used our dataset generator three times, with different seeds and number of samples.

```python
# Generate dataset (train)
np.random.seed(47)
n_points_train = 1000
train_val1_list, train_val2_list, train_inputs, train_outputs = create_dataset(n_points_train, min_val, max_val)
print(train_inputs.shape)
print(train_outputs.shape)
```

```
(1000, 2)
(1000, 1)
```

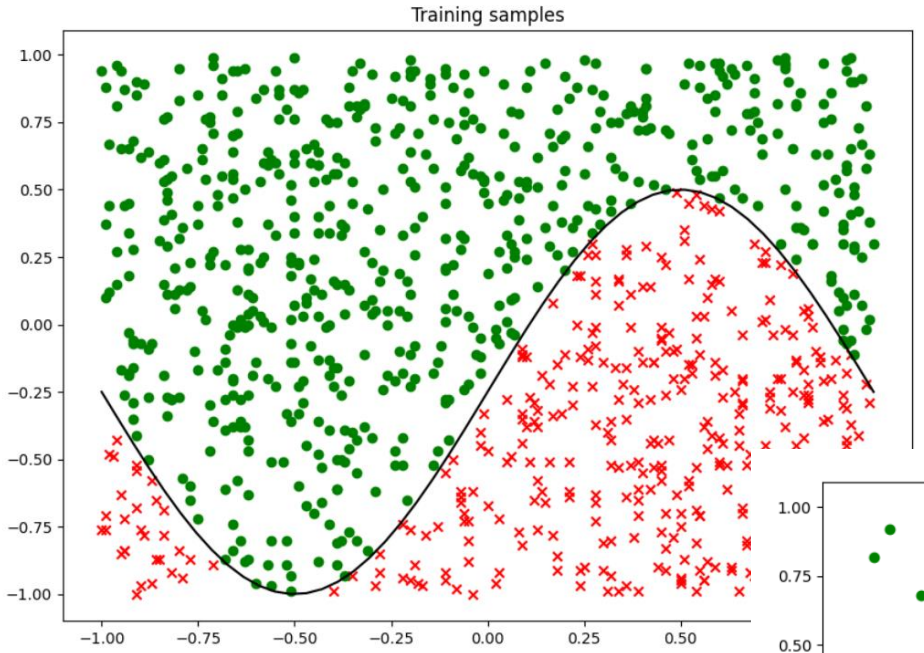
```python
# Generate dataset (test)
np.random.seed(17)
n_points_test = 100
test_val1_list, test_val2_list, test_inputs, test_outputs = create_dataset(n_points_test, min_val, max_val)
print(test_inputs.shape)
print(test_outputs.shape)
```

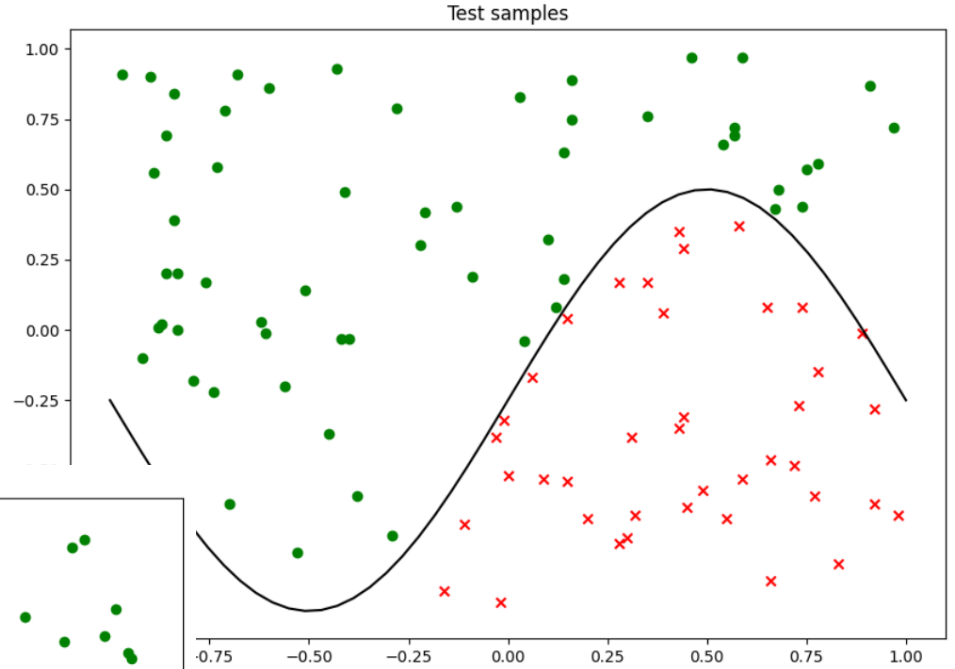
```
(100, 2)
(100, 1)
```

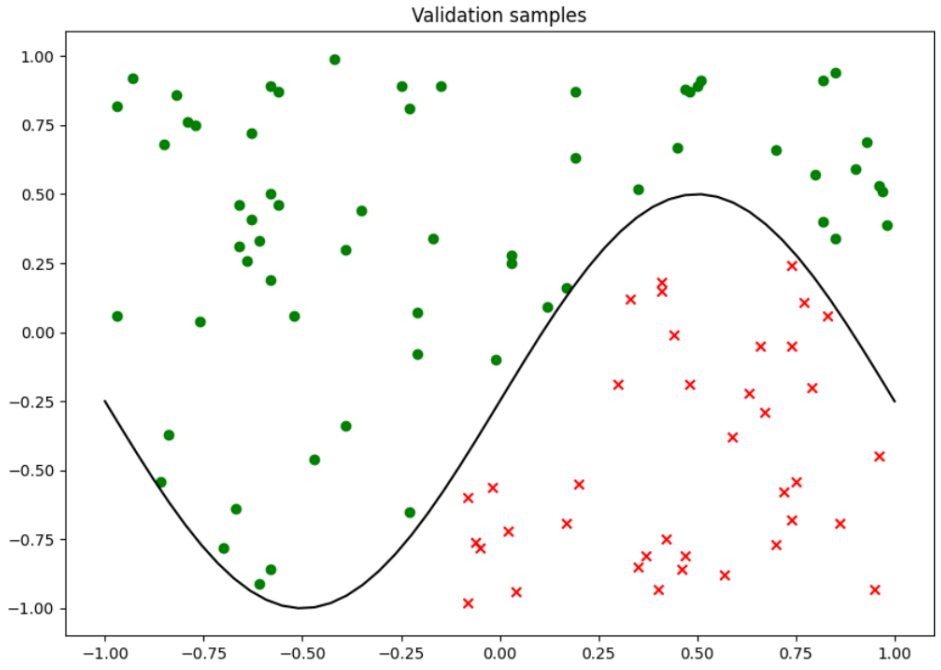
```python
# Generate dataset (valid)
np.random.seed(27)
n_points_valid = 100
valid_val1_list, valid_val2_list, valid_inputs, valid_outputs = create_dataset(n_points_valid, min_val, max_val)
# Check a few entries of the dataset
print(valid_inputs.shape)
print(valid_outputs.shape)
```

```
(100, 2)
(100, 1)
```

Good Practice #2: using a train-test-valid split







Good Practice #2: using a train-test-valid split

During training pass all three datasets as parameters

```
104     def train(self, train_inputs, train_outputs, test_inputs, test_outputs, valid_inputs, valid_outputs, \
105               N_max = 1000, alpha = 1e-5, beta1 = 0.9, beta2 = 0.999, \
106               delta = 1e-5, batch_size = 100, display = True):
```

Good Practice #2: using a train-test-valid split

During training pass all three datasets as parameters

1. Track losses and accuracies during training on both training and validation sets.

```
110         # List of losses and accuracies
111         self.train_losses_list = [self.CE_loss(train_inputs, train_outputs)]
112         self.train_accuracies_list = [self.accuracy(train_inputs, train_outputs)]
113         self.valid_losses_list = [self.CE_loss(valid_inputs, valid_outputs)]
114         self.valid_accuracies_list = [self.accuracy(valid_inputs, valid_outputs)]
```

```
132                 # Update losses list
133                 train_loss = self.CE_loss(train_inputs, train_outputs)
134                 self.train_losses_list.append(train_loss)
135                 valid_loss = self.CE_loss(valid_inputs, valid_outputs)
136                 self.valid_losses_list.append(valid_loss)
137
138                 # Update accuracies
139                 train_acc = self.accuracy(train_inputs, train_outputs)
140                 self.train_accuracies_list.append(train_acc)
141                 valid_acc = self.accuracy(valid_inputs, valid_outputs)
142                 self.valid_accuracies_list.append(valid_acc)
```

Good Practice #2: using a train-test-valid split

During training pass all three datasets as parameters

2. On each iteration, display losses and accuracies on both the training and validation sets.

```
# Display
if (display):
    message = "Iteration {} ".format(iteration_number)
    message += "\n - Train Loss = {} - Train Acc = {}".format(train_loss, train_acc)
    message += "\n - Validation Loss = {} - Validation Acc = {}".format(valid_loss, valid_acc)
    print(message)
```

Good Practice #2: using a train-test-valid split

During training pass all three datasets as parameters

3. After training has completed, check accuracy values (and, optionally, loss values) on the test set for confirmation.

```
# Display Accuracy on test
print("Test accuracy = {}".format(self.accuracy(test_inputs, test_outputs)))
```

Good Practice #2: using a train-test-valid split

During training pass all three datasets as parameters

4. Training curves will now include training and validation values.

```
168     def show_training_curves(self):
169         # Initialize matplotlib
170         fig, axs = plt.subplots(1, 3, figsize = (15, 7))
171         axs[0].plot(list(range(len(self.train_losses_list))), \
172                     self.train_losses_list, "b--", \
173                     label = "Train loss")
174         axs[0].plot(list(range(len(self.valid_losses_list))), \
175                     self.valid_losses_list, "r--", \
176                     label = "Valid loss")
177         axs[0].set_xlabel("Iteration number")
178         axs[0].set_ylabel("Losses")
179         axs[1].plot(list(range(len(self.train_losses_list))), \
180                     self.train_losses_list, "b--", \
181                     label = "Train loss")
182         axs[1].plot(list(range(len(self.valid_losses_list))), \
183                     self.valid_losses_list, "r--", \
184                     label = "Valid loss")
```

```
185         axs[1].set_xlabel("Iteration number")
186         axs[1].set_ylabel("Losses (in logarithmic scale)")
187         axs[1].set_yscale("log")
188         axs[2].plot(list(range(len(self.train_accuracies_list))), \
189                     self.train_accuracies_list, "b--", \
190                     label = "Train Acc")
191         axs[2].plot(list(range(len(self.valid_accuracies_list))), \
192                     self.valid_accuracies_list, "r--", \
193                     label = "Valid Acc")
194         axs[2].set_xlabel("Iteration number")
195         axs[2].set_ylabel("Accuracies")
196         # Display
197         axs[0].legend(loc = "best")
198         axs[1].legend(loc = "best")
199         axs[2].legend(loc = "best")
200         plt.show()
```

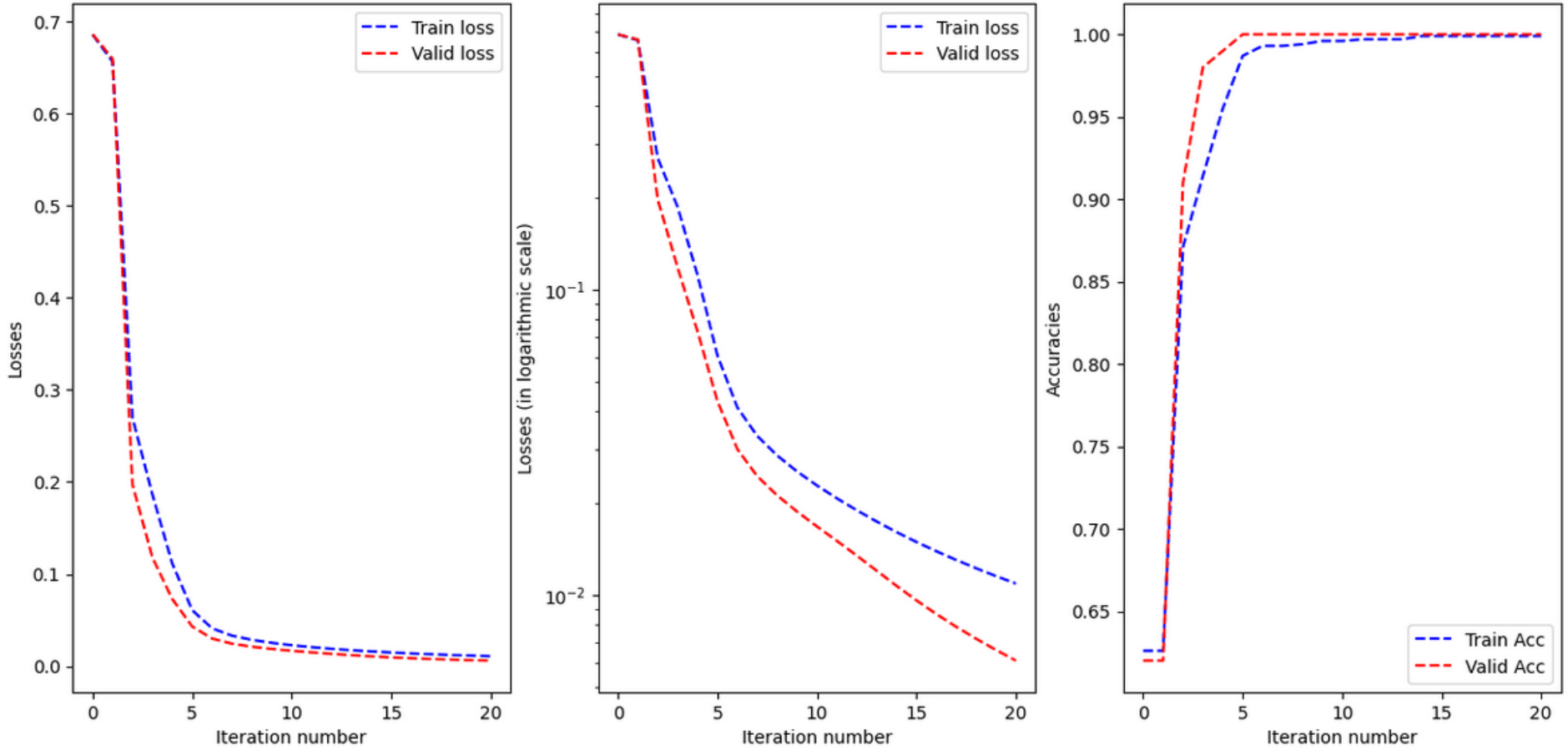
Good Practice #2: using a train-test-valid split

Training model gives following display.

```
Iteration 1
 - Train Loss = 0.6562206116565713 - Train Acc = 0.626
 - Validation Loss = 0.6592760519158617 - Validation Acc = 0.62
Iteration 31
 - Train Loss = 0.2830951890174539 - Train Acc = 0.869
 - Validation Loss = 0.20063836446117492 - Validation Acc = 0.91
Iteration 61
 - Train Loss = 0.2656823064976081 - Train Acc = 0.876
 - Validation Loss = 0.19536548122888026 - Validation Acc = 0.91
Iteration 91
 - Train Loss = 0.2051948666756941 - Train Acc = 0.91
 - Validation Loss = 0.12551601511035104 - Validation Acc = 0.98
Iteration 121
 - Train Loss = 0.15131533920216939 - Train Acc = 0.934
 - Validation Loss = 0.10093479006170472 - Validation Acc = 0.99
Iteration 151
 - Train Loss = 0.1115951833149475 - Train Acc = 0.955
 - Validation Loss = 0.07298127188796165 - Validation Acc = 0.99
Iteration 181
 - Train Loss = 0.07802364083046055 - Train Acc = 0.98
 - Validation Loss = 0.05391519243728255 - Validation Acc = 1.0
Iteration 211
 - Train Loss = 0.05500636101156745 - Train Acc = 0.991
 - Validation Loss = 0.039277569946238516 - Validation Acc = 1.0
Iteration 241
 - Train Loss = 0.04363952867730853 - Train Acc = 0.993
 - Validation Loss = 0.03176801602040892 - Validation Acc = 1.0
Iteration 271
 - Train Loss = 0.03726340017086438 - Train Acc = 0.993
 - Validation Loss = 0.02735269123594779 - Validation Acc = 1.0
Stopping - Maximal number of iterations reached.
Test accuracy = 1.0
```

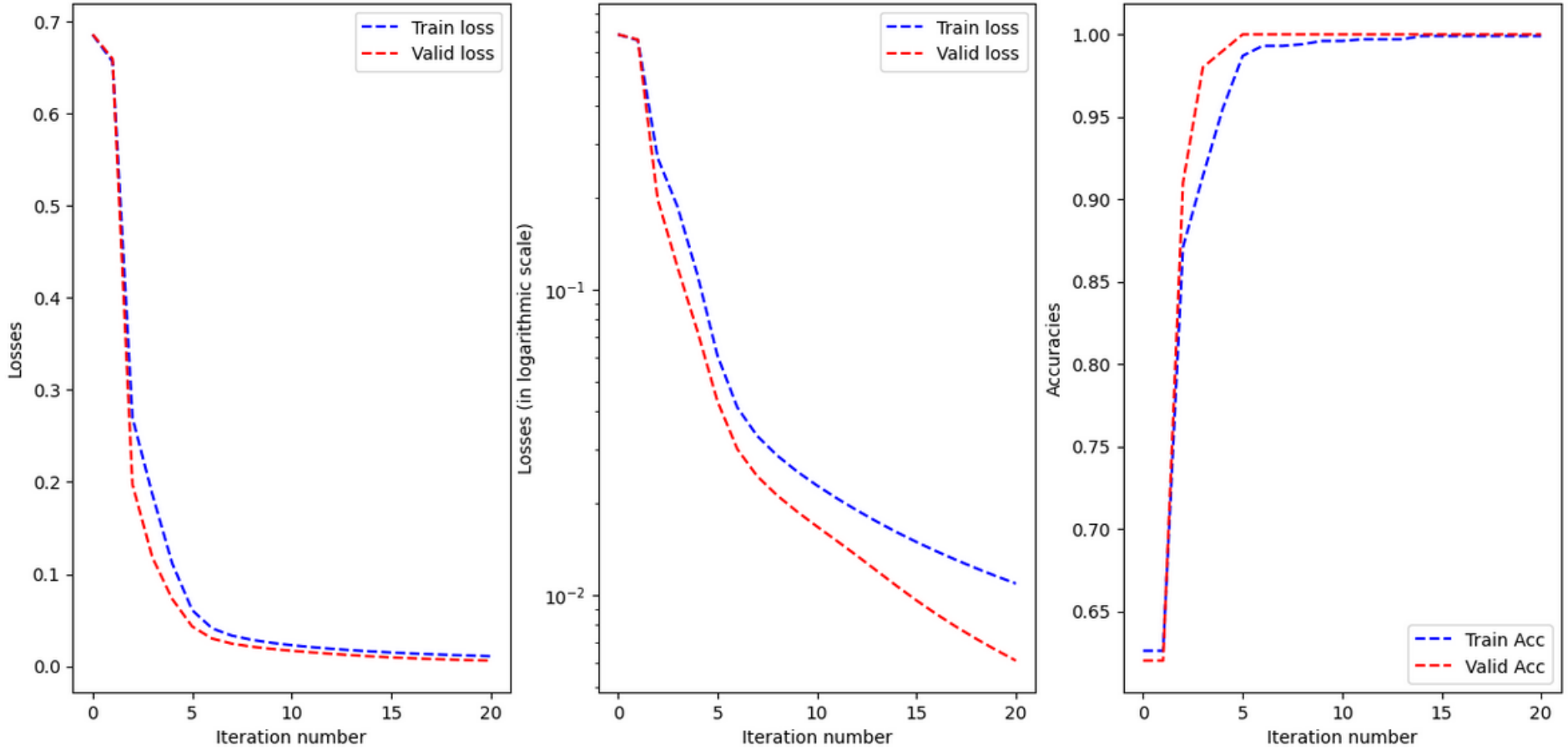
Good Practice #2: using a train-test-valid split

Training model gives following training curves (good training).



Good Practice #2: using a train-test-valid split

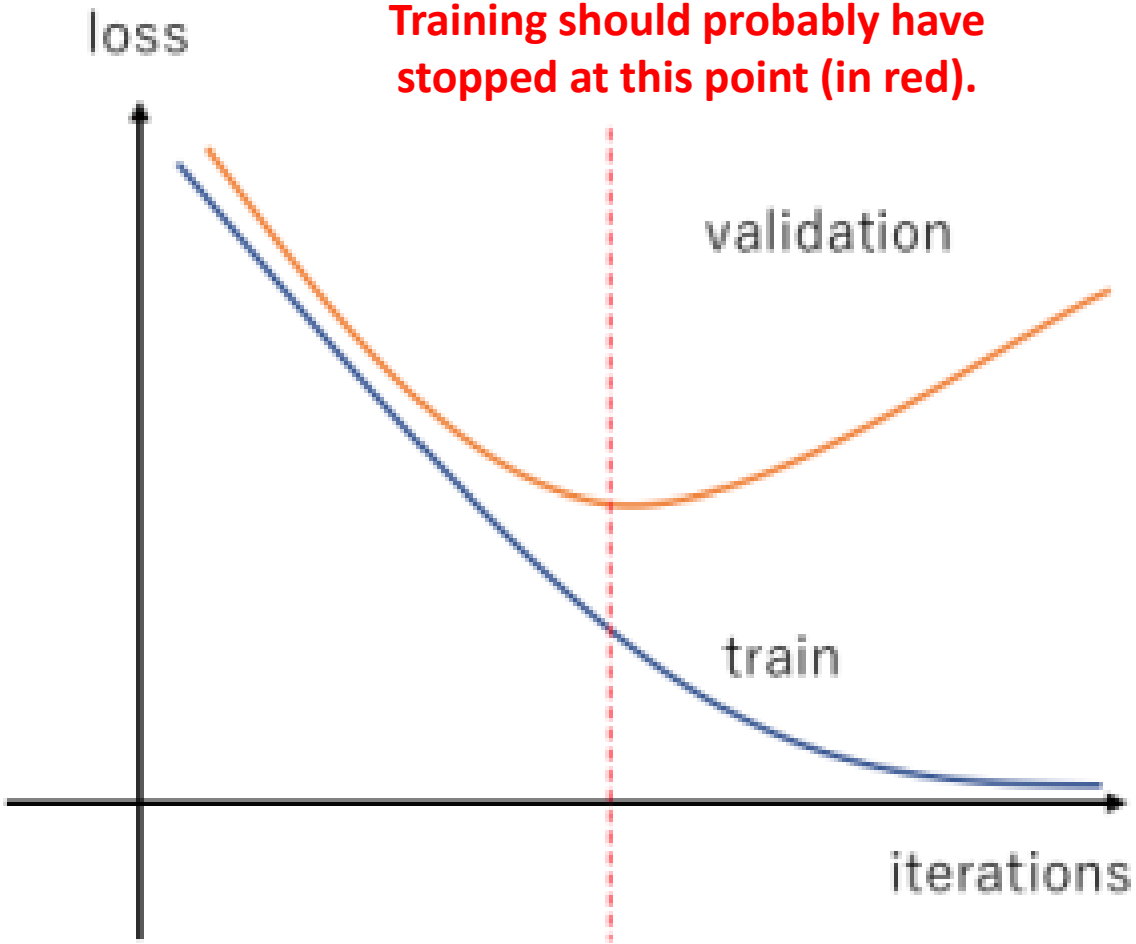
Note: A model that can generalize well will often have close curves on train and validation sets. And a good final validation accuracy value.



Good Practice #2: using a train-test-valid split

In general,

- Model will start by **underfitting** the data, which is normal.
- After a few rounds of training models will (hopefully) achieve **good generalization**.
- Then, if training is pursued, the model will often attempt to **minimize loss at all costs**, **sacrificing generalization (!)** in the process, and **overfitting.**



Good Practice #3: implementing an early stop

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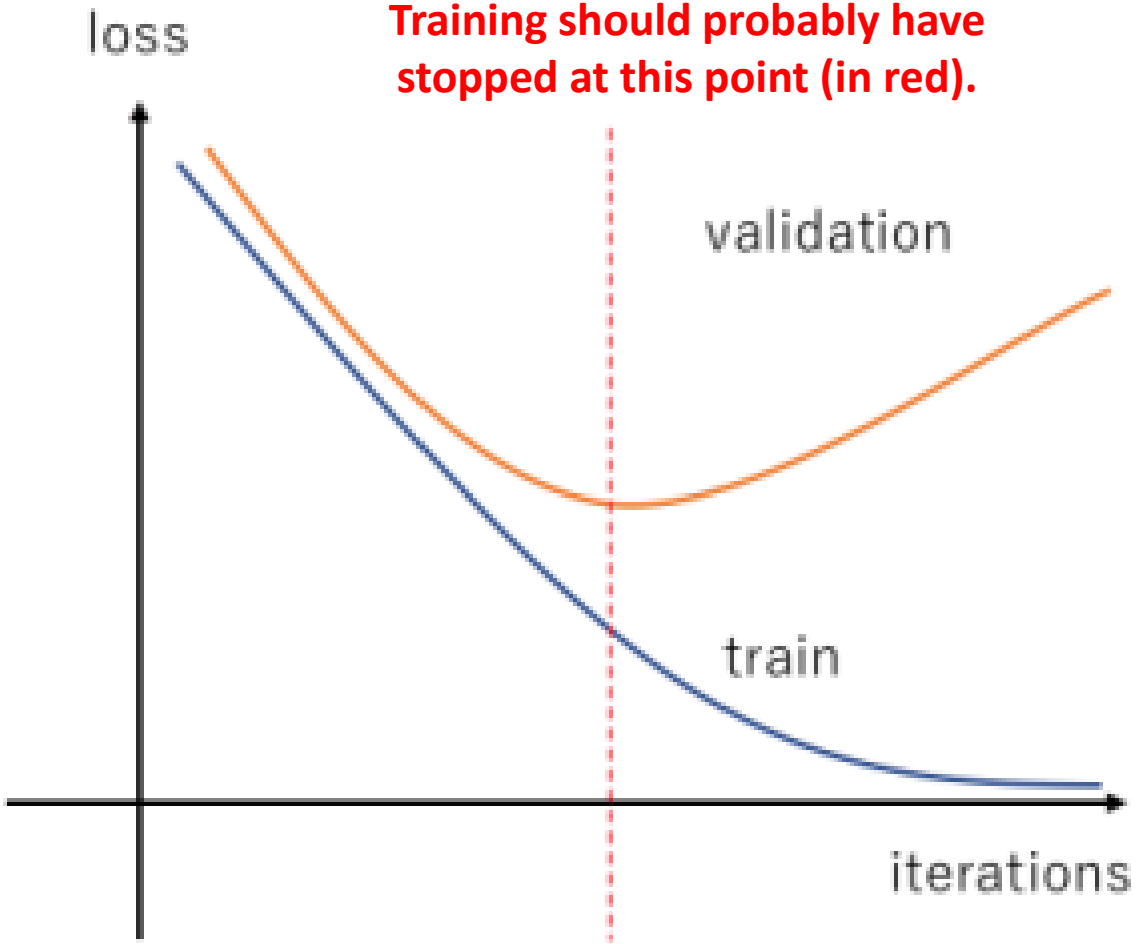
It is often a good idea to try and stop the training when the model starts losing it generalization capabilities and starts overfitting.

We often want to stop when:

- Validation loss is minimal.
- Validation and training curves start going in opposite ways.



Good Practice #3: implementing an early stop

Other approaches suggest to simply track the validation accuracy metric and define an early stopping, which interrupts training when:

- a high level of accuracy has been obtained (say, at least 98%),
- and the accuracy is no longer increasing (i.e. the change between two consecutive values of the accuracy is falling below a threshold).

```
# Check for delta value and early stop criterion
difference = abs(self.valid_accuracies_list[-1] - self.valid_accuracies_list[-2])
if(difference < delta and self.valid_accuracies_list[-1] > 0.98):
    if(display):
        message = "Stopping early - obtained good daccuracy (at least 98%)"
        message += " and accuracy evolution was less than delta on"
        message += "iteration {}.".format(iteration_number)
        print(message)
        break
```

Good Practice #3: implementing an early stop

Other approaches suggest to simply track the validation accuracy metric and define an early stopping, which interrupts training when:

- a high level of accuracy has been obtained (say, at least 98%),
- and the accuracy is no longer increasing (i.e. the change between two consecutive values of the accuracy is falling below a threshold).

Problem: we will often stop after it is too late (we need to see the model starts losing generalization capabilities to decide we should have stopped earlier!)

Good Practice #4: saver and loader functions

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Idea: how about we **save** the model parameters (W_1, W_2, b_1, b_2) to a file (along with the iteration number) every K iterations?

Good Practice #4: saver and loader functions

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Problem: we will often stop after it is too late (we need to see the model starts losing generalization capabilities to decide we should have stopped earlier!)

Idea: how about we save the model parameters (W_1, W_2, b_1, b_2) to a file (along with the iteration number) every K iterations?

```python
def save(self, path_to_file, iter_num = "final"):
    # Display
    folder = path_to_file + "/" + iter_num + "/"
    print("Saving model to", folder)

    # Check if directory exists
    if(not os.path.exists(folder)):
        os.mkdir(folder)

    # Dump
    with open(folder + "W1.pkl", 'wb') as f:
        pickle.dump(self.W1, f)
    f.close()
    with open(folder + "W2.pkl", 'wb') as f:
        pickle.dump(self.W2, f)
    f.close()
    with open(folder + "b1.pkl", 'wb') as f:
        pickle.dump(self.b1, f)
    f.close()
    with open(folder + "b2.pkl", 'wb') as f:
        pickle.dump(self.b2, f)
    f.close()
```

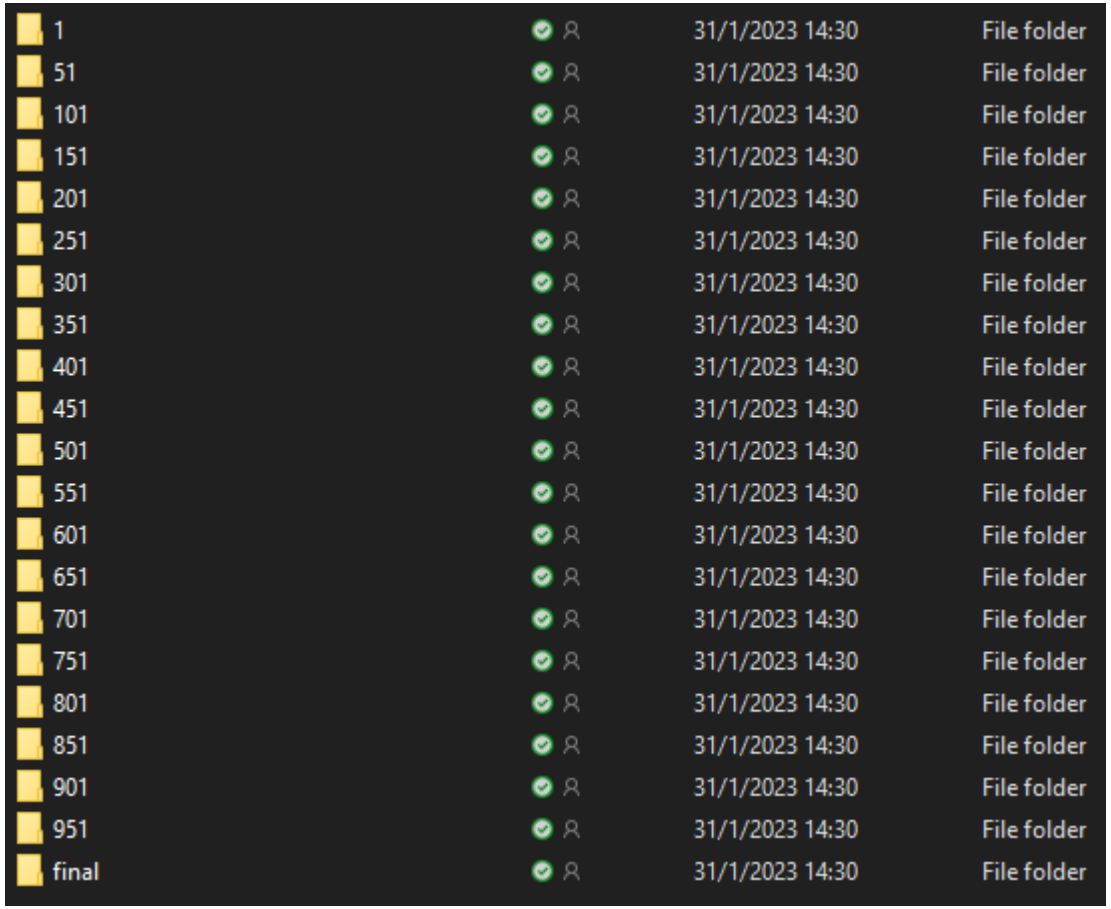
```python
# Save model
self.save("./save", iter_num = str(iteration_number))
```

Good Practice #4: saver and loader functions

Good Practice #4: saver and loader functions.

Problem: we will often stop after it is too late (we need to see the model starts losing generalization capabilities to decide we should have stopped earlier!)

Idea: how about we save the model parameters (W_1, W_2, b_1, b_2) to a file (along with the iteration number) every K iterations?



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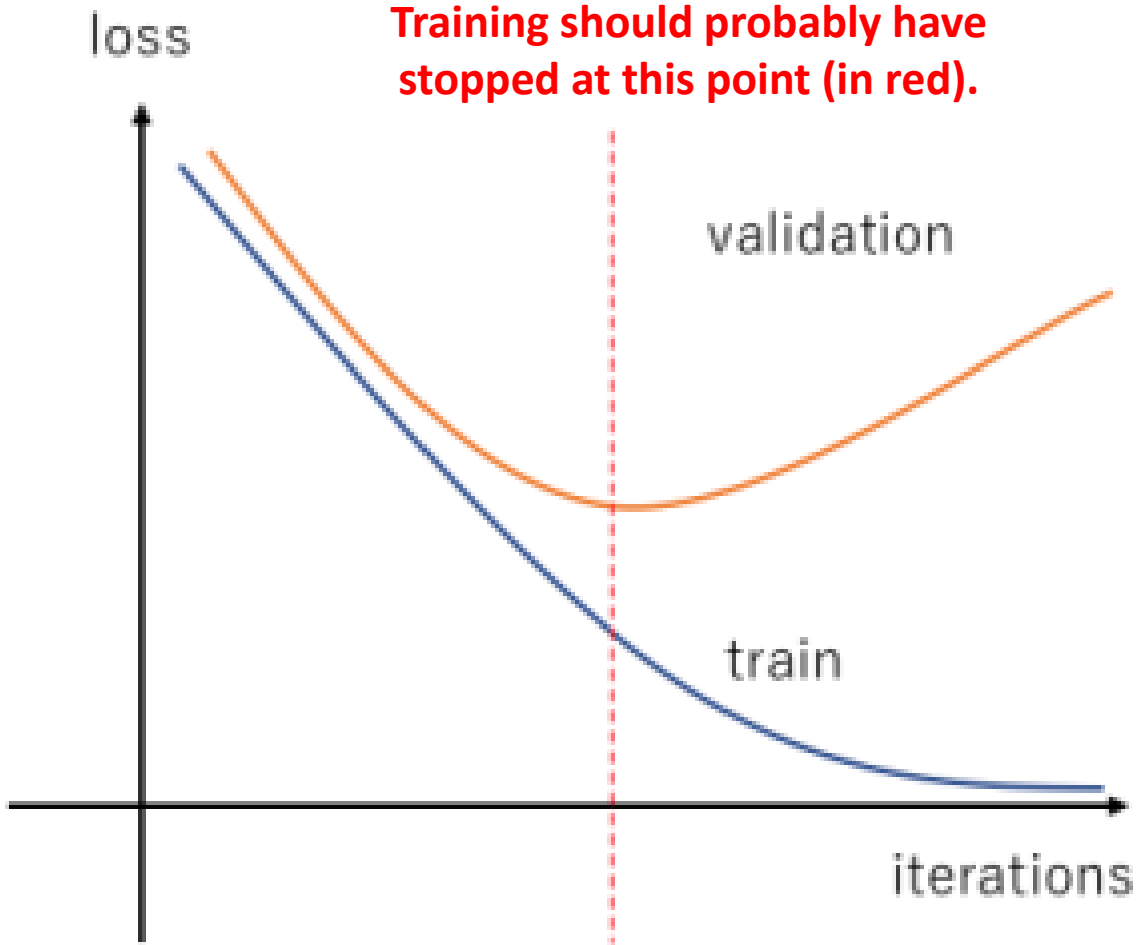

Trained for too long? No big deal, load the weights corresponding to the best iteration!

Good Practice #4: saver and loader functions

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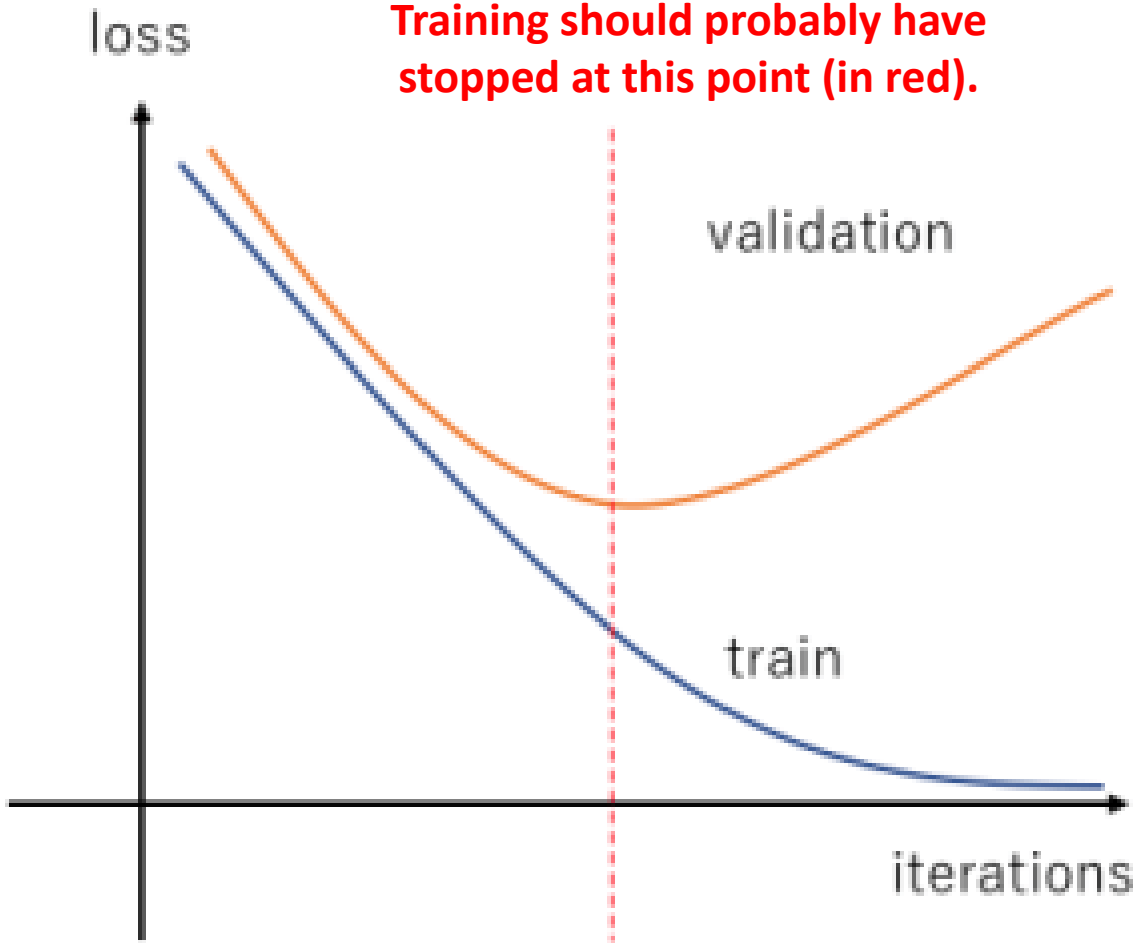
After training, look at your training curves and **load** the model parameters (W_1, W_2, b_1, b_2) to a file corresponding to the best iteration for the model in terms of **generalization**!



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After training, look at your training curves and **load** the model parameters (W_1, W_2, b_1, b_2) to a file corresponding to the best iteration for the model in terms of **generalization**!

(Iteration number to be decided manually by analysing the training curves.)

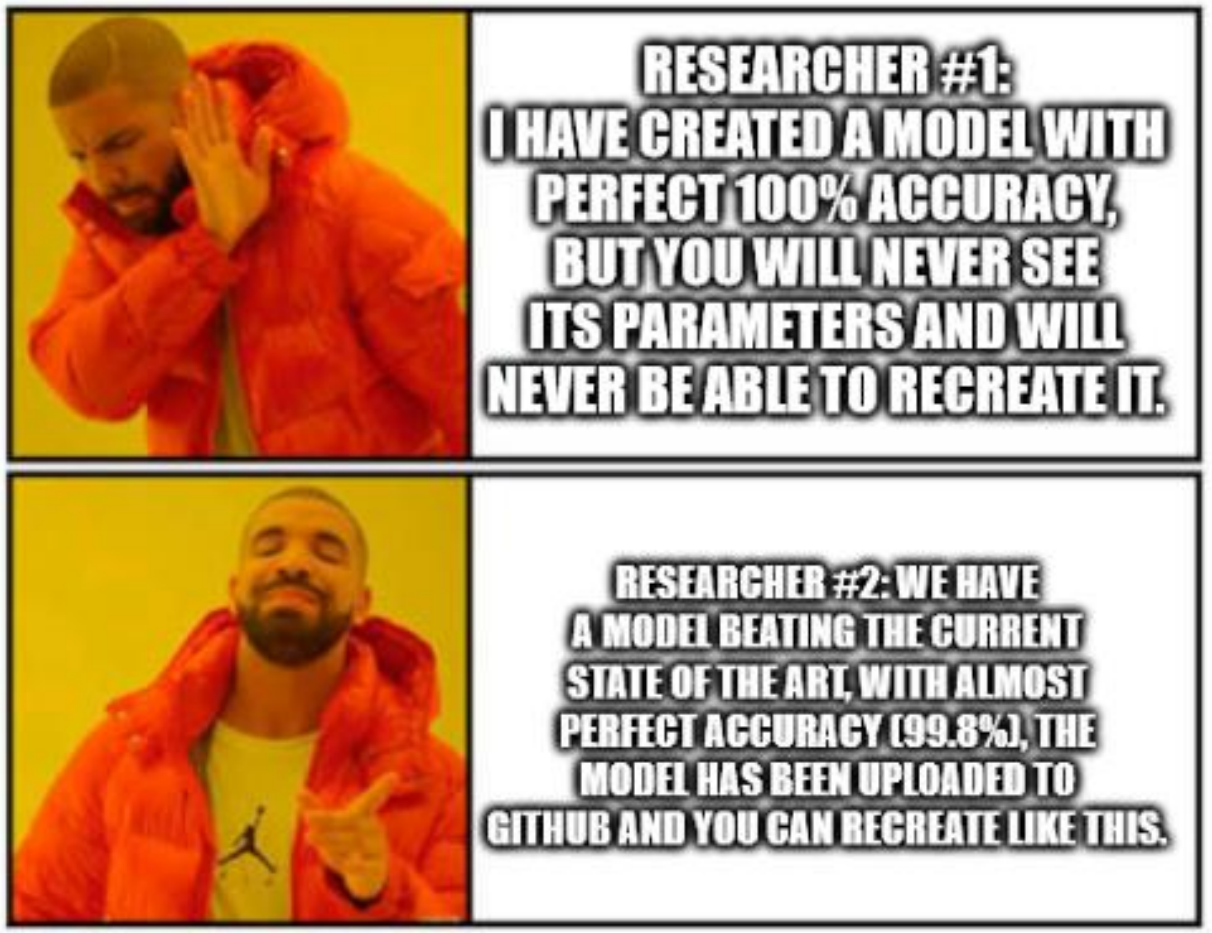
```
def load(self, path_to_file, iter_num = "final"):
    folder = path_to_file + "/" + iter_num + "/"
    print("Loading model from", folder)

    # Load
    with open(folder + "W1.pkl", 'rb') as f:
        self.W1 = pickle.load(f)
    f.close()
    with open(folder + "W2.pkl", 'rb') as f:
        self.W2 = pickle.load(f)
    f.close()
    with open(folder + "b1.pkl", 'rb') as f:
        self.b1 = pickle.load(f)
    f.close()
    with open(folder + "b2.pkl", 'rb') as f:
        self.b2 = pickle.load(f)
    f.close()
```

Saver/loader functions are critical

Reproducibility: after training, it is important that you give your client a simple way to load your trained model. You would not want the client to re-run the training (especially if it takes a VERY long time to train!)

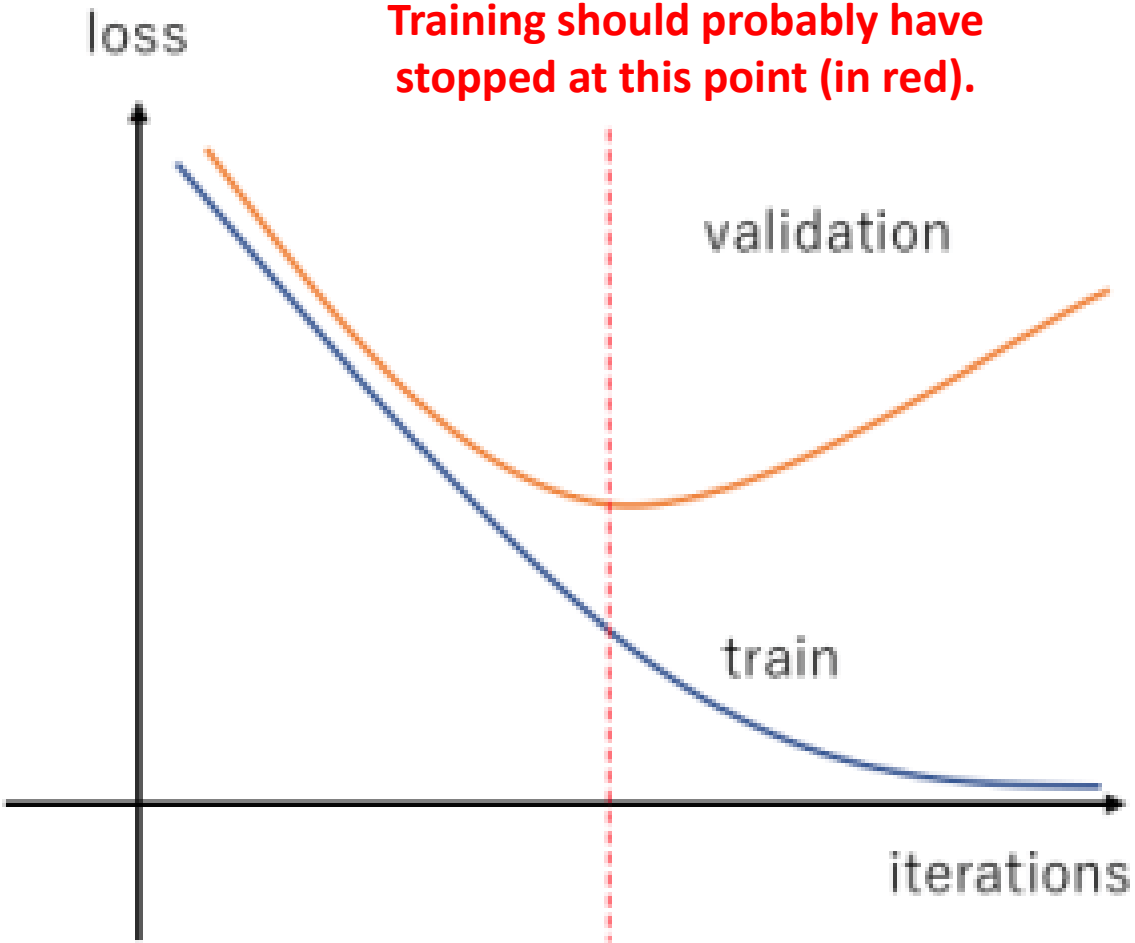
It is also important if you do research, as your research will have little credibility if you are not able to show the model at work.



Saver/loader functions are critical

Restoring model: Saving the model at regular intervals during training allows you to evaluate the model's performance on a validation set at various stages of training.

In scenarios where you failed to stop at the appropriate time, you can load a previous version of the model, that was saved on an iteration before overfitting started to occur.



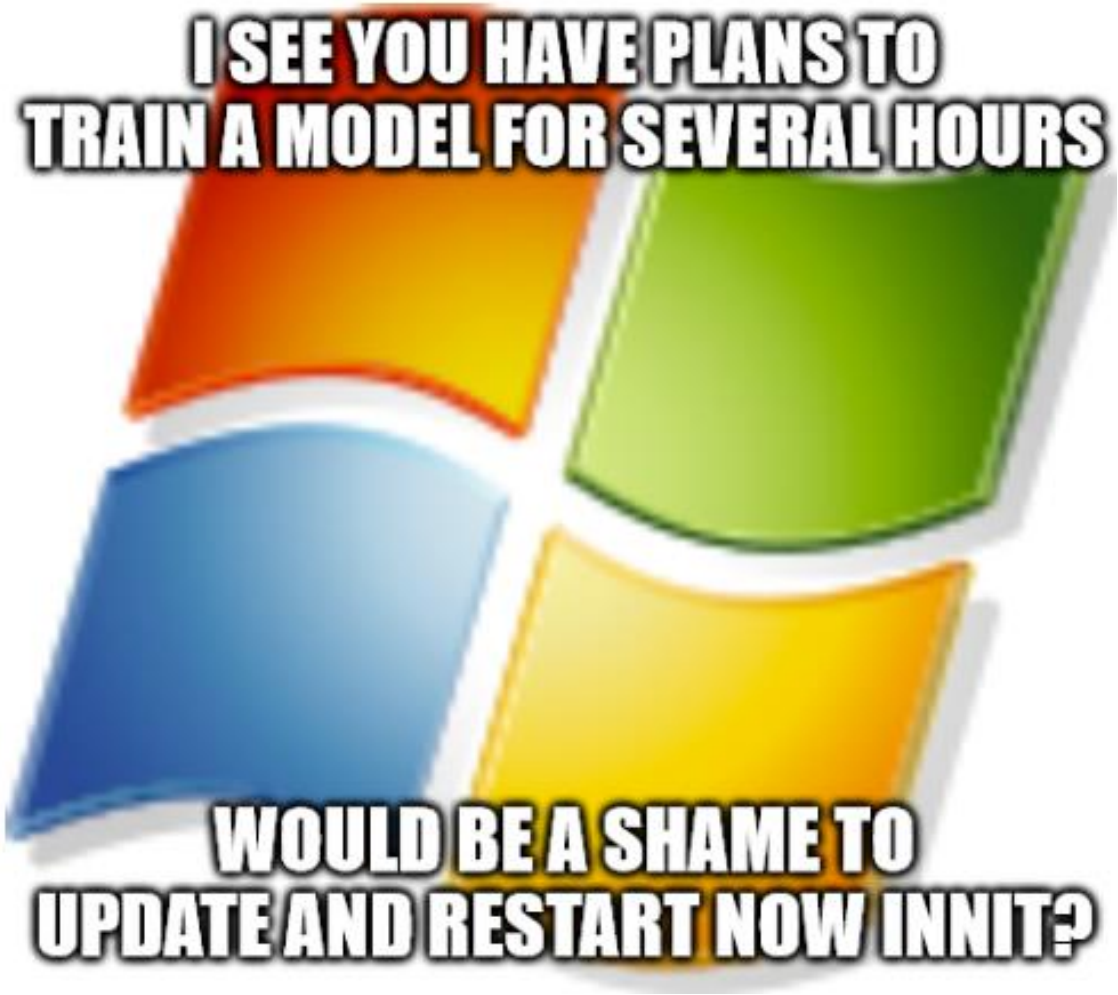
Trained for too long? No big deal, load the weights corresponding to the best iteration!

Saver/loader functions are critical

Preventing data loss: Training a model can take a long time, sometimes even days or weeks if the architecture is massive.

If the training process is interrupted, all the progress made so far will be lost unless the model has been saved.

In case of an interruption, we can simply load the latest save of the model, and resume the training, instead of restarting from scratch.



Typical questions about model architecture

Typical questions asked by students regarding the size of a neural network model.

- **How many layers does my model need?**
- **How many neurons should I put in each layer?**
- **Is it better to have more layers or more neurons per layer?**

The answer to the first question will surprise you.

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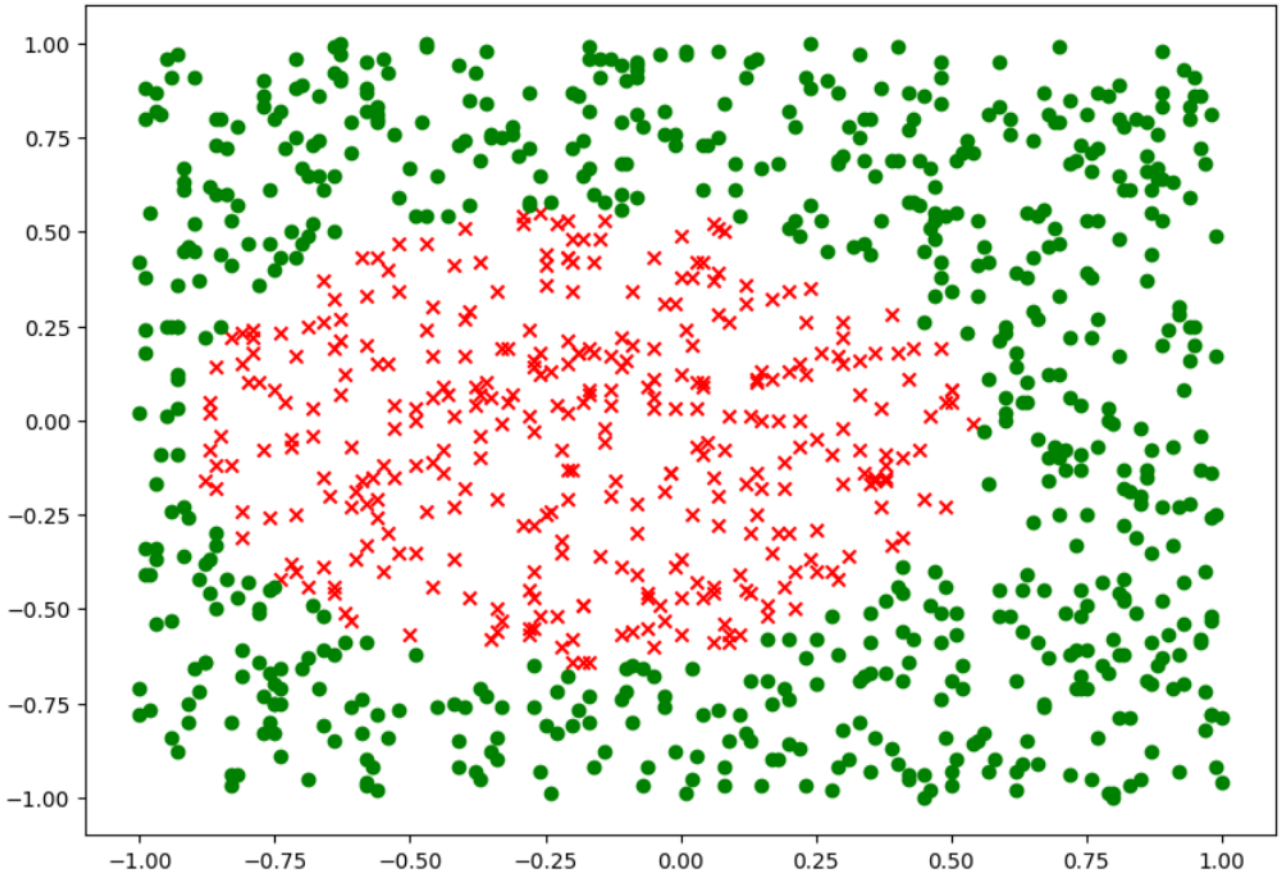
The answer to the first question will surprise you.

Well, let us experiment then?

Have a look at notebook 8, it comes with three practice tasks.
(Solutions are also available in the solutions folder).

Problem statement

Consider the following binary classification dataset: follows the same logic as our previous dataset, but the boundary equation is not given.



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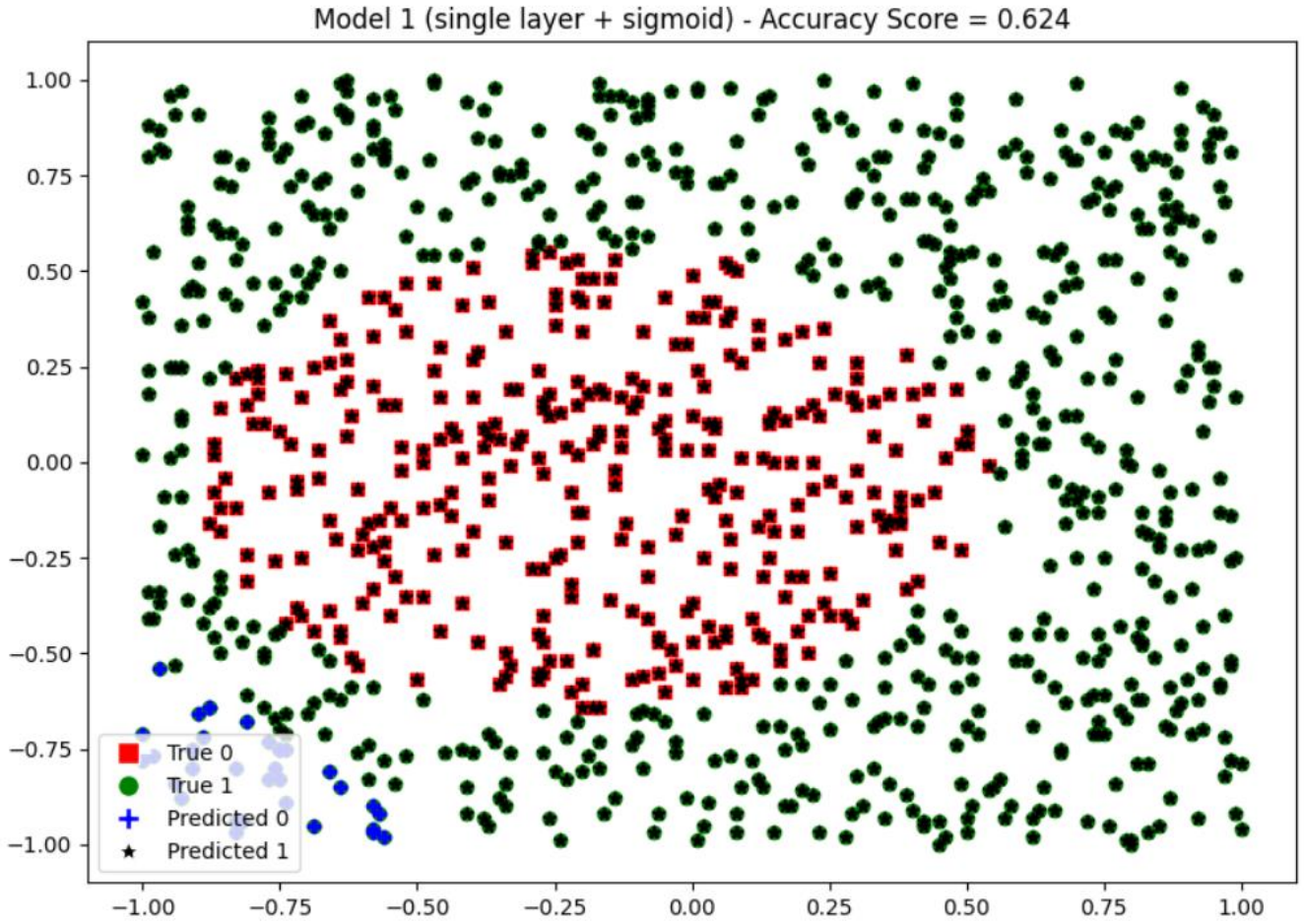
Unfortunately, mixed results.



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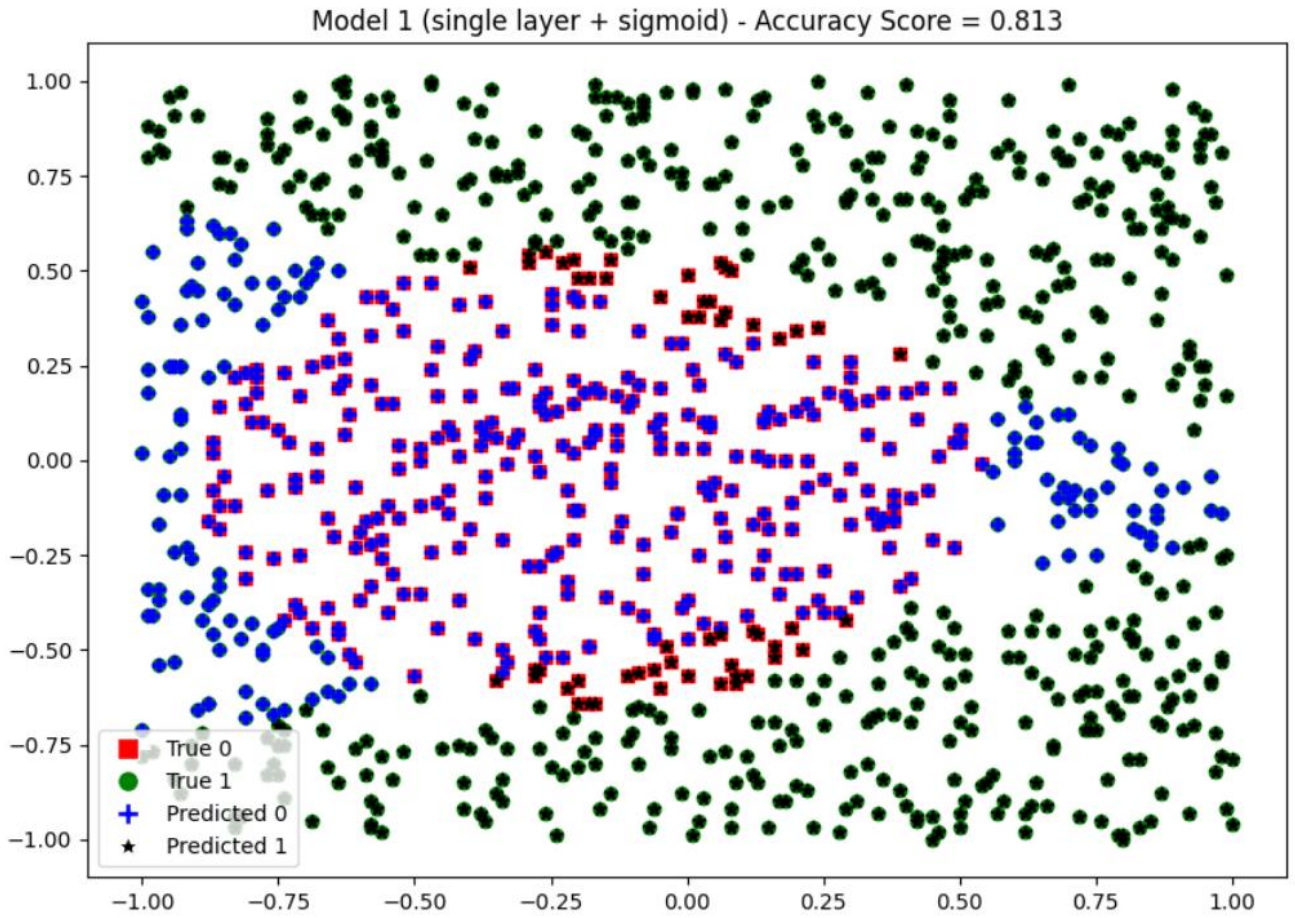

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Unfortunately, mixed results.

Three suggested approaches/tasks

- Adding a second layer helped, let us try adding a third one! (will need to rework methods)
- How about 2-layers, but more neurons on each layer?
- How about a bit of feature engineering? (i.e. reworking our dataset a bit to help our neural networks)

Well, let us experiment then?

Have a look at notebook 8, it comes with three practice tasks.
(Solutions are also available in the solutions folder).

Lesson #1: features engineering is king!

In general, feature engineering is the direction which offers the largest improvement potential for our models.

If you have a hunch about which features could help the network classify better, you should attempt some feature engineering.

Problem: need to have a strong mathematical intuition sometimes!

- Here, what helped was recognizing that the squared values of the inputs could help as the boundary looked like a circle and circles equations are usually relying on squared values of the inputs.

$$x_1^2 + x_2^2 = K$$

- Our boundary equation was in fact

$$2x_1^2 + 3x_2^2 + 0.75x_1 + 0.25x_2 = 0$$

Lesson #2: larger layers vs. more layers

- The number of layers to use in a neural network can vary depending on the complexity of the task and the size of the data. It is a hyperparameter that can be tuned through experimentation.

- **In general, deeper networks (more layers) can learn more complex representations, but they are also more computationally expensive and prone to overfitting.**
- **On the other hand, shallower networks are less expensive and less prone to overfitting, but they may not have enough capacity to learn the task.**

Lesson #2: larger layers vs. more layers

As far as I know, there is no rule of thumb formula for determining the number of layers to use based on the number of samples in a dataset.

The number of layers in a neural network model is determined by a variety of factors, including the complexity of the problem, the size of the input data, and the available computational resources.

1. If the data is linearly separable then you do not need any hidden layers or activation functions, just use a linear regressor already!
2. If data is low-complexity and has few dimensions/features, then 1 to 2 hidden layers would often work and are a good starting point.
3. If data is high-complexity or has many dimensions/features then using 3 to 5 hidden layers often gives good results.

Lesson #2: larger layers vs. more layers

However, “adding an extra layer to a model that is failing and already has many layers in the hopes of making it suddenly fixing it” is often foolish and will have limited results.

You need enough layers to match the complexity of the task, anything beyond that is overkill and most likely will not help.

More often than not, you are not using the right TYPE of layers that fits the TYPE of data you are playing with (more on this later).

Lesson #2: larger layers vs. more layers

In fact, it is often better to add more neurons to a layer (as we have seen in task #3).

As far as I know, there is no rule of thumb formula for determining the number of neurons to use in a layer.

But some people ([StackNN]) have been experimenting and suggest to have a number of neurons in layers, N_n, such that

$$N_n = \frac{N_s}{(N_i + N_o)\gamma}$$

With N_s the number of samples in dataset, N_i the number of inputs (or inputs dimensionality), N_o the outputs dimensionality and γ a value between 2 and 20.

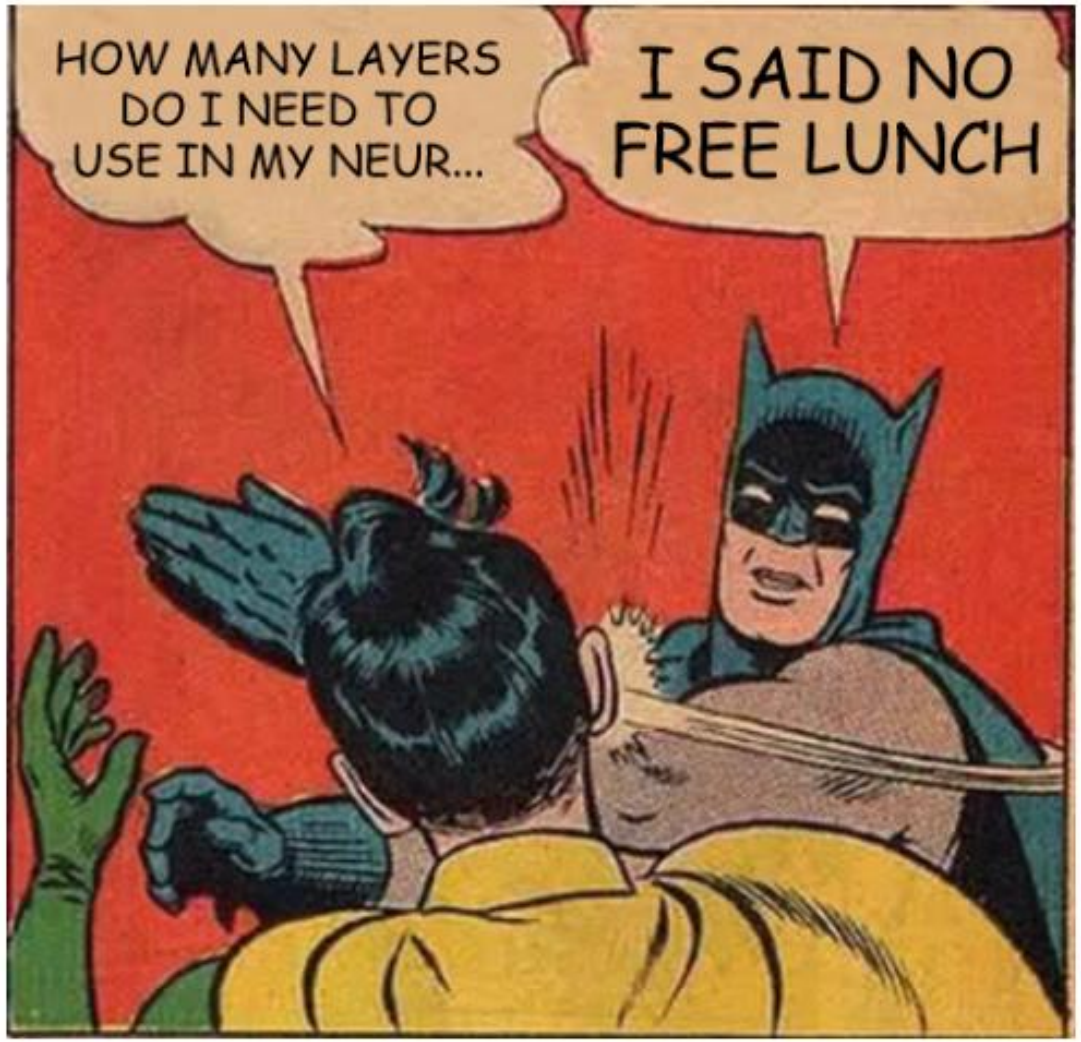
Lesson #2: larger layers vs. more layers

In addition, dataset will often have a high inputs dimensionality N_i and a low outputs dimensionality N_o.

It is often commonly accepted to have the number of Neurons progressively decrease, for instance dividing by two (or more) the number of neurons after each layer.

$$N_i = 50 \rightarrow N_{h_1} = 16 \rightarrow N_{h_2} = 8 \rightarrow N_{h_3} = 4 \rightarrow N_o = 1$$

Keep in mind however



Hyperparameters tuning and searching

Definition (hyperparameters tuning and searching):

Earlier, we have identified that several parameters in our neural networks had to be manually decided by the user and called those **hyperparameters**.

Unfortunately, the **NFL theorem** tells us there is often **no closed-form formula** to tell you what is the **best value to use for those hyperparameters**.

Typical **hyperparameters** include:

- Number of layers and their sizes,
- Initializers to use for parameters,
- Activation functions to use,
- Learning rate, momentum and other parameters related to optimizers,
- Etc.

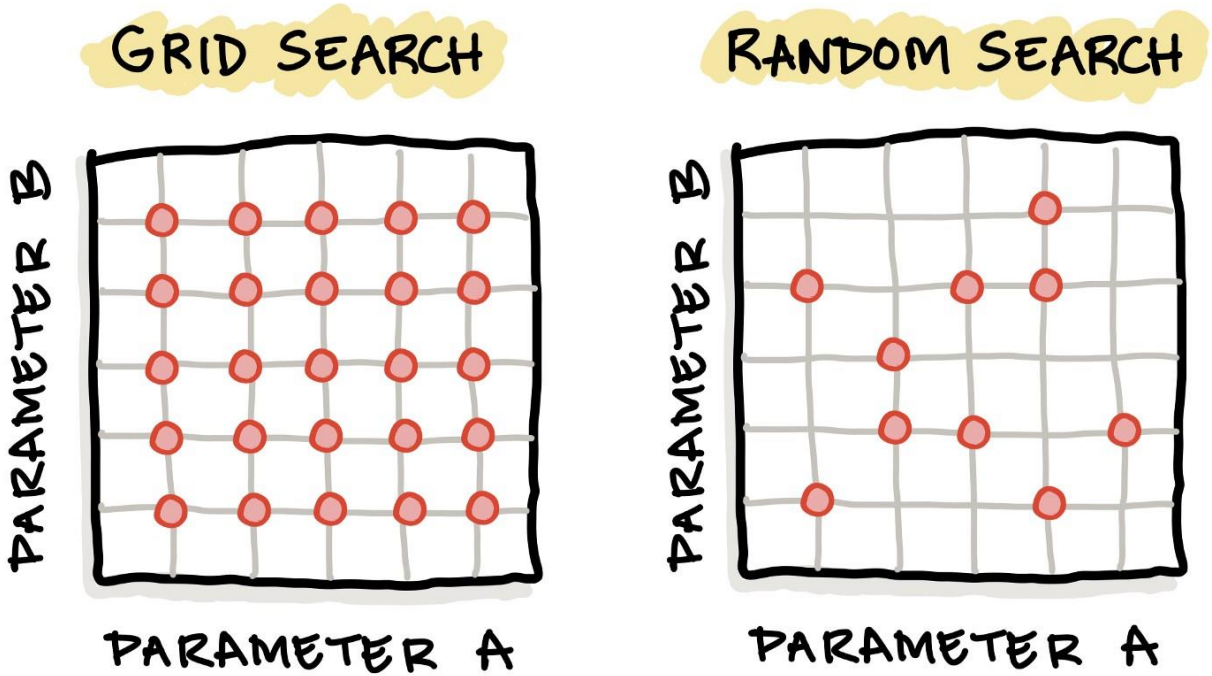
No choice: try different values and possibilities.

Hyperparameters tuning and searching

Definition (hyperparameter grid searching):

Grid search is **the simplest algorithm for hyperparameter tuning**.

Basically, we divide the domain of possible values for each of the hyperparameters into a discrete grid. Then, we will try every combination of values of this grid, calculating some performance metrics.

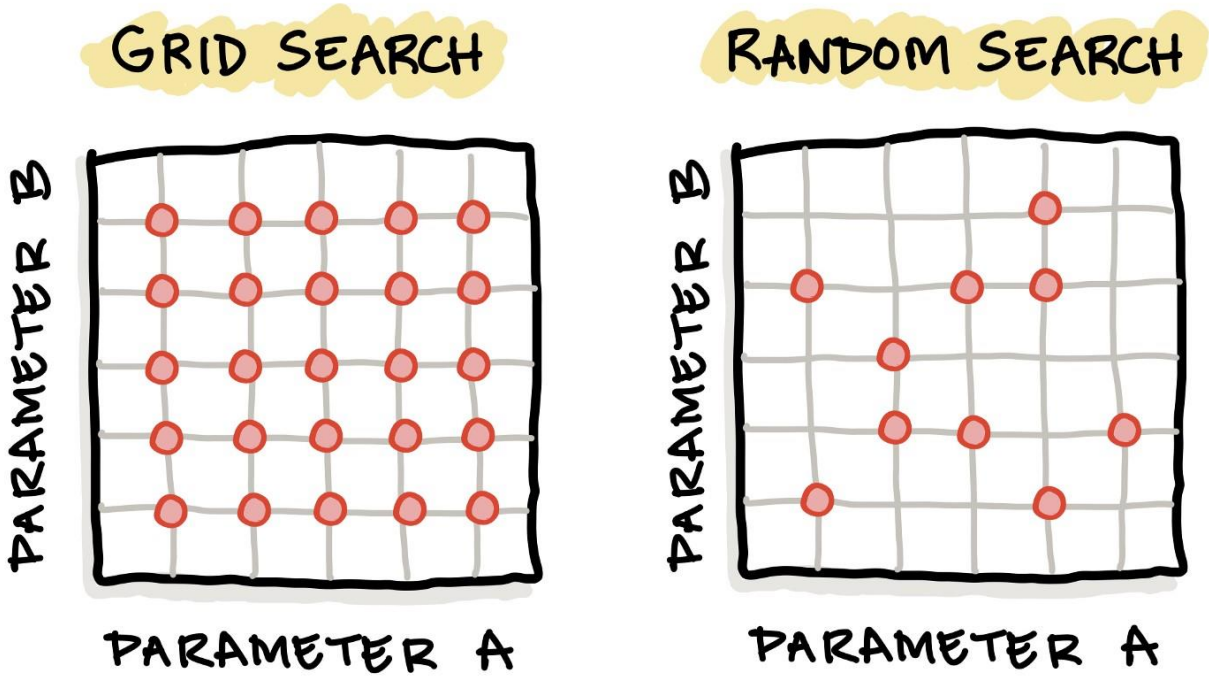


Hyperparameters tuning and searching

Definition (hyperparameter random searching):

Random search is **the another algorithm for hyperparameter tuning**.

Random search defines a search space as a bounded domain of hyperparameter values and randomly sample points in that domain. After trying enough values, keep the best hyperparameters configuration.

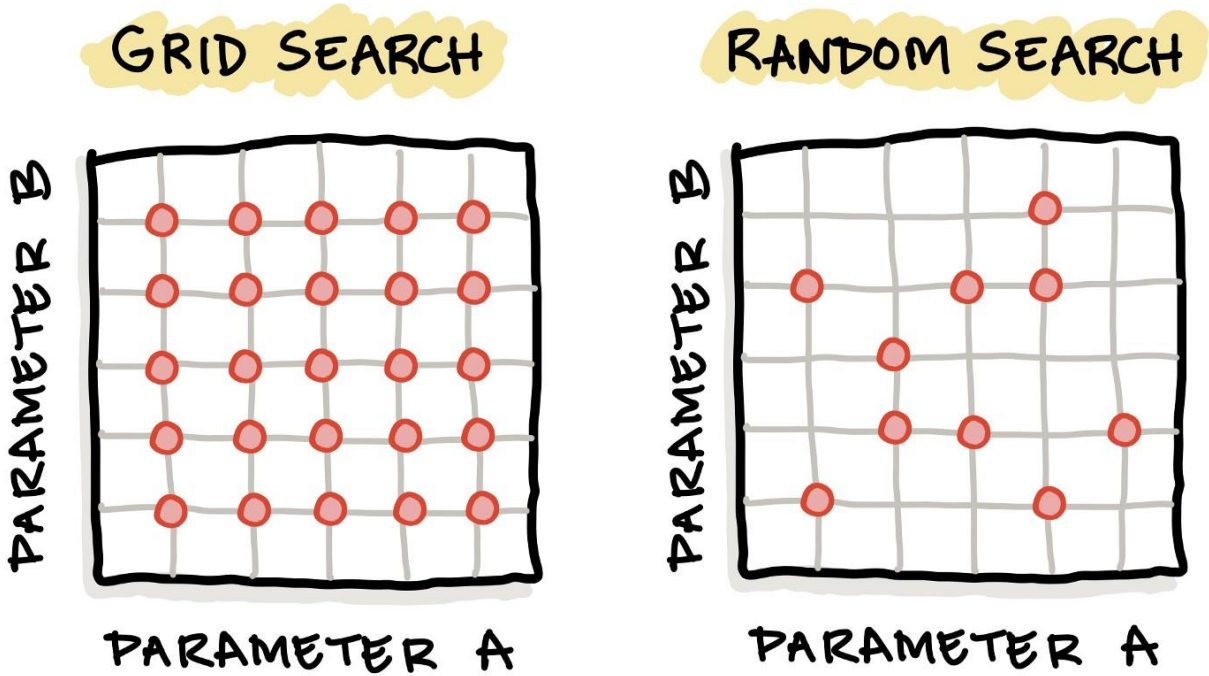


Hyperparameters tuning and searching

In general ([HypSearch]),

- grid search is often better on small spaces,
- whereas random search is better on large domains, but has no guarantee of returning a good configuration.

More advanced techniques than these two exist, such as Bayesian Optimization and Evolutionary Optimization.



Conclusion (Week 2)

- Symmetries in Neural Networks and why it is essential to break them
- Implementing some common initializers and their uses
- Exploding gradient problem, spotting it and fixing it
- Vanishing gradient problem, spotting it and fixing it
- Activations functions for introducing non-linearity
- Typical examples of activations functions and their uses
- The universal approximation theorem
- Some advanced optimizers
  - Adagrad
  - RMSProp
  - Adam
- Stochastic gradient descent
- Mini-batch gradient descent
- Combining into a great optimizer

Conclusion (Week 2)

- The no free lunch theorem
- Train-test-validation split
- Early stopping
- Saver and loader functions
- A few more commonly accepted good practices
- Hyperparameter search

Next week?

- Introduction to PyTorch framework and tensors
- Implementing shallow Neural Networks in PyTorch
- The power of AutoGrad and CUDA processing
- Optimizers, initializers in PyTorch
- Datasets and dataloaders
- From shallow to deep NNs

Learn more about these topics

Some extra (easy) reading and videos for those of you who are curious.

- [HypSearch] How to run hyperparameters searching in Python, implementations using Scikit learn and more advanced methods.
  https://towardsdatascience.com/7-hyperparameter-optimization-techniques-every-data-scientist-should-know-12cdebe713da
  And
  https://machinelearningmastery.com/hyperparameter-optimization-with-random-search-and-grid-search/
- [StackNN] How to decide on a number of neurons and layers in Neural Networks?
  https://stats.stackexchange.com/questions/181/how-to-choose-the-number-of-hidden-layers-and-nodes-in-a-feedforward-neural-netw