Memorizing is not learning! — 6 tricks to prevent overfitting in machine learning.

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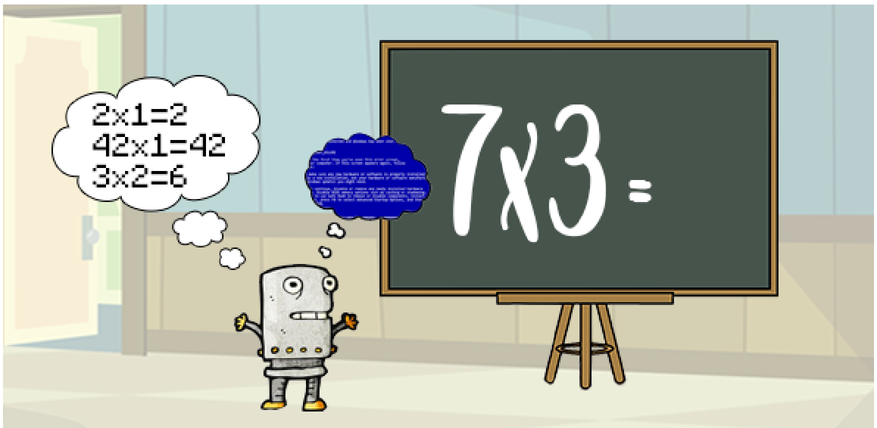
Introduction

Overfitting may be the most frustrating issue of *Machine Learning*. In this article, we're going to see **what it is**, **how to spot it**, and most importantly **how to prevent it from happening**.

What is overfitting?

The word **overfitting** refers to a model that models the training data too well. Instead of learning the genral **distribution** of the data, the model learns the *expected output* for every data point.

This is the same a **memorizing the answers** to a maths quizz instead of **knowing the formulas**. Because of this, the model cannot *generalize*. Everything is all good as long as you are in *familiar territory*, but as soon as you step outside, you're lost.



Looks like this little guy **doesn't know how** to do a multiplication. He only **remembers** the answers to the questions he has already seen.

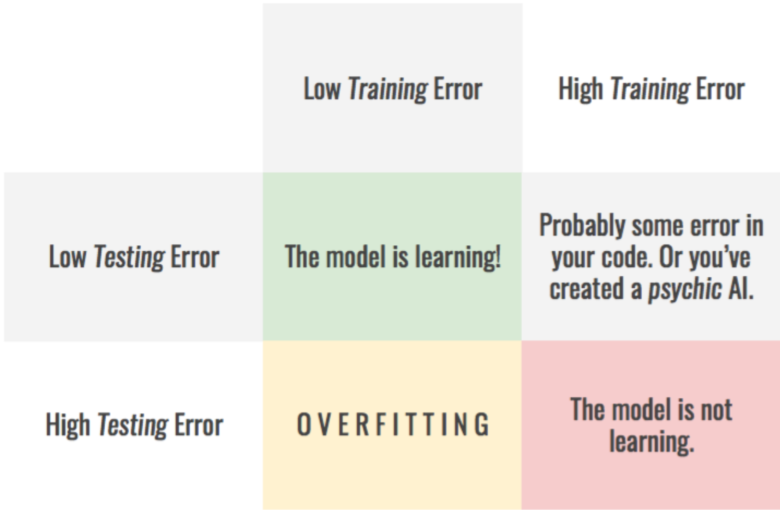
The tricky part is that, at first glance, it **may seem** that your model is performing well because it has a very **small error** on the *training* data. However, as soon as you ask it to **predict new data points,** it will **fail**.

How to detect overfitting

As stated above, overfitting is characterized by the **inability** of the model **to generalize**. To test this ability, a simple method consists in splitting the dataset into two parts: the **training set** and the **test set.** *When selecting models, you might want to split the dataset in three, I explain why here*.

1. The *training* set represents about **80%** of the *available* data, and is used to train the model (you don't say?!).
2. The *test* set consists of the remaining **20%** of the dataset, and is used to *test* the **accuracy** of the model on data it has **never seen before**.

With this split we can check the performance of the model on **each set** to gain insight on **how** the *training* process is going, and spot *overfitting* when it happens. *This table* shows the different cases.



	Low *Training* Error	High *Training* Error
Low *Testing* Error	The model is learning!	Probably some error in your code. Or you've created a *psychic* AI.
High *Testing* Error	OVERFITTING	The model is not learning.

Overfitting can be seen as the **difference** between the **training** and **testing** error.

Note: for this technique to work, you need to make sure both parts are **representative** of your data. A *good practice* is to **shuffle** the order of the dataset before *splitting*.

Overfitting can be pretty *discouraging* because it **raises** your **hopes** just before *brutally crushing* them. Fortunately, there are a few tricks to **prevent** it from happening.

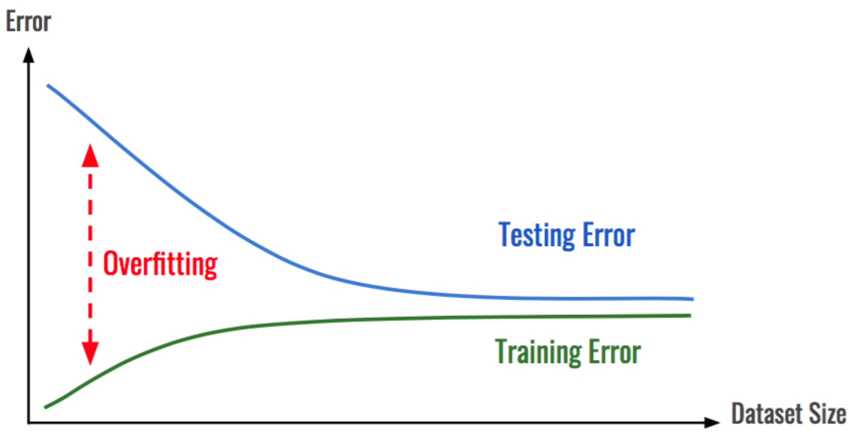
How to prevent overfitting - Model & Data

First, we can try to look at the *components* of our system to find solutions. This means changing *data* we are using, or which *model*.

Gather more data

You model can only *store* so much information. This means that the **more training data** you feed it, the **less likely** it is to **overfit**. The reason is that, as you **add** more **data**, the model becomes **unable** to **overfit** all the samples, and is **forced** to **generalize** to make progress.

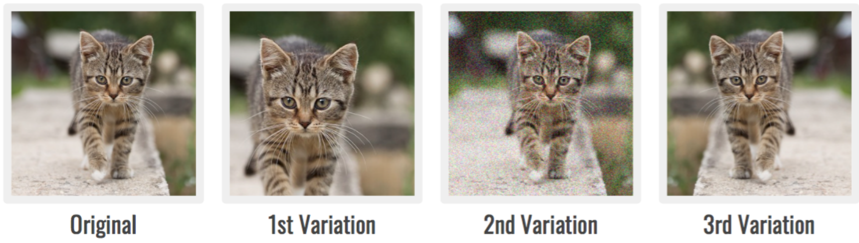
Collecting more examples should be the *first step* in every data science task, as more data will result in an *increased accuracy* of the model, while reducing the chance of *overfitting*.



The **more data** you get, the **less** likely the model is to **overfit.**

Data augmentation & Noise

Collecting more data is a *tedious* and **expensive** process. If you can't do it, you should try to make your data *appear* as if it was **more diverse**. To do that, use data augmentation techniques so that each time a sample is processed by the model, it's slightly different from the previous time. This will make it **harder** for the model to *learn parameters* for each sample.



Each iteration sees as **different variation** of the original sample.

Another good practice is to add **noise:**

- **To the input**: This serves the same purpose as data augmentation, but will also work toward making the **model robust** to *natural perturbations* it could encounter **in the wild**.
- **To the output**: Again, this will make the training more diversified.

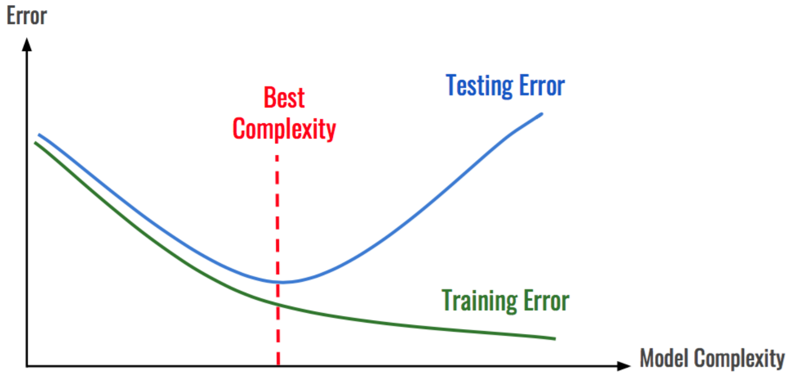
Note: In both cases, you need to make sure that the **magnitude of the noise** is not too *great*. Otherwise, you could end up respectively *drowning* the information of the input in the noise*, or* make the output *incorrect.* Both will hinder the training process.

Simplify the model

If, even with all the data you now have, your model *still* manages to overfit your training dataset, it may be that the model is **too powerful**. You could then try to **reduce the complexity** of the model.

As stated previously, a model can only overfit *that much* data. By progressively reducing its complexity—*# of **estimators** in a **random forest**, # of **parameters** in a **neural network** etc.*—you can make the model *simple* enough that it *doesn't overfit,* but *complex* enough to *learn* from your data. To do that, it's convenient to look at the **error** on **both datasets** depending on the model complexity.

This also has the advantage of making the model **lighter**, **train faster** and **run faster**.



On the left, the model is too simple. On the right it overfits.

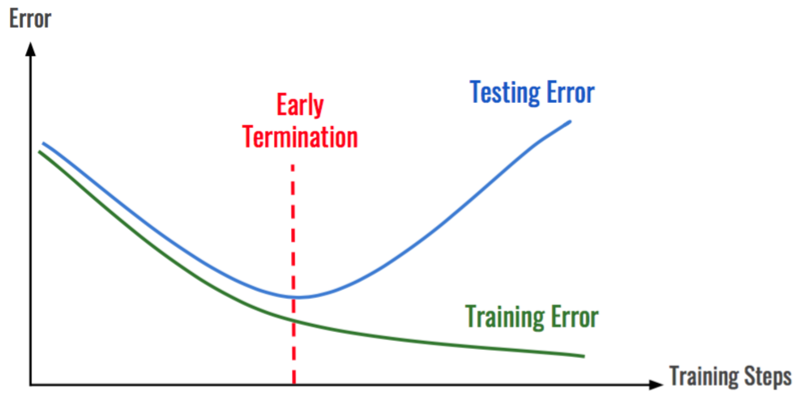
. . .

How to prevent overfitting - Training Process

A *second* possibility it to change the way the **training** is done. This includes altering the **loss function,** or the way the model *functions* during training.

Early Termination

In most cases, the model **starts** by learning a correct distribution of the data, and, at some point, starts to overfit the data. By identifying the *moment* where this **shift occurs**, you can **stop the learning process** *before* the overfitting happens. As before, this is done by looking at the *training error* over time.



When the **testing error** starts to **increase**, it's time to stop!

How to prevent overfitting— Regularization

Regularization is a process of **constraining** the **learning** of the model to *reduce* **overfitting**. It can take many different forms, and we will see a couple of them.

L1 and L2 regularization

One of the most *powerful* and well-known technique of regularization is to **add a penalty** to the **loss function**. The most common are called *L1* and *L2*:

1. The **L1 penalty** aims to minimize the **absolute value** of the weights
2. The **L2 penalty** aims to minimize the **squared magnitude** of the weights.

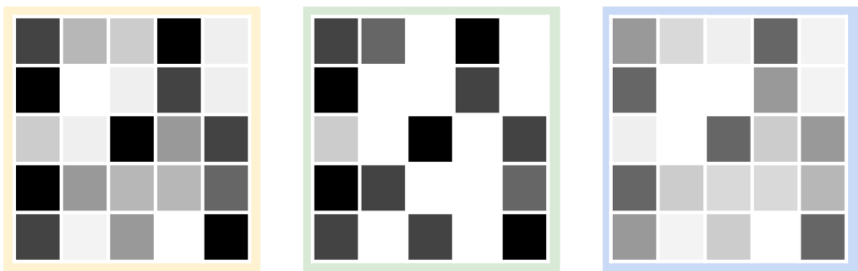
$$\lambda \sum_{j=0}^{M} |W_j| \qquad \lambda \sum_{j=0}^{M} W_j^2$$

L1 Penalty L2 Penalty

With the penalty, the model is forced to *make compromises* on its weights, as it can no longer make them **arbitrarily large**. This makes the model **more general**, which helps combat overfitting.

The *L1* penalty has the added advantage that it enforces **feature selection**, which means that it has a tendency to set to 0 the *less useful* parameters. This helps identify the **most relevant features** in a *dataset*. The downside is that it is often **not** as **computationally efficient** as the *L2* penalty.

Here is what the weight matrixes would look like. Note how the **L1** matrix is **sparse** with many zeros, and the **L2** matrix has *slightly* **smaller weights**.



Baseline L1 Regularization L2 Regularization

Another possibility is to add noise to the *parameters* during the training, which helps **generalization**.

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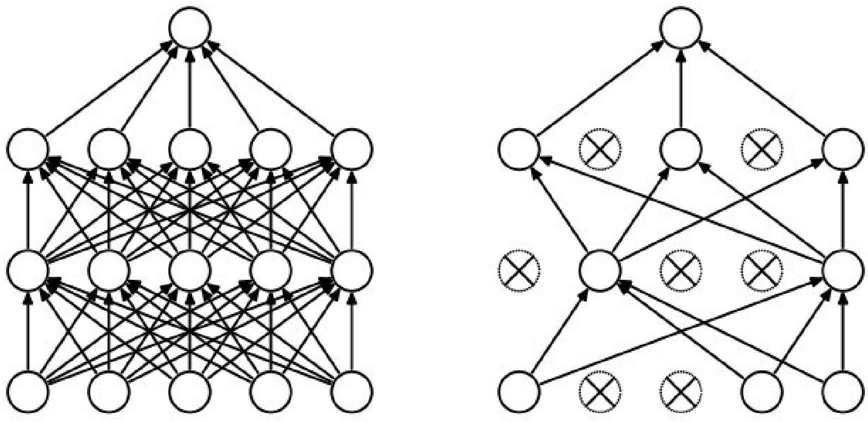
For Deep Learning: Dropout and Dropconnect

This **extremely effective** technique is specific to **Deep Learning,** as it relies on the fact that *neural networks* process the information from one **layer** to the next. The idea is to randomly deactivate either **neurons** (*dropout*) or **connections** (*dropconnect*) during the training.



(a) Standard Neural Net (b) After applying dropout.

This forces the network to become **redundant**, as it can no longer **rely** on *specific* **neurons** or **connections** to extract *specific* **features**. Once the training is done, all neuraons and connections are restored. It has been shown that this technique is *somewhat equivalent* to having an **ensemble** approach, which **favorises generalization,** thus reducing overfitting.

Conclusion

As you know by now, overfitting is one of the main issues the *Data Scientist* has to face. It can be a *real pain* to deal with if you don't know how to *stop* it. With the techniques presented in this article, you should now be able to *prevent* your models from **cheating** the learning process, and get the **results** you deserve!

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