Why are training data and test data separated?



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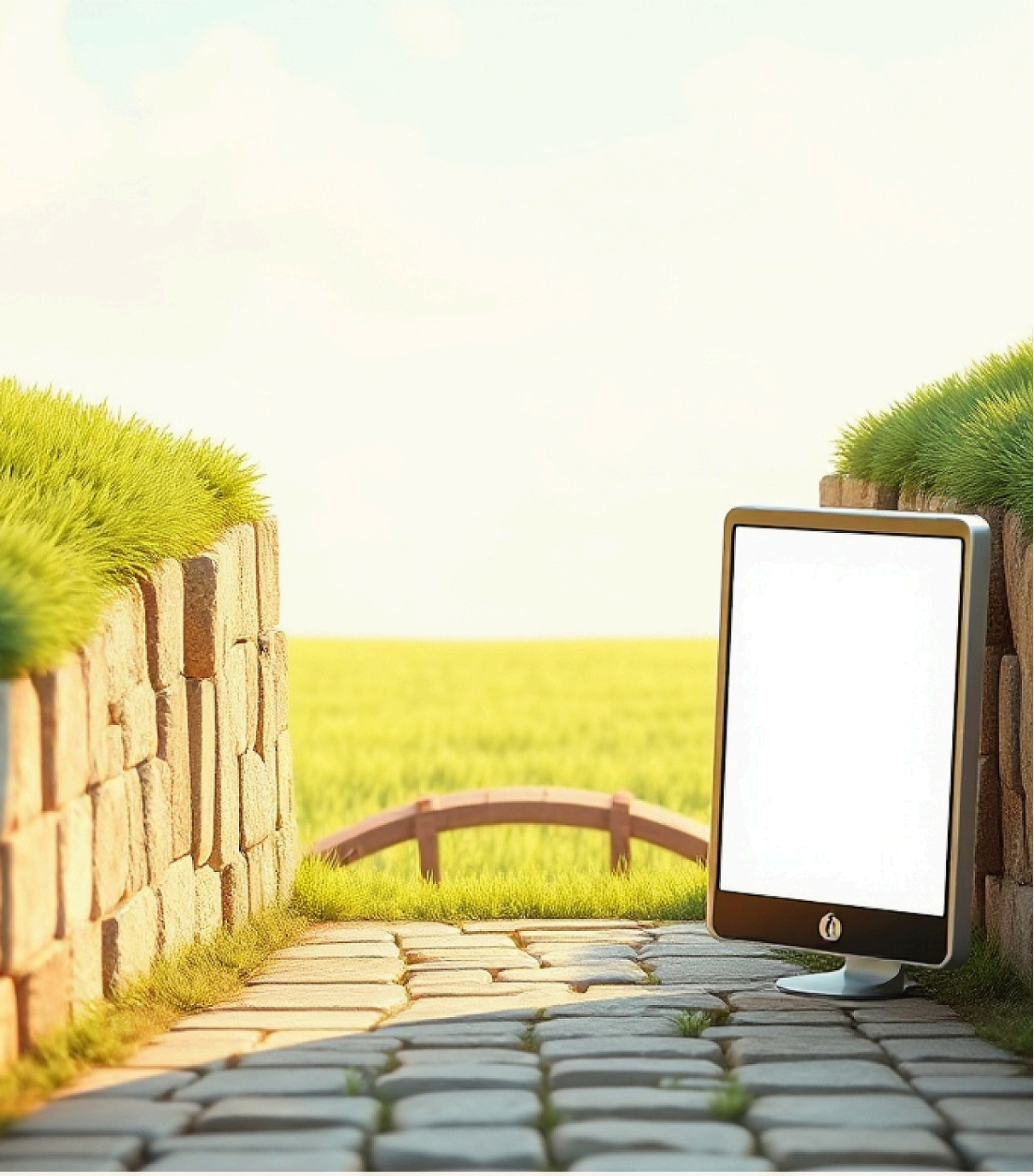
A model learns from a set of examples called training data. If you judge the model only on those same examples, you get a flattering but false picture. The short answer is that doing well on learned examples does not prove doing well on new ones. So some data is saved for a final check. This book explains why training data and test data are kept apart, step by step, for a complete beginner.



Training data is the set of examples a model learns from. The model looks at these examples again and again and adjusts itself each time. Think of it as the practice material you study before a test. The model's internal settings change based on what it sees in this data. Without training data, the model has nothing to learn from.



Test data is a separate set of examples the model never learns from. You use it only at the end to check how well the model handles examples it has not seen. It is like a final exam you take after studying. The model has no chance to adjust to this data. Its only job is to measure real ability on new examples.



Success on examples the model has learned does not show it will succeed on new examples. A model can look good on old data and still fail on fresh data. This is the core idea behind separating the sets. The model may have simply adapted to the specific examples it saw. New examples test whether it learned a general pattern or just the details of the training set.



Picture a student who memorizes the exact questions they already solved. That student may score perfectly on those questions but struggle with new ones. A model trained on a set of examples can behave the same way. It may reproduce answers it has seen without understanding the underlying rule. High scores on training data alone can be misleading.



Compare that with a student who can solve questions they have never seen. That is the real skill we want, and it is what test data is meant to measure in a model. A good model should generalize, meaning it should handle new examples well. Test data gives you a realistic view of that ability because the model has not learned from it.



We need an honest final check of the model's ability. Test data provides that check because the model had no chance to learn from it. Without a separate test set, you cannot tell whether the model truly learned or just memorized. The final check should reflect how the model will perform on new examples in real use. That is why the test set must stay apart.



What goes wrong if test data leaks into training? The model has already seen the answers. The final check then measures memory, not real skill. This is called data leakage, and it happens when test examples accidentally end up in the training set. Even a small leak can make the results unreliable. The model may appear to perform well, but only because it has seen the test examples before.



When test data leaks into training, reported success looks higher than the model's true ability. The numbers become misleading and you cannot trust them. You might think the model is ready for real use when it is not. This overestimation is dangerous because decisions based on it can fail in practice. Keeping the sets separate prevents this false confidence.



The simple rule is: test data stays untouched during training and is opened only for the final evaluation. Do not use it to adjust the model in any way. Keep it in a separate place, and do not look at it until the model is fully built. Keeping the test set clean keeps the final result honest. This rule is easy to state but important to follow.



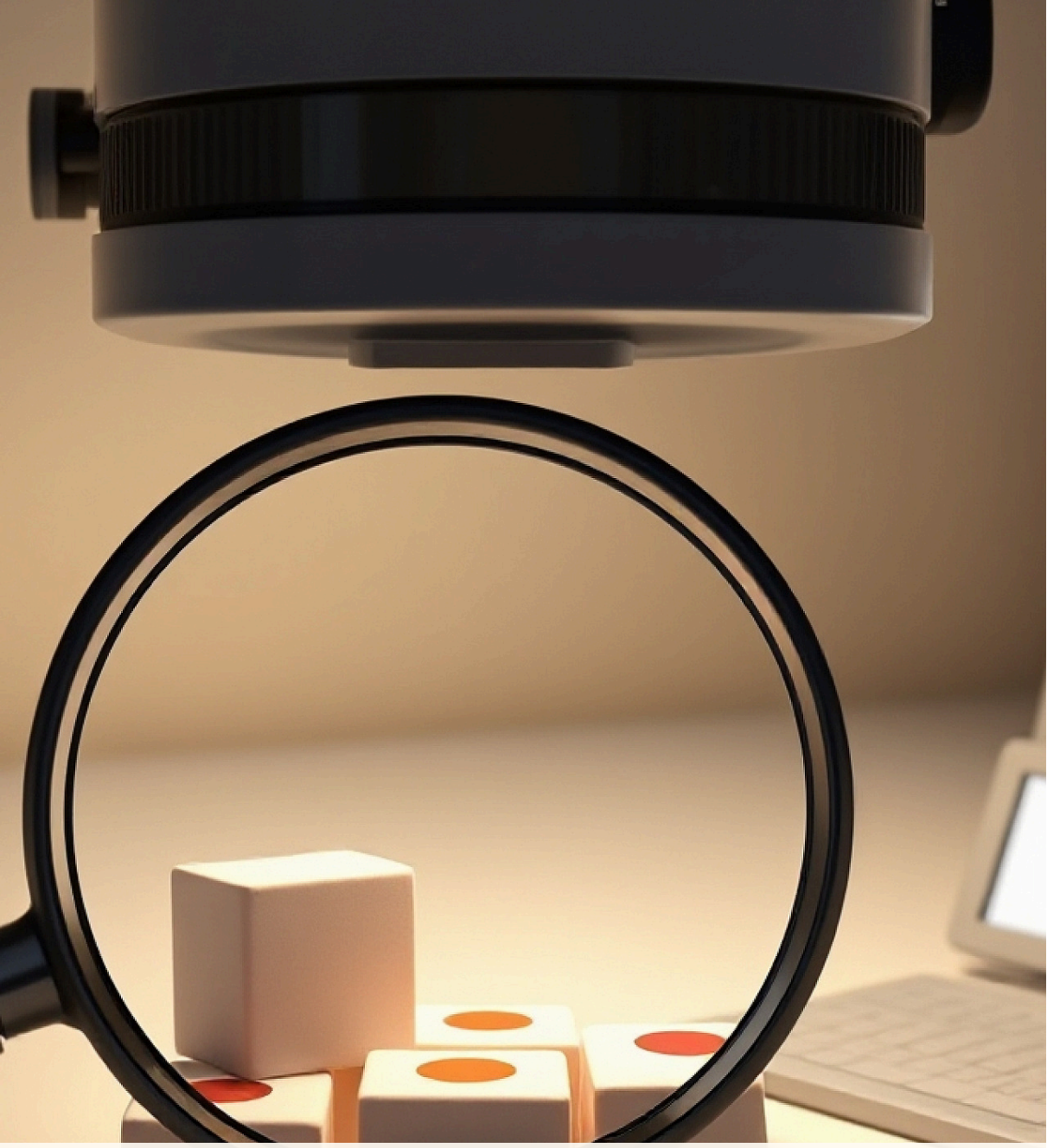
Validation data is another separate set used while building the model. It helps you choose between options, such as which version of the model to keep. You use it to compare models or tune settings, not to train the model directly. Validation data acts like a practice test you use to prepare. It gives you feedback during development without touching the final test set.



Validation data must also be kept apart from training, for the same reason. If validation examples leaked into training, the choices made during building would be based on memorized examples. You would pick a model that looks good on data it has already seen. That would mislead you about which model is truly better. Keeping validation separate ensures your choices are based on new examples.



Picture three separate piles: training data to learn from, validation data to choose with, and test data for the final check. Each pile has one clear job. The training pile teaches the model. The validation pile helps you pick the best version. The test pile gives the final, honest score. Mixing the piles ruins their purpose.



A common beginner mistake is judging the model on the same data it learned from. This gives a flattering but false picture of how well it works. The model may have memorized the training examples, so its score looks high. Always evaluate on separate data to see the true performance. Testing on training data is like grading a student on the exact questions they memorized.



Another mistake is looking at test data too early or tuning the model against it. Once you do that, the test set is no longer a fair final check. You might adjust the model to do well on the test examples, which is a form of leakage. The test set should be used only once, at the very end. Protect it from any influence during development.



Learned examples do not prove new-example success, so data is kept apart. Remember the three separate sets: training to learn, validation to choose, and test for the final check. A clean test set gives an honest final result. Keep test data untouched until the end, and never judge a model on the data it learned from. These simple habits make your evaluation trustworthy.