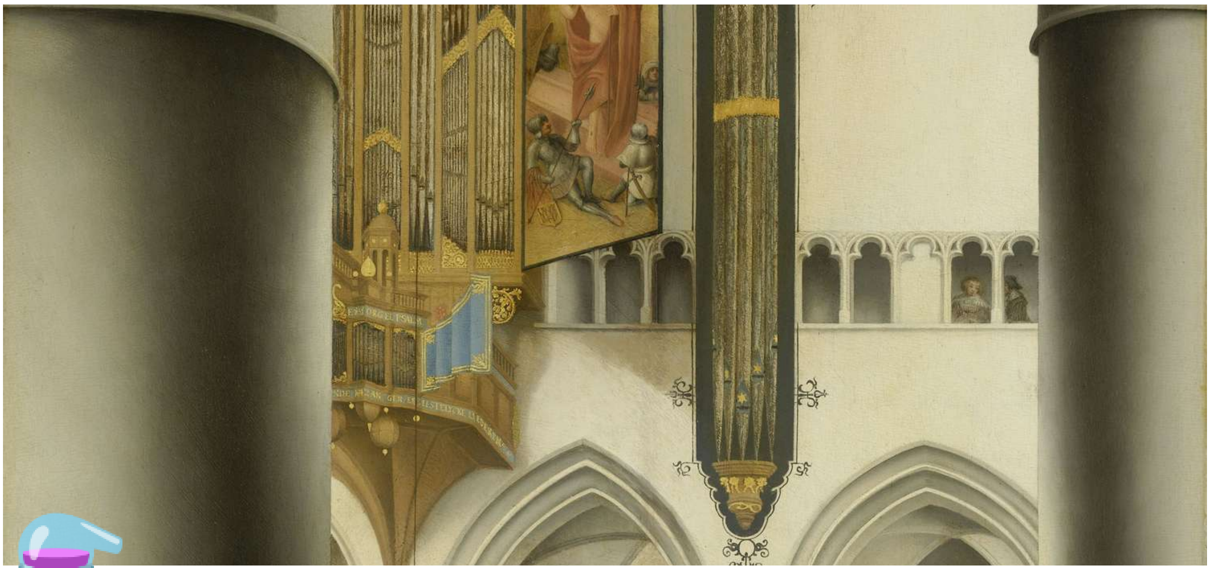


IBM ML/DL MOD2

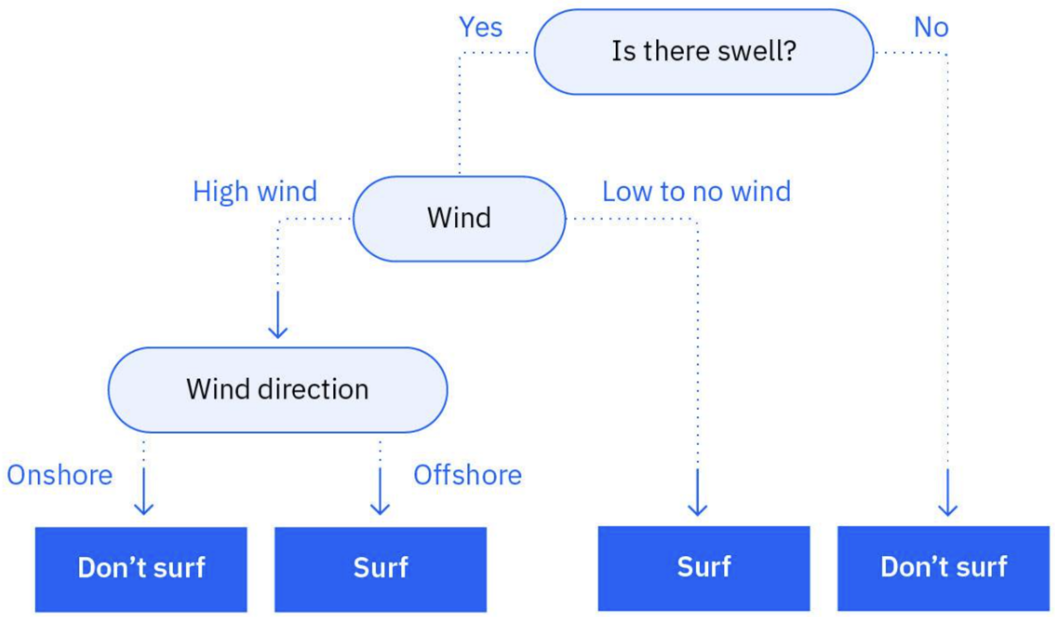
CLASSICAL MACHINE LEARNING

- **Origins**: Classical machine learning emerged in the 1950s.
- **Pattern Recognition**: AI systems learned to recognize patterns in data.
- **Prediction Abilities**: They could predict values like distances or intensities.
- **Algorithmic Basis**: Classical ML relies on mathematical algorithms.
- **Binary Outputs**: Some algorithms produce binary results (e.g., 1 or 0, YES or NO).
- **Complex Algorithms**: Others yield complex results, such as positions on multidimensional graphs.
- **Common Algorithms**: Three typical classical learning algorithms are:
    - Decision tree
    - Linear regression
    - Logistic regression

DECISION TREE

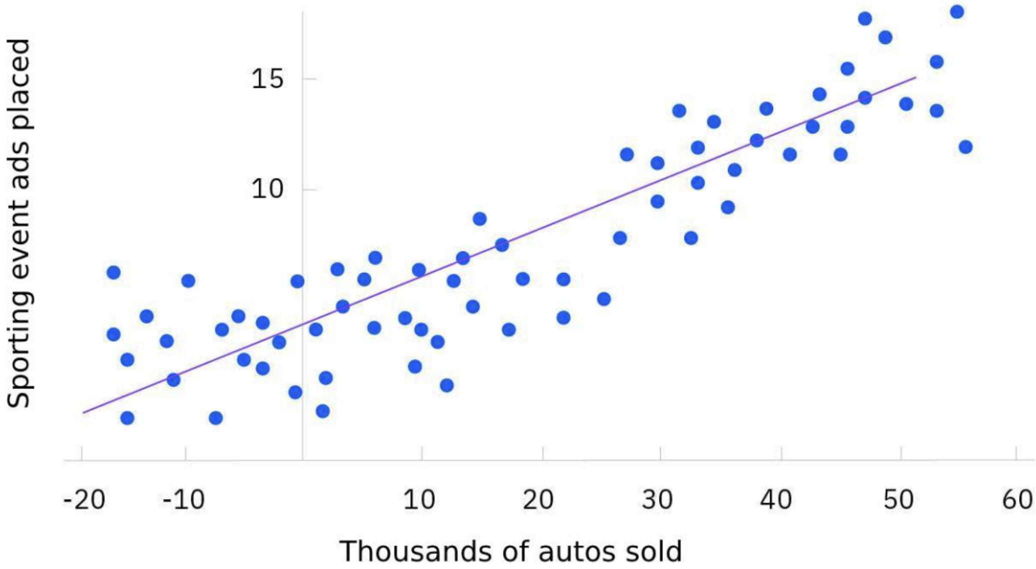
> A **decision tree** is a supervised learning algorithm. It operates like a flowchart. You can think of a flowchart as an upside-down decision tree. The flowchart has a **root node** (where the flowchart begins), branches that connect to **internal nodes**, and more branches that connect to **leaf nodes**.

EXAMPLE



LINEAR REGRESSION

Linear regression is another type of algorithm. It relates to data that might be graphed as a straight line. For example, a business might believe that more advertising spending leads to better sales. This could be graphed as a series of dots that form a rising straight line, as depicted here.

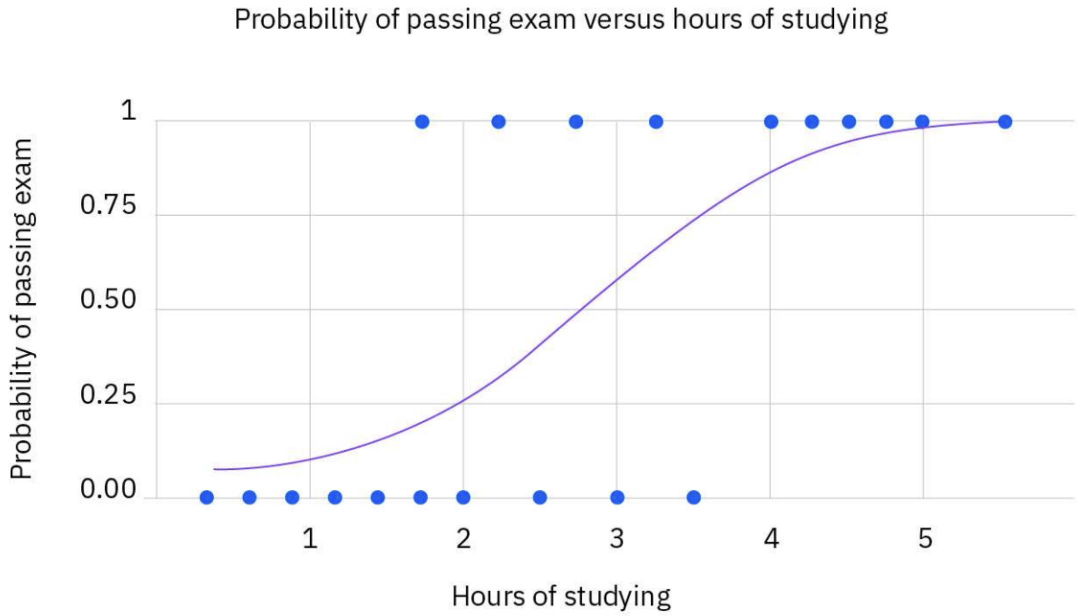


As suggested in the chart, as advertising increases, so do sales. There are many possible outcomes (different amounts of advertising lead to different amounts of sales), but the change rises on the graph in a straight line.

The situation is more complicated if a company's actual sales show different data for different products, at different locations, on different dates, and so on. With a large number of variables and instances, the graph becomes a mass of dots that don't arrange into a straight line at all. Without adjustment, resulting graph is too general to help a business make a good decision. That's where linear regression can help. Linear regression can learn all the variables, then calculate a reasonably accurate prediction of how advertising will impact sales at some time and location in the future. In effect, linear regression resolves the mass of dots into a "most likely" line that can be used for simple prediction.

LOGISTIC REGRSSION

In some situations, a relationship does not fall in a straight line. Sometimes a system uses values that require a specific, limited kind of outcome, such as something between 0 and 1 (or NO and YES). In this situation, a graph can form what's called a **sigmoid function,** or an S-shaped curve, as shown in the accompanying example. For any set of variables, the outcome (which is a point on the S-curve) falls between 0 and 1.



Here's a real-world example. Refer to the previous graph. Let's say you want to know how many hours you should study in order to pass an exam. You have the number of study hours and passing or failing status for 10 other students. "Hours of studying" is a varying amount, in this case, between 1 and 5 hours. Passing the exam is a matter of NO or YES (either FAIL or PASS).

If you plot these two factors together as a logistical regression, you get an S curve in which 0 hours of study results in a very low chance of passing, while 5.5 hours results in a very high chance. As shown in the chart, the variable "Hours of studying" is along the x-axis. The values along the y-axis represent the values for the variable "Probability of passing exam".

Here's another way to understand the graph: it predicts that studying at least 4 hours gives you a very good chance of passing the course.

Comparing linear and logistic regressions

Linear and logistic regressions are useful in the following ways:

- A **linear** regression answers a question such as "If this increases by X, how much will Y increase?"
- A **logistic** regression answers a question such as "If this increases by X, will the value of Y be closer to 0 or 1?"

Classical machine learning is not obsolete

Classical machine learning can be outperformed, at some tasks, by newer methods that are part of the deep learning ecosystem. But there are still reasons to use classical machine learning. These include:

- Work with structured data

  Classical machine learning is used mostly with structured data from databases, such as hours studied compared to grades earned.

- Lower expense to operate

  Classical machine learning requires less computing power than deep learning ecosystems. They can run on less expensive computers with less powerful processors, which lowers the price for smaller businesses, communities, or healthcare systems that share time on them in pay-as-you-go arrangements.

- Easier to interpret

  Deep networks are so complex that even AI researchers don't entirely understand what's going on inside. As a result, AI researchers are not always able to determine when deep network systems are producing invalid outputs. Compared to these mysteries, classical results can be easier to debug, and to test for accuracy and lack of bias.