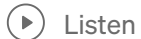


# Problems you can solve with ML in your company



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What, if ChatGPT is not enough for you and your business?

When OpenAI unveiled ChatGPT in November 2022, the world was swept by an AI wave in a storm. Many commentators drew parallels and called it the “iPhone moment of AI”.

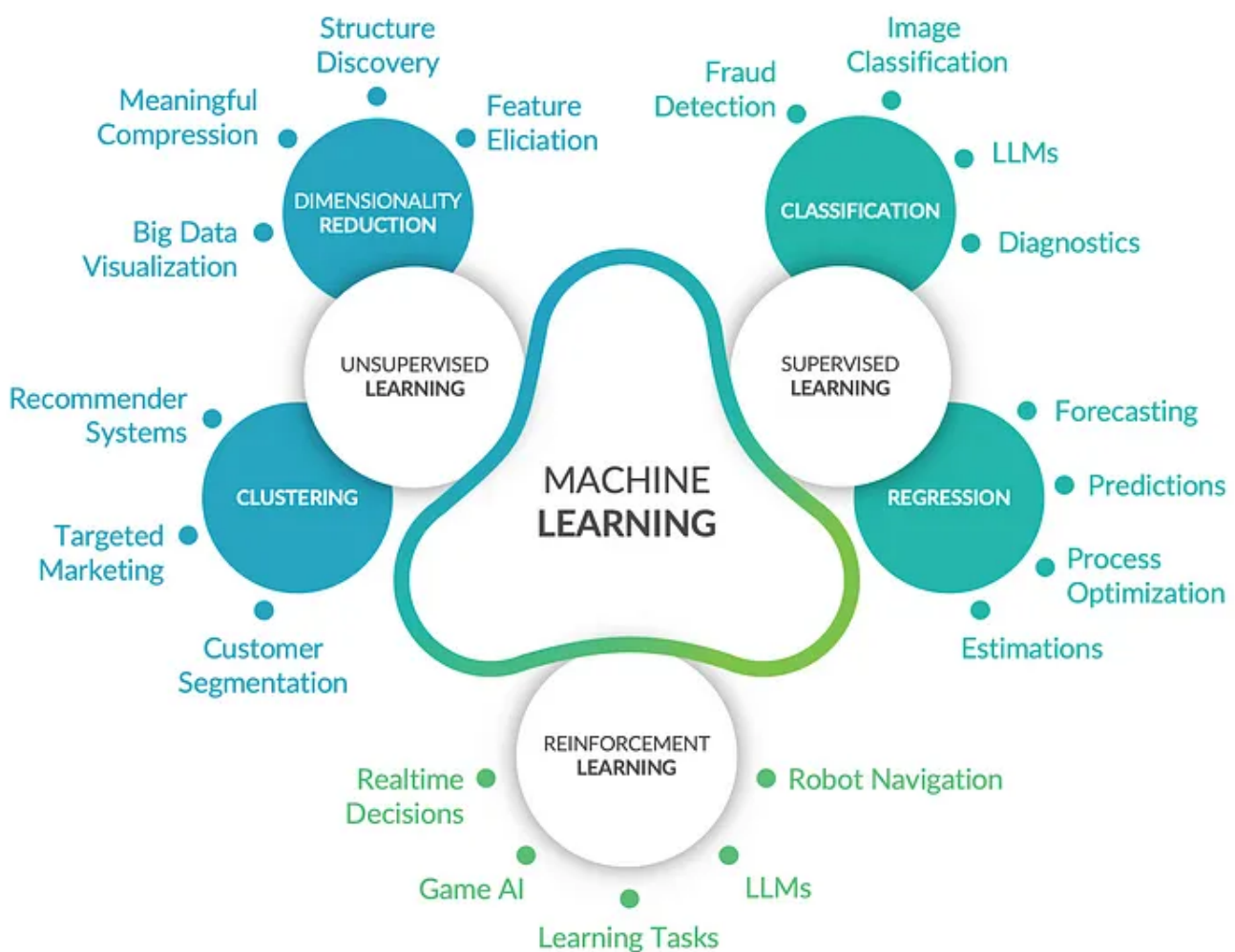
OpenAI disclosed the next Generative Pre-trained Transformer 4 (GPT-4) model in mid-March 2023. I was again excited by the technology and its possibilities. However, as I read the [technical report](#), something else caught my eye: The paper’s author list is nearly 3 pages long. It includes about 85 *main authors* and many times that number of additional authors, with an unknown effort needed to label the data.

You don't need supernatural powers, but common sense and practical experience in the manufacturing industry are enough to see that such a model is not an economically feasible path for a production company.

So what can be done in manufacturing? What problems can we solve in industrial environments? Let's break it down into practice. That's what the fourth article in our series on industrial artificial intelligence (AI) is about.

### What kind of problems ML can solve

There are many good introductory and intermediate texts on AI and machine learning (ML). They often give an overview on the types of problems that one can solve using ML. I like the one by [Tarek Hamdi](#), which I have adopted and slightly adapted over time.



Overview on ML techniques and examples of problems that can be solved.

Keep in mind that AI advances at insane speed. New algorithms and computing principles are developed as you are reading. Nevertheless, I like the simple picture above to make basic concepts of ML understandable. So let's dive into some of it.

### Unsupervised learning sorts your data

In unsupervised learning — you will already guess — the system learns without a teacher. The data do not contain labels and the system tries itself to find existing correlations or to find interesting transformations or representations.

Typical categories are *clustering* or *dimensionality reduction*, among others. Clustering algorithms are often used, for example, to categorize shoppers in an online store. With dimensionality reduction, the goal is to condense the data without losing the relevant information. It is often used for data compression tasks or to prepare data for subsequent supervised learning. In industrial practice, such algorithms can be used to classify suppliers or to identify key parameters in complex systems, to name just two examples.

### **Reinforcement learning brings your robots to life**

In reinforcement learning, the training system is called an *agent*. The agent learns by trial and error. The key is that it is rewarded for good behavior and punished for bad behavior. Typical examples can be found in robot learning or in games, such as DeepMind's famous [AlphaGo](#).

### **Supervised learning is the new oil in a data-driven world**

The most common case in ML is *supervised learning*. The system is trained with training data for a specific task. This means that the training data must describe the solution space with sufficient accuracy so that the system can subsequently make meaningful statements.

The training data is *labeled*. For example, if we want to distinguish dogs from cats in images, we have to show the ML algorithm enough pictures during training that we have previously labeled as “dog” or as “cat”. In practice, this means an effort that should not be underestimated, since labeling usually starts manually and can only be partially automated over time. This is a potential cost-driver that you have to keep in mind.

In supervised learning, we typically solve problems from the following two categories: *classification* and *regression*. In classification, an input is assigned to a class, e.g., the image is either of class “dog” or of class “cat”. In regression tasks, in the simplest case, a value is predicted. For example, predicting the purchase price of a house based on its location is a typical regression-type problem.

Mapped on to industrial problems, in classification tasks, we can use ML to decide whether the void in the material is critical or not, for instance. On the other hand, predicting the lifetime of a component is an example of a regression problem. Keep in

mind that these industrial examples sound very simple, but are demanding to put into practice.

## **Neural networks are the powerhouse for supervised learning**

In the context of ML, one term keeps coming up: neural networks (NNs, and variations thereof). They – and the associated advances in computational methods – are a key technology for modern ML algorithms to learn new representations of the data.

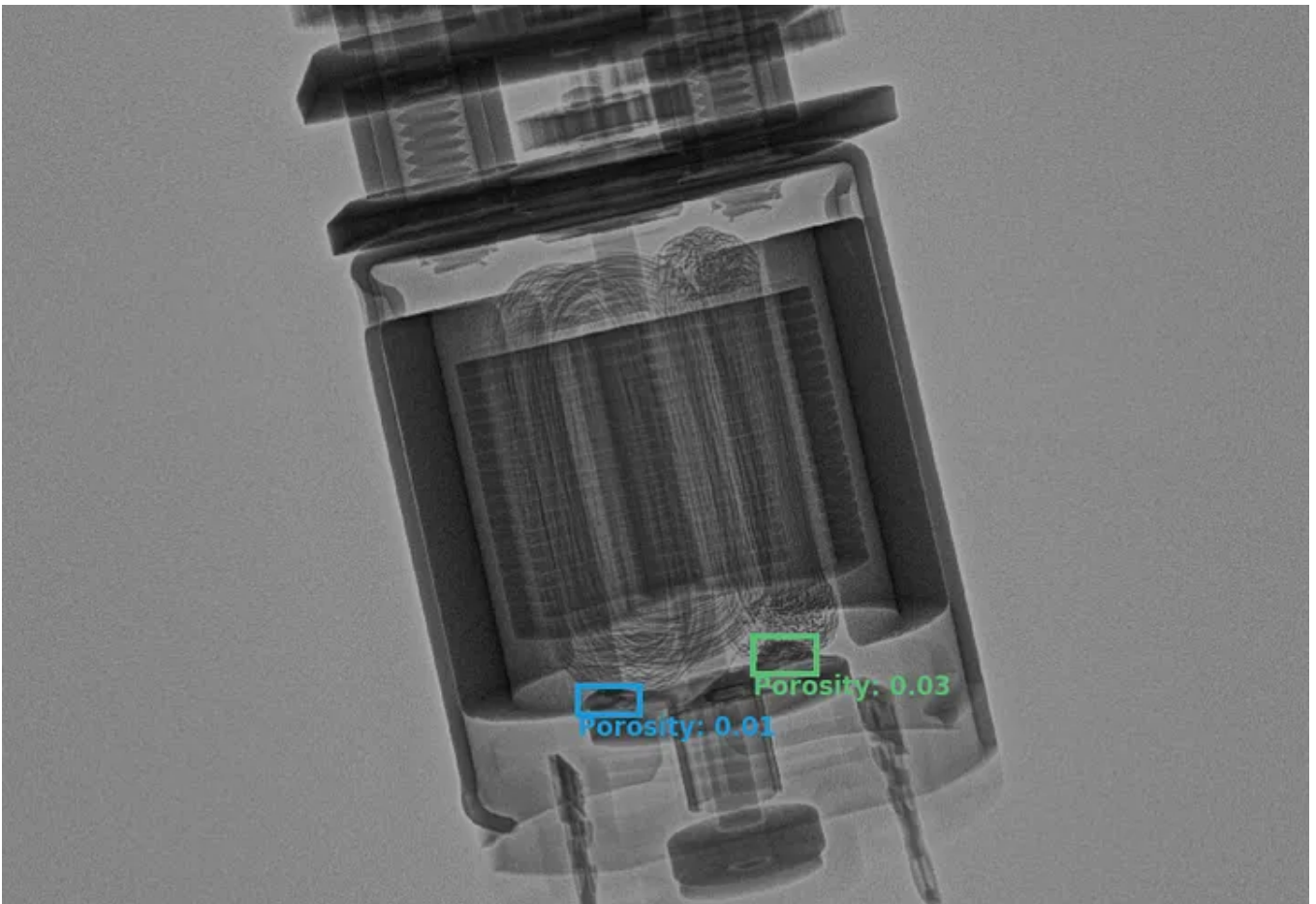
When training neural networks, weights of individual nodes are trained and adjusted over and over again until they predict the features in the training dataset as accurately as needed. These are computationally intensive tasks that are performed on so-called graphics processing units (GPUs) locally or in the cloud, and can take hours or even days. So it is good not to underestimate costs for training and the infrastructure needed.

We can also understand that more data leads to better predictions in the long run; although in reality, it is not black and white as outlined here. We usually make an economic tradeoff rather than a technical tradeoff in data preparation. So here, it is important for you to understand, what accuracy you need to achieve and how reliable you want the ML system to work.

However, all this still does not explain why NNs have only become the powerhouse in ML applications in recent years – the underlying concepts have already been available for years. It is three main factors: (i) the availability of large data sets, (ii) GPUs and massively parallelized computing, and (iii) handy machine learning libraries and improved algorithms for trainings. Voilà – ready is the machinery that is just waiting to be unleashed on all sorts of industrial problems.

## **Understood... now what?**

Now it is up to you to see whether an industrial problem could be suitable for ML. In the industrial environment, there is a lot of image data that lends itself to ML processing. That was exactly the idea behind our startup [maXerial](#): to evaluate 2-dimensional image data and 3-dimensional volume data using AI and therefore to understand materials better.



2D X-ray image of a demo motor.

But also data from production machines are ideal starting points. It can be used to detect and predict patterns of certain features over time using different machine and deep learning approaches. This can decrease downtimes and failures, or reduce scrap rates.

The effort for such industrial tasks is reduced by orders of magnitude compared to training a large language model as ChatGPT. It comes into a range that is feasible in terms of time and money for production companies. That's where the real "gold" lies in your data: Using your own company data to carve out a new unique selling proposition and gain a competitive advantage in your market.

To me, that is the real promise of industrial AI!

Stay tuned to our next article: How to start as simple as possible, grow with your ML technology, and steer the project to success.

### **Further reading**

This is the fourth article in our series on industrial artificial intelligence (AI). More articles in this series (list updated on release):

(1) [How to bring AI to your manufacturing company](#)

- (2) Get machine-readable data for industrial AI
- (3) Build sandboxes and let them play
- (4) What kind of problems can you solve with ML in your company?
- (5) Your route to success in industrial AI: Think big, start simple
- (6) From pilot to maintainable AI technology stack
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