Beyond Clustering: The New Methods that are Pushing the Future of Unsupervised Learning

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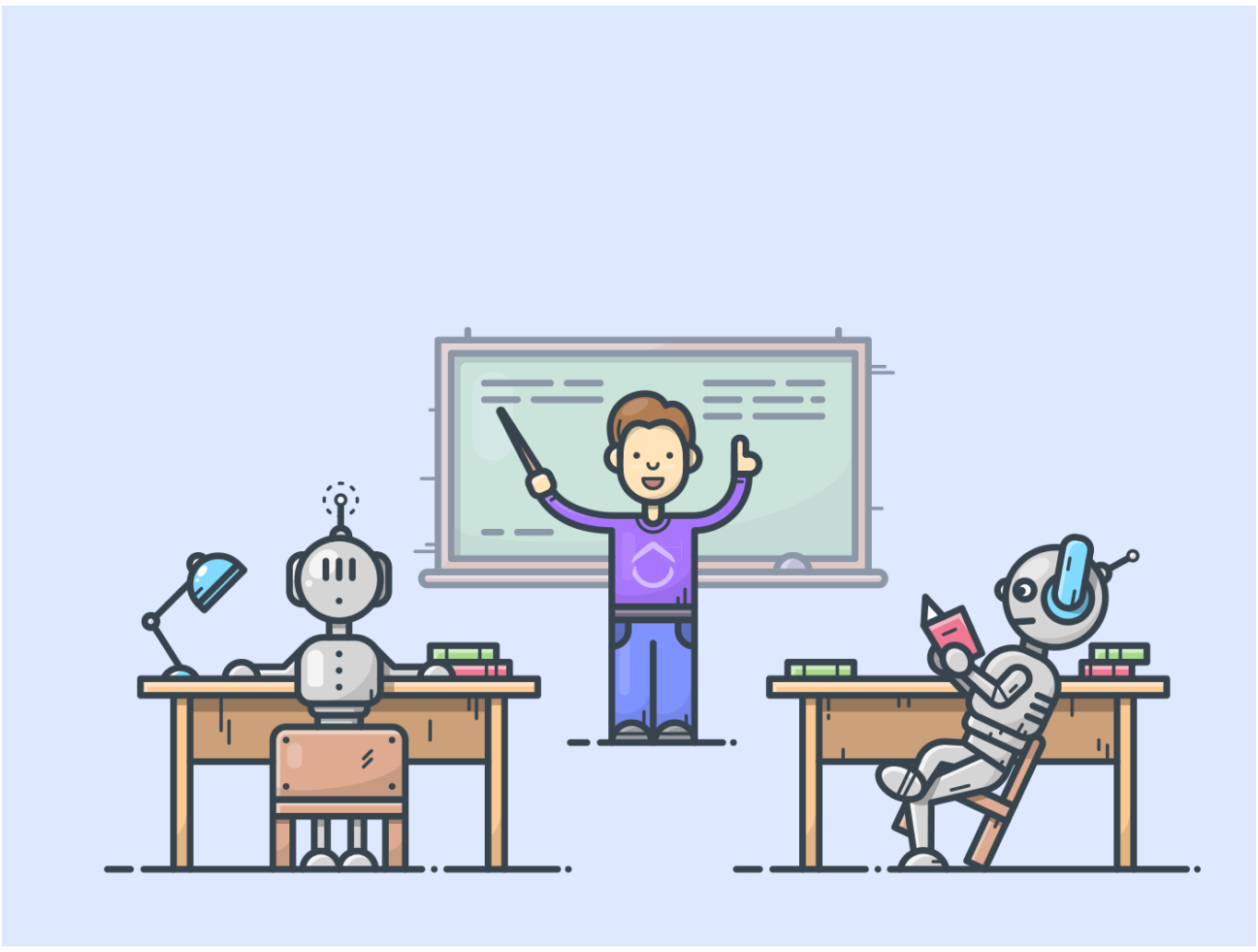

If you ask any group of data science students about the types of machine learning algorithms, they will answer without hesitation: supervised and unsupervised. However, if we ask that same group to list different types of unsupervised learning, we are likely to get an answer like clustering but not much more. While supervised methods lead the current wave of innovation in areas such as deep learning, there is very little doubt that the future of artificial intelligence(AI) will transition towards more unsupervised forms of learning. In recent years, we have seen a lot of progress on several new forms of unsupervised learning methods that expand way beyond traditional clustering or principal component analysis(PCA) techniques. Today, I would like to explore some of the most prominent new schools of thought in the unsupervised space and their role in the future of AI.

The transition towards more unsupervised forms of learning for AI models seems inevitable. Some experts would argue that to achieve any form of meaningful general intelligence, models need to develop independent learning strategies based on observing and exploring an environment. This

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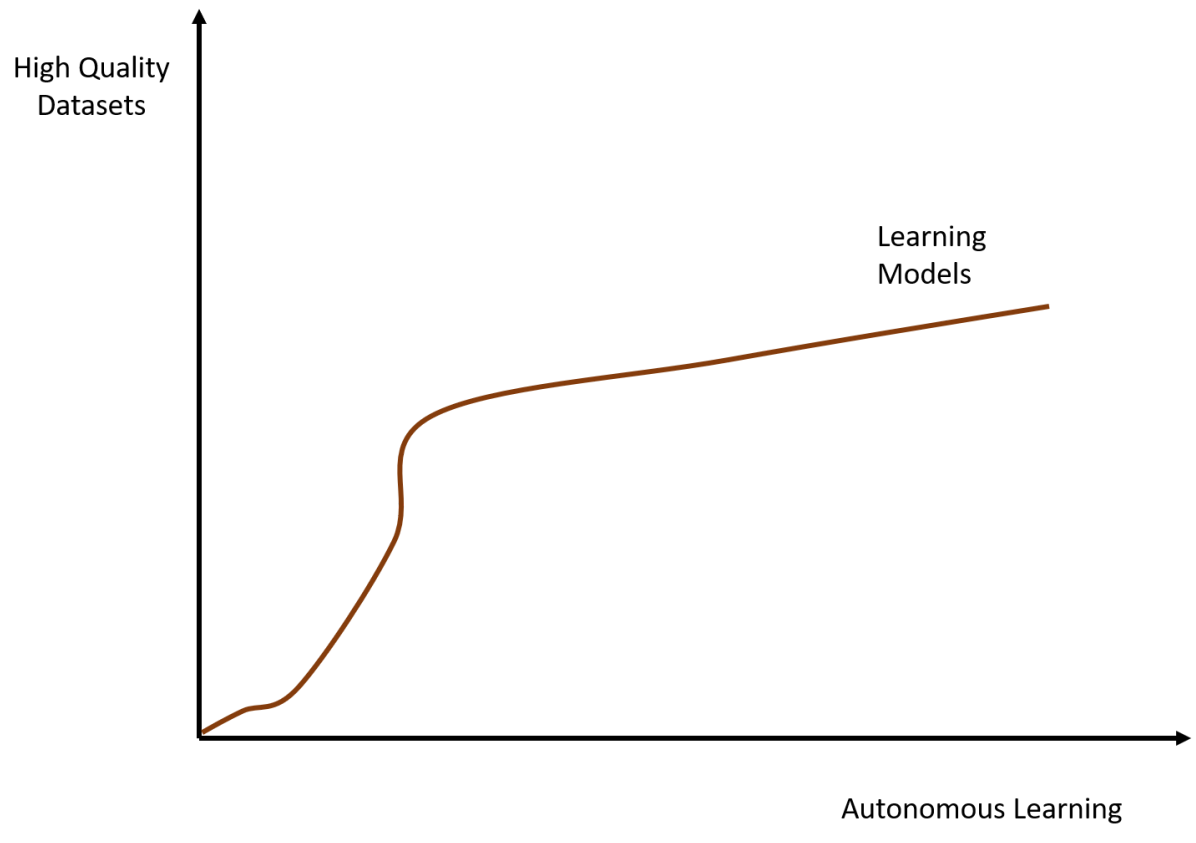
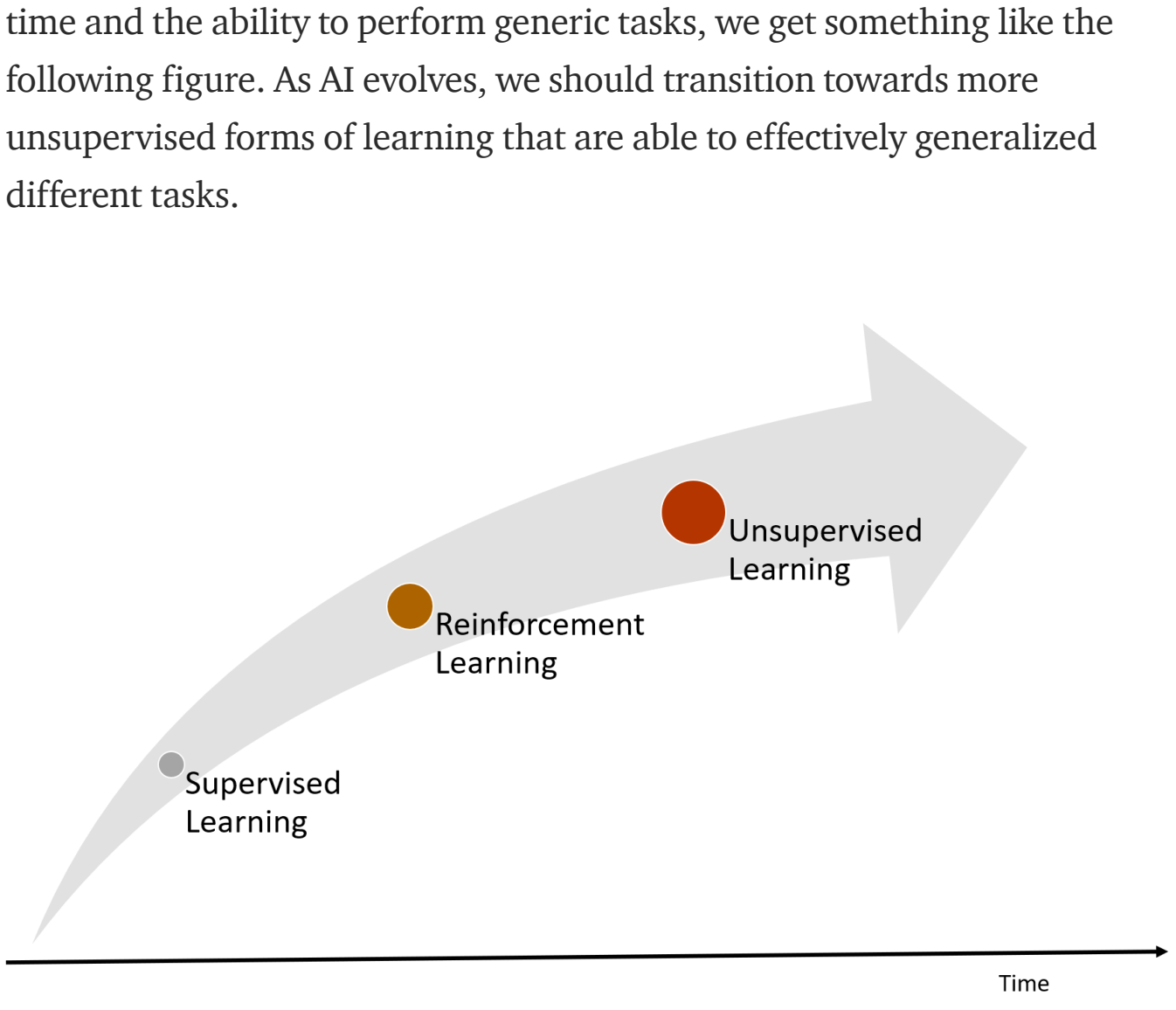
generation of supervised learning methods are based on rich datasets and sparse rewards which creates algorithms that are great at understanding a dataset but not so much at applying knowledge to multiple tasks. An even more pragmatic argument in favor of unsupervised learning is related to the monumental effort that it takes to build and maintain large scale supervised learning solutions. Building high quality labeled datasets is a difficult challenge and is simply impossible for some tasks. Looking into the future of AI through a pragmatic lens, we can accelerate the ability of AI agents to learn independently faster than we can build high quality data sets.



If we divide AI into its three main forms of learning: supervised, reinforcement and unsupervised and we plot them in a graph related to time and the ability to perform generic tasks, we get something like the following figure. As AI evolves, we should transition towards more unsupervised forms of learning that are able to effectively generalized different tasks.



One of the key ways to understand new forms of unsupervised learning is to analyze how do we acquire knowledge in the absence of a teaching. Imagine that you land on a new planet with other astronauts. You have no prior knowledge of this planet and no way to search for information so how do you learn about it? There are four intuitive methods that you are likely to use:

1) **Let me try this…:** Interact with the environment and see the outcomes.

2) **This looks like…:** Intuitively use analogies from our current knowledge and previous experiences to explain the new environment.

3) **What do you think this is….:**Discuss with others in order to form better opinions and knowledge.

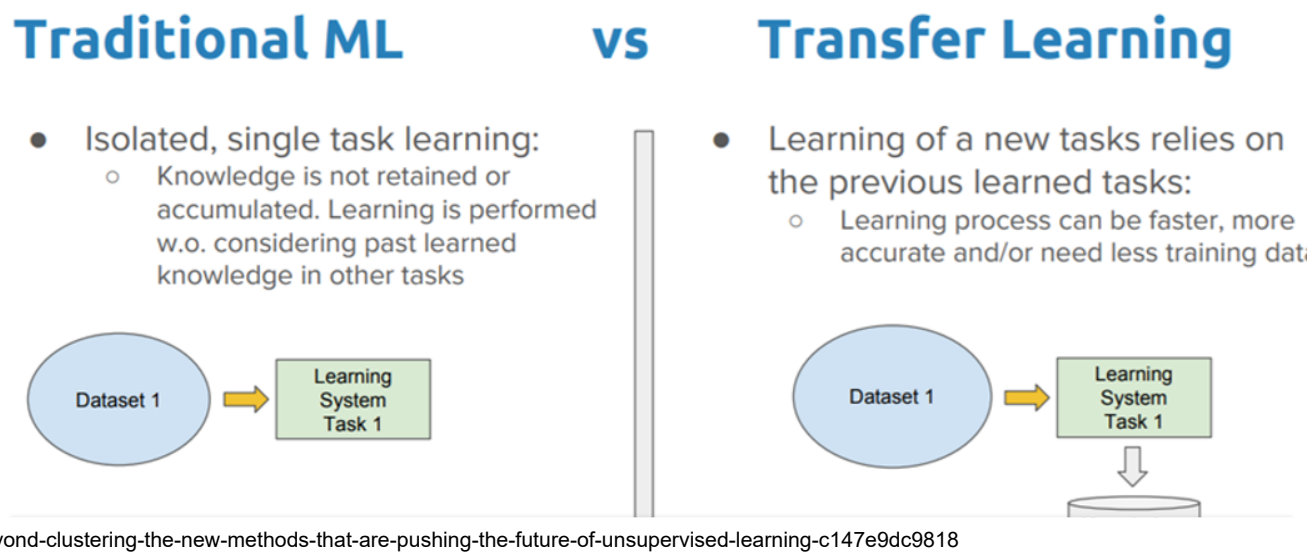
4) **What would happen if:** Try to predict the outcome of potential actions in the new

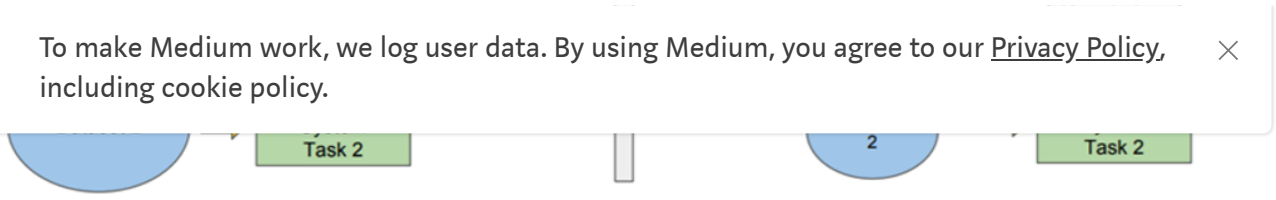
Extrapolating those four methods to the world of deep learning give us that the first form of knowledge building is closer to reinforcement learning methods that learn by trial and error while the other three are more related to new forms of unsupervised learning. More specifically, there are three forms of unsupervised learning methods that are related to points 2, 3 and 4: transfer learning, generative adversarial methods and autoregressive models.

Learning by Knowing: Transfer Learning

Transfer learning is a form of representation learning based on idea of mastering a new task by reusing knowledge from a previous task.

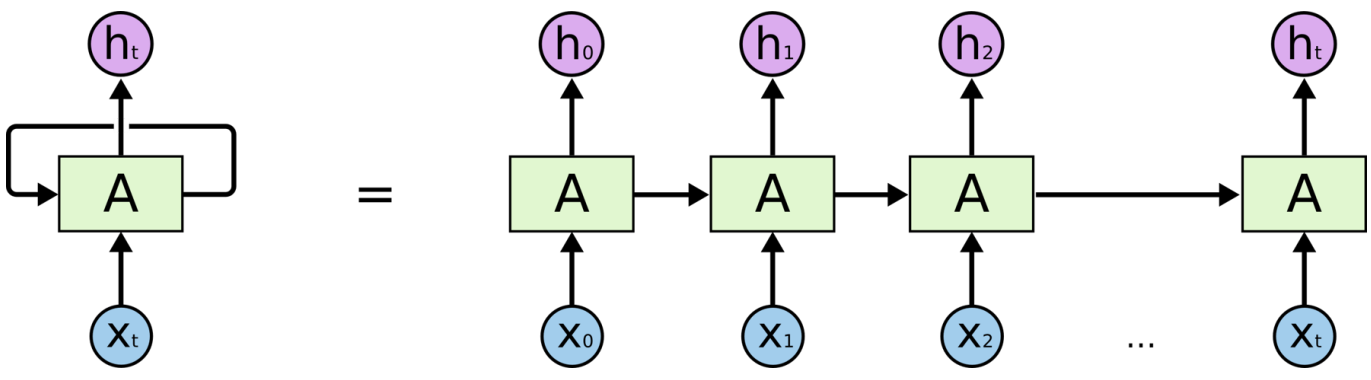
Traditional learning is isolated and occurs purely based on specific tasks, datasets and training separate isolated models on them. No knowledge is retained which can be transferred from one model to another. In transfer learning, you can leverage knowledge (features, weights etc) from previously trained models for training newer models and even tackle problems like having less data for the newer task!





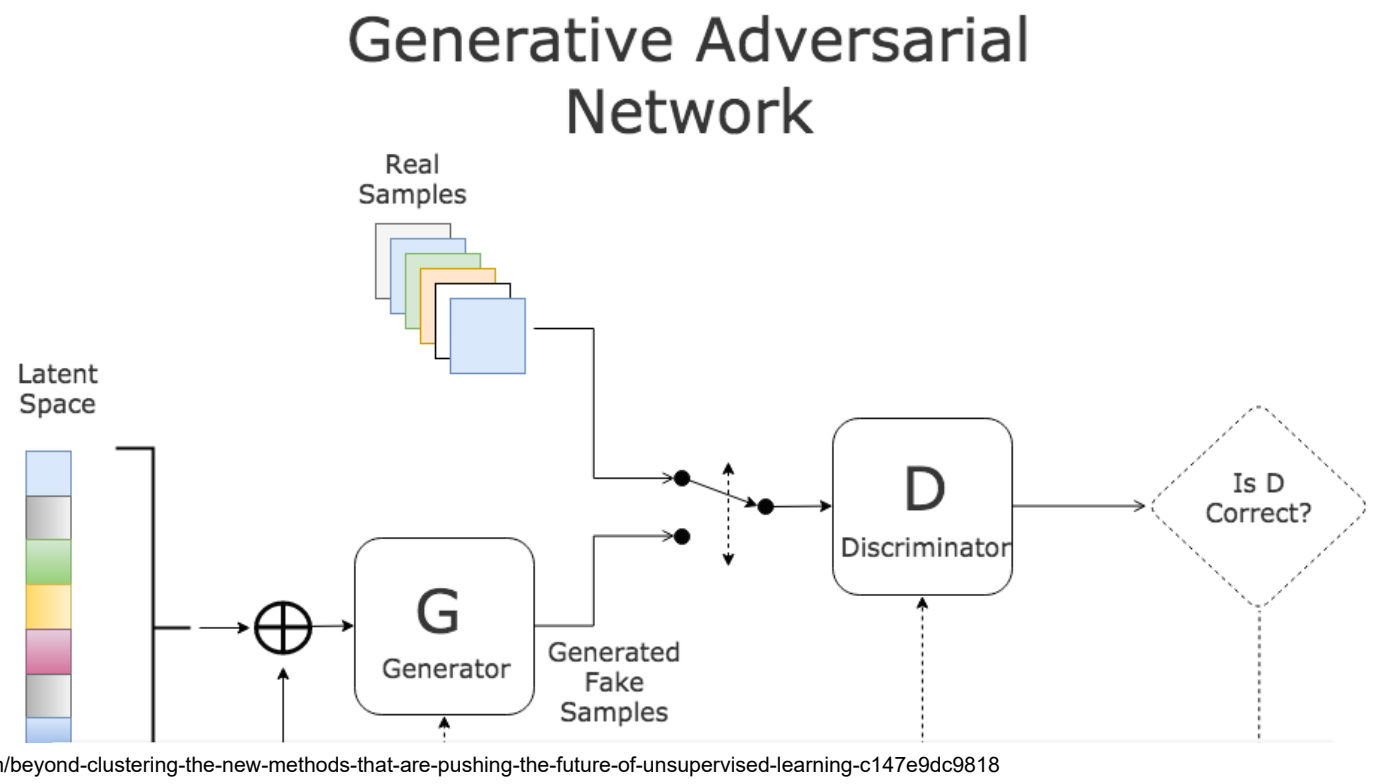
Learning by Interacting: Adversarial Models

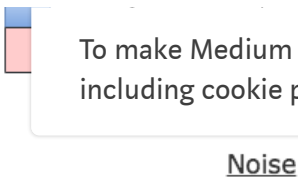
Adversarial models are based on the idea of building knowledge by creating competitions(debates) between multiple agents. One of the most popular forms of adversarial models is known as generative adversarial neural networks(GANs). Conceptually, GANs are a form of unsupervised learning in which two neural networks build knowledge by competing against each other in a zero-sum game. While GANs are a great mechanism for knowledge acquisition, they can also be used to generate attacks against deep neural networks. In a very well-known example, a GAN attacker can cause imperceptible changes in training images to trick a classification model.



Learning by Predicting: Autoregresive Models

The family of autoregressive models focuses on learning by making small predictions. In autoregressive models, the data is split into a sequence of small pieces, each of which is predicted in turn. Such models can be used to generate data by successively guessing what will come next, feeding in a guess as input and guessing again. Autoregressive models effectively learn about data by attempting to predict each piece of it in a particular order. A good example of autoregressive models are language models in which each word is predicted from the words before it.





Unsupervised learning is likely to be at the forefront of the next decade of machine learning research. As AI evolves, we will start hitting roadblocks with the availability of high quality datasets and would need to look for more organic forms of learning. At least at the moment, the future of AI looks very unsupervised.

Machine Learning Deep Learning Artificial Intelligence Data Science Invector Labs