

Application of combined machine learning methods to boost AI creative thinking in IT Companies

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Abstract: Machine learning (ML) is widely used in contemporary IT as vital part of AI (Artificial Intelligence) systems. The aim of the article is to make a systematization of main learning approaches. The goal is to explore different combinations of methods and their possible impact on overall AI performance from creative point of view. It does not include new or adjusted learning methods but holds its focus on the implementation process. It is mainly conceptual proposal that provides guidelines on how to leverage creativity via different learning techniques.

Using one or another method can vary depending on the purpose aimed at achieving. Different approaches to AI learning provide different results. More novelty and uniqueness in the output results do not mean certainly better creativity. New ideas must be applicable in current or perspective company product portfolio. That means there are some boundaries that must be respected during the creative process. Management of learning techniques is critical to achieve those goals - efficient AI creative results with effective practical application, and its proper adjustment would lead to better results.

Keywords: Artificial Intelligence, Learning Techniques, Creative Thinking.

JEL: M15, O31

I. INTRODUCTION

AI (Artificial Intelligence) is widely used in IT companies' operation activities. Many companies even encourage strongly using AI in all project management and development activities as AI-first policy (Paradis et al., 2025). AI should be properly incorporated in company's project management, and by using proposed by Anguelov & Angelova, 2016 indicators, we can measure its efficiency. Those indicators can be partially reused for AI implications. On the other hand, effectiveness of AI application depends on properly chosen learning algorithm which depends on available inputs and specific desired output. Olson et al., 2018 explicitly said that "learning better data representations can significantly improve machine learning performance".

AI systems have the ability for self-education and self-improvement based on available data. However, there are different approaches depending on that data and expected AI outputs. AI learning is done based on labeled data, in which right output is already known. The other approach is based on unlabeled data, in which AI finds hidden dependencies and models.

Besides that, there are other derivatives or different approaches applicable for specific scenarios. For example, AI can learn during its interaction with surrounding environment.

II. OVERVIEW OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Machine Learning (ML) is often confused with other terminology like AI and deep learning. In order to understand properly the concept, we need to know what is behind its meaning. Janiesch et al., 2021 is describing ML as teaching approach based on giving an example of object instead of describing the rules that define its capabilities. Authors point out that ML is using programming methods that are self-improving via experience, and ML is more widely used definition which includes process automation as well. This automation is not usually directly linked to AI. ML methods evolve dramatically during the years with most significant updates become visible after widespread AI implementation.

Next step in evolution to improve artificial capabilities are Artificial Neural Networks (ANN) which according to Janiesch et al., 2021 "consist of mathematical representations of connected processing units called artificial neurons". Next stage of development is the introduction of Deep Learning methods (DL). Schmidhuber, 2015 is defining DL as a subfield in Artificial Neural Networks which manages the system to follow desired behaviour by more than one hidden layer between input and output. Janiesch et al., 2021 tend toward the same understanding and emphasize the use of multiple activation functions for every neuron. In other words, DL is deemed to be the most advanced, but it has some disadvantages:

- in order to be effective DL requires large number of parameters (in some cases trillions). This leads to performance demand and complex systems which are not always effective from one side and difficult to be controlled by humans on the other. Due to the complexity of calculations in hidden layers issue of human understanding and control over learning processes become more challenging;
- sometimes is valuable or required not only to get accurate output, but to understand the concept how that output is reached (Krenn et al., 2022), (Choudhary et al., 2022);
- heavy dependence on large datasets that need to be accurate.

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We can note down as conclusion that for specific tasks most advanced learning methods are not always effective.

III. AI LEARNING TYPES

AI learning is more or less like human teaching, choosing the best approach would lead to better results. The main differences are:

- While humans have different capabilities and their behavior depends on many factors from environment, machine parameters can be defined ahead of time. Thus, machines can have equal basis before learning is started.
- Machine processing does not rely on specific medical factors of the human body and processing of data can be technically and mathematically managed by parameters.

These differences are advantageous from one perspective as machine behavior is more predictable, but it also reduces creativity potential. Barelli et al., 2025 noted that the fact the machine's predictability following execution instructions in a specific order limits creativity. Franceschelli & Musolesi, 2024 suggest that, although creativity has no single accepted definition, the concept of creativity has four main dimensions – person, press, process and product. Authors pointed out that creativity is studied traditionally from product dimension as a resulting output of creativity itself.

Silver et al., 2018 refers to AI ability to play chess and other logic games, but those games rely on rules and predictive moves that can be algorithmized. When we consider creative thinking or out-of-the-box decision that means in many cases something completely new which breaks the current status quo and rules, but at the same time it is within acceptable boundaries. Those boundaries are often purely human specific establishments. For IT Companies they are client preferences about features, company vision for future products, company existing products with their architecture design. As conclusion, learning methods should enable stochastic and random decisions, but respecting the limitations marked above.

Schmidt et al., 2019 present three traditional AI learning methods: supervised (SL), unsupervised (UL) and reinforcement learning (RL).

SL is defined as learning technique that uses already mentioned labeled data with known outcomes (Jiang et al., 2020). It is particularly useful for predictions.

SL techniques include various methods summarized by Caruana & Niculescu-Mizil, 2006, Kaur, 2022: Support Vector Machine (SVM), Logistic Regressions, Linear Regressions, Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbours (KNN), Sequence-to-Sequence, etc. Important note is that these methods can be algorithmized and programmed.

UL uses unlabeled data designated to discover hidden patterns without the need to use predefined categories. Kaur, 2022 lists Clustering, Principal Component Analysis (PCA) and Autoencoders. Fotopoulou, 2024 puts UL methods in three main groups: Clustering, Modern Approaches (Transfer and Domain Adaptation and mixed supervision

methods), Dimensional Reduction (Component analysis methods, Manifold learning methods, etc.).

RL is technique where agents learn to make activities in designed environment to maximize cumulative reward (Kaur, 2022). RL includes Q-Learning and Deep Q-network. These techniques allow AI to learn from environment, but “trial-and-error” interactions require learning algorithm to choose from set of behaviors or to use statistical techniques and advanced dynamic programming (Kaelbling et al., 1996).

Both SL and RL use the technique “Dynamic programming” (Schmidhuber, 2015).

Those three main approaches are extended to variation like semi-supervised learning, studied by van Engelen & Hoos, 2020. This approach uses both labeled and non-labeled data, taking advantage of using largely available unlabeled data with small, but more reliable, labeled data. It is particularly useful to extend the boundaries of supervised learning and thus it is an object of interest to AI creative thinking improvement.

IV. APPROACH TO BOOST CREATIVITY THROUGH AI LEARNING

Based on analysis above we can summarize that purpose and results that are expected from AI are correlated with the selected learning method/technique or combination of them. Author's proposal to enhance AI creative thinking is to use the following learning design:

- **step 1** is to use Imitation learning to achieve base line for creative ideas;
- **step 2** is using transformer with stochastic sampling to put neural network into unstable and chaotic state thus make it to generate more diversity outputs;
- **step 3** is to use learning method studied by Liu et al., 2023 – Generative self-supervised learning. This will benefit from less need of raw data and increased processing power as algorithms will skip human labeling;
- once the ideas are enough for assessment, on **step 4** the algorithm switches to supervised learning models with active human labeling. Supervised fine-tuning is proposed as an approach that will increase the adaptation of ideas to existing products if required. This step will allow the system when cycle is restarted to have reliable data to start with imitations.

If we want to measure the results of the above approach, we should have specifically designed AI aimed at generating creative ideas. We simply call that AI Creative core.

During the learning process we should respect novelty, but new ideas should respect client requirements from one point of view and company existing products from another as they were already noted. Specific AI learning methods can be applied to AI Creative core. Focus is on innovation and creativity. One of the creative idea boosters is entering more chaos into AI proposed ideas, which could be achieved by stochastic learning within defined frameworks and limitations like company goals, stakeholder proposals,

developed business requirements, software architecture patterns and design, etc.

Selected approach for AI Creative core learning is:

(1) independent idea generation and conceptualization;
(2) define proximity to existing solutions (K-Nearest Neighbors);

(3) present the idea/solution, that is in line with adopted general approach and expert review of its creative potential – by human or machine;

(4) send approved solution to learning algorithm, which uses RNN and Sequence-to-Sequence methods;

(5) obtained results are interpolated to Kernel Support Vector Classifier (KSVC), to determine the better solution/idea or set of solutions/ideas often positioned in 3-dimensional space.

If we continue to elaborate, we can point out that some of the mandatory learning specifics for creative AI are stochastic dynamic sampling and RNN. RNN allows supervised learning to produce accurate and effective outputs.

Figure 1 presents the steps of learning AI Creative core to generate new solutions/ideas.

Proposed approach can be additionally enhanced with specific reward parameters for creativity.

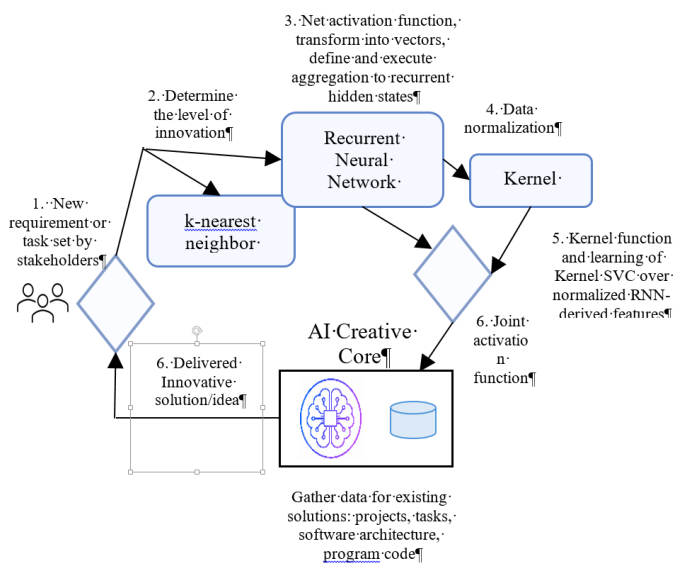


Figure 1: AI Creative core learning sequence

V. CONCLUSION

Using contemporary learning methods AI can successfully handle creative thinking intensive tasks. Effectiveness of the output is task dependent and relies on the available data and the proper selection of learning methods. Creative thinking is specific task which requires specific learning approach just the way humans are trained. Using different combinations of techniques and methods, author proposes combination that can significantly boost creativity with practically valuable solutions.

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