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USING TRIZ TO HANDLE SMALL DATASETS IN ARTIFICIAL INTELLIGENCE

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Abstract: *Various algorithms used nowadays in artificial intelligence need big data to train and test the models such that to ensure high accuracy and generality of the model and avoid the so-called underfitting problem. However, not all practical applications have sufficient data in their sets to train and test such models. This is a major challenge for the adoption of traditional machine learning or deep learning algorithms in areas where the processes are not suitable to collect big data. There are also cases no big data is needed, but small data are of interest. In such cases, novel algorithms of artificial intelligence are required to design models that can provide customized solutions based on small datasets. This paper highlights how TRIZ can be used to formulate some inventive strategies to handle these two categories of problems.*

Key words: *TRIZ, small data, artificial intelligence, inventive problem solving, .*

1. INTRODUCTION

Artificial Intelligence (AI) refers to the field of imbuing machines with human-like intelligence, allowing them to solve problems as effectively as humans [1]. The ability to learn, understand, and imagine are natural qualities of humans, which is not the case with machines. An artificially intelligent system refers to a man-made system that possesses similar or superior levels of these qualities [2]. The ultimate goal of AI is to create systems that can match or exceed human intelligence. Examples of AI today include Data Science, Knowledge Representation, Machine Learning, and Deep Learning [3].

Artificial intelligence algorithms today primarily seek to identify patterns and forecast future trends in analyzed systems using data collected from those systems, typically input, and output data [4]. Despite recent advancements, AI is still limited in its ability to provide explanations. The current state of AI is often referred to as "narrow-AI" or "weak-AI", as it is designed to perform specific tasks that are narrowly defined and structured. Artificial Narrow Intelligence (ANI) refers to any AI algorithm that can outperform humans in these limited tasks, such as handwriting recognition or facial detection, but it is not capable of broader intelligence [5].

AI remains untrustworthy for decision-making in sensitive and high-risk areas, such as finance, healthcare, and energy, where even slight inaccuracies of 0.01% could have serious consequences. The term AI may eventually be replaced with "pseudo-AI" once it is widely recognized that AI still falls short of true intelligence. Additionally, experts often play a significant role in operating AI systems, acting as a "person-in-the-loop". Therefore, a more accurate and transparent term for AI is "computational intelligence" [6].

2. THE PROBLEM

Machine Learning (ML) and Deep Learning (DL) have become increasingly popular areas in the field of artificial intelligence due to their practical applications. ML employs algorithms to analyze data, learn from it, and make predictions or determinations about the subject matter. By learning from vast amounts of data, ML enables computers to perform complex tasks

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that were previously impossible for humans. This is achieved by "training" the computer with data and algorithms that allow it to learn how to execute the task [7].

DL is a specific subset of ML that uses a category of algorithms known as neuronal networks (NN) to perform tasks. Different models of NN have been developed for various types of problems, and they all require a large amount of data to be trained effectively [8]. The success of a model in ML or DL depends on how well it generalizes new input data from the problem domain. This is crucial to making accurate predictions or analyses on future input data that the model has never seen before. Algorithms that overfit or underfit in relation to the training dataset are considered to have poor performance [9]. An algorithm is said to be underfitting when it cannot capture the underlying trend of the data, which leads to inaccurate results. This condition results in high bias and low variance in technical terms [10].

When a small dataset is used to build a model, or when a linear model is built with insufficient non-linear data, the resulting model may make inaccurate predictions or analyses [11]. On the other hand, overfitting occurs when an ML (DL) model is trained with excessive amounts of data, leading the model to learn from noise and inaccurate data entries in the dataset. Too much detail and noise can hinder the model's ability to generalize a problem [12].

In the field of artificial intelligence, the true challenge lies not in having too much data, as established procedures exist to reduce data sets to manageable sizes. Instead, the real obstacle is presented by situations where data is scarce, yet an AI model designed for big data is required. In some cases, acquiring large amounts of data is simply not feasible, necessitating the development of AI algorithms tailored for smaller datasets. Humans often rely on small amounts of data to make decisions and seek personalized solutions that fit their individual characteristics, rather than approximations. Personalized medicine, which provides unique treatments tailored to an individual's genetic makeup, and shoes that fit perfectly to the unique pattern of one's feet, are examples of this personalized approach. Therefore, AI algorithms should be approached from another perspective, one that recognizes the importance of identifying small yet logical relationships within data that can be understood within the context of a specific problem. Though big data can also be adapted to personalized problems, small data presents a unique set of advantages and must not be overlooked in the development of AI algorithms.

Thus, in the field of artificial intelligence, one major challenge is the lack of sufficient data in certain use cases to properly train machine learning algorithms or neural network models. Another challenge is creating AI models based on small datasets. Addressing these challenges requires a creative engineering process and the exploration of inventive problem-solving techniques. One effective tool in this group is the TRIZ method, which offers a system of concepts and tools for approaching barriers or conflicting problems in a creative way [13]. In the following sections, we will explore the potential of TRIZ to address these two types of AI-related challenges. The paper will conclude with key findings, limitations, and insights for future research on this topic.

3. OVERCOMING UNDERFITTING IN AI

Figure 1 portrays underfitting in several machine learning and deep learning cases.

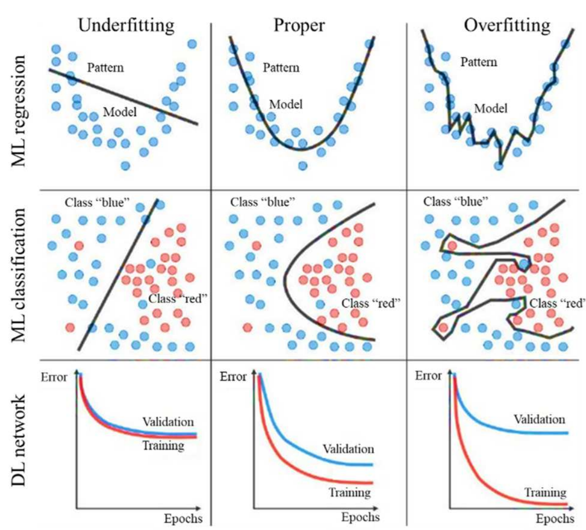

Fig. 1. Appropriateness of models in artificial intelligence

Figure 1 illustrates the wrong models used for a set of data (left, right columns), and the good one (middle). To apply TRIZ to address underfitting, the first crucial step is to transform the specific problem into a general one. Therefore, it is essential to clearly define the problem. However, a problem arises when we encounter the scenario depicted in Figure 2, where we only have access to a portion of the complete dataset. In this situation, even if the model accurately describes the small dataset, it is inappropriate for the entire system, which is defined by the complete dataset.

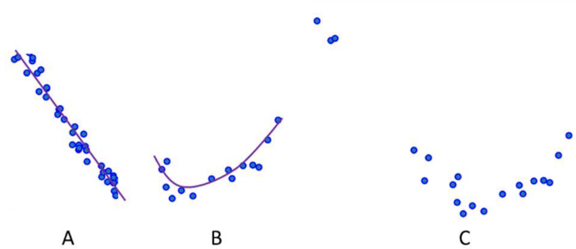

Fig. 2. The problem with access to few data

Data from Figure 2 is extracted from a bigger data set, shown in Figure 3. Graphs in Figure 2 and Figure 3 are created with Matplotlib / Python. In Figure 3, we have introduced a function $y=\cos(1.5\cdot\pi^{X})$ (see the cyan curve). Around this function we have created deviations, generating the dataset represented by the blue dots. Using ML algorithms (here polynomial regression), we have created a representation model with polynomials.

The left graph in Figure 3 illustrates a model represented by a first-degree polynomial. We see that the model is wrong because it underfits the dataset. In the second graph from the middle, we modelled the dataset with a degree 4 polynomial, which describes quite accurately the dataset. The third graph from the right side uses a degree 15 polynomial to describe the data set. It overfits the dataset. In Figure 3, "MSE" stands for "mean square error".

Assuming that only a subset of the complete dataset was collected in our experiments (as shown in subsets A and B of Figure 2), we can use a machine learning algorithm to generate a linear model for case A and a second-degree polynomial model for case B. Although both models appear to be accurate, they only provide a partial representation of the complete data set due to missing data resulting from poor experimentation or time constraints. Moreover, the linear model in subset A is not the same as the one depicted in the left graph of Figure 3. In a new scenario illustrated in Figure 2, subset C, where it was not possible to collect a large data set, but the available data covers the margins of the complete dataset, there is a zone in the dataset with missing information.

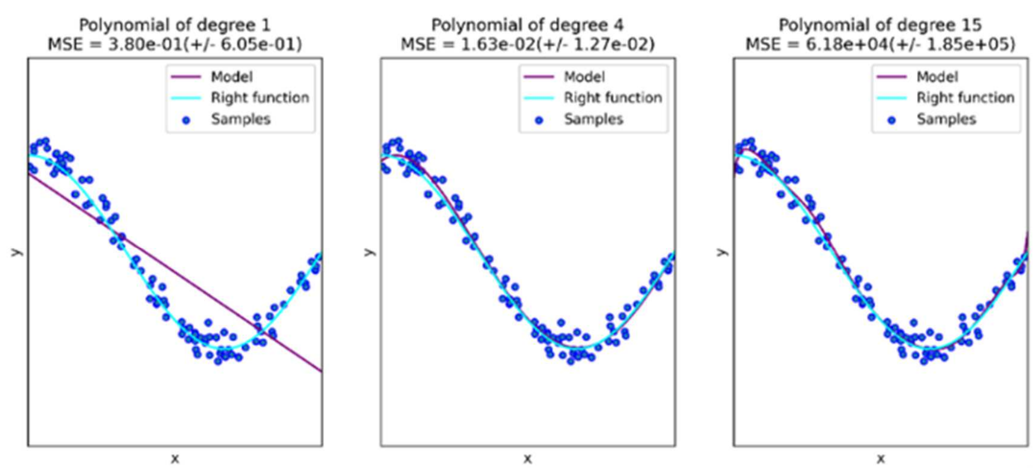

Fig. 3. The problem with over and underfitting

We are able to find the right model for the system even with a limited amount of data (Figure 2, C), without knowing the values of the missing data set from the complete set, which is shown in Figure 3. The polynomial of degree 4 from the middle graph in Figure 4 provides the proper model, highlighting the possibility of adopting strategies to generate adequate models even with small datasets. In this case, the strategy involves operating the system at its limits and collecting data from the margins and center of the system's outputs. Despite the small dataset (only 20% of the whole set), an ML algorithm (polynomial regression) can generate the correct model. It's worth noting that overfitted models are not valid with small datasets (compare the third graph from the left in Figure 4 with the right graph in Figure 4). Graphs in Figure 4 are visualized with Matplotlib / Python.

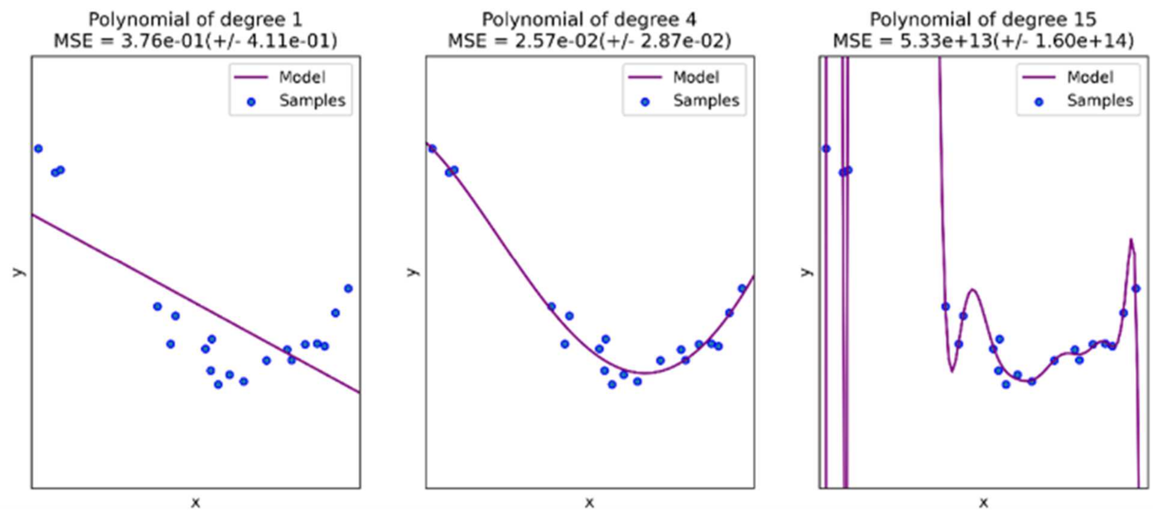

Fig. 4. Finding the appropriate model for a system using a small dataset

To ensure an ML model can properly generalize any new input data in the problem domain, we need to understand two crucial indicators: bias and variance (see Fig. 5).

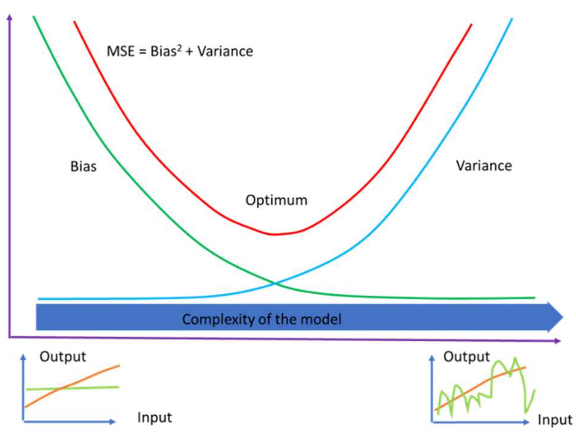

Fig. 5. Bias and variance in ML

Bias refers to the assumptions made by a model to facilitate learning, while variance measures the error in training models. In case the model is trained on training data and obtains a low error, but after changing the data and training the same model, we experience a high error; the deviation between the two cases reflects the variance. In underfitting problems, the bias is high, and the variance is low, while the opposite is true for overfitting problems, where the bias is low, and variance is high. The mathematical formulas for bias and variance are:

$$Bias^2 = \frac{1}{N}\sum_{i=1}^{N}(\bar{f}(x_i) - y_i)^2 \quad (1)$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{B}\sum_{k=1}^{B}(f(x_i; D^k) - \bar{f}(x_i))^2, \quad (2)$$

where N is the number of testing data, B is the number of training set sampled from the whole training data, y_i is the value of the target output (target property), $f(x_i;D^k)$ is the output predicted by the model using the training set D^k, $\bar{f}(x_i)$ is the average of predicted output for the sample i.

4. TRIZ TO TACKLE UNDERFITTING

In this section, we introduce the application of TRIZ to formulate strategies that can handle the underfitting problem when dealing with small datasets. Although it is not the aim of this paper to cover all possible strategies, we demonstrate that it is feasible to find solutions to this problem using structured innovation tools such as TRIZ.

The problem we face is achieving a "high accuracy model (low variance, low bias)" without requiring a large dataset. In TRIZ terminology, this problem can be expressed as follows:

- Reduce the "quantity of data (principle 26 [14])" without compromising the "accuracy of measuring system's performance (principle 28)."
- Reduce the "complexity of the system, method, or tool (principle 36)" without affecting the "accuracy of measuring system's performance (principle 28)."

Applying the matrix of contradiction from the TRIZ toolbox [14], we can derive the following generic recommendations, as described in the following paragraph:

- Inversion or reversion
  - Instead of taking an action that is dictated by the specifications of the problem, implement an opposite action.
  - Make a mobile (movable) part of the system (or the outside environment) immobile and vice versa.
  - Turn the system "upside-down".
- Extract, retrieve or remove some elements from the system.
  - Extract, remove or separate a "disturbing" element (unit) or property from the system.
  - Extract only the necessary element, component, or property from the system.
- Replacement of a traditional system
  - Replacement of a traditional system by a softer system.
- Copying
  - Use simple and inexpensive copies instead of a system that is complex, expensive, or inconvenient to operate.
  - Replace a "hard" system by its "soft" copies.
- Prior action
  - Carry out in advance the required actions or changes (completely or partially) to the system.
  - Arrange/place parts of the system in advance in a way they can go immediately into action when required and they do this from the most convenient position.
- Rejecting and regenerating parts
  - After an element of the system has completed its function or becomes useless, it should be rejected or modified during the work process.

The set of generic indications is further used to formulate some smart strategies to deal with an underfitting problem in the case where only small datasets are available.

5. EXEMPLIFICATION

Applications of artificial intelligence cover a wide area. A good strategy also imposes to consider the context where it is applied. Therefore, the next proposals must be seen in the context, and not universally applicable.

5.1 Exemplification in material science

To illustrate the application of TRIZ in addressing the underfitting problem with small datasets, we provide an example from the field of material science. Compared to other fields, datasets in materials science tend to be smaller and more diverse.

In this context, the "degree-of-freedom" of the machine learning (ML) model can help address the issue of small data. However, the presence of the "accuracy-degree of freedom" association can result in underfitting and a large prediction bias, thereby reducing accurate predictions in unknown fields.

One approach to improving accuracy is by manipulating the training data, such as by adding more examples to the training set (see formulas (1) and (2)). However, expanding the dataset leads to a highly complex ML model, and the physics incorporated in it can be difficult to interpret. Additionally, increasing the amount of experimental data can also result in higher costs.

Empirical studies in material science have shown that doubling the size of the data can decrease the error by approximately 23%. However, this approach also exponentially increases the cost of conducting additional experiments, which poses practical challenges to improving accuracy by adding new materials data.

For this case, we consider from the above list of TRIZ inventive principles the one referring to "instead of taking an action that is dictated by the specifications of the problem, implement an opposite action" in combination with "extract only the necessary element, component, or property from the system".

This leads to the following particular strategy: the ML model can be constructed by restricting the configurational space of materials, such as predicting the band gaps of selected families of materials with fixed composition or crystalline structure instead of modeling combinations covering a wide compound space. The constructed ML model gains more accuracy but sacrifices generality when it is applied outside of the restricted field. Considering the less flexibility of training data, the strategy imposes to design appropriate feature space in the ML model. This means, besides the data used in the ML model to make predictions, some external metric is considered to assist this prediction (to introduce an offset to the expected low accuracy result from the ML model). This external indicator can be generated from simulations.

5.2 Exemplification on chatbot design

Another example that demonstrates the application of TRIZ to tackle the underfitting problem involves chatbots used by public administration for citizen interaction. To enable a more natural and profound interaction between humans and virtual assistants, natural language processing (NLP) algorithms are used to train the machine learning (ML) model. However, in many cases, there may not be sufficient data to properly train the chatbot, especially in the early stages of deployment.

To address this issue, we can apply the TRIZ inventive principle of arranging or placing parts of the system in advance so that they can immediately go into action from the most convenient position. This principle can be combined with the inventive principle of rejecting and regenerating parts of the system that have completed their function or become useless during the work process.

The combination of these principles leads to the solution of "learning transfer," which involves extracting knowledge from ML models trained on one class of problems to solve another class of problems with less data. Of course, as more data is accumulated over time, the ML model will continue to improve.

In summary, the application of TRIZ can provide structured and innovative solutions to address the underfitting problem in various domains, such as material science and chatbot development. By leveraging TRIZ inventive principles, we can find solutions that may not be immediately apparent, enabling us to overcome the limitations of small datasets and improve accuracy in machine learning models.

5.3 Exemplification on image handling

Another example that illustrates the application of TRIZ to overcome the underfitting problem involves the use of automatic vision systems for quality assurance tasks in manufacturing processes. These systems are designed to detect defects, such as scratches, in the product. However, the database with images containing shapes of scratches is often limited, which can pose a challenge for training a highly accurate machine learning model.

To address this problem, we can apply the TRIZ inventive principle of copying, which involves using simple and inexpensive copies instead of a complex, expensive, or inconvenient system. This principle can be implemented by creating artificial images with scratches using generative art algorithms through randomization, deep learning with GAN algorithms (generative adversarial network), variational autoencoders, or image augmentation. These approaches can superimpose various shapes of defects over a proper image, providing a diverse dataset for training the machine learning model.

By using these TRIZ-based strategies, we can train highly accurate machine learning models for quality assurance tasks in manufacturing processes, even when the available dataset is limited. This demonstrates the power of structured innovation tools like TRIZ in finding effective and unconventional solutions to challenging problems.

5.4 Exemplification from robotics

This example concerns social robotics, where we aim to create a robot capable of interacting with children and drawing together. As this is a new task, there is a lack of data available, which presents a challenge for training an accurate machine learning model. To address this issue, we can use the TRIZ inventive principle of "carrying out in advance the required actions or changes (completely or partially) to the system," combined with the principle of "inversion."

One potential solution that follows this approach is "self-supervised learning." To implement this, we could take various images of pre-existing drawings, break them into puzzles, and ask the system to reconstruct the original image. By asking the model to solve this "fake" problem, it will gain domain knowledge that can be used as a starting point for the new task, which has limited available data. By leveraging TRIZ-based techniques, we can overcome challenges in developing new and innovative solutions in the field of robotics, such as developing a robot that can interact with children and draw together. These methods help us to develop unconventional solutions that are effective in solving complex problems.

5.5 Exemplification on security

In the security field, an example where TRIZ can be applied is the installation of a new ATM system, where a vision system is needed to monitor potentially malicious activities. However, the problem arises from the lack of sufficient data, as there are not enough videos or images of bad behaviors available for training the machine learning model. To address this issue, we can apply the TRIZ inventive principle of "turning the system upside-down".

This involves training the model with only proper behaviors instead of searching for problematic ones. By doing so, the machine learning algorithm can learn to recognize and signal any activity that deviates significantly from the norm, alerting security as a potential threat.

Applying TRIZ in this manner can help us overcome the challenge of limited data in the safety field, enabling us to create effective solutions for ensuring the safety of individuals and systems.

5.6 Exemplification in quality assurance

This example concerns quality assurance in small series or customized production. Unlike in mass production, where large data sets can be collected and statistical analysis used for quality assurance, small series production often lacks such large data sets, making manual inspection by operators the norm. However, manual inspection can be prone to errors, and in the case of premium products, such errors are unacceptable. Therefore, we propose using automatic systems to perform inspection, and to achieve this, we suggest applying the TRIZ inventive principle of "replace a 'hard' system with its 'soft' copies."

To put this principle into practice, we can train the machine learning model in hundreds, and over time, thousands of easy inspection tasks, each with a very small number of samples. By doing so, the ML model learns to identify the most relevant patterns of defects, as each test has very few data points. Once we have trained the model in this way, we can expose it to more complex inspections with very few samples. Because the system is now trained to analyze situations with small data sets, it is better able to handle the demands of small series or customized production.

5.7 Exemplification on no-data cases

In some situations, it may not be possible to collect previous data about a system, yet automatic recommendations are still desirable. Machine learning models heavily rely on data, so what can we do when there is no data available? In this case, the TRIZ inventive principle "replacement of a traditional system by a softer system" can be applied. Combining this principle with "carry out in advance the required actions or changes (completely or partially) to the system" leads to the idea of encoding human knowledge. This can be accomplished by leveraging the knowledge of people involved in the current process and experts in the field to engineer an ML system that incorporates human expertise.

To put this strategy into action, we can translate human knowledge into numerical values and model the correlations and relationships between various inputs and outputs. We can then validate the model's accuracy using a limited set of data. Once the system is calibrated, it can be used to predict outputs at a given moment in the future based on specific values of the inputs collected in the present. This approach can be called "human-coded knowledge," and it offers a way to develop an ML system that does not require previous data, yet still delivers automatic recommendations.

5.8 Exemplification on poor-data cases

In some cases, designing a good model from the beginning can be difficult because the available data cannot be augmented or transformed to generate a larger dataset for training the model. In such situations, we can apply the TRIZ inventive principle of "making an immovable part movable" or, if that's not possible, "acting upon the external environment and turning it from immovable into movable."

This strategy suggests building the ML model with the available data while accepting that the model may be weak and prone to errors in predictions or classifications. However, the system should be designed with the possibility of a human expert being in the loop to make corrections to the results. The deviation between the predicted and actual results can be used as a lesson for the system to adjust its predictions, thereby improving its accuracy over time. This approach is known as "human-in-the-loop learning."

5.9 Exemplification on limited-data cases

When faced with limited data but a clear idea of the data boundaries, the TRIZ inventive principle "use simple and inexpensive copies instead of a system that is complex, expensive, or inconvenient to operate" can be applied. To generate more data, we can create simulated environments that mimic the real world and use the data collected from these simulations to train the ML model. With the ability to easily reset and run many simulations, we can improve the accuracy of the model. In addition, techniques such as Monte Carlo simulation can also be employed to generate more data. Synthetic data, which mimics the schema and statistical properties of real data, can also be created to supplement the limited data.

5.10 Exemplification on object recognition

In certain applications, such as object recognition in a scene, obtaining a small dataset can be a challenge. To overcome this, we can apply the TRIZ inventive principles "reject or modify an element of the system after it has completed its function or becomes useless" and "arrange/place parts of the system in advance in a way they can go immediately into action when required and they do this from the most convenient position". This can be achieved by augmenting the small dataset through techniques such as rotation, decolorization, scaling, and zooming of images, among others. These techniques enhance the dataset and improve the training of the ML model to avoid underfitting problems.

It is worth noting that there are several strategies to tackle this problem, and each one suits a particular case. Therefore, customized strategies must be designed after careful analysis of the particular problem. Using structured methodologies such as TRIZ can assist in this process, as it offers a wide range of tools beyond the contradiction matrix, which was explored in this paper. These additional methods are likely to have even greater potential to aid model design in artificial intelligence.

6. TRIZ FOR SMALL DATA BASED AI

In this section, we explore another perspective of artificial intelligence that utilizes small data. These are models that differ from traditional ones in the field of machine learning or deep learning, as they don't require massive amounts of data for training. Small data refers to information that can be observed and processed without special algorithms, such as data about an individual student in a class. In contrast, big data is collected from many sources and requires advanced algorithms to process. Numerous opinions suggest that over 65% of the greatest inventions in the world are based on small data, indicating that AI driven by small data may be the future instead of traditional approaches that rely on big data. However, the value of AI driven by big data remains and will continue to be useful. Nevertheless, the power and intelligence of AI will improve further when AI algorithms can effectively train with small data.

Complex systems exhibit a behavioral characteristic where the agents within the system tend to follow a collective pattern of behavior over time. This phenomenon is prevalent in the scientific community as well. When a certain field or approach gains popularity in publishing scientific papers, many researchers succumb to the temptation to imitate. Similarly, in the field of AI, the prevailing trend is to use deep learning models in cited publications. However, in many cases, complex machine learning models or deep learning with neural networks are unnecessary to create powerful AI models. Moreover, big data is often seen as a panacea for AI models, but the institutional movement to adopt AI models based solely on big data is not always well-founded. In reality, many problems cannot be solved with big data, and instead, small data are required to derive meaningful conclusions.

For instance, when a manager seeks to understand each employee's profile, they require small data and intelligent algorithms that can translate it into the individual profile of a particular employee. Thus, we need AI algorithms that can derive meaning from unique, individual data. If we want to create customized production instead of mass production, we must handle small data and design a distinctive value proposition for each customer. Personalized medicine cannot rely on big data. Big data can sometimes support AI algorithms that work with small data to generate optimized solutions, such as personalized medical treatments. Since the human DNA sequence (genes) is unique to each individual, medical treatment is optimized when it incorporates the patient's unique pattern. Combining AI models that integrate big and small data is expected to provide significant value-added to our current knowledge. In fact, AI is about handling knowledge, not just processing data.

In this section, we will illustrate how TRIZ can be applied to create a strategy for a small data-driven AI model. To demonstrate this, let's consider a fashion business that specializes in designing and manufacturing shirts for men. Currently, the company uses big data to tailor shirts, which results in a limited number of sizes, ranging from XXXS to XXXL, based on the chest and neck circumference. For instance, an XL size is tailored to fit chests between 106 and 111 cm in circumference, and necks between 44 and 45.5 cm in circumference, using the average data from a large number of men. The pattern for the standard shirts in XL size is shown in Figure 6, A.

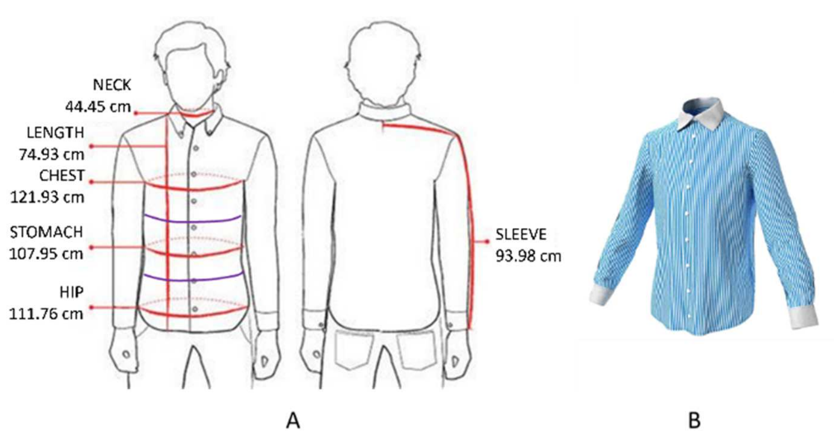

Fig. 6. The standard pattern for tailoring XL size men shirts

The mass customization business model aims to create individualized products, which requires a solution to produce cost-effective shirts for each customer. Personal data such as neck, length, chest, stomach, hip, and sleeve measurements can be collected to automatically create a personalized pattern for each piece of the shirt.

Using robotic systems, these pieces can be automatically cut according to the pattern indicated by the computer and sent to the maker-shop for final assembly. However, the challenge is to create personalized patterns for each piece of the shirt using only a set of five data points, specific to each customer and not just average values derived from big data.

This problem is characterized by the conflicting parameters of "highly accurate patterns" vs. "the use of many measurements," which can be translated into TRIZ language as ("Accuracy of measurement") vs. ("Amount of substance"). To address this, we can use a set of TRIZ inventive principles. They are:

- Extraction: extract, remove or separate the disturbing parts or properties from an object or single out the only necessary part or property.
- Universality: if the object can perform multiple functions, there is no need for other/additional objects.
- Changing color: a) change the color of an object or its external environment; b) change the degree of transparency of an object or its external environment; c) use colored additives to observe an object or process which is difficult to see; d) if such additives are already being used, add luminescent traces or tracer elements.

To enable a mass customization business model, a cost-effective solution is required to produce personalized products. This can be achieved by collecting specific data points such as neck, length, chest, stomach, hip, and sleeve measurements from the customer. These data points are used to create a personalized pattern for each garment using an AI algorithm, which then instructs robotic systems to cut the fabric pieces accordingly. These pieces are then sent to the maker-shop where they are sewn into the final garment.

However, creating highly accurate patterns with only a limited number of measurements is a challenging problem. To solve this, we can apply the TRIZ inventive principles of "extraction," "universality," and "changing color." The extraction principle involves identifying and extracting the "disturbing" parts of the garment, such as the stomach and hip, and creating predictive fitting metadata around these areas. The universality principle suggests creating a separate AI model for each customer using a parametric model that depends on the specific measurements collected from the individual. These measurements, which can be called "predictive fitting classifiers," are used to generate a personalized pattern for each garment.

The third inventive principle, changing color, involves expanding the data collection process to include more specific measurements from the customer, such as the circumferences marked in dark blue on Figure 6, A. While 3D scanning technology is an option, it may not be cost-effective. Instead, a mobile app can be used to capture a photo of the customer from the front and lateral views, which is then converted into a 2D shape model. The AI algorithm then converts this information into a 3D shape and associates it with the parametric patterns of the garment pieces and the predictive fitting metadata. This process creates a customized garment at an affordable price point.

Over time, personalized data can be used to improve the predictive fitting metadata, further enhancing the accuracy of the personalized patterns. Additionally, a 3D model of the garment can be created and sent to the customer for approval before production begins (Figure 6, B). This step increases customer satisfaction and loyalty to the brand.

7. CONCLUSION

In this paper, we investigate the application of structured innovation to address challenges in designing AI algorithms. Specifically, we focus on two cases: the underfitting problem caused by insufficient data for a good fit AI model driven by big data, and the design of AI frameworks when small data are the driving force and big data are no longer relevant. Our aim is to provide illustrative examples of TRIZ applications that inspire developers to create strategies that compensate for the lack of data to train the AI models.

We explore the potential of the TRIZ Contradiction Matrix in these examples, but we expect that other TRIZ related tools can also enhance the space of possibilities and stimulate non-conventional thinking in the field of artificial intelligence.

The domain of artificial intelligence is vast and presents challenges at every step. Combining creative engineering tools with traditional AI approaches can facilitate the creation of the next generation of AI models and algorithms. For models driven by big data, such as those used in machine learning and deep learning, the main challenge is not the model itself, but rather the collection and preparation of adequate data to train the model.

Traditional AI models have been formulated in many cases several decades ago, and even those related to deep learning have been around for a few years. However, recent developments in neural network algorithms for specific problems in deep learning indicate that progress is ongoing. The collection of big data requires significant investments in a company's IT infrastructure and a clear understanding of the insights the data can provide. Systematic analysis of the space of interest could be another area for exploration using structured innovation tools.

8. REFERENCES

[1] Dick, S. *Artificial Intelligence,* Harvard Data Science Review, DOI: 10.1162/99608 f92.92fe150c, Issue 1.1, Summer, 2019.

[2] Steinkruger, D., Markowski, P., Young, G. *An Artificially Intelligent System for the Automated Issuance of Tornado Warnings in Simulated Convective Storms,* Weather and Forecasting, Vol. 35, Issue 5, pp. 1939-1965, 2020.

[3] Jackson, P.C. *Introduction to Artificial Intelligence,* Dover Publications, Mineola, ISBN 0486832864, 2019.

[4] Hamet, P., Tremblay, J. *Artificial Intelligence in Medicine,* Metabolism, Vol. 69, Supplement, pp. S36-S40, 2017.

[5] Barr, A., Feigenbaum, E.A. *The Handbook of Artificial Intelligence*, Vol. II, Heuristech Press, Stanford, 2014.

[6] Kacpryk, J., Pedrycz, W. *Springer Handbook of Computational Intelligence,* Springer, Heidelberg, ISBN 978-3-662-43504-5, 2015.

[7] Jordan, M.I., Mitchell, T.M. *Machine Learning: Trends, Perspectives, and Prospects,* Science, Vol. 349, Issue 6245, pp. 255-260, 2015.

[8] Goodfellow, I., Bengio, Y., Courville, A. *Deep Learning,* MIT Press, Cambridge, ISBN 9780262035613, 2016.

[9] Jabbar, H.K., Khan, R.Z. *Methods to Avoid Overfitting and Underfitting in Supervised Machine Learning (Comparative Study),* Computer Science, Communication & Instrumentation Devices, AET-2014, ISBN: 978-981-09-5247- 1, pp. 163-172, 2015.

[10] Belkin, M., Hsu, D., Ma, S., Mandal, S. *Reconciling Modern Machine Learning Practice and the Classical Bias-Variance Trade-off,* Proceedings of the National Academy of Sciences of the United States of America, Vol. 116, Issue 32, pp. 15849-15954, 2019.

[11] Gavrilov, A.D., Jordache, A., Vasdani, M., Deng, J. *Preventing Model Overfitting and Underfitting in Convolutional Neural Networks,* International Journal of Software Science and Computational Intelligence, Vol. 10, Issue 4, 10 pp., 2018.

[12] Briscoe, E., Feldman, J. *Conceptual Complexity and the Bias-Variance Trade-off,* Cognition, Vol. 118, Issue 1, pp. 2-16, 2011.

[13] Ilevbare, I.M., Probert, D., Phaal, R. *A Review of TRIZ and Its Benefits and Challenges in Practice,* Technovation, Vol. 33, pp. 30-37, 2013.

[14] Pokhrel, C., Cruz, C., Ramirez, Y., Kraslawski, A. *Adaptation of TRIZ Contradiction Matrix for Solving Problems in Process Engineering,* Chemical Engineering Research and Design, Vol. 103, pp. 3-10, 2015.

UTILIZAREA TRIZ PENTRU A MANIPULA SETURILE DE DATE MICI ÎN INTELIGENTĂ ARTIFICIALĂ

Rezumat: Diferiți algoritmi utilizați în prezent în inteligența artificială au nevoie de date multe pentru a antrena și a testa modelele astfel încât să asigure o acuratețe ridicată și generalitate a modelului și să evite așa-numita problemă de slabă adecvare. Cu toate acestea, nu toate aplicațiile practice au suficiente date în seturile acestora pentru a antrena şi testa astfel de modele. Aceasta este o provocare majoră pentru adoptarea algoritmilor tradiționali de învățare automată sau de învățare profundă în zonele în care procesele nu sunt adecvate pentru a colecta date multe. Există, de asemenea, cazuri în care nu sunt necesare date multe, dar datele puține fiind cele de interes. În astfel de cazuri, sunt necesari algoritmi noi de inteligență artificială pentru a proiecta modele care pot oferi soluții personalizate bazate pe seturi mici de date. Această lucrare evidențiază modul în care TRIZ poate fi utilizat pentru a formula unele strategii inventive pentru a gestiona aceste două categorii de probleme.

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