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Meta Learning challenges and Benefits

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Abstract: Learning as a process is very important aspect of growth in nature. Meta-learning in machine learning refers to learning algorithms that learn from other learning algorithms [7]. Meta-learning benefits all the machine learning systems from their repetitive application. But meta-learning differs a lot from the base-learning in the scope of the level of adaptation. It has its own benefits and challenges with gradual growth in its process towards evolution over the year. optimization-based formulation of meta-learning that learns to design an optimization algorithm automatically, which we call Learning to Optimize [8]. Understanding how it actually affects various sectors and making things simpler or difficult is a complex analysis of meta-learning in detail.

This paper best bit is the challenges lying in front of us to reach such goal and benefits to use for research. Meta-learning is one of the most vibrant regions of research in the profound learning space. A few ways of thinking inside the Artificial Intelligence(AI) people group buy in to the postulation that meta-learning is one of the venturing stones towards opening Artificial General Intelligence(AGI) [14].

Keywords: Meta-learning, Adaptive learning, learning to learn

I. INTRODUCTION

Meta-learning generally refers to the process of learning to learn where a top-level AI optimizes a bottom-level AI or several of them [5].

The reason behind Why Meta-learning? is that it makes the AI systems faster, more adaptable to changes in the environment and the most important artefact to understand and learn everything in the system.

Meta-learning at present includes multiple iterations and computations to discover new ways to handle different situations and process them accordingly to get the optimal solution or result for if there is any change in the environment.

Meta learning can be used for various machine learning models like reinforcement learning, natural language processing, etc. Meta learning algorithms make predictions by taking the outputs and metadata of machine learning algorithms as input. Meta learning algorithms can learn to use best predictions from machine learning algorithms to make better predictions. [10]

Companies like Google and Uber are currently using evolutionary computation algorithms like neuro evolutionary which is a part of meta-learning to understand and optimize the given data and parameters in the given environment.

Most commonly, this means the use of machine learning algorithms that learn how to best combine the predictions from other machine learning algorithms in the field of ensemble learning.

However, meta-learning might also mention to the manual practice of model selecting and algorithm regulation performed by a practitioner on a machine learning project that modern automl algorithms pursue to automate. [7]

Meta-learning studies how the hypothesis output by a learner can improve through experience. The goal is to understand how learning itself can become flexible according to the domain or task under study. Meta-learning differs from base-learning in the scope of the level of adaptation: meta-learning studies how to choose the right bias dynamically, as opposed to base-learning where the bias is fixed a priori, or user-parameterized [9].

II. OBJECTIVES

The main objective of this paper is to highlight the meta-learning benefits in various sectors with its use and the challenges, we face to put it into use for its purpose. The performance of any learning model depends on its training dataset, the algorithm and the parameters of the algorithm. After numerous ways of approach through meta-learning it becomes easier to optimize the number of experiments or predictions to reach a certain output.

Meta-learning algorithms learn from the output of other machine learning algorithms that learn from data. Meta-learning requires the presence of other learning

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algorithms that have already been trained on data. [7]
Despite the great success of machine learning, a clear gap between human and artificial intelligence is the ability to learn from small samples, e.g., learning to recognize objects from limited examples. Inspired by human's ability of learning to learn from experience, meta-learning [19] aims to transfer the generic experience learned from multiple tasks of limited data to efficiently complete new tasks.

III. LITERATURE

A meta-learning system is essentially composed of two parts. One part is concerned with the acquisition of meta knowledge from machine learning systems. The other part is concerned with the application of meta knowledge to new problems with the objective of identifying an optimal learning algorithm or technique.
After understanding a particular instance of algorithm, it is expected that meta-learning would faster the process of learning the new task because of its previous knowledge on the basis of using a similar approach and get close to the required output for that instance.
Meta-learning is often seen as a way of redefining the space of inductive hypotheses searched by the learning algorithm(s). This issue is related to the idea of search bias, that is, search factors that affect the definition or selection of inductive hypotheses. [1]
There has been recent interest in the optimization community in the problem of hyper parameter optimization, wherein one seeks a set of hyperparameters for a learning algorithm, usually with the goal of obtaining good generalization and consequently low loss. [2]
The application of machine learning systems to classification and regression tasks has become a standard, not only in research but also in commerce and industry. The most successful application is custom-designed, the result of skilful use of human expertise.
One of the ways is Metric learning which requires a measure of distance between two data points. This can be used to perform various tasks like KNN classification, Clustering, and Information retrieval. This model gives good results in few-shot classification tasks.
Another proposed algorithm in meta-learning is that, Model-agnostic. It is compatible with any model which is trained with gradient descent and applicable to a variety of different learning problems, including classification, regression, and reinforcement learning [3]. The goal of such meta-learning models has been to train a model on multiple tasks, such that it can find new learning techniques using fewer samples of data than previous experiments.
Recurrent neural networks are class/type of artificial neural networks and they are applied to different machine learning problems such as problems which have sequential data or time series data. RNN models are commonly used for language translation, speech recognition and handwriting recognition tasks. RNN's can learn important things from the received input because of their internal memory which makes prediction more efficient for this algorithm. During training, they use their own experiments as additional input data and observe their own errors to learn how to modify these experiments in response to the new task at hand. Thus, making it a preferable choice for sequential data like times series, speech, text, financial data, audio, video, weather and much more.

Stacking or Stacked Generalization being a subfield of ensemble learning is used in various meta-learning models [6]. It is seen as a way of combining multiple models that have been learned for different classified tasks. In this a combiner algorithm is used to combine all the predictions of these algorithms, which are known as ensemble members. It is even noted that a combiner algorithm is also put to use to make final predictions sometimes. Meta-learning is implemented by also learning the parameterization of the learners that adapt to each task. The goal is to find a set of parameters that work well across all of the different tasks so that the learners start with a bias that allows them to perform well despite receiving only a small amount of task-specific data. [11]
[17] Meta-learning is most commonly understood as learning to learn, which refers to the process of improving a learning algorithm over multiple learning episodes. In contrast, conventional ML improves model predictions over multiple data instances. During base learning, an inner (or lower/base) learning algorithm solves a task such as image classification [18].
A key challenge in scaling these approaches is the need to differentiate through the inner loop learning process, which can impose considerable computational and memory burdens. By drawing upon implicit differentiation, we develop the implicit MAML algorithm, which depends only on the solution to the inner level

optimization and not the path taken by the inner loop optimizer. [21]

Metal earning differs from base-learning in the scope of the level of adaptation; whereas learning at the base-level is focused on accumulating experience on a specific task (e.g., credit rating, medical diagnosis, mine-rock discrimination, fraud detection, etc.), learning at the meta level is concerned with accumulating experience on the performance of multiple applications of a learning system. [22]

In general, metal earning can recommend more than one algorithm. Typically, the number of recommended algorithms is significantly smaller than the number of all possible (available) algorithms [23]

IV. BENEFITS

The aim of this section is to show that meta knowledge can be useful in many different settings.

Higher model prediction accuracy:

- Enhancing learning algorithms: For example, optimizing hyperparameters to find best outcomes. Thus, this optimization task, which is generally done by a human, is done by a meta learning algorithm.
- Helping learning algorithms better familiarize to changes in conditions, categorizing clues to design better learning algorithms.
- A faster, cheaper training process, supporting learning from fewer examples, increase speed of learning processes by reducing necessary experiments
- Building more generalized models: learning to solve many tasks not only one task: meta learning does not focus on training one model on one specific dataset. [10]

Higher model prediction accuracy is one way it makes itself better than any present algorithm [4]. It makes optimization process of learning algorithms more efficient than a human study over the solution to an algorithm. Thus, reducing human effort it performs optimization of task, replacing human over a machine.

It is seen to providing a faster, cheaper training process [4]. This part is justified when we understand that its supports learning and finding solutions through an algorithm from fewer examples or observation.

The aim is even to build more generalized models [4]. It would make the process and task more efficient. This is on the basis that it would focus to help solve many tasks not only one task. Meta-learning does not focus on training one model on one specific dataset. Benefits of Meta learning are;

As metal earning profits from knowledge obtained while looking at data from other problem domains, having sufficient datasets at one's disposal is important. [13]

Users of predictive methods are handled with a hard choice of an ever increasing number of models and techniques. Metal earning can assist to ease the amount of experimentation by providing vibrant advice in form of assistants, decrease the time that has to be spent on introducing, tuning and maintaining models and help to promote machine learning outside of an academic environment. [14].

A lot of publications on metal earning focus on selecting the base-learning method that is most likely to perform well for a specific problem. Fewer publications like [15] and [16] consider ranking algorithms, which can be used to guide combination weights and to increase robustness of a metal earning system

V. CHALLENGES

This section would highlight the challenges that meta-learning persists with its existence. The amount of dataset is one the hurdle that meta-learning faces. The need is sometimes very high for the required datasets used for training and can be a major challenge for an algorithm.

As the data increases so the cost would also increase, and making this process not so cheap anymore. It then shows a high operational cost due to multiple number of experiments during the training phase itself. While implementation would have some more extra number of steps.

Users of predictive systems are faced with a difficult choice of an ever in- creasing number of models and techniques. Metal earning can help to reduce the amount of experimentation by providing dynamic advice in form of assistants, decrease the time that has to be spent on introducing, tuning and maintaining models and help to promote machine learning outside of an academic environment. [12].

If we find a growth in price due to increase in dataset, then it expected that time for an algorithm learning process would increase. Experiments would take longer time depending on the model to be used for the expected result to more accurate. Time here would also be dependent on the certain type of dataset that a particular algorithm requires.

Research in the area of metal earning is ongoing in several directions. One area is the identification of meta features. The vast majority of publications investigates extracting features from the dataset, mostly in the form of statistical or information theoretic measures. [12]
The biggest challenge of meta-learning is taking abstract "experience" and structuring it in a systemic, data-driven way. Depending on the type of meta-data employed a meta-learning model can be broadly put into three categories: learning from previous model evaluations, learning from task properties, and learning from the prior models themselves. [20]
Metal earning will be unable to exploit past knowledge to improve prediction performance. Performance estimation may be unreliable because of the natural limitations of estimating the true performance of the dataset. Different met features might be applicable to each dataset. These issues emphasise the importance of being critical when designing a metal earning system. [24]
Nevertheless, research in this area can still continue an extended way additional exploring continuous alteration, upgrading or disposal of base-learners with the help of metal earning approaches.
Metal earning would assist to cut the amount of research by providing dynamic advice in form of assistants, decrease the time that has to be spent on introducing, tuning and maintaining models and help to promote machine learning outside of an academic environment.

VI. CONCLUSION

Meta-learnings existence has been of a great importance and it cannot be ignored that it will be of great use to humans with its prolonging growth. The very purpose of this research was to highlights its presence with benefits and challenges that it persisted. Although meta-learning seems to be very in trend, utilizing these algorithms on real-life problems remains particularly challenging. With the continually advancing computational power, dedicated machine learning hardware, and advancements in meta-learning algorithms, these will likely become more reliable and trustworthy.
Meta-Learning has extended substantial attention from the scientific community, with a growing set of tools towards rapid learning, adaptation, few-shot learning, and other areas.

A lot of publications on metal earning focus on selecting the base-learning method that is most likely to perform well for a specific problem. Fewer publications. [25] and [26] consider ranking algorithms, which can be used to guide combination weights and to increase robustness of a metal earning system.

VII. REFERENCES

[1] Mitchell, T. (1997). Machine Learning, McGraw Hill
[2] Xu, L. and Hutter, F. and Hoos, H. and Leyton-Brown, K. (2008). Cross-Disciplinary Perspectives on Meta-Learning for Algorithm Selection. Journal of Artificial Intelligence Research, 32:565--606.
[3] Chelsea Finn, Pieter Abbel, Sergey: Proceedings of the 34th International Conference on Machin Learning
[4] https://research.aimultiple.com/meta-learning/
[5] https://towardsdatascience.com/meta-learning-learning-to-learn-a0365a6a44f0.
[6] David H. Wolpert. Stacked Generalization, Neural Networks, Vol. 5, pp. 241-259, Pergamon Press.
[7] What Is Meta-Learning in Machine Learning?
by Jason Brownlee on December 18, 2020 in Ensemble Learning.
[8] Meta-Learning: Why It's Hard and What We Can Do April 09, 2020, AFFILIATION, Member, School of Mathematics by Ke Li.
[9] Research Directions In Meta-Learning Ricardo Vilalta IBM T.J. Watson Research Center 30 Saw Mill River Rd., Hawthorne, NY., 10532 U.S.A. Youssef Drissi IBM T.J. Watson Research Center 30 Saw Mill River Rd., Hawthorne, NY., 10532 U.S.A. Proceedings of the International Conference on Artificial Intelligence, 2001.
[10] What is Meta Learning? Techniques, Benefits & Examples,(https://research.aimultiple.com/meta-learning/
[11] Doing more with less: meta-reasoning and meta-learning in humans and machines, Thomas L Griffiths1, Frederick Callaway, Michael B, Chang, Erin. Grant, Paul M Krueger1 and Falk Lieder.
[12] Learning How to Learn: Meta Learning Approach to Improve Deep Learning, Dr. Ashish Kr. Chakraverti, Sugandha Chakraverti, Dr. Yashpal Singh, Paper ID: IJERTCONV8IS10001, Volume & Issue: ENCADEMS – 2020 (Volume 8 – Issue 10), Published (First Online): 18-07-2020, ISSN (Online): 2278-0181.Publisher Name: IJERT
[13] Soares, C.: UCI++: Improved support for algorithm selection using datasetoids. In: T. Theeramunkong, B. Kijsirikul, N. Cercone, T.B. Ho (eds.) Advances in

Knowledge Discovery and Data Mining, Lecture Notes in Computer Science, vol. 5476, pp. 499–506. Springer Berlin Heidelberg (2009)

[14] Learning How to Learn: Meta Learning Approach to Improve Deep Learning, International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 Published by, www.ijert.org ENCADEMS - 2020 Conference Proceedings

[15]. Brazdil, P., Soares, C., de Costa, P.: Ranking learning algorithms: Using IBL and meta learning on accuracy and time results. Machine Learning 50(3), 251–277 (2003).

[16] Prudencio, R.B., Ludermir, T.B.: Meta-learning approaches to selecting time series mod- els. Neurocomputing 61, 121–137 (2004).

[17] Meta-Learning in Neural Networks: A Survey Timothy Hospedales, Antreas Antoniou, Paul Micaelli, Amos Storkey.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet Classification With Deep Convolutional Neural Networks,” in NeurIPS, 2012.

[19] Vanschoren, J. 2018. Meta-learning: A survey. arXiv preprint arXiv:1810.03548.

[20]. A Beginner’s Guide to Meta-Learning, Abacus.AI May 12, 2020. http://www.iaeng.org/IMECS2021/submission.html

[21] Meta-Learning with Implicit Gradients
Aravind Rajeswaran, Chelsea Finn, Sham Kakade, Sergey Levine Submitted on 10 Sep 2019].

[22] Pavel Brazdil, LIAAD-INESC Porto L.A./Faculdade de Economia, University of Porto, Portugal Ricardo Vilalta, Department of computer Science, University of Houston, USA Christophe Giraud-Carrier, Department of Computer Science, Brigham Young University, USA.

[23] Brazdil P., Giraud-Carrier, C., Soares, C. and Vilalta, R. (2009). Metalearning – Applications to Data Mining, Springer.

[24] Metalearning: a survey of trends and technologies Christiane Lemke, Marcin Budka & Bogdan Gabrys

[25] Brazdil P, Soares C, de Costa P (2003) Ranking learning algorithms: using IBL and meta-learning on accuracy and time results. Mach Learn 50(3):251–277.

[26] Prudencio RB, Ludermir TB (2004a) Meta-learning approaches to selecting time series models. Neurocomputing 61:121–137