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A Look at Top 35 Problems in the Computer Science Field for the Next Decade

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ABSTRACT: Due to rapid enhancement in technology, several problems have been raised in computer science (in the previous decade) like Class imbalance problem, duplicity of data in cloud, response of nodes in minimum time with high accuracy in Internet of Things (IoT) devices, deep optimization or use of Artificial intelligence or Machine learning in e-commerce, medical applications/ in agriculture to increase prediction with better accuracy (with reasonable price/ investment), etc. A new researcher belonging to computer science, faces several problems like finding or choosing/ selecting a problem before starting his/ her research work. But he/ she does not have enough material regarding to solve these problem (or selection of a feasible problem). Hence, this article solves this problem with a clear-cut solution, i.e., provide 35 problems/ problems related to 35 hot areas (i.e., to computer science field) to focus in near future with an idea/ explanation about each and every problem.

Keywords: Problems in Computer Science, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Code Optimization

1 DEEP LEARNING

Deep Learning (DL) is nothing but a (part) subset of Machine Learning. Deep learning is a class of models (works on neurons with the help of neural network) which is inspired from the neurons in our brain. DL plays a vital role in Artificial Intelligence (AI) like language translation, in playing computer games etc. It is an important area/ hot topic to do research now days. Some form of DL can be discussed as:

A. Deep Learning Optimisation

The Deep Neural Networks (DNN) can be regularised with the help of some methods like Whitening Neural Networks (WNN) and batch normalisation. The main bottleneck to apply whitening, is the computational practice of building covariance matrix and resolving Singular Value Decomposition (SVD). In [1], Ping Luo explained a new method known as "Generalised Whitening Neural Networks (GWNN)" which helps to reduce the computational overhead with improved representations. Further, Budden et al. in [2] proposed a method called "Winograd style faster computation" to overcome the limitations to implement higher dimensional kernels for ConvNets. Having benchmarked the algorithmic design against great and famous institutions like Caffe, TensorFlow, which support the AVX and Intel Math Kernel Library (Intel MKL) optimised libraries, they have concluded that the prime reason for ongoing CPU (Central Processing Unit) drawbacks are due to software rather than hardware. Extending the class of faster computations like Fast Fourier Transform (FFT), Winograd, etc., Cho et al. [3] proposed a computation named as Memory-Efficient Computation (MEC) which helps in reducing the memory requirement and improves the convolution process. Efficient computation is obtained on repeated tallying with Kernel Matrix Multiplication (KMM). Note that the rapid rise in number of feature maps leads to increased redundancy, thus leading to inefficient memory usage. Further, Wang et al. [4] proposed a method called "RedCNN" which preserves the intrinsic information to reduce the dimensionality of the feature maps and also try to reduce the correlation among feature maps.

Circulant matrix (a Toeplitz matrix, in which each row vector is rotated one element to the right relative to the preceding row vector) is what they used for tackling this issue as it gives rampant speed to trailing and mapping. In this, Correlation between gradients decreases very slowly with depth in the network. These shattering gradients can be found in feed forward networks, but, skip-connection networks can resist this. The authors in [4] introduced Looks Linear (LL) initialisation which helps in resolving the cataclysmic gradients in feed forward networks without the addition of any form of skip connections.

B. Applications of Deep Learning

Sleep patterns identification are very helpful in diagnosing the sleep and for the better medication. However, there are many approaches present for identifying the sleeping patterns. They make use of sensors which is attached to patient's body and for this hospital or lab is required. The main problem with the existing approach is that the experimental set up itself would make difficult for the patient to sleep. A team from Massachusetts Institute of Technology (MIT) (Mingmin Zhao et al. in [5]) has conducted a research on wireless Radio Frequency (RF) signals which helps to identify the sleeping patterns without using any sensors. They make use of a neural network CNN-RNN (Convolutional Neural Networks-Recurrent Neural Networks) which is a combination to identify the patterns for sleeping stage prediction. But, the main problem with the radio frequency signals are the effect of noise reflected from any sources nearby in the environment. Hence, the need of an adversarial training as this can very easily discard any unnecessary information which may be pertained to a particular individual but at the same time retains the information required to predict the sleeping stage. The existing result using hand crafted signal features are around 64% but using this method they achieved significantly good results which are approximately 80%.

The authors in [6] have not only presented their works on Deep Voice but have also put forth the five preliminary essentials consisting of phoneme conversion to audio synthesis with the help of a variant of Wavenet. The interesting fact to be noted is that the entire architecture is based on Neural Network (NN), and hence this system is more flexible than any existing system which is based on text to speech systems. Moreover this, in near future deep learning uses in following areas [34] like in Self-driving cars, Healthcare, Voice Search and Voice-Activated Assistants, Automatically Adding Sounds to Silent Movies, Automatic Machine Translation, Text Generation and Handwriting Generation., will change the future and will make user's life convenient and easy to live.

In continuation to this article, now each (further) section will discuss an area and its related problems for requiring attention from research communities in near future.

2 REINFORCEMENT LEARNING

Reinforcement Learning (RL) involves "learning the way a human being learns." This necessitates and calls for an agent who converses with the environment so passionately to obtain a numeric pay with a set goal of learning sequential actions to optimize his long term pay. As human beings, we also learn from the experience as with the RL agents who work on the very same proposition to increase his own pay in the long term. With the help of RL a computer program of Google's Alpha Go beats the world championship in 2017. After many decades of limited visibility (with a notable exception) in the past decade, reinforcement learning has come to the foreground of AI, also being at the core of unhoped for breakthroughs. Based on the simple principles of trial-and-error, reinforcement learning systems are able to self-learn "how to successfully solve tasks, without the need for a wealth of labelled data".

A. Reinforcement Learning and its Real World's Applications

The environment in which the agent sustained it may have benefits as well as some limitations and to overcome from its limitations user has to follow some constraints. Recently, a project titled Constrained Policy Optimisation (CPO) discussed in [7] put forward by a team from Berkeley AI Research (BAIR), has presented on the constraints motivated by safety for policy search and for this BAIR has published an article on CPO illustrating and elucidating their work on it. Further, McGlashan et al. [8] has propositioned an algorithm "Convergent Actor-Critic by Humans (COACH)", it is for trained the agents according to the feedback provided by non-technical users. The authors of [8] have rightly defined "how seem less and helpful it is for the COACH to learn a number of behaviours on a manual robot involving noisy images".

If RL agents want to perform some household activities, then they need a large no of sequence of instructions and further they need to generalise them for new subtasks. Sometimes, unexpected instructions like battery low etc., may occur and then it requires a deviation to complete the left subtasks. To overcome these hurdles, Oh et al. [9] had introduced a novel perspective collects the sequential tasks in its natural language and accomplishes them in an ordered fashion. He tried to solve the issue in few steps: a) a generalisation framework based on analogy and to learn the skills to perform the sub tasks. b) A meta-controller to predict the orderly fulfilment of minor tasks. The highly notable framework tendered by Andreas et al. [10] talks about learning in depth about sub policies related to a multitask setting. The algorithm is indeed led by the intangible sketches of superior behaviour. As we know, reinforcement learning means learning from its feedback (without intervention of human). Similarly, we human beings also learn from the experience as with the RL agents who work on the very same proposition to increase his/ her own pay/ salary in the long term.

3 MACHINE LEARNING FOR DATA MINING

Data mining is the study of data with the purpose of identifying patterns and relationships. We need to handle different types Machine Learning techniques for Data Modelling and Mining. Also, we need to focus on the interplay between black and white-box techniques focusing on explain ability. On the other hand, Machine Learning (ML) is the field of developing algorithms that can learn and automate nontrivial tasks. For example, ML recommender systems, medical diagnosis, image segmentation, face recognition, fraud detection, sentiment analysis, and many more. We need to develop algorithms that should be applicable on some real-world problems like where the users and computers actively collaborate for more accurate, reliable, and faster decision making. Whereas for most problems, users are more accurate but slower and machines are faster but less accurate. We need to develop such systems that combine the accuracy of humans with the speed of machines through interactive and intelligent algorithms. Applications include computers and human collaborating to detect and identify people in large volumes of surveillance video, diagnose patients more accurately, detect fraud in hundreds of thousands of tax records, etc. In near future, artificial intelligence and Blockchain technology (in integration) will solve problem of weak security and frauds (with identifying attacks on network/ records via analysing, i.e., in minimum time). Also, we need researchers (in future) to focus on decision trees and Support Vector Machines (SVMs), to the modern version of neural networks and deep learning.

4 MACHINE LEARNING OPTIMIZATIONS

Recently, Microsoft research India came with the highly powerful tree-based models. With the use of these models, it can run machine learning with very less use of RAM (<2kb). It can also come up with the problem of classification with the use of Gradient Boosted Decision Trees. The occurrence of a highly dimensional and sparse output from the multilabel classification may adhere to agonisation from memory issues and long run times. Si et al. [11], in the proposed GBDT-Sparse algorithm, has elucidated on how high dimensional sparse data can be handled and how one can achieve apt prediction time with a reduced model size.

A. Class imbalance problem

The main cause of this problem in machine learning is due to the presence of a humongous number of classes of positive data and less number of another class of negative data [12]. It is a common practice to observe that most of these algorithms work efficiently when the number of instances of each class is equal in nature. The variety of fields including detection of fraud, oil spillage and anomalies, diagnosis in the medical sector, facial recognition, etc. have a higher chance of susceptance to class imbalance problems. Degree of data overlapping among the classes causes another problem known as small disjuncts problem. Also, data duplication in classifiers/ database is also a problem to focus. Finding a good relation between class imbalance and training set size is also itself a problem. The occurrence of a highly dimensional and sparse output from the multi-label classification (a generalization of multiclass classification) may adhere to agonisation from memory issues and long run times. A necessary explanation about this popular problem has been discussed in [35, 36] with a detailed comparative and Graphical analysis.

5 ROBOTICS

Robotics has a separate branch, but in some cases, it overlaps with Artificial Intelligence. With the help of AI, navigation in the dynamic environment in Robots is possible. Advances in Deep Learning (DL), Reinforcement Learning (RL) will have answered for such type of questions in the area of Robotics. Researchers are invited to do their research work in the field of Robotics (need to work) for betterment of humanity.

6 NATURAL LANGUAGE PROCESSING

With its unique capabilities to see, comprehend and communicate in the language common to all human life, Natural Language Processing (NLP) consists of a great many sub tasks consisting of speech recognition, generation and translation. The existence of a plethora of languages across the globe is one of the key reasons for the ultimate success of these systems. For example, we need system to understand the language/ sign of disabled people (which is highly essential for betterment for humanity/ human lives). Development of chat bots (dynamically interacting in nature with humans), identification of sign boards (over the road), etc., are some current research topic in this field.

A. Machine Translation

If a machine can understand the text properly, it can perform accurate translation. A machine must have the audacity to obey its master, so as to obtain the ability for logical reasoning. Apart from this, it must have an in-depth knowledge to grasp whatever is being discussed, i.e., it should always be comfortable with any predictable practicalities that a common human interpreter may understand. A part of the learning is accessible explicitly, but majority of the information is accessible as unconscious and is firmly attached to the human body. For example, the machine may need to get data on “how an ocean makes one feel” to accurately translate a specific metaphor in the text. The thought behind this is to imitate the author’s intentions, desired tasks, and emotional well-being to rightly replicate them into a brand-new language. To break it down, the machine calls for a plethora of human cognitive skills, including reasoning abilities, sound common sense and the perception that underlie motion, manipulation, insight and social intelligence. In summary, machine translation is believed to be AI-complete, i.e., it might require solid AI to do function as people can do it.

7 RECOMMENDER SYSTEMS

Recommender Systems (RS) can be seen everywhere like what we have to purchase, what we require or where we have to go. They have completely replaced the annoying salesperson in this virtual world. Various organisations like Netflix, Amazon, Flipkart, Alibaba, and many more heavily rely on Recommendation System. A recommendation system considers a user’s past choices, preferences of its peers and trends for making an effective recommendation. This area is also a hot topic to build trust in customers or creating efficient recommendation algorithms for e-commerce/ organisations

8 ALGORITHMIC GAME THEORY AND COMPUTATIONAL MECHANISM DESIGN

The collaboration and cooperation of skilled and learned agents from the different fields including economics and scientific perspective leads to the emergence of Algorithmic Game Theory. It basically provides an overview of the agents based on the choices they make supported by various incentives to keep them motivated and encouraged. This system includes human members who are self-motivated and keenly interested to work along with other agents with limited resources. Note that a Multi-Agent System (MAS or “self-organized system:) is a loosely held network of software agents/computerized system indulged in by various interacting intelligent agents who link with each other to tackle problems which are way ahead of the individual capacities or knowledge of each problem solver [13, 14].

9 INTERNET OF THINGS

Internet of Things (IoT) mainly refers to the interconnectivity of substances which is extensively used in physical and manual devices which are very often linked to the internet and facilitates the exchange of data and other details. Further, the collected data is processed in such a way that it could make the device smarter. Devices connected in IoT are generating (everyday) a huge data (called Big Data). This data can be useful for prediction or find patterns for solving several problems raised now days, for example, consumption of energy, utilization of resources, etc. Security and Privacy issues [37] are popular problems in IoTs to solve, i.e., require attention from researchers in near future.

10 NEUROMORPHIC COMPUTING

The emphasise and rapid growth in Deep Learning motivate and boost the research scholars to develop hardware chips and boards, directly giving birth to neuromorphic computing. In the primitive stages, these tiny boards used to carry all the necessary details to be transferred from CPU and storage blocks consuming a lot of time as well as energy. However, in the modern advancement, the data is very safely and accurately stored in its analogue form, thus generating synapses as and when required.

11 STATISTICAL PREDICATE INVENTION

Coming to statistical learning Predicate invention in Inductive Logic Programming (ILP) and hidden variable discovery are its consequences causing a hectic trouble to the researchers and yet predicate invention is a necessity for the learning purpose in the 21st century. The best example is to consider the words in a dictionary which are invented predicates, indulging in different layers of complications between it and the physical comprehension on which it is based. However, the progress in this field is highly restricted. The tough nature of this problem is considered to be at an extremely higher level, but new breakthroughs can be attained by the incorporation of predicate invention and latent variable discovery into a single problem of statistical predicate.

12 GENERALIZING ACROSS DOMAINS

"The generalization of responsibilities from the same field" is what defines Machine Learning and in the golden ages, we were able to dwell deep into this field as well. The main difference between authentic machine learners and mundane is with respect to the issue of generalisation. Considering an example, Wall Street brings in a large number of physicists for predicting the stock market and this is where the harsh truth breaks in: Machine learners can not do work based on prediction. A point to be kept in mind is that the domains being described by the predicates must be related to each other or else the learner would not find it fruitful. Consider the situation we all know; a mathematician can predict something with the help of probability and simultaneously cope up with problem related to computer science. The major point of understanding here is that most of the domains have structural similarities which can be easily identified and exploited. For example, two domains may be depicted by the equivalent formula (s) however with various predicates. So, it can be easily rediscovered in one domain if we learned the same formula in another domain. This appears to be perfect challenge for relational learning, since in some sense its "extreme relational learning": We must realize that simple, straight forward relations are not the ones being used for generalisation. Rather we use relations embedded in relations. Even though Defence Advanced Research Projects Agency (DARPA) has recently started a project in this field, so far, they have only scratched the surface.

13 LEARNING MANY LEVELS OF STRUCTURE

The use of statistical Relational Learning (SRL) is exploited completely in the field of structured inputs and outputs rather than in the field of structured internal representations.

The two tiers of structures involved in this field are Inductive Logic Programming (ILP) and statistical learning. Consider this case, the kernel and the linear combinations are the two strata in Support Vector Machines (SVMs) and this is a case common in IL. Though two layered structures are efficient to put forth any function of liking, they are not the best of ways to embody majority of them. Multi-tiered reusable structures help in acquiring more compact representation. Consider this example, clausal form requires an exponential number of operations to represent the parity but Boolean Decision Diagram (BDD) can achieve the same with a linear number of operations. This compactness is very helpful for learning, but the outreach it has obtained amongst the people is very less.

In spite of the presence of numerous layers of neurons in the brain, backpropagation may not necessarily work efficiently with everyone. Learning of "deep networks" established by Hinton and a few others were in vain as they were unable to do so in depth as it was available only for unstructured data. Details like dates, numbers, facts, etc., are certain things that do not have a pre-set data prototype or an organised form of data collection and multimedia content (videos, photos, audio files), e-mail messages, webpages [15, 16]. Recursive random fields, proposed in [17] are a potentially "deep" SRL representation, but main disadvantage of this is back-propagation which calls for the necessity of more attention and development in this area.

14 DEEP COMBINATION OF LEARNING AND INFERENCE

Structured learning seems to be incomplete without inference. However, research on this is genuinely isolated till date. This leads to the production of a compelling situation wherein we can spend lots of data and CPU time on adapting to different models. The core value to be inculcated is that learners are to be biased while inference is to be highly efficient which results in efficient inference being biased. To get well acquainted with the superior models, planning and modelling needs to be done right from rock bottom provided that the inference over them is exponentially productive (in practice). For example in [18], "Naive Bayes Models for Probability Estimation", the models surveyed by them were extremely precise as Bayesian networks, however the inference was always linear with time instead of being exponential. Due to the precedence of SRL, they need to be learned and comprehended considering it to be our goal and target destination.

15 LEARNING TO MAP BETWEEN REPRESENTATIONS

Structured Learning is affected to a greater extent in the case of representation mapping. Resolution of entity (matching of objects), predicate matching, and matching of concepts are the three major problems in this arena. It is extremely easy to solve each of these problems individually but the herculean task is to be solving them in its combined form when they are all merged together. This is the key reason why a majority of the organisations exhaust their IT budgets quickly and also paves way to the lack of development of "automated web" (Web Services, Semantic Web, etc.). This is also the best concern for joint interference, i.e., the equivalence of two fields will gradually result in the equivalence of ideas and points respectively. Due to these reasons, the learning part becomes similar to that of SRL (i.e., it becomes a "killer app"). Conversion of a problem representation from one logical sense to another is another herculean task. Humans have the talent of recognizing the presence of two sets proving the same thing though they may not be logically equivalent and hence it is the need of the hour for AI systems to be performing the same.

16 LEARNING IN THE LARGE

Structured learning is quite easy to handle when it comes to larger fields. But most of us spend quality time in solving the micro-problems (e.g., identifying promoter regions in DNA); and it is high time we shifted to macro-problems (e.g., modelling the entire metabolic network in a cell).

Gaining in depth knowledge about large sized data sets have varying dimensions like: learning about those fields and domains with interdisciplinary approaches; learning more about data and analysing it; replacing the age-old pipeline structure and design with joint inference and learning; learning models with trillions of parameters and knowing more about those which are continuous and involve open ended learning, etc.

17 STRUCTURED PREDICTION WITH INTRACTABLE INFERENCE

Max-margin training of the structured models is similar to Hidden Markov Model (HMM) and Probabilistic Context-Free Grammars (PCFGs) which has become very popular in recent years. One of its appealing features is that if the inference is tractable, learning is also tractable (easy to deal with). This contrasts with the maximum likelihood (the chance that something will happen or almost certainly) and Bayesian methods (which remain intractable). But the fact is that most interesting AI problems involve intractable inference. This leads to following questions like "how can we optimize margins with approximate inference value"? "How do the approximate inference and the optimizer interact with each other"? To make the algorithm robust, can we use the existing optimization algorithm, or do we need to develop new ones? The answer to all these questions is yet to be found out if max-margin methods are to break out of the steep and mild range of structures.

18 REINFORCEMENT LEARNING WITH STRUCTURED TIME

The well - known Markov assumption can be adopted to control the complexity of a series of decisive problems (in which utility depends on a sequence of decisions) but it is also a constraint in disguise. In practicality, each of the systems do have a memory cache and because of the balance in interactions, some seem to look fast while others may appear slow and long and may tend to showcase uneventful periods in alternation with bursts of activity. We not only need to learn scales simultaneously but also with a rich structure of events and durations. Though this may make the system sophisticated by a notch, it helps in making Reinforcement Learning (RL) much better. At stiffer scales, the incentives obtained are highly instantaneous and RL can be easily executed but at smoother and finer scales, rewards may seem too far away in spite of an increased speed of learning.

19 EXPANDING STATISTICAL RELATIONAL LEARNING TO STATISTICAL RELATIONAL ARTIFICIAL INTELLIGENCE

Fields of Artificial Intelligence (AI) should be looked into with great vigour as they are similar areas having a higher scope for research and development. For example, even though they have logical and statistical approaches to give solution, they solve only a portion of the problem, and what is actually expected is a blend of both the worlds. This milestone can be achieved by applying learning to a larger and complete AI system. The best example is that of natural language processing which can be easily divided into a number of subtasks. Up until now, the very approach towards learning was solving each issue individually in a single-handed manner ignoring their interactive nature. Hence, the need to resolve this problem arises (i.e., including interaction among sub task). Robotics and Computer vision can also make use of this perception. In our work we must avoid falling into local optima: once a problem is solved "80/20", we should concentrate on the consecutive bigger one and must not proceed with the older answer just to refine our answer with an adequate one. Generally, we try to do the latter, but this greatly slows down the progress of research. Moreover, the solutions which seem to be best for solving sub-problems in isolation may not be the best ones in combination. Due to this reason, refinement of answers for the inferior issues may tend to be counter-productive, i.e., digging further into the complication instead of jumping out of it.

20 LEARNING TO DEBUG PROGRAMS

Machine Learning spreads its wings across a variety of domains of computer science including networking, software engineering, databases, architecture, graphics etc.

This is indeed a good sign as we can cultivate a number of problems to drill the field forward. However, there is one area that needs a serious break-through and it is automated debugging. Being highly time consuming in nature, it is considered to be one of the best applications of Inductive Logic Programming (ILP). Researchers constantly face the constraint of unavailability of data. However, in the 21st century, Internet seems to pave way for rescue supported by mass collaboration. Every time a programmer fixes a bug, a piece of training data is generated and if these could be simultaneously stored in a repository (which is centrally controlled), it can further act a training data sets for new types of bugs and errors. Of course, learning to change problems with bugs into bug-free data is a herculean task, but it is also highly structured, noise-free, and the grammar is known. So, this also may be a “killer app” for structured learning.

21 COMPUTATIONAL BIOLOGY

The only place where you can observe a blend of development and application of data-analytics and theoretical ways is Computational Biology. Mathematical analysis and computational simulation techniques are the key tools used for studying the biological, behavioural and social systems. Identification and analysis of the information processing capacity of proteins, analyses of chronic diseases like Chronic Myeloid Leukaemia (CML) with the help of a mathematical model of the hematopoietic system and assisting public health officials on mitigation of infectious diseases (influenza, HIV etc.) through the study of epidemiological models are some of the hot topics for future research.

22 COMPUTATIONAL CREATIVITY

Computational Creativity (CC) is the workmanship, science, reasoning and building of computational frameworks which, by taking on specific responsibilities, exhibit behaviours that unbiased observer consider to be creative. This area really required a break-through in formalizing what it implies for programming to be innovative, along with the different energizing and important utilizations of inventive programming in sciences, expressions, writing, gaming and other areas.

23 COMPUTER VISION AND DEEP LEARNING

Deep Learning falls under the umbrella of data representations and follows a structured approach to extract useful information from data. We need to be interested in deep learning which applied to computer vision, mainly the problems of classification, localization, segmentation and 3D models. Also, research from satellite imagery and hyper-spectral un-mixing, to computational fluid dynamics is a major area to focus.

24 EVOLUTIONARY LINGUISTICS

An intensive research can help us identify the plethora of ways in which artificial agents can self-organise their languages in comparison with properties similar to that of natural language and how the meaning can be evolved. Our investigation would serve the best when hypothesised as the languages are a complex ad versatile framework formed through the adaptive linkages between the operators. We also need to investigate this theory by implementing the full cycle of speaker and listener as they play arranged language games and watching the qualities of the languages that emerge.

25 GAME THEORY

Game theory is the study of circumstances among competing, or cooperative, operator, it can be human being or machines. It is the study of methodology and ideal basic leadership in a key setting. We need to focus on “how machine learning techniques can be used to determine” and “what kind of strategies people use to make their decisions”.

Also, researcher needs to make use of time response distributions to determine which actions are intuitive and which deliberate. In summary, our aim is to understand “how humans perceive and forecast risk and uncertainty on those scenarios”.

26 LEARNING IN MULTI-AGENT SYSTEMS

Telecommunications, economics, traffic simulation, electricity smart grids are all the examples of systems in which decentralisation of data and the distribution of control is either required or already exist inherently. All of these areas need attention from research communities to do research is in respective areas.

27 PREFERENCE HANDLING

Wherein humans interact among themselves (in different situations) or through technologies in hybrid socio-technical systems, resemble social dilemmas, i.e., situations where participants have to select between short-term personal profits and long-term social benefits. The behavioural outcome in those dilemmas is very much dependent on “how successful the participants are in calculating the risk associated to the uncertainty of future rewards and on anticipating the opponents’ choices”.

28 META LEARNING

The concept of Model Agnostic Meta Learning (MAML) was proposed by Finn et al. [19]. With the required help from a variety of parameters, a random sampling over well dispersed duties are performed, and a sample is created. With the help of some training samples and iterations, this model can easily adapt the new tasks. Cortes et al. [20] suggested the method of “AdaNet” which learns the network architecture with the knowledge of the network structure and weights. The new network’s k^{th} layer is connected to existing network’s k^{th} and $k\text{-}1^{th}$ layers. Wichrowska et al. [21] had put forth an able gradient descent optimiser which can speculate to the newly developed tasks with decreased memory size and calibration requirements. They used a hierarchical Recurrent Neural Networks (RNN) architecture in defining the optimiser and it outperformed Adam on Modified National Institute of Standards and Technology (MNIST - a large database of handwritten digits) dataset.

29 SEQUENTIAL MODELING

In daily life we ponder upon a number of sequences like phrases in a group of letters while identifying phonotactic rules, but the segmented structure is a native pattern that comes about. Wang et al. [22] introduced a sequence modelling approach with segmentation. The popular implementation from Facebook AI Research (FAIR) of using the Convolutions for Sequence to Sequence learning [23] is also an emerging/prime field to do research work. In [23], authors created hierarchical structures using multilayer convolutions along with which they have explained more about gated linear units, residual connections and attention in every decoder layer. Later in [24], Bamler et al. discussed the temporal evolutions of word embedding (i.e., in paper “Dynamic Word Embeddings”).

30 GENERATIVE MODELS APPLICATIONS

In [25], people from Google Brain presented an idea of “audio synthesis using Wavenet auto encoders”. On observation, they realised that Wavenet auto encoder architecture includes a temporal encoder being built over dilute convolutions, thus instilling a sequential hidden code with differentiated dimensions for time and channel. NSynth dataset, also introduced by them, contains an approximate of 300k annotated musical notes from an approximate of 1k instruments. Long Short-Term Memory and Recurrent neural networks are quite comparable as it calls for the need of parameters to model huge data because of which it is highly inaccessible. But other models like LDA can bring about data in a highly interpretable form while compensating and sacrificing their performance level.

Zaheer et al. [26] proposed a Latent LSTM Allocation (LLA) approach for condemning this issue by combining hierarchical bayesian models with LSTMs. The image compression algorithm introduced by Rippel and Bourdev [27] used Generative Adversarial Networks (GANs) instead of autoencoders. This solution has a number of fields like pyramidal decomposition encoder capable of extracting the image features at various scale values which are then broken up into equally sized value quantisation, arithmetic coding and regularization succeeded by the reconstruction of adversarial training.

31 NATURAL LANGUAGE GENERATION ARCHITECTURES

The problem of discriminative models for native language text production is a common problem faced by all. To overcome this challenging hurdle, Wen et al proposed a Latent Intention Dialogue Model for apprehending the main aim of using the latent variable which further comprises of an apt machine response. The soul idea of this paper is to represent the latent intention distribution as an innate policy, reflecting human verdicts which can be grasped using policy gradient-based reinforcement comprehension. Hu et al. [28] proposed a wonderful perspective to the natural language generation using latent semantic structure. Variational Autoencoders (VAEs) have the capability to bring about text samples which are conditioned on latent featured codes. These codes are then invoked with the help of individual discriminator for each portion of it which helps in comparing and matching the samples between the created and the desired attributes using SoftMax approximation.

32 EFFICIENT ONLINE LEARNING

For the online multi-class bandit algorithms, the older works of Banditron, though was computationally effective, was able to achieve only O ($T^{2/3}$) expected regret. This was considered to be a flagrant act as the Exp4 algorithm achieves O ($T^{1/2}$) regrets for the 0–1 loss. Beygelzimer et al. [29] had suggested a streamlined and effective online bandit multi class learning with O ($T^{1/2}$) regret. The judgement of contextual multi-armed bandits poses a threat as the online judgment is heavily priced to evaluate the various policies while the off-policy judgment measures are prone to variance in estimations and calculations. Other available measures like Inverse Propensity Score (IPS) (which gives accurate estimations on the Mean Squared Error (MSE)) do not take into account the context details while choosing the action. Wang et al. [30] proposed an algorithm SWITCH which very efficaciously uses the Reward model and IPS, hence leading to variance reduction in comparison to the prior works.

33 GRAPH BASED ALGORITHMS

There are so many ways and existing methods to generate the information graphs from the data. Trivedi et al. [31] has stated that the knowledge graphs and statistics evolve temporarily as they have nurtured a multidimensional process to prototype the graph. Maystre et al. [32] has proposed an iterative algorithm named ChoiceRank, which can learn edge transition probabilities by observing only node-level traffic.

34 SOFTWARE BRITTLENESS

The meek and mere versions of AI-complete problems can be solved with the currently used, highly advanced AI systems. When the AI researchers try to innovate and bring about advanced changes in their machines and systems to adapt to complex real world problems and cases, the programs often tend to be brittle due to lack of powerful apprehension of the current status. They find it completely unusual to tackle problem which come from out of the provided material or portion. Humans gain a great deal each time they face and deal with new situations as they have a better view of the things surrounding them and the sole purpose of their existence. They have the superior talent of identifying unexpected possibilities and adapt accordingly. A machine without strong AI has no other skills to fall back on.

35 FORMALIZATION

Computational complexity theory is very well associated with the relative computational difficulty of computable functions and yet it does not help in covering problems whose solutions are yet to be known. Since most of the issues related to AI are not accompanied by formalisation conventional complexity theory does not define AI-completeness. A complexity theory for AI has been proposed in [33] to address the above-mentioned problem in which there is an equal division of computational process between the computer and a human, i.e., one portion of it is done by the computer while the other bit is performed by the humans. This is formalised by a human-assisted Turing machine. The formalisation defines the complexity of the algorithm, problem complexity and reducibility which in turn allow the equivalence classes to be defined.

CONCLUSION

Today's selecting or finding a problem is always a tough task for doing any research work. New Researchers have to face this problem multiple times, in result, they feel that problems are not properly explained/ cleared to choose, or not interested in respective problems. So, keeping this thing in our mind, we solve this problem via providing maximum problems, i.e., 35 problems related to hot areas (with respect to computer science field) with easy explanation. Hence, we invite all researchers who are willing to work in near future/ working in current (in computer science field) are kindly invited to do their work according to their interests/ areas (in selection of any problem from given above).

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REFERENCES

[1] Ping Luo, Learning Deep Architectures via Generalized Whitened Neural Networks, Proceedings of the 34th International Conference on Machine Learning (ICML), Sydney, Australia, PMLR 70, 2017.
[2] David Budden, Alexander Matveev, Shibani Santurkar, Shraman Ray Chaudhuri, Nir Shavit, Deep Tensor Convolution on Multicores, Proceedings of the 34thICML, Sydney, Australia, PMLR 70, 2017.
[3] Minsik Cho, Daniel Brand, MEC: Memory-efficient Convolution for Deep Neural Network, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[4] Yunhe Wang, Chang Xu, Chao Xu, Dacheng Tao, Beyond Filters: Compact Feature Map for Portable Deep Model, Proceedings of the 34thICML, Sydney, Australia, PMLR 70, 2017.
[5] Mingmin Zhao, Shichao Yue, Dina Katabi, Tommi S. Jaakkola, Matt T. Bianchi, Learning Sleep Stages from Radio Signals: A Conditional Adversarial Architecture, Proceedings of the 34thICML, Sydney, Australia, PMLR 70, 2017.
[6] Sercan O¨. Arık, et al. Deep Voice: Real-time Neural Text-to-Speech, Submitted February 24, 2017 for review for 34th International Conference on Machine Learning (ICML), 2017.
[7] Joshua Achiam, David Held, Aviv Tamar, Pieter Abbeel, Constrained Policy Optimization, Accepted to ICML 2017.
[8] James MacGlashan, Mark K Ho, Robert Loftin, Bei Peng, David Roberts, Matthew E. Taylor, Michael L. Littman, Interactive Learning from Policy-Dependent Human Feedback, ICML 2017, arXiv:1701.06049.
[9] Junhyuk Oh, Satinder Singh, Honglak Lee, Pushmeet Kohli, Zero-Shot Task Generalization with Multi-Task Deep Reinforcement Learning, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[10] Jacob Andreas, Dan Klein, Sergey Levine, Modular Multitask Reinforcement Learning with Policy Sketches, Proceedings of the34thICML, Sydney, Australia, PMLR 70, 2017.
[11] Si Si, Huan Zhang, S. SathiyaKeerthi, DhruvMahajan, Inderjit S. Dhillon, Cho-Jui Hsieh, Gradient Boosted Decision Trees for High Dimensional Sparse Output, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[12] G. Rekha, Amit Kumar Tyagi, et al. A Novel Approach to Solve Class Imbalance Problem Using Noise Filter Method, ISDA, 2018.
[13] https://www.igi-global.com/dictionary/using-multi-agent-systems-support/19363
[14] https://en.wikipedia.org/wiki/Multi-agent_system
[15] https://en.wikipedia.org/wiki/Unstructured_data
[16] https://www.webopedia.com/TERM/U/unstructured_data.html
[17] Daniel Lowd et al., Recursive Random Fields, Proceedings of the 20thInternational Joint Conference on Artificial Intelligence, pp. 950-955, Hyderabad, India: AAAI Press, 2007.

[18] Daniel Lowd et al.,Naive Bayes Models for Probability Estimation, Proceedings of the 22nd International Conference on Machine Learning, pp. 529-536, 2005. Bonn, Germany: ACM Press.
[19] Chelsea Finn, Pieter Abbeel, Sergey Levine, Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[20] Corinna Cortes, Xavi Gonzalvo, VitalyKuznetsov, MehryarMohri, Scott Yang, AdaNet: Adaptive Structural Learning of Artificial Neural Networks, arXiv:1607.01097
[21] Olga Wichrowska, NiruMaheswaranathan, Matthew W. Hoffman, Sergio Gomez Colmenarejo, MishaDenil, Nando deFreitas, JaschaSohl-Dickstein, Learned Optimizers that Scale and Generalize, ICML 2017, arXiv:1703.04813.
[22] 22. ChongWang, Yining Wang, Po-Sen Huang,Abdelrahman Mohamed,Dengyong Zhou, Li Deng, Sequence Modeling via Segmentations, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[23] Jonas Gehring, Convolutional Sequence to Sequence Learning, ICML, 2017. arXiv:1705.03122v3.
[24] Robert Bamler, Stephan Mandt, Dynamic Word Embeddings, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[25] Jesse Engel,CinjonResnick, Adam Roberts, Sander Dieleman, Douglas Eck, Karen Simonyan, Mohammad Norouzi, Neural Audio Synthesis of Musical Noteswith WaveNetAutoencoders, arXiv:1704.01279v1
[26] Manzil Zaheer, Amr Ahmed, Alexander J Smola, Latent LSTM AllocationJoint Clustering and Non-Linear Dynamic Modeling of Sequential Data, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[27] Oren Rippel, LubomirBourdev, Real-Time Adaptive Image Compression, Proceedings of the 34th ICML, Sydney, Australia, 2017. JMLR: W&CP.
[28] Zhiting Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, Eric P. Xing, Toward Controlled Generation of Text, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[29] Alina Beygelzimer, Francesco Orabona, Chicheng Zhang, Efficient Online Bandit Multiclass Learning with $\tilde{O}(\sqrt{T})$ Regret Proceedings of the 34th International Conference on Machine Learning, Sydney, Australia, PMLR 70, 2017.
[30] Yu-Xiang Wang, Alekh Agarwal, Miroslav Dudik, Optimal and Adaptive Off-policy Evaluation in Contextual Bandits, arXiv: 1612.01205.
[31] Rakshit Trivedi, Hanjun Dai, Yichen Wang, Le Song, Know-Evolve: Deep Temporal Reasoning for Dynamic Knowledge Graphs, Proceedings of the 34th ICML, Sydney, Australia, PMLR 70, 2017.
[32] Lucas Maystre, Matthias Grossglauser, ChoiceRank: Identifying Preferences from Node Traffic in Networks, ICML 2017, arXiv:1610.06525.
[33] DafnaShahaf and Eyal Amir, Towards a theory of AI completeness. Commonsense, 8th International Symposium on Logical Formalizations of Common sense Reasoning, 2007.
[34] Amit Kumar Tyagi, Rekha, “Challenges of Applying Deep Learning in Real-World Applications”, Book- Challenges and Applications for Implementing Machine Learning in Computer Vision, IGI Global, 2020.
[35] Gillala Rekha et al. / Journal of Computer Science 2019, 15 (7): 886.929.
[36] G Rekha, Amit Kumar Tyagi, “Necessary Information to Know to Solve Class Imbalance Problem: From a User’s. Perspective”, ICRIC 2019, March 2019.
[37] Tyagi A.K., Rekha G., Sreenath N. (2020) Beyond the Hype: Internet of Things Concepts, Security and Privacy Concerns. In: Satapathy S., Raju K., Shyamala K., Krishna D., Favorskaya M. (eds) Advances in Decision Sciences, Image Processing, Security and Computer Vision. ICETE 2019. Learning and Analytics in Intelligent Systems, Vol 3. Springer, Cham.