



Cross-Stitch Multi Task Feature Learning For Resource Allocation in IOT

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Abstract

Growth in network technologies has led the world towards the era of disruptive technologies like IOT, Machine Learning etc. With growing technology like IOT, the generation of data and devices are increasing tremendously. So resource allocation problem in such environment has become a major research area. There are many existing machine learning and deep learning solutions for resource allocation problem but these models are trained for



specific application and to solve a specific problem. So, small changes in nature of problem will require restructuring of architecture and retraining of model on timely manner which is cumbersome task for real time systems. I proposed a multi-task learning based approach to handle resource allocation problem. Deep learning multi-task will help in generalization of resource allocation problem and to tackle rare situation related to this problem. Multi-task learning will help to generalize machine learning solutions for multiple tasks by sharing some of the information between them.

Keywords: Multi-Task Learning, Resource Allocation, IOT

Introduction

Internet -of-Thing (IOT) is a heterogeneous networks formed with the connection of smart devices to the internet. IoT becomes upraising domain which connects an extent amount of smart devices which are capable of environmental sensing, data processing, data transmission and etc. Though developing the Internet of Things on such a large scale presents difficulties, it also holds great promise for future smart devices. Network design, smart device storage architecture, effective communication protocols, IoT device security, and malware protection protocols are a few of these difficulties. Device management, data management, diversity, and interoperability are some other or typical concerns. A wireless network's capacity is determined by its frequency bands, time slots, controllable traffic volume, and the manner in which various users are granted access to the wireless channel. The performance of an wireless network depends on time slots, it frequency bands, hoe well traffic load are managed, how wireless channel access are provide to different users. Any new IoT



application would require high efficiency, high throughput, data rates for this resource allocation became crucial part for IoT devices and applications.

There are multiple resource that an IoT device would require but also it is possible that every use do not require all resources depends on the requirement and interest of different users. This article only covers a small portion of the available resources, which include resource management, power allocation and interference management, user association or cell selection, coverage extension, dependable low latency communication, and power management. Resource management means when number of users tries to access same channel at the same time it overload the channel and cause network congestion solution for it setting prioritization nad probability among different classes. Interference Management in IoT network inter and intra cell interference become very crucial so, to respond to physical channel changing and network condition in heterogeneous network would be difficult. In case of cell selection, it could be possible that users association with base station or node is not symmetrical uplink and downlink transmission which shows that resource management and resource allocation is necessary. Coverage extension, traditionally IoT devices have low storage and low computational capabilities for coverage extension relay-based and D-2-D techniques could be helpful for providing this resource. Energy management, to provide QoS (Quality of Services) for lot devices with limited energy or battery capacity energy efficient resource allocation and protocol is required. Low-Latency Communication, those IoT application and devices which are responsible for providing safe transport system and public



safety require low-latency and reliable communication this leads to delay free resources.

One technology for allocating resources is machine learning. The ability to extract knowledge from particular data and then use that knowledge to modify or adapt an agent's behavior based on machine learning is known as machine learning (ML). The three main applications of machine learning techniques are density estimation, regression, and classification. Large volumes of data are generated by IoT devices, and machine learning techniques use this data to create solutions that can be used to maintain IoT devices. When large-scale, multi-dimensional data is available, deep learning (DL), a subset of machine learning, is used to help extract features and classify the necessary data. In situations where there is insufficient knowledge about a system or network and no suitable parameters, control decisions must be made based on the circumstances. Machine learning techniques are employed to forecast and determine what is required. supervised learning, unsupervised learning, and reinforcement learning are the three subcategories of machine learning.

Under supervised learning, an input is labeled with a dataset, indicating that the model has already been trained on it and that the output is accessible. This system makes use of markers to forecast unknown parameters for spectrum sensing, channel estimation, and positioning. Numerous algorithms, including Decision Trees (DT) and Naive Bayes, are used in supervised learning to model data sets. Studying without a guide. Unsupervised learning occurs when a dataset is given without a label or category assigned to it. Using this approach, the model generates outputs by exploring unlabeled data and inputs.



Principal component analysis and K-means clustering are the algorithms used for load balancing and clustering in Internet of Things networks.

Unsupervised Learning: While in unsupervised learning the dataset that provided as an input will not be labeled and no category will be defined for that data. In this technique the models use unlabeled data and input data in way investigating manner and reached to the output. In IoT networks the algorithms that use for clustering and load balancing are K- means clustering, Principal Component Analysis.

Reinforcement Learning: RL technique based on learning optimal policy it do not require any training dataset. Under changing network conditions it use for decision making and extracting knowledge from that environment. RL technique is used for providing BS association to users and channel access in case of unknown channel availability. The most popular algorithm for Reinforcement Learning is Q-Learning. This research is focused on providing multi-tasking for resource allocation in IOT network. For real-time application, the purpose of multi-tasking is to allocate different to ML model which means if change occurs in an environment it should be possible for the model to train itself and use required resource for required output.

In our methodology we used Adversarial learning for extraction of invariant features, Orthogonality constraints on similar features, then back propagation method is used to extract shared feature from different task. Adversarial Learning, the main idea is to insert some already exist example in training dataset and then at every step it generate a new adversarial example. It also trains models to make it robust to attacks and generate clean



inputs for test errors and his mechanism is use to fool the model to take that decision foe which it is not trained.

On a range of RNN testing problems, orthogonality shows how this approach can yield a robust optimization method with orthogonal constraints that exhibits faster, more accurate, and more stable convergence. A neural network's weights are modified during the back propagation training process in response to the error rate produced by earlier iterations. When the weights are set correctly, the error rate decreases, which enhances the model's robustness and generalization.

The remainder is distributed on paper. A review of the literature is given in the second section. The solutions based on the most cutting-edge technologies available today are presented in Section 3. Section 4 contrasts the current systems with our suggested configuration. Concluding remarks, future work prospects, and limitations of the work are presented in Section V.

Literature Review

In [1] a search economic based resource allocation algorithm SEIRA is proposed to solve resource allocation problem in IOT. This algorithm divides the search space into sub regions and then initiate researchers in those regions. These researchers, after accomplishing certain expected value, are moved to other regions. This algorithm also depicts the geography of solutions to make it possible to find candidate solutions in higher potential regions. They used eight different datasets of gateways and IOT resources to perform experiments and compared the performance of their proposed method to genetic algorithm based resource allocation algorithm. They also showed that when k-mean was used to



initialize initial population gave better performance than when population was generated randomly.

In [2] a method to resolve limited resource problem and varying network conditions in edge computing using multi task learning is proposed. They proposed multitask learning based feed forward neural network model to resolve these problems. As data to be uploaded on multi access edge computing (MEC) server is very large so they used non orthogonal multi access on MEC server. Offloading decision to server is determined by MINLP. This model was trained offline then implemented in real time to make computational decisions. In proposed method they considered n devices connected to one MES through access point AP. Each device has a single computation intensive task and capability of MES is limited. Offloading strategy depends upon two vectors D and F , where D is a binary vector whose value is 1 if task is to offloaded on MES and 0 if it can be computed locally and F number of cycles. Task depends upon computation size, number of cycles, and tolerable delays. For multi task learning they proposed that two vectors D and F can be predicted for resource allocation problem using machine learning tasks as they are related to each other.

In [3] they addressed offloading computation issues in IOT due to bandwidth constraints by utilizing gateway resources. In their system model they considered a network with N devices connected to a gateway. Parameters of each device are computation offloading levels and data transmission rate. They formulated multi choice knapsack problem to optimize battery life to bandwidth constraints. The proposed method worked well for larger number of offloading levels but when numbers of offloading



levels are small and data transmission rate are high then it caused issues. So they proposed to switch between offloading levels to give gateway a view of multiple offloading levels. They tested proposed method on a health monitoring case study and proposed method improved edge device's battery life by 40%.

In [4] a novel approach is proposed by using 2 reinforcement learning algorithms and quality of experience to solve resource allocation problem in resource constrained heterogeneous networks. In the proposed method a dynamic programming algorithm was used to resolve conflicts of strategy generation time and performance in content centric networks. RL along with quality of experience was used to create pre stored cost table for resource allocation by smart agent. They used directed tree graph to estimate lowest cost for resource allocation problem. Resource allocation decisions were made by smart agent dynamically based on reward and quality of experience feedback. They also used QOE and rewards to update pre

Stored table. They observed that training time was effected by number of computational nodes and training tasks. In [5] they proposed intelligent resource allocation framework in collaborative edge network. This method has the ability to adapt to changing environment by self-learning the changes. In proposed method they used Monte Carlo Tree search method to locate resources and then train the dataset based on this data to make resource allocation process self-sufficient to train itself. They divide the layers of deep neural network to predict higher dimensions action using multi task learning. Then resource is allocated in dynamic environment to optimize performance and battery life. The Proposed approach will minimize latency and maximize battery life.



They compared their proposed method with deep Q-learning and greedy approach and obtained improvement in performance by 51.71% and 59.27%.

In [6] a deep neural network DeepNOMA for resource allocation in NOMA is proposed. It had a transmission channel module, multiple user detection module, which is used to generate regular shaped signatures and multiple mapping access module which was trained in data driven manner. They used multi task learning to train DeepMUD and DeepMAS module. In proposed methodology NOVA network were used as multiple tasks. They used synthetic dataset to train their model and then tested their model with computational complexity and BER.

IOT is responsible for providing secure interaction of tenant devices and applications with cloud applications and devices. The broker services are considered to be one of those devices which could provide secure connection between devices and application. In [7] resources allocated which include buffering, scheduling, rate limiting for current SLA (Service Level Agreement). They proposed three control parameters for resource allocation which are over-provision capacity, CPU scheduling, policing. Traffic patterns related information of iot application almost ignored by all cloud providers which leads to problem that resource allocation for SLAs is required. The weakness of SLA is its enforcement period, the cloud provider don't want to complex the statement of SLA with traffic information which allocating resources a difficult problem. In provision capacity by increasing capacity will reduces extended enforcement times effect, CPU Scheduling for independent customers queuing is proposed, control rate of messages added in policing from overwhelming the server resources.



[8] investigated how to allocate resources for uplink transmission in Internet of Things networks in order to increase user productivity and network lifetime. The low complexity ECAA (Efficient Channel Allocation Algorithm) algorithm is based on matching theory and is used to assign users to available channels. To get the best throughput for users, a power algorithm based on single-link MDP is then suggested. By rejecting conflicting users in ECAA, the likelihood of retransmission is decreased and the user's battery life is increased. To optimize network throughput in the MDP power allocation algorithm, data transmission and power collection must be carried out at distinct time intervals. Phases are defined in MDP-based Algorithm Planning and Transmission phase in Planning phase look up table for optimal sequence of transmitting policy while in transmission phase battery power is determined to see if data transmission is possible.

[9] suggested a productive offloading method for edge computing on mobile devices. The primary issue raised is that offloading computation to the cloud can result in significant interference and slow down the speed of data transfer if multiple mobile users access the same channel. Two crucial elements must be taken into account in order to accomplish compute offloading effectively: 1) How users select between cloud computing and local computing (on their devices); 2) How users select channels for effective computing. Game theory techniques are used to solve the issue of allocating computing mechanisms to users according to their interests since different users may have different interests. Initially, in order to distribute computation among several users, it was challenging for them to identify the best center channel when interference was present. The Nash equilibrium can then be found



using multiplayer game theory. The suggested algorithm can perform efficiently in terms of decreasing computational effort and volume while simultaneously increasing the number of users, according to numerical results.

[10] went into great detail about resource management in cellular networks and the Internet of Things using machine learning and deep learning. Numerous devices access wireless channels concurrently in large-scale IoT networks, which can cause network congestion and a host of other network issues. In order to address these issues, he investigates a range of issues pertaining to Internet of Things resource management as well as significant fields of study in machine learning and deep learning. With machine learning (ML), or more specifically deep learning (DL), one can extract features and classify data. Deep learning is a branch of machine learning that implements the learning process using artificial neural network (ANN) classification layers.

In [11] many multi-task learning algorithms are discussed and how to implement those algorithms in different research domains. Multi task learning approach provides generalization to resolve unseen scenarios in computing. The supervised multi-task learning approach is being studied and implemented in many fields to train models on rare scenarios. In this paper they also discussed novel semi-supervised, active-graphical and reinforcement learning based multi-task learning approaches to train models without labeled data or in the absence of training data. [12] talked about using fog networks to allocate resources. Because fog nodes have limited resources, users upload task data to the closest fog node. This makes it challenging to upload complete data to the master node, which is where the user runs



the application. As a result, the primary node chooses how much information to upload to the cloud or the secondary node. The researchers looked at a number of tasks that result in different delays in processing user requests and concentrated on searching to ascertain the data volume of tasks to be offloaded. In this paper, they formulate an optimization problem related to multi-task loading and unloading, convert it into a quadratic constraint programming (QCQP) problem, and solve it using heuristics. It is noted that the task delay will increase if input size will exceed the proposed Scheme called as fixed resource allocation in which resources that need to be transmit distributer on the fog node equally and fog-node provide each task with the required CPU resources. Multiple end users also an important factor for deciding which fog-node to use because these users need same channel it means multi-tasking will happen and data from multiple users will be offloaded.

In [13] a multi task learning approach is used to extract features form images and then recognize images based with this training. They defined some task invariant features for this task. They used adversarial learning for extracting task invariant features. Then some task dependent variables were used for training. These two set of features could have some redundant features for example there may be some common features in task invariant and task specific feature set. So they use orthogonality constraints on this set of features. Now these features were used to extract shared features from image processing tasks.

In [14] a method to provide fast uber service and trips for uber users based on machine learning approach was introduced. Feed



Forward Neural Network is shown below They used long short term memory for detecting nearest

Vehicle minimizes wait time. To train this model they used features other than task specific features to incorporate this model in real world. To avoid encoding features manually they introduced auto encoder in their model that learn features.

Proposed Methodology

Resource allocation problem in an IOT environment can be because it generalize well in real world. Existing machine learning models can be implemented in one particular network Formulated as cross stitch multitask feature learning Approach. Divide task into k sub-tasks for example task of channel estimation in IOT network for computational offloading or storage can be divided into two sub tasks such as estimating load of network (T1) and access techniques (T2). We want to minimize latency for optimal resource allocation. Our training sample for T1 is D_i and for T2 is D_j which contains training instances for them.

$$D_i = \{(x_{i1}, y_{i1}) (x_{i2}, y_{i2}) (x_{in}, y_{in})\}$$

$$D_j = \{(x_{j1}, y_{j1}) (x_{j2}, y_{j2}) (x_{jn}, y_{jn})\}$$

We'll feed these training instances to feed forward neural network. We'll also give some task invariant features learned via adversarial learning. These features will help our model to -generalize well in changing real world settings. Our learning process will use back propagation method. This method is based on regularization framework. The objective function for this type of setting is discussed in [11] as In above objective function l is hinge or square loss function And λ regularization parameter. This objective function -enforces that the row-sparse A and orthogonal

constraints. So in above settings there will be no redundant features in hidden layer.

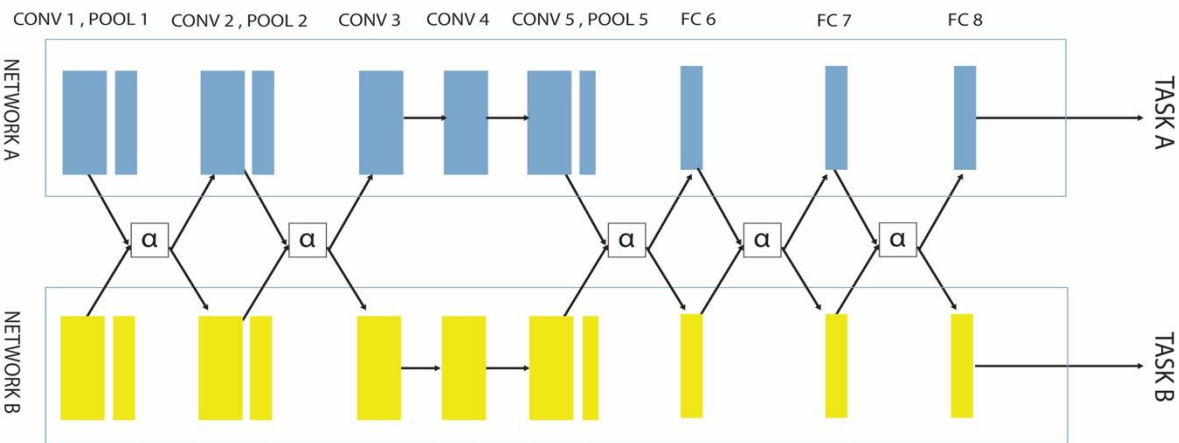
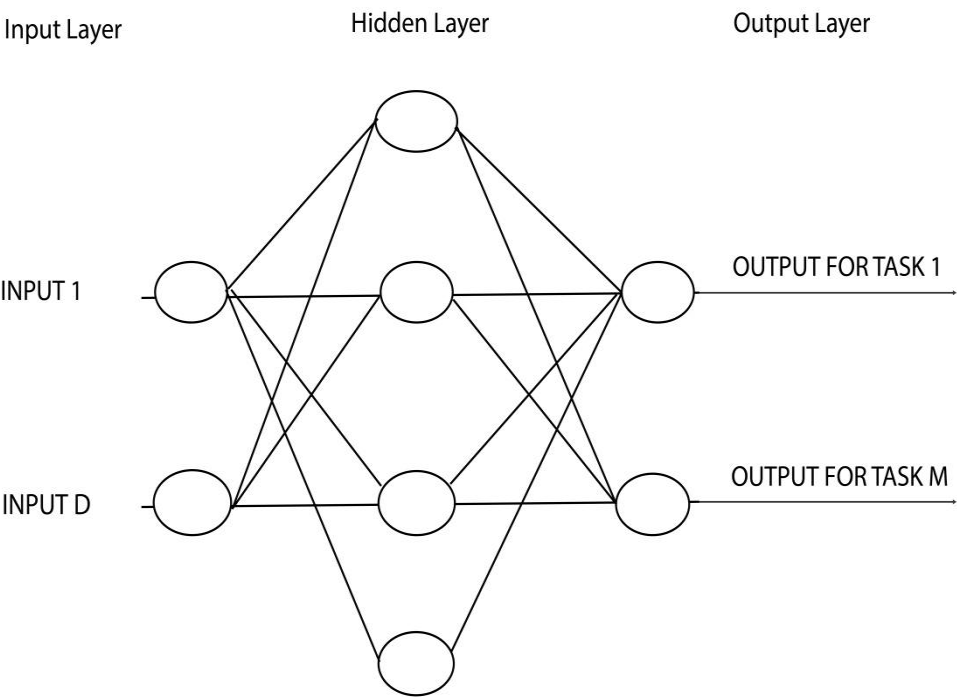


Fig. 2: Feed Forward Neural Network Hidden Layer

Feed Forward Neural Network is shown below





Comparison and Analysis

Our proposed cross stitch multi-task feature learning approach can be implemented on any network and for any resource allocation problem. It is better than existing technologies because it generalize well in real world. Existing machine learning models can be implemented in one particular network In favorable conditions only. When conditions change the machine learning algorithm can't work properly and need Restructuring. Every time when conditions change restructuring and retraining of machine learning algorithm becomes very time consuming and require lots of human efforts. Moreover in real world some adversarial settings can harm machine learning algorithms decisions. But our multi task feature learning model will help to cope with these adversarial settings and it will generalize well in real world.

Conclusion

The foundation of IoT network is constitute of communication, storage, processing of different smart devices. With rapid development IoT considered as it revolutionized our daily lives in many aspects such as business, environment and infrastructure and etc. With respect to different devices, networks and data IoT played big role in making network heterogeneous which showed the importance of network scalability, efficiency and required to improve network management mechanism. Resource allocation is one the important aspect in heterogeneous IoT network and in IoT environment it has become a major problem. There are many existing machine learning and deep learning solutions for resource allocation problem but these models are trained for specific application and to solve a specific problem. So, small changes in nature of problem will require restructuring of architecture and retraining of model on timely manner which is cumbersome task for real time systems.



In summary, resource management technologies are necessary for IoT networks in addition to the challenges associated with resource allocation. The management of resources and processes, including the decision-making necessary for big networks and the dynamic changes in Internet of Things applications, is greatly aided by machine learning and deep learning technologies. This research focuses on the following resources: dependable low-latency communications, coverage extension, user association or cell selection, power management, interface management, and power allocation. In this paper, multitasking is suggested. methods based on learning for resolving issues with resource distribution.

Deep learning multi-task will help in generalization of resource allocation problem and to tackle rare situation related to this problem. Multi-task learning will help to generalize machine learning solutions for multiple tasks by sharing some of the information between them. In our methodology we used Adversarial learning for extraction of invariant features, Orthogonality constraints on similar features, then back propagation method is used to extract shared feature from different task.

Adversarial Learning, the main idea is to insert some already exist example in training dataset and then at every step it generate a new adversarial example. It also trains models to make it robust to attacks and generate clean inputs for test errors and his mechanism is use to fool the model to take that decision foe which it is not trained. Orthogonality demonstrates how this approach builds a strong optimization strategy with orthogonal constraints, exhibiting more rapid, accurate, and stable convergence on a range of RNN testing tasks. A neural network's weights are modified during the backpropagation training process in response to the error rate



produced by earlier iterations. When the weights are set correctly, the error rate decreases, which enhances the model's robustness and generalization.

Future Work

Numerous opportunities exist to examine resource allocation for future wireless communications through machine learning. There are still a lot of unanswered questions that need to be looked into and researched. From our perspective, some of the most significant points are explained in this section.

In network, many users exist at the edge of base station and if the users relies on only one BS signal quality will be very low so, require resources from multiple BS jointly. How can we improve resource allocation using historical data with multiple base stations need to studied and explore bit more. Since all models are trained on the basis of historical data with fast growth and changing in environment will lead to loss in performance. It required in machine learning to build predictive models where if new data will come. Therefore, new data could be stored temporarily on base station and then update this dataset this is possible for all those application which are cloud based. This is one of the challenging point for resource allocation.

Creating machine learning models that are better suited for processing data from diverse network devices presents another area of research opportunity. Reducing processing and storage expenses is critical for the deployment of machine learning and deep learning models on resource-constrained Internet of Things devices. Therefore, additional study is required to address these issues with IoT devices.

The Price of ML and DL Model Training Costly datasets are necessary for training machine learning models, and training these models itself



is costly. An architecture that facilitates model updating is necessary for the model suggested by this method to be continuously trained and updated automatically.

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