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Channel Assignment in Uplink Wireless Communication using Machine Learning Approach

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Abstract—This letter investigates a channel assignment problem in uplink wireless communication systems. Our goal is to maximize the sum rate of all users subject to integer channel assignment constraints. A convex optimization based algorithm is provided to obtain the optimal channel assignment, where the closed-form solution is obtained in each step. Due to high computational complexity in the convex optimization based algorithm, machine learning approaches are employed to obtain computational efficient solutions. More specifically, the data are generated by using convex optimization based algorithm and the original problem is converted to a regression problem which is addressed by the integration of convolutional neural networks (CNNs), feed-forward neural networks (FNNs), random forest and gated recurrent unit networks (GRUs). The results demonstrate that the machine learning method largely reduces the computation time with slightly compromising of prediction accuracy.

Index Terms—Resource allocation, convex optimization, machine learning, deep learning.

I. INTRODUCTION

Driven by the rapid development of advanced multimedia applications, next-generation wireless networks must support massive connectivity. The connectivity always results in the integer optimization problem, which was solved by conventional algorithms mostly operating in an off-line manner with high computation complexity and depending largely on accurate channel state information [1]. Machine learning tools [2], [3] can exploit big data for wireless network state estimation and find the relationship between the decision variables and objective functions in an online manner so as to reduce the computational complexity.

There are many research attentions of applying machine learning for solving integer optimization problems in wireless communication. For integer user association problem, the authors in [4] investigated the use of deep learning to perform user-cell association for sum-rate maximization in massive multiple input multiple output (MIMO) networks. For integer cache placement problem, the optimization of the caching locations was transformed to a grey-scale image-based problem and deep convolutional neural network (CNN) was adopted accordingly [5]. Also, the linear sum assignment problems were solved through using the deep neural networks (DNNs) [6]. Moreover, in device-to-device (D2D) networks, a

novel graph embedding based method for link scheduling was proposed [7]. Further reinforcing the generalization ability in D2D networks, a DNN structure was proposed in [8] with a novel loss function to achieve better dynamic control over optimality and computational complexity. However, the above contributions [4]–[8] all restricted that the number of users is assumed to be the same as wireless resources, which cannot meet the massive number of devices in future communication systems. Besides, the machine learning approaches in [4]–[8] are all neural networks and have the limitations of prediction performance. To further investigate machine learning methods' capacity and potential in wireless communication domains, this letter employs several machine learning algorithms as base learners and integrates them by an ensemble learning approach. By employing different machine learning methods, we aim to improve the diversity of base models and the final prediction performance as well as the model's generalization capability and robustness when exposed to contaminations.

The contributions of this letter is summarised as follows:

- The channel assignment problem is formulated for the case that the number of users is larger than the number of subchannels. A convex optimization based algorithm is proposed to obtain the globally optimal channel assignment despite of the integer constraints.
- The convex optimization problem is converted to a regression problem and solved by machine learning frameworks, which yield rigorously optimal and computationally efficient solutions.
- Ensemble learning is utilized to combine different machine learning models and improve the prediction performance. Also, different combinations of optimization algorithms are adopted and compared.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider an uplink single cell network with M users and N subchannels. Denote $\mathcal{M} = \{1, 2, \dots, M\}$ as the set of all users and $\mathcal{N} = \{1, 2, \dots, N\}$ as the set of all subchannels. Let p_i denote the uplink transmission power for user i . Binary variable x_{ij} reflects the association relationship between user i and subchannel j , i.e., $x_{ij} = 1$ means that user i occupies subchannel j ; otherwise $x_{ij} = 0$.

Due to massive number of users and limited number of channels, i.e., $M \geq N$, non-orthogonal multiple access (NOMA) scheme is utilized by serving multiple users in each subchannel [9]. With successful interference cancellation in NOMA¹, the sum rate of all users occupying subchannel j is given by [9]:

$$r_j = B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right), \quad (1)$$

¹The transmission power of each user is assumed to be fixed, thus the power constraints are not involved in the optimization problem.

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where B is the bandwidth of each subchannel, h_{ij} is the channel gain between user i and the base station (BS) on subchannel j , and σ^2 is the power density of Gaussian noise.

The sum rate maximization problem for assigning users with subchannels can be formulated as:

$$\max_{\mathbf{x}} \sum_{j=1}^N B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right) \quad (2a)$$

$$\text{s.t.} \quad \sum_{j=1}^N x_{ij} = 1, \quad \forall i \in \mathcal{M}, \quad (2b)$$

$$\sum_{i=1}^M x_{ij} = A, \quad \forall j \in \mathcal{N}, \quad (2c)$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in \mathcal{M}, j \in \mathcal{N}, \quad (2d)$$

where $\mathbf{x} = [x_{11}, x_{12}, \dots, x_{MN}]^T$ and A is the allowed number of associated users in one subchannel. Constraints (2b) ensure that each user only occupies one subchannel.

III. CONVEX OPTIMIZATION BASED ALGORITHM

Due to integer constraints (2d), it is hard to solve linear integer problem. By temporarily relaxing the integer constraints (2d) with $x_{ij} \in [0, 1]$, problem (2) is a linear problem, also convex. For convex problem (2) with relaxed constraints, the optimal solution can be effectively obtained by using the dual method [10].

Let λ_i denote the dual variable associated with constraint i in (2b), we obtain the dual problem of the problem in (2), which is given by:

$$\min_{\boldsymbol{\lambda}} D(\boldsymbol{\lambda}), \quad (3)$$

where

$$D(\boldsymbol{\lambda}) = \begin{cases} \max_{\mathbf{x}} & \mathcal{L}_1(\mathbf{x}, \boldsymbol{\lambda}) \\ \text{s.t.} & \sum_{i=1}^M x_{ij} = A, \quad \forall j \in \mathcal{N}, \\ & x_{ij} \in [0, 1], \quad \forall i \in \mathcal{M}, j \in \mathcal{N}, \end{cases} \quad (4)$$

$$\begin{aligned} \mathcal{L}_1(\mathbf{x}, \boldsymbol{\lambda}) &= \sum_{j=1}^N B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right) + \sum_{i=1}^M \lambda_i \left(\sum_{j=1}^N x_{ij} - 1 \right) \\ &= \sum_{j=1}^N B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right) + \sum_{j=1}^N \left(\sum_{i=1}^M \lambda_i x_{ij} - \lambda_i \right), \end{aligned} \quad (5)$$

and $\boldsymbol{\lambda} = [\lambda_1, \dots, \lambda_N]^T$.

To minimize the objective function in (4), the optimal x_{ij} can be calculated via the Karush-Kuhn-Tucker (KKT) conditions. Since both the objective function and constraints can be decoupled into N subchannels, the subproblem of (4) in subchannel j can be given by:

$$\max_{x_j} B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right) + \sum_{i=1}^M \lambda_i x_{ij} \quad (6a)$$

$$\text{s.t.} \quad \sum_{i=1}^M x_{ij} = A, \quad (6b)$$

$$x_{ij} \in [0, 1], \quad \forall i \in \mathcal{M}, \quad (6c)$$

where $\mathbf{x}_j = [x_{1j}, x_{2j}, \dots, x_{Mj}]^T$.

It can be proved that (6) is a convex problem, and the Lagrangian function of problem (6) is

$$\begin{aligned} \mathcal{L}_2(\mathbf{x}_j, \alpha, \boldsymbol{\beta}, \gamma) &= B \log_2 \left(1 + \frac{\sum_{i=1}^M x_{ij} p_i h_{ij}}{\sigma^2 B} \right) + \sum_{i=1}^M \lambda_i x_{ij} \\ &+ \alpha \left(\sum_{i=1}^M x_{ij} - A \right) + \sum_{i=1}^M \beta_i x_{ij} + \sum_{i=1}^M \gamma_i (1 - x_{ij}). \end{aligned} \quad (7)$$

The KKT conditions of problem (6) are [10]

$$\frac{p_i h_{ij}}{(\ln 2) \left(\sum_{i=1}^M x_{ij} p_i h_{ij} + \sigma^2 B \right)} + \lambda_i + \alpha + \beta_i - \gamma_i = 0, \quad (8a)$$

$$\sum_{i=1}^M x_{ij} = A, \quad (8b)$$

$$\beta_i x_{ij} = 0, \quad (8c)$$

$$\gamma_i (1 - x_{ij}) = 0. \quad (8d)$$

In the left hand side of (8a), it is founded that the denominator of the first term is the same for every user i . With this finding, we introduce a new variable κ , which is defined as:

$$\kappa = (\ln 2) \left(\sum_{i=1}^M x_{ij} p_i h_{ij} + \sigma^2 B \right). \quad (9)$$

With the help of κ , we can directly obtain the optimal solution of x_{ij}^* according to the following analysis. Substituting (9) to (8a) yields:

$$\frac{p_i h_{ij} + \kappa \lambda_i}{\kappa} = \gamma_i - \beta_i - \alpha. \quad (10)$$

Based on (8c)-(8d), we can obtain that (i) $x_{ij} = 1$ if and only if $\gamma_i > 0$ and $\beta_i = 0$ and (ii) $x_{ij} = 1$ if and only if $\gamma_i = 0$ and $\beta_i \geq 0$, which indicates that the right hand side of (10) should be as large as possible for the case $x_{ij} = 1$. Besides, there are only A users such that $x_{ij} = 1$ according to (8b). Thus, the user with $x_{ij} = 1$ should have the A highest values of $\frac{p_i h_{ij} + \kappa \lambda_i}{\kappa}$, i.e.,

$$x_{ij}^*(\kappa) = \begin{cases} 1, & \text{if } i \in \mathcal{M}_A \\ 0, & \text{otherwise,} \end{cases} \quad (11)$$

where set \mathcal{M}_A means the index of A users with the top A highest values in $p_i h_{ij} + \kappa \lambda_i$. Equation (11) indicates that the optimal x_{ij}^* is only a function of κ . To calculate the value of κ , we combine (9) and (11), which yields:

$$\kappa = (\ln 2) \left(\sum_{i=1}^N x_{ij}^*(\kappa) p_i h_{ij} + \sigma^2 B \right). \quad (12)$$

With the increase of κ , the user with lower value in $p_i h_{ij}$ can have higher value in $p_i h_{ij} + \kappa \lambda_i$, i.e., the value of $\sum_{i=1}^N x_{ij}^*(\kappa) p_i h_{ij}$ decreases, which indicates that the right hand side of (12) decreases with κ . Since the left hand side of (12) increases with κ and the right hand side of (12) decreases with κ , the unique value of κ can be obtained by the bisection method. Given \mathbf{x} , the value of $\boldsymbol{\lambda}$ can be determined by the gradient method [11]. By iteratively optimizing primal variable \mathbf{x} and dual variable $\boldsymbol{\lambda}$, the optimal subchannel allocation is obtained. The dual method used to obtain the optimal subchannel allocation is given in Algorithm 1. Notice that the optimal x_{ij} is either 0 or 1 according to (11), even though we relax x_{ij} as continuous constraint in (2). Therefore, we can obtain optimal solution to problem (2).

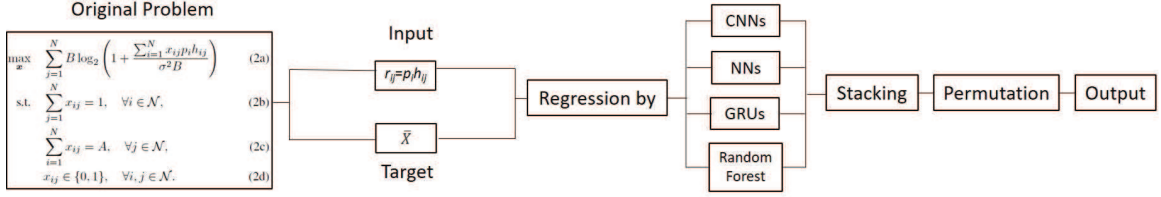


Fig. 1: Block diagram of the implementation procedure in this letter.

Algorithm 1 Dual Method for Subchannel Association

- 1: Initialize dual variable λ .
- 2: **repeat**
- 3: Update subchannel allocation \mathbf{x} according to (11).
- 4: Update dual variable λ by the gradient method.
- 5: **until** the objective value (2a) converges

IV. DEEP LEARNING BASED APPROACHES

In this letter, the machine learning approaches are also involved to obtain computational efficient solutions for the optimization problem. The overall implementation procedures are shown in Fig. 1. The key of machine learning methods is to learn the relationship between the constant input parameters $R = \{r_{ij} = p_i h_{ij}\}, i \in \mathcal{M}, j \in \mathcal{N}$ and the subchannel arrangements $X = \{x_{ij}\}, i \in \mathcal{M}, j \in \mathcal{N}$. To make the problem solvable, we convert the target one-hot matrix $X = \{x_{ij}\}, i \in \mathcal{M}, j \in \mathcal{N}$ to vector form $\bar{X} = \{\bar{x}_i \in \mathcal{N}\}, i \in \mathcal{M}$ so that the problem can be considered as a regression problem. Each column in X , i.e., $\{x_{i1}, x_{i2}, \dots, x_{iN}\}^T, i \in \mathcal{M}$ is transformed to an integer $\bar{x}_i \in \mathcal{N}, i \in \mathcal{M}$ which denotes the index of non-zero value (i.e., 1) in the each column, meaning the index of user in the j -th subchannel, i.e., $x_{i\bar{x}_i} = 1$.

After obtaining the input and target, the optimization problem is converted to a regression problem which can be modelled by machine learning frameworks. The adopted methods for regression consist of CNNs, feed-forward neural networks (FNNs), random forest and gated recurrent unit networks (GRUs). In addition, ensemble learning method is utilized to combine different models and further improve the regression performance. After regression, the output of machine learning models are permuted according to the output values, thus, the integer outputs which represent the indices of users are obtained in the end.

A. Data Information

1) *Data generation*: We deploy M users uniformly in a square area of size $500 \text{ m} \times 500 \text{ m}$ with the BS located at its center. In each independent run, the channel gains of users on the subchannels are determined, i.e., R is obtained. The output X is accordingly calculated by using Algorithm 1. The total number of generated samples is 1 million.

2) *Data splitting*: The generated data are splitted to training, validation and test datasets. 70% of the data are used for training while 10% for test. 20% of data are held out for validation which plays an important role in model ensemble stage, i.e., the stacking procedure.

B. Machine Learning Methods

Different machine learning methods are employed to solve the regression of the input R and the target \bar{X} . Ensemble learning is then utilized to make different models complement

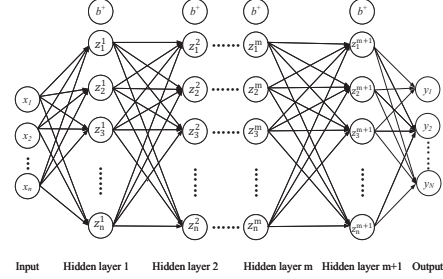


Fig. 2: The structure of FNNs.

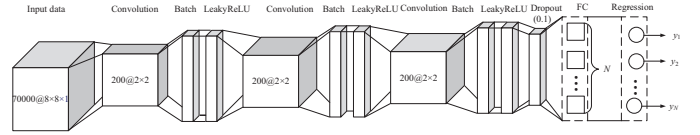


Fig. 3: One CNN structure used in this letter.

each other and improve the regression performance. Different base learners are used as they can render diversity of the whole structure, which is beneficial for models' prediction accuracy, robustness and generalization capability when exposed to contaminations. The models are selected mainly through referencing published literatures of the successful models on similar datasets and trial and error of existed models. After comparing the performance of existed machine learning models, FNNs, CNNs, random forest and GRUs are employed as the base learners. The configurations of adopted models are shown in Table I, which are determined mainly through trial and error and taking into consideration of the input size.

1) *Deep Learning Models*: FNNs are used in function approximation, pattern recognition and data classification. Due to its superiority in data fitting problems, we adopted FNNs as one of models to solve the regression problem. The general structure of FNNs used in this letter is shown in Fig. 2.

CNNs have advantages in processing the high-dimensional data, such as images and time-series data due to (a) its convolutional setting in which the hidden units are not fully connected to the input but instead divided into locally connected segments; (b) pooling methods which reduce the dimensionality of the feature space and achieve invariance to small local distortions [12]. One CNN architecture used in this letter is shown in Fig. 3.

GRU architectures have superiority in capturing dependences of different time scales. GRUs are similar to Long Short-Term Memories (LSTMs) which have gating units to adjust the information flow inside the unit but do not have a separate memory cells [13] and thus are faster to be trained than LSTMs but on a par with LSTMs' performance. When applying GRUs, the input data $R = \{r_{ij}\}, i, j \in \mathcal{N}$ are reshaped to vectors so as to form the sequence inputs for GRU

FNNs	CNNs	GRU	Random Forest
Structure: basic FNN structure is shown in Fig. 2. Three hidden layers used in this letter are of the size ([10, 10, 10], [10, 10, 10, 10], [20, 20, 20]); Optimizer: LM*; Epoch: 300; Loss function: MSE**.	Structure: basic CNN structure is shown in Fig. 3. Layers' depth and filter size vary according to the input size; Optimizer: Adam + SGD with momentum; Batchsize: 500; Epoch: 40–60; Loss function: MSE.	Structure: Two GRU layers with 50 units each, followed by dropout layer and 4 Dense layers; Optimizer: Adam; Batchsize: 200; Epoch: 40; Loss function: MSE.	The number of trees in forest: 500; Criterion: Gini Impurity; The minimum number of samples required to split an internal node and to be at a leaf node: 2, 1, respectively.

* LM: Levenberg-Marquardt method.
 ** MSE: mean squared error.

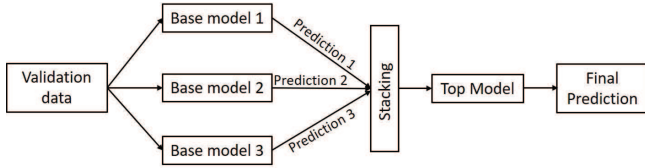


Fig. 4: Stacking process.

networks. As the correlation of channel model is based on the fact that the channel gain of each user is correlated in time domain [14], the GRU model is selected accordingly as one of the base learners.

Stacking is a widely used ensemble method to boost the prediction performance [15] of base learners. In this letter, we applied stacking method to a holdout dataset, i.e., the validation dataset, the predictions of base learners fed by validation data are then stacked to form a new dataset for training the top model. The stacking structure used in this letter is shown in Fig. 4. The complexity of base learners and top models is no more than $\mathcal{O}(N^2)$ [6]. The details of base models and top models in each case will be illustrated in the following section.

2) *Training method*: The optimization algorithm utilized for CNNs' training in this letter is the combination of Adam and stochastic gradient descent (SGD) with momentum. In implementation, Adam is used first to realize fast gradient decent, then SGD is used for further optimizing the parameters.

As shown in Fig. 5, the conversion from Adam to SGD is implemented in two ways: i) SWATS: adopting the SWATS strategy proposed in [16] which automates the process of switching over by determining both the switchover point and the learning rate of SGD; ii) Customize: using Adam in the first half of training, i.e., the first 20 epochs of the example shown in Fig. 5; then use SGD in the second half of training, i.e., the last 20 epochs. From Fig. 5, it can be seen that at epoch 20 (the switchover point of the Customize method), there occurs obvious decrease of training loss from Adam to SGD. These two methods are compared in each case and the one having the better performance is employed in this letter.

V. EXPERIMENT CONFIGURATION

This section will introduce the experiment procedure, platforms and the methodology for calculating the final accuracy. The experiments were implemented in Matlab R2019a, Tensorflow 1.13.1 and Nvidia GPUs. Matlab is for training FNNs with Levenberg-Marquardt (LM) algorithm, other classifiers were trained in Tensorflow and sped up by Nvidia P100/GTX 1050 GPUs.

A. Experiment Procedures

After transforming the optimization problem to a regression problem, the machine learning methods including FNNs,

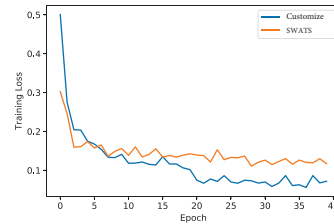


Fig. 5: Training loss of two training methods. SWATS is the method proposed in [16], Customize refers to the combination of Adam and SGD that the first half of training adopts Adam while the second half uses SGD algorithm.

CNNs, GRUs, random forest as well as the stacking method are employed to learn the pattern of channel assignment. Two type of cases were considered in this letter: 1) $M = N$, meaning the same number of users and subchannels, which is a conventional problem; 2) $M > N$, i.e., different subchannels and users. They are investigated in this letter as the channel resource tends to be limited, which means the number of subchannels could be smaller than the number of users. The details of each case are as follows.

1) $N = M$: We consider three situations for this case, $M = N = 2$, $M = N = 4$ and $M = N = 8$.

When $N = M = 2$, there are two users and two subchannels in the optimization problem. Denote the index of an arbitrary sample by m , each input is a matrix with the size of 2×2 : $R^m = \{r_{ij}^m\}, i, j \in 1, 2$ and the target is a vector of the size 1×2 : $\bar{X}^m = \{x_1^m, x_2^m\}$. The targets have two kinds of values: $\{1, 2\}$ and $\{2, 1\}$. Three FNNs are employed as base models, the top model is also a FNN fed by the stacked outputs of the base learners.

When $N = M = 4$, for each sample (R^m, \bar{X}^m) , R^m and \bar{X}^m respectively have the size of 4×4 and 1×4 . Three base models are composed of two CNNs and a GRU. The top model is a CNN which is fed by the input with the size 12×1 obtained by stacking the outputs of three base models.

When $N = M = 8$, the samples are (R^m, \bar{X}^m) where R^m and \bar{X}^m respectively have the size of 8×8 and 1×8 . After comparing the performance of CNNs, GRUs, FNNs and random forest, we chose CNNs as the base and top learners. The top model is fed by the stacked outputs of three base models, hence the input size of the top model is 1×24 .

2) $M > N$: We also consider three situations for this case: $M = 4, N = 2$; $M = 8, N = 4$ and $M = 10, N = 5$. With the same procedures, the base models include CNNs, NNs, random forest, and the top model (CNN or NN) is used for models' stacking.

B. Permutation

After regression, machine learning models usually output decimal values, however, integer outputs are needed as we need to know the exact indices of users. Thus, permutation (or sorting) approach is employed in the end to process the outputs

TABLE II: Test performance of the cases $N = M = 2, 4, 8$.

Cases	Base model 1	Base model 2	Base model 3	Top Model	Training time
$N = 2$	99.97%	99.91%	99.95%	99.99%	24.8s
$N = 4$	97.90%	98.41%	97.90%	98.95%	604.5s
$N = 8$	89.83%	89.83%	89.83%	90.67%	1218.6s

TABLE III: Test performance of the cases which have different subchannels and users: $(M, N) = (4, 2), (8, 4), (10, 5)$.

Cases	Base model 1	Base model 2	Base model 3	Top Model	Training time
$M = 4, N = 2$	99.51%	99.26%	95.20%	99.73%	87.47 s
$M = 8, N = 4$	94.59%	93.09%	93.40%	96.13%	595.06 s
$M = 10, N = 5$	86.03%	85.74%	85.09%	86.69%	867.85 s

of machine learning models so as to obtain outputs in integer form. More specifically, assume that the target of one sample is $\{3, 1, 4, 2\}$ and the real output is $\{2.15, 0.76, 4.43, 1.55\}$, the real output should be change to integers. The intuitive operations here might be floor, ceil and round. However, these operations are not appropriate in implementation, as rounding provides the result $\{2, 1, 4, 2\}$, floor renders $\{2, 0, 4, 1\}$ and ceiling leads to $\{3, 1, 5, 2\}$, all of which are unsatisfied outcomes. Permutation sorts the four values based on their relative size and obtains $\{3, 1, 4, 2\}$ as the final prediction result, which is more reasonable and capable to provide better performance in practical applications.

C. Accuracy Calculation

In order to provide comprehensive observations of models' capacity and predictive results, the proportion of correctly predicted users is defined as the prediction accuracy. More specifically, assuming that the number of samples is K , the accuracy is formulated as follows.

$$\text{Accuracy} = \frac{\text{The number of correctly predicted } \bar{x}_j^m}{KN}.$$

VI. TEST RESULTS

The test results are shown in Tables II and III. From these tables, it can be seen that although the prediction accuracy decreases as N increases, the prediction results are satisfactory and the general relationship between the optimization matrix R and the final assignments X can be learned by the integration of base and stacking models. When $N = M = 2$; $N = M = 4$; $M = 4, N = 2$; $M = 8, N = 4$, the prediction accuracy is more than 95% which is better than the published results in literature [6]. The test accuracy of the cases $N = 4$ and $N = 8$ in literature [6] is respectively 92.76% and 77.86% (in both cases the data generation and the training of the deep learning models are done offline in [6]), which is lower than the performance of the proposed method about 6% and 12%. TABLE IV: Time consumed (sec) of 10000 samples using Algorithm 1 and machine learning methods for 6 cases discussed in this letter.

Cases	Methods					
	$M = 2, N = 2$	$M = 4, N = 4$	$M = 8, N = 8$	$M = 4, N = 2$	$M = 8, N = 4$	$M = 10, N = 5$
Algorithm 1	41.85s	48.28s	48.64s	50.12s	52.66s	56.59s
ML methods	0.04s	0.93s	2.85s	0.09s	1.26s	2.69s

To compare the time efficiency of Algorithms 1 and machine learning methods, we tested the computation time of 10000 samples using the same computer (i7-7700 CPU, Nvidia Geforce GTX 1050). The results are shown in Table IV, from which we can see that the transformation to regression problem which is solved by machine learning techniques largely improves the time efficiency of computation and provides a new perspective of optimization problem solving.

VII. CONCLUSION

This letter employs convex optimization based algorithm and machine learning based methods to solve the channel assignment problem. The optimization problem is converted to regression problems for different cases and solved by machine learning methods: CNNs, FNNs, GRUs, random forest and stacking approach. The results demonstrate that machine learning based methods have superiority in improving time efficiency without compromising much prediction accuracy. The future studies may investigate more comprehensive machine learning techniques to achieve higher performance in more complicated scenarios.

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