Transfer Learning Based Diagnosis for Configuration Troubleshooting in Self-Organizing Femtocell Networks

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Abstract—Diagnosis for configuration troubleshooting in femtocell networks is extremely important for end users and network operators. However, because the small-size femtocell only serves several users, the historical data are very scarce. The data scarcity makes traditional cellular troubleshooting solutions which require a large amount of historical data not applicable. In this paper, we propose a new framework based on transfer learning technology to address the data scarcity so as to enhance the accuracy of the diagnosis model. The proposed framework extracts additional diagnosis knowledge by transferring data information from other femtocells. Based on this framework, we design a Cell-Aware Transfer scheme (CAT), which splits data for each femtocell to further enhance the diagnosis accuracy. Extensive evaluations show that our approach can achieve higher accuracy than traditional methods in self-organizing femtocell network scenarios.

Index Terms—automated diagnosis, femtocell, transfer learning.

I. INTRODUCTION

Femtocell is a key technology that provides ubiquitous network coverage to meet the demands for higher data rates for indoor cellular services. Given the importance of the mobile phone to our daily life, high-reliability and high-quality cellular network services are expected. However, unlike the operator-deployed traditional cellular networks, the user-deployed femtocells are not well-planned. Thus, inappropriate configuration problems occur more likely. Such problems can occur within homes due to users' wrong operations or inappropriate self-configuration algorithms beyond operator's control and management, which we refer to as *misconfigurations* in this paper. Moreover, the number of the femto Access Points (femto AP) is much larger than macro Base Stations (macro BS), making the distributed-manner configurations in user-deployed femtocells more error-prone. Thus, efficient diagnosis for configuration troubleshooting in femtocell is highly motivated.

Existing diagnostic systems for traditional cellular networks fall short for femtocell diagnosis. These diagnostic systems are mainly based on classification reasoning methods, such as Bayesian Network (BN) [1] [2]. The traditional approaches for cellular networks are not applicable in femtocell networks because of the two data scarcity challenges: 1) the indoor femto AP only supports several users, so the data from user end are much less when compared with traditional cellular networks; 2) different from well-planned cellular networks, topology of femtocells is highly dynamic because Femto APs can be re-deployed and turned on/off by end users, so that historical data can be easily outdated. Without enough usable historical data, the accuracy of the classification models in traditional approaches cannot be guaranteed.

In this paper, we propose a novel framework to address the data scarcity challenges. Our framework utilizes the existing transfer learning techniques to leverage historical data from other femtocells. However, there are challenges when leveraging the transfer learning techniques. Since the wireless environment (e.g. indoor propagation, neighboring cell layouts) of each femtocell is different, characteristics of femtocells can be very different from each other. How to extract useful information from other femtocell's historical data needs to be carefully designed. Another challenge lies in that the target femtocell may be just deployed or re-deployed, the misconfiguration instances can be very rare. General transfer learning techniques based on historical misconfiguration instances are not accurate. To address these challenges, we design a Cell-Aware Transfer scheme (CAT). In the scheme, we weight the data for each femtocell in order to leverage the data from similar femtocells while eliminate the misleading information from the cells whose scenarios are quite different from the target femtocell. Considering that the misconfiguration instances may not be enough, CAT extracts information from measurement data when femto AP is properly configured. By considering these characteristics of femtocell networks, CAT can diagnose misconfigurations accurately even when the instances are rare in the past.

The main contributions of this paper are as follows: 1) We propose a transfer learning framework for femtocell configuration troubleshooting. As the best of our knowledge, this is the first diagnosis framework proposed for the femtocell configuration troubleshooting. 2) We develop a diagnosis scheme based on our transfer learning framework to address the data scarcity challenges in femtocell scenario. 3) Simulation results show that our scheme can achieve higher accuracy than traditional approaches for configuration troubleshooting in self-organizing femtocell networks.

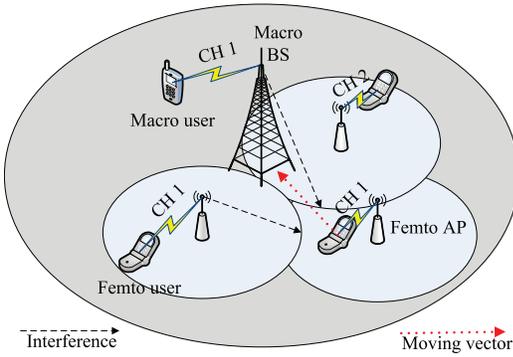The rest of the paper is organized as follows. In Section

Fig. 1. Two-tier femtocell-macrocell network scenario

II, the overview of self-organizing femtocell network and configuration problems in femtocell is discussed. In Section III, we presents the transfer learning framework for femtocell configuration troubleshooting, and then propose our cell-aware scheme CAT. In Section IV, the simulation results are described. Finally, we conclude our work in Section V.

II. CONFIGURATION PROBLEMS IN FEMTOCELL

A. Network Scenario

We consider a multi-channel cellular system and a typical two-tier femtocell network scenario depicted in Fig. 1 where a macrocell is embedded with multiple femtocells. Macrocell and a set of femtocells use orthogonal channels to transmit data. The interference from neighbor femto APs to femto user will be restricted to the femto APs that operate on the same channel [3]. Further, the femto user will be interfered by the macro BS if the femto AP configures its operating channel to the macro dedicated channel. Users periodically report measurement data, including Received Signal Strength (RSS) from femto APs and macro BS, and the channel quality estimations. Users can handover from femtocell to macrocell as well as from macrocell to femtocell in the movement whenever handover conditions are satisfied.

B. Configuration Troubleshooting and Challenges

Misconfigurations easily occur and cause interference and coverage gap problems. Since femto APs are considered as customer devices, installed and configured without the operator's precise plan, misconfigurations can be caused by manual setup or inappropriate self-configuration algorithms. If the configurations of a femtocell network are not carefully managed, the complex topology can originate severe interference or coverage gap problems.

Misconfigurations that cause the above mentioned problems are described as follows:

- *Operating Channel*. Since the existing macrocell network is overlaid on femtocell networks utilizing the limited set of operating frequency channels, inappropriate operating channel configurations on femtocell will result in severe co-channel interference with neighboring femtocells or macrocell.

- *Transmission Power*. Inappropriate strong transmission power can interfere neighboring cells that operate on the same channel, while too weak transmission power can result in coverage gap for its serving users.

- *Handover Parameters*. The bad mobility control parameters (e.g. Handover Margin in hard handover algorithm) can also cause the interference and coverage gap problems. User will stay in a cell with weak signals, or handover to a cell that causes strong interference if handover parameters are not set properly (e.g. Handover Margin too large or too small).

Diagnosing misconfigurations is a difficult task because of the similar symptoms of different misconfigurations, as well as user mobility and time-vary wireless environments. The dropped calls and blocked calls caused by different configuration problems have similar symptoms at user end. Measurement data at user end containing channel quality and received signal information can only tell whether dropped calls and blocked calls are caused by high interference or coverage gap, while specific misconfiguration leading to the problems are not obvious. Further, measurement data collected at user end also vary due to user mobility and time-vary wireless environments even if the configurations stay unchanged, which makes the diagnosis for femtocell configurations even more difficult.

Additionally, the small size and user-deployed characteristics of femtocell make the diagnosis task even more challenging. First, since femto AP only serves several users, traditional cellular diagnosis approaches that require data from a large number of users are not well-suited to our femtocell scenario. Another challenge lies in user-deployed characteristics. Since femtocells are deployed by different individual users, neighboring cell layouts are more dynamic than operator-planned cellular networks. Femto AP can be re-deployed and turned on/off by users; and as more and more femtocells are installed, the situations that new neighboring cells join the network often occur. Historical data are easily outdated due to these deployment changes. The scarcity of usable historical data caused by the above reason undermines the performance of previous work [1] [2], which require months or even years to collect enough fault instances. Thus, new solution that addresses the above-mentioned challenges is required.

III. CELL-AWARE TRANSFER DIAGNOSIS DESIGN

A. Overview of Transfer Learning Framework in Femtocell Diagnosis

In this paper, we propose a transfer learning framework for configuration troubleshooting in self-organizing femtocell networks, which leverages historical data from other femtocells to address the data scarcity challenges. The architecture of our framework is illustrated in Fig. 2. Traditional classification-based diagnosis approaches for cellular networks are shown in the upper box. In these approaches, historical data are put into a classifier to train a diagnosis model to predict unknown faults when given specific measurement data of current network. In
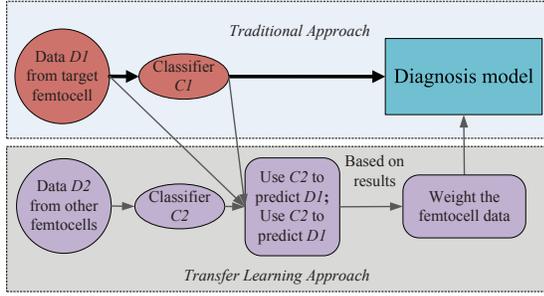
Fig. 2. Architecture of our transfer learning framework

our proposed framework, historical data from other femtocells are also leveraged to enhance the diagnosis model, as depicted in the bottom box. The classifiers $C1$, $C2$ are trained by data from target femtocell $D1$ and data from other femtocells $D2$, respectively. The classifier $C2$ is used to predict $D1$, and $C1$ to predict $D1$. Based on the misclassification rate of prediction results, we weight each instance. Then all the weighted instances are put into the diagnosis model as additional historical data. The proposed framework can extract useful information from other femtocells to address the data scarcity challenges in femtocell diagnosis. In the following, we design CAT, which splits data for each femtocell and specifies the femtocell weights by femtocell similarity and misclassification cost.

B. Cell-Aware Transfer Scheme

In order to design a scheme more suitable to femtocell diagnosis, we have two observations: 1) When a misconfiguration is misclassified as other misconfigurations, different misclassifications have different degrees of impact on the diagnosis model; 2) the characteristics of femtocells can be very different. Based on these observations, we specify the misclassification cost and femtocell dissimilarity, and then propose our scheme CAT.

First, we describe our observation on misclassification and then introduce the misclassification cost into CAT. Intuitively, both strong transmission power and wrong channel could lead to interference problem while weak transmission power results in coverage gap problem. If we misclassify interference problem as coverage gap problem, the impact will be much worse than misclassification within interference problems. Based on this observation, we introduce the misclassification cost to the transfer algorithm in this paper. One important assumption in the design rationale for classification-based diagnosis is that different faults correspond to different symptoms, i.e. different distribution of measurement data (e.g. user reports and AP configurations in our scenario). Thus, we could specify the misclassification cost according to the different distributions of data between different kinds of misconfigurations, which can be calculated by three steps: first we calculate the divergence of each kind of measurement data (e.g. RSS, SINR) distributions in historical instances of two kinds of misconfigurations, then we weight each kind of measurement data based on its decisiveness, and at last sum up the weighted divergences. In

this paper, Kullback-Leibler (K-L) divergence [4] is used to estimate the measurement data distribution difference, which is:

$$Div(P^{F_1}, P^{F_2}) = \sum_i P^{F_1}(i) \log \frac{P^{F_1}(i)}{P^{F_2}(i)} + \sum_i P^{F_2}(i) \log \frac{P^{F_2}(i)}{P^{F_1}(i)}, \quad (1)$$

where P^{F_1}, P^{F_2} denotes the distributions of the one kind of measurement data in two kinds of misconfigurations. The K-L Divergence presents how different the two kinds of misconfigurations in the consideration of certain kind of measurement data. Further, the weight of each kind of measurement data is specified by information gain, which is defined as:

$$Gain(A_i) = H(I) - H(I|A_i), \quad (2)$$

where $H(I)$ denotes the entropy of the misconfiguration instances in historical data, and $H(I|A_i)$ denotes the condition entropy of misconfiguration instances given one kind of measurement data A_i. If $Gain(A_i)$ is larger, A_i is more decisive to the diagnosis results, i.e., for the kind of measurement data with larger information gain, the same amount of divergence devotes more to the difference of the diagnosis results. Thus, the misclassification cost for two kinds of misconfiguration F_1, F_2 is defined as:

$$Cost_{F_1,F_2} = \sum_i Gain(A_i) \times Div(A_i^{F_1}, A_i^{F_2}), \quad (3)$$

where, $A_i^{F_j}$ is the distribution of A_i in one kind of misconfiguration F_j.

Another key observation is that characteristics of femtocells can be very different. Some femtocells, which have similar indoor propagation properties and similar neighboring layouts, share more latent knowledge with the target femtocell, while femtocells with very different wireless environments can even transfer wrong knowledge to the target cell, which even undermines the diagnosis model. Thus, the transfer algorithm should be cell-aware. Our proposed cell-aware scheme CAT distinguishes the data from different femtocells to let the data from similar femtocells have stronger impact than data from dissimilar femtocells. In our scheme, femtocell dissimilarity are also specified based on information gain. Since misconfiguration instances in the target cell can be very rare, the original historical instance based transfer scheme is not reliable to estimate the weight for each femtocell. To address this problem, we use the information that lies in large number of measurement data in normal situations to calculate the dissimilarity of two femtocells, The dissimilarity is calculated as:

$$D_{f_1,f_2} = \sum_i Gain(A_i) \times Div(A_i^{f_1}, A_i^{f_2}), \quad (4)$$

where, $Gain(A_i)$ is the information gain of one kind of measurement data computed by (2), $Div(A_i^{f_1}, A_i^{f_2})$ is the
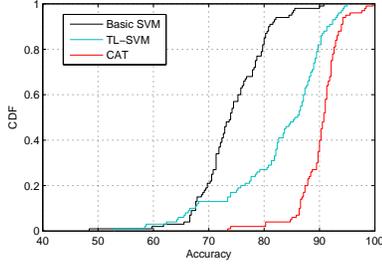
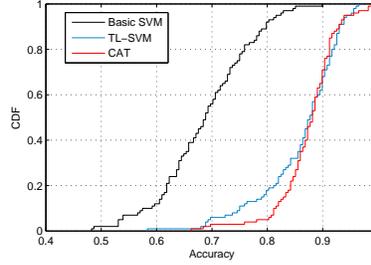Fig. 3. CDF of diagnosis accuracy for overall misconfigurations

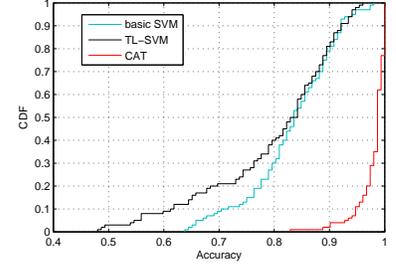Fig. 4. CDF of diagnosis accuracy for interference problems

Fig. 5. CDF of diagnosis accuracy for coverage gap problems

divergence of two femtocell f_1, f_2 in consideration of A_i computed by (1).

After specifying misclassification and femtocell dissimilarity, we describe how femtocells are weighted in CAT. We first divide the historical data sets by cells and train a classifier for each femtocell, which can be denoted by a vector $\mathbf{C} = [C_1, C_2, ..., C_F]$. Based on these classifiers, historical instances I^t from target cell can be predicted, noted as I_p^t. Let $l_i^t = |I^t - I_p^t|$ be the loss of instances from target femtocell predicted by C_i. l_i^t is calculated by summing the misclassification cost of the each wrong predicted instance based on C_i. According to Transfer AdaBoost algorithm [5], the error on the target cell instances can be calculated by:

$$\varepsilon_t = \sum_{i=1}^{F} \frac{w_i^t \times l_i^t}{\sum_{i=1}^{F} w_i^t}, \tag{5}$$

where w_i^t is the weight for femtocell i. Then, we decrease the weight for the transfer cell to reduce its effect according to the loss by multiplying β^{l^t}, where $\beta = \varepsilon_t/(1 - \varepsilon_t)$ and ε_t is required to be less than 1/2. Note that β^{l^t} belongs to (0,1]. As we can see, if ε_t gets larger, the weights for all cells will decrease more sharply, which implies that the similarity between the target cell and all the other cells is smaller, and there less knowledge in the whole network can be transferred to enhance the diagnosis model. For each femtocell, if l^t is larger, the weight drops more sharply, which implies that this cell will affect the diagnosis process less.

After weighting each femtocell, the classifiers trained for femtocells are treated as voters in the diagnosis model. The votes are weighted by weights of the femtocells. The final result is the certain misconfiguration that gets most votes. Thus, the femtocells dissimilar with the target cell will be neglected for their weaker impact on the diagnosis model, while the similar cells with high weights can provide knowledge to the diagnosis model.

IV. SIMULATION RESULTS

A. Simulation Scenario

As a realistic communication environment, we consider a two-tier cellular network comprised of multiple femtocells overlaid on a macrocell. Femto APs are randomly distributed within 500 meters to the macro BS. Each femto AP serves a single user that moves around the serving AP within 50

meters from it with a speed of 1.5 meters per second and random direction. The propagation model of AP or BS to a user are determined based on the ITU and COST231 models which are described as [6] [7]:

- Macro BS to outdoor user (outdoor link):

$$L = 10^{4.9}(\frac{r}{1000})^4 f^3 10^{S/10};$$

- Serving femto AP to indoor user (indoor link):

$$L = 10^3 r^{3.7} 10^{S/10} 10^{L_i/10};$$

- Otherwise (outdoor-to-indoor or indoor-to-outdoor link):

$$L = 10^{4.9}(\frac{r}{1000})^4 f^3 10^{S/10} 10^{(L_i+L_e)/10}.$$

Where r is the transmitter-receiver separation distance in meters; f is the frequency in MHz; S is the log-normal shadowing factor with a standard deviation of 8 dB; L_i and L_e are internal and external wall losses, and L_i is set to be $6.9n$ where n denotes the number of the walls varying from 0 to 3 with uniform distribution, while L_e is set to be 7 dB, in our simulation. If user is within the range of 10 meters from its serving femto AP, user position is considered to be indoor; otherwise, user position is considered as outdoor.

Both macro BS and femto APs operate at the carrier frequency of 2.5 GHz with 5 MHz channel bandwidth. Thermal noise power density is set -169 dBm/Hz. At the initial configuration, the transmission power of macro BS and femto APs are set 40 dBm and 5 dBm, respectively. Only femto-to-macro and macro-to-femto handovers are considered in our scenario. The handover model we adopt here is according to hard handover in [8]. Call is blocked or dropped when RSS of the serving AP is less than -104 dBm, or the Signal to Interference plus Noise Ratio (SINR) is below -20 dB. The channel assignment scheme we adopt in this paper is based on split resource allocation [9]. First we split the channels between macro users and femto users. For the channel assignment among femtocells, each femto AP greedily chooses the channel with highest SINR.

Five kinds of misconfigurations are considered: transmission power too strong, transmission power too weak, wrong operating channel, Handover Margin too large, Handover Margin too small. For each instance, a random kind of misconfiguration is injected to a random femtocell by altering the value of the very configuration which makes either SINR below -20 dB or RSS
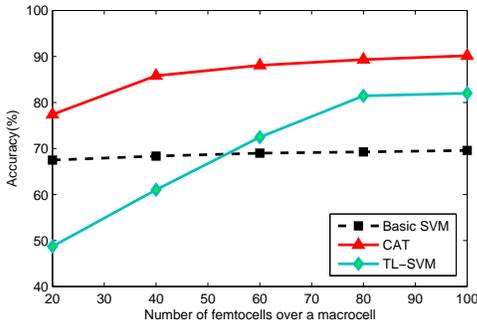
Fig. 6. Diagnosis accuracy against femtocell density

of serving AP below -104 dBm. The diagnosis process is to find out which kind of misconfiguration that leads to interference or coverage gap problem, when given the configuration values and user measurement data on SINR, as well as RSSs from serving cell and neighbor cells. The diagnosis accuracy is defined as the percentage of misconfiguration instances that are successfully classified.

B. Results

We illustrate the Cumulative Distribution Function (CDF) of the diagnosis accuracy of different methods in Fig. 3, Fig. 4 and Fig. 5, where ten of total twenty channels are assigned to 100 femtocells. Interference problems refer to instances with SINR below -20 dB, and coverage gap problems refer to instances with RSS below -104 dBm. The overall misconfigurations are the sum of these two kinds of problems. We compare the performance of CAT with two other existing schemes, Support Vector Machine based scheme (basic SVM) and transfer learning assisted SVM (TL-SVM). SVM is used as basic classifier in all methods. Basic SVM is traditional method that only use the target femtocell data. The TL-SVM method transfers other femtocells' instances based on the original Transfer AdaBoost approach. TL-SVM splits data into two parts, data from target cell and data from other cells, and then weight each instances; while CAT splits data for each cell and introduces misclassification cost and femtocell dissimilarity to weight each cell. Fig. 3, Fig. 4 and Fig. 5 show that CAT achieves higher accuracy than the other approaches in troubleshooting all misconfiguration problems, coverage gap problems and interference problems, respectively. CAT and TL-SVM outperform basic SVM because of the extra diagnosis information extracted from other femtocells. CAT achieves higher accuracy than TL-SVM. By considering the cell different and misclassification cost, CAT eliminates the bad impacts from instances that undermine the diagnosis model in the TL-SVM method. The results demonstrate that our diagnosis scheme outperforms the other two methods in our self-organizing femtocell network scenario.

We next study the performance of the diagnosis methods in networks with different femtocell density in Fig. 6. The number of the femtocells deployed in the macrocell varies from 20 to 100, while the ratio of femtocell number to the channel numbers assigned to femtocell to is kept 10 in this paper. We can see that diagnosis accuracy of the basic SVM keeps almost unchanged while TL-SVM and CAT can diagnose with higher accuracy in a network with more femtocells in that there are more historical data can be leveraged to further enhance the diagnosis model. The accuracy of the CAT drops less sharply than TL-SVM when femtocell number decreases. This is because that even in the scenario that there are fewer instances can be transferred, CAT can eliminate the negative impacts from dissimilar femtocells by weighting each femtocell.

V. CONCLUSION

In this paper, we presented a transfer learning framework for diagnosing femtocell configuration problems. The framework leverages transfer learning technology to address the data scarcity challenges in femtocell networks. Based on this framework, we propose the Cell-Aware Transfer scheme, which accounts for special characteristics of femtocell networks. During the design of CAT, we assign weights for each femtocell, and specify the misclassification cost and dissimilarity of femtocell based on information gain, to enhance the accuracy of the approach. Simulation results demonstrate that CAT outperforms the traditional diagnosis schemes in a variety of network scenarios.

VI. ACKNOWLEDGEMENT

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