Massive Device Connectivity in IoT Networks:Phase Transitions via Convex Optimization

A Project Report

submitted by

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CERTIFICATE

This is to certify that the report titled **Massive Device Connectivity in IoT Networks:Phase Transitions via Convex Optimization**, submitted by **SOWMYA SIVVANNAGARI (EE19M029)**, to the Indian Institute of Technology Madras, for the award of the degree of **MASTER OF TECHNOLOGY** is a bonafide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Massive device connectivity is a must for Internet of Things networks, which are made up of a huge number of devices that have intermittent traffic. Joint device activity detection and channel estimation are of main concern in such scenario. Also due to the huge number of users, we need to allot non-orthogonal signature sequences to the devices. In this work, to detect active devices and estimate their channels, we use a group-structured sparsity estimation approach. This decreases the length of the signature sequence while allowing for huge connection and erratic traffic. We use the phase transitions behavior of the group sparsity estimation issue to identify the appropriate signature sequence length. Simulated results provide an optimal way of choosing acceptable signature sequence length in practise. The results presented in this work are implemented with reference to the approach mentioned in [1]

KEYWORDS: Massive device connectivity, Phase transitions, Activity Detection, Channel estimation, Machine-type Communication(MTC), Signature Sequence length.

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ABBREVIATIONS

BS	Base Station
IoT	Internet of Things
MTC	Machine Type Communications
CS	Compressed Sensing
NOMA	Non orthogonal Multi User Access
AMP	Approximate Message Passing
CSI	Channel state information
ADMM	Alternating Direction Method of Multipliers
JADE	Joint Activity Detection and Channel Estimation

NOTATION

$\mathcal{CN} \sim (0, \sigma^2)$	Complex Gaussian random variable with mean zero and variance σ^2
$\|\bullet\|_F$	Frobenius norm of a vector **X**
$\|\bullet\|_2$	spectral norm of a vector
$(\bullet)^T$	Transpose of a vector
$diag(a_1, ..., a_N)$	diagonal matrix with entries $a_1, ..., a_N$

CHAPTER 1

INTRODUCTION

1.1 Need for IoT

Internet of Things is a recent technology that creates a global network of machines and devices that are capable of communicating and exchanging data with each other. Because it enhances productivity and lowers costs, the Internet of Things has been hailed as an economic development engine. As the Internet of Things (IoT) gains traction in the industry, the number of devices deployed is increasing. IoT platform provides solutions in the domains of smart cities, smart grids, smart homes, and connected cars that could bring a qualitative improvement in people's lives by collaborating physical sensing with data processing to create significant information.

The Internet of Things (IoT), which is projected to provide a variety of services, will be made possible by devices that are equipped with sensing and communication capabilities. Connecting a home automation system to the Internet, for example, allows us to control and manage various gadgets in order to save energy. Many IoT-related applications exist, including smart homes, smart cities, and smart healthcare, among others.

IoT comprises of many technologies which includes near field, short range and wide-area communication networks; device to device communication; device technologies for sensing, actuation, and energy harvesting; device and application software platforms for big data, security, and cloud processing.

1.2 Applications of IoT

A growing number of physical devices are being connected to the Internet at an increasing rate, utilizing the concept of the Internet of Things (IoT). The IoT enables the devices to see, hear, think and perform jobs by having them communicate with each other, to share information and to coordinate decisions. The IoT transforms these objects from being traditional to smart by exploiting its underlying technologies such as ubiquitous and pervasive computing, embedded devices, communication technologies, sensor networks, Internet protocols and applications [2].

Fig.1.1 illustrates the overall concept of the IoT in which every domain specific application is interacting with domain independent services, whereas in each domain sensors and actuators communicate directly with each other. While the concept of IoT has been in use for a long time, a group of recent advances in a number of different technologies has made it practical.

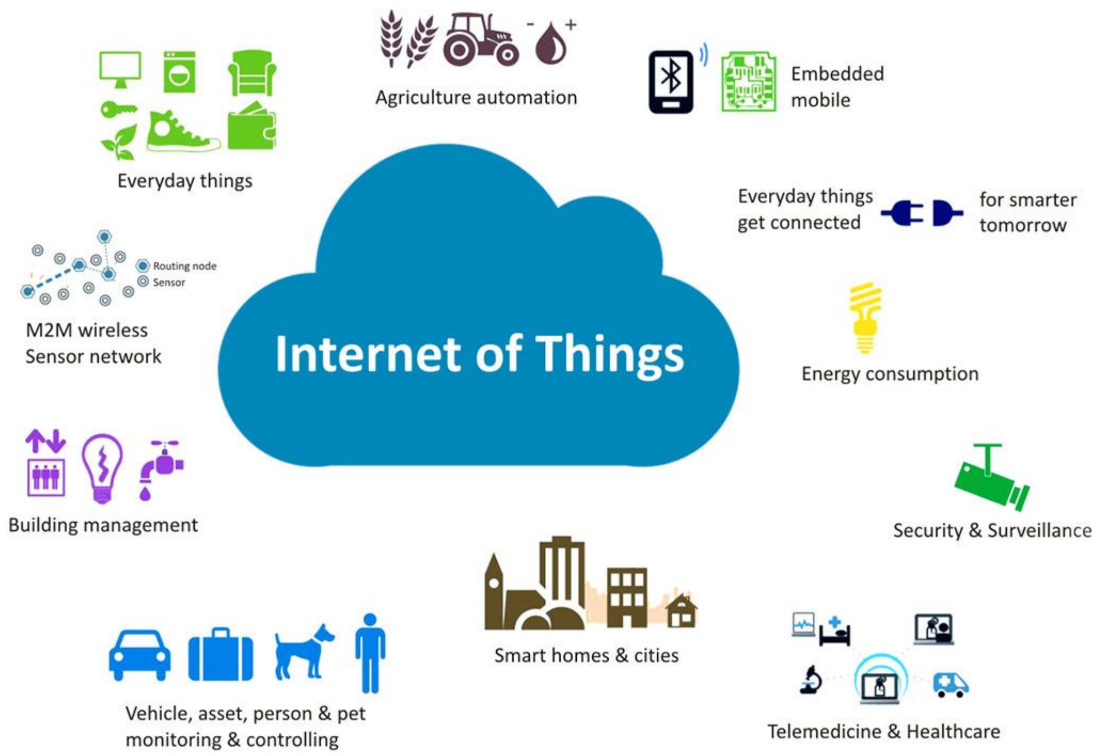

Figure 1.1: Applications of IoT

For example, detection of active devices will improve the efficiency of data transmission in IoT networks. Technological enhancements that support this incredible growth include the speed and bandwidth of the underlying networks, extended battery life of IoT devices, broader capabilities of wireless communication protocols, and more secure management of devices and networks. These advancements have allowed a significant number of industries to replace expensive, and often unreliable, wired communication with wireless communication.

1.2.1 Emerging Technologies

Access to low-cost, low-power sensor technology. Affordable and reliable sensors are making IoT technology possible for more manufacturers.

Connectivity. A host of network protocols for the internet has made it easy to connect sensors to the cloud and to other “things” for efficient data transfer.

Cloud computing platforms. The increase in the availability of cloud platforms enables both businesses and consumers to access the infrastructure they need to scale up without actually having to manage it all.

Machine learning and analytics. With advances in machine learning and analytics, along with access to varied and vast amounts of data stored in the cloud, businesses can gather insights faster and more easily. The emergence of these allied technologies continues to push the boundaries of IoT and the data produced by IoT also feeds these technologies.

Conversational artificial intelligence (AI). Advances in neural networks have brought natural-language processing (NLP) to IoT devices (such as digital personal assistants Alexa, Cortana, and Siri) and made them appealing, affordable, and viable for home use.

1.3 Proposal Definition

A huge variety of application areas bring new challenges for IoT networks design.To provide universal connectivity to enable such IoT-based applications, massive machine-type communications(MTC) and ultra reliable and low latency communications become critical in the upcoming 5G networks. In many scenarios, there are large numbers of devices to be connected to the Internet through the BS. Thus, supporting massive device connectivity is a crucial communication prerequisite for IoT networks.

Machine-centric communications have two distinctive features as compared to conventional human-centric communications:

(i) the overall system needs to support massive connectivity - the number of devices connected to each cellular base-station (BS).

(ii) the traffic pattern may be sporadic at any given time,it implies only a small fraction of all physical devices are active.

For such a network, accurate user activity detection and channel estimation are crucial for establishing successful communication between the IoT devices and the Base Station.

To identify active devices and to estimate their channels, each device has to be assigned a unique signature sequence. However,large number of potential devices puts limitation on coherence time and frequency in the wireless fading channel, making it impossible to assign mutually orthogonal signature sequences to all users.Therefore, we assign non-orthogonal signature sequences to each device .

In this work, by utilizing the concept of sparsity of device activity patterns, we implement a group-structured sparsity formulation to solve the joint active device identification and channel estimation problem in massive IoT networks.This method does not depend on the prior information of channel distribution. This is achieved by using convex optimization to characterize the phase transition behavior of the group-structured sparsity estimation problem.The whole problem formulation mentioned in this work is in reference to [3].

1.4 Literature Survey

Various strategies for dealing with enormous device connection and the high-dimensional channel estimation challenge have been developed in recent research. By utilising the sparsity of channel structures in the time, frequency, angular, and Doppler domains, compressed sensing (CS)-based channel estimate approaches have been developed. [4],[5]. In a dense wireless cooperative network, the spatial and temporal prior information was also used to tackle the high-dimensional channel estimation problem [6].

Nevertheless, in IoT networks with a short channel coherence time, it's vital to take use of the device sparse activity pattern to improve channel estimation. [7], [8], thereby reducing the training overhead. Because of the huge nature of IoT communications, developing efficient techniques to address the computation issue is particularly crucial.[1]. The topic of sporadic device activity detection has lately been looked into.

The random access strategy was researched in the context of cellular networks in order to deal with the high overhead incurred by the large number of devices[9], [10]. If the orthogonal signature sequence randomly picked by the active device is not used by other devices, a connection between the active device and the BS must be created in the random access method.[1].

To accommodate a large number of devices, we focus on the non orthogonal multi user access (NOMA) strategy, which uses non orthogonal resource allocation to simultaneously service numerous devices. In [11], the opportunities and problems of using NOMA to provide large connection are examined. Furthermore, by deploying more radio access points in IoT networks [12], network densification [13] appears to be a potential solution to boost network capacity, enable low-latency mobile apps, and support enormous device connectivity.

[14] looked at the information theoretical capacity of vast connection. The sparsity activity pattern generates a CS-based formulation to recognise active devices and estimate channels[8] , [15]. CSI refers to the distribution information in the linked statements of "previous knowledge of CSI." [16] suggested a neural network approach for predicting channel conditions for unmanned aerial vehicle communication.

In [8], and [6], a joint design of channel estimation and user activity detection was developed using the approximate message passing (AMP) algorithm, which uses statistical channel information and large-scale fading coefficients to improve the Bayesian AMP algorithm with rigorous performance analysis. However, in order to reduce signalling cost, the technique mentioned in [1] does not require prior knowledge of CSI distribution.

The research work in [1] focuses on recognising active devices in vast IoT networks, whereas the previous work [17] suggested an effective channel reservation strategy for hand-off to minimise the probability of dropping and blocking calls. The joint user detection and channel estimation strategy for cloud radio access network through the alternate direction method of multipliers (ADMM) algorithm was introduced in [18] without performance study, assuming no prior information of the distribution of CSI.

[1] offer a structured group sparsity estimation approach to tackle the JADE problem without prior knowledge of the CSI distribution to avoid the overheads of gathering large scale fading coefficients and statistical channel information. It provides the exact characterization for phase transition behaviours in the structured group sparsity estimation problem to estimate the best signature sequence length.

In [19], a convex geometry technique was used to generate precise estimates of the number of measurements needed for correct and reliable structured signal recovery. This technique, on the other hand, can only ensure the success conditions for signal recovery. Following that, based on the theory of conic integral geometry, the phase transition of a regularised linear inverse problem with random measurements was addressed in [20] and [21], which established both the success and failure conditions for signal recovery. In particular, the location and width of the transition are essentially controlled by the statistical dimension of a descent cone associated with the convex regularizers. However, these results are only applicable in the real domain[1].

When tackling the JADE issue with a fixed time budget, the enormous number of devices in IoT networks presents distinct computational challenges. Unfortunately, due to their limited scalability, second order approaches like the interior point method are inapplicable non large-scale optimization situations. First-order approaches, on the other hand, such as gradient methods, proximal methods[22], ADMM algorithm [23], and rapid ADMM algorithm [24], are particularly useful for tackling large-scale issues.

Accelerating the convergence rate without raising the computational cost of each iteration is a different technique. [25] demonstrated that with more data, the step-size in the projected gradient approach may be increased, resulting in a faster convergence rate. Smoothing approaches like convex relaxation [26] or just adding a good smooth function to smooth the nondifferentiable goal function [27] achieve a faster convergence rate in general. To ensure the performance of sporadic device activity detection in IoT networks, the level of smoothing should be carefully determined.

By speeding the convergence rate, the smoothing method will be used in [1] to solve the high-dimensional group sparsity estimation issue with a fixed time budget. As a result, there is a trade-off between computing cost and estimation accuracy, as increasing the smoothing parameter reduces estimation accuracy.

1.5 Organization

The project flow has been clearly indicated below for the purpose of better understanding. The thesis report comprises of four chapters.

This chapter has the basic introduction to the project and the necessity of IoT, along with the literature survey done prior to selecting the paper. In chapter 1, we discussed about the proposal definition which gives more insight to the work. Before attempting any project or designing it, it is essential to learn its system model. The system model, phase transitions, different forms of optimality conditions has been discussed in detail in chapter 2.

In chapter 3, we presented the experimental results depicting the phase transition behaviour. We also found out the optimal signature sequence length from the phase transition plot. Finally, chapter 4 concludes the work and also future scope is discussed.

CHAPTER 2

SYSTEM MODEL AND ANALYSIS

2.1 System Model

IoT network with one BS serving N single antenna IoT devices, where the BS is equipped with M antennas is considered. The channel vector from device i to the BS is denoted by $h_i \sim \mathbb{C}^M$, i = 1,...,N. Since IoT data traffic is sporadic, only a few devices are active out of all devices as shown in Fig.2.1. We consider the synchronized wireless system with block fading. That is, each device is active during a coherence block, and is inactive otherwise[1]. In each block, we define the device activity indicator as follows:$a_i = 1$ if device i is active, otherwise $a_i = 0$.

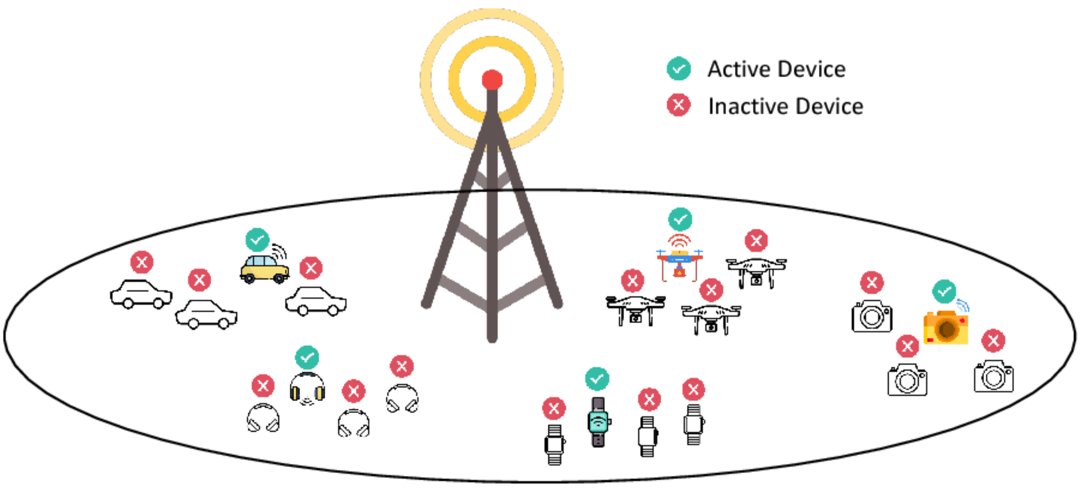

Figure 2.1: IoT Network with sporadic traffic devices

Received Signal is given by,

$$y(l) = \sum_{i=1}^{N} h_i a_i q_i(l) + n(l) \tag{2.1}$$

for all l=1,2,...,L. Here $q_i(l) \in \mathbb{C}$ is the signature symbol transmitted from device i at time slot l, y(l) $\in \mathbb{C}^M$ is the received signal at the BS,and n(l) $\in \mathbb{C}^M$ is the additive noise distributed as CN$(0, \sigma^2 I)$.

With massive devices and a limited channel coherence block, the length of the signature sequence(L) is typically smaller than the total number of devices(N)i.e, $L << N$. It is thus impossible to assign mutually orthogonal sequences to all the devices. Therefore, we generate the signature sequences from i.i.d. complex Gaussian distribution with zero mean and variance one, i.e., each device i is assigned a unique signature sequence $q_i \sim \mathcal{CN}(0, 1)$ [1]. Note that these sequences are non orthogonal.

Let Y = $[y(1), ..., y(L)]^T \in \mathbb{C}^{LXM}$ denote the received signal across M antennas, H = $[h_1, ..., h_N]^T \in \mathbb{C}^{NXM}$ be the channel matrix from all the devices to the BS antennas, and Q = $[q(1), ..., q(L)]^T \in \mathbb{C}^{LXN}$ be the known signature matrix with q(l) = $[q_1(l), ..., q_N(l)]^T \in \mathbb{C}^N$.

We can rewrite equation 2.1 as

$$\boldsymbol{Y} = QAH + N \tag{2.2}$$

where A = diag$(a_1, ..., a_n) \in \mathbb{C}^{NXN}$ is the diagonal activity matrix and N = [n(1), . . . , n(L)] $\in \mathbb{C}^{LXM}$ is the additive noise matrix.We need to jointly estimate the channel matrix H and then detect the activity matrix A.

Let Θ_0 = AH $\in \mathbb{C}^{NXM}$. This matrix has the structured group sparsity pattern in its rows. The above linear model 2.2 can further be written as

$$\boldsymbol{Y} = Q\Theta_0 + N \tag{2.3}$$

To estimate Θ_0, we make use of l_1/l_2-norm in the form of:

$$R(\Theta) = \sum_{i=1}^{N} \|\theta_i\|_2 \tag{2.4}$$

This norm will help to induce a group sparsity structure in the solution. Thus the group sparsity problem can be formulated as the following convex optimization problem:

$$\begin{aligned} P: \quad & \min_{\Theta \in \mathbb{C}^{NXM}} \mathcal{R}(\Theta) \\ \text{subject to} \quad & \|Q\Theta - Y\|_F \leq \epsilon \end{aligned} \tag{2.5}$$

where ϵ is an upper bound on $\|N\|_F$and we assume it is known a priori[1].

Given the estimate matrix $\hat{\Theta}$, the activity matrix can be recovered as $\hat{A}$ = diag$(a_1, ..., a_n)$, where a_i = 1 if $\|\hat{\theta^i}\|_2 \geq \gamma_0$ for a small enough threshold $\gamma_0(\gamma_0 \geq$ 0); otherwise,a_i = 0. The estimated channel matrix for the active devices is thus given by $\hat{H}$ with its ith row as $\hat{h}^i$ = $\hat{\theta}^i$ where i $\in \{j|\hat{a}_j$ = 1$\}$

2.2 Phase Transitions

As we have limited resources, it is important to find optimal signature sequence length needed for massive device connectivity. As we have limited resources, it is important to find optimal signature sequence length needed for massive device connectivity. This can be accomplished by solving a convex optimization problem to precisely locate the phase transition zone of the formulated issue statement.

An example of such scenario is depicted in Fig.2.2,where BS has two antennas, total number of IoT devices is 100 and number of active devices are 10. We considered noiseless case here. We observe that optimal signature sequence length depends on number of active devices and also on number of antennas associated with the base station(BS).

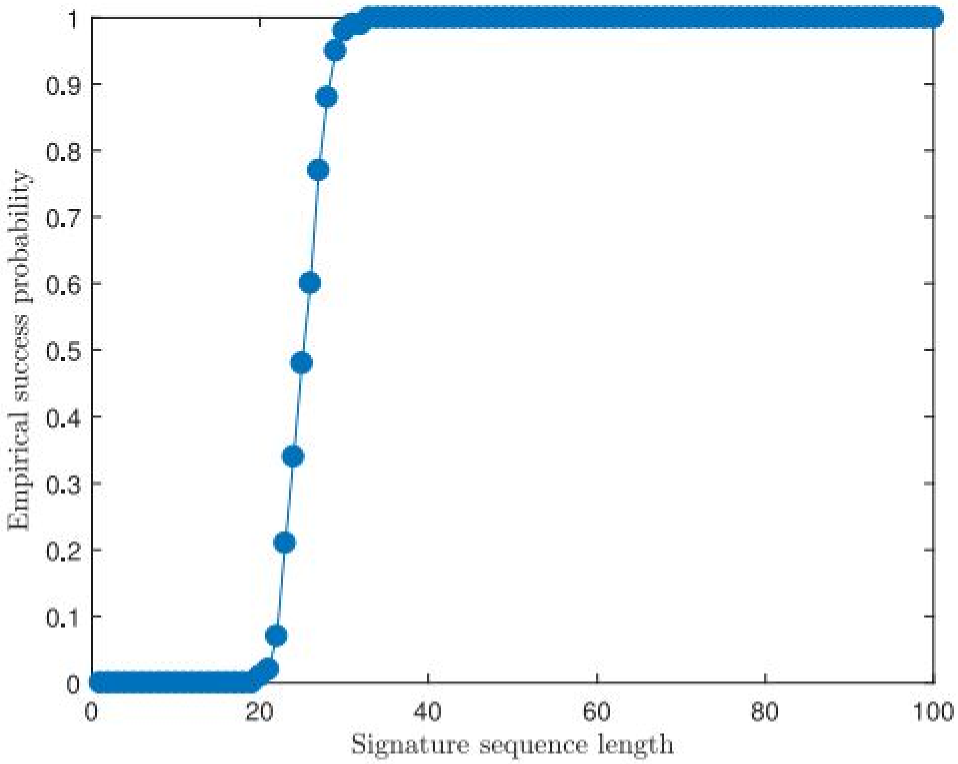

Figure 2.2: Empirical success probability via CVX in noiseless case[1]

From Fig.2.2,we can see that the signature sequence length around 30 is sufficient to achieve exact signal recovery for 100 devices out of which 10 are active. This huge reduction in signature sequence length is due to exploitation of group sparsity estimation method. Thus, by finding the location of phase transition precisely, we can choose optimal signature sequence length thereby supporting massive connectivity.

The conic integral geometry approach is only applicable in the real field scenario, hence it can't be used directly for issue P in the complex field. To solve this problem, we aim to approximate the original complicated estimation problem P with a genuine estimation problem, then do accurate phase transition analysis using conic integral geometry [20].

2.3 Optimality Conditions

2.3.1 Noiseless Case

We consider different forms of optimality conditions to solve the sparsity problem via convex optimization. First of all, we consider the optimization problem in real domain as follows:

$$\begin{aligned} P_r : \quad & \min_{\tilde{\Theta} \in \mathbb{R}^{2NXM}} \quad \mathcal{R}_G(\tilde{\Theta}) \\ \text{subject to} \quad & \|\tilde{Q}\tilde{\Theta} - \tilde{Y}\|_F \leq \epsilon \end{aligned} \tag{2.6}$$

where the linear observation in the real domain is given by $\tilde{Y} = \tilde{Q}\tilde{\Theta}_0 + \tilde{N}$ The regularizer is defined as $\mathcal{R}_G(\tilde{\Theta}) = \sum_{i=1}^{N} \|\tilde{\Theta}_{\mathcal{V}i}\|_F$. Here,$\tilde{\Theta}_{\mathcal{V}i}$is the row sub matrix of $\tilde{\Theta}$ consisting of rows indexed by $\mathcal{V}_i$ = {i,i+N}.

We can further approximate P_r as the following structured group sparse estimation problem with group size 2M:

$$\begin{aligned} P_{\text{approx}} : \quad & \min_{\tilde{\Theta} \in \mathbb{R}^{2NXM}} \quad \mathcal{R}_G(\tilde{\Theta}) \\ \text{subject to} \quad & \|\bar{Q}\tilde{\Theta} - \tilde{Y}\|_F \leq \epsilon \end{aligned} \tag{2.7}$$

where $\bar{Q} \in \mathbb{R}^{2LX2N} \sim \mathcal{N}$(0,0.5I) is a Gaussian random matrix. The distribution of the randomly measured matrix has very little effect on the locations of phase transitions. Therefore, we focus on characterizing the phase transitions of the approximate problem P_{approx} in the real field.

We rewrite the approximate problem in noiseless case as follows:

$$\begin{aligned} P_a : \quad & \min_{\tilde{\Theta} \in \mathbb{R}^{2NXM}} \quad \mathcal{R}_G(\tilde{\Theta}) \\ \text{subject to} \quad & \tilde{Y} = \tilde{Q}\tilde{\Theta}. \end{aligned} \tag{2.8}$$

In the noiseless case, we can see that the proposed formulation P_a gives perfect signal Θ_0 recovery with exponentially high probability if and only if the number of signature sequence length L exceeds the range of phase transition. Second, increasing the number of antennas M in BS will narrow the range of phase transition[1].

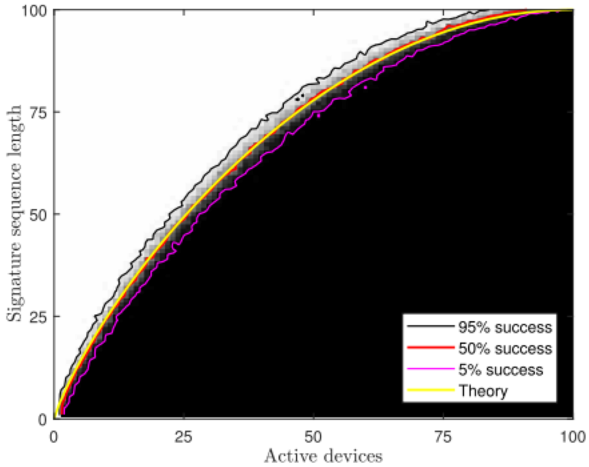

Figure 2.3: Heap map for noiseless case[1]

In Fig.2.3, the empirical success probability as function of number of active devices and signature sequence length. The brightness corresponds to the empirical recovery probability (white = 100%, black = 0%). On top of this heap map, the empirical curves of 5%, 50%, 95% are success probabilities calculated from data.

As the number of antennas at the BS grows to infinity, the size of the transition area can be lowered to zero asymptotically. As a result, massive MIMO is well suited to facilitating vast IoT connectivity by accurately forecasting phase transition location. As a result, the results of the sharp phase transition can be used to guide the duration of the signature sequence.[1].

2.3.2 Noisy Case

Let the estimated matrix be $\tilde{\Theta}^*$ of the ground truth matrix $\tilde{\Theta}_0$.To measure the accuracy of the above estimation problem, we evaluate average squared error given by,

$$R(\tilde{\Theta}^*) = \frac{1}{2LM}\|\tilde{Q}\tilde{\Theta}^* - \tilde{Q}\tilde{\Theta}_0\|_F^2 \tag{2.9}$$

In noisy case, we formulate the problem statement as follows:

$$\begin{aligned} P_b : \quad & \min_{\tilde{\Theta} \in \mathbb{R}^{2NXM}} \quad \|\tilde{Q}\tilde{\Theta} - \tilde{Y}\|_F^2 \\ & \text{subject to} \quad \mathcal{R}(\tilde{\Theta}) \leq \mathcal{R}\tilde{\Theta}_0. \end{aligned} \tag{2.10}$$

The problem statement in 2.10 is equivalent to P_{approx} for some value of the parameter ϵ. The behavior of empirical estimation error $\hat{R}(\tilde{\Theta^*})$ provides guidance for choosing parameter ϵ in problem P_{approx}.

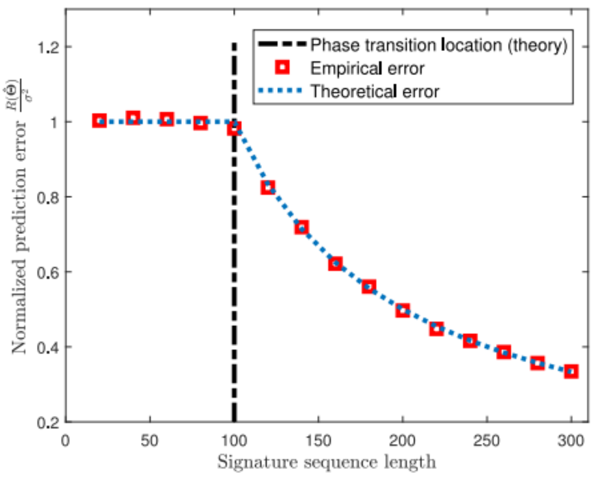

Figure 2.4: Normalized Prediction error[1]

In noisy case, we considered to evaluate the average prediction error as mentioned in the eq.2.9. This error is normalized using the noise variance as normalizing factor.the prediction error as a function of signature sequence length is plotted as shown in Fig.2.4.

The normalized error can be used to measure the accuracy of the estimation problem.From Fig.2.4, we can say that normalised squared error begins to reduce when the signature sequence length is optimum enough to get successful connectivity among massive number of devices. Therefore it can be used as a parameter to measure the accuracy of the estimation problem.

CHAPTER 3

SIMULATION RESULTS

The whole simulation process is carried out in MATLAB. For solving sparsity estimation problem using convex optimization, we made use of CVX package[28] where necessary changes were made according to the problem statement.

3.0.1 Noiseless Case

To get the phase transitions behaviour, we considered the case where the BS has two antennas and total number of IoT devices is 100.

To solve the optimization problem in noiseless case, the channel matrix and signature matrix are generated as H $\sim \mathcal{CN}$(0,I) and Q $\sim \mathcal{CN}$(0,I), respectively.We declare a event as successful if $\|\hat{\Theta} - \Theta_0\|_F <= 10^{-5}$.

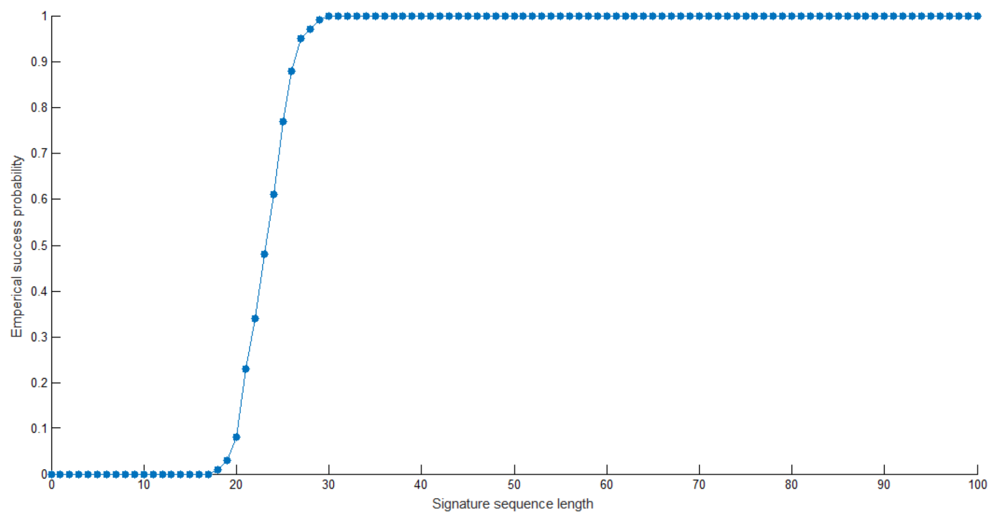

Figure 3.1: Phase Transition in Noiseless Case

In Fig 3.1, the plot shows the empirical success probability as a function of signature sequence length. The process is repeated 50 times before plotting the final result. Fig.3 depicts, in an IoT network consisting of 50 devices out of which only 8 devices are active, an optimal signature sequence length of 15 is sufficient in order to achieve massive device connectivity.

3.0.2 Noisy Case

In noisy case, we considered the scenario where the BS is equipped with three antennas and total number of IoT devices is 30. The channel matrix is generated as H $\sim \mathcal{CN}$(0,I), the signature matrix as and Q $\sim \mathcal{CN}$(0,I) and the additive noise matrix as N $\sim \mathcal{CN}$(0,0.001I) . A case is declared as successful if $||\hat{\Theta} - \Theta_0||_F <= 10^{-5}$. Simulated result of noisy case is as shown in Fig.3.2.

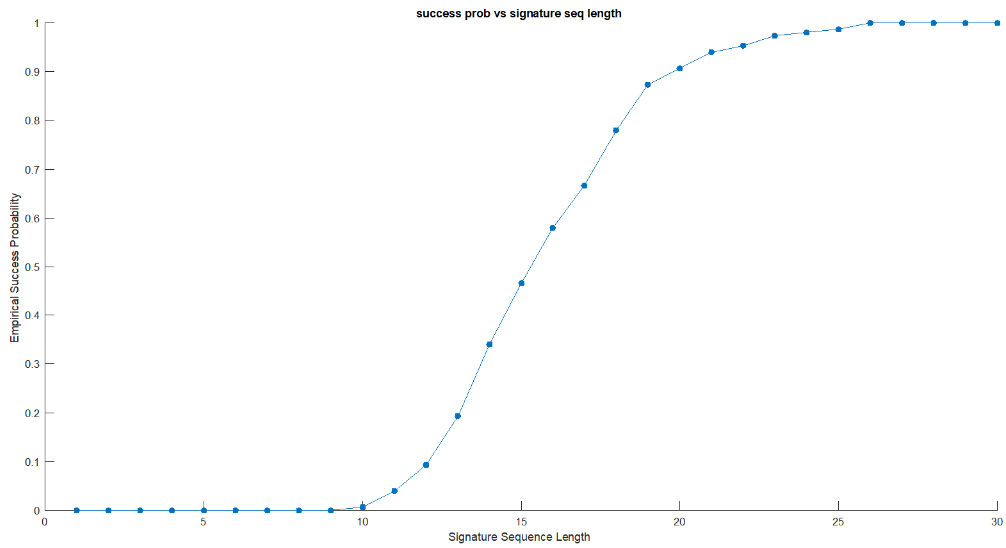

Figure 3.2: Phase Transition in Noisy Case

When noise is considered while solving optimization problem, to get the same optimal signature sequence length as in the noiseless case, we increase the number of antennas at base station(BS). Here, we increased the number of antennas at base station(BS) from two (in previous case) to three.

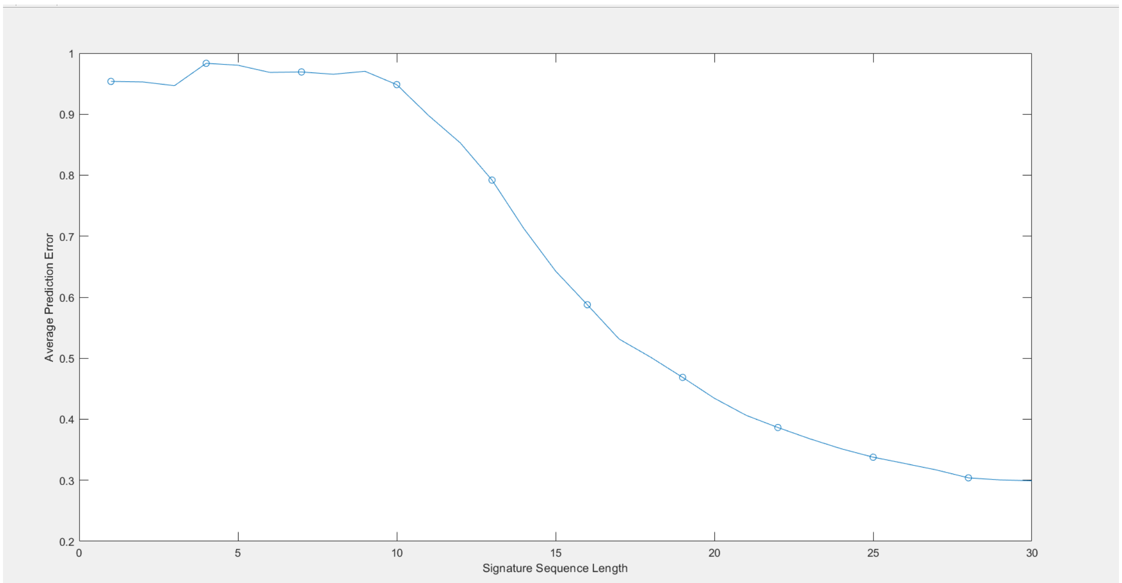

Figure 3.3: Average Prediction Square error

In this case, we evaluate the average prediction square error as mentioned in the eq.2.9. This error is normalized using the noise variance(assumed as 0.001) as normalizing factor. The prediction error as a function of signature sequence length is plotted as shown in Fig.3.3.

The prediction error $\hat{R}(\tilde{\Theta}^*)$ starts decreasing when sequence length is 15 as shown in fig 3.3. Also 15 is the optimal sequence length in this case. Therefore,this normalized prediction error can be used as a means to assess the accuracy of our experimental results. Also, we can interpret the location of phase transition. From fig.3.3, we can interpret the optimal signature sequence length as 15 which is same when interpreted from the plot fig.3.2. Thus, we can say the simulated results achieved by solving the formulated optimization problem are accurate.

CHAPTER 4

CONCLUSION AND FUTURE SCOPE

4.1 Conclusion

To handle the combined activity detection and channel estimation problem in vast IoT networks, we implemented a structured group sparsity estimation approach with reference to [1]. We were able to do so by taking advantage of the sparsity pattern in the device activity pattern. The optimal value for signature sequence length was determined using the phase transition plot.

Simulated results provide a way of locating phase transition region for choosing appropriate signature sequence length. Also, each device has been assigned non-orthogonal sequences[8] thereby paving a way to increase the number of devices in the network.

4.2 Future Scope

User privacy and low-latency communications are high demands in emerging mobile apps, which can be met by adopting more generic mathematical models and formulations. Sparse (low rank) optimization models were investigated. However, applying these findings to generic optimization issues is complex. As a result, this work could lead to new queries with the use of more randomised algorithms.

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