

# Time Prediction Algorithm for Hospital Queuing-Recommendation and Parallel Patient Treatment

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Abstract: Effective patient queue management to minimize patient wait delays and patient overcrowding is one of the major challenges faced by hospitals. Unnecessary and annoying waits for long periods result in substantial human resource and time wastage and increase the frustration endured by patients. For each patient in the queue, the total treatment time of all the patients before him is the time that he must wait. It would be convenient and preferable if the patients could receive the most efficient treatment plan and know the predicted waiting time through a mobile application that updates in real time. Therefore, we propose a Patient Treatment Time Prediction (PTTP) algorithm to predict the waiting time for each treatment task for a patient. We use realistic patient data from various hospitals to obtain a patient treatment time model for each task. Based on this large-scale, realistic dataset, the treatment time for each patient in the current queue of each task is predicted. Based on the predicted waiting time, a Hospital Queuing-Recommendation (HQR) system is developed. HQR calculates and predicts an efficient and convenient treatment plan recommended for the patient. Because

of the large-scale, realistic dataset and the requirement for real-time response, the PTTP algorithm and HQR system mandate efficiency and low-latency response. We use an Apache Spark-based cloud implementation at the National Supercomputing Center in Changsha to achieve the aforementioned goals. Extensive experimentation and simulation results demonstrate the effectiveness and applicability of our proposed model to recommend an effective treatment plan for patients to minimize their wait times in hospitals.

# I. INTRODUCTION

Currently, most hospitals are overcrowded and lack effective patient queue management. Patient queue management and wait time prediction form a challenging and complicated job because each patient might require different phases/ operations, such as a checkup, various tests, e.g., a sugar level or blood test, X-rays or a CT scan, minor surgeries, during treatment. We call each of these phases /operations as treatment tasks or tasks Here. Each treatment task can have varying time requirements for each patient,



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which makes time prediction and recommendation highly complicated [1]. A patient is usually required to undergo examinations, inspections or tests (refereed as tasks) according to his condition. In such a case, more than one task might be required for each patient. Some of the tasks are independent, whereas others might have to wait for the completion of dependent tasks. Most patients must wait for unpredictable but long periods in queues, waiting for their turn to accomplish each treatment task. Here, we focus on helping patients complete their treatment tasks in a predictable time and helping hospitals schedule each treatment task queue and avoid overcrowded and ineffective queues [2]. We use massive realistic data from various hospitals to develop a patient treatment time consumption model. The realistic patient data are analyzed carefully and rigorously based on important parameters, such as patient treatment start time, end time, patient age, and detail treatment content for each different task. We identify and calculate different waiting times for different patients based on their conditions and operations performed during treatment.

Here, a Patient Treatment Time Prediction (PTTP) model is trained based on hospitals' historical data [3]. The waiting time of each treatment task is predicted by PTTP, which is the sum of all patients' waiting times in the current queue. Then, according to each patient's requested treatment tasks, a Hospital **Queuing-Recommendation** (HQR) system recommends an efficient and convenient treatment plan with the least waiting time for the patient. The patient treatment time consumption of each patient in the waiting queue is estimated by the trained PTTP model [4]. The whole waiting time of each task at the current time can be predicted, such as  $\{TA = 35(min),$ TB = 30(min), TC = 70(min), TD = 24(min), TE =

87(min)}. Finally, the tasks of each patient are sorted in an ascending order according to the waiting time, except for the dependent tasks.

A queuing recommendation is performed for each patient, such as the recommended queuing {B,D, A} for Patient1, {B, A, C, E} for Patient2, and {D, C, E} for Patient3. To complete all of the real-time. Because the waiting queue for each task updates, the queuing recommendation is recomputed in real-time [5].

# **1.1 Problem Definition**

Currently, most hospitals are overcrowded and lack effective patient queue management [6]. Patient queue management and wait time prediction form a challenging and complicated job because each patient might require different phases/ operations, such as a checkup, various tests, e.g., a sugar level or blood test, X-rays or a CT scan, minor surgeries, during treatment. We call each of these phases /operations as treatment tasks or tasks Here [7]. Each treatment task can have varying time requirements for each patient, which makes time prediction and recommendation highly complicated. A patient is usually required to undergo examinations, inspections or tests (refereed as tasks) according to his condition. In such a case, more than one task might be required for each patient.

Effective patient queue management to minimize patient wait delays and patient overcrowding is one of the major challenges faced by hospitals. Unnecessary and annoying waits for long periods result in substantial human resource and time wastage and increase the frustration endured by patients. It would be convenient and preferable if the patients could receive the most efficient treatment plan and know the predicted waiting time through a mobile application that updates in real time. Therefore, we



propose a Patient Treatment Time Prediction (PTTP) algorithm to predict the waiting time for each treatment task for a patient. We use realistic patient data from various hospitals to obtain a patient treatment time model for each task. Based on this large-scale, realistic dataset, the treatment time for each patient in the current queue of each task is predicted. Based on the predicted waiting time, a Hospital Queuing-Recommendation (HQR) [8] system is developed. HQR calculates and predicts an efficient and convenient treatment plan recommended for the patient.

# II. RELATED WORK

Due to the huge increase in population hospitals are overcrowded and because of this it become difficult for hospital management system to control and to minimize the patient waiting time while getting treatment done in the hospital. Doctors recommend multiple number of different tests to diagnose the disease so that proper treatment can be given. Thus, while evaluating all these tests patient must wait in a queue. The patient must wait till all the patient before him or her get treated. Unnecessary waiting waste time of the patient and increases their frustration level while waiting in queue. It would be more convenient if patient could get the predicted waiting time and treatment plan which shows the sequence of different tests, their schedule and overall predicted waiting time on real time. To increase the efficiency and to meet the patent requirement we have come up with a technique called PTTP Patient Treatment Time Prediction along with HQR i.e. Hospital Queuing Recommendation system which is being developed. In this method PTTP algorithm predicts the treatment time on the basis, of hospital previous data collected. On the basis, of this waiting time HQR recommend the treatment plan for the patient. As the historical

patient data is huge in size we are using Apache Spark to achieve the goal.

Gradient Boosted Regression Trees (GBRT) is the current state-of-the-art learning paradigm for machine learned web search ranking - a domain notorious for very large data sets. Here, we propose a novel method for parallelizing the training of GBRT. Our technique parallelizes the construction of the individual regression trees and operates using the master-worker paradigm as follows. The data are partitioned among the workers. At each iteration, the worker summarizes its data-partition using histograms. The master processor uses these to build one layer of a regression tree, and then send this layer to the workers, allowing the workers to build histograms for the next layer. Our algorithm carefully orchestrates overlap between communication and computation to achieve good performance. Since this approach is based on data partitioning, and requires a small amount of communication, it generalizes to distributed and shared memory machines, as well as clouds.

Here, a new splitting criterion to build a decision tree is proposed. Splitting criterion specifies the best splitting variable and its threshold for further splitting in a tree. Giving the idea from classical Forward Selection method and its enhanced versions, the variable having the largest absolute correlation with the target value is chosen as the best splitting variable in each node. Then, the idea of maximizing the margin between classes in SVM is used to find the best threshold on the selected variable to classify the data. This procedure will execute recursively in each node, until reaching the leaf nodes. The final decision tree has a comparable shorter height than the previous methods, which effectively reduces more useless variables and the time of classification for future data. Unclassified regions are also generated, which can be



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interpreted as an advantage or disadvantage for the proposed method. Simulation results demonstrate this improvement in the proposed decision tree.

The major problems faced by hospital are patients wait delay and patient overcrowding. various examinations, inspection or tests must be done by patient usually according to his medical conditions. Similarly, there are various reasons for a patient to wind up his visit in hospital as soon as possible. For this an effective queue management must be maintained which gives an ease to fast track treatment process. But, patient queue management and wait time prediction brings challenges and complications because each patient requires different phases of treatment and operations such as check-up. Therefore, a Random Forest Algorithm (RFA) is used to categorize the patients on big data platform. Furthermore, this implementation is applied to Time Prediction for each patient.

Here, we propose a general framework for distributed boosting intended for efficient integrating specialized classifiers learned over very large and distributed homogeneous databases that cannot be merged at a single location. Our distributed boosting algorithm can also be used as a parallel classification technique, where a massive database that cannot fit into main computer memory is partitioned into disjoint subsets for a more efficient analysis. In the proposed method, at each boosting round the classifiers are first learned from disjoint datasets and then exchanged amongst the sites. Finally the classifiers are combined into a weighted voting ensemble on each disjoint data set. The ensemble that is applied to an unseen test set represents an ensemble of ensembles built on all distributed sites.

A widely used approach for locating points on deformable objects in images is to generate feature response images for each point, and then to fit a shape model to these response images. We demonstrate that Random Forest regression-voting can be used to generate high quality response images quickly. Rather than using a generative or a discriminative model to evaluate each pixel, a regressor is used to cast votes for the optimal position of each point. We show that this leads to fast and accurate shape model matching when applied in the Constrained Local Model framework. We evaluate the technique in detail, and compare it with a range of commonly used alternatives across application areas: the annotation of the joints of the hands in radiographs and the detection of feature points in facial images. We show that our approach outperforms alternative techniques, achieving what we believe to be the most accurate results yet published for hand joint annotation and state-of-the-art performance for facial feature point detection.

Botnet is a distributed malware which spreads widely without the knowledge of the end user. The effect of botnet increases very fast today. Researches on detection of botnet in real time are less. It is necessary to detect the presence of botnet instantly to avoid the effects of botnet. Storm is a real time, distributed fault tolerant system and supports online machine learning techniques. Random Forest classifier can be used to produce higher accuracy rate for massive data. This paper presents a new framework for detecting the presence of botnet in real time using the Storm tool. The framework consists of three main components. First, preprocessing the data and extracting features for classification. Second, Training and testing the dataset in the classification algorithm and finally, predicting the presence of botnet in Storm.



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Experimental results show that the presence of botnet can be predicted with higher accuracy rate.

#### **III.SYSTEM ANALYSIS**

The Systems Development Life Cycle (SDLC), or Software Development Life Cycle in systems engineering, information systems and software engineering, is the process of creating or altering systems, and the models and methodologies that people use to develop these systems. In software engineering the SDLC concept underpins many kinds of software development methodologies.

Here, we focus on helping patients complete their treatment tasks in a predictable time and helping hospitals schedule each treatment task queue and avoid overcrowded and ineffective queues. We use massive realistic data from various hospitals to develop a patient treatment time consumption model. The realistic patient data are analyzed carefully and rigorously based on important parameters, such as patient treatment start time, end time, patient age, and detail treatment content for each different task. We identify and calculate different waiting times for different patients based on their conditions and operations performed during treatment.

#### 3.1 Collaboration diagram

A collaboration diagram describes interactions among objects in terms of sequenced messages. Collaboration diagrams represent a combination of information taken from class, sequence, and use case diagrams describing both the static structure and dynamic behavior of a system.





#### **3.2 Component Diagram**

In the Unified Modeling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems

Components are wired together by using an assembly connector to connect the required interface of one component with the provided interface of another component. This illustrates the service consumer service provider relationship between the two components.





#### Fig 2. Component diagram

#### **3.3 Deployment Diagram**

A **deployment diagram** in the Unified Modeling Language models the physical deployment of artifacts on nodes. To describe a web site, for example, a deployment diagram would show what hardware components ("nodes") exist (e.g., a web server, an application server, and a database server), what software components ("artifacts") run on each node (e.g., web application, database), and how the different pieces are connected (e.g. JDBC, REST, RMI).

The nodes appear as boxes, and the artifacts allocated to each node appear as rectangles within the boxes. Nodes may have sub nodes, which appear as nested boxes. A single node in a deployment diagram may conceptually represent multiple physical nodes, such as a cluster of database servers.



# Fig 3. Deployment diagram

#### 3.4 Activity diagram:

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow form one activity to another activity.



Fig 4. Activity diagram

### IV. RESULT AND DISCUSSION



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# Fig 5. Uploading tasks

Patient Treatment Time Pred	iction				- d ×
	A PARALL	EL PATIENT TREATMENT T	IME PREDICTION ALGO	RITHM AND ITS APPLICATIONS	
		IN HOSTING YOLDING-REC	COMMENDATION IN A DI	O DATA LAVINONDLAT	
atient ID	Tasks	Gender	Age	Start Time	End Time
		_			
		Message			
		0	Dataset reading process completed		
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uck • Tack A Waiting tim	14 - 513 Sec				
sk : TaskB Waiting tim	ie : 584 Sec				
isk : TaskD Waiting tim	ie : 1095 Sec ie : 468 Sec				
isk : TaskE Waiting tim	e : 1281 Sec				
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ient ID	Tasks	Gender	Age	Sta	rt Time	End Time
entl	A B D	Male	55	08:3	0:45	08:31:20
ent2	E B C A	Female	43	08:3	1:25	08:32:20
ent3	DEC	Male	35	08:3	2:35	08:33:10
ent5	A D C E	Male	15	08:3	3:45	08:34:05
ent6	E B C A	Male	20	08:3	4:15	08:34:59
ent7	A E C	Female	25	08:3	5:05	08:35:55
y .	Noisy	-				
iy ent4	Noisy A B D	Female	. 22	08:3	3:10	10:31:20
y ent4 k : TaskA Waiting tin k : TaskB Waiting tin k : TaskC Waiting tin k : TaskC Waiting tin k : TaskE Waiting tin	Noky A B D = 513 Sec = 544 Sec = 1695 Sec = 1695 Sec = 1281 Sec	Female	22	08:3	5:10	10-31:20

# Fig 7. Preprocessing

atient ID	Tasks	Gender	Age	Start Time	End Time
atient1	A B D	Male	55	08:30:45	08:31:20
atient2	E B C A	Female	43	08:31:25	08:32:20
atient3	DEC	Male	35	08:32:35	08:33:10
atient5	🛃 View Tree	No.		08:33:45	08:34:05
atient6	Burden Terr		*	08:34:15	08:34:59
atient7	Kanoomiree			08:35:05	08:35:55
oisy	nid = Patient] : 55 (10)				
atient4	pid = Patient2 : 43 (1/0)			08:33:10	10:31:20
	pid = Patient3 : 35 (2/0) nid = Patient4 : 15 (0/0)				
	pid = Patient4 : 15 (0.0) pid = Patient5 : 15 (0.0)				
	pid = Patient6 : 20 (1/0)				
	pid = Patient7 : 25 (2/0)		-		
	Size of the tree : 8				
ask : TaskA Waiting t					
ask : TaskB Waiting t	Out of bag error: 1				
ask : TaskU Waiting t					
ask : TaskE Waiting t					
	Accuracy % = 71.428571428571	43	-		
	Tabad Tasks Pales I B	tinta Duranta I	Berdister Berden Frend	Noise December	Charat Field
	Cpicad Tasks Cpicad P	attents rreprocessing	Fredktion Kandom Forest Ke	Commendation Nonsy Records	EXIL

# Fig 8. Prediction random forest

L View Prediction	Tester		Sector 1			Start Time	End Time
Patient ID	Tasks	Gender	Age	Start Time	End Time	08:30:45	08:31:20
atient1	D,468 A,513	Male	55	08:30:45	08:31:20	08:31:25	08:32:20
Patient2	A,513 B,584	Female	43	08:31:25	08:32:20	08:32:35	08:33:10
Patient3	D,468 E,1281	Male	35	08:32:35	08:33:10	08:33:45	08:34:05
Patient5	D,468 A,513	Male	15	08:33:45	08:34:05	08:34:15	08:34:59
Patient6	A,513 B,584	Male	20	08:34:15	08:34:59	08:35:05	08:35:55
Patient7	A,513 E,1281	Female	25	08:35:05	08:35:55		
faskB Waiting ti faskB Waiting ti faskD Waiting ti	ne ; 013 Jes. ne : 584 Sec ne : 1695 Sec ne : 465 Sec						

### Fig 9. Recommendation





# Fig 10. Noisy records chart

#### CONCLUSIONS AND FUTURE WORK

A PTTP algorithm based on big data and the Apache Spark cloud environment is proposed. A random forest optimization algorithm is performed for the PTTP model.

The queue waiting time of each treatment task is predicted based on the trained PTTP model. A parallel HQR system is developed, and an efficient and convenient treatment plan is recommended for each patient.

Extensive experiments and application results show that our PTTP algorithm and HQR system achieve high precision and performance.

Hospitals' data volumes are increasing every day. The workload of training the historical data in each set of hospital guide recommendations is expected to be very high, but it need not be. Consequently, an incremental PTTP algorithm based on streaming data and a more convenient recommendation with minimized path-awareness are suggested for future work.

Further, a mobile application can be developed to give the exact waiting time for the user.

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