

Centralized Decision Support System for Expert Selection

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Abstract - A centralized decision support system that selects from CDSS (Clinical Decision Supporting System) and a set of human experts to make diagnosis recommendations. The expert selection system is working on the basis of the information about the patient. It assigns experts to patient. The context include information about the patient; that is patient health condition, age, gender, previous drug doses etc... The contexts may be different for different health conditions. To address these challenges, here develop a new class of algorithms aimed at discovering the most relevant contexts and the best clinic and expert to use to make a diagnosis given a patient's contexts. It also provides a blood bank facility which helps the patient for getting available blood group from the nearest place. It proves that as the number of patients grows, the proposed selection model algorithm will discover the optimal expert to select for patients with a specific context. Moreover, the algorithm also provide confidence bounds on the diagnostic accuracy of the expert it selects, which can be considered by the physician before making the final decision. The selection model algorithm is general and can be applied in numerous medical scenarios.

Keywords- Semantic computing, clinical decision support systems, healthcare informatics, distributed multi-user learning, selection model.

I.INTRODUCTION

Healthcare informatics is one of the applications of semantic computing. Healthcare organizations are tasked with developing metrics for measuring quality in terms of results, patient experience, workflow efficiency, access and organization. Electronic Health Records (EHRs) is the storage to capture data routinely generated as part of standard of care is yielding. An ongoing challenge is how to effectively apply high-dimensional and unstructured dataset to support clinical decision making and improve resource management. This paper is aims to optimize the expert selection procedure by Clinical Decision Support System (CDSS). The selection procedure is based on the context of patients such as patient's health condition, age gender, previous treatments and so forth. This paper develops algorithms that use semantic knowledge about the patient to assess and recommend expertise with the goal of optimizing the process for selecting an expert.

The diagnostic accuracy of an expert is depends on the contexts of patient. All information in the context to the patient that can be utilized in the decision making process. We propose in this paper learns the most relevant context is the current health condition of the patient and uses to estimate the level of expertise exhibited by the expert. The level of expertise is defined based on the accuracy of their diagnosis. The different clinics have healthcare

professionals with different expertise and some of these clinics may have access to CDSSs from different manufacturers and of different types while some others just rely on human experts. In the proposed system, these clinics can cooperate with each other to improve diagnostic accuracy by learning the contextual specializations of the other clinics (see Fig. 1).

Based on the context of the patient, the expert selection strategy updated every time after the health condition of the patient is revealed. Based on this feedback, the diagnostic accuracy of the chosen expert is updated. The patients can provide the feedback to the expert, clinic, and facilities to evaluate the success rate of CDSS. The expert selection procedure is based on scoring of the expert taken by the feedback of patients. To select an expert we provide scoring of experts. Additionally, symptoms of certain patients and facilities of clinics are the other criteria for the expert selection procedure. This criterion is known as Convergence Criteria is to optimizing selection of a best expert to the patient.

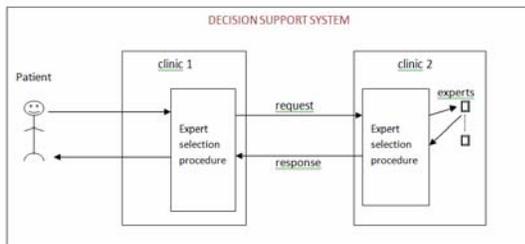


Fig.1. Operations of CDSS.

II. RELATED WORK

The related work categorized into two key areas: work related to semantic computing, and work related to data mining and online learning.

A. SEMANTIC COMPUTING

Semantic computing focuses on computing based on semantics and it addresses all types of resources including data, document, tool, device, process and people. Within the area of semantic computing, rule-based reasoning systems have emerged which deploy a database of the facts that are known about the problem

currently being solved, and a decision engine which combines rules with the data to produce predictions. In these systems the decision rule is developed by a group of human experts, and rules are updated over time based on their effectiveness. The proposed methodology fits within the class of semantic-based reasoning systems. However, in contrast to the existing work, consider multiple experts, each adopting its own decision rule. Moreover, how well a specific decision rule (diagnostic) performs when applied to a patient, characterized by a specific context, is not known a priori. Hence, in this work interested in developing a rigorous and efficient methodology for learning how to select the expert adopting the best decision rule (diagnostic) for each patient.

B. DATA MINING AND LEARNING

Most of the prior work in online stream mining provides algorithms which are asymptotically converging to an optimal or locally-optimal solution without providing any rates of convergence. We do not only prove convergence results, but we are also able to explicitly characterize the performance loss incurred at each time slot (for each patient) with respect to the optimal solution.

Some of the existing solutions propose ensemble learning techniques which combine the diagnosis of multiple experts into a final diagnosis. In our work we only consider choosing the best expert (initially unknown), where the expert selection process is driven by the patient's context. This is especially important in resource constrained scenarios like healthcare informatics, where the human resources are limited either in terms of the number of experts that are making diagnostic decisions or the number of healthcare personnel that acts as an interface between the patient and the CDSS. We provide a detailed comparison to our work in Table 1. As seen from Table 1, our proposed system is context-adaptive, distributed, outputs confidence bounds, and provides an explicit rate of convergence to the optimal expert selection strategy as the number of patients grows.

In addition to the problems in data mining, our methods can be applied to any problem that can be formulated as a distributed contextual bandit

problem. Our work is very different from these because (i) we consider decentralized agents (clinics) who can learn to cooperate with each other, (ii) the set of available (diagnostic) actions and the context arrivals to the agents can be very different for each agent, (iii) instead of learning to take the best action considering the entire context vector, an agent learns to take the marginally best action by independently considering each types of contexts, hence learning is much faster than existing learning algorithms whose convergence speed slows down exponentially with the dimension of the context space. Due to its context-adaptive property, the order of the convergence speed of the algorithm we propose in this paper is independent of the dimension of the context space.

	Bagging predictors -channel aware decision fusion in wireless sensor network	Distributed sparse linear regression, Collective data mining	Contextual bandits with similarity	Contextual multi-armed bandits	This work
Message exchange	None	Context	Training residual	None	Context(adaptively)
Learning approach	Offline/online	Offline	Offline	Non-Bayesian online	Non-Bayesian online
Learning from other's contexts	N/A	No	No	No	Yes
Using other's experts	No	All	All	No	Sometimes-adaptively
Rate of convergence	No	No	No	Yes-dimension dependent	Yes-dimension independent
Context adaptive	No	No	No	No	Yes
Confidence bounds	No	No	No	Yes	Yes

TABLE.1. Comparison with related work in data mining and learning

III. PROBLEM FORMULATION

A number of clinics are indexed by the set of large clinics data. These clinics are obtained in each of clinic. As we discussed an expert can either be a human expert or a CDSS. The set of all experts are being the set of clinics can choose from to send its patient's context for diagnosis. The expert selection is provided by the feedback is given by the

patients. The feedback is the integer value that gives the success rate of clinics in this system. The patient can also provide the scoring to the clinics, experts etc. The expert selection procedure is provided the optimal selection of best expert to the patients. This expert selection procedure is results the best expert by CDSS that additionally includes the symptoms of patients, facilities in clinics etc. There is a term *convergence criteria* introduced in the expert selection procedure system. Convergence criteria are the optimal solution of best expert selection criteria based on the symptoms of patients and facilities provided in the clinics.

For each patient the following events happen sequentially: (i) the patient with a context vector arrive to clinic. The set of contexts is called the context space. (ii) Each clinic assigns one of its own experts or another clinic to recommend an expert for the patient. (iii) After some delay, the true health state of patient is revealed only to the clinic where the patient has arrived. (iv) if another clinic provided the expert for that patient, then the clinic where the patient arrived passes the true health state of the patient to that clinic.

For each patient n , clinic i can either assign one of its experts or forward the patient's context to another clinic to have him/her diagnosed. The clinics are cooperative which implies that the clinic j will return a diagnostic recommendation to i when called by i using its expert with the highest estimated diagnostic accuracy for i 's context vector. Our results hold for the case when other clinics are not forwarding their patient context to i , they will also hold when other clinics forward the patient's context to i . Indeed, learning is faster for clinic i when other clinics ask clinic i for an expert recommendation for their patients.

Fig.2 and Fig.3 shows the two system model. The Fig.2 represents the patient chooses its own expert. That is the clinic i assigns an expert to the patient who can handle this case. The Fig.3 represents the patient chooses recommended expert. That is clinic i may recommended to an expert from other clinic (clinic j) to the patient when clinic i cannot handle the case. Clinic j may be able to handle this case and the feedback is updated by patient. The both figures are shown as assigning an expert to the

patient. There is a clinical decision support system is used to select a best expert from the clinic.

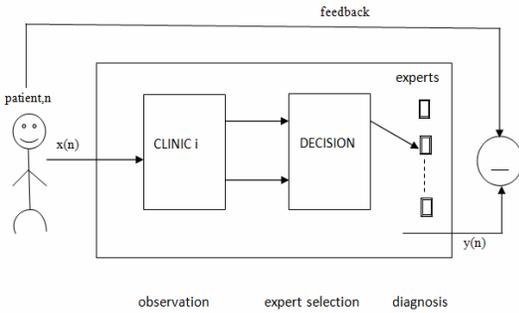


Fig.2. Patient chooses its own expert.

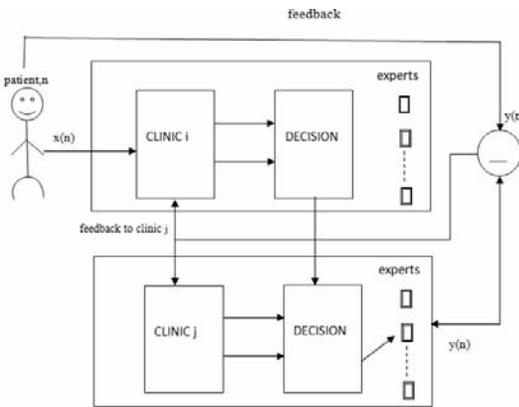


Fig.3 Patient chooses recommended expert.

IV. ALGORITHM

SELECTION MODEL ALGORITHM (LEX)

- a. Make choice.
- b. Assign score to clinic, expert based on feedback.
- c. Call LEX-OP or LEX-RP based on choice.

LEX-OP

- a. Generate feedback for clinics and experts.
- b. Generate score for clinics and experts.
- c. Take convergence criteria for select best option based on symptoms and lab tests.

- d. Select best expert by the action $\max\{([\text{feedback}(\text{clinic}) \times \text{score}(\text{clinic})] + [\text{feedback}(\text{expert}) \times \text{score}(\text{expert})]) + \dots n\}$ – convergence criteria.

LEX-RP

- a. Generate feedback for clinics and experts.
- b. Generate score for clinics and experts.
- c. Create feature vector for patients based on symptoms and lab tests.
- d. Take C1 is the convergence criteria for patients and C2 is the convergence criteria for clinics.
- e. Select best expert by the action : $\max\{([\text{feedback}(\text{clinic}) \times \text{score}(\text{clinic})] + [\text{feedback}(\text{expert}) \times \text{score}(\text{expert})]) + \dots n\} - (C1+C2)$

The main algorithm is the selection model algorithm or LEX. The LEX-OP and LEX-RP are two sub algorithm. The first step is making a choice; it is based on two conditions. One of the conditions is choosing expert its own condition and the other is choosing recommended patient.

□ The methods and algorithms presented here are:

- 1) Organizing the clinical data.
- 2) Discovering the most relevant context.
- 3) Having the ability to provide confidence estimates.
- 4) Having the ability to select the ‘optimal’ expert.

LEX is the learning expertise to learn the accuracies of different clinics and experts by requesting diagnosis recommendations in a cost effective way. Using LEX, a clinic can perform two tasks: (i) decide the diagnostic action to take for own patient; (ii) decide the expert to assign to the patients of other clinics which requested a diagnosis recommendation. Task (i) is performed by sub-

algorithm LEX for own patients (LEX-OP), while task (ii) is performed by sub-algorithm LEX for recommended patients (LEX-RP).

LEX provides three operation phases: exploitation, safe training and safe exploration. For any clinic and any patient LEX is only in one of these phases. In an exploitation phase, LEX is very confident about its expert selection decision. In the safe training phase, clinic i is not confident about how well some other clinic j knows its best expert for clinic i 's patient. Hence, clinic i requests a diagnosis recommendation from clinic j which helps clinic j learn the accuracy of its own experts. In the safe exploration phase, clinic i is not confident about the accuracy of its diagnostic actions. It will choose a diagnostic action and receive a diagnosis recommendation to update the accuracy of the chosen diagnostic action (which is done after the true health state is revealed). Trainings and explorations are safe, which means that LEX alerts the clinician that is in charge of the patient that the diagnosis recommendation comes from an expert which may not be very reliable. Knowing this, the clinician may assign another expert or may choose to follow the recommendation based on his/her own expertise. This way the system learns, while the patient safety is not compromised. Whenever refer to training and exploration, it means safe training and safe exploration.

LEX adaptively divides the context space into finer and finer regions as more patients arrive such that the regions of the context space with large number of arrivals are trained and explored more accurately than regions of the context space with small number of arrivals, and then only uses the observations in those regions when estimating the rewards of diagnostic actions in K_i for contexts that lie in those regions. For each patient, LEX chooses a diagnostic action adaptively based on the estimated marginal accuracy of the diagnostic action given the context vector. For each context, LEX starts with a partition with a single element which is the entire context space, then divides the space into finer regions and explores them as more patients with those contexts arrive. In this way, LEX focuses on parts of the context space in which there are large number of patient arrivals, and does this

independently of each type of context of the patients. The LEX algorithm is learning independently for each expert. When the number of experts is large, learning for groups of experts using the similarity between their contexts can speed up the learning process. Moreover, depending on the context of expert, the set of patients that can be assigned to that expert can be different. LEX can be easily adapted to teach the best group of experts and clinics to assign to a patient given its context vector. Moreover, LEX can also use the contextual information of experts when creating groups. For instance, similarity of the experts can be used when creating the groups of experts. While forming groups with experts that have contexts that are very similar to each other may not improve the diagnosis accuracy a lot, adding experts with different contexts may significantly improve the diagnostic accuracy because one expert may look to the patient data from a different perspective from the other experts within the group.

LEX algorithm can be applied to discover the expertise in many applications such as personalized education, recommended systems and task assignments.

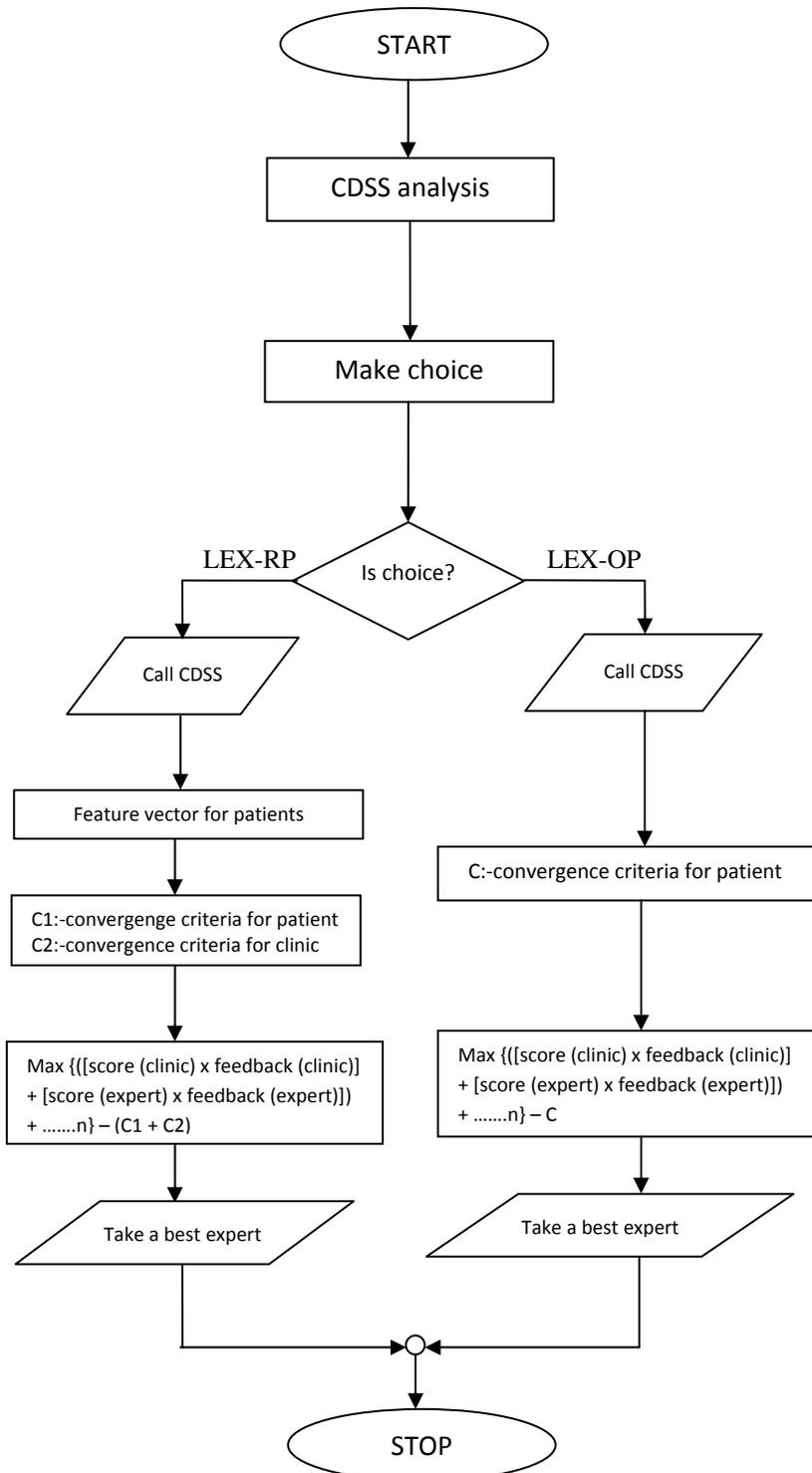
LEX algorithm defines the selection of the best expert for treating patients. Selection procedure is based on the scoring getting by patients. The expert selection is provided by two sub algorithms: LEX-OP and LEX-RP. The system can select the expert for patients by one of these algorithms. These two algorithms are reducing the lack of reference caused by unique or incorrect decision making. The observations are properly logged for future reference. Diagnostic quality is accountable in this system. The expert selection is provided by the system adaptation.

Fig.3. shows the flowchart representation of LEX algorithm. To select a best expert to patients provided by one of these algorithms. These two algorithms are providing the optimal selection of a best expert to the patient. The action of selection procedure is explained follow: We consider a CDSS analysis that provides the score and feedback of clinic and expert by the patients. Based on the choice we consider one of the algorithms for expert selection. The choice is considered by the decision system. The decision making provided from the

electronic health records that contains details about the clinical system such as details of clinics, experts, department, facilities etc. Each of the algorithms provides the convergence criteria based on clinic and patients. In LEX-OP algorithm, convergence criteria of clinic (C) are updated. In this algorithm, the convergence criteria based on the facilities provided in the clinic.

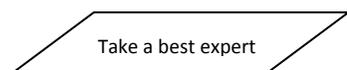
Fig.3. Flowchart representation of LEX algorithm

The selection procedure of this algorithm is evaluated by the maximum scoring provided by the system based on the score and feedback of an expert and clinic. The selection of a best expert is calculated by the elimination of convergence criteria of clinic to the scoring of the system. This algorithm selects an own expert whose experienced in treating certain diseases of patients. The LEX-RP algorithm is same as that of LEX-OP algorithm but it includes additional factor such as the feature vector for patients. The feature vector provides the context of patients and their observations. The LEX-RP algorithm considers the convergence criteria for patients (observations of patients) and the convergence criteria for clinics (facilities in the clinic). The selection procedure is evaluated by the maximum of the scoring based on score and feedback of clinic and expert. To calculate the optimal solution, the sum of converge criteria of patients and clinics are eliminated in the scoring result. This algorithm provides a recommended expert to the patient from other clinic. These two algorithms are providing an optimal solution of selecting a best expert for treating the patient.



V. DISCUSSIONS AND EXTENSIONS

Our current algorithm LEX is learning independently for each expert. When the number of expert is large, learning for groups of experts using the similarity between their contexts can speed up the learning process. The diagnosis accuracy of these experts for the patient will depend on how similar these experts are. Clinic takes diagnostic action, it randomly selects an expert from to assign to the patient. In our current setting the clinics cooperate with each other by making diagnosis recommendations for each other's patients when requested. Such cooperation is very beneficial when the expertise of the experts vary among the clinics. However, LEX assigns a single expert to each patient (whether an own expert of the clinic or another clinic's expert). In some clinical applications, such as some complex diseases, multiple experts and clinics



can work simultaneously to diagnose a patient, which can significantly improve the diagnosis accuracy. LEX can be easily adapted to teach the best group of experts and clinics to assign to a patient given its context vector. For instance, similarity of the experts can be used when creating the groups of experts. While forming groups with experts that have contexts that are very similar to each other may not improve the diagnosis accuracy a lot, adding experts with different contexts (background, education, etc.) may significantly improve the diagnostic accuracy because one expert may look to the patient data from a different perspective from the other experts within the group. Making a diagnosis for a new patient requires a certain amount of time devoted by the expert. Hence, an expert gets congested when too many new patients are recommended, which results in delay in making a diagnosis.

Our proposed algorithm is general, can be applied to discover the expertise in many applications such as personalized education, recommender systems and task assignments. Our proposed algorithm is centralized, i.e., they require a central clinic which has direct access to all the experts of all clinics. The algorithm is run on a centralized system in which the clinic has access to all experts. They learn considering all the contexts in the context vector, rather than learning for the most relevant context.

In order to assess the effect of cooperation between clinics, we simulate the performance of LEX for different numbers of clinics that clinic can forward its patient's context for diagnosis recommendation. Diagnosis accuracy of LEX increases with the number of clinics that clinic i is connected to. This is due to the diversity of the expertise among different clinics. While a clinic can be good at making diagnosis recommendation to patients with a specific type of context, another clinic may be better specialized for other types of contexts. How and when the clinics cooperate with each other depends on several factors including the expertise of the clinics, contexts of the patients. Moreover, as the number of patients *increases*, the diagnostic accuracy increases because LEX learns the expertise of the

experts with a higher accuracy as more patients arrive.

In our paper, we propose a blood bank facility to provide patient to getting required blood group from nearest place. This blood bank facility is very helpful to patients for search the nearest location where certain blood groups are available.

VI. FUTURE ENHANCEMENT

The application can be enhanced to mine information on disease history.

Clustering algorithm can be applied to group patients based on their observation parameters.

K means clustering algorithm can be applied to generate user communities.

VI. CONCLUSION

The Centralized decision support system select from CDSS (Clinical Decision Support System) and a set of human expert to make diagnosis recommendations. The expert selection system is working on the basis of the information about the patient. We prove that the diagnostic accuracy of the proposed system converges to the accuracy of the best expert, which means that the best diagnosis mechanism (whether a human expert or a CDSS) for each context is perfectly learned. Moreover, the proposed algorithm selection model (LEX) learns the best expert for treating a patient with a specific context with a clinic; hence, its performance is better than the performance of the best expert within any given clinic. Here a top admin is present whose person co-ordinate the entire authentication process. It provides the security of the proposed system. . It also provides a blood bank facility which helps the patient for getting available blood group from the nearest place. The future works include it can be enhanced to mine information on disease history, Clustering algorithm can be applied to group patients based on their observation parameters and K means clustering algorithm can be applied to generate user communities.

VII. REFERENCES

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