Stable Teamwork Marriages in Healthcare: Applying Machine Learning to Surgeon-Nurse-Patient Matching

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Hospitals are plagued with a multitude of logistical challenges amplified by a time-sensitive and high intensity environment. These conditions have resulted in burnout among both doctors and nurses as they work tirelessly to provide critical care to patients in need. We propose a new machine-learning-powered matching mechanism that manages the surgeon-nurse-patient assignment process in an efficient way that saves time and energy for hospitals, enabling them to focus almost entirely on delivering effective care. Through this design, we show how incorporating artificial intelligence into management systems enables teams of all sizes to meaningfully coordinate in highly chaotic and complex environments.

INTRODUCTION

The impetus of this paper is to craft a solution to a highly pressing problem in hospital operations by applying computational thinking to complex teams of teams' problems. Specifically, hospitals often struggle with matching nurses and surgeons to patients in an efficient way that minimizes delays (Wong et al, 2010). We designed a staff management system that accomplishes the matching process through an algorithm, so that the cognitively intensive team assignment process can be outsourced to a computational mechanism.

The findings of this research have largely significant implications for both practitioners and patients. In particular, matching clinicians with patients efficiently through an algorithm will reduce surgery times and lower the risk of complications arising from surgery, and gains in efficiency enable patients to be treated much sooner due to decreased delays given to mis-managed time frames. Practitioners gain efficiency from shortened surgery time, as less effort and energy are required to achieve the same outcomes now that the matching process is efficient. Because of this efficiency, burnout among both nurses and surgeons can be expected to be less as both the workflow itself and the length of the surgery become less physically and mentally strenuous.

Most research suggests strong links between work-related stress and burnout, which in turn is connected to turnover (Leiter & Maslach, 2009). In France alone, over 30% of nurses met the standard for Burn Out Syndrome (BOS) (Poncet et al 2007). The issue of burnout and by extension turnover is not by any means limited to nurses: it affects residents as well. Internal work demand and a perceived lack of control over work that leads to work-home interference are among some of the factors that are associated with resident burnout (Thomas 2004).Burnout and turnover impose are also one of the largest financial burdens on a healthcare provider.

The work outlined in this paper aims to demonstrate the many ways in which incorporating user-centric technology can lower costs without compromising quality of care or workplace satisfaction. To articulate this vision, we are going to ground our model for team behavior through the multi-team system construct, and by analyzing the challenges of multi-team systems in the healthcare domain we are going to design a management system that leverages cutting edge technology (machine learning) and industrial engineering (stable marriage algorithm).

PRACTICE INNOVATION

To address issues of congestions, surgery delays, and clinician burnout within the healthcare system, we set out to identify an effective model to visualize the complexity of behind surgery. To manage this complexity, we resolved to unload burden of clinician assignment away from a human team by making the assignment process directed by a matching algorithm running on top of a neural network.

Multi-Team Systems in Healthcare

The accomplishment of a successful surgery is the result of highly complex processes with multiple components. A patient's surgery needs to be classified based on urgency and difficulty, a surgeon out of the pool of surgeons on call, needs to be selected, and a team of nurses needs to be matched with the surgeon in order to effectively assist the operation. Such a multi-dimensional problem requires multi-dimensional solutions, which necessitates the construct of multi-team-systems (MTS), defined as *"two or more teams that interface directly and interdependently in response to environmental contingencies toward the accomplishment of collective goals*" (Mathieu et al. 2001).

Leaders within the healthcare sector have highlighted MTSs key role in addressing the series of challenges involved through all the steps of patient care (DiazGranados et al., 2014; Misasi et al., 2014; Weaver et al., 2014). Since separate teams of people deal with each aspect of the sequence of operations and services to be delivered to the patient, each group needs to manage to communicate effectively both internally and externally in order to make the care-delivery process as smooth as possible.

The MTS community has called for the study of the information sharing procedures involved between teams as the patient passes through different phases of the care-delivery process (DiazGranados et al., 2014). This call is due to the complexities engrained within the healthcare setting, which provides the perfect setting to study how teams interact with other teams at a large scale, thereby creating a multi-team system in the process.

The Challenges faced by MTS

Although traditional teams work effectively for small and confined problems or tasks, as the complexity and scale of the task increases, a formal coordination structure becomes necessary (Davison et al 2012). Specifically, in the case of healthcare delivery, MTSs need an effective coordination structure to manage fluctuating amounts and degrees of gravity of the patients while still operating under the constraints of personnel availability and talent density.

Although both the private sector and the research community have expressed interest in making improvements to the operation of teams in the healthcare system, progress has been slow but steady (Shuffler et al, 2015). Fortunately, a substantial amount of research has been directed towards refining the problems faced by teams transitioning to MTSs as the organization grows.

First, as the organization grows, it becomes more complex, and inter-team communication breaks down. The issues arise from the disconnect between the larger scope of the organization's objective and teams' difficulty in scaling their communication with each other (Zaccaro et al., 2012).

Second, at a large scale teams become more dispersed, a process that creates obstacles to meaningful coordination between teams, such as suboptimal scheduling. These limitations have potentially substantially negative consequences on synchronicity and coordination (DeCostanza et al., 2014).

Third, a lack of synchronicity often results in the misallocation of tasks between teams, which is a problem that easily undermines coordination on a macro-level. Prior research also shows that a disproportionate workload allocation within a team or between teams in an MTS leads to cognitive overload, which results in higher error rates (Misasi et al., 2014).

Fourth, the procedure of classifying patients and matching them with the appropriate surgeon-nurse team increases in complexity as the organization gets larger and resources become constrained. Resource constraints for MTSs with an increasing number of component teams has shown to lead to competition for resources, which may affect outcomes in a negative way (Kanfer et al1994). The only way to avoid the negative consequences of scarcity is through effective coordination, which becomes increasingly difficult as the organization gets larger and specialization leads different departments and teams to isolate themselves.

Ironically, prior research has suggested that actions stemming from attempts at coordination are actually counterproductive, as they generate challenges that detract from the team's focus of achieving its objective (Davison et al. 2012). This research implies that there is a tradeoff between maximizing coordination and task completion efficiency. However, such a tradeoff may be transcended through an entirely different approach: human-centered and motivated technology.

Technology's role in MTSs

Although prior research in human factors exists on how to improve shared mental models (SMM), much research remains to be conducted about the impact technology can have on improving SMM in healthcare scenarios. At best, research has demonstrated how virtual tools impact team-formation and MTS SMM-development, but even then it is confined to text-based technology such as chats and messaging services (Jiménez-Rodríguez, 2012).

Approaching MTSs as a network, where individual nodes connected to each other represent team-members, and interconnected hubs represent sub-teams, has proven to be very effective in explaining emergent phenomena within the organization (Klein & Kozlowski, 2000b). Therefore, approaching MTSs as networks becomes an effective way to model all the properties of MTS through computational methods. Assuming a computational view of MTS networks, better technologies can be built to improve upon various aspects of the MTS, ranging from accelerating information flow to directing team-formation. The most promising approach involves machine learning.

Machine Learning and Neural Networks

Machine Learning (ML) refers to the area of computer science that seeks to model and replicate learning mechanisms through computation. It's a field that has led to the most promising advances in artificial intelligence, as researchers have effectively managed to replicate human vision techniques into computer vision, to create the best Go player in the world, and cancer-detection systems that outperform doctors (Rosten & Drummond, 2006; Chen, 2016; Bejnordi et al, 2017).

One of the most promising techniques in ML relies on the concepts of artificial neural networks. A neural network (NN) is a network of processing units with weighed connections to each other analogous to the neurons in brains. Just like the human brain, the NN processes large amounts of data, learns patterns, makes predictions and recalibrates its own model to minimize its errors (Kaur & Wasan 2006, Lu & Liu 1996).

There are many algorithms upon which a NN can be built, and this work seeks to test out how a NN designed with the Gale-Shapley Algorithm can improve surgeon-nurse team formation by matching MTSs to patients.

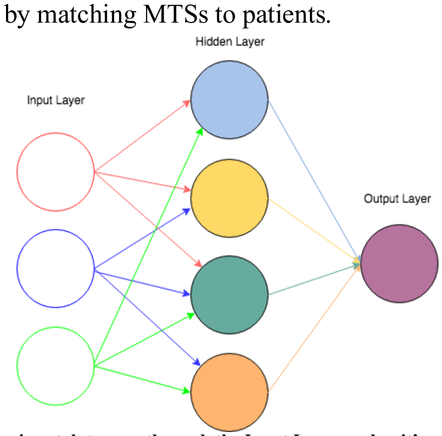

Figure 1. The input data goes through the Input Layer nodes, it's proceed by the Hidden Layer nodes, and is the node in the Output layer gives the recommendation

The Stable Marriage Algorithm

The Gale-Shapley algorithm, colloquially known as the Stable Marriage Algorithm (SMA), matches 2 equally sized sets of elements with ranked preferences. The algorithm's applied scenario is usually posited in the context marriage: each man in a set of men is asked to rank by preference every woman in an equally sized set of women. The Gale-Shapley algorithm demonstrates that a stable allocation, defined as the state in which no couple is better off exchanging partners, exists irrespective of the preference and that such an allocation can be achieved through "deferred acceptance", whereby for every iteration, each unmatched man proposes to the woman at the top of his preference list who has yet to reject him (Gale & Shapley 1962). At the end of the process, the men and women find themselves paired in such a way that even though their partner is not their top choice, any person they'd rather be with would rather be with someone else thereby making divorce impossible.

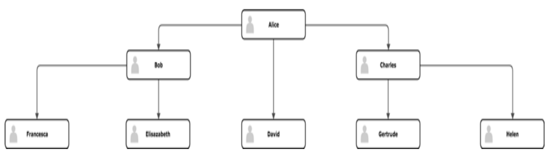

Figure 2. Even though Alice would rather be matched with Bob or Charles, David is the only stable match.

The SMA has since been applied to match residents with hospitals, and became so successful that it gave birth to the National Resident Matching Program (NRMP), which has been used ever since 1984, albeit with some variations (Roth 1984, Roth & Peranson 1999). In real-world applications, the SMA enables mechanism designers to tailor the system towards a particular outcome. For example, experiments have been conducted in Ohio and New England to set up a kidney transplant system predicated upon SMA. The results have been overwhelmingly positive, as the matching engine seeks to optimize for patient outcomes, and researchers have theorized that a wide application of SMA would not only lead to between 1000 and 2000 additional transplants a year, but also to over $750 million dollars in savings for dialysis costs (Goldfarb 2005).

PRACTICE APPLICATION

In order to address the coordination issues arising from MTS in healthcare delivery, we propose a design of a NN that computes a match for nurses, surgeons, and patients to optimize for surgery outcomes and reduce congestion. In order to make this design accessible to every hospital, our research team is constructing an abstract model so that the system can be implemented on each hospital's idiosyncratic technical infrastructure.

Human-Machine Interface

Every human-machine system needs an interface that effectively enables two-way communication between the human and the machine. In this particular case, the hospital employees need to communicate data effectively to the NN, and in turn the NN needs to communicate to nurses and doctors where to go. This interface has three sub-components: patient classification, team member geolocation, post-surgery assessment.

First, the patient needs to be classified. Hospitals already classify cases based on urgency of the procedure, magnitude of the condition, and confidence of initial diagnosis, therefore the NN uses these variables to compute the priority level of each patient.

Second, each practitioner needs to be geolocated. Many technologies already exist to track location, but purely for the sake of the example, we are using sociometric badges. The badge tracks the location of the practitioner when they are in the hospital, so that the NN can optimize the matching process so that neither the nurses nor the doctors have to walk back and forth to figure out which room they have been assigned, and can instead be pointed directly to the patient they have been matched with.

Lastly, entries need to be made after each surgery. Each practitioner is asked to rank every teammate in terms of team-compatibility, and this data will be entered into a web form alongside the length of procedure as well as its degree of success. Teammate satisfaction, procedure length, and surgery success are the three variables the NN uses to calibrate its model and improve its matching over time.

Procedural Overview of the Network

The NN runs a diverse set of computations to arrive at its matching recommendation. The objective is to reduce congestion (measured by how often surgeries are rescheduled), minimize lag (accomplished by removing the need for nurses and doctors to walk back and forth to pick up assignments), and maximize coordination (avoiding double booking people and forming "stable" teams where members have positive relationships with one another). The algorithm can be broken down into several steps:

1) The NN models the resources available. Initially, the NN will be gathering data about which nurses and doctors in its directory are available as well as their location.
2) The NN drafts a schema for MTS. At this step, the NN matches nurses together through SMA, and then runs SMA once again to match the team of nurses to surgeon, creating the first MTS. Iterating through this process, the NN will build out a schema of all possible MTSs arising from combinations of the available staff on call.
3) The NN matches a MTS to a patient. At this step, the NN once again uses SMA to match the patient to one of the potential MTSs within its schema to optimize for surgery success.
4) The NN notifies each member of the MTS as to which room to go to.
5) The NN updates its database by removing the matched patient and MTS.
6) The NN updates it database with any new data from a surgery accomplished since its last iteration.

This sequence of steps (Figure 3) is repeated endlessly as the NN matches incoming patients with MTSs composed of the available staff.

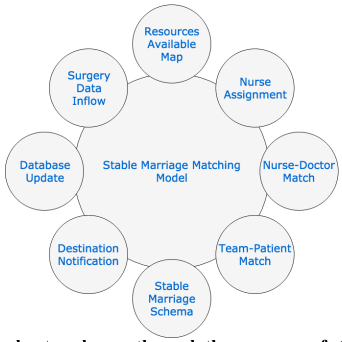

Figure 3. The neural network goes through the sequence of steps, improving its matching every time through its learning process

Metrics and Parameters

In order to keep track of the NN's performance and improvements, a few metrics should be tracked.

Surgery Duration: The time taken from when the patient was assigned to the surgeon-nurse team until the operation was officially completed. This is measured automatically by the system as it starts tracking from the when the notification of patient assignment is sent out until the MTS members walk out of the operating room.

Computational Complexity: The NN will track how many calculation it needs to perform in order to make its recommendation.

Team-member satisfaction rate: Measured through hospital's internal performance review system in order to control for the potentially confounding factor of using a different questionnaire than the surgeons and nurses are accustomed to.

Congestion: The hospital will record how often surgeries are rescheduled, both prior to the system's implementation and afterwards.

DISCUSSION

Healthcare delivery is a dynamic multi-variable problem, therefore a static patient-MTS matching mechanism would not be useful in most scenarios. A NN, on the other hand, is dynamic and crafts unique solutions depending on the circumstances. It operates at computational speed, which is vastly superior to the human speed of the human-managed matching system used by default, and the speed differential is a major factor when dealing with emergency care. Lastly, NNs have been shown to conceive entirely brand new solutions to highly complex problems, thereby offering the opportunity in this case to achieve new heights in healthcare effectiveness by discovering MTSs configurations that would have most likely gone unexplored otherwise.

Additionally, automating the matching process and team-formation process removes tasks from both the surgeons and nurses' workflow, thereby decreasing the cognitive overhead associated with such tasks, and thus enabling the MTS to redirect that energy towards communication and coordination. Since the NN is grounded in SMA, the MTS will be structured not only to maximize coordination but more importantly to maximize the chances of patient care success.

MTS in large organizations has also proven to be a difficult visualization problem. The MTS life cycle influences the sequence of actions and outcomes between component teams. The entire development of an MTS is vastly more difficult than that of teams because of disjointed timeline between the component teams as they operate on different schedules and are responding to different parts of the problem faced by the organization (Shuffler et al 2015). Despite this complexity, a NN is perfectly positioned to visualize these high-level dynamics, for its model reconstruct the MTS as a network, which is a mathematical object NNs are naturally poised to process very well.

MTSs also experience life-cycles related to their formation as a response to a particular situation, structured to evolve over time to address a particular goal or outcome (Mathieu et al., 2001). Because of the dynamic nature of MTSs then, a dynamic solution provided by a NN makes the MTS-formation process self-directed as opposed to emergent, thereby enabling the MTSs that forms in response to a task to be not just sufficiently effective at the task but rather optimally effective because it was designed with purpose by the NN as opposed to by circumstance and availability.

PRACTITIONER TAKEAWAYS

1. Healthcare-related problems are becoming so complex that human cognition alone is not sufficient: technology needs to be designed to augment human capability
2. Task overload and logistical breakdowns result in clinician burnout, and algorithmic management is perfectly positioned to solve these problems.
3. Deep problems within the healthcare system require new approaches that don't just marginally improve workflows, and consulting areas like computing expands the options available to solve these problems.
4. Technology and data science have evolved so much that healthcare problems that used to be deemed intractable are now within reach.

REFERENCES

Bejnordi, B. E., Veta, M., van Diest, P. J., van Ginneken, B., Karssemeijer, N., Litjens, G., ... & Geessink, O. (2017). Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. *Jama*, *318*(22), 2199-2210.

Carter, D. R. (2014). *The impact of leadership network structure on multiteam system innovation* (Unpublished thesis). Georgia Institute of Technology, Atlanta.

Carter, D. R., & DeChurch, L. A. (2014). Leadership in multiteam systems: A network perspective. In D. V. Day (Ed.), *Oxford handbook of leadership* (pp. 483-505). New York, NY: Oxford University Press. doi:10.1093/oxfordhb/9780199755615.013.024

Chen, J. X. (2016). The evolution of computing: AlphaGo. *Computing in Science & Engineering*, *18*(4), 4-7.

Davison, R. B. (2012). *Implications of regulatory mode and fit for*

goal commitment, identity and performance in the domain of multiteam systems (Unpublished doctoral dissertation). Michigan State University, East Lancing, MI.
Davison, R. B., Hollenbeck, J. R., Barnes, C. M., Sleesman, D. J., & Ilgen, D. R. (2012). Coordinated action in multi-team systems. *Journal of Applied Psychology*, *97*, 808-824. doi:10.1037/a002668
DeCostanza, A., DiRosa, G., Jiménez-Rodríguez, M., & Cianciolo, A. (2014). No mission too difficult: Army units within exponentially complex multiteam systems. In M. L. Shuffler, E. Salas, & R. Rico (Eds.), *Pushing the boundaries: Multiteam systems in research & practice* (pp. 61-76). Bingley, UK: Emerald. doi:10.1108/S1534-085620140000016003
DiazGranados, D., Dow, A., Perry, S., & Palesis, J. (2014). Understanding patient care as a multi-team system. In M. L. Shuffler, E. Salas, & R. Rico (Eds.), *Pushing the boundaries: Multiteam systems in research & practice* (pp. 187-206). Bingley, UK: Emerald. doi:10.1108/S1534-085620140000016004
Gale, D., & Shapley, L. (1961). College Admissions And The Stability Of Marriage. 9-15. doi:10.21236/ad0251958
Goldfarb, D. A. (2005). Kidney Paired Donation and Optimizing the Use of Live Donor Organs. *The Journal of Urology, 174*(5), 1911-1912. doi:10.1016/s0022-5347(01)68837-2
Jiménez-Rodríguez, M. (2012). *Two pathways to performance: Affective- and motivationally-driven development in virtual multiteam systems* (Unpublished doctoral dissertation). University of Central Florida, Orlando.
Kanfer, R., Ackerman, P. L., Murtha, T. C., Dugdale, B., & Nelson, L. (1994). Goal setting, conditions of practice, and task performance: A resource allocation perspective. *Journal of Applied Psychology*, *79*, 826-835.
Kaur, Harleen & Wasan, Siri Krishan (2006) Empirical Study on Applications of Data Mining Techniques in Healthcare. *Journal of Computer Science.* (pp. 194-200) 1549-3636
Klein, K. J., & Kozlowski, S. W. J. (2000a). From micro to meso: Critical steps in conceptualizing and conducting multilevel research. *Organizational Research Methods*, *3*, 211-236.
Klein, K. J., & Kozlowski, S. W. J. (2000b). *Multilevel theory, research and methods in organization*. San Francisco, CA: Jossey-Bass.
Larsen, S., Nystad, E., & Taylor, C. (2014). Coordinating mechanisms for multiteam systems: A case study from the petroleum industry. In M. L. Shuffler, E. Salas, & R. Rico (Eds.), *Pushing the boundaries: Multiteam systems in research and practice* (pp. 115-133). Bingley, UK: Emerald.
Leiter, M. P., & Maslach, C. (2009). Nurse turnover: the mediating role of burnout. *Journal of Nursing Management, 17*(3), 331-339. doi:10.1111/j.1365-2834.2009.01004.x
Mate Labs. (2017, November 1). Operations at one neuron of a neural network [Digital image]. Retrieved from https://hackernoon.com/everything-you-need-to-know-about-neural-networks-8988c3ee4491
Mate Labs. (2017, November 1). Basic Neural Network Layout [Digital image]. Retrieved from https://hackernoon.com/everything-you-need-to-know-about-neural-networks-8988c3ee4491
Mate Labs. (2017, November 1). Backward Propagation [Digital image]. Retrieved from https://hackernoon.com/everything-you-need-to-know-about-neural-networks-8988c3ee4491
Wikimedia. Animation showing an example of the Gale-Shapley algorithm [Digital Image]. Retrieved from https://en.wikipedia.org/wiki/Stable_marriage_problem#/media/File:Gale-Shapley.gif
Mathieu, J. E., Marks, M. A., & Zaccaro, S. J. (2001). Multiteam systems. In N. Anderson, D. S. Ones, H. K. Sinangil, & C. Viswesvarin (Eds.), *Handbook of industrial, work and organizational psychology* (pp. 289-313). Thousand Oaks, CA: Sage. doi:10.4135/9781848608368.n16
Misasi, P., Lazzara, E., & Keebler, J. R. (2014). Understanding multiteam systems in emergency care: One case at a time. In M. Shuffler, E. Salas, & R. Rico (Eds.), *Pushing the boundaries: Multiteam systems in research and practice* (pp. 157- 183). Bingley, UK: Emerald.
Poncet, M. C., Toullic, P., Papazian, L., Kentish-Barnes, N., Timsit, J., Pochard, F., . . . Azoulay, É. (2007). Burnout Syndrome in Critical Care Nursing Staff. *American Journal of Respiratory and Critical Care Medicine, 175*(7), 698-704. doi:10.1164/rccm.200606-806oc
Rosten, E., & Drummond, T. (2006, May). Machine learning for high-speed corner detection. In *European conference on computer vision* (pp. 430-443). Springer, Berlin, Heidelberg.
Roth, A. E. (1984). The Evolution of the Labor Market for Medical Interns and Residents: A Case Study in Game Theory. *Journal of Political Economy, 92*(6), 991-1016. doi:10.1086/261272
Roth, A., & Peranson, E. (1999). The Redesign of the Matching Market for American Physicians: Some Engineering Aspects of Economic Design. doi:10.3386/w6963
Sabour, S., Frosst, N., & Hinton, G. (2017). Dynamic Routing Between Capsules. *Cornell University Library* . doi:arXiv:1710.09829
Shuffler, M. L., Jiménez-Rodríguez, M., & Kramer, W. S. (2015). The Science of Multiteam Systems. *Small Group Research, 46*(6), 659-699. doi:10.1177/1046496415603455
Simon, B.P. and C. Eswaran, 1997. An ECG classifier designed using modified decision based neural networks
Thomas, N. K. (2004). Resident Burnout. *Jama, 292*(23), 2880. doi:10.1001/jama.292.23.2880
Wong, J., Khu, K. J., Kaderali, Z., & Bernstein, M. (2010). Delays in the operating room: signs of an imperfect system. *Canadian Journal of Surgery*, *53*(3), 189–195.
Zaccaro, S. J., & DeChurch, L. A. (2012). Leadership forms and functions in multiteam systems. Multiteam systems: An organization form for dynamic and complex environments. In S. J. Zaccaro, M. A. Marks, & L. A. DeChurch (Eds.), *Multiteam systems: An organization form for dynamic and complex environments* (pp. 253-288). New York, NY: Routledge Taylor & Francis Group.
Zaccaro, S. J., Marks, M. A., & DeChurch, L. A. (2012). Multiteam systems: An introduction. In S. J. Zaccaro, M. A. Marks, & L. A. DeChurch (Eds.), *Multiteam systems: An organization form for dynamic and complex environments* (pp. 3- 32). New York, NY: Routledge Taylor & Francis Group.