Dynamic Manning

Detailing Marketplace Pilot for US Navy

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February 19, 2019

Abstract

New Abstract.

Contents

1 Introduction

Under the backdrop of the President of the United States issuing the Executive Order on Maintaining American Leadership in Artificial Intelligence in February 2019, we created the algorithmic foundation for advancement of artificial intelligence and machine learning (AI/ML) in military talent allocation. Before the US Government can accomplish its both lethal and non-lethal AI/ML goals, however, it must embrace the essential building blocks underlying the buzzwords. One of those cornerstones is algorithmic linear programing, specifically the use of mixed integer programming (MIP). In this piece, we reveal the most exquisite MIP algorithm completed thus far for the US Navy.

We believe the world to be arcing toward the need for humans to grow as increasingly specialized workers, and in the vicious games of statecraft and war, allocating talent with hyper specificity will become a necessity for victory. To that end, we theorized, coded, and prototyped an MIP algorithm that matches job seekers (sailors) and job owners (commanding officers).

1.1 Problem Description

Human talent allocation is a resource intensive process for an institution. This paper outlines the mathematics necessary to lay the groundwork for such a task within one of the most complex institutions of the American psyche – the Department of Defense (DoD). We dove into this problem with a specific service branch in mind. Focusing our work on the Navy, and within it, the sailors assigned to the National Security Agency (NSA) for cryptologic and cyber warfare efforts, we honed our test case to a group of officers most aligned with technical advancement. Furthermore, despite the small prototype sample, the algorithm is greatly scalable.

Market forces appear are largely the drivers behind a job marketplace – this concept is not new for the American economy. However, given a captive audience such as service members ordered to specific jobs, the mathematical benefit of benevolent autocracy is immense. Rather than the suboptimal fate to which current servicemembers are subjected, the DoD is shopping for a better way forward.

In the Navy, terminology of a detailing marketplace refers to the attempts to detail, or place, warfighters into their next job. This detailing marketplace is a system by which military members can transparently rank their job preferences and the people who own those jobs can supply their preference of incoming personnel. This problem is rather unique to the military due to the aforementioned captive market of many members obligated to remain in service due to contract, desiring to stay in for a pension, wishing to stay in through a sense of service, complemented by an inability for lateral entry – almost all members needing to start from the entry level. Additionally, servicemembers change jobs nearly every one to three years.

There are ontological parallels to other communities, too. This process is shared in some regards by the medical school graduates applying to the residency stage of their training. These graduates are applying to a pool of US residency programs. This pool is also rather narrow, mostly coming from US based medical schools, and the specificity of skill set required for success is better understood than success as a military officer.

This general similarity is the reason our initial matching algorithm (Gale-Shapely Deferred Acceptance Algorithm) is similar one used by that process, the National Residency Match Program. The Gale-Shapely algorithm's application to the residency matching problem earned the Nobel Prize in 2012.

This paper also proposes an optimization based solution to the matching process. The optimization is not found in the National Residency Match Program as medical students have the ability to reject their assigned position, a choice not always given to military members. Thus an optimization can often more optimal solution for the DoD system at the expense of a few forced members.

Due to the importance of co-locating dual-military households (where two family members are in the military), we focus our matching algorithm and optimization proposals on solutions that would guarantee 95% or greater co-location rate.

Acknowledging the difficulty of wrangling disparate and dated personnel data, this paper also explores helpful metrics that can be gleaned simply from submitted, ordered preferences by job seekers and job owners. These are competitiveness, similarity, generalism, and specialization. Interestingly, due to the fact that preferences are expressed on job seekers and the jobs themselves, these metrics can be developed about the jobs or the job seekers.

Further the paper ends with suggested metrics that would be gleaned if personnel data beyond preferences was accessible, clean, and structured. These include a similarity measure based on quality encodings and a suggested ordering of possible jobs or applicants. The latter is proposed to be enabled by deep learning (the underlying technology of Artificial Intelligence (AI)). The suggested ordering would not make decisions on placement, but rather provide job seekers and job owners with metrics distilling the vast amount of information about

2 Literature Review

The most important people in this field, and the winners of the 2012 Nobel Prize in Economics for their work in stable marriage matching, are Roth [1] and Shapely [2].

1962

The intent of this algorithm is to provide stable pairings between job owners and job seekers based on their ranked preferences. The algorithm's initial conception and definition of stability can be found in Gale and Shapely's 1962 publication in the January *The American Mathematical Monthly* [2]. The algorithm completes in polynomial time and was originally written for application in collage admissions.

1982

Roth explores the incentives of conveying true preferences and whether is it in everyone's best interest to do so. [4] **working through the proofs to understand this better** In his work he specifically points to the applications to "civil servants with civil service positions".

1985

Roth explores the stable marriage problem specifically in the terms of 'firms and workers', also calling upon the lens of game theory. [5] He discussed an extension of the model from one assignment for each worker or firm, to multiple workers for each firm, to a situation where each firm can have multiple workers and each worker could have multiple firms. He also explored, under the constraint of stability, how in each model the optimal assignment set for one party (eg: firms) is the least optimal for the other (eg: workers). He elaborates that this final phenomenon creates difficulty in the institutional decision of how to formulate the matching algorithm.

1989

Irving explored indifference preferences and the follow on adoption for the Gale-Shapely algorithm. [3] This provides the theoretical framework allowing for indifference in our own formulation. Though much of his focus is on differing forms of stability (weak, stongl, and super) these lie outside of our investigation due to the Navy's authority to compel its members to placement.

1993

Roth, Rothblum, and Vande Vate explored the concept of partial matches, discovering in fact this forms a lattice of solutions as well. These fractional matches could represent lotteries or time splitting. [1]

1994

Khuller et.al have developed an algorithm for stable matching on-line (matching people as they enter the system), as opposed to the typical formulation of having complete market participants and preferences at the time of matching. [6] This could be interesting in future work of understanding the Navy detailing process as a continuous, rather than discrete, process.

[1] `http://stanford.edu/~alroth/PapersPDF.html`
[2] `http://www.econ.ucla.edu/shapley/ShapleyBiblio.1.html`

3 Solution Description

3.1 Algorithm

A basic algorithm, like Gale-Shapelys set of instructions for stable marriages, is an important first step in talent allocation. We moved onto a linear programming concept, oriented around solvers – algorithms that are adaptable. These solvers have varying types like linear, convex, and mixed integer. Our group followed a path paved by Stanford operations researcher Alvin Roth and adapted a mixed integer solution to leverage its flexibility. While Gale-Shapelys algorithm can be solved in n-squared time, ours is n-p-complete, indicating polynomial time completion. What we lose in speed, we gain in the ability to alter the formulation without total overhaul. These qualities make the approach particularly conducive to constraint creation, a vital requirement for stakeholders utilizing our solution.

Ours is a unique subset of mixed integer programming (MIP), binary optimization, to reflect the nature of either placement in a specific job, or not (i.e. only 1 or 0). The resulting lattice has an incredibly large number of dimensions manifesting every potential job placement for every individual. Subsequently, we apply constraints – the inherent reason we utilize MIP. These constraints cut away pieces of the lattice to reveal a viable search space to run the minimization function. Finding the minimum point within that constrained lattice provides us with a matrix of the optimally matched jobs and sailors.

3.2 Metrics

3.2.1 Pre-Match Metrics

Competitiveness Definition. Competitiveness measures the relative desirability of a given sailor or job based on the expressed preference ranking of the other party. We wanted to consider a more sophisticated way of determining this metric beyond an average ranking for either the sailor or job as it is very susceptible to a right tail bias. For example, a position ranked 1st by ten individuals and hundredth by twenty individuals has the same average ranking as a job ranked seventh by all thirty individuals; yet the prior is much more competitive. To attempt to compensate for this, we adjust the average by a power of one half is to lessen the impact of very low preferences thereby weighting favorable preference more in our score consideration. In order to generalize the competitiveness score we scale the resulting average by the total number of jobs or sailors within the system. This allows for competitiveness to range from 1 being most competitive, and 0 being not competitive at all.

[math here]

Impact. Competitiveness will be used to rapidly identify the most attractive candidates. (E.g. Sailor A has a 0.98 competitiveness score and is therefore a top ranked candidate amongst all job owners.) These candidates would be good fits in many jobs and therefore could be considered ideal individuals to screen for command. On the job side, a low competitiveness would be a great way to decide on incentive structures. These jobs are those that very few sailors prefer and therefore either promotion based assignment or additional compensation could to targeted towards these positions.

Specialization Definition. Specialization measures the extent to which the maximum desire for a sailor or job differs from the mean. Sailor A is highly specialized if one job owner highly desires them much more than the mean job owner (e.g. Sailor A is the 1st preference choice of Job Owner X, but is on average the 21st ranked preference).

[math here]

Impact. A sailor with a high specialization has some skill set that will serve a specific job function well; the seeker has an advantage over peers for a single role compared to the other roles the seeker is qualified for. If most job owners rate a seeker with low preference but a single owner rates that seeker with a high preference, the marginal gains of that seeker being matched with that owner are high. Matching the sailor with this particular role utilizes their specialization and produces a disproportionate positive contribution to the Department of the Navy. Intuitively, the matching algorithm will favor creating high-specialization matches. Failing to make these matches has a more negative impact on the system than failing to make non-specialized matches, because the usefulness of the sailor goes down significantly between their optimal match and average matches. This metric may be useful in the future to examine if very particular aspects of jobs or sailors make them attractive to small subsets of the other population.

Preference Correlation Definition. Preference correlation is the R-squared score of job owner and job seeker preferences. A strong positive correlation indicates that job owners and seekers mutually desire each other.

[example plot + line...strong correlation]

[example plot + line...weak correlation]

Impact. A lack of correlation indicates an information gap between job seekers and owners; seekers may not understand what skills a particular job requires or job owners may lack an understanding of what skills would be beneficial to have on their team.

Similarity Definition. Similarity indicates how closely the preferences of two Sailors or two job owners preferences are aligned.

[math here]

Impact. High similarity scores between pairs of sailors or pairs of job owners may be used to identify hidden groups; clusters of skills or jobs that are not clear to the naked eye. It may reveal unseen jobs or sailors, creating a more perfect information space. For instance, imagine two sailors, A and B, who have a high similarity score. If Sailor B did not know about a job, X, or did not rank that job for another reason, the similarity score may alert Sailor B that they are a good fit for that job if they did not receive any of their other preferences.

3.2.2 Post-Match Metrics

Preference Allocation Windows Preference allocation indicates how many individuals received their top preference, how many individuals got a top three, top five, and top 10 preference, and how many failed to be matched with any preference.

Talent Distribution Some job owners have multiple jobs. Ideally, such job owners would get an approximately equal set of preferences; one owner with five job slots would not get their 1st-5th choices while another job owner with five job slots gets their 20th-25th preferences.

Preference Difference Gap This metric helps to illuminate the separation between job owner and sailor preferences. This can be an indicator for senior leaders that neither sailors nor job owners had their preferences unduly weighted within the optimization system.

4 Pilot

4.1 Overview

Overview of the pilot, still narrowing this in.

4.2 Data

4.3 Results

5 Alternate Formulations

5.1 Wagering

5.2 Specialization Objective

6 Future Work

This is where our future work will go.

1. Explore implications of a “Separation” (u) preference

2. Explore strategic Importance of positions. This can either be an iteration where billets in priority tranche’s are run iterative (tier 1 billets all matched, those sailors and billets are taken out of the

pool, then tier 2 billets all matched, etc.). Or a weighting where in a single matching optimization the preferences of higher tiered billets are given a greater weighting

3. Does adding weight for specialization Im objective function help the Navy better? Did job owners who wanted specialized sailors get them? Did sailors who wanted specialized jobs get them?
4. Tailored Compensation descisions.
5. Incorporate timelines of expected roation date for availability windows.
6. Multiple firms and multiple workers, each sailor can opt into collaterals and other roles [4]

Appendices

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