Workforce Planning Tool for the consulting industry using LinkedIn data

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DS785: Capstone

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December 11, 2022

Abstract

I developed a Workforce Planning Tool to help a management consulting executive to launch a new service line and plan the organization structure aligned with its growth goal. As rapid change in talent demands in the management consulting industry, the tool aimed to give a simulation of career progressions for emerging professionals whose pattern is not well known in traditional consultants and recommend recruiting plan to maximize future revenue growth. Literature review confirmed applications of stochastic processes to organizations dynamism, e.g., recruiting, promotion and resignation. Additional review found operations research methods to solve human resource assignment problems. In this study, I used LinkedIn user profile from a bench mark firm to imitate a new organization. 502 LinkedIn profiles from Deloitte Digital UK was trained on a Semi-Markov model to forecast future organization structure. Semi-Markov Chain was implemented via msSurv R package to model the transition probabilities between job titles. Finally, a Linear Programming was solved to generate optimized number of additional recruits to maximize revenue growth in five years. It obtained approximately 535% revenue growth with additional 269 recruits for five years planning horizon. The sensitivity analysis revealed that retention of Associate level is critical to make the organization structure grow healthy. The tool also demonstrated the capability to control preferable ratio between staff and managers through solving optimized recruiting plan. With the capability the different recruiting plans were obtained for the typical organization strategies (1) Junior leveraging and (2) Gray Hair model. While demonstrated the usefulness of LinkedIn data as an organization benchmark on Workforce Planning, lessons such as lower sample size, time consuming data collection were left for a future opportunity.

Keywords: Workforce Planning, Professional Services, Markov Chain, LinkedIn

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Chapter 1: Introduction

Management Consulting Firms' expansion

Management consulting industry is generally known as one of service industry which provides business expertise to clients. The industry is unique for its high intensity of labor and dependency on professionals' knowledge (Nordenflycht, 2010). Originated from a theory of management engineering in 19th Century, Management Consulting firms expanded its service lines to Corporate Strategy, Operations, Human Resources, Information Technology and so on (Laffitte, 2022). Recently since the 2010s to the current, many consulting firms are expanding into implementing Digital Transformation.

Problem Statement

Although its covered areas are increased, management consulting firms have been struggling in deploying enough size of workforce. One reason is a high turnover rate (Williams, 2022). Consultants have a sense of independence and do not hesitate to leave if they do not find an opportunity to grow.

Another reason is that they are facing diversity of talents. Traditional management consulting firms such as Mckinsey, Boston Consulting Group, and Deloitte are recruiting Data Scientists, UX Designer and so on (BCG Digital Ventures, n.d.; BCG Platinion, n.d.; Deloitte Digital, 2017.; Mckinsey & Company, n.d.). Focusing more on skills and experiences rather than educational qualifications, the industry needs more diverse talent pool (Stephani, 2022). However, many firms do not have enough information for their career models e.g., how many years they need to develop senior level engineer.

In summary, there are two strategic problems for firms to address in order to grow along with market demand.

Problem Statement 1. Workforce Planning aligning with Strategy

Management consulting firms should equip capability to create long term workforce plan that is consistent with their strategic goal. Underestimating turnover and promotion of employees causes huge gap with desirable speed of organization growth. The gap is difficult to detect earlier because the process to grow employees is long-term exercise and opportunity cost from losing them comes suddenly.

In this sense, it is critical for a management consulting firm to track employees' career progression in the firm and reduce as many resignations as possible. At the same time, it is critical to have an accurate prediction of employees' resignations on the way.

Problem Statement 2. Understanding career patterns in new type of talent

Input for workforce planning should be expanded to external data. Under rapidly changing demand for consulting practice, management consulting firms are lacking internal data to create long-term workforce plan. They need benchmark information about promotion rate and retention rate of the new talents. There is an opportunity to leverage external data to gain insight into career pattern of new professions, e.g., Data Scientist or Designer.

Rational of the project

This project provides a workforce planning tool for consulting leaders to solve the above two problems. This tool will add business value through helping them to understand workforce dynamics and establish a competitive advantage by recruiting demanded professionals in the market place. Potential stakeholders of this project are leading partners in consulting firms who create and lead growth strategy of the firm’s emerging practice. With the outcome of the tool, there are benefits: the leading partners become able to validate if the headcount plans are feasible, in case recruiting is not progressing on the plan, they are able to predict the impact on achievement of firm’s growth strategy and take immediate actions to recover recruiting delay.

Markov Chain Model as workforce dynamic system

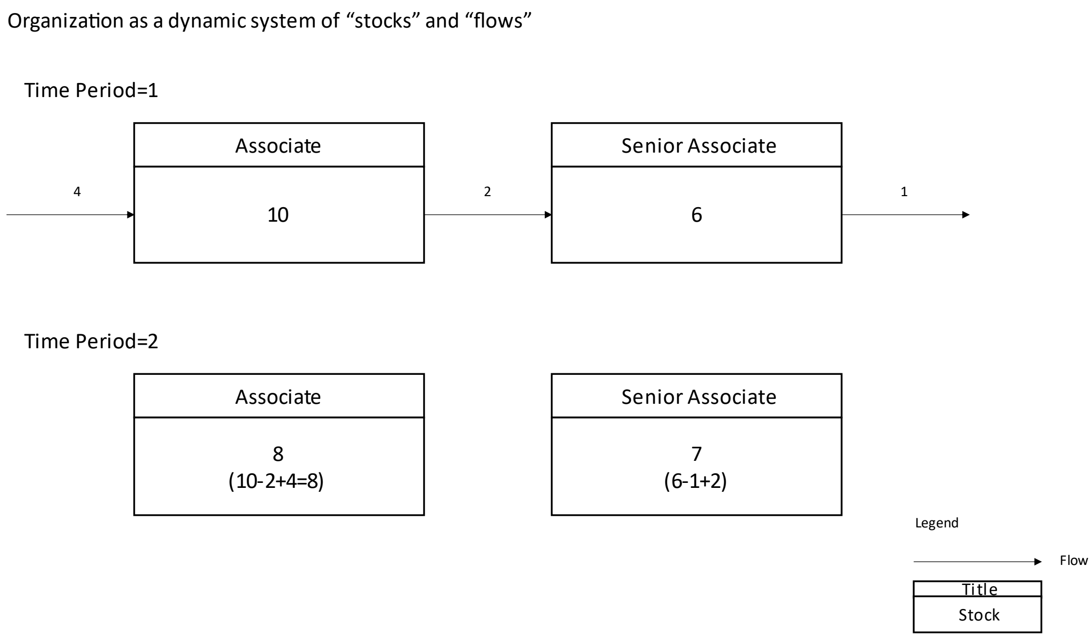
For the first problem statement of how firms should be capable to plan workforce aligned with growth strategy, there have been real-world applications of mathematical models for organization dynamics over time. The most traditional method is to apply Markov Chain Model to historical data for employees' transition from a job title to another. Markov chain is a type of stochastic process in which an individual subject can move from one state to another state in a fixed probability (Ross, 2014). In this process, whether the subject moves to another state in a time period depends only on the current state, independent of the past state. Markov Chain Model is used for several purposes: Weather Forecasting, Predicting stock price, Predicting machine failure, and so on. Using Markov Chain Model, an organization is modeled as a dynamic system of stocks and flows of members in an organization (Bartholomew et al., 1991). In an organization, "stock" represents members of a job title in a time period. The "flow" represents an inbound or outbound flow of members on the job title. In workforce planning, Markov Chain Model is used to describe transitions of members across multiple titles across multiple time periods.

The main part of the Markov Chain statistical model is to estimate Transition Probabilities which is a matrix of probabilities to move from one state to another. To predict the future state of stock of each job title in an organization, transition probabilities from one job title to another should be estimated from the organizations' historical data.

While there are researches to apply Markov Models to organizations in other industries, there are limited cases for Consulting Industry. The only research I found was an application of transition probability to answer questions about an opportunity for a new associate to promote in a consulting firm (Sheskin, 1995).

Figure 1

Organization as "stock" and "flows"



Operations research to make recruiting decision

Once workforce dynamics are quantified, firms should transform the insight into actionable recruiting strategy. Here, there is an opportunity to apply operations research technique. The idea is to formulate objective function as total revenue and number of recruiting for each job title as decision variable. To simplify a consulting business model, revenue can be calculated as multiplication of headcount and billable fee per consultant. Headcount is an updated "stock" of people at the end of a time period after reflecting inbound and outbound "flows". Number of recruiting is added as inbound flow into its respective job title. Without assuming any constraint, the more people a firm recruit, the more revenue is achieved.

Operations research allows to solve feasible number of recruiting under constraint of resources in real world. The typical constraints around a workforce planning and recruiting are: maximum number of recruiting by job title, realistic proportion of headcount between titles, i.e., ratio between manager and associate should be controlled within 2 to 4 and so on.

LinkedIn as a valuable data source to understand career pattern outside company

For the second problem for management consulting firms to understand career pattern for new technology talents, one potential solution is to leverage open professional network data.

LinkedIn is the world's largest professional network on the Internet. As of December 2021, LinkedIn had more than 850 million users in more than 200 countries (Geyser, 2022). On the platform, professionals publish own work histories in a similar manner as they create their resume to apply jobs. Recruiters can identify potential candidates through reviewing the work histories.

With the increasing popularity of the platform and access to public, there have been academic researches to study career patterns of professions. Case et al (2012) Investigated 175 graduates from Information System program and analyzed patterns of career progressions 10 years after graduation e.g., changing from technical role to managing role. Li et al (2016) conducted descriptive analyses to identify common knowledge necessary for IT professionals through collecting Information Systems Alumni from LinkedIn profile.

Though no research was found for LinkedIn data analysis in management consulting industry, preceding researches implies that LinkedIn data is valuable to answer questions about professional career pattern in specific professions.

Purpose of the study

The purpose of the study was to

- Build data driven workforce planning tool for a consulting firm leveraging LinkedIn data
- Apply data analysis on the tool and create recommended action as to when, where and how many the firm should recruit new people

I explored LinkedIn professional career data and build a model of a technology consulting firm whose organization headcount and pyramid structure are evolving over multiple years. This model enabled prediction of future size of the organization and its consecutive revenue growth. On top of the model, I built an operations research model to draw the optimized number of recruiting to maximize future revenue growth maintaining a healthy pyramid structure.

Around 500 professional data in Deloitte Digital UK was collected. Using collected professional data, I built (1) an estimated probability matrix of employee transitions, (2) a descriptive analysis of the evolution of organization structure using the estimated transition matrix, and (3) Linear Programming Model to solve an optimized number of recruiting.

The study was to answer the following questions:

1. How do number of employee change differently for different hierarchy level in a consulting organization without recruiting any new member?
2. How do proportion among different hierarchy level change over time without any recruiting? What is the implication of the change?
3. What is a recruiting strategy i.e., which job title should the organization recruit to maximum revenue growth? How many people should they recruit?
4. What constraint is affecting an optimized solution for number of recruiting?

Definitions of Terms

#	Term	Definition
1	Workforce Planning	A process to analyze, forecast and plan employee supply against demand (Indeed Editorial Team, 2021).
2	Cycle	Six-month time period at which movement of employee and recruiting is measured
3	Job Title	Name of position in an organization general and in the studied consulting firm
4	Transition Probability	Probability of people in a job title to move to another job title or leave the organization.
5	Junior	Set of non-management job titles in the studies consulting firm. It consists of Associate, Consultant and Senior Consultant

Chapter 2: Literature Review

As mentioned in Chapter 1, Management Consulting Firms are struggling with workforce issues such as uncertain mobilities of employees and acquiring new talents to meet their strategic goals. There are three possible solutions to address: (1) Building mathematical models such as Markov Chain to gain insight into organization evolutions, (2) Making decisions based on accumulated data through operations research methods, and (3) Leveraging open data such as LinkedIn. In this chapter, the literatures were reviewed to confirm the effectiveness and potential gaps along with these three approaches.

Markov Chain Model as workforce dynamic system

The history of the Markov Chain model in workforce planning is not new. (Bartholomew et al., 1991) There are studies to demonstrate the validity of the Markov Chain model in multiple industries. Trivedi et al. (1987) developed a semi-Markov model to predict training, supply, and demand for primary care workforces in the United States. In manufacturing, Bányai et al. (2018) developed a Markov Chain model to deploy assembly line operators in the manufacturing industry.

Common motivation to apply the Markov model is that it helps to quantify the probability to move from one job title to another. However, there are variations of modeling depending on fitness with required assumptions. Some studies took the traditional Markov Model assuming a time-homogeneous probability of transition. Time homogeneity is one of the assumptions in the Markov Model that people have the same chance to leave regardless of years in their current job title. Multiple studies took this assumption. Ochieng et al. (2020) applied the Markov model to quantify the turnover rate of university staff. Sheskin (1995) and Bányai et al. (2018) applied Markov Model with this assumption to consulting industry, and manufacturing industry respectively. On the other hand, there were studies that loosen this assumption. Trivedi et al. (1987) adopted the Semi-Markov model for its flexibility over the traditional Markov model. The study developed a semi-Markov formulation for modeling transitions of physicians, nurse practitioners, and physician assistants between different settings and locations within a geographic area. The study succeeded to obtain lower standard error using a semi-Markov model than the Markov chain.

Another direction in existing studies is forecasting future workforce structure through simulations. Trivedi et al. (1987) study emphasized forecasting the future supply of primary healthcare providers in the state of Washington and its comparison with demand. "Once the statistical tests on the data were satisfactorily completed and the input parameters were estimated, the semi-Markov model was run for predicting the supply of primary health care services during the planning horizon 1982 to 1990 for the state of Washington". Bányai et al. (2018) demonstrated with simulations that the future deployment of employees for each job title can be varied depending on the rate of promotion and recruitment in the current time period.

The software tools to implement Markov Chain are also available. Ferguson et al. (2012) provided an R package to model Semi-Markov Chain for generic purposes. “msSurv” package provides functions to calculate transition probabilities between states from directed graph data. This package uniquely covers transition probabilities at different periods which can be utilized to quantify different transitions rate for different tenures in the same job title.

Despite ranging studies from theoretical to practical, a limited number of studies are found for the management consulting industry. The only research I found was an application of transition probability to answer questions about an opportunity for a new associate to promote in a consulting firm. (Sheskin, 1995)

Operations Research to make recruiting decision

Application of operations research to workforce planning is not new area. Traditional formulation is called as 'Assignment problem'. (Hillier et al. ,2014) In an assignment problem, assigning a person to a particular task is a decision variable. Since each person has hours to complete a task, the objective function is a minimization of total cost of the entire work.

As an implementation of assignment problem, Hargaden et al. (2015) developed an integer programming to optimize workforce allocation for professional engineering services firms. While it followed the traditional assignment problem, this study identified unique variables specific to a professional services industry e.g., constraint about required skillset, organization structure, and customer projects. In the integer programming model, objective function was a revenue at entire firm which was earned from assignment of people to available projects. Though this study brought sophistications of algorithm and variables, I see some challenges in deployment to real business. While Hargaden et al. (2015) solved optimal assignment of employee to any available project, day-to-day operation of the model appeared to be challenging. The main reason is that the model requires frequent data update for large scale variables e.g., list of available projects, required work effort for the projects and skill data of employee.

While Hargaden et al. (2015) emphasized decision making to assign professionals to project at day-to-day cycle, some studies evolved for balancing short-term efficiency and human resource strategy. Feyter et al. (2017) developed a mixed integer programming to achieve two goals simultaneously: “Cost-effectiveness” of recruiting and “Desired Team Structure”. In the model, number of recruited employees by job titles were defined as decision variable. Two objective functions were defined: Cost effective ratio through recruiting new person and Deviation of attained members from planned headcount for each job title. Llort et al. (2018) developed a mixed integer programming for consulting business to achieve long-term workforce capacity. Two measures were chosen as objective function; Profit of the firm, and Pyramid structure of a firm. Decision variables were: Number of recruiting, promotion and firing which were measured by client service line and job title. Interestingly, both Feyter et al. (2017) and Llort et al. (2018) proposed maintaining proper pyramid structure as objective function of the model. Feyter et al. (2017) defined 'Desirability degree' which is to measure the desired personnel structure.

LinkedIn use for understanding career pattern

There are multiple studies to investigate career patterns using LinkedIn data. One approach is to investigate career trajectory over time among same cohort group. Case et al. (2012) and Li et al. (2016) investigated career progression patterns among alumni in Information System degree programs. The motivation of those study was to demonstrate usefulness of LinkedIn data to gain insight into effectiveness of education program on future career outcome.

Another direction of study was the development of career planning tools at an individual level. Ghosh et al. (2020) developed a novel machine learning model to predict an individual's next career given his/her final career goal and past job history. They used approximately one million LinkedIn user profiles published on Kaggle along with approximately four million Indeed profiles. They defined the user's next career which is a combination of company and job title as a response variable. A sequence of past job history was collected as an explanatory variable along with the user's career goal as a combination of company and job title. The model is unique because it not only provides recommended next career but also provides the required skillset to reach the next.

Despite the range of research directions of those studies, they had commonly mentioned the importance of managing data quality issues in LinkedIn profiles. Case et al. (2012) observed numerous LinkedIn profiles who have more than 10 years had no or less information at their entry position. Li et al. (2016) encountered variations of names for the same job title. They defined three dimensions to represent the job title: “Category” e.g., Administrator or Analyst, “Knowledge Domain” e.g., Application or Security, and “Seniority” e.g., Entry or Middle. Each job title observed in LinkedIn profile was classified into a combination of the three dimensions. Ghosh et al. (2020) applied a threshold to filter out profiles whose job titles were occurred infrequently.

Another implication is that obtaining enough sample data is a challenging part of the study using LinkedIn data. Case et al. (2012) mentioned its study had a weakness in the statistical significance of career patterns for non-traditional students who had military experience before college.

All the above-mentioned studies demonstrated business value of using LinkedIn data because it filled the gap found in organization's internal HR data with their needs for labor market insight in niche area. Although no research was found for LinkedIn data analysis in management consulting industry, preceding researches implies that LinkedIn data is valuable to answer questions about professional career pattern in specific professions.

Final thought

Reviewed studies suggested that workforce planning has been delt by scientific method for long. Based on established theory, more efforts are increasingly put on service industries as industry becomes more knowledge-based. Although operations research models were proposed for the industry, those contemporary studies are still focusing on theoretical advancements. No studies were observed in regards with use of external big data. For only career planning purpose, use cases of LinkedIn data were identified. Here, I can see an opportunity to combine LinkedIn data with workforce planning in the Management Consulting Industry.

Chapter 3: Method

Introduction

The objective of chapter 3 was to introduce theories of modeling workforce dynamics and describe design of data analysis in this project. As examination of modeling theories, I examined Markov Chain statistical model as a baseline theory. Next, I described a mathematical formulation of Semi-Markov Chain which loosen an assumption of time-independence of employee transition probability.

In the second part of this chapter, entire process of data analysis was explained. First, Data collection of career history from LinkedIn was explained. Next, standardized hierarchy structure of the studied organization and translation rule of job titles were described. In the forecasting modeling part, algorithms and variables to forecast future headcount and revenue growth were explained. Finally, formulation of a linear programming model for recruiting plan and its sensitivity analysis were explained.

Part1: Theory

Markov Chain Model

Markov chain is a type of stochastic process in which an individual subject can move from one state to another state in a fixed probability (Ross, 2014). In this process, whether or not the subject moves to another state depends only on the current state independent of the past state. Markov Chain Model has been used in several purposes: Weather Forecasting, Predicting stock price, Predicting machine failure and so on.

To describe the concept of the model, I take daily weather as an example. Suppose that if it rains today, then it will rain tomorrow with probability σ. If it does not rain today, then it will rain tomorrow with probability β. The system of weather is formulated as a matrix of the four probabilities.

Table 1

Formulation of Transition Probability for tomorrow's weather

		Tomorrow	
		Rain	Not Rain
Today	Rain	α	$1-\alpha$
	Not Rain	β	$1-\beta$

The matrix is called as one-step transition probability. We calculate probability of transitioning from one state to another for multiple time windows so that we can calculate probability to be rainy two days later in case it is rain at the first day. As per Chapman-Kolmogorov equations, we obtain two-step transition probabilities $P(2)$ by multiplying one-step transition probability (Ross, 2014).

$$P(2) = \begin{bmatrix} \alpha & 1-\alpha \\ \beta & 1-\beta \end{bmatrix} * \begin{bmatrix} \alpha & 1-\alpha \\ \beta & 1-\beta \end{bmatrix}$$

$$= \begin{bmatrix} \alpha \cdot \alpha + (1-\alpha) \cdot \beta & \alpha \cdot (1-\alpha) + (1-\alpha) \cdot (1-\beta) \\ \beta \cdot \alpha + (1-\beta) \cdot \beta & \beta(1-\alpha) + (1-\beta) \cdot (1-\beta) \end{bmatrix}.$$

if $\alpha = 0.7, \beta = 0.4$, then the two-step transition probabilities are calculated as follows.

$$P(2) = \begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix} * \begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix}$$

$$= \begin{bmatrix} 0.61 & 0.39 \\ 0.52 & 0.48) \end{bmatrix}.$$

Table 2

Example of two-steps Transition probabilities for tomorrow's weather

		Day After Tomorrow	
		Rain	Not Rain
Today	Rain	0.61	0.39
	Not Rain	0.52	0.48

Application of Markov Model to Workforce Planning

Organization dynamics can be modeled as stochastic process of individual worker across multiple job titles in a same organization over time. Hence, suppose the system is divided into k states which represent job title e.g., Associate, Manager. Also suppose each transition from one to another has a fixed probability. The stochastic system of workforce is formulated as stock and flow notation:

$$n_j(T) = \sum_{i=1}^{k} n_{ij}(T-1) + R_j(T) \; (j = 1,2,\ldots,k).$$

$n_j(T)$ denotes number of employees at the point of time T. n_{ij} $(T\text{-}1)$ denotes number of flow from job title i to j at from time $(T\text{-}1)$ to (T). $R_j(T)$ denotes number of recruited for job title j at the time T. Since flow between job titles is happening with fixed probability, an expected number of employees for job title j at time T is formulated as

$$\bar{n}_j(T) = \sum_{i=1}^{k} n_i(T-1)p_{ij} + R_j(T) \;\; (j = 1,2,\ldots,k).$$

p_{ij} denotes transition probability from job title i to j (same probability over time). A simple example of workforce system is given as vector of number of three job title A, B and C at time 0.

$$n(0) = [20,10,5].$$

In this scenario, suppose following transition probability matrix P and number of recruited people $R(T)$ are given:

$$P = \begin{bmatrix} 0.90 & 0.10 & 0 \\ 0 & 0.85 & 0.15 \\ 0 & 0 & 1.00 \end{bmatrix}$$

$$R(T) = [4,2,1].$$

The cell P_{11} (0.90) means that it is 90 percent chance for an employee at job title A remains the same job title. The cell P_{12}(0.10) means that it is 10 percent chance to move from job title A to B. Number of employees for each job title at time T=1 is calculated:

$$n_A(1) = 20 * 0.90 + 4 = 22.0.$$

$$n_B(1) = 20 * 0.10 + 10 * 0.85 + 2 = 12.5.$$

$$n_C(1) = \ 10 * 0.15 + 5 * 1.00 + 1 = 7.5.$$

In the similar manner, number of employees can be forecasted in Table 3.

Table 3

Example of forecasted number of employees by job title

T	A	B	C
0	20.0	10.0	5.0
1	22.0	12.5	7.5
2	23.8	14.8	10.4
3	25.4	17.0	13.6

Semi-Markov Model

Despite the simple aspect of Markov Model, it is not realistic to apply this to a system of employee dynamics in an organization. One of the reasons is that the probability to move to another job title or quit the current employer is time-dependent by nature. It is common for an employee to stay at the same job title in the first year, but the chance of promotion becomes higher as he or she develops skills over years. Hence, I examined another probability model called as Semi-Markov model. Semi-Markov Model loosens an assumption that transition probabilities are the same regardless of time spent in the grade.

The probability of eventually making the transition from S_i to S_j is given by

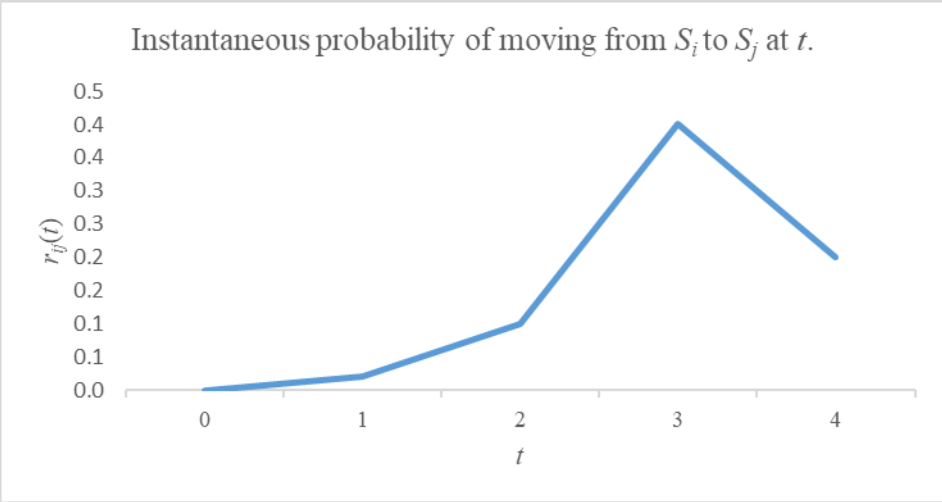
$$p_{ij} = \int_0^\infty \Pr\{\text{still in } S_i \ at\ t\} \times \Pr\big\{S_i\ to\ S_j\ in\ (t, t+dt)\big\}\, dt$$

$$= \int_0^\infty r_{ij}(t) G_i(t) dt\,.$$

G_i(t) denotes a probability to stay in S_i at time t. r_{ij}(t) denotes the instantaneous probability of moving from S_i to S_j at *t*.

Figure 2

Example of time dependent probability of moving from one job title to another



As an example, suppose there is an organization that consists of two job titles *i* and *j*. In the beginning, 40 people are recruited into job title *i*. Once a year, some of them are promoted to *j*. In this scenario, there are three possible transitions as follows: (1) Staying in *i*, (2) Promoting to *j* and (3) Staying in *j*. Illustration of estimating the probability of transition from job title *i* to *j* over time period 0 to 3 i.e., $p_{ij}(0,3)$ is calculated as shown in Table 5. n_i denotes beginning number of people. d_{ij} denotes number of people who transitioned from *i* to *j*. r_{ij}(t) is an instantaneous probability as d_{ij}/n_i. $G_i(t+1)$ is a probability to stay in *i* at time(t+1) given by

$$G_i(t+1) = G_i(t) \times \{(n_i(t) - d_{ij})/n_i(t)\}.$$

Table 4

State matrix of employee transition

		Next Year	
		i	*j*
This year	*i*	Stay	Promotion
	j	n/a	Stay

Table 5

Example of calculating multi-time-period transition probability

t	n_i	d_{ij}	$r_{ij}(t)$	$G_i(t+1)$	$r_{ij}(t) * G_i(t)$
0	40	0	0.000	1.000	0.000

1	40	4	0.100	0.900	0.100
2	36	5	0.139	0.861	0.125
3	31	6	0.194	0.806	0.150
					0.375

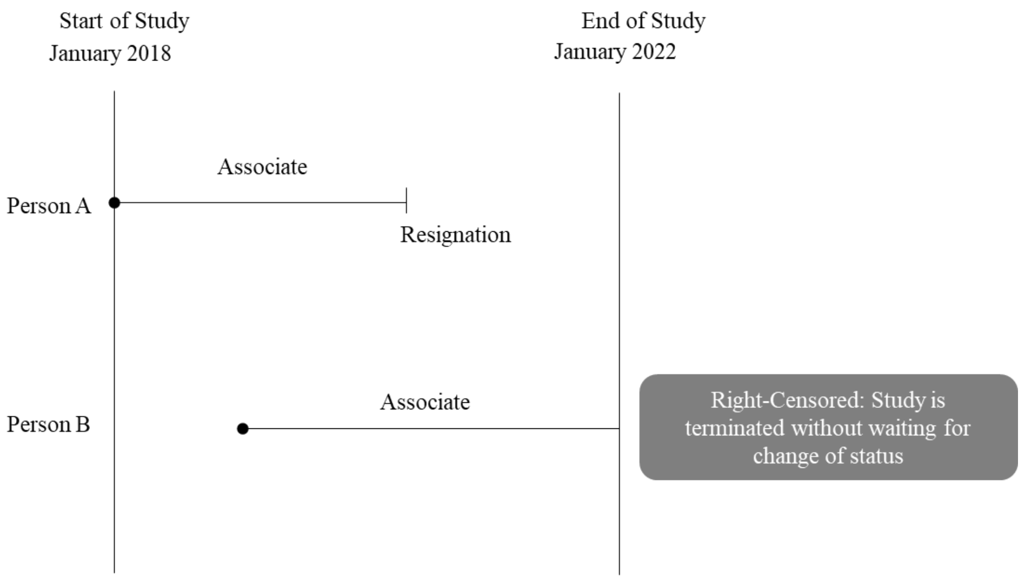
Note. p_{ij} (0,3) = $r_{ij}(1)*G_i(0) + r_{ij}(2)*G_i(1) + r_{ij}(3)*G_i(2) = 0.375$

Right-censored data

State of being a certain job title can be ended without moving to any other state. In many cases, it is happening when the employee stays in the job title until we terminate a data collection. Such data condition is considered as 'Right-Censoring'. In Semi-Markov Model, right-censored data should be removed from subjects.

Figure 3

Example of Right-Censored data



Nelson-Aalen estimator and Aalen-Johansen estimator

Semi-Markov Modeling was conducted using R package 'msSurv' which was publicly available in CRAN repository until May 2022. This package was built for any multistate model including both Markov Model and Non-Markov Model such as Semi-Markov model (Ferguson et al. ,2012). The msSurv package implemented Nelson-Aalen estimator and Aalen-Johansen estimator which are components to calculate transition probabilities between states in Markov process. Nelson-Aalen estimator is estimated probability of event such as change of job titles for an employee within a time period (Nelson, 2000). This cumulative probability over time is called 'cumulative hazard rate' and is defined as following formula.

$$\bar{A}(t) = \sum_{t_i \le t} \frac{d_i}{n_i}.$$

d_i denotes the number of transitions at t_i and n_i denotes the total number of individuals at risk at t_i. Aalen-Johansen estimator of the transition probability matrix of a Markov multi state model is defined as a product integral of $\bar{A}(t)$ (Aalen, O.O et al, 1978).

$$\hat{P}(s,t) = \prod_{(s,t]} \big(I + d\hat{A}(u)\big).$$

Where

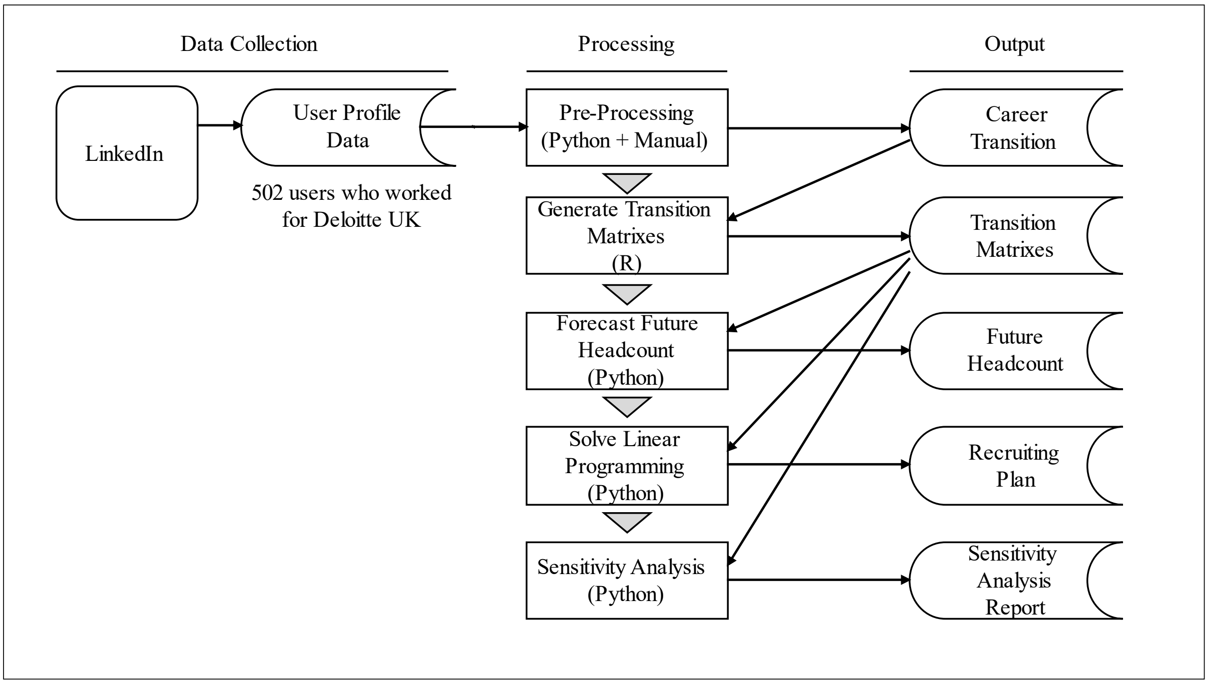
$$\hat{A} = \{\hat{A}_{j\,j'}\}.$$

Part2: Data Analysis Process

Entire process of data analysis was depicted in figure 4.

Figure 4

Data Analysis Process



Data Collection

LinkedIn user profiles were collected on January 2021 using my own LinkedIn account. I chose Deloitte Digital UK as a studied company because the available size of profiles looked suitable for time constraints in this project. Due to prohibited use of any scraping tool (LinkedIn, n.d.), I manually copied the search result into text files. In the LinkedIn search window, 852 user profiles were obtained in the search condition: Location='United Kingdom' and Past Company='Deloitte Digital'. Out of 852 results, the first 502 profiles were manually saved into text files.

Pre-Processing

LinkedIn profile files take semi-structured text data. In each profile, combinations of company name, job title and duration are sequentially recorded. Since many profiles had work experiences in other companies than Deloitte Digital, I wrote Python code in order to extract only sequence of career in Deloitte organization. Example of extracted work history was provided in table 6. In some profiles, two similar company names appeared: ‘Deloitte’ and ‘Deloitte Digital’. Since it is the case that organization name was changed in the same company, I kept ‘Deloitte’ in the data set as well as ‘Deloitte Digital’.

Table 6

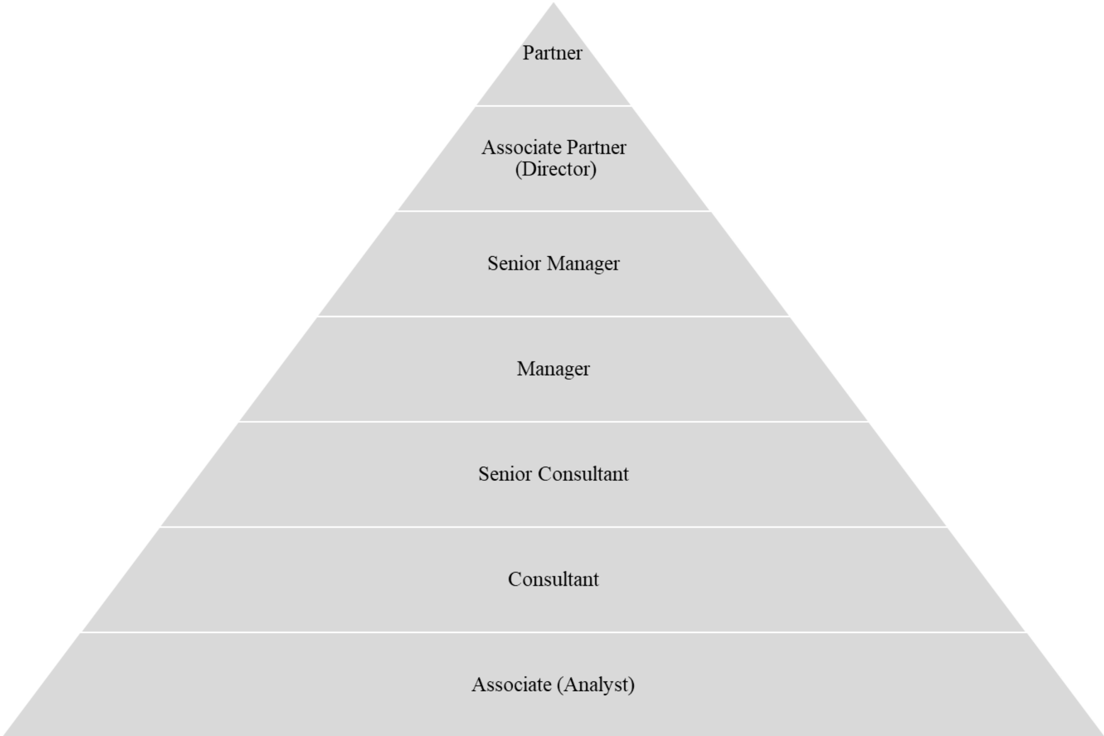
Table format for career transition

User	company	Job Title	Started Year Month	Ended Year Month
1	Deloitte	Blockchain Lead - UK	Oct2015	Present
	Deloitte Digital	CRM & Digital Transformation Specialist	Oct2012	Oct2015
2	Deloitte ? Full-time	Manager	Sep2021	Present
	Deloitte Digital	Senior Consultant	Sep2019	Aug2021
	Deloitte Digital	Consultant	Jan2018	Aug2019
	Deloitte UK	Analyst	Sep2015	Dec2017

Since typical Deloitte organizations constitute seven job titles (Management Consulted, 2022), work histories were classified into seven job titles: Partner, Associate Partner (known as Director), Senior Manager, Manager, Senior Consultant, Consultant and Associate (known as Analyst)

Figure 5

Job titles in Deloitte organizations



I observed many users used different job title names even in the same Deloitte organization. Total 443 different job titles were classified into seven standardized job titles. The classification was performed in the following procedure: (1) If the job title exactly matches or contains a standard job title, assign the standard name, (2) If the job title matches with compatible job titles in Table 7, assign the corresponding job title, (3) Irrelevant roles such as student, recruiter and contractor were removed, and (4) For any remaining job title undecided, one standardized job title was assigned through reviewing the entire job history for the profile, i.e., a job title was inferred from job titles before and after it. In case the same job titles are repeating with different period, the records were merged into single job history as shown in Table 6.

Table 7

Standard Job Title and its compatible job titles

Standard Job Title	Compatible Job Titles
Partner	Chief xx Officer
Associate Partner	Associate Director
Senior Manager	Associate Director
Manager	Scrum Master

Senior Consultant	Assistant Manager, Senior Engineer, Solution Architect
Consultant	Senior Analyst, Consulting
Associate	Analyst, Specialist

Table 8

Job titles that were filtered out

Job Title	Words in filtering out from the dataset
Student	‘Student’, ‘Intern’
Recruiter	‘Recruiter’
Contractor	‘Contractor’

Figure 6

Manual merge of repeating job titles

Company	Job Title	Standardized Job Title	Start Period	End Period
Deloitte	Salesforce Consultant	Consultant	Feb2014	Jun2017
Deloitte	Salesforce Consultant	Consultant	Jul2017	Sep2019

Company	Job Title	Standardized Job Title	Start Period	End Period
Deloitte	Salesforce Consultant	Consultant	Feb2014	Sep2019

Generating Transition Matrixes

Once career transition records were created, I performed Semi-Markov modeling on the dataset to generate estimated transition matrixes. As many consulting firms have two review cycles of employees performance per year, each matrix was created for six months window, i.e., total 10 different matrixes were generated. To do this, transition records were realigned to subgroup by job title and tenure month in the job title. For example, profile A, B and C, who had different time to join Deloitte as Associate, were grouped into the same members. They were processed to estimate probabilities in promoting to Consultant. To make such groupings, starting Year Month was converted into relative number of months counting from the first month of joining Deloitte and relative month number of transition was added (see

Figure 7).

As mentioned in part 1 in this chapter, I used msSurv R package for this process. As msSurv package is for Markov modeling for general domain, career transition records were transformed in a generic format described in Table 9. Entire data flow to generate transition matrix was described in Figure 8.

Figure 7

Illustration of sub groups in a transition matrix

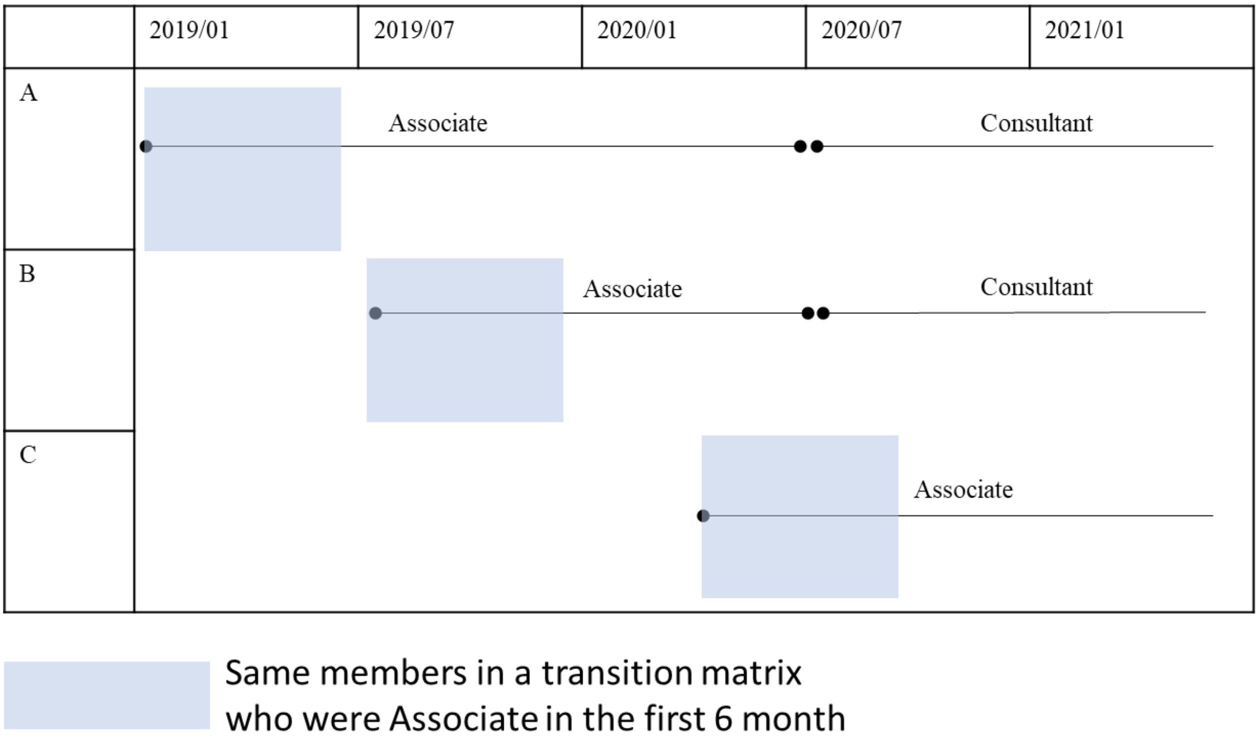


Table 9

Record layout for Semi-Markov Analysis in msSurv package

#	Field	Description	Example
1	Id	Unique id for employee	2
2	Stop	Month number in which transition happened	28
3	start.stage	Job title code before transition	1
4	end.stage	Job title code after transition	2
5	start.stage_str	Job title before transition	Associate
6	end.stage_str	Job title after transition	Consultant

Figure 8

Data flow to generate Transition Matrixes

Career transition data

User	company	Job Title	Started Year Month	Ended Year Month
	Deloitte UK	Analyst	Sep2015	Dec2017
	Deloitte Digital	Consultant	Jan2018	Aug2019
	Deloitte Digital	Senior Consultant	Sep2019	Aug2021
2	Deloitte ? Full-time	Manager	Sep2021	Present

Career transition data for msSurv package

id	stop	start.stage	end.stage	start.stage_str	end.stage_str
2	28	1	2	Associate	Consultant
2	48	2	3	Consultant	Senior Consultant
2	72	3	4	Senior Consultant	Manager
2	77	4	0	Manager	Right-Censored

Semi-Markov Transition Probabilities Estimation
(R msSurv package)

Transition probabilities at 1st cycle of planning window

		2nd cycle							
		Associate	Consultant	Senior Consultant	Manager	Senior Manager	Associate Partner	Partner	Exit
1st cycle	Associate	0.93	0.02						0.05
	Consultant		0.94						0.06
	Senior Consultant			0.98					0.02
	Manager				0.96				0.04
	Senior Manager					0.96			0.04
	Associate Partner						1		
	Partner							1	
	Exit								1

…

Each transition probabilities for 2nd to 10th cycles

Forecasting Future Headcount

The next step is to forecast future headcount from the initial number of employees in each job title. For each cycle, a number of headcounts by job title was calculated by multiplying the transition probability matrix and the beginning number of headcounts. As explained in part 1 theory, beginning number of headcounts for cycle *n* was calculated from the headcount at the previous cycle *n-1*. Forecasted numbers of headcounts from cycle 1 to cycle 10 were saved as a csv file and visualized to evaluate the evolution of team structure over time.

Solving Linear Programming for recruiting plan

On top of forecasting future headcount, I incorporated a number of recruits for each combination of job title and cycle as a decision variable and formulated a linear programming problem. Linear programming script was implemented using the Pyomo Python library.

Objective function. The objective of solving a linear programming problem is to find optimal recruiting plan that maximize future revenue growth. Hence, revenue growth rate from initial time period to 5 years future $(REV_{10} - REV_0)/ REV_0$ was defined as objective function. The revenue amount per cycle was defined as multiplication of headcount (*FTE*) and billable amount (*REVH*).

$$\text{Maximize } (REV_{10} - REV_0)/ REV_0.$$

$$REV_{10} = \sum_{j=1}^{7} FTE_{10,j} \times REVH_{j.}$$

$$REV_0 = \sum_{j=1}^{7} FTE_{0,j} \times REVH_{j.}$$

$FTE_{c,j}$ denotes a number of headcount at cycle *c* for job title *j*. This is a sum of transitioned people from the previous cycle (including people staying the same job title) and number of newly recruited ($REC_{c,j}$). Number of transitioned people is identified by multiplying transition probability and headcount at the previous cycle. Hence, $FTE_{c,j}$ is formulated as follows.

$$FTE_{0,j} = a_j.$$

$$FTE_{1,j} = \sum_{i=1}^{7} TP_{1,i,j} \times FTE_{0,i} + REC_{1,j}.$$

...

$$FTE_{10,j} = \sum_{i=1}^{7} TP_{10,i,j} \times FTE_{9,i} + REC_{10,j}.$$

Table 10

Indexes in a Linear Programming Formulation

#	Index	Definition
1	*c*	Cycle (0≤c≤10)
2	*i*, *j*	Job title. 1: Associate, 2: Consultant, 3: Senior Consultant, 4: Manager, 5: Senior Manager, 6: Associate Partner, 7: Partner

Table 11

Variables in a Linear Programming Formulation

#	Variable	Description
1	REV_c	Revenue amount at cycle *c* in thousand USD.
2	$FTE_{c,j}$	Number of people in job title *j* at cycle
3	$REVH_j$	Revenue Per Head for job title *j* in thousand USD. This is fixed billable amount of an employee for single month.
4	$REC_{c,j}$	Number of recruited people for job title *j* at cycle *c*. This is a decision variable of this linear programming.
5	$TP_{c,i,j}$	Transition probability from job title *i* to *j* at cycle c

In this project, dummy values listed in Table 12 were set for Revenue Per Head ($REVH_j$).

Table 12

Value for Revenue Per Head ($REVH_j$)

#	Job Title	Billable amount per month (Thousand USD)
1	Associate	20
2	Consultant	24
3	Senior Consultant	30
4	Manager	40
5	Senior Manager	50
6	Associate Partner	60
7	Partner	80

Constraint. In order to set conditions for recruiting capability and desirable team structure into the model, following constraints were added.

- $\boldsymbol{REC_{c,j}}$: Depending on seniority of job title, different number of maximum recruited people were set. I set lower value to senior job title (See Table 13).
- **Supervisor-to-Staff Ratio**: Best balance between junior and senior members can be determined by the types of work that a firm prefers to deliver. In general, more senior members are directly involved to solve forefront problems while assigning many juniors is preferable for

procedural tasks (Maister, 1997). In this model, Supervisor-to-Staff Ratios are defined as parameters and they are subject to constraint as minimum values. Considering the rule of thumbs that three to six people are a maximum span of control (Encyclopedia.com, 2018), or one to four subordinates under one manager (Consultant's Mind, n.d.) is general, minimum values were set for different levels of job titles (See Table 14).

Table 13

Constraint against Number of recruited people ($REC_{c,j}$)

#	Job Title	Maximum number of recruiting in a cycle
1	Associate	10
2	Consultant	10
3	Senior Consultant	10
4	Manager	5
5	Senior Manager	2
6	Associate Partner	1
7	Partner	1

Table 14

Constraint against Supervisor-to-Staff Ratio

#	Supervisor-to-Staff Ratio	Minimum value
1	Associate-to-Manager Ratio	2
2	Consultant-to-Manager Ratio	2
3	Senior Consultant-to-Manager Ratio	1
4	Manager-to-Senior Manager Ratio	2
5	Manager-to-Partner Ratio	2.5
6	Senior Manager-to-Partner Ratio	2
7	Senior Manager-to-Associate Partner Ratio	2

Sensitivity Analysis

After solving a linear programming, sensitivity analyses were conducted for several scenarios. The objective of these analyses was to identify variables that have effect on optimal solution in a linear programming problem. Following analyses were conducted.

Transition Probability. This analysis was to solve linear programming by changing transition probability for a certain transition in a cycle to find the transition that needs more accurate estimation. To do this, I computed the confidence intervals of transition probabilities in the following formula (Ferguson, et al., 2012).

$$\hat{p}(s,t) \pm c_{\frac{\alpha}{2}}\hat{\sigma}(s,t).$$

$\hat{p}(s,t)$ is a transition probability from time s to t which can be translated into $TP_{c,i,j}$. $\hat{\sigma}(s,t)$ is the corresponding variance of $TP_{c,i,j}$. $c_{\alpha/2}$ is the upper $\alpha/2$ percentile of the standard normal distribution. With level of confidence 0.95, confidence interval is computed as:

$$TP_{c,i,j} \pm 1.96 \times \sqrt{TP_{c,i,j}(1 - TP_{c,i,j})/n_{c,i}}$$

where $n_{c,i}$ is the total number of people who were in job title i at cycle c.

Supervisor-to-Staff Ratio. Linear Programming was solved against multiple values for Supervisor-to-Staff Ratio to see impact on revenue growth and recruiting plan. I defined two kinds of parameter sets which reflects different organization strategies: (1) Junior Leverage model and (2) Gray Hair model. In Junior Leverage model, projects are executed intensively by junior members with limited involvement of middle managers. This organization strategy generally fit with procedural projects e.g., IT outsourcing (Maister, 1997). In contrast, Gray Hair model deploys more middle managers so that the firm is able to execute knowledge-intensive projects (Maister, 1997). I set minimum and maximum values for each variable in the linear programming so that headcount plan is controlled under intended organization structure. Values for each variable in the two scenarios were shown in Table 15.

Table 15

Constraints for Supervisor-to-Staff Ratio in two organization strategies

#	Variable	(1) Junior Leverage model		(2) Gray Hair model	
		Minimum	Maximum	Minimum	Maximum
1	Associate-to-Manager Ratio	3	8	1	2

2	Consultant-to-Manager Ratio	3	8	1	2
3	Senior Consultant-to-Manager Ratio	2	8	1	2
4	Manager-to-Senior Manager Ratio	1	4	1	3
5	Manager-to-Partner Ratio	2	4	4	10
6	Senior Manager-to-Partner Ratio	2	4	3	10
7	Senior Manager-to-Associate Partner Ratio	2	4	3	10

Chapter 4: Results and Findings

Introduction

The study was to

- Build data driven workforce planning tool for a consulting firm leveraging LinkedIn data
- Apply data analysis on the tool and create recommended action as to when, where and how many the firm should recruit new people

With this tool, leaders should be able to design the organization structure for a new service line. The tool also aimed to give an insight into career progressions for emerging professionals whose pattern is not well known in traditional consultants.

As mentioned in Chapter 3, LinkedIn career data from Deloitte Digital UK was fed into a Semi-Markov model and transition probabilities at each cycle were generated. In Chapter 4, visualization of transition probabilities was attempted for both promotion and resignation patterns. Next, visualization of five years headcount forecast was described. The visualization was demonstration of natural evolution of organizations size and pyramid structure without any additional recruiting. Finally, results from the linear programming model were present as five years recruiting plan and future headcount. After grasping the outlook of the linear programming outcome, results from Sensitivity Analysis were discussed.

Transition Probabilities

Time-dependent probabilities to promote to the next level for junior level (Associate, Consultant, and Senior Consultant) were depicted in Figure 9. Associate is more likely to promote than other two. Associate's peak of promotion is concentrated in cycle 4 and 5 i.e., 2 to 2.5 years tenure. On the other hand, chances of promotion for Consultant and Senior Consultant are moderately distributed.

Not only junior levels but also middle level (Manager and Senior Manager) had the promotion peak between cycle 4 and cycle 6, i.e., 2 to 3 years. This appears to be consistent with industry common sense (Hacking The Case Interview, n.d.). Time-dependent probabilities to leave the firm were depicted in Figure 12, Figure 13, and Figure 14. Similarly, Figure 12 suggests that Associates have higher probabilities to leave than Consultants and Senior Consultants.

What is suggested through the above analysis is that quantifying speed of promotion or resignation in the benchmark firm gives input to their own organization strategy. For example, the business will be able to adjust promotion speed to the industry standard so that they will be competitive in recruiting and reduce churn of existing employee into competitor firms.

While the analysis revealed high speed of transitions in Associate level, I observed a variance in the estimated probabilities in Senior job titles. Table 16 shows standard deviation and Coefficient of Variance (CV) of promotion probabilities during cycle 4 to cycle 6. Comparing CV values, I can see relatively larger values in senior tiles e.g., Senior Manager and Associate Partner. This result left a lesson that more sample size is required for senior positions to make the model more robust.

Forecasting Future Headcount without recruiting

The multi-year forecast of headcount also revealed the impact of high transition in Associate. The number of employees in each job title was simulated using identified probability matrixes. Headcount was obtained by multiplying the initial headcount and transition probability at each cycle. Initial headcount (10,8,6,4,2,1,1) was set for the cycle 0. The evolution of headcount from cycle 1 to cycle 10 was present in Table 17 and Figure 15. As shown in Table 17 and Figure 15, headcounts of all titles are forecasted downwards. Especially, the proportion of junior members (Associate, Consultant, and Senior Consultant) are getting decreased. Among them, decreasing speed of Associate is evident. It makes it difficult to run enough amounts of projects because of top-heavy structure. There might be two possible measures to fix this. One is to recruit enough amount of Associate from the early cycle. Another approach will be to increase Associate's salary to a competitive level.

Linear Programming for recruiting plan

A headcount plan incorporating recruiting was identified through linear programming (See Table 18). Evolution of the organization structure was visualized in Figure 16. In contrast with Figure 15, Figure 16 illustrates a steady trend toward larger organization size. The plan recommended to recruit Associate and Consultants in almost every cycle with full capacity of recruiting 10 people (See Table 19).

For upper titles above Manager, recruits are prescribed only in the second half of the planning horizon. The recruiting for senior titles is critical to the business because of its importance to business development and its scarcity. In general, it is taking longer to find senior level candidate than finding junior people. Given this prescription, the business should validate if the firm can recruit planned people from the market. If it is unrealistic plan, the leader needs to come up with another strategy such as acquisition of an existing firm.

Along with the optimized recruiting plan, the Linear Programming answered the revenue growth in five years. The value of the objective function produced 535.05% of revenue growth from cycle 0 to cycle 10 (See Table 20).

The plan for active recruiting of junior titles and increased forecast of future revenue in the Linear Programming is convincing because it is consistent with implicated solutions drawn in the previous 'Forecasting Future Headcount without recruiting' section. It appears that the linear programming method effectively demonstrated the alignment of the firms' recruiting strategy with its financial goal.

Sensitivity Analysis

Transition Probability

This analysis was to solve linear programming by changing transition probability for a certain transition in a cycle to find the transition that needs more accurate estimation. Table 21 presented top 5 transitions that have the largest variances in optimum solution. All the transitions were retention probability for Junior titles at longer tenure. Transition probability 0.5 for 'Transition from Associate to Associate i.e., staying in the same position in cycle 9' had 535.0% in its estimate, but its upper boundary 1.1 obtained 645.4% growth in its upper boundary.

Since impact on objective function appeared to be large in Junior titles' retention probability, I performed additional sensitivity analysis. In each of Associate, Consultant and Senior Consultant title, I increased retention probabilities for all cycles by 20 percent and 40 percent. The growth rate of each case was present in Table 22. For all the job titles, I observed increase in growth rate. In case of 20 percent increase, they increased to 570.48%, 546.44% and 536.90% respectively. In case of 40 percent increase, growth rate increased to 605.94%, 558.99% and 538.44% respectively. The scenario for Associate's retention 40 percent increase obtained the largest growth rate.

Sensitivity analysis of transition probability suggests to estimate more accurate transition probability for junior roles at longer tenure. More importantly, high retention probability in Associate can allow active recruiting for other job titles. For example, Scenario 3 (Associate's retention rate 40% increase) subscribed 74 recruits in Senior Consultant (SC) while the default scenario subscribed 60. This change might be explained in the way that the scenario 3 might have allowed to add more Senior Consultants who can work with retained Associates.

The above result prompts a discussion. In traditional promotion policy, the culture called 'up or out' is adopted in some consulting firms. The policy does not allow a consultant to stay in the same rank longer than the expected. The person who stays longer is asked to leave the firm. This is thought to be helpful for the firm's moral to be competitive. As long as the firm keeps hiring younger people easily, the policy helps to keeping only high-performing people. The sensitivity analysis implies that there could be another organization strategy than ‘Up or Out’ culture. It is intuitively reasonable to extend the expected tenure for a new role e.g., UX designer. It might take longer years for the role to develop technical expertise than traditional strategy consultants. The sensitivity analysis will add value in terms of pushing the intuition to tangible strategy. For example, you should be able to setup another career track in which some people pursue the moderate career progressions with reasonable level of compensations.

Supervisor-to-Staff Ratio

Linear Programming was solved against two scenarios for Supervisor-to-Staff Ratio: (1) Junior Leverage model and (2) Gray Hair model. Estimated growth rate in five years and recruiting plan was shown in Table 23. Junior Leverage model estimated 406.9% growth while Gray Hair model estimated 639.2% growth. Interestingly, Gray Hair model had larger number of planned junior recruiting. Gray Hair model subscribed much more recruiting for Associate, Senior Consultant, Manager and Senior Manager than Junior Leverage model.

Figure 17 and Figure 18 shows the time series organization structure of the two scenarios. Table 24 and Table 25 describes Supervisor-to-Staff Ratio in each cycle of the two. As shown in Figure 17 and Table 24, the proportion of junior (Associate, Consultant, and Senior Consultant) is getting large for Junior Leverage model. In contrast, the proportion of junior over middle managers is restricted for Gray Hair model (See Figure 18 and Table 25).

In terms of growth rate, Gray Hair model had a higher growth rate than Junior Leverage model. This might be because Gray Hair model had larger recruiting plan in both junior and middle levels. Extra headcount for middle managers might have contributed growth rate due to their higher billing amount. It is suggested that for both strategies, it is critical to constantly recruit Associate level to maintain a desirable portion of Supervisor-to-Staff ratio. As both Table 24 and Table 25 show, the headcount ratio was controlled across cycles. The linear programming model appeared to be successful to incorporate different organization structures.

Business Significance

As reviewed the above sections in Chapter 4, several business values were identified through the attempts to develop workforce planning tool on LinkedIn data. First, the power of quantifying employee dynamics helps navigate a management consulting firm towards its financial goal. The recruiting plan for five years estimated approximately 535 percent growth of revenue. The improvements of retention rate by 40 percent estimated 606 percent growth. Here the workforce planning has consistent connection with corporate growth strategy.

The second is that the entire framework allows different consultancies to incorporate different parameters. Different recruiting plan and revenue maximization was generated from variable constraints such as transition probability and Supervisor-to-Staff Ratio. This implies that each firm does not necessarily own the tool and the capability can be provided by other provider as a service. Considering that the frequency to use the tool is limited to a particular point of strategy design and refine, the operating model by external provider might be beneficial for firms in terms of investment.

The third is that leveraging LinkedIn data provided the business with an insight into the competitive organization strategy. The quantified metrics obtained from external data such as average tenure at each job title and promotion probability at a particular tenure helps to come up with concrete HR strategy such as recruiting and competitive compensation.

Chapter 5: Discussion

This study was conducted to demonstrate an analytical tool to plan an organization that navigates a management consulting firm's growth strategy. The rigorous quantification of internal career progressions enables long-term plan of talent acquisitions. In addition, the tool should be able to equip an organization model from emerging talent market under the pressure to expanding consulting firms' service lines.

Discussion

For the first objective to develop workforce planning tool, the combination of Semi-Markov model and Operations Research method revealed the critical points on which recruiting and retention is required to achieve multi-year revenue growth. The tool also demonstrated capability to simulate different results from different constraints and preferences in user firm. These two outcomes will add business values in navigating human resource strategies along with firms' growth strategy.

The second attempt to bring external insight into new talent dynamics was successfully implemented. Collected LinkedIn profile produced reasonable statistics of transition probabilities in many segments. Trained on Semi-Markov model and solved in Operations Research, the raw data was transformed into insight such as the quantified revenue growth by retaining moderate performers who have slower speed of promotion than traditionally expected.

Recommendations for Future Research

Based on the results of the study, there are several recommendations for future research. First, some of the limitations were observed in the robustness of the model due to lower sample size. Due to constraint of manual data collection effort, only 502 users were processed to build the transition model. To improve standard errors of the estimated transition probabilities, more amount of user profiles could be recommended. Second, to collect open professional data in more large scale, systematic method could be studied. In this study, data collection through the manual copying and pasting was necessary to comply with LinkedIn's user agreement. However, there are ongoing discussions whether applying scraping tool is illegal (Smith, 2022). Continuous examinations to legally collect open professional data is recommended. I also encountered that there were slight changes of format of career history section in the search results across multiple points of data collection. Due to this, I had to update text processing scripts to adapt with new format. Finally, this study did not assume any constraint on revenue growth. This was because of my personal perception that management consulting in Asia Pacific where I work is growing faster than other matured markets e.g., U.S. or E.U. The study was focused on prescribing as much recruits as possible to maximize revenue. However, to make this tool useful in realistic use case, it could have any parameter to set achievable revenue goal.

Conclusion

The discussions of this study lead to the three major conclusions. Firs, the attempt to develop data driven workforce planning tool leveraged by LinkedIn career was successful. The tool demonstrated a unique capability to forecast five years headcount and revenue growth through combining benchmark firms' career data and users' own business parameters. The prescribed recruiting plan will navigate the firm leaders through their growth strategy. The granularity and visual presentation of data analysis was also successfully implemented.

The second conclusion is that LinkedIn has a potential to gain insight into future organization dynamism which is not currently available in a firm. The findings implied that retaining Associate levels might solve the bottleneck to recruit upper levels. Though this contradicts the industry norm that recruiting fresh talents is better than retaining slow learners, the findings shed light on different organization strategy. In fact, it is essential to rethink the highly competitive work environment under increasing shortage of younger population over the world (Maister, 1997).

The third conclusion is complexity of data analytics process. The overall process from data collection to executing analysis took more than six months. It is overwhelming for one firm to conduct the analytics end to end. Especially the challenges lie in data collection and cleaning of constantly changing data source structure. It is suggested that any data product is developed by third party company in the future.

The idea to combine LinkedIn career data with workforce planning in the consulting industry was compelling. The technical foundation was comprehensively examined through the case study approach. However, this study was just a one of simplified use case. Further studies will be open to opportunities for developing additional capabilities.

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Appendix 1: Chapter 4 Tables

Table 16

Standard Deviation and Coefficient of Variation for Promotion Probabilities

Job Title	cycle	Promotion Probabilities	Standard Deviation	Coefficient of Variation (CV)
Associate	4	0.32	0.06	0.2
Associate	5	0.30	0.11	0.35
Associate	6	0.00	0.00	0.00
Consultant	4	0.10	0.02	0.25
Consultant	5	0.12	0.03	0.26
Consultant	6	0.04	0.02	0.48
Senior Consultant	4	0.07	0.02	0.34
Senior Consultant	5	0.10	0.03	0.28
Senior Consultant	6	0.03	0.02	0.59
Manager	4	0.00	0.00	0.00
Manager	5	0.06	0.03	0.47
Manager	6	0.00	0.00	0.00
Senior Manager	4	0.09	0.05	0.59
Senior Manager	5	0.07	0.05	0.71
Senior Manager	6	0.07	0.06	0.80
Associate Partner	10	0.13	0.08	0.59

Table 17

Forecasted headcount without recruiting activity

cycle	Associate	Consultant	Senior Consultant	Manager	Senior Manager	Associate Partner	Partner
0	10	8	6	4	2	1	1
1	4.67	3.84	2.78	1.88	0.95	1.00	1.00

2	4.13	3.64	2.42	1.70	0.90	1.00	0.90
3	2.90	3.40	2.43	1.47	0.82	0.94	0.90
4	1.41	3.53	2.24	1.56	0.67	0.92	0.84
5	0.75	2.93	2.16	1.52	0.65	0.87	0.75
6	0.58	2.47	2.19	1.47	0.50	0.82	0.58
7	0.28	2.18	2.17	1.49	0.50	0.81	0.50
8	0.24	2.05	2.08	1.38	0.50	0.70	0.42
9	0.12	1.95	1.99	1.43	0.48	0.70	0.33
10	0.12	1.76	1.88	1.38	0.43	0.57	0.43

Table 18

Headcount plan through linear programming

Cycle	Associate	Consultant	Senior Consultant	Manager	Senior Manager	Associate Partner	Partner
0	10	8	6	4	2	1	1
1	19.3	17.7	5.6	4.0	2.0	1.0	1.0
2	27.1	26.7	4.9	4.0	2.0	1.0	0.9
3	20.2	34.6	6.3	3.8	1.9	0.9	0.9
4	19.8	41.9	8.4	4.3	2.2	1.0	1.1
5	20.5	45.6	22.0	4.5	2.3	1.1	1.0
6	25.9	48.5	33.5	4.8	2.4	1.1	1.2
7	22.1	54.7	44.6	8.7	2.8	1.2	1.4
8	29.0	61.5	52.9	8.7	4.3	2.1	2.2
9	24.5	75.1	61.0	12.2	6.1	3.1	2.7
10	34.5	77.9	67.7	17.2	7.5	3.7	3.7

Table 19

Recruiting plan to maximize revenue growth from cycle 0 to cycle 10

Cycle	Associate	Consultant	Senior Consultant	Manager	Senior Manager	Associate Partner	Partner
1	10	10	0	0	0	0	0
2	10	10	0	0	0	0	0
3	1	10	0	0	0	0	0
4	10	10	0	0	1	0	0
5	10	10	10	0	0	0	0
6	10	10	10	0	1	0	0
7	10	10	10	0	0	0	0
8	10	10	10	0	2	1	1
9	10	10	10	0	2	1	1

10	10	10	10	4	2	1	1
Total	91	100	60	4	8	3	3

***Note.* Number in Associate to Partner column indicates required number of hiring**

Table 20

Revenue amount by job title and its growth rate from cycle0 to cycle10

	Associate	Consultant	Senior Consultant	Manager	Senior Manager	Associate Partner	Partner	Total
Cycle0	200	192	180	160	100	60	80	972
Cycle10	689.8	1870.1	2029.9	689.8	374.0	220.0	299.2	6172.7

Revenue Growth Rate (%)	535.05%

Table 21

Top 5 transitions that have largest variances in optimum solutions

			Transition Probability			Growth Rate		
Cycle	Job Title	Transition	estimate	lower	upper	Estimate	Lower Boundary	Upper Boundary
9	Associate	Stay	0.5	-0.1	1.1	535.1%	No Solution	645.4%
7	Associate	Stay	0.5	0.1	0.8	535.1%	No Solution	611.8%
9	Senior Consultant	Stay	0.9	0.9	1.0	535.1%	490.3	572.6%
8	Associate	Stay	0.9	0.6	1.1	535.1%	471.7	562.3%
9	Consultant	Stay	0.9	0.8	1.0	535.1%	501.5	557.8%

Table 22

Growth rate by increasing retention probabilities

			Total planned hiring						
#	Scenario	Growth %	A	C	SC	M	SM	AP	P
1	Default	535.05%	91	100	60	4	8	3	3
2	Associate's retention rate 20% increase	570.48%	100	100	64	5	8	3	3
3	Associate's retention rate 40% increase	605.94%	100	100	74	4	9	3	4
4	Consultant's retention rate 20% increase	546.44%	90	100	59	4	7	3	4
5	Consultant's retention rate 40% increase	558.99%	100	100	51	4	7	3	3
6	Senior Consultant's retention rate 20% increase	536.90%	89	100	60	4	8	3	3

7	Senior Consultant's retention rate 40% increase	538.44%	89	100	58	5	8	3	2

Note. A: Associate, C: Consultant, SC: Senior Consultant, M: Manager, SM: Senior Manager, AP: Associate Partner, P: Partner

Table 23

Estimated Growth and Recruiting Plan for the two organization strategies

Scenario	Growth (%)	Recruiting Plan						
		A	C	SC	M	SM	AP	P
Junior Leverage model	406.9%	71	64	35	3	10	4	4
Gray Hair model	639.2%	98	63	100	21	20	3	6

Note. A: Associate, C: Consultant, SC: Senior Consultant, M: Manager, SM: Senior Manager, AP: Associate Partner, P: Partner

Table 24

Ratio between layers – Junior Leverage model

Cycle	Junior	Middle	Senior	Junior-Middle Ratio	Junior-Senior Ratio	Middle-Senior Ratio
0	24.0	6.0	2.0	4.0	12.0	3.0
1	30.1	6.9	2.0	4.4	15.0	3.4
2	27.7	6.3	1.9	4.4	14.6	3.3
3	25.7	5.7	1.8	4.5	14.0	3.1
4	29.8	5.6	2.0	5.4	14.8	2.8
5	43.9	6.9	2.8	6.4	15.8	2.5
6	58.4	6.9	2.6	8.4	22.4	2.7
7	69.8	11.9	3.9	5.9	18.1	3.1
8	94.2	12.1	5.3	7.8	17.7	2.3
9	114.9	15.7	6.8	7.3	16.8	2.3
10	137.6	20.2	8.9	6.8	15.5	2.3

Note. Junior consists of Associate, Consultant and Senior Consultant. Middle consists of Manager and Senior Manager. Senior consists of Associate Partner and Partner.

Table 25

Ratio between layers – Gray Hair model

Cycle	Junior	Middle	Senior	Junior-Middle Ratio	Junior-Senior Ratio	Middle-Senior Ratio
0	24.0	6.0	2.0	4.0	12.0	3.0
1	50.6	12.7	2.3	4.0	22.0	5.5
2	74.9	18.6	3.5	4.0	21.2	5.3
3	93.6	23.6	3.7	4.0	25.0	6.3

4	99.9	26.7	5.2	3.7	19.3	5.1
5	106.2	29.2	5.4	3.6	19.7	5.4
6	120.9	28.9	6.4	4.2	18.9	4.5
7	132.6	34.1	7.3	3.9	18.2	4.7
8	144.8	35.0	6.4	4.1	22.7	5.5
9	152.0	39.4	7.8	3.9	19.5	5.1
10	173.1	45.3	10.1	3.8	17.2	4.5

Appendix 2: Chapter 4 Figures

Figure 9

Probability to promote to the next level – Junior titles

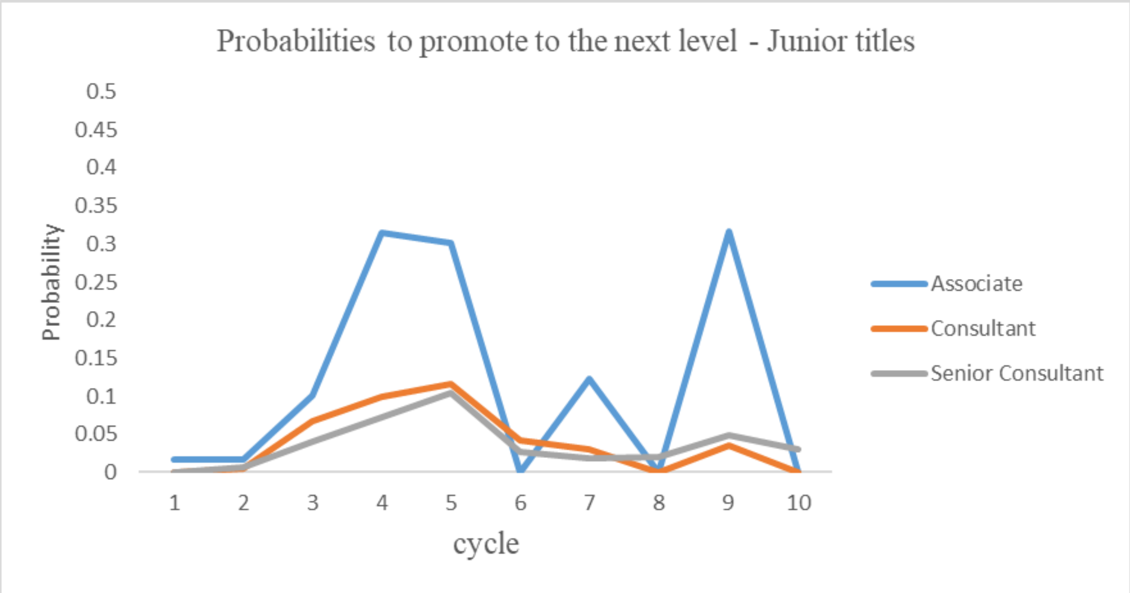


Figure 10

Probability to promote to the next level – Middle titles

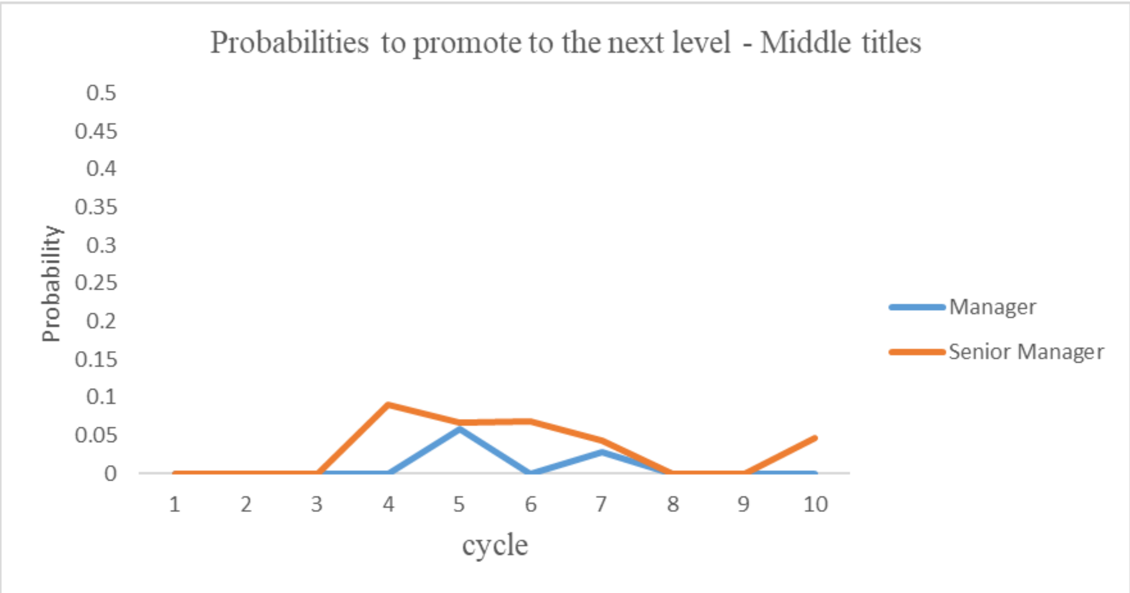


Figure 11

Probability to promote to the next level – Senior titles

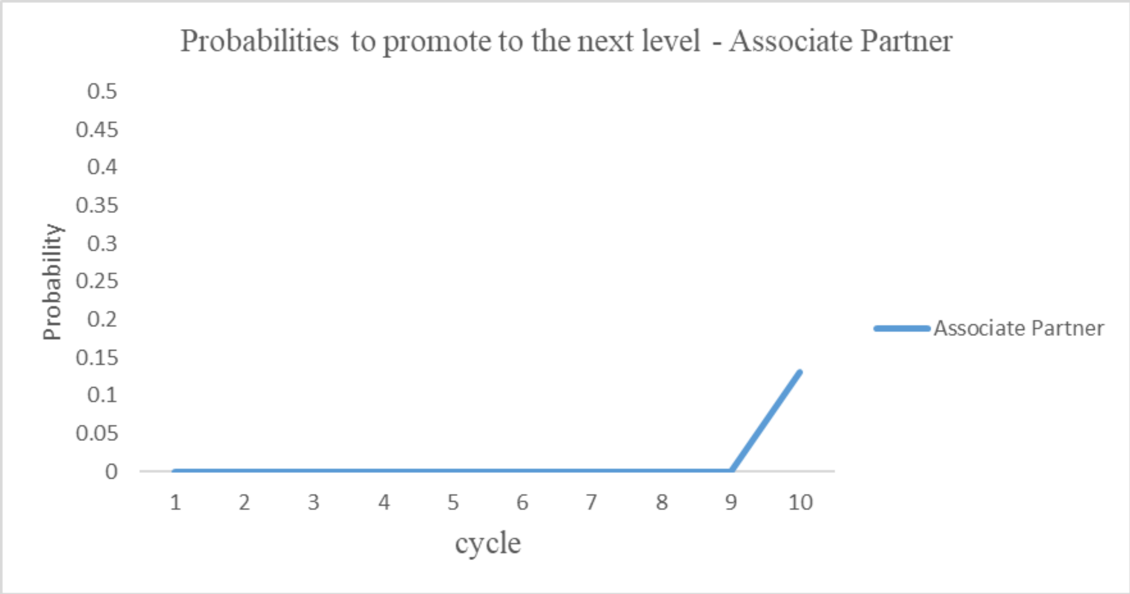


Figure 12

Probability to leave – Junior titles

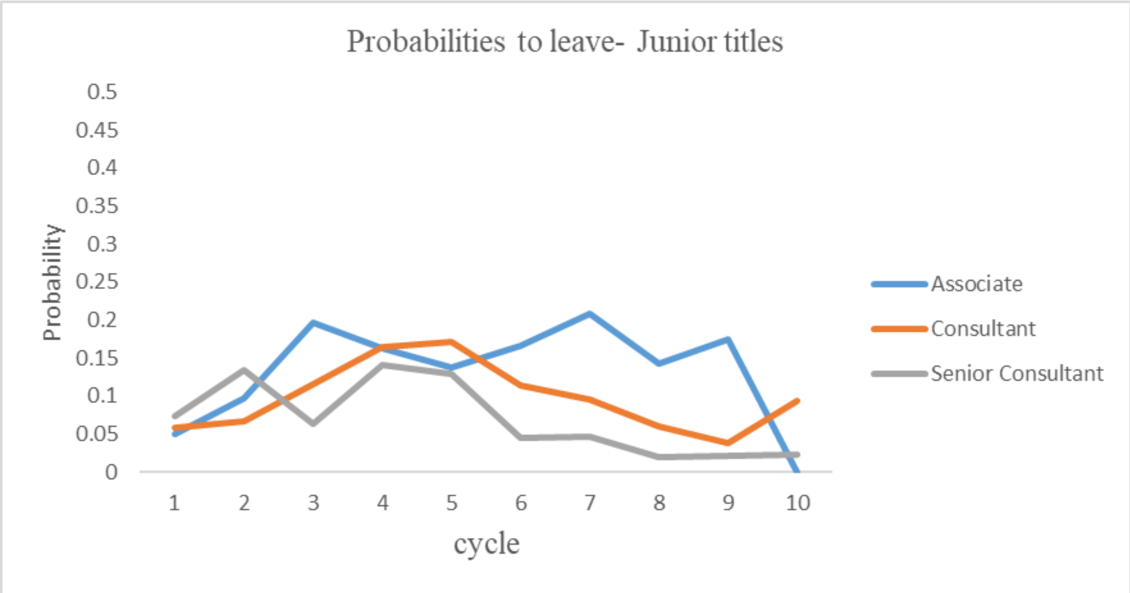


Figure 13

Probability to leave – Middle titles

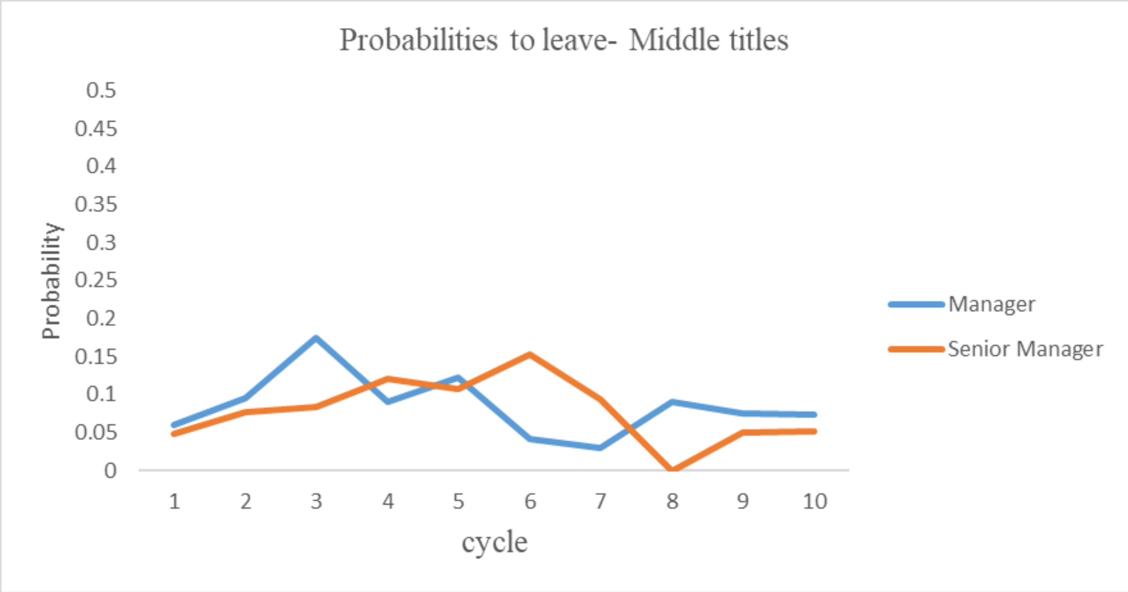


Figure 14

Probability to leave – Senior titles

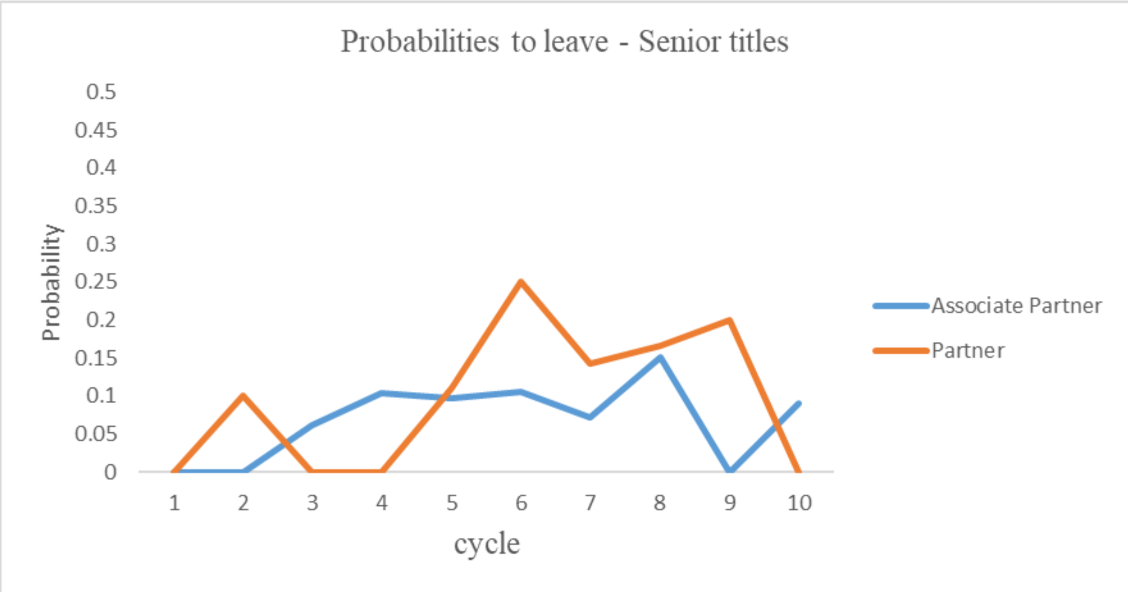


Figure 15

Evolution of organization structure without recruiting activity

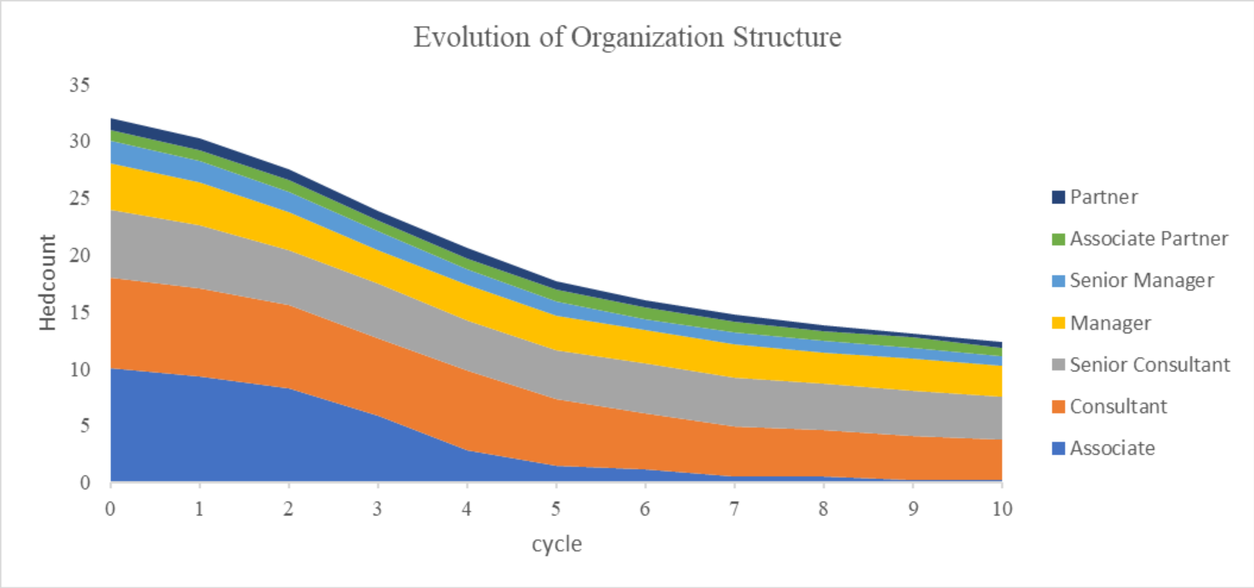


Figure 16

Evolution of organization structure linear programming

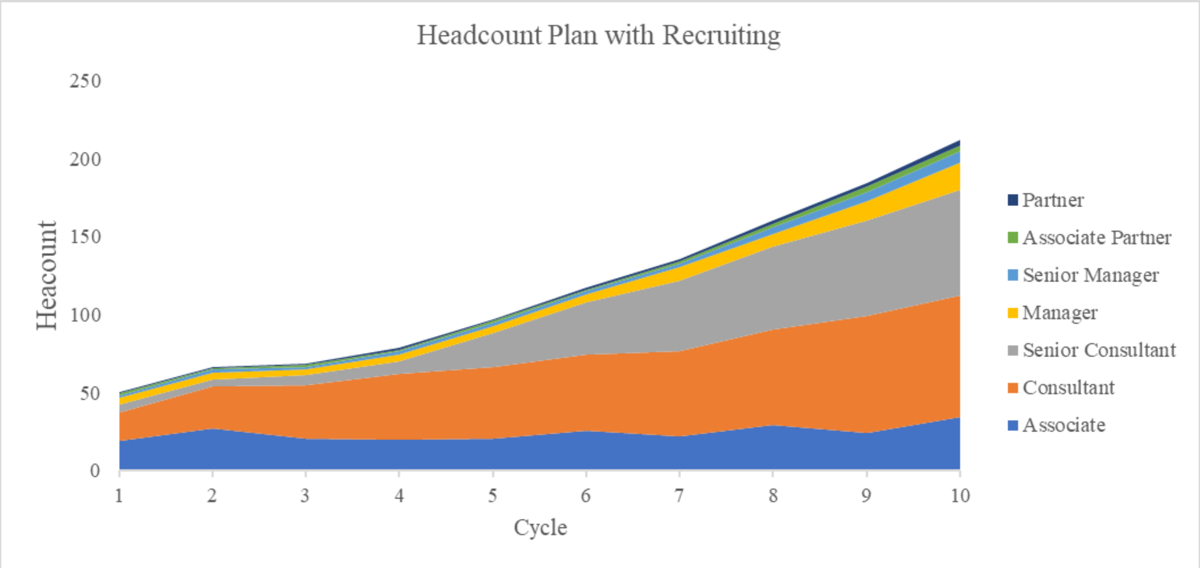


Figure 17

Evolution of organization structure – Junior Leverage model

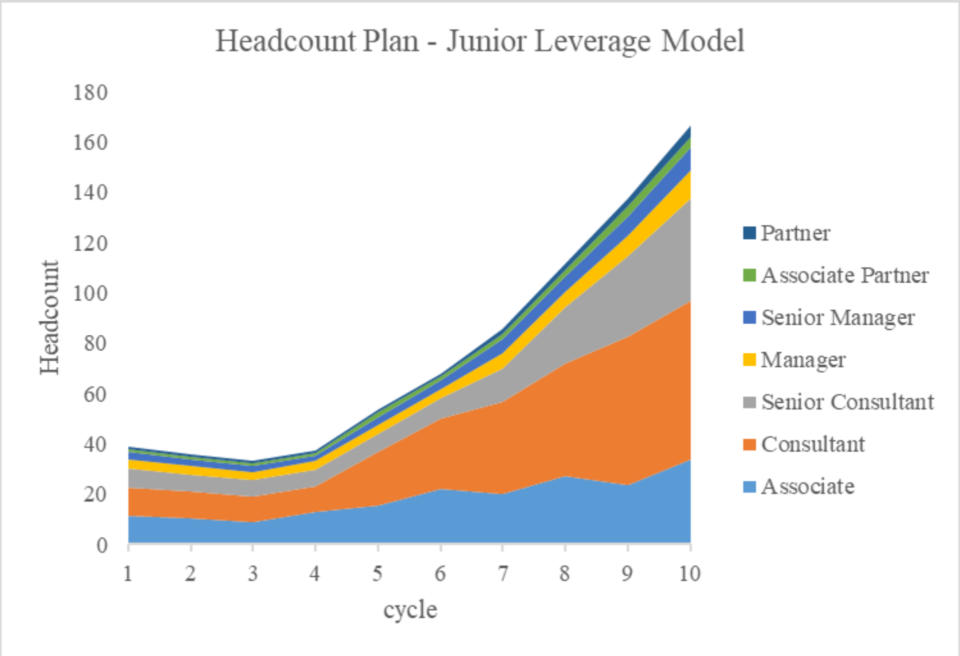
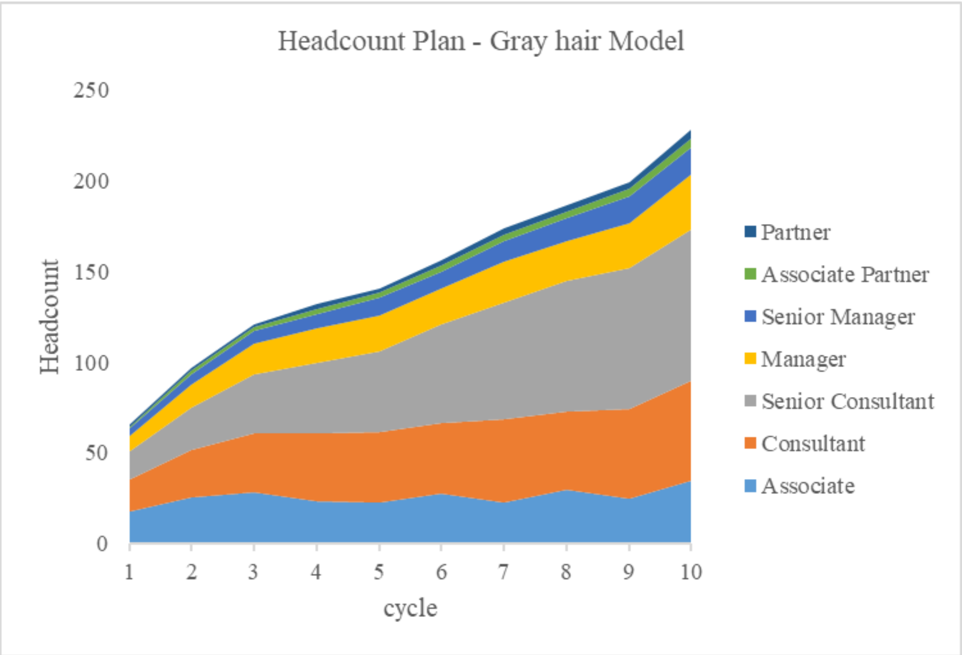


Figure 18

Evolution of organization structure – Gray hair model



Appendix 3: Code

The code written for this project is available in a GitHub repository:

https://github.com/tak-oda/DS785