THE LINKEDIN DELIGHT ELEMENT

LI CASE STUDY | JOBS

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CONTEXT –

The mission of LinkedIn is to create opportunity for every member of the global workforce. One way we realize this mission is connect members and employers. Many of our Talent Solutions products are built around mathematical models that try answer a simple question: is this opportunity of interest to this member at this time? Answering that question requires a multidisciplinary approach, drawing on tools from machine learning and data mining and utilizing insights from psychological and sociological research.

Our models are trained on labelled data sets. We employ professional recruiters to tag member-job pairs for us (good fit, not a good fit). For positive labels, we also use our members current positions as well as their job transitions.

A big challenge is that member preferences change over time. At certain points in their tenure, people are likely to **look for a new job**. People are sometimes willing to relocate to a new city, but at other times they want to stay in the same place. Many people are happy with their job, and will only move for a promotion. Other people may be dissatisfied and interested in doing the same job at a competing firm. We use long term and short term personalization methods to capture these **latent preferences**.

Introduction

A huge part of personalizing pathways to opportunities for LinkedIn users is by recognizing their strengths and helping them make the best use of it. The LinkedIn Economic Graph takes into account the present state of person and environment, and possibly uses hyperparameter training for matchmaking parameters (since you primarily need the final recommendation rather than presenting the full explanation as to why that recommendation) and reinforcement learning systems to derive future desirable state, thus being able to provide a suggestion!

But what if I told you - a LinkedIn user, that once I've presented an opportunity for you to exploit, I help you give yourself a personal edge when pitching your strengths?

The job market has a lot of tough competition. I used to run a raging part-time hustle just helping opportunity seekers personalize their pitches and be natural and confident about it. A huge part of landing a job on LinkedIn is communication. And the ones who've leveraged LinkedIn in a short time are the ones who took control and directly reached out to their opportunities.

There is a major skill-gap that seekers struggle to overcome when they attempt to do that. And hence a great selling point for us in other words. So this hypothesis is for a feature to help a seeker from current point A to recommended point B.

Involved Domain Knowledge

Every AI system I design starts with user research and psychology profiling for two major reasons –

1. To deduce, infer, and extract higher weightage features that may or may not be grasped by biases and omissions from past data.

2. To develop proper tests for the final algorithms used to track that each step in the algorithm is reasoned and needed for the accomplishment.

In this case, the user research needed would be information on –

1. The kind of opening messages get different types of decision-makers to open the message and read it.

2. The bias of interests based on open content publicly available and consented by LinkedIn users.

3. The extent of decision-making possible WITH RESPECT TO progress that the seeker may be searching for.

An interesting feature space for our models is the **Person-Environment Fit** (P-E fit). It captures the degree to which a person fits within their workplace. Tools from machine learning and data science applied to the **LinkedIn Economic Graph** can help us quantify certain aspects of P-E fit and be predictive of workplace success and happiness. In particular, Person-Job fit measure how well a person has the skills and experience necessary for a specific role. A particular challenge with matching members and jobs is that both member profiles and job advertisements are incomplete. In order to be successful, we must infer the missing information. For instance, we can utilize similar profiles and endorsements to learn **inferred skills** for each member. We can utilize **career trajectory** to infer likely next steps. We can use the characteristics of members who apply to a job to create a **virtual profile** for that position.

Involved Data and Navigation Structure

The goal is to not only be able to direct job seekers to the right decision makers (this may be paired with job recommendations and people from the company having an open message option), but to be able to help them deliver their strengths effectively.

Graph for pitch personalization where every node is mapped by –

1. Probable job seeker / decision maker ID – Primary Key
2. Environment variables – on profile
   a. Education institutions
   b. Workplaces
   c. Project work associations (derived)
   d. Interests
   e. Descriptions of all types
3. Environment variables – feed interaction
   a. Following
   b. Decision-making followers (must view/click on posts)
   c. Comment history [poster ID, engage-response frequency]
   d. Posted open content linguistic and field breakdown (derived)
4. Influence score (derived)
5. Success rate in terms of message responses
6. Node summary

Probable Algorithms in Brief

1. Derived variable – Project work associations

Extracting keywords and doing comparisons wouldn't be enough. Hence constructing a network of associations for related words of interest and then running it across 1st and 2nd connection project work content will become one option for an opening statement for seekers.

2. Derived variable – Open content linguistic and field breakdown

User research will show that many successful conversations happen when the manner of speech and thinking between the seeker and the decision-maker match. Linguistic components involve rhetoric, hyperbole, poetic, storytelling, and formal elements that posters employ. It gives an assessment of the kind of language decision-makers would be familiar with and be delighted by. There are ways to deduce such structures with a trustworthy probability score.

3. Derived variable – Influence score

This is an analysis of how much say someone may have on their network, and in their company, based on their title, their public on-feed engagement success, size of the company and other unverified factors that the data might reveal.

4. The final algorithm is a general one –

a. Based on recommended jobs, use a custom matchmaking algorithm on the influencer score to suggest decision-makers (part of them indirect for referrals and part of them direct for hiring managers). A game-based matchmaking algorithm would work well since it ensures that the referrals are at the same level or helpfully more advanced than the seeker which makes them approachable and capable of change in the right amount.

b. Run conversation psychology, professional stature, and interest overlap analysis and construct phrases and questions (**some of them can literally be what the system was itself not sure of!)** to generate talking points.

c. Present these sets of talking points in order of most pertinent (highest probability) and suggest manner of delivery by incorporating it into matching linguistic forms that the reader might possibly enjoy.

d. Record the success of response for the seeker and use A/B testing to get better constructions for the next iteration of the product.