Translate Theory into Model

Decipher Job Mobility

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Overview

Two Main Theory

We attribute job mobility to the following two theories:

Theory I: Categorization Theory & Prototype Logic

An employee with high typicality in relation to a target title will be more likely to obtain that title.

Theory II: Social Influence Logic

If two employees have previously shared a title, and one of the employees switched to a different title, then the other employee will be more likely to obtain that title.

Hypothesis

The integration of Theory I and Theory II explains the major variability in job mobility.

Our Objective

Objective

The main objective is to mathematize theory I & II and incrementally build an explainable model to validate our hypothesis.

Approach

Build a probabilistic model for the conditional distribution of the target job,

$$\mathbb{P}(\textit{next job title} = t' \mid \textit{context } \mathcal{F}) = G(\textit{context}) \tag{1}$$

$\mathcal{F}$ encodes the information available before knowing the next job title. We make no assumption here, the advanced probability theory enforces the existence of $G(\cdot)$ as a function of context. Therefore, all we need is to propose a parametric form for G.

Translate Theory I (Markovian Setting)

Theorem I – Markovian Typicality

Assume $\mathcal{F} = \{current\ citle\}$, then the next job only depends on the current title, i.e.,

$$\mathbb{P}(next\ job\ title = t' \mid \mathcal{F}) = G(current\ title) \tag{2}$$

Proposals for $G(\cdot)$

Suppose each title has a lower-dimensional representation $z_\cdot$, the likelihood of getting job title t' while being currently titled t can be modeled as:

- Weighted Inner Product: $G_1(t) = [\langle z_t,\, z_{t_1}\rangle_w, \cdots \langle z_t,\, z_{t_m}\rangle_w]$;
- Generalized Linear Model: $G_2(t) = \mathtt{GLM}_w(z_t)$.

The parameter w adds flexibility. For instance, here, we make the assumption that the employee is fully representable by his/her title. If the employee has additional features, we need a parametric transformation to map it to the title space.

Translate Theory I (Non-Markovian Setting)

Theorem II – Past Title Dependent Typicality

Assume $\mathcal{F} = \{\textit{past job titles}\}$, then the next job only depends on the title history, i.e.,

$$\mathbb{P}(\textit{next job title} = t' \mid \mathcal{F}) = G(\textit{past job titles}) \tag{3}$$

Proposals for $G(\cdot)$

Denote the period i title as t_i and the representation (of employee) at period i by $h(i)$, we propose a path-dependent dynamic embedder,

$$h(i) = f(t_i) + h(i-1) \tag{4}$$

where $f(\cdot)$ encodes title t_i in lower-dimensional space. By self-substitution (and proper boundary condition), Eq (4) is equivalent to $h(i) = \sum_{j=1}^{i} f(t_j)$, the sum of all past title embeddings. Applying $G_1(\cdot)$ or $G_2(\cdot)$ on $h(i)$, we obtain the likelihood of getting t' as,

$$G_3(t) = G_x\big(h(i)\big), \; x = 1 \textit{ or } 2 \tag{5}$$

where $h(\cdot)$ follows Eq (4).

Translate Theory I (Non-Markovian Setting)

Theorem III – Past Experience Dependent Typicality

Assume $\mathcal{F} = \{\textit{past title and tenure}\}$, then the next job depends on the past title-tenure pairs, i.e.,

$$\mathbb{P}(\textit{next job title} = t' \mid \mathcal{F}) = G\big((\textit{title}_1, \textit{tenure}_1), \ldots, (\textit{title}_i, \textit{tenure}_i)\big) \tag{6}$$

Proposals for $G(\cdot)$

Keeping everything the same, we extend Eq (7) to a time-aware path-dependent dynamic embedder,

$$h(i) = f(t_i, \Delta_i) + \textit{df}(i-1, i) \cdot h(i-1) \tag{7}$$

where $f(\cdot)$ accounts for the tenure of each job, and discount factor $\textit{df}(\cdot)$ captures time decay of the past experience and satisfies $\textit{df}(i-k, i) = \prod_{j=i-k}^{i-1} \textit{df}(j, j+1)$. Self-substituting renders

$$h(i) = \sum \textit{df}(j, i) f(t_i, \Delta_i) \tag{8}$$

Essentially, each past title is re-weighted depending on its tenure and recency.

<u>Remark:</u> for instance, $\textit{df}(i-k, i) = e^{-r\sum_{j=i-k}^{i} \Delta_j}$ satisfies the above criterion.

Translate Theory II

Theorem IV – Social Influence

Assume $\mathcal{F} = \{\textit{all individuals' past titles}\}$, then the next job depends on the employee social network evolution, i.e.,

$$\mathbb{P}(\textit{next job title} = t' \mid \mathcal{F}) = G\big(\textit{social network evolution}\big) \tag{9}$$

Proposal for $G(\cdot)$

We break it down into 3 steps:

- Build a network to identify potential jobs through a referenced employee and the shared job title.
- For each individual, generate a lower-dimensional representation based on the network built above.
- Apply G_1 or G_2 to calculate the likelihood of getting the next job title.

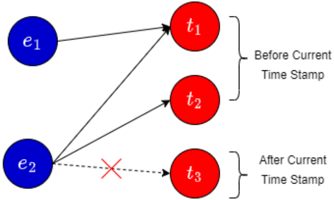
In the next, we detail the first 2 steps.

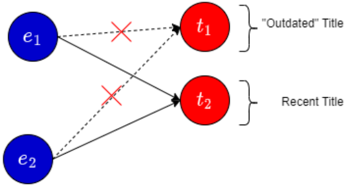
Translate Theory II – Build A Social Influence Network

Impose Constraints

When building the network at period i, we impose the following constraints:

- Non-Anticipativity: an employee cannot refer to the titles of another employee that occur in the future (left-hand-side).
- Limited-Memory: an employee shall not refer to the "outdated" titles of another employee (right-hand-side). That is to summarize social networks at a certain frequency (every k-year).





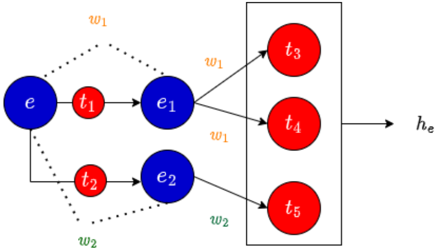
Translate Theory II – Representation Learning

Employee Weighted Node Semantics

Given a focal employee e, we denote his neighbor reference employees as $\mathcal{N}_{\text{emp}}(e)$ and neighbor potential titles (led by $\mathcal{N}(e)$) as $\mathcal{N}_{\texttt{title}}(e)$. The embedding of individual e is then

$$h = \sigma\left(\sum_{t \in \mathcal{N}_{\texttt{title}}(e)} w(e, e') \cdot z_t \right) \tag{10}$$

where e' is associated with title t, and $w(e, e')$ measures the similarity between focal employee e and reference employee e'.



Digression: Dynamic Title Embedding

Dynamic Title Embedding

To account for the evolving relationships among job titles, we can fine-tune the embedding with a title network. Fix a moderate sampling frequency, we periodically build a title graph $\mathcal{G}^{\texttt{title}}$, where the nodes are titles, and the edge weights are the number of transitions between connecting titles. Standard graph representation model can generate a modified embedding $\hat{z}_t$.

Concerns

- If we choose to use cosine similarity, the title embedding matrix changes over time, which makes learning unstable. That is, $z_e \cdot Z^T$ with a moving target Z^T.
- The edge weights of the title network can change dramatically, which makes title embedding very unstable.

Dynamic Embedding Smoothing

In objective function, using KL(Kullback–Leibler) Divergence, we penalize the modified embedding $\hat{z}_t$ deviates too far from the original embedding z_t.

Translate Integrated Theory

Theorem V – Prototype Logic & Social Influence

Assume $\mathcal{F} = \{\textit{all individuals' past titles including him/herself}\}$, then the next job depends on the employee's social network evolution, i.e.,

$$\mathbb{P}(\textit{next job title} = t' \mid \mathcal{F}) = G\big(\textit{social network evolution and self-evolution}\big) \tag{11}$$

Proposal for $G(\cdot)$

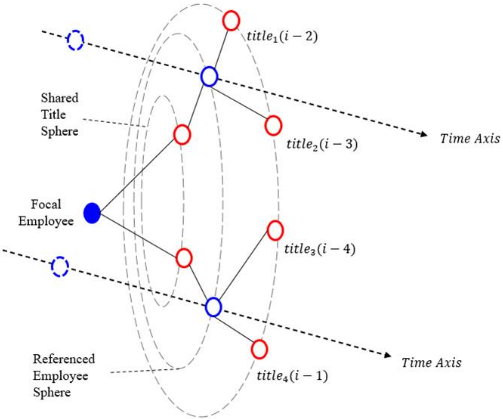
Given an individual e, at any period i,

- **(Optional*)** Generate dynamic title embedding z_t via title network;
- Generate time-aware employee embedding z_e via Eq (8) using dynamic title embedding z_t;
- Fuse social influence in generating final employee embedding $\hat{z}_e$ via Eq (10).
- Use GLM (G_2) to produce next title distribution;

Translate Integrated Theory – Measurable Tree

Measurable Tree

We propose a new structure measurable tree, which characterizes how a SINGLE agent interacts with a complicated environment, dynamic and has feedbacks). The proposed $G(\cdot)$ relies on this tree.



Engineering Considerations – Make Math AI Look

Add Buzz Word

- $G_1(\cdot)$ is called projection + cosine similarity;
- $G_2(\cdot)$ is called SoftMax;
- Eq (4) is the transition equation for RNN;
- Social influence based representation is called Meta-Path + HAN;

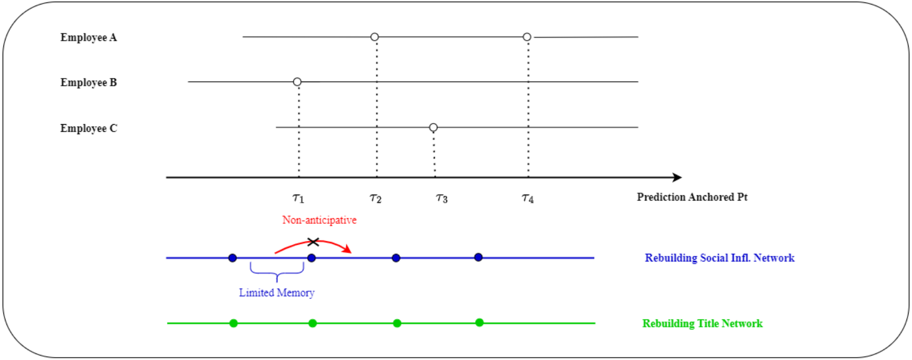
Our Additions So Far

- Eq (7) is inspired by Optimal Control and Financial Mathematics;
- Graphical Constraints is inspired by Branch and Bounding technique from Optimization;
- Employee Weighted Node Semantics generalized the original HAN node semantics aggregation;
- Using KL for stabilization is inspired by Reinforcement Learning for Language Model;

Engineering Considerations – Model Scheduler

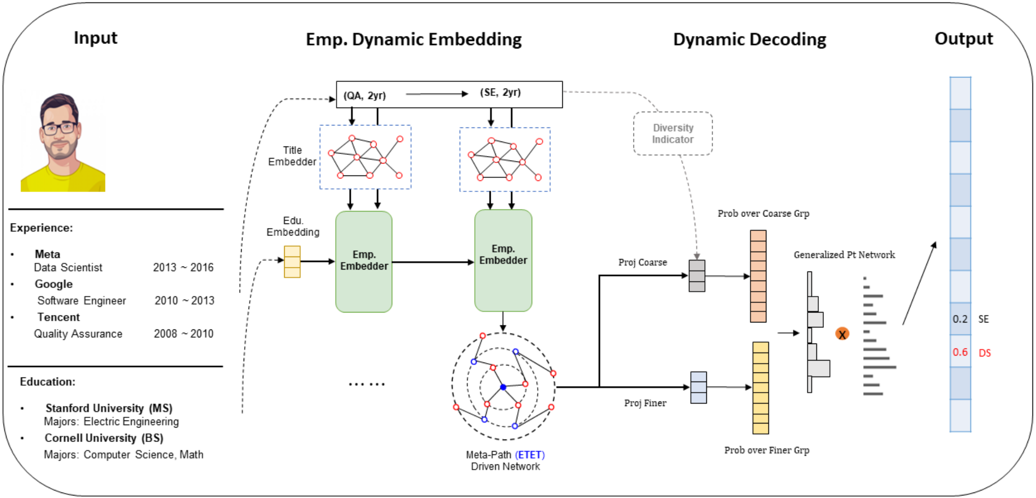
Tractable Scheduling

The prediction anchored points differ from employee to employee, while social infl. network and title network are rebuilt at a fixed frequency.



Model Scheduler

Engineering Considerations – Workflow



Engineering Considerations – Additional Tricks

Attention via Generalized Pointer Network

To derive the distribution over all titles, we leverage the coarse title grouping. Namely,

- Project employee embedding to a coarse embedding z_c and finer embedding z_f.
- Generate probability distribution over the finer titles using $G_2(\cdot)$, i.e., $\texttt{dist}(\cdot; z_f)$.
- Generate probability distribution over coarse title groups using $G_1(\cdot)$, based on z_c and personalized information, such as diversity score. That is, $\texttt{dist}(\cdot; z_c, \texttt{div})$;
- Compile $\texttt{dist}(\cdot; z_f)$ and $\texttt{dist}(\cdot; z_c, \texttt{div})$ into the ultimate distribution over title universe.

Remarks:

- Why use G_1 for coarse? Unlike evolving titles, we fix a static embedding for each title group. Therefore, we can use them as benchmarks to assess the likelihood of falling into each group.
- What's the intuition behind plugging diversity score into $\texttt{dist}(\cdot; Z_c, \texttt{div})$? Diversity controls the shape of the distribution. When diversity is high, the distribution becomes more even, when diversity is low, the distribution becomes more uni-modular.

Conclusion

Summary

In this paper, we build up a theory-driven AI framework to decipher job mobility. In particular,

- we capture prototype logic via a tenure-recency adjusted dynamic model.
- we capture social influence logic via a meta-path driven network with novel node semantic aggregation scheme.
- we capture evolving relationships among titles via a title graph and propose dynamic embedding smoothing to stabilize model learning.
- we integrate both theories via a novel Seq2Graph architecture.
- we capture personalized info, e.g., diversity, via entropy to control the likelihood in each title group (coarse title);
- we apply attention via a generalized pointer network to incorporate title group distribution in generating ultimate distribution over title universe.

The End