Extracting Job Title Hierarchy from Career Trajectories: A Bayesian Perspective

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Abstract

A job title usually implies the responsibility and the rank of a job position. While traditional job title analysis has been focused on studying the responsibilities of job titles, this paper attempts to reveal the rank of job titles. Specifically, we propose to extract job title hierarchy from employees’ career trajectories. Along this line, we first quantify the Difficulty of Promotion (DOP) from one job title to another by a monotonic transformation of the length of tenure based on the assumption that a longer tenure usually implies a greater difficulty to be promoted. Then, the difference of two job title ranks is defined as a mapping of the DOP observed from job transitions. A Gaussian Bayesian Network (GBN) is adopted to model the joint distribution of the job title ranks and the DOPs in a career trajectory. Furthermore, a stochastic algorithm is developed for inferring the posterior job title rank by a given collection of DOPs in the GBN. Finally, experiments on more than 20 million job trajectories show that the job title hierarchy can be extracted precisely by the proposed method.

1 Introduction

A job title is a short term in a few words which describes a job position held by an employee. It implies both the responsibility and the rank of the corresponding job position within an organization [Harper, 2015]. For instance, ‘senior software engineer’ is a job title for a position with an engineering function in the software domain, and it has a higher rank than that of ‘software engineer’. Generally, the underlying rank of a job title denotes the credentials necessary to qualify for the corresponding job position, and a higher ranked job title is usually more difficult to get than a lower ranked one. In addition, the universe set of job titles in an organization naturally form a hierarchical directed graph, where nodes denote job titles and edges denote promotions, and the rank of a node denotes its level in the hierarchy. Figure 1a shows an example graph, where the alphabets represent job titles.

There have been thorough researches on modeling job titles with respect to the responsibilities [Bekkerman and Gavish, 2011; Javed et al., 2016]. However, limited research attention has been paid to the hierarchy of job titles, whereas a properly defined hierarchy is desired in many applications, including career success evaluation [Heslin, 2005], career planning [Liu et al., 2016], and job recommendation [Tang et al., 2016; Li et al., 2016]. For instance, during an interview, it is needed to assess the performance of candidates according to their working experience. Once the job title hierarchies of organizations that they worked for are presented, their performance can be evaluated by comparing their held job titles in resumes with the corresponding rank in the hierarchies to identify key indicators (e.g., early or late promotions).

In this paper, we attempt to explore a justifiable definition of job title hierarchy and hence design a robust method to establish the hierarchy. The core issue in the problem is determining the ranks of the job titles, but ranks are difficult to be detected from the name of job titles due to the ambiguity of phrases. For example, there are divergent titles for identical job positions or polysemous for distinctive job positions.

Fortunately, the universalized Online Professional Networks (OPNs) make a huge number of resumes publicly available. It provides a large collection of career trajectories, and each trajectory contains several job transitions, where a transition comprises two job titles and the tenure of the first job position till transiting to the second one. To this end, instead of analyzing the titles directly, we propose to infer the ranks of job titles by distilling their correlations with career trajectories. Particularly, from the perspective of career trajectories, a properly defined rank should have two essential properties. First, the relative ranks are consistent with the order of job titles in career trajectories, i.e., lower ranked job titles are usually followed by higher ranked ones. Second, the difference of two ranks should reflect the difficulty of being promoted from the former title to the latter one in a career.

However, finding the job title ranks possessing these two properties is nontrivial due to the wide variability of career moves, which commonly exist in workplaces, such as early promotion, lateral or even downward moves [Hess et al., 2012]. This brings three challenges in revealing the ranks. First, it is hard to quantify the difficulty of being promoted to a job title, because the difficulty is an abstract concept that depends heavily on subjective cognition. Second, finding a common rank adaptive to individual diversity is difficult, because the difficulty of being promoted between identical job title pairs is different from person to person. Figure 1 illust-
2 Job Title Hierarchy Model

In this section, we elaborate the insights observed from career trajectories, and then introduce the job title hierarchy model.

2.1 Measuring Difficulty of Promotion

The tenure of a job position is the time interval from the beginning timestamp of the position till transiting into a latter one in a career trajectory. A career trajectory contains one or more job transitions, where a transition comprises two job titles and the tenure of the former job position. We use $t_{ij}$ to denote the LOT of a job position with job title $i$ until transiting to a job position with job title $j$. In general, a longer $t_{ij}$ usually implies a greater difficulty to get promoted from $i$ to $j$. Thus the LOT provides an objective way to quantify the DOP between a pair of job titles.

However, the LOT of a given job title pair is hard to be described by a fixed number due to the wide variability of career performance. For instance, in a company, one employee may spend much shorter time than another to get promoted due to a better performance. The LOT usually has a different value in different career trajectories for an identical job title pair. Thus we treat $t_{ij}$ as a random variable and describe it by its probability distribution to capture the underlying true value as well as its variability.

We have observed that, when measured by the number of months, the LOT follows a positively-skewed unimodal distribution. It means that most of the employees work on a job position for a short time period (e.g., around three years), and some of them work for an even shorter period (e.g., five months), while a minority of them keep a title for a longer period (e.g., ten years). Figure 2 shows the distribution of the LOT from job title ‘software engineer’ to ‘senior software engineer’ in our data sample. The LOT is concentrated in the interval from 10 to 30 months, with a less emphasis on five to ten months, while a long tail continues even after 100 months.

There are several well-known distributions that may fit the LOTs well, including Lognormal, Gamma, and Weibull [Wang et al., 2013] distributions. Among these alternatives, we choose the Lognormal distribution for two reasons. First, it has optimal result in the goodness-of-fit test on the LOT data (see Section 4.2 for details). Second, it motivates an interpretable and computationally tractable job title hierarchy extraction model. In fact, because $\log(t_{ij})$ follows a Gaussian distribution, the joint distribution of DOPs and job title ranks can be modeled by a GBN, in which the posterior distribution of ranks in the GBN is derived. Based on this, a computationally efficient algorithm is designed to detect the job title hierarchies.

The precision of the proposed method is evaluated on a dataset with 20 million job trajectories that are collected from a large OPN. The experimental results show that the proposed model could extract the job title hierarchy precisely comparing to the state-of-the-art benchmarks.
The job title hierarchy detection problem is revealing appropriate ranks \( r \) that satisfy the above requirements. To satisfy the first requirement, we assume that for a set of job titles, \( r \) has a factorizing Gaussian prior distribution, i.e.,

\[
p(r) = \prod_{i=1}^{m} \mathcal{N}(r_i | \mu_i, \sigma_i^2),
\]

where \( \mu_i \) denotes the expected rank of job title \( i \), and \( \sigma_i^2 \) represents the variance of the rank. The priors could be interpreted as that the rank of a job title has an underlying true value, but it varies due to the wide variability of the promotion process. The value of \( \sigma_i^2 \) represents the confidence of our estimation, which will be described in Section 3.

For a specific employee, the actual difficulty of pursuing a job position usually depends on several personal-dependent factors, such as the work performance or the educational background. This makes the difficulty for an individual deviating from the collective DOP. Thus we use a Gaussian noise \( a = \mathcal{N}(0, \beta^2) \) to introduce this variance into the model. Specifically, \( h_i = (r_i + a) \) is the personalized rank of job title \( i \) for an individual.

\[
p(h_i | r_i) = \mathcal{N}(h_i | r_i, \beta^2).
\]

To satisfy the second requirement, the expectation of collective DOP (i.e., \( \mu_{ij} \)) is set to be as the difference of two personalized ranks, i.e.,

\[
p(d_{ij} | h_i, h_j) = \mathcal{N}(d_{ij} | h_i - h_j, \sigma_{ij}^2),
\]

where \( d_{ij} = g(t_{ij}) \) is the collective DOP from job title \( i \) to \( j \). We refer \((h_i - h_j)\) as the individual DOP because it reflects the difficulty of being promoted of an individual.

In summary, the model is a GBN [Kschischang et al., 2001] specified by the conditional distributions in Equations 3, 4 and 5. An example of the model applied on a career trajectory is shown in Figure 3, where there are three job titles \( i, j \) and \( k \) in a queue in the career trajectory.

For clarity, we use symbols \( h := \{h_i | i \in V\} \) and \( d := \{d_{ij} | (i, j) \in E\} \) to represent the personal ranks and collective DOPs, correspondingly. The joint distribution of these variables in a career trajectory is denoted by \( p(r, h, d) \). Without loss of generality, we arrange the random variables in a career trajectory by their subscripts in a natural order such that \((r, h, d) = (r_1, \ldots, r_m, h_1, \ldots, h_m, d_{12}, \ldots, d_{m-1,m})\).

The joint distribution of \( r, h, \) and \( d \) can be derived by combining Equations 3, 4 and 5 according to Theorem 1. Please refer to Section 2.3 in [Bishop, 2007] and Section 7.2 in [Koller and Friedman, 2009] for proof of the theorem.

**Theorem 1. Conditional and joint distribution of linear Gaussian model.** Let random variable \( y \) be a linear Gaussian of its parents \( x \), i.e., \( p(y | x) = \mathcal{N}(y | \theta^T x, \sigma^2) \). Assume that \( x = (x_1, \ldots, x_k) \) are jointly Gaussian with distribution \( \mathcal{N}(\mu, \Sigma) \). Then the distribution of \( y \) is a Gaussian distribution \( p(y) = \mathcal{N}(y | \mu_y, \sigma_y^2) \), where:

\[
\mu_y = \theta^T \mu \quad \text{and} \quad \sigma_y^2 = \sigma_x^2 + \theta^T \Sigma \theta.
\]

The joint distribution \( p(x, y) \) is a normal distribution where

\[
\text{Cov}[x_i; y] = \sum_{j=1}^{k} \theta_j \Sigma_{i,j}.
\]
According to Theorem 1, the joint distribution is a multivariate Gaussian distribution and has the form of
\[ p(r, h, d) = \mathcal{N}(r, h, d | \mu_J, \Sigma_J), \]
where the mean vector and the covariance matrix are
\[ \mu_J = \begin{bmatrix} \mu^r \\ \mu^h \\ \mu^d \end{bmatrix} \quad \text{and} \quad \Sigma_J = \begin{bmatrix} \Sigma^{rr} & \Sigma^{rh} & \Sigma^{rd} \\ \Sigma^{hr} & \Sigma^{hh} & \Sigma^{hd} \\ \Sigma^{dr} & \Sigma^{dh} & \Sigma^{dd} \end{bmatrix}. \]
The components of the mean vector are \( \mu^r = \mu^h = [\mu_1, \ldots, \mu_m]^T \) and \( \mu^d = [(\mu_2 - \mu_1), \ldots, (\mu_m - \mu_{m-1})]^T \), where \( \mu_i \) is defined in Equation 3. The components of the variance matrix are \( \Sigma^{rr} = \Sigma^{hh} = \Sigma^{tt} = \text{diag}(\sigma_1^2, \ldots, \sigma_y^2) \), \( \Sigma^{sh} = \text{diag}(\sigma_1^2 + \beta_1^2, \ldots, \sigma_m^2 + \beta_2^2) \), and \( \Sigma^{dd} = \text{diag}(\sigma_1^2 + \sigma_2^2 + 2\beta_1^2 + \sigma_2^2 + 2\beta_2^2, \ldots, \sigma_{m-1}^2 + \sigma_m^2 + 2\beta_1^2 + \sigma_m^2 + 2\beta_2^2, \sigma_{m-1}^2 + \sigma_m^2 + 2\beta_1^2 + \sigma_m^2 + 2\beta_2^2) \). (Equation 8) for proof of the theorem.

According to Theorem 2, we have
\[ p(r, h, d) = \mathcal{N}(r, h, d | \mu_J, \Sigma_J), \]
where the mean vector and covariance matrix is calculated by substituting Equations 12, 13 and 14 into Equations 9 and 10.

3 Hierarchy Extraction

In this section, we first present the analytic form of the posterior distribution of \( r \) given corresponding DOPs in a career trajectory in the proposed model, and then present a stochastic job title rank extraction algorithm based on the posteriors.

3.1 Posterior Distribution Inference

We use \( p(r, h | d) \) to represent the posterior probability of \( r \) and \( h \) given \( d \) in a career trajectory. Based on the joint distribution in Equation 8, the posterior distribution can be derived by Theorem 2. Please refer to [Castillo and Kjærulff, 2003] for proof of the theorem.

Theorem 2. Conditionals of a Gaussian distribution. Let \( x \) and \( y \) have a joint multivariate Gaussian distribution with mean vector and variance matrix given by
\[ \mu = \begin{bmatrix} \mu^x \\ \mu^y \end{bmatrix} \quad \text{and} \quad \Sigma = \begin{bmatrix} \Sigma^{xx} & \Sigma^{xy} \\ \Sigma^{yx} & \Sigma^{yy} \end{bmatrix}, \]
where \( \mu^x \) and \( \Sigma^{xx} \) are the mean vector and covariance matrix of \( x \), \( \mu^y \) and \( \Sigma^{yy} \) are the mean vector and covariance matrix of \( y \), and \( \Sigma^{xy} = (\Sigma^{yy})^T \) is the covariance of \( x \) and \( y \). Then the conditional probability of \( x \) given \( y \) is a multivariate Gaussian with mean vector \( \mu_{x|y} = \) and covariance matrix \( \Sigma_{x|y} = \) that are given by
\[ \mu_{x|y} = \mu^x + \Sigma^{xy}(\Sigma^{yy})^{-1}(c - \mu^y), \]
\[ \Sigma_{x|y} = \Sigma^{xx} - \Sigma^{xy}(\Sigma^{yy})^{-1}\Sigma^{yx}. \]

According to Theorem 2, we have
\[ p(r, h | d) = \mathcal{N}(r, h | \mu_J, \Sigma_J), \]
where the mean vector and covariance matrix is calculated by substituting Equations 12, 13 and 14 into Equations 9 and 10.

Equation 10 shows that the posterior variance of \( r \) decreases when the number of observations on the job title increases. Thus the variance is the confidence of our estimation of \( r \), and a smaller variance indicates a higher confidence.

3.2 Hierarchy Extraction Algorithm

Based on the derived posterior distribution, we propose an algorithm to extract the hierarchy from job trajectories, as shown in Algorithm 1. Specifically, we use \( T = \{(i, j, t_{ij}) | i, j \in V, (i, j) \in E\} \) to denote all of the job transitions observed within an organization. The algorithm first calculates the variance of DOP (i.e., \( \sigma_d^2 \)) for each \( (i, j) \in E \). It then iteratively updates the job title ranks by a stochastic posterior updating mechanism. In each iteration, the priors of ranks are set by an adjacent prior assignment strategy, and the posteriors are then calculated according to Equations 9 and 10.

<table>
<thead>
<tr>
<th>Algorithm 1: Stochastic job title hierarchy extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input:</strong> ( T, E, R = \emptyset, \beta^2, \mu_0, \sigma_0^2 )</td>
</tr>
<tr>
<td><strong>Output:</strong> ( R )</td>
</tr>
<tr>
<td>1 for ( (i, j) \in E ) do</td>
</tr>
<tr>
<td>2 ( \sigma_i^2 \leftarrow \text{variance}[g(t_{ij})] )</td>
</tr>
<tr>
<td>3 for ( (i, j, t_{ij}) \in T ) do</td>
</tr>
<tr>
<td>4 if ( i \notin R ) and ( j \notin R ) then</td>
</tr>
<tr>
<td>5 ( \mu_j \leftarrow \mu_i; \sigma_j^2 \leftarrow \sigma_0^2 )</td>
</tr>
<tr>
<td>6 else if ( i \notin R ) and ( j \in R ) then</td>
</tr>
<tr>
<td>7 ( \mu_i \leftarrow \mu_j; \sigma_i^2 \leftarrow \sigma_0^2 )</td>
</tr>
<tr>
<td>8 else if ( i \in R ) and ( j \notin R ) then</td>
</tr>
<tr>
<td>9 ( \mu_i \leftarrow \mu_0; \mu_j \leftarrow \mu_0; \sigma_i^2 \leftarrow \sigma_0^2; \sigma_j^2 \leftarrow \sigma_0^2 )</td>
</tr>
<tr>
<td>10 ( \mu_i, \mu_j \leftarrow \mu_{id} = g(t_{ij}) )</td>
</tr>
<tr>
<td>11 ( \sigma_i^2, \sigma_j^2 \leftarrow \text{stochastic}[g(t_{ij})] )</td>
</tr>
<tr>
<td>12 ( R \leftarrow R \cup {i, j, \mu_i, \mu_j, \sigma_i^2, \sigma_j^2} )</td>
</tr>
</tbody>
</table>

The stochastic posterior updating is an incremental strategy, which computes the posterior ranks for job titles in one job transition at a time. It has three advantages comparing to batched methods. First, it is conflict tolerant, because an unusual job transition only causes a small update of posterior and the impact is overwhelmed by principal transitions. Second, the ranks will be updated when new job transitions are available, which makes the algorithm adaptive when the organizational structure is adjusted. Third, it avoids calculating matrix inverse of Equations 9 and 10. In specific, \( y \) is a scalar in this strategy such that \( (\Sigma^{yy})^{-1} \) is implemented by \( \frac{1}{\sigma_y^2} \).

The adjacent prior assignment strategy is that when a job title \( i \) appears the first time, \( \mu_i \) is assigned by the value of \( \mu_j \) in current job transition. When both \( i \) and \( j \) are first appearing, the priors are set to as default values (i.e., \( \mu_0, \sigma_0^2 \)). This strategy is designed to rank a title when it is from an employee hired from outside (e.g., \( j \) in Figure 1a), since a title usually has a close rank with its adjacency title in job transitions.

4 Experiments

4.1 Dataset

We have collected 20,243,120 digital resumes from a large OPN until October 2017. In each resume, there is a career trajectory that contains a list of job records, and each record
consists of a job title, and a start and an end timestamp of the corresponding job position. After data cleaning, 10.2 million job transitions with complete information are extracted. Precisely, a job transition is a tuple \((o, i, j, t_{ij})\), where \(o, i, j\) and \(t_{ij}\) are the organization, the first job title, the second job title and the number of months (i.e., LOT), respectively. The hierarchies are extracted from 3.3 million job transitions among about 500,000 job titles, which are identified from top 10,000 organizations with the largest number of job transitions.

### 4.2 Normality Test of DOP

We elaborate the observation that the DOP (i.e., \(g(t_{ij})\)) can be well fitted by the Gaussian distribution, where \(g(x)\) is one of the transitions in \(\log(x)\), \(\sqrt{x}\), \(\sqrt[3]{x}\) and \(\sqrt[4]{x}\). Figure 4 shows an example of \(g(t_{ij})\) and the fitted Gaussian distribution, where the data are the same as those in Figure 2. Specifically, the density of \(g(t_{ij})\) is smoothed by the kernel density estimation method with the Gaussian kernel for clarity, and the Gaussian distribution is fitted by the maximum likelihood estimation method. It shows that the fitted Gaussian density is a close approximation to the original density.

![Figure 4](image-url)  
**Figure 4**: An example \(g(t_{ij})\) and the fitted Normal distribution.

To provide quantification evidence of the approximation, we test the distribution of the DOP by Shapiro-Wilk (SW), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) hypothesis tests [Razali and Wah, 2011]. These tests are designed to evaluate the goodness-of-fit of a distribution to a data sample, and they work well on evaluating whether a sample follows a Gaussian distribution (i.e., the normality) [Razali and Wah, 2011]. Specifically, these tests are conducted on top 1000 most frequently appeared job title pairs for data sufficiency, and the null hypothesis is that the sample comes from a normal distribution. Generally, the null hypothesis (i.e., normality) can not be rejected when the \(p\)-value is larger than a significance level.

Figure 5 shows the results of these normality tests on different \(g(x)\), where the boxes denote the distribution of \(p\)-values and the dotted line shows the significance level of 0.05. It turns out that the \(p\)-values of KS test are far larger than the significance level, and the majority of \(p\)-values of SW and AD tests are larger than the significance level. The results suggest that, for a majority of tested job title pairs, the distribution of \(g(t_{ij})\) can be well fitted by a Gaussian distribution.

![Figure 5](image-url)  
**Figure 5**: The results of three different normality tests on \(g(t_{ij})\).

### 4.3 Validating Ordinal Concordance of Ranking

In the extracted job title hierarchy, the job titles in an organization are partially ordered regarding their ranks. A subset of the rank results is shown in Table 1, where the benchmarks include methods developed in TrueSkill™, Dot and Agony\(^1\) (see Section 5). We use GBN to represent the proposed model, and only show the results of \(g(x) = \log(x)\) because four types of \(g(x)\) have identical results regarding the orders. Hyperparameters are tuned on 5% of the dataset. The numbers in Table 1 are the mean (for GBN and Trueskill), the level (for Agony), or the normalized y-coordinate (for Dot).

We validate the ranks of job titles following typical paths in the graph by comparing them to a set of standard path templates. For example, \((\text{consultant} \rightarrow \text{senior consultant} \rightarrow \text{manager} \rightarrow \text{senior manager} \rightarrow \text{partner})\) is one of the standard templates for the job titles in Table 1. These templates are provided by human experts, and we collected 7,100 paths consists of 1.8 thousand job titles from online services\(^2\).

The evaluating metrics are Kendall tau coefficient \((\tau)\) and Spearman’s rank correlation coefficient \((\rho)\). Specifically, both \(\tau\) and \(\rho\) have high values when the compared two ranks are similar (or identical for a value of 1), and low when they are dissimilar (or fully different for a value of –1). The Normalized Discounted Cumulative Gain (NDCG) [Järvelin and Kekäläinen, 2002] is a widely used metric. We do not choose NDCG as a metric because it assumes that the items with higher ranks are more important to be right positioned, but there is no difference of importance in our situation.

Figure 6 shows the distribution of \(\tau\) and \(\rho\) by comparing the results with the standard templates. Compared to the benchmarks, the proposed model achieves better performance regarding the majority values of \(\tau\) and \(\rho\). In addition, almost all of the paths have a \(\tau\) and \(\rho\) larger than 0.85 and most of them are near 1. It indicates that the model generates nearly perfect job title orders on the majority of the template paths.

### 4.4 Validating DOP in Hierarchy

In addition to the orders, the difference of ranks should reflect the difficulty of being promoted. To validate this, we use the

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1\(^{Acquired from http://trueskill.org/, https://www.graphviz.org/}

2\(^{http://users.ics.aalto.fi/ntatti/software/agony.zip.}

3\(^{For example, https://www.hierarchystructure.com}

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3603
typical required years in job posting as an indicator for the real difficulty, and we take the difference of required years between two job titles as their DOP. We use the Root Mean Squared Error (RMSE) as a metric to evaluate the accuracy of our inference comparing to the real DOP. Specifically, $\epsilon = \frac{1}{|S|} \sum_{ij} (g^{-1}(\mu_j) - \mu_i)^2$, where $g^{-1}$ represents the required months from $i$ to $j$ for a set of job title pairs $(i, j) \in S$, and $g^{-1}(\cdot)$ is a function that maps the job title ranks among organizations in the future. We plan to map the job title ranks among organizations in the future.

There have been extensive studies focusing on job title classification tasks regarding job responsibilities [Bekkerman and Gavish, 2011; Javed et al., 2016], but limited research efforts have been put on ranking job titles [Xu et al., 2016; 2015]. From the application’s perspective, organizational chart inference (OCI) [Zhang et al., 2015] is similar to our problem, for it infers the reporting relations among employees according to their interactions in a social network. OCI differs from our work in that the difference of ranks is constant. This makes it difficult to integrate LOTs into these methods.

### 5 Related Work

There have been extensive studies focusing on job title classification tasks regarding job responsibilities [Bekkerman and Gavish, 2011; Javed et al., 2016], but limited research efforts have been put on ranking job titles [Xu et al., 2016; 2015]. From the application’s perspective, organizational chart inference (OCI) [Zhang et al., 2015] is similar to our problem, for it infers the reporting relations among employees according to their interactions in a social network. OCI differs from our work in that the difference of ranks is constant. This makes it difficult to integrate LOTs into these methods.

Table 2: The RMSE of the detected DOPs.

<table>
<thead>
<tr>
<th>Job Title</th>
<th>Method</th>
<th>GBN</th>
<th>TrueSkill</th>
<th>Agony</th>
<th>Dot</th>
</tr>
</thead>
<tbody>
<tr>
<td>GBN log x</td>
<td>0.91</td>
<td>1.00</td>
<td>1.04</td>
<td>1.04</td>
<td>1.04</td>
</tr>
<tr>
<td>GBN log y</td>
<td>1.07</td>
<td>1.13</td>
<td>1.04</td>
<td>4.90</td>
<td>10.83</td>
</tr>
<tr>
<td>GBN log z</td>
<td>0.91</td>
<td>1.00</td>
<td>1.04</td>
<td>1.04</td>
<td>1.04</td>
</tr>
</tbody>
</table>

5 Conclusion and Future Work

In this paper, we proposed a job title hierarchy extraction model. A novel measurement of the difficulty of promotion in careers was defined based on an observation about the length of tenure. A GBN was adopted to model both the job title ranks and the difficulty of promotion in career trajectories, and an efficient algorithm was designed to infer the posterior ranks in the model. The proposed method was validated by a real-world dataset. The model might be applicable to other hierarchy detection problems, where the difference of levels in the hierarchy can be quantitatively measured. We plan to map the job title ranks among organizations in the future.

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