Learning Career Mobility and Human Activity Patterns for Job Change Analysis

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***Abstract*—Discovering the determinants of job change and predicting the individual job change occasion are essential approaches for understanding the professional careers of human. However, with the evolution of labor division and globalization, modern careers become more self-directed and dynamic, which makes job change occasion difficult to predict. Fortunately, the emerging online professional networks and location-based social networks provide a large amount of work experience and daily activity records of individuals around the world, which open a venue for the accurate job change analysis.**

In this paper, we aggregate the work experiences and check-in records of individuals to model the job change motivations and correlations between professional and daily life. Specifically, we attempt to reveal to what extent the job change occasion can be predicted based on *the career mobility* and *daily activity patterns* at the individual level. Following the classical theory of job mobility determinants, we extract and quantify the environmental conditions and personal preference of careers from the perspective of industrial/regional constraints and personal interests/demands. Besides, we investigate the factors of activity patterns which may be correlated with job change as cause and effect results. First, we quantify the consumption diversity, sentiment fluctuation and geographic movement from the check-in records as indicators. Then, we leverage the *center-bias level assignment* and *multi-point snapshot* mechanism to capture historical and parallel migration. Finally, experimental results based on a large real-world dataset show that the job change occasions can be accurately predicted with the aggregated factors.

I. Introduction

Job mobility refers to the occupational transitions over the course of an individual's professional career [1]. Indeed, a transition of job is a turning point of employees' work experience and essentially determines their life-long occupational development. While job mobility acts as a key part of social life, a pivotal and opening question still exists: when will individuals transfer from a job position to another?

Traditionally, the ideal pattern of job mobility is a long-term internal and upward sequence of positions within a single organization [2]. Therefore, the job change occasion of people working in the ideal traditional career patterns can be approximately predicted with an *age and stage* theory [3], in which enterprises take the record of service as a key reference when promoting their stuffs. With the evolution of labor division and globalization, corporations are streamlining their hierarchies in response to the challenges of new economics. There has been less opportunity and willingness for individuals to engage in a single organization for a lifetime [2], thus more and more employees are forced to choose external, lateral or even downward job changes. The dynamic and flexible career mobility in modern economy pushes the job change occasion prediction into a more sophisticated situation comparing to traditional society.

Throughout individuals' life-long careers, there is usually an intermittent sequence of job change instances. According to the "punctuated equilibrium model" [4], after each transition, individuals adapt to a new position and reach a "equilibrium point", where they are satisfied with their working environments and there are few chances to break the equilibrium. The career equilibrium may be disrupted by two major aspects: environmental factors and individual differences [1][2][5]. Specifically, environmental factors, e.g., societal, regional/industrial economic and labor market status, affect the opportunities for job mobility and restrict the overall career shifting. Also, the individual differences can decide the preference for some types of mobility over the others.

In order to understand the career mobility, we must take a deep insight into the environmental and individual factors of career-related information. Traditional researches mainly rely on limited surveys to gain the resumes and personal data to drive their investigation [1][2], which makes it difficult while expanding the scale and time scope. Recently, the universalized Internet, especially online social and professional networks, have made those information digitized and publicly available timely. Online professional networks (OPNs) like LinkedIn[1] maintain huge resume warehouses which are dynamically spanning career records from hundreds of industries and companies [6]. Meanwhile, location-based social networks (LBSNs) like Foursquare[2] traces the human trajectories from all over the world, carrying rich sentiment information about human daily activities including geographical, textual and social interaction data. The growing clues carried on OPNs and LBSNs provide unprecedented opportunities to understand career mobility in a meticulous way.

In this paper, we attempt to reveal what extent the job change occasion can be predicted based on the career mobility and daily activity patterns of individuals. To be specific, we

[1]https://www.linkedin.com/
[2]https://foursquare.com/

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conduct a trajectory-based job change occasion prediction framework for confusing the job-related and daily activity-related features to understand the underlying regularity. The main contributions of this paper are summarized as follows:

1) **Aggregating professional and daily activity trajectories to exploring career mobility.** We investigate features from both work experience and daily activity records to show the correlations between profiles and job preferences under the guide of career mobility theory.
2) **Proposing a job change prediction framework.** With the prediction framework, we could predict job change occasion with a reasonable accuracy and investigate the impact of different factors separately.
3) **Discovering major factors which impact individual job change occasions.** Based on the experimental results, we find that job change occasion has a strong correlation with both environmental conditions and personal activity patterns, while environmental factors hold a more general influence comparing to personalities.

II. PROFESSIONAL AND SOCIAL LINKAGE DATASET

The data of each individual include personal resumes and historical check-in records in LBSN. Specifically, resume consists of educational and career experience profile that are collected from LinkedIn, which is an online professional social networking maintaining over 238 million members [6]. The check-in records are collected from Foursquare, which is a popular LBSN service.

One of the major issues in data collection is how to link LinkedIn and Foursquare at the individual level. To this end, we crawled a public homepage service provider "about.me"[3] in a random manner to gain the linkage user set. The service of about.me provides individuals a way to show their identifier from different social media sites on a single web page (i.e., homepage). The homepage of each person acts as a digital form of visiting card, and these pages are publicly available.

We crawled a dataset that contains 607,846 individuals, in which 63,234 users have both LinkedIn and Foursquare accounts. Resumes from LinkedIn contain work and education experience. The accounts are filtered by the number of positions and followers to guarantee that there is no public media or organization account in our user sets.

Since the complete check-ins are treated as private information in Foursquare, we collected the "tips" and "photos" of users as the alternative daily activity records. The tips are typically generated when users write a review for a shop, left some comments to an event or just show their mood by text, while photos are usually uploaded if the users take pictures of interesting scenes or landmarks. Both tips and photos are marked with geographic locations. The time stamp of check-in records spans from June 2011 to October 2014.

Because the text is leveraged in prediction and most of the well-studied natural language processing techniques are focusing on English, we filtered the data by region and text to grantee only English speaking users left. After the link, crawl and clean process, we sorted out a *professional and social linkage dataset*, which contains 44,100 users, 269,533 check-ins and 119,442 resume records.

[3]https://about.me/

III. CAREER MOBILITY AND ACTIVITY PATTERNS

A. Determinants of career mobility

The determinants of job mobility differ from person to person, and time to time. Generally, it can be summarized into two categories, i.e., environmental conditions and personal preferences [1]. Specifically, the environmental conditions contain a wide variety of factors including economic conditions, societal characteristics, industry differences and organizational staffing policies. Personal preferences include personality traits, career interests, values and family demands. Since career plays an indispensable role in social life, job mobility also has intrinsic impact on human daily activity patterns.

1) Job mobility rate: The *entire job mobility rate* is the job change ratio of all employees, and is an important indicator of global economic conditions. Global economic conditions influence the expansion or downsizing of firms, and inherently cause the change of employee rate. We use $n_{change}(m)$ to represent the number of employees who change job in month *m* (1 to 12), and $n_{employee}(m)$ to denote the total number of employees who work in m. We can quantify the job mobility rate by Eq.1.

$$JMR = \frac{n_{change}(m)}{n_{employee}(m)}. \tag{1}$$

Thus, the *entire job mobility rate (EJMR)* is the *JMR* of all users, which has a trend of rising and a seasonal regularity.

Indeed, social characteristics like regional segmentation, public policy and technology development can impact people's careers in limited regions. Regional segmentation is a common phenomenal in all over the world. We use *regional job mobility rate (RJMR)* to trace the impact of regional characteristics. Specifically, we segment firms to regions at the city level in a total of 78 cities, according to the address of firms in LinkedIn.

The change nature of industry is partially indicated by *industrial job mobility rate (IJMR)*, where industry is classified manually into 9 categories referring to the international standard industrial classification (ISIC) from the United Nation.

Organizations in the same industry may have contrasting staffing policies, thus organizations can be divided into totally different classes in terms of career mobility. Different human resource polices may lead to different *organizational job mobility rate (OJMR)*.We crawled data from LinkedIn of the firms we concerned and used those data to calculate the monthly change rate in each organization.

2) Personal career preferences: Environmental conditions constrain the job mobility options, which are necessary but not sufficient conditions to motivate employees to pursue job mobility options. The final decision is up to the personal preferences and demands.

People often prefer mobility options that involve promotions and resist downward moves. We use *personal job mobility rate (PJMR)* to reflect mobility preference.

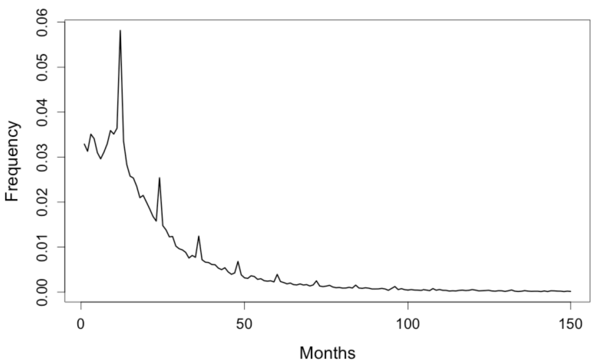

Fig. 1. Job change interval distribution.

Educational background is tightly binded to abilities, especially in high-tech industries. We divide educational background into three categories according to the highest degree users represented on their LinkedIn page: low (without a degree), medium (received a bachelor's or master's degree) and high level (Phd or higher).

Another important observation is that the most frequent length of work period is a whole year (12 months), as Fig.1 shows. The longer the time tl from last job change, the bigger the chance to change the job, especially when time segment period is the times of full year. We use the *spanning of time change (STC)* to simulate the rising of job change possibility. Given an employee e and the months from last job change occasion tl, the cumulative distribution function $cdf(tl)$ could reflect both the probability rising with time and the special peaks of whole year.

B. Correlation between activity patterns and job change

The majority time of normal people is dedicated to work, and the main source of their house-hold income gains from the corresponding salary. Thus a change of job could lead to many activity or mood swing in their life, which can be observed from their traces of daily activity like records in LBSNs. Career mobility may affect employees' consumption structures, sentiment fluctuation, activity sphere and activation.

1) Social activity: Consumption diversity usually have a good match with income level, which change tremendously along with job and age. The consumption diversity can be revealed from the visiting history of location types in LBSNs, since the activity purpose could be well identified through location categories[7]. The diversity can be calculated by information entropy with appropriate constrains which matches consumption structure migration. We use Pc_i to denote the visiting probability of type i, which is normalized by the visiting frequency of each type of locations. The consumption diversity is then calculated by Eq.2.

$$E = -\sum_{i=1}^{|C|} Pc_i \log_2 Pc_i, \tag{2}$$

where i is the index of location category.

A more subtle phenomena related to work change is *sentiment fluctuation*. When one knows that she will be promoted or shift to a preferred position, she usually feels exciting or maybe sometimes nervous. We follow the mechanism used in [8] to quantify sentiment from tips posted by users monthly. The sentiment polarity is normalized to a scale of 0-1, where 0 denotes "the most negative" and 1 "the most positive" polarity.

With the migration of career, the employee's social status transformed simultaneously. From the view of social network, social status can be represented by one's followees or fans [9]. We use the normalized likes number of tips and photos as an indicator of *social status*. The social status of a user e in month m is calculated by Eq.3.

$$Status(e) = \frac{n_{likes}(m)}{n_{check-ins}(m)}, \tag{3}$$

where $n_{likes}(m)$ and $n_{check-ins}(m)$ are the likes and check-in number of the user gained from her tips and photos.

2) Geographic movement: The geographic movement of off-line activity is an abundant resource of personal real world life. The *returning probability*, *migration of geographic center* and *radius of gyration* are informative and proved properties of human mobility patterns [9].

Returning probability is a measure of periodic behavior of mobility, which has a strong weekly cycle in regular life [9]. We use the difference from overall mean returning probability to cover the returning uncertainty. The value of difference is normalized by the largest variance into the scale of -1 to 1.

Geographic center of activity is closely connected to home and work place, and also impacted by regular egress like business trip. These activities are shaped by work and positions. We use the mean of latitude and longitude in a month m of a user as the activity center $r_{cm}(m)$ and calculate the distance between $r_{cm}(m)$ and $r_{cm}(m-1)$ as the migration of geographic center.

Radius of gyration mainly indicates how far a user moves in a certain time period. It is measured by the standard deviation of distances between the check-in points and the center of mass. A low radius of gyration typically indicates a user who travels mainly locally, while a high radius of gyration indicates many long-distance travels. We quantify the radius of gyration by Eq.4,

$$R_g(m) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i(m) - r_{cm}(m))^2}, \tag{4}$$

where n is the number of check-ins of the user in month m, and $r_i(m) - r_{cm}(m)$ is the geographic distance between a particular check-in r_i and the user's center of mass r_{cm} . r_{cm} is the average location in latitude and longitude over all check-in records.

Activation is refer to the check-in update frequency, and is shaped by work type in an involuntary manner. It is not rare that one changes job from a technologist to a sales manager. We use relative check-in number to indicate the activation, which could reflect the openness and regularity of individuals.

IV. PREDICTION FRAMEWORK

A. Problem definition

The primary goal of this paper is to investigate what extent the job change occasion can be predicted based on the career mobility and daily activity pattern of individuals. We achieve the goal by firstly solving an equal problem:

Problem statement Given an employee e and a month m, predict whether e will change job or not in the next n months, based on the *professional and social linkage datasets*.

In the statement, "change" means e will change job once or more in n months after m, including internal or external organization migration, upward or downward position adjustment, or any other changes that are showed in the resume. Employee e should be one of the users in our dataset, and m is earlier than the end time of data collection with a form of "year-month" like $2014/04$. Intuitively, the prediction problem is well formed to a binary classification

B. Feature construction

1) Center-bias level assignment: The multi-level environmental factors and activity patterns of individuals are varying temporally, which means at different aiming months, the observation of each feature is different correspondingly. Besides absolute values, the primary task of job occasion prediction requires capturing two attributes of these features at individual scale: *differences among comparable individuals* and *abnormality from its own history*.

The job market and human actions have their intrinsic regularity and stability, which are clearly visible while there is no special event. These objective facts clew that abnormality should be strictly concerned for sensing changes.

On one hand, significant *differences* to comparable individuals are direct results of unusual appearance, especially when the reference crowd is large enough to represent the nature laws. Since each feature at each month is quantified and normalized by the same process, the absolute value is an appropriate indicator of *differences to comparable individuals*. On the other hand, individual difference exists between any peer of users. One may be more positive than others for everything, thus hold a higher sentiment level in all the tips comparing to the mean of crowd. To capture the stability and individual differences properly, another feature difference that we concerns here is the *abnormality from its own history*. We use a center-bias level assignment mechanism to implement the level labeling task.

Center-bias level assignment (CBLA) mechanism Given the complete value sequence of a feature, we normalize it to have a mean of *0* and a standard deviation of *1*. Then we allocate each point of feature f into five levels f_l, i.e., ex-low, low, medium, high, ex-high, according to predefined breakpoints $B_i(i = 0, 1, 2, 3, 4, 5)$. B_i is a sorted list of numbers which satisfies the constraint that the area under a $N(0, 1)$ Gaussian curve from B_i to $B_{i+1} = 1/5$. According to the statistic table, values of B_i is $<-\infty$, *-0.84, -0.25, 0.25, 0.84,* $+\infty>$. Feature points that are below the B_1 are mapped to the level "ex-low", points greater than or equal to the B_1 and less than the B_2 are mapped to the level "low", etc.

The level assignment approach is similar to part of the Symbolic Aggregate approXimation (SAX) [10] scheme, which has a discretization phase via Piecewise Aggregate Approximation (PAA) [11] and more compatible attributes for time series distance measurement. *Center-bias level assignment mechanism* only concerns about the abnormality from historical levels, and has been simplified to gain computational efficiency. The middle value ($B_i = 3$) represent the normal level of feature, and the ex-low and ex-high level reflect the abnormality thus would have more effect on the prediction.

2) Multi-point snapshot: All the features extracted are discrete time series with a monthly frequency. On one hand, we can use a snapshot of the features at the given month, and initial them as cross-sectional data. On the other hand, directly using time series satisfies the information completeness constraint, but will lead to a dimensional explosion. Furthermore, people with different data start time point will have a varying length of feature, which will cause a incomparable dimension between them. To find a reasonable tradeoff between snapshot and time series, we use a *multi-point snapshot (MPS)* of features in our model. The primary goal of using MPS is to cover enough historical traces but guarantee linear computation increase.

Generally speaking, most recent history has more impact on behaviors. The forgetting mechanism is a common solution to simulate this kind of regularity [12]. The sampling point satisfy the constraints that the recent values to be emphasis and put less focus on the far away changes. We choose Fibonacci number as the sampling point, i.e., at a given month m, we sample data at months $m_k = m - Fb_k$ where $Fb_k = Fb_{k-1} + Fb_{k-2}(Fb_1 = 1, Fb_2 = 2, andk = 1, 2, 3...)$. The target variable at sampling month m_k is determined by job change status in month m to $m + n$.

Since we formulate the prediction into a binary classification problem, there are lots of effective algorithms could be used to address it. Although latent variable-based algorithms like matrix decomposition are proved better for classification, we choose classical algorithms rather than latent factor models. It is because we put more focus on the predictive ability mining and the explanation of prediction. Latent factor related models like singular value decomposition and neural networks may be more powerful but less explainable.

V. EXPERIMENTS

A. Experimental setup

Because the average work segment is longer than two years, the target variable balance is hard to maintain with a too short or too long predict period n. To ensure the basic balance

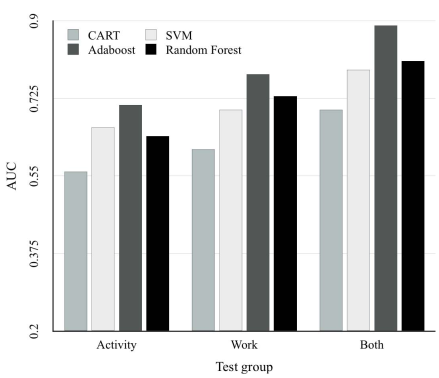

Fig. 2. AUC of feature types and algorithms.

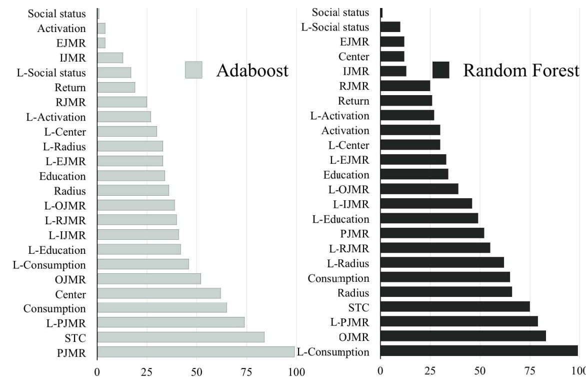

Fig. 3. Relative importance of features.

of the instances, we set the month $n = 10$ in most of our experiments, such that the proportion of positive instance is close to 0.5. As to the starting time m, because the job change records ended at October 2014, m should be earlier than December 2013. We choose m as October 2013, and also conduct experiments to show the impact of different m. We also conducted an experiment with respect to different n to illustrate the affect of prediction period scale.

B. Experimental results

1) Feature group test: We divide the feature into three groups: group *work* which contains job mobility determinants features (*JMR*, *educational background* and *STC*) only, group *activity* which contains daily activity pattern-related features (*consumption diversity*, *social status*, *migration of geographic center*, *radius of gyration* and *activation*) only, and group *both* which contains all the features. The testing algorithms are classification and regression trees (CART), support vector machine (SVM), Adaboost and random forest.

The dataset contains 40 thousand individuals, and 30% of them are randomly selected as test set. We use area under the receiver operating characteristic (ROC) curve as accuracy indicator to evaluate the effectiveness of prediction. The jointly test results of different group and algorithms are showed in Fig.2. It is clear that the test group *both* outperforms the other two groups and algorithm Adaboost has the highest accuracy in four algorithms. When segment features into work-related and activity-related parts, the prediction ability decreases shapely (67% in average), especially when using activity-related features only (64% in average). The correlation between work-related features and job change is more subtle than the work-related features, but combining both of the features could capture much reacher information than sole one. To detail the correlation between different features and career mobility, we further investigate the importance of features next.

2) Feature importance: We examine the relative importance of features to investigate which feature have realistic impact on the prediction. The feature importance of Adaboost and random forest is show in Fic3, in which L-* represents the center-bias level of the corresponding feature. The importance of social status and L-social status are low in both of algorithms, which may be because social status itself is subtle and not closely related to job change. On the contrary, most of the JMRs have distinct importance, especially PJMR, which indicates that people may keep stable job change preference from their historical experience and follow the job mobility regularity of environment. Hence, the stability shows that self-directed career mobility does not override traditional patterns. At the mean time, educational background has a fundamental effect on job, and has an middle impact according the result. Another important feature in the result is *STC*, which suggests that the punctuated equilibrium model is suitable for most individuals. The importance of *JMR*, *STC* and education suggests that although modern job market becomes more dynamic, the traditional career patterns still commonly exits among employees.

Physical trajectory patterns like *radius of gyration* and *migration of geographic center* impact the result a lot, which validates the assumption that job type and position transition could change spatial scope of activity. Furthermore, *consumption diversity* has top importance in random forest, and also have high importance in Adaboost. These features are impacted by job properties and income level, thus should just change after job transition intuitively. The result claims that people may change their life style before a job transfer.

3) Effectiveness of CBLA and MPS: In order to demonstrate the effectiveness of *CBLA* and *MPS*, we generate four types of feature set: *bare* features without CBLA and MPS, *CBLA* features only, *MPS* features only, *bare+CBLA* features, *bare+MPS* features and *all* features. Feature sets with MPS have 5 to 6 times of instances than the corresponding non-MPS feature sets, thus we randomly sample 20% to 50% of the individuals in feature set with MPS to fit the control condition.

The AUC of different feature combination is showed in Fig.4. Four algorithms are all classified poor (51% in average) with *bare* feature sets, and have a better performance on *CBLA* (64%) and *MPS* (57%). Combining *bare* and other two sets separately improve accuracy in about 10%, and *CBLA*

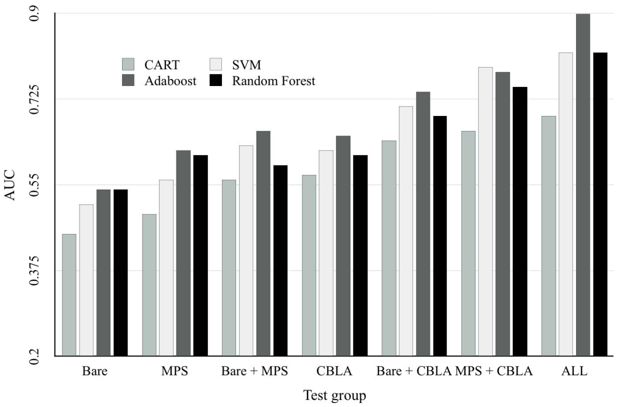

Fig. 4. AUC of features set with CBLA and MPS.

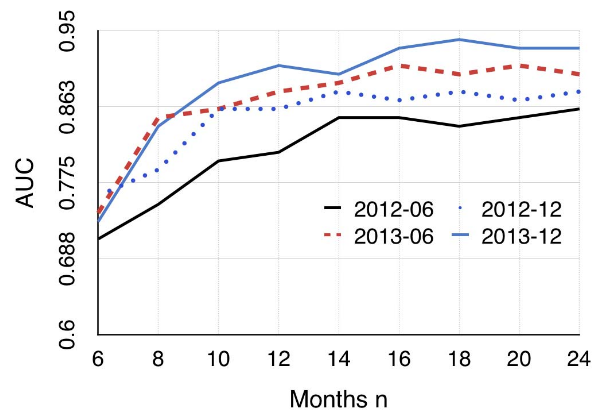

Fig. 5. AUC of different prediction period.

outperforms *MPS* in each test group. The performance of combining *CBLA* and *MPS* reaches a fair good level, which suggests that *CBLA* and *MPS* raise the prediction a lot and has better effective when cooperating with each other.

4) Prediction time and period: The prediction period scale n and start month m decide the structure of instances, thus could impact the prediction result. We conduct a test on different n and m with Adaboost, where we n is set from 6 to 24 and m is set to June 2012, December 2012, June 2013 and December 2013. As showed in Fig.5, the accuracy increases along the month n, and reaches a relatively high level when $n > 16$. The job change probability rises when n grows, and most of the individuals change their position once or more in 30 months. The career transition behavior becomes more stable in a long period. When prediction start month m runs back to 2012, the prediction accuracy decreases in all the cases. This phenomena may caused by the increasing sparsity of activity record, because the sampling point of MPS becomes less at June 2012.

VI. Conclusion

In this paper, we explored the problem of job change prediction based on the career mobility and daily activity under the guidance of theoretic career mobility determinants framework and human activity patterns. We have shown that the traditional punctuated equilibrium model of job mobility has instructional effect on modern career population even when the global labor market is becoming more and more flexible. Specifically, the determinants of career mobility including environmental conditions and personal preference have a strong correlation with job change opportunities and decisions. The daily activity patterns are also related to job change from the perspective of consumption diversity, sentiment and geographic movements. Experimental results based on a large real-world dataset shown that the job change occasions can be accurately predicted with the aggregated factors.

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