Senior Research

The tracking skills of Thai labour market using unsupervised machine learning with internet data

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This paper uses internet data in Thai labour market by scraping job portal websites and using natural language processing technique to extract the meaning in job description data. This paper uses the job description data posted in job portal websites to cluster the job by skills and finding which skill set gain more and less wage than the market wage data.

This paper finds that we can cluster jobs in Thai labour market into 8 groups by skill set – customers service, engineering, sales, production, accounting and finance, language works, office works, and marketing. The marketing skill set gain most wage with respect to other groups, meanwhile, the customer service skill set gain least wage with respect to other groups.

All codes and documentations are under the MIT Licence and they can be accessed at github.com/sikawit/EconSR.

Keywords: Thai labour market, machine learning, unsupervised clustering, web scraping, Natural Language Processing, Word2Vec, Bag of Words

1. Introduction

In the era of disruption by technologies, a lot of jobs in the labour market are disappearing. However, a lot of new jobs are presented in the market. For example, the pager operator was disappeared in 2000s, while a brand-new job like data scientist was created in 2010s.

In the traditional way, to study the labour market, a lot of researchers use the Labour Force Survey to track the status of labour market and the dynamic of the data. However, there are a lot of drawbacks in this traditional study, which is shown in Table 1. The Labour Force Survey (LFS) data are quarterly lagged and monthly collected from the survey respondents which is not reflected the instant labour market status. Moreover, to access LFS, I need to require permission to access data from the National Statistical Office (NSO). Moreover, the data from NSO is not free.

Moreover, the type of jobs and the job description in LFS are predefined by human which does not capture the dynamic of jobs in this disruptive era that a lot of new jobs are created and disappeared. To capture the dynamics of jobs, it is better to use the real-time job posting datasets from job portal sites.

Because of these limitations of the traditional study with LFS, I decided to use text mining technique for online job postings dataset from the Internet Employment websites which are instantly and totally free to access. Even there is a study to find the insight in Thai labour market, but this paper uses the Google Trends data as a proxy to study in the labour market. (Nuarpear Warn Lekfuangfu, 2016) Thus, there is no paper using Thai online datasets from job portal sites to track Thai labour market.

Table 1, The difference between 2 studying methods

Topics	**Traditional Study**	**Text Mining**
Source of Data	Labour Force Survey	Online Dataset
Availability	Require Permission	Public Data
Time to get access	Few weeks	Immediately
Cost to access	Not Free	Free
Frequency of Data	Monthly	Real Time
Lagging Period	Quarterly	Real Time
Type of Jobs	Predefined by human	Adaptive by actual data
Job Description	Predefined by human	Dynamic

From the text mining approach, there are a lot of applications that policymakers can use data from the Internet to find the insight from labour market data. For example, tracking real time labour demand, measuring a set of skill embedded in each job in the market, clustering jobs on skill set, planning the education curriculum to serve the market demand, analyzing wage by skill set.

In this paper, I use the Natural Language Processing (NLP), machine learning, and web scraping techniques to answer 2 main questions. First, how can we cluster the job by skills from appearing words in the job description. Second, which skill set gain higher (or lower) wage than the average wage in the Thai Labour market.

This paper is divided into 8 parts, introduction, dataset in this paper, data pre-processing, empirical results, limitation, summary, code licence, and acknowledgement.

2. Dataset

In this study, I use 2 online datasets for labour demand and labour wage. The labour demand data are collected from Jobtopgun, one of the largest Thai online job posting website. In this dataset, there are composed of the job position name, and job descriptions. I collected the data from Jobtopgun monthly from December 2018 to March 2019. Data on Jobtopgun website is shown in Figure 1 and the number of observations from Jobtopgun is shown in Table 2.

Figure 1: Data in Jobtopgun site

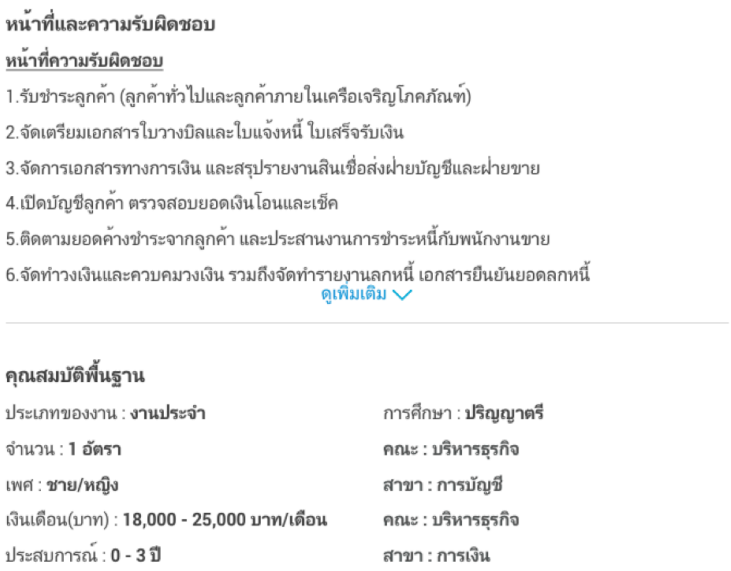
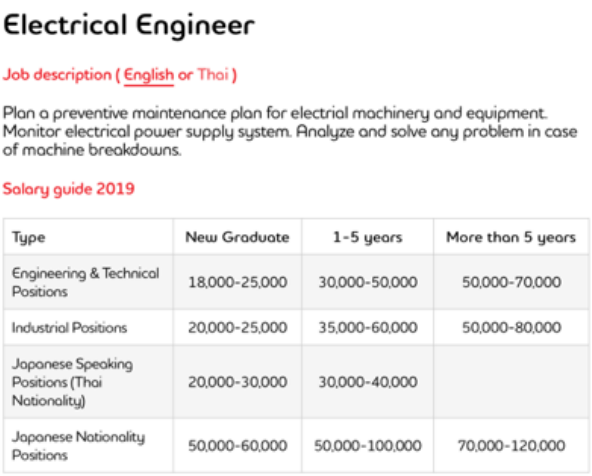


Table 2, The number of observations of Jobtopgun dataset

Period	Number of observations
December 2018	13,564
January 2019	11,418
February 2019	8,281
March 2019	9,285

The labour wage dataset is collected from Adecco Thailand Salary Guide 2019. The salary data are provided by Adecco, a global human resource consultant. In this dataset, there are 766 observations based on job description and work experience. In this dataset, I use the midpoint in the wage's range for calculating wage in the regression equation. Moreover, I only use the data in the first row because data in this row are mostly related with the job description. Data on Jobtopgun website is shown in **Error! Reference source not found.**.

Figure 2, Data in Adecco Thailand Salary Guide 2019 site



Electrical Engineer

Job description (English or Thai)

Plan a preventive maintenance plan for electrial machinery and equipment. Monitor electrical power supply system. Analyze and solve any problem in case of machine breakdowns.

Salary guide 2019

Type	New Graduate	1-5 years	More than 5 years
Engineering & Technical Positions	18,000-25,000	30,000-50,000	50,000-70,000
Industrial Positions	20,000-25,000	35,000-60,000	50,000-80,000
Japanese Speaking Positions (Thai Nationality)	20,000-30,000	30,000-40,000	
Japanese Nationality Positions	50,000-60,000	50,000-100,000	70,000-120,000

3. Data Pre-Processing

Due to text mining technique, this study uses Python for scraping job posting data from Jobtopgun and Adecco. Data in the labour demand and labour pricing is rich of text. My objective is converting text into computable object by using the Natural Language Processing (NLP). In NLP, I use translation, Bag of Words and Word2Vec to convert text into a computable object.

a. Translation

Scraped data in both datasets are both in Thai and English. For analysing purposes and limitation in NLP techniques, I translate all job descriptions and job position names into English by using Google Translate service.

b. Bag of Words

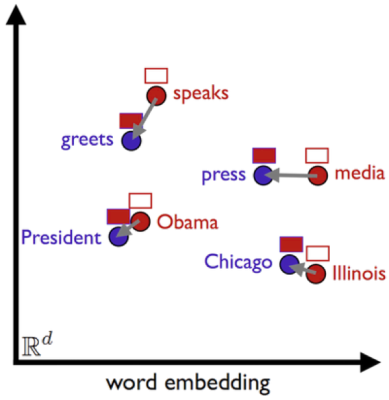
After scraping data from Jobtopgun and Adecco, I translated all text data into English for using Bag of Words technique. Bag of Words is considering the occurrence of word in each sentence, but do not consider the order of words. For example, the sentence “John likes to watch action movies. Mary likes movies too,” can be written as a dictionary by {“John”:1, “likes":2, “to":1, “watch":1, “movies":2, “Mary":1, "too":1}. This dictionary counts the occurrence of each word in this sentence. In this paper, each job description is considered as a bag of appering words in the job description sentence.

c. Word2Vec

Word2Vec is a computational method that converts words that appeared in the job descriptions into vector, a mathematical object. The nearness of vectors depended on the meaning of the word vectors. The more nearness between vectors means the same meanings between word vectors. This concept is illustrated in Figure 1. I use the Word2Vec technique for all job descriptions to find all required skills in each job. In this paper, I use Google News pre-trained model for converting word into vectors (Google Inc., 2019). Each word vector in the model has 300 dimensions. In each job description, I calculate the arithmetic mean of all

words (except stop words, words that do not have meaning in the sentence) that appeared in the job description. I will use the job description vector from calculated vector from this process.

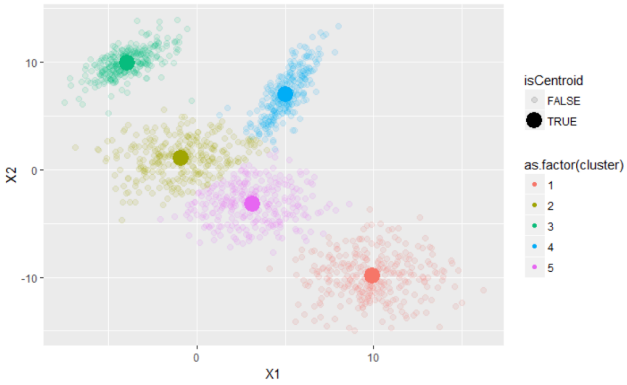
Figure 3, Example of Word2Vec nearness of word vectors (Kernix, 2016)



d. k-means clustering

In the clustering process, k-means technique is selected by clustering each job description vector. Figure 2 illustrated how k-means clustering vectors. In Figure 2, each small dot represents vector in 2 dimensions X1, X2. K-means is the process of clustering all vectors in the 2-dimensional space by finding centroid points, in this case, there are 5 cluster points represented by different colours.

Figure 4, k-means clustering process (Antoine Guillot, 2017)



The concept of k-means is applied in this paper by clustering all job description vectors based on the meaning of words in job descriptions; however, the dimension of the word vector in the model is 300, so I cannot plot job description vectors.

This paper mainly uses a job description in the data pre-processing process because job descriptions reflect the required skills in this job and some different job descriptions use the same job position names.

4. Empirical Results

In this paper, I will analyse the result into 2 parts based on the different dataset, labour demand data from Jobtopgun and labour pricing data from Adecco.

a. Jobtopgun, the labour demand data

In this part, I use the data from Jobtopgun site to find the insight of the labour market dataset into 3 ways. First, I will classify job types from the vector of job description in the monthly data. Second, I will show the number of jobs in each cluster. Finally, I plot the WordCloud chart to find the most skill words that appeared in each cluster.

In the classification section, I clustered the December 2018, the first dataset, job description vectors into 8 clusters and compute the centroid of these 8 clusters by finding the mean of all vector in each cluster. Then, I fixed these cluster points for finding the dynamic of labour demand, by using the December centroid data to cluster the job description vectors from January to March 2019. In next 3 datasets, I vectorised the job description and clustered by choosing the minimum distance from the vector to each cluster point.

To illustrate job clustering in each cluster, I consider the appearing words in the job description. So, I print the most 10 common words appeared in the job description in each cluster (excluding stop words) on Table 3. Then I name each group based on the most common words on Table 4.

Table 3, Most 10 occurrence words in each cluster group

Group 0:	work, check, customers, care, customer, company, clean, assigned car service
Group 1:	maintenance equipment repair electrical control systems system work installation machine
Group 2:	customers sales customer company products new service product care assigned
Group 3:	control production quality work system project process design management plan
Group 4:	accounting tax check financial documents prepare accounts report assigned company
Group 5:	japanese design thai work assigned support media thailand company english
Group 6:	work assigned company management documents duties training control tasks coordinate
Group 7:	sales marketing company business customer customers new team management plan

Table 4, Job types based on clustering process

Group 0:	customers services
Group 1:	engineering
Group 2:	sales
Group 3:	production
Group 4:	accounting and finance
Group 5:	language works
Group 6:	office works
Group 7:	marketing

After naming and clustering job from job descriptions, I get the number of jobs in each cluster on Table 5.

Table 5, The number of jobs based on clustering process

	Cluster Name	Dec 18	Jan 19	Feb 19	Mar 19
Group 0:	customers services	1446	1118	639	865
Group 1:	engineering	935	759	374	477
Group 2:	sales	1925	1590	1005	1198
Group 3:	production	2954	2578	2042	2182
Group 4:	accounting and finance	1189	981	704	794
Group 5:	language works	814	652	475	477
Group 6:	office works	2202	1930	1434	1585
Group 7:	marketing	2099	1810	1608	1707
	Total	13564	11418	8281	9285

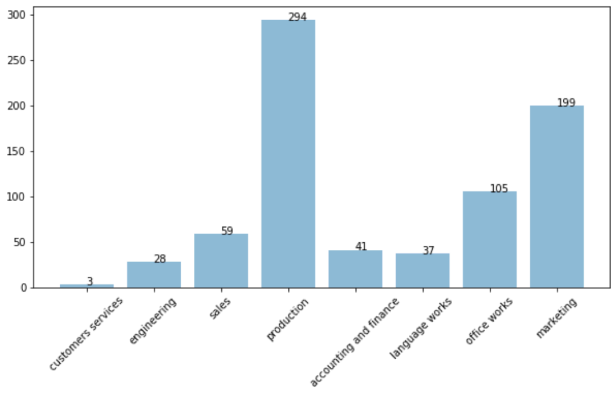
I also plot the WordCloud chart, the visualisation of all words in each cluster based on the frequency of words in each cluster. The larger size of the word means the more frequent of words in the cluster. In Figure 5, showing the WordCloud plot for cluster group 3, production jobs. The word “system” is the most appeared word in this cluster due to the largest size in this chart. In this figure show that the main skills in the “production” group is the word in the WordCloud plot.

Figure 5, The main skill set in word cloud plot for "production" jobs in December 2018.

b. Adecco Salary Guide

In this part, I use the job clustering point of part a. to cluster all jobs in Adecco data, then I measure the norm of each job description vector to each cluster point. Then, I use these data to calculate wage based on skill set from each job description. Numbers of jobs based on 8 clusters on part a are shown in Figure 6.

Figure 6, The number of jobs based on 8 clusters



With 766 observations based on job descriptions and work experience, I set the regression equation that wage is depended on 2 main parts. First, after converting each job description into vector, I consider the distance from each job description to each cluster point. The more distance means the farness from each observation to the cluster point. I defined that each cluster represents the skill set for that cluster of job. For example, a job that has a low level of distance to the cluster point means that the job has a high level of skill in the cluster point.

Second, the dummy variable vector that shows work experience. Because Adecco divided jobs into 3 groups, new graduate level, 1-5 years of experience level and more than 5 years of experience level. This paper name these variables “newgrad”, “junior”, and “senior” respectively.

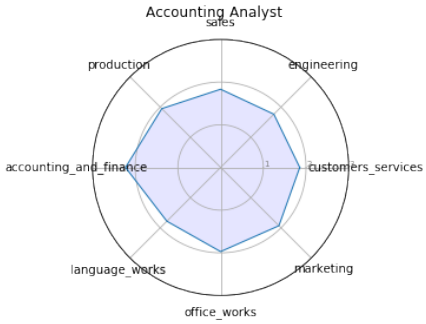
I construct the regression equation based on the log-linear Ordinary Linear Regression (OLS) to find the relationship of the percentage change in distance of the job description vector to each cluster point (norm of a vector) as shown in Equation 1.

Equation 1, Log-linear model of wage and skill in labour pricing data

$$\ln(wage) = f(dist_0, \ldots, dist_7, D_{newgrad}, D_{senior})$$

To illustrate this concept, I will plot the level of skill set which equals 1 – (the normalise distance between job vector to the cluster point)^0.10. In Figure 7 show the skill set of Accounting Analyst based on 8 types of skills, based on the first clustering in Jobtopgun dataset.

Figure 7, The skill set plot of Accounting Analyst based on main skills



In Figure 7, the "Accounting Analyst" requires most of "accounting_and_finance" skill sets due to the least distance between this job vector to "accounting_and_finance" cluster that means the most radius of "accounting_and_finance" in the spider chart in Figure 7.

The regression result is shown in Figure 8.

Figure 8, The summation of OLS Regression

Dep. Variable:	wage	**R-squared:**	0.694
Model:	OLS	**Adj. R-squared:**	0.690
Method:	Least Squares	**F-statistic:**	171.4
Date:	Sun, 12 May 2019	**Prob (F-statistic):**	1.14e-186
Time:	00:22:34	**Log-Likelihood:**	-325.32
No. Observations:	766	**AIC:**	672.6
Df Residuals:	755	**BIC:**	723.7
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	11.0472	0.747	14.789	0.000	9.581	12.514
customers_services	-15.7890	3.032	-5.208	0.000	-21.741	-9.837
engineering	10.5283	2.250	4.678	0.000	6.110	14.946
sales	-7.8899	2.257	-3.495	0.001	-12.321	-3.458
production	-10.1945	2.465	-4.136	0.000	-15.034	-5.355
accounting_and_finance	3.6898	1.524	2.422	0.016	0.699	6.681
language_works	-2.9823	1.789	-1.667	0.096	-6.494	0.530
office_works	2.4608	2.308	1.066	0.287	-2.070	6.992
marketing	24.7426	3.062	8.082	0.000	18.732	30.753
newgrad	-0.5284	0.039	-13.704	0.000	-0.604	-0.453
senior	0.7092	0.031	22.678	0.000	0.648	0.771

Omnibus:	56.065	**Durbin-Watson:**	1.535
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	67.712
Skew:	0.666	**Prob(JB):**	1.98e-15
Kurtosis:	3.587	**Cond. No.**	376.

From the regression result, the coefficient beta represents the percentage change for the skill set in the cluster of jobs has more or less wage than the average wage of all observations. More magnitude of beta means the percentage change of the distance between job and cluster point (more distance means less of skill set). Because of the inverse relationship between the distance from job description vector and the required skill, I multiply -1 to the distance in this regression for the ease of interpreting beta coefficient as shown in Equation 2.

Equation 2, The coefficient interpretation

$$\beta = \frac{d\ln(wage)}{d(distance)}$$

I write down the regression equation as shown in Equation 3. Skills in this regression equation are the negative of distance from job description vectors to each cluster point on Table 4.

Equation 3, The regression equation on wage and skills

$$\begin{aligned}\ln(wage) = {} & 11.0472 - 15.7890skill_0 + 10.5283skill_1 - 7.8899skill_2 - 10.1945skill_3 \\ & + 3.6898skill_4 - 2.9823skill_5 + 2.4608skill_6 + 24.7426skill_7 \\ & - 0.5284D_{newgrad} + 0.7092D_{senior}\end{aligned}$$

The result is shown in 2 parts. First, the relationship between the skill set and wage. I found that the coefficient in marketing group is the highest coefficient, 24.7426, means a job that have the marketing skill set gains most wage than other jobs with other skills. Meanwhile, the "customers_services" gains least wage than other jobs with other skills. The coefficient in this part is -15.7890 which is the lowest coefficient.

In the dummy variable analysis, the controlled group is the job that requires at least 1 year but less than 5 years of experiences. From the coefficient in "newgrad" – a group that the work experience less than 5 years, it shows that the wage is reduced by 52.84% with respect to the controlled group. In the "senior" group – a group that requires more than 5 years of work experiences, it shows that the wage is increased by 70.92% with respect to the controlled group.

5. Limitation

In this paper, I only use 2 sources for tracking Thai labour demand and labour pricing which might not cover all of Thai labour market. Adecco Thailand Salary Guide is the only public data that have salary data in Thai labour market; however, jobs in Adecco does not fully cover all jobs in Thai.

By economic theory, in labour pricing part, there are a lot of factors that determined wage, for example, age, education level. This paper only uses data which provided from scraping technique, distance between job description vector to cluster point and dummy variable data.

6. Summary

The key technique that I use in this paper is Word2Vec, a branch of Natural Language Processing (NLP) by converting all text I into mathematical objects and using them in machine learning part. After converting text, especially in the job description, I use k-means

clustering to cluster all jobs by searching hidden skills which embedded in the job description. I found the skills in each job type by using NLP techniques. Moreover, I also use the econometric method to find that how each skill set earned wages. The regression equation shows that the marketing skill sets gain the most wage with respect to other job skills while as the customer service skill sets gain the least wage with respect to other job skills.

7. Code Licence

All codes and documentations are under the MIT Licence and they can be accessed at github.com/sikawit/EconSR.

8. Acknowledgement

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