An analysis of nonimmigrant work visas in the USA using Machine Learning

Dhanasekar Sundararaman 1, Nabarun Pal 2, Aashish Kumar Misraa 3

1 Department of Information Technology SSN College of Engineering, 2 Department of Metallurgical and Materials Engineering IIT Roorkee, 3 Department of Electronics Engineering Department SV National Institute of Technology dhansaker312213@gmail.com

Abstract

High-skilled immigrants are a very important factor in US innovation and entrepreneurship, accounting for roughly a quarter of US workers in fields such as computer science and delivering in terms of patents or firm starts. Their contributions to the US are rapidly increasing in the past three decades and are found to be well trained and skilled on average than their native counterparts. While the impact of these high-skilled workers is signified, the way in which they compete to enter a tech hub like the US is rather not fair. H-1B, the work visa to import high-skilled workers, is not used for high skilled anymore but rather used to import cheap labor to displace native workers in many cases. Many billionaires, experts, pundits and even the government are looking for many amendments in H-1B to abolish this by bringing in a merit system or increasing the minimum wages to awarding these visas. We attempt to analyze the petitions filed from 2011-16 and classify the petitions filed as positive or negative, indicating whether the petition is highly skilled or not. After classifying, we build a model using Random Forest to predict any visa petition in any state of US as positive or negative. Experimental results show the companies that are classified as abusing these visas (negative) are well consistent with the ones shown in reports and news articles.

Introduction

A visa is typically a stamp issued to an alien (foreigner) to visit a country for purposes ranging from travel to business. There are many classes of visa depending on the country to which one intends to travel. The United States of America also has many classes like H1, L1, J1 etc. The specific category of visa that caught the limelight for all wrong reasons recently in the USA is the H-1B. It is a temporary non-immigrant work visa created in 1989 by the USA to attract highly skilled foreign workers and to tackle the severe labor shortages in the country. Here we stress the term ‘highly skilled foreign workers’ as the visa is often awarded to people who have exceptional skills in their field and often with an advanced educational background.

The visa program has contributed the USA by bringing in the CEOs, CTOs, and founders of today’s many Fortune 500 companies. Though the visa contributed greatly to the economy of the USA by bringing in foreign talents, there have been many reports in the recent times of the case of visa abuse (Trimbach et al. 2016), where companies use these visas to bring cheap labor at the expense of Americans working at these positions. These are not the high skill demanding jobs, the purpose for which the visa was created but rather the usual entry-level jobs mainly in the field of computer science. The exploitation of loopholes in the visa system permits filing multiple positions for a person to secure their chances in the lottery. This situation creates two problems. First one is the highly skilled person who applies for the work visa has a greater chance of denial due to the mass booking of visas by outsourcing firms. The second one is native residents who are entry-level workers lose their job due to their cheap foreign replacements. The authorities responsible for visas along with the government are taking actions to prevent this and ensure these visas go to the deserved people. Some of the proposed methodologies include merit-based and salary based granting of the visa. In this paper, we attempt to analyze the case of visa abuse state wise by finding the positions for which the number of petitions is high, and the salary is low in each state.

To summarize,

- First, we group all the information about a visa petition like salary, position, employer state wise for each of the 50 states.
- Second, we perform basic statistical operations like mean, range, highest and lowest salary for which the petition was filed for each state.
- Third, we use clustering to find the absolute pay value for each state, below which too many peti-
tions are filed to be classified as abuse, i.e., the cut-off value.

- Finally, we train a Random Forest model with the labeled data to predict future petitions as a correct or abuse.

By finding such absolute pay value, which we call the cut-off value, it would be useful to design an efficient visa system in which visas are granted for people who at least draw the cut-off value salary. In other words, visas are granted to the deserved people, and the usage of visas to hire cheap labor is drastically reduced.

**Dataset and Preprocessing**

The data set for performing analysis on H-1B visas were obtained from Kaggle. The data contains all the H-1B petitions filed from 2011-16 in the USA. It contains fields such as case status which describes whether the visa petition was approved or not, job title, whether the visa petition is for part time or full time, prevailing wage, worksite year and latitude, and longitude. Since the cut-off value is defined only through prevailing wage, more importance is given to that field. These cut-off values are calculated for each state, and the entire data is grouped based on the state to counter the disproportionate salaries offered across the states. The dataset has many NA fields (Not Available), and these were carefully analyzed. For e.g.: suppose for the grouping of data sets by means of the ‘state,’ if a row encounters NA in the field ‘state,’ these rows are not completely ignored, but rather treated as a separate state of NA’s.

**Related Works**

Though the data set comprising all the visa petitions filed in the United States is readily available, there has not been any considerable work of analyzing these petitions, to the best of author’s knowledge. Many of the works mainly deal with exploratory data analysis, while others go to the next level, in which they analyze the trending job in a state, well-paying jobs and jobs to watch out. Our work is much more focused in the way that, we first do the exploratory data analysis to gather insights about the data and apply machine learning algorithms such as clustering and Random Forest to learn about the usage of visa petitions.

A work on the analysis of H-1B shows the employers outsource work and pay less to the foreign worker compared to the US counterparts (Trimbach et al. 2016). Another work (Doran et al. 2014) compares winning and losing firms in the FY 2006 and FY 2007 lotteries for H-1B visas. Winning corresponds to a moderate increase in the firm’s overall employment, leads to a lower average employee earning and higher firm profits and has an insignificant effect on firm’s patenting and use of the research and experimentation tax credit. They found extra H-1B increase median firm profits, decrease in median earnings per employee.

One of the recent work (Bound et al. 2017) signify the advantages of H-1B on US economy and the reduction of the prices of computer-related technology and increased the output. It also tells how firms earn a lot of profits using these visas, in place of native people. Another work (Mithas et al. 2010) finds that the salary for noncitizens and those on work visas fluctuate in response to supply shocks created by caps on new H-1B visas. Lower and fully utilized caps results in a higher salary for noncitizens and those on work visas. Nowadays, these caps are filled by lottery which indirectly suggests that too many undeserving people apply.

Though there is various theoretical and survey works on advantages of H-1B and how these visas are exploited in the recent times, there isn’t a solid practical implementation to find out the usage of these visas. We attempt to prove it by taking a practical H-1B dataset and find the companies, which pay lower than most of the others, and companies, which file most of these applications and term them negative.

**Exploratory Data Analysis**

After obtaining and preprocessing the data, we have the following. The dataset grouped state wise. As we already said, the data is grouped state wise because of the severe variance of pay across states. e.g., wages for a software developer is found to be much lower in Florida than that of California. Now after grouping the data state wise, we perform several data analysis tasks and visualize them for exploration. The following are the data analysis tasks involved for a state.

- The visa petitions are grouped based on the status of the visa. The four status of the visa are withdrawn, denied, certified and certified-withdrawn.
- Based on the employer name and the salary offered. The visa petitions are grouped based on the name of the employer and the corresponding salary offered. The three cases of min, mean and max are taken for a clear analysis. E.g. The mean salary offered by Google Inc. in Oregon.
- Based on the position name and the salary offered. For e.g. the mean salary offered for software developer in Oregon.
The mean salary offered in a state for a particular year. This trend is gathered and plotted for analysis.

Exploratory data analysis like grouping petitions by case status, employer, position, and the year is displayed for the state of Oregon. A full comprehensive report for all the 50 states is generated encompassing many interesting statistics. These exploratory data analyses reveal many intuitive answers about the data like the most trending job, most paid job, most paying employer, least paying employer, the variation of pay over the years and so on.

Determining cut-off value

The cut-off value as explained before is the minimum wage below which a petition is classified as negative. We employ clustering to determine this value as the data is unlabeled and clustering proves to be the best method for this scenario. The entries of a state are analyzed to find out three centroid points—high paying, low paying, and average paying.

\[
C_K = \frac{1}{n} \sum_{i=1}^{n} R_i \times Pr(R_i) / n
\]  

Where I: 1-n traverses through all the rows of a state, R denotes a row, R_i denotes the salary of that row, Pr(R_i) denotes the priority of the company in that row. We explain the importance of this priority metric in the upcoming subsection. Let \(R_i \times Pr(R_i) = V_i\)

- First, the centroid \(C_K\) is found by finding the mean of all the entries of salary offered to the product of priority of that company.
- Second, \(C_L\) and \(C_U\) are found for all entries that have \(V_i\) lower and greater than \(C_K\) respectively using Equation 1.

Finding the priority of the company

For our clustering algorithm, it would not be beneficial to cluster companies just based on the salary offered. That may be absurd sometimes. To classify a company negatively just based on one entry, i.e., just one petition filed by an employer may prove costly. There is a need for a metric that signifies the global importance (nation-wise) of that company while using it to classify petitions inside a state. Hence, we find a priority metric for each company. Priority
metric for a company varies proportionally with the average salary offered across all the states, positions, and petitions. It is the average of all the petition salaries of a company. Hence, a company with a good reputation of paying high will carry a higher priority and vice versa. Hence the centroid calculated based on the product of salary offered and priority of that company would penalize outsourcing companies even if the salary offered is high rarely. It saves companies such as startups to be not classified as negative even though the salary offered may be low, because of this priority metric as the priority of startups tend to be higher than outsourcing companies due to the very few petitions filed by these startups. An outsourcing company with a reputation for offering low salaries to import cheap labor will have a lower priority than a startup as we penalize companies with many petitions.

\[ \text{Pr}(C) = \frac{M(C) \times 100}{(\text{max} - \text{min})} \]  
\[ \text{Pr}(C) - \text{Priority of company C, } M(C) - \text{Mean salary of company C, } \text{max} - \text{maximum salary, } \text{min} - \text{minimum salary} \]

**Labelling data**

Now after finding the cut-off value \((C_L / \text{Pr}(R_C))\), next step is to determine each petition as negative or positive. The cut-off value is different for each company in a state. It is formed by the right mix of the average wage in a state and the reputation of the company nationally.

Label = positive if \(R_I > C_L / \text{Pr}(R_C)\), Negative else  
(3) We label petitions with the salary offered greater than cut-off value \((R_I > C_L / \text{Pr}(R_C))\), as positive, else as negative.

**Results and Discussion**

After extracting the data, preprocessing, exploring it visually, and labeling, we present the results with few discussions. As discussed in the previous section, we labeled each petition as positive and negative. After labeling, we analyzed each state and grouped companies or employers with maximum negatively classified petitions for each state.

Figure 5 to 9 shows the top abuse companies by the count in the states of Arizona, Wisconsin, and Washington etc. The figures show some universities in that region with some industrial companies too. The plots for other states are also generated and attached. After analyzing the plots for all the states, it is found that there are certain groups of companies, who feature in almost each of the state’s abuse list. Quite evidently, our results are supported by many articles such as news that these companies acquire H-1B visas disproportionately. A report by NYTimes states 13 companies that abuse the visa and many of the companies featured in that list are found in our list too. Infosys, Tata Consultancy Services, Cognizant Technology Solutions, Wipro, and HCL are few companies to be named that feature commonly in our analysis.
Training Random Forest to predict Visa Petitions

Now, after labeling the data using clustering, we build a model that incorporates the features such as salary, company, and priority to predict any future visa petitions as positive or negative. Decision Trees and ensemble methods like Random Forests are good machine learning algorithms to create models, which classify based on categorical features. In this paper, Random Forests are used owing to their superior performance and faster training times. The Random Forest in scikit-learn (Pedregosa et al. 2011) uses the Random Forest algorithm and the Extra-Trees method, both are perturb-and-combine techniques (Breiman et al. 1998) specifically designed for trees. This is in contrast to the original publication (Breiman et al. 2001), the scikit-learn implementation combines classifiers by averaging their probabilistic prediction, instead of letting each classifier vote for a single class.

The input data is split in 75:25 ratio for training and testing on a randomized basis. When we use 100 decision trees as estimators, the accuracy comes out to be 99% on classifying the visa petitions.

Conclusion and Future Work

As stated in our abstract, we identified companies that acquire H-1B visas disproportionately with non-competitive salary offerings, the exact opposite reason this visa system is designed. It was designed to acquire superiorly talented people across disciplines, which the native people lack or in the case of shortage of abundant talent for vacant positions. There are reports such as the one about Disney that this visa system is used by companies to train their cheap foreign replacements, which is unacceptable.

Our model has certain limitations in that it does not include experience, year of analysis and job level etc. In future, we would develop a more sophisticated classifier, which further uses synthesized features such as weight for job type, experience and develop a complete merit-based visa petition classifier.

References

Trimbach, S., 2016. Giving the Market a Microphone: Solutions to the Ongoing Displacement of US Workers through the H1B Visa Program. Nw. J. Int’l L. & Bus., 37, p.275.
Doran, K., Gelber, A. and Isen, A., 2014. The effects of high-skilled immigration policy on firms: Evidence from H-1B visa lotteries (No. w20668). National Bureau of Economic Research.
Bound, J., Khanna, G. and Morales, N., 2017. Understanding the Economic Impact of the H-1B Program on the US. In High-Skilled Migration to the United States and its Economic Consequences. University of Chicago Press.
Mithas, S. and Lucas Jr, H.C., 2010. Are foreign IT workers cheaper? US visa policies and compensation of information technology professionals. Management Science, 56(5), pp.745-765.
Kaggle H-1B dataset, https://www.kaggle.com/nsharan/h-1b-visa
13 outsourcing companies took nearly one-third of all H-1B visas in 2014, https://www.nytimes.com/interactive/2015/11/06/us/outourcing-companies-dominate-h1b-visas.html
Disney ‘forced 250 of its American IT workers to train up the Indian workers who replaced them’, http://www.dailymail.co.uk/news/article-4037392/Disney-fired-250-American-workers-replaced-Indian-staff-visas-suit-says.html
Breiman, L., 1998. Arcing classifier (with discussion and a rejoinder by the author). The annals of statistics, 26(3), pp.801-849.
Breiman, L., 2001. Random forests. Machine learning, 45(1), pp.5-32.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V. and Vanderplas, J., 2011. Scikit-learn: Machine learning in...
Python. Journal of Machine Learning Research, 12(Oct), pp.2825-2830.