Proposal for the Fall 2017 NABE Tech Economics Conference

AI Technology and the Future of Employment

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ABSTRACT

This project integrates the latest data science methods to identify critical impacts of artificial intelligence and data science on future labor market. The goal is to clarify the specific nature of possible disruptions to the job market, identify and analyze relevant data, and use visualization techniques to identify potential possible actions and policies that may mitigate the impact of automation on jobs. United States employment patterns are a complex mix of factors, including demographics, economics, growth in technology, and government policies on job creation. The issues vary due to regional differences, incentives for new businesses, and the growth in technology. Automation potential estimated by McKinsey is used as the technology index in this project. The research reported here focuses on a particular region first, the Commonwealth of Virginia, as an example of using data science to anticipate disruptions in future employment by artificial intelligence and data science. Further, the analysis is extended from VA to industries on the national level.

Keywords—Employment, Occupations, Technology, Data Science, Artificial Intelligence, Automation

Introduction

United States employment patterns are a complex mix of factors, including demographics, economics, growth in technology, and government policies on job creation. The issues vary due to regional differences, incentives for new businesses, and the growth in technology. The research reported here focuses on a particular region, the Commonwealth of Virginia, as an example of using data science to anticipate disruptions in future employment by artificial intelligence, cognitive assistance, and data science applications. The project uses data on trends in demographics and the economy, models for assessing automation potential of different occupations, and recent technological advances to predict occupation and employment trends in the next decade.

Technology has advanced rapidly for autonomous systems that are human-friendly and provably safe. As decision-making increasingly falls to artificial intelligence, scientists and system developers need to be in conversation with disciplinary experts from philosophy to policymaking to anticipate the impact of autonomous technology on society. This calls for cross-disciplinary research and collaboration to anticipate problems and recommend policies for the future [1-9]. Our position paper exemplifies the cross-disciplinary collaboration typical of artificial intelligence research, and addresses one major example using data for the Commonwealth of Virginia.

AI technologies are advancing rapidly. The technologies at the recent focus have emerged from disciplines including artificial neural networks, brain science, cognitive science, data science, machine learning, and deep learning. Cognitive tasks are no longer secure from being automated [7].

II. Current Work on Technologies and the Labor Market

In the McKinsey articles [1,2], researchers use the concept of *automation potential* to evaluate quantitatively whether a given occupation could be automated by adopting currently demonstrated technologies. To be more specific, the automation potential refers to the percentage of time spent on activities that can be automated by adapting currently available technologies for a given occupation. On O*Net, each occupation is characterized by several work activities that need to be done. Based on 2014 BLS data and O*Net activities descriptions, McKinsey calculated automation potentials for nearly 800 different occupations in the US. Occupations that involves managing, or creating skills, or unpredictable physical work, generally have low automation potential, while occupations that mainly require data collection, or data processing skills, or predictable physical work, have high automation potential.

More specifically, according to the MGI (the McKinsey Global Institute) report [1], the **automation potential** is the technical likelihood of automation. Given currently demonstrated technologies, almost every occupation has partial automation potential, as a proportion of its activities could be automated. So MGI focused on analyzing the automation potential of individual activities rather than the entire occupations. They used the state of technology in respect to 18 performance capabilities to estimate the technical automation potential of more than 2,000 work activities from more than 800 occupations across the US economy (based on data from the US Department of Labor), and then broadened the analysis across the global economy. Specifically, they used a disaggregation of occupations into constituent activities that people are paid to do in the global workplace. Each of these activities requires some combination of 18 performance capabilities, which are in five groups: sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities. Then they estimated the level of performance for each of these capabilities that is required to perform each work activity successfully, based on the way humans currently perform activities—that is, whether the capability is required at all, and if so, whether the required level of performance was at roughly a median human level, below median human level, or at a high human level of performance (for example, top 25th percentile). They then assessed the performance of existing technologies today based on the same criteria.

III. Application to Artificial Intelligence and Jobs

Employment trends over the past decade will be useful and meaningful in identifying features employment patterns and drawing conclusions about future trends in the number and types of jobs. The introduction of AI and data science technologies into business and industry can be tracked for the past decade and that information is available on new and existing technologies expected in the next decade.

Maps may show important relationships of residential centers to areas of high levels of disruption for employment. Demographics for different levels of employment changes may reveal correlations with age, gender, economic level, nationality, religion, health, profession, and employment type. An outcome could be estimates of economic impact of AI and data science technologies on business, industry, and government, including loss of revenue, unemployment levels, and optimism about the future. Our data comes from interviews and surveys of technology and employment subject matter experts, as well as employment data from Virginia agencies. Some anticipated products are geographic distributions of jobs in Virginia, economic impacts of technology, and disruptions in the workplace as a result of recent and anticipated advances in AI and data science technologies. The following figures are examples of the GW group's work on applying ideas from McKinsey to the analysis of automation and employment in Virginia.

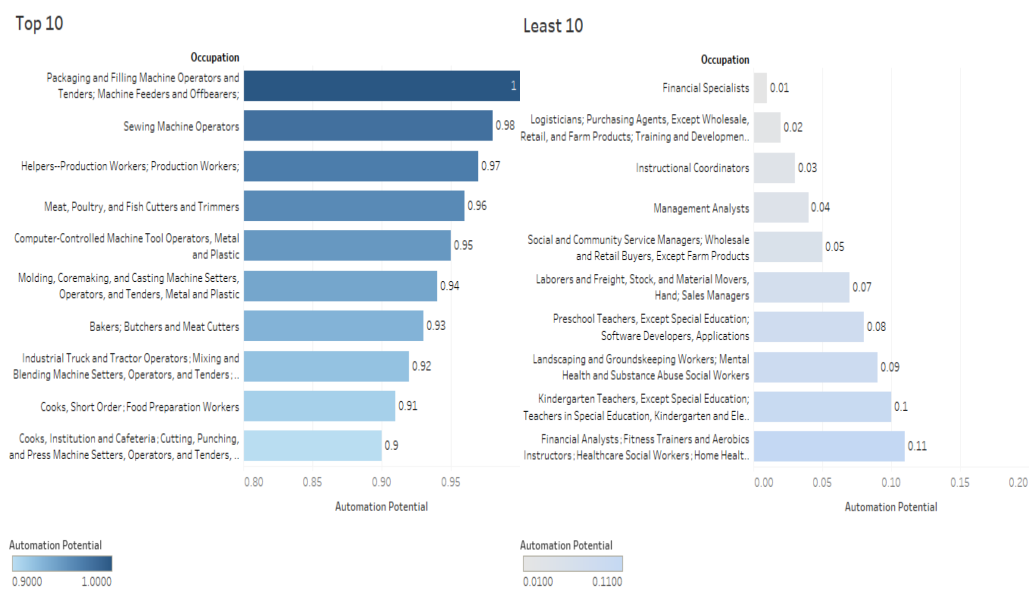

Fig. 1. Occupations with top 10 and bottom 10 automation potential

Fig. 1 shows the detailed occupations that have the top 10 and bottom 10 automation potential from McKinsey. As shown in Fig. 2, we plot the trend of employment (number of employees) of occupations in high and low automation potential group respectively. Most occupations in high automation potential group have decreasing trends, while the other group has a steady increasing trend.

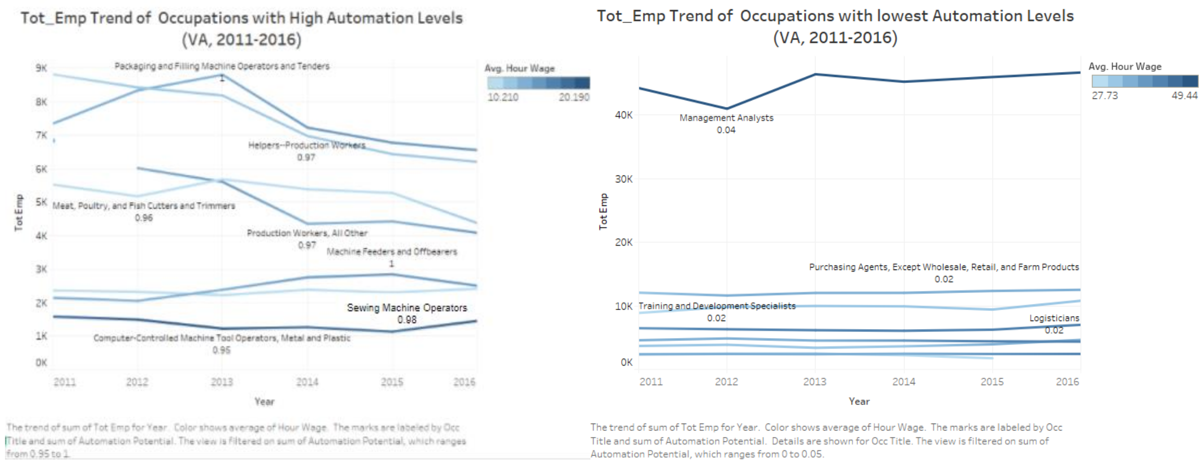

Fig. 2. Top 10 and bottom 10 automation potential occupations employment trend

As demonstrated in Fig. 3, overall, there is a negative correlation between automation potential and the average hourly wage. In this figure, VA occupations that have small populations (<1,000) are omitted. All the occupations are divided into three groups: 1. High automation potential group (the blue points in the figure, automation potential>=0.8); 2. High hourly wage group (the red points in the figure, hour wage>=40$); 3. Others (the yellow points in the figure) All occupations in high automation potential group have relatively low hourly wage (<$25). Correspondingly, the automation potential levels of high hourly wage group are all low and most of them are lower than 0.4. Within each group, the negative correlation still exists.

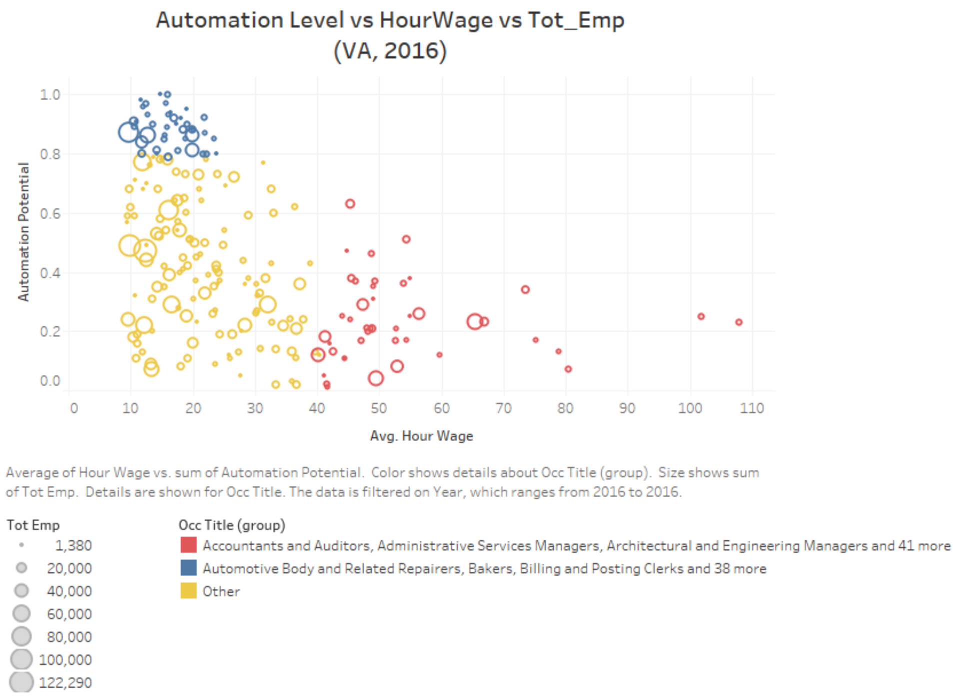

Fig. 3. Correlation analysis between automation potential and hourly wage

Since McKinsey only provided automation potential for detailed occupations in 2014. To extend our analysis, we need to produce automation potential for higher hierarchy (automation potential of each occupation family, state, national industries) data. We use the average (expected) automation potential (weighted by population ratio) according to the following formula:

$$AP_{X_i} = \sum\nolimits_{O_i \epsilon X_i} AP_{O_i} \cdot \eta_{O_i}$$

where $\eta_{O_i} = \frac{n_{O_i}}{n_{X_i}}$, X_i denotes the ith area X of interest

The formula is very easy to implement, and we use this formula to create Fig. 4 and Fig. 6-8. For example, if we want to know the automation potential for VA, we first calculate the population ratio of each detailed occupation in VA, and sum the product of this ratio and its corresponding automation potential over all detailed occupations. The change of average automation potential implies the population flows in different occupations with different automation potential.

Fig. 4 shows the top 5 fast growing occupation families in VA in terms of the average employment number change from 2011-2016. Dark color indicates high automation potential, and “Tot Emp” represents total employment (number of employees). It can be observed that “Food Preparation and Serving Related Occupations” has high average automation potential (>80%), while the other 4 occupation families have relatively low automation potential. Also, the high automation potential occupation has slowest growth regarding hourly wage.

Fig. 4. Fast growing occupation families in VA

As demonstrated in Fig. 5, in these fastest growing occupations, if we select the detailed occupations with top 5 automation potential within each occupation family, it can be seen that most detailed occupations in “Food Preparation and Serving Related Occupations” have very high automation potential (~90%), and they also have relatively high number of employees (18,740 for food preparation workers). Therefore, in the next decade, this occupation family could be impacted most by AI technologies in VA. More analysis and prediction will be done when we collect more detailed data from VA government for in this occupation family.

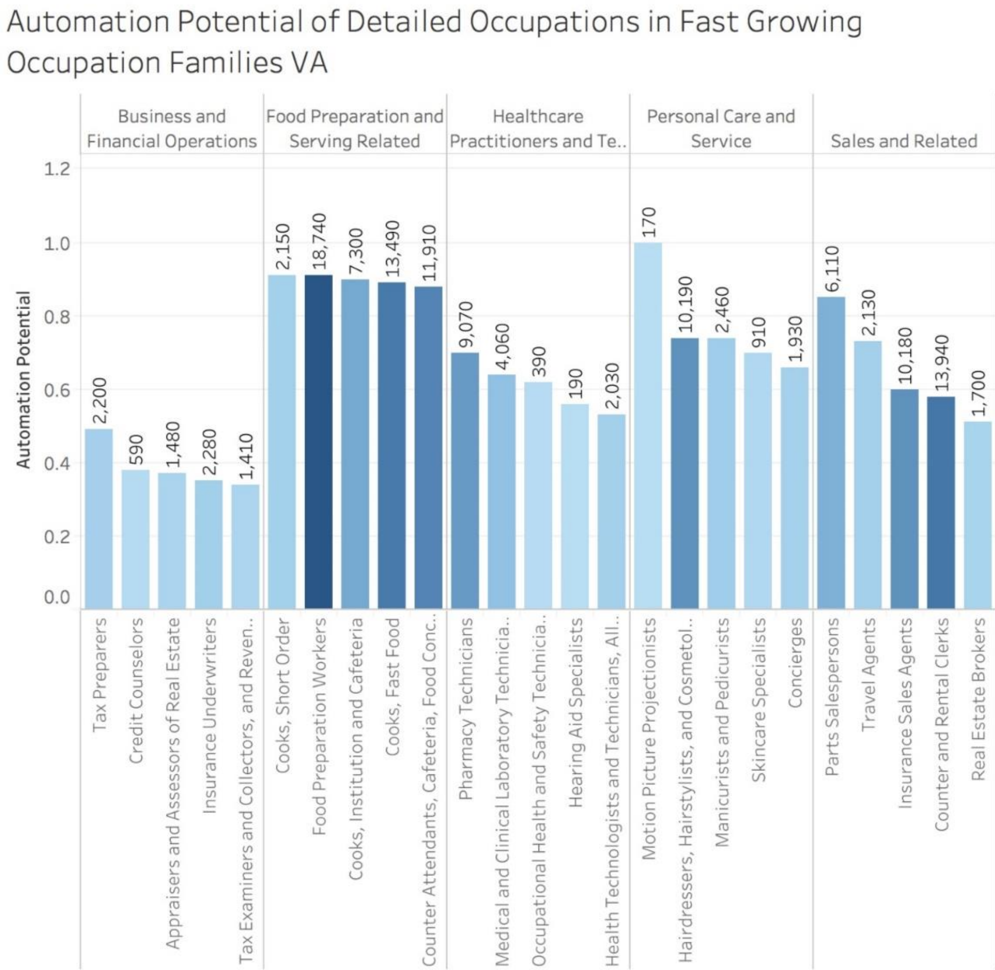

Fig. 5. Detailed occupations with top 5 automation potential in fast growing occupation families

Unlike the results from our analysis of the extreme cases (highest and lowest automation potential in VA), the negative effect of AI on employment is not shown on higher level data. Fig. 6 shows the state map of correlation between automation potential and unemployment rate across 2011-2016. Dark blue color indicates higher negative correlation. We can see that all states (so does Alaska and Hawaii) have negative correlation, and almost all correlations are significant (correlation coefficient <-0.5). Similarly, Fig. 7 shows the state map of correlation between automation potential and employment number across 2011-2016. Dark orange color indicates higher positive correlation. Most states have significant positive correlation (coefficient >0.5). This means AI technologies have not yet impacted the overall labor market at state level.

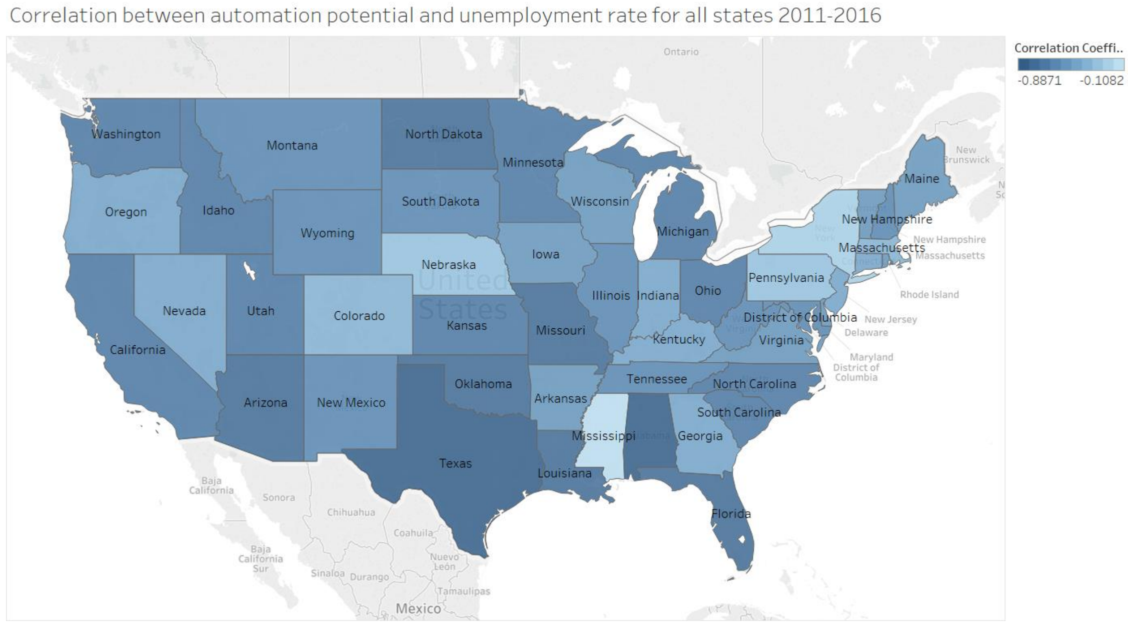

Fig. 6. Correlation between automation potential and unemployment rate by states 2011-2016

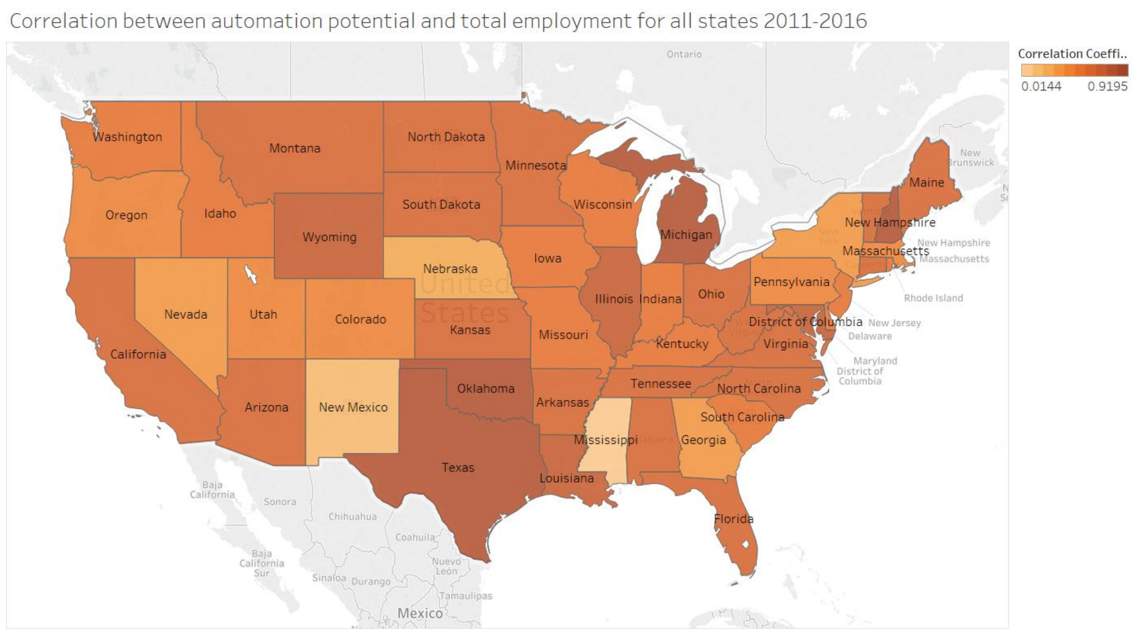

Fig. 7. Correlation between automation potential and total employment by states 2011-2016

Finally, we evaluate the automation potential of each industry at national level. Each industry can have multiple occupation families with multiple detailed occupations. Fig. 9 shows the industries that were in the top 10 and bottom 10 for automation potential in 2016. On one hand, from the top 10 industries, we can see that most industries are related to restaurant and food service, which agrees with our results of analysis on VA occupation families. On the other hand, most bottom 10 industries are related to education. We are going to narrow down our research to these specific occupations and industries under impacts of more specific AI technologies. Section IV shows our initial analysis of impact of cognitive assistance on VA public areas, which might be one of government's interest.

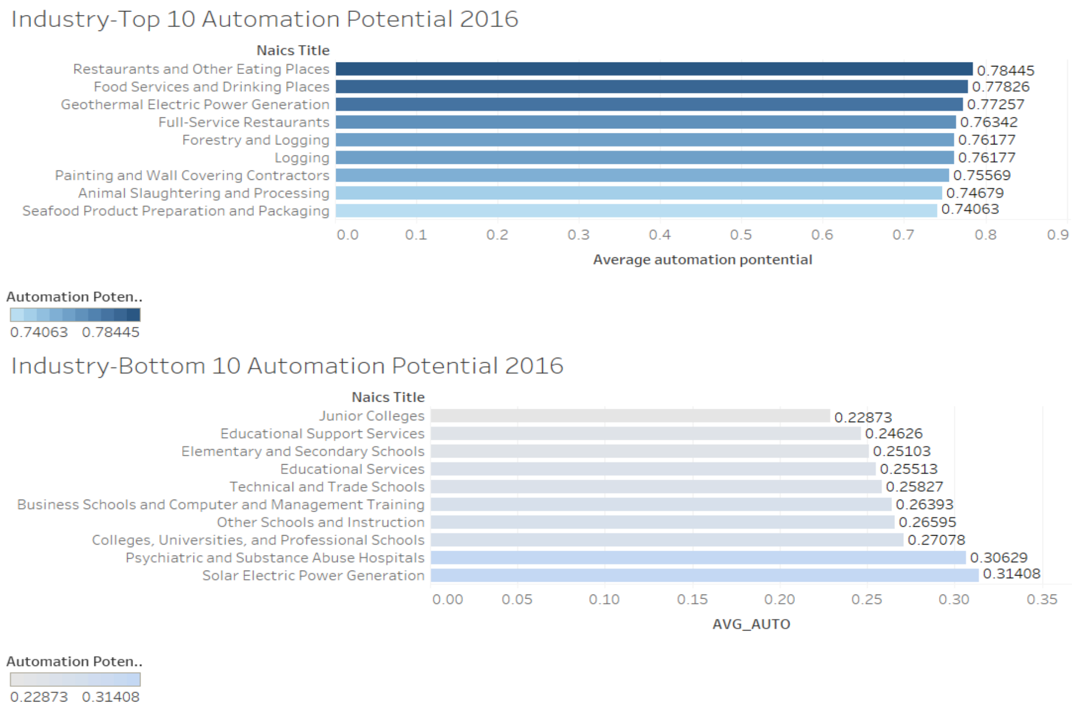

Fig. 8. Industries in the top 10 and bottom 10 for automation potential 2016

IV. A Particular Case: Cognitive Assistance and VA Public Areas

Our research has a focus on the employment areas and occupations expected to be particularly impacted by cognitive assistance technologies. According to Deloitte University Press, "Cognitive technologies are products of the field of artificial intelligence. They are able to perform tasks that only humans used to be able to do" [5]. Current cognitive assistance technologies include uses of machine learning, computer vision, recognition, natural language assistance technologies include processing and robotics. These technologies will have a profound impact on job markets in the next 3-5 years.

On the one hand, they will bring widespread technological unemployment. On the other hand, they will also redesign work, create new positions for employees. We hope all employment areas and occupations that will be impacted (increase or decrease in employment) will be located through our research. What's more, the research aims to predict how big the impact will be and then provide corresponding suggestions for mitigation to government, employees and employers. Currently, we are interested in how cognitive assistance technologies might affect the employment in public areas, including healthcare, education, and community and social service.

Table 1 compares automation potentials in 2011 and 2016 for occupations of interest for growth in cognitive assistance applications.

Year	Occupation Family	OCC_TITLE	TOT_EMP	Automation Potential	HourWage ($)
2011	Healthcare Support	Dental Assistants	7,980	0.51	17.45
2016	Healthcare Support	Dental Assistants	8,230	0.51	19.56
2011	Healthcare Support	Home Health Aides	13,610	0.11	9.46
2016	Healthcare Support	Home Health Aides	11,340	0.11	10.88
2011	Healthcare Support	Medical Assistants	10,220	0.54	14.63
2016	Healthcare Support	Medical Assistants	12,510	0.54	15.68
2016	Healthcare Support	Nursing Assistants	37,170	0.44	12.52
2016	Healthcare Support	Phlebotomists	3,640	0.89	15.94
2011	Healthcare Practitioners and Technical	Dental Hygienists	4,490	0.13	39.08
2016	Healthcare Practitioners and Technical	Dental Hygienists	4,970	0.13	39.76
2011	Healthcare Practitioners and Technical	Licensed Practical and Licensed Vocational Nurses	20,570	0.16	18.88
2016	Healthcare Practitioners and Technical	Licensed Practical and Licensed Vocational Nurses	21,410	0.16	19.93
2016	Healthcare Practitioners and Technical	Nurse Practitioners	4,630	0.21	48.58
2011	Healthcare Practitioners and Technical	Occupational Therapists	2,350	0.25	38.23
2016	Healthcare Practitioners and Technical	Occupational Therapists	2,850	0.25	43.97
•	••••••••	•••••••••	••	•	•
2011	Education and Training	Self-Enrichment Education Teachers	3,490	0.23	20.17
2016	Education and Training	Self-Enrichment Education Teachers	••	0.23	20.73
2016	Education and Training	Special Education Teachers, Kindergarten and Elem	5,240	0.1	•
2011	Education and Training	Teacher Assistants	30,100	0.2	•
2016	Education and Training	Teacher Assistants	30,360	0.2	•
2016	Education and Training	Teachers and Instructors, All Other, Except Substitu	9,080	0.19	•
2011	Education and Training	Vocational Education Teachers, Postsecondary	1,410	0.12	25.68
2016	Education and Training	Vocational Education Teachers, Postsecondary	1,790	0.12	25.74
2011	Community and Social Service	Child, Family, and School Social Workers	8,050	0.19	22.46
2016	Community and Social Service	Child, Family, and School Social Workers	8,620	0.19	24.42
2011	Community and Social Service	Educational, Guidance, School, and Vocational Cou	6,230	0.14	28.05
2016	Community and Social Service	Educational, Guidance, School, and Vocational Cou	6,610	0.14	30.89
2011	Community and Social Service	Healthcare Social Workers	2,490	0.11	23.88
2016	Community and Social Service	Healthcare Social Workers	2,990	0.11	26.01
2011	Community and Social Service	Mental Health and Substance Abuse Social Workers	2,950	0.09	22.14
2016	Community and Social Service	Mental Health and Substance Abuse Social Workers	4,210	0.09	23.68
2011	Community and Social Service	Mental Health Counselors	7,390	0.26	21.31
2016	Community and Social Service	Mental Health Counselors	8,980	0.26	23.23
2011	Community and Social Service	Rehabilitation Counselors	4,100	0.31	16.93
2016	Community and Social Service	Rehabilitation Counselors	3,010	0.31	20.07
2011	Community and Social Service	Social and Community Service Managers	2,370	0.05	34.30
2016	Community and Social Service	Social and Community Service Managers	2,440	0.05	41.16
2011	Community and Social Service	Social and Human Service Assistants	6,870	0.42	14.35
2016	Community and Social Service	Social and Human Service Assistants	6,750	0.42	15.38

Table 1. Data of occupations in public areas 2011 vs. 2016

As illustrated in Fig. 9, except for several occupations in healthcare support, most occupations in public areas have a relatively low automation potential (<30%).

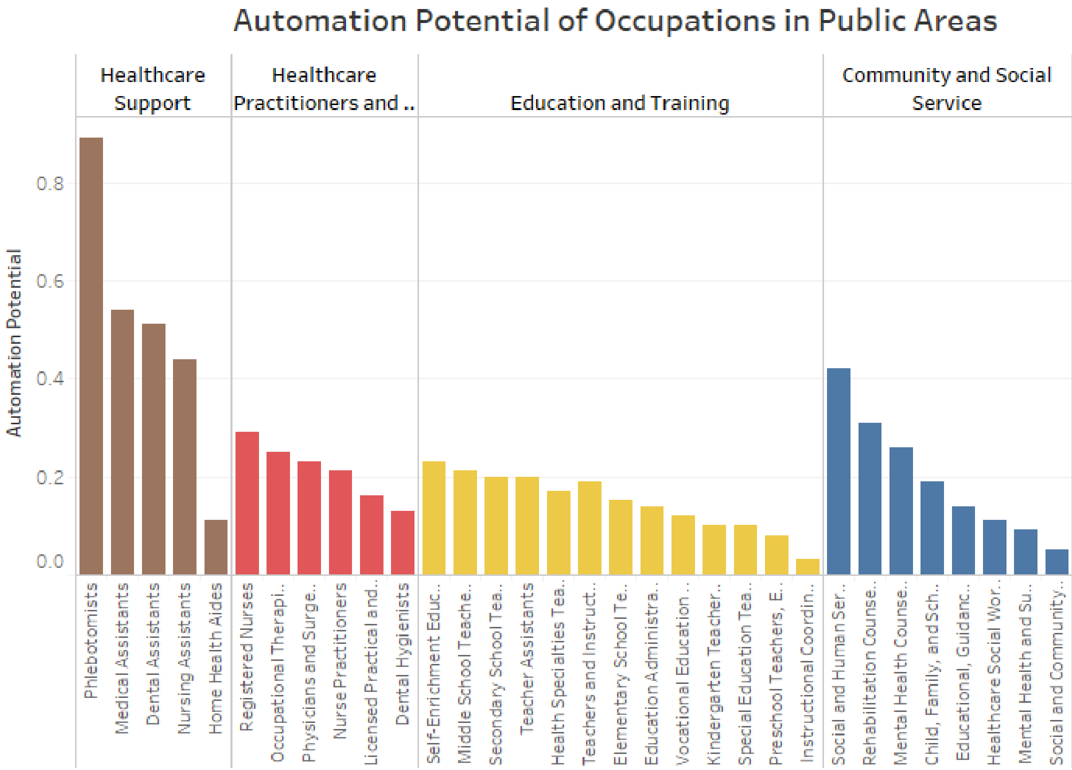

Fig. 9. Automation potential of detailed occupations in public areas

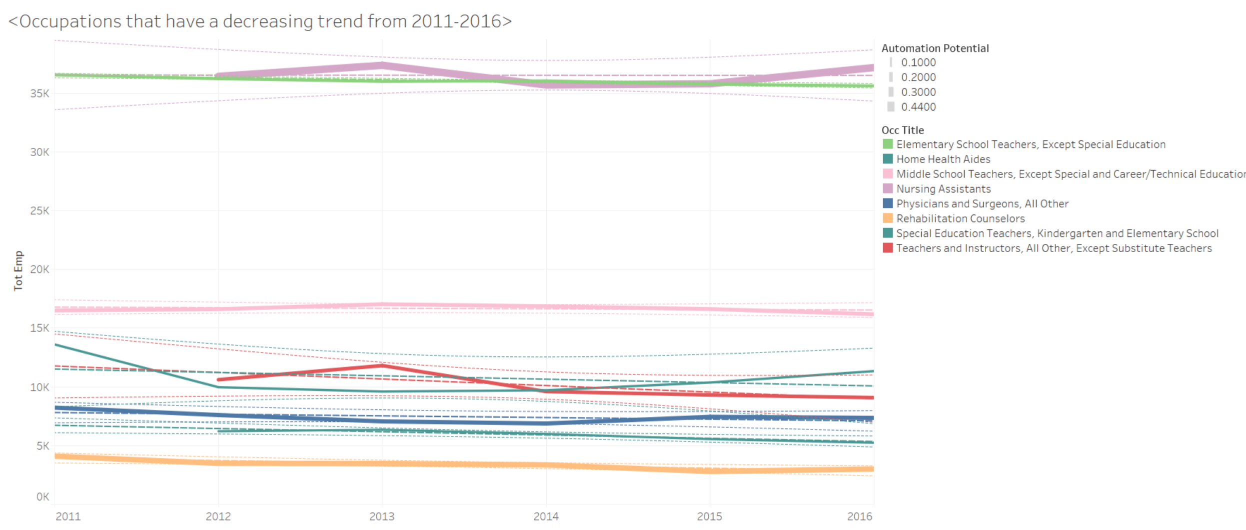

Fig. 10. VA occupations in public areas with decreasing trends 2011-2016

As shown in Fig. 10, fitting linear models, 8 out 32 of these occupations have a decreasing trend; however, the decreasing over the last 6 years is not significant.

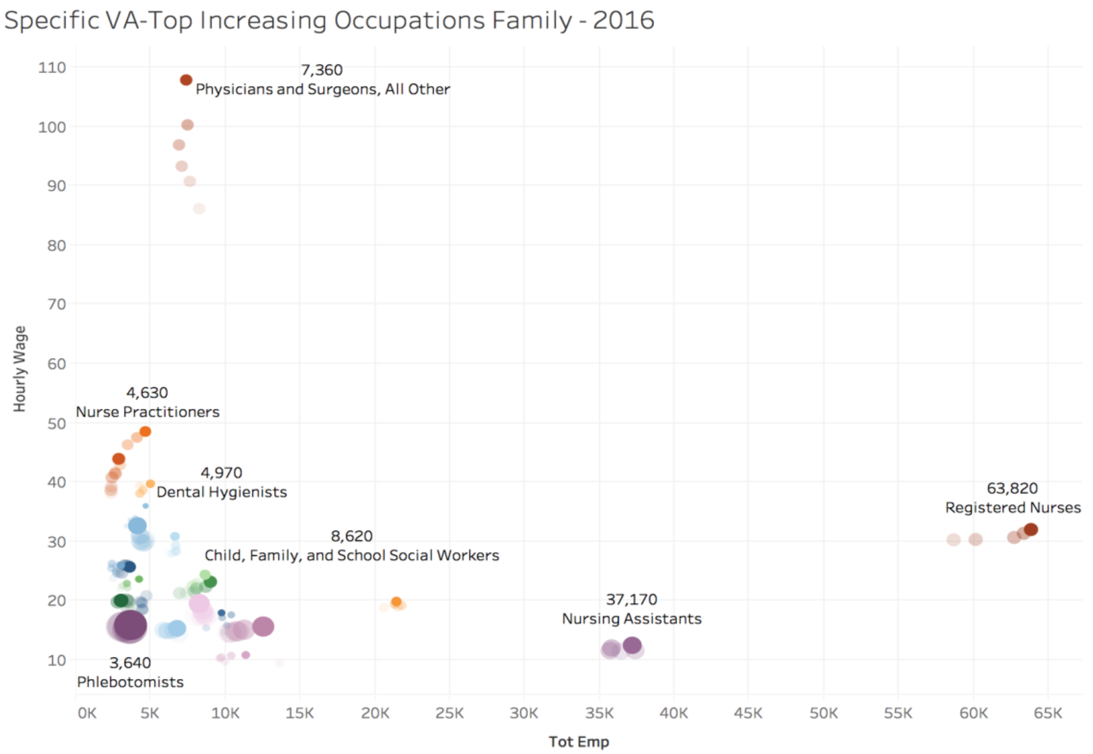

Fig. 11. VA top increasing occupations in public areas 2011-2016

In the bubble chart illustrated by Fig. 11, colors indicate different areas of occupations (green/Government, orange/Healthcare Practitioners and Technical, purple/Healthcare Support, and blue/Education) The size of bubbles indicates the automation potential (AP) of all occupations, we are able to tell that occupations with low AP were more likely to have a speedy increase in wage and employment amount (jobs in Government, Education and Healthcare Practitioners and Technical areas). Those occupations with high AP were increasing slowly or even decreasing (Healthcare Support). Except for the extraordinary growth on the amount of mental health counselors in Virginia, the state level movement almost syncs with the national level movement. Furthermore, although most education-related and government related occupations were less likely to be replaced by AI, and also the total amount was increasing, they still shared a low pay raise in both nationwide and Virginia-wide. Furthermore, although most education-related and government-related occupations were less likely to be replaced by AI, and also the total amount was increasing, they still shared a low pay raise in both nationwide and Virginia-wide.

V. Discussion and Next Steps

We have shown the possible usefulness of adapting the McKinsey model to gain insight into the impact of AI technologies on the labor market. To summarize our preliminary findings, in the extreme cases (for occupations with highest and lowest automation potentials), automation potentials and employment (number of employees) have a negative correlation. However, overall, at state and national levels, automation potential has a negative correlation with unemployment rate, and has a positive correlation with number of employees. For most states, the expected automation potentials are increasing. In our model, this means population flows from occupation with relatively low automation potential to high automation potential. If this trend keeps growing, it could be dangerous for the labor market in the next decade, when most people in these occupations can be replaced. There is a negative correlation between automation potential and salary, which implies increasing automation potential in one occupation might lead to stagnate salary. Occupations in most public areas have relatively low automation potential, and these occupations can probably be considered still “safe” from being automated by current technology. Applying new technology to these related industries could be more beneficial (such as applying cognitive assistance technologies to education and healthcare areas).

Interesting issues that arise from this study are the dual roles of cognitive assistance for decreasing and increasing employment. As a member of the technologies involving AI and data science, occupations with high automation potential could be negatively impacted by cognitive assistance technologies. Cognitive assistance could however enhance and expand jobs negatively impacted by other technologies AI, thus mitigating the effect of AI. Occupations with low automation, while not threatened by AI, could use cognitive assistance to improve productivity and job satisfaction.

Some of the technologies McKinsey modeled have not likely yet reached their eventual peak in adoption. In addition, the automation potential was evaluated and computed in 2014, which might be out of date considering the rapid development of AI in the last few years. The results we presented here might be too optimistic. We can potentially follow their research methods, combining some AI technology, to develop a useful expect system with machine learning techniques to produce timely automation potentials for more in-depth analysis.

Our next step is to obtain a large amount of more detailed data on individual employment and job loss. We will then apply machine learning techniques and economic models to evaluate occupations and industries with highest automation potential (such as restaurants and food service) using deep learning techniques in Tensorflow to produce timely automation potential data.

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