Effects of Technology on Jobs and Employment

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Introduction

Introduction of digital computers transformed work in every sector in past decades. We are now seeing such another major transformation of society and work force due to rapid advances of artificial intelligence and automation and there are mixed feelings about this phenomenon

As the robots and technology develops and replace some of the previous work, there are questions about the future of jobs: will the robots replace humans at the workplace. The worry and questions seems justified. However, history shows that robots and technology does often lead to growing employment

According to James Bessens, the reasons why impact of this automation on jobs is different because the nature of demand for the employment (job skills) is changing over time. That’s why the automation sometimes leads jobs growth and sometimes not.

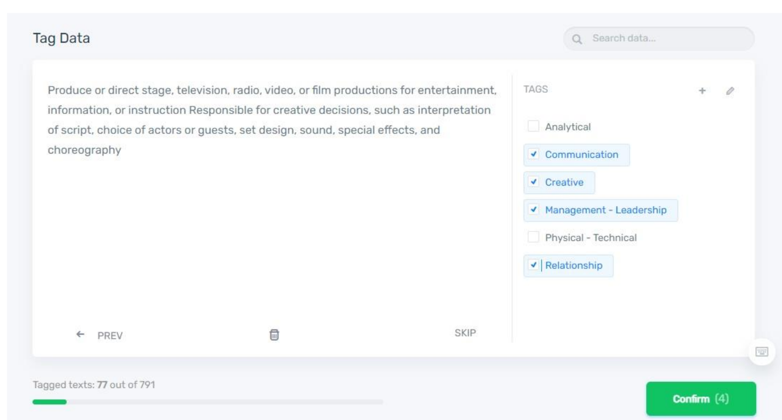
In my research I will be identifying these job skills, making connection with automation and using this information then will be trying to estimate the overall effect of automation on job growth and how it can affect the future.

Methodology

Required Skill Estimation: I aimed to define the skills required for each occupations and how much of it can be automated. For that I used the **qualitative secondary data** about description of occupation and skill categories.

For estimating the required skills for each occupation I used the MonkeyLearn’s Text classifier which works in the following way:

1. Create the categories you want to classify any text (in our case: you create <u>6 categories</u> for <u>*skills*</u>)
2. Input the data you want to train the text (in our case: you input the descriptions of jobs which we are going to classify with necessary categories – <u>791 minor job descriptions</u> (data) in detail)
3. Train the data (subjectively classify each data with skill category. In our case: I trained 100 data out of 791)
4. Test the data (input any text you want to classify, In our case: description of the major occupation group)

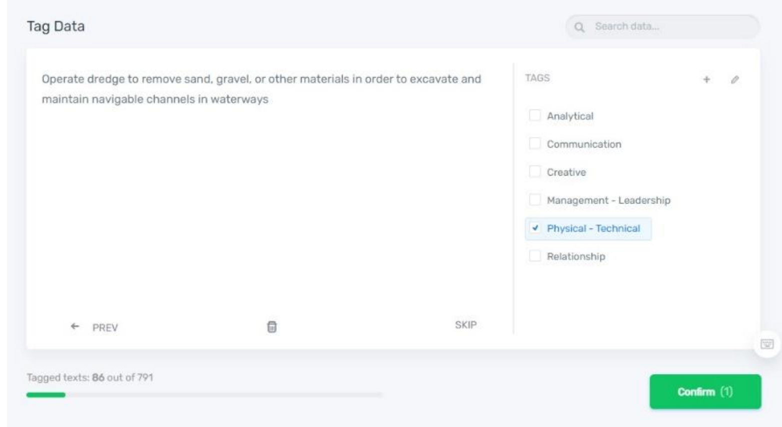


*(Job Descriptions, above: **Producers and Directors**, below: **Dredge Operators**)*

Remark: For skill categories I used the skill classification of SkillScan.com, which classifies skills into 6 categories:

Relationship, Communication, Management-Leadership, Physical-Technical, Creativity and Analytical.

Source: https://www.skillscan.com/sites/default/files/chart-of-skill-sets.pdf



Remark: For minor job descriptions I used the data from the U.S. Bureau of Labor Statistics, which divides occupations into major, broad and minor categories.

Source: https://www.bls.gov/soc/2018/home.htm

Biases and Shortcomings: When training the data, I was generous with classifying jobs in “Management – Leadership” category, because we can argue that in every occupation there are hierarchies and hierarchies need management. So, there can be unexpectedly high value for this category for some jobs.

When classifying the “Communication” and “Relationship” categories, which are very similar, many times I didn’t consider classifying some jobs for both of them and I chose the “Communication” category more often. It can give more biases for these categories.

Text classifier shows the assigned categories for test data with just HIGH confidence. Which means that if some occupation uses the few “Physical – Technical” skills (such as for voice and audio operators – which can be automated by AI generated voice operators), we cannot estimate. Therefore, our analysis only estimates the potential of HIGH automation values of major occupation groups

When we check the text classifier’s “Physical – Technical” word cloud – which is generated after training the data (in our case: after training 100 data) and then is used to test the new data:

From the word cloud we see that there are words which cannot be fully automatized. For example: devise, navigation – which still need the human management for these. Therefore we have to adjust our potential automatable measures: if we find that occupation “x” has “y” percent of “Physical – Technical” skills, we will say that 90% of this “y” percent can be technically automatized (85% is subjective choice).

Note as well that NOT ONLY “Physical – Technical” skills can be automated, but also some of the “Management” or “Communication” skills as well, but not as widely and as strongly as the former one. Our analysis is concerned only with “Physical – Technical” skills and our estimate is considered to be the MINIMAL possible automatable potential for employment.

Forte: In spite of all the biases and flaws of our method, there is no better way to estimate the skill requirement for occupations:

1. You need to have JOB DESCRIPTION for each job to decide which skills it needs.

2. How much of each job skill is needed can be estimated by how STRONGLY or CLEARLY it is stated in the description of this job -> and estimation of that can be mostly subjective, because not every job is exactly same even in the same occupations.
3. Deep Learning (built in Text Classifier) can estimate Frequency or Confidence of category that is written in given description (text).

The main point is that, we cannot have EXACT answer or estimation for statistics that we are using, but we can ALWAYS make the estimation better with training of more data and with using better models making our subjections more objective.

Forecast: My goal was to give the future prediction on the historical data based on the past. In this case, historical data was about the global employment since 1990s. I used the International Labour Organization website (https://www.ILOStat.ILO.org/) for source. Downloaded quantitative secondary data then processed in R software. Used the `forecast` package and made the forecast prediction using ARIMA Model.

Bias: There can be used much better models for predictions, but among the others that I could choose – naïve and VAR – I used the one that looked good and easy to use.

Results & Analysis

Data Table 1: Occupation Classification According to Skills

	Employment Quota of Total (%)	Relationship	Communication	Management / Leadership	Analytical	Creative	Physical / Technical
Architecture and Engineering Occupations	1.04%			96.3%	100.0%		71.6%
Arts, Design, Entertainment, Sports, and Media Occupations	0.92%		69.5%	65.0%		73.0%	
Building and Grounds Cleaning and Maintenance Occupations	6.49%			100.0%			100.0%
Business and Financial Operations Occupations	9.27%		75.8%	100.0%	92.2%		
Community and Social Service Occupations	2.48%			91.6%			
Computer and Mathematical Occupations	2.00%			61.7%	100.0%	92.1%	
Construction and Extraction Occupations	4.93%			84.0%			100.0%
Educational Instruction and Library Occupations	7.21%	100.0%	93.0%	100.0%			
Farming, Fishing, and Forestry Occupations	0.41%			100.0%		85.5%	
Food Preparation and Serving Related Occupations	5.53%	100.0%	86.8%	100.0%			72.3%
Healthcare Practitioners and Technical Occupations	0.71%		83.3%	100.0%			
Healthcare Support Occupations	0.78%	85.6%	100.0%	100.0%			
Installation, Maintenance, and Repair Occupations	5.20%			100.0%			100.0%
Legal Occupations	0.50%		100.0%	100.0%	100.0%		
Life, Physical, and Social Science Occupations	1.03%				100.0%		
Management Occupations	3.27%			100.0%			
Office and Administrative Support Occupations	10.27%			93.5%	100.0%		
Personal Care and Service Occupations	3.68%		95.6%	100.0%			
Production Occupations	13.06%			82.9%			98.4%
Protective Service Occupations	2.97%			100.0%	60.1%		77.4%
Sales and Related Occupations	14.11%		94.2%	100.0%			
Transportation and Material Moving Occupations	4.15%			100.0%			70.7%

So potential automaticity for future employment is :

$$\begin{pmatrix} 1.04\% * 71.6\% + 6.49\% * 100\% + 4.93\% * 100\% + 5.53\% * 72.3\% + \\ +5.20\% * 100\% + 13.06\% * 98.4\% + 2.97\% * 77.4\% + 4.15\% * 70.4\% \end{pmatrix} * 90\% =$$

$$= 39.44\% * 90\% =$$

$$= \mathbf{35.5}\%$$

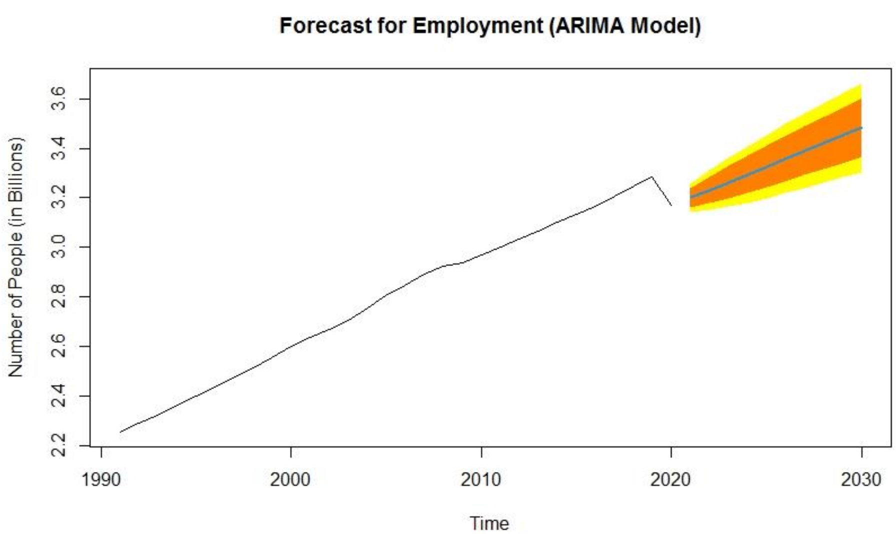
Note that, according to the McKinsey&Company research and analysis the estimated 49% activities that people are paid to do in the global economy have the potential to be automated by adapting currently demonstrated technology.

If we had trained our data more and well, if we had considered automation in other skill categories, and if we had estimated precisely how much of Physical – Technical skills are related to ONLY machines, we could have gotten better estimate.

However, goal in our research is to find the least boundary for the estimation.

Global Trend for Employment

Let's see how the trend for employment was doing in the last 30 years, and let's project the forecast of this trend in following 10 years



Code is generated from R language with plot function
*Orange Line – **80%** confidence area, Yellow Area – **95%** confidence area*

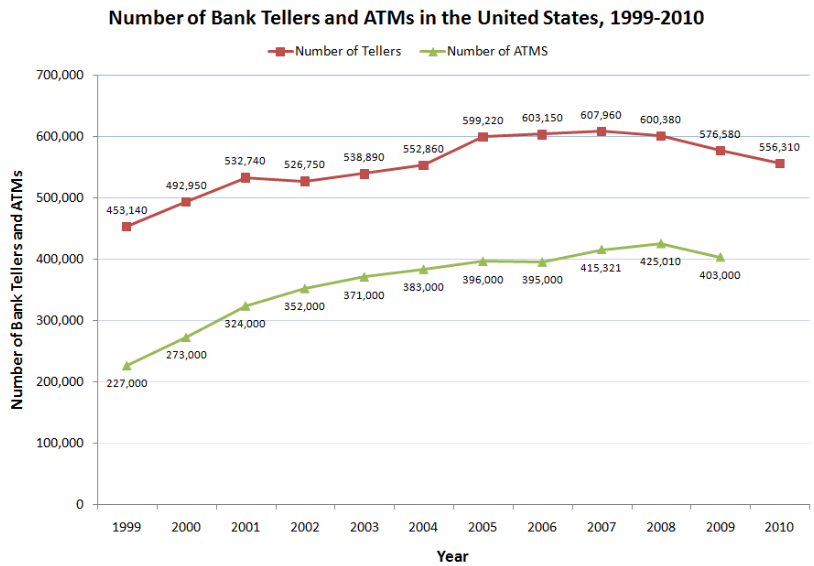
Year	Employment (In Billions)
2021	3.20
2022	3.23
2023	3.26
2024	3.29
2025	3.33
2026	3.36
2027	3.39
2028	3.42
2029	3.45
2030	3.48

According to our analysis, as of 2030 there is potential that up to billions (35.5% of 3.48 billion) people worth of job can be automated assuming that in the following 10 years the required technology would be developed, which sounds alarming. However we have to approach this differently.

Trend for employment was growing since 90s, with one exception in 2020 due to pandemic, where we see that line is going down, and is projected to grow in the future as well. There has been many technological changes in the past but the employment always kept increasing not just globally, but in its very own sector where this change was happened.

For example, introduction of Excel in early 1990s should have threatened the jobs for accountants and bookkeepers and their employment because almost all of their functions can be executed in Excel and can be executed in different files simultaneously and instantly. However, opposite of this happened and there was boom for demand on accountants and auditors and it is still now.

Introduction of ATM machines in late 1990s would suggest that people needed behind the counters in the bank would decrease because one of the most important function for bank teller was deposit or withdraw from guy's bank account and now with the ATM, it can be done instantly and waiting for hours can be avoided. Thus, demand would decrease and there wouldn't be need for many bank tellers. But again, number of bank tellers increased as the number of ATMs increased.



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This is not straightforward: more technological advancements doesn't imply that people will be kicked from their jobs. It can even have the positive effect and here is why:

With the help of automation
workers can use time and energy effectively by reducing the doing of repetitive and redundant tasks,
people and companies can have higher productivity from decreasing the errors and mistakes,
some teams and individuals by using AI and deep learning can be equipped with high-level, complex analytical and research skills and used for god know what. The limits and boundaries for use and application of machine learning are yet to be identified.

Improves **productivity** and **effectiveness** of People and Business

Increases the **profitability** of the business and the **growth** of capital of the business

Growth of business implies more people will be **employed**

So, this is very hard to identify: Exactly what factors correlate with automation and job employment positively, and at what rate. This is very delicate subject to do research about it and it goes beyond my energy, time and ability.

Conclusion

The question about technology and man and how they work and coexist together has been, is, and will be the actual and important topic to discuss about it. We are witnessing the development of new technology which is predicted to bring more consequences that any other predecessor did. The study of this phenomenon is very actual and mainstream thing.

And I did some researching and some studying as well: considered the different ways automation can affect the job growth, estimated the capacity of how much can automation affect the world employment and tried to forecast the results for the following 10 years. At least 35% of jobs can be gone in the future but we don't know this exactly. We can only observe current events and trends, take some guesses about the future situation and have hopes for the better and improved life and environment. We have come this far having many ups and downs in our history, and we can continue from now on as well.

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