AUTOMATION, UNEMPLOYMENT, AND GPT-3

UNIVERSAL BASIC INCOME AS A COUNTERMEASURE TO AUTOMATION-RELATED UNEMPLOYMENT

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By
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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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As the fourth industrial revolution boosts productivity and efficiency through automation, the labor market is simultaneously jeopardized as, "47% of people employed in the US are at risk of being replaced by machines" (Gray, 2017, p.3). Widespread automation will lead to higher corporate profit margins at the cost of an increased unemployment rate, which has real-world consequences and could wreak havoc on society unless countermeasures are directly taken to offset increased unemployment.

The technical research and strongly coupled STS research aim to provide information that will lead to increased public awareness of the risks of automation. More specifically this research aims to present the relationship between automation and the unemployment rate, the effect of a changing unemployment rate on society, and what can be done to mitigate possible negative societal consequences resulting from automation. The technical objectives are threefold: (1) to present an overview of the current research defining the relationship between automation and the unemployment rate; (2) to quantify the changes resulting from an increased unemployment rate; (3): to examine a case study on the automation of the software development industry using the natural language processing model GPT-3. The findings will be presented in a state-of-the-art report. Tightly coupled, the STS research explores using different variants of Universal Basic Income (UBI) as a countermeasure to the negative consequences associated with mass unemployment as a result of widespread automation and analyzes this solution through the STS framework of technological momentum.

AUTOMATION AND UNEMPLOYMENT

While many researchers propose that automation in the fourth industrial revolution will lead to an increased unemployment rate through workers being replaced, some researchers argue that automation will lead to a decreased unemployment rate tying parallels to the first industrial revolution where many factory jobs were created. Rising wages led to, "The average worker was[being] much better off in any decade from the 1830s on than any decade before 1820" (Majewski, 1986, p.4). One particular case study can be analyzed to predict the effects of the fourth industrial revolution. By examining the statistical relationship between automation and the unemployment rate, Anakpo & Kollamparambil (2021) sought to quantify the economic impact of automation. Applying a pVAR-Granger Causality Wald test on "panel data collected from 2004 to 2017 on 10 Southern African countries" (p. 3), Anakpo & Kollamparambil discovered the following:

> The result (see Table 5) shows that automation is significantly positively related to unemployment (that is, it reduces employment). This finding reinforces studies by Frey and Osborn (2013) and Anakpo and Kollamparambil (2021) that the explosion of digital technology and computerisation with cases of automation displaces labour especially in routine tasks, which involves explicit rule-based activities, and causes a high level of deskilling, which leads to a major shift in the occupational structure of the labour market. The authors (Frey & Osborn, 2013) conclusively predicted a total of 47% job loss in the United States (US) by 2030. Estimates of how many jobs are vulnerable to being replaced by machines vary but it is clear that developing countries such as those in Southern Africa are more susceptible to automation due to the fact that the majority of workers are in routine occupations compared to high-income countries. For instance, it was estimated that over 90% of workers in Southern Africa are at risk of losing their job in the near future due to automation (since most work in routine occupations with relatively low skill requirement) as compared to an estimated amount of 47% of the total US in the near future (Anakpo & Kollamparambil 2021, p.8).

HUMAN COST OF UNEMPLOYMENT

With nearly half of all US workers and over 90% of South African workers being a risk of losing their job to automation, it is crucial to examine the societal impact of an increased automation rate. Crudele (2020) argues that an increased unemployment rate has disastrous real-world consequences as only a, "1 percent increase in the unemployment rate will be associated with 37,000 deaths" (p. 3). Many of these deaths are preventable and could be saved if an offset to the increased unemployment rate was considered. Additionally, of these 37,000 deaths, 20,000 are caused by heart attacks and 920 are from suicide (p. 3). Despite manifesting as a physical ailment, heart attacks are frequently caused by excess stress which can be attributed to deteriorating mental health, something that simultaneously increases the risk of suicide. While addressing mental health concerns may reduce some of the negative societal impact caused by an increased unemployment rate, a universal basic income is posed to be a better remedy. In the STS project, I will more thoroughly examine possible countermeasures to mitigate the negative societal impact described by Crudele.

GPT-3: A CASE STUDY

In order to better understand how the automation of an industry occurs, the technical research will explore a case study of the automation of programming in the software development industry by the autoregressive natural language processing model GPT-3. Natural Language Processing (NLP) models are used to make computers understand and generate new language. Despite most modern NLP's using newer technology such as neural networks and deep learning, NLP's have been around since the Georgetown-IBM experiment where, "on January 7th 1954… the IBM 701 computer automatically translated 60 Russian sentences into English for the first time in history" (Mandal 2019, p.1). The two main types of NLP's are rule-based and deep learning based. An example of a rule-based NLP, which is commonly referred to as a classical NLP, can be seen in Figure 1 below:

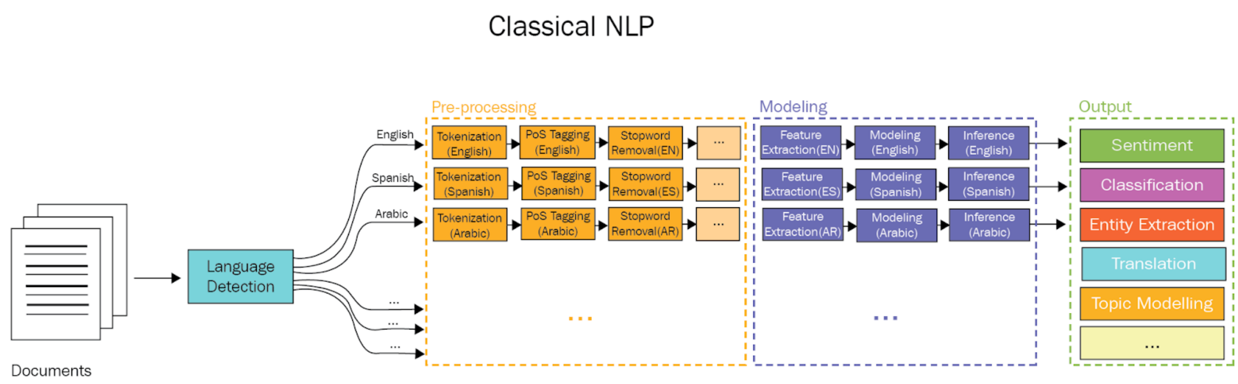

Figure 1: Rule-Based Classical Approach NLP Model. Uses modeling to generate an output (Thanaki 2022).

It is essential to note the laborious pre-processing that is needed to correctly format the text before the model can be constructed. When describing the disadvantages of using a classical rule-based NLP model Dorash (2017) argues, "Rules need to be manually crafted and enhanced all the time. Moreover, the system can become so complex, that some rules can start contradicting each other" (p.2). Language is nuanced and complicated, riddled with tonality and sarcasm at times. Additionally, slang is frequently used stopping a rule-based NLP model from being able to generate useful output. Having a system that can adapt to changes and is not boxed in by strict rules is extremely beneficial when dealing with language processing. Deep learning comes in handy as there are no strict rules, but instead, "Deep learning algorithms attempt to draw similar conclusions as humans would by continually analyzing data with a given logical structure" (Oppermann 2019, p.4). An example of a deep learning NLP can be seen in Figure 2 below.

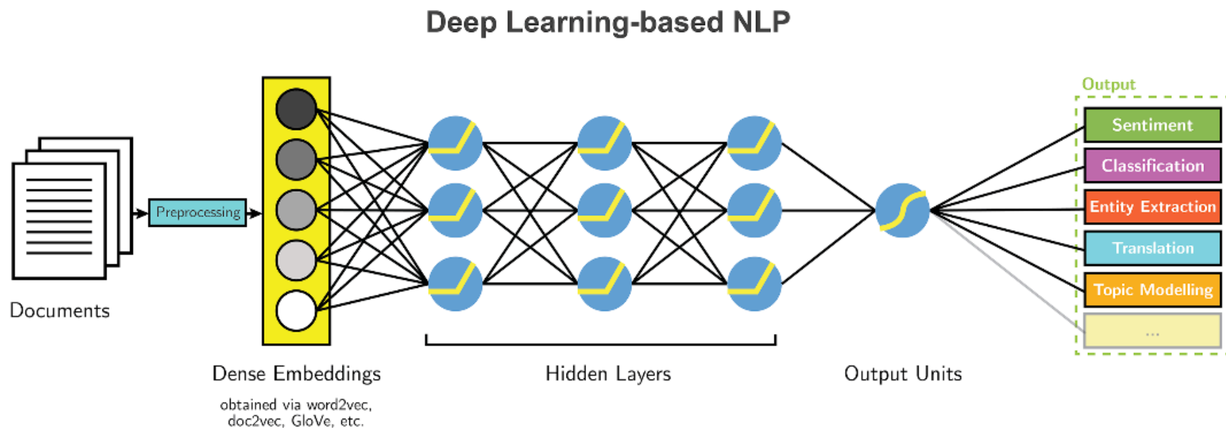

Figure 2: Deep Learning Approach NLP Model. Uses hidden layers with many nodes to generate an ouput (Thanaki 2022).

GPT-3, an autoregressive deep learning natural language processing model made by the AI company OpenAI, is the most advanced NLP model known to date and has been described as, "An AI that is better at creating content that has a language structure – human or machine language – than anything that has come before it" (Marr 2020, p.1). As well as being used for common uses of NLP such as language translation, speech recognition, and classification, the technology behind GPT-3 is used to run Copilot by GitHub which is, "a new machine learning tool that translates your text in the English language into code… designed to speed up the work of professional programmers" (Vincent 2021, p.1). Though still in the initial stages, Copilot can autocomplete code based on an English description. As the name implies, Copilot is designed to boost the efficiency of software developers and has not currently replaced software developers. However, some researchers who extrapolate the current progress of NLP's into the future have raised concerns about the automation of the software development industry. Gherciu (2022) argues, "more sophisticated future code generation tools could potentially lead to the displacement of some programmer or engineer roles, and could change the very nature of programming work" (p.191). This case study on GPT-3 can be applied to view how many highly education white-collar industries risk displacement through automation as NLP's get exponentially more powerful and skill diverse. For the technical project, I will be writing a scholarly article.

UNIVERSAL BASIC INCOME AS A COUNTERMEASURE

As automation increases, countermeasures will need to be taken to offset and mitigate the consequences stemming from automation in order to preserve a functioning society. As unemployment directly increases the heart attack and suicide rate, one mitigating solution is to expand mental health care access and provide supplemental health care benefits to those laid off as a result of automation. Heart attacks and suicide are frequently caused by excess stress which can be attributed to deteriorating mental health, something that can be improved by improving access and affordability. More impactful though, would be a form of Universal Basic Income (UBI) to those laid off as a result of automation. UBI is not a new concept dating back to Ancient Rome where Julius Caesar, " distributed his wealth to the people of Rome, leaving 300,000 sesterces to each citizen" (Fife 2012, p.1). UBI in its simplest form is, "a government program in which every adult citizen receives a set amount of money regularly" (Peters 2021, p.1). As a result, UBI would mitigate the negative consequences stemming from automation by bringing those unemployed as a result of automation above the poverty line until they could acquire the skills and training necessary to become hirable again.

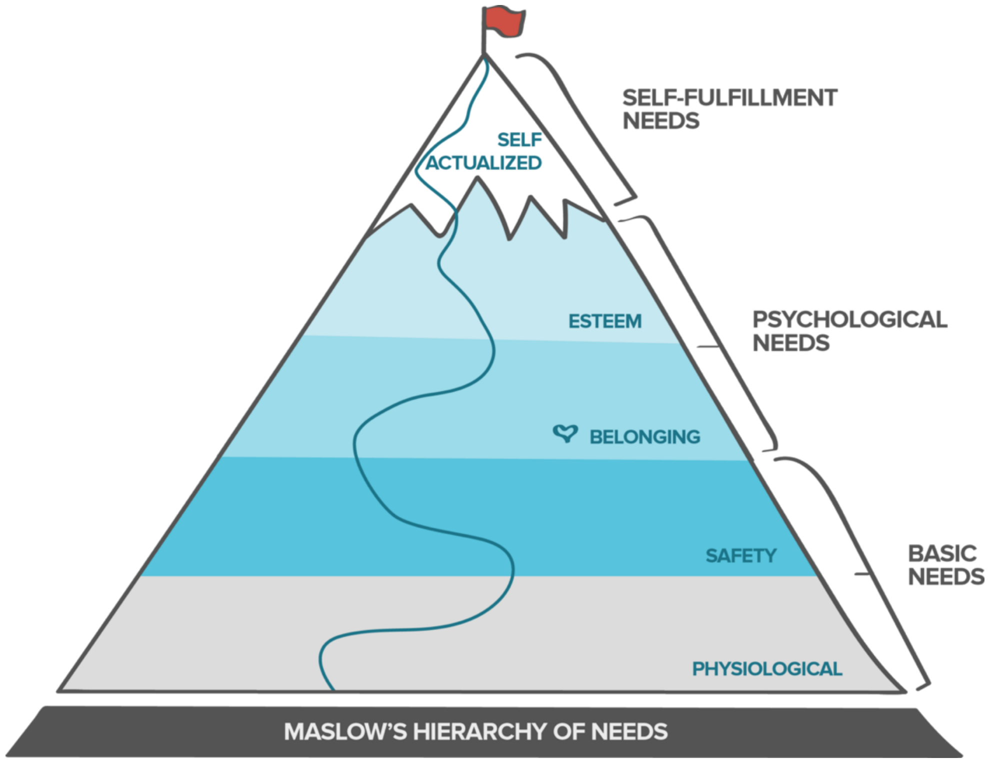

Figure 3: Maslow's Hierarchy of Needs. A five tier model of human needs with the most essential for life being the bottom tier (Santens 2017).

Additionally, Santens (2017) argues that we all desire to be in the top section of Maslow's Triangle, as seen in Figure 3, but the majority of people below the poverty line are stuck in the first and second quadrants. Through, a UBI many people stuck in a loop in the first and second quadrants would be lifted to the third quadrant, giving them more autonomy and the ability to climb the rest of the triangle (p.8). Though counterarguments for UBI exist, suggesting that it would disincentivize workers along with increasing inflation, UBI is the strongest current countermeasure to automation.

In order to better understand the consequences of the use of UBI in an automated society the STS research will use the Technological Fix framework proposed by Alvin M. Weinberg, an American nuclear physicist who worked on the Manhattan Project. Weinberg goes into detail on using both technical and social solutions to fix problems. Weinberg (1978) observes, "Both technological and social fixes are likely to bring with them detrimental and unforeseen side effects" (p.ii). Though disincentivization and inflation are the most popular counterarguments against UBI, according to Weinberg, UBI is inherently a social fix and will inevitably be accompanied by damaging unpredictable side effects. These side effects could appear inconsequential before the implementation of a UBI, but cascade into a butterfly effect rewiring society and the economy. Careful consideration of all the possible side effects of a UBI is therefore imperative before the implementation of one in an automated society. Through the use of a scholarly article for the STS project, I hope to inform the public and policymakers on the countermeasures that can be taken to mitigate the damage caused by automation-related unemployment.

EDUCATION FOR THE PUBLIC AND POLICYMAKERS

Both the technical project and STS project aim to discuss the effect of widespread unemployment on society. Specifically, the technical project will focus on the relationship between automation and the unemployment rate, the real-world consequences of an increased unemployment rate, and a case study to demonstrate how automation will replace white-collar industries. Tightly coupled, the STS project will examine what can be done to offset the negative consequences found in the first and second parts of the technical project, as well as examine this solution through the STS framework of technological fix in order to test the plausibility of Universal Basic Income. Through both the technical project and STS project, I aim to educate the public and policymakers on the risks that automation poses to them as well as what can be done to mitigate the negative effects of automation.

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