Predicting the Work Task Replacement Effects of the Adoption of Machine Learning Technology

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Abstract

This paper develops a methodology to attempt to predict which tasks in the workforce will be resistant to the replacement of labor by machine learning technology in the near future[1] given current technology and technology adoption trends. Tasks are individual activities completed as parts of a job. Prior research in the field suggests that characteristics of tasks (non-roteness, creativity, analysis/cognitive work) that make them harder for machine learning technology to complete are good predictors of whether those tasks will be resistant to replacement in the workforce. This study utilizes O*NET (Occupational Information Network) task description and education data from October 2015 to August 2020 and Bureau of Labor Statistics salary data to use task characteristics to predict tasks' resistance to replacement. Normalized scores, average salaries, and average worker education levels are calculated to quantify the relative presence or absence of non-roteness, creativity, and cognitive work in a task. This paper then uses the calculated scores, salary, and education data, as well as a number of interaction terms as inputs to a support vector machine (SVM) model to predict which tasks will be resistant to decline in their shares of workplace tasks weighted by the jobs under which the tasks fall. Using task characteristics, the SVM predicts that just approximately 39% of tasks are likely to be resistant to replacement. These tasks tend to be highly non-deterministic (very non-rote, analytical/cognitive, and/or creative) in nature.

JEL classification: J23; J24; O33

Keywords: Labor Demand; Human Capital; Skills; Labor Productivity; Technology

[1] Roughly five years into the future.

I. Introduction

Technological improvements allow tasks that previously required human labor to be automated. Repetitive and deterministic (producing a consistent output) manual and cognitive tasks are more efficiently completed by machines than by humans. If enough of the tasks that comprise a job are automated, the job itself becomes automated and disappears. Jobs primarily composed of repetitive and deterministic tasks are disappearing due to their high substitutability of capital for labor (Autor, Levy, and Murnane, 2003). Tasks at a low skill level, which are deterministic and generally associated with low wages, such as sorting items or fitting non-standardized assembly-line parts to each other, often disappear due to their repetitive and deterministic nature (Autor, Levy, and Murnane, 2003). Meanwhile, in jobs composed of non-deterministic tasks (high-skill jobs), capital and labor tend to complement each other. These jobs, historically, have not been easily automated due to their more complex nature – they are non-deterministic, requiring individuals employed in them to make decisions. While some of the more rote tasks under such jobs might be automated, the decisioning tasks can be too idiosyncratic or complex for computers to complete.

However, with the advent and broader adoption of machine learning, tasks previously difficult or impossible to automate are becoming vulnerable to replacement. Machine learning allows computers to make decisions, opening the way for technology to complete non-deterministic, non-repetitive tasks. Computers can now learn from experience, create non-parametric models, and make out-of-sample predictions, utilizing data from a given set of scenarios to make decisions about never-before-seen scenarios. While machine learning technology is not so advanced as to have eliminated all need for human decision-making, it does allow simple decisioning tasks to be automated, eliminating the need for them to be performed by humans, while complementing tasks requiring more complex decisioning. While truck drivers on remote routes may see themselves replaced by computers, radiologists and lawyers may see their jobs become more lucrative, becoming more productive as simpler, time-consuming tasks are automated away, leaving more time for complex, valuable tasks. These thoughts on the impact of machine learning on the labor market are, however, largely conjecture. **The impact of machine learning has been little explored. Which tasks will disappear, and which will remain or become more valuable due to differences in relative substitutability of labor and capital has not yet been fully and systematically considered.**

In the past, automation has created task polarization – it concentrates existing jobs at two "poles" of skill, while eliminating tasks in the middle of the spectrum. Autor, Levy, and Murnane (2003) identified low-skill, low-wage work as routine and deterministic, and high-skill, high-wage work as non-routine and non-deterministic. Automation destroys the repetitive low-skill tasks in which capital is highly substitutable for labor while adding value mostly to the high-skill tasks in which capital complements labor. As repetitive low-skill tasks are often also concentrated in low-wage jobs, and high-skill tasks involving decisioning tend to be concentrated within high-wage jobs, task polarization leads to job polarization, which then leads to wage polarization. Wages become concentrated at the high and low ends of the spectrum as jobs that paid wages in between are eliminated. Income inequality has been increasing in the United States since the 1970s, rising to levels unseen since the 1920s, a trend concerning many economists. Wage polarization resultant from job polarization is a driver of this inequality (Abel and Deitz, 2012). Thomas Piketty and Emmanuel Saez suggest that the force behind increasing income inequality is a growing rate of return to capital that outpaces overall economic growth

(Piketty and Saez, 2003). If automation, including machine learning-based labor replacement, increases returns to capital by increasing productivity and worker efficiency, then automation and replacement could be causes of income inequality.

Wide adoption of machine learning technology could then lead to increased job polarization as jobs previously safe from elimination or task loss due to requiring simple decisioning skills will begin to lose value or disappear entirely. While it is not the goal of this paper to establish this whole causal chain, it will begin the empirical investigation of this provocative topic. Predicting which tasks are (or are not) likely to be replacement resistant and are likely to become more lucrative as a result of broader adoption of machine learning in the near future[2] is a first step in understanding how machine learning will exacerbate job polarization, wage polarization, and income inequality in turn. In investigating this question, first, in section II, relevant literature will be examined to establish background and motivate the direction of this research and the methodology used. The data will be summarized in section III. The support vector machine to be utilized in predicting which tasks are likely to be resistant to replacement will be introduced in concept in section IV. The predictions of the model will then be presented and discussed in sections V and VI.

II. Literature Review

Although the impact of the introduction of machine learning on task polarization has not yet been thoroughly explored, there is a large body of existing research on automation and its labor market effects. To identify a basis for the investigation of a new form of automation, I will

[2] The data observes change in task share over a period of roughly five years, so it is reasonable to assume that the near future period for which predictions are made is five years into the future, although there is no clear time bounding in the SVM model used in this paper.

situate my proposed work within the context of this research and the theories from which it draws.

Prior research suggests that automation drives task polarization due to differences in the relative substitutability of capital for labor across tasks. As industries computerized from 1960 – 2000, they also began to increase demand for college-educated workers, while decreasing demand for less-educated, less-skilled workers (Autor, Levy, and Murnane, 2003). Meanwhile, the adoption of technology was correlated with an increase in job polarization. Autor, Levy, and Murnane (2003) identify a causal connection between the two, finding that job polarization in this time period was driven by the automation of low-skilled (routine, non-cognitive) tasks and jobs. Given that low-skill jobs and tasks are not substitutes for high-skill (non-routine, cognitive) jobs and tasks, and given that the United States educational system in its current state is unable to produce enough high-skilled workers to keep up with labor demand, jobs polarization results from technology complementing labor in high-skill tasks and substituting for labor in low-skill tasks (Goldin and Katz, 2008; Acemoglu and Autor, 2012). Autor, Levy, and Murnane (2003) construct a general equilibrium model correlating the price of computing power (a dimension of the ease of adopting new technology used as a proxy for the whole) and labor demand. Regression analysis supported the hypothesis suggested by the model, establishing a causal link between change in labor demand and the varying substitutability of capital for labor across tasks and jobs of different skill levels (Acemoglu and Autor, 2012).

Machine learning will replace a different array of tasks than previous automation, and thus, a different set of tasks are likely to be resistant to its effects. Previously, technology could only substitute for labor in deterministic tasks, while it is now capable of substituting for labor in basic decisioning tasks (non-deterministic). While previous technological advances may have complemented human labor at a lower skill level (i.e., the introduction of trucks created jobs for truck drivers), machine learning does not. Machine learning models can make simple decisions, teach themselves and self-correct, working with them tends to require a grasp of statistical techniques, and working alongside them requires human workers to have abilities that go beyond the models' (Agrawal, Gans, and Goldfarb, 2019; Kurakin, Goodfellow, and Bengio, 2017). Machine learning thus allows simple non-deterministic tasks to be replaced (Agrawal, Gans, and Goldfarb, 2019).

Automation resultant from machine learning impacts the labor market much like traditional automation. As tasks become obsolete, more deterministic tasks disappear, while non-deterministic tasks become more valuable – although the deterministic tasks replaced by machine learning are less deterministic than those replaced by traditional automation. Basic decision-making allows computers to drive vehicles, replacing the task of driving in jobs (Agrawal, Gans, and Goldfarb, 2019). Meanwhile, natural language processing allows a computer to "read with comprehension" and allows document review to be completed without the labor of a lawyer (Agrawal, Gans, and Goldfarb, 2019). Image recognition technology allows computers to complete basic assessments of medical scans, bringing potential symptoms to the attention of radiologists (Agrawal, Gans, and Goldfarb, 2019). While machine learning may automate different types of tasks and jobs than previous technological advances, there is evidence to conjecture that it will affect task and job polarization similarly.

To date, little research has been conducted to predict the precise impact of machine learning on the labor market. The only paper on potential labor market effects of widespread adoption of machine learning makes predictions on resultant job and wage polarization. It uses natural language processing to match the capabilities of newly patented technology with tasks and jobs by matching keywords in job descriptions with keywords in descriptions of patented technology (Webb, 2020). A match in tasks and capabilities would suggest that the technology in question would replace tasks requiring those capabilities. If a given number of tasks within a job become replaced, then the job itself would become replaced. Webb uses the canonical task-based model from Acemoglu and Restrepo (2018) that optimizes task "production" with respect to the costs of different factors of production, as well as the automatability of different tasks. Webb then conducts simple regression analysis (assuming that patterns of labor market impact due to machine learning adoption are similar to those due to automation resulting from robots and computerization) to predict that high-skill, high-wage jobs are likely to be benefited by automation, while low-skill, low-wage jobs are likely to be replaced by automation, thereby exacerbating both job and wage polarization.

My scope of investigation will fall within existing research; I will attempt to predict which tasks are likely to be resistant to broader machine learning replacement. I will also make standard assumptions about the substitutability of high- and low-skill tasks. My methodology, however, is original. I intend to utilize a support vector machine (SVM) model to increase the accuracy of predictions of which tasks will be likely to be resistant to replacement by machine learning, assuming broader adoption of existing technology. SVMs make few assumptions about the relationships (between variables) that might cause a task to become replaced or be resistant, allowing predictions to remain independent of potentially incorrect assumptions. The Webb paper assumes that trends in job polarization regarding the adoption of machine learning will mirror the trends regarding computerization and robotization, but such a generalization likely simplifies the true relationships involved in ways that a support vector machine would not. This paper's use of an SVM model to predict which tasks will be resistant to automation should bring a new methodology to a thus far little-studied topic.

III. Data Overview

Michael Webb's research on AI replacement indicates that the resistance of tasks to machine learning replacement depends on how non-deterministic those tasks are (2020). Webb (2020) paper, Agrawal et. al. (2019), and my own analysis of the topic suggest that factors indicating the degree of determinism present in a given task are how rote/repetitive the task is (captured by a non-roteness measure[3], average salary, and average education level, assuming less repetitive tasks are remunerated more highly to reflect the skill required to perform them, and that tasks for which workers tend to be more educated are less repetitive, requiring some degree of analysis), how much thinking/decisioning is involved in completing that task (captured by a cognitive measure[4] and an education level, assuming more analytical tasks require the higher levels of education that foster analytic and problem-solving skills), and how much originality the task requires (captured by a creativity measure[5]). If a task is not very repetitive and requires a lot of analysis or creativity, then it is unlikely to be able to be completed in the same way each time, making it non-deterministic. If a task is well-remunerated, it is likely a task that is nondeterministic, as it is likely non-rote. A well-remunerated task is also likely to be more cognitive, as more complex analysis and problem-solving skills are likely to be highly compensated. While high compensation could also be compensation for the risk inherent in a job,

[3] The number of verbs in a given task description I determined to be associated with non-roteness divided by the number of verbs in the description. Construction of this measure is discussed later in this section.
[4] The number of verbs in a given task description I determined to be associated with cognitive work divided by the number of verbs in the description. Construction of this measure is discussed later in this section.
[5] The number of verbs in a given task description I determined to be associated with creativity divided by the number of verbs in the description. Construction of this measure is discussed later in this section.

or the unpleasantness of a job, because wage/salary data is available at the job level, and the compensation for a task would be an average of the compensation over all the different jobs the task falls under, the noise from these other factors should be minimized. Finally, if a task is generally performed by workers with higher levels of education, then it is likely to involve the higher-level problem solving, analysis, and decision-making skills that are fostered by higher levels of education, and is also thus likely to be non-repetitive. Therefore, non-roteness, creativity, and cognitive measures, as well as average salaries and education levels, are predictors of interest in this study.

Autor, Levy, and Murnane (2003) used the Directory of Occupational Titles (DOT) in their influential paper "The Skill Content of Recent Technological Change: An Empirical Exploration" to identify the tasks that comprised the jobs existent at the time and establish a correlation between task type and rate of automation. To predict which tasks will be automated in the future using task characteristics in this paper, the Occupational Information Network, or O*NET will be used. O*NET is the most updated version of DOT released by the Bureau of Labor Statistics, although new variables, such as task descriptions, have been introduced in recent years since the publication of the Autor, Levy, and Murnane (2003). O*NET data contain task labels and task descriptions spanning from October 2015 to August 2020, as well as the jobs different tasks fall under. There are around 22,000 entries in each of the datasets, which contain roughly under 1000 jobs and around 2000 unique tasks. These datasets describe the jobs and tasks existent in America and known to the Bureau of Labor Statistics in the past five years. The data also contain information on the levels of education, from Level 1, less than a high school diploma to Level 12, post-doctoral training, reported by individuals holding the jobs included in the data.

The O*NET task description data are very useful in that they provide information to make predictions based on task characteristics of which tasks in the workforce are likely to increase in share as machine learning is adopted (remain resistant to machine learning replacement). The data are limited in that the task descriptions are qualitative. They must be translated into quantitative data to be useful in making predictions using an algorithm/formula, a process that is inherently subjective, and therefore subject to error.

Meanwhile, the education levels provided by O*NET are quantitative data. The data is limited in that for 23 out of 974 jobs in 2015 and 7 out of 974 jobs in 2020 have no reported levels of education available. As a result, average levels of education for the missing jobs cannot be calculated. Attempting to use this education data to identify the average level of education required for a task (by averaging education levels across all the jobs in which the task is present) could, therefore, introduce bias. However, relatively few jobs are missing education levels, and there is no apparent pattern in the jobs that are missing education levels - jobs generally associated with low and high salaries, education levels, and determinism are all missing data. Additionally, task education levels are averaged across the many jobs under which each task is falls. Therefore, this bias should be negligible.

Salary data used in this paper come from the Bureau of Labor Statistics (BLS) May 2019 National Occupational Employment and Wage Estimates for the United States. It contains the mean annual salaries in 2019 of 1064 occupations. Salaries likely did not change in the period from 2015 to 2020 enough to make 2019 values for salaries inappropriate approximations for salary values in 2015 and 2020. However, out of the 974 jobs present in the O*NET data, only 597 jobs have matches in the salary dataset. Some of the O*NET jobs appear to lack matches because the same jobs are (ambiguously) listed under different titles in the BLS dataset, while others are simply not included at all in the BLS dataset. There does not appear to be a trend in the salaries of the jobs are that unmatched – which jobs do not have associated mean salary information appears to be random, and jobs generally associated with high and low levels of salary, education, and determinism are all missing information. This diminishes the probability that there is bias in the salary data that could bias task automation predictions. Additionally, because the salary data will be averaged across the multiple jobs in which a task is included, the effects of the missing data will be further minimized. Of course, the quantity of data missing is significant, and it is likely that despite mitigating factors, the quality of predictions made will be diminished as a result.

Average annual salary and education data are easily obtained (by averaging salaries and education levels across all the jobs within which a given task is present). However, non-roteness, cognitive, and creativity measures by task were not readily available. To extract scores to represent this information from the O*NET data of tasks and task descriptions, task descriptions have to be processed. This is inherently a subjective process. Because the task descriptions are generally phrased in ways that prioritize verbs, and generally make use of active verbs in illustrating what work is done in a given task, I believed verbs were key in creating Non-Roteness, Creativity, and Cognitive Scores. The Python nltk package was used to extract the verbs from the task descriptions. Investigating the popular software development website StackOverflow suggested this is the most commonly used package for this purpose, and could be considered to be industry standard. The unique set of verbs present in the task description data was individually scored manually as being Non-Rote, Cognitive, and/or Creative (dummy variable for each), creating a sort of verb dictionary[6]. A verb was Non-Rote if it seemed likely,

[6] See Appendix A1.

from the general context of its usage in task descriptions, to suggest non-repetitive work. A verb was Cognitive if, similarly, it suggested analysis. A verb was Creative if it suggested originality in the work to which it applied.

To construct the task scores, a list of all the descriptions[7] of each given task was compiled and the verbs extracted, again, using the nltk package. From these extracted verbs for a given task, counts were established for Non-Rote verbs, Creative verbs, and Cognitive verbs by matching extracted verbs with their scores in the verb dictionary. The counts were converted to scores by normalizing the counts by dividing them by the total number of verbs found in a description. This normalization accounts for the fact that some tasks will simply have longer description sets and more verbs than others as a result of simply being more widespread in jobs. However, as a natural language processing package, nltk is liable to err (it is *predicting* whether a word is a verb, given sentence context), and, in fact, missed some verbs in the extraction process. However, as long as this error is random with respect to the omitted verbs' Non-Roteness, Creativity, and Cognitive characteristics (there is no strong reason this would not be the case, given that a word's identification as a verb by the nltk package is dependent on the word's place in sentence structure in relation to other parts of speech, etc., and not any features relevant to the characteristics of interest to this paper), the error should not bias this study's results. Non-Roteness, Creativity, and Cognitive Scores are calculated for the 2015 and 2020 data because task descriptions changed over the years, as tasks were added to or disappeared from, jobs.

[7] The task descriptions are job-specific – a task listed under multiple jobs often has differing expressions of the same general task, and has different descriptions under each job to reflect this. All of these descriptions were compiled together for task scoring.

Variables salient in predicting task automation are then: Non-Roteness Score, Creativity Score, Cognitive Score, all descriptions of task characteristics, Education Level, and Salary. Data are provided/calculated for 2015 as well as 2020, although values did not change significantly between the years for each of the tasks. A short discussion of each of these variables and the trends they suggest are present in the data, follows.

An overview of the O*NET data shows that from October 2015 to August 2020, 43 of 1900 tasks that have education and salary data at all available have declined in share in the workforce, or have declined in the proportion of all workplace tasks they make up (declines have been converted into a dummy variable that simply marks whether or not a given task has declined for ease of use with the SVM model). The 10 tasks experiencing the biggest declines are listed in Table 1 below. They include tasks that have likely declined due to the increasing adoption of machine learning technology. These tasks are bolded in the table.

Table 1: 10 Tasks with the Biggest Declines in Share Oct. 2015 – Aug. 2020

Tasks	Education Level 2015	Education Level 2020	Salary 2015	Salary 2020	Non-Roteness 2015	Non-Roteness 2020	Creativity 2015	Creativity 2020	Cognitive 2015	Cognitive 2020
Operate photographic developing or print production equipment.	2.916558	2.916558	39798.26	39980	0.6	0.62963	0.133333	0.148148	0.433333	0.444444
Mount attachments or tools onto production equipment.	2.156626	2.156626	38204.73	38206.61	0.7	0.724138	0.066667	0.068966	0.466667	0.482759
Apply decorative coloring to photographs or printed materials.	2.4014	2.4014	36890	36890	1	1	0.4	0.25	0.4	0.25
Remove products or workpieces from production equipment.	**2.07163**	**2.07163**	**35123.53**	**34660**	**0.472222**	**0.424242**	**0.055556**	**0**	**0.25**	**0.212121**
Feed materials or products into or through equipment.	**2.091574**	**2.091574**	**36555.65**	**36406.36**	**0.583333**	**0.636364**	**0.083333**	**0.090909**	**0.416667**	**0.454545**
Inspect facilities.	**3.575933**	**3.575933**	**29723.33**	**29920**	**0.833333**	**0.75**	**0**	**0**	**0.833333**	**0.75**
Maintain inventories of materials, equipment, or products.	4.426961	4.426961	54686.4	54686.4	0.875	0.875	0	0	0.6875	0.6875
Prepare proposal documents.	**7.062562**	**7.062562**	**90621.25**	**86324.29**	**0.75**	**0.75**	**0.25**	**0.25**	**0.25**	**0.25**
Advise customers on the use of products or services.	**4.931708**	**4.931708**	**71702.22**	**71737.06**	**0.933333**	**1**	**0.066667**	**0.076923**	**0.933333**	**1**
Execute sales or other financial transactions.	**3.592058**	**3.592058**	**40818.5**	**40818.5**	**0.333333**	**0.333333**	**0**	**0**	**0.416667**	**0.416667**

The bolded tasks are likely candidates for machine-learning automation because they are activities that from their titles, appear to be non-rote and require a low level of decisioning ability. Machine learning technology to date is capable of taking over such tasks, while remaining incapable of automating tasks that require significant originality/creativity, skill, or extremely complex problem-solving. Six out of the 10 tasks in this table are good potential candidates for automation by machine learning. The other four, “Operate photographic developing or print production equipment,” for example, are likely in decline due to traditional automation and technological progress, in this case, the widespread adoption of smartphones with cameras and digital photography.

As can be seen in the table, the bolded tasks require, with the exception of “Prepare proposal documents,” fairly low education levels, suggesting they do not require the high levels of analytic ability that are fostered by higher education. Aside from “Advise customers on the use of products or services,” and “Prepare proposal documents,” they also have relatively low average salaries, suggesting that for the most part, they do not require the kind of highly skilled workers that would demand high renumeration for their skills. While the tasks have middling to high Non-Roteness scores in the time period under study, they all have low Creativity scores, and with the exceptions of “Inspect facilities,” and “Advise customers on the use of products or services,” low to middling Cognitive scores. Assuming a degree of error in the task characteristic scoring process, it is still evident that the tasks that appear to be good candidates for machine learning automation fit the profile of being non-deterministic, non-creative, and somewhat analytical.

“Advise customers on the use of products or services,” is a good candidate for machine learning replacement, as understanding and answering customers’ questions about a product is work that requires a human worker to be fairly reactive to his/her environment to correctly answer the questions appropriately, requires perhaps a little low-level analysis to comprehend the questions and provide the appropriate information, and essentially no creativity. "Execute sales or other financial transactions," is another good candidate for replacement, having similar characteristics to "Advise customers on the use of products or services," And in fact, the replacement of these tasks by machine learning technology can be readily observed. Chatbots are currently able to advise customers using natural language processing to comprehend and respond to the customers' requests. Meanwhile, sales is being taken over by algorithms that can predict what products a customer is likely to want to see or purchase based on his or her digital presence and purchasing history.

On the other hand, 378 of the 1900 tasks in this dataset have increased in share. Table 2 shows the 10 tasks that have experienced the largest increases in share. It demonstrates that the tasks increasing in share are mostly those that are moderately to highly non-rote, creative, and/or cognitive/analytical – i.e., hard to replace with machine learning technology as it currently stands. The bolded tasks are those which, from their descriptions and titles, from the intuition developed thus far, seem to be too complex for machine learning replacement.

Table 2: 10 Tasks with the Biggest Increases in Share Oct. 2015 – Aug. 2020

Tasks	Education Level 2015	Education Level 2020	Salary 2015	Salary 2020	Non-Roteness 2015	Non-Roteness 2020	Creativity 2015	Creativity 2020	Cognitive 2015	Cognitive 2020
Clean facilities or work areas.	2.737356	2.737356	41544.45	38913	0.75	0.818182	0	0	0.75	0.818182
Write reports or evaluations.	**7.863185**	**7.863185**	**49923.33**	**71132.86**	**0.875**	**0.875**	**0**	**0**	**0.875**	**0.875**
Teach classes in area of specialization.	**7.265114**	**7.265114**	**112400**	**105845**	**1**	**0.8**	**0**	**0.2**	**1**	**0.8**
Evaluate student work.	**8.771803**	**8.771803**	**84257.36**	**84382.86**	**1**	**1**	**0**	**0**	**1**	**1**
Order materials, supplies, or equipment.	2.988706	2.988706	43625.22	43745.58	0.821429	0.821429	0.035714	0.035714	0.571429	0.571429
Collect payments for goods or services.	3.646172	3.646172	76741.25	61414.29	0.2	0.375	0	0	0	0
Proofread documents, records, or other files to ensure accuracy.	4.674075	4.674075	40022.15	50644.12	0.5	0.5	0	0	0.4	0.4
Support the professional development of others.	**9.023429**	**9.023429**	**49440**	**82366**	**1**	**1**	**0**	**0**	**1**	**1**
Present research results to others.	**8.455556**	**8.455556**	**99546.66**	**96286.66**	**0**	**1**	**0**	**1**	**0**	**1**
Perform basic equipment maintenance.	**3.045156**	**3.045156**	**36626.67**	**38246.67**	**0.333333**	**0.333333**	**0.333333**	**0.333333**	**0.333333**	**0.333333**

The bolded tasks are, for various reasons, likely to be resistant to automation. Tasks like "Write reports or evaluations," and "Teach classes in area of specialization," are highly non-rote and cognitive. Writing and teaching require a high degree of attunement to the audience and an understanding of how to best communicate with that audience. This, in turn, necessitates constant analysis of and reactivity to the audience. The complexity and non-deterministic nature of these tasks is also reflected in their comparatively high renumerations and levels of education of the workers that perform them. Higher levels of non-roteness and cognitive effort (reflected in the Non-Roteness and Cognitive Scores in Table 2) put these tasks beyond the current capabilities of machine learning. As current machine learning technology is adopted and begins to replace human labor in specific tasks, tasks with profiles like these (complementary to machine learning) are likely to increase in share in the near future. These complex tasks are relatively resistant to machine learning replacement.

The odd tasks out in this list appear to be "Perform basic equipment maintenance," and "Collect payments for goods or services," which have low Non-Roteness, Creativity, and Cognitive scores. However, the values for "Perform basic equipment maintenance," may be artifacts of errors in the scoring process[8], as it would seem that maintaining equipment would likely be a highly non-rote task, requiring a human worker to contend with adjusting machinery in various conditions and evaluating his or her work to ensure the machinery was in a functional state. "Collect payments for goods or services," meanwhile, may owe its unusual task characteristic scores (for having experienced a big increase in share) to this same scoring process issue to an extent. However, collecting payments (paying off bets, cashing checks) is not a task that would seem to require highly non-rote behavior, creativity, or analytical/cognitive ability, so the scores may in fact be correct. One explanation for its increase in share may be that machine learning replacement has not yet occurred in the more low-tech industries and jobs this task falls under, while the adoption of traditional forms of technology have automated away other tasks. As traditional automation caused the decline of other tasks, the endurance of "Collect payments for goods or services," might have caused its share to rise, even if the task itself is a good candidate for machine learning replacement.

Overall, a majority of the tasks that experienced the greatest increases in share had high Non-Roteness, Creativity, and/or Cognitive scores, high Education Levels, and high Salaries. A majority of the tasks that experienced the greatest decreases in share had low Non-Roteness, Creativity, and/or Cognitive scores, low Education Levels, and low Salaries. The preceding preliminary examination of the data suggests the associated education level, salary, and Non-

[8] Potentially due to the subjectivity of manually identifying the non-roteness, creativity, and cognitive work associated with given verbs, as well as errors with nltk package in identifying verbs in the task descriptions for scoring to begin with.

Roteness, Creativity, and Cognitive Scores of a given task are reasonable predictors of whether it will be resistant to machine learning replacement.

IV. Empirical Specification

Whether human labor in a given task will be too difficult to replace with machine learning in the near future, given current technology is predicted using a support vector machine (SVM). An SVM is a simple classification algorithm that uses independent variables to identify in which of multiple groups or classes a new observation belongs. The SVM learns from training data which values of independent variables are associated with classification in different groups (where the group is the dependent variable). Leveraging the training data, the SVM identifies classification boundaries between different groups. These boundaries define a region for each classification group. If the values given for independent variables place a new observation within the region for a given group, then that observation is classified as a member of that group. The boundary definition function type and allowed margin of misclassification are specified to increase predictive accuracy and precision in a process of trial and error.

An SVM suits the prediction problem posed in this study well. An SVM is a classification model, useful in classifying tasks into two groups – (1) resistant to machine learning replacement in the near future and (2) not resistant to machine learning replacement. The agnostic nature of the SVM model avoids the pitfall of making assumptions about the relationships between the dependent and independent variables (assuming a polynomial or exponential function, as a regression model would, for example). This prevents predictions from being biased by the exact relationships described in theory, which may be inaccurate – a traditional linear regression model would not have done well by this measure. In utilizing an

SVM, bias is limited to the effects of choosing to include or exclude independent variables and to the effects of skewed or unrepresentative input data. To account for all the independent variables in predicting which tasks will be resistant to replacement in the face of broader adoption of machine learning technology, without presuming the relationships between the variables, an SVM model is an appropriate choice.

An SVM requires a dependent variable on which it will be making predictions. This variable must be some kind of class variable, where each observation is or can be identified as belonging to a class or category. The dependent variable in this paper is based on the change over a five-year interval (2015-2020) in the share of all tasks a given task made up. This paper is directed at predicting which tasks will likely remain resistant to automation (and which will not). Therefore, the classes represented by a dummy class variable: 0, the class of tasks which will likely not remain resistant to replacement, and 1, the class of tasks that will. Over the 2015-2020 time period, machine learning technology was being adopted by industry. Tasks that increased in share over this time period seem most likely to be tasks in which human labor is complemented by machine learning, as they seem to grow in prominence in correlation with the growth in adoption of machine learnings. Thus, their profiles seemed to be most representative of tasks resistant to machine learning automation. These tasks are thus chosen to comprise the class that will be resistant to replacement, class 1. The remaining tasks, which do not evidence an increase in share in conjunction with the adoption of machine learning by industry, and so do not demonstrate clear complementarity, are tagged as unlikely to remain resistant, class 0. Admittedly, this may lead to aggressive predictions on which tasks will not remain resistant to replacement; tasks that experienced no change in share may have resisted a decline in share because they are resistant to replacement. However, given that simple machine learning technology is becoming more and more ubiquitous and is replacing labor in tasks, it is also possible that these tasks' lack of growth in importance in the face of replacement is in fact indicative of their limited complementarity to machine learning technology.

In identifying the appropriate input independent variables for the SVM model, relationships between the variables were also considered. Interaction terms were included in the predictive model to account for these relationships. Interaction terms relating the Cognitive Score and the Non-Roteness Score; the Creativity Score and the Non-Roteness Score; the Cognitive Score and the Creativity Score; the Cognitive Score and Salary; the Creativity Score and Salary; the Non-Roteness Score and Salary; Education and Salary; Education and the Non-Roteness Score; and Education and the Cognitive Score were included. A brief discussion of each of these interaction terms follows the correlation matrix in Figure 1. The matrix does not contain separate 2015 and 2020 versions of the independent variables – instead, the data is divided[9] into two sets, one for training the SVM and one on which predictions will be made. In the matrix, 2015 values of the independent variables are used[10] for observations in the training data and 2020 values are used for the test data.

Figure 1: Correlation Matrix of Independent Variables

	Education Level	Salary	Non-Roteness	Cognitive	Creativity
Education Level	1				
Salary	0.687022127	1			
Non-Roteness	0.202198728	0.217721891	1		
Cognitive	0.334067532	0.300831763	0.740200819	1	
Creativity	0.126421723	0.071819752	0.210227806	0.210924489	1

[9] This division is further discussed in the Results section.
[10] The 2015 values of independent variables in the training data and the 2020 values in the test data are the only values the SVM will use, as this paper is attempting to predict changes in task share over a time period, given tasks' characteristics/profiles at the beginning of that time period.

Cognitive Score and Non-Roteness Score Interaction Term

I expect that the Non-Roteness Score for a given task has a relationship with the Cognitive Score, because problem-solving and analysis are generally not repetitive processes, but rather require adjustments to the considerations of every new problem or issue being analyzed.

Creativity Score and Non-Roteness Score Interaction Term

A relationship between Creativity Score and Non-Roteness Score was expected, as originality, by definition, cannot be repetitive.

Cognitive Score and Creativity Score Interaction Term

Cognitive Score and Creativity Score are expected to be correlated, as originality, i.e., creating a business plan, must have basis in the analysis of circumstances.

Cognitive Score and Salary Interaction Term

Cognitive Score and Salary are expected to have a relationship, as more analytical tasks generally require a higher level of skill that in turn requires higher remuneration.

Creativity Score and Salary Interaction Term

A relationship between Creativity Score and Salary is expected. Work involving originality, such as leading a team in pursuing an initiative, is likely remunerated for such originality.

Non-Roteness Score and Salary Interaction Term

A relationship between Non-Roteness Score and Salary is expected – as a task required more reactivity, it seemed likely that renumeration would increase to reflect the increased skill necessary to complete the task.

Education and Salary Interaction Term

A relationship between Education and Salary is expected. If a task had a higher associated education level, it was likely less deterministic and required more skill to complete, and the salary paid for that task is believed to reflect this.

Non-Roteness Score and Education Interaction Term

Non-Roteness Score and Education Level are expected to have a correlation, as tasks requiring a higher level of reactivity, such as diagnosing a patient, or many communication tasks, often require higher education levels. Of course, as even more manual tasks can also be highly non-rote, while requiring little education to perform (i.e., "Operate heavy-duty construction or installation equipment."), the relationship between these two variables is not expected to be an especially strong one.

Cognitive Score and Education Interaction Term

A relationship between Cognitive Score and Education Level is expected. Tasks necessitating a higher level of education would likely tend to be those that require the analytical skills that higher education tends to foster.

Inputs to the SVM ultimately are, then, as follows: a score indicating where a task lies on a scale of rote to non-rote (Non-Roteness score), a score indicating where a task lies on a scale of manual to cognitive (Cognitive score), a score indicating where a task lies of a scale of creative to non-creative (Creativity score), the average salary for each task (averaged across all the jobs each task falls underneath), the average education level for each task (averaged across all the jobs each task falls underneath), and all the interaction terms listed and explored above. Further model specifications (the optimal training-test split of the data, data resampling ratios, and margin of misclassification), identified by a process of trial and error, are discussed in the Results section below.

V. Results

This study was implemented in two steps. First the SVM model was fitted to 2015-2020 training data (2015 independent variables – Education Level, Salary, Non-Roteness Score, Creativity Score, and Cognitive Score – and the Increased dependent variable for the October 2015- August 2020 period) and tested on data from the same period. The training-test split of the data was 80:20 to optimize predictivity, with observations being selected at random for training and test groups. While this was not truly predictive, it was an important step in assessing whether the SVM model is identifying the trends in the data that I believe are associated with machine-learning-related automation. Then, the SVM model was trained on 2015-2020 training data again, but was given the independent variable values from 2020 to predict what tasks would be automated in the future.

The first stage of this study had ambiguous results. The model performed well in terms of accuracy, but only slightly better than chance on precision. However, this was not an indicator of failure, as a number of factors may have contributed to its performance, not the least of which was the fact that this model was intended for forward prediction, not for predicting within the present.

The parameters of the SVM model were optimized through trial and error. When the model was tested on the 2015-2020 data, the fit was assessed by Accuracy and Macro-Averaged Precision scores, as well as by the results depicted by a confusion matrix.

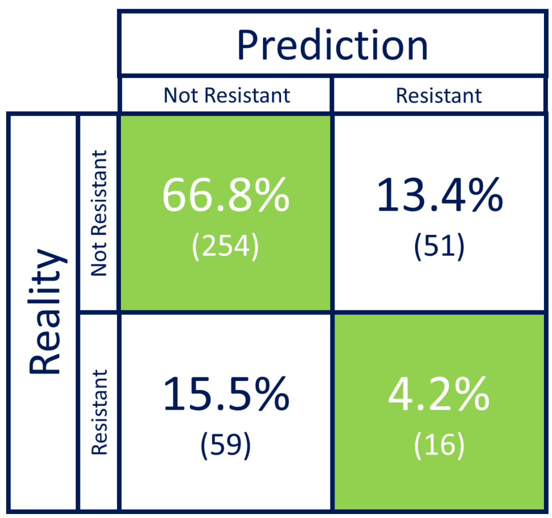
$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \quad (1)$$

$$Macro - Averaged\ Precision = \frac{1}{2}\left(\frac{True\ Positive}{True\ Positive\ +\ False\ Positive} + \frac{True\ Negative}{True\ Negative\ +\ False\ Negative}\right) \quad (2)$$

The dataset was imbalanced, with roughly 20% of the tasks in the data in the class that increased in share and the other roughly 80% of tasks in the class that did not. Providing a machine learning model with many more examples of one class than the other gives it fewer opportunities to identify the trends of the minority class, and makes it more likely to misclassify observations as belonging to the majority class as a result. To minimize the effects of this issue, the data was resampled, dropping majority class observations and oversampling the minority class to get a 60:40 majority to minority observation ratio (in the training data). But in predicting what tasks would be resistant to machine learning replacement, accurately classifying tasks in both classes (resistant to replacement and not as resistant to replacement) is important. The Macro-Averaged Precision score better accounts for the impact of misclassifications with respect to the minority class compared to the Accuracy score, making it an important measure to consider when evaluating the predictivity of the model when predicting on an imbalanced dataset. Considering Macro-Averaged Precision guards against the problem of an algorithm overclassifying observations as belonging to the class of which it has seen more examples in training, which given the imbalanced dataset I am using, is a real concern.

The optimized model identified in this paper (C, or boundary threshold = 100, sigmoid kernel class separation function) in this testing process had a high Accuracy of 0.711 and a Macro-Averaged Precision of 0.525. The high boundary threshold makes the model more sensitive to correctly classifying outliers than to maximizing the distance of the classification boundary from both classes. The confusion matrix depicting the classification and misclassification of observations is depicted below:

Figure 2: Confusion Matrix of Prediction vs. Reality for First Stage of Study



Testing the SVM model's ability to identify whether given tasks are likely to be resistant to automation over the 2015-2020 period shows us that out of a set of 380 tasks, 66.8%, or 254, were classified as Not Resistant (and did not increase in share over the given time period), 13.4%, or 51, were classified as Resistant (but did not increase in share), 15.5%, or 59, were classified as Not Resistant (but increased in share), and 4.2%, or 16, were classified as Resistant (and increased in share). The results of this test appear to suggest that this SVM model suffers from a tendency to misclassify observations, particularly erring in its over-classification of observations as resistant to automation. It may in fact be the case that the variables used in making these assessments are poor indicators of what makes a given task resistant to replacement. However, the supposed error may in fact result from other sources.

First – this model is intended to be used in forward prediction. Just because a task has not yet increased in share as a result of features that make it resistant to machine learning replacement does not mean that it will not increase in share in the future. The independent variables used in making these predictions may be entirely appropriate; it may just be that the appropriate technology has not yet been adopted in industry.

Second – this model is predicting resistance to machine learning replacement, not resistance to all forms of automation. Some tasks that have grown in share in recent years may be tasks resistant to traditional automation, not necessarily tasks resistant to machine learning replacement. Thus, the “error” in categorization of resistant tasks as non-resistant may in fact not be an error at all.

Third – some tasks that grew in share over the 2015-2020 time period may not have grown in share because they have traits that make them likely to be resistant to machine learning replacement. They may instead be tasks that grew in share due to proportional declines in share of other tasks that are being automated away. Tasks predicted to be non-resistant despite having increased in share, then, are not necessarily miscategorized.

Finally – the methodology used in this paper is an early attempt at generating task characteristic variables (Non-Roteness, Creativity, and Cognitive Scores). As such, it leaves room for improvement. First, the nltk package, while the most commonly available and used package for the purpose, did not extract all verbs from the task description sets. The descriptions' sentence structure, which frequently placed verbs at the beginnings of sentences, proved difficult to parse for the Python package. The package frequently omitted identifying the verbs that were at the beginning of sentences, which prevented these verbs from being used in scoring tasks on characteristics, although the verbs likely provided valuable information on the actions and skills required in performing tasks. As the nltk package predicted which task description words were verbs based on sentence structure, these omission were likely because the nltk package had not been trained on sentence structures that began with verbs. This loss of information likely led to Non-Roteness Score, Creativity Score, and Cognitive Score providing less consistent predictive value to the SVM model than they may have done otherwise. Additionally, the utilization of verbs alone in determining task characteristic scores may have been somewhat problematic. The verb "write," for example, can connote different task characteristics depending on whether it is used in the context of writing code (creative, cognitive, and non-rote) or writing a grocery list (non-creative, non-cognitive, non-rote). Not assessing verbs in the context of their sentences by *extracting* them for scoring likely led to a loss of information relevant to task profiles, resulting in the task characteristic scores having decreased predictive value. However, as the tasks with the greatest increases and decreases in share have score profiles that suggest, respectively, complementarity and replaceability with machine learning as expected given Webb (2020) and Agrawal et. al. (2019), the effects of nltk package errors were likely limited.

The results by task from the second stage of this study, where I attempt to predict the future, are in the appendix; a few selected predictions will be discussed here.

Roughly 39% of the tasks in the test data are predicted to be likely to remain resistant to replacement in the near future[11]. 61% of the tasks, then, are likely susceptible to replacement by machine learning. This may be an aggressive prediction, especially for the near future. However, it may also be a reflection that an increasingly small number and increasingly specific types of tasks will be the only ones in which human abilities cannot be well-simulated by technology. These tasks, in which human labor is a complement, and not a substitute, to technology, will begin to dominate the jobs under which they fall, as other, replaceable tasks are automated.

Two tasks that are predicted to be resistant to automation are "Evaluate the effectiveness of counseling or educational programs," and "Interpret financial information for others." Both of these tasks involve thinking about how other people might perceive information, which requires analysis (cognitive). This means the tasks are likely not very repetitive in nature (non-rote). As machine learning has not yet evolved to the point that it can complete highly non-rote and analytical tasks, it is logical that these tasks are predicted to be resistant to automation, at least in the short run.

Two tasks that are not predicted to be resistant to replacement are "Examine marketing materials to ensure compliance with policies or regulations," and "Interview claimants to get information related to legal proceedings." While evaluating marketing materials for legal compliance likely requires some level of analysis and might vary by the kind of document being examined, it is also likely not analytical enough or non-repetitive enough to not see human labor replaced by current machine learning technology. Natural language processing as well as computers' image recognition capabilities will likely allow for the average compliance check to

[11] Roughly five years from 2020, given that the SVM inputs in the test data for forward prediction are August 2020 values.

be completed more automatically. Machine learning technology is adopted and trained to identify and flag phrases or combinations of images and phrases that may be out of compliance and bring them to the attention of humans for confirmation, diminishing the importance of human labor in this task, and potentially phasing it out in jobs in which the compliance-checking process for marketing materials is fairly simple and straightforward. On the other hand, "Interview claimants to get information related to legal proceedings," is a task that requires human interaction in its current iteration, and may even require some analysis to identify lines of further questioning to get the appropriate information from a claimant. However, in a majority of cases, there may be a "flowchart" of relevant questions to follow, depending on a claimant's responses. Upon adoption of machine learned technology, natural language processing could allow a claimant's responses to questions to be parsed, so the appropriate questions can be asked, and information can be gathered. This information can be conveyed to a human, who might follow up on a claimant's answers that leave out salient details. The use of machine learning technology could cause this task to diminish in relevance for many of the jobs under which it is listed, leading to the task declining in share as time goes on.

VI. Conclusions

The predictions made by the SVM are listed in appendices A2 and A3. Their accuracy cannot be verified at this time; instead, changes in task share must be observed over a period in the near future to determine whether the predictions of this model are relatively accurate.

The model utilized in this paper could be further developed into the future to better capture features affecting a given task's resistance to machine learning replacement, and even to capture more such features. The task characteristic features (Non-Roteness, Creativity, and

Cognitive Scores) could be better captured by utilizing a more sophisticated natural language processing algorithm to detect verbs. A better-trained verb-identification algorithm would not fail, as the nltk package did, to capture verbs in task descriptions that happened to be at the beginnings of sentences. This more complete set of verbs could then be scored. This better verb-identification algorithm would then also be better able to match scored verbs to their instances in the task descriptions to extract final task characteristic scores.

Features that might be investigated to improve predictions of a task's resistance to machine learning replacement are task industries and the risk inherent in performing a given job. Controlling for the industry a task "belongs" to would likely control for the confounding variable of technology adoption rates. Data for an industry variable was not readily available when this paper was written, but should be collected to potentially improve the model it describes. The SVM is more likely to correctly predict a task's resistance to automation if it is given information on whether the industry the task falls under is one that tends to adopt machine learning technology or not. It may be that a given task in the training data has the profile of a very deterministic task, but has increased in share in the workforce due to traditional automation decreasing the share of other tasks and the lack of machine learning replacement adoption in the industry to which the task most commonly "belongs." Without a control variable for industry, this will likely confuse the SVM on the profile of a task that is likely to be resistant to replacement, and thus decrease the accuracy of its predictions. This is in fact a probably source of error in the predictions of the SVM in this paper, which lacks such a control. Meanwhile, capturing the risk of the jobs under which the tasks fell would control for risk's role in determining salaries, allowing the Salary variable to function as a purer proxy for the skill required to perform a given task. These data, too, were not readily available at the writing of this paper, but should be collected so average task risk levels can be calculated and risk can be used as a control variable in the SVM to improve its predictions. It is likely some of the prediction error of the SVM will be due to the absence of such controls in this paper.

The relatively aggressive predictions of this paper, of which tasks will and will not remain resistant to machine learning replacement can be used by policymakers to prepare for the economic impacts of task and job polarization and its resulting income inequality (Abel and Deitz, 2012). With foreknowledge of which tasks are vulnerable to replacement and the ability to trace these tasks to the jobs they fall under, policymakers can gain an understanding of which jobs are likelier to be vulnerable as well. Policymakers can then shape economic policy to potentially cushion the impact of machine learning replacement on jobs to avoid the devastating consequences of income inequality. The utility of predicting which tasks are likely to be resistant to replacement and which are not, then, is clearly evident. It is imperative to monitor replacement in the workplace to verify the accuracy and utility of the model developed in this paper, and to improve upon it, if this model in fact proves to be an appropriate one.

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Appendix

A1. Task Description Verb Categorizations as Non-Rote, Cognitive, and/or Creative

TaskVerb	NonRote	Cognitive	Creative
examine	0	1	0
solicit	1	1	0
compose	1	1	1
move	1	0	0
Disburse	0	0	0
heat	0	0	0
restore	1	0	0
conserve	1	1	0
review	1	1	0
reroute	1	0	0
consolidate	0	0	0
fasten	0	0	0
process	0	0	0
elucidate	1	1	1
compress	0	0	0
Listen	1	1	0
gather	1	1	0
Develop	1	1	1
offset	1	1	1
draw	1	1	0
Treat	1	1	0
Change	1	0	0
attend	1	0	0
resize	0	0	0
Manage	1	1	0
search	0	0	0
Present	1	1	1
supervise	1	1	0
study	1	1	0
Inform	0	0	0
deodorize	0	0	0
lengthen	0	0	0
produce	1	1	1
Review	1	1	0
integrate	1	1	0
Give	1	0	0
clarify	1	1	0
seize	1	0	0
transfer	0	0	0
license	1	0	0
satisfy	1	1	0
set	1	0	0
compute	0	1	0
discuss	1	1	1
center	0	0	0
request	1	0	0
reweave	0	0	0
weed	1	0	0
repressurize	0	0	0
drive	1	0	0
weld	1	0	0
restitch	1	0	0
anticipate	1	1	0
stow	0	0	0
obtain	0	1	0
circulate	0	0	0
check	1	0	0
navigate	1	0	0
Check	0	0	0
scale	0	0	0
lead	1	1	1
mitigate	1	1	0
animate	1	0	1
disinfect	0	0	0
target	1	1	1
master	1	1	1
cover	0	0	0
reuse	0	0	0
punch	0	0	0
Seek	1	1	0
fuel	0	0	0
submit	0	0	0
run	1	0	0
service	1	0	0
Compare	1	1	0
reconstruct	1	0	0
promote	1	1	0
tap	0	0	0
outline	1	1	0
decrease	1	1	0
Publicize	1	1	0
isolate	0	1	0
tamp	0	0	0
operate	0	0	0
lease	1	0	0
tend	1	0	0
highlight	1	1	0
reconcile	1	1	0
confirm	0	0	0
shorten	0	0	0
disburse	0	0	0
map	1	1	0
lower	0	0	0
sweep	0	0	0
add	0	0	0
ascertain	0	0	0
upgrade	0	0	0
secure	1	0	0
patrol	0	0	0
sew	1	0	0
purchase	0	0	0
demolish	1	0	0
score	1	0	0
confiscate	1	0	0
carve	1	0	0
eject	0	0	0
detonate	0	0	0
impart	1	1	0
knead	0	0	0
rebuild	1	0	0
precipitate	0	0	0
delineate	1	1	0
Assist	1	1	0
pump	0	0	0
propel	0	0	0
encase	0	0	0
crimp	0	0	0
distill	1	1	0
counteract	1	1	0
store	0	0	0
assure	1	1	0
plot	0	0	0
suggest	1	1	0
educate	1	1	0
communicate	1	1	0
weatherproo	1	0	0
immerse	0	0	0
define	1	1	0
pronounce	1	0	0
refund	0	0	0
motivate	1	1	0
predict	1	1	0
cauterize	0	0	0
solve	1	1	0
steer	0	0	0
restock	1	0	0
preheat	0	0	0
exchange	1	1	0
monitor	0	0	0
reflect	1	1	0
Teach	1	1	1
wash	0	0	0
update	1	1	0
hoist	0	0	0
Pour	0	0	0
stir	0	0	0
classify	1	1	0
sharpen	0	0	0
rebind	1	0	0
guide	1	1	0
stimulate	1	0	0
recommend	1	1	0
burn	0	0	0
peel	0	0	0
remove	0	0	0
plate	0	0	0
administer	1	1	0
adopt	1	1	0
Explain	1	1	0
combat	1	1	0
disseminate	1	0	0
reinstall	0	0	0
authenticate	0	0	0
harvest	0	0	0
rinse	0	0	0
calculate	0	1	0
grant	1	1	0
transact	0	1	0
seat	1	0	0
push	0	0	0
participate	1	1	0
evacuate	1	0	0
corroborate	0	0	0
influence	1	1	0
introduce	1	1	0
recognize	1	1	0
complement	1	1	0
differentiate	1	1	0
incorporate	1	1	0
bake	0	0	0
testify	1	1	0
strengthen	1	0	0
affix	0	0	0
bring	0	0	0
supply	1	0	0
Employ	1	1	0
blend	0	0	0
accommodat	1	1	0
accomplish	1	1	0
terminate	1	1	0
stabilize	0	0	0
log	0	0	0
realign	0	0	0
refill	0	0	0
deduce	1	1	0
represent	1	1	0
cut	0	0	0
Visit	1	0	0
load	0	0	0
replenish	1	0	0
oversee	1	1	0
illustrate	1	1	1
withdraw	1	0	0
prepare	1	1	0
approve	1	1	0
Demonstrate	1	1	0
adjust	1	1	0
Update	1	1	0
tie	0	0	0
construct	1	0	0
couple	0	0	0
Swear	1	1	0
deny	1	0	0
Establish	1	1	0
listen	1	1	0
melt	1	0	0
broadcast	1	0	0
Participate	1	1	0
equalize	1	0	0
select	1	1	0
meet	1	1	0
Maintain	1	1	0
stamp	0	0	0
tune	1	0	0
schedule	1	0	0
rectify	1	1	0
neutralize	1	0	0
carry	0	0	0
interpret	1	1	0
identify	1	1	0
dispatch	0	0	0
preserve	1	0	0
manage	1	1	0
designate	1	1	0
generate	1	1	0
arrange	1	1	0
insulate	1	0	0
Pay	0	0	0
maximize	1	1	0
locate	1	0	0
Promote	1	1	0
observe	1	0	0
combine	1	1	0
restart	0	0	0
activate	0	0	0
Remove	1	0	0
sell	1	1	0
sort	1	0	0
settle	1	1	0
Tend	1	0	0
reproduce	0	0	0
wax	1	0	0
dispose	1	0	0
Form	0	0	0
account	1	1	0
sample	1	0	0
Consider	1	1	0
travel	1	0	0
rewrite	1	1	1
bolt	1	0	0
synchronize	1	0	0
unwind	0	0	0
start	0	0	0
Keep	1	1	0
Evaluate	1	1	0
refine	1	1	0
Order	1	0	0
cure	1	0	0
advise	1	1	0
elicit	1	1	0
Supply	1	0	0
justify	1	1	0
inquire	1	1	0
intercept	1	0	0
Resolve	1	1	0
straighten	1	0	0
Operate	1	0	0
rig	1	0	0
Purchase	0	0	0
Plan	1	1	0
Choose	1	1	0
save	0	0	0
reestablish	1	1	0
transport	1	0	0
discharge	1	0	0
detect	1	0	0
reheat	0	0	0
inject	0	0	0
wet	0	0	0
test	1	1	0
degrade	1	0	0
tour	1	0	0
come	1	0	0
convert	0	0	0
pursue	1	1	0
refer	1	1	0
improve	1	1	0
emphasize	1	1	0
reach	1	1	0
uncover	0	0	0
Track	1	0	0
finalize	1	1	0
grind	0	0	0
strain	0	0	0
expand	1	1	0
patch	1	0	0
evaluate	1	1	0
Write	1	1	1
Obtain	0	1	0
inform	0	0	0
maneuver	1	0	0
authorize	0	1	0
achieve	1	1	0
dispense	0	0	0
dress	1	0	0
attain	0	0	0
alleviate	1	1	0
catalyze	1	1	0
Regulate	1	1	0
dehydrate	1	0	0
reset	0	0	0
salvage	1	0	0
reload	0	0	0
establish	1	1	0
quote	0	1	0
Study	1	1	0
shape	1	0	0
recharge	0	0	0
embed	0	0	0
refresh	1	1	0
videotape	1	0	0
respond	1	1	0
choose	1	1	0
split	0	0	0
ignite	0	0	0
unload	0	0	0
Determine	1	1	0
code	1	1	1
tailor	1	1	0
spray	0	0	0
redistribute	1	0	0
refinish	1	0	0
immobilize	1	0	0
pull	0	0	0
reattach	1	0	0
collaborate	1	1	0
revise	1	1	0
relay	0	0	0
assist	1	1	0
microincinera	1	0	0
decide	1	1	0
Call	1	1	0
Define	1	1	0
ease	1	1	0
Reorganize	1	1	0
certify	0	0	0
foster	1	1	0
smooth	1	0	0
gain	1	1	0
flush	0	0	0
expose	1	0	0
prevent	1	1	0
award	1	0	0
forecast	0	1	0
incubate	0	0	0
depict	1	1	1
orchestrate	1	1	1
adhere	1	1	0
regulate	1	1	0
contrast	1	1	0
accompany	1	0	0
distribute	1	0	0
explore	1	1	0
encourage	1	1	0
solder	1	0	0
open	0	0	0
Replicate	1	1	0
consider	1	1	0
investigate	1	1	0
frame	1	0	1
Paint	1	0	0
hedge	1	1	0
pasteurize	0	0	0
send	0	0	0
fuse	1	0	0
serve	1	1	0
amend	1	1	0
quantify	0	1	0
label	0	0	0
prescribe	1	1	0
escort	1	0	0
match	0	0	0
Identify	1	1	0
disable	0	0	0
clear	1	0	0
attract	1	1	0
shut	0	0	0
restructure	1	1	0
encode	1	0	0

assess	1	1	0	direct	1	1	0	read	1	1	0	hold	1	0	0
preview	1	0	0	Create	1	1	1	create	1	1	1	drag	1	0	0
coordinate	1	1	0	scoop	0	0	0	saw	1	0	0	decontamina	0	0	0
Estimate	1	1	0	reinforce	1	0	0	lift	0	0	0	assume	1	1	0
photograph	1	1	1	support	1	1	0	route	1	0	0	change	1	0	0
procure	1	1	0	rewire	1	0	0	waterproof	1	0	0	Investigate	1	1	0
pour	1	0	0	impose	1	0	0	keep	1	1	0	Supervise	1	1	0
talk	1	1	0	loosen	0	0	0	rotate	1	0	0	compare	1	1	0
avoid	1	1	0	erect	1	0	0	sand	1	0	0	enhance	1	1	0
notify	0	0	0	ride	1	0	0	describe	1	1	0	entice	1	1	0
compile	1	1	0	capture	1	0	0	Produce	1	1	0	determine	1	1	0
bind	1	0	0	ask	1	0	0	digitize	1	0	0	sterilize	0	0	0
conform	0	1	0	transmit	1	0	0	calibrate	1	0	0	entertain	1	1	1
strip	0	0	0	import	0	0	0	qualify	1	1	0	measure	1	0	0
solidify	0	0	0	compensate	1	0	0	infiltrate	0	0	0	inspect	1	0	0
optimize	1	1	0	govern	1	1	0	institute	1	1	0	facilitate	1	1	0
contact	1	0	0	issue	1	0	0	place	1	0	0	regasify	0	0	0
memorize	0	0	0	readjust	1	0	0	correct	1	0	0	know	1	1	0
customize	1	1	0	Examine	0	1	0	Prepare	1	1	0	alert	1	0	0
ensure	1	1	0	rehearse	1	1	1	enforce	1	1	0	amuse	1	1	0
copy	0	0	0	reline	1	0	0	further	1	1	0	execute	1	1	0
stun	1	0	0	turn	0	0	0	compete	1	1	0	Hold	1	0	0
shear	1	0	0	Organize	1	1	0	Authorize	0	1	0	sign	0	0	0
Package	1	0	0	mask	1	0	0	include	1	1	0	modify	1	0	0
stack	1	0	0	receive	1	0	0	involve	1	1	0	saturate	0	0	0
duplicate	0	0	0	deploy	1	1	0	bend	1	0	0	train	1	1	0
reclaim	0	0	0	deliver	1	1	0	Clean	1	0	0	specify	1	1	0
Lay	1	0	0	clean	1	0	0	provide	1	1	0	Coordinate	1	1	0
convey	0	0	0	cancel	1	0	0	inflate	0	0	0	conduct	1	1	0
reshape	1	0	0	mix	0	0	0	press	1	0	0	report	1	1	0
indent	1	0	0	drop	1	0	0	find	1	1	0	soften	1	0	0
delegate	1	1	0	assemble	1	0	0	discover	1	1	0	estimate	1	1	0
Transfer	0	0	0	protect	1	0	0	trim	1	0	0	Apply	1	1	0
Use	1	1	0	acquire	1	1	0	raise	1	1	0	Calculate	0	1	0
stop	0	0	0	License	1	0	0	demonstrate	1	1	0	arrest	1	0	0
blow	0	0	0	Propose	1	1	0	detail	1	0	0	guard	1	0	0
sustain	1	1	0	retrieve	1	0	0	use	1	1	0	mount	1	0	0
trap	1	0	0	verify	0	1	0	paint	1	0	0	trace	1	0	0
appraise	0	1	0	wrap	1	0	0	pay	0	0	0	manufacture	1	1	0
engage	1	1	0	liquefy	0	0	0	remediate	1	1	0	enable	1	1	0
assign	1	1	0	retouch	1	0	1	call	1	0	0	grade	1	1	0
expedite	1	1	0	aid	1	1	0	Select	1	1	0	become	1	1	0
buy	0	0	0	track	1	0	0	publish	1	1	0	translate	1	1	0
indicate	1	0	0	synthesize	1	1	0	Characterize	1	1	0	approximate	1	1	0
fertilize	1	0	0	persuade	1	1	0	remake	1	0	0	extract	0	0	0
Contact	1	0	0	tear	1	0	0	accustom	1	0	0	Train	1	1	0
hook	1	0	0	write	1	1	1	maintain	1	1	0	rule	1	1	0
audition	1	1	1	harden	0	0	0	package	1	0	0	fix	1	0	0
edit	1	1	1	glue	0	0	0	cook	1	0	0	bore	0	0	0
perform	1	1	1	implement	1	1	0	reserve	1	0	0	tidy	1	0	0
tag	0	0	0	organize	1	1	0	show	1	1	0	familiarize	1	0	0
express	1	1	1	attach	0	0	0	balance	0	1	0	excavate	0	0	0
twist	1	0	0	Research	1	1	0	debug	1	1	0	lock	1	0	0
analyze	1	1	0	acquaint	1	1	0	give	1	0	0	mediate	1	1	0
simulate	1	1	0	shelve	1	0	0	put	0	0	0	help	1	1	0
Direct	1	1	0	crate	0	0	0	act	1	1	0	redeem	0	0	0
Serve	1	0	0	relax	1	0	0	prioritize	1	1	0	suspend	1	0	0
negotiate	1	1	0	develop	1	1	1	permit	0	0	0	Translate	1	1	0
brighten	1	0	0	haul	0	0	0	lay	1	0	0	Learn	1	1	0
Grind	1	0	0	scrub	1	0	0	render	1	0	0	adapt	1	1	0
transcribe	0	0	0	hire	1	1	0	relate	1	1	0	explain	1	1	0
tutor	1	1	1	accept	1	0	0	insert	1	0	0	address	1	1	0
shunt	0	0	0	complete	1	0	0	conceal	1	0	0	acidize	1	0	0
teach	1	1	1	fill	1	0	0	build	1	0	0	increase	1	1	0
admit	1	0	0	view	1	0	0	extrude	1	0	0	plow	1	0	0
apply	1	1	0	manipulate	1	1	0	advance	1	1	1	hang	1	0	0
watch	1	0	0	rewind	0	0	0	etch	1	0	0	handle	1	0	0
revolve	0	0	0	decalcify	1	0	0	kill	1	0	0	compact	1	0	0
tow	0	0	0	align	1	0	0	moor	1	0	0	level	1	0	0
Perform	1	1	1	alter	1	1	0	stretch	1	0	0	Provide	1	1	0
reorder	1	0	0	format	0	0	0	narrate	1	1	1	devise	1	1	0
break	0	0	0	suit	1	1	0	suppress	1	0	0	coat	1	0	0
seam	1	0	0	continue	1	1	0	whiten	1	0	0	Carry	0	0	0
dilute	0	0	0	purify	0	0	0	lubricate	1	0	0	troubleshoot	1	1	0
configure	1	1	0	resolve	1	1	0	relieve	1	0	0	record	0	0	0
Walk	0	0	0	augment	1	1	0	ship	1	0	0	Cook	1	0	0
separate	1	0	0	plug	0	0	0	substitute	1	1	0	rub	0	0	0
reopen	0	0	0	inspire	1	1	1	minimize	1	1	0	warn	1	0	0
fabricate	0	0	0	cultivate	1	1	0	join	1	0	0	learn	1	1	0
look	1	0	0	design	1	1	1	Support	1	1	0	feel	0	0	0
defend	1	1	0	document	1	0	0	agitate	1	0	0	breed	1	0	0
control	1	1	0	arbitrate	1	1	0	diagnose	1	1	0	dust	1	0	0
tighten	0	0	0	plan	1	1	0	Inspect	1	0	0	treat	1	1	0
streamline	1	1	0	initiate	1	1	0	induce	1	0	0	reduce	1	1	0
microwave	0	0	0	present	1	1	1	collapse	0	0	0	touch	1	0	0
impregnate	0	0	0	collect	1	0	0	pack	1	0	0	relocate	1	0	0
display	0	0	0	file	1	0	0	safeguard	1	1	0	validate	1	1	0
consult	1	1	0	darken	1	0	0	cool	0	0	0	return	0	0	0
dump	0	0	0	form	0	0	0	offer	1	1	0	denote	1	0	0
instruct	1	1	0	Stay	1	1	0	advertise	1	1	1	count	0	1	0
capitalize	1	1	0	seal	1	0	0	require	1	1	0	install	1	0	0
mark	1	0	0	pick	1	0	0	hasten	1	0	0	characterize	1	1	0
fulfill	1	1	0	scribe	1	0	0	replace	1	0	0	Send	0	0	0
eliminate	1	1	0	Enhance	1	0	0	close	1	0	0	Lift	0	0	0
remain	1	1	0	take	1	0	0	heal	1	1	0	standardize	1	1	0
appeal	1	1	0	retain	1	1	0	switch	0	0	0	curl	1	0	0
publicize	1	1	0	rescue	1	0	0	Recommend	1	1	0	decorate	1	0	0
restrain	1	0	0	Control	1	1	0	drill	1	0	0	scrape	1	0	0
comply	1	0	0	polish	1	0	0	drain	1	0	0	Customize	1	1	0
Put	0	0	0	Settle	1	1	0	skid	1	0	0	rehabilitate	1	1	0

extend	1	1	1
referee	1	1	0
follow	1	1	0
confer	1	1	0
Prioritize	1	1	0
seek	1	1	0
flatten	0	0	0
dissect	1	0	0
Verify	0	1	0
fund	1	1	0
emboss	1	0	0
Secure	1	0	0
Collect	1	0	0
formulate	1	1	0
recover	1	0	0
print	0	0	0
screen	1	0	0
Approve	1	1	0
redevelop	1	1	0
throw	1	0	0
interact	1	1	0
hunt	1	0	0
feed	0	0	0
allocate	1	1	0
nail	1	0	0
transpose	1	0	0
understand	1	1	0
Educate	1	1	0
weigh	0	0	0
shave	1	0	0
fit	1	0	0
engrave	1	0	0
conceptualize	1	1	0
mystify	1	0	0
divert	1	0	0
model	1	1	0
summarize	1	1	0
repair	1	0	0
connect	1	0	0
redesign	1	1	0
smoke	1	0	0
Raise	1	1	0

A2. List of Tasks Predicted to be Resistant to Machine Learning Replacement

Install computer hardware.
Collect archival data.
Calculate geographic positions from survey data.
Communicate patient status to other health practitioners.
Discuss performance, complaints, or violations with supervisors.
Gather financial records.
Rebuild parts or components.
Prepare medical supplies or equipment for use.
Calculate financial data.
Investigate legal issues.
Monitor vehicle movement or location.
Develop exercise or conditioning programs.
Design costumes or cosmetic effects for characters.
Adjust routes or speeds as necessary.
Apprehend criminal suspects.
Select staff, team members, or performers.
Provide recommendations to others about computer hardware.
Provide basic health care services.
Inspect systems to determine if they are operating properly.
Monitor financial indicators.
Protect wildlife or natural areas.
Prepare sales or other contracts.
Clean equipment, parts, or tools to repair or maintain them in good working order.
Perform clerical work in medical settings.
Inspect condition or functioning of facilities or equipment.
Inspect facilities for cleanliness.
Confer with clients to determine needs.
Test mechanical systems to ensure proper functioning.
Advise customers on the use of products or services.
Coach others.
Prepare documentation for contracts, transactions, or regulatory compliance.
Develop treatment plans for patients or clients.
Administer personnel recruitment or hiring activities.
Recommend products or services to customers.
Write operational reports.
Resolve customer complaints or problems.
Interpret financial information for others.
Analyze forensic evidence to solve crimes.
Package materials for transport.
Monitor operational procedures in technical environments to ensure conformance to standards.
Coordinate logistics for productions or events.
Resolve issues affecting transportation operations.
Inspect sustainable energy production facilities or equipment.
Examine condition of property or products.
Operate ships or other watercraft.
Determine types of equipment, tools, or materials needed for jobs.
Review laws or regulations to maintain professional knowledge.
Estimate costs or terms of sales.
Install gauges or controls.

Collect biological specimens.
Review accuracy of sales or other transactions.
Create maps.
Monitor equipment fluid levels.
Test electrical circuits or components for proper functioning.
Write informational material.
Coordinate personnel recruitment activities.
Prepare documentation for permits or licenses.
Enter patient or treatment data into computers.
Direct material handling or moving activities.
Advise others on human resources topics.
Evaluate the effectiveness of counseling or educational programs.
Teach health management classes.
Recommend types of assistive devices.
Advise others on financial matters.
Inspect telecommunications equipment to identify problems.
Assess individual or community needs for educational or social services.
Install machine or equipment replacement parts.
Evaluate characteristics of individuals to determine needs or eligibility.
Estimate construction project costs.
Promote products, services, or programs.
Disburse funds from clients accounts to creditors.
Assign class work to students.
Authorize financial actions.
Analyze jobs using observation, survey, or interview techniques.
Determine presentation subjects or content.
Process forensic or legal evidence in accordance with procedures.
Maintain operational records.
Convert data among multiple digital or analog formats.
Adjust the tension of nuts or bolts.
Notify others of emergencies, problems, or hazards.
Provide educational information to the public.
Coordinate athletic or sporting events or activities.
Coordinate operational activities.
Monitor market conditions or trends.
Create electronic data backup to prevent loss of information.
Estimate costs for projects or productions.
Manage organizational or program finances.
Train staff members in social services skills.
Implement therapeutic programs to improve patient functioning.
Inspect work environments to ensure safety.
Develop financial or business plans.
Document events or evidence, using photographic or audiovisual equipment.
Review license or permit applications.
Arrange physical or mental health services for clients.
Develop proposals for current or prospective customers.
Inspect plumbing systems or fixtures.
Monitor medical equipment to ensure proper functioning.
Create graphical representations of mechanical equipment.
Develop promotional strategies for religious organizations.

Manage inventories of products or organizational resources.
Check quality of diagnostic images.
Rewire electrical or electronic systems.
Direct vehicle traffic.
Monitor computer system performance to ensure proper operation.
Direct fire fighting or prevention activities.
Inspect completed work to ensure proper functioning.
Intervene in crisis situations to assist clients.
Assist engineers or scientists with research.
Compile technical information or documentation.
Maintain the order of legal documents.
Maintain current knowledge related to work activities.
Prepare investigation or incident reports.
Confer with clients to discuss treatment plans or progress.
Observe individuals' activities to gather information or compile evidence.
Monitor activities of individuals to ensure safety or compliance with rules.
Adjust equipment to ensure optimal performance.
Verify employee information.
Verify accuracy of financial information.
Monitor student behavior, social development, or health.
Establish operational policies.
Operate still or video cameras or related equipment.
Conduct eligibility or selection interviews.
Complete documentation required by programs or regulations.
Disassemble equipment to inspect for deficiencies.
Adjust settings or positions of medical equipment.
Maintain mechanical equipment.
Interview people to gather information about criminal activities.
Mix sound inputs.
Update knowledge of legal or regulatory environments.
Record information from legal proceedings.
Operate control consoles for sound, lighting or video.
Develop tools to diagnose or assess needs.
Encourage patients during therapeutic activities.
Conduct research to inform art, designs, or other work.
Train others in operational procedures.
Schedule product or material transportation.
Sterilize medical equipment or instruments.
Provide information about landscaping services or costs.
Obtain documentation to authorize activities.
Investigate personal characteristics or activities of individuals.
Fit eyeglasses, contact lenses, or other vision aids.
Perform manual service or maintenance tasks.
Supervise workers providing client or patient services.
Repair electronic equipment.
Time vehicle speed or traffic-control equipment operation.
Create marketing materials.
Install audio or communications equipment.

A3. List of Tasks Predicted to Not be Resistant to Machine Learning Replacement

Balance receipts.
Trim client hair.
Analyze security of systems, network, or data.
Monitor work areas to provide security.
Provide patrons with directions to locales or attractions.
Communicate with government agencies.
Groom wigs or hairpieces.
Select equipment, materials, or supplies for cleaning or maintenance activities.
Administer first aid.
Create diagrams or blueprints for workpieces or products.
Smooth surfaces of objects or equipment.
Test chemical or physical characteristics of materials or products.
Direct quality control activities.
Conduct amusement or gaming activities.
Evaluate technical data to determine effect on designs or plans.
Examine personal documentation to ensure that it is valid.
Teach others to use computer equipment or hardware.
Evaluate potential of products, technologies, or resources.
Analyze patient data to determine patient needs or treatment goals.
Evaluate project designs to determine adequacy or feasibility.
Test mechanical equipment to ensure proper functioning.
Attach equipment extensions or accessories.
Research engineering aspects of biological or chemical processes.
Sort materials or products for processing, storing, shipping, or grading.
Review blueprints or specifications to determine work requirements.
Enter commands, instructions, or specifications into equipment.
Teach classes in area of specialization.
Sharpen cutting or grinding tools.
Establish standards for products, processes, or procedures.
Meet with coworkers to communicate work orders or plans.
Clean work sites.
Install masonry materials.
Measure environmental characteristics.
Align equipment or machinery.
Provide escort or transportation.
Remove products or workpieces from production equipment.
Confer with organizational members to accomplish work activities.
Examine marketing materials to ensure compliance with policies or regulations.
Cut carpet, vinyl or other flexible materials.
Read work orders or descriptions of problems to determine repairs or modifications needed.
Conduct anthropological or archaeological research.
Clean tools or equipment.
Apply lubricants or coolants to workpieces.
Assist disabled or incapacitated individuals.
Maintain inventory records.
Research hydrologic features or processes.
Inspect facilities or sites to determine if they meet specifications or standards.
Operate detonation equipment.
Classify organisms based on their characteristics or behavior.
Conduct opinion surveys or needs assessments.

Advise others on healthcare matters.
Negotiate sales or lease agreements for products or services.
Plan experiential learning activities.
Conduct climatological research.
Operate equipment to print images or bind printed images together.
Process customer bills or payments.
Adjust flow of electricity to tools or production equipment.
Communicate with clients about products, procedures, and policies.
Clean facilities or sites.
Prepare proposals or grant applications to obtain project funding.
Trim trees or other vegetation.
Recommend changes to improve computer or information systems.
Remove parts or components from vehicles.
Estimate time or monetary resources needed to complete projects.
Gather medical information from patient histories.
Prepare foods for cooking or serving.
Prepare graphics or other visual representations of information.
Prepare information or documentation related to legal or regulatory matters.
Drive passenger vehicles.
Load materials or equipment.
Develop sustainable organizational policies or practices.
Cut meat products.
Measure equipment outputs.
Remove debris or vegetation from work sites.
Maintain electronic equipment.
Inspect vehicles to determine overall condition.
Design industrial processing systems.
Arrange facility schedules.
Advise others on analytical techniques.
Estimate labor requirements.
Train personnel in organizational or compliance procedures.
Cut materials according to specifications or needs.
Replace worn equipment components.
Read work orders or other instructions to determine product specifications or materials requirements.
Inspect operational processes.
Monitor resources.
Smooth surfaces with abrasive materials or tools.
Interview claimants to get information related to legal proceedings.
Communicate dining or order details to kitchen personnel.
Smooth garments with irons, presses, or steamers.
Route mail to correct destinations.
Cut tile, stone, or other masonry materials.
Check quality of foods or supplies.
Collaborate with others to develop or implement marketing strategies.
Sort materials or products.
Implement advanced life support techniques.
Provide notifications to customers or patrons.
Prepare research or technical reports on environmental issues.
Thread wire or cable through ducts or conduits.
Determine operational compliance with regulations or standards.

Repair medical or dental assistive devices.
Plant crops, trees, or other plants.
Inspect lumber or raw woodstock.
Remove trash.
Operate communications equipment or systems.
Manage financial activities of the organization.
Remove worn, damaged or outdated materials from work areas.
Monitor access or flow of people to prevent problems.
Weld metal components.
Operate cash registers.
Prepare documentation of legal proceedings.
Clean vehicles or vehicle components.
Develop educational programs.
Treat chronic diseases or disorders.
Communicate with customers to resolve complaints or ensure satisfaction.
Identify strategic business investment opportunities.
Direct construction activities.
Explain engineering drawings, specifications, or other technical information.
Attach identification information to products, items or containers.
Apply information technology to solve business or other applied problems.
Fill cracks, imperfections, or holes in products or workpieces.
Provide medical or cosmetic advice for clients.
Warn individuals about rule violations or safety concerns.
Load agricultural or forestry products for shipment.
Read maps to determine routes.
Monitor alarm systems.
Spread concrete or other aggregate mixtures.
Load items into ovens or furnaces.
Develop new or advanced products or production methods.
Measure dimensions of completed products or workpieces to verify conformance to specifications.
Operate mining equipment.
Manage construction activities.
Conduct research to increase knowledge about medical issues.
Prepare materials or solutions for animal or plant use.
Enforce rules or regulations.
Assemble machine tools, parts, or fixtures.
Review customer information.
Heat material or workpieces to prepare for or complete production.
Remove snow.
Monitor activities affecting environmental quality.
Determine methods to minimize environmental impact of activities.
Clean machinery or equipment.
Type documents.
Shovel materials.
Remove debris from work sites.
Inspect garments for defects, damage, or stains.
Skim impurities from molten metal.
Control pumps or pumping equipment.
Operate grinding equipment.
Cut trees or logs.

Apply protective coverings to objects or surfaces near work areas.
Provide first aid or rescue assistance in emergencies.
Connect cables or electrical lines.
Determine construction project layouts.
Develop organizational policies or programs.
Operate heavy-duty construction or installation equipment.
Confer with others about financial matters.
Construct patterns, templates, or other work aids.
Design electromechanical equipment or systems.
Inspect metal, plastic, or composite products.
Serve on institutional or departmental committees.
Provide customers with general information or assistance.
Shape metal workpieces with hammers or other small hand tools.
Collect deposits, payments or fees.
Test computer system operations to ensure proper functioning.
Develop mathematical models of environmental conditions.
Mark reference points on construction materials.
Lay out parts to prepare for assembly.
Adjust equipment controls to regulate flow of production materials or products.
Pour materials into or on designated areas.
Develop software or computer applications.
Install computer software.
Repair furniture or upholstery.
Conduct scientific research of organizational behavior or processes.
Move furniture.
Plan environmental research.
Refinish wood or metal surfaces.
Use weapons or physical force to maintain security.
Measure clients to ensure proper product fit.
Prepare employee work schedules.
Estimate technical or resource requirements for development or production projects.
Operate farming equipment.
Position safety or support equipment.
Advise patients on effects of health conditions or treatments.
Prepare contracts, disclosures, or applications.
Confer with clients to exchange information.
Prepare hot or cold beverages.
Position construction or extraction equipment.
Prepare excavation or extraction sites for commissioning or decommissioning.
Develop instructional objectives.
Assist patrons with entering or exiting vehicles or other forms of transportation.
Finish concrete surfaces.
Design structures or facilities.
Attend training sessions or professional meetings to develop or maintain professional knowledge.
Administer anesthetics or sedatives to control pain.
Record information about parts, materials or repair procedures.
Inspect cargo to identify potential hazards.
Advise others about land management or conservation.
Secure watercraft to docks, wharves or other vessels.
Assess risks to business operations.

Inspect motor vehicles.
Install green structural components, equipment or systems.
Stock products or parts.
Establish nursing policies or standards.
Monitor the handling of hazardous materials or medical wastes.
Maintain vehicles in good working condition.
Adjust dental devices or appliances to ensure fit.
Dispose of trash or waste materials.
Research diseases or parasites.
Clear equipment jams.
Direct activities of agricultural, forestry, or fishery employees.
Represent the organization in external relations.
Test patient hearing.
Select tools, equipment, or technologies for use in operations or projects.
Prepare breads or doughs.
Write reports or evaluations.
Mark materials or objects for identification.
Conduct research of processes in natural or industrial ecosystems.
Inspect completed work to ensure proper installation.
Maintain security.
Supervise scientific or technical personnel.
Remove parts or components from equipment.
Collect samples of materials or products for testing.
Assess educational needs of students.
Coordinate timing of food production activities.
Manage budgets for appropriate resource allocation.
Evaluate new technologies or methods.
Develop computer or information security policies or procedures.
Develop scientific or mathematical models.
Assist individuals with paperwork.
Collect medical information from patients, family members, or other medical professionals.
Prepare scientific or technical reports or presentations.
Train employees on environmental awareness, conservation, or safety topics.