TECHNOLOGICAL UNEMPLOYMENT IN BRAZIL: EFFECTS OF AUTOMATION ON JOB MARKET OCCUPATIONS

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Resumo:
O desemprego tecnológico é visto como a perda de empregos que uma sociedade sofre devido à substituição de trabalhadores por máquinas ou algoritmos. Esses componentes de capital podem estar evoluindo rapidamente como um substituto para o trabalho humano ao invés de ser complementar ao aumento da produtividade. O presente estudo emprega técnicas de aprendizado de máquina em uma combinação de PCA com análise de aglomerados com três diferentes classificadores, o modelo de Probabilidade Linear (MPL), modelo de Regressão Logística e a Análise de Discriminante Linear (ADL) a fim de investigar padrões de habilidades e correlações das ocupações, ranqueando-as de acordo com suas probabilidades de automação, baseado em Osborne e Frey (2017). Encontra-se que as ocupações com tarefas intensivas em destreza manual sem a necessidade de habilidade de originalidade, belas artes, persuasão ou negociação possuem o mais alto risco de automação. Por outro lado, tarefas que requerem altos níveis de inteligência social e criativa são vistas com menor chance de substituição pelas máquinas.

Palavras-chave: Desemprego tecnológico; Automação; Aprendizado de máquina; Mercado de trabalho.

Abstract:
Technological unemployment is seen as the loss of jobs a society endures due to replacement of workers by machines or algorithms. This component of capital can be evolving more rapidly as substitute for human labor than a complementarity to raise productivity. The study borrows techniques from machine learning applying a combination of PCA with cluster analysis and three different classifiers, the Linear Probability Model (LPM), Logistic Regression Model and the Linear Discriminant Analysis (LDA) to investigate patterns of abilities correlations and ranking occupations accordingly to its automation probabilities, in line with Osborne and Frey (2017). It finds that occupations intensive in finger and manual dexterity tasks without the need for originality, fine arts, persuasion or negotiation abilities have the highest risk of automation. On the other hand, tasks that require high levels of social and creative intelligence are seen as less likely to be substituted by machines.

Keywords: Technological unemployment; Automation; Machine learning; Job market.

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1. Introduction

For centuries, workers, labor parties and unions have disputed on the impact of new technologies over employment. Back in 1811, the luddites initiated a movement to destroy machines that they feared could replace workers leaving every family unassisted in an epoch of precarious conditions. In their eyes, technology worked as a perfect substitute for human labor.

As the industrial revolution matured, fear dissipated with the creation of new occupations, and capital became complementary to labor. Its role was to increase worker's productivity with new tools and techniques that made goods cheaper leading to two centuries of increasing productivity and lowering prices of goods and capital. The standards of living increased significantly since the 1800 and the 2000's (ACEMOGLU, 2002).

The widespread of internet, communication technologies and high quality education since the 1980's lead to the development of techniques known as Artificial Intelligence (AI). For long, AI has been a concept (and a fear) that started to materialize with the possibilities of applying statistical and computation techniques that evolved into the field of machine learning and deep learning. AI was seen as a very distant concept when every single action a machine does needed to be coded by a human. Even the simplest actions programmed into a robot, like walking, required years of developing and human coding. But machine learning techniques recently changed this scenario, providing the possibility to teach machines by "training" them on large data sets of data, images, speech and movement.

Since, the need to code every single action was dismissed and machines could learn by themselves by analyzing data, in ways much more accurately and faster than human workers could do. This revolution has the potential to affect directly the labor market. Robots are increasing in quality and can replace a considerable number of workers tasks in production (Industry 4.0), accounting and finance (algorithms), transportation (self-driving cars and trucks), assisting other people (Siri, Google Assistant).

The accelerating development of new technologies brings back the concern from the 1800: capital and technology could be evolving more rapidly as substitutes for human labor than a complementarity to raise productivity. Therefore, technological unemployment represents the loss of jobs due to machine substitution that outruns the pace of new uses for displaced labor (KEYNES, 1933; FREY and OSBORNE, 2017).

In this context, the study investigates Brazilian job market transformations to answer which jobs are under the risk of automation and its effects over technological unemployment.

Therefore, capital can be seen as complementary, augmenting worker's productivity, or substitute, by replacing workers with machines. The impact of automation is to increase labor-capital substitutability rather than its complementarities. Both effects are possible, but we focus on the occupations that can be replaced by new technologies. By analyzing the Brazilian Code of Occupations (CBO) classification, we seek to identify the relationship between automation probabilities with specific tasks and skills characteristics of each occupation.

The investigation allows the discussion on the most prominent occupations of the next decades and which of them societies should prepare to assist, retrain and focus to lower the transition costs for these workers. The insights may have social implications for education, polarization of jobs, wage and inequality in the labor markets, regional disparities and unemployment. This work does not consider offshoring effects - that is, the relocation of a business process from one country to another that can eliminate or create jobs elsewhere.

The next section shows the literature related to technological unemployment. The third section brings and exploratory analysis while section four shows the ranking of occupations accordingly to its probabilities of automation.

2. Literature Review

The literature on technological unemployment offers evidences that introduction of new information technologies (IT) have opened possibilities to automate routine tasks executed by workers, raising the risk to be dismissed as they are substituted by machines or computers, with the advantage of being easy scalable and with high potential of costs reduction and efficiency gains. (FREY and OSBORNE, 2017; WEF, 2015; AUTOR, 2015).

Acemoglu and Autor (2011) defines a *task* as a unit of work activity that produces an output, like goods or services. A skill is a worker's endowment of capabilities for performing various tasks. Therefore, workers apply their skill endowments to tasks in exchange for wages, producing the output.

Santens (2016) suggests that work can be classified into routine and nonroutine, or cognitive and manual. Routine work is the same activities day in and day out, has standard procedure or tasks that are repetitive. On the other hand, nonroutine work varies in context and execution periodically. Routine tasks can be correlated to tasks that requires mostly manual work, while nonroutine work requires mostly thinking (cognitive).

The impact of technological changes is stronger over routine tasks, since rules can be written for work that does not change, and that work can be better handled by machines.

Jaimovich and Siu (2012) stresses the decline in manufacturing jobs and the disappearance of routine tasks based on jobs as of the causes of high unemployment rates measured in the economy of United States.

Technological unemployment affects routine tasks that can be substituted by rules reproduced as algorithms. Otherwise, occupations intensive in manual tasks that are not subject to substitution by algorithms can experience a higher demand, since it can lack routines or be so specific that cannot be coded into machines. This tasks typically require higher levels of flexibility or physical adaptation, even in occupations of low qualification and salary (AUTOR, et al., 2003; GOOS and MANNING, 2007; AUTOR and DORN, 2013).

Makridakis (2017) considers that the uniqueness of the artificial intelligence (AI) technologies is the potential to supplement, substitute and amplify practically all tasks that are currently performed by humans, with significant impacts over worker's productivity but at the same time increasing the probability of technological unemployment.

Rutkin (2013) considers that the technological takeover will happen in stages. At first, computers start replacing people in vulnerable fields like transportation/logistics, production labor, and administrative support, following the positions in services, sales, and construction. Nonetheless, this should not be seen as a limit to the extent that technological unemployment can affect societies. The rate of replacement can slow down due to bottlenecks in harder-to-automate fields.

Once a "technological plateau" is reached, it can be overcome by subsequent waves of computerization. A second wave of computerization dependents on the development of general artificial intelligence. This second wave could put jobs in management, science and engineering, and the arts at risk (RUTKIN, 2013).

Stewart et al. (2015) stresses that there may be a transitional period of increased unemployment until new opportunities are created by emerging needs. A difficulty would be to know which would be the net effect of AI improvements over society. It is exactly routine work that once formed the basis of the American middle class. Such jobs are increasingly unavailable, leaving only two kinds of jobs with polarized outlooks: jobs that require little thought, so people are paid little to do them, and jobs that require so much thought, employing people very well paid (AUTOR and DORN, 2013; RUTKIN, 2013).

The polarization of US labor markets arises as a social problem beyond the rise in inequality. This polarization is characterized by the growth in high income cognitive jobs and growth in low income manual occupations, while the middle of the distribution is deflated

(GOOS et al., 2009). This implies a raise in income inequality and a distortion in labor markets, since the people with intermediary education moves toward jobs that pays less and do not employs the worker's full capacity. These distortions imply losses in efficiency and raises questions of over qualification of workers.

Frey and Osborne (2017) build upon literatures of technological unemployment (AUTOR et al., 2003; GOOS and MANNING, 2007; AUTOR and DORN, 2013) and technological innovation future impacts (BRYNJOLFSSON and MCAFEE, 2014) to estimate the probabilities of disappearance of jobs in United States, based on the O*NET skills database.

The authors estimate the probability of computerization for 702 detailed occupations, using a Gaussian process classifier, and examine the impacts of future computerization on US labor market outcomes. Intrinsic characteristics of the tasks are used to classify the jobs with high or low risk of automation, considering the required finger dexterity, manual dexterity, work in cramped work spaces, awkward positions; required originality, abilities in fine arts; social perceptiveness; skills in negotiation; persuasion; and assisting and caring for other people.

The turning point in their study is that they are not only looking behind or diagnosing what is set. Machine learning techniques are applied in an effort to foresee jobs most likely to disappear. They find that about 47 percent of total US employment is at risk. Evidence is provided that wages and educational attainment exhibit a strong negative relationship with an occupation probability of computerization.

A problem in the studies that try to estimate which jobs are most likely to disappear is that they do not account jobs that are likely to appear. There are some complementarity and substitution effects between jobs that are not accounted by the researchers. New jobs can arise from three sources:

- new technologies require a new set of skills and tasks;
- transformation in jobs tasks;
- complementarities with growing jobs.

Considering the possibility of creation of new jobs, we cannot ascertain the net effect on total employment, or the time that unemployment would take to dissipate as workers migrate between tasks, developing new sets of skills necessary for the new jobs.

Computerization impacts countries in different pace. The trend in computerization is widespread between all countries as the price of automation technologies decreases significantly year after year. The great leap of this wave of automation is based on algorithms, which have a low cost of reproducibility in other countries, with a number of this technologies being free or open source. Therefore, we can extend the analysis of United States to Brazil's labor market, because it's a question of time until different markets are affected.

3. Exploratory Analysis

The strategy is to use the intrinsic characteristics of each occupation described in O*NET and seen as probable of being automated by other studies, and transpose these characteristics to Brazilian Code of Occupations (CBO). Frey and Osborne (2017) considers nine variables that acts as automation bottlenecks.

These variables are seen as Perception and manipulation tasks (Finger dexterity, Manual dexterity, Cramped Spaces), Creative intelligence tasks (Originality, Fine Arts), and Social intelligence tasks (Negotiation, Persuasion, Social Perceptiveness, Assisting and Caring for others). The probability of an occupation being automated can be described as a function of these task characteristics.

Perception and manipulation tasks includes tasks that relate to an unstructured work environment, dealing with objects, tools or in positions not easily foreseeable. It makes jobs less susceptible to computerization. In line with Frey and Osborne (2017), robots are still unable to match the depth and breadth of human perception, so these difficulties have ramifications for manipulation tasks, and, as handling irregular objects, or planning out the sequence of actions required to move an object from one place to another.

Creativity, by definition, is about generating novelty and value. Values are highly variable across societies and context, so it follows that many arguments about creativity are rooted in disagreements about value. Thus, even if a machine could identify and encode human creative values, there would still be disagreement about whether the computer appeared to be creative. In the next few years, there appears to be no feasible solution to this problem, so it seems unlikely that occupations requiring a high degree of creative intelligence tasks can be automated in the near future.

Social intelligence tasks are seen as intensively dependent on human interaction, involving negotiation, persuasion and care for others. Machines can reproduce some aspects of human social interaction, but the real-time interpretation of natural human emotions is a challenging problem, and the ability to respond intelligently to such inputs is even more difficult. The complete descriptions of occupation characteristics in O*NET database can be seen in the attachments, Table A1.

The variables express occupations bottlenecks of automation selected and classified in high, medium or low level of importance of the particular ability for each occupation. The O*NET database considers 967 different occupations for the US job market. Based on this frequencies, the occupations are transposed to the Brazilian Code of Occupations (CBO), grouping the occupations in Brazil and attributing the same levels of importance of each variable in US. We used a sample with 195 occupations grouped in categories (Subgroups CBO). After importing the corresponding characteristics of each occupation from O*NET database, we get 161 occupations.

In this context, there are considerable differences between countries labor markets. United States (US) has a higher productivity and is more capital intensive then Brazil. Therefore, the tasks composition of each occupation can vary and not have an exact match, a limitation that imposes a need to further improvements in these area.

The characteristics were transformed into dummies, attributing values 0, 1 or 2 according to each tercile occupied inside the characteristics distribution. For example, Finger Dexterity ranges from 0 (Singers) to 5,5 (Jewelers). So, we have low Finger Dexterity below 1,83 (Security Guards), medium Finger Dexterity between 1,83 and 3,66 (Wood Model Makers) and high Finger Dexterity above 3,66 (Anesthesiologists). As in Frey and Osborne (2017), the values used are marked as the Level value, except Cramped Work Space, Awkward Positions that uses the Context value.

Table 1. Frequencies of worker characteristics

Level	Finger Dexterity	Manual Dexterity	Origina-lity	Negotia-tion	Persua-sion	Social Percepti-veness	Fine Arts	Camped Spaces	Assisting and Caring
High	22	1	21	57	77	31	4	53	11
Medium	124	103	125	95	82	126	12	93	93
Low	15	57	15	9	2	4	145	15	57

Source: by the authors.

Table 1 shows the distribution of worker characteristics classified into high, medium or low level or requirement for the specific occupation. We can see that the majority of Occupations seen as high level of Finger Dexterity includes Jewelers, Craft Artists, Musical

Instrument Repairers and Tuners, Gem and Diamond Workers, Cabinet Makers and Carpenters, Electrical and Electronic Equipment Assemblers. These workers need the “ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects” (O*NET, 2019). On the other side, amongst the lower Finger Dexterity we have Professors, Social Scientists, Managers and Supervisors of Production and Sales, Magistrates and Auditors.

Manual dexterity is seen as “the ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects” (O*NET, 2019). The top is held by Jewelers, while Biologists, Physicists, Mathematicians, Researchers and Market Research Analysts and Specialists sits on the bottom of Manual dexterity requirements.

Originality is described as “the ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem” (O*NET, 2019). The most intensive occupations in originality is Physicists, Mathematicians, Engineers and Architects, Technical designers, Social Scientists and Professors. The least original is Shoe and Leather workers, Production Packers and Packagers, Maids and Housekeeping Cleaners, Bookkeeping, Accounting, and Auditing Clerks.

Negotiation is described as the ability to bring “others together and trying to reconcile differences” (O*NET, 2019). The top occupations are Lawyers, Judges, and Magistrates, Police Patrol Officers, Religious activities members, Engineers and Architects. With the least negotiation abilities, we can cite Timing Device Assemblers and Adjusters, Production Packers and Packagers, Textile Workers and Biological Technicians.

Persuasion is the ability in “persuading others to change their minds or behavior” (O*NET, 2019). Lawyers, Religious activities members, Door-To-Door Sales Workers, News and Street Vendors lead in persuasion. On the other hand, we have Production Packers and Packagers, Textile Workers, Siderurgy and Construction workers and Food Cooking Machine Operators.

Social Perceptiveness requires “being aware of others’ reactions and understanding why they react as they do” (O*NET, 2019). The top occupations are Healthcare Social Workers, Physicians and Healthcare workers in general. The least Social Perceptiveness is required from Production Packers and Packagers, Textile Workers, Electro-Mechanical Technicians and Industrial Truck and Tractor Operators.

Fine arts abilities are the "knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture" (O*NET, 2019). Technical and Exhibit Designers, Professionals of Shows and Arts, Graphic designers, Urban and Rural Craft Artists and Sound and Projection Engineering Technicians are the most versed in the Fine arts. On the other side, Logging Preparation workers, Electrical, Electronic and Timing Device Assemblers, Food Cooking Machine Operators and Tenders, Structural Iron and Steel Workers, Bookkeeping, Accounting, and Auditing Clerks, Medical and Clinical Laboratory Technicians rates low in this ability.

Assisting and caring for others includes the ability to provide "personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients" (O*NET, 2019). Healthcare workers in general, Fire Fighting and Prevention Officials, Police Officers are those with the highest need of Assisting and caring for others. Otherwise, Popular Artists and Models, Information Technology Professionals, Glass Blowers, Molders, Benders, and Finishers and Craft Artists requires low levels of this ability.

The ability of working in Cramped work spaces, or awkward positions answers to the question of "how often does this job require working in cramped work spaces that requires getting into awkward positions?" (O*NET, 2019). The most frequent are Insulation of Metal Surface Workers, Farm Equipment Mechanics and Service Technicians, Farm Equipment Mechanics and Service Technicians, Mineral Extraction Workers, Industrial Machinery Mechanics, Energy Generation and Distribution Operators, Telecommunications Line Installers and Repairers. The occupations that hardly work in these conditions are Researchers, Hairdressers, Hair Stylists, and Cosmetologists, Security Guards, Door-To-Door Sales Workers, News and Street Vendors, and Related Workers and Social Scientists.

Table 2. Correlations of CBO Jobs Characteristics

	Finger Dexterity	Manual Dexterity	Originality	Negotiation	Persuasion	Social Percep.	Fine Arts	Cramped Spaces	Assisting and Caring
Finger Dexterity	1,00	0,46	-0,03	-0,28	-0,21	-0,30	0,00	0,31	-0,33
Manual Dexterity	0,46	1,00	-0,35	-0,43	-0,41	-0,37	-0,07	0,51	-0,11
Originality	-0,03	-0,35	1,00	0,49	0,51	0,42	0,44	-0,20	0,13
Negotiation	-0,28	-0,43	0,49	1,00	0,75	0,55	0,17	-0,17	0,35
Persuasion	-0,21	-0,41	0,51	0,75	1,00	0,56	0,29	-0,29	0,27
Social Perceptiveness	-0,30	-0,37	0,42	0,55	0,56	1,00	0,13	-0,17	0,36
Fine Arts	0,00	-0,07	0,44	0,17	0,29	0,13	1,00	-0,22	-0,06
Cramped Spaces	0,31	0,51	-0,20	-0,17	-0,29	-0,17	-0,22	1,00	0,00
Assisting and Caring	-0,33	-0,11	0,13	0,35	0,27	0,36	-0,06	0,00	1,00

Source: by the authors.

Table 2 shows how characteristics interact with each other. The correlations express how much these characteristics are complementary or substitutes amongst the occupations. It can be seen that occupations that require high Finger Dexterity, usually require a considerable level of Manual Dexterity (0.46) and the ability to work in Cramped Spaces or Awkward Positions (0.31). Occupations with high Finger Dexterity requires low Assisting and Caring for Others (-0.33), Social Perceptiveness (-0.30) and Negotiation (-0.28) abilities. These occupations are intensive in Perception and manipulation tasks, such as Carpenters, Electro-Mechanical, Industrial, Avionics and Farm Equipment Technicians and Jewelers.

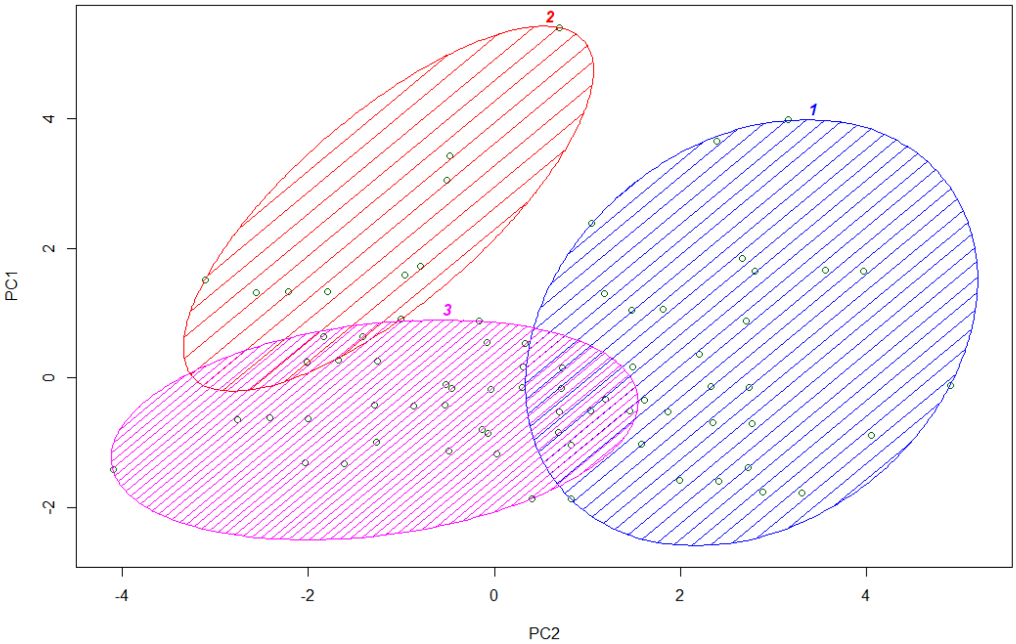
Originality, a characteristic positively correlated with Negotiation (0.51), Persuasion (0.49) and Fine Arts (0.44). On the other hand, is negatively correlated with Manual Dexterity (-0.35) and the ability to work in Cramped Spaces or Awkward Positions (-0.20). These occupations can be seen as intensive in Creative intelligence tasks, and includes Craft and Rural Artists, Graphic Designers, Architects and Modelers, Elementary School Teachers.

Negotiation and Persuasion are closely related (0.75), as Social Perceptiveness (0.55) and Originality (0.51). Assisting and Caring for others is also positively correlated (0.35). In general, Negotiation is negatively correlated with Manual Dexterity (-0.43) and Finger Dexterity (-0.28) tasks. This group includes the occupations intensive in Social intelligence tasks such as Directors and Managers, Lawyers, Reporters and Correspondents, Social Scientists, Firefighters and Police officers, Criminal Investigators, Physicians and Healthcare Workers.

A cluster analysis is conducted in order to explore patterns in the data and group occupations by similarity. If each characteristic were seen as a dimension, the graphic would need a nine dimensions clustering. To avoid this and make the visualization possible, we apply a Principal Components Analysis (PCA) reducing its dimensionality down to two. The combination of PCA with cluster analysis is a common practice in data analysis and machine learning algorithms (EREMENKO and PONTEVES, 2018). The Figure 1 shows three clusters of occupations.

The three clusters show the groupings of Social intelligence tasks (cluster number 1), Creative intelligence tasks (2), Perception and manipulation tasks (3). The PC1 axis weights for more Originality and Fine Arts skills, while the PC2 component weights for more Persuasion and Negotiation skills.

Figure 1. Clusters of Characteristics of Occupations in Brazil



Source: by the authors.

From now on, we can start to speculate that occupations sitting in group 3 will be more likely to have higher automation probabilities than groups 1 and 2 since they are less intensive in tasks that require Social and Creativity intelligence abilities. The occupations more intensive in Finger and Manual Dexterity without components of persuasion or originality can suffer the most from the automation waves. This will be explored in the next section.

4. Automation Rankings

Following the procedures of Frey and Osborne (2017), we manually attribute automation probabilities weights to the jobs considered as the most probable of being impacted by automation. To attribute manually the certainty of which jobs will or will not be automated in the future is a grey area. In order to achieve a reasonable criterion to label occupations, the authors worked with a group of machine learning researchers, asking "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment" (FREY and OSBORNE, 2017).

Labels were assigned only to the occupations about which the authors were most confident all tasks considered automatable. This reflects the possibility of task simplification, possibly allowing some currently non-automatable tasks to be automated.

The training data was labelled as either ‘0’ (not computerisable) or ‘1’ (computerisable), respectively, getting 24 of the 161 occupations, 15% of the total number. Only occupations that matched exactly the name of the occupations taken as computerisable or not by Frey and Osborne were labelled. The authors labelled 70 of 702, 10% of the total.

Therefore, we train three different classifiers in order to predict the weights of the other CBO occupations, making inference to the whole database of occupations. The model used to classify occupations by their relative probabilities of automation can be seen as:

$$P_{(automation)} = FD + MD + CA + OR + FA + SP + NG + PS + AC$$

which *P* is the Probability of Automation, *FD* the Finger Dexterity, *MD* the Manual Dexterity, *CA* the Cramped Work Space or Awkward Positions, *OR* the Originality, *FA* the Fine Arts, *SP* the Social Perceptiveness, *NG* the Negotiation, *PS* the Persuasion, *AC* the Assisting and Caring for Others.

The three different classifiers considered includes a Linear Probability Model (LPM), a Logistic Regression Model (Logit) and the Linear Discriminant Analysis (LDA). The probabilities were standardized between 0 and 1. As did Frey and Osborne (2017), we call the occupations with a probability higher or equal than 0.7 as high risk occupations, between 0.3 and 0.7 as the medium risk, and below or equal to 0.3 as the low risk of automation.

The differences between the techniques are subtle but the positions in the rankings can vary with the model chosen. The Logit model shows 46 occupations with a high risk, 109 with medium risk, and 6 with low risk of automation. The mean is 0.59. with a standard deviation of 0.16. The LPC model shows 18 occupations with a high risk, 131 with medium risk, and 12 with low risk. The mean is 0.55 with a standard deviation of 0.16. The LDA shows a mean of 0.55 with a standard deviation of 0.5. Since its classification is binary, it shows 89 as high risk, and the other 72 as low risk of automation. The correlation between Logit and LPC ranking is of 0.90, while the Logit and LDA correlation is of 0.86. This shows a consistency between the results of the models.

The Table 3 shows the Top 10 occupation with higher probability of automation ordered accordingly to the results of the Logit model. The columns LPC and LDA brings the results for that occupation using alternative models.

Table 3. Top 10 occupations with higher automation probability - ranked by Logit model.

Rank	Title	Logit	LPC	LDA
1	EMBALADORES E ALIMENTADORES DE PRODUÇÃO	1	1	1
2	TRABALHADORES ARTESANAIS DAS ATIVIDADES TÊXTEIS, DO VESTUÁRIO E DAS ARTES GRÁFICAS	1	1	1
3	PROFISSIONAIS EM NAVEGAÇÃO AÉREA, MARÍTIMA E FLUVIAL	0,87	0,71	1
4	AUXILIARES DE SERVIÇOS DE BIBLIOTECA, DOCUMENTAÇÃO E CORREIOS	0,87	0,82	1
5	ESCRITURÁRIOS EM GERAL, AGENTES, ASSISTENTES E AUXILIARES ADMINISTRATIVOS	0,87	0,82	1
6	SECRETÁRIOS DE EXPEDIENTE E OPERADORES DE MÁQUINAS DE ESCRITÓRIOS	0,87	0,82	1
7	TÉCNICOS DE SERVIÇOS CULTURAIS	0,87	0,82	1
8	TRABALHADORES DE INFORMAÇÕES AO PÚBLICO	0,87	0,82	1
9	TÉCNICOS DA CIÊNCIA DA SAÚDE ANIMAL	0,84	0,62	1
10	TRABALHADORES DOS SERVIÇOS DE TRANSPORTE E TURISMO	0,84	0,83	1

Source: by the authors.

The probabilities analysis confirms a suspect raised by the cluster analysis. The group intensive in manual tasks, aka Perception and manipulation tasks with low needs of social and creative intelligence are the most prone to automation. Production Packers and Textile Workers were shown as the least intensive in Originality, Fine Arts, Social Perceptiveness, Negotiation and Persuasion.

Helpers and Secretaries can have its jobs replaced by personal assistants like Siri or Google assistant. This tools already offer voice recognition and can answer and execute simple tasks. In a recent presentation of Google Assistant, the company demonstrated how the tool was used to automatically dial to a saloon and schedule the service without the human interference, just talking with a (human) attendant.

Law firms are already using technologies that can write documents and clauses that needs only to be revised and signed by the Lawyer of Judge in charge. This kind of technology displaces documentation and juridical technicians allocated to this tasks. Powerful algorithms of search and organization of files can dismiss the need of people to execute this administrative and routine functions.

The occupations with higher automation probability have in common the routine non cognitive tasks, and these are the easiest to be replaced by machines. As the algorithms and technologies evolve, lowering its costs and becoming widespread in the markets, these occupations will probably see a significant drop in the demand by the firms, forcing these workers to accept lower wages or to acquire new skills to occupy another occupation.

Table 4 shows the Top 10 occupation with lowest probability of automation ordered accordingly to the results of the Logit model. The columns LPC and LDA brings the results for that occupation using alternative models. The complete listing of occupations estimated probabilities can be request to the corresponding author.

Table 4. Top 10 occupations with lower automation probability - ranked by Logit model.

Rank	Title	Logit	MPL	LDA
1	JOALHEIROS E OURIVES	0	0	0
2	PROFISSIONAIS DE ESPETÁCULOS E DAS ARTES	0,21	0,22	0
3	DESENHISTAS TÉCNICOS E MODELISTAS	0,24	0,17	0
4	SUPERVISORES DE VENDAS E DE PRESTAÇÃO DE SERVIÇOS	0,24	0,23	0
5	SUPERVISORES DE ATENDIMENTO AO PÚBLICO	0,24	0,23	0
6	TRABALHADORES DA PRODUÇÃO GRÁFICA	0,27	0,26	0
7	PROFESSORES DO ENSINO MÉDIO	0,30	0,28	0
8	SUPERVISORES NA EXPLORAÇÃO FLORESTAL E PESCA	0,31	0,27	0
9	SUPERVISORES EM SERVIÇOS DE REPARAÇÃO E MANUTENÇÃO MECÂNICA	0,31	0,27	0
10	SUPERVISORES DE MANUTENÇÃO ELETROELETRÔNICA E ELETROMECÂNICA	0,31	0,27	0

Source: by the authors.

Jewelers ranks as the least probable occupation to be automated because it has high scores in Finger and Manual dexterity, Originality, Negotiation and Persuasion. The CBO classification shows that Jewelers executes tasks of team coordination and administration, high standard quality control and inspection of the products, negotiation with suppliers and customers. These are all tasks that require a combination of social, creative intelligence and perception, posing a great challenge to automation.

Professionals of Shows and Arts is defined by its originality and fine arts requirements. This profession ranks as the second less probable to be automated since machines greatest challenge is to reproduce human creativity, originality and humor, so this profession may not be automated anytime soon.

In general, the other occupations with low probabilities of automation are intensive in human negotiation and persuasion. They are all intensive in human contact and managing, like the Supervisors of different industries. Ground work can be replaced by machines, but there always be a need to someone to make strategic decisions of innovation, production and organization.

5. Final Considerations

Borrowing techniques from machine learning to study automation, the study applied a combination of PCA with cluster analysis and three different classifiers, the Linear Probability Model (LPM), Logistic Regression Model (Logit) and the Linear Discriminant Analysis (LDA) in order to investigate patterns in occupations data and rank occupations accordingly to its automation probabilities.

The occupations with higher automation probability have in common the routine non-cognitive tasks, and these are the easiest to be replaced by machines. As the algorithms and technologies evolve, lowering its costs and becoming widespread in the markets, these occupations will probably see a significant drop in the demand by the firms, forcing these workers to accept lower wages or to acquire new skills for occupations.

The occupations with low probabilities of automation are intensive in human negotiation and persuasion. They are all intensive in human contact and managing, like the Supervisors of different industries. Ground work can be replaced by machines, but there always be a need to someone to make strategic decisions of innovation, production and organization.

The present study has some limitations. Firstly, it is assumed that the skills of occupations in the United States matches perfectly skills of occupations in Brazil. This assumption is necessary to transpose the O*NET weights to the CBO database. Secondly, the occupations manually labelled as certain of automation were too few (24) and adapted from the Frey and Osborne (2017). The criteria for considering an occupation it is not completely clear and needs to be improved.

Future developments aims at resolving some of these limitations includes considering a more detailed classification and description of occupations, using a more disaggregate level of CBO, with 2267 groups. By analyzing the tasks of each occupation described in the CBO lowest level of aggregation (167.027) we can better approximate the weights of skills required to each profession, reconstructing a similar O*NET database for Brazil.

The investigation of the most prominent occupations of the next decades can reveal which of occupations societies should prepare to assist, retrain and focus to lower the transition costs for this workers. These insights may have social implications for education, polarization of jobs, wage and inequality in the labor markets, regional disparities and unemployment.

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Attachments:

Table A1. Description of occupation characteristics in O*NET database

Worker Characteristic	Code	Description
Originality	1.A.1.b.2	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
Manual Dexterity	1.A.2.a.2	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
Finger Dexterity	1.A.2.a.3	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
Cramped Work Space, Awkward Positions	4.C.2.b.1.e	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Fine Arts	2.C.7.c	Knowledge of the theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social Perceptiveness	2.B.1.a	Being aware of others' reactions and understanding why they react as they do.
Persuasion	2.B.1.c	Persuading others to change their minds or behavior.
Assisting and Caring for Others	4.A.4.a.5	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.
Negotiation	2.B.1.d	Bringing others together and trying to reconcile differences.

Source: by the authors, based on the O*NET (2019) Content Model Reference.

Table A2. Manually attributed automation weights based on O*NET database.

Weight	Title
0	ADVOGADOS DO PODER JUDICIÁRIO E DA SEGURANÇA PÚBLICA
0	ADVOGADOS, PROCURADORES, TABELIÃES E AFINS
0	ATLETAS, DESPORTISTAS E AFINS
0	CIENTISTAS SOCIAIS, PSICÓLOGOS E AFINS
0	DIRETORES E GERENTES EM EMPRESA DE SERVIÇOS DE SAÚDE, DE EDUCAÇÃO, OU DE SERVIÇOS CULTURAIS, SOCIAIS OU PESSOAIS
0	DIRETORES GERAIS
0	DIRIGENTES E ADMINISTRADORES DE ORGANIZAÇÃO DE INTERESSE PÚBLICO
0	ENGENHEIROS, ARQUITETOS E AFINS
0	FÍSICOS, QUÍMICOS E AFINS
0	MEMBROS DE CULTOS RELIGIOSOS E AFINS
0	MEMBROS SUPERIORES DO PODER LEGISLATIVO, EXECUTIVO E JUDICIÁRIO
0	PROFESSORES DE NÍVEL MÉDIO NA EDUCAÇÃO INFANTIL, NO ENSINO FUNDAMENTAL E NO PROFISSIONALIZANTE
0	PROFESSORES DE NÍVEL SUPERIOR NA EDUCAÇÃO INFANTIL E NO ENSINO FUNDAMENTAL
0	PROFISSIONAIS DA MEDICINA
0	PROFISSIONAIS DA MEDICINA, SAÚDE E AFINS
0	TRABALHADORES DOS SERVIÇOS DOMÉSTICOS EM GERAL
0	TRABALHADORES NOS SERVIÇOS DE EMBELEZAMENTO E CUIDADOS PESSOAIS
1	AUDITORES FISCAIS PÚBLICOS
1	CAIXAS, BILHETEIROS E AFINS
1	CONDUTORES DE VEÍCULOS E OPERADORES DE EQUIPAMENTOS DE ELEVAÇÃO E DE MOVIMENTAÇÃO DE CARGAS
1	ESCRITURÁRIOS CONTÁBEIS E DE FINANÇAS
1	MONTADORES E INSTALADORES DE EQUIPAMENTOS ELETROELETRÔNICOS EM GERAL
1	PROFISSIONAIS DE RELAÇÕES PÚBLICAS, PUBLICIDADE, MARKETING E COMERCIALIZAÇÃO
1	TÉCNICOS EM CONSTRUÇÃO CIVIL, DE EDIFICAÇÕES E OBRAS DE INFRAESTRUTURA

Source: by the authors.