The Impact of Automation on Green Jobs

Eleanor Thompson
Supervised by Prof. Michael Osborne
Department of Engineering Science
University of Oxford

Introduction

Improving environmental quality, in particular tackling climate change, has become an increasingly high priority on the global agenda. As a result, countries are turning to green policies that promote sustainable economic growth without degrading the environment. The ramifications of these green policies on employment is a topic of fierce debate in the US, recently fuelled by President Joe Biden unveiling a $2tn infrastructure plan which is half composed of climate-related spending (The Economist, 2021). This debate is also gaining publicity as a result of the pandemic leaving 4 million jobless in the US (Bureau of Labor Statistics, 2021). Critics of green policies highlight the jobs inevitably lost in traditional energy sectors. Proponents claim they will boost employment, for example by pointing to Obama's post-financial crisis clean energy spending which created nearly a million jobs between 2013 and 2017 (Popp, Vona, Marin, & Chen, 2020) and a host of literature which claims that green policies create numerous high-quality jobs.

Beyond green policies, a second, potentially greater force on the labour market is automation. Automation has been predicted to displace many jobs (e.g., Frey & Osborne, 2013, 2017; Arntz et al., 2016; McKinsey, 2017), which may occur quicker than expected due to the coronavirus pandemic (Chernoff & Warman, 2020). An analysis of 30 studies which aim to predict green job creation from green policies revealed that automation is never accounted for, therefore these studies may overestimate the number of green jobs that will be created.

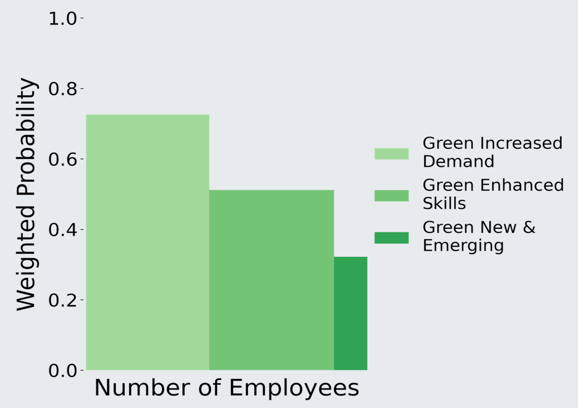
Objective

This project aimed to address this deficiency through assessing the impact of automation on the green jobs in the US which are anticipated to be created by green policies. The main implication was that if the impact was found to be high, policymakers should not seek to justify green policies by the quantity of jobs they create, as many may not be performed by humans by the time they are realised. To assess the impact of automation on the green jobs in the US, a machine learning model was trained which determined the probability of a green job being automatable.

Results

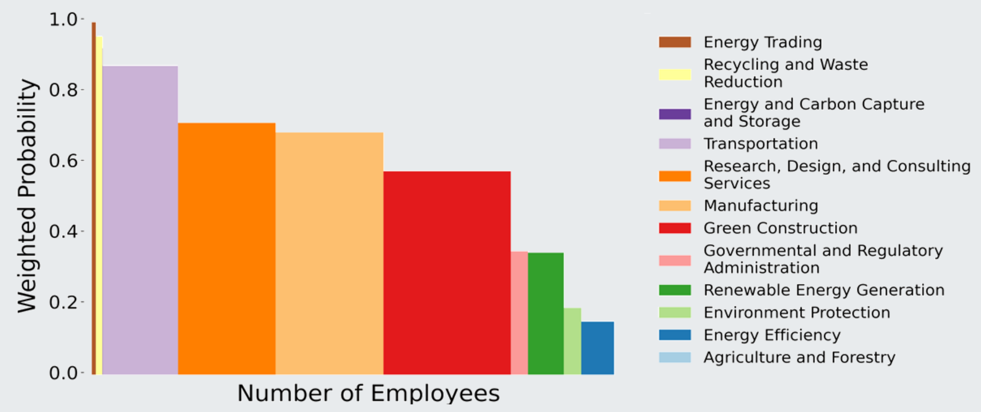
58% of green jobs in the US are expected to be automatable, compared with 51% of all jobs. This will be lower than the percentage of green jobs which in fact are automated, due to economic, social and legal barriers to adoption. However, this upper bound shows that the projected green job creation is overestimated, therefore policymakers should be aware that many green jobs will never materialise, or will disappear soon after they are created. How automatability varies with different categorisations of green jobs is explored below. In the following charts, the area of the bars is proportional to the number of people affected.

Greenness



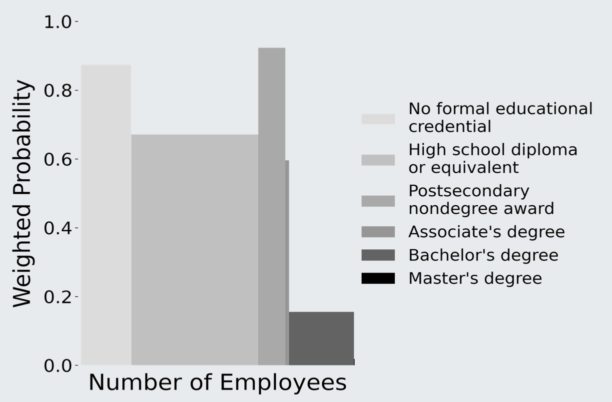
These three categorisations are given in order of how 'directly green' the jobs are. Evidently the 'greenest' jobs, such as 'Wind Turbine Engineers', are less automatable than indirectly green jobs, such as the 'Structural Iron and Steel Workers' which would support the construction of wind turbines. It was shown by Bowen et al. (2018) that the 'greenest' jobs require the most retraining to transition into, thus to create green jobs that are less at risk of automation, substantial retraining programmes need to be invested in.

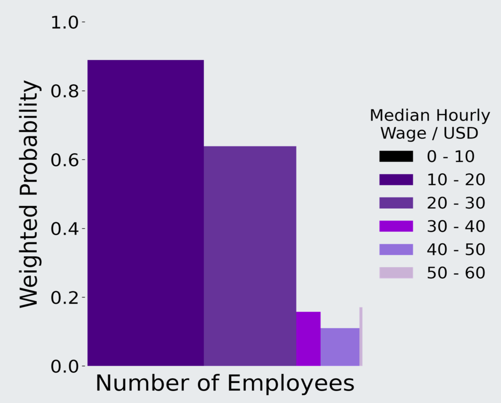
Sector



The two sectors with the greatest number of people affected are 'Green Construction', and 'Manufacturing'. The high automatability of construction is particularly alarming as the green jobs promised in President Biden's recently announced $2tn infrastructure plan are largely concentrated in construction (Rainey & Wolff, 2021). If future green stimulus packages aim to create jobs in these highly automatable sectors, many of those jobs may never be performed by humans.

Skill Level





Education and hourly wage are both negatively correlated with the probability of being automatable. This presents two challenges for policymakers. Firstly, the majority of green employees are in the most high risk categories; and secondly, automation will exacerbate social inequality and polarise the labour market further.

Machine Learning Method

Aim: To train a probabilistic binary classifier which outputs the probability of a job being automatable when given a feature vector describing the job.

Training the Binary Classifier

Inputs: 70 occupations described by 120 features (either skills, knowledge or abilities) from the O*NET Database. Example below.

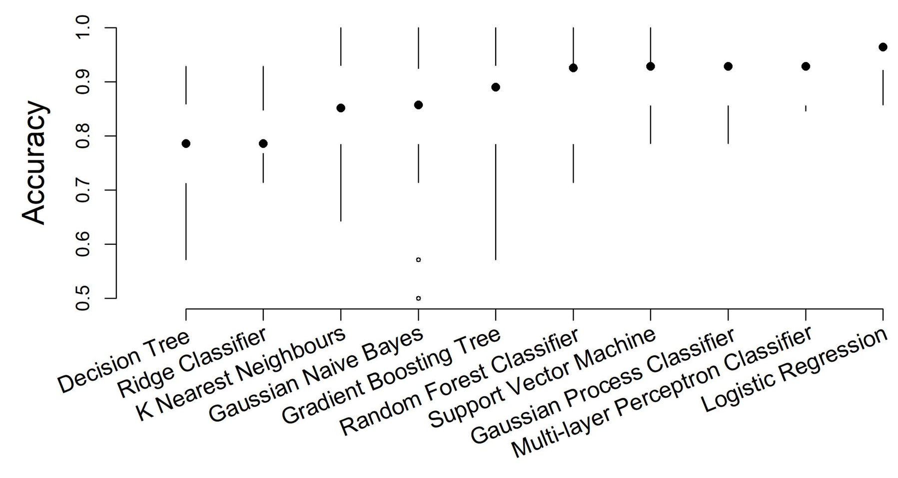
O*NET-SOC Code	Occupation	Features				
		Active Learning	Active Listening	Complex Problem Solving	Coordination	...
19-3091.02	Archeologists	3.88	4.12	3.75	4	...

Outputs: Binary labels – fully automatable (class 1) or fully unautomatable (class 0) – for each of the 70 occupations. Compiled by Frey and Osborne (2013).

Model Evaluation

10 binary classifiers were evaluated to determine which had the best predictive ability. Nested stratified k-fold cross-validation was used to tune the hyperparameters of the model and to assess ability of the model to generalise to unseen data.

The models were assessed using accuracy (top right), F1 Score and AUC-ROC curve. Logistic regression was selected as the optimal classifier with the highest median accuracy (0.964), F1 score (0.933) and AUC-ROC curve (1.000).



Logistic Regression

Using a logistic regression model, the probability of an unseen occupation, described by its feature vector $\boldsymbol{x}$, being automatable (i.e. belonging to class y=1) is

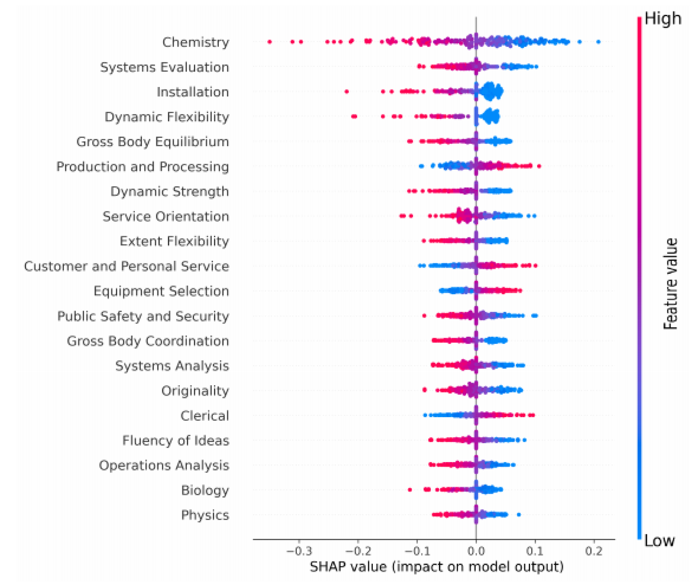
$$P(y=1|\boldsymbol{x};\mathbf{w}) = \sigma(\mathbf{w}^T\boldsymbol{x}) = \frac{1}{1+e^{-\mathbf{w}^T\boldsymbol{x}}}.$$

The weight vector $\mathbf{w}$ of the logistic regression model is learnt through minimising the following loss function

$$\min_{\mathbf{w}}\left(\frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i}^{n} -y_i\log(\sigma(\mathbf{w}^T\boldsymbol{x}_i)) - (1-y_i)\log(1-\sigma(\mathbf{w}^T\boldsymbol{x}_i))\right)$$

Where C is a hyperparameter that determines the relative strength of the L2 Regularisation and is determined by a grid search in the nested cross-validation process. This model therefore yielded the probability of each green job in the US being automatable.

Model Interpretation



The features which were most and least predictive of automatability can be seen above. The features which are indicative of unautomatability (such as those related to science, social intelligence, and creative intelligence) can inform reskilling programmes aimed to mitigate the effects of automation.

Conclusion

- The main takeaway is that 58% of green jobs in the US will be automatable, in comparison to 51% of all US jobs.
- This indicates that green employment estimates are overstated, as many of the jobs will not be performed by humans by the time they materialise or will disappear soon after they are created.
- Green policymakers who aim to create lasting jobs should therefore be aware of the impact of automation, especially given the fact that many green policies within pandemic recovery plans will be aimed at boosting employment.
- Those most affected are in low-skill and indirectly green jobs.
- To mitigate the impact on those in low-skill jobs, and as more directly green jobs require more retraining (Bowen et al., 2018), green policymakers should invest substantially in retraining affected employees, for example through upskilling and reskilling programmes.
- The features found to be highly predictive of unautomatability (such as those related to social intelligence and creative intelligence) can inform policymakers about which skills would be worthwhile investing in.
- The green sectors most affected were found to be 'Green Construction' and 'Manufacturing'. This is cause for concern as post-recession stimulus packages often disproportionately create jobs in the construction sector. For example, almost half of the jobs created by green investments from the American Recovery and Reinvestment Act of 2009 were in construction. Consequently, such packages aimed at catalysing post-pandemic recovery may yield fewer jobs than anticipated, unless automation is accounted for in green job estimates.

References:

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries.

Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition.

Bureau of Labor Statistics. (2021, Apr). The employment situation - march 2021. Retrieved from www.bls.gov/news.release/pdf/empsit.pdf

Chernoff, A. W., & Warman, C. R. (2020). Covid-19 and implications for automation

The Economist. (2021). Joe biden's climate gamble. The Economist Newspaper. Retrieved from https://www.economist.com/leaders/2021/04/10/joe-bidens-climate-gamble

Frey, C. B., & Osborne, M. A. (2013, 2017). The future of employment: How susceptible are jobs to computerisation?

McKinsey. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation.

Popp, D., Vona, F., Marin, G., & Chen, Z. (2020, Jun). The employment impact of green fiscal push: Evidence from the American Recovery Act.

Rainey, R., & Wolff, E. (2021, Apr). Biden's green energy plans clash with pledge to create union jobs.