The Future of Employment: How Susceptible are Jobs to Computerization?

Carl Benedikt Frey and Michael A. Osborne
Presenter: Benedikt Dengler

European University Institute

March 21, 2017

Preview (1)

- Motivating question: What is the likelihood of technological unemployment in the near future?
- This paper takes a first step: How likely is automation of current (2010) occupations?
- Basic Idea: Forward-looking analysis of automatability of occupations
  - Apply the forward-looking methodology of Blinder (2009) on offshorability to automatability.
  - Build on Autor, Levy and Murdane (2003) (ALM) by updating their measure of automatability
- Focus on technological preconditions for automatability
  - Identification of *potential* automatability rather than prediction of actual future developments

Preview (2)

- Data
  - O*NET: occupational characteristics
  - Standard Occupation Classification: employment and wages
- Method
  - Use combination of subjective categorization and ML-tools to generate an automatibility score for each SOC occupation.
- Results
  - up to 47% of employment susceptible to automation in the near future ("jobs at risk")
  - Probability of automation inversely related to wages and education: Break of polarization pattern observed since 1980s

Outline

- Brief Historical Overview
- Recap of ALM
- Technology in the 21st Century
- Data and Measurement
- Results

Historical Overview of Technological Impact on Labor

- Initial mechanization in 19th century primarily *deskilling*: artisan craftsmen replaced by unskilled factory workers
- Slow shift towards capital-skill complementarity over time
- Up until around 1980: compressed wage differentials due to supply effects (schooling)
- Since 1980: strong increase in skill premium and *polarization*
- Main driver: ICT revolution
- Two competing effects of technology:
  - direct substitution of labor in particular tasks
  - expansonary effects on labor via complementary tasks
- Historically, second effect has dominated but unclear whether this will remain so
- In this paper: assess the potential technological scope for substitution in the near future

Adaption of ALM methodology

- Recap ALM:
  - categorize jobs in 2×2 matrix: *routine/non-routine* vs *manual/cognitive*.
  - motivation: only codifiable tasks are automatable $\rightarrow$ focus on routineness of tasks, given state of technology
- Precondition for automation: *ability to codify problem in a set of procedural rules to appropriately direct the technology for each contingency potentially arising*
- With ML: codifiability mainly requires access to training data
- Adapt ALM model sketch from routineness (L_R/L_{NR}) to codifiability (or susceptibility) of labor (L_S/L_{NS})
  - Assumption: L_S and computer capital C perfect substitutes, both substitute for L_{NS} with elasticity $\beta \in [0, 1]$
  - C assumed to be supplied at exogenously declining price p_C
  - With $p_C \downarrow$, reallocation of labor from L_S to L_{NS} (Roy, 1951)

What are (non-)susceptible tasks?

- Susceptible tasks defined as tasks amenable to ML
- Subject to distinct engineering bottlenecks: speed in overcoming those will determine speed of automation

1. perception and manipulation
   - Challenge mainly in unstructured work environments w/ outside interference and irregular objects/failure recovery
   - Sidestep by task design
2. creative intelligence
   - Creating ideas: unfamiliar combinations of familiar ideas
   - Challenge: evaluation of creative outcomes in codifiable way
3. social intelligence
   - both recognition and reaction to human emotions very challenging

- Bottom line: 1. relatively easily automatable while 2./3. much less likely in short/medium run

Data

- O*NET contains data on 903 occupations
- O*NET provides different types of information on individual occupations:
  - Standardized and measurable set of variables, comparable across occupations
  - Verbal occupation-specific task descriptions
- O*NET occupations closely correspond to DoL Standard Occupational Classification (SOC), for which employment and wage data are available
- Aggregation into 6-dig SOC occupations
  - take (simple?) average of underlying O*NET variables for aggregation
  - exclude SOC categories w/o O*NET correspondence
- Arrive at 702 final occupations for analysis

Implementation Steps – Overview

1. Subjectively hand-label 70 occupations into (not) automatable based on occupation-specific task descriptions by asking *Can the tasks of this job be sufficiently specified, conditionally on the availability of big data, to be performed by state of the art computer-controlled equipment?*
   - binary labelling
   - Choice aided by experts from AI/ML engineering
2. Identify objective O*NET variables corresponding to specific engineering bottlenecks
   - Multiple numerical scales indicating relevance/complexity for performing particular task
   - 'level': indicates required capability of the respective skill
   - The selection of variables is a subjective choice!
3. Based on variables selected, assign automation probability to remaining 632 occupations using supervised learning
   - Validate subjective hand-labelling using variables chosen in 2.
   - Use classification algorithm to assign automation probabilities to remaining 632 occupations

Step 2: Selected O*NET Variables

Computerisation bottleneck	O∗NET Variable	O∗NET Description
Perception and Manipulation	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped Work Space, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative Intelligence	Originality	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.
	Fine Arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social Intelligence	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behavior.
	Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

Step 3: Classification Method (1)

- Variables selected in Step 2 serve as *feature vector* $\underline{x} \in \mathbb{R}^9$.
- 'automatable' label constitutes a *class* $y \in \{0, 1\}$
- Hand-assigned occupations serve as *training data* $\mathcal{D} = (X, \underline{y})$
  - $X \in \mathbb{R}^{70 \times 9}$ matrix of variables
  - $\underline{y} \in \{0, 1\}^{70}$ associated labels
- Probabilistic classification algorithm: exploit information in $\mathcal{D}$ to return

$$P(y_* = 1 | \underline{x}_*, X, \underline{y})$$

- Achieve prob. class. through *discriminant function* $f : \underline{x} \to \mathbb{R}$
- Given $f(\underline{x}_*) \equiv f_*$, assume

$$P(y_* = 1 | f_*) = \frac{1}{1 + \exp(-f_*)}$$

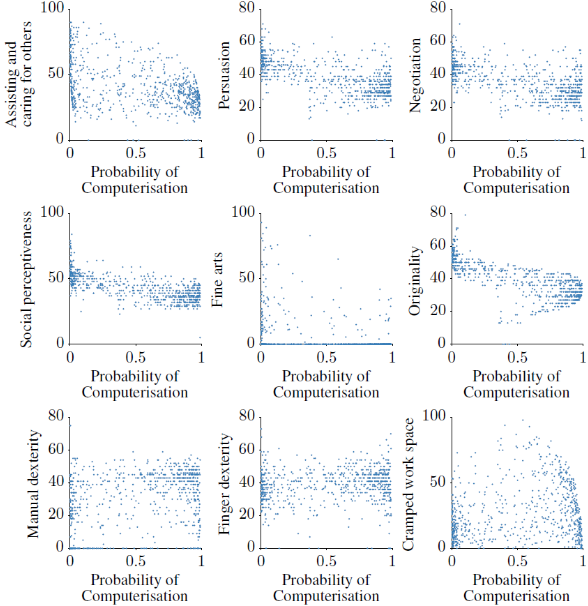
Step 3: Classification Method (2) – discriminant function

- GP is a statistical distribution over functions $f : \chi \to \mathbb{R}$ such that the function value $f(x)$ observed at x is just a sample of some multivariate Gaussian distribution
- Prior distribution of function values f completely specified by covariance function K: $f \sim N(0, K)$
- Choice of specific GP classifier boils down to choosing particular covariance function K.
- three different models for the discriminant function (i.e. K)
    1. logit function: $f(\underline{x}) = \underline{w}'\underline{x}$, $\underline{w}$ unknown weights (chosen using training data?) (GP with linear covariance)
    2. exponentiated quadratic Gaussian process (GP) classifier
    3. rational quadratic GP classifier
- Given $\mathcal{D}$, use GP to predict function value f_* at input $\underline{\mathsf{x}}_*$
- To infer label probability $p(y_*|\underline{\mathsf{x}}_*, \mathcal{D})$ use Approximate Expectation Algorithm (Minka, 2001).

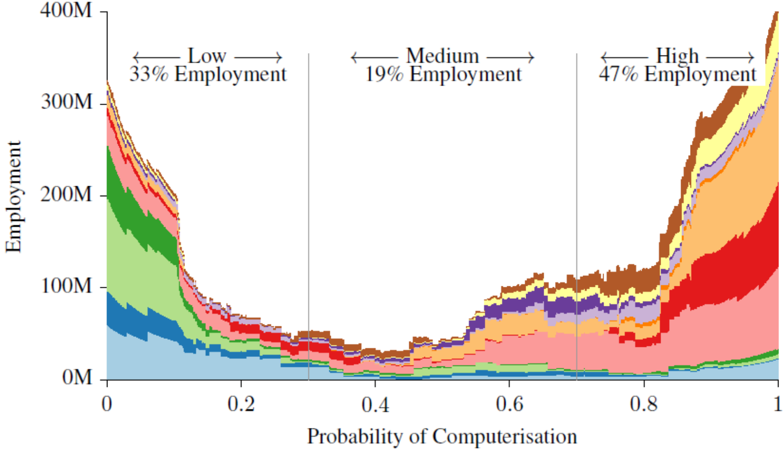
Step 3: Classification Method (3) – model evaluation

- Test models $1. - 3.$ using GPML toolbox (Rasmussen and Nickisch, 2010)
- Validation procedure:
  - randomly draw 35 observations from training data and use to predict other half; compare against hand-matched labels
  - repeat 100 times and evaluate using Receiver Operating Characteristic curve (ROC) and log-likelihood.
  - Choose exponential quadratic: ROC about 0.9
- Apply the model to *test features* $X_* \in \mathbb{R}^{702\times 9}$ comprising entire sample of occupations
- Obtain probability of automation as $P(\underline{\mathsf{z}}_* | X_*, \mathcal{D})$
- Since GP nonlinear: captures potentially complex relationships between variables (next slide)

Variation of Feature Vector with Probability of Automation

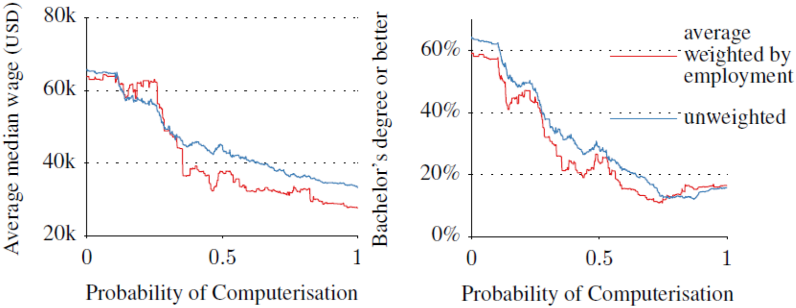


Results (1) – Employment and Risk of Automation



- admin (orange), sales (red) and services (pink): high risk (bottleneck 1)
- management/STEM (blues), educ/health (greens): low risk (bottlenecks 2, 3)

Results (2) – Automation, Education and Wages



- Predicts break in polarization patter observed since 1980s

Summary

- Data
  - O*NET: occupational characteristics
  - Standard Occupation Classification: employment and wages
- Method
  - Use combination of subjective categorization and ML-tools to generate an automatibility score for each SOC occupation.
- Results
  - up to 47% of 2010 employment susceptible to automatization in the near future ("jobs at risk")
  - Probability of automatization inversely related to wages and education: Break of polarization pattern observed since 1980s
- Note
  - Focus on *potentially automatable* jobs in 2010: No stance on expected actual future numbers

Literature

[1] Alan S Blinder et al. How many us jobs might be offshorable? *World Economics*, 10(2):41, 2009.

[2] Frank Levy, Richard J Murnane, and David Autor. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333, 2003.

[3] Thomas P Minka. Expectation propagation for approximate bayesian inference. In *Proceedings of the Seventeenth conference on Uncertainty in artificial intelligence*, pages 362–369. Morgan Kaufmann Publishers Inc., 2001.

[4] Carl Edward Rasmussen and Hannes Nickisch. Gaussian processes for machine learning (gpml) toolbox. *Journal of Machine Learning Research*, 11(Nov):3011–3015, 2010.