Why Are There Still So Many Jobs? The Past and Future of Workplace Automation

David Autor, MIT Department of Economics
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An Era of Automation Anxiety

Erik Brynjolfsson
Andrew McAfee
Race Against The Machine
How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy

Martin Ford
RISE OF THE ROBOTS
Technology and the Threat of a Jobless Future
Why Are There Still So Many Jobs?

1. Automation anxiety: Two centuries of fear
2. Three technological revolutions
3. Job quantity vs. job quality
4. The workplace of the future?
5. Waiting for the singularity…
6. Conclusion
An Earlier Era of Technology Anxiety

Ned Ludd

“Machine Trashing” 1812 – 1813
The ‘Productivity Problem’ of 1964

- 1964: President Johnson establishes “Blue-Ribbon National Commission on Technology, Automation, and Economic Progress”
- U.S. Dept. of the Interior, 1974: “Leisure, thought by many to be the epitome of paradise, may well become the most perplexing problem of the future.”

The Milwaukee-Matic Industrial Machining Tool, 1963
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Three Technological Revolutions: Green Revolution, Industrial Revolution, Computer Revolution

U.S. Employment Shares in Agriculture, Industry and Services, 1840 - 2010

Agriculture
1840: 68%
1900: 40%
1950: 11%
2010: 2%

Industry
1840: 22%
1900: 27%
1950: 37%
2010: 33%

Services
1840: 78%
1900: 52%
1950: 33%
2010: 78%

Johnston 2012
Automation of ‘Routine Tasks:’ Jacquard Loom (1801)

Two Centuries of Productivity Growth in Computing: 2+ Trillion Fold Decline in Cost of Computing v. Labor

Figure 2. The cost of computer power for different technologies

Nordhaus 2007
<table>
<thead>
<tr>
<th>Task Description</th>
<th>Example Occupations</th>
<th>Impact of Computerization</th>
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<tbody>
<tr>
<td>Routine Tasks</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Rules-based</td>
<td>• Bookkeepers</td>
<td>• Direct Substitution</td>
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<tr>
<td>• Codifiable</td>
<td>• Assembly Line Workers</td>
<td></td>
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<tr>
<td>• Procedural</td>
<td></td>
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<tr>
<td>Abstract Tasks</td>
<td></td>
<td></td>
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<tr>
<td>• Abstract problem-solving</td>
<td>• Scientists</td>
<td>• Strong Complementarities</td>
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<tr>
<td>• Mental flexibility</td>
<td>• Attorneys</td>
<td></td>
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<tr>
<td>• Managers</td>
<td>• Doctors</td>
<td></td>
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<tr>
<td>Manual Tasks</td>
<td></td>
<td></td>
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<tr>
<td>• Environmental Adaptability</td>
<td>• Flight Attendants</td>
<td>• Limited Complementarity or Substitution</td>
</tr>
<tr>
<td>• Interpersonal Adaptability</td>
<td>• Health Aides</td>
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<td></td>
<td>• Waiters</td>
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<tr>
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<td>• Cleaners</td>
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Employment Polarization in the U.S: Changes in Employment by Major Occupation, 1979–2012

Notes:
(16–64) civilian noninstitutionalized population. Employment is measured as full-time equivalent workers.

Sources:

Figure 2 illustrates this pattern for the United States by plotting percentage point changes in employment (more precisely, the figure plots 100 times log changes in employment, which is close to equivalent to percentage points for small changes) by decade for the years 1979–2012 for ten major occupational groups encompassing all of US nonagricultural employment. (More specifically, the x-axis represents the percentage point change in employment, and the y-axis plots 100 times log changes in employment, which is nearly equivalent to percentage points for small changes.)

Table 1 shows the growth of low-wage service employment does not commence in the United States until the 2000s, a finding that is at odds with all other work using contemporary occupation codes of which I am aware (including the Bureau of Labor Statistic's own tabulations of Occupational Employment Statistics for this time period provided in Alpert and Auyer 2003, table 1). At a methodological level, work in this area always requires adjustments and judgment calls in comparing occupational data across Census years, but the adjustments that Mishel et al. apply to the data generate occupational patterns that appear anomalous. Substantively, I believe the main issue is not whether employment polarization has occurred—wage polarization or wage inequality more broadly.

Figure 2 shows that retail trade, service, and personal care service have experienced significant growth as a share of employment, while production and manufacturing have experienced significant decreases. This trend is consistent across all decades, with the most pronounced changes occurring in the 1980s and 1990s. The chart also highlights the growth of high-wage professional and managerial occupations, which have increased as a share of employment in recent decades.
Employment Polarization in Sixteen European Union Countries, 1993 - 2010

Goos, Manning and Salomons, 2014
Tacit versus Explicit Knowledge

- **Routine, codifiable tasks use formal tools that humanity developed to address formal problems**
  - Counting, mathematics, logical inference

- **Non-routine tasks use capabilities that humanity evolved rather than developed**
  - Spoken language, sensorimotor skills, physical flexibility
  - Judgment, intuition, creativity

- **Automating non-routine tasks requires...**
  - *Reverse-engineering* tasks that we accomplish using only tacit understanding
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Polanyi’s Paradox

Tacit Versus Explicit Knowledge

“We can know more than we can tell…”

Michael Polanyi, *The Tacit Dimension*, 1964

Two implications of Polanyi’s Paradox

1. **Technical**: Cannot automate what we don’t explicitly understand

2. **Economic**: Tasks that are not substituted by machines are typically complemented by machines
Three Factors that Shape Automation’s Impact on Earnings

1. **Substitution versus complementarity**
   - Workers benefit if their primary job tasks are *partially but not fully* substituted.

2. **Elasticity of final demand**
   - Can either dampen or amplify the gains from automation.

3. **Labor supply elasticity**
   - If labor supply is elastic (i.e., ‘responsive’), this limits wage gains.

**Dispensing jobs**
As more ATMs were installed in the United States, the number of tellers employed did not drop.

(Thousands)

Three Factors that Shape Automation’s Impact on Wages

1. **Substitution versus complementarity**
   - Workers benefit if their primary job tasks are *partially but not fully* substituted.

2. **Elasticity of final demand**
   - Can either dampen or amplify the gains from automation.

3. **Labor supply elasticity**
   - If labor supply is elastic (i.e., ‘responsive’), this limits wage gains.
U.S. Has Added 14 Million Non-Farm Jobs Since 2010

U.S. Bureau of Labor Statistics and St. Louis Fed (FRED Graphs)
College Educated Workers Have Benefited from Computerization – They’re Complements

Real entry-level wages of college graduates, by gender, 1973–2013

- Men, age 23–29
- Women, age 23–29

Economic Policy Institute 2014
Wages of Non-College Workers Have Been Falling For 35 Years

Real entry-level wages of high school graduates, by gender, 1973–2013

Economic Policy Institute 2014
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The Workplace of the Future?

• Artificial Intelligence (AI) rapidly advancing…
  • Driving vehicles
  • Reading legal documents
  • Interpreting radiological x-rays

• Is Artificial Intelligence overcoming Polanyi’s paradox? Two angles of attack
  1. Environmental Control
  2. Machine Learning
Environmental Control -- Kiva Systems Order Fulfillment: Robotic Drive Units Move Shelves to Workers for Picking
Kiva-Worker Interaction: Guided by Laser Pointer, Worker Picks Items from Shelves for Shipping
Machine Learning

- **Problem**
  - Cannot program a machine to “simulate” a non-routine task by following a scripted procedure

- **Solution: Inductive reasoning**
  - Develop machines that master tasks autonomously by studying successful examples of the task being carried out by people
What Makes a Chair a Chair?

Figure 3. Common approaches for object detection use many training samples to build an appearance model of the category. However, many categories might be better described by the functions they support. Hence, we propose to imagine how well an actor could perform a specific activity with a scene part, in order to detect such objects.

at some spot in a scene, there is evidence for the existence of an object class with such affordance. We assume the availability of 3d data to probe the interaction, as coming from structure-from-motion or depth cameras.

In this paper, we focus on objects that involve full body human interaction. Furthermore, we only consider interactions where the action can be described by key poses. For example, a typical sitting position of a human infers a sitable place. However, the general principle can also be applied to body parts or other objects. In general, the concept of actor corresponds to the active part in an object-object relation, which can be a human as in our example, but it might be also another object, e.g., a key that opens a lock.

Our approach is inspired by shape sorting toys as shown in Fig. 4(a). To perform matching between shapes, we represent the human action by key poses that are matched with the 3d scene, see Fig. 4(b). For instance, when observing a chair at a table, one can imagine how to sit on the objects. However, the traffic cone does not imply a comfortable sitting posture as illustrated in Fig. 4(c). Using an actor for representing the functionality of an object has the advantages that (i) the relevant parts for the functionality are automatically recovered from the observed actor-object interactions and that (ii) the relevant parts are mapped to an unified representation, namely the actor. The core of the concept is a probabilistic model defined on the actor's shape that is able to encode both variations in action style and variations in object shape.

2.2. Model

In order to learn the relation between a human and an object, we require at least one training example where we observe the functionality, i.e., showing the object in use.

Key Poses. For each training example \( u \), we assume a model of the object represented as 3d triangle mesh \( M \) and a model of the actor interacting with the object, which is also represented as 3d triangle mesh \( M \). We further assume that the triangles and connectivity of the meshes are consistent over all training examples. This is achieved by using a consistent human model [11] for annotation.

To make the detection process efficient, we reduce the number of poses to a small set of key poses \( \bar{M} \). The key poses can be obtained by clustering and taking the mean of each cluster, i.e., the vertices \( \mathbf{v}_i \in \bar{M} \) are given by

\[
\mathbf{v}_i = \frac{1}{\mathcal{E}} \sum_{u \in \mathcal{E}} \mathbf{v}_i^u,
\]

where \( \mathcal{E} \) is the number of training examples within cluster and \( \mathbf{v}_i^u \) denotes the \( i \)-th vertex of mesh \( M \). For simplicity, but without loss of generality, we now refer to a single key pose \( \bar{M} \).

Grabner, Gall and Gool, 2001
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Moore’s Law: Transistor Density on Integrated Circuits Doubling Approximately Every Two Years

Sources: Intel; press reports; Bob Colwell; Linley Group; IB Consulting; The Economist

*Maximum safe power consumption

The Economist Technology Quarterly, March 2016
Median Zero-to-Sixty Time of U.S. Vehicles Dropped by Half (!) Between 1983 and 2010

Acceleration Performance of U.S. Vehicles

0 - 60 mph time (seconds)

Model year


McKenzie and Heywood 2012
Hours of Annual Motor Vehicle Delay Per Traveler Rose 100% - 250% Between 1982 and 2005

U.S. Department of Transportation, Federal Highway Administration
Workplace Robotics: Employment Apocalypse or the Last Mile?

U.S. Employment Shares in Agriculture, Industry and Services, 1840 - 2010

Johnston 2012
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1. **Underappreciated complementarities**
   • Farmers: 40% of employment in 1900 to 2% in 2000

2. **Hard to see where new jobs are coming from**
   • Process is always disruptive, not ‘Pareto improving’

3. **The question is not job quantity but job quality**
   • Will be many personal service jobs, but they will pay poorly

4. **The singularity is not upon us**
   • Not evident in employment data, nor in productivity data, nor in investment data

5. **What if I’m wrong… robots will take ‘our’ jobs?**
   • That’s good news too—though a different set of challenges
The Challenge: Scarcity or Abundance?

Heilbroner’s concern in ’64

“As machines continue to invade society, duplicating greater and greater numbers of social tasks, it is human labor itself… that is gradually rendered redundant.”

Herbert Simon’s response to Heilbroner in ‘66

“The world’s problems in this generation and the next are problems of scarcity, not of intolerable abundance. The bogey-man of automation consumes worrying capacity that should be saved for real problems…”