# The Automated Life - Technical Document

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This document describes the methodology and data used in The Automated Life, a simulation based game developed at Scalable Cooperation group, MIT Media Lab and the Centre for Humans and Machines, Max Planck Institute for Human Development. The game can be accessed at (theautomated.life and the source code is available at github.com/frnsys/the_automated_life)

## 1 Game Overview

The game is played from the perspective of a worker at the beginning of their career at age 18. The worker begins in a low wage job that is prone to automation by machines. The objective is to retire at age 65 with $500,000 in retirement savings. In order to do so, the player must move to a high wage job through gaining experience and also education. This is made harder by the introduction of new technologies that are periodically released which automate components of jobs known as tasks. As a job is automated, the wage decreases.

The Purpose of the game is to promote empathy and better understanding of the effects of automation. It is inspired by evidence from other domains that games can provoke changes in attitudes [4].

## 2 Automation Technologies

New technologies, embodied by robots, are continually released at irregular intervals that are able to replace humans by performing part of a job (know as work tasks). Work tasks include *Critical Thinking, Time Management* or Explosive Strength. The effect of each automation is modeled based on *Artificial Intelligence, Automation and Work* by Acemoglu & Restrepo [1]. Each new technology introduces the following effects in the following order:

1. **Displacement** Workers are displaced from jobs that use the skills which are automated (wage decreases).
2. **Productivity Gains** Jobs that are *complementary* to jobs that are automated benefit from increased efficiency (wage increases).
3. **New Skills & Jobs** New technologies require new skills to maintain and design equipment and technology.
4. **Deepening Automation** As the quality of automation technologies increases, subsequent productivity gains are felt globally (wage increases).

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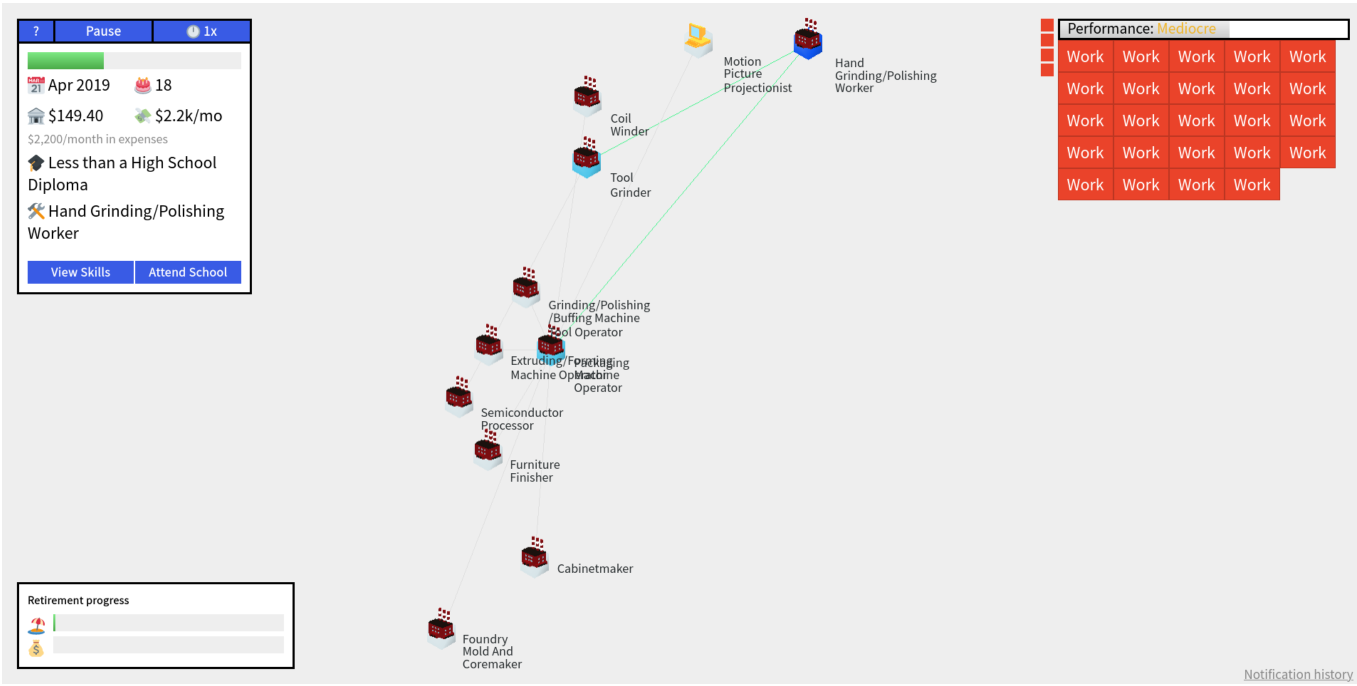


Figure 1: Screenshot of game interface. The network of jobs and other jobs accessible from that job (centre), work tasks to be completed (top right), information on current job (top left) and progress towards retirement (bottom left).

These appear in the game as notifications

e.g. *After years of research and devleopment, RoboCo has released Ju-9572. It excels at enduring uncomfortable sounds. Any jobs involving this skill will be impacted.*

# 3 Data

The game is boostrapped on empirical data on jobs, wages, skills, educational courses and financing.

## 3.1 ONET

The occupational network database (or ONET data[1]) is produced by the United States Bureau of Labour Statistics and provides the majority of the data used in the game.

### 3.1.1 Jobs & Skills

We make use of the 734 jobs in ONET and 230 skills (pruned to 190 for playability purposes, see full list here). An importance is ascribed to each skill for each job, from which we calculate the Revealed Comparative Advantage (RCA) as in [2]

$$\mathrm{RCA}(j,s) = \frac{\mathrm{onet}(j,s) / \sum_{s`\in S} \mathrm{onet}(j,s`)}{\sum_{j`\in J} \mathrm{onet}(j`,s) / \sum_{j`\in J, s`\in S} \mathrm{onet}(j`,s`)} \tag{1}$$

The RCA provides a weighting of a skill to each job. This determines how the wages of a job change in response to the automation of skills it relies upon.

[1] https://www.onetonline.org/

### 3.1.2 Education

We make use of education, training and experience provided at ONET Online. ONET defines the following education levels

1. Less than a High School Diploma
2. High School Diploma (or GED or High School Equivalence Certificate)
3. Post-Secondary Certificate - awarded for training completed after high school
4. Some College Courses
5. Associate's Degree (or other 2-year degree)
6. Bachelor's Degree
7. Post-Baccalaureate Certificate
8. Master's Degree
9. Post-Master's Certificate
10. First Professional Degree
11. Doctoral Degree
12. Post-Doctoral Training

Based on surveys, ONET describes the number of people in a given job title with each level of education. This provides a distribution over 12 possible categories. A player begins at education level 1 i.e. pre-high school. We drop levels 4 and 5 for playability. A Bachelor's level degree provides sufficient training/apprenticeship for a specific job, that a user is placed directly into the corresponding job upon graduation.

### 3.1.3 Industry

For each job we have an associated distribution over 20 industries e.g. 'Arts', 'Educational Services' (specified here). We assign the most commonly occurring industry to a job.

## 3.2 University Course Data

We make use of data from Career One Stop provided by the Bureau of Labour Statistics. This provides a mapping from ONET job codes to relevant university courses in each state. We scrape and compile the following for each course relevant to each job

1. Course name
2. Institution name
3. Course length
4. Course cost

We assign a course length to each job based on the modal course length for that job across all states and institutions.

### 3.3 Exposure to Automation

We make use of the survey of ONET jobs and the associated exposure to automation undertaken by Webb [5]. We assign a score to each *skill* by regressing the automation exposure against skill importance for each job as in [2]. The regression coefficients, which may be negative in the case of skills that are unlikely to be automated, are then rescaled and used as a probability of automation for each skill. This automation exposure determines in a probabilistic fashion, the order in which skills are automated.

# 4 Job Network

The job network is formed based on skill similarity defined in [3]. We set a minimum similarity of $s = 0.7$ and only create edges between jobs satisfying this minimum similarity. However, we also require that the graph is connected, so if a job has no edge that satisfies this constraint, we gradually relax it by 0.05 until at least one edge is formed.

# 5 Job Application Success Probability

The success in applying for a job is determined by a probability based on

1. Skill similarity: $\frac{\sum_{k \in J} P_k * RCA(j,k)}{\sum_{k \in j} RCA(j,k)}$ where $P_k \in [0, 1]$ is the player's proficiency for skill $k$ at time of application.
2. Education level: the proportion of people at or below the player's education level that have that job (source: Education, Training, and Experience Categories.csv)
3. Most recent performance: The player's performance $\in [0, 1]$ in their current job at time of application.

The mean of these values is then used as the probability for application acceptance.

# 6 Finances

Players receive the median wage for their current job paid net based on 2018-2019 "Head of Household" tax brackets. If they choose to undertake college education then they must take out a loan with regular repayments over 10 years at a fixed rate of 5.8%, based on the average described in [2]. In addition, fixed living expenses are taken. Debt can be accumulated up to $100,000 at which point the player loses the game.

# 7 Player State

The game state is specified by the following

1. Player Age
2. Player Savings
3. Player Current wage
4. Player Skill level

[2] https://www.nerdwallet.com/blog/loans/student-loans/student-loan-interest-rates/

5. Player Education level
6. Previously automated skills

It should be noted that the timeline of release of automation technologies is deterministic and so age, which is a proxy for game time, determines the current state of automation.

# 8 Wage Update Equations

## 8.1 Displacement

It is a non-trivial task to assign a wage to a particular skill since skills are likely to have different contributions to wage depending on sector and the other skills with which they co-occur. We model wages for each job as being reduced in proportion to the importance of the automated skill relative to the importances of all skills to that job. For job $j$ faced with automation of skill $s*$

$$\Delta w_{j,s*} = w \times \frac{\mathrm{RCA}(j, s*)}{\sum_s \mathrm{RCA}(j, s)} \tag{2}$$

## 8.2 Productivity Gains

Since productivity gains are felt by jobs that *complement* jobs that are exposed to automation, we make use of an indicator function $I_{ij}$ that is 1 if jobs i and j are in the same industry but is 0 otherwise. For automated skill $s*$

$$\Delta w_j = \frac{\sum_{k \in J} I_{jk} \mathrm{RCA}(k, s*)}{\sum_{k \in J} \sum_{l \in S} I_{jk} \mathrm{RCA}(k, l)} \tag{3}$$

Intuitively, the wage is updated by the ratio between (i) the total importance of the automated skill to all jobs in the same industry and (ii) the total importance of all skills to all jobs in the same industry.

## 8.3 New Skills & Jobs

Some automation technologies are sufficiently efficient and innovative that they give rise to new skills. In this case, a job with non-zero exposure to an automated skill s introduced by robot r, has s replaced by a new skill s*. The associate wage change is given

$$\Delta w_j = \frac{\mathrm{RCA}(j, s)}{\sum_{k \in S} \mathrm{RCA}(j, k)} \times \mathrm{efficiency}(r) \tag{4}$$

## 8.4 Deepening Automation

Each new technology is assigned a timeline for ‘deepening‘, this is the time it takes for the efficiency of the robot to improve and give rise to universal wage gains through increased productivity.

$$\Delta w_j = \alpha * w_j * \mathrm{efficiency}(r) \tag{5}$$

where $\alpha$ is a small parameter determining growth. The efficiency of each new robot is chosen randomly and uniformly from the range [0-1].

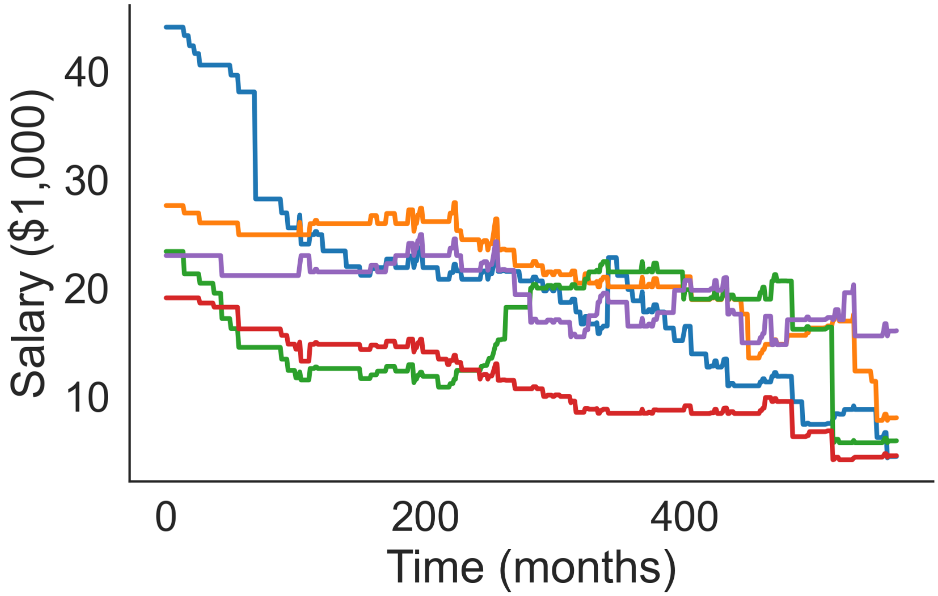


Figure 2: Dynamics of wages of 5 randomly selected jobs over time

# 9 Randomised Game Conditions

Players are assigned to treatment conditions at random. These conditions determine the information available to the player in order to understand how this affects subsequent choices and actions in navigating the job network.

# 10 Ethics Approval and Privacy Requirements

The Automated Life was approved by the Ethics Committee of the Max Planck Institute for Human Development.

# Acknowledgement

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