Inferring Work Task Automatability from AI Expert Evidence

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Abstract

Despite growing alarm about machine learning technologies automating jobs, there is little good data on what activities can be automated using machine learning. We contribute the first dataset of its kind by surveying over 150 academics and industry experts in machine learning, robotics and AI, receiving over 4,500 ratings of how automatable specific tasks are using these technologies. We present a probabilistic machine learning model to learn the patterns connecting expert estimates of task automatability and the skills, knowledge and abilities required to perform those tasks. Our model infers the automation potential of 1,753 work activities. We present how automatability differs across types of activities and types of occupations, as well as what skills, knowledge, and abilities drive higher or lower automatability. We believe that activity-level data will create better automation frameworks to address the fear, uncertainty, and doubt surrounding ML-driven automation.

Introduction

Machine learning (ML) technologies have rapidly become real substitutes and complements to human labor. This work aims to better understand that automation. For example, Amazon Go is a recently opened grocery store that uses computer vision to replace cashiers, of which over 3.5 million are employed in the United States (Grewal, Roggeveen, and Nordfaelt, 2017; OES, 2017); 500,000 designers in the US are beginning to use constraint-based generative design to automate creative designs of buildings, industrial appliances, and more (Autodesk, 2017; OES, 2017). As a result, ML researchers often confront examples of media and public concern about the effect of technologies we develop. While advances in ML seem able to automate *intelligent* work, we lack good data on the scope of such automation. As a result, we remain uncertain about the impact on work (Smith, 2016).

We collected a detailed *task*-based survey of 150+ machine learning, robotics, and automation researchers. This is the first dataset of its kind with over 4 500 datapoints about what specific tasks are automatable according to *current* technology. In this "nowcasting" exercise, technologists provide their knowledge of the extent to which a specific task can or cannot be automated with technology that exists *today*. We use a probabilistic model to infer the automation potential for thousands of activities for which it would be prohibitively hard to collect expert-labelled data.

Traditionally, researchers have developed frameworks based on the "types" of occupations and the skills they require (Acemoglu and Restrepo, 2016; Autor, 2013; Frey and Osborne, 2017), such as "manual or cognitive" or "routine and non-routine" in order to identify what work is automatable. We believe that while useful, these frameworks are a broad starting point that don't reflect that *tasks* (or groups of tasks), not *entire occupations*, are the unit of automation. (Manyika et al., 2017a) is a first step in this task-oriented direction, but critically lacking in transparency of data and method.

Our main contributions are our new dataset, which will be made publicly available, a brief summary of implications, and review of future analyses that can now be performed with task-level data. Through

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collecting task-specific data, we believe we can develop richer, more accurate frameworks about what can be automated. The application for our methodology is one of central importance to the community. As a community at the heart of creating automation technology, we must shoulder some responsibility for addressing the resultant impacts on employment. Better estimates of task automatability can be used to guide our community's efforts in sympathy with societal and economic needs.

Data and Model

We surveyed 156 academic and industry experts of machine learning, robotics, intelligent systems, and operations research online about how automatable specific tasks are using current technology. Each expert was presented with 5 occupations and their 5 "most important" tasks, taken from the Occupational Network (O*NET) 2016 database (National Center for O*NET Development) produced by the US Department of Labor. Each expert then labelled each task as either: *Not automatable today* (1), *Mostly not automatable today (human does most of it)* (2), *Could be mostly automated today (human still needed)* (3), *Completely automatable today* (4), or *Unsure*.

Our dataset contains 4 599 task level responses (survey response statistics are presented in Appendix B). We combine each task's multiple expert labels using Independent Bayesian Classifier Combination (IBCC), a principled Bayesian approach to combine multiple classifications (Kim and Ghahramani, 2012; Simpson et al., 2013). IBCC creates a posterior over labels that reflects the individual labellers' tendencies to agree with other labellers over ultimately chosen label values.

Each task t is then represented as a feature vector, $\boldsymbol{x}_o$, of its containing occupation, o. This is comprised of 35 skills features, 33 knowledge groups features, and 52 abilities features measured quantitatively on a 1 to 5 scale by dozens of employees and experts in the O*NET database. To introduce activity-specific feature vectors, we aggregate the roughly 20 000 tasks into the 2 068 Detailed Work Activities as specified by O*NET (which we refer to as "work activities"), to create a feature vector $\boldsymbol{x}_w$ representing each work activity w. The activity feature vector is a weighted average of its constituent task vectors: $\boldsymbol{x}_w = \sum_{t \in w} w_{(t,w)} \boldsymbol{x}_o$, where $w_{(t,w)}$ is a normalized weight of the task's relative importance to its occupation and its work activity, i.e. $w_{(t,w)} = I_{(t,o)} I_{(t,w)} / \sum_{t \in w} I_{(t,o)} I_{(t,w)}$. The relative importance of the task to its occupation is calculated as $I_{(t,o)} = {}^{I_t}/_{\sum_{t \in o} I_t}$, while the relative importance of a task to its work activity is $I_{(t,w)} = {}^{I_t}/_{\sum_{t \in w} I_t}$. Task importance I_t is a numeric measure also supplied by O*NET. Combining more than 4,500 expert task labels, the training dataset consists 314 labelled work activities $\in \mathcal{R}^{120}$, and 1,753 unseen test-set activities.

Model Comparison and Validation

We seek a flexible function estimation capable of modeling complex, non-linear relationships between the features (skills, knowledge, abilities) and automatability in high-dimensional space. Given the social scientific nature of the study, we also desire a measure of model uncertainty. We compare models based on their "tolerance accuracy" score – the percent of posterior prediction means, $\hat{\boldsymbol{y}}_w$, that are within 0.5 of the ground truth post-IBCC survey value $\boldsymbol{y}_w$. We first consider a Gaussian Process (GPs) using the ordinal likelihood function introduced in (Chu and Ghahramani, 2005), to reflect the nature of having discrete labels with an ordinal interpretation on uncertain data. For other candidate models, we consider ordinal logistic classification (Pedregosa-Izquierdo, 2015), random forests, and neural networks with an ordinal loss function (Hart, 2017). The ordinal GP with an RBF kernel is the best at predicting the posterior mean values of automatability over the space of work activities. It also allows us to compute average and point posterior gradients.

Experiments and Results

Question 1: What is automatable?

We use the best performing GP model to infer the automatability score for 1 753 unlabelled work activities. Table 1 presents a sample of work activities' automatability from the unlabelled data with uncertainties (see Appendix C). We observe that activities such as "route mail" have a high automatability (and indeed, it already is widely automated). However, we also notice that many white-collar activities are also highly automatable with current technology. Insights such as these propose likely future automatable areas, where automation could be achieved in the real world with

Table 1: Example inferred automatability scores on unlabelled activity data (with uncertainty).

Activity	Automatability	Activity	Automatability
Adjust fabrics... garment production.	4.00 (0.67)	Teach humanities courses...	1.06 (0.65)
Store records or related materials.	3.92 (0.66)	Conduct scientific research...	1.19 (0.70)
Route mail to correct destinations.	3.82 (0.64)	Counsel clients... personal issues.	1.42 (0.61)

relatively little further attention to the underlying technology (though conditional on the economic and organizational factors leading to its realization.) The mean automatability scores of 2.7 indicates the model, learned from expert estimates, believes that tasks are on average more likely to be mostly automatable than not.

Listing a sufficient number of tasks here would be prohibitively long (which we partially leave for the appendix). Instead, we review implications for *groups* of activities and occupations, and leave detailed task analysis for follow-on work. In Figure 1 (left) we plot the automatability of activities by the number of currently-employed individuals who perform them, and classify into nine higher-level activity groups. It becomes evident that while most activities are between mostly and mostly not automatable, work tends to lie closer to “mostly automatable”. Four times as much work lies between “mostly” and “completely” automatable than between “mostly not” and “not at all” automatable. Activities classified as “reasoning and decision making” and “coordinating, developing, managing, and advising” are less likely than other activities to be automatable. However, “administering” and “information and data processing” and (perhaps surprisingly) “performing complex and technical activities” are more likely to automatable. Greater variation in activity groups might be found when stratified into more than 9 groups, as we did here for aesthetic reasons.

Additionally, we average the automatability scores of an occupation’s activities to create an occupation-level automatability score. (How to most properly aggregate activities for an occupation-level score is a subject of further research.) We classify occupations into 12 higher-level “Major Occupation Groups”, as in Figure 1 (right). We see that the model predicts high automatability in office administrative support (orange), and sales occupations (red), which together employ about 38 million people in the United States (OES, 2017). This contrast with the popular emphasis on the automation of physical processes such as production (yellow), farming, fishing and forestry (dark orange), and transportation and material moving (brown), which employ about 20 million people total (OES, 2017).

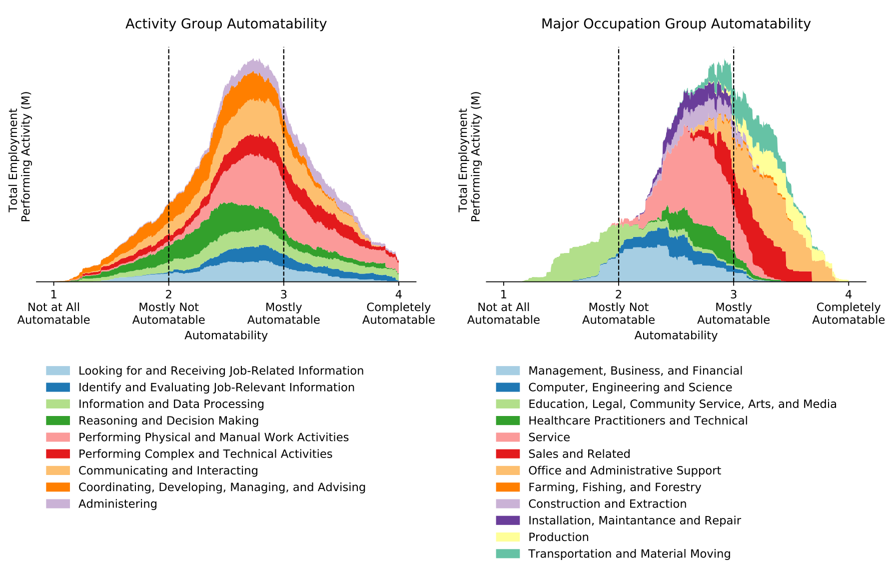

Figure 1: (left:) Amount of employment affected across automatability scores, by 9 high level activity groups. (right:) Employment affected across automatability scores, by 12 major occupation groups.

Question 2: What makes work automatable?

We now consider what increases or decreases the automatability of some activities. We compute the average derivative of automatability with respect to each numeric feature as described in (Baehrens et al., 2010) over the space of work activities. For the nth feature, this is computed as $AG(n) := \mathbb{E}(\partial m(\boldsymbol{x})/\partial \boldsymbol{x}_n)$, where $m(x)$ is the posterior mean distribution. This average derivative measures the expected increase in automatability for a unit increase in the feature. Table 2 presents a sample of the highest and lowest global average derivatives of the posterior mean function per feature (see Appendix D, Table 9). The gradients might, for example, be used by employers/employees and policy makers to understand the attributes that are most or least protective against automatability.

Table 2: Highest and lowest global average derivatives of automatability w.r.t feature score.

Feature (type)	Average Derivative (std)	Feature (type)	Average Derivative (std)
Telecommunications	0.16 (0.03)	Installation	-0.18 (0.08)
Clerical	0.14 (0.03)	Programming	-0.14 (0.04)
Wrist-Finger Speed	0.13 (0.02)	Technology Design	-0.14 (0.03)

These gradients seem to reflect what intelligent technology increasingly offers: work that is clerical, repetitive, precise, and perceptual can increasingly be automated. Increases in the features *Clerical, Number Facility, Depth Perception, Control Precision* and *Production and Processing* tend to increase an activity's automatability. On the other hand, work that is more creative, dynamic, and human oriented tends to be less automatable. While highly variable, the three strongest features driving decreased activity automatability are *Installation, Programming* and *Technology Design*. That is to say, the experts who answered our survey are relatively safe, or at least strongly misperceive themselves to be. The gradients might, for example, be used by employers/employees and policy makers to train different skills, modify work activities, or set policy to incentivize the development of particular skills, knowledge, abilities, or occupations. We also present trends by occupation education level and income in Appendix E.

Societal Impact of Better Automation Data

Automation is a notably data-sparse yet opinion-heavy area of study (Mitchell and Brynjolfsson, 2017; National Academies of Sciences, Engineering and Medicine, 2017). We need more clarity about what can be automated, at the *actual* level of automation (tasks), and more granular frameworks based on this more granular data. Policymakers would be able to design better, more targeted policy responses, such as incentives to preemptively modify occupations or programs to reskill workers. Workers would be able to retrain in a more targeted way (towards or away from certain tasks) to be robust to automation, instead of abandoning entire occupations. We also note the large *psychological* burden of fear, uncertainty, and doubt that comes from unpredictability; we hope to replace it with the optimism, clarity, and confidence that comes from having clearer predictions. Last, we would be able to better spot ethically-challenging cases of activity automation (e.g. in policing and surveillance) *before* they happen, so that we can hold preparatory, informed ethical discussion.

Conclusion & Future Work

By using a more granular approach to "now-casting" task-level automation, we can unlock more nuanced frameworks about what *actually* can be automated, and why. While we propose some implications in this paper, our goal is to first introduce this new activity-level dataset for analysis. We've identified six important research gaps that our dataset and approach are uniquely useful for answering, and we propose them to the community for further study: **Surprising automation**: What tasks are more, or less, automatable than previous models predicted? **Automatable vs. automated**: *Why* are some very automatable tasks not automated, while others are? **Real-world validation**: Does our model accurately identify tasks that are already automated? **Economic value**: What is the monetary value of automation potential for highly automatable tasks? (See (Manyika et al., 2017b).) **Occupation patterns**: What are the patterns of income, demographics, industry, technology use, and other characteristics of occupations with low- and high-automatability tasks? **Likely future automation**: Which automatable tasks are not already automated in the real world?

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Appendix A: Expert Survey Description

Table 3: 70 occupations with tasks labeled to construct the training set.

O*NET-SOC Code	Title
11-1011.00	Chief Executives
11-3071.01	Transportation Managers
11-9033.00	Education Administrators, Postsecondary
11-9199.01	Regulatory Affairs Managers
13-1022.00	Wholesale And Retail Buyers, Except Farm Products
13-1075.00	Labor Relations Specialists
13-2053.00	Insurance Underwriters
15-1134.00	Web Developers
15-1143.01	Telecommunications Engineering Specialists
17-1011.00	Architects, Except Landscape And Naval
17-3022.00	Civil Engineering Technicians
21-1011.00	Substance Abuse And Behavioral Disorder Counselors
21-1023.00	Mental Health And Substance Abuse Social Workers
21-1093.00	Social And Human Service Assistants
23-1011.00	Lawyers
25-1011.00	Business Teachers, Postsecondary
25-1071.00	Health Specialties Teachers, Postsecondary
25-1194.00	Vocational Education Teachers, Postsecondary
25-2032.00	Career/Technical Education Teachers, Secondary School
25-2053.00	Special Education Teachers, Middle School
25-9041.00	Teacher Assistants
27-1011.00	Art Directors
27-1026.00	Merchandise Displayers And Window Trimmers
27-2011.00	Actors
27-2022.00	Coaches And Scouts
27-2042.01	Singers
29-1063.00	Internists, General
29-1199.01	Acupuncturists
29-2032.00	Diagnostic Medical Sonographers
29-2052.00	Pharmacy Technicians
29-9011.00	Occupational Health And Safety Specialists
31-9091.00	Dental Assistants
33-1021.01	Municipal Fire Fighting And Prevention Supervisors
33-3012.00	Correctional Officers And Jailers
33-9091.00	Crossing Guards
35-1011.00	Chefs And Head Cooks
35-2012.00	Cooks, Institution And Cafeteria
35-3011.00	Bartenders
35-9011.00	Dining Room And Cafeteria Attendants And Bartender Helpers
35-9021.00	Dishwashers
39-9011.00	Childcare Workers
41-2022.00	Parts Salespersons
41-4012.00	Sales Representatives, Wholesale And Manufacturing, Except Technical And Scientific Products
41-9021.00	Real Estate Brokers
43-3021.01	Statement Clerks
43-4121.00	Library Assistants, Clerical
43-4141.00	New Accounts Clerks
43-4181.00	Reservation And Transportation Ticket Agents And Travel Clerks
43-5021.00	Couriers And Messengers
45-2093.00	Farmworkers, Farm, Ranch, And Aquacultural Animals
47-1011.00	First-Line Supervisors Of Construction Trades And Extraction Workers
47-2021.00	Brickmasons And Blockmasons
47-2051.00	Cement Masons And Concrete Finishers
47-2181.00	Roofers
49-2022.00	Telecommunications Equipment Installers And Repairers, Except Line Installers
49-3021.00	Automotive Body And Related Repairers
49-9052.00	Telecommunications Line Installers And Repairers
51-1011.00	First-Line Supervisors Of Production And Operating Workers

51-2022.00	Electrical And Electronic Equipment Assemblers
51-4021.00	Extruding And Drawing Machine Setters, Operators, And Tenders, Metal And Plastic
51-4072.00	Molding, Coremaking, And Casting Machine Setters, Operators, And Tenders, Metal And Plastic
51-4121.06	Welders, Cutters, And Welder Fitters
51-6021.00	Pressers, Textile, Garment, And Related Materials
51-6031.00	Sewing Machine Operators
51-9111.00	Packaging And Filling Machine Operators And Tenders
51-9198.00	Helpers–Production Workers
53-1021.00	First-Line Supervisors Of Helpers, Laborers, And Material Movers, Hand
53-1031.00	First-Line Supervisors Of Transportation And Material-Moving Machine And Vehicle Operators
53-3022.00	Bus Drivers, School Or Special Client
53-7062.00	Laborers And Freight, Stock, And Material Movers, Hand

Table 4: Five randomly selected occupations and their surveyed tasks.

Title	Task	Importance
Chief Executives	Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency.	4.54
	Appoint department heads or managers and assign or delegate responsibilities to them.	4.48
	Analyze operations to evaluate performance of a company or its staff in meeting objectives or to determine areas of potential cost reduction, program improvement, or policy change.	4.40
	Direct, plan, or implement policies, objectives, or activities of organizations or businesses to ensure continuing operations, to maximize returns on investments, or to increase productivity.	4.39
	Prepare budgets for approval, including those for funding or implementation of programs.	4.17
Lawyers	Represent clients in court or before government agencies.	4.59
	Present evidence to defend clients or prosecute defendants in criminal or civil litigation.	4.50
	Select jurors, argue motions, meet with judges, and question witnesses during the course of a trial.	4.50
	Study Constitution, statutes, decisions, regulations, and ordinances of quasi-judicial bodies to determine ramifications for cases.	4.47
	Interpret laws, rulings and regulations for individuals and businesses.	4.47
Diagnostic Medical Sonographers	Observe screen during scan to ensure that image produced is satisfactory for diagnostic purposes, making adjustments to equipment as required.	4.87
	Observe and care for patients throughout examinations to ensure their safety and comfort.	4.85
	Provide sonogram and oral or written summary of technical findings to physician for use in medical diagnosis.	4.84
	Select appropriate equipment settings and adjust patient positions to obtain the best sites and angles.	4.83
	Operate ultrasound equipment to produce and record images of the motion, shape, and composition of blood, organs, tissues, or bodily masses, such as fluid accumulations.	4.83
Cooks, Institution And Cafeteria	Clean, cut, and cook meat, fish, or poultry.	4.64
	Cook foodstuffs according to menus, special dietary or nutritional restrictions, or numbers of portions to be served.	4.61
	Clean and inspect galley equipment, kitchen appliances, and work areas to ensure cleanliness and functional operation.	4.61
	Apportion and serve food to facility residents, employees, or patrons.	4.58
	Direct activities of one or more workers who assist in preparing and serving meals.	4.27
Brickmasons And Blockmasons	Remove excess mortar with trowels and hand tools, and finish mortar joints with jointing tools, for a sealed, uniform appearance.	4.63
	Construct corners by fastening in plumb position a corner pole or building a corner pyramid of bricks, and filling in between the corners using a line from corner to corner to guide each course, or layer, of brick.	4.60
	Measure distance from reference points and mark guidelines to lay out work, using plumb bobs and levels.	4.47
	Break or cut bricks, tiles, or blocks to size, using trowel edge, hammer, or power saw.	4.39
	Interpret blueprints and drawings to determine specifications and to calculate the materials required.	4.31

Appendix B: Expert Survey Responses

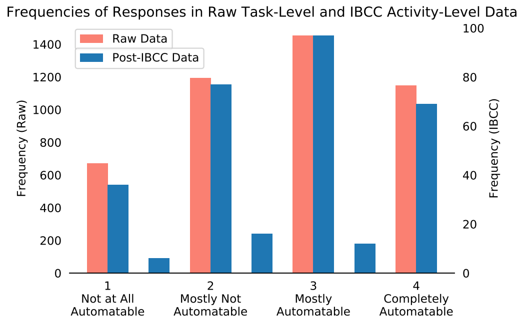

Figure 2: Distribution of expert task-level responses, and the IBCC combined activity labels.

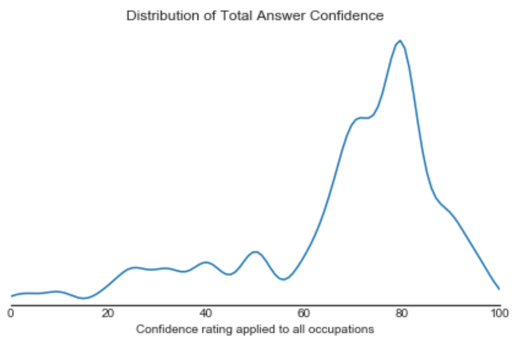

Figure 3: The distribution of respondents confidences they assigned to their answers (in total). (μ = 67.9, σ = 20.7)

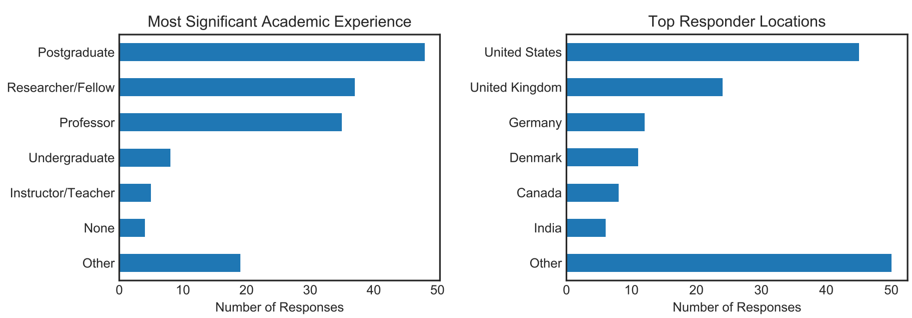

Figure 4: Expert survey response statistics. Responses by: (left:) academic experience. (right:) geographic location.

Appendix C: Inferred Work Activity Automatability

Table 5: The 25 most and least automatable work activities.

Activity	Automatability Score (var)
Examine physical characteristics of gemstones or precious metals.	4.00 (0.86)
Adjust fabrics or other materials during garment production.	4.00 (0.67)
Sew materials.	4.00 (0.91)
Assemble garments or textile products.	4.00 (0.68)
Sew clothing or other articles.	4.00 (0.72)
Repair textiles or apparel.	4.00 (0.71)
Attach decorative or functional accessories to products.	3.96 (0.62)
Operate sewing equipment.	3.95 (0.68)
Design templates or patterns.	3.95 (0.68)
Prepare fabrics or materials for processing or production.	3.95 (0.67)
Evaluate log quality.	3.93 (0.71)
Cut fabrics.	3.93 (0.64)
Estimate costs of products, services, or materials.	3.92 (0.67)
Store records or related materials.	3.92 (0.66)
Position patterns on equipment, materials, or workpieces.	3.87 (0.62)
Shape metal workpieces with hammers or other small hand tools.	3.85 (0.65)
Measure physical characteristics of forestry or agricultural products.	3.84 (0.65)
Maneuver workpieces in equipment during production.	3.83 (0.62)
Operate office equipment.	3.83 (0.62)
Route mail to correct destinations.	3.82 (0.64)
Select production input materials.	3.81 (0.61)
Polish materials, workpieces, or finished products.	3.81 (0.64)
Design jewelry or decorative objects.	3.80 (0.78)
Record shipping information.	3.80 (0.63)
Confer with customers or designers to determine order specifications.	3.80 (0.63)
Teach humanities courses at the college level.	1.06 (0.65)
Teach online courses.	1.07 (0.63)
Teach social science courses at the college level.	1.15 (0.61)
Coordinate training activities.	1.16 (0.69)
Conduct scientific research of organizational behavior or processes.	1.19 (0.70)
Choreograph dances.	1.19 (0.86)
Entertain public with comedic or dramatic performances.	1.21 (0.68)
Design video game features or details.	1.22 (0.79)
Advise others on educational matters.	1.32 (0.70)
Evaluate training programs, instructors, or materials.	1.33 (0.65)
Draft legislation or regulations.	1.35 (0.63)
Support the professional development of others.	1.36 (0.74)
Counsel clients on mental health or personal achievement.	1.38 (0.70)
Design psychological or educational treatment procedures or programs.	1.40 (0.65)
Guide class discussions.	1.40 (0.59)
Conduct research on social issues.	1.41 (0.71)
Lead classes or community events.	1.42 (0.66)
Counsel clients or patients regarding personal issues.	1.42 (0.61)
Display student work.	1.43 (0.58)
Develop methods of social or economic research.	1.43 (0.69)
Manage organizational or program finances.	1.44 (0.68)
Evaluate scholarly materials.	1.44 (0.66)
Evaluate effectiveness of educational programs.	1.44 (0.58)
Develop promotional strategies for religious organizations.	1.44 (0.77)
Stay informed about current developments in field of specialization.	1.44 (0.59)

Table 6: Average automatability scores of each of the nine high level work activity groups.

Activity Group	**Automatability Score (std)**
Performing Physical and Manual Work Activities	2.96 (0.45)
Identify and Evaluating Job-Relevant Information	2.88 (0.48)
Administering	2.79 (0.55)
Performing Complex and Technical Activities	2.70 (0.52)
Information and Data Processing	2.58 (0.56)
Communicating and Interacting	2.58 (0.47)
Looking for and Receiving Job-Related Information	2.52 (0.48)
Reasoning and Decision Making	2.44 (0.50)
Coordinating, Developing, Managing, and Advising	2.29 (0.49)

Table 7: Automatability scores of each of the 22 major occupation groups.

Major Occupation Group	**Employment Weighted Automatability Score (std)**
Production	3.40 (0.19)
Office and Administrative Support	3.30 (0.18)
Farming, Fishing, and Forestry	3.16 (0.28)
Sales and Related	3.16 (0.20)
Transportation and Material Moving	3.12 (0.17)
Building and Grounds Cleaning and Maintenance	2.87 (0.10)
Healthcare Support	2.79 (0.15)
Healthcare Practitioners and Technical	2.75 (0.14)
Construction and Extraction	2.74 (0.15)
Food Preparation and Serving Related	2.66 (0.10)
Architecture and Engineering	2.66 (0.23)
Installation, Maintenance, and Repair	2.65 (0.19)
Business and Financial Operations	2.60 (0.31)
Personal Care and Service	2.59 (0.23)
Protective Service	2.53 (0.13)
Arts, Design, Entertainment, Sports, and Media	2.44 (0.35)
Computer and Mathematical	2.42 (0.18)
Life, Physical, and Social Science	2.37 (0.31)
Management	2.17 (0.13)
Legal	1.98 (0.58)
Community and Social Service	1.83 (0.16)
Education, Training, and Library	1.72 (0.21)

Table 8: The 25 work activities where our model disagrees positively and negatively with the ground truth label.

Activity	**Ground Truth**	**Predicted**	**Disagreement**
Connect electrical components or equipment.	1.0	2.69	1.69
Travel to work sites to perform installation, repair or maintenance work.	1.0	2.61	1.61
Clean food service areas.	1.0	2.53	1.53
Locate suspicious objects or vehicles.	1.0	2.52	1.52
Collect dirty dishes or other tableware.	1.0	2.49	1.49
Update knowledge about emerging industry or technology trends.	1.0	2.48	1.48
Arrange tables or dining areas.	1.0	2.47	1.47
Search individuals for illegal or dangerous items.	1.0	2.43	1.43
Collaborate with others to resolve information technology issues.	1.0	2.39	1.39
Operate vehicles or material-moving equipment.	2.0	3.31	1.31
Communicate with customers to resolve complaints or ensure satisfaction.	1.0	2.31	1.31
Exchange information with colleagues.	2.0	3.30	1.30
Direct operational or production activities.	2.0	3.16	1.16
Evaluate employee performance.	1.0	2.15	1.15
Collaborate with others to determine design specifications or details.	1.0	2.14	1.14
Examine animals to detect illness, injury or other problems.	2.0	3.07	1.07
Meet with individuals involved in legal processes to provide information and clarify issues.	1.0	2.04	1.04
Direct material handling or moving activities.	2.0	3.03	1.03
Advise customers on the use of products or services.	2.0	3.02	1.02
Test materials, solutions, or samples.	2.0	3.00	1.00
Monitor loading processes to ensure they are performed properly.	2.0	3.00	1.00
Clean medical equipment.	2.0	2.98	0.98
Assist practitioners to perform medical procedures.	2.0	2.98	0.98
Hire personnel.	1.0	1.98	0.98
Conduct employee training programs.	1.0	1.95	0.95
Maintain student records.	3.5	1.55	-1.95
Count prison inmates or personnel.	4.0	2.32	-1.68
Estimate supplies, ingredients, or staff requirements for food preparation activities.	4.0	2.38	-1.62
Advise others on career or personal development.	3.0	1.45	-1.55
Administer tests to assess educational needs or progress.	3.0	1.55	-1.45
Process customer bills or payments.	4.0	2.55	-1.45
Measure equipment outputs.	4.0	2.63	-1.37
Implement security measures for computer or information systems.	4.0	2.65	-1.35
Conduct research to gain information about products or processes.	4.0	2.73	-1.27
Record patient medical histories.	4.0	2.77	-1.23
Analyze test or performance data to assess equipment operation.	4.0	2.77	-1.23
Position construction forms or molds.	4.0	2.80	-1.20
Refer clients to community or social service programs.	3.0	1.82	-1.18
Maintain client records.	3.0	1.82	-1.18
Prepare reports detailing student activities or performance.	3.0	1.83	-1.17
Create graphical representations of structures or landscapes.	4.0	2.84	-1.16
Plan work operations.	4.0	2.85	-1.15
Create electronic data backup to prevent loss of information.	4.0	2.86	-1.14
Measure materials or objects for installation or assembly.	4.0	2.86	-1.14
Maintain inventory of medical supplies or equipment.	4.0	2.88	-1.12
Manage control system activities in organizations.	3.0	1.92	-1.08

Balance receipts.	4.0	2.92	−1.08
Refer customers to appropriate personnel.	4.0	2.94	−1.06
Care for animals.	4.0	2.94	−1.06
Maintain inventories of materials, equipment, or products.	4.0	2.98	−1.02

Appendix D: Sensitivity Analysis

Table 9: The 25 most automatability-increasing and decreasing features across the activity space.

Feature	Average Gradient (std)
Telecommunications	0.16 (0.03)
Clerical	0.14 (0.03)
Wrist-Finger Speed	0.13 (0.02)
Number Facility	0.11 (0.02)
Mathematics	0.09 (0.02)
Depth Perception	0.08 (0.01)
Mathematical Reasoning	0.08 (0.02)
Economics and Accounting	0.07 (0.02)
Response Orientation	0.07 (0.02)
Building and Construction	0.07 (0.04)
Control Precision	0.07 (0.02)
Arm-Hand Steadiness	0.06 (0.02)
Equipment Selection	0.06 (0.02)
Finger Dexterity	0.06 (0.01)
Perceptual Speed	0.06 (0.01)
Visual Color Discrimination	0.06 (0.01)
Static Strength	0.05 (0.01)
Sales and Marketing	0.05 (0.06)
Far Vision	0.04 (0.01)
Spatial Orientation	0.04 (0.02)
Flexibility of Closure	0.04 (0.01)
Night Vision	0.04 (0.02)
Manual Dexterity	0.03 (0.01)
Multilimb Coordination	0.03 (0.03)
Production and Processing	0.03 (0.02)
Installation	−0.18 (0.08)
Programming	−0.14 (0.04)
Technology Design	−0.14 (0.03)
Fine Arts	−0.11 (0.05)
Gross Body Equilibrium	−0.10 (0.07)
Dynamic Flexibility	−0.10 (0.03)
Speed of Limb Movement	−0.10 (0.02)
Psychology	−0.10 (0.02)
Personnel and Human Resources	−0.09 (0.02)
Sociology and Anthropology	−0.09 (0.03)
History and Archeology	−0.09 (0.03)
Science	−0.09 (0.04)
Food Production	−0.08 (0.07)
Management of Personnel Resources	−0.07 (0.02)
Glare Sensitivity	−0.07 (0.03)
Troubleshooting	−0.07 (0.02)
Gross Body Coordination	−0.06 (0.03)
Coordination	−0.06 (0.01)
Learning Strategies	−0.06 (0.02)
Law and Government	−0.06 (0.02)
Negotiation	−0.06 (0.01)
Management of Financial Resources	−0.06 (0.02)
Social Perceptiveness	−0.06 (0.01)
Chemistry	−0.06 (0.02)
Explosive Strength	−0.06 (0.04)

Interpretation: On average, an increase of an activity's *Clerical* score by one point (1 to 5 scale), tends to to *increase* its automatability by 0.14.

Appendix E: Education and Income

Figure 5: The relationship between occupation education level and its aggregated automatability score. The education level is measured as the percent of experts who estimate at least a bachelor's degree is required to perform the occupation. This measure is given in O*NET. Each point is an occupation and its size is proportional to the occupation's current employment.

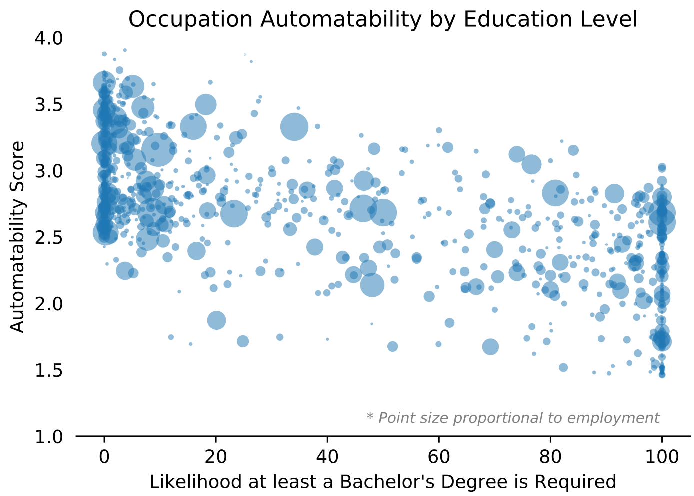

Figure 6: The relationship between occupation median annual income and its aggregated automatability score. The income is derived from (OES, 2017) Each point is an occupation and its size is proportional to the occupation's current employment.