The differential impact of AI

Programmers vs. Machine Learning

Truck Drivers vs. Autonomous Vehicles
The differential impact of AI

Unpacking complexity in workplace skills

Morgan R. Frank

- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education
Embrace Complexity

- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education

Unpacking complexity in workplace skills

Morgan R. Frank
Constructing the Skillscape

\[ rca(i, s) = \frac{onet(i, s) / \sum_{s' \in \text{Skills}} onet(i, s')}{\sum_{i' \in \text{Jobs}} onet(i', s) / \sum_{s' \in \text{Skills}, j' \in \text{Jobs}} onet(i', s')} \]

\[ I(i, s) = \begin{cases} 1 & \text{if } rca(i, s) > 1, \\ 0 & \text{otherwise}. \end{cases} \]
Constructing the Skillscape

Occupations

j₁
j₂
j₃

Workers

Skills

s₁
s₂
s₃

Skills

s₁
s₂
s₃
s₄
s₅
s₆

The Product Space

Occupations

Skills

Skills

s₁
s₂
s₃
s₄
s₅
s₆

Unpacking complexity in workplace skills

Morgan R. Frank
Unpacking the polarization of workplace skills
Skill polarization explains occupational polarization

Increasing annual wages

Pearson Correlation: 0.417 (p<10^{-26})
Skill polarization and economic well-being


Increasing median household income (also population)

\[
cognitive_j = \frac{\sum_{s \in C} onet(j, s)}{\sum_{s \in S} onet(j, s)}
\]

Pearson Correlation: 0.254 (p<10^{-4})

Unpacking complexity in workplace skills

Morgan R. Frank
Skill polarization and career mobility


Low Cognitive Skill
- Waitstaff ($23k)
- Bartender ($24k)
- Mechanical Tool Setter ($38k)
- Mechanics Supervisor ($66k)

Mid Cognitive Skill
- Sales Engineer ($107k)

High Cognitive Skill
- Retail Supervisor ($43k)
Explaining low- and high-skill employment

Unpacking complexity in workplace skills

Morgan R. Frank
Connecting Occupations

$$rca(i, s) = \frac{onet(i, s)}{\sum_{i' \in \text{Jobs}} \sum_{s' \in \text{Skills}} \frac{onet(i', s')}{\sum_{j' \in \text{Jobs}} \text{onet}(i', s')}}$$

$$I(i, s) = \begin{cases} 1 & \text{if } rca(i, s) > 1, \\ 0 & \text{otherwise}. \end{cases}$$

$$\text{skillsim}(i, j) = \sum_{s \in \text{Skills}} w_s \frac{I(i, s) + I(j, s)}{2}$$
Connecting Occupations

Total Skill Similarity\((i) = \sum_{j \in \text{Jobs}, j \neq i} \text{skillsim}(i, j)\)
Connecting urban workforces

Chicago, IL

Orlando, FL

Chicago-Orlando Employment Overlap
Connecting urban workforces

Boston, MA

Napa, CA

Boston-Napa Employment Overlap

\[
\bar{c}_a = [..., I(a, j), ...]_{j \in \text{Jobs}}
\]

job tightness \((a, b) = \frac{\langle JJ \cdot (\bar{c}_a + \bar{c}_b) \rangle}{\langle JJ \rangle}
\]
Connecting skills to *spatial* mobility

Two Types of Intercity Mobility:

Enplaned Passengers

Migration
Connecting skills to *spatial* mobility

\[
\tilde{c}_a = [\ldots, I(a, j), \ldots]_{j \in \text{Jobs}}
\]

\[
\text{job tightness}(a, b) = \frac{\langle J_J \cdot (\tilde{c}_a + \tilde{c}_b) \rangle}{\langle J_J \rangle}
\]
Not all skills are equal

Use supervised CMA-ES to learn skill weights ($w_s$)
## Connecting skills to spatial mobility

### Dependent Variable: \( \log_{10}(\text{enplaned passengers}_{a,b}) \)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Job Tightness</td>
<td>0.867***</td>
<td>0.815***</td>
<td>0.841***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Employment</td>
<td>0.560***</td>
<td>0.085***</td>
<td>0.203***</td>
<td>0.091***</td>
<td></td>
</tr>
<tr>
<td>Log Distance</td>
<td>0.095***</td>
<td>0.016**</td>
<td>0.097***</td>
<td>0.013*</td>
<td></td>
</tr>
<tr>
<td>Characteristic Job Overlap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.585***</td>
</tr>
</tbody>
</table>

\( \text{adj. } R^2 \) 0.752  0.330  0.757  0.545  0.757

\( p_{val} < 0.1^*; p_{val} < 0.01^{**}; p_{val} < 0.001^{***} \)

### Dependent Variable: \( \log_{10}(\text{migration}_{a,b}) \)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Job Tightness</td>
<td>0.520***</td>
<td>0.548***</td>
<td>0.631***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Employment</td>
<td>0.404***</td>
<td>0.114***</td>
<td>0.155***</td>
<td>0.132***</td>
<td></td>
</tr>
<tr>
<td>Log Distance</td>
<td>−0.306***</td>
<td>−0.395***</td>
<td>−0.357***</td>
<td>−0.395***</td>
<td></td>
</tr>
<tr>
<td>Characteristic Job Overlap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.427***</td>
</tr>
</tbody>
</table>

\( \text{adj. } R^2 \) 0.271  0.225  0.427  0.340  0.429

\( p_{val} < 0.1^*; p_{val} < 0.01^{**}; p_{val} < 0.001^{***} \)
Explaining Job Tightness

tightness(Chicago, New York) = 0.98

tightness(Chicago, Indianapolis) = 0.81

Unpacking complexity in workplace skills

Morgan R. Frank 21
Unpacking complexity in workplace skills

Morgan R. Frank

Unifying Perspectives

- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education

Local Labor Markets

Occupations & Employment

Tasks & Skills

Executive

Programmer

Bartender

Persuasion

Stamina

Mathematics

Vision
Unifying Perspectives

Cities

Occupation Space

Skill Space

Unpacking complexity in workplace skills

Morgan R. Frank
Unpacking complexity in workplace skills

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Unifying Perspectives
The structural resilience of urban labor markets

Beveridge Curve

- Job Vacancy Rate (%)
- Unemployment Rate (%)
- Year
- 2002
- 2004
- 2006
- 2008
- 2010
- 2012
- 2014
- 2016
- 2018

- Current Employment
- Low Employment
- Tipping Point

Densely-Connected Labor Force
Sparsely-Connected Labor Force
Skill Removal

Unpacking complexity in workplace skills

Morgan R. Frank
The structural resilience of urban labor markets


- occupations -> animals, skills -> plants, cities -> ecosystems

- exp. impact from automation strongly correlates with structural resilience measure from ecology

\[
\text{Pearson } \rho = -0.66 \ (p_{\text{val}} < 10^{-48})
\]

\[
\text{Pearson: } -0.86 \text{ without outliers}
\]
Fellow Laborers (to name a few):

Lijun Sun
Manuel Cebrian
Hyejin Youn
Erik Brynjolfsson

Iyad Rahwan
César Hidalgo
Ahmad Alabdulkareem
Daniel Rock

Esteban Moro
Alex Rutherford
Inho Hong
Dashun Wang

**Skill polarization and education**
Skill polarization and Education

High School Diploma

Bachelor's Degree

Doctoral Degree

Pearson Correlation

Unpacking complexity in workplace skills

Morgan R. Frank
Explaining Job Tightness

20 Least Tight City Pairs vs. 20 Most Tight City Pairs

ΔTightness = 0.309

<table>
<thead>
<tr>
<th>Contribution to Difference</th>
<th>Contribution to Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>industrial machinery mech.</td>
<td>camera operators, televis...</td>
</tr>
<tr>
<td>first-line supervisors of</td>
<td>radio, cellular, and t...</td>
</tr>
<tr>
<td>registered nurses</td>
<td>bakers</td>
</tr>
<tr>
<td>secondary school teachers</td>
<td>pressers, textile, garmen...</td>
</tr>
<tr>
<td>occupational therapists</td>
<td>cooks, fast food</td>
</tr>
<tr>
<td>special education teacher</td>
<td>photographic process work...</td>
</tr>
<tr>
<td>physical therapists</td>
<td>amusement and recreation...</td>
</tr>
<tr>
<td>court, municipal, and lic.</td>
<td>public address system and...</td>
</tr>
<tr>
<td>recreational therapists</td>
<td>bicycle repairers</td>
</tr>
<tr>
<td>slot supervisors</td>
<td>textile cutting machine s...</td>
</tr>
<tr>
<td>ophthalmic laboratory tec.</td>
<td>painters, construction an...</td>
</tr>
<tr>
<td>magnetic resonance imagin.</td>
<td>reinforcing iron and reba...</td>
</tr>
<tr>
<td>nuclear medicine technolo...</td>
<td>architectural and civil d...</td>
</tr>
<tr>
<td>veterinary technologists</td>
<td>costume attendants</td>
</tr>
<tr>
<td>nurse anesthetists</td>
<td>slaughterers and meat pac...</td>
</tr>
<tr>
<td>separating, filtering, cl.</td>
<td>health educators</td>
</tr>
<tr>
<td>court reporters</td>
<td>stonemasons</td>
</tr>
<tr>
<td>cardiovascular technologi...</td>
<td>licensed practical and li...</td>
</tr>
</tbody>
</table>

Sales & Marketing
- Oral Comprehension
- Deal With External Customers
- Management of Material Resources
- Documenting/Recording Information
- Telecommunications
- Reaction Time

Exposure to Radiation
- Hazardous Equipment
- Crammed Work Space
- Deductive Reasoning
- Wear Safety Equipment

Social Perceptiveness
- Trunk Strength
- Indoors
- Negotiation
- Depth Perception
Cities race with the machines

Skill polarization and economic well-being

\[ \text{cognitive}_j = \frac{\sum_{s \in C} \text{onet}(j, s)}{\sum_{s \in S} \text{onet}(j, s)} \]

Pearson Correlation \( \rho = 0.417 \) (\( p_{\text{val}} < 10^{-26} \))

Chief Executive ($166k)

Chiropractor ($80k)

Taxi Driver ($23k)

Dishwasher ($18k)

Yuma, AZ ($41k)

Detroit, MI ($52k)

New York, NY ($67k)