Remote Work: *Fad or Future?*

Team 15440

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Overview

**Part I:
Ready or Not**

Problem

→ Percentage of remote ready jobs in 5 given cities.

Approach

→ Exponential regression on industries; percentage in each industry.

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Remote Control

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→ Conditional probability on demographic factors

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→ Conditional probability on demographic factors

Part III:
Just a Little Home-Work

Problem

→ Determine true remote worker percentage in each city.

→ Rank WFH's impact on the 5 cities.

Approach

→ Population Simulation Method combining models I and II.

Global Assumption

G.1: "Working from home" is a general term including partial and full remote work.

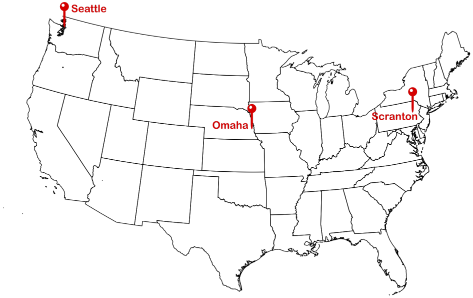
Part I: Ready or Not

Problem Statement

Given Problem

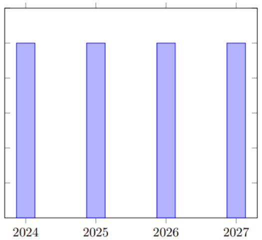
→ Create a model which, for a given city, estimates the percentage of workers whose jobs are currently remote-ready. The model should be applied to the following cities:

Seattle **Omaha** **Scranton** **Liverpool** **Barry**



Assumptions

1. Remote Work Rate Constant
within industries over time.



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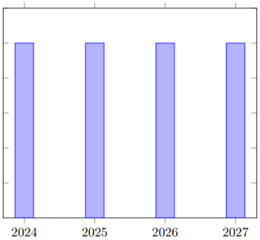

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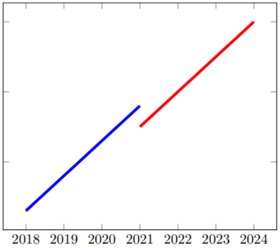

Pre-Pandemic trends in sector workforce share, from lower base of post pandemic levels.

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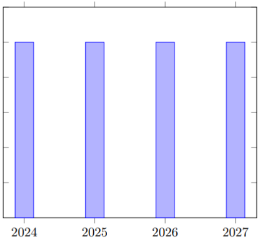

3 Profession Only - "Remote readiness" defined by job; not employee.

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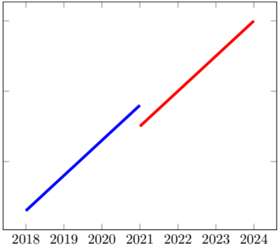


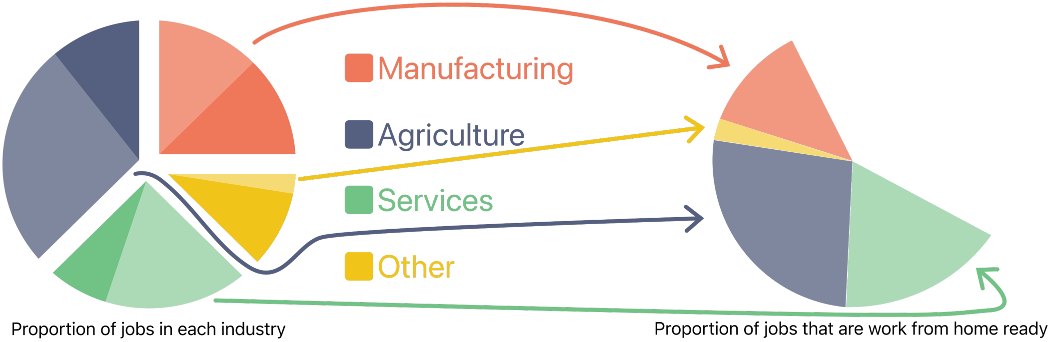
Pre-Pandemic trends in sector workforce share, from lower base of post pandemic levels.

Variables & Constants

Type	Symbol	Definition	Units
Variable	t	Time since 2000.	years
Variable	$N_{I,C}(t)$	Number of workers in industry I in city C at time t.	1000 people
Variable	$P_{I,C}(t)$	Proportion of city C's jobs being in industry I at time t.	%
Variable	$R_C(t)$	Percentage of city C's jobs being remote ready at time t.	%
Constant	H_I	Proportion of remote ready jobs in a given industry I.	%

Model Development

$$R_C(t) = \sum_I [P_{I,C}(t) \cdot H_I]$$



[1] Chart for intuition only; not real data!

Finding Industry Trends

$$\boxed{P_{I,C}(t) = a \cdot e^{bt}}$$

Justifications

- An exponential model better **fits the data**. *Visually & Mathematically (measuring PMCC of the data after logged)*

[1] $P_{I,C}$ - Proportion of city C's jobs being in industry I at time t.
[2] a,b are constants fitted to the data

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- An exponential model demonstrates **asymptotic behaviour**.
- Exponentials are established to represent **changes in populations** over time.

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$P_{I,C}(t)$ Exponential Regression

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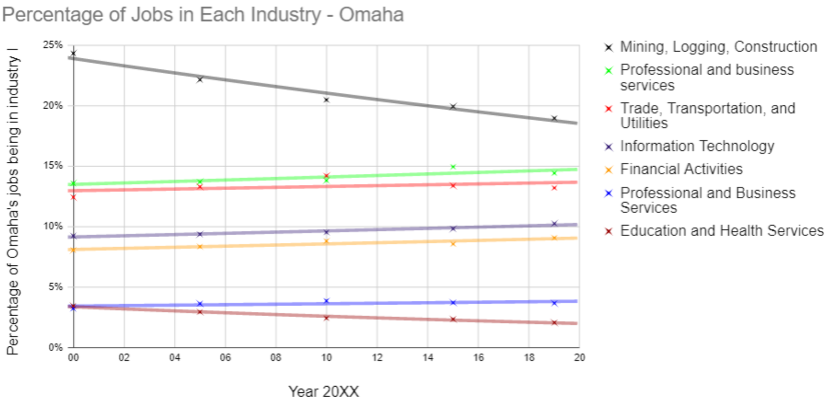

Figure: $P_{I,C}(t)$ vs t with exponential trend lines; some industries omitted for clarity.

[1] Note: All jobs; not just remote ready ones.

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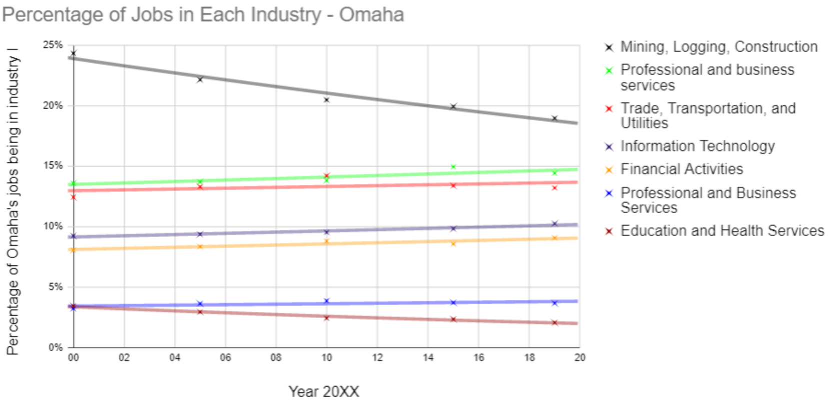

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The H_I constant

- $P_{I,C}(t)$ industries don't perfectly match given H_I values' industries.
  $\implies$ weighted average where necessary

$P_{I,C}(t)$ **Industry**	**Given** H_I **industry values**	**Weights**	H_I
Education and Health Services	Education / Health Services	0.3 / 0.7	34%
Professional and Business Services	Sales / Office and Administrative / Management	0.5 / 0.4 / 0.1	49%
Information Technology	Computer and Mathematical	-	100%
Leisure and Hospitality	Food Preparation and Service Related	-	0%
...	...	...	...

[1] H_I is the percentage of jobs in industry I being remote ready.

Results

Example Regression for Industry Labour Market Share

$$P_{\text{trade,Omaha}}(t) = 0.237 \cdot e^{-0.0117t}$$
$$P_{\text{trade,Omaha}}(24) = 17.90\ \%$$
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City	2024	2027
Seattle	41%	42%
Omaha	40%	40%
Barry	39%	39%
Scranton	36%	36%
Liverpool	31%	31%

Table: Percentage of jobs being remote ready.

Evaluation

+ Consistent with recent studies[1] suggesting 36 % on average.

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- – Over longer periods of time (20+ years), model will become unsuitable:
  - – Assumes each H_I is constant over time; doesn't account for tech. advancements
  - – Exponential models for each industry independent; total not guaranteed to be 100%.

[1] Holgersen, H., Jia Z., Svenkerud, S., Who and How Many Can Work From Home? Evidence From Task Descriptions (April 20, 2020).

Part II: Remote Control

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→ Create a model to determine the percentage probability that a worker with a given set of characteristics who can work from home will do so.

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Remark

This definition is advantageous as the model can be used in two ways:

1. Compare probability to 0.5 for binary answer in Part II.
2. Take percentage as expected value in Part III.

Key Assumptions

1. Independent: Desire to work from home is independent of employer's permission and remote readiness.

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   - Impact of pandemic on desire to WFH can be modelled by a constant multiple.
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4. Age Distribution: Workers' age can be normally distributed with $\mu = 35$ and $\sigma = 10$, capped at a minimum of 20 and a maximum of 80.

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Feature Identification

Included

- Age
- Sex
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- Level of Education
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- Full Time / Part Time
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Excluded

- Family Characteristics
- Income
- Size of Team

Defining Events & Model Parameters

- W: the worker wants to work from home.

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We also define c, the pandemic correction constant[1], so that:

$$\boxed{P(W) = c \cdot P(W_p)}$$

[with $P(W)$ capped at 1]

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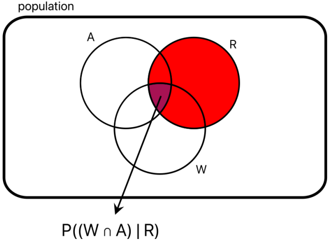
Expressing the Probability in Terms of Known Variables



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All probabilities for a **particular** *individual worker.*

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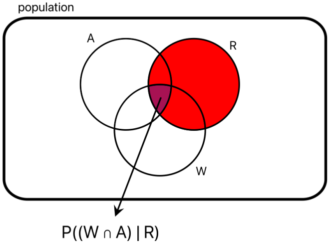

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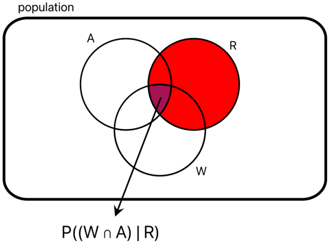

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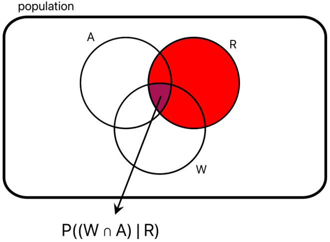

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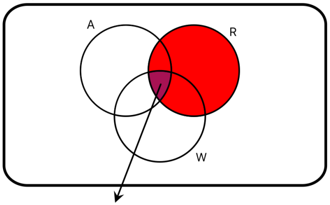

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Estimating $P(W_p \cap A \cap R)$ for a Given Worker

Full-time

	Agriculture, forestry and fishing (A)			
	Never	Mainly	Recently	Occasionally
2011	62.90%	3.83%	7.10%	26.17%
2012	69.38%	2.45%	7.19%	20.98%
2013	64.42%	4.21%	5.30%	26.08%
2014	59.32%	3.90%	10.67%	26.11%
2015	66.54%	5.11%	6.41%	21.93%
2016	63.34%	5.62%	8.73%	22.32%
2017	68.70%	4.34%	6.55%	20.41%
2018	67.36%	5.87%	4.48%	22.29%
2019	62.22%	6.95%	6.03%	24.81%
2020	67.63%	7.49%	10.73%	14.14%

$$P((W \cap A)|R) \equiv \frac{(1.4) \cdot P(W_p \cap A \cap R)}{P(R)}$$

[1] Homeworking in the UK, work from home status, ONS, 2021

Estimating $P(W_p \cap A \cap R)$ for a Given Worker

$$P((W \cap A)|R) \equiv \frac{(1.4) \cdot P(W_p \cap A \cap R)}{P(R)}$$

Equation Equivalent to the OOP Technical Computing Algorithm

$$P(W_p \cap A \cap R)_{est} = B \cdot \prod_{char} \left(\frac{\text{ONSRate2019(char)}}{B} \right) \cdot \tanh(C) \cdot (1.5 - 0.5 \cdot e^{\frac{Y-20}{80}})$$

[1] B = 'base' WFH rate for the whole population ≈ 0.266; C = commute distance; Y = age in years; char = one characteristic of a *particular worker's* demographic, e.g. *their particular* ethnicity or industry.

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e.g. 0.2 when char = 'Asian' if, in 2019, 20% of Asians worked from home.

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Commute distance scaling factor.

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Age scaling factor.

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Problem II Model

$$P((W \cap A)|R) \approx \frac{c \cdot P(W_p \cap A \cap R)_{est}}{P(R)}$$

[1] P(R) : Remote Work: Fad or Future, M3 Challenge 2022 Dataset, D3

Results

Sex	Ethnicity	Sector	Education	FT/PT	Commute Distance, m	Age	WFH Probability	Effect of change
Male	White	IT	Degree	FT	1000	40	0.63493	-
Male	White	IT	Degree	FT	1000	80	0.32672	↓
Male	White	IT	No Qualification	FT	1000	40	0.19411	↓
Female	White	IT	No Qualification	FT	1000	40	0.55491	↑
Female	Asian	IT	No Qualification	FT	1000	40	0.13247	↓
Female	Asian	Retail	No Qualification	FT	1000	40	0.17857	↑
Female	Asian	Retail	No Qualification	FT	400	40	0.08909	↓
Female	Asian	Retail	A Level (High School)	FT	400	40	0.23094	↑

Table: Example work-from-home probabilities for candidates with different characteristics, showing incremental changes.

Part III: Just a Little Home-work

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2. Apply to Seattle, Omaha, Scranton, Liverpool, and Barry in 2024 and 2027.
3. Use to relatively rank the different cities by the impact of remote work on them.

Assumptions & Variables

Critical Assumption

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Features & Variables

→ We use the same factors as in the previous two parts, as we combine those models to produce this one.

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1. Part I gives industry sizes each year, each city; other demographic data researched.
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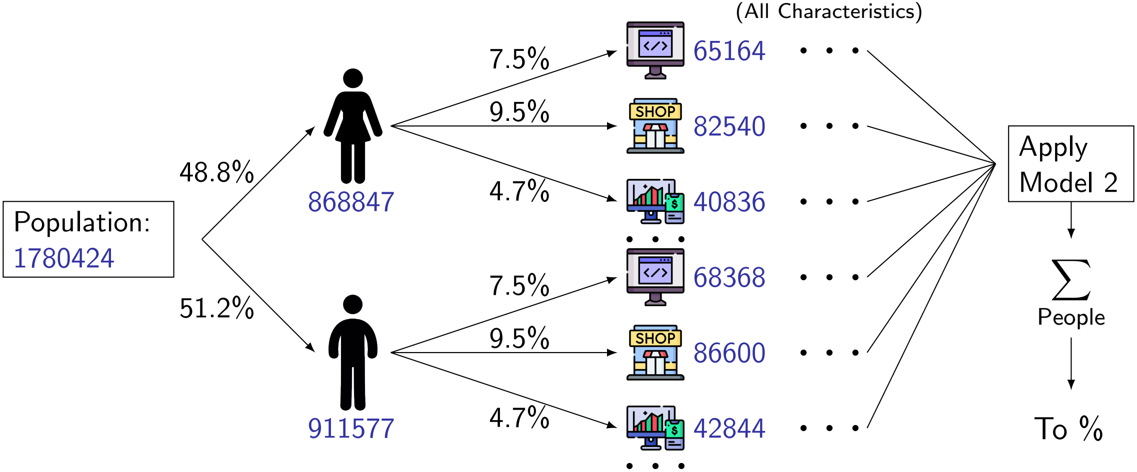
3. Run each Person through model II; aggregate over the city.

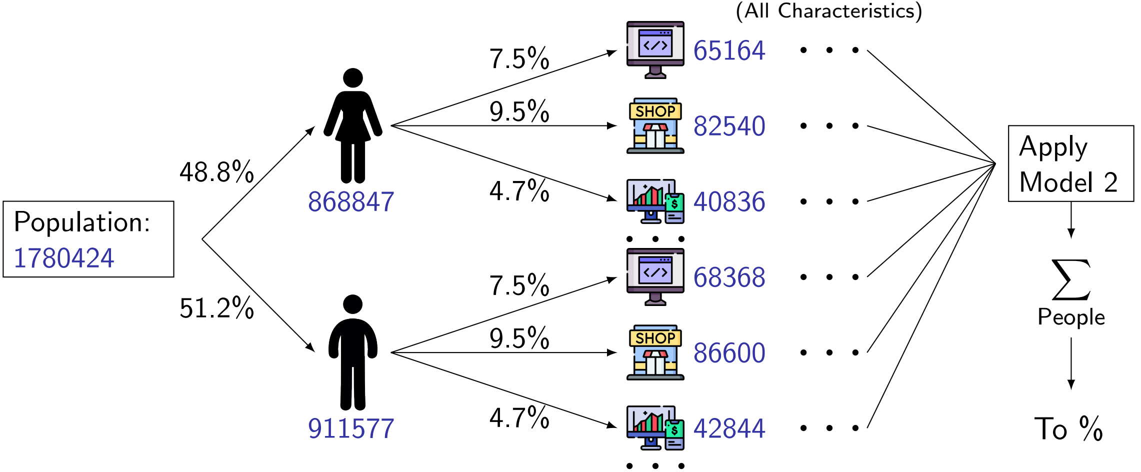
The RecursiveGen Procedure : Diagrammatic Representation

Seattle, 2024



The RecursiveGen Procedure : Diagrammatic Representation

Repeat for all cities, in 2024 and 2027



Problem III Results

Actual Work From Home Percentage

City	2024 predictions	2024 ranking	2027 predictions	2027 ranking
Seattle	30.73%	1st	32.45%	1st
Omaha	29.07%	2nd	29.26%	2nd
Liverpool	27.37%	3rd	29.13%	3rd
Barry	26.51%	4th	26.59%	5th
Scranton	26.36%	5th	26.63%	4th

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— Sub-demographic assumption time-saving but not necessarily realistic.

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- Explore causes of US vs UK differences in our model.

Thank you!

Any questions?