Summary of Memo on (Task) Complexity Measurement

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So, What Is Complexity?

- Per Caines et al. (2017), there is a given "bundle" of "higher-order" (e.g., deductive reasoning) skills used for the delivery of given tasks in an occupation; "complex" tasks/occupations use these skills to a larger degree
- Authors select 35 (out of 277) O*NET occupational task "descriptors" they deem most relevant to the notion of "complexity"
  - Descriptors are quantified via scores from Likert scale-type questions within O*NET worker surveys
  - Q: "What level of DESCRIPTOR [e.g., "critical thinking"] is needed to perform your current job?"; scale from 0 to 7

▸ Scatter plot of descriptor scores

...But How Is Complexity Measured?

- Following Yamaguchi (2012) (which follows Bacolod and Blum (2010)): apply **Principal Component Analysis (PCA)** to map 35 O*NET descriptors into one-dimensional "complexity index" ▸ Code
- PCA performs dimension reduction while preserving as much variance as possible ▸ Details of PCA
- A high factor loading indicates that the corresponding descriptor score strongly influences the complexity index ▸ PCA factor loadings
- But PCA is difficult to interpret, a more intuitive way of understanding how scores "go into" the complexity index is by considering the complexity *score* (which is a dot product):

$$C_o = \gamma \cdot X_o$$

γ: 1×35 factor loadings; X_o: 35×1 descriptor scores of occupation o

...And Whose Job Is More Complex?

- Higher descriptor scores across the board $\Rightarrow$ higher position in "complexity" ranking
- Two occupations with same descriptor score sum, but one with high descriptor scores concentrated in high-factor loading descriptors $\Rightarrow$ higher position in "complexity" ranking
- No "breadth" (# descriptors/worker) vs. "depth" (descriptor score level) trade-off; complexity score just a dot product
- Q: Whose occupation is more complex? X's having all 5s in 20/35 descriptors or Y's having all 3s in 35/35 descriptors?
- ANS: If factor loadings are identical across descriptors, the one w/ the largest descriptor score sum (Y's, in this case, since $100 < 105$)
- So, is University Professor more "complex" than School Janitor? Yes, if the former's dot product of descriptor scores and factor loadings is larger than the latter's ▸ Ranking comparison

How Sensitive Is This Complexity Measure?

- Quite a bit! Ranking changes wrt. Caines et al. (2017) when we keep only 30, 20, 10 highest-factor loading descriptors
- Additional simulation with "pseudo"-occupations: added "occupations" w/ fictional scores: each w/ all 1s, 2s, 3.5s, 7s; and 6.125s in top 20 highest-factor loading descriptors
- Alternative measures of complexity show results for highest/lowest-end descriptor rankings similar to Caines et al. (2017), mid-tier descriptor rankings diverge

What About The Underlying Data?

- Caines et al. (2017) do not provide any intuition or sensitivity analysis re: choice of descriptors (why 35 descriptors instead of 30?); choice seems arbitrary, imposes given dimension on PCA vector
- Caines et al. (2017) ignore Likert scale-type survey questions on descriptor "Importance", focus on "Level" of descriptor used in given occupation
- Descriptors hard to compare across occupations (how comparable is a descriptor score of 4 in "critical thinking" vis-a-vis a descriptor score of 7 in "inductive reasoning"?)
- Further issues: workers do not give themselves scores of more than 6 due to extreme anchoring of Likert scale for values above 6, over-representation of more educated workers (due to survey sophistication), no published external evaluation of O*NET (Handel, 2016) ▸ descriptor score densities

Conclusion

- Issues concerning complexity measure source data, implementation in statistical software packages, interpretation, and sensitivity (incl. to choice of descriptors!)
- Caines et al. (2017) seem to suggest skill "bundles" drive wage returns (as opposed to individual skill types Deming (2017))
- Gaps in literature re: internal consistency and comparability of task (and skill) measures not yet adequately addressed

RESERVE SLIDES

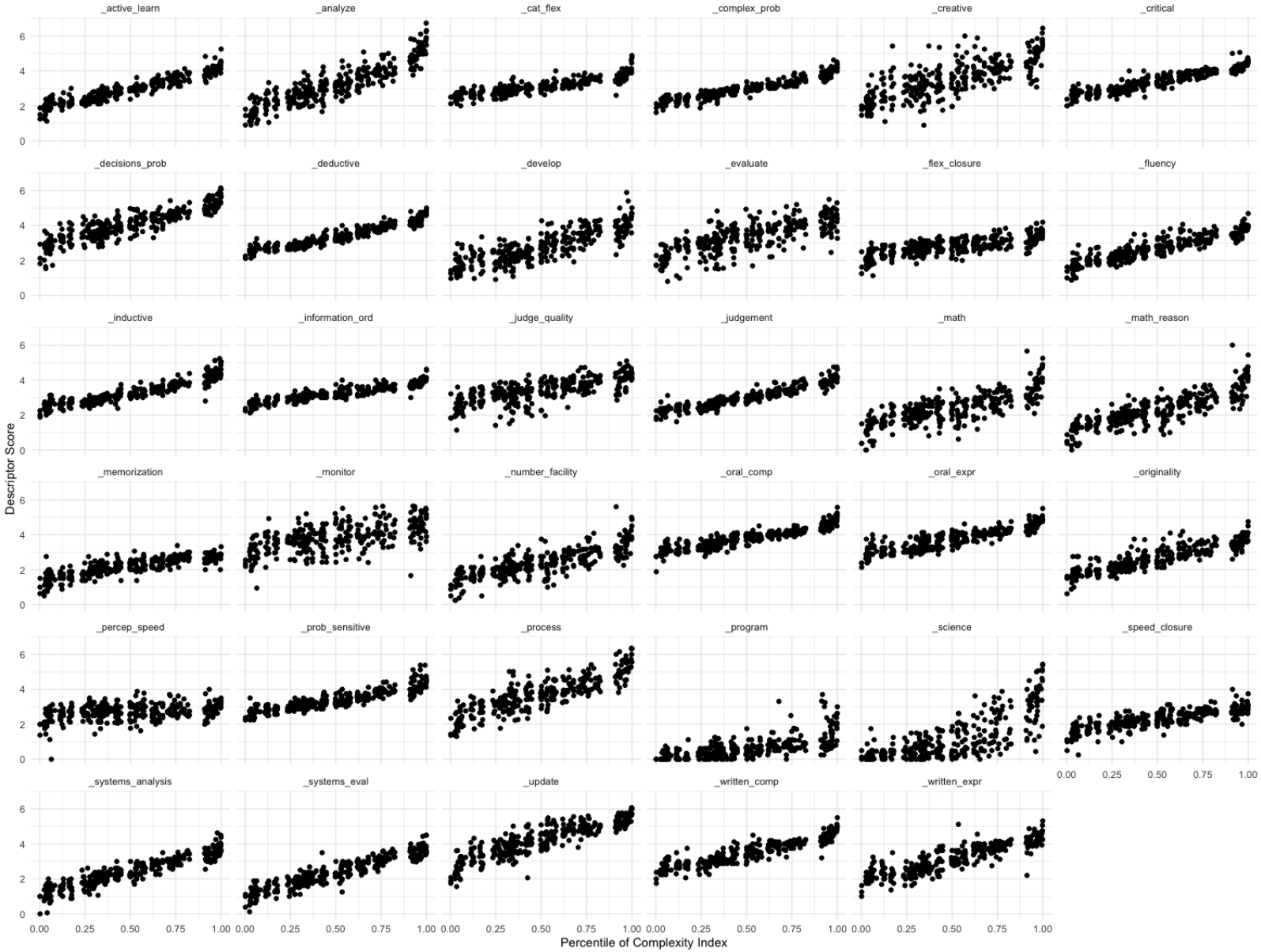

Figure: Scatter plot of descriptor scores by percentile of complexity index

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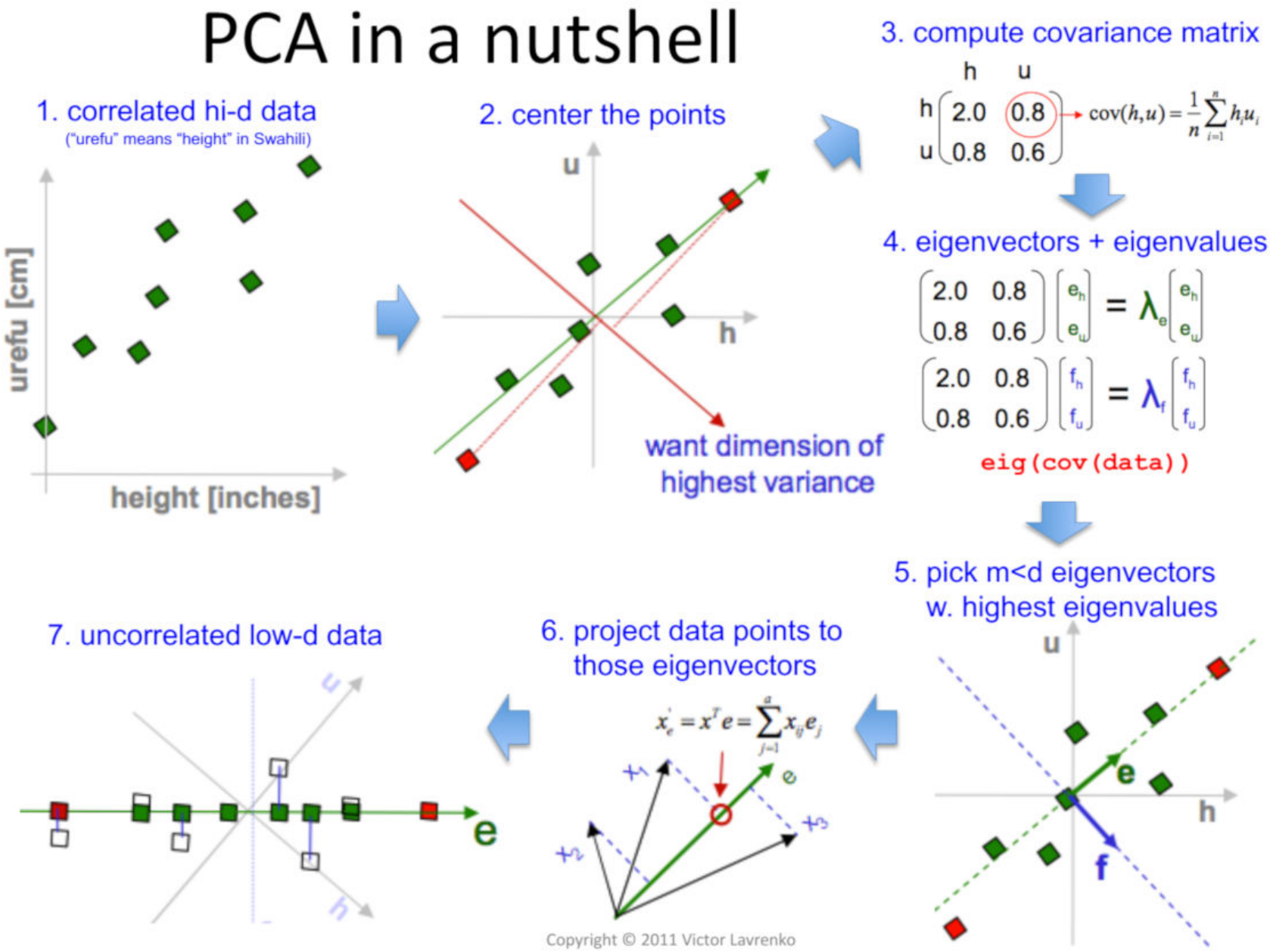

Figure: Overview of Principal Component Analysis (PCA) Procedure

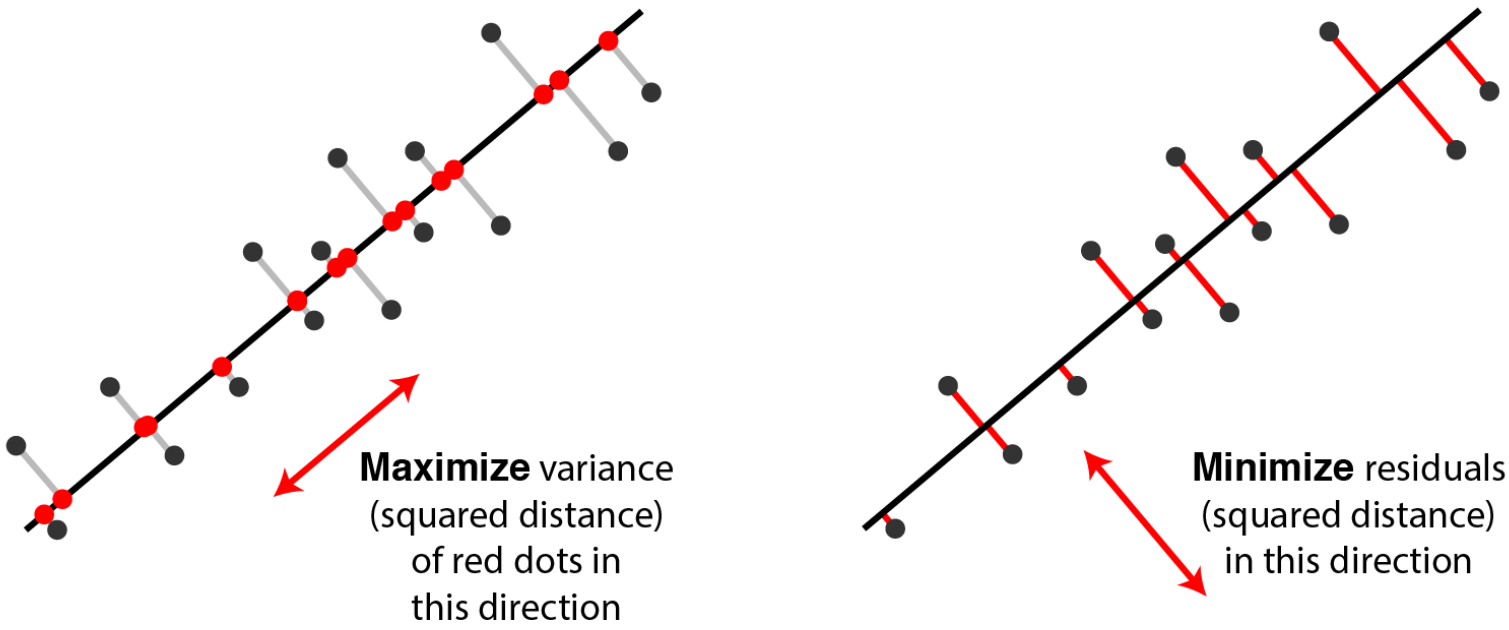

Figure: While reducing dimension, PCA preserves as much of the variance as possible and minimizes errors/residuals

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```
361  ************************************************************
362  *
     ↳
363  *       PCA ANALYSIS - O*NET
364  *
     ↳
365  ************************************************************
366
367
368  use "data_files/Census1980.dta", clear
369  keep occ1990dd weight
370  egen temp = sum(weight)
371  replace weight = weight / temp
372  drop temp
373  collapse (sum) weight, by(occ1990dd)
374
375  merge 1:1 occ1990dd using "data_files\occ1990dd_ONET.dta"
376  keep if _merge==3
377  save "data_files\occ1990dd_ONET_2.dta", replace
378
379
380  * OVERALL
381      drop _install _troubleshooting _repair
382      pca _* [aw=weight]
383      predict complexind
384      sort complexind
385      gen pctile_complexind = sum(weight)
```

Figure: Code for PCA used by Caines et al. (2017) (line 382 and 383 of `data_build_occ_level.do` provided here)

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Caines et al. (2017): PCA Factor Loadings

Descriptor	Factor loading
O*NET worker abilities	
Oral comprehension	0.1818
Oral expression	0.1763
Written comprehension	0.1848
Written expression	0.1797
Fluency of ideas	0.1813
Originality	0.1772
Problem sensitivity	0.1799
Deductive reasoning	0.1870
Inductive reasoning	0.1814
Information ordering	0.1761
Category flexibility	0.1734
Mathematical reasoning	0.1702
Number facility	0.1640
Memorization	0.1688
Speed of closure	0.1629
Flexibility of closure	0.1407
Perceptual speed	0.0796

Source: Caines et al. (2017)

Caines et al. (2017): PCA Factor Loadings, cont'd

O*NET skills	
Mathematics	0.1589
Science	0.1402
Critical thinking	0.1835
Active learning	0.1859
Complex problem solving	0.1867
Programming	0.1400
Judgment and decision making	0.1862
Systems analysis	0.1832
Systems evaluation	0.1847
O*NET activities	
Monitor processes, materials or surroundings	0.1106
Judging the qualities of things/services/people	0.1520
Processing information	0.1712
Evaluating information to determine compliance with standards	0.1493
Analyzing data or information	0.1807
Making decisions and solving problems	0.1774
Thinking creatively	0.1647
Updating and using relevant information	0.1761
Developing objectives and strategies	0.1662

Source: Caines et al. (2017)

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Occupation List and Complexity/Routineness Percentiles

Table 2
Comparison of complexity and routinization.

Occupation title	Routine index percentile	Complexity index percentile
Routinizable occupations with high complex content		
Financial managers	82.825	96.109
Real estate sales occupations	87.416	66.033
Accountants and auditors	95.502	78.977
Insurance underwriters	95.976	65.348
Statistical clerks	93.661	93.177
Clinical laboratory technologist and technicians	74.922	73.236
Other financial specialists	77.201	75.251
Non-routinizable occupations with low complex content		
Waiters and waitresses	12.038	3.617
Baggage porters, bellhops and concierges	9.357	26.968
Recreation facility attendants	27.036	11.736
Taxi cab drivers and chauffeurs	5.054	28.085
Personal service occupations	26.624	30.395
Door-to-door sales, street sales, and news vendors	26.855	6.419
Bus drivers	3.775	12.672

Notes: The table reports values of the routine and complexity indices for a selection of occupations. The index values are converted to percentiles of the occupation-level distribution. See Sections 2.2 and 2.3 for construction of the routine index and the complexity index.

Source: Caines et al. (2017)

- O*NET-SOC occupations mapped into Census occupation codes

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Caines et al. (2017): Descriptor Score Densities

Source: Caines et al. (2017)

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References I

Bacolod, Marigee P and Bernardo S Blum, "Two sides of the same coin us "residual" inequality and the gender gap," *Journal of Human resources*, 2010, *45* (1), 197–242.

Caines, Colin, Florian Hoffmann, and Gueorgui Kambourov, "Complex-task biased technological change and the labor market," *Review of Economic Dynamics*, 2017, *25*, 298–319.

Deming, David J., "The growing importance of social skills in the labor market," *The Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

Handel, Michael J, "The O* NET content model: strengths and limitations," *Journal for Labour Market Research*, 2016, *49* (2), 157–176.

Yamaguchi, Shintaro, "Tasks and heterogeneous human capital," *Journal of Labor Economics*, 2012, *30* (1), 1–53.