U.S. Army Research Institute for the Behavioral and Social Sciences

Relative Weights Analysis is a "Grey Box" Relative Importance Algorithm

Briefing for:

George Mason University

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ARI Mission

<u>Mission</u>: Drive scientific innovation to enable the Army to acquire, develop, employ, and retain professional Soldiers and enhance personnel readiness.

Personnel Assessment

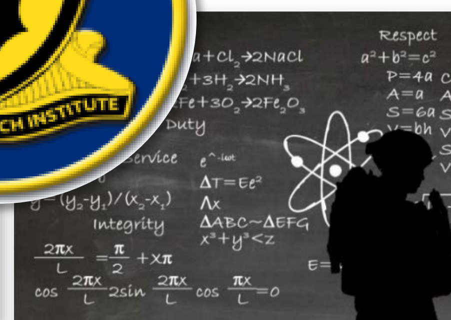
Innovative measures and methods to maximize personnel and unit readiness of the Future Army.

Leader Development

Novel methods to accelerate leader development of critical competencies for Multi-domain Operations.

Team Effectiveness

Innovative assignment and development methods to maximize team and squad readiness for the future battlefield.



Basic Research

Fundamental theories and new domains in behavioral and social sciences with high potential impact on Army issues.

WHERE PERSONNEL SCIENCE MEETS PERSONNEL PRACTICE

Basic Research Strategic Direction

Defense Workforce Strategic Direction

- National Defense Strategy
- Army Operating Concept
- Talent Management Strategy
- Army Warfighter Challenges

Scientific Opportunity

- Psychometric advances
- Data analytics and modeling
- Organizational context and culture
- Team dynamics and performance

ARI Core

- Personnel
- Organizational Effectiveness
- Leader Development
- Training & Learning

Strategic Focus Areas

- Science of Measurement of Individuals and Collectives
- Understanding Multilevel and Organizational Dynamics
- Context of Behavior in Military Environments
- Formal/Informal Learning and Development

“Right person, right job, right time”

“Optimize individual and team performance”

“Develop smart, thoughtful, & innovative leaders”

“Deliberate management of Soldier & Officer Talent”

“Employ each individual to maximum effect”

Basic Research Strategic & Technical Goals

	Near (FY20-27)	Mid (FY28-35)	Far (FY36-45)
Science of Measurement of Individuals and Collectives	**Strategic Goal: Advanced psychometric theory for deriving valid measurements from complex assessments and continuous streams of data**		
	Computational psychometrics for modeling dynamic data Dynamic Team composition & staffing models	Measurement theory for dynamic constructs Context-sensitive measures of adaptability & flexibility	Measurement theory for simulation-based assessment Embedded assessments of individual and group attributes
Understanding Multilevel and Organizational Dynamics	**Strategic Goal: Develop multilevel theory and methods for understanding dynamic restructuring, coordination, and composition processes in complex organizations**		
	Non-linear models for assessing team processes Integrating geospatial concepts into team effectiveness	Computational models of individual & group dynamics Modeling dynamic organizational restructuring	Complex computational models of multi-layered organizations for experimentation
Context of Behavior in Military Environments	**Strategic Goal: Integrative theory specifying the interactive relationships between individual characteristics and contextual drivers in predicting human behavior**		
	Leadership theory for complex organizations Identify contextual factors impacting social & decision processes	Multilevel contextual effects on organizational behavior Models for strategically activating organizationally-relevant identities	Models integrating individual, group, and contextual factors to predict organizational behavior
Formal/Informal Learning and Development	**Strategic Goal: Holistic model of individual and collective learning across work settings and contexts throughout the career span**		
	Understand the role of narratives in learning Characteristics that impact individual & collective learning	Unobtrusive measures for assessing career learning Non-linear models of learning & development	Complex computational models of development across the career span

Basic Research Model

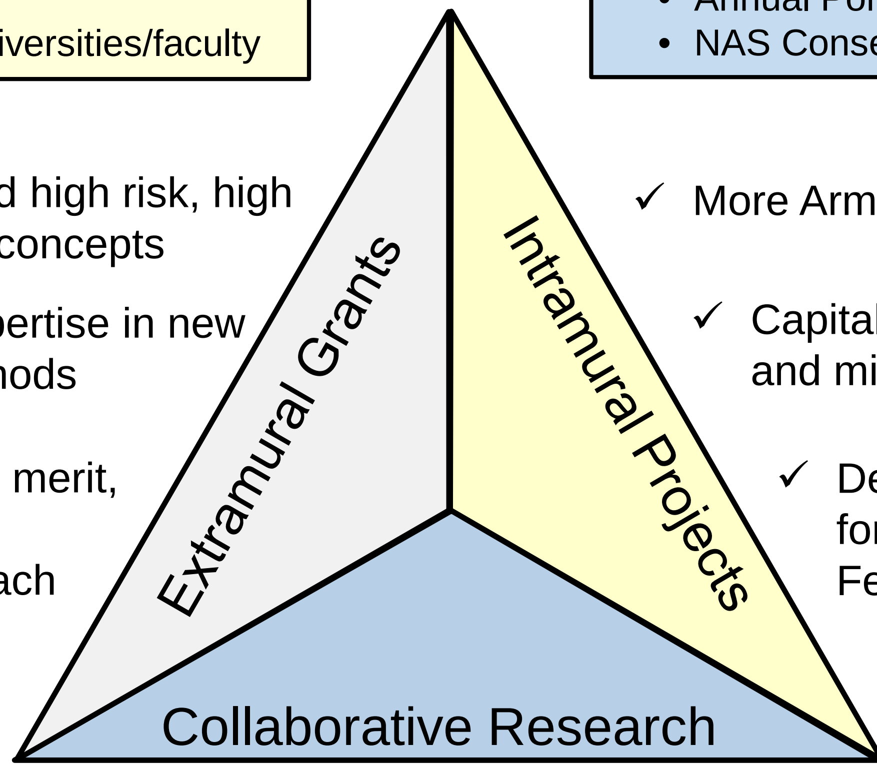
Strategic Enablers
- Consortium Fellows: Faculty, Post-Docs, Graduate students
- Site visits with targeted universities/faculty

Oversight & Guidance
- Biennial External Program Review
- Annual Portfolio Progress Reviews
- NAS Consensus Studies

✓ Targeted high risk, high reward concepts

✓ Capitalizes on expertise in new domains and methods

✓ Emphasis on technical merit, innovativeness, interdisciplinary approach



✓ More Army focused

✓ Capitalizes on internal expertise and military perspective

✓ Developmental opportunities for Post-Docs and Graduate Fellows

✓ Engages Army researchers within the scientific community

✓ Large scale, topic-focused collaborative research programs with ARI researchers and external scientists

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Background

- Whole-person approach for Soldiers
- Combine multiple pieces of diverse information
- Often *relative importance* methods to determine information's importance given the other pieces of information
- The volume and variety of information pieces has outpaced relative importance methods common in applied psychology

Aims

- Give overview of two algorithmic perspectives of importance
- Describe prevalence of methods in personnel selection
- Argue that personnel selection needs to either:
  1. Acknowledge and embrace uncertainty of more sophisticated machine learning methods, OR
  2. Abandon use of relative importance methods (at least as currently practiced)

Relative Importance Overview

- Emerged from desire for predictor-specific effect sizes in multiple regression
  - Practical versus statistical significance
- General goal is twofold:
  1. Put all predictors on common metric
  2. Incorporate predictor correlations into effect size calculation
- Began as exploratory tool to supplement regression
  - More like a descriptive statistic
- More recently also included non-parametric inferential methods (e.g., bootstrapping)

Relative Importance Algorithms

- Exhaustive
  - Examine all possible comparisons between objects of interest
  - Apply corrections for multiple comparisons as necessary
  - Aggregate across all comparisons
  - Becomes increasingly more difficult as number of objects increase
- Heuristic
  - Uses pre-defined rules and mathematical optimization to search for important areas of the object space
  - Searches for “good enough” approximation
  - Often used when exhaustive search would be impractical (as with most real-world problems)

Quick Example

- Calculating the similarity of a set of observations
- Exhaustive
  - Compare all possible combinations of scores (e.g., kernel density estimation)
- Heuristic
  - Calculate standard deviation of scores

Selection and Relative Importance

- Often want to know if a new predictor offers anything over existing ones, namely GMA and Big 5
  - Step 1: GMA + Big 5
  - Step 2: GMA + Big 5 + New Thing
- Only accounts for ***<u>unique</u>*** contribution of New Thing
  - Shared contribution or common variance is attributed to the set of old things
- What if we care about the ***<u>common</u>*** or don't have strong theory for order?
  - Use relative importance

Selection and Relative Importance

- Two primary methods in psychology:
  - Exhaustive: dominance analysis / LMG / Shapley decomposition
  - Heuristic: relative weights analysis
- Dominance
  - Relatively* well-defined statistical interpretation
  - Combinatorial explosion (requires 2^*p* regressions)
- Relative Weights
  - Not well defined statistically
  - Fast via the singular value decomposition (SVD)

Interpreting Relative Weights

- Squared structure coefficient from standardized principal components regression
- Weights summing to squared multiple correlation due to principal components extracted, ***not*** original variables
- Importance weights are calculated via contribution to principal components, which are themselves linear combinations of original variables (i.e., basically a black box)

Howardson, G. H. (in prep). Johnson's relative weights are the squared structure coefficients from a standardized principal components regression.

So What?

- Personnel selection seems skeptical about machine learning relative importance methods
  - How can we demonstrate construct validity if we don't know what model we're using or if there are arbitrary parameters?
- I would argue that using relative weights analysis <u>*is*</u> using a machine learning method (regularization via PCR)
- I would even argue that are several machine learning methods that can account for relative importance in a less opaque way than relative weights (e.g., ridge regression)

Conclusion

- Can’t have it both ways
  - If we’re comfortable with relative weights analysis, we should be comfortable with regularization methods in general
- I advocate more regularization methods in selection and construct validation
  - Regularization methods are really just real-world regression methods
  - Do require understanding the uncertainty tradeoffs, but arguably so does any real-world method

References

Howardson, G. N. (April, 2019). *A relative weights algorithm for ill-conditioned problems.* Poster presented at the 34th annual meeting of the Society for Industrial-Organizational Psychology, Washington, DC.

Howardson, G. H. (2020). Johnson's relative weights are the squared structure coefficients from a standardized principal components regression. *Manuscript in preparation*.

Thank You!

- Questions?
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13. SUPPLEMENTARY NOTES
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14. ABSTRACT
Relative weights and dominance analysis offer two promising relative importance methods for multiple regression. Whereas dominance analysis offers more statistically interpretable solutions, calculating such solutions is computationally burdensome. Conversely, although relative weights are computationally simpler, interpreting said weights statistically is more difficult. Trading statistical interpretability for computational simplicity is sometimes called “black box” prediction or using “black box” machine learning algorithms, which is often viewed skeptically in applied psychology. The purpose of this talk is to highlight that despite this machine learning skepticism, many applied psychologists are comfortable using relative weights analysis, which, as I argue, is itself a relatively opaque or “grey box” statistical method. In other words, applied psychological researchers seem comfortable with the computational simplicity / statistical interpretability tradeoff when conducting relative importance analysis while also rejecting said tradeoff for a wider range of machine learning analytical methods. I argue here that making meaningful progress as a science requires applied psychological researchers to reconsider their perspectives on relative importance analysis and machine learning in general.

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