Leveraging Trace Data in Game-Based Assessments

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Agenda

1. Trace data in Game-based Assessments
2. Predicting *g* with GBA game scores (prior work)
3. Predicting *g* with GBA trace data (present study)

Trace Data & Game-based Assessments

- GBAs produce two types of data reflecting in-game behaviors as indicators of KSAOs
  1. **Game Score:** resulting from planned measurement approach
  2. **Trace Data:** micro-behavioral data points typically used for system monitoring and debugging

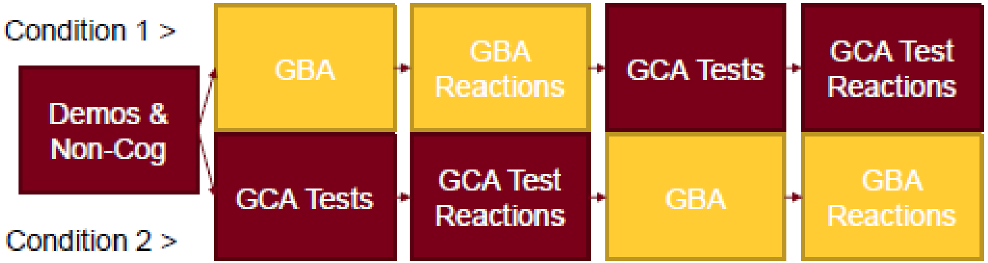
Predicting *g* with Game Scores

Revelian's Cognify

- GBA with a series of mini games designed to target specific cognitive abilities
- Game score composite for general intelligence

Predicting *g* with Game Scores

- Previous validation study supports this link (Landers, Armstrong, Collmus, Mujcic, & Blaik, 2017)
  - 530 undergraduate students in semi-controlled environment



- Improved motivational and attitudinal reactions for GBA (*d*s ranging from .106 - .814)
- Construct validity evidence: *latent g* $\longrightarrow$ *latent game performance* (*r* = .968)

Predicting *g* with Trace Data

- Is trace data untapped potential for improving construct measurement and predicting criteria?
  - Greater range of behaviors
  - But, log files can be big, messy, and tricky to derive meaning from
  - Requires data science techniques: feature engineering & modern prediction methods

Feature Engineering

- Raw Trace data (from previous study):
  - 3 GB
  - ~ 13 million rows (~26 k/participant)
  - Structured by event & time stamp

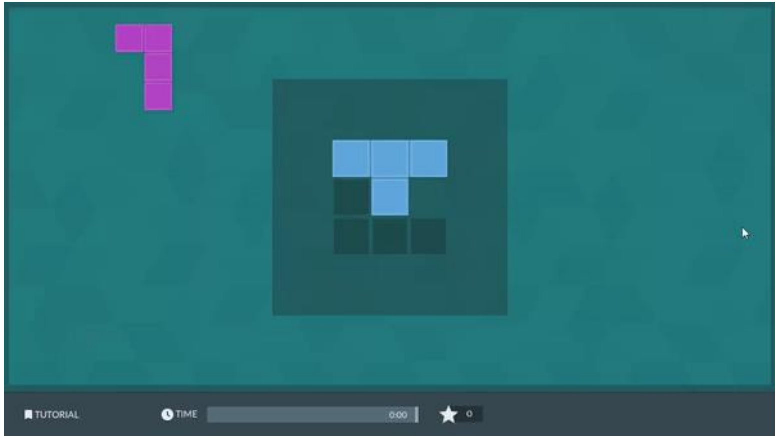
sequence_number	event_time	event_type	event_content
1195	2017-02-13 15:58:57.8+00	DestroyObject	{""id"":""56dad974-d5ef-4940-84b6-f3b1dca8
1196	2017-02-13 15:58:57.957+00	MousePosition	{""y"":127,""context"":null,""x"":722}
1197	2017-02-13 15:58:58.304+00	StartRound	{""roundNumber"":35,""round"":""6b8012c9-24
1198	2017-02-13 15:58:58.372+00	MousePosition	{""y"":127,""context"":null,""x"":722}
1199	2017-02-13 15:58:58.781+00	MousePosition	{""y"":127,""context"":null,""x"":722}
1200	2017-02-13 15:58:59.182+00	MousePosition	{""y"":127,""context"":null,""x"":722}
1201	2017-02-13 15:58:59.38+00	DestroyObject	{""id"":""5e66cef2-550a-4098-b217-3bb6aa8e
1202	2017-02-13 15:58:59.38+00	CreateObject	{""id"":""d8a6bcaa-1fcf-41fc-96ac-6b9b54fd8

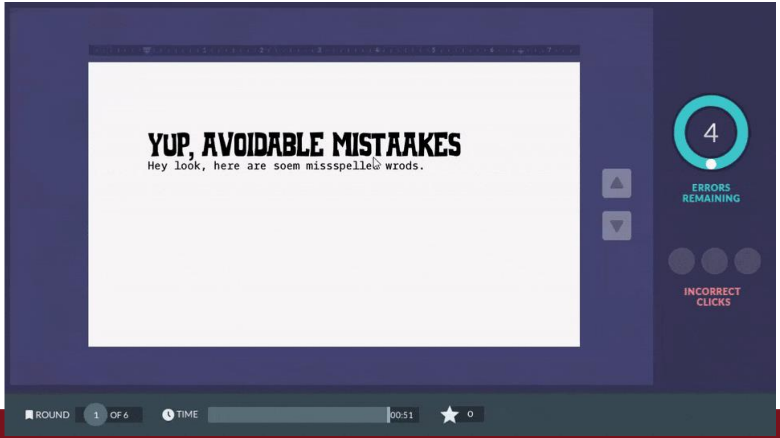
Feature Engineering & Selection

- Top-down (theory-driven) and bottom-up (data mining and machine learning) approach
  – SMEs examined log dataset
  – Machine learning models with feature selection

Feature Engineering

- Engineered Features: 65
- A few examples:
  - Time spent/game or /round
  - Average # of clicks/game
  - # of rotations (game specific)
  - # of words selected (game specific)





Predicting *g*: Modeling Approach

- Use-cases for modern prediction methods (e.g., machine learning) in social science (Putka, Beatty & Reeder, 2017)
  - lack of comprehensive theory
  - a need to balance model complexity with parsimony
  - predictors occur on a variety of measurement scales
  - high degree of uncertainty in the model selection process
- Working with trace data involves all of these

Predicting *g*: Modeling Approach

- R's Caret Machine Learning Package (Kuhn, 2014)
  - k-fold cross-validation (for tuning model parameters)
  - Training & holdout split (to calculate validity estimates)
- Models: *Putka, Beatty & Reeder (2018) provides an overview of each of these models

Elastic Net	Random Forest	Gradient Boosted Trees	Support Vector Machines
Regularized regression (ridge & lasso)	Regression trees with bootstrapped sampling & random subset of predictors	Regression trees with a forward step-wise-like regression component	Robust regression variant, focused on predicting difficult to predict cases

Findings

Predicting g (from traditional measures) using GBA **trace data**

Model	Validity
Elastic Net	0.605
Random Forest	0.693
Gradient Boosted Trees	0.683
Support Vector Machines	0.630

Note: Validity refers to the correlation between the predicted g score from each machine learning model and the composite g score from the holdout sample.

Findings

Predicting g (from traditional measures) using GBA **composite game score**

Model	Validity
OLS Regression	0.633

Note: Validity refers to the correlation between the predicted g score from OLS Regression model and the composite g score from the holdout sample.

Findings

Predicting g using **GBA trace data**

Model	Top "Important" Variables
Elastic Net	• number of Timeout Rounds in Short Circuit game • **time spent on make a splash and short circuit games** • missed choices in quick comparison game
Random Forest	• **time spent on short circuit game** • total time spent per round on balloon blast game • **time spent on make a splash game**
Gradient Boosted Trees	• **total time spent per round on balloon blast game** • **time spent on make a splash and short circuit games** • Time spent on quick comparison game tutorial
Support Vector Machines	• **time spent on short circuit game** • time spent on short circuit tutorial • **total time spent per round on balloon blast game**

Findings

Predicting GPA: incremental validity of trace data (predicted g) over game score composite

Elastic Net

Regressions of GPA on Comparisons of Hierarchically Nested Regression Models

					Comparison to Model 3			
Model	R^2	F	df	p	ΔR^2	F	df	p
Model 1: Game Score Composite	.027	13.98	1, 509	< .001	0.00	0.02	1,509	.891
Model 2: Trace Data Score	.018	9.27	1,509	.002	0.01	4.52	1,509	.032
Model 3: Model 1 + Model 2	.027	6.986	2,508	.001				

Findings

Predicting GPA: incremental validity of trace data (predicted g) over game score composite

Random Forests

Regressions of GPA on Comparisons of Hierarchically Nested Regression Models

					Comparison to Model 3			
Model	R^2	*F*	*df*	*p*	ΔR^2	*F*	*df*	*p*
Model 1: Game Score Composite	.027	13.98	1, 509	< .001	0.01	6.63	1,509	.010
Model 2: Trace Data Score	.039	20.59	1,509	< .001	0.00	0.20	1,509	.653
Model 3: Model 1 + Model 2	.039	10.38	2,508	< .001				

Findings

Predicting GPA: incremental validity of trace data (predicted g) over game score composite

Gradient Boosted Trees

Regressions of GPA on Comparisons of Hierarchically Nested Regression Models

					Comparison to Model 3			
Model	R^2	*F*	*df*	*p*	ΔR^2	*F*	*df*	*p*
Model 1: Game Score Composite	.027	13.98	1, 509	< .001	0.00	0.22	1,509	.636
Model 2: Trace Data Score	.022	11.48	1,509	< .001	0.005	2.67	1,509	.103
Model 3: Model 1 + Model 2	.027	7.09	2,508	< .001				

Findings

Predicting GPA: incremental validity of trace data (predicted g) over game score composite

Support Vector Machines

Regressions of GPA on Comparisons of Hierarchically Nested Regression Models

					Comparison to Model 3			
Model	R^2	F	df	p	ΔR^2	F	df	p
Model 1: Game Score Composite	.027	13.98	1, 509	< .001	0.013	6.84	1,509	.009
Model 2: Trace Data Score	.040	21.00	1,509	< .001	0.00	0.02	1,509	.881
Model 3: Model 1 + Model 2	.040	10.49	2,508	.009				

Summary of findings

- Trace data (from this GBA) can be used to predict composite *g* (avg hold-out sample *r* = .65)

- Across models, some features were consistently weighted more heavily

- Evidence of *some* incremental validity when predicting GPA, depending on modeling approach
  - Machine learning model changes construct measurement

Conclusions & Future Directions

- Trace data vs. Game Score Composite
- **Infinite** number of features and modeling approaches
- Trace data-related findings are generally **context dependent and data-driven**, limiting generalizability
- Research opportunities are abundant
  - Why are some models better than others?
  - Inductive & data driven benefits?

Thank you!

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References

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Putka, D. J., Beatty, A. S., & Reeder, M. C. (2018). Modern prediction methods: New perspectives on a common problem. *Organizational Research Methods, 21*(3), 689-732.

Correlation Matrix

Variable	1	2	3	4	5	6
1. Game Score (composite)	1					
2 . g (composite)	.63	1				
3. GPA	.16	.20	1			
4. Predicted g from trace data (GLMNET)	.84	.62	.13	1		
5. Predicted g from trace data (RF)	.77	.91	.20	.77	1	
6. Predicted g from trace data (GBM)	.84	.69	.15	.86	.85	1
7. Predicted g from trace data (SVM Radial)	.84	.77	.20	.82	.90	.87