

Recent work in the Personality-Motivation-Cognition Lab (aka the telemetrics lab)

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Outline

Synthetic Aperture Personality Assessment is for everyone

How low can you go? Work with Elizabeth Dworak, Sonja Heintz

BISCUIT versus the black box

Lorien Elleman and machine learning

Thinking by analogy

Profile Correlations to understand structure

Profile correlations

Profile correlations of college majors

Summary

Personality profiles of countries

Synthetic Aperture Personality Assessment (SAPA)

1. SAPA gives each subject a sample of items (25-200) sampled from larger (1,000-10,000) items.
2. We do this for many subjects taken over time.
3. Allows us to recover structure of large item pool without giving everyone the same items
4. I will first show analyses on a sample data set of 135 items for 4,000 subjects.
5. I will then use a data set of 250K taken from the larger data set of 850K

SAPA is not just for large samples

1. Although David Condon and I tend to report SAPA results from large samples, it also works for smallish samples.
2. Elizabeth Dworak and Sonja Heintz (U. Zurich) have examined SAPA results for as few as 200-400 subjects with 120 items
3. Each subject is given 30 items but we recover the structure for 120 items.
4. Can apply this technique to ESM data as well
5. Recommendation is to use SAPA procedures to increase item pool at low cost to precision

Best Items Scales that are Cross validated, Unit weighted, Informative, and Transparent

1. BISCUIT: Old fashioned unit weighted item derivation and cross validation
 - Choose items with largest zero order correlations with a criterion
 - Replicate across 10 folds or 10-1000 bootstrap resamples
 - Unit weight them to form predictive scales
 - Compare to more elegant machine learning algorithms
 - Work being done by Lorien Elleman and Sarah McDougald
2. Compare BISCUIT to
 - LASSO regression
 - Elastic Nets
 - Random Forests

Thinking by analogy: GWAS and the genetic correlation

1. GWAS is the analysis across the entire Genome
2. In genetic research it is possible to examine the effect size of each SNP across 10^6 SNPS across $5 * 10^5$ subjects
3. each SNP has a very low effect size, but the power allows detection of reliable (but tiny) effects
4. The genetic correlation is then the correlation of the *pattern* of effect size for two phenotypic variables
5. For instance, although the phenotypic correlation of two neuroticism items is $\approx .2 - .3$, the genetic correlation $> .6$
6. Can we do this across the Persome?

Persome wide studies

1. If we have 100-10,000 items, can we apply GWAS techniques to people?
2. The math is basically the same
3. Focus on the item level data, not the “Big 5” or facet level analysis
4. Examples will be from the SPI data set in *psych*
 - 135 items, 10 criteria, complete data for 4000 subjects
5. Further example from the “demonstration set” of SAPA (the first 250K subjects)
 - 900 items, college majors, 250K participants

Sample items from each of the SPI 27

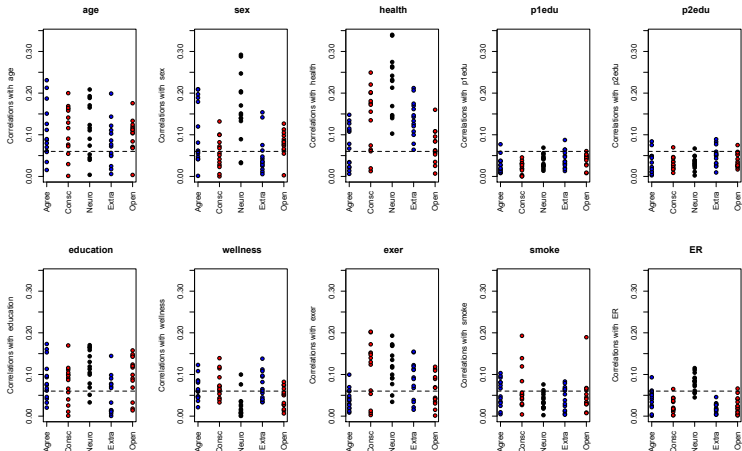
Each scale has 5 items

SPI	Item	Item
Compassion	Am sensitive to the needs of others.	Am concerned about others.
Irritability	Get angry easily.	Lose my temper.
Sociability	Usually like to spend my free time with people.	Avoid company.
WellBeing	Dislike myself.	Feel a sense of worthlessness or hopelessness.
SensationSeeking	Love dangerous situations.	Seek danger.
Anxiety	Worry about things.	Would call myself a nervous person.
Honesty	Tell a lot of lies.	Tell the truth.
Industry	Find it difficult to get down to work.	Start tasks right away.
Intellect	Learn things slowly.	Am quick to understand things.
Creativity	Am full of ideas.	Am able to come up with new and different ideas.
Impulsivity	Act without thinking.	Make rash decisions.
AttentionSeeking	Make myself the center of attention.	Like to attract attention.
Order	Keep things tidy.	Leave a mess in my room.
Authoritarianism	Believe that laws should be strictly enforced.	Respect authority.
Charisma	Am skilled in handling social situations.	Find it difficult to approach others.
Trust	Trust what people say.	Trust people to mainly tell the truth.
Humor	Laugh a lot.	Laugh aloud.
EmotionalExpressiveness	Am open about my feelings.	Have difficulty expressing my feelings.
ArtAppreciation	Do not enjoy going to art museums.	Believe in the importance of art.
Introspection	Love to reflect on things.	Spend time reflecting on things.
Perfectionism	Dislike imperfect work.	Want every detail taken care of.
SelfControl	Never splurge.	Rarely overindulge.
Conformity	Like to be thought of as a normal kind of person.	Would hate to be considered odd or strange.
Adaptability	Dislike changes.	Don't like the idea of change.
EasyGoingness	Like to take it easy.	Like a leisurely lifestyle.
EmotionalStability	My moods don't change more than most people.	Experience very few emotional highs and lows.
Conservatism	Tend to vote for conservative political candidates.	Don't consider myself religious.

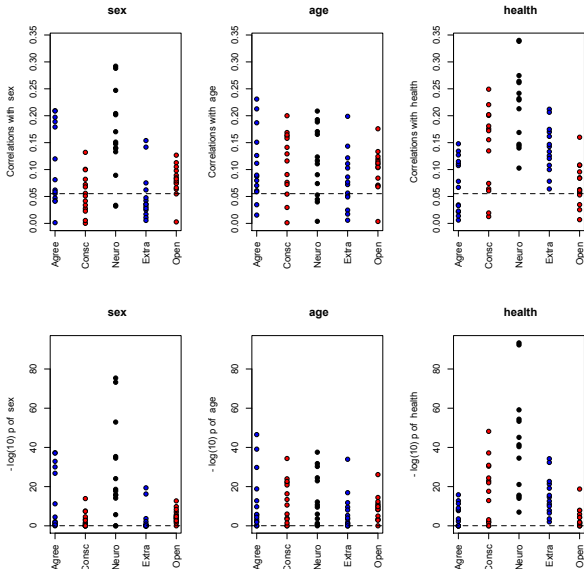
Items as analogous to SNPs in GWAS studies

1. In Genome Wide Association Studies one examines phenotypic variation as it correlates with differences in SNP frequencies across the genome.
2. Do the same by examining phenotypic variation and correlation across the persome (Möttus, Sinick, A.Terracciano, Hřebíckova, Kandler & Jang, 2018)
3. A typical approach is to show the correlations and their probability values (corrected for multiple tests)
 - Typically displayed in “Manhattan Plots” across the genome. We do this across the “Persome”.
4. First show plots for an open source data set (spi) available in the *psych* package.
 - This is a set of 135 temperament items with 10 criteria for 4,000 subjects.
5. Then do the same for items from the Big 5, then an extend set (the little 27), then for a bigger data set with even more items.

A “Manhattan plot” of the spi items on the big 5 for 10 criteria



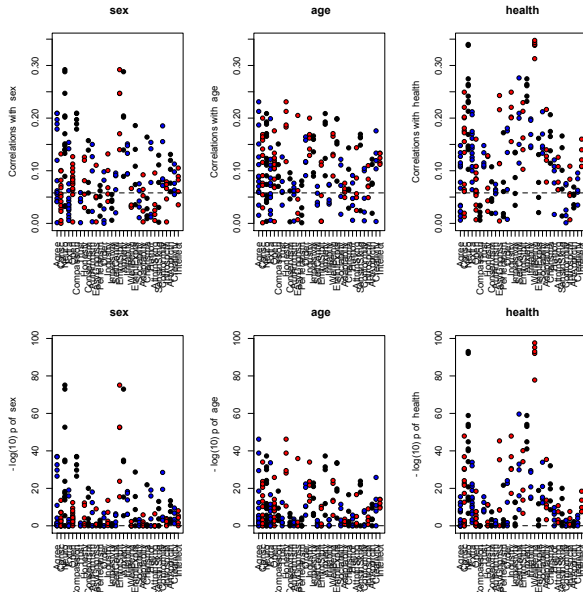
A “Manhattan plot” of the spi items for 3 criteria big 5



Correlations
(absolute
values)

Log p values
(Holm
corrected for
multiple
tests)

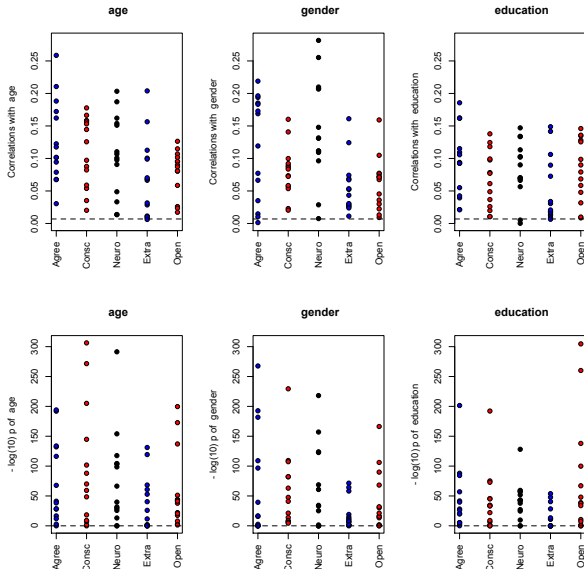
More predictors: 3 criteria big 5 + spi 27, N =4000

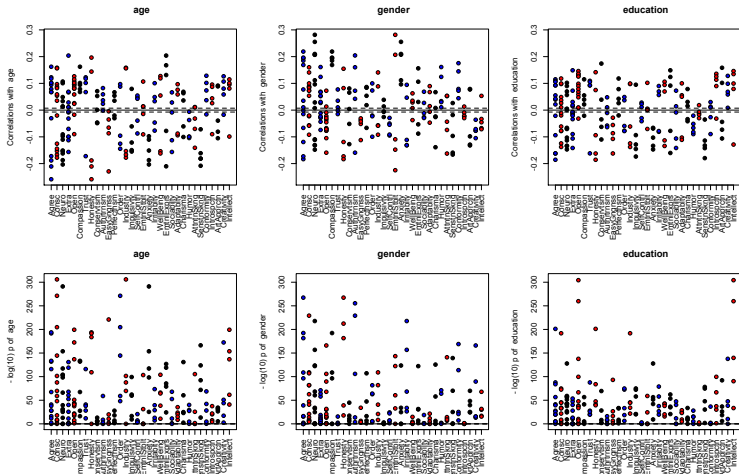


Correlations
(absolute
values)

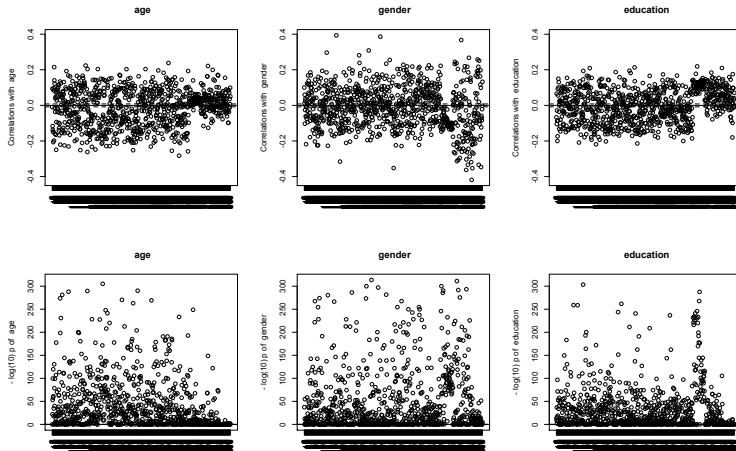
Log p values
(Holm
corrected for
multiple
tests)

More subjects: 3 criteria big 5, N = 255,000





More subjects: 3 criteria - 904 items (temperament, abilities, interests)

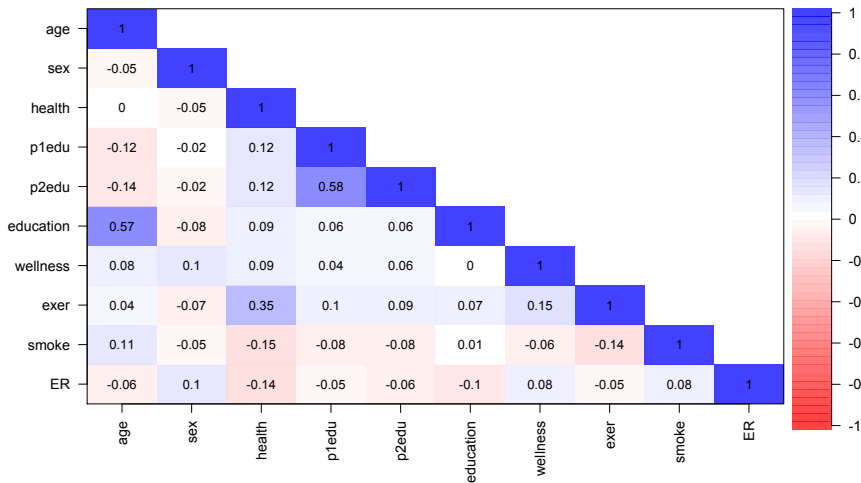


Profile correlations are analogous to the “genetic correlation”

1. For any set of criteria or grouping variables we can find a vector of validity correlations across our predictor set.
2. We can then correlate these vectors. This is analogous to the genetic correlation across SNPs.
3. Basically, we are correlating the profiles of the Manhattan plots
4. I show this using the 10 criteria in the spi data set
5. First the raw correlations, then the profile correlations

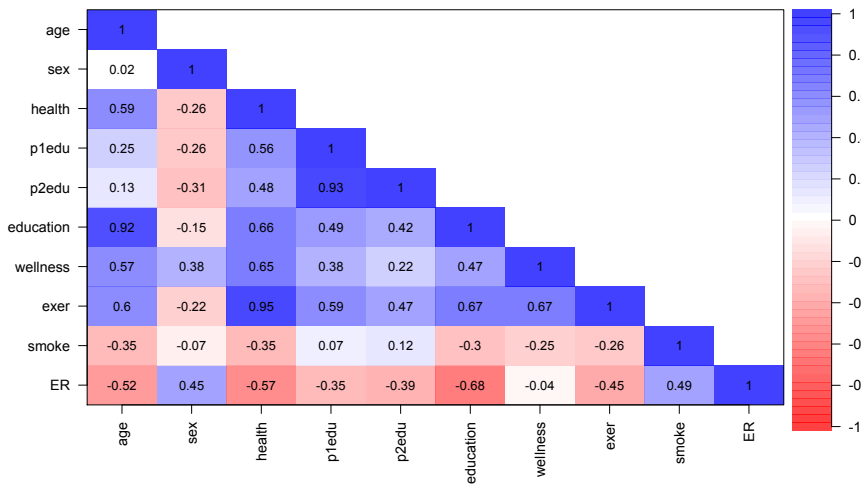
10 criteria from the SPI data set, raw correlations

Correlations of 10 SPI criteria



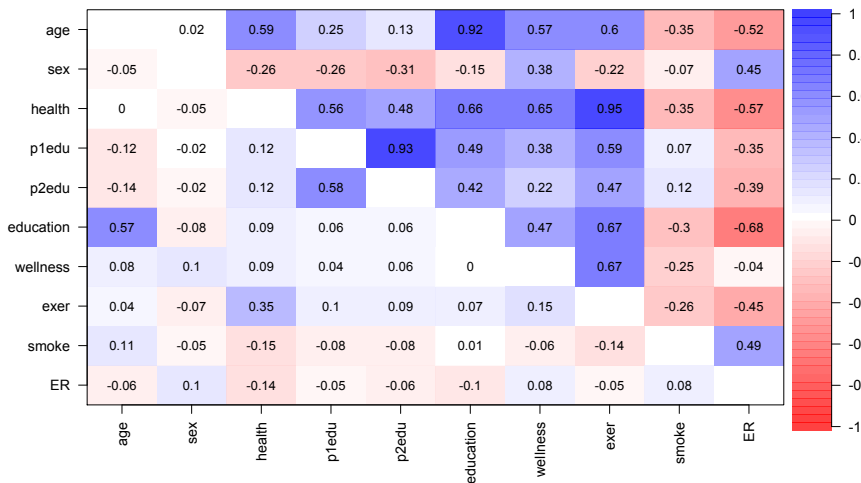
10 criteria from the SPI data set, profile correlations

Profile correlations of 10 SPI criteria across 135 items



Comparing raw and profile correlations from the SPI dataset

Comparing raw to profile correlations

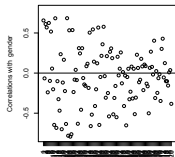


Demographic correlates of college majors

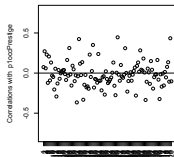
1. Dummy code each major
2. Find the correlation of persome with each major
3. Similarity of majors to majors
4. Predictability of major profiles from demographic profiles
5. Caution is required

Manhattan plots of majors by demographics

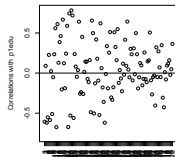
Manhattan Plot of gender



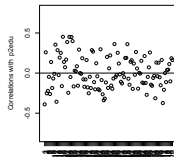
Manhattan Plot of p1occPrestige



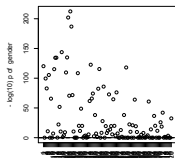
Manhattan Plot of p1edu



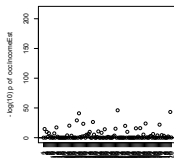
Manhattan Plot of p2edu



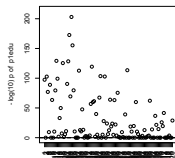
Manhattan Plot of gender



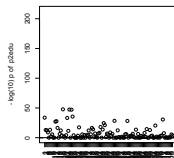
Manhattan Plot of occincomeEst



Manhattan Plot of p1edu



Manhattan Plot of p2edu



Profile correlations with Gender

Table: Gender

A table from the psych package in R

Variable	gendr	p1ccP	p1edu	p2edu
Mechanical Engineering	-0.79	0.29	0.32	0.32
Electrical Engineering	-0.78	0.31	0.33	0.33
Computer Engineering	-0.76	0.34	0.38	0.36
Other Engineering and Technology Major	-0.70	0.16	0.21	0.22
Social Work	0.68	-0.46	-0.49	-0.48
Computer Programming	-0.68	0.37	0.41	0.38
Elementary Education	0.68	-0.41	-0.42	-0.40
Physics	-0.66	0.52	0.58	0.56
Psychology	0.66	-0.08	-0.07	-0.07
Aerospace Engineering	-0.65	0.24	0.24	0.24
Civil Engineering	-0.65	0.23	0.29	0.30
Computer and Information Systems - General	-0.65	0.19	0.23	0.20
Other Computer and Information Sciences Major	-0.63	0.24	0.28	0.26
Economics	-0.63	0.46	0.55	0.56
Other Social Sciences Major	0.62	-0.30	-0.26	-0.23
Nursing	0.61	-0.56	-0.69	-0.70
Kindergarten/Preschool Education	0.58	-0.49	-0.51	-0.50
Other Medicine and Allied Health Major	0.57	-0.52	-0.60	-0.60
Special Education	0.57	-0.28	-0.31	-0.29
Industrial Engineering	-0.55	0.19	0.21	0.21
Other Community and Social Services Major	0.54	-0.41	-0.40	-0.38
Chemical and Biological Engineering	-0.54	0.36	0.40	0.39
Medical Assisting	0.54	-0.61	-0.74	-0.74
Health Services and Administration	0.53	-0.62	-0.72	-0.71
Mathematics	-0.52	0.38	0.44	0.43
Health Sciences - General	0.52	-0.56	-0.66	-0.66
Mathematics - General	0.51	-0.35	-0.34	-0.33

Profile correlations of major with Parent 1 education

A table from the psych package in R

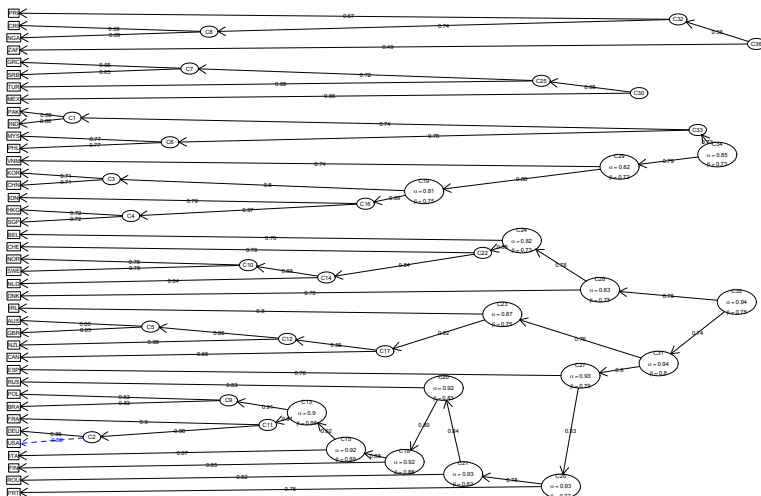
Variable	gendr	p1ccP	p1edu	p2edu
Medical Assisting	0.54	-0.61	-0.74	-0.74
Health Services and Administration	0.53	-0.62	-0.72	-0.71
Nursing	0.61	-0.56	-0.69	-0.70
Health Sciences - General	0.52	-0.56	-0.66	-0.66
Criminal Justice and Corrections	0.17	-0.54	-0.63	-0.61
Philosophy	-0.41	0.54	0.62	0.62
Other Medicine and Allied Health Major	0.57	-0.52	-0.60	-0.60
Physics	-0.66	0.52	0.58	0.56
Neuroscience	-0.31	0.54	0.56	0.54
Economics	-0.63	0.46	0.55	0.56
Kindergarten/Preschool Education	0.58	-0.49	-0.51	-0.50
Social Work	0.68	-0.46	-0.49	-0.48
Political Science	-0.33	0.42	0.48	0.49
Human Development and Family Studies	0.50	-0.43	-0.47	-0.45
Dentistry	0.31	-0.38	-0.46	-0.46
Music	-0.14	0.39	0.45	0.43
Anthropology	-0.05	0.37	0.45	0.43
Mathematics	-0.52	0.38	0.44	0.43
English	0.06	0.33	0.43	0.43
Fiction Writing	-0.05	0.38	0.43	0.41
Business Administration and Management	-0.07	-0.38	-0.43	-0.40
History	-0.08	0.34	0.42	0.43
Criminology	0.04	-0.33	-0.42	-0.40
Elementary Education	0.68	-0.41	-0.42	-0.40
Human Resource Administration	0.25	-0.42	-0.42	-0.41
Linguistics	-0.13	0.33	0.42	0.41
Computer Programming	-0.68	0.37	0.41	0.38
Chemical and Biological Engineering	-0.54	0.36	0.40	0.39
Statistics	-0.32	0.32	0.40	0.37
Other Community and Social Services Major	0.54	-0.41	-0.40	-0.38

Conclusion

1. Item level responses have a great deal of information
2. More information than just scale scores.
3. Need to develop procedures for collecting many items across people
4. Thinking analogically leads to intriguing analyses

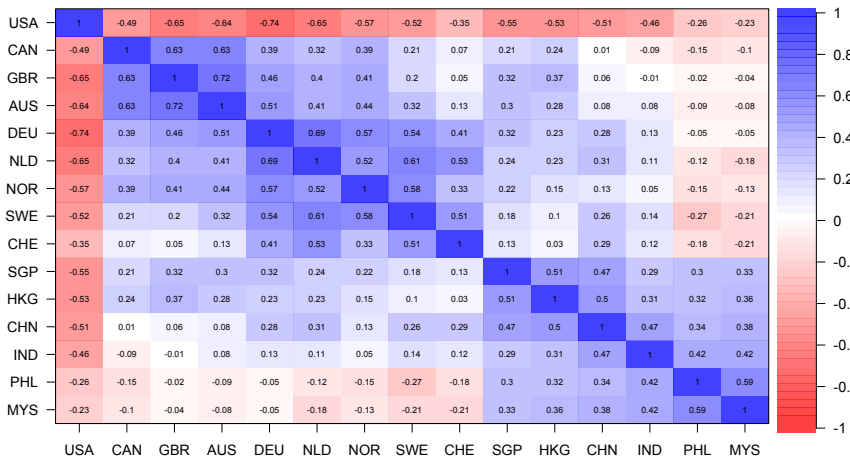
40 countries across 908 items

ICLUST of 40 country profiles across 908 items



40 countries across 908 items

Profile correlations across 908 items for selected countries



Best Items correlating with being from Switzerland

Table: Top correlations with being from CHE

Top items			
CHE		item	
0.05		ICAR	VF
0.05		Would like to play a musical instrument.	Artistic - ONET
0.05		Would like to keep inventory records.	Conventional - ONET
-0.05		Would like to paint sets for plays.	Artistic - ONET
0.05		Would like to teach a high-school class.	Social - ONET
-0.04		Would like to operate a calculator.	Conventional - ONET
-0.04		Like to stand during the national anthem.	
0.04		Would like to buy and sell stocks and bonds.	Enterprising - ONET
0.04		ICAR	R3
0.04	Would like to develop a spreadsheet using computer .		Conventional - ONET
0.04		ICAR	V
0.04	Would like to do laboratory tests to identify diseases.		Investigative - ONET
0.04	Would like to take care of children at a day-care center.		Social - ONET
-0.03		Suffer from sleeplessness.	EF
0.03		ICAR	M

Best Items correlating with being from the UK

Table: Top correlations with being from GBR

GBR	item	itm_s
-0.18	Like to stand during the national anthem.	IPIP
-0.10	Just know that I will be a success.	IPIP
-0.09	Believe in one true religion.	IPIP
0.08	ICAR	VRiq10
-0.08	Like to compete in athletic events.	ORVIS - Adventure
-0.08	Am an extraordinary person.	IPIP
0.08	Dont consider myself religious.	IPIP
0.08	Dislike myself.	IPIP
-0.07	Go straight for the goal.	IPIP
0.07	Have a low opinion of myself.	IPIP
0.07	ICAR	VRiq14
0.07	Would like to put out forest fires.	Realistic - ONETshort
-0.07	Like to make important things happen.	ORVIS - Leadership
0.07	Do too little work.	IPIP
0.07	Waste my time.	IPIP

Best Items correlating with being from USA

Table: Top correlations with being from USA

USA		item
0.24		Like to stand during the national anthem
-0.20	People spend too much time safeguarding their future with savings and insurance	
-0.19		ICAI
-0.18	Think marriage is old-fashioned and should be done away with	
0.18		Work hard
-0.18		Get even with others
-0.17	Believe that there is no absolute right and wrong	
0.17		Will do anything for others
0.16		Laugh aloud
-0.16	Believe that I am better than others	
0.15	Push myself very hard to succeed	
-0.15		Dislike routine
-0.15		ICAI
-0.15	Dont consider myself religious	
-0.15	Admire a really clever scam	
-0.15	Would like to be a foreign correspondent	
-0.15		Never splurge
0.15		Laugh at

Profiles across 908 items of countries correlated with demographic profiles suggest sampling differences across countries

Table: Profile correlations of demographics by countries

Variable	gendr	age	BMI	exer	smoke	edctn	p1edu	p2edu
USA	0.57	0.18	0.52	0.32	-0.13	-0.12	-0.40	-0.38
CAN	-0.27	-0.23	-0.28	-0.37	0.24	-0.01	0.47	0.46
GBR	-0.30	-0.37	-0.32	-0.55	0.29	-0.14	0.36	0.36
AUS	-0.36	-0.10	-0.24	-0.31	0.31	0.16	0.48	0.47
DEU	-0.38	-0.02	-0.44	-0.14	0.06	0.27	0.52	0.50
NLD	-0.52	0.00	-0.45	0.08	0.06	0.26	0.50	0.48
NOR	-0.30	0.02	-0.34	-0.07	0.05	0.23	0.41	0.39
SWE	-0.39	0.37	-0.21	0.24	-0.11	0.56	0.36	0.34
CHE	-0.26	0.20	-0.26	0.32	-0.07	0.36	0.31	0.27
SGP	-0.17	-0.12	-0.25	-0.32	-0.17	0.01	0.01	0.02
HKG	-0.24	-0.32	-0.33	-0.36	-0.02	-0.18	0.05	0.07
CHN	-0.26	-0.04	-0.31	0.00	-0.15	0.08	0.02	0.02
IND	-0.32	0.04	-0.17	0.06	0.03	0.13	0.02	0.01
PHL	-0.03	-0.34	-0.14	-0.29	-0.07	-0.35	-0.23	-0.23
MYS	0.04	-0.23	-0.07	-0.28	-0.03	-0.30	-0.32	-0.32

Möttus, R., Sinick, J., A.Terracciano, Hřebíckova, M., Kandler, C., & Jang, J. A. . . . K. L. (2018). Personality characteristics below facets: A replication and meta-analysis of cross-rater agreement, rank-order stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*.