

Better Poster and ÚFAL Templates

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unless otherwise stated

1. Redesigning poster
2. Better poster design
3. What works and what not so much
4. ÚFAL templates

Preparing Poster

Preparing Poster

- pack the most information as possible
- designing poster understandable after 10 or more minutes
- doing the poster last minute




Non-Cognitive Predictors of Student Success:

A Predictive Validity Comparison Between Domestic and International Students

Jacob Smith, Dr. Thea Schofield, Dr. Antonio Ibarra, Stephen Choi, Benn Mullins, Dr. Emily Williams

Michigan State University



Abstract

Given increasing interest in utilizing non-cognitive predictors in the college admissions process and rising enrollment of international students, research is warranted to compare the predictive validity of these measures across domestic and international students. Results indicate some predictive validity differences do exist, and an explanation for this differential validity, as well as a moderator of these relationships, are tested.

Method (cont.)

Measures:
Biographical Data - Standardized inventory of an individual's experiences, attitudes, and behavioral tendencies relevant to college student experience and performance.
Consensus of seven scales: Knowledge, Leadership, Social Responsibility, Adaptability, Perseverance, Continuous Learning, Academic Ethics
Situational Judgment Test (SJT) - Presents typical situations college students would face and possible responses to situations, utilized to measure individuals ability to judge and react appropriately.
GPA - 1st semester cumulative GPA on 0.0 to 4.0 scale.
COLEGE - Standardized test to measure "ability to use and understand English at a university level" (ETS.org).
International Status - Dichotomous variable representing international status of student (Sample 1 - Based on residence code, Sample 2 - Based on residence country).
Cultural Distance - Euclidean distance between individual's residence country and United States, based on nine GLOBE cultural dimensions (Hofstede et al., 2004).
Perceived Cultural Distance - 12-item scale measuring perceptions regarding cultural differences between U.S. and home country on variety of aspects (e.g. values and beliefs, family life) (Dennis & Geisner, 2014).

Background

- Though cognitive predictors of student success (e.g. ACT, HDGPA) remain popular, there is increasing interest in non-cognitive predictors of student success (e.g. situational judgment, adaptability), and these have been found to predict student performance (Owens et al., 2004; Kenney et al., 2009).
 - From 05-06 to 15-16 academic year, the number of international students studying in U.S. increased yearly. In 2016, 5.2% of students international with over 1 million enrolled (Institute of International Education, 2016).
 - Previous work by Prasad and colleagues (2016) found mean differences in non-cognitive measures across Chinese and Caucasian American students, along with differential validity for a Perseverance non-cognitive measure.
 - The current research is an extension of Prasad et al., 2016, exploring differential validity in two large samples of students, testing an explanation for these differences in validity, and testing a possible moderator of these relationships between non-cognitive predictors and GPA.

Results

- Correlations between non-cognitive predictor scores and 1st semester GPA (Table 1) indicate strong relationship for international students on seven of eight measures.
 - Regression results (Table 2) indicate consistent differential validity for international students for SJT, Continuous Learning, Social Responsibility, and Perseverance.
 - Including TOEFL scores in regression, available for a subset of 963 individuals from Sample 1, did not substantially alter standardized regression weights ($\Delta\beta = .012$ to $.016$) (Results not shown).
 - Medial-level regression was utilized to test if cultural distance via GLOBE moderated validity for non-cognitive predictors utilizing subset of 767 international students from Sample 1 from 10 cognitive. Results indicate culture distance did not significantly moderate validity ($p > .05$) (Results not shown).
 - Utilizing subset of 73 international students from Sample 2, did not find that perceived cultural distance moderated validity of non-cognitive predictors ($p > .05$) (Results not shown).
 - Correlations between GLOBE cultural distance and perceived cultural distance $r = -.313$ (s.e.)

Research Question & Hypotheses

Research Question 1: Will non-cognitive measure display differential validity between domestic and international students?

- Non-cognitive measures may be functioning as a proxy for English ability.
H1: Differential validity will be accentuated for English proficiency.

- Non-cognitive predictors may be more important for individuals from a more culturally distant country, as adjustment may be more difficult necessitating greater non-cognitive abilities.
H2: Non-cognitive measures will exhibit greater validity for international students from more culturally distant countries.

Discussion

Results indicate consistent differential validity for some non-cognitive measures for international students, specifically for SJT, Continuous Learning, Social Responsibility, and Perseverance.
 Differential validity for international students does not seem to be the result of functioning as a proxy for English language ability.
 Cultural distance does not seem to moderate validity of non-cognitive measures.

Method

Samples
 Sample 1: 7702 students at large, Midwestern university
 - 54.1% (4163) female
 - 11.2% (871) international (8.2% Chinese)
 Sample 2: 563 students at large, Midwestern university
 - 52.8% (4060) female
 - 13.7% international (10.4% Chinese)

Table 1. Relationship between non-cognitive predictors and 1st semester GPA by Sample.

	Overall Sample 1	Overall Sample 2	Domestic Sample 1	Domestic Sample 2	International Sample 1	International Sample 2
SJT	0.34	0.18	0.06	0.16	0.23	0.24
Knowledge	0.19	0.16	0.13	0.13	0.18	0.19
Leadership	0.06	0.10	0.03	0.06	0.04	0.11
Social Responsibility	0.06	0.10	0.07	0.07	0.02	0.04
Adaptability	0.04	0.07	0.01	0.02	0.04	0.04
Perseverance	0.10	0.12	0.02	0.02	0.14	0.17
Learning	-0.06	-0.06	-0.06	-0.06	0.16	0.14
Academic Ethics	0.21	0.22	0.07	0.09	0.26	0.24
	.7702	.563	.7402	.6942	.6012	.519

** Bold numbers indicate significant relationships ($p < .05$)

Table 2. Moderated Regression Results for Non-Cognitive Predictors Relationship with 1st Semester GPA.

	Sample 1		Sample 2	
	Step 1	Step 2	Step 1	Step 2
SJT	0.06	0.04	0.12	0.04
Knowledge	0.18	0.22	0.17	0.16
Leadership	0.04	0.03	0.07	0.07
Social Responsibility	0.06	0.06	0.03	0.04
Adaptability	-0.06	-0.03	-0.03	-0.01
Perseverance	0.02	-0.06	0.04	-0.04
Learning	-0.16	-0.18	-0.22	-0.20
Academic Ethics	0.02	0.02	0.02	0.01
International Status	-0.15	-0.14	-0.14	-0.14
SJT X Int	0.04	0.06	0.06	0.06
Learn X Int	-0.02	0.00	0.00	0.00
Know X Int	-0.04	-0.04	-0.04	-0.04
Adapt X Int	-0.04	0.00	0.00	0.00
Per X Int	0.06	0.06	0.06	0.06
Ethics X Int	0.06	0.06	0.06	0.06
R Squared	0.04	0.08	0.08	0.12
F	7702	7702	563	563

** Bold numbers indicate significant relationships ($p < .05$)

Implications

Non-cognitive abilities may be useful in predicting international student performance, but differential validity may be an issue.
 Negative, non-significant relationship between cultural distance via GLOBE scores and perceived cultural distance warrants caution in generalizing country-level scores to individuals.
 More research is warranted to explain differential validity for international students.

Acknowledgements

I would like to thank Sergio Marquet for assistance in data collection, as well as Aaron Huang and Rick Deffen for advice regarding data analysis.

Attendee Point of View

Goals of Attendee

- Planning to learn the most
- Planning to talk in depth (15 minutes) with 2-3 people
- Restricted time (90 minutes)
- Too many posters (40-50 posters per session of ACL 2019)
- Leaving 2 minutes per poster > Need to skim through most posters

**Perfection is not when you have
nothing to add, it is when you have
nothing to take away.**

Improving Poster Design

1. Maximize first insight
2. Keep only the good stuff
3. Easy and fast to create

Better Poster Concept

We found consistent differential validity for some non-cognitive measures for predicting international student GPA, specifically with SJT, Continuous Learning, Social Responsibility, and Perseverance.

For **international students**,
perseverance and a sense of
social responsibility are extra
important for predicting
first-year **GPA**.

For **international students**, **perseverance** and a sense of **social responsibility** are extra important for predicting first-year **GPA**.

The image shows a vertical thumbnail of a research poster. It is divided into several sections: a title at the top, followed by an abstract, an introduction, and a methodology section. The text is small and difficult to read, but the layout is typical of an academic poster. The poster is positioned on the right side of the slide, partially overlapping the dark green background.

Non-Cognitive Predictors of Student Success: A Predictive Validity Comparison Between Domestic and International Students

Jacob Smith, Dr. Thea Schofield, Dr. Antonio Ibarra, Janis Choi, Bern Mullins, Dr. Emily Williams

INTRO

- Increasing interest in utilizing non-cognitive predictors in the college admissions process
- Rising enrollment of international students

METHODS

- We compare the predictive validity of these measures across domestic and international students.
- Results indicate some predictive validity differences do exist and an explanation for this differential validity, as well as a moderator of these relationships, are tested.

RESULTS

- Consistent differential validity for some non-cognitive measures for international students, specifically for SJT, Continuous Learning, Social Responsibility, and Perseverance.
- Differential validity for international students does not seem to be the results of functioning as a proxy for English language ability.
- Cultural distance does not seem to moderate validity of non-cognitive.

DISCUSSION

- Non-cognitive abilities may be useful in predicting international student performance, but differential validity may be an issue.
- Negative, non-significant relationship between cultural distance via GLOBE scores and perceived cultural distance warrants caution in generalizing country-level scores to individuals.
- More research is warranted to explain differential validity for international students.



Table 2. Multivariate Regression Results for Two Correlate Predictive Relationships with Academic Outcomes

Predictor	Sample 1		Sample 2	
	B	SE	B	SE
SJT	0.08	0.04	0.12	0.06
Continuous Learning	0.04	0.11	0.07	0.04
Social Responsibility	0.04	0.05	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Control	0.00	0.01	0.01	0.01
Interaction Effect	0.11	0.01	0.11	0.11
Adjusted R-squared	0.11		0.11	
Control	0.00		0.00	
Sample 1	0.00		0.00	
Sample 2	0.00		0.00	
Sample 3	0.00		0.00	
Sample 4	0.00		0.00	
Sample 5	0.00		0.00	
Sample 6	0.00		0.00	
Sample 7	0.00		0.00	
Sample 8	0.00		0.00	
Sample 9	0.00		0.00	
Sample 10	0.00		0.00	
Sample 11	0.00		0.00	
Sample 12	0.00		0.00	
Sample 13	0.00		0.00	
Sample 14	0.00		0.00	
Sample 15	0.00		0.00	
Sample 16	0.00		0.00	
Sample 17	0.00		0.00	
Sample 18	0.00		0.00	
Sample 19	0.00		0.00	
Sample 20	0.00		0.00	

Table 3. Multivariate Regression Results for Single Predictor Models

Predictor	Sample 1		Sample 2	
	B	SE	B	SE
SJT	0.11	0.04	0.12	0.06
Continuous Learning	0.04	0.11	0.07	0.04
Social Responsibility	0.04	0.05	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Control	0.00	0.01	0.01	0.01
Adjusted R-squared	0.11		0.11	
Control	0.00		0.00	
Sample 1	0.00		0.00	
Sample 2	0.00		0.00	
Sample 3	0.00		0.00	
Sample 4	0.00		0.00	
Sample 5	0.00		0.00	
Sample 6	0.00		0.00	
Sample 7	0.00		0.00	
Sample 8	0.00		0.00	
Sample 9	0.00		0.00	
Sample 10	0.00		0.00	
Sample 11	0.00		0.00	
Sample 12	0.00		0.00	
Sample 13	0.00		0.00	
Sample 14	0.00		0.00	
Sample 15	0.00		0.00	
Sample 16	0.00		0.00	
Sample 17	0.00		0.00	
Sample 18	0.00		0.00	
Sample 19	0.00		0.00	
Sample 20	0.00		0.00	

Method

Stepwise regression was used to identify predictors of GPA. Multivariate regression was used to test for differential validity between domestic and international students. Control variables were included in all models. The interaction term was used to test for moderation of the relationship between predictors and GPA. All predictors were standardized.

QR Code for People Who Want to Read it Later

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- Cultural distance does not seem to moderate validity of non-cognitive.

DISCUSSION

- Non-cognitive abilities may be useful in predicting international student performance, but differential validity may be an issue.
- Negative, non-significant relationship between cultural distance via GLOBE scores and perceived cultural distance warrants caution in generalizing country-level scores to individuals.
- More research is warranted to explain differential validity for international students.



For international students, perseverance and a sense of social responsibility are extra important for predicting first-year GPA.



Table 2. Multivariate Regression Results for Non-Cognitive Predictors Relationship with Continuous Learning

Variable	Sample 1		Sample 2	
	B	SE	B	SE
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
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Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
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Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
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Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07	0.06	0.04	0.06
Continuous Learning	0.07	0.06	0.07	0.06
Perseverance	0.07	0.06	0.07	0.06
Continuous Learning	0.07	0.06	0.07	0.06
SJT	0.08	0.04	0.12	0.04
Perseverance	0.14	0.13	0.17	0.04
Continuous Learning	0.04	0.02	0.07	0.07
Social Responsibility	0.07	0.06	0.07	0.07
Perseverance	0.07			

What Really Works in NLP

What Really Works in NLP

Non-Cognitive Predictors of Student Success: A Predictive Validity Comparison Between Domestic and International Students

Jacob Smith, Dr. Thea Schofield, Dr. Antonio Ibarra, Janis Choi, Berni Mullins, Dr. Emily Williams

INTRO

- Increasing interest in utilizing non-cognitive predictors in the college admissions process
- Rising enrollment of international students

METHODS

- We compare the predictive validity of these measures across domestic and international students.
- Results indicate some predictive validity differences do exist and an explanation for this differential validity, as well as a moderator of these relationships, are tested.

RESULTS

- Consistent differential validity for some non-cognitive measures for international students, specifically for SJT, Continuous Learning, Social Responsibility, and Perseverance.
- Differential validity for international students does not seem to be the results of functioning as a proxy for English language ability.
- Cultural distance does not seem to moderate validity of non-cognitive.

DISCUSSION

- Non-cognitive abilities may be useful in predicting international student performance, but differential validity may be an issue.
- Negative, non-significant relationship between cultural distance via GLOBE scores and perceived cultural distance warrants caution in generalizing country-level scores to individuals.
- More research is warranted to explain differential validity for international students.



For international students, perseverance and a sense of social responsibility are extra important for predicting first-year GPA.



Table 2. Multivariate Regression Results for Non-Cognitive Predictors Relationship with Academic Outcomes

Non-Cognitive Predictor	Sample 1		Sample 2	
	Beta	SE	Beta	SE
SJT	0.08	0.04	0.12	0.06
Continuous Learning	0.04	0.11	0.07	0.14
Social Responsibility	0.14	0.05	0.17	0.07
Perseverance	0.07	0.06	0.09	0.08
Openness	0.00	0.05	0.00	0.12
Conscientiousness	0.02	0.06	0.04	0.08
Extraversion	0.02	0.06	0.04	0.08
Neuroticism	0.00	0.05	0.02	0.08
Intelligence	0.15	0.02	0.15	0.02
Controlled	0.12	0.02	0.12	0.02
Uncontrolled	0.03	0.02	0.03	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
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Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
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Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02	0.04	0.02
Uncontrolled	0.04	0.02	0.04	0.02
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Conscientiousness	0.04	0.02	0.04	0.02
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Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
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Uncontrolled	0.04	0.02	0.04	0.02
Openness	0.04	0.02	0.04	0.02
Conscientiousness	0.04	0.02	0.04	0.02
Extraversion	0.04	0.02	0.04	0.02
Neuroticism	0.04	0.02	0.04	0.02
Intelligence	0.04	0.02	0.04	0.02
Controlled	0.04	0.02		

Real Examples

Towards Integration of Statistical Hypothesis Tests into Deep Neural Networks

Dr. Ahmad Aghaerabian
Zurich University of Applied Sciences

Prof. Dr. Mark Clefbeck
Zurich University of Applied Sciences

Introduction

We propose a new deep architecture which works in tandem with a statistical test procedure for training a text classifier jointly on texts and their label descriptions.

The model leverages the use of label descriptions in addition to the input text to improve text classification performance.

Intuition

The intuition is to help the model to concentrate on more informative words rather than more frequent ones hence enhancing the model performance.

Conclusion

Using statistical hypothesis testing methods, we extract the most informative words for each class as the class descriptors. We also propose an architecture for actively attending over class descriptors hence improving the state-of-the-art in text classification.

Our method is entirely data-driven, has no dependency on other sources of information than the training data, and is adaptable to different classification problems by providing appropriate training data without major hyper-parameter tuning.

Zurich University of Applied Sciences

Jointly Training Deep Neural Classifiers on Text and χ^2 Labels using χ^2 Hypothesis test

Take a picture to
download the full paper

System Architecture

Key Steps

- Extracting class descriptors
- Explicit attention on class descriptors
- Jointly learning from text and class descriptors

System Results

The state-of-the-art system results on the Hate speech dataset

Hate Speech dataset (Davidson et al., 2017)	P (%)	R (%)	F1 (%)	AUC (%)
(Frantz et al., 2018)	89	88	89	92
This work+ χ^2 50	88.7	90.4	90	92.9
This work+ χ^2 100	90.3	92.5	91.4	93.9
This work+ANGVA/50	89.2	89.4	89.3	92.1
This work+ANGVA/100	89.8	89.2	89.4	92.4

Class Descriptors

Here are the extracted χ^2 descriptors for some classes in the AG News dataset:

Class	Informative words
World	inaj, minister, president, prime, hagháad, inaj, dig, pubolition, military, military, israeli, ...
Sports	dig, season, league, team, game, cup, right, coach, victory, win, sports, championship, olympic, ...
Business	oil, stocks, prices, percent, quarterly, target, profit, company, shares, billion, quarter, sales, earnings, ...
Science	microsoft, software, internet, space, music, computer, users, web, search, windows, technology, ...

57th annual meeting of the Association of Computational Linguistics

Unsupervised word segmentation models perform above chance & stably across languages → They could be potential strategies employed by infants.

Take a photo to get the full paper



Is word segmentation child's play in all languages?

Georgia Loukatou, Steven Moran, Damian Blasi, Sabine Stoll, Alex Cristia

INTRO

- Infants can segment speech into words/morphemes.
- This process can be mimicked with unsupervised segmentation models.
- Ideal models should work similarly across languages.

RESEARCH QUESTIONS

- Do models perform above chance?
- Is their rank ordering similar across languages?

METHODS

WordSeg package¹:

- 2 baselines (cut anywhere at $p=0$, $p=1$)
- ...

- ... DiBS: diphone prob, optimal choice
- ... TP: diphone prob (backwards, FW, MI)

- ... AG: lexical & generative
- ... PUDDLE: lexical & memory-based

AcqDiv database²:

- 8 languages
- child-centered speech transcriptions

RESULTS

- DiBS performed above baselines in all languages. The others performed above baselines for nearly all languages.
- Spearman corr showed a similar rank ordering of model performance across languages. Only Inuktitut and Russian differed.
- Bigger differences in performance across models (Table 1) than across languages (Table 2).

DISCUSSION

- Many proposed models perform above chance & stably across languages.
- If infants used similar strategies, they could get a head start in segmenting word-like units regardless of what their native language is.

Table 1 For each model number of languages for which it performed above baseline of correctly segmented words (and the corresponding languages)

Model	Number of languages	Languages
DiBS	8	EN, JA, ZH, HI, TR, DA, RU, IN, KW
TP	7	EN, JA, ZH, HI, TR, DA, KW
AG	7	EN, JA, ZH, HI, TR, DA, KW
PUDDLE	7	EN, JA, ZH, HI, TR, DA, KW
Baseline	0	-

Table 1 For each model number of languages for which it performed above baseline of correctly segmented words (and the corresponding languages)



Table 2 Means (standard deviation) of number of correctly segmented words for each language (and the corresponding algorithms)

Language	DiBS	TP	AG	PUDDLE
EN	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
JA	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
ZH	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
HI	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
TR	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
DA	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
RU	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
IN	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)
KW	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)	25.0 (1.0)

Table 2 Means (standard deviation) of number of correctly segmented words for each language (and the corresponding algorithms)

For cross-lingual word embeddings, a little preprocessing can drastically increase word translation accuracy.

Are Girls Neko or Shōjo? Cross-Lingual Alignment of Non-Isomorphic Embeddings with Iterative Normalization

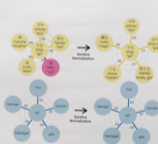
Mozhi Zhang, Keyulu Xu, Ken-ichi Kawarabayashi, Stefanie Jegelka, Jordan Boyd-Graber

Background

How to train bilingual word embeddings

- Train two monolingual embeddings
- Align with an orthogonal mapping
- Definition: $W^T W = I$
- Preserve dot-products: $x^T y = (Wx)^T (Wy)$

Why does it work?



Iterative Normalization

Preprocess monolingual embeddings before learning the alignment.

For $k = 1, 2, \dots$

Length normalization:
$$y_i^{(k)} = x_i^{(k-1)} / \|x_i^{(k-1)}\|$$

Mean centering:
$$x_i^{(k)} = y_i^{(k)} - \frac{1}{N} \sum_{j=1}^N y_j^{(k)}$$

Word translation accuracy

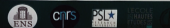
	Before	After
EN-JA	1.7	44.3
EN-ZH	32.5	44.2
EN-HI	33.3	36.7
EN-TR	44.9	48.7
EN-DA	54.0	58.4

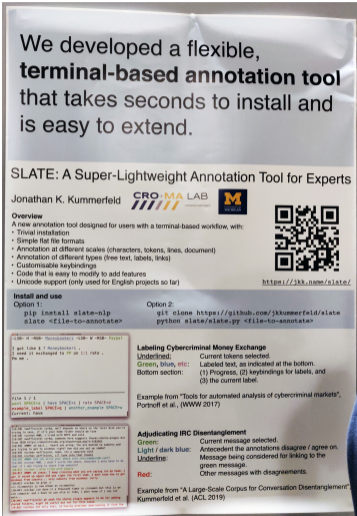
- Results on MUSE
- Improve on 39 target languages
- Helpful for both orthogonal and non-orthogonal methods (such as RCSSL)

Two conditions that help orthogonal mapping:

1. Every vector has the same length.
 2. Each language's mean has the same length.
- Condition 1 unifies objectives: dot-product for training monolingual embedding, cosine-similarity for evaluating monolingual embedding, and Euclidean distance for cross-lingual alignment.
 - Condition 2 is a necessary condition for orthogonal alignment.
 - Iterative Normalization uses alternating projection to provably satisfy both.

Research partially funded by the National Science Foundation under Grant IRI-1545307. We thank the anonymous reviewers for their helpful comments and suggestions.





Add Main Message in Plain English

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Main finding goes here,
translated into plain English.

Emphasize the important!

The Title of Your Amazing Paper

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Charles University Faculty of Mathematics and Physics
Department of Formal and Applied Linguistics
Prague, Czech Republic

Introduction

This section is for participants to read through by themselves without your interaction. Remember, that you are standing on the right side of the poster, thus on the left side can several people stand and read this section without your interruption.

First specify what was your problem, maybe add some graph or illustration



Methods

Describe your contribution, what is your main goal. Add explanatory equation, etc.

$$\int_0^1 f(x) dx = F(b) - F(a). \quad (1)$$

Results

Be brief about your results, maybe list them as individual items.

- The first item.
- The second item.
- The third item.

Note: if you want to scale a graph or something to the full width of a column, use:

YOUR OBJECT

Here you can add **supplementary material**. Remember, this section will be right next to you. Use this section for supplementary material that is needed for YOUR oral explanation. Do not care about titles or naming the sections because you will tell the participants what is what.

For instance, a table:

Country Name	ISO ALPHA-2	ISO ALPHA-3
Afghanistan	AF	AFG
Atand Islands	AK	ALA
Albania	AL	ALB
Algeria	DZ	DEA
American Samoa	AS	ASM
Andorra	AD	AND
Angola	AO	AGO

Or very important and cute kittens:



Features built from unlabeled data improve automatic evaluation of coherence



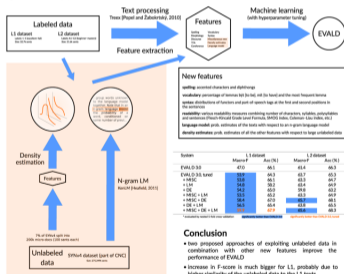
Exploiting Large Unlabeled Data in Automatic Evaluation of Coherence in Czech

Michal Novák, Jiří Mirovský, Kateřina Rysová and Magdaléna Rysová
Institute of Formal and Applied Linguistics, Faculty of Mathematics and Physics, Charles University, Czech Republic



Introduction

We look into possibilities of using large unlabeled data to improve quality of automatic evaluation of surface coherence in student essays. Particularly, we propose two approaches to benefit from the large data: (I) n-gram language model, and (II) density estimates of features used by the evaluation system. In our experiments, we integrate these approaches that exploit data from the Czech National Corpus into the evaluator of surface coherence for Czech, the EVALD system, and test its performance on two datasets: essays written by native speakers (L1) as well as foreign learners of Czech (L2).



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Methods for Assessing Theme Adherence in Student Thesis

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Student's Theses Analysis

The task of analyzing students' theses is complex and consists of many factors, two of which are the theme adherence. Many students' theses contain a large amount of non-theme information to increase their size.

"Flight of Thought"

An example of a irrelevant passage to the thesis.

This case: During the evaluation of students of the National State Planning College in the educational process.

Fragment: Received by the student's thesis, described by the necessity to control, to control you have found the writing such as if there is an even more beautiful word with the meaning of the words.

Main questions

- What is the theme of thesis?
- What is the main passage?
- How to find irrelevant passages?
- How to determine the degree of theme adherence?

General Info About Student's Theses

Special structure
"Big" paragraphs
Lack of contents
Unconventional
Typically without great title, header

Differences from essay scoring

In this study scoring thesis is similar to one that is done in the process of writing and is a component of the assessment process in writing. The main difference is that the thesis is a long text and the assessment is done by a person.

Theme header

NTU CR - Safety and technical education of the National State Planning College in the educational process.
NTU CR - Evaluation of safety and technical education of the National State Planning College in the educational process.
NTU CR - Evaluation of the quality and safety of the educational process.
NTU CR - The organization of the educational process.

Dataset

NTU CR - Safety and technical education of the National State Planning College in the educational process. 2017-2018.
NTU CR - Evaluation of safety and technical education of the National State Planning College in the educational process. 2017-2018.
NTU CR - Evaluation of the quality and safety of the educational process. 2017-2018.

Evaluation

Ranking problem: find themes from "noise" to "text".

$$R = \frac{1}{N} \sum_{i=1}^N \frac{1}{1 + \exp(-\frac{1}{\sigma} \cdot \frac{C_i}{L_i})}$$

NTU CR reference score:
2.000 - 1.0
7.000 - 1.0
8.000 and greater - 0.0

Results

Features built from unlabeled data improve automatic evaluation of coherence

ÚFAL Exploiting Large Unlabeled Data in Automatic Evaluation of Coherence in Czech

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Introduction

We look at the possibilities of using large unlabeled data to improve quality of automatic evaluation of coherence reference in student essays. For this, we propose two approaches to build new large-scale EFL agent-based models, and to derive and evaluate features used for the evaluation system. In our experiments, we integrate these approaches that exploit data from the Czech National Corpus into the evaluation of surface coherence for Czech, the EFLD system, and test its performance on two datasets: essays written for college students EFL as well as foreign learners of Czech EFL.

Flowchart:

```

    graph LR
        LD[Labelled data] --> TP[Text processing  
Pre-tokenization, POS-tagging]
        LD --> FE[Feature extraction]
        TP --> FE
        FE --> NLF[New features]
        FE --> ML[Machine learning  
Multi-Perceptron Neural Network]
        NLF --> ML
        ML --> EVAL[EVAL]
    
```

New Features

These features are built from unlabeled data and are used for the evaluation of coherence reference in student essays. They are built from the unlabeled data and are used for the evaluation of coherence reference in student essays.

Feature	Mean	Std	Min	Max
ENTRANCE	0.000	0.000	0.000	0.000
EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000
ENTRANCE_EXIT	0.000	0.000	0.000	0.000

Conclusion

Our proposed approach of exploiting unlabeled data in combination with other (over features) improves the performance of EFLD.

Thanks to Fráňa to Mark Řeháček for L1, available also as higher outputs of the unlabeled data to the L1 text.

Word-embedding space has a structure that can be examined and visualised with PCA.

Examining Structure of Word Embeddings with PCA

ÚFAL

Introduction

Word embeddings are a powerful tool for representing words in a high-dimensional space. This paper examines the structure of word embeddings using PCA. The results show that word embeddings have a clear structure that can be visualized using PCA.

Results

The results show that word embeddings have a clear structure that can be visualized using PCA. The plots show that words related to the same topic cluster together in the embedding space.

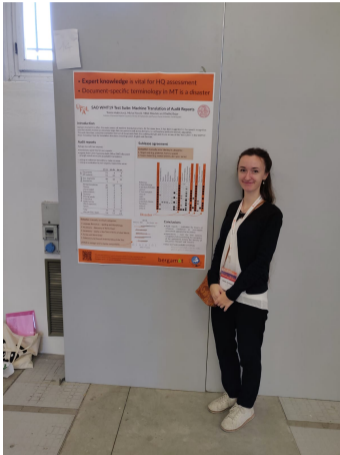
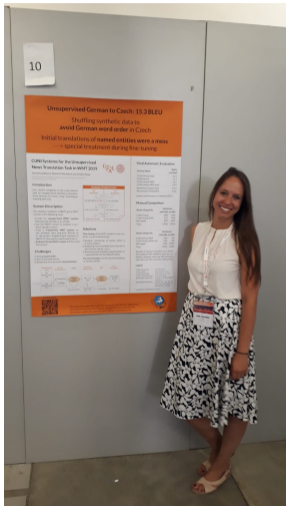
Conclusion

Our results show that word embeddings have a clear structure that can be visualized using PCA. This structure can be used to improve the performance of word-based models.

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Beamer Template for ÚFAL

`https://github.com/tomkocmi/betterposter-latex-template`

`https://github.com/ufal/beamer-template`

Summary

1. Add the main message in plain English
2. Do not be scared of negative space
3. ÚFAL consistency

<https://wiki.ufal.ms.mff.cuni.cz/presentations>