Automating is the Future: Improving Research Scalability with Predictive Modeling

Bryan Acton (Durham University)

Nick Koenig (Modern Hire)

2022 SIOP ANNUAL CONFERENCE

SEATTLE • APRIL 27-30

Background of Symposium

- Organizations are continually adopting more data-driven approaches
- Unfortunately, these methods often are highly resource intensive (e.g. money, time)
- Implementing large survey efforts, data coding, etc presents a scalability problem
- **Papers in this symposium all represent ways of utilizing predictive modeling for addressing organizational problems**
- **Different topics, same goal**

Selected References: Putka & Oswald, 2015; Stahl, 2021

Order of Talks in this Symposium

1. Acton, B.P., Hansbrough, T.K., Foti, R.J., Delice, F., Lord, R.G. (2022). Using Predictive Analysis to Identify The Memory Processing of Leadership Items.
2. Chekili, A. & Hernandez, I. (2022). What's in a Name? Using Neural Networks to Infer Organizational Diversity from Employee Rosters.
3. Chen, C., Landers, R.N., Gore, R., Auer, E.M. (2022). Affect-related Psychological Traits are Reflected by the Sentiment of Publicly Shared Text.
4. Minton, B., & Hernandez, I. (2022). Comparison of Social Support Seeking Online Across Workers in Essential Industries.
5. Dahlke, J.A. & Putka, D.J. (2022). Automating the Generation of Vocational Interest Profiles from Occupation Descriptions.

- Q&A Led by Nick Koenig at the end

USING PREDICTIVE TEXT ANALYSIS TO IDENTIFY THE MEMORY PROCESSING OF LEADERSHIP ITEMS

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LEADERSHIP RATINGS IN PRACTICE

- Most organizations rely on follower reported questionnaires to understand a person's leadership capacity
- Ratings used to make important personnel decisions
- Ratings useful in applied context:
  - Historical precedence
  - Availability of various scales
  - Ease of use
- So, what's the problem?

Selected References: Finkelstein & Hambrick, 1996; Hansbrough et al., 2015

RATINGS FROM TWO MEMORY SOURCES

- Leadership perceptions largely derive from two sources of memory: episodic & semantic

Episodic Memory	Semantic Memory
• Localized, concrete representations of others' behaviors	• General, abstract representations of others (e.g., prototypes)
• Ratings based on events that occurred in the past	• Ratings based on general knowledge or cognitive frameworks

- Past research has shown that these two sources of memory represent (1) different information, and have (2) different relationships with outcomes
- Capturing memory source of leadership ratings is key to improving measurement

COST OF CAPTURING MEMORY SOURCE OF RATINGS

- Most work identifying memory source has used costly neuroscience tools such as Functional Magnetic Resonance Imagine (FMRI)
- Tulving (1989) introduced remember/know paradigm to capture memory source information
- Adapted to ratings, Remember/know protocol involves two step process:
  1. Provide raters with definitions of a Remember Judgement, and a Know judgments, preferably with examples (Use Martell & Evans, 2005, JAP, for example)
  2. After each scale item, ask raters to indicate whether that judgement was based on either a A) Remember or B) Know Judgement

Example Instructions:

We have two different ways that we make judgments about other people, remembering and knowing. **Remembering** is based on a vivid recollection of a specific event. For example, we might describe someone as outgoing because we can recall specific examples of their behavior.

Alternatively, **knowing** is based on a general feeling or impression about a person. It is important to note that both types of memory are useful and that one is not inherently better than the other. Moreover, remember and know judgments do not differ in terms of their confidence or certainty. For example, we can be equally confident about a judgment even though we might not associate it with a specific event.

Step 2:

Instructions: For each of the following items that you will see, please rate the following statements and then **using the definitions above indicate whether your rating reflects a "remember" or "know" judgment.**

RATINGS FROM TWO MEMORY SOURCES

- Leadership perceptions largely derive from two sources of memory: episodic & semantic

Episodic Memory	Semantic Memory
• Localized, concrete representations of others behaviors	• General, abstract representations of others (e.g. prototypes)
• Ratings based on events that occurred in the past	• Ratings based on general knowledge or cognitive frameworks
• Aligned with Recollection or "Remember" Judgment	• Aligned with Familiarity or "Know" Judgment

PURPOSE OF WORK/METHOD

- Can we use predictive text analytics to train a model that can identify the likely memory source of leadership items?
- Can be useful from an instrument development perspective

"My manager does not allow me to interact with my co-workers"

73% possibility of episodic memory

27% possibility of semantic memory

METHOD

Item	Episodic Strength
1	0.67
2	0.78
3	0.55
4	0.42
5	0.68
6	0.53
7	0.83
8	0.7
9	0.43
10	0.55

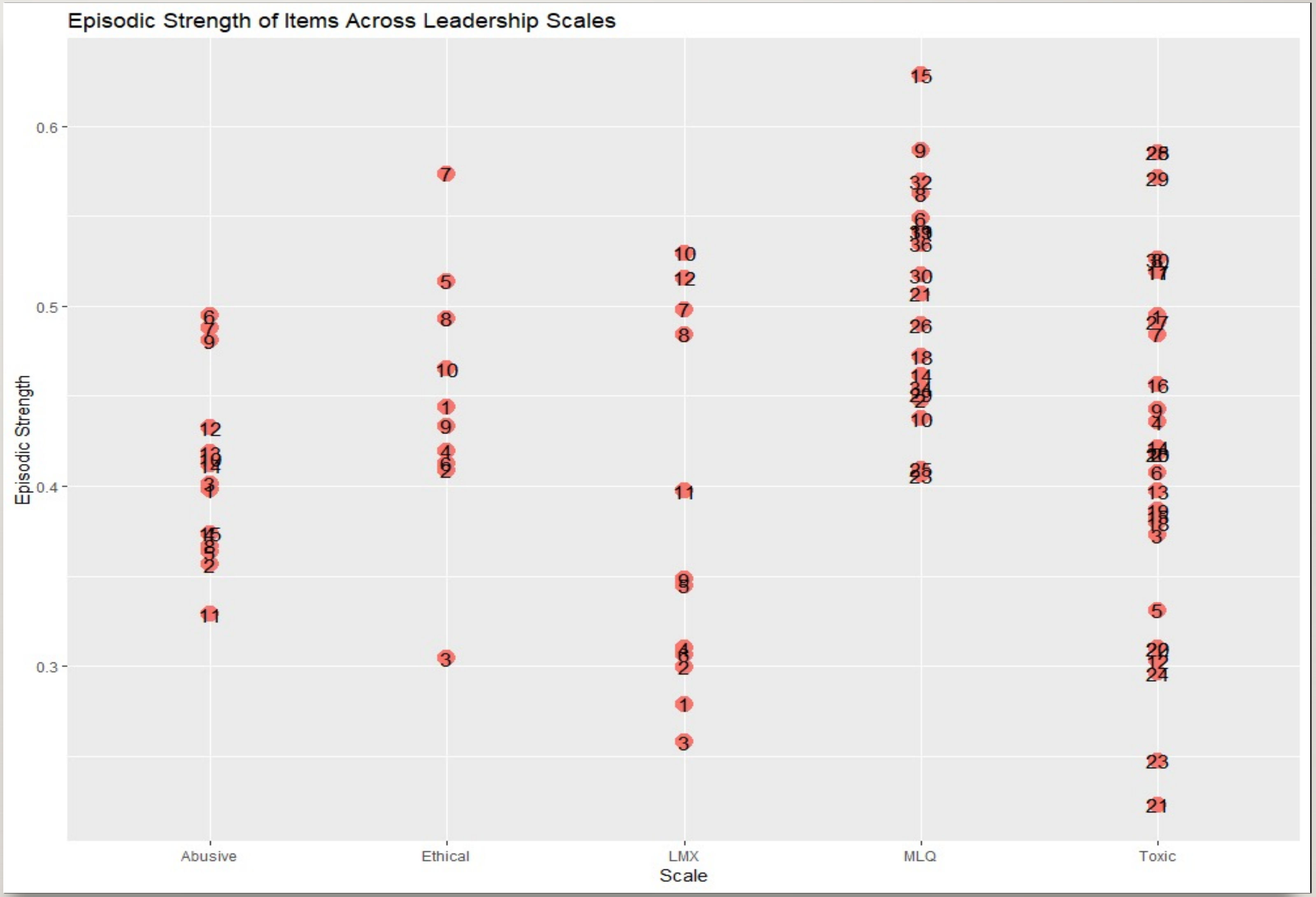
urk

ip scales

ale

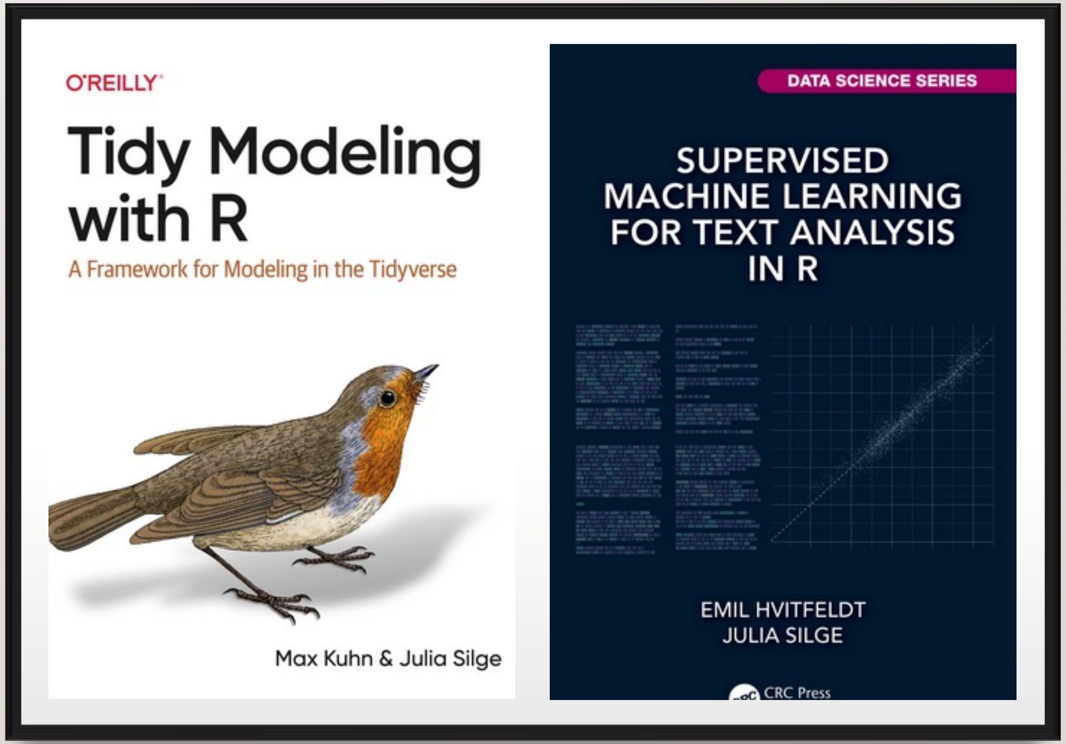
MEMORY SOURCE OF LEADERSHIP ITEMS

- Y axis represents extent to which item was rated as Episodic ("Remember judgment")



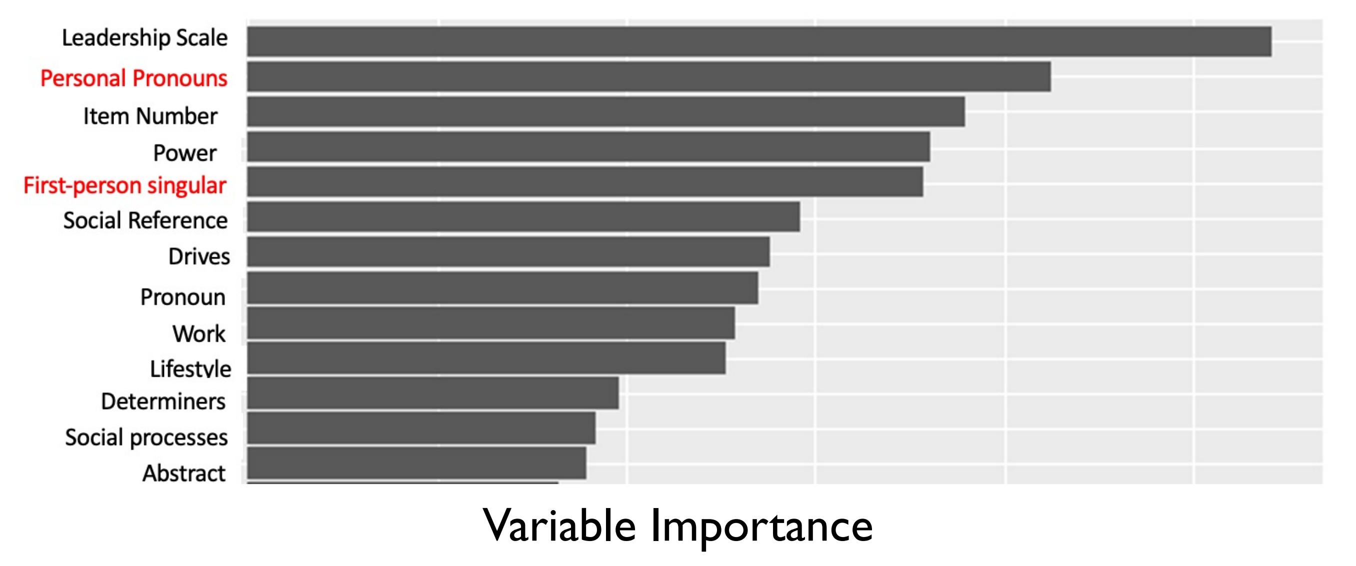
METHOD: PREDICTIVE TEXT ANALYTICS

- Trained two types of predictive models for predicting the memory source of leadership items
- Top-down model:
    - Utilized core dictionary from LIWC
    - Linguistic Category Model dictionary
- Bottom-Up model:
    - Train models based on words in items
    - Relied on support vector machine model



TOP-DOWN MODEL RESULTS

- Random forest model was trained on subset of data before being tested
  - Data trained based on subset of items and trained on the rest of items
- Variables importance metric was calculated to assess which “features” were most important
- Overall prediction metrics were subpar relative to predictive text models (R^2 = .32, RMSE = .005)
- Notable important text features were the scale, personal pronouns, and references to work and power



BOTTOM-UP MODEL RESULTS

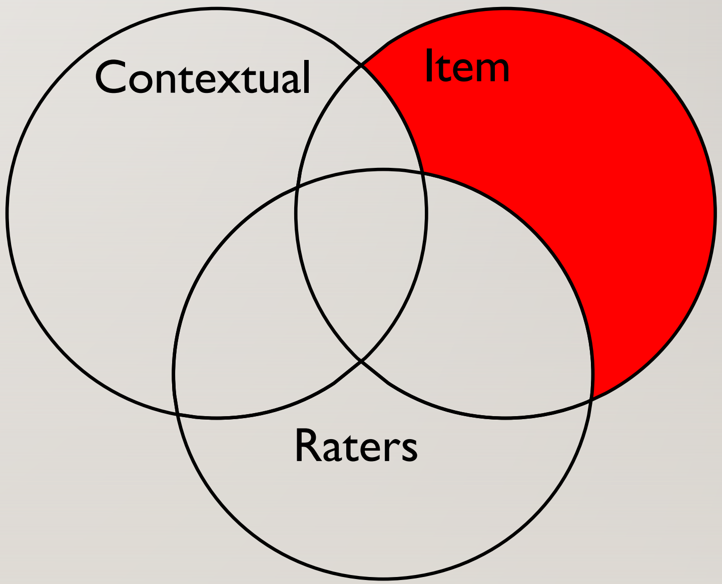
- Utilized support vector machines-–to train a model based on the text in the items
- Used cross-validation to tune/train model using "LiblineaR" engine
- Results from bottom-up model accounted for less variance than "top-down" model (.23 R^2)
- Importance metric identified self-reference as another key metric in memory processing

Rank	Most Important Words
1	Competent
2	Hard
3	Manager
4	Personal
5	My
6	I

TAKE AWAYS, NEXT STEPS

- Overall, models did not account for large amounts of variation in memory processing
  - Possible explanation: In using multilevel modeling, individual raters accounted for 30% of the variance in ratings (ICC1)
- Important text features align with past work identifying (1) self-reference, and (2) abstract characteristics as key linguistic features in memory processing
- Memory source represents complex system beyond items
  - Currently collecting data on hundreds of more items with the hope to improve prediction with more complex models (i.e. deep learning, NN)
  - Goal would be to design an application similar to talks later in this symposium!

Factors influencing memory source



Selected References: Renoult et al., 2012; Hansbrough et al., 2015

THANK YOU!

- THANK YOU TO THE ARMY RESEARCH INSTITUTE
- THANK YOU TO COLLABORATORS
- IDEAS/SUGGESTIONS ARE APPRECIATED!

USING NEURAL NETWORKS TO INFER ORGANIZATIONAL DIVERSITY

Amel Chekili & Ivan Hernandez

OVERVIEW

- Researching Diversity
- Model Architecture
- Validation Study
- Application Study

RESEARCHING DIVERSITY

Diversity & Positive work outcomes

Broader range of knowledge, expertise,

& perspectives

→ increase organizational flexibility,

creativity & problem solving

Diversity & Negative work outcomes

Dissimilarities between individuals

triggers an “out-of-group” feeling.

→ withdrawal behaviors when

members feel incompatible

TRADITIONAL METHODS FOR MEASURING ORG DIVERSITY

Survey

Directly ask employees to fill out forms that include information about their demographics

Community-based inference

Use the demographic composition of the region an organization is embedded within

Hand coding - Human inferred

Infer each employee's demographic from their face or name using trained coders

LIMITATIONS OF TRADITIONAL METHODS

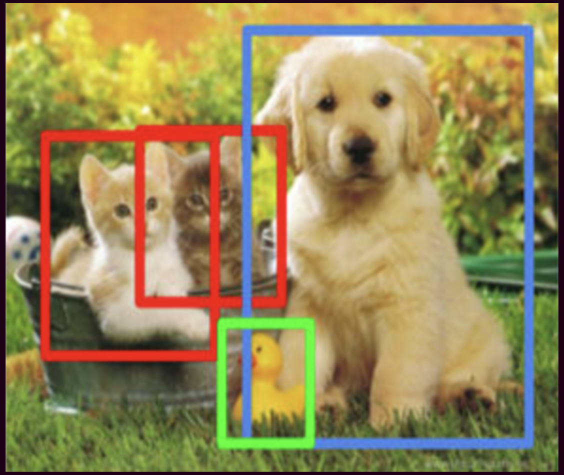
- Can be used on limited sample sizes
- Time consuming
- Labor intensive
- Inaccurate

CNN MODEL TO INFER ORG DEMOGRAPHICS BASED ON PEOPLE'S FULL NAMES

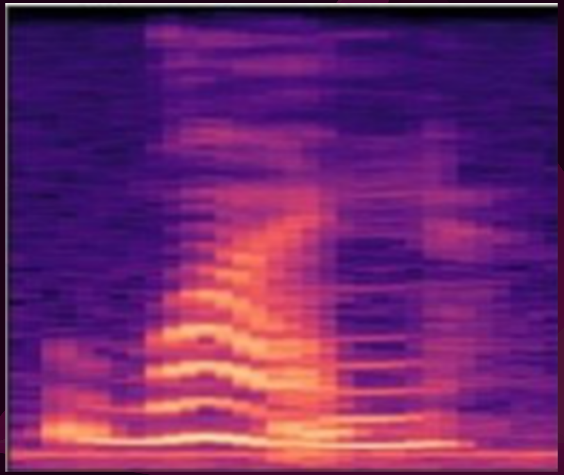
CNN POPULAR APPLICATIONS

Image Classification

Object Recognition

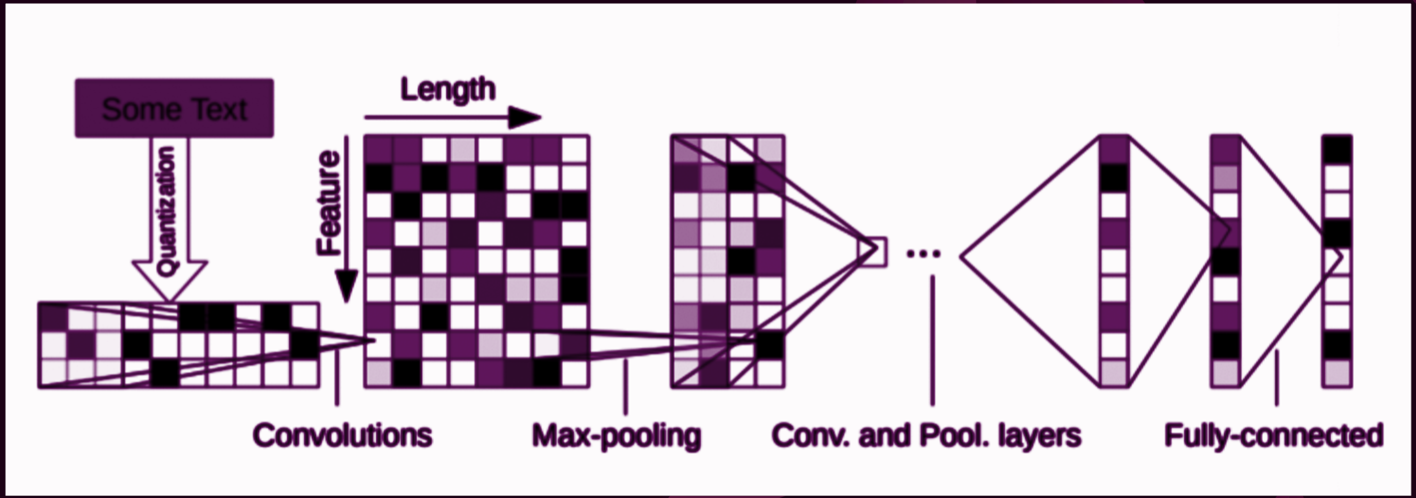


Audio Analysis



CHARACTER-LEVEL CNN

Analyzing characters in a word instead of pixels in image



CHARACTER EMBEDDING LAYER

I	V	A	N		H	E	R	N	A	N	D	E	Z

1
0
0
0
0
0
0
0
1

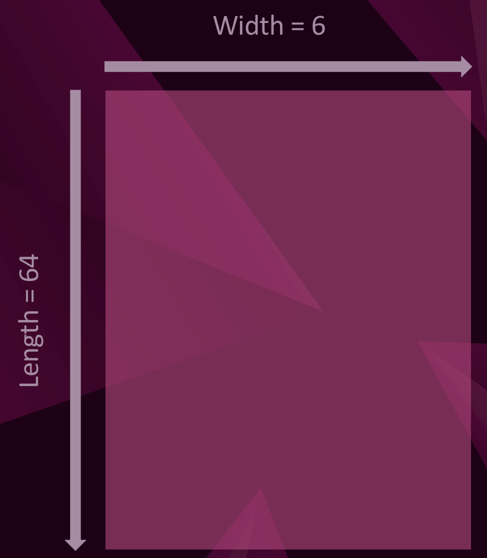
CHARACTER EMBEDDING LAYER

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

1-D Kernel



Discover patterns within every 6-character sequence of embeddings

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21								

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21	.32							

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z

1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21	.32	.43						

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1
					.21	.32	.43	.55					

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
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0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

					.21	.32	.43	.55	.61				

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
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0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21	.32	.43	.55	.61	.11			

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z

1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21	.32	.43	.55	.61	.11	.17		

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z
1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1
					.21	.32	.43	.55	.61	.11	.17	.09	

CHARACTER-LEVEL CNN

I	V	A	N		H	E	R	N	A	N	D	E	Z

1	1	1	1	0	1	1	1	1	1	1	1	1	1
0	0	0	1	0	0	1	0	1	0	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	0	1	0	0	0	1	0	1
0	1	0	0	0	1	0	1	0	0	0	1	0	1
1	1	0	0	0	1	0	1	0	0	0	1	0	1

.21	.32	.43	.55	.61	.11	.17	.09	.68

Pattern Matrix

PROPOSED MODEL

i v a n H e r n a n d e z

#1	#2	#3	...	#64
.25	.33	-.14	.45	-.02
.37	.49	-.88	-.12	.65
.12	-.28	-.99	.31	.87
.32	.17	-.12	-.37	-.11
.37	.49	-.88	-.12	.65
.55	-.55	-.27	.02	-.03
.12	.56	.43	.29	.44
.37	.49	-.88	-.12	.65
.12	-.28	-.99	.31	.87
.97	.12	-.77	-.52	.14
.32	.17	-.12	-.37	-.11
.37	.49	-.88	-.12	.65
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
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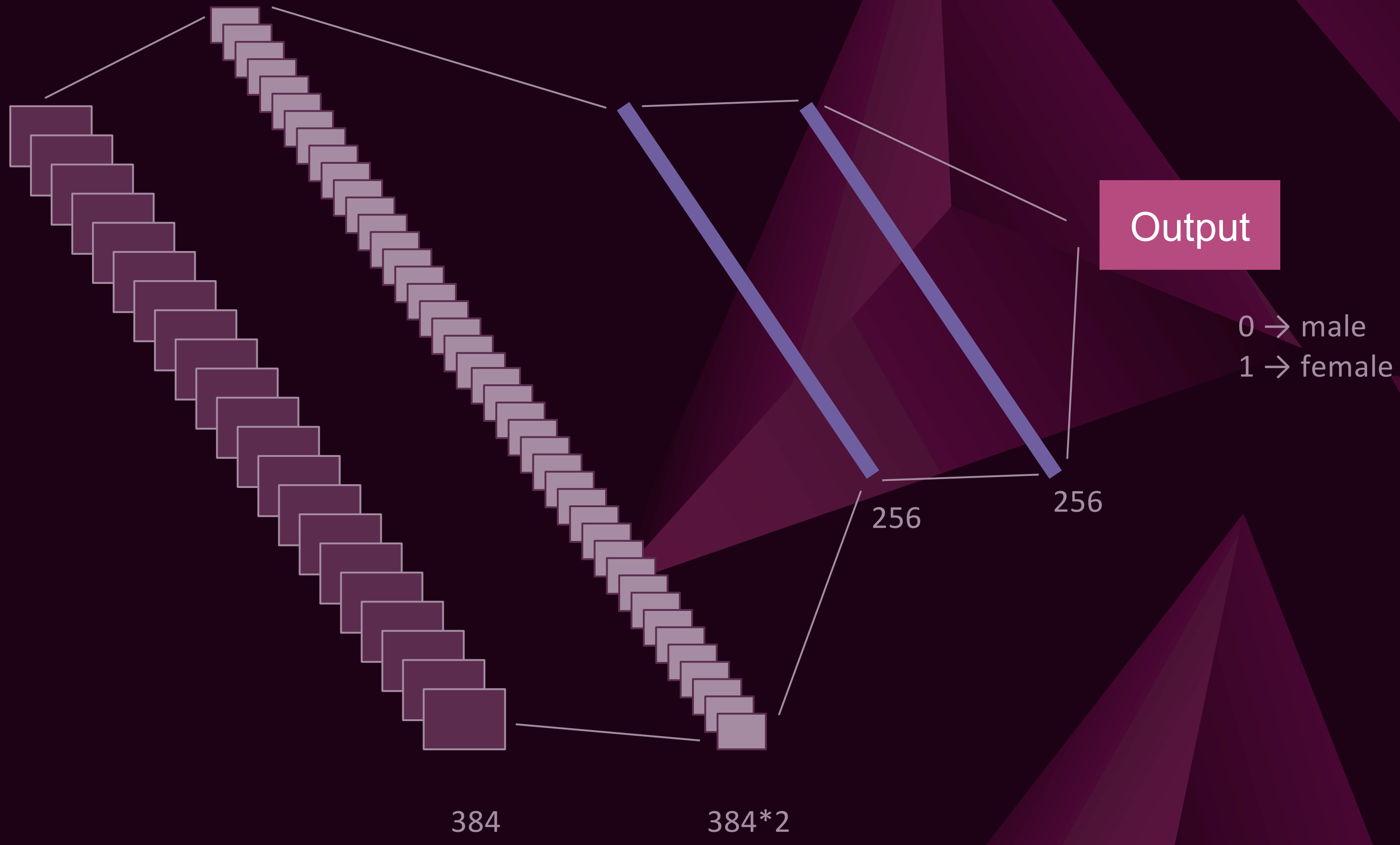
0	0	0	0	0



CODE FOR GENDER MODEL

```
import tensorflow as tf
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Embedding(
        input_dim=vocab_size+1,
        output_dim=32*2,
        mask_zero=True))
model.add(tf.keras.layers.Conv1D(192*2, 6, activation='relu', strides=1))
model.add(tf.keras.layers.Conv1D(384*2, 5, activation='relu', strides=1))
model.add(tf.keras.layers.GlobalAveragePooling1D ())
model.add(tf.keras.layers.Dense(128*2))
model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.Dense(128*2))
model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.Dense(1, activation='linear'))
model.summary()
```

MODEL TRAINING

DBpedia 380771

IMDB 523051

Bejda 120777

Training data size = 908422

Epochs = 100

Goal: minimize the MSE between the predicted gender and actual gender

VALIDATION STUDY PROCEDURE

Using the 2021 Texas state employee database **(*N*=144,738)** that lists employees' gender

- We calculated the group level diversity using the **inverse Simpson's Diversity Index**
- We compared both the individual and group level diversity estimations of our model to the actual diversity

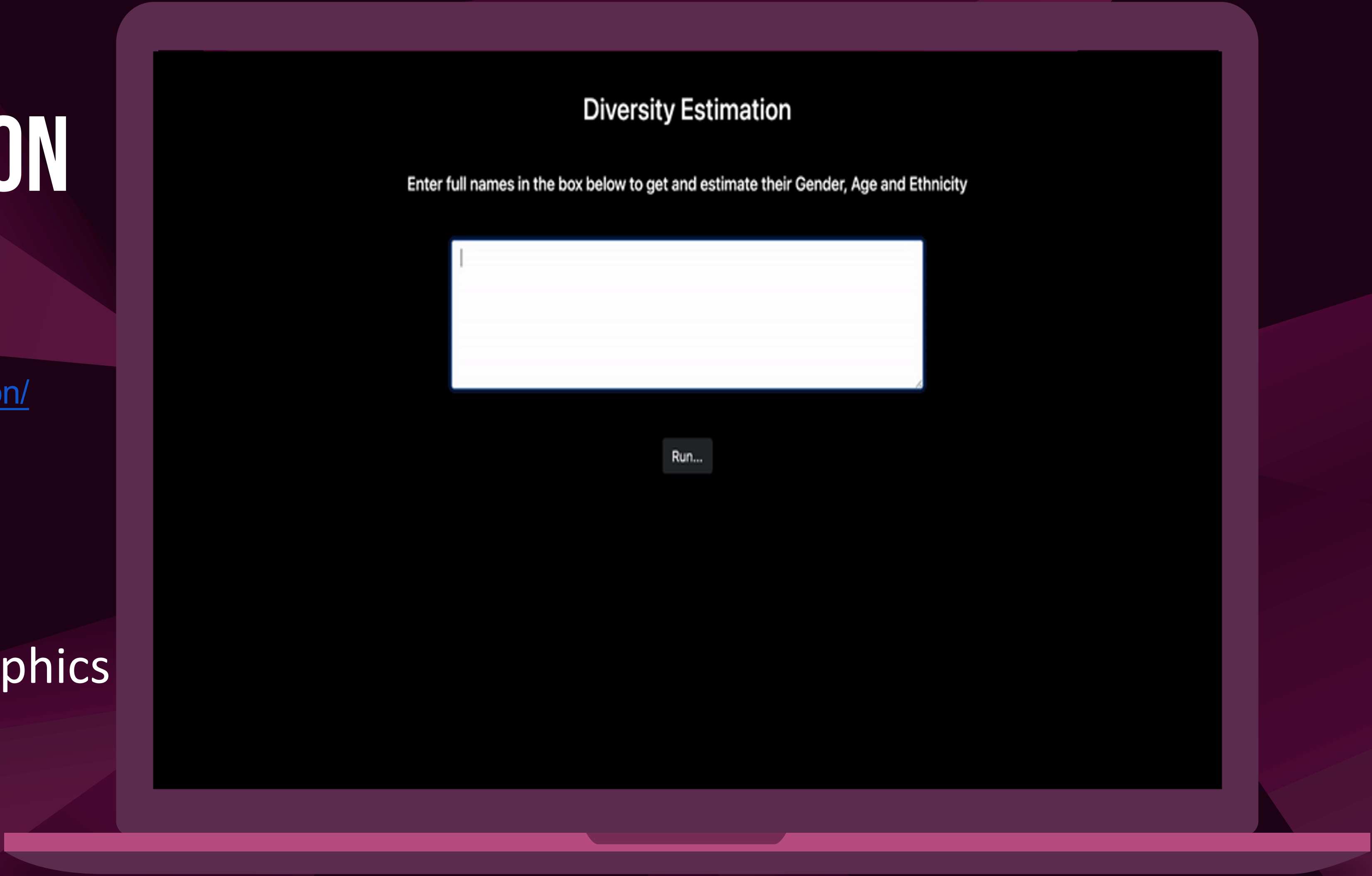
VALIDATION STUDY RESULTS

	Individual level		Group level	
	r	95% CI	*r*	95% CI
Gender	0.87	[.869,.871]	0.91	[.909,.911]

DIVERSITY ESTIMATION WEBPAGE

https://amel-chekili.github.io/diversityestimation/

- Copy names
- Click on **Run**
- Get a table with demographics estimations



DIVERSITY ESTIMATION MODEL ADVANTAGES

- Efficient
- Allows studies on large samples
- Require less time & effort
- Does not trained coders
- Relies on only names to infer diversity

APPLICATION STUDY METHOD

Explore how office diversity affects the turnover behavior of employees of different demographics

Using a dataset of all California school district employees from 2012-2019 ($N_{employees}$=**200,039**; $N_{Organizations}$=844; $\%_{female}$=.61)

Step 1

Step 2

Step 3

We inferred each employee's Gender using our model

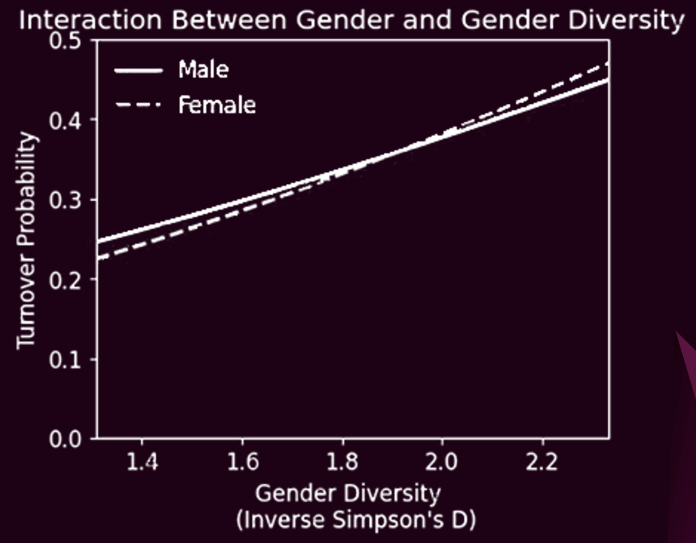
We calculated the gender diversity of each employee's office.

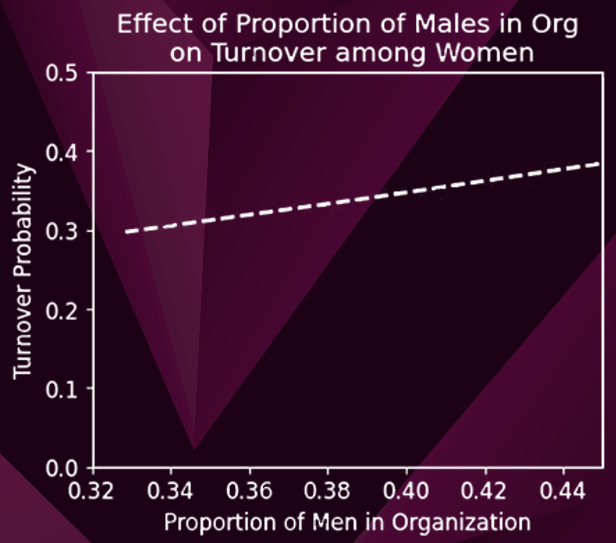
We compared the employees within an office from one year and the subsequent year

* Employees no longer in that office were considered to have turned over

APPLICATION STUDY RESULTS

- Women were more likely to turnover in gender diverse offices
- Turnover increases as the proportion of males increase in a typically female environment.





FUTURE DIRECTIONS

Incorporate additional nuances

- Non-binary names
- Support for additional character sets

Use newer sources to train the data

- Additional languages from Wikipedia
- Social media

Use transformer model instead of CNN

SPECIAL THANKS

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THANKS!

Any questions?

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Affect-related Psychological Traits are Reflected by the Sentiment of Publicly Shared Text

Chulin Chen, Richard N. Landers, Ross Gore, and Elena M. Auer

28/04/2022

University of Minnesota
Driven to Discover®

Background

- High-stakes decisions are increasing made based on publicly available sentiment data.
  - Politics, public health, demographics, business…
- Twitter is the most common source.
- Advantages of sentiment in modeling:
  - Simplicity of computation
  - Wide applicability
  - Dimension reduction

Problem

- To what extent do sentiment reflects variance in psychological traits vs. variance in the situational context?
- Most sentiment research focus on shared variance across people, treating human variation as error.
- Psychometric approach: traits are the focus, treating situational variation as unsystematic error.

Research Question and Hypothesis

- Apply the psychometric approach to sentiment data to measure “latent trait sentiment” (LTS).
  - The degree to which sentiment is consistent across topics within the broader Tweet platform.
- *H1*: Shared variance of LTS within individual across contexts can be modeled as a latent psychological trait.
- *RQ1:* Is LTS related to affect-related psychological trait variables?

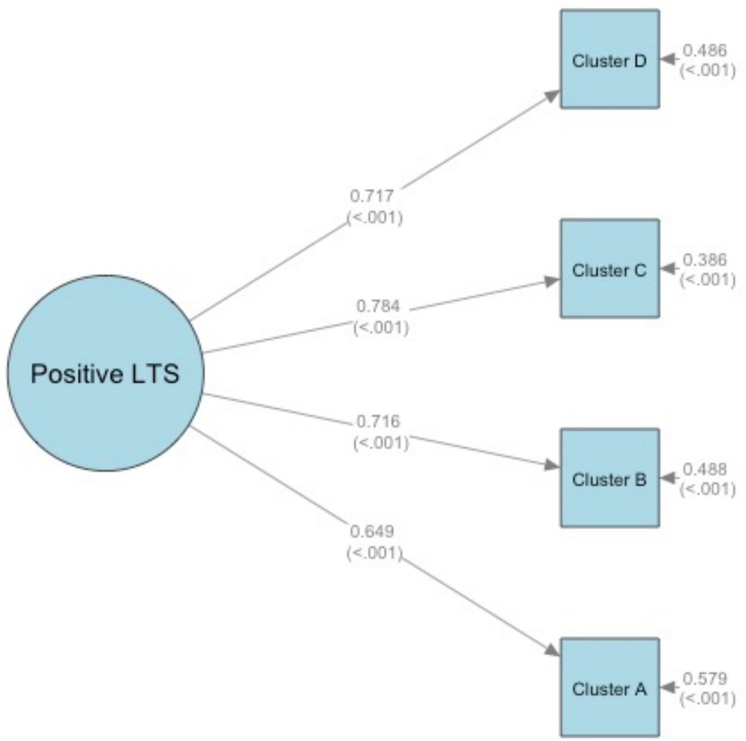
Method

- 985 participants (Qualtrics, UMN psychology students)
- Shared Twitter handle and answered questionnaires
- 842 participants left after data quality screening
  - Account activity, Multivariate outliers, Direct response questions
- Timelines within 3-months before participation were collected

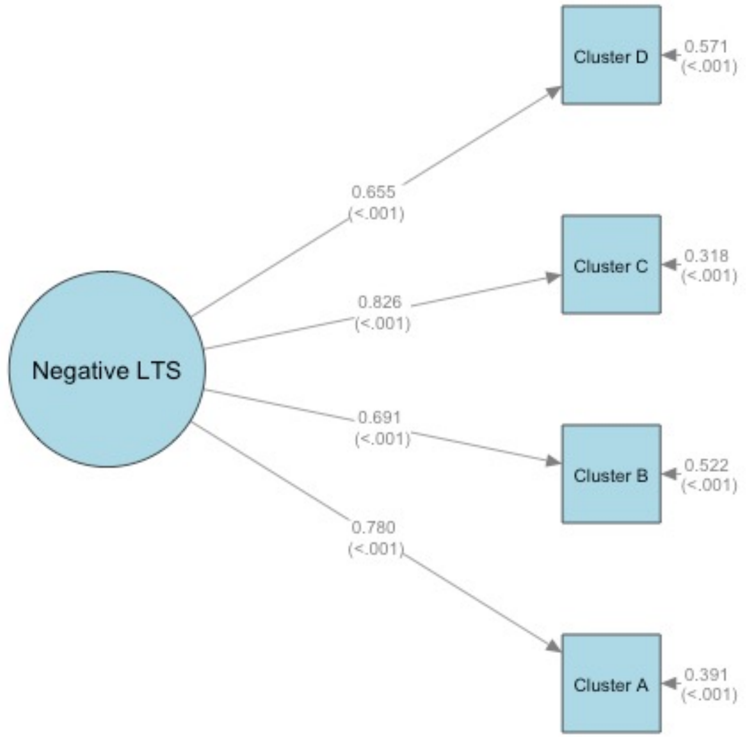
Method

1. A cross-validated Hierarchical Latent Dirichlet Allocation (hLDA) was trained over 50,000 tweets.
2. Applied to the Twitter timelines of study subjects to classify individual tweets into four LDA topic clusters.
3. Positive and negative sentiments of each tweet were measured by an aggregate of established word emotion lexicons (NRC, the general inquirer, LIWC).
4. Averaged positive/negative sentiment for tweets classified into each topic cluster were computed for each individual.

Result



CFA for positive LTS, N = 842.



CFA for negative LTS, N = 842.

- Positive: ($\chi 2(2)$ = 33.10, p <.001, CFI =.97, RMSEA = .14, SRMR = .03, omega = .80, AVE =.51
- Negative: ($\chi 2(2)$ = 5.09, p =.08, CFI = 1.00, RMSEA = .04, SRMR = .01, omega = .82, AVE =.54
- H1 is supported.
- Positive and negative sentiment could each be predicted by several affect-related variables.

Reliability of Psychological Constructs and Results of Individual Psychological Predictor and Positive/Negative Latent Trait Sentiment models.

Predictors	α	Positive B	Negative B
Positive affect	.89	.04	-.15**
Negative affect	.88	-.15**	.29***
Self-monitoring; expressive behavior	.80	.08	.03
Self-monitoring, self-presentation	.79	.06	.11*
Behavioral activation, drive	.74	.07	.13
Behavioral activation, fun-seeking	.68	.21***	.22***
Behavioral activation, reward	.70	.14	.17
Behavioral inhibition	.56	.30***	.32***
Optimism	.86	-.01	-.19***
Life satisfaction	.90	.08**	-.08**
Counterproductive work behavior	.86	.15**	.22***
Extraversion	.85	.08	-0.06
Agreeableness	.77	.07	-0.22***
Conscientiousness	.60	-.09	-0.36***
Neuroticism	.87	.15***	0.31***
Openness	.76	-.27***	-0.1

*$p < .05$. **$p < .01$. ***$p < .001$.

- SEM models of affect-related psychological variables predicting positive/negative LTS are tested to explore the nomological network around LTS.
- Some relationships are consistent with theory but some are not.
- Results associated with negative LTS was generally consistent with prior findings, except for self-monitoring, self-presentation.
- Some differences occurred in the positive LTS models.
- Possible difference between positive affectivity and expressing positivity on social media.

Summary

- Psychometrically reliable and valid measures of LTS can be created.
- Stable affect-related psychological traits predicted variance in LTS
- This level of prediction can be achieved by small samples.

Application and Limitation

- Application: Correcting for the bias that LTS introduce in between-subjects comparisons → better prediction.
  - Using affect to predict work outcomes on social media
  - broader situationally-dependent predictors of work outcome.
- Limitation: difficulty with interpreting situations represented by topic clusters

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Comparison of Social Support Seeking Online Across Workers in Essential Industries

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Agenda

Stressors incurred from COVID

The role of social support

Impact on essential workers

BERT Model overview

Data collection

Results

Discussion

Impact of COVID: An Occupational Health Perspective

- The COVID-19 pandemic has been closely connected with several work- and family-related stressors (Sun et al., 2020)
- These stressors could be related to:
    - Health concerns (Trougakos et al., 2020)
    - Increases in job demands (Shao et al., 2021)
    - Potential loss of employment (Wilson et al., 2020)

How do we handle this stress?

- One important means of coping with stress is social support seeking (Cohen et al., 2015; Hostinar & Gunnar, 2015; Langford et al., 2018)
- Social support is widely considered to encompass supportive behaviors including:
    - Appraisal support
    - Emotional support
    - Informational support
    - Instrumental support
- Support seeking tends to increase in the face of new stressors (Eisenberger, 2013)
- An examination of social support seeking during specific events could allow for a better understanding of how and when coping occurs

The Current Project

- We sought to compare temporal trends in support seeking across four essential industries (Economic Policy Institute, 2019)
    1. Construction
    2. Education
    3. Grocery
    4. Travel
- We leveraged a neural network-based Natural Language Processing model that evaluates the extent to which a string of text is indicative of support seeking (Minton, 2021)
- Examined changes in support seeking
    - Over time
    - Between industries

The Model Utilized

- A BERT neural network model (Devlin et al., 2019) pre-trained on Reddit data to receive a post from social media, and then provide a continuous evaluation (endpoints = 1 to 5)
  - 1 → Not at all Indicative of Support Seeking
  - 5→ Very Indicative of Support Seeking
- Cross-Validated Correlation Coefficient = 0.79
- Cross-Validated Mean Absolute Error = 0.54

```
statements_to_predict = ["My coworker stole my lunch for the third day in a row."]

tokenized_statements_to_predict = tokenizer.batch_encode_plus(
                    statements_to_predict,                      # Sentence to encode.
                    add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                    truncation=True,
                    padding="max_length",
                    return_tensors = 'np',     # Return pytorch tensors.
               )
predictions = model.predict([tokenized_statements_to_predict['input_ids'],tokenized_statements_to_predict['attention_mask']])
predictions
```

```
TFSequenceClassifierOutput([array([[3.912705]], dtype=float32)])
```

Data Collection

- Text posts were mined from industry-specific forums on Reddit.com
- All mined messages contained user text (not images or videos)
- All mined messages were posted from January, 2019 – July, 2021
- N = 208,936
- Predictions of each post for each respective industry were mean-centered

Subreddits Mined for Data Collection

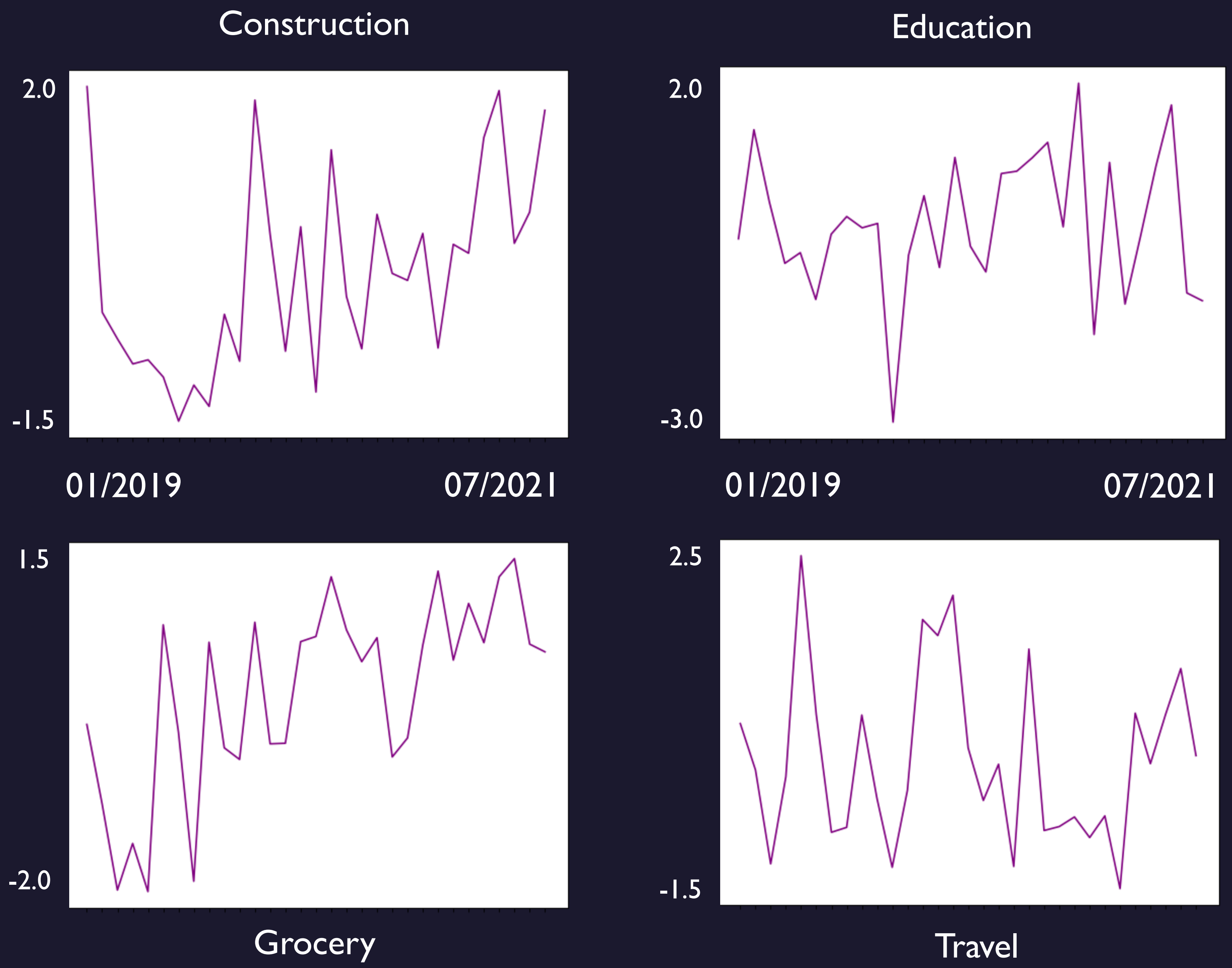
Industry	Subreddit	General Audience
Construction	Construction	Employees who work in construction
Construction	ConstructionManagers	Employees who manage construction sites/companies
Construction	BuildingScience	Employees in disciplines such as civil engineering
Education	Education	Employees in education or education administration roles
Education	Teachers	Elementary, middle, and high school teachers
Education	Professors	Collegiate-level professors
Education	LearningScience	Employees broadly within the educational system
Grocery	Kroger	Employees of Kroger grocery stores
Grocery	Publix	Employees of Publix grocery stores
Grocery	Tjcrew	Employees of Trader Joe's grocery stores
Travel	Flights	Employees of airlines/airports and frequent fliers
Travel	Cruise	Employees of cruise ships
Travel	FlightAttendants	Flight Attendants

Reliability & Aggregation

- Examined internal consistency of the monthly maximum scores for each subreddit within an industry
- Sufficient internal consistency was found for all 4 industries:
  - Construction: (α=0.60)
  - Education: (α=0.82)
  - Grocery: (α=0.70)
  - Travel: (α=0.72)
- Took the average support seeking score across subreddits for each month

Results

- We mean-centered the aggregated monthly means for each subreddit across time
- Because of overall industry-level differences in posting frequency, discussion is confined to the within-industry level



Discussion

- The variability of these results suggests there is no "one size fits all" description of pandemic-related effects on support seeking
- Each industry demonstrated "peaks" and "valleys" at different, but specific, points in time relative to their general means
- The social support seeking BERT Model could lends itself to future analyses
  - The uncertainty of the pandemic can bring some research to a grinding halt
  - However, this data source and analytic approach makes ongoing research in a pandemic world more feasible

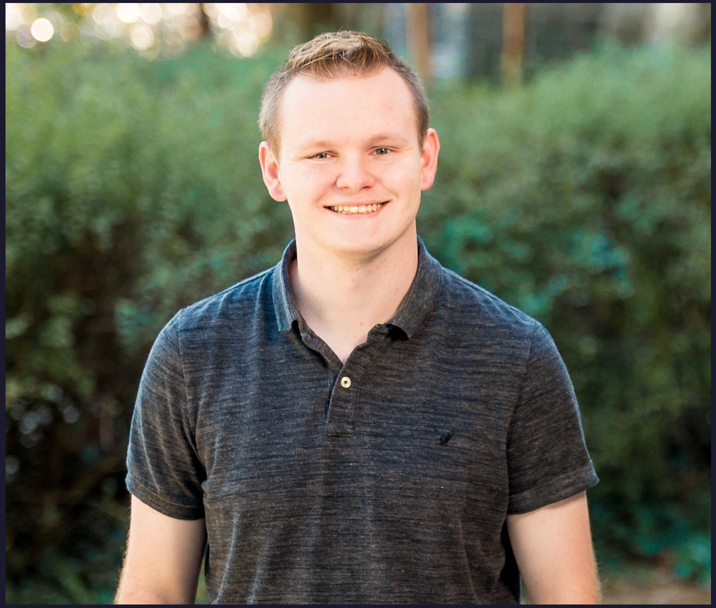
Limitations

- The participants used to develop the model were not broad subject matter experts
- Support seeking is more than a linguistic expression on social media
  - Contextual information (emojis, images, previous posts by the user) is unaccounted for
- Moderators that could improve model performance (such as personality differences) are not considered

Future Directions

- Implementation of the model in intervention/clinical settings to scalably identify people who need support
  - Optimization of recall metric to minimize missing a real occurrence of support seeking
  - Optimization of a precision metric to maximize the efficacy of an intervention
- Develop a model that can predict responses that would be perceived as most supportive
- Explore the generalizability of the results within other cultures

Research Team



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Automating the Generation of Vocational Interest Profiles from Occupation Descriptions

Presenter: Jeff Dahlke, HumRRO
Co-Author: Dan Putka, HumRRO

Annual Conference
2022 SIOP
SEATTLE • APRIL 27-30

The Value of Vocational Interests

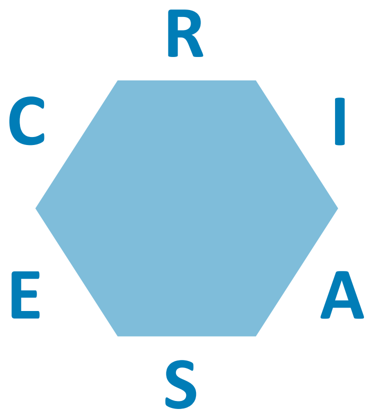
- Vocational interests are important non-cognitive attributes that contribute to individuals' occupational choices

- Interest dimensions can be used to profile both individuals and occupations
  - Useful for career guidance and occupation exploration
  - Contributes to our understanding the "O" part of occupations' KSAOs
  - Helps to understand person-job congruence

- Quantifying the interests associated with occupations typically requires SME input
  - Time consuming
  - Costly

Interest Models: A High-Level Overview

- **Holland's RIASEC model**
  - The most widely known and used vocational interest framework
  - Dimensions are general enough to apply across industries and cultures
  - Organizes Realistic, Investigative, Artistic, Social, Enterprising, and Conventional interests in a circumplex structure



- **Basic interests**
  - Specific, homogenous units of interests represented by work activities that have similar properties
  - Provides a more fine-grained picture of interests than is available with RIASEC
    - E.g., the "writing" and "performing arts" basic interests are distinct, but are both associated with RIASEC's Artistic dimension

Premise for the Present Research

- The Occupational Information Network (O*NET) maintains a rich database that includes occupational profiles on interest dimensions
  - Well-curated
  - Freely available
  - However, it requires lead time to collect information about the interests associated with new and emerging occupations
  - Currently only offers RIASEC interest profiles; no data about basic interests

- We explored how natural language processing (NLP) could automate the generation of occupation-level interest profiles using only:
  - Text from O*NET describing the work performed in occupations
  - Text from vocational interest measures

- We aimed to determine whether synthetic NLP-based interest profiles could supplement or replace profiles informed by SMEs

Method

Method: Sources of Data

- O*NET 25.3 Database
  - Source of data for 874 O*NET Standard Occupational Classification (O*NET-SOC) codes with the following information:
    - RIASEC profiles
    - Occupation descriptions
    - Task statements
    - Detailed work activities (DWAs)

- Interest Measures
  - RIASEC
    - O*NET Interest Profiler Short Form (Rounds et al., 2010)
    - Interest Profiler Sets A and B (Armstrong et al., 2008)
  - Basic Interests
    - Comprehensive Assessment of Basic Interests (CABIN; Su et al., 2019)
    - Basic Interest Markers (BIM; Liao et al., 2008)

Method: Procedure

- Treated each interest item, task statement, DWA, and occupation description sentence as a separate “document”
- Converted each document’s text into quantitative dimensions (embeddings) using the Sentence-BERT transformer model (SBERT; Reimers & Gurevych, 2019)
- Computed cosines between the embeddings for all O*NET documents and all interest items
- Averaged the cosines between documents from each pair of O*NET-SOCs and interest scales
  - Produced an aggregate metric of similarity between occupations and interest dimensions
  - Served as our synthetically derived interest scores
  - Performed this averaging procedure separately for O*NET documents representing tasks, DWAs, and occupation descriptions
- Averaged the results from the three types of O*NET text (tasks, DWAs, and descriptions)
  - Exploratory analyses suggested this improved recovery of the RIASEC circumplex structure

Results

Correlations Between Occupation-Level O*NET RIASEC Scores and Synthetic Scores on RIASEC Instruments

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Interest Measure	Interest Scale	*R*	Strongest Correlate	Correlations with O*NET RIASEC Scores					
				R	I	A	S	E	C
O*NET IP Short Form	Realistic	.87	R	.76	-.21	-.31	-.69	-.42	-.03
Rounds et al. (2010)	Investigative	.78	I	.35	.65	-.07	-.24	-.49	-.21
	Artistic	.79	A	.18	-.01	.50	-.29	-.29	-.24
	Social	.91	S	-.53	.18	.32	.84	.13	-.29
	Enterprising	.74	E	-.04	-.39	-.17	-.24	.37	.30
	Conventional	.73	C	.08	-.15	-.28	-.49	.03	.55
IP RIASEC Markers Set A	Realistic	.84	R	.76	-.16	-.28	-.69	-.45	-.06
Armstrong et al. (2008)	Investigative	.78	I	.11	.74	.15	-.02	-.41	-.31
	Artistic	.79	A	.20	-.06	.49	-.28	-.24	-.27
	Social	.89	S	-.55	.09	.27	.83	.21	-.22
	Enterprising	.71	R	.25	-.48	-.29	-.34	.16	.24
	Conventional	.74	C	-.14	-.14	-.31	-.31	.22	.65
IP RIASEC Markers Set B	Realistic	.87	R	.76	-.23	-.35	-.65	-.40	-.03
Armstrong et al. (2008)	Investigative	.74	I	.06	.72	.03	.12	-.37	-.25
	Artistic	.80	A	.18	.04	.49	-.31	-.28	-.24
	Social	.90	S	-.33	.18	.26	.75	-.04	-.35
	Enterprising	.69	E	.06	-.43	-.06	-.30	.24	.20
	Conventional	.73	C	-.40	-.11	-.16	-.11	.39	.63

Correlations Between Occupation-Level O*NET RIASEC Scores and Synthetic Basic Interest Scores

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Comprehensive Assessment of Basic Interests (CABIN; Su et al., 2019)

Interest Scale	Strongest Correlate	Correlations with O*NET RIASEC Scores R	I	A	S	E	C
Construction/Woodwork	R	.74	-.21	-.20	-.61	-.46	-.15
Mechanics/Electronics	R	.72	-.07	-.34	-.62	-.41	-.03
Physical/Manual Labor	R	.71	-.38	-.41	-.68	-.31	.08
Nature/Outdoors	R	.70	-.15	-.30	-.56	-.29	-.17
Transportation/Machine Operation	R	.67	-.26	-.46	-.53	-.23	.04
Engineering	R	.51	.29	-.14	-.53	-.41	-.13
Agriculture	R	.47	.15	-.17	-.39	-.26	-.19
Culinary Art	R	.43	-.08	.11	-.36	-.35	-.15
Applied Arts and Design	R	.40	-.06	.29	-.50	-.29	-.22
Visual Arts	R	.39	.01	.36	-.44	-.42	-.30
Protective Service	R	.18	.04	-.37	-.18	.08	.18
Life Science	I	-.05	.73	.18	.00	-.29	-.20
Physical Science	I	.19	.69	.08	-.32	-.40	-.13
Medical Science	I	-.26	.66	.14	.47	-.16	-.25
Mathematics/Statistics	I	-.18	.65	.24	-.18	-.12	.01
Social Science	I	-.65	.57	.40	.45	.22	-.13
Information Technology	I	.07	.36	-.08	-.32	-.12	.18
Animal Service	I	.24	.24	-.15	.18	-.23	-.27
Writing	A	-.64	.25	.63	.27	.23	.02
Media	A	-.42	.28	.61	.08	.15	-.08
Humanities	A	-.48	.54	.58	.35	-.07	-.22
Performing Arts	A	.03	-.06	.54	-.08	-.17	-.28
Social Service	S	-.56	.11	.19	.81	.25	-.19
Religious Activities	S	-.58	.16	.48	.79	.13	-.31
Personal Service	S	-.64	-.10	.19	.70	.50	.04
Professional Advising	S	-.74	.18	.37	.63	.44	-.04
Public Speaking	S	-.82	.13	.48	.62	.51	-.03
Health Care Service	S	-.22	.45	.03	.58	-.14	-.20
Teaching/Education	S	-.39	.32	.51	.58	-.06	-.36
Athletics	S	.05	.06	.12	.38	-.14	-.38
Politics	E	-.78	.23	.33	.51	.59	.02
Human Resources	E	-.67	.08	.11	.38	.56	.22
Finance	E	-.60	.19	.09	.02	.54	.36
Marketing/Advertising	E	-.43	-.04	.20	-.09	.50	.24
Management/Administration	E	-.46	.08	.18	.27	.44	.02
Law	E	-.70	.37	.22	.36	.42	.14
Sales	E	-.19	-.28	.00	-.08	.35	.20
Business Initiatives	E	-.18	-.08	.03	-.29	.35	.22
Accounting	C	-.48	-.08	-.10	-.05	.47	.59
Office Work	C	-.54	-.05	.01	.08	.42	.53

Basic Interest Markers (BIM; Liao et al., 2008)

Interest Scale	Strongest Correlate	Correlations with O*NET RIASEC Scores R	I	A	S	E	C
Manual Labor	R	.75	-.38	-.40	-.62	-.39	.00
Skilled Trades	R	.75	-.10	-.30	-.67	-.47	-.07
Outdoor-Agriculture	R	.69	-.10	-.32	-.53	-.32	-.16
Engineering	R	.63	.16	-.21	-.64	-.43	-.08
Physical/Risk-Taking	R	.35	.12	-.07	-.01	-.21	-.37
Protective	R	.30	-.08	-.47	-.08	.03	.10
Social Sciences	I	-.55	.62	.48	.51	.05	-.26
Physical Science	I	.37	.58	.01	-.45	-.47	-.17
Life Science	I	.25	.57	.04	-.22	-.42	-.20
Mathematics	I	-.04	.54	.27	-.24	-.27	-.04
Law	I	-.66	.37	.21	.36	.37	.16
Information Technology	I	.10	.31	-.02	-.34	-.15	.13
Creative Writing	A	-.57	.24	.71	.26	.15	-.10
Performing Arts	A	-.11	.05	.59	.15	-.10	-.34
Creative Arts	A	.22	.08	.51	-.30	-.35	-.32
Religious Activities	S	-.58	.17	.45	.81	.12	-.28
Social Service	S	-.61	.09	.21	.80	.30	-.16
Personal Service	S	-.41	-.21	.18	.59	.35	-.04
Athletic Coaching	S	-.26	.11	.20	.56	.12	-.27
Professional Advising	S	-.67	.29	.35	.56	.36	-.07
Teaching	S	-.51	.39	.52	.55	.01	-.24
Medical Service	S	-.09	.46	.02	.50	-.23	-.29
Family Activity	S	-.06	-.22	.29	.40	-.04	-.31
Management	E	-.56	.00	.06	.27	.59	.23
Politics	E	-.80	.26	.40	.46	.54	.01
Human Relations Management	E	-.66	.20	.19	.45	.49	.08
Finance	E	-.62	.18	.12	.04	.48	.37
Business	E	-.34	.06	.07	-.17	.45	.25
Sales	E	-.10	-.24	-.11	-.17	.31	.25
Office Work	C	-.14	-.23	-.25	-.14	.28	.47
Technical Writing	C	.04	.13	.12	-.35	-.12	.17

Takeaways

Innovative. Responsive. Impactful.

Takeaways

- We used NLP methods to relate text describing occupations to text from vocational interest measures
- We found promising evidence that these methods can produce construct-valid occupational interest profiles
    - Synthetic interest scores for RIASEC instruments exhibited convergence with RIASEC scores from O*NET
    - Synthetic scores for basic interest instruments produced meaningful patterns of correlations with O*NET's RIASEC scores
- Our results support the potential value of NLP-based interest profiles when SME-based profiles are unavailable or impractical to develop

Thank You!

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THANK YOU!

- Q&A Guided by Nick Koenig