NLP and Related Faculty

Niranjan Balasubramanian
Ritwik Banerjee
Owen Rambow
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Steven Skiena
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Paul Fodor
Jordan Kodner
Jeffrey Heinz
Jason Jones
Thomas Graf
Tuhin Chakrabarty
Yuan Gong
SBU NLP-related Research Groups

- Cognitive States Group - Owen Rambow
- Cognitive Science and Language Learning - Jordan Kodner
- DSL: Data Science Lab - Steven Skiena
- Grammatical Inference - Jeffrey Heinz
- HLAB: Human Language analysis Beings - H. Andrew Schwartz
- Ipseology and Identity Trends - Jason J. Jones
- KALM: Knowledge Authoring Logic Machine - Paul Fodor
- LAIR: Language and AI Research - Ritwik Banerjee
- LUNR: Language Understanding and Reasoning - Niranjan Balasubramanian
Artificial Intelligence

Psychology + Health

Stony Brook University
Human Language Analysis Beings
Artificial Intelligence

Psychology + Health
The Health of Individuals is Improving

(Source: US Centers for Disease Control; Age Adjusted Rates)
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25% increase since 1999

(Source: US Centers for Disease Control; Age Adjusted Rates)
Data in Health Care
Data in Health Care
Data in Health Care
Data in Health Care

Heart Disease Mortality Rate

Cancer Mortality Rate
Data in Health Care

Suicide Mortality Rate
Data in Health Care

Suicide Mortality Rate
Data in Health Care

Limited across

- **Time** - How frequent?
- **Spatial** - How many people?
- **Conceptual** - What aspects of daily life, who we are?
Data in Health Care

Limited across
● Time - How frequent?
● Spatial - How many people?
● Conceptual - What aspects of daily life, who we are?

~1960s Technology
Data in Health Care

Limited across
- **Time** - How frequent?
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Data in Health Care
Data in Health Care

Survey: Yes
Excellent:
Good:
Fair:
Poor:

Mental Health
683 Patients

Posts prior to first documented diagnosis.

Facebook Language
949,530 status updates

Diagnoses from Medical Record

Depression

683 Patients

Posts prior to first documented diagnosis.

Depression

Patient Language Encoding

Facebook Language
949,530 status updates

"Ugh stomach hurts, but still goin to the store later. :(")

"Sh** someone help me!")

"I am blessed to spend all day with my daughter"

Diagnoses from Medical Record

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Posts prior to first documented diagnosis.

Depression

Predict Diagnosis using Machine Learning

Patient Language Encoding

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Predict Diagnosis using Machine Learning

Patient Language Encoding

Survey:
- Excellent:
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Facebook Language

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Diagnoses from Medical Record

Depression

683 Patients
Prediction of Depression Diagnosis

False Positive Rate (Prob. of False Alarm)

True Positive Rate (Prob. of Detection)

Screening Surveys vs. Medical Records (Noyes et al., 2011)

Prediction of Depression Diagnosis

Facebook language predicts depression in medical records. Proceedings of the National Academy of Sciences. DOI:10.1073/pnas.1802331115

False Positive Rate (Prob. of False Alarm)

True Positive Rate (Prob. of Detection)

Screening Surveys vs. Medical Records (Noyes et al., 2011)
Prediction of Depression Diagnosis

Topics that predict depression

cry, tears, pain, sad, emotional, times, already, wish, baby, miss, soon, boy, missing, cold, stomach, headache, ugh, feel, hurt, ill, bad, hand, now, annoyed,ayed, nwupset, right, rite, confused.

False Positive Rate (Prob. of False Alarm)

True Positive Rate (Prob. of Detection)

Facebook Language Prediction vs. Medical Record

Screening Surveys vs. Medical Records (Noyes et al., 2011)

Social media language change prior to hospital visit

Social media language change prior to hospital visit

Social media language change prior to hospital visit

Addiction Treatment Outcome Risk Assessment

Addiction Treatment Outcome Risk Assessment

- Both (AUC = 0.81)
- Digital Phenotype (AUC = 0.75)
- Addiction Severity Index (AUC = 0.66)
- chance (AUC = 0.50)

AI for Mental Health

1. Digital footprints

2. Populations

3. Automated Interviews
AI for Mental Health

1. Digital footprints

2. Populations

3. Automated Interviews
Population Assessment

Population Assessment

1. Digital footprints

2. Population

3. Automated Interviews
1. Digital footprints

2. Population

3. Automated Interviews
accepted psychological scores

$r = 0.65$ to $0.85$

rating-scale assessments
"reliability"
accepted psychological scores

Good old-fashioned AI

$r = 0.4$ to $0.60$

rating-scale assessments

"reliability"

$r = 0.65$ to $0.85$
accepted psychological scores

theoretical upper-limit!

Good old-fashion AI

$r = 0.4 \text{ to } 0.60$

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$r = 0.4 \text{ to } 0.60$ — the theoretical upper-limit!
Good old-fashion AI

$r = 0.4$ to $0.60$

rating-scale assessments
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$+$ prompted language

LBAs with Transformers

$r = ??$

accepted psychological scores

Lund University


Good old-fashion AI

\[ r = 0.4 \text{ to } 0.60 \]

accepted psychological scores

\[ r = 0.65 \text{ to } 0.85 \]

rating-scale assessments "reliability"

\[ r = 0.84 \]

Lund University

+ prompted language

LBAs with **Transformers**

matches the theoretical upper-limit!
Clinic Application

Current and Future PTSD Severity (PCL Score)
<table>
<thead>
<tr>
<th>Interview language features</th>
<th>r (direct correlation with symptom slope)</th>
<th>( \beta ) (adjusted for age, gender, occupation, days since 9-11, Interview PCL)</th>
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<td>0.30* (0.08–0.49)</td>
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- **Predict?**
- **Time**
- **Interview date**
- **PTSD symptoms future trajectories**
- **Symptom severity**
- **External Validity!**
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**Figure:**

- The graph illustrates the future trajectories of PTSD symptoms over time for those with high usage vs. those with low usage.
- The $y$-axis represents symptom severity.
- The $x$-axis represents time difference (years) since the interview date.

**Legend:**

- **Red Line:** Those with high usage.
- **Blue Line:** Those with low usage.

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**PTSD-STOP:**

**Symptom Tracer and Outcome Prognosticator**

communication

1. video
2. audio
3. language

![New multimodal AI model (PTSD-STOP)]

- hyper-arousal
- numbing
- avoidance
- re-experiencing
- open-vocab markers

Oscar Kjell (Psychology, Lund Univ)
Roman Kotov (Psychiatry, SBU)
Dimitris Samaras (CS, SBU - Vision)

Overarching Goal: Develop and evaluate AI-based communication assessment of current symptoms and future outcomes.
AI for Mental Health

1. Digital footprints

2. Populations

3. Automated Interviews
Thank You:
Collaborators

Johannes Eichstaedt  Oscar Kjell  Ryan Boyd  Katarina Kjell  Niranjan Balasubramanian

MZ Zamani  Veronica Lynn  Salvatore Giorgi  Matthew Matero  Rediet Abebe  Roman Kotov  Martin Seligman

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World Well-Being Project

Stony Brook University
Human Language Analysis Beings
Thank You!

Artificial Intelligence

Psychology + Health

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Stony Brook University
Human Language Analysis Beings