Flattening the Emotional Curve with New AI Systems

Computer simulation as a tool for policymakers and stakeholders in times of crisis

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AnyLogic Conference
Sept. 2021

September, 2021

Overview

1) Background
2) COVID Modeling
3) Model Validation
4) The CulturePulse Pipeline and AnyLogic
5) Automated Model Initialization
6) Future Research and Applications

Background

- Open call from the Norwegian government. Approached by NORCE (Norway's largest think tank)
- Project needed to track emotion and misinformation on Twitter.
- Multi-Agent AI model would be used
- Validated with a survey for national representativeness "on the ground"
- Validated through social media data "in silico"

Project Leaders

Dr. Justin E. Lane

D.Phil, University of Oxford

10+ Years Simulation Experience

CTO, Co-Founder
ALAN Analytics

Prof. F. LeRon Shults

2x Ph.D, Princeton

6+ Years Simulation Project Management

CEO, Co-Founder
ALAN Analytics

COVID Modeling

Most COVID-19 models focused on modeling the spread of the virus (SIR models).

Our specialty is not epidemiology. Our specialty is human sociality. So our model focuses on the spread of emotional and how it affects human behaviors in realistic ways.

Specifically, we wanted to answer the questions:
Who will follow regulations?
When is misinformation more engaging?
What effects do anxiety have on political leanings and identities?

Model Validation

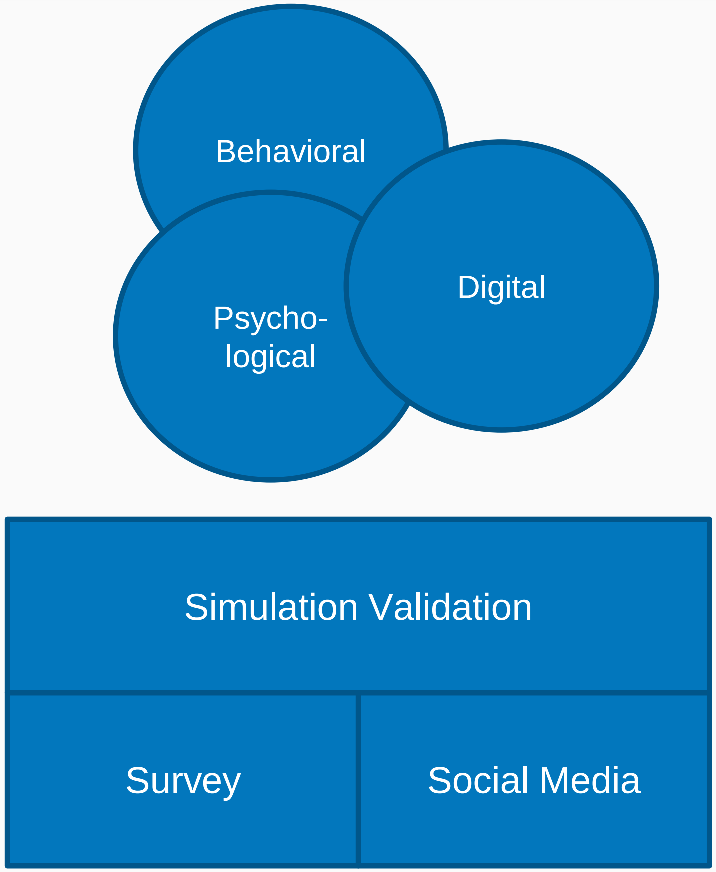
The models' key outputs are to be behavioral, psychological, and digital.

For behavioral, we will rely on survey data.

To get psychological and digital data, we can combine surveys with social media.

Surveys will use psycho-metrically validated measures

Social media data will be analyzed using new AI systems for creating psychographic profiles.



Model Validation – Behavioral

We completed a nationally representative survey.

Deployed over two waves to measure dynamics.

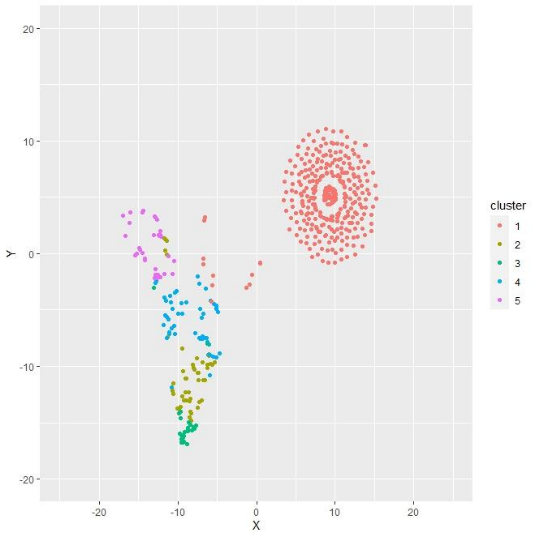
Measures were sociological, political, and psychological.

Belief questions about what kinds of misinformation they would spread revealed two clusters which showed a slight convergence over time.

Psychological measures were chosen by our team to address key cognitive metrics that can help us to measure:

1) How an individual will act or react to policy
2) How an individual has been affected by policy
3) Similarities and links to the social media data.

Behavioral



Cluster change over time.

Model Validation - Psychological

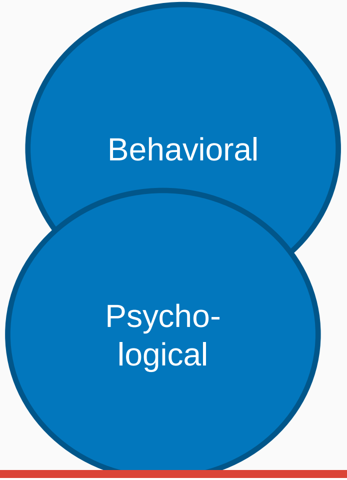
We completed a nationally representative survey.

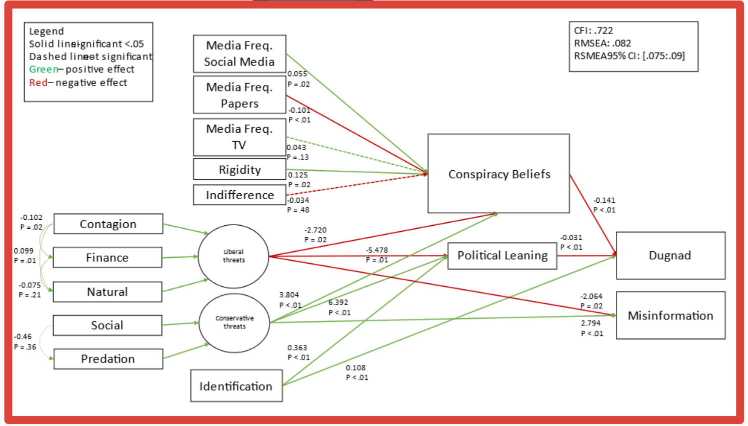
Deployed over two waves to measure dynamics.

Psychological questions were aimed at creating links between psychology and behavior that can also reach to the social media analytics pipeline.

Key findings:

1) Different perceived threats have real world effects on political leanings,
    1) which in turn interact with identification to promote conspiracy, misinformation, and lessen following of regulations
2) Social media frequency has an effect on conspiracy beliefs. Papers don't.
3) Cognitive rigidity also promotes conspiracy beliefs.





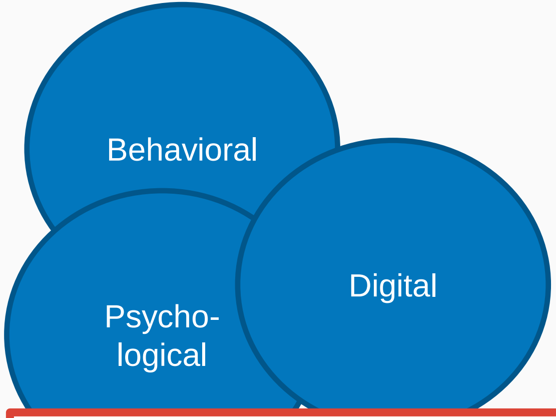
Model Validation - Digital

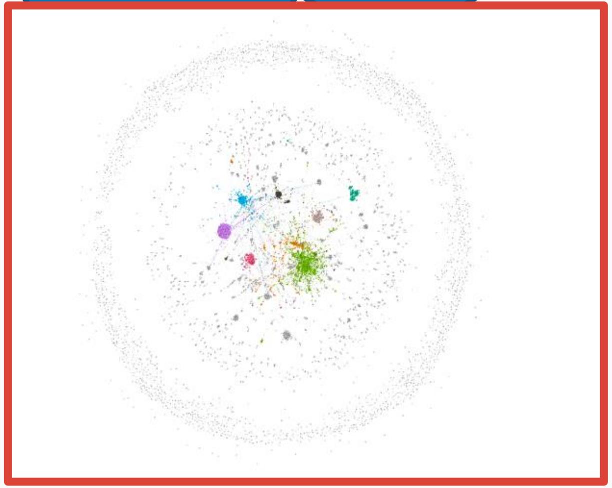
Social media scraping was used to create two critical initialization functions for the platform.

1) Social Networks- From the data provided by the Twitter API

2) Psychographic maps of users-From analyzing text data using the CulturePulse API.

The Social network revealed large influences outside of Norway, but that clusters were more related to language use than beliefs.





The CulturePulse Pipeline

To approximate psychology from social media data we used CulturePulse's psychographic mapping tools.

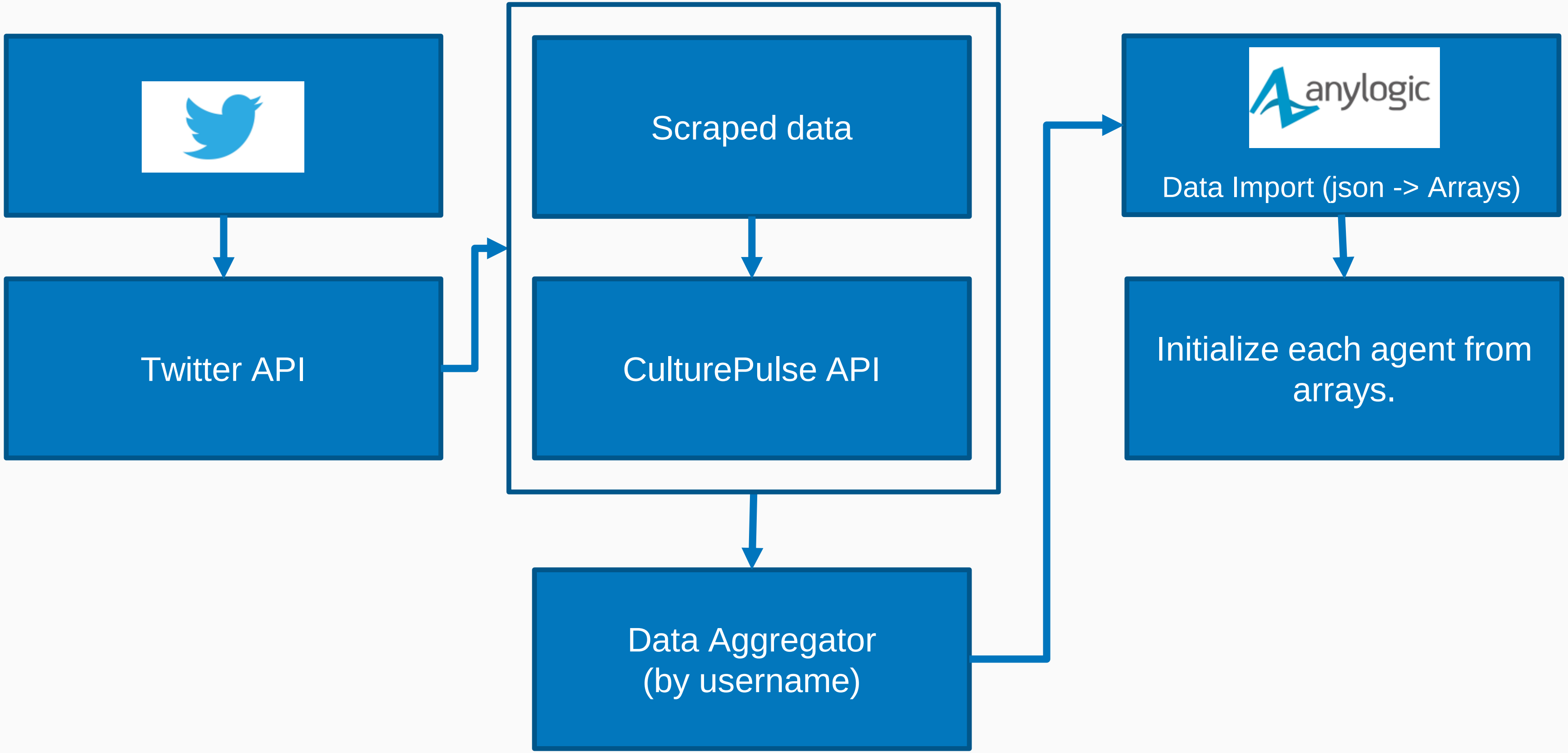
This allows us to input the raw unstructured text and return approximate psychographic parameters:

- Developed from **10 years of lab research**
- Currently functional across **40 languages and cultures**
- Provides accuracy levels acceptable in clinical research settings.
- Methods and ontology has undergone external validation in several studies going back to 2009.
- Goes beyond sentiment and includes anger, anxiety, personality, morality, family, friends, finances, inclusivity, racism, and **50+ other categories***
- Deployable on client servers without API for security and compliance

*See full taxonomy for all categories in CulturePulse's ontology on Slide 15

Disclosure: CulturePulse Inc. is a spinoff company from ALAN Analytics.

Connecting with AnyLogic



Automated Model Initialization

By creating automated model initialization functions from social media we:

- Significantly speed up model initialization.
    - Psychologicla traits (modeled as agent parameters are often correlated, but creating those correlations at initialization can be tricky.
        - If you figure that out, you still have mediating variables between those correlations that can affect it.
        - Using snapshots of psychological traits from social media data allows for real-world approximations to be directly imported.
- Increase accuracy of social network construction.
    - Social networks can be tracked and imported directly. Often from APIs.
- Can spend more time developing agent behaviors and statecharts.
- Using psychometrically validated algorithms, we are able to draw direct links to psychological empirical literature that can be used in validation.

Initial Results

Initial results suggest that different geographic regions (Scandinavia vs outside Scandinavia) have different belief and value signals that are affecting the spread of misinformation as well as the kinds of misinformation that are spread.

	Dependent variable:	
	misinformation	
	(1)	(2)
moral_isauthorityvice	-0.268	-3.339***
	(-1.007, 0.472)	(-4.603, -2.075)
moral_isauthorityvirtue	1.110***	-0.464***
	(0.837, 1.384)	(-0.760, -0.168)
moral_isfairnessvice	-0.701	2.168**
	(-4.565, 3.164)	(0.036, 4.300)
moral_isfairnessvirtue	0.395	1.175*
	(-0.764, 1.555)	(-0.073, 2.422)
moral_isharmvice	-0.101	0.271
	(-0.387, 0.184)	(-0.269, 0.812)
moral_isharmvirtue	-0.708***	0.855***
	(-1.200, -0.216)	(0.426, 1.283)
moral_isingroupvice	5.318***	5.703***
	(3.510, 7.127)	(1.420, 9.985)
moral_isingroupvirtue	-0.576***	-0.368*
	(-0.904, -0.248)	(-0.806, 0.070)
moral_ispurityvice	1.110***	0.044
	(0.819, 1.401)	(-0.435, 0.523)
moral_ispurityvirtue	-0.797	2.930***
	(-1.809, 0.216)	(1.885, 3.975)
moral_ismoralitygeneral	3.223***	0.463**
	(2.869, 3.577)	(0.061, 0.864)
Constant	0.390***	0.452***
	(0.385, 0.396)	(0.443, 0.461)
Observations	17,000	6,620
Residual Std. Error	0.440 (df = 16988)	0.441 (df = 6608)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

	Dependent variable:	
	Engagement Count	
	(1)	(2)
Readability (LIX)	0.233**	-0.840***
	(0.044, 0.421)	(-0.921, -0.758)
Misinformation	-2.118	-5.371**
	(-10.708, 6.473)	(-9.618, -1.124)
Eating/Drinking	6.976	-331.325***
	(-194.116, 208.069)	(-423.411, -239.240)
Sexual language	-166.423*	-307.852***
	(-353.427, 20.580)	(-384.918, -230.787)
Corporeal Language	-249.196***	46.766
	(-433.026, -65.367)	(-31.997, 125.530)
General Biology	375.930***	280.930***
	(186.128, 565.733)	(198.259, 363.600)
Health Concerns	-72.752	-346.052***
	(-259.380, 113.876)	(-431.373, -260.730)
Female Gender Focus	337.591***	-1.658
	(271.741, 403.441)	(-37.570, 34.254)
Male Gender Focus	52.839	-38.167***
	(-12.003, 117.681)	(-65.956, -10.377)
Focus Past	38.498	6.816
	(-17.055, 94.050)	(-23.251, 36.884)
Focus Present	64.199***	15.238**
	(34.652, 93.746)	(0.958, 29.518)
Focus Future	62.834	-16.264
	(-35.694, 161.362)	(-69.480, 36.951)
logSigma	5.097***	3.915***
	(5.083, 5.111)	(3.894, 3.935)
Constant	-59.458***	53.991***
	(-72.705, -46.211)	(47.897, 60.086)
Observations	17,000	6,620
Log Likelihood	-74,276.650	-26,178.400
Akaike Inf. Crit.	148,581.300	52,384.810
Bayesian Inf. Crit.	148,689.700	52,479.980
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Future Research and Applications

- Create more robust models and applications toward policy related to ethnic conflict resolution.
- Demonstrate to policy-makers that utilizing relevant data from representative surveys and social media can provide the cultural attenuation required to make cross-cultural models more contextually relevant.
- Working with new social media companies (ex. Minds.com) to utilize simulation results to better understand (and possibly reverse) radicalization processes .

- Initialize previous models of social instability using this approach to further validate policy-relevant models and increase predictive power. Examples:

BBC


Tech

Can artificial intelligence help stop religious violence?

By Mark Easton
Home editor

31 October 2018

VICE


MOTHERBOARD

Researchers Simulated Religious Groups With AI to Try to Understand Religious Violence

The researchers modeled how xenophobia and anxieties mutually escalate between religious groups using "psychologically realistic" AI.

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TECHNOLOGY 2 October 2019

By Graham Lawton

SCIENCELINE
THE SHORTEST DISTANCE BETWEEN YOU AND SCIENCE


TECH

Can we use AI to predict social unrest?

A team of researchers has created an artificial intelligence (AI) system that mimics human religiosity, laying the groundwork for psychologically accurate AI that can predict human behavior

PASSANT RABIE • FEBRUARY 28, 2019

“No one ever made a decision because of a number. They need a story.”

— Daniel Kahneman
(2002 Nobel Prize Winner: Economics)

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Appendix

CulturePulse Taxonomy

Demographics
Age, gender, ethnicity

Psychological
Affect, anger, sadness, anxiety, positive emotion, negative emotion

Personality
Big-5 personality factors: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism

Moral
Harm, fairness, ingroup, authority, purity
Trust

Personal interest
Finance, work, religion, mortality

Social
Family, friends, general sociality, inclusivity, exclusivity, conflict

Biological
General, contagion, sexual, food/beverage

Financial
Finance general, stocks (NYSE and NASDAQ), crypto (top 50 crypto by market cap 2021)

Threat
Social, contagion, financial, natural, predation

Linguistic
Pronoun use and part of speech tagging

Language focus patterns
Focus on gender, past, present, or future, focus on numerical or quantification, etc.

Hate speech
Hate speech, offensive speech, neither

Space-Time language
Relative space and time dimensions