Computational Social Science: From Digital Traces to Generative Agents

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slides at dgarcia.eu/MUCSS-2024

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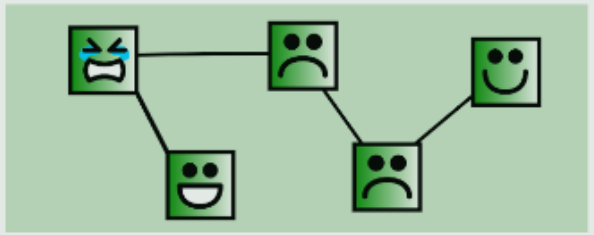
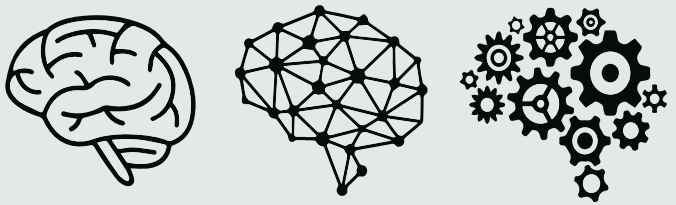
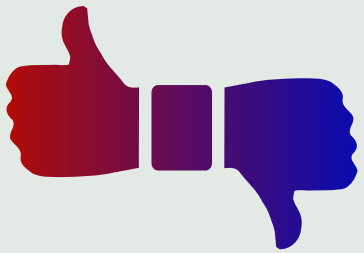
Research



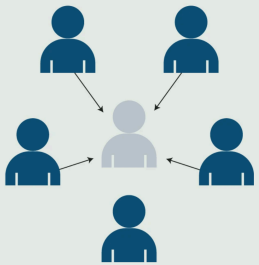
Computational Affective Science



Information Disorder



Inequality and Polarization



Complex Privacy

Education

ETH zürich

CSS
COMPUTATIONAL
SOCIAL SYSTEMS

MSc Social and Economic Data Science (SEDS)

Universität Konstanz

Outline

1. A View of Computational Social Science

2. Studying Emotions from Digital Traces

3. CSS with Generative Agents

Computational in Computational Social Science

It can have three meanings:

- **Digital**
  Based on large datasets of human behavior, for example produced by the Web and social media

- **Computerized**
  The quantitative analysis of data in an automated, tractable, repeatable, and extensible fashion

- **Generative**
  Application of data and results to design of agent-based models that explain complex social phenomena and motivate interventions

Avoiding data piñatas

TOP DEFINITION

data piñata

Big Data method that consists of **whacking** data with **a stick** and hopefully some insights will come out.

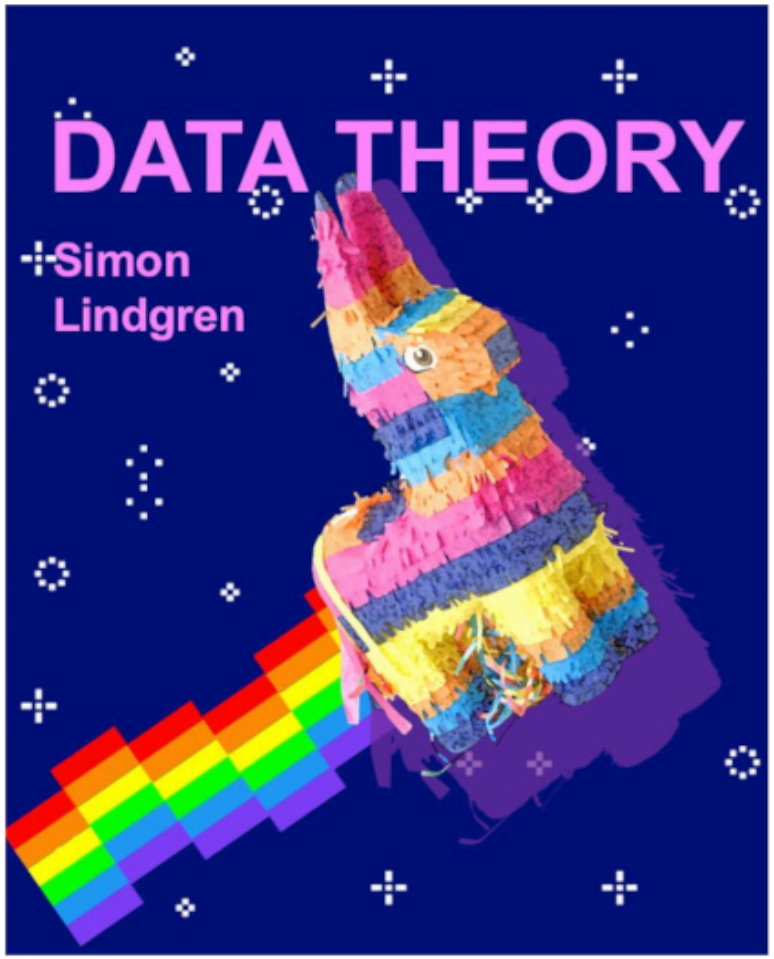
*The Big **Data Scientist** made a Twitter data piñata and found that **Saturdays** are the weekdays with the most tweets **linking** to kitty pictures.*

#big data #facebook #twitter #bullshit #hot air #

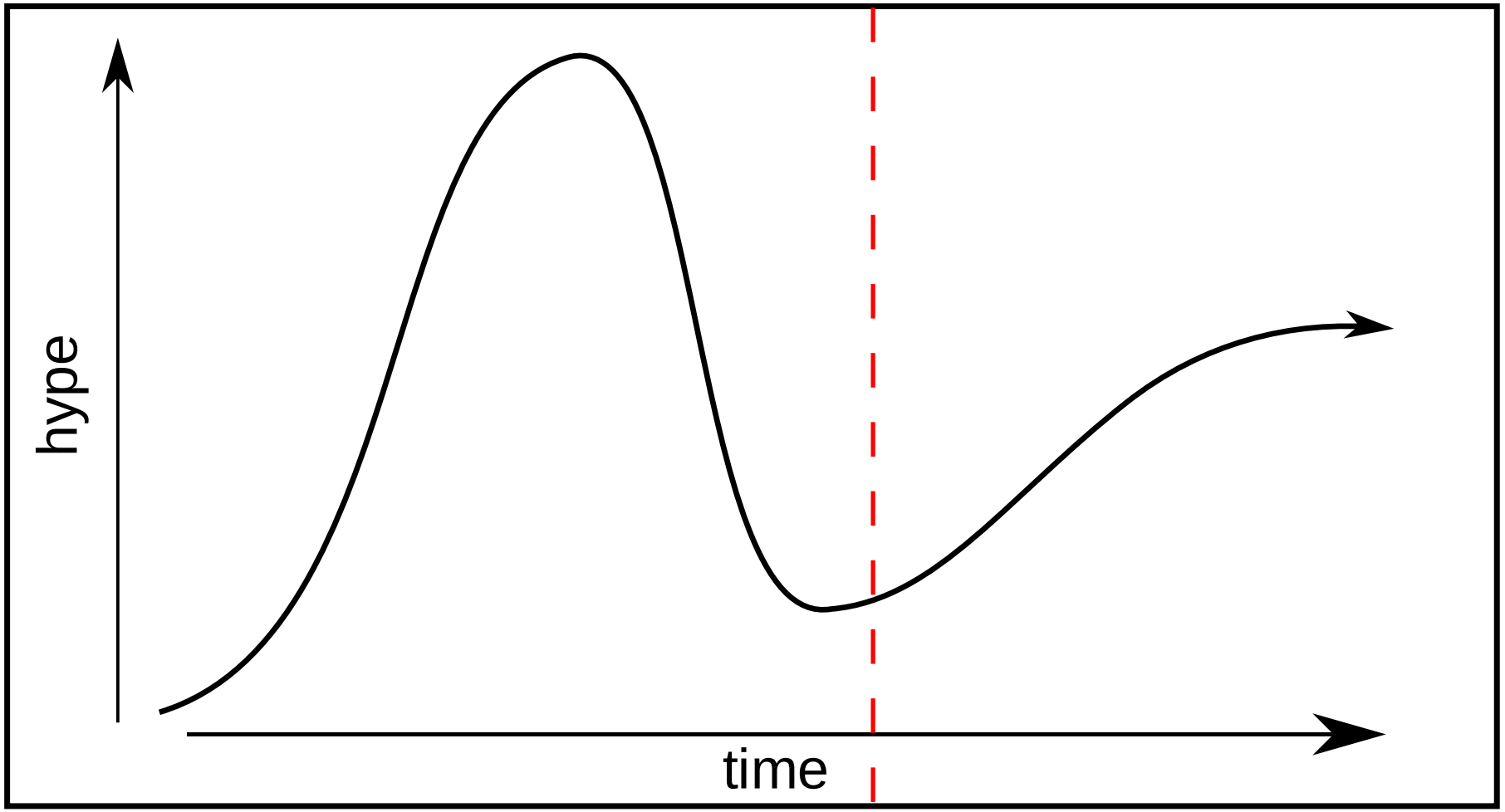
by dgarcia_eu January 16, 2015

10 0

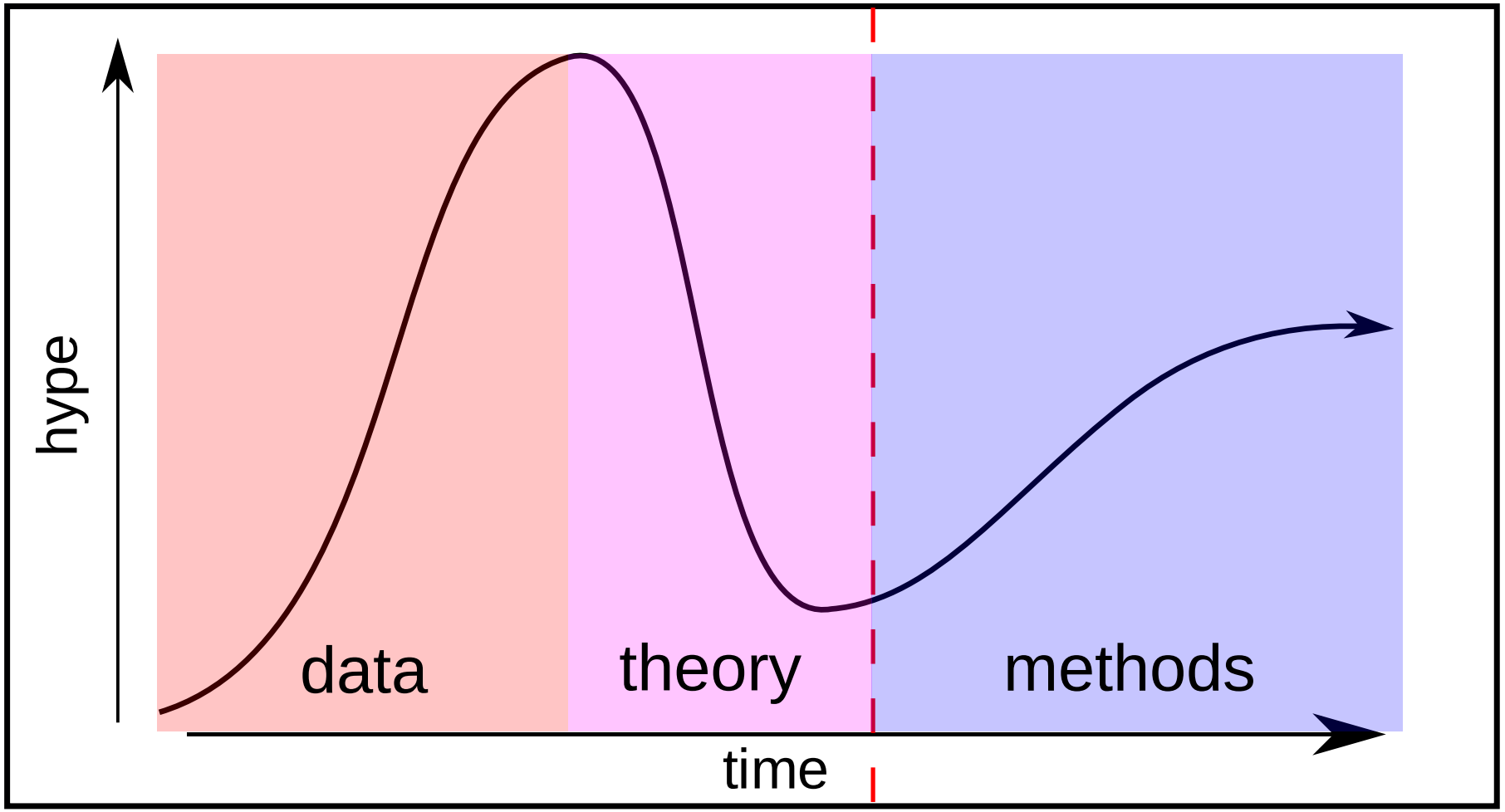
Get a data piñata mug for your coworker Yasemin.



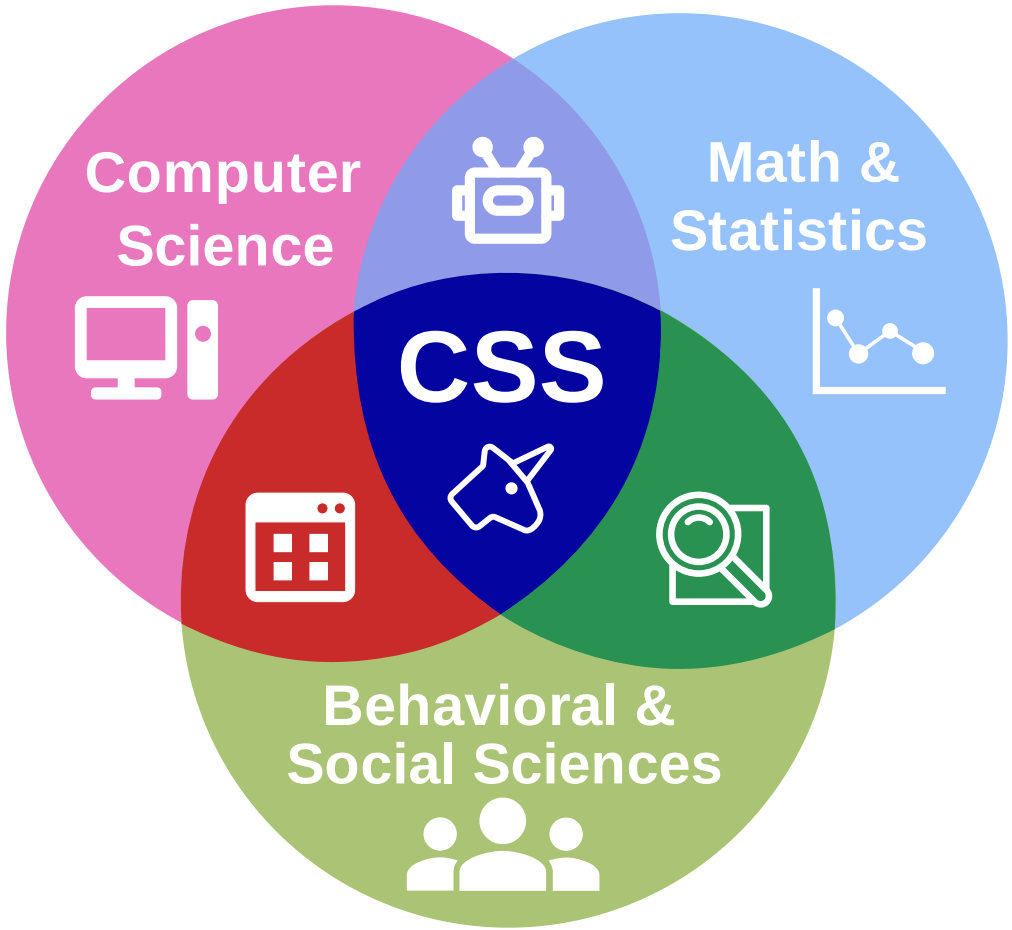
The Hype Cycle of Computational Social Science



The Hype Cycle of Computational Social Science

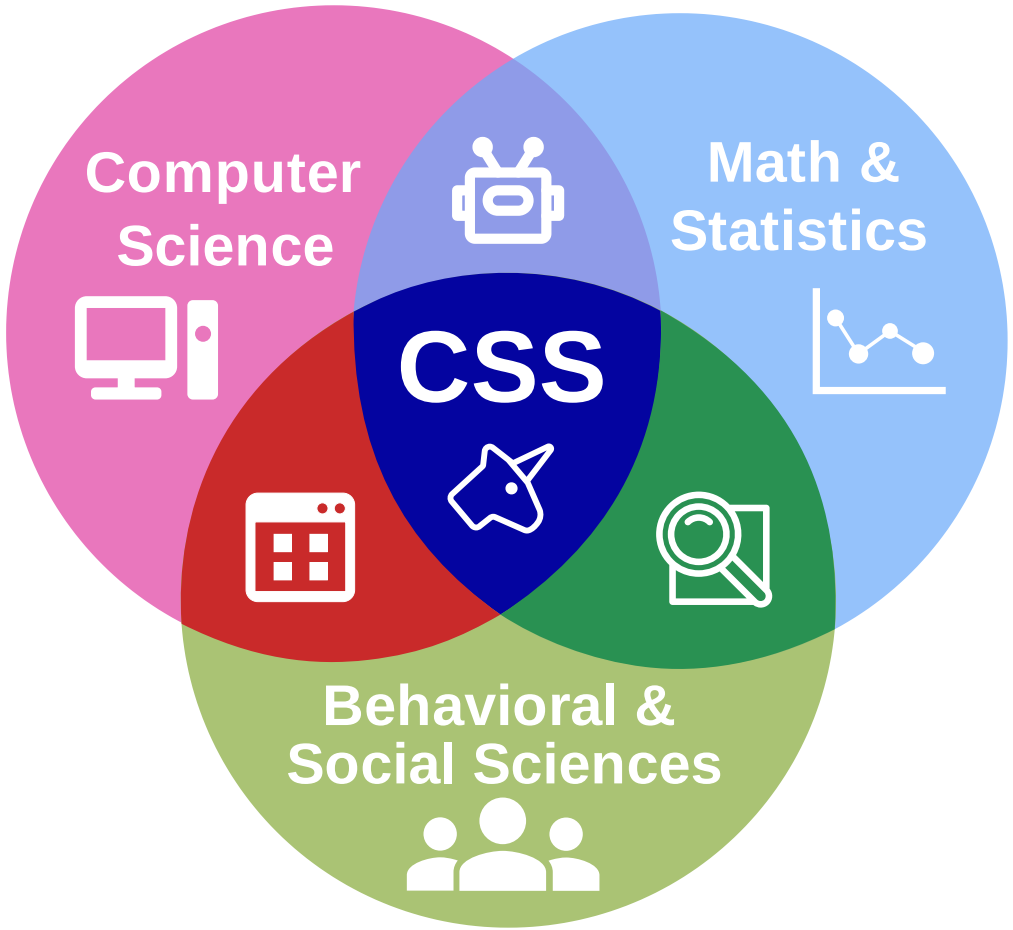


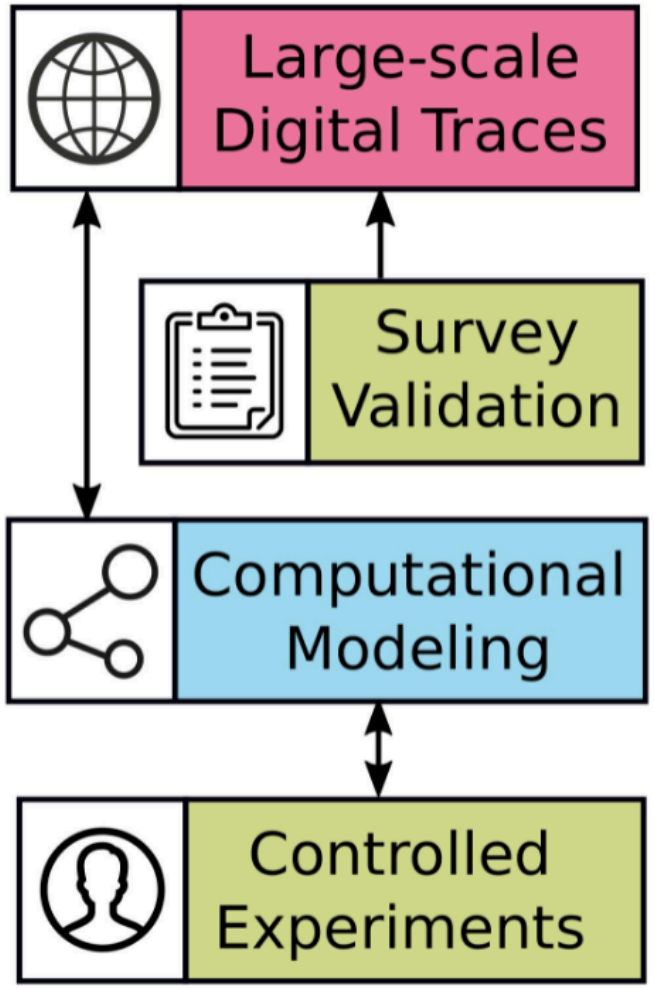
Bridging Disciplines in CSS



Statistics: Making sound inferences from too little data
CSS/SDS: Making meaningful inferences from too much data

Bridging Disciplines in CSS





Statistics: Making sound inferences from too little data
CSS/SDS: Making meaningful inferences from too much data

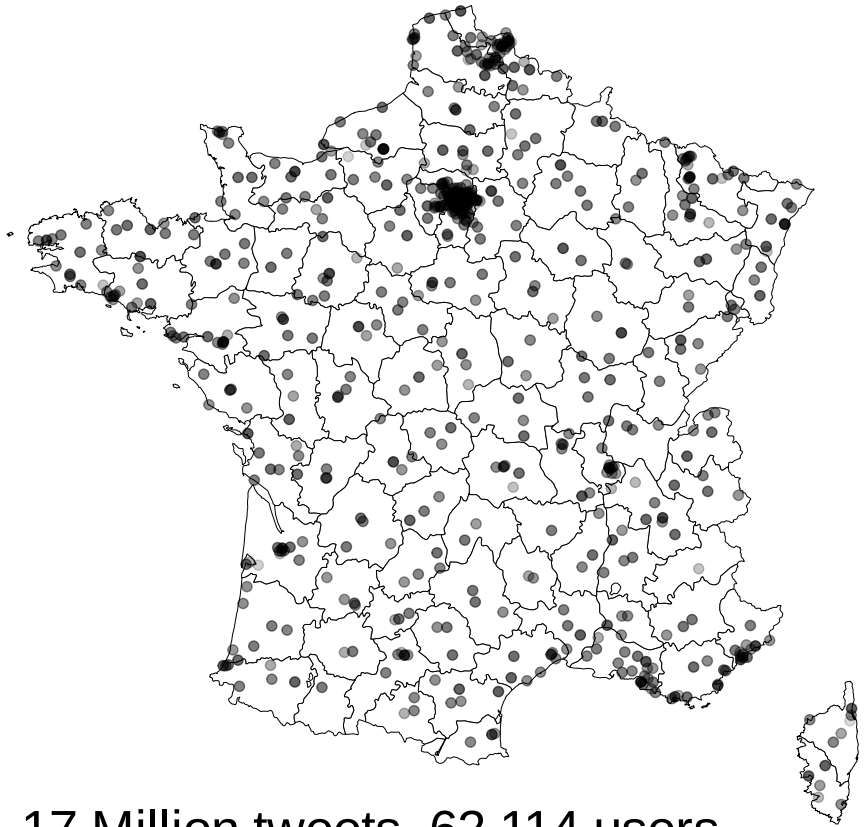
Studying Emotions from Digital Traces

1. A View of Computational Social Science

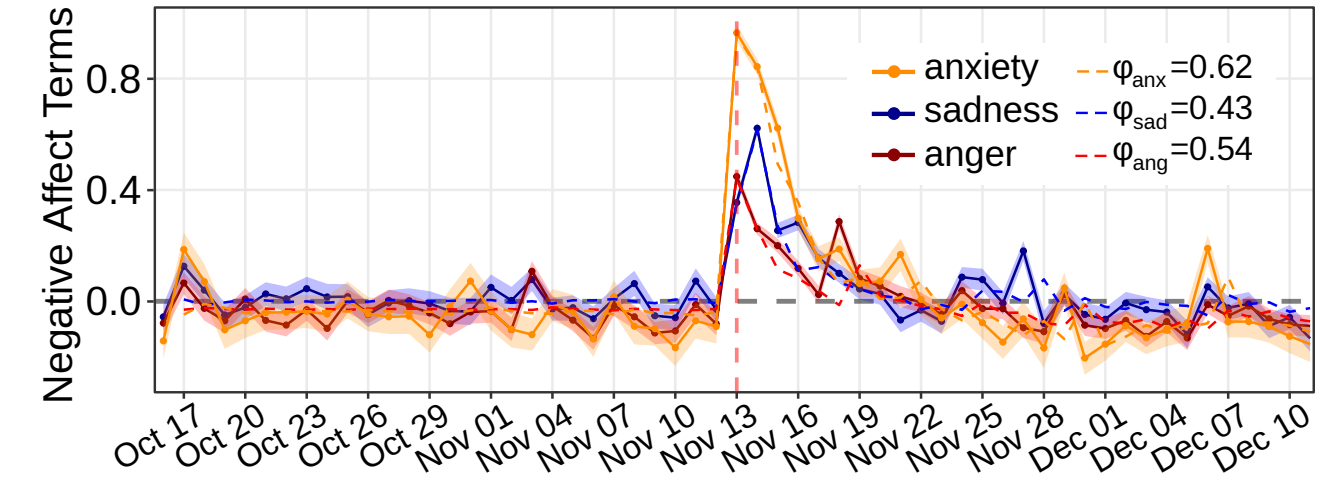
2. Studying Emotions from Digital Traces

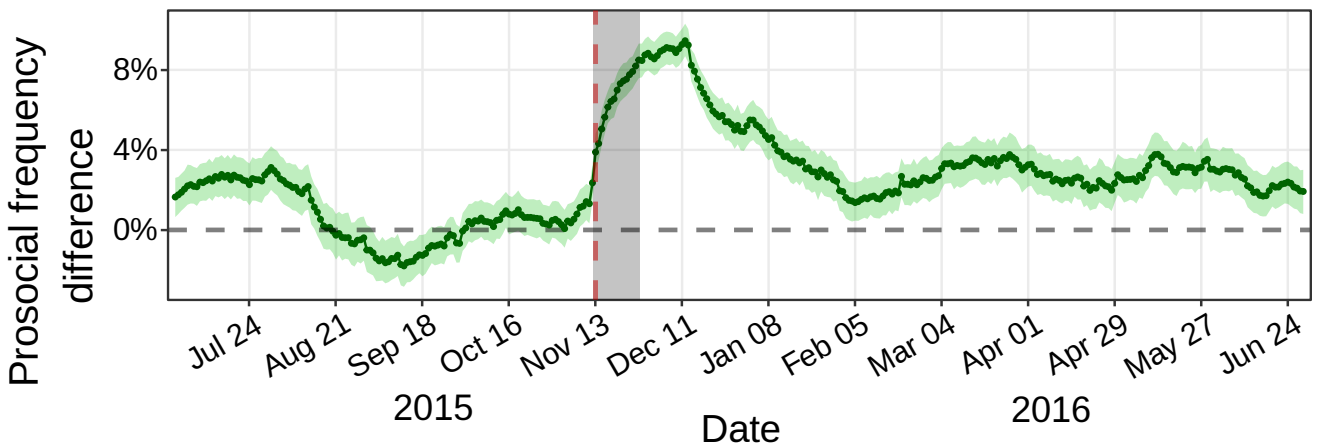
3. CSS with Generative Agents

Social Media Macroscopes of Emotions



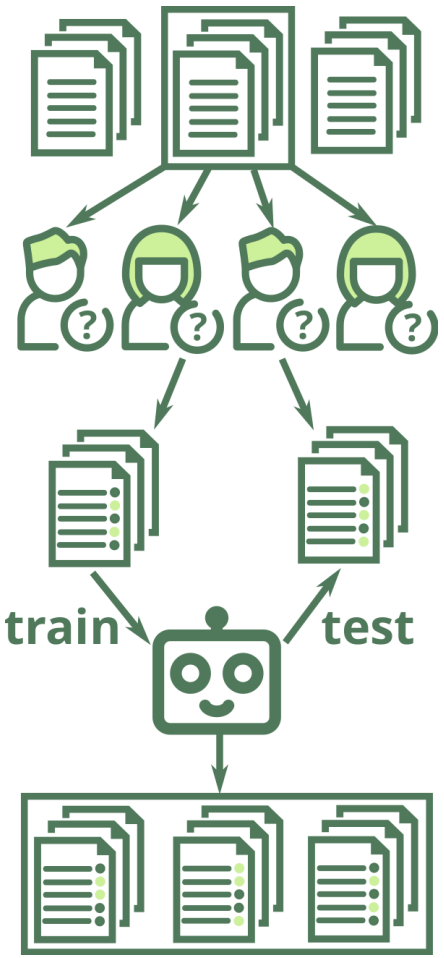
17 Million tweets, 62,114 users





Collective Emotions and Social Resilience in the Digital Traces After a Terrorist Attack.
D. Garcia & B. Rimé, Psychological Science (2019) http://dgarcia.eu/ParisAttacks.html

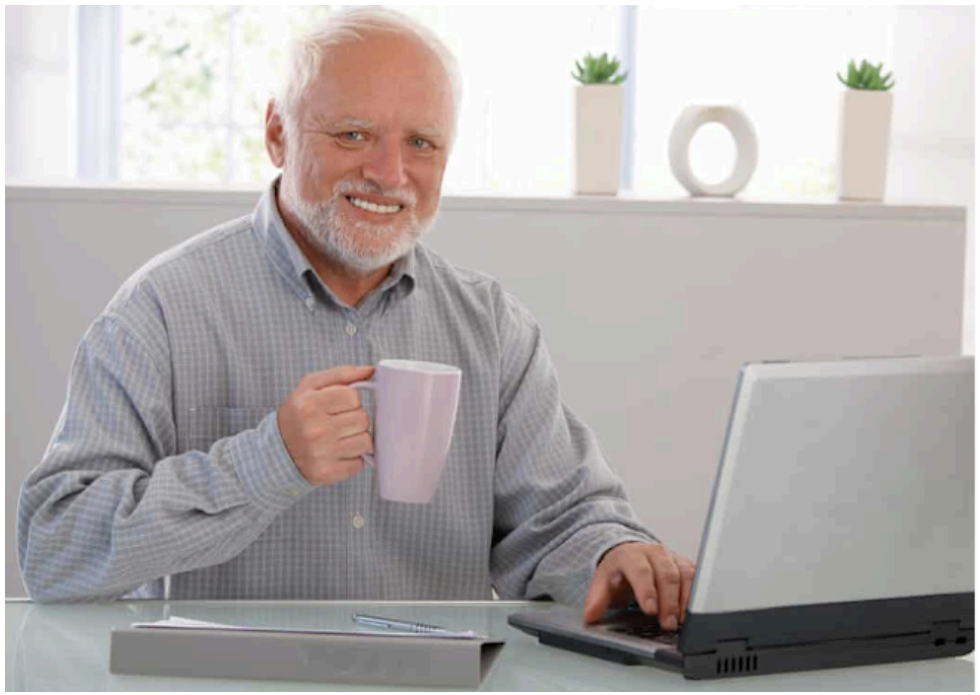
State-of-the-practice Sentiment Analysis Pipeline

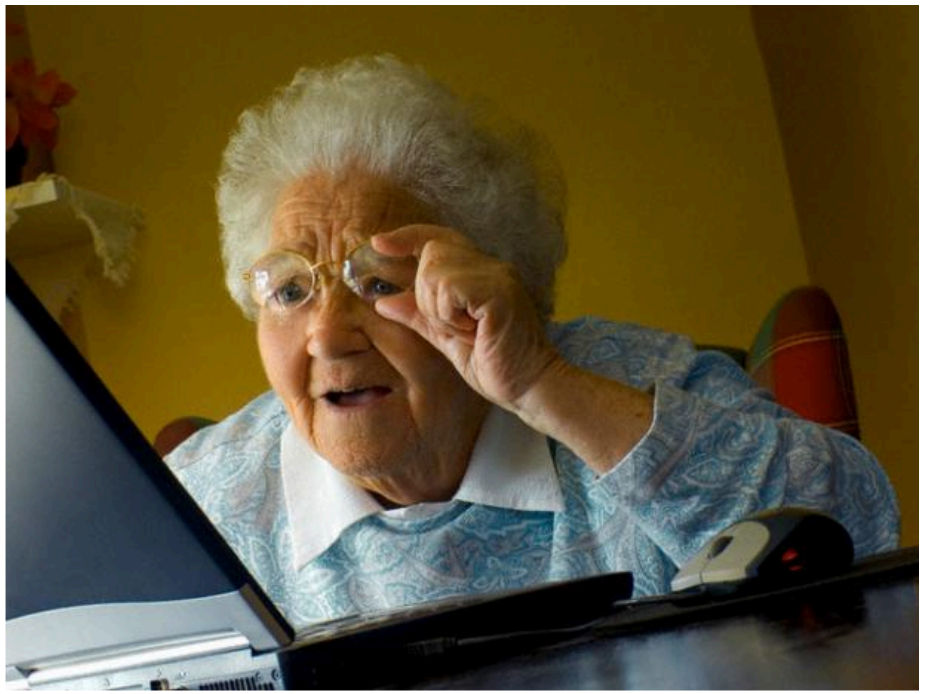


1. Create representative sample of documents from application case
2. Crowdsource annotations (e.g. Mechanical Turk, FigureEight, students...)
3. Split development/training/test samples from annotated documents
4. Develop model using the development sample, evaluate on training sample with cross-validation
5. Train final model on full train sample
6. One evaluation run over test sample. Report performance versus a benchmark including other models and methods
7. Apply model over rest of documents

LEIA: Linguistic Embeddings for the Identification of Affect. Segun Taofeek Aroyehun, Lukas Malik, Hannah Metzler, Nikolas Haimerl, Anna Di Natale, David Garcia. EPJ Data Science (2023)

Challenges in Emotion Identification





Current sentiment analysis approaches assume that the **ground truth** is an annotation of emotions by **a reader**, often a student or a crowdsourcing worker

Noise in ground truth creates **unmeasured error** and potential biases

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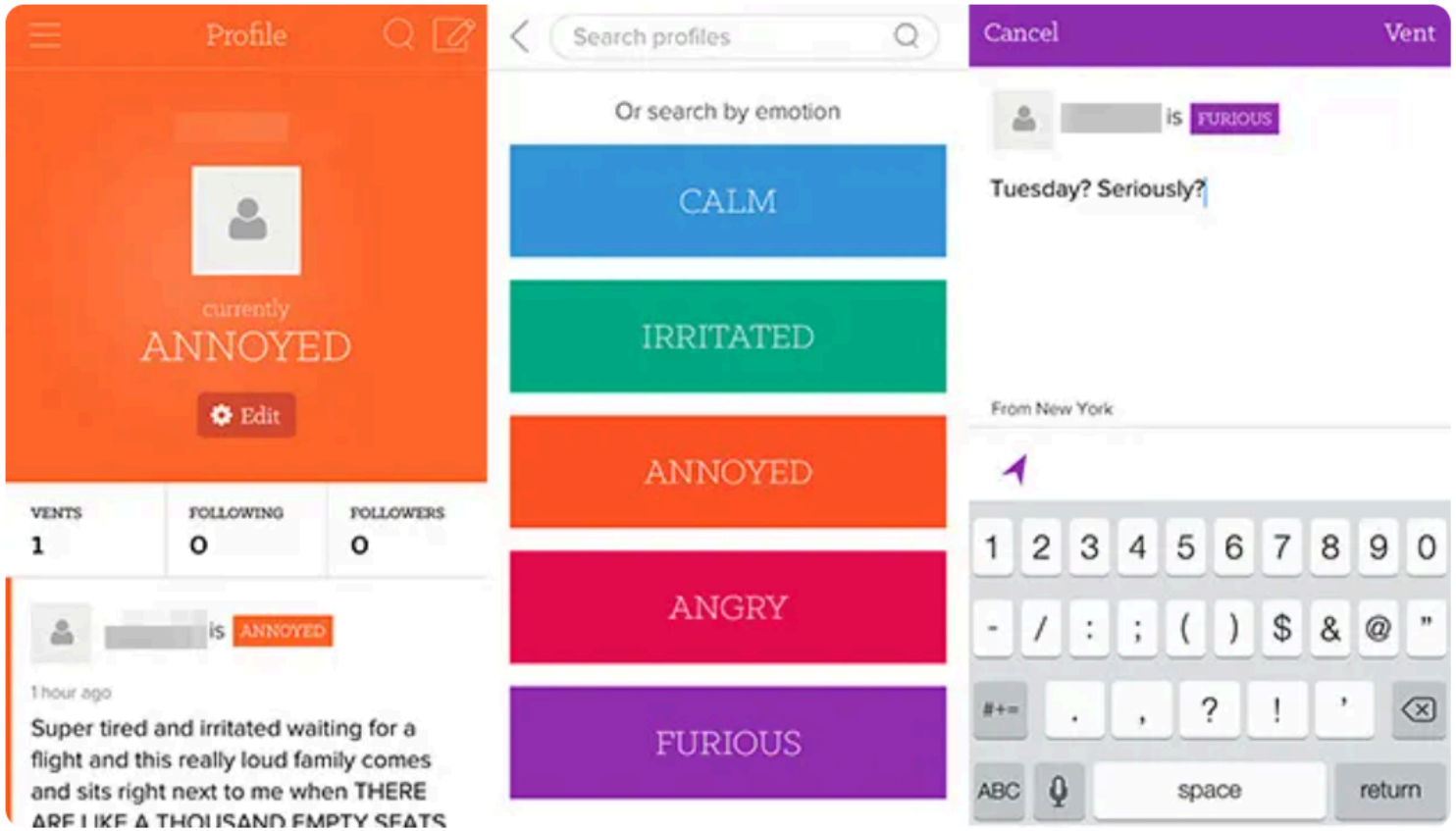
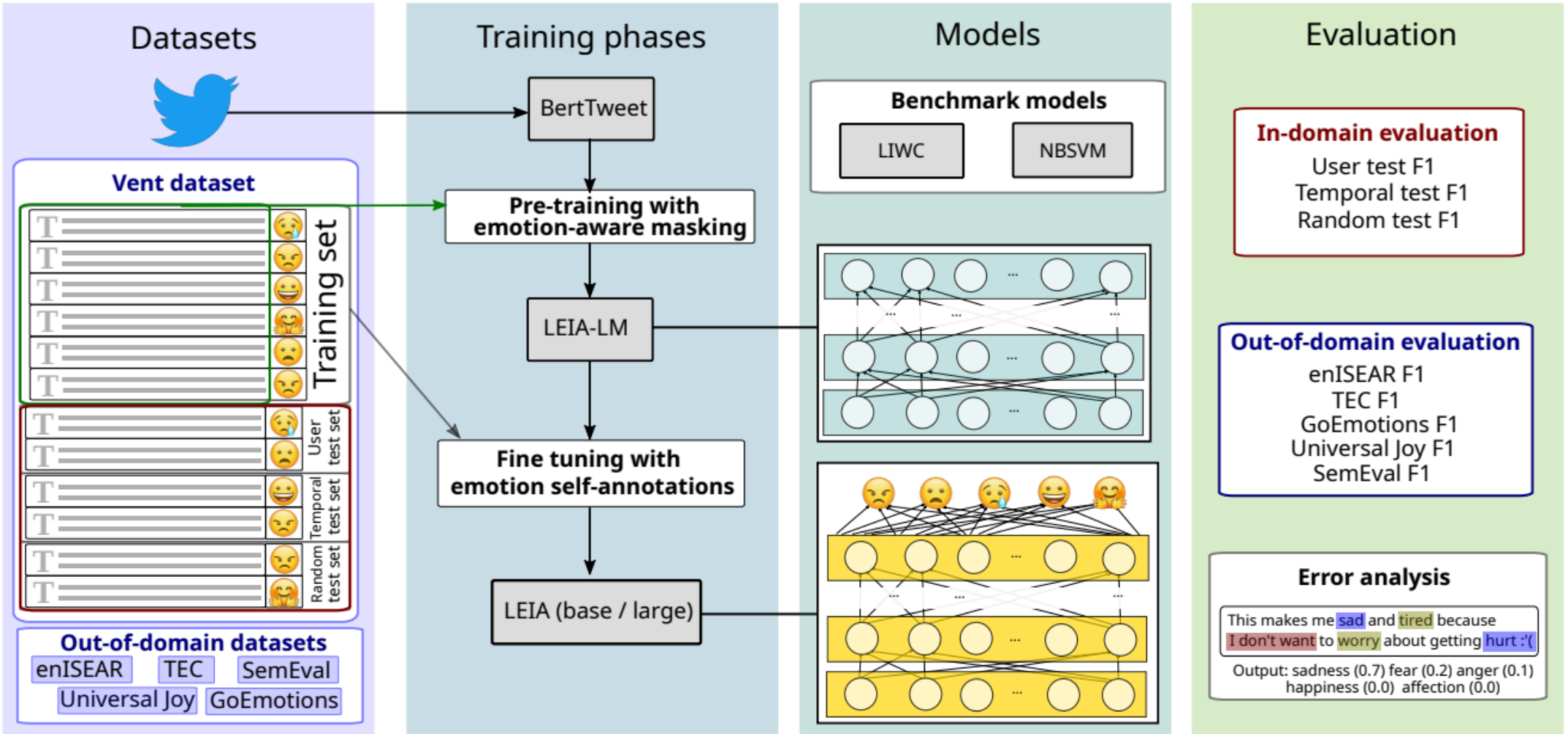
Vent: Self-annotated Social Media Emotions

VENT



Lykousas, N., Patsakis, C., Kaltenbrunner, A., & Gómez. Sharing emotions at scale: The vent dataset. ICWSM (2019)

LEIA: Linguistic Embeddings for the Identification of Affect



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Vent Datasets Summary

Label	Train	Development	User Test	Time Test	Random Test
Sadness	1,712,985	199,890	262,999	293,993	264,906
Anger	1,517,282	147,778	224,997	205,598	226,068
Fear	1,341,624	138,929	198,264	185,461	201,563
Affection	979,019	144,175	161,018	191,022	158,017
Happiness	795,363	74,369	118,290	91,127	116,647
Total	**6,346,273**	**705,141**	**965,568**	**967,201**	**967,201**

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Out-Of-Domain Datasets

- We gathered datasets of emotion annotations from previous research
- We use only test samples to allow future benchmarks
- enISEAR and UniversalJoy are reader-annotated. TEC similarly with #-tags
- Affection not present in OOD datasets
- Not a hard test of generalizability but a way to explore other domains

Dataset	Source	Year	Sadness	Anger	Fear	Happiness	Total
enISEAR	Writing tasks	2019	143	143	143	143	572
TEC	Twitter #emo	2012	765	305	499	1,627	3,196
GoEmotions	Reddit	2020	259	520	77	1,598	2,454
Universal Joy	Facebook	2021	128	58	11	384	581
SemEval	Twitter	2018	312	511	165	706	1,694

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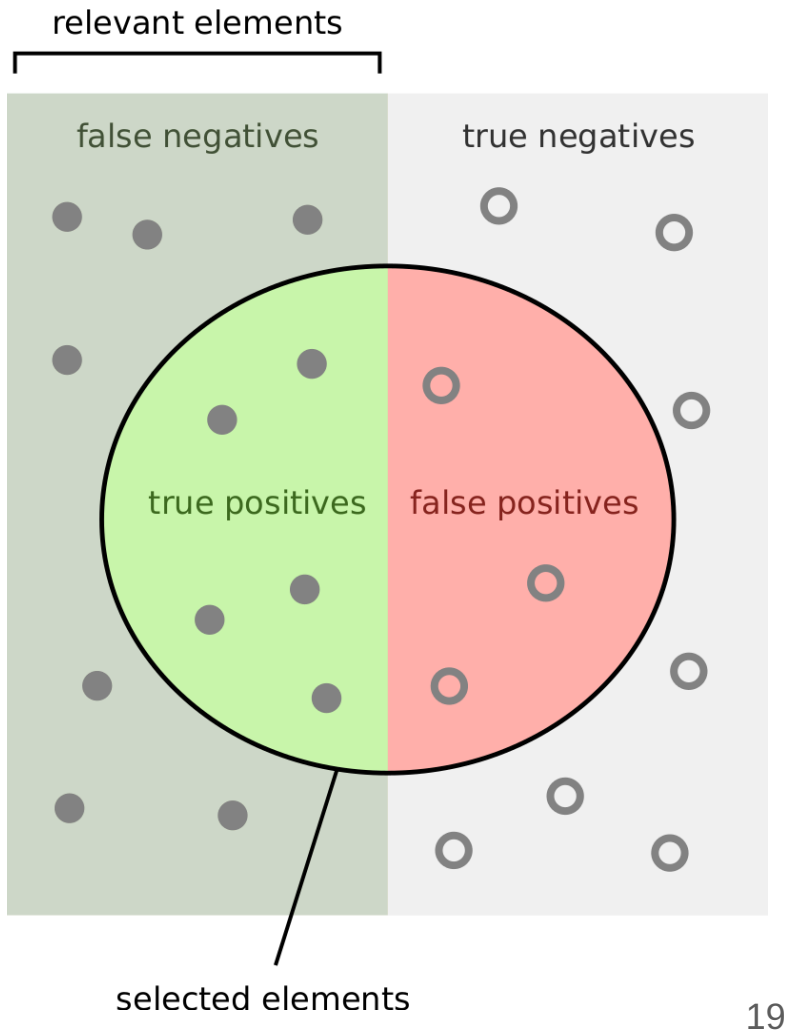
Evaluating classifiers: The F_1 Score

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

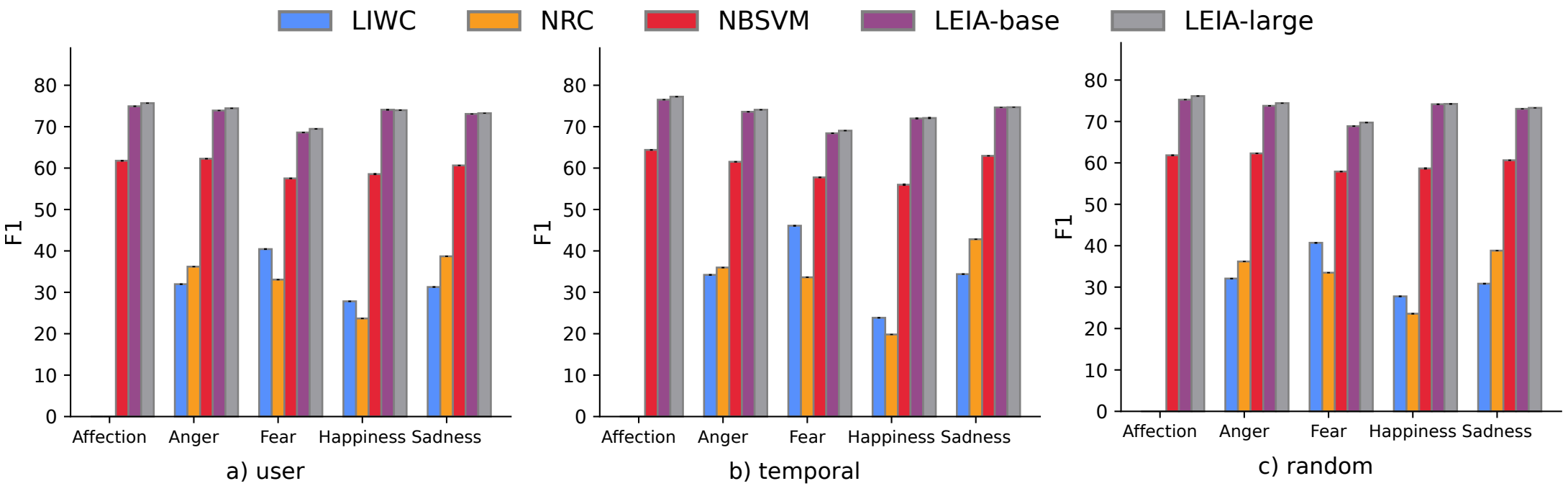
$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$



Results in Vent



LEIA outperforms supervised and unsupervised methods for all emotions and test datsets. F_1 values between 70 and 80.

Out-of-domain results

	LIWC	NRC	NBSVM	LEIA-base	LEIA-large
Universal Joy	23.45	28.98	41.70	**54.18**	54.17
GoEmotions	45.81	32.68	48.23	**46.31**	45.75
TEC	36.02	33.92	39.07	43.87	**44.12**
SemEval	66.72	49.86	68.77	**71.68**	70.04
enISEAR	23.51	42.72	55.33	70.37	**79.94**

- LEIA is best or tied with the best in all out-of-domain tests
- LEIA is best or tied with the best in all emotions except Fear in TEC
- Note: very different media, sampling methods, and labelling schemes

Comparing with GPT models

	LEIA-base	LEIA-large	GPT-3.5	GPT-4
Affection	74.48	**75.67**	41.38	37.43
Anger	72.92	**72.98**	61.79	66.82
Fear	69.01	**70.26**	51.55	60.86
Happiness	**77.69**	77.58	67.69	68.70
Sadness	67.28	**68.00**	59.94	64.00
Average	72.28	**72.90**	56.47	59.56

- Evaluation on a sample of 1000 texts per emotion label from the user test sample. GPT models used with a standard prompt for zero-shot classification
- LEIA greatly outperforms GPT-3.5-turbo and GPT-4 in each emotion

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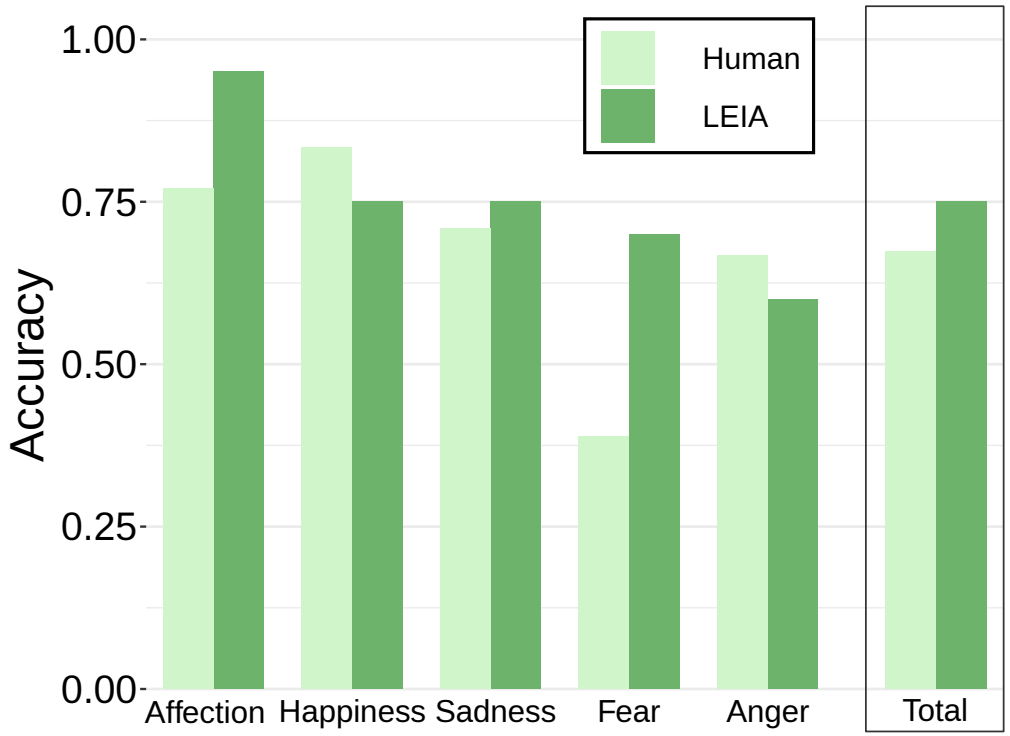
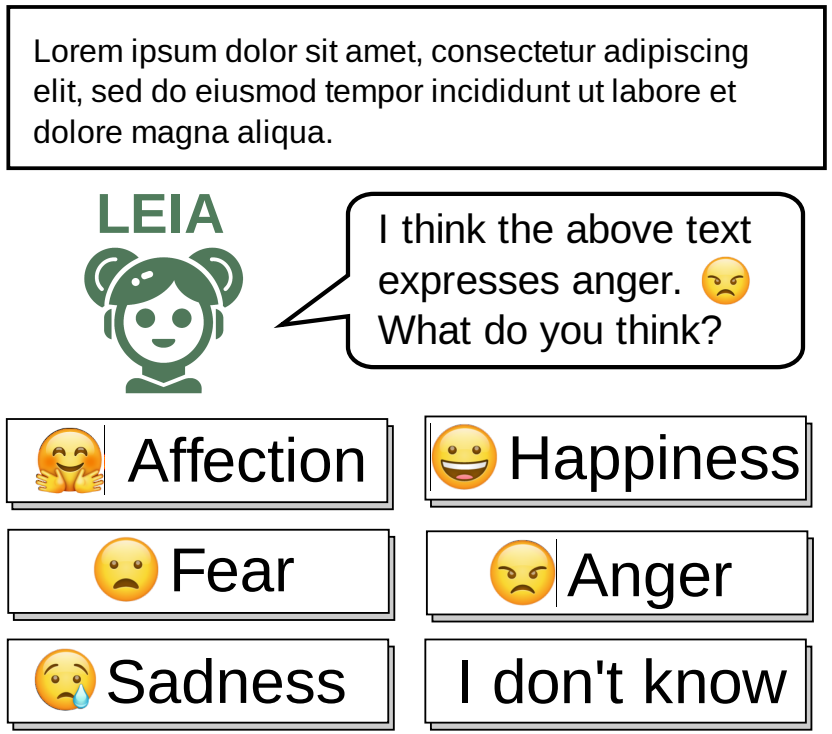
Comparing with GPT models (OOD)

	LEIA-base	LEIA-large	GPT-3.5	GPT-4
Universal Joy	54.18	54.17	52.89	**56.43**
GoEmotions	46.31	45.75	**59.06**	56.45
TEC	43.87	44.12	52.66	**54.82**
SemEval	71.68	70.04	80.13	**81.72**
enISEAR	70.37	79.94	84.96	**89.97**

- GPT models outperform LEIA in GoEmotions, TEC, SemEval, and enISEAR
- LEIA en par with GPT for Universal Joy
- Model contamination? test samples for all these datasets are public and GPT models could have been trained with them
- Universal Joy might be younger than the cutoff date

LEIA (versus) Humans





- Students annotating a balanced Vent sample (N=100, 720 annotations)
- Initial results suggest that LEIA is comparable to humans
- **Artificial Affective Intelligence:** Can LEIA help humans read emotions?

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CSS with Generative Agents

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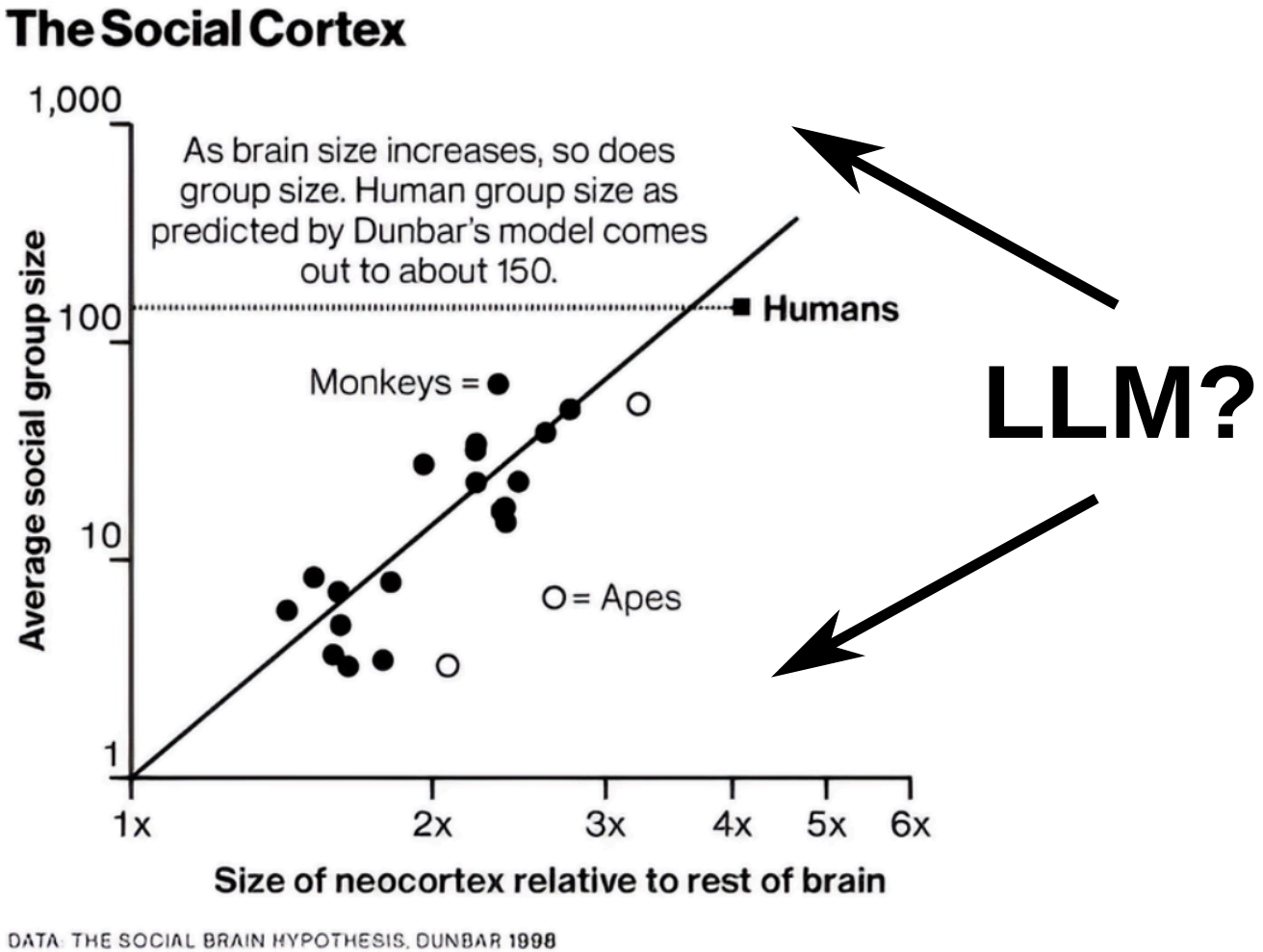
Social Simulacra and Simulation

Generative Agents: Interactive Simulacra of Human Behavior. S. Park et al.

LLMs within society

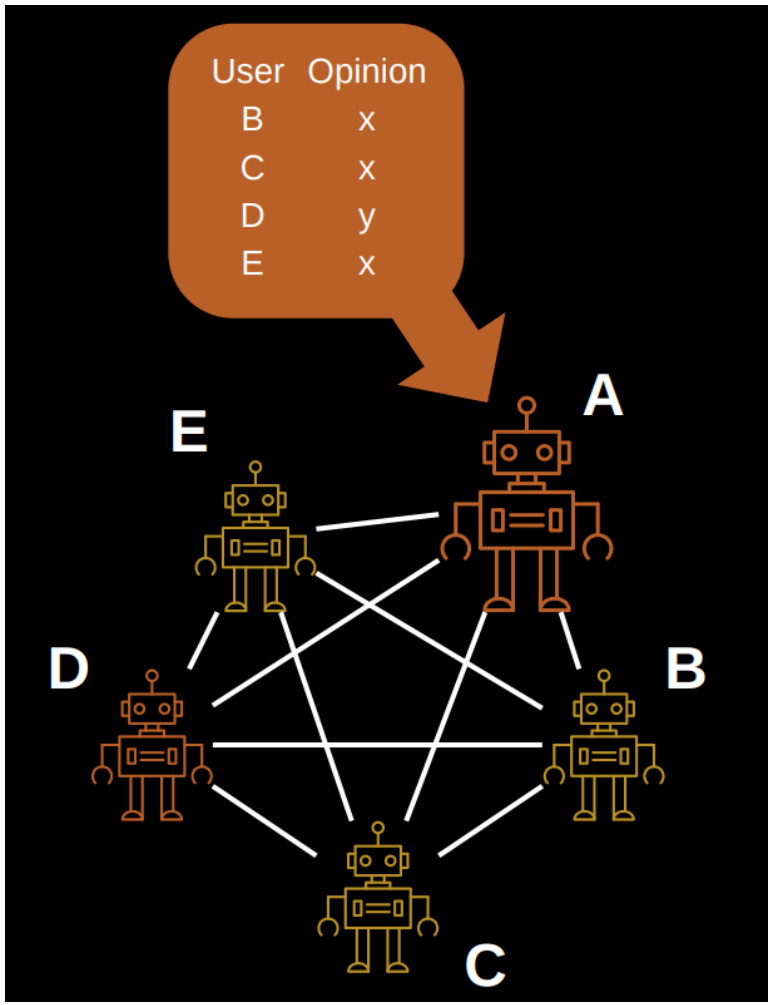
- AI "chiefs of staff" promise to interact with each other in our behalf
- Coordination and competition (reservations, negotiations, applications)
- Could norms emerge, for example rules to be more efficient?
- Could they have risk of alignment, like flash crashes?

LLMs as social brains



Language Understanding as a Constraint on Consensus Size in LLM Societies. G de Marzo, C. Castellano, D. Garcia. Arxiv preprint (2024)

Opinion dynamics simulation with LLM



- Simulation of a tight group of N interacting agents
- Agents start with a random opinion of two options
- Each iteration, they see the opinions of all others (prompt)
- They respond to the question of their opinion
- Opinion labels need to be random and shuffled to avoid token biases
- Consensus is achieved if all have the same opinion

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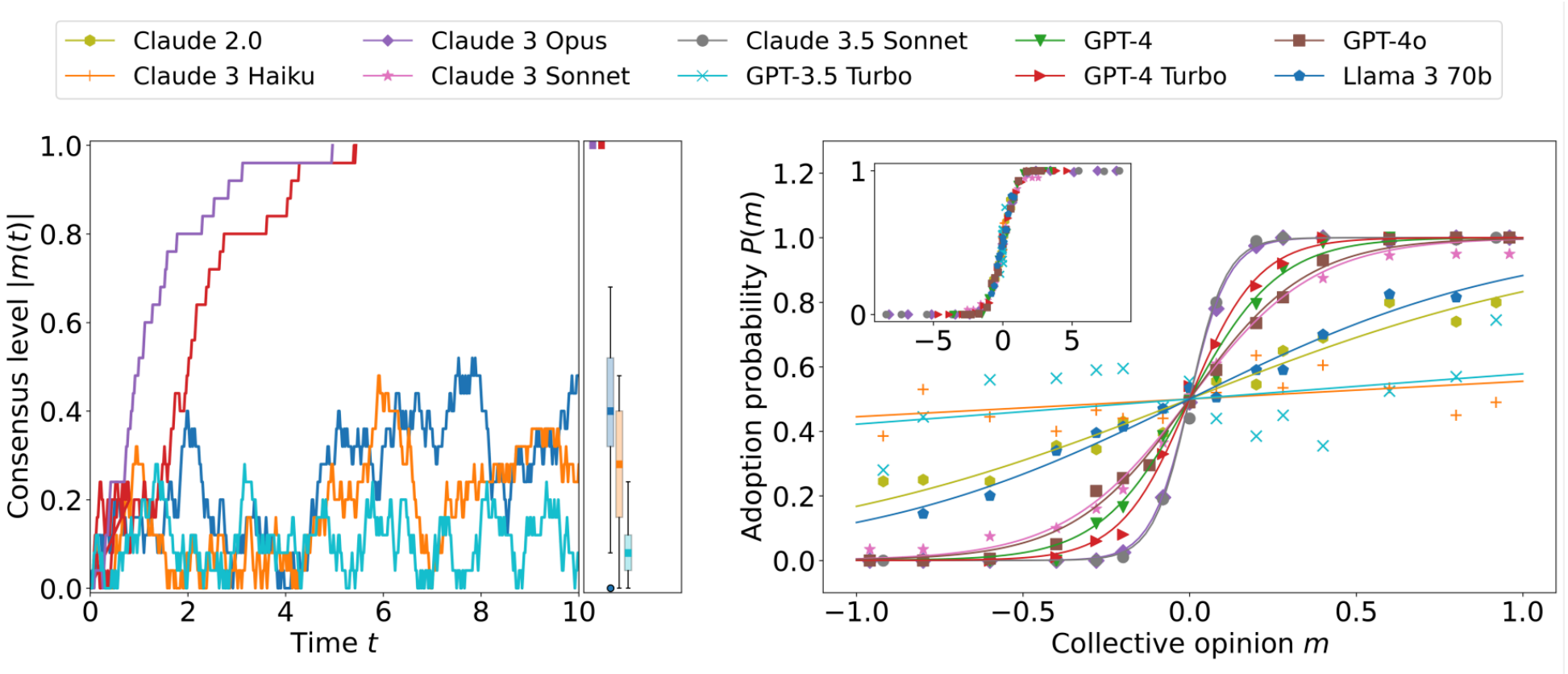
LLM-dependent consensus formation



Opinion dynamics can be modeled as an S-function parametrized by a majority force β. Consensus is possible for $\beta > 1$

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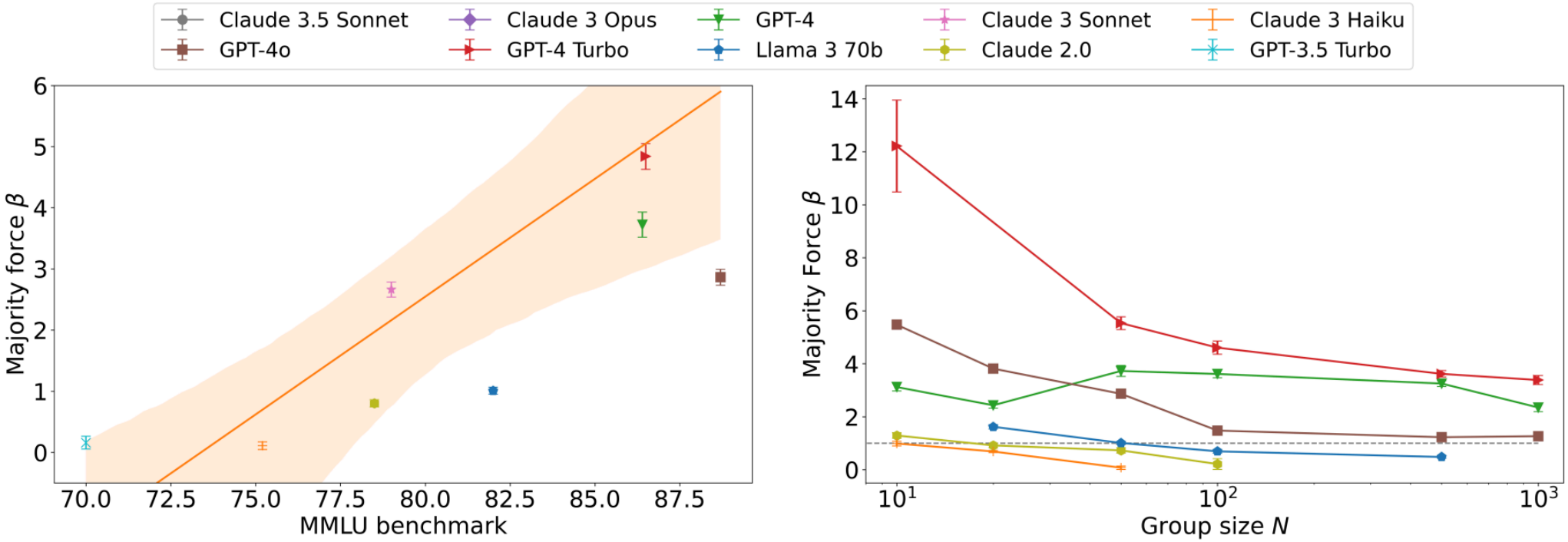
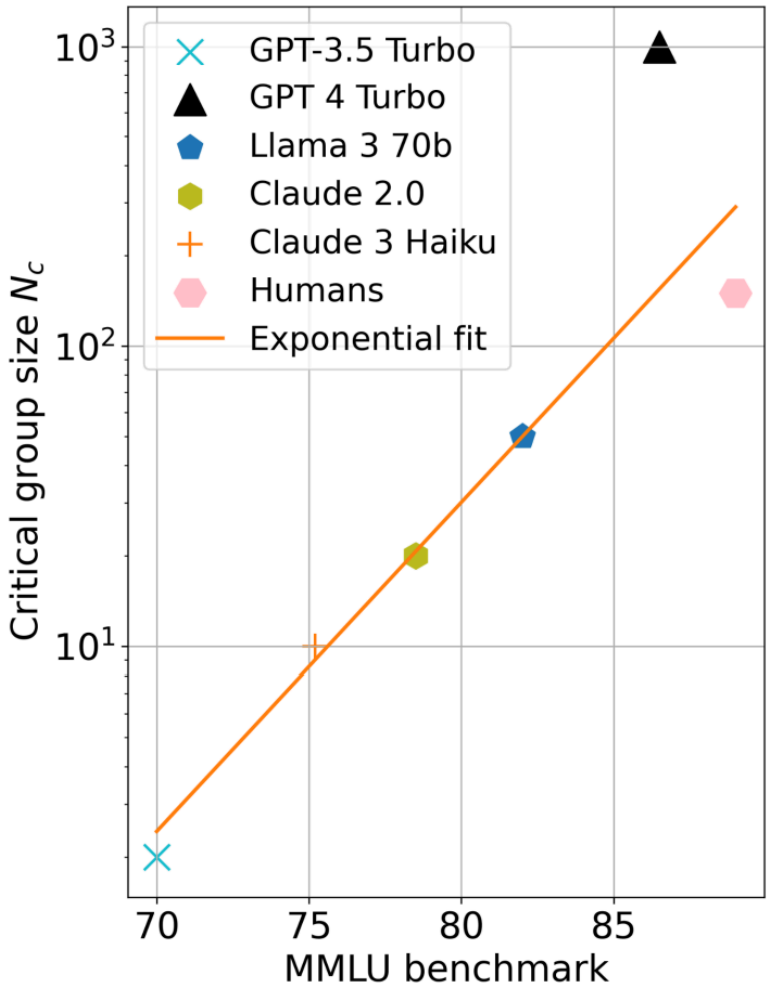
Majority force factors



- Majority force is higher for models with higher language understanding capabilities (MMLU benchmark)
- Majority force decreases for larger group sizes

Group size and language understanding

- Analysis of majority force and exhaustive simulations to measure **critical consensus size**
- Exponential function of MMLU benchmark
- Humans close to the line
- GPT4 and Claude3 opus reach consensus for $N = 1000$
  - LLM emergent consensus scale beyond humans



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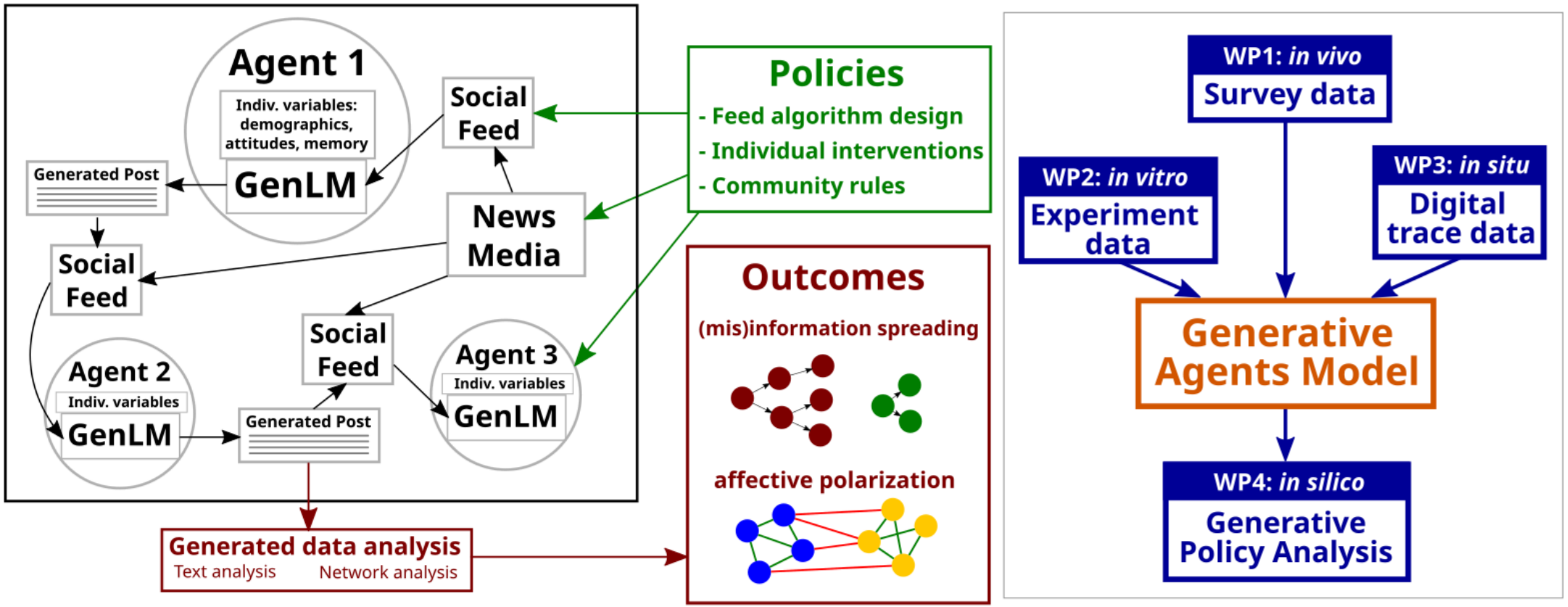
INSILICO: Social Simulation with LLMs



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Summary

- My key to CSS: Questions first, then data
- Methods for measurement and modelling the future of CSS
- LEIA to have Affect Identification with valid training data
- LLM consensus scale predicted by language understanding capabilities
- LLMs can reach emergent consensus at scales beyond humans
- Future: Social Simulation with LLMs

LEIA: Linguistic Embeddings for the Identification of Affect. S. Aroyehun, L. Malik, H. Metzler, N. Haimerl, A. Di Natale, D. Garcia. EPJ Data Science (2023)
Try it yourself: https://huggingface.co/LEIA/LEIA-base

Language Understanding as a Constraint on Consensus Size in LLM Societies. G de Marzo, C. Castellano, D. Garcia. Arxiv preprint (2024)

More at: www.dgarcia.eu