CONTEXTUALIZING SOCIAL AI

FOR GENDER, CULTURE, AND MORE

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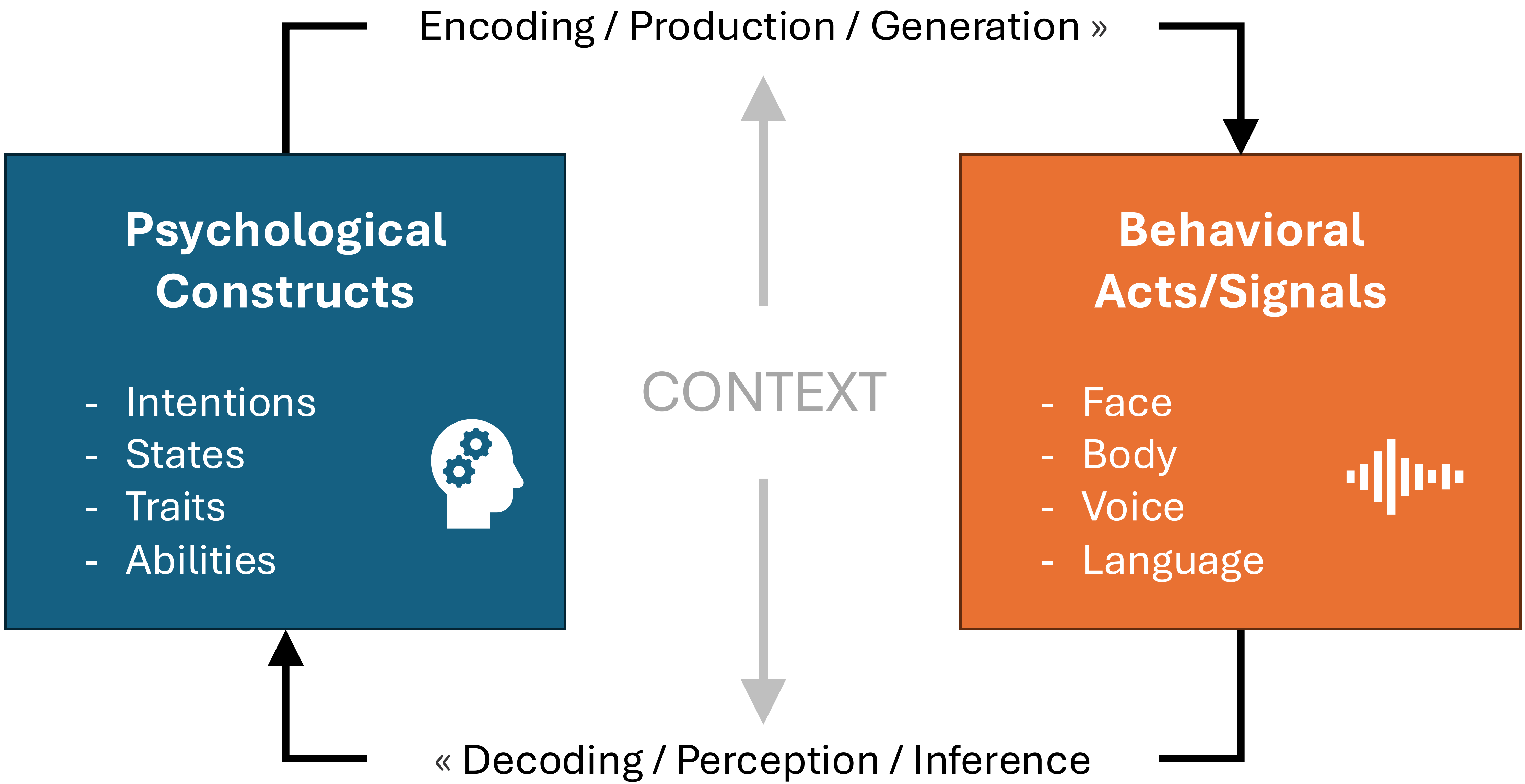
Goals of the Presentation

1. Define key aspects of communication
2. Argue for the importance of context
3. Establish gender and culture as context
4. Define descriptive and prescriptive norms
5. Propose large-scale observational studies
6. Quantify descriptive smiling norms in two studies
7. Model norms across countries and genders
8. Discuss challenges, concerns, and open questions


Encoding / Production / Generation »
Psychological Constructs
- Intentions
- States
- Traits
- Abilities
CONTEXT
Behavioral Acts/Signals
- Face
- Body
- Voice
- Language
« Decoding / Perception / Inference

Social AI Needs Contextual Knowledge

- Improved understanding of situations
- Accurate construct perception/inference
- Nuanced behavior generation/synthesis
- Adaptability and flexibility to environment
- Increased authenticity and human-likeness
- Enhanced user experience

The encoding and decoding of a given behavior is influenced by its **surrounding context**. For example, the same behavior may differ depending on the **demographics of the person** producing it.

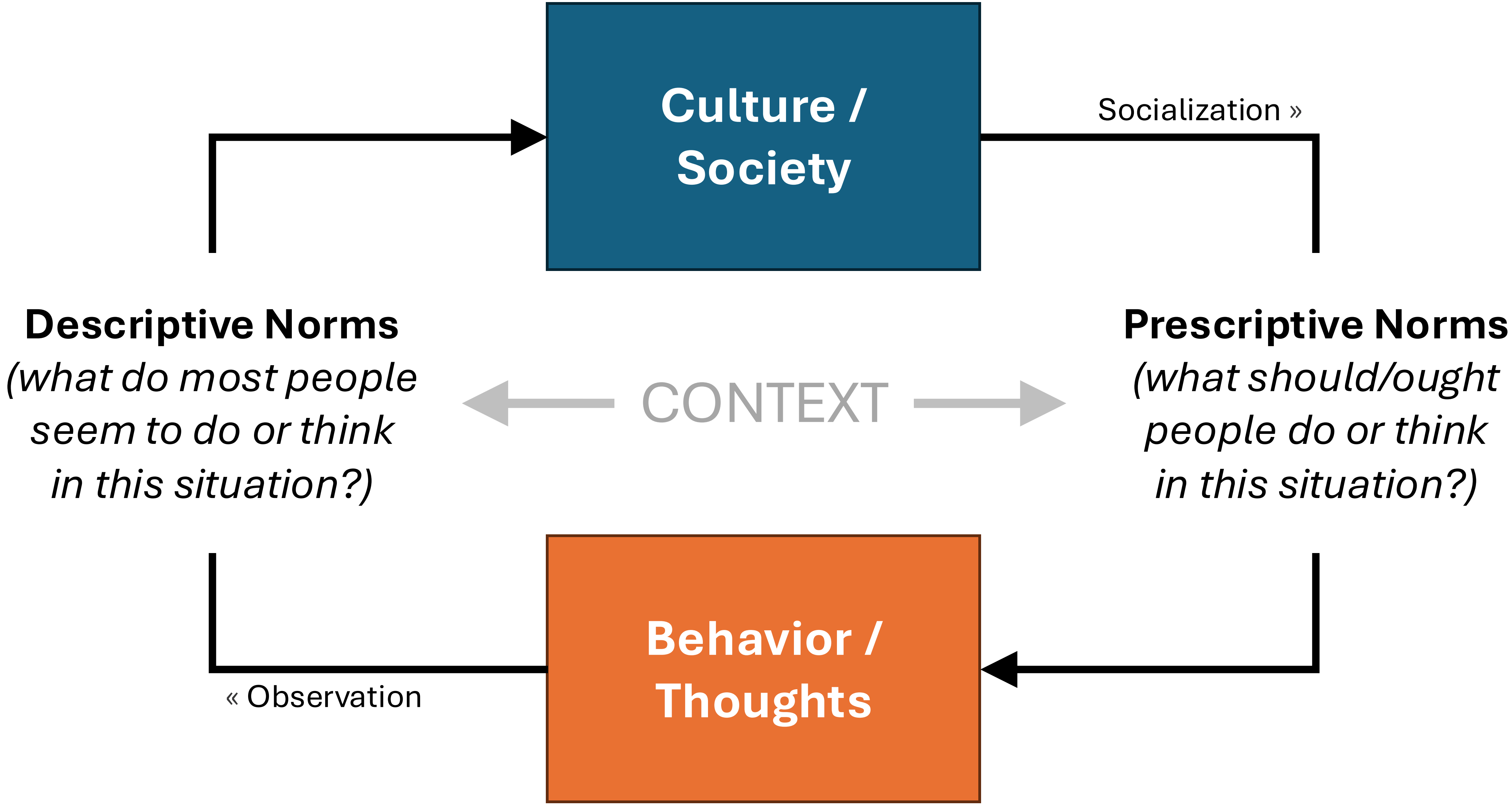
Demographics as Context

Coarse Categorizations

- Sex & Gender
- Age & Generation
- Race & Ethnicity
- Country & Culture
- Wealth & Social Status
- Education & Occupation
- Sexual Orientation & Identity
- Relationship & Parental Status
- Religion & Region & Politics
- Health & Disability

Presumed Mechanisms

- Hormones (testosterone, estrogen)
- Neurobiology (amygdala, PFC)
- Appraisal Patterns and Regulation Strategies
- Personality Traits and Motives/Goals
- Norms and Display Rules / Socialization
- Interpersonal Context / Dynamics
- Social Roles and Relationships
- Cultural Models of the Self
- Cultural and Religious Values
- Cultural Scripts and Rituals
- Historical and Societal Context
- Abilities and Disabilities


Culture / Society
Socialization »
Descriptive Norms
(what do most people seem to do or think in this situation?)
CONTEXT
Prescriptive Norms
(what should/ought people do or think in this situation?)
Behavior / Thoughts
« Observation

Social AI Needs Normative Knowledge

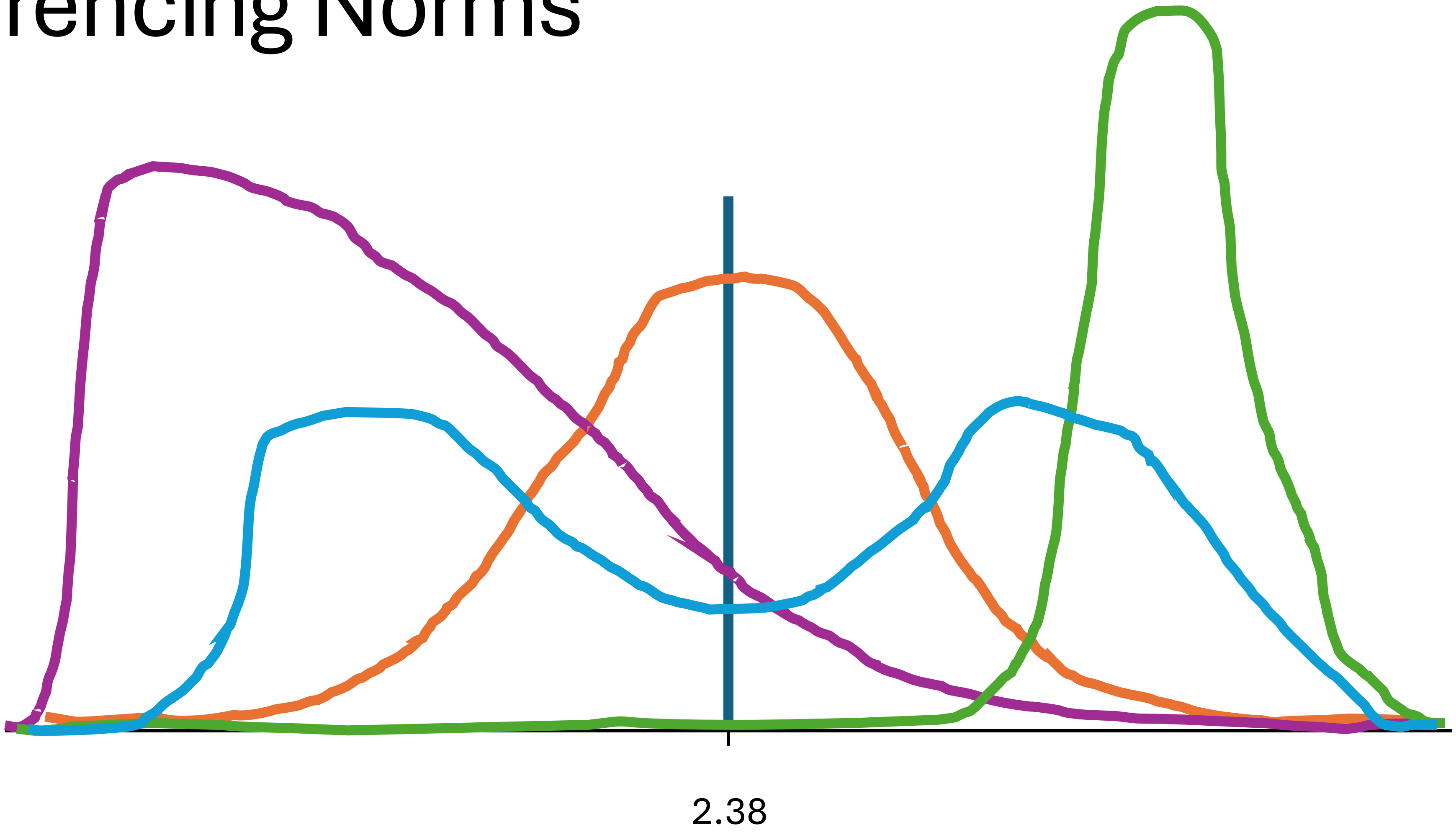
- Anticipating User Behavior
- Social Appropriateness
- Better User Interaction
- Adaptive Problem-Solving
- Cultural Sensitivity

- Avoiding Miscommunication
- Avoiding Confusion
- Avoiding Cultural Offense
- Avoiding Awkwardness
- Avoiding Uncanny Valley

The Importance of Norms

- How should our decoding/interpretation of behavior X change after learning that the person is part of a demographic group?
  - *What behaviors are normal or prescribed for this group in this situation?*
  - *How does the observed behavior compare to those expectations?*
- How should our encoding/generation of construct X into behavior change when synthesizing for a member of a different group?
  - *What behaviors are normal or prescribed for this group in this situation?*
  - *How will the generated behavior compare to those expectations?*
- How can we collect, quantify, and use normative knowledge?

Referencing Norms



Large-scale observational research

- Previous studies of descriptive norms relied on self-reports of what participants believe about normal and abnormal behavior
- But we also need to compare this to observational measures of how people actually behave, e.g., *empirical* descriptive norms
- But observational research is expensive and time-consuming
  - Previous studies typically collected observational records of dozens or hundreds of participants from around 2 to 4 convenient countries
- Data science and affective computing can help us scale up!

DATASET 1

ONLINE CELEBRITY IMAGES

Focus on celebrities as they are “trend setters” and public figures

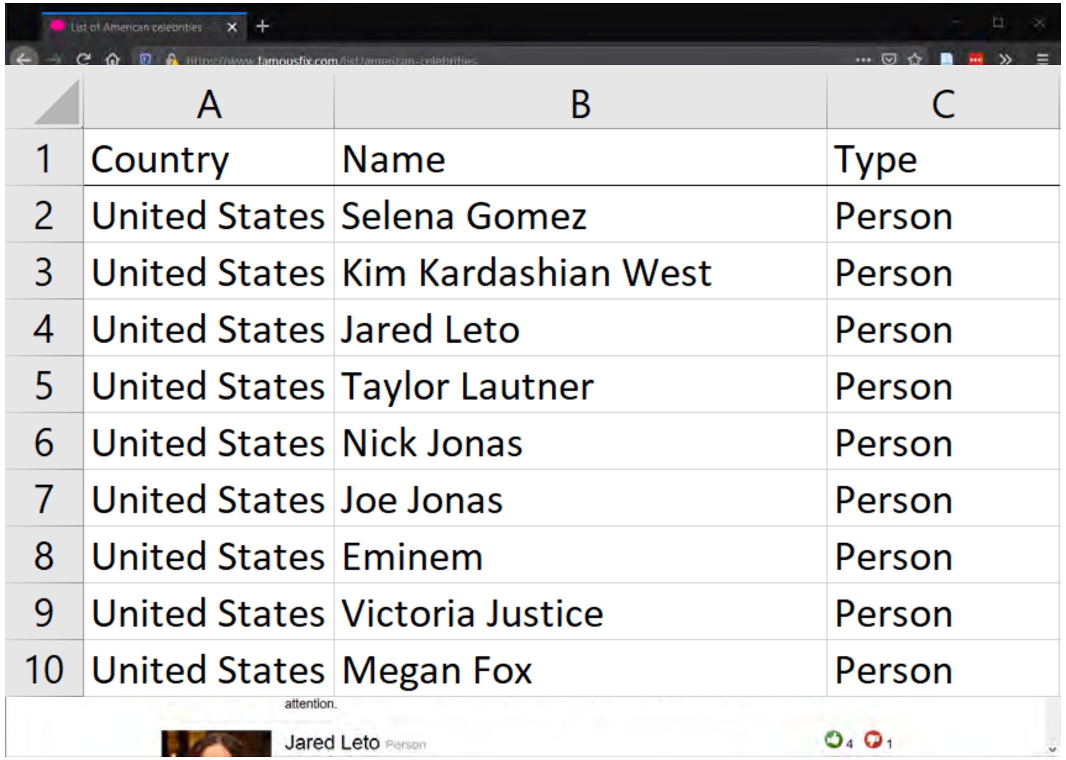
Attempt to maximize number of countries and individuals

Focus on smile intensity as an important social/affective signal

Data Collection (Text Scraping)

Goal: Construct a list of celebrities from as many countries as possible

1. Find list of celebrities by country
2. Loop through each country list
3. Parse HTML as structured text
4. Loop through top 1000 results
5. Extract country, name, type
6. Format into tidy data frame



	A	B	C
1	Country	Name	Type
2	United States	Selena Gomez	Person
3	United States	Kim Kardashian West	Person
4	United States	Jared Leto	Person
5	United States	Taylor Lautner	Person
6	United States	Nick Jonas	Person
7	United States	Joe Jonas	Person
8	United States	Eminem	Person
9	United States	Victoria Justice	Person
10	United States	Megan Fox	Person

Data Collection (Image Scraping)

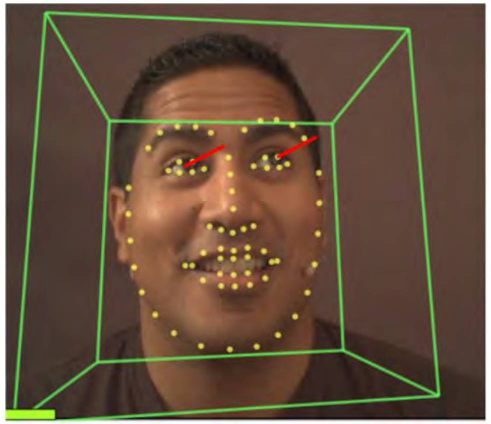
Goal: Search for and download photos of all celebrities on the list

1. Use Microsoft Bing Search API
2. Search for each celebrity name
3. Filter results for facial photos
4. Filter top 12 results per name
5. Extract and save image data

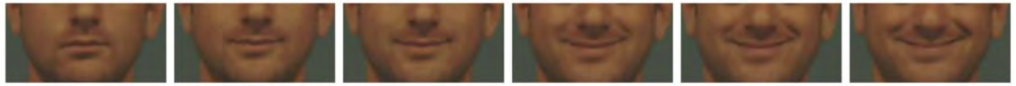
Data Processing (Smile Estimation)

- **Goal:** Estimate the absence or intensity of the smile on each face

1. Detect faces in each image
2. Locate facial landmark points
3. Extract visual features
4. Apply trained ML model
5. Predict smile intensity level



OpenFace Output Visualization



0 1 2 3 4 5

Smile Intensity Level Examples

Data Processing (Smile Validation)

Goal: Provide evidence that the smile intensity estimates are trustworthy

1. Select a subset of 300 images balanced by country and gender
2. Recruit 5 crowdworkers to rate images' positivity and smile
3. Recruit 1 expert FACS coder to code the smile (AU12) intensity
4. Compare human ratings to estimates from OpenFace

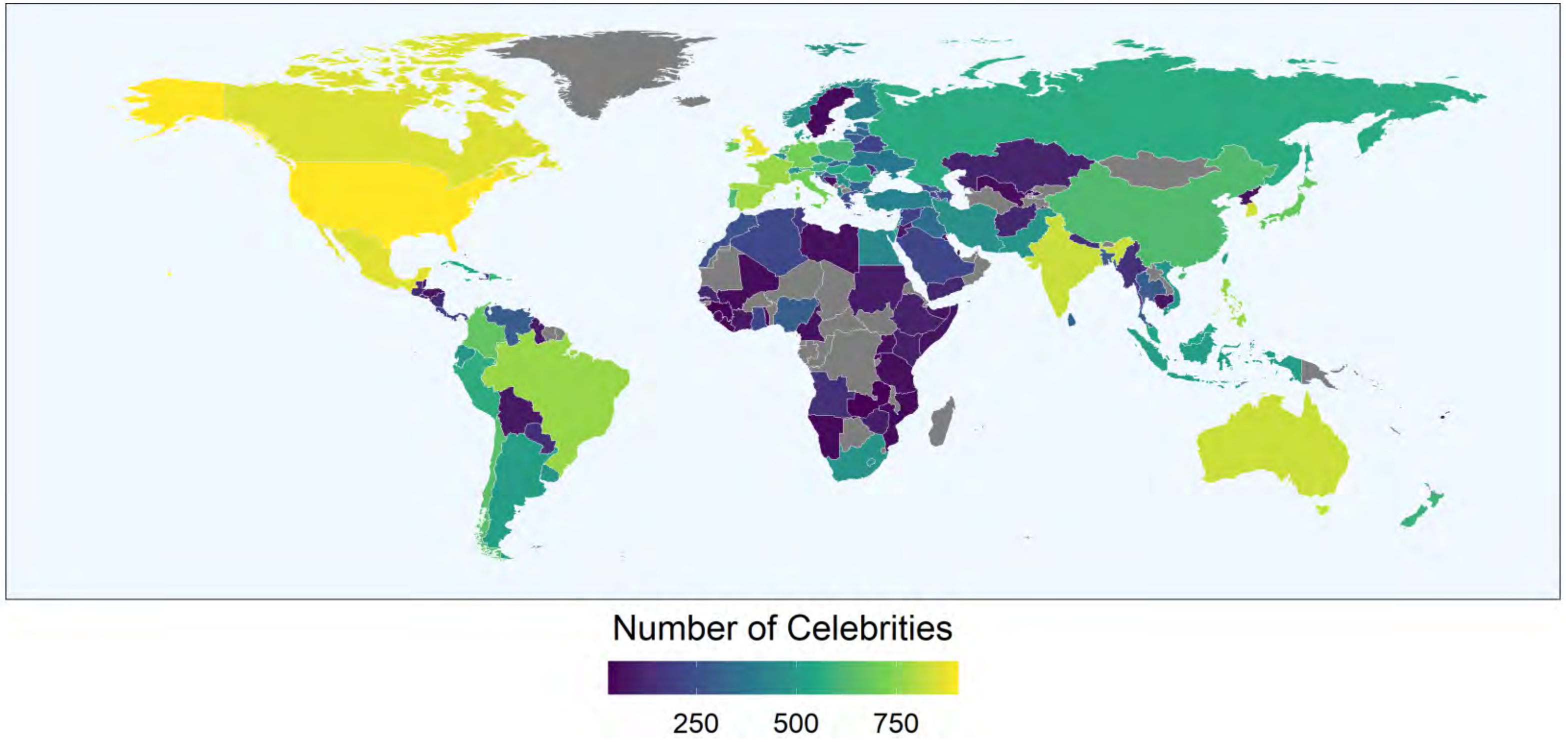
Inter-Rater Reliability Estimates

Measure	ICC(A,5)	95% CI
Positive Rating	0.90	[0.88, 0.92]
Smile Rating	0.90	[0.88, 0.92]

Heterogeneous Correlation Matrix

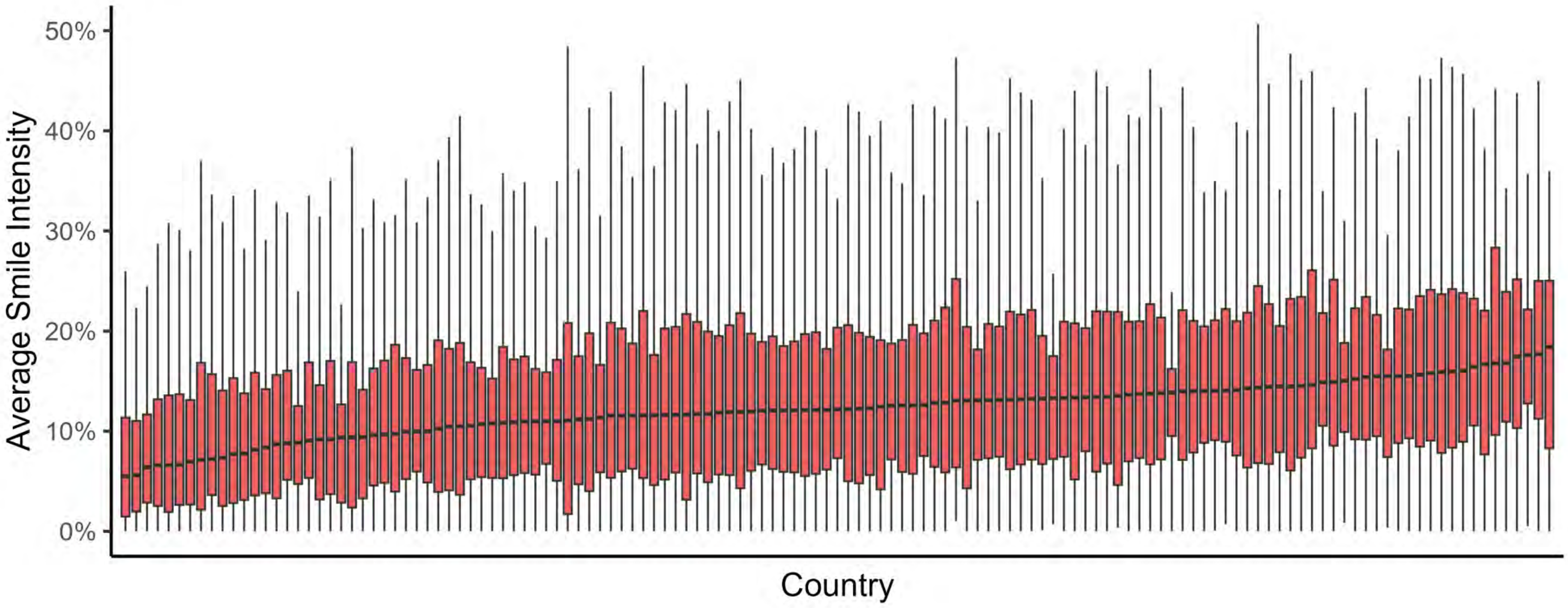
Measure	OpenFace	Positive	Smile
Positive Rating	0.79		
Smile Rating	0.78	0.94	
Expert FACS	0.87	0.97	0.94

Data Exploration (Counts by Country)



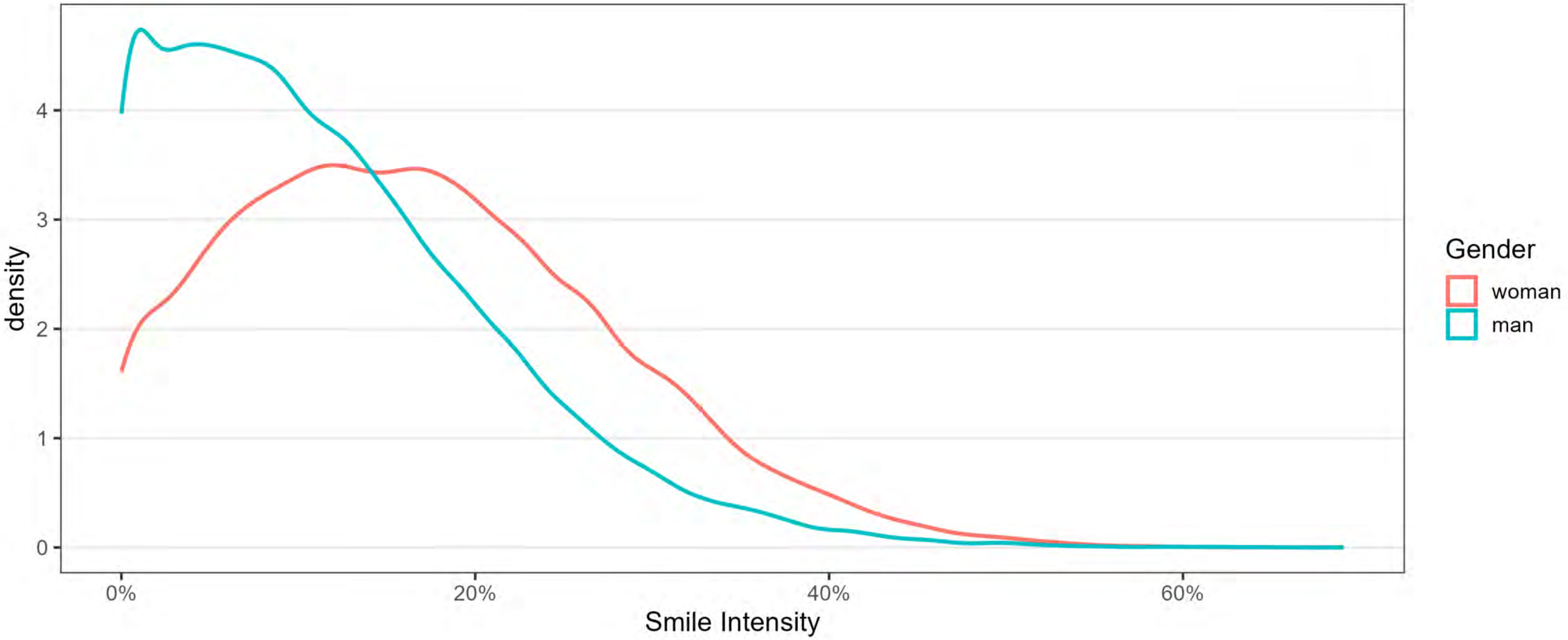
Final Count: 276,811 images; 44,602 celebrities; 133 countries

Country Distributions (Ignoring Gender)



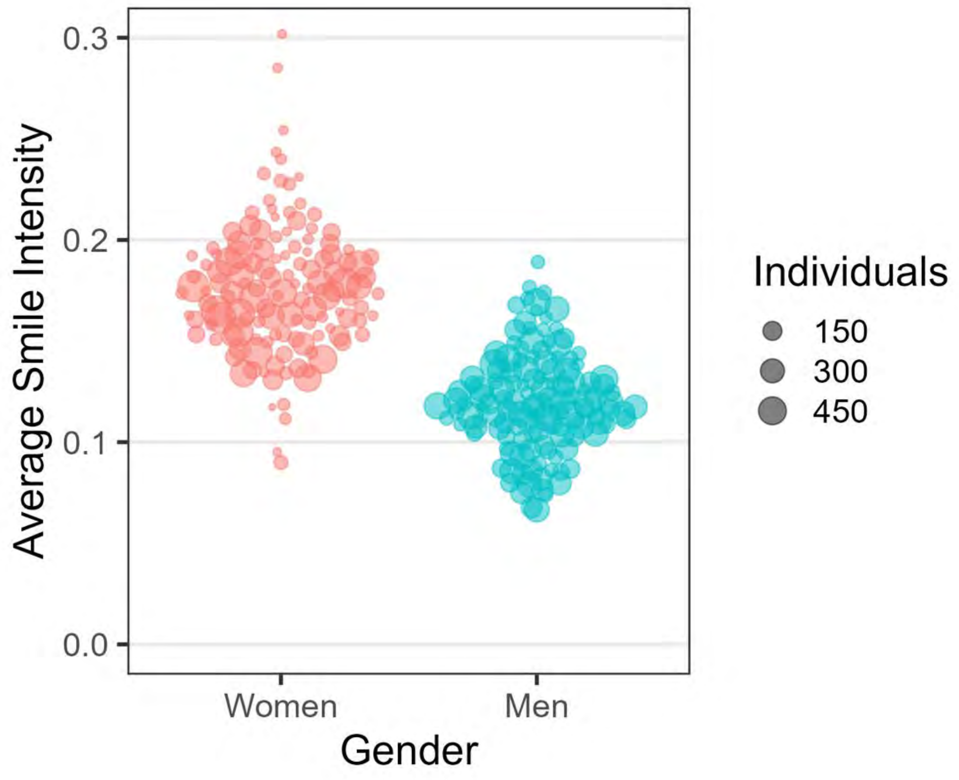
Low: Azerbaijan, Georgia *Mid:* Ireland, Thailand *High:* Venezuela, Philippines

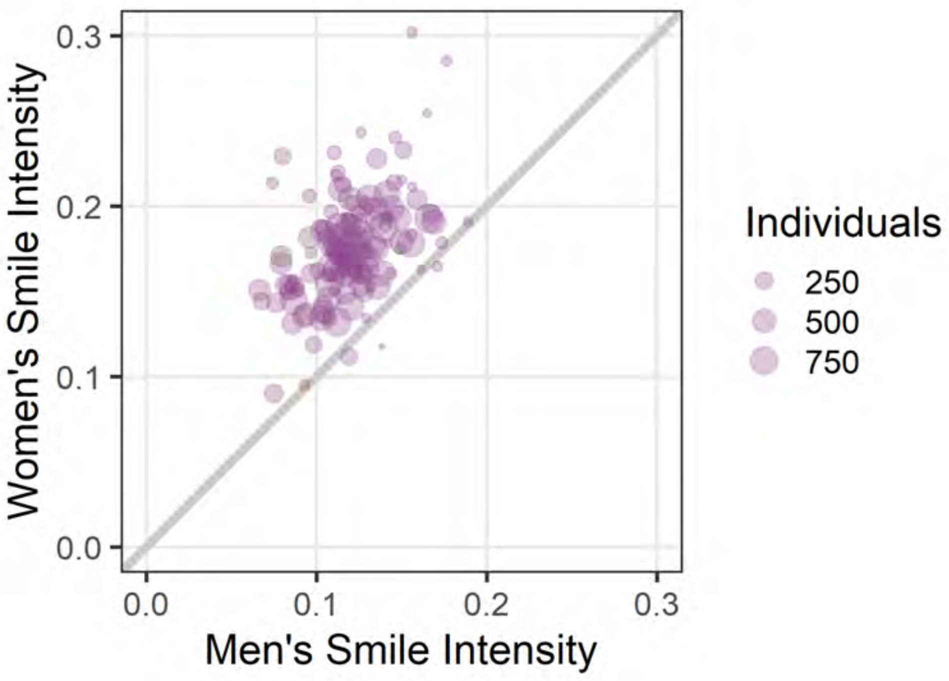
Gender Distributions (Ignoring Country)



Gender Distributions by Country

Note: In these visualizations, each bubble is one country (sized by the number of individuals in the sample).





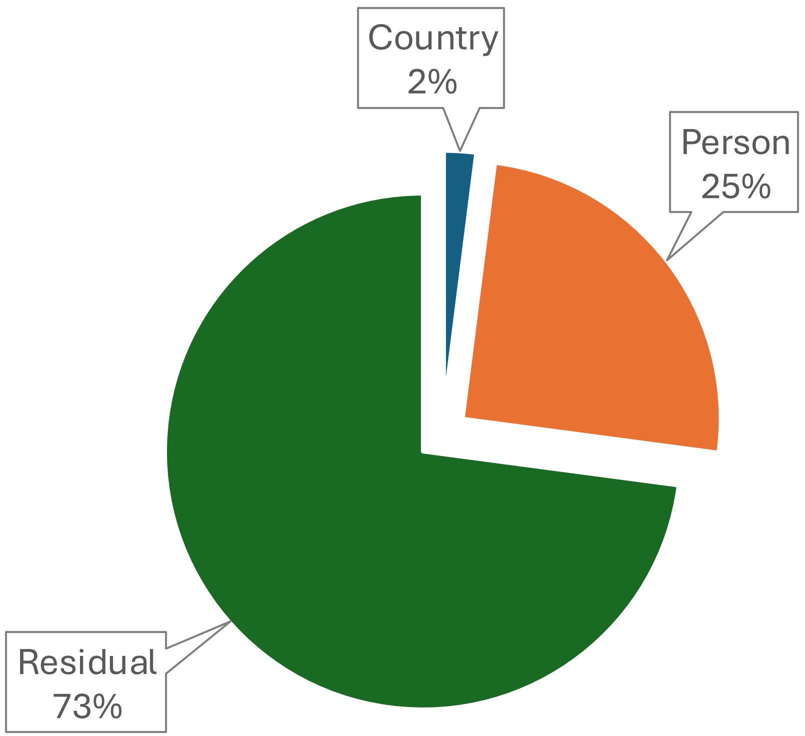
Variance Decomposition

$$\sigma_x^2 = \sigma_c^2 + \sigma_p^2 + \sigma_{i,e}^2$$

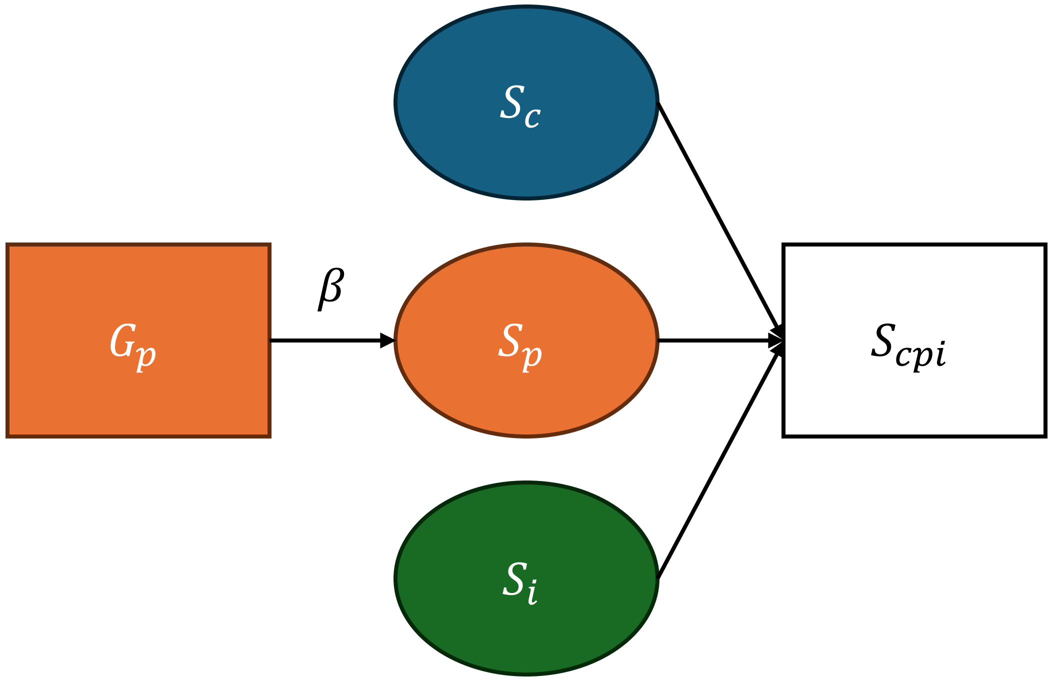
Most of the variance was residual (within-people, unexplained, error)

Countries explained very little variance, which means cultural influences on smiling are weak or “country” is too coarse a proxy

These results highlight the importance of person-level and image-level context



Variance Explained by Gender



$$\beta = 0.33 \quad p < .001$$

$$R^2 = .026$$

Women's average smile intensity was 0.33 SDs higher than Men's

Gender explained 2.6% of the total (and 10.4% of the person) variance.

DATASET 2

INSTAGRAM INFLUENCER IMAGES

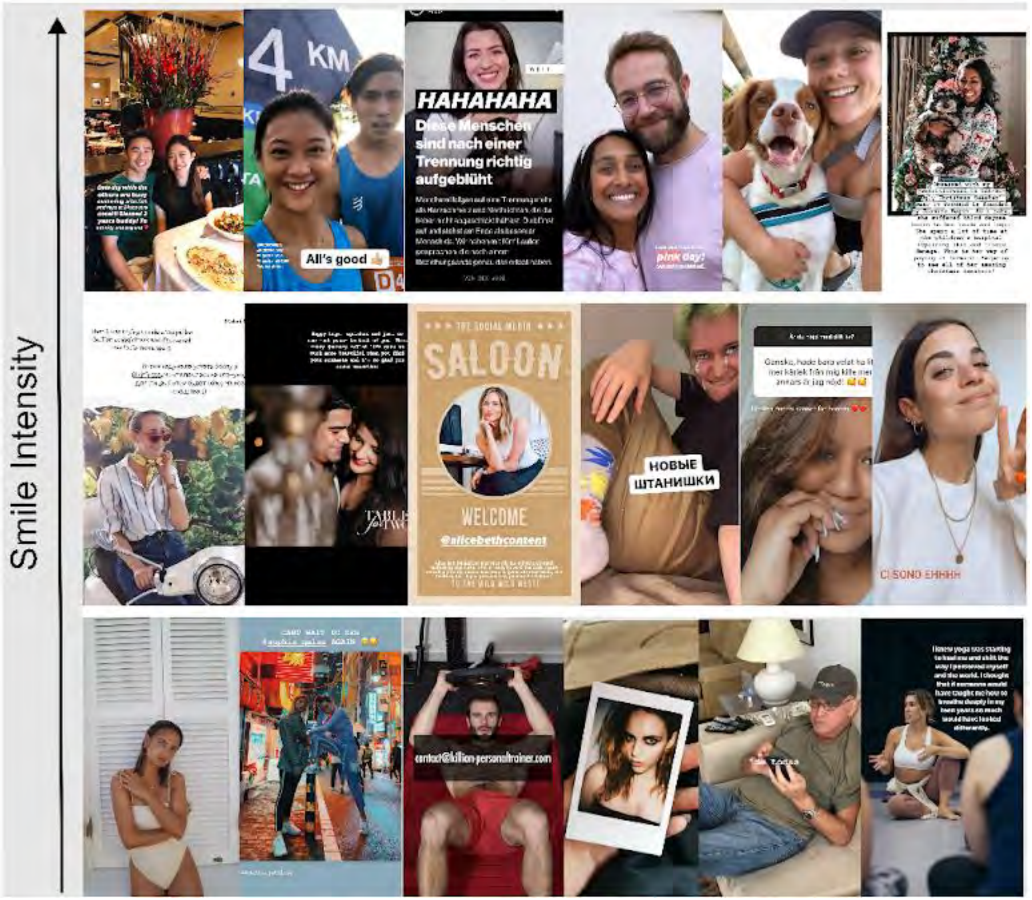
Follow individuals over time to assess within-person variability

Extend findings from celebrities to social media influencers

Extend images from headshots to more varied image types

Data Sourcing

- Partnered with an international influencer management agency
- Gained access to their internal database of Instagram influencers (with self-reported gender/country)
- Downloaded all images uploaded between May 2019 and Oct. 2021
- Images were analyzed for smile intensity using OpenFace
  (criterion validity of r = 0.41 with human ratings in a subsample of 595 images)



Data Exploration (Counts by Country)

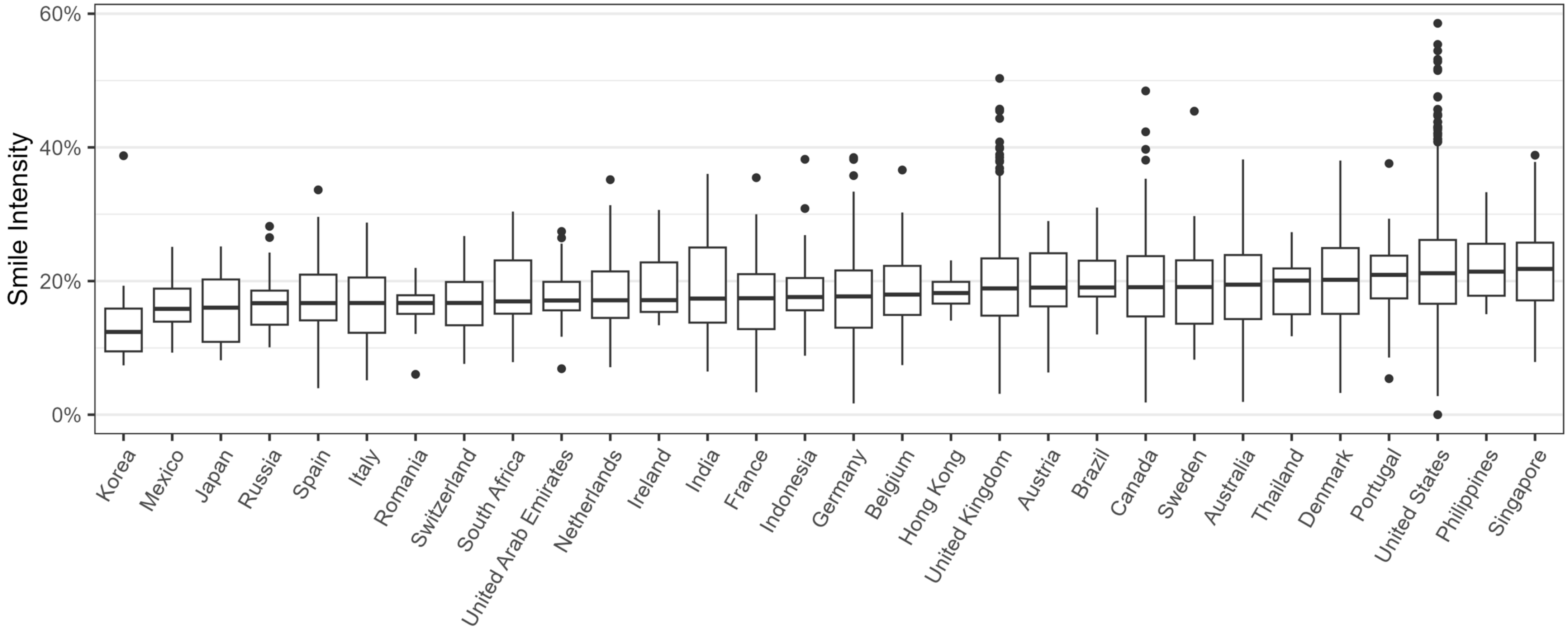
Country	People
United States	3096
United Kingdom	1536
Germany	199
Canada	151
France	144
Italy	100
Spain	87
Australia	74
Singapore	71
Netherlands	61

Country	People
Brazil	49
Sweden	45
Russia	40
India	33
Mexico	32
Philippines	32
Portugal	30
Belgium	26
Indonesia	23
Thailand	20

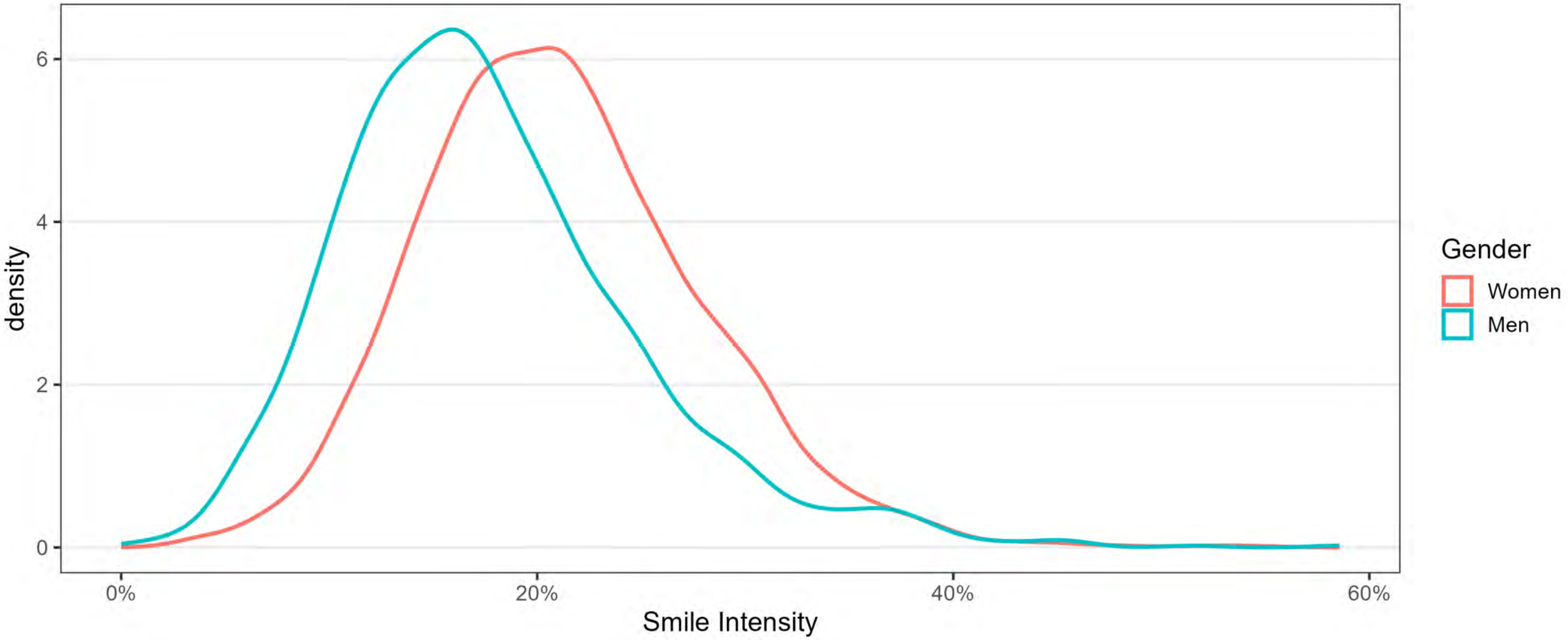
Country	People
South Africa	19
United Arab Em.	19
Ireland	19
Hong Kong	17
Japan	16
Romania	14
Denmark	14
Austria	13
Switzerland	12
Korea	12

Final Count: 1,930,376 images; 6,004 celebrities; 30 countries

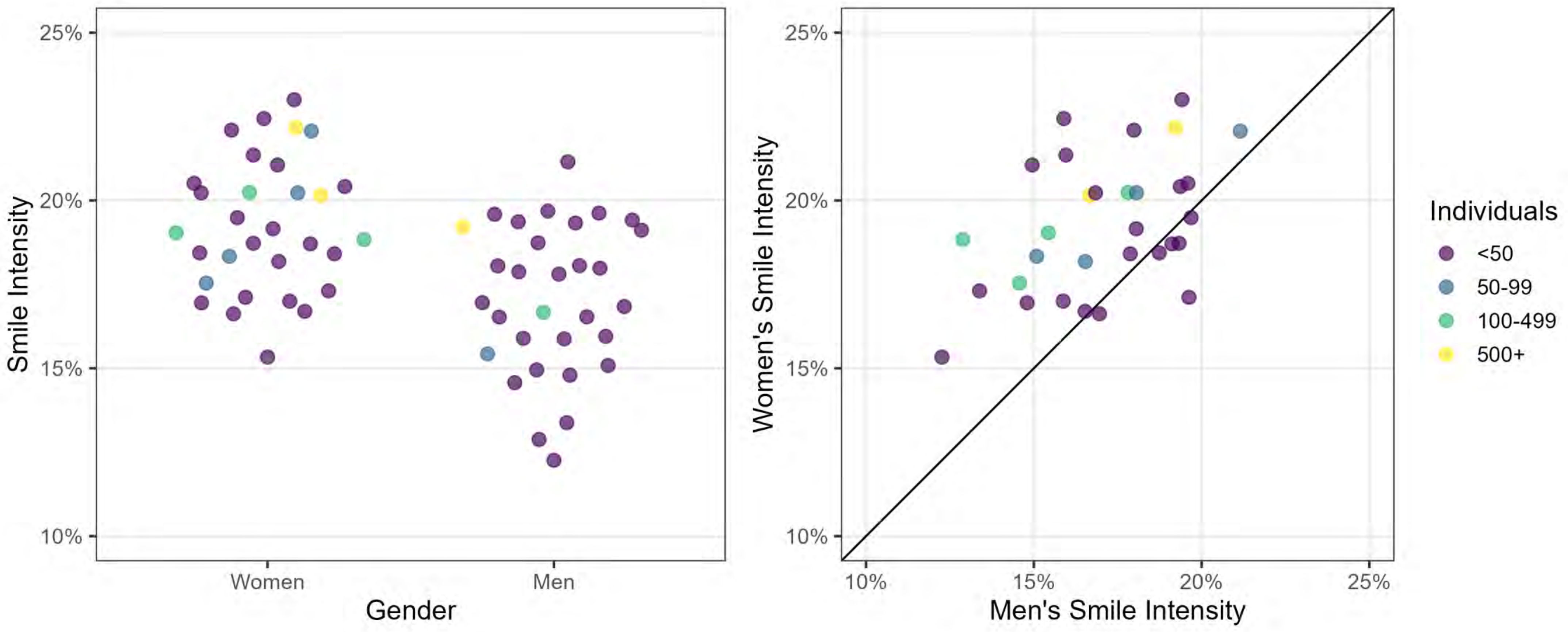
Country Distributions (Ignoring Gender)



Gender Distributions (Ignoring Country)



Gender Distributions by Country



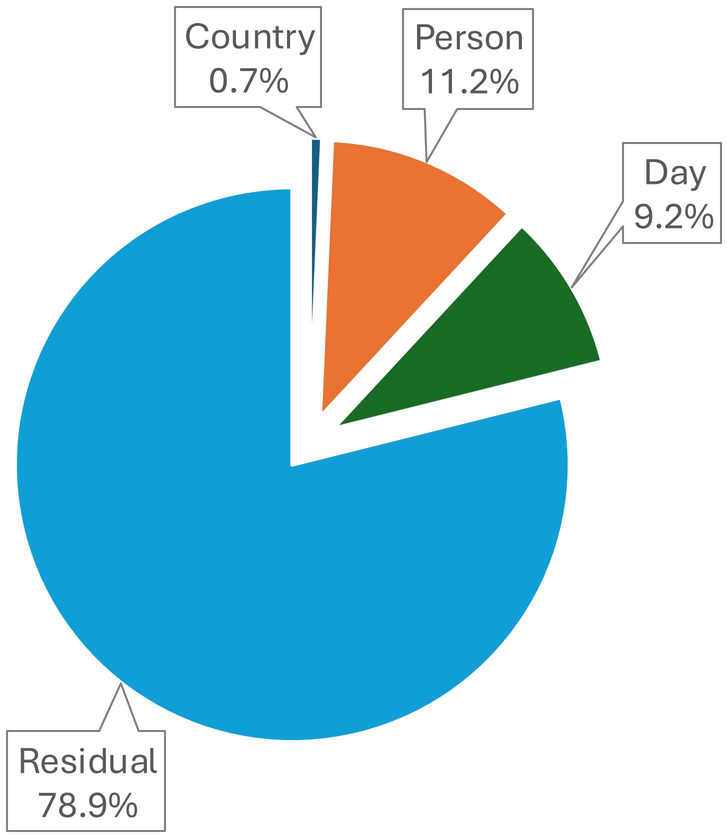
Variance Decomposition

$$\sigma_x^2 = \sigma_c^2 + \sigma_{p:c}^2 + \sigma_{d:p:c}^2 + \sigma_{i,e}^2$$

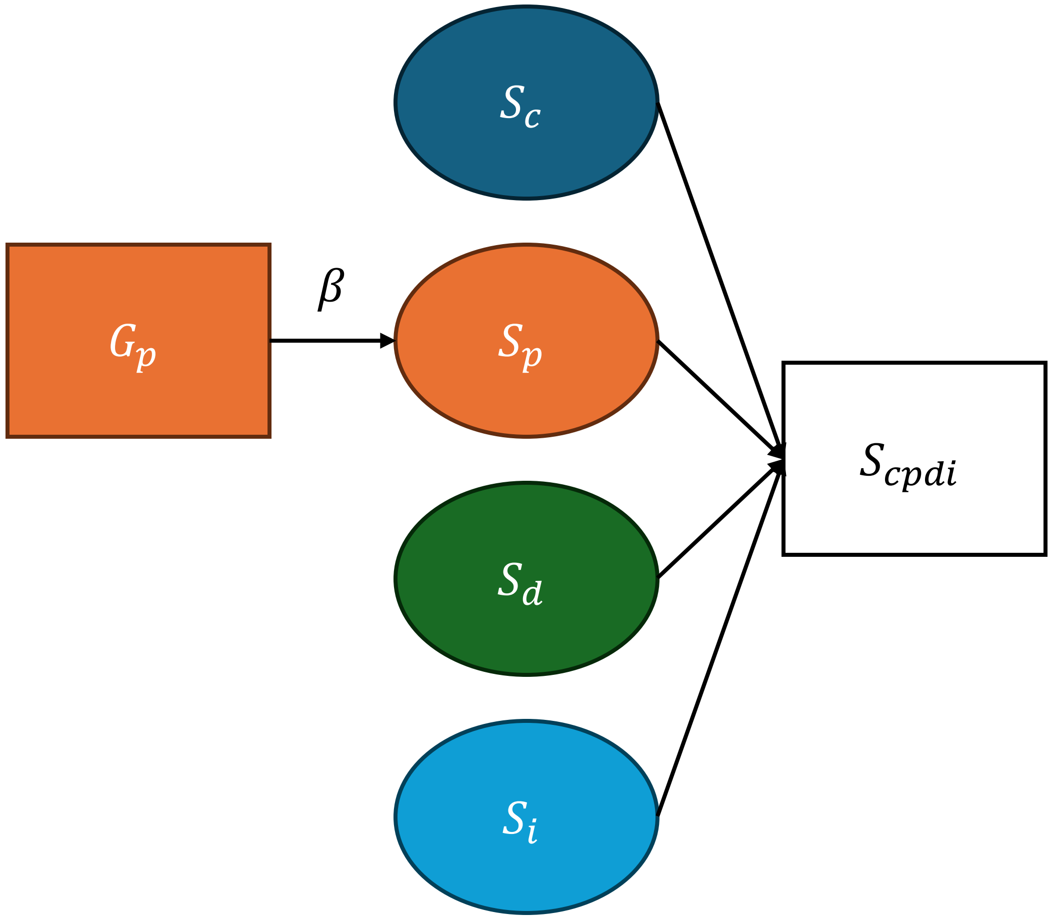
Most of the variance was residual (within-days, unexplained, error)

Countries and people explained less variance this time and day emerged as an important cluster

These results highlight the primary importance of *momentary context*



Variance Explained by Gender



$$\beta = 0.18 \quad p < .001$$

Women's average smile intensity was 0.18 SDs higher than Men's

$$R^2 = .004$$

Gender explained 0.4% of the total (and 3.6% of the person) variance.

CLOSING

Conclusion and Take-Aways

Open Challenges and Concerns

References and Discussion Questions

Conclusions

- Country explained disappointingly little of the total variance (<2%)
  - The impact of culture may be relatively weak on (posed) smiling
  - Or country may be too coarse a proxy to represent culture
- Individuals differed considerably within countries (11-25%)
  - Gender had a significant, global, and replicable effect on smiling
  - However, the vast majority of person variance and total variance remain
  - There is ample room for further research into individual differences
- Images differed substantially within individuals and within days
  - Local, momentary contextual features may be the most impactful

Challenges and Concerns

- Biases in Normative Data
  - Avoid reinforcing or reifying harmful or outdated stereotypes
- Privacy and Confidentiality
  - Personal data must be handled with care to protect privacy
- Transparency
  - Users should know when and why the system is adapting to norms
- Generalizability
  - Spontaneous behavior from non-celebrities may be quite different

References

- McDuff, D., Girard, J. M., & El Kaliouby, R. (2017). Large-scale observational evidence of cross-cultural differences in facial behavior. *Journal of Nonverbal Behavior*, *41*(1), 1–19.
- Girard, J. M., & McDuff, D. (2017). Historical heterogeneity predicts smiling: Evidence from large-scale observational analyses. *Proceedings of the 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG)*, 719–726.
- McDuff, D., & Girard, J. M. (2019). Democratizing psychological insights from analysis of nonverbal behavior. *Proceedings of the 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, 220–226.
- Girard, J. M., El Kaliouby, R., Campbell, C., Rosengren, S., & McDuff, D. (in preparation). Quantifying descriptive smiling norms in multiple contexts around the world using large-scale observational methods.

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THANK YOU!
QUESTIONS?

Special Thanks to:

- Daniel McDuff
  (Google, Univ. Washington)
- Social AI Group
  (Univ. Glasgow)

Discussion Questions

1. What are some examples of prescriptive or descriptive norms related to emotion or interpersonal communication that you have noticed?
2. How can we most effectively build knowledge of prescriptive and descriptive norms into social artificial intelligence (SAI) systems?
3. What are some examples of situations in which we might want an SAI system to deliberately generate/produce “abnormal” behaviors?
4. How can we further improve large-scale observational research?
5. How can SAI systems handle bias, privacy, and complexity concerns?