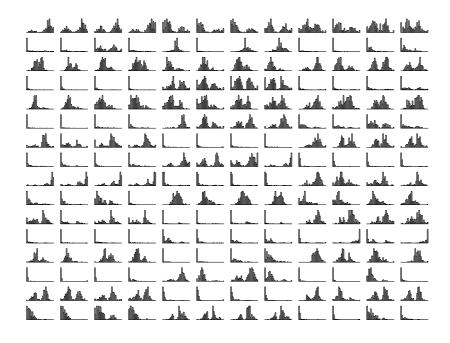
# Multimodality and Skewness in Emotion Time Series

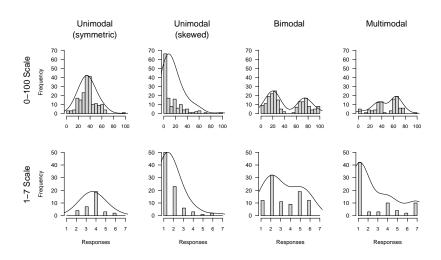
Oisín Ryan, Jonas Haslbeck, & Fabian Dablander

DynaNet Meeting, June 20, 2022

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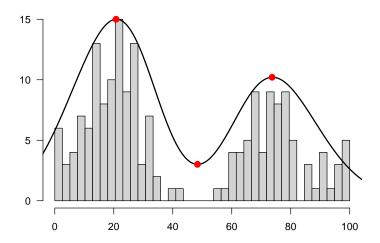
### Distributional Forms in Emotion Time Series



All measurements are for the emotion Sad.

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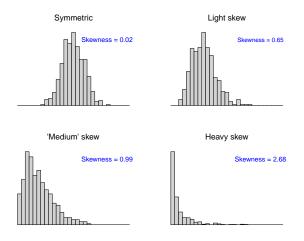
### Determining the Number of Modes



### Two steps:

- 1. Get (Gaussian) kernel-density estimate (black curve)
- 2. Count roots;  $M = \frac{\#roots+1}{2}$

### **Determining Skewness**

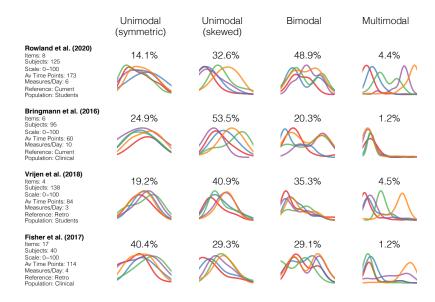


To get an overview, we use a conservative cutoff:

- ► Skew  $< \frac{2}{3}$ : Symmetric
- ► Skew  $> \frac{2}{3}$ : Skewed

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# Modality & Skewness Results 1/2



# Modality & Skewness Results 2/2

|  | Unimodal<br>(symmetric) | Unimodal<br>(skewed) | Bimodal | Multimodal |
|--|-------------------------|----------------------|---------|------------|
| Bringmann et al. (2013)<br>Items: 5<br>Subjects: 130<br>Scale: 1-7<br>Av Time Points: 89<br>Measures/Day: 10<br>Reference: Current<br>Population: Clinical | 32.1%                   | 49.1%                | 18.1%   | 0.6%       |
| Fried et al. (2021)<br>Items: 9<br>Subjects: 79<br>Scale: 1-5<br>Av Time Points: 50<br>Measures/Day: 4<br>Reference: Retro<br>Population: Students         | 31.6%                   | 68.2%                | 0.2%    | 0%         |
| Wendt et al. (2020)<br>Items: 31<br>Subjects: 228<br>Scale: 1-5<br>Av Time Points: 111<br>Measures/Day: 3.7<br>Reference: Current<br>Population: Clinical  | 20.6%                   | 76.1%                | 3.1%    | 0.3%       |

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### Implications for Measurement

We have no explanation for how 0-100 scales induce multimodality

caveat: anchoring, but only present in 2/4, so does not explain away results

But we have an explanation for how Likert-scales mask multimodality

If emotion is state-like, 0-100 scales might help pick this up

### Implications for Theory

Establish basic phenomena of emotion dynamics which theories should explain

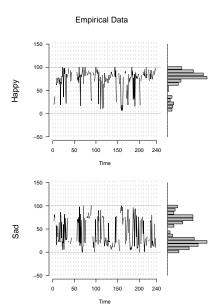
### Multimodality implies:

- Qualitatively different states with varying intensity per state
- Is a feature of many dynamical-systems-inspired accounts of psychological processes

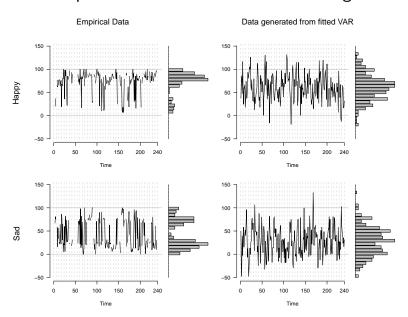
Large degree of person heterogeneity in distributional forms

Characterizes patterns of emotion regulation which might map onto e.g. symptom profiles

# Implications for Time Series Modeling



### Implications for Time Series Modeling



# Implications for Time Series Modeling

### (V)AR models:

- ► May not fit the data well
- ▶ What to do with VAR then?
  - descriptive: extremely useful
  - generative: probably misleading

### Worth exploring other modeling ideas:

- Descriptives
- Regime switching models

### Multimodality and Skewness in Emotion Time Series

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#### Abstract

The ability to measure emotional states in daily life using mobile devices has led to a surge of these data still remains untapped. In this paper, we re-analyze emotion measurements from seven openly available Experience Sampling Methodology (ESM) studies with a total of 835 individuals to systematically investigate the modality (unimodal, bimodal, multimodal) and skewness of within-person emotion measurements. We show that both multimodality and skewness are highly prevalent. In addition, we quantify the heterogeneity across items, individuals, and measurement designs. Our analysis reveals that multimodality is more likely in studies using an analogue slider scale than in studies using a Likert scale; negatively valenced items are consistently more skewed than positive valenced items; and longer time series show a higher degree of modality in positive and a higher skew in negative items. We end by discussing the implications of our results for theorizing, measurement, and time series modeline.

Preprint: https://psyarxiv.com/qudr6

# Additional Slides

### In total: 11520 univariate time series

- ▶ 835 different individuals, with in total 55 unique emotions
- A variety of different measurement and design choices

### Digging deeper:

- Negatively valenced items consistently more skewed than positively valenced
- ► Longer time series → more modality in *positive items*
- ► Longer time series → more skewneess in *negative items*
- In the three studies which measured neuroticism: higher neuroticism → lower skewness of negatively valenced emotions

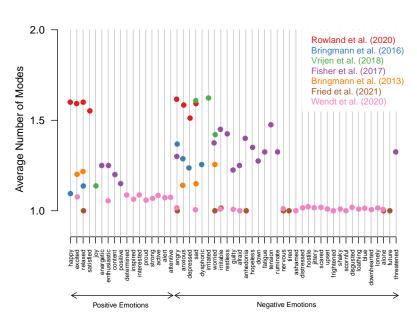
### Study Design

Studies were quite heterogenous with respect to design choices

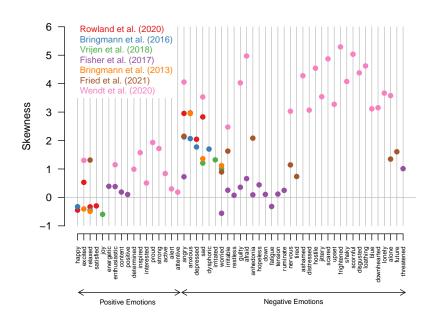
- ► Measurement frequency
- ► Measurement length
- Item phrasing (current vs retrospective)
- Population (students vs clinical)

With only 7 studies we lack the power to detect design-level differences

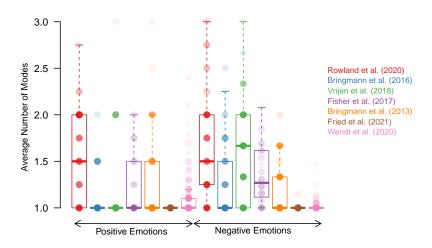
### Item-level: Modality



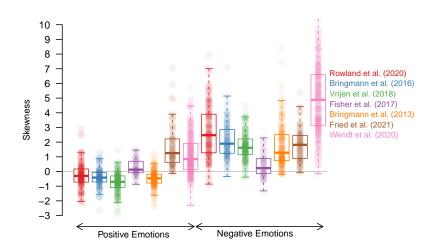
### Item-level: Skew

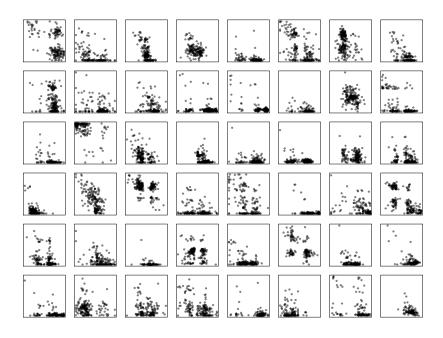


### Person-level: Modality

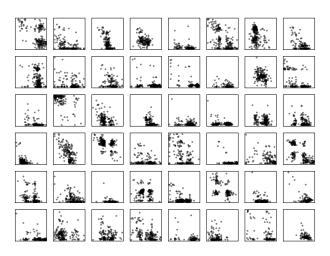


### Person-level: Modality

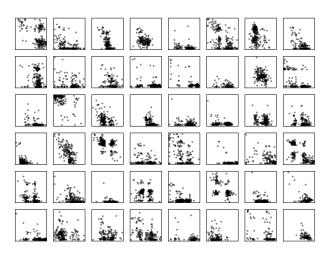




# What to make of Heterogeneity?

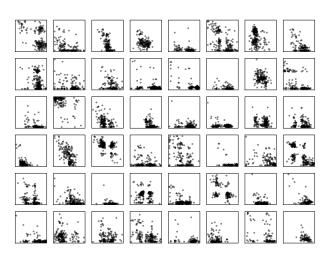


# What to make of Heterogeneity?



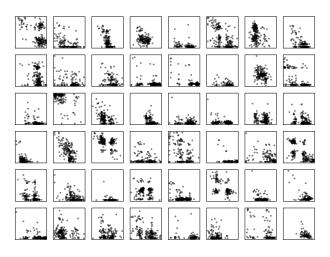
► From statistical perspective: disaster!

# What to make of Heterogeneity?



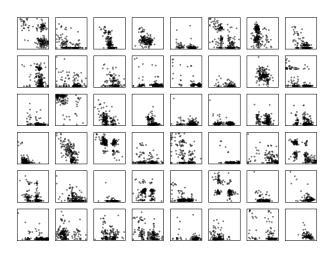
- ► From statistical perspective: disaster!
- ► From science perspective: great!

# Disorders & Emotion Dynamics



Disorder = f(Emotion time series)

### Disorders & Emotion Dynamics



Disorder = f(Emotion time series)

... so far we explored very little