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# About human activity, long-term memory, and Gibrat's law

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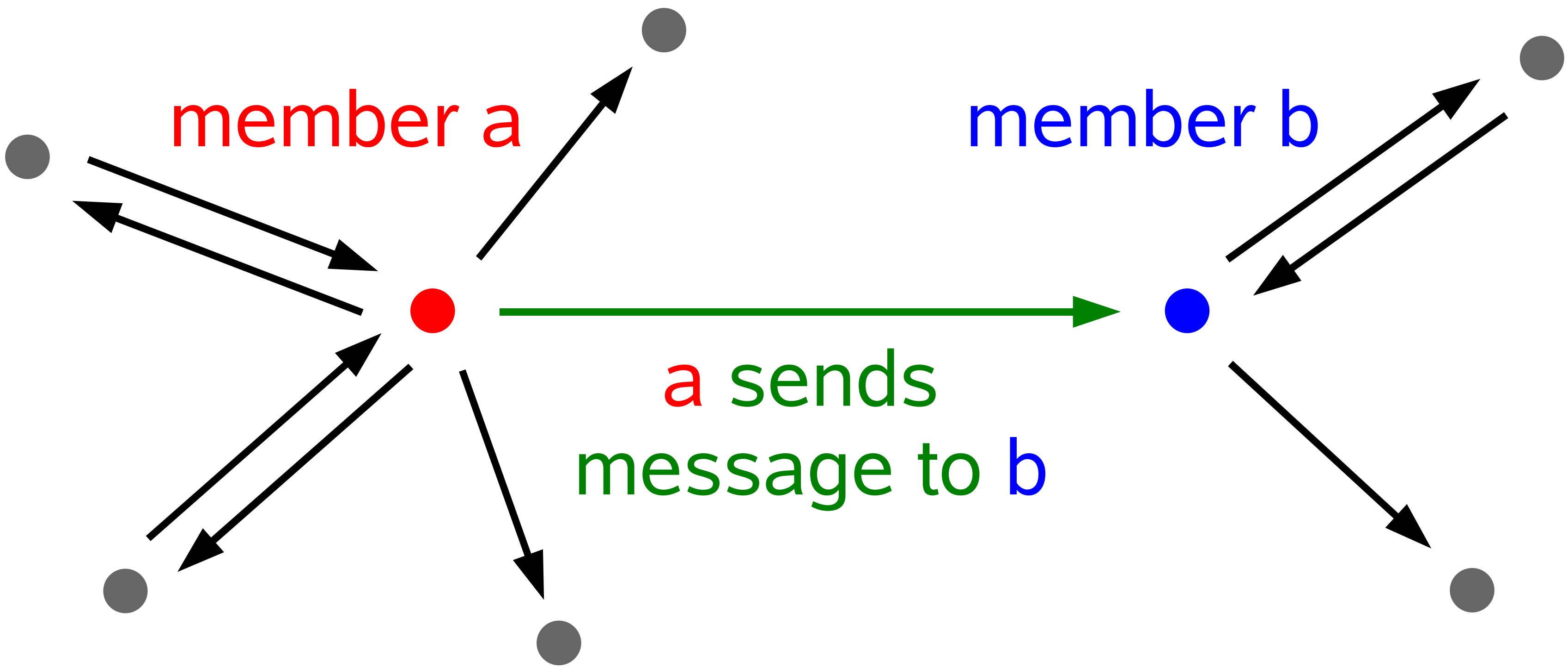
the City College of New York
OF THE CITY UNIVERSITY OF NEW YORK

# Motivation

online community: members sending messages




either following an existing link $m_\mathrm{a} \longrightarrow m_\mathrm{a} + 1$

or creating a new one $k_\mathrm{a}^\mathrm{out} \longrightarrow k_\mathrm{a}^\mathrm{out} + 1$

=> **growth process**

# Outline

1. online-community data
2. growth process
3. temporal correlations
4. missing link
5. conclusions

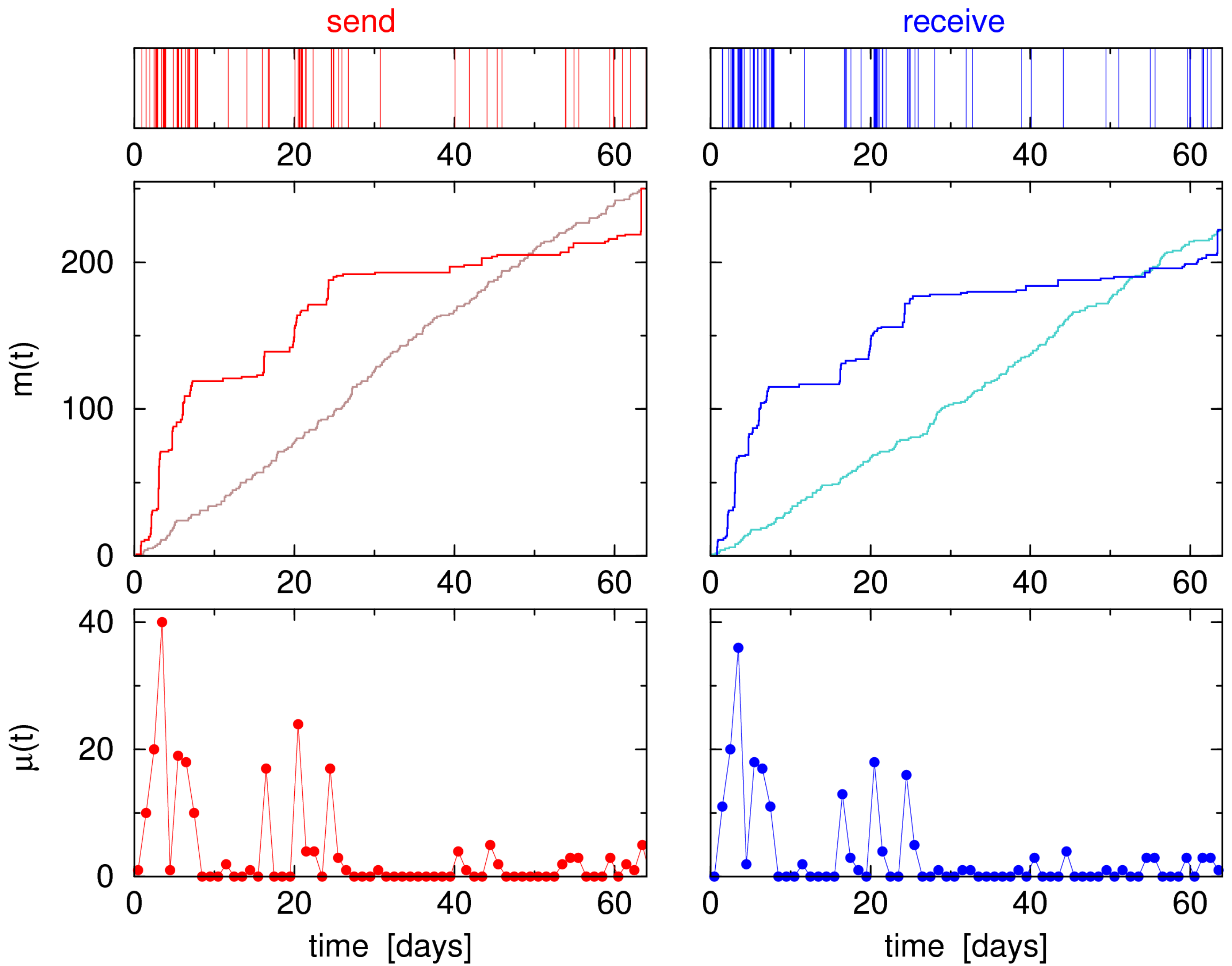
# Online-community data

online community 1 (OC1):
- 80,000 members
- 12.5 million messages
- 63 days

online community 2 (OC2):
- 30,000 members
- 500,000 messages
- 492 days

both are dating-communities
also used for social interaction in general
completely anonymous

# Typical activity (OC1)



# Growth process

for each member:

cumulative number of messages $m(t)$

logarithmic growth rate $r = \ln \frac{m_1}{m_0}$

between two time-steps $t_0, t_1$

two quantities:

conditional average growth $\langle r(m_0) \rangle = \langle r | m_0 \rangle$

cond. standard deviation $\sigma(m_0) = \sigma(r | m_0)$

see e.g. M.H.R. Stanley et al., nature, 1996.

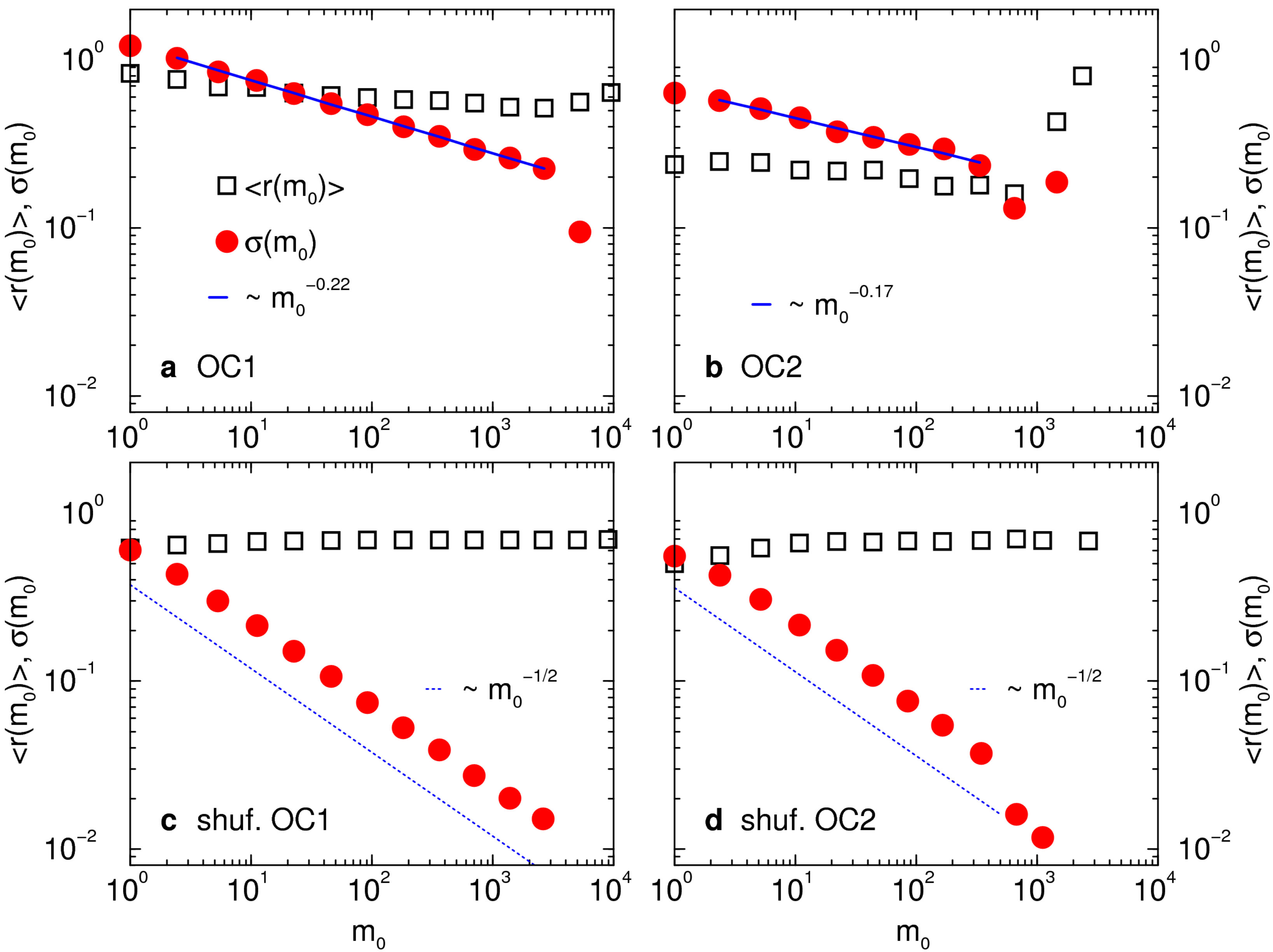
# Analogy to other data, such as city growth

(1) The members of a community represent a population similar to the population of a country.

(2) The number of members fluctuates and typically grows analogous to the number of cities of a country.

(3) The activity or number of links of individuals fluctuates and grows similar to the size of cities.

# Growth process: results



# Growth process: results

$$\sigma(m_0) \sim m_0^{-\beta}$$

OC1: $\beta_{\mathrm{OC1}} = 0.22 \pm 0.01$
OC2: $\beta_{\mathrm{OC1}} = 0.17 \pm 0.03$
shuffled: $\beta_{\mathrm{rnd}} = 1/2$

# Gibrat's law of proportionate growth

multiplicative process
to explain broad distributions (log-normal)

involves assumption: $\langle r(m_0) \rangle = \mathrm{const.}$
$\sigma(m_0) = \mathrm{const.}$

=> $\beta_{\mathrm{G}} = 0$

# Temporal correlations

- shuffling destroys temporal correlations, leading to $\beta_{\mathrm{rnd}} = 1/2$

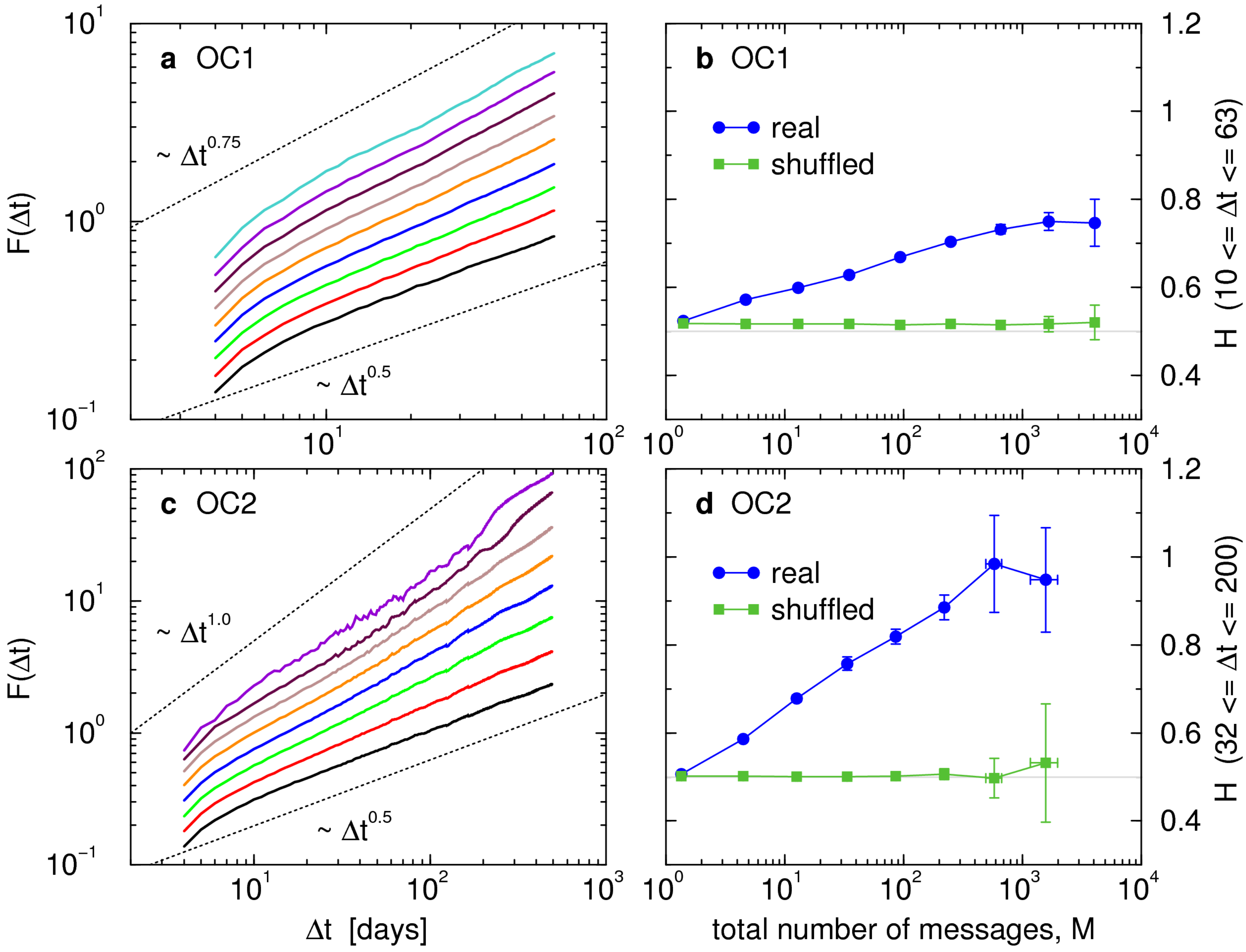
- this suggest $\beta \approx 0.2$ might be due to temporal correlations

- we use Detrended Fluctuation Analysis (DFA) to quantify long-term correlations in the activity (messages per day): $\mu(t)$

fluctuation function: $F(\Delta t) \sim (\Delta t)^{H}$

$1/2 < H < 1$ => ltc

# Temporal correlations: results



# Missing link

derivation leads to:

$$\beta = 1 - H$$

accordingly:

$$\beta \approx 0.2 \quad \Rightarrow \quad H \approx 0.8 \qquad \text{OCs}$$

$$\beta_{\mathrm{rnd}} = 1/2 \quad \Rightarrow \quad H_{\mathrm{rnd}} = 1/2 \qquad \text{shuffled}$$

$$\beta_{\mathrm{G}} = 0 \quad \Rightarrow \quad H_{\mathrm{G}} = 1 \qquad \text{Gibrat's law}$$

# Conclusions

1. human activity sending messages is long-term correlated

2. scaling in growth $\sigma(m_0) \sim m_0^{-\beta}$ is due to long-term correlations

=> this may also be the case for other data

Thank you for your attention