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Exploring online manifestations of real-world inequalities on the Nextdoor Social Network

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Can we identify

rich & poor?

Can we **identify**
rich & **poor**
from their
online **text**?

Nextdoor: within neighbourhood interactions

How Nextdoor works?

Mile End
(QMUL neighbourhood)

Bethnal Green
(Adjacent neighbourhood)

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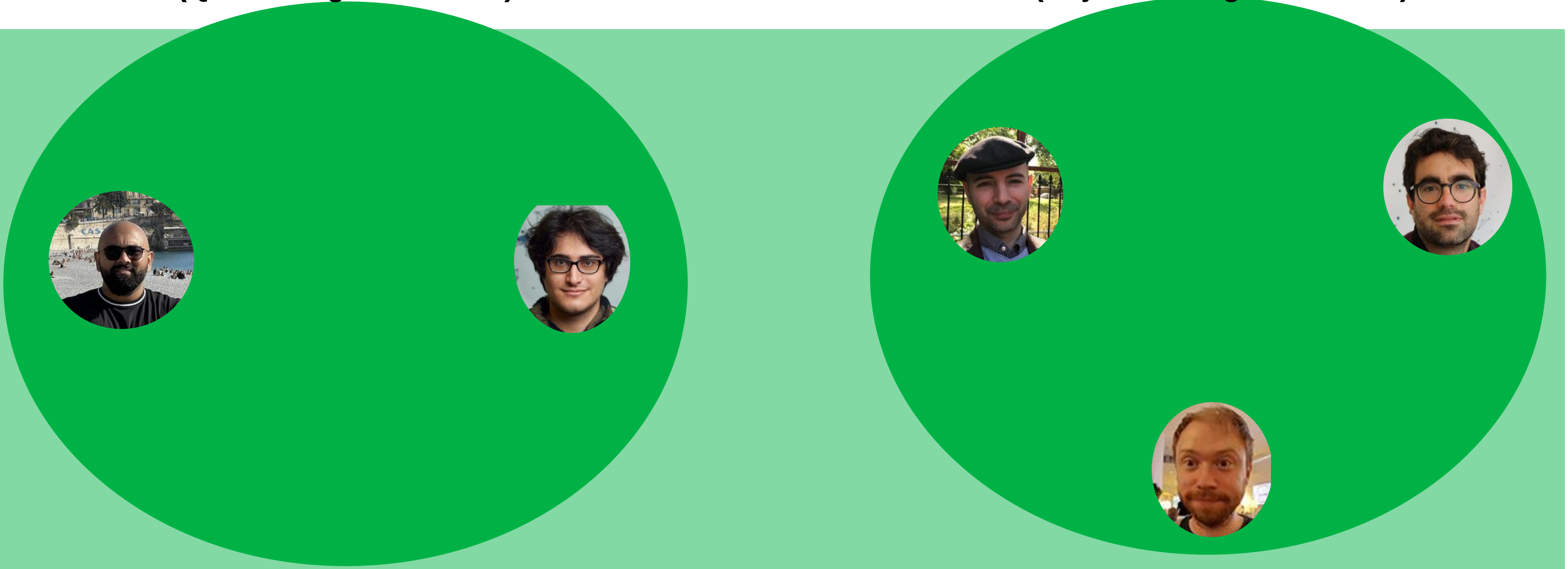

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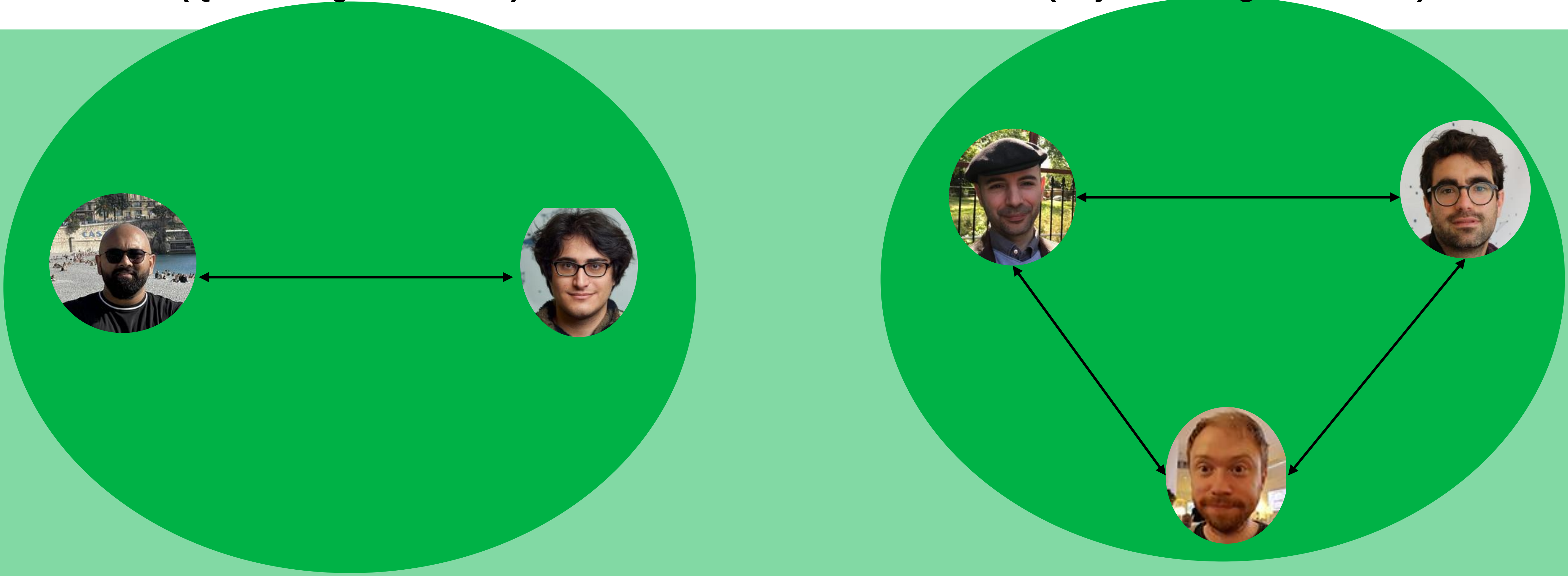

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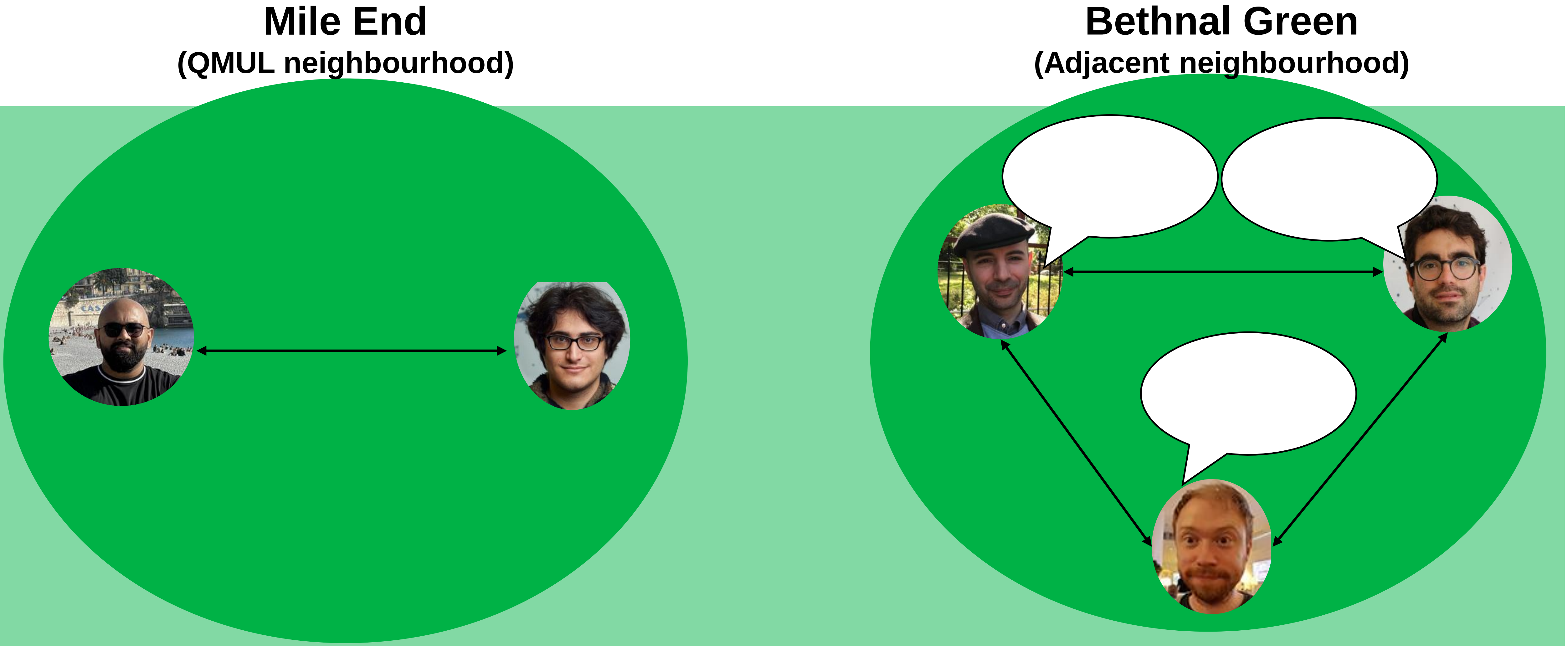

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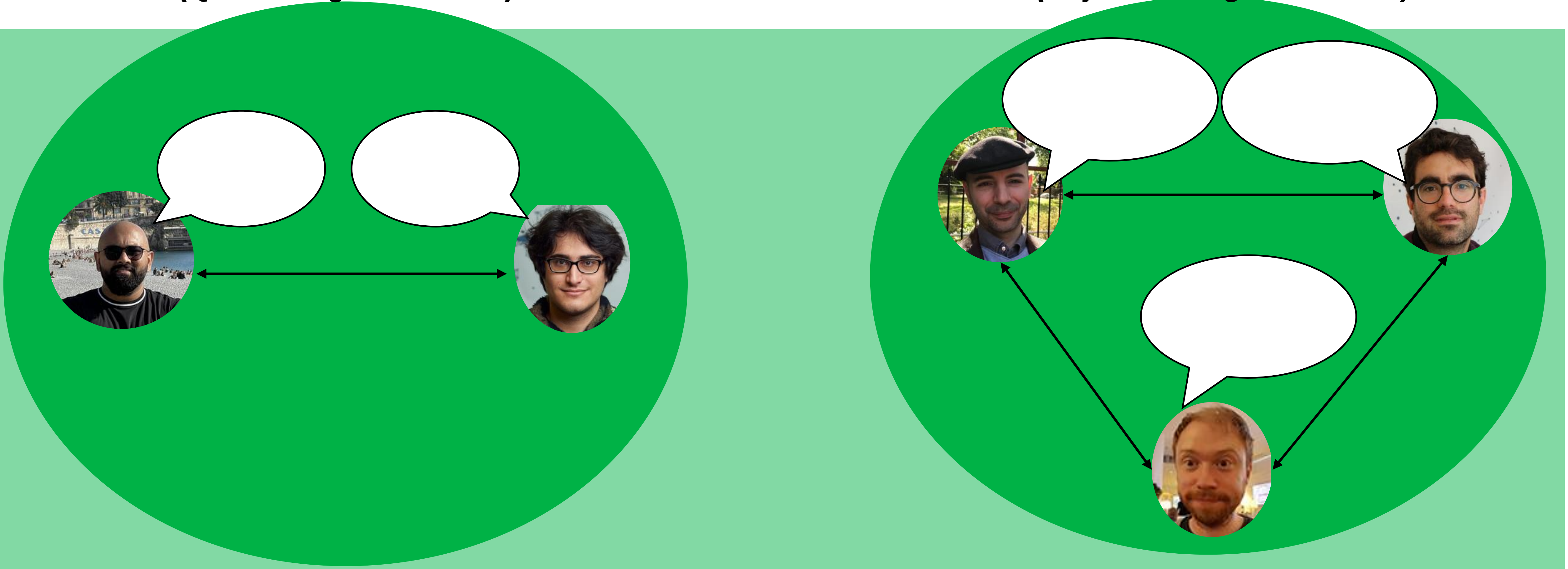


Nextdoor data

Attributes	USA	UK	Total
Posts	2,201,051	351,894	2,602,045
Neighborhoods	64,283	3,325	67,608
Cities	5,849	10	5,859
zip code(USA)/LSOA(UK)	30872	2512	33284
Comments	17,421,050	2,246,814	19,667,864
Neighbors	6,6480,730	1,744,948	68,225,678

lowest geo-units

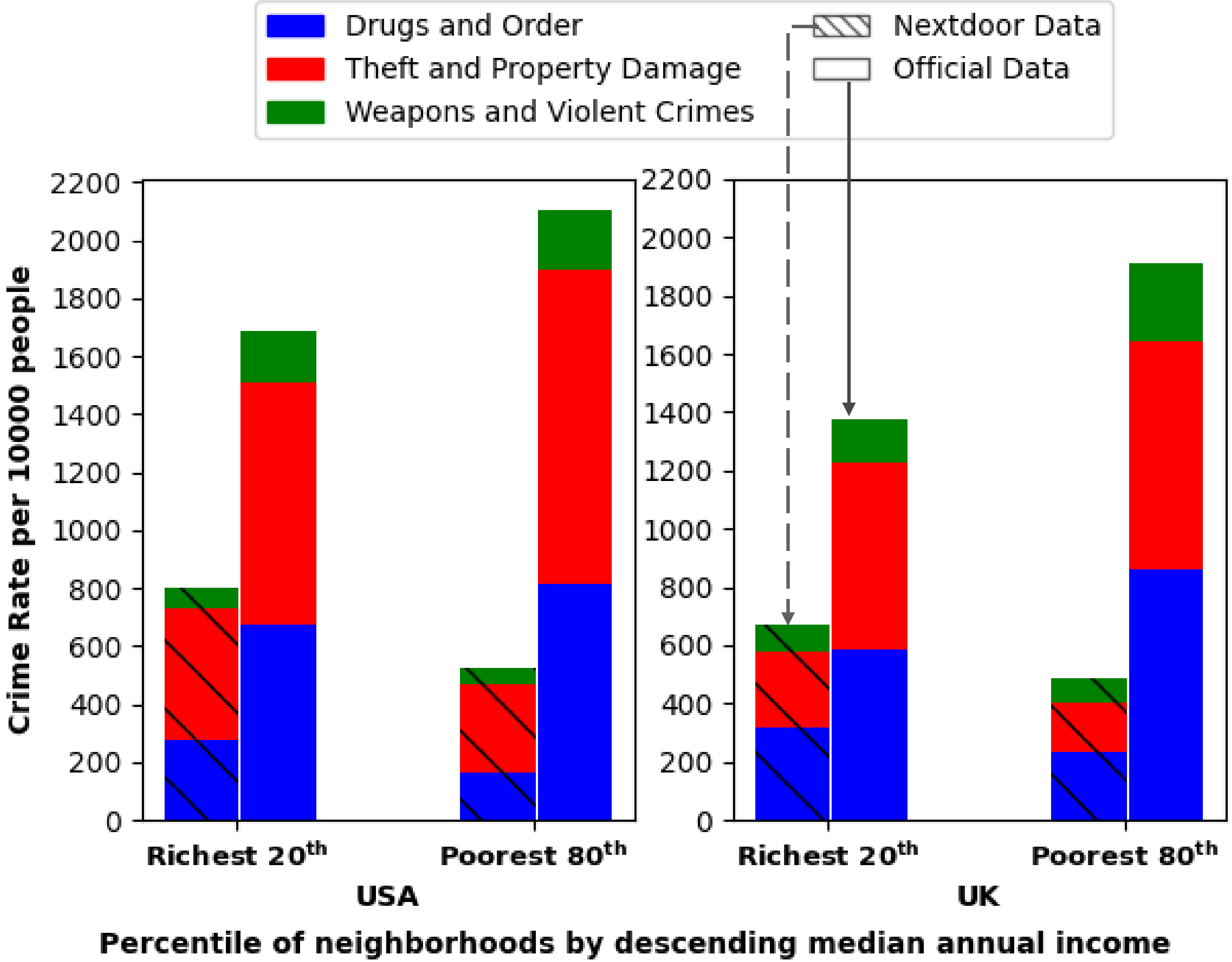
Methodology

- Neighbourhood→ geolocation→ Official statistics
  - Median income
  - Crime
- Identify crime related conversations: Semantic Search S-BERT
- Sentiment: VADER

Does the online text of **rich** & **poor** **differ**?

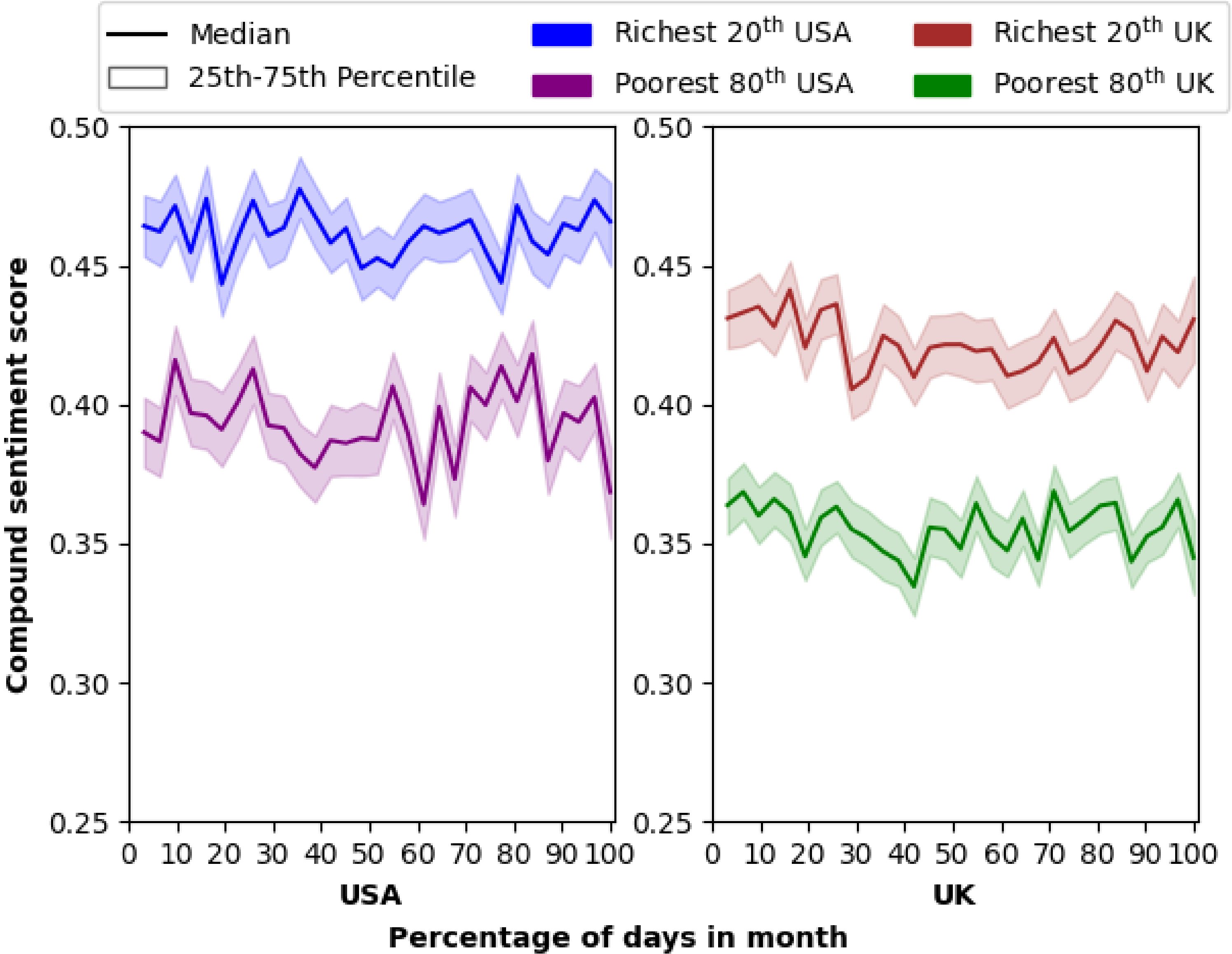
Who talks more about crime?

Richer neighbourhoods talk more about crime



Will richer have more negative sentiment?

More positive sentiment in richer neighbourhoods

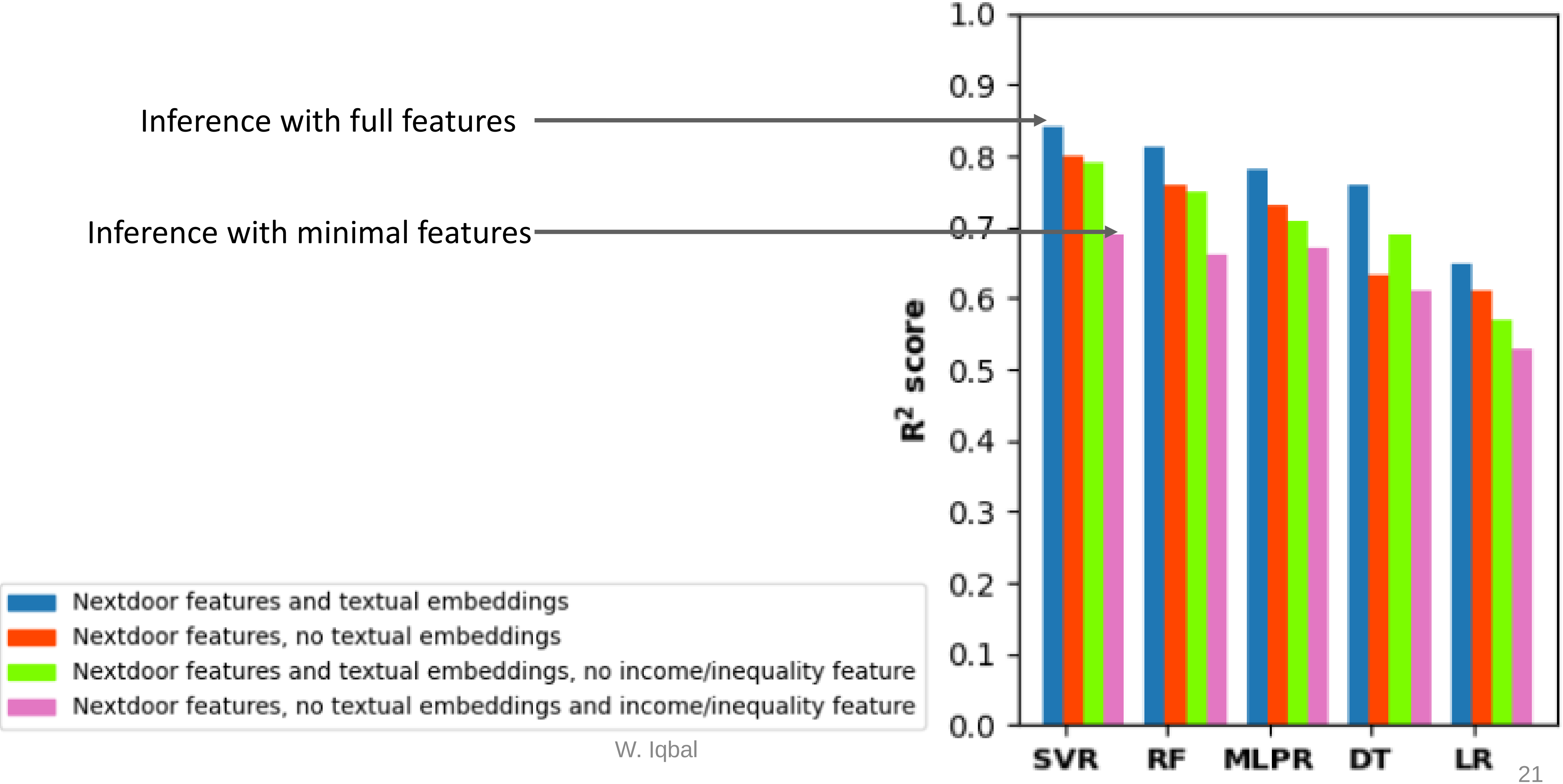


Can we **infer neighbourhood's income** by the **text** posted **online**?

Can we infer who is rich/poor just from the text?

- Embeddings: dimensionality reduction (768→5)
- Discussed-to-official crime ratio
- Other features
- Multiple common ML models

We can infer the level of income from the text



Politics and **income**

(Preliminary Results)

Datasets

- Twitter → Politician tweets
  - 10.1 Million from UK
  - 2.2 Million from USA

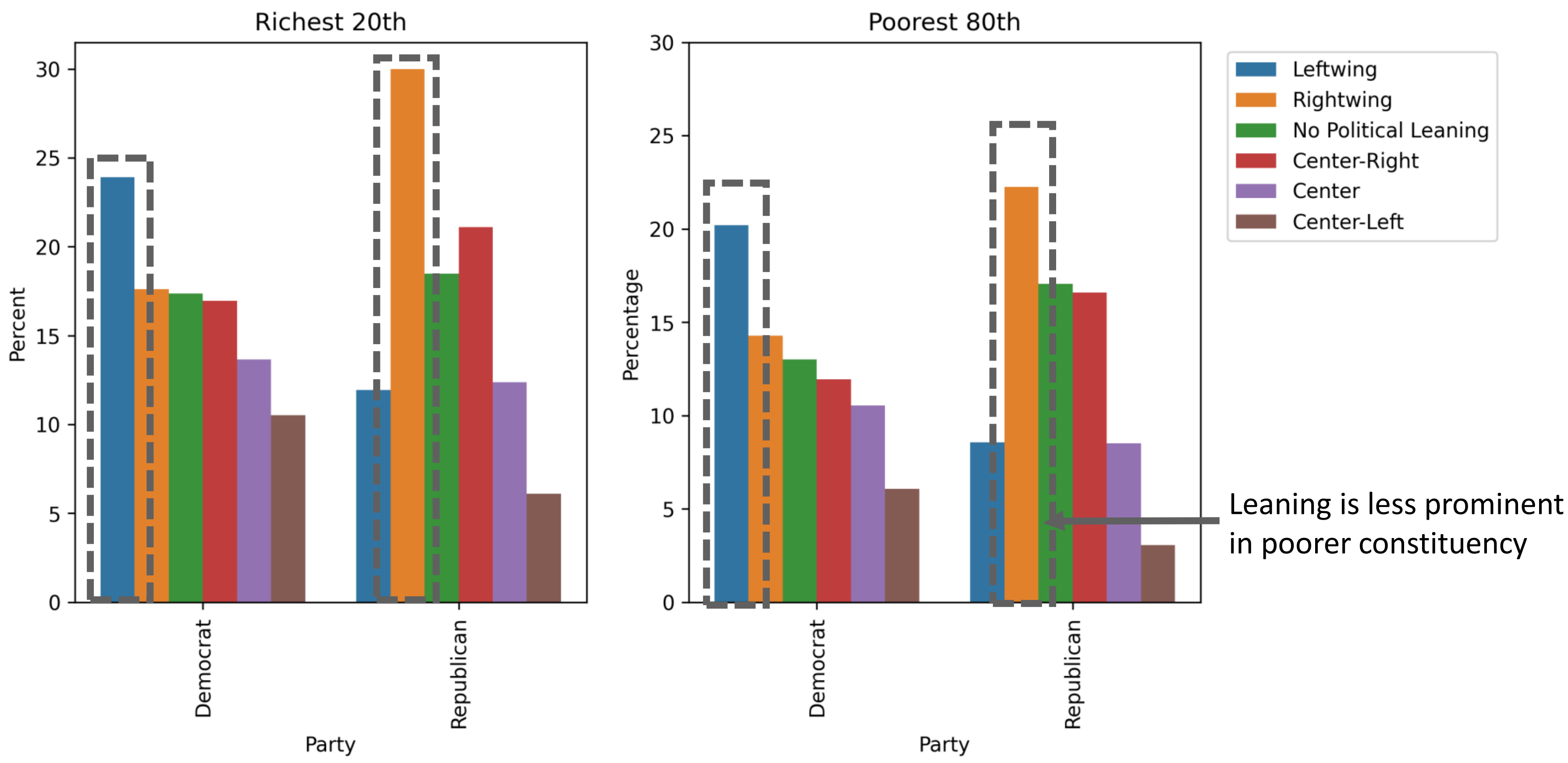
- Nextdoor → Neighbourhood posts
  - 4.5 Million from UK
  - 24.3 Million from USA

Methodology

- Neighbourhood→ constituency→ Official statistics
  - Median income

- Political leaning in tweets → ChatGPT, manual annotation
  - Fine-tuned BERT
    Setfit Model
  - Few shot Learning

Politician agrees with party ideology



USA (Twitter)

Conclusion

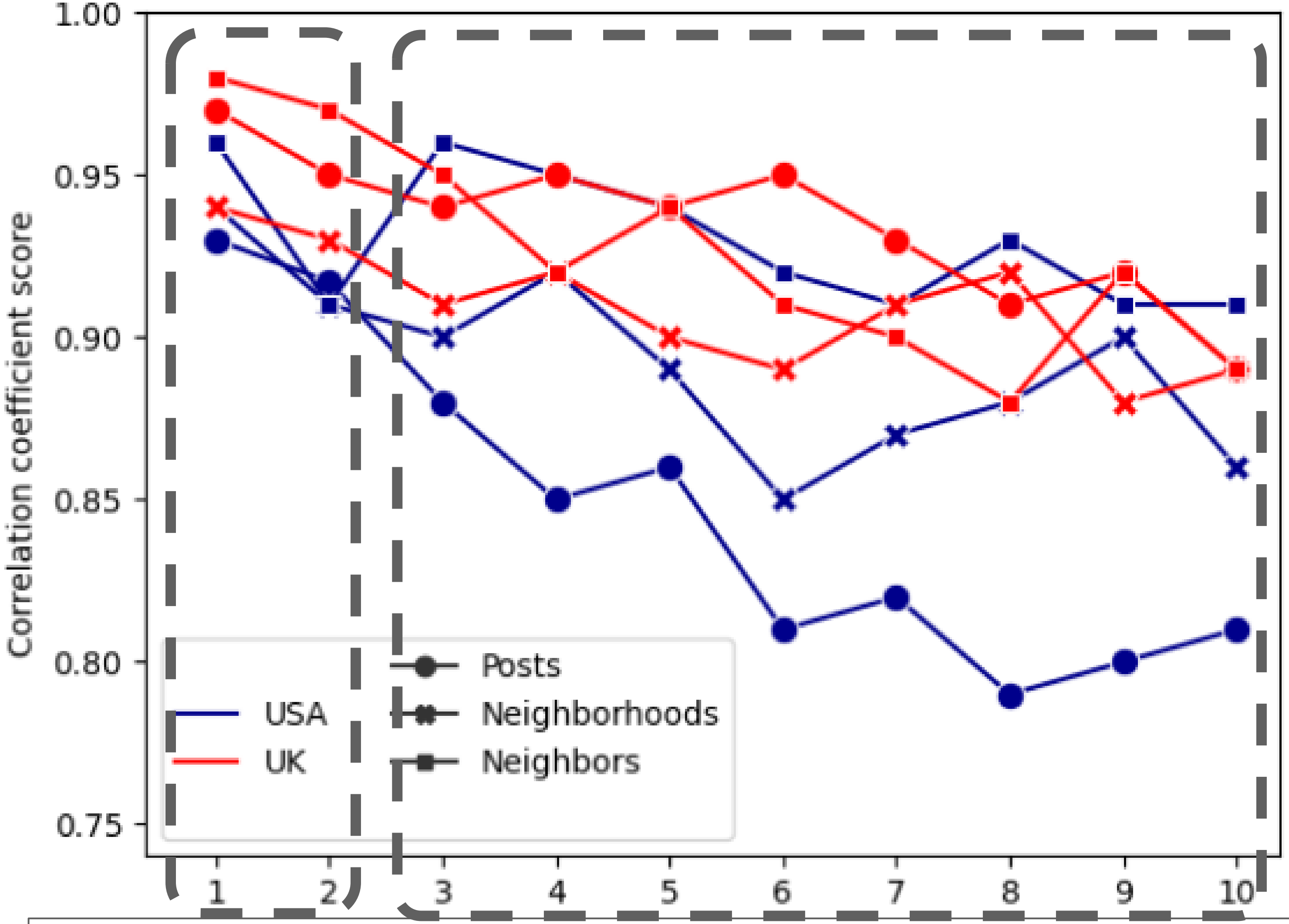
- Rich and poor neighbourhoods have distinct online text.
- User generated posts can predict neighbourhood's income.

Future work

- What about politics?
- What about inequality?
- Can we generalise?
- We are also in talk to collaborate with Nextdoor.

Backup Slides

How representative the data is?



20% Richest

80% poorest

Inequality across neighborhoods

Vicinity of a neighborhood:

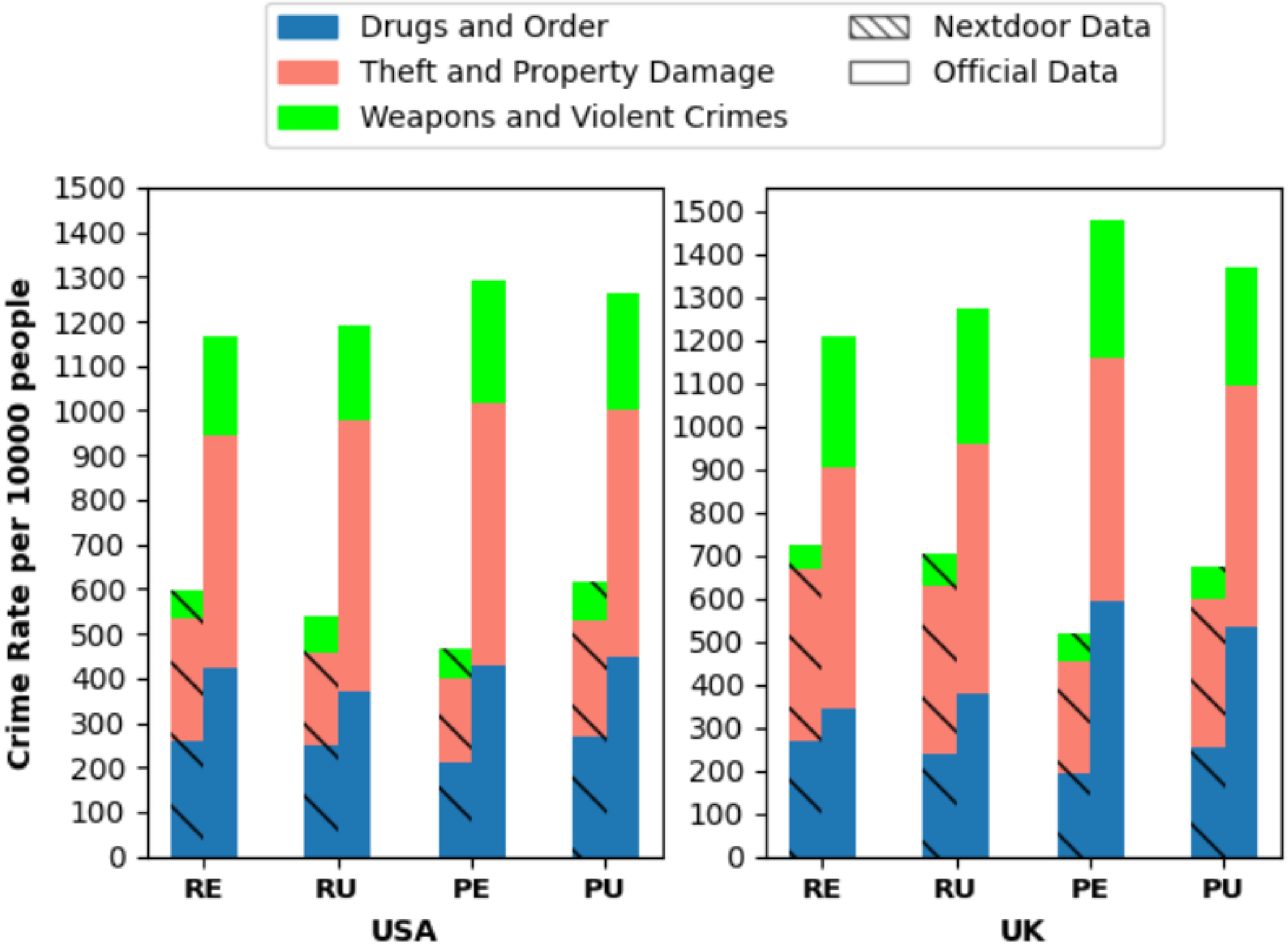
Neighborhoods within 25 (USA) and 3 (UK) miles

Atkinson Index for each neighborhood:

1 → inequality

0 → equality

Inequality matters for poorer neighborhoods



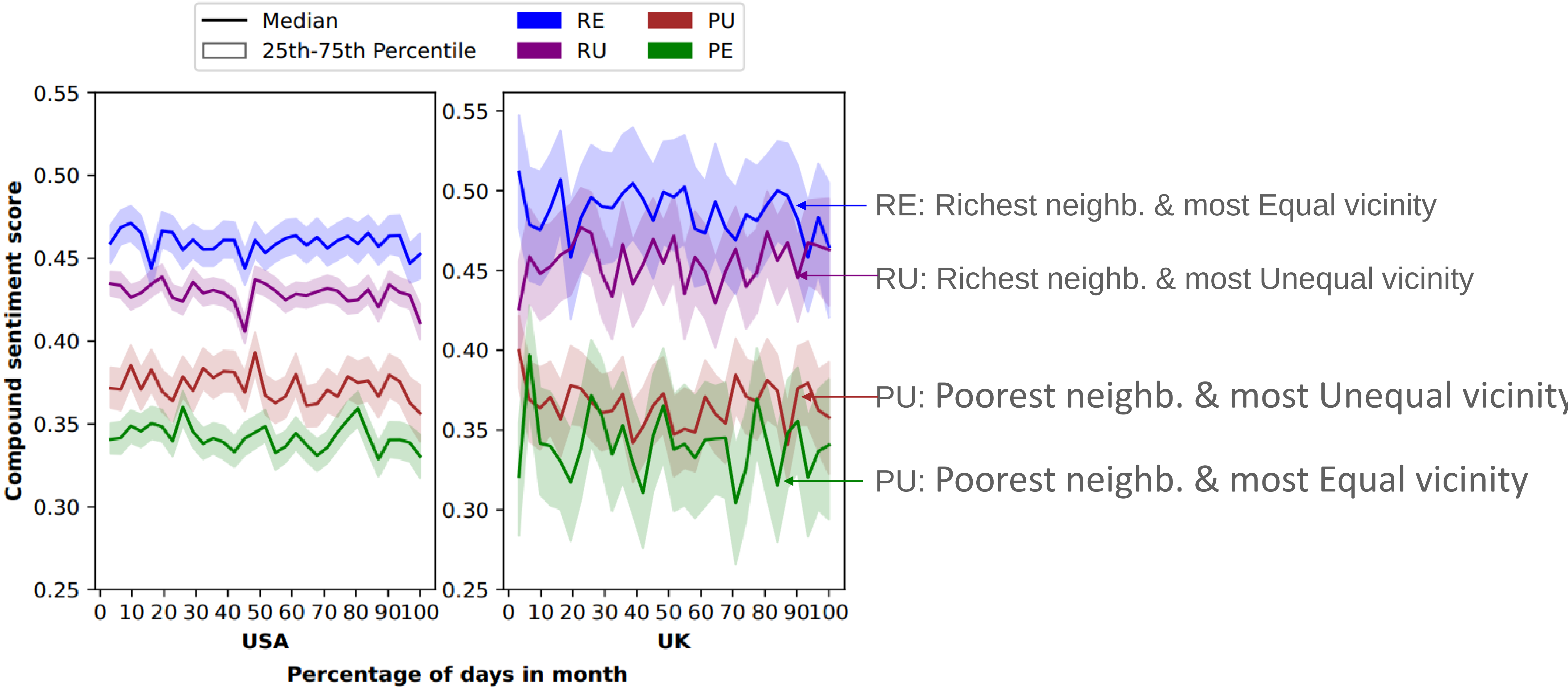
RE: Richest neighb. & most Equal vicinity

RU: Richest neighb. & most Unequal vicinity

PE: Poorest neighb. & most Equal vicinity

PU: Poorest neighb. & most Unequal vicinity

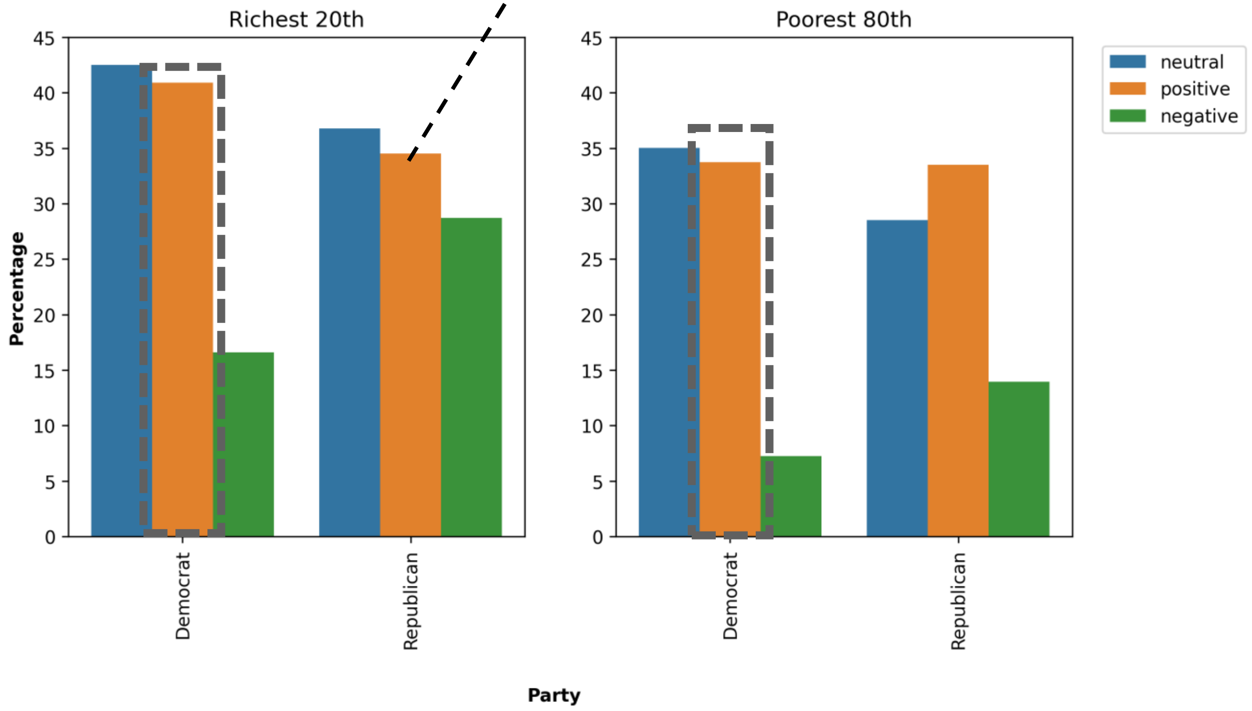
Inequality matters for poorer neighborhoods



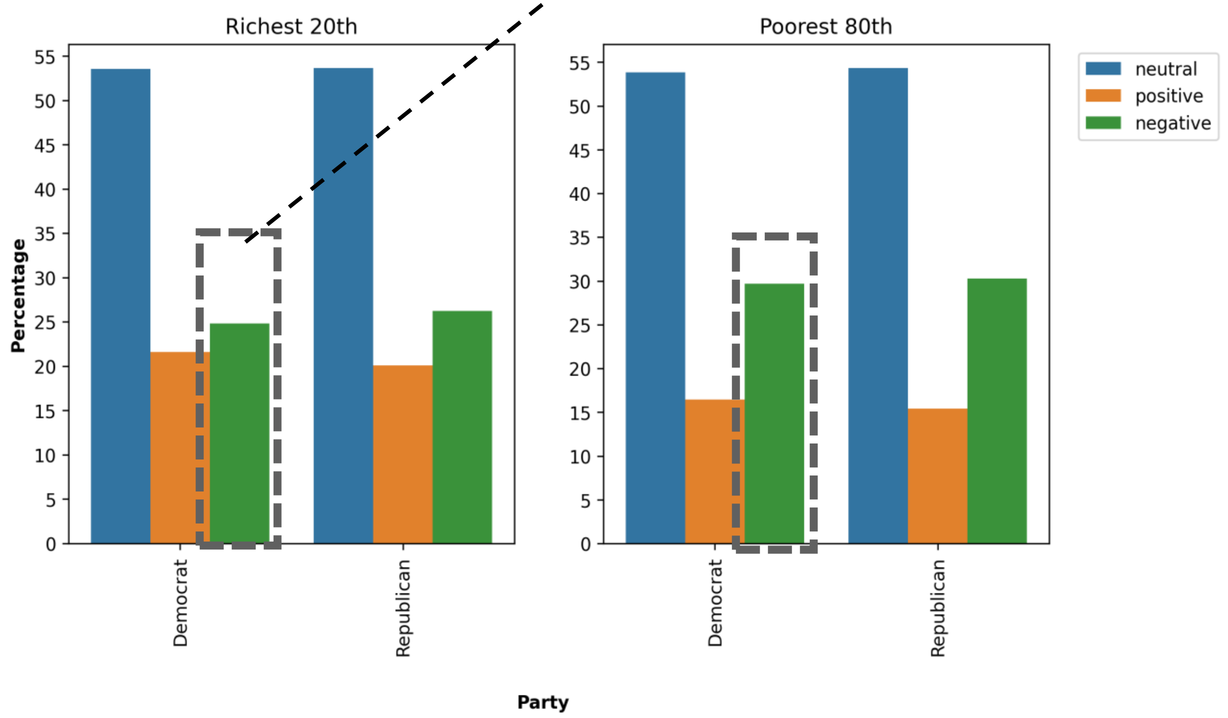
Richer neighborhoods have more positive stance

Politicians have higher positive stance.

ND users have negative stance on political posts



Twitter



Nextdoor