Introduction to Social Big Data for research

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MAX PLANCK INSTITUTE
FOR DEMOGRAPHIC
RESEARCH

About the instructor

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Materials

Workshop materials can be found here:
`https://github.com/jisukimmmm/ASA2023`

Reading

Sîrbu, A, et al. "Human migration: the big data perspective." International Journal of Data Science and Analytics 11.4 (2021): 341-360.
Link: `https://link.springer.com/article/10.1007/s41060-020-00213-5`

Outline

- Limitations of traditional data and social media data as an alternative data
- Twitter data format
- Twitter and related researches
- Web-scraping
- Ethics and privacy

Study of migration

Immigrants touch upon multidimensional aspects of both the host country and the home country.

- Economics:
  - Jobs
  - Unemployment
- Society:
  - Integration
  - Friends
  - Well-being
  - Population density
  - Fertility
- Culture:
  - Food
  - Language
  - Inter-marriage
  - more...
- Politics

and many more...

Migration research

Who is an **Immigrant**?:

- "A person who moves to a country other than that of his or her usual residence for a period of at least a year.[1]"
- "Whose movement across borders-whether legal or illegal- is essentially permanent[2]"
- "is defined on the ground of the place of birth (foreign-born) or of the citizenship (foreigners)[3]"

[1] United Nation
[2] World Bank
[3] OECD

Limitation of traditional data sources

Census, survey, register data

- Costly
- Outdated
- Time consuming
- Inconsistent
- Unavailable
- Lack of data on emigration
- Incomplete answers/misunderstanding questions etc.
- Immigrants are often underrepresented traditional data sources.
- limited in hard-to-reach contexts and societies.

Social media

Big data

is "information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation"[4]Laney, 2001. It can be described in 3 Vs which are:

- Volume: As the name suggests, the size of the data is Big, hence the volume of the data.
- Velocity: Big data such as Twitter allow us to stream data at real-time.The rate at which we obtain data is faster than the traditional data sources.
- Variety: Traditional data are mostly structured data. Big data, on the other hand, come in various forms. It can be videos, photos, texts, and audios. It requires a thorough data processing before extracting information/knowledge from it.

[4] https://www.gartner.com/en/information-technology/glossary/big-data

Alternative data sources: Big data

Twitter, Facebook, Yahoo, Web...

- Free
- Granular data
- Large scale data
- Continuously generated
- Information/opinion shared by users from an uncontrolled environment
- various forms of data: video, image, text, audio etc.

Required information

- Geo-location
- Information on time
- Personal identifier

So how do we get this Big data?

WIRED LONG READS BUSINESS CULTURE GEAR SCIENCE SECURITY VIDEO SUBSCRIBE

CHRIS STOKEL-WALKER BUSINESS 20.10.2022 02:20 PM

Elon Musk's Twitter Will Be Chaos

The entrepreneur's laundry list of ideas includes scrapping content moderation, charging subscription fees, and even branching out beyond social media.

PHOTOGRAPH: CARINA JOHANSEN/GETTY IMAGES

5

[5] source: https://www.wired.co.uk/article/elon-musk-twitter-deal-chaos

What is he going to do???

Price

"The basic tier costs $100 per month but allows researchers to collect only 10,000 tweets per month-a mere 0.3% of what could previously be collected for free in one day. The Enterprise tier, which ranges from $42,000 to $210,000 per month, is not affordable for researchers"[6]

[6] https://independenttechresearch.org/letter-twitters-new-api-plans-will-devastate-public-interest-research/

Don't cry...

- `archive.com`
- `https://www.trackmyhashtag.com/blog/free-twitter-datasets/`
- `https://data.world/datasets/twitter`
- ...

Twitter data format

- Tweet object
- User object
- Entity object

Tweet object

“id”: ”1050118621198921728”
“text”: ”Apply now for our week-long open online course on Digital and Computational Demography hosted by @MPIDRnews scientists ...”
“Context annotations”:
‘name’: ‘Interests and Hobbies Category’, **‘description’**: ‘A grouping of interests and hobbies entities, like Novelty Food or Destinations’, **’entity’**: ’id’: ’852291840472629248’, ’name’: ’Online education’, ’description’: ’Online education’
“created_ at”: ”202x-09-xxTxx:xx:xx.000z”
“conversation_id”: “1435336531519197188”
“lang”: “en”
“geo”: e.g., “coordinates”: [-73.999xx, 40.7416xxx]
“place_id”: “01a9a39529b27f36”

Context annotation

3 - TV Shows 4 - TV Episodes 6 - Sports Events 10 - Person 11 - Sport 28 - NFL Football Game 35 - Politicians 38 - Political Race 40 - Sports Series 47 - Brand 48 - Product 49 - Product Version 54 - Musician 55 - 56 - Actor 58 - Entertainment Personality 60 - Athlete 67 - Interests and Hobbies 68 - Hockey Game 71 - Video Game 85 - Book Genre 86 - Movie 87 - Movie Genre 88 - Political Body 89 - Music Album 92 - Sports Personality 93 - Coach ...and more[7]

[7] https://developer.twitter.com/en/docs/twitter-api/annotations/overview

Entity object

“hashtags”: [”tag”: ”BuildWhatsNext”],
“mentions”: “tag”: “@TwitterDev...”,
“url”: “`https://t.co/z5RhIVxJFK`”,

“expanded_url”:“`https://twittercommunity.com/t/updates-to-retweets-lookup-and...`”,
“description”: “Thanks for your feedback on the v2 Retweets and Likes endpoints. We've heard you. Starting today, you can retrieve the complete list of accounts that have Liked or Retweeted a Tweet,...”

Collecting tweet object

- Streaming keywords/hashtags: e.g. #migrants, #refugees
- Streaming for specific geo-locations: place, country, point radius, bounding box
- Collecting tweets for a specific user: by user ID or user name
- Searching for historic tweets for a keyword

Query:

- from: twitter user
- −is : excluding retweets
- place_country: country
- has: e.g. media, geo, images
- conversation_id: returns all tweets in the conversation thread with conversation id. xxx
- lang: en, kr, ch, etc.

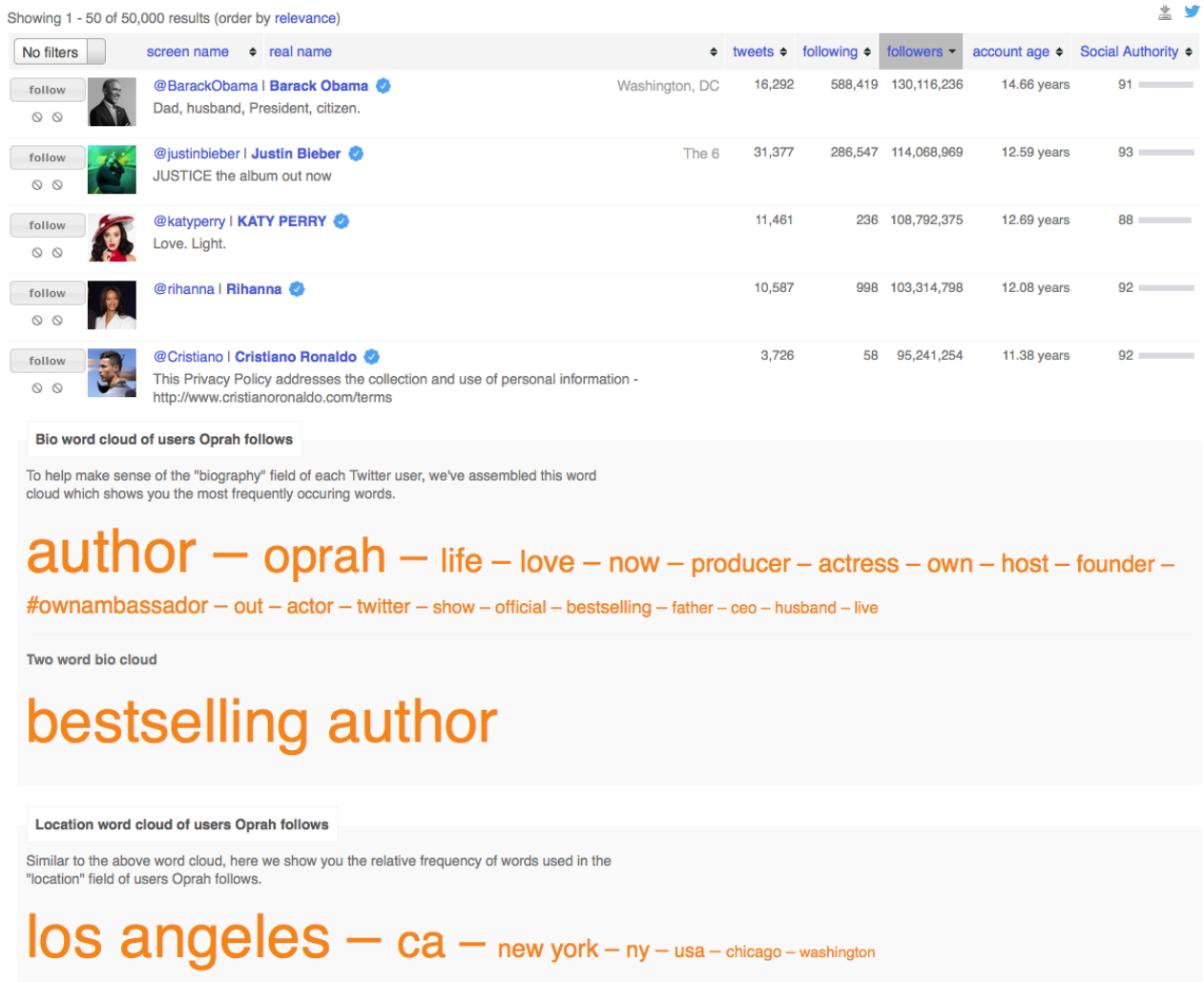
User object

“id”: “2244994945”,
“name”: “Twitter Dev”,
“username”: “TwitterDev”,
“location”: “127.0.0.1”,
“verified”: true,
“protected”: false,

“description”: “The voice of the #TwitterDev team and your official source for updates, news, and events, related to the #TwitterAPI.”,
“url”: `https://t.co/3ZX3TNiZCY`,
“profile_image_url”: `https://pbs.twimg.com/profile_images/1267175364003901441/tBZNFAgA_normal.jpg`,
“created_at”: “2013-12-14T04:35:55.000Z”

Collecting user object

- Searching by user: user ID, user name, `https://followerwonk.com/bio`
- Social network: followers and friends



Twitter data and migration research

Information from Twitter data that can be used in migration research:

- Geo-tagged tweets
- Self-declared location information from profile
- Social networks: followers and friends
- Name
- Language

Anything else?

Potential issues

- Tourists
- Travel blogs
- Bots
- ...

Definitions of migrants on Twitter in the literature

- "A Twitter user has the nationality that others believe you have." (Huang et al., 2014)
- "Any individual leaving Venezuela during the time window of observation."(Mazzoli et al., 2020)
- "Anyone who tweeted exclusively from Venezuela in the time period between Feb. 1 and April 30 2017." (Hausmann et al., 2018)
- "Migrants are users that are identified as people who moved to a different country for at least one of the 4-month periods." (Zagheni et al., 2014)
- "A migrant is a person that has the residence different from the nationality." (Kim et al., 2020)

Identifying migrants (Mazzoli et al., 2020)

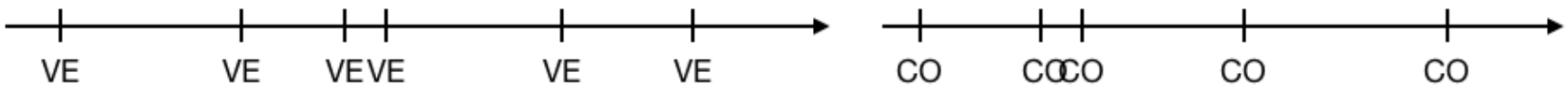


Figure: Mock example of geo-tagged tweet timeline

Inferring nationalities of Twitter users (Huang et al., 2014)

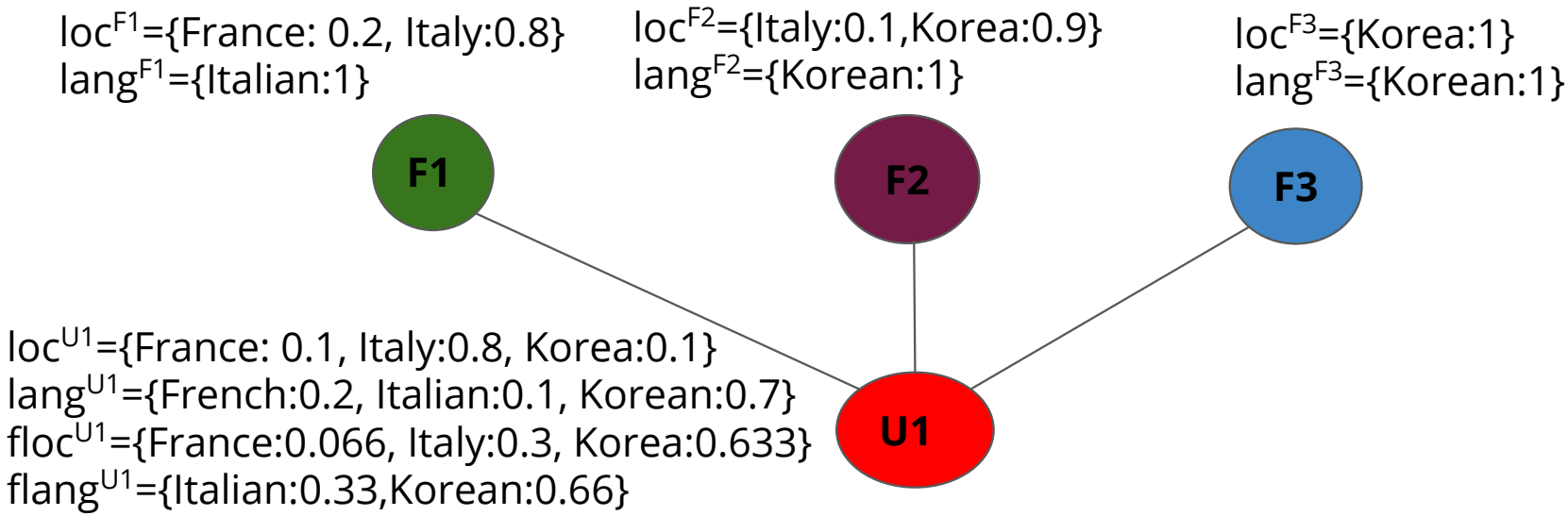
- Twitter page: xx
- Homepage: XX
- Location: Germany
- Time zone: CET
- Interface language: English
- Tweets languages: (1) English: 97% (2) Italian: 2% (3) Korean: 1%
- Follower locations: (1) US: 151 (2) KR: 72 (3) DE: 3
- Following locations: (1) US: 80 (2) KR: 40 (3) IT: 30
- Tweets from (1) IT: 30 (2) KR:29

Identifying migrants on Twitter (Kim et al., 2020)

"A migrant is a person that has the residence different from the nationality."

- Country of residence: "the country with the longest length of stay"
- Country of nationality: "the ensemble of features that make a person feel like they belong to a certain country"

Identifying migrants on Twitter (Kim et al., 2020)



Validation

Are we correctly identifying migrants?
Are there good ground truth data to compare?

Validation-Gold standard data (Huang et al., 2014)

	Pre.	Rec.	F1
QA	86.67%	95.37%	90.81%
ARA	82.96%	71.16%	76.56%
WES	70.86%	70.62%	70.64%
SA	93.35%	90.48%	91.89%
IN	82.19%	71.13%	76.00%
OTH	78.76%	40.72%	53.54%
UN	30.78%	15.13%	20.16%

Table: The average Precision, Recall, and F1 scores for each nationality group Huang et al., 2014

Validation-Official statistics (Kim et al., 2020)

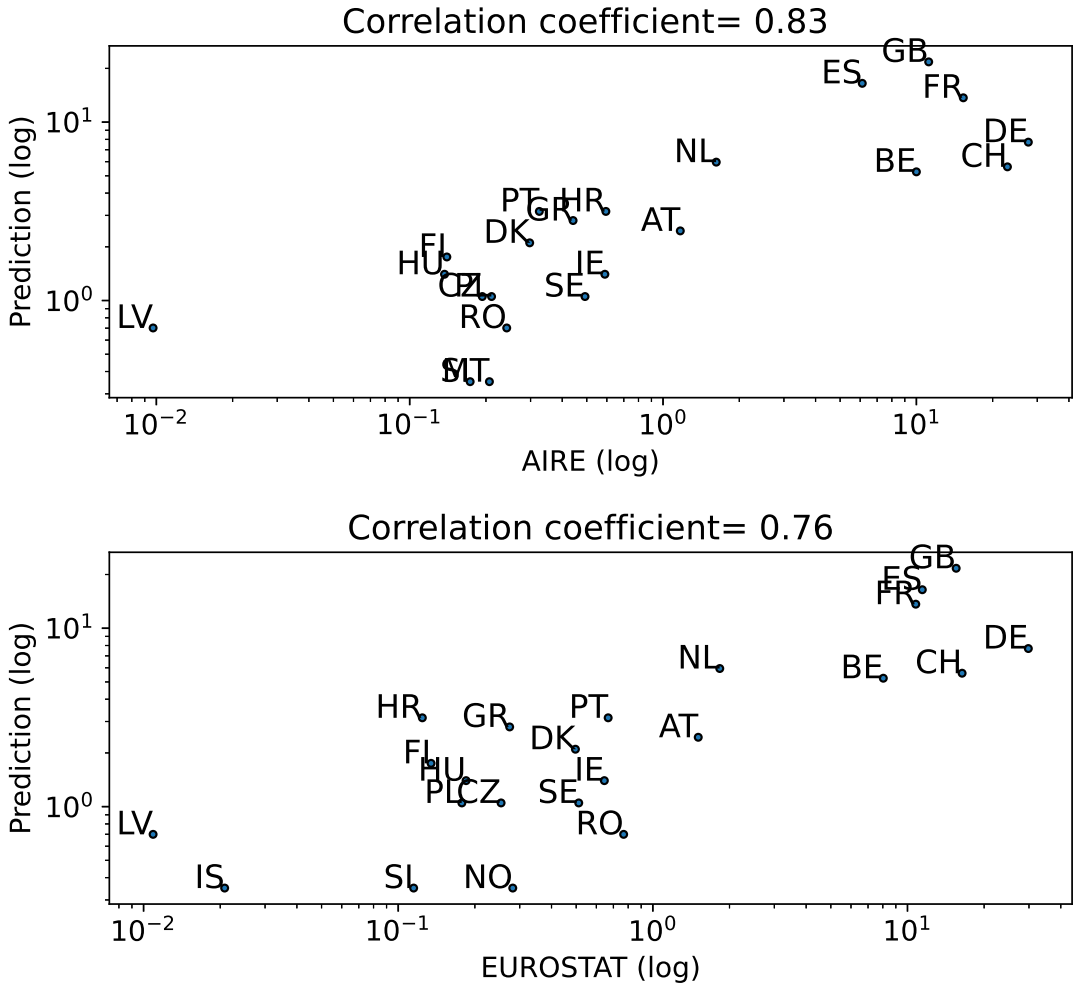


Figure: Correlation between predicted data and official statistics (Kim et al., 2020)

Inferring international and internal migration patterns from Twitter data (Zagheni et al., 2014)

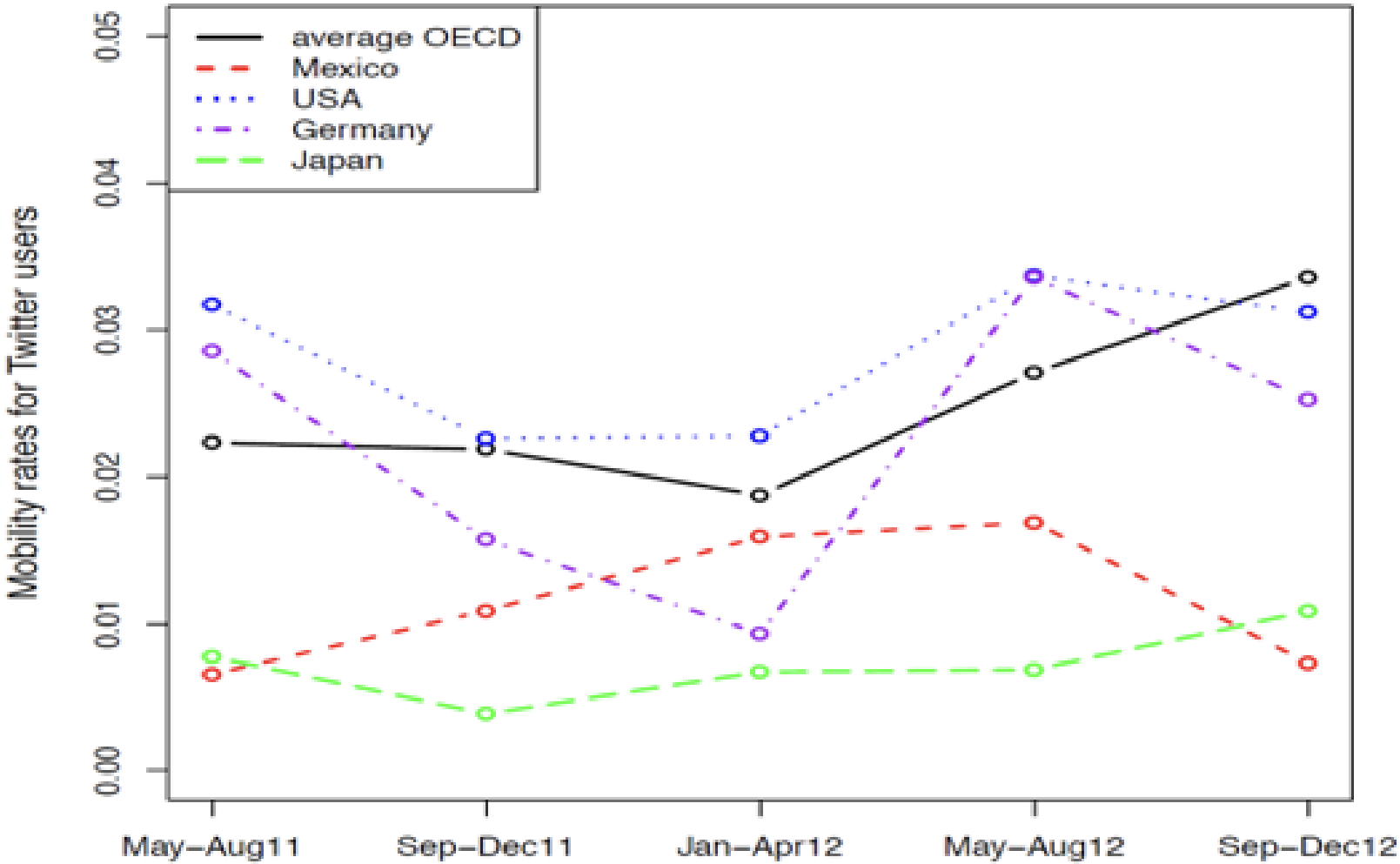


Figure: Mobility rates for Twitter users Zagheni et al., 2014

Difference-in-Differences

- Out-migration rates clearly an overestimate
- Non-representative user set
- Selection bias is changing over time
- Focus on between-country differences

$$\hat{\delta}_c^t = (m_c^t - m_{oecd}^t) - (m_c^{t-\overset{\Delta}{\cdot}} - m_{oecd}^{t-\overset{\Delta}{\cdot}})$$

$\rightarrow$ Diff-in-diff estimator to evaluate relative changes in trends (Zagheni et al., 2014)

Cont.

Figure: (Soft) Validation:Ireland out-migration rate grew by 2.2% 2011 -¿ 2012, more than most countries (Irish Central Statistics Office) Mexico also sees a reduction in out-migration (Pew Research Center)

Other migration related researches

- Cultural integration (Kim et al., 2021)
- Spatial integration (Mazzoli et al., 2020; Lamanna et al., 2018)
- Sentiment analysis (Öztürk et al., 2018; Arcila-Calderón et al., 2021)
- Social integration (Kim et al., 2023; Kim et al., 2022)

Cultural integration (Kim et al., 2021)

Q. *How much do migrants absorb the culture of their destination society? Do they lose connection with their home country?*
Traditional studies focus on elements such as:

- Language proficiency
- Marital status
- Role of media ...

	Low OA	High OA
Low DA	Marginalisation	Separation
High DA	Assimilation	Integration

Table: Theories of integration and their relation to OA and DA Kim et al., 2021

Origin and Destination attachment indexes (Kim et al., 2021)

$$H(h) = \frac{-\sum_c P_h(c) \log P_h(c)}{\log(|P_h(c)|)} \quad (1)$$

$$OA(u) = \frac{\#\ C_n(u)\ hashtags}{\#\ total\ hashtags} = \frac{HT(u, C_n(u))}{HT(u)} \quad (2)$$

$$DA(u) = \frac{\#\ C_r(u)\ hashtags}{\#\ total\ hashtags} = \frac{HT(u, C_r(u))}{HT(u)} \quad (3)$$

```
'Salvini':
  {'CH': 1,
   'CL': 1,
   'CZ': 2,
   'DE': 2,
   'ES': 3,
   'FR': 2,
   'GB': 1,
   'IT': 544,
   'LU': 1,
   'NL': 2,
   'PL': 1,
   'TH': 2,
   'TR': 1,
   'US': 6}
      /569
Entropy score=0.11
∴ Italian specific
```

OA & DA indexes

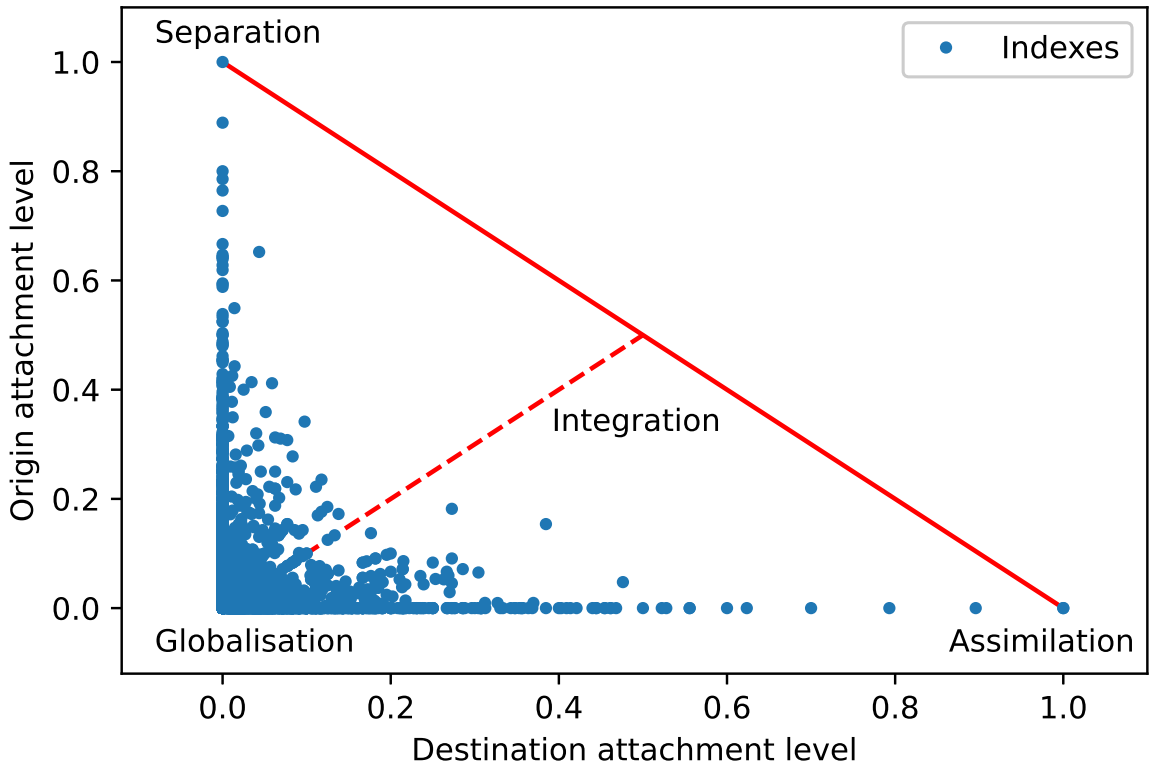


Figure: Relationship between OA & DA

Italian emigrants in overseas

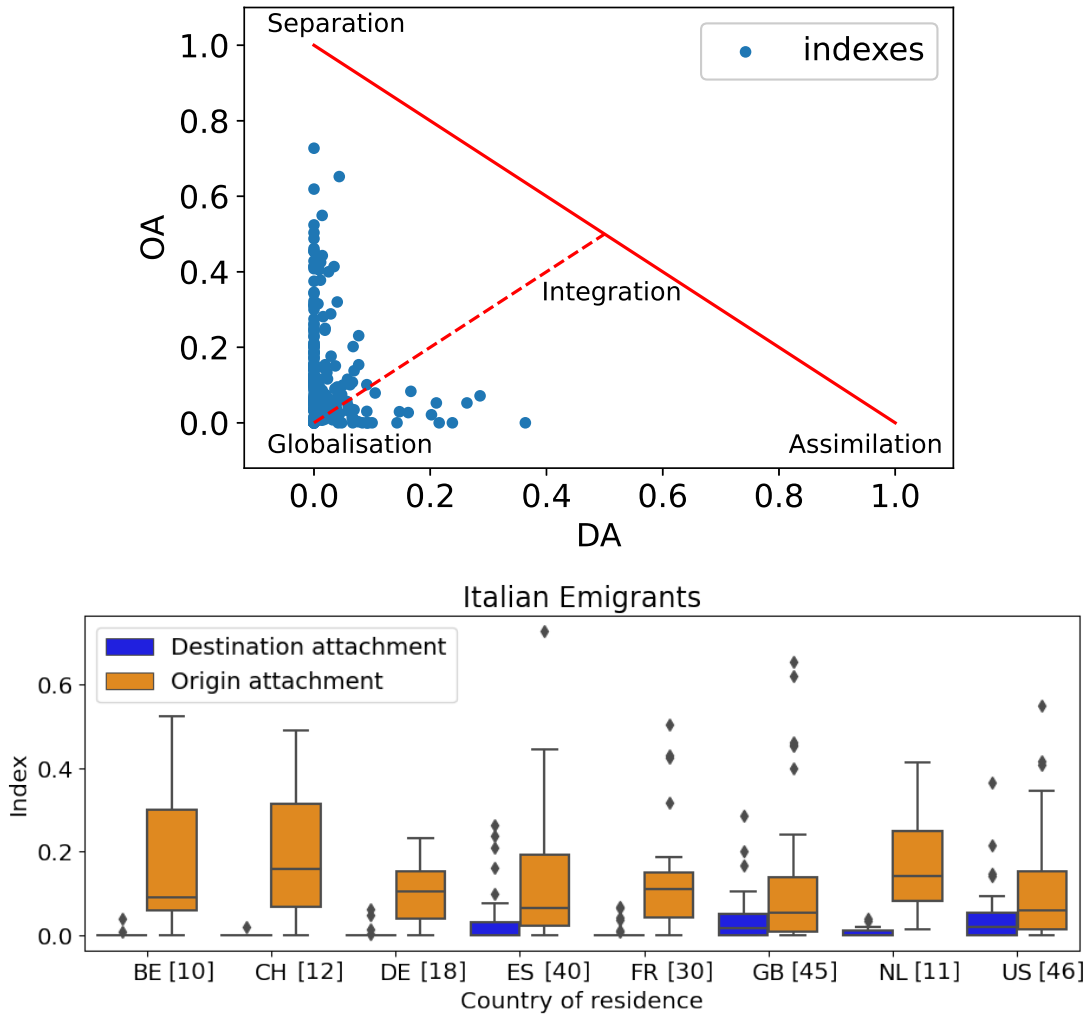
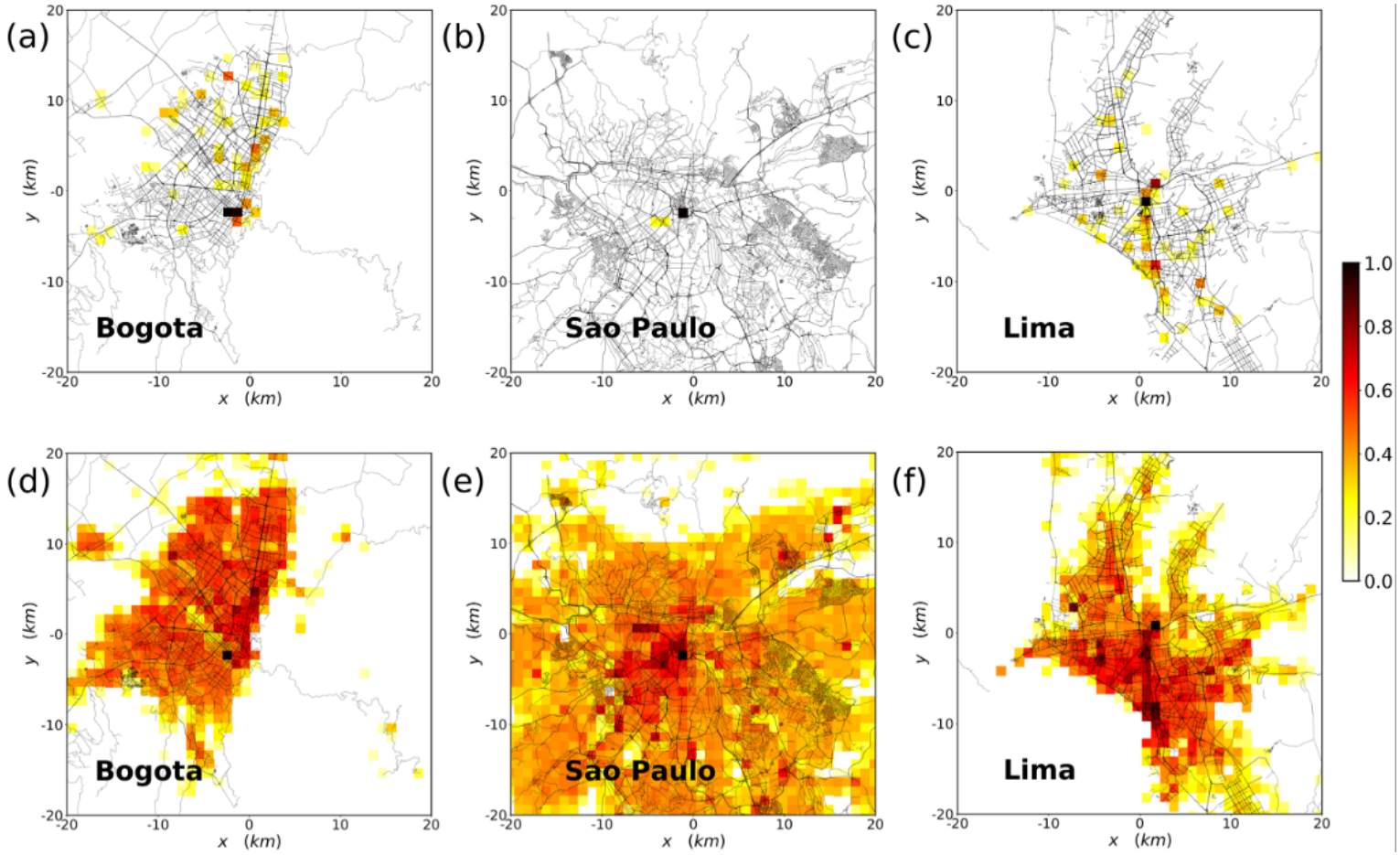


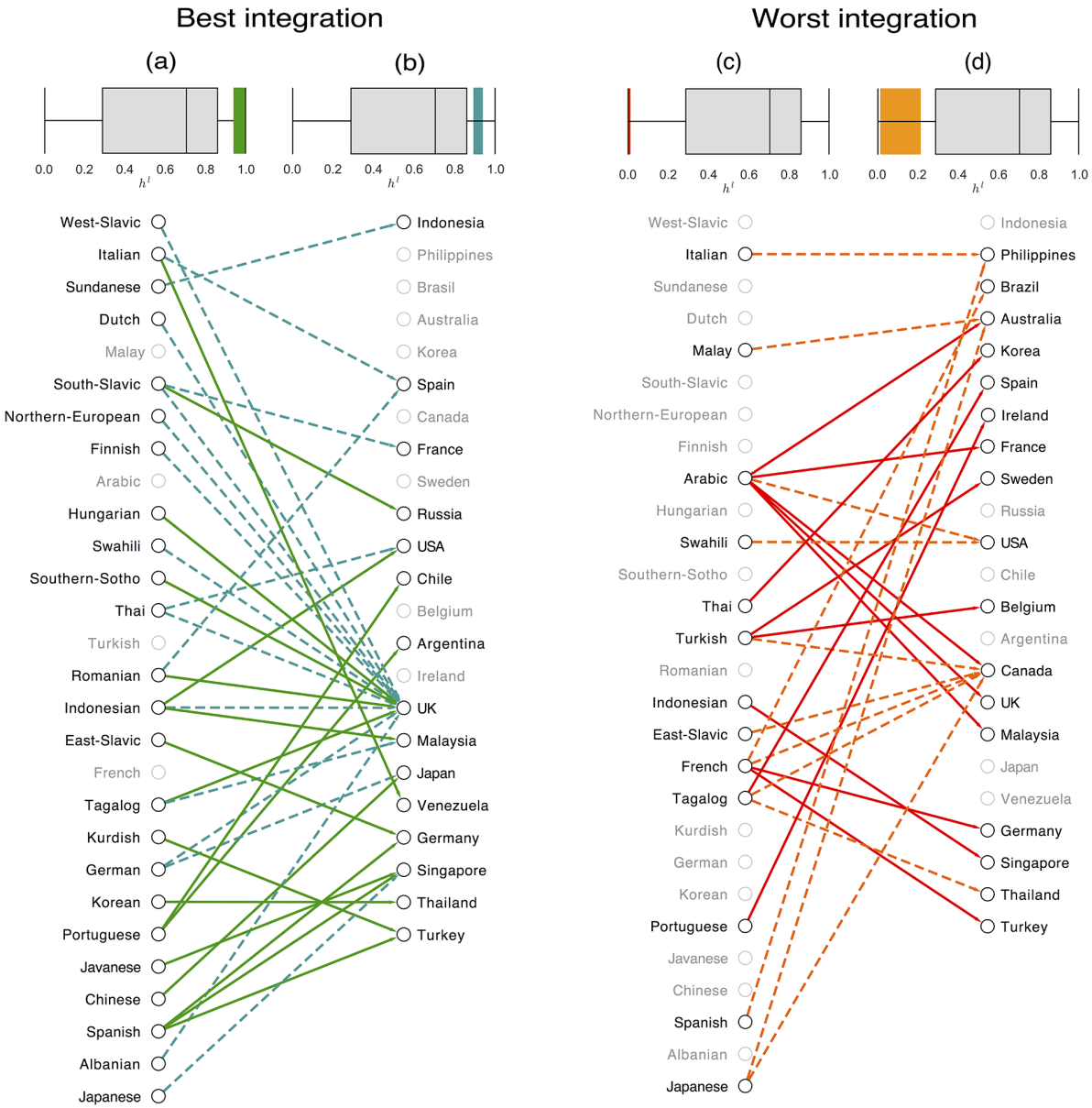
Figure: Case study of Italian emigrants in overseas

Spatial integration (Mazzoli et al., 2020)



Spatial integration in Colombia, Brazil and Peru

Language integration network (Lamanna et al., 2018)



Sentiment analysis (Arcila-Calderón et al., 2021)

Hate speech towards migrants/refugees? What are the main topics behind the messages in Twitter in Spain with hate speech against refugees?

Topic	Most Common Words and Their Frequency within the Topic (the Underlined Words are the Most Determinant for the Labelling of the Topic)
Pull effect and consequences	"immigrants" (0.008) + "spain" (0.007) + "boat" (0.005) + "effect" (0.005) + "pull" (0.004) + "goes" (0.004) + "valencia" (0.004) + "consequences" (0.004) + "europe" (0.004) + "concentration" (0.004)
Pull effect and not welcoming "illegals"	"immigrants" (0.013) + "people" (0.008) + "spain" (0.008) + "pull" (0.007) + "effect" (0.007) + "illegal" (0.007) + "protectyourborders" (0.007) + "spaniards" (0.006) + "harbor" (0.006) + "aquariusnotwelcome" (0.006)
Not welcoming and terrorism	"go" (0.008) + "spain" (0.008) + "people" (0.006) + "aquariusnotwelcome" (0.005) + "country" (0.005) + "boko" (0.005) + "haram" (0.005) + "immigrants" (0.005) + "boat" (0.004) + "have" (0.004)
Smugglers and NGOs	"immigrants" (0.023) + "spain" (0.010) + "spaniards" + "come" (0.008) + "mafias" (0.008) + "people" (0.007) + "go" (0.006) + "illegal" (0.006) + "ngos" (0.006) + "boat" (0.006)
Money and jobs	"refugees" (0.011) + "immigrants" (0.009) + "pay" (0.007) + "spain" (0.007) + "countries" (0.005) + "boat" (0.005) + "spaniards" (0.005) + "people" (0.005) + "solution" (0.005) + "work" (0.005)
Entrance to Europe	"spain" (0.018) + "immigrants" (0.009) + "europe" (0.006) + "boat" (0.006) + "valencia" (0.005) + "spaniards" (0.005) + "government" (0.005) + "immigration" (0.005) + "north" (0.004) + "millions" (0.005)

Characteristics of migrants on Twitter (Kim et al., 2022)

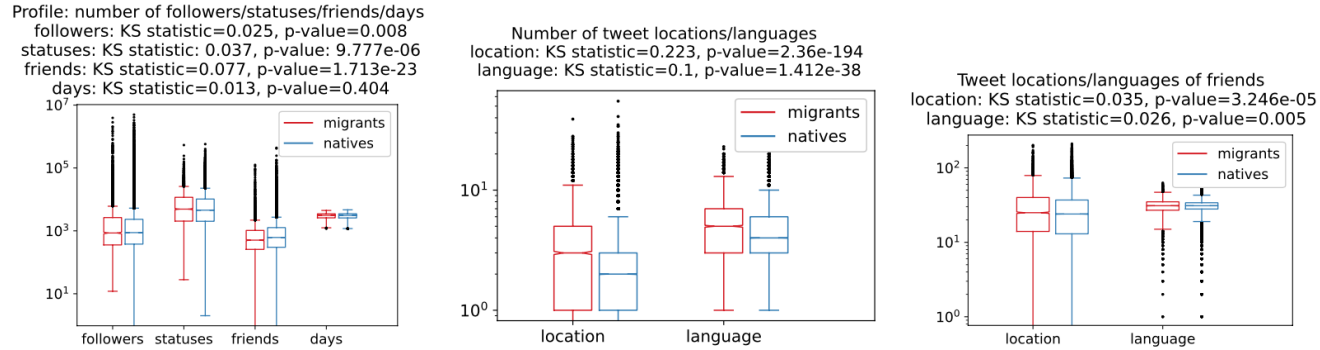


Fig. 2 Left: Distributions of profile features: number of followers, tweets published (statuses) and friends and number of days since the account was created until 2018, respectively. Centre: Distribution of tweet locations and languages. Right: Distribution of tweet locations and languages of friends

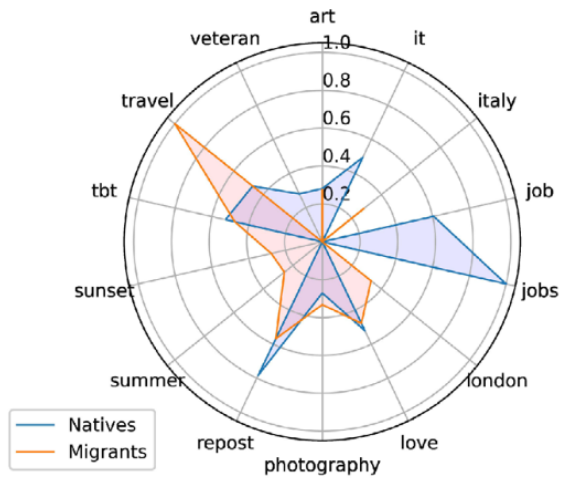


Figure: Distributions of profile features and top hashtags used by migrants and natives

Social integration (Kim et al., 2023)

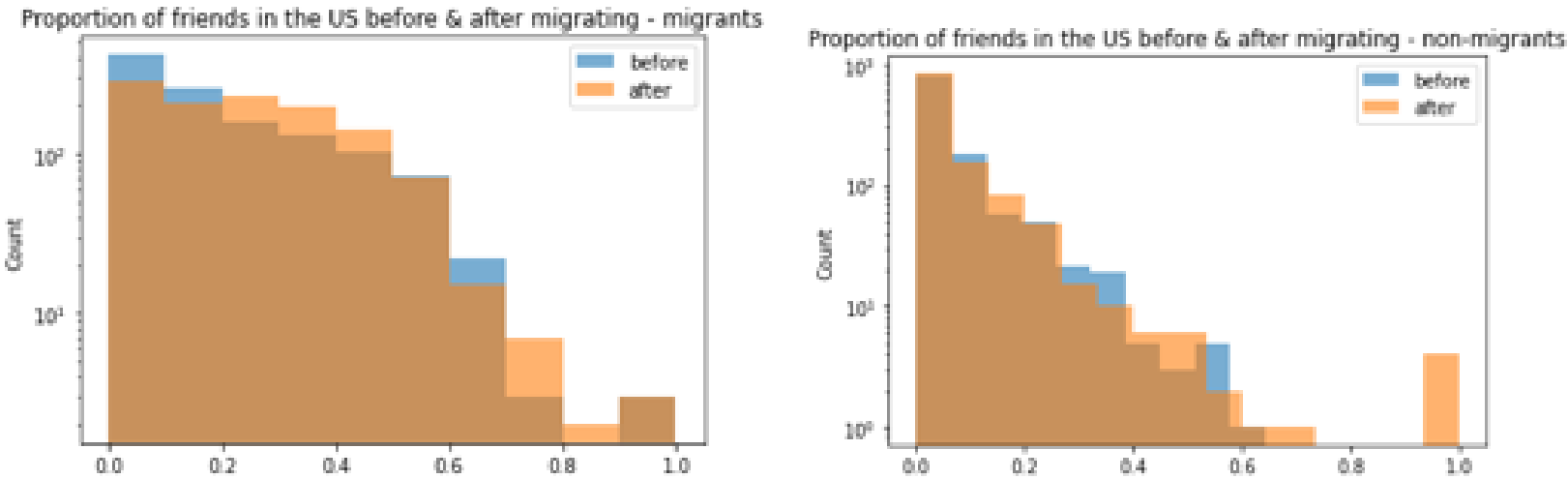
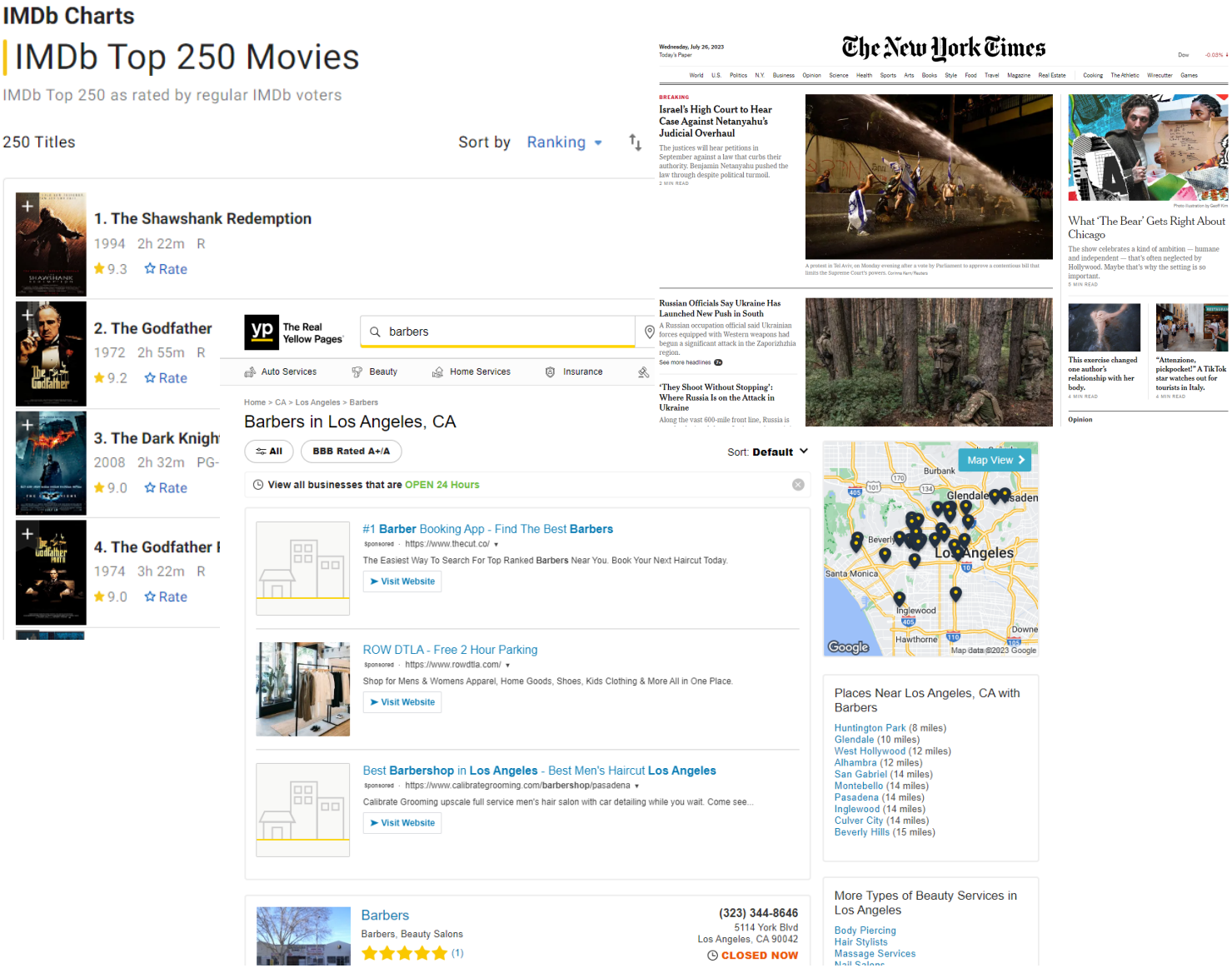


Figure: Distribution of fraction of friends residing in the United States before and after migration for migrants (left) and for propensity-score matched non-migrants (right).

Web-scraping



Hands-on example

`https://colab.research.google.com/`

Ethics and privacy

BUT

Bias in the data:
"Twitter users are younger, more educated and more likely to be Democrats than general public"[8]

What about in other countries?

Sample size: Started BIG, ended small...

[8] https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/

Pros and cons

Pros:

- Access
- Open box (Twitter)
- Longitudinal: access to historical data
- Aggregated data (FB)

Cons:

- Bias
- Sample size
- Black box (FB)

Issue:

- **Ethics and Privacy**

What can we do to mitigate the issues related to Ethics and Privacy?

Ethics and Privacy

Twitter API is an open-access

Eavesdropping someone's conversation in a bus $\rightarrow$ can I expose this information?

Does this mean that we can do anything with the data?

$\rightarrow$ Quick answer= NO!

GDPR

General Data Protection Regulation was enacted in 2016: An EU law that aims to protect and regulate data and privacy.
7 principles[9]:

- **Lawfulness, fairness and transparency**
- Purpose limitation
- Data minimisation
- Accuracy
- **Storage limitation**
- **Integrity and confidentiality (security)**
- Accountability

For more info: `https://gdpr.eu`

[9] `https://www.onetrust.com/blog/gdpr-principles/`

Consent

Article 4(11) defines consent: "Consent of the data subject means any freely given, specific, informed and unambiguous indication of the data subject's wishes by which he or she, by a statement or by a clear affirmative action, signifies agreement to the processing of personal data relating to him or her."[10]

Consent also means that "the data subject knows your identify, what data processing activities you intend to conduct, the purpose of it and that they can withdraw their consent at any time."[11]

[10] https://gdpr.eu/gdpr-consent-requirements/

[11] Idem.

Confidentiality

- Pseudonymization: jisu $\rightarrow$ DKjxid73
- Anonymization: jisu $\rightarrow$ ******
- Data transformation: By modifying the format, value, or structure of data

Data storage limitation

How, where and for how long can one store sensitive and personal data?
$\rightarrow$ Before storing the data, think of pseudonymizing, anonymising or transforming the data

$\rightarrow$ Secure data storage: need to store data where it is safe and well protected where it can prevent possible attacks or loss of data

$\rightarrow$ The length of the time that you are planning to store the data is required by the GDPR.

When sharing Tweets

Sharing your Twitter is permitted as long as they are for non-commercial purposes. BUT you should not share entire tweets directly!

So how? $\rightarrow$ By dehydrating your data!

"Dehydrated" data set - each tweet is reduced to its unique ID number, and a list of these IDs is saved as a text document.[12]

Check out also this webpage: `https://covid.dh.miami.edu/2020/06/11/hydrating-tweetsets/`

[12] `https://scholarslab.github.io/learn-twarc/06-twarc-command-basics#dehydrated-and-rehydrated-data-sets`

Take home message

"Social big data can be proposed to fill some of the gaps and complement traditional data types but cannot replace them".


Arcila-Calderón, Carlos et al. (2021). "Refugees Welcome? Online Hate Speech and Sentiments in Twitter in Spain during the Reception of the Boat Aquarius". In: *Sustainability* 13.5, p. 2728.


Hausmann, Ricardo et al. (2018). *Measuring venezuelan emigration with twitter*. Tech. rep. Kiel Working Paper.


Huang, Wenyi et al. (2014). "Inferring nationalities of twitter users and studying inter-national linking". In: *Proceedings of the 25th ACM conference on Hypertext and social media*, pp. 237–242.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Kim, Jisu et al. (July 2023). "Online social integration of migrants: Evidence from Twitter". In: *Migration Studies*, mnad017. ISSN: 2049-5846. DOI: 10.1093/migration/mnad017. eprint: https://academic.oup.com/migration/advance-article-pdf/doi/10.1093/migration/mnad017/50827695/mnad017.pdf. URL: https://doi.org/10.1093/migration/mnad017.


Lamanna, Fabio et al. (2018). "Immigrant community integration in world cities". In: *PloS one* 13.3, e0191612.


Laney, Doug (2001). *3D data management: Controlling data volume, velocity and variety*. URL: http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-%20Management-Controlling-Data-Volume-Velocity-and-Variety.pdf.


Mazzoli, Mattia et al. (2020). "Migrant mobility flows characterized with digital data". In: *PloS one* 15.3, e0230264.


Öztürk, Nazan et al. (2018). "Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis". In: *Telematics and Informatics* 35.1, pp. 136–147.


Zagheni, Emilio et al. (2014). “Inferring international and internal migration patterns from twitter data”. In: *Proceedings of the 23rd International Conference on World Wide Web*, pp. 439–444.

Supplement materials

F1-score measures the accuracy;

$$F1score = 2 * \frac{precision * recall}{precision + recall}$$

- Precision: How many selected items are relevant?

$$\frac{Truepositive}{Truepositive + Falsepositive}$$

- Recall: How many relevant items are selected?

$$\frac{Truepositive}{Truepositive + Falsenegative}$$

The score ranges from its worst score of 0 to its best score 1.