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Cross-Dialect Social Media Dependency Parsing for Social Scientific Entity Attribute Analysis

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Eighth Workshop on Noisy User-generated Text (W-NUT 2022)

Paper available online at github.com/slanglab/TweetIE_WNUT2022

Motivation

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- Our work seeks to synthesize a key application of dependency parsing, information extraction, with this computational social scientific perspective.
- We hope to enable information extraction applications focusing not on fact, but beliefs and opinions held by communities and individuals online.

Contributions

1. State-of-the-art social media syntactic dependency parser

   We achieve SotA performance using a pretrained transformer pretrained on Twitter and biaffine attention.

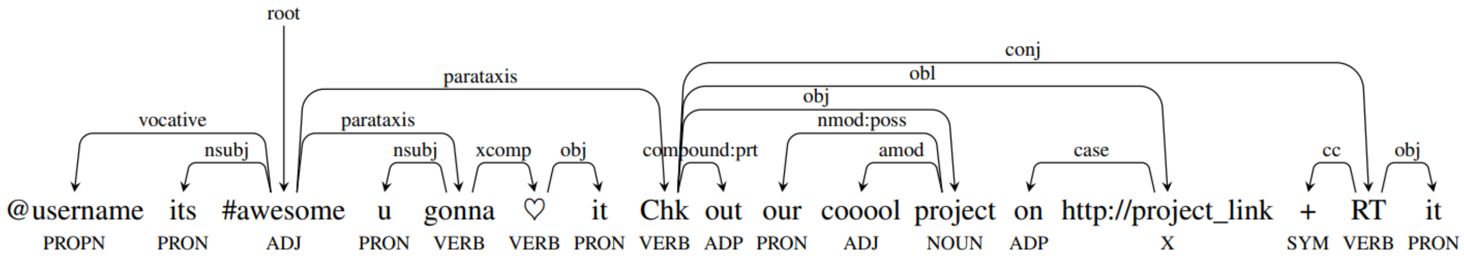

Figure 1: A contrived example of social media syntactic dependencies. Figure 2 from (Liu et al 2018).

Contributions

1. State-of-the-art social media syntactic dependency parser
2. Analysis of its performance with regards to dialectical disparity

   Using Mainstream American English (MAE) and African American English (AAE) segments, we show that our SotA model is not only more performant, but also has less relative error between MAE and AAE than other pretrained models.

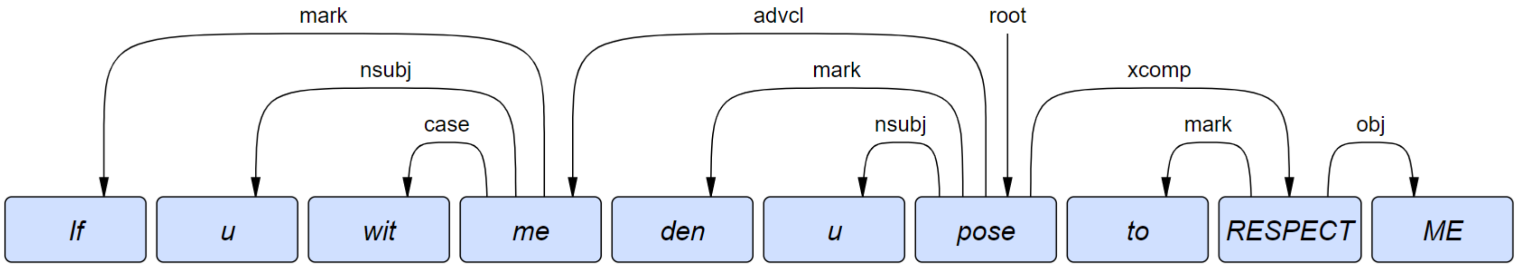

Figure 2: An AAE universal dependencies sample from the TwitterAAE dependencies corpus (Blodgett et al 2018). It features two null copulas and is interpreted as “If you (are) with me, then you (are) supposed to respect me”.

Contributions

1. State-of-the-art social media syntactic dependency parser
2. Analysis of its performance with regards to dialectical disparity
3. Its application – belief extraction with our system TweetIE

   We design a system for extracting beliefs from our dependency parses and compare its application to alternatives using open information extraction.

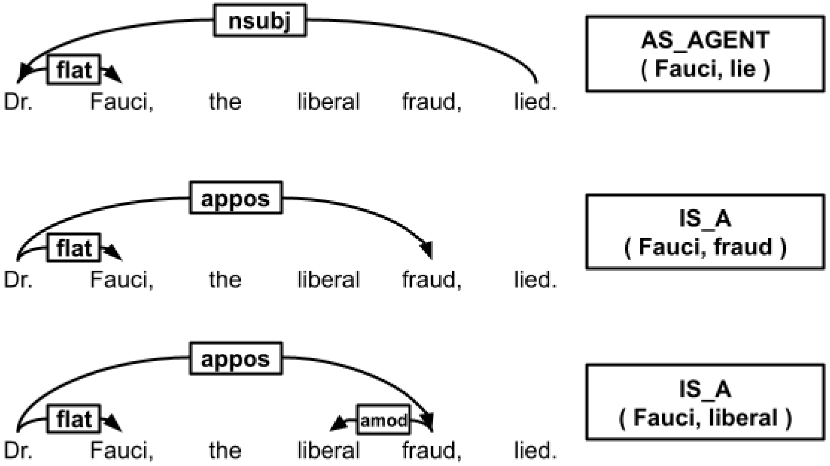

Figure 3: Examples of some of the rules for TweetIE: figure 1 from our paper.

Contributions

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3. Its application – belief extraction with our system TweetIE
4. Case study on COVID-19 political polarization

   A case study using the system above to observe and study beliefs concerning Dr. Anthony Fauci. Replicated studies on public opinion towards him found in sociological literature.

Figure 4: Contrived examples of political discourse towards Dr. Anthony Fauci, inspired from results in the case study.

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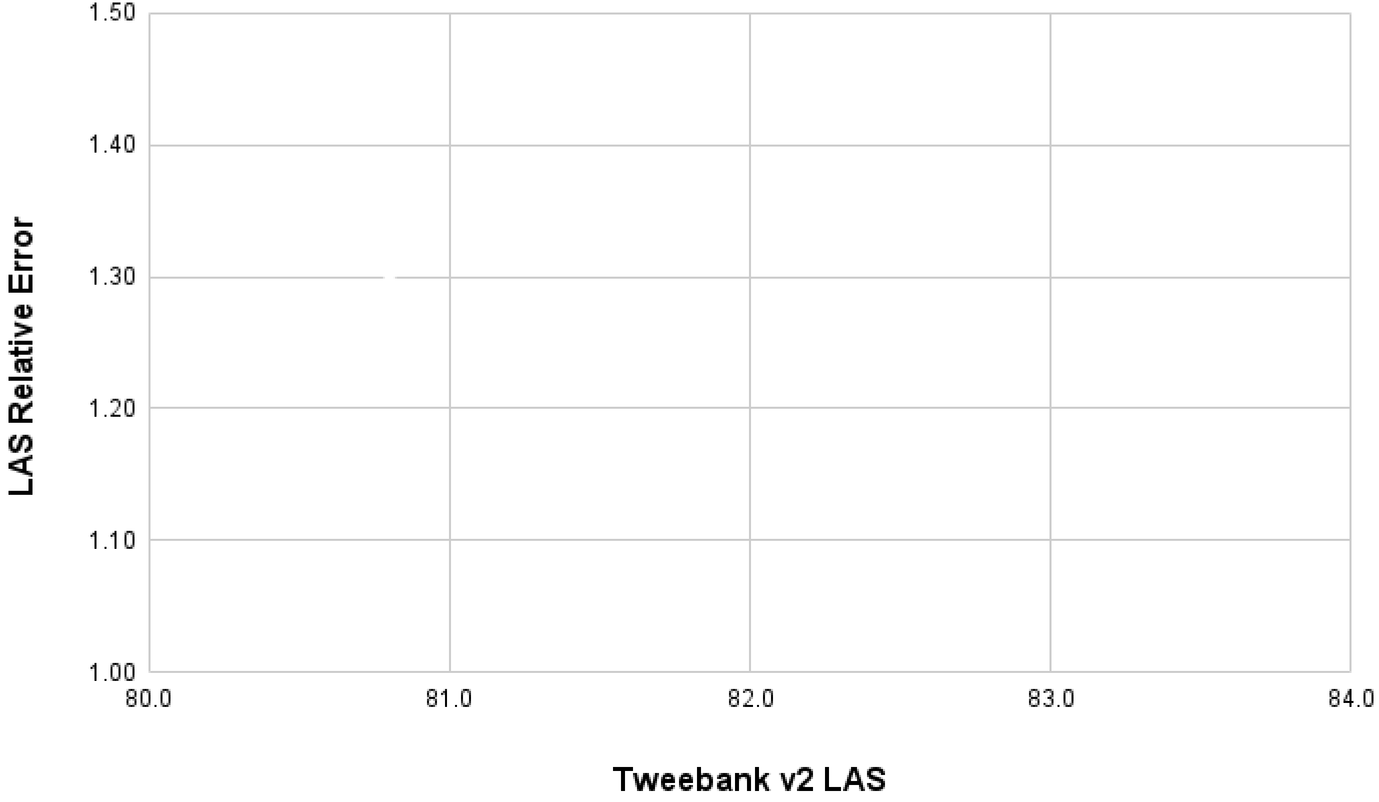
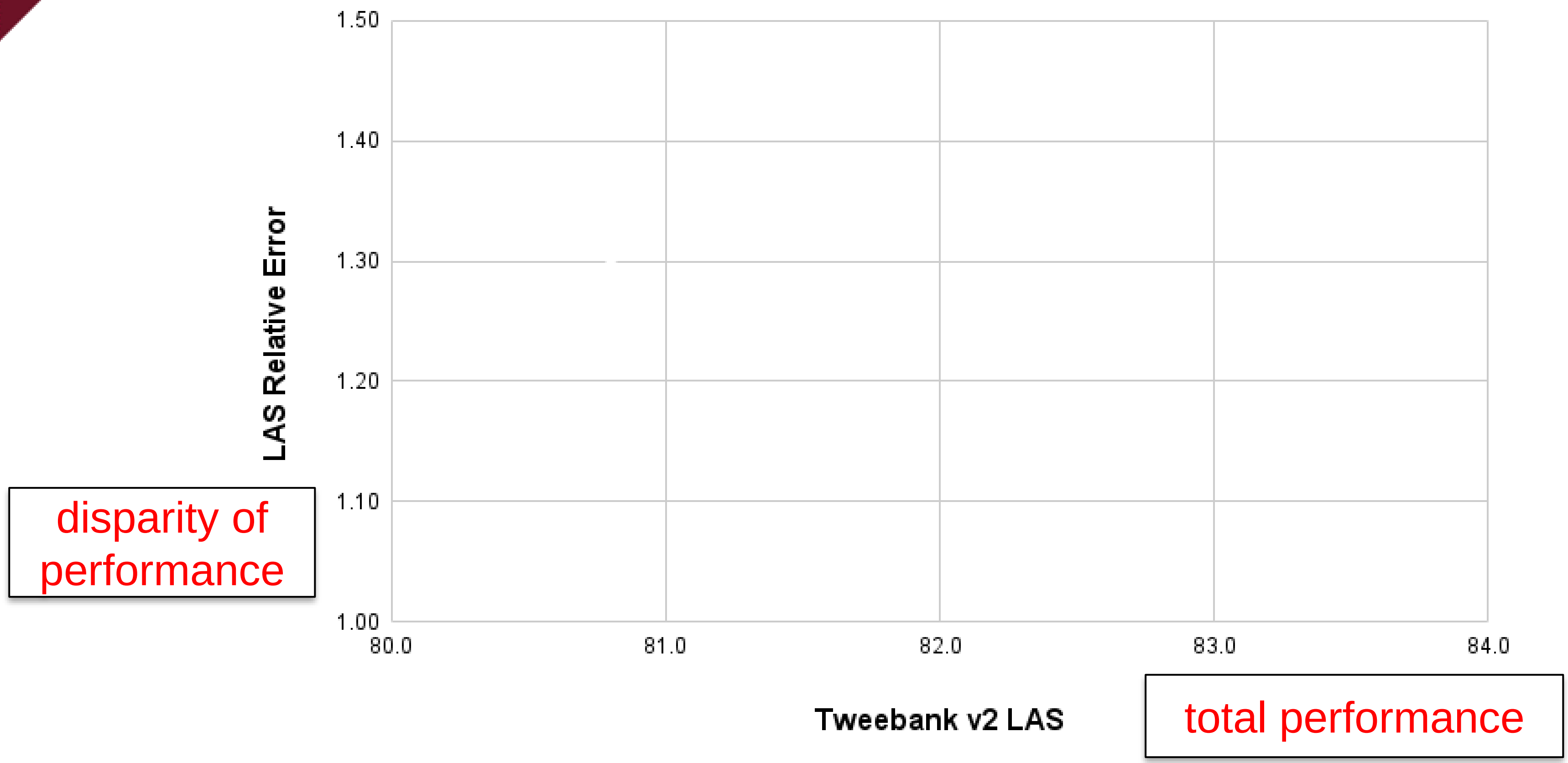
- This is shown through the *relative error* of the MAE/AAE sets.


1.50
1.40
1.30
1.20
1.10
1.00
80.0
81.0
82.0
83.0
84.0
LAS Relative Error
Tweebank v2 LAS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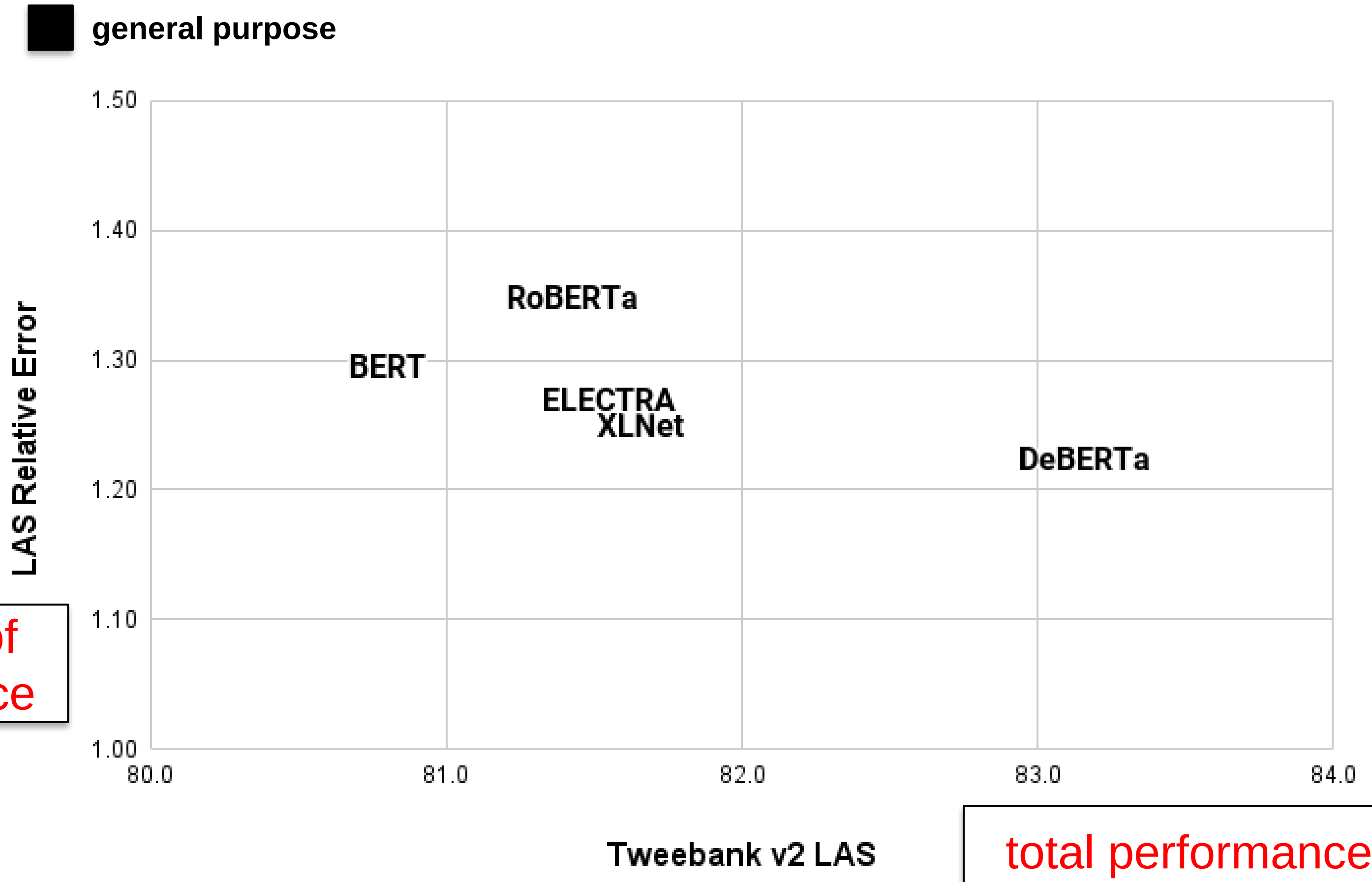
Tweebank v2 LAS
disparity of performance
total performance



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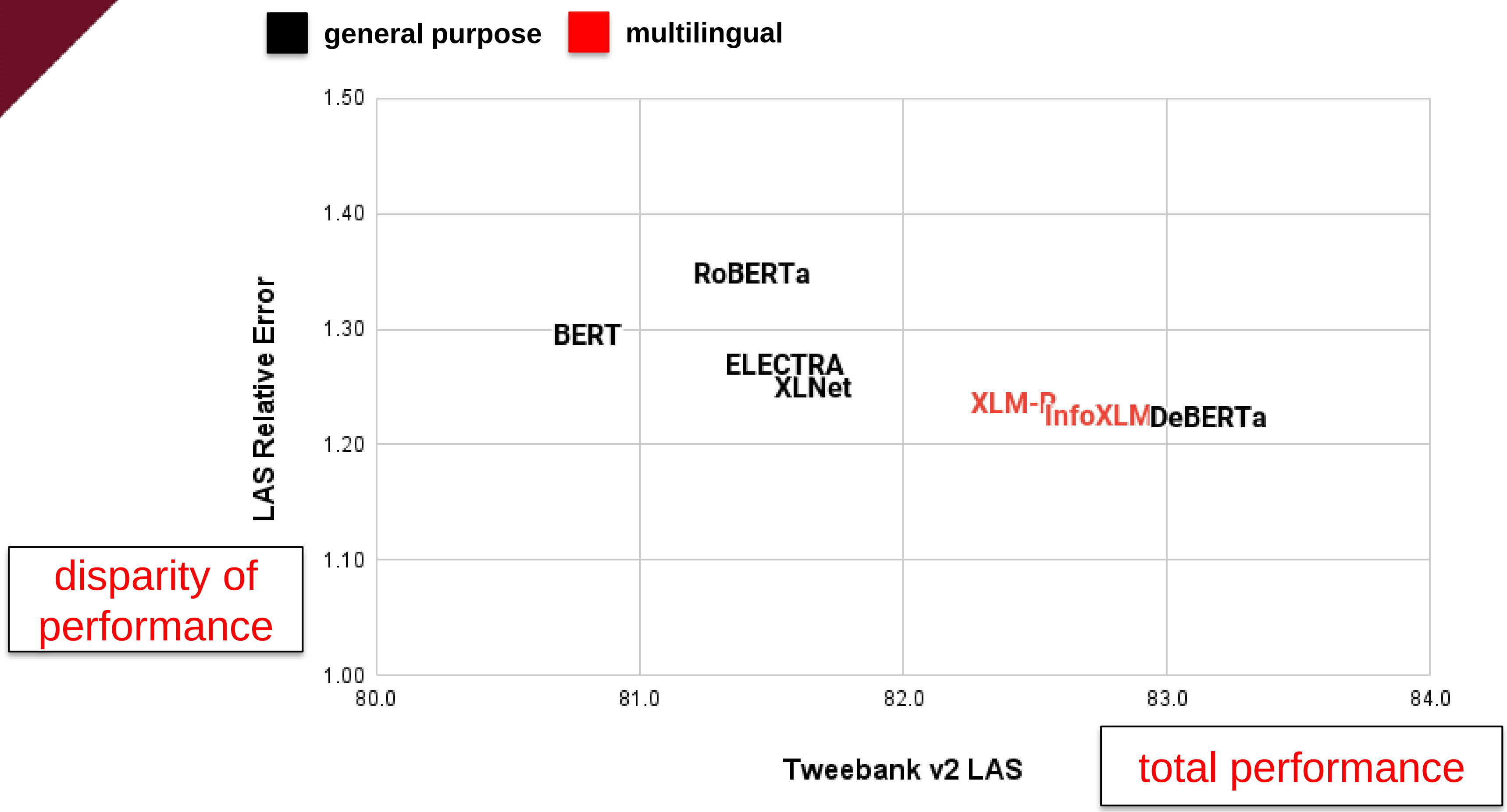
general purpose
multilingual
1.50
1.40
1.30
1.20
1.10
1.00
LAS Relative Error
RoBERTa
BERT
ELECTRA
XLNet
XLM-R
InfoXLM
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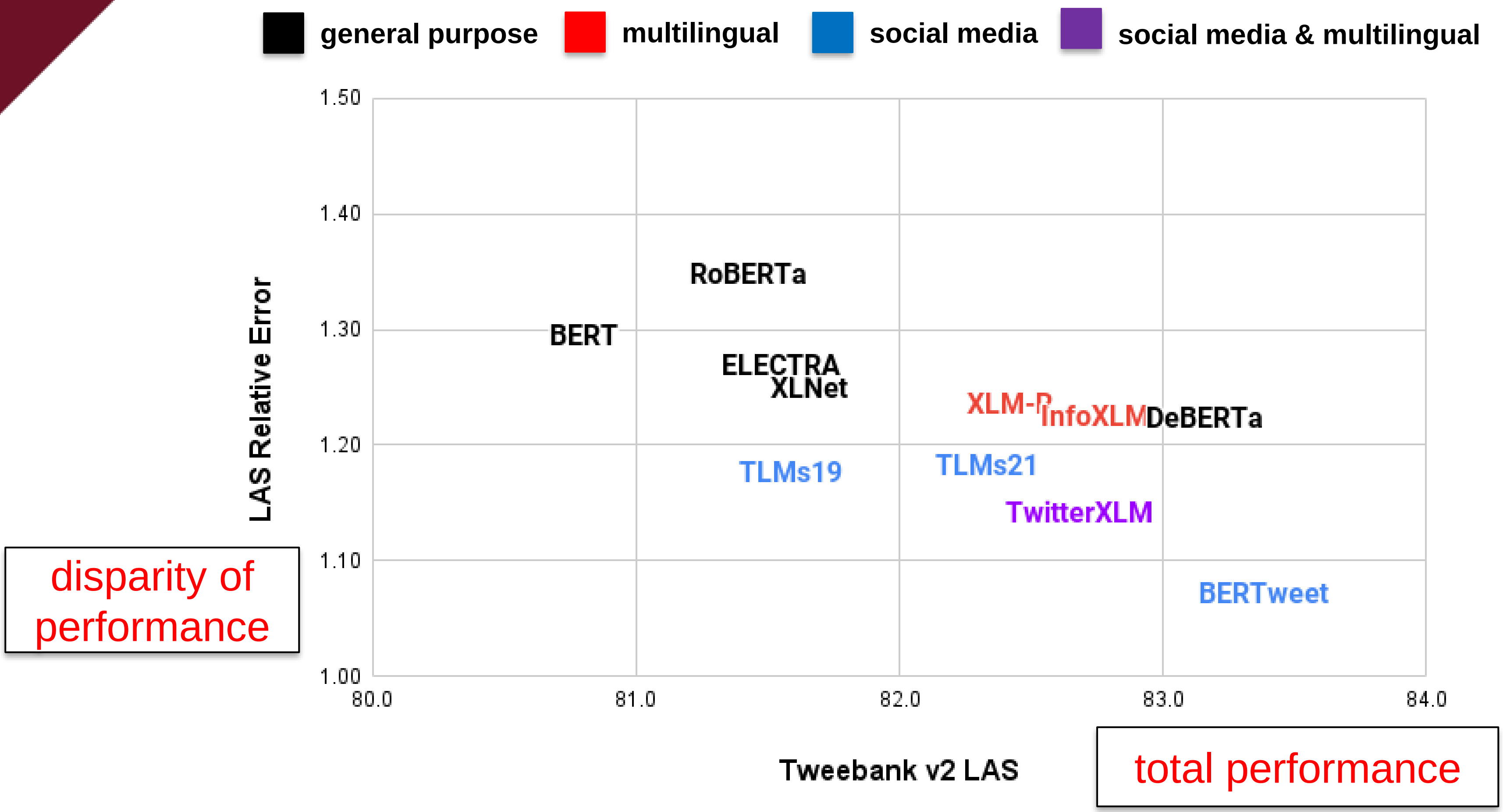

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social media & multilingual
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TLMs19
TLMs21
TwitterXLM
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Belief Extraction using TweetIE

- With a performant and equitable dependency parsing core, we now establish our application of it: a system of belief extraction we call TweetIE. This system extracts relations attributed to specified name entities.

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- TweetIE infers the following relations using our dependency parses:
  - IS_A: entity is a *what?*
  - HAS_A: entity has a *what*?
  - AS_AGENT: entity does *what?*
  - AS_PATIENT: *what* is done to the entity*?*
  - AS_CONJUNCT: entity and *what* do … / entity and *what* are …

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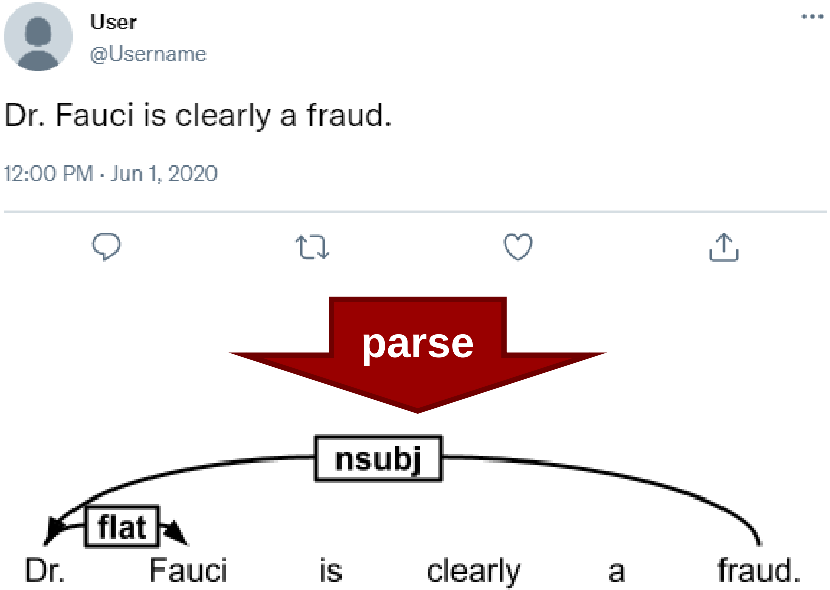
- We demonstrate that is has larger yield than alternative systems (OIE frameworks: ReVerb and ClausIE), and perform a precision evaluation, showing that it is more precise than both.

User

@Username

Dr. Fauci is clearly a fraud.

12:00 PM · Jun 1, 2020


User
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parse
nsubj
flat
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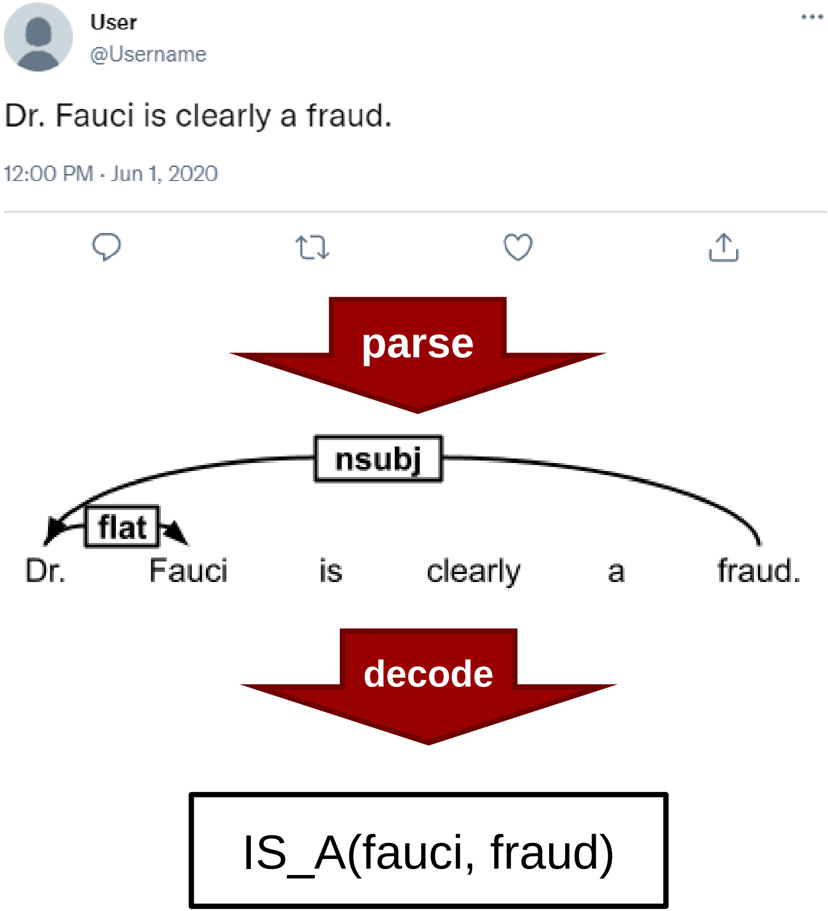
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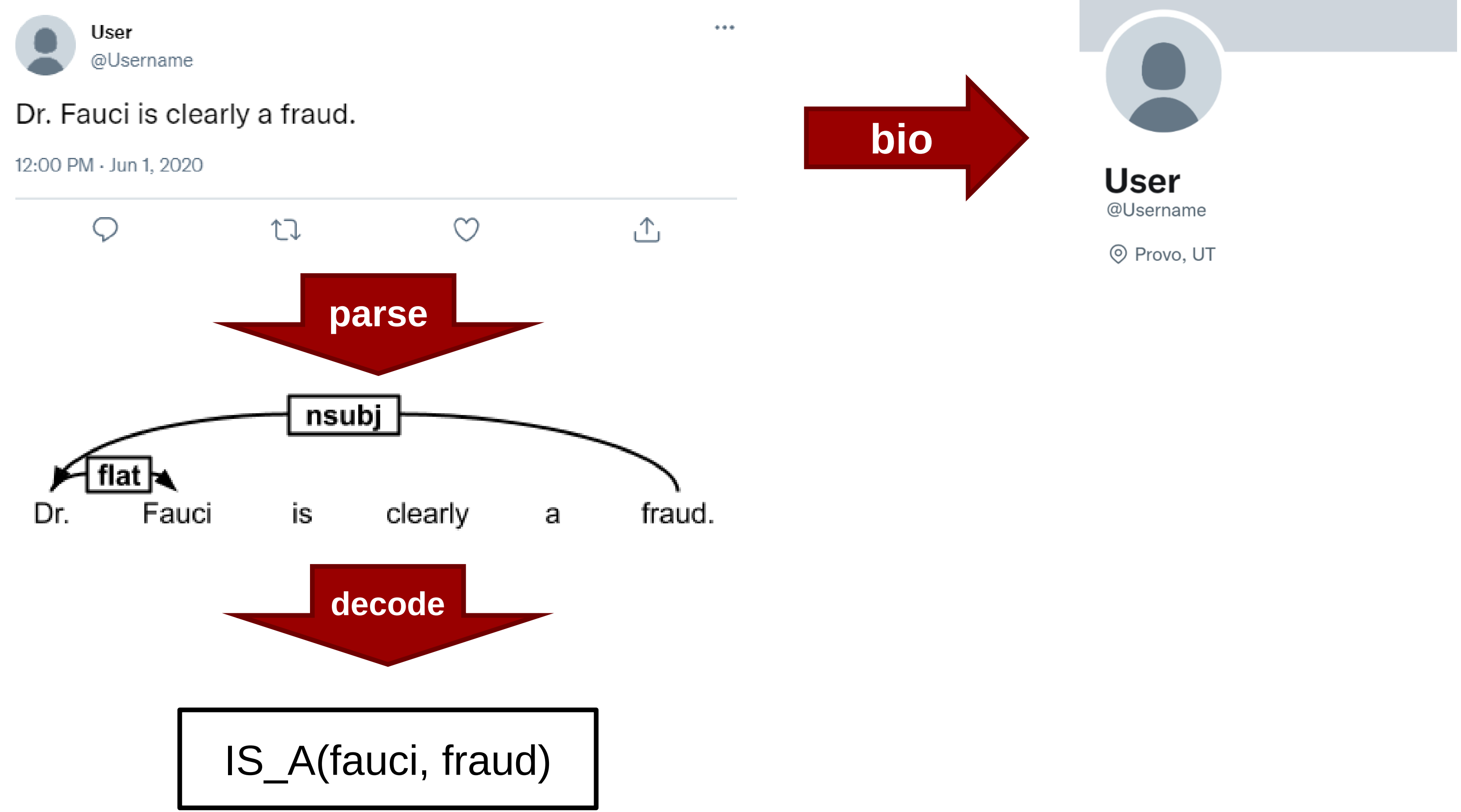
decode
IS_A(fauci, fraud)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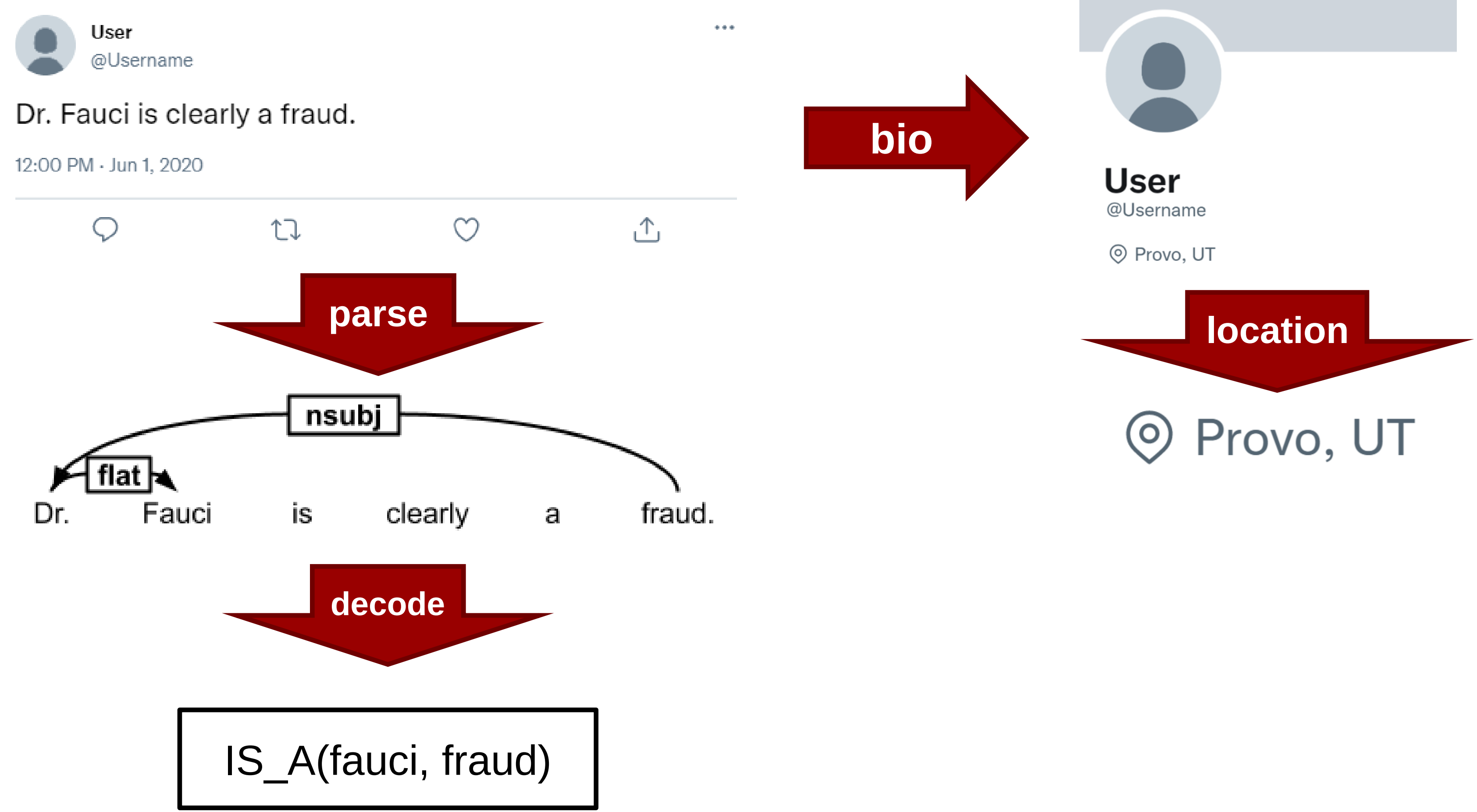
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location
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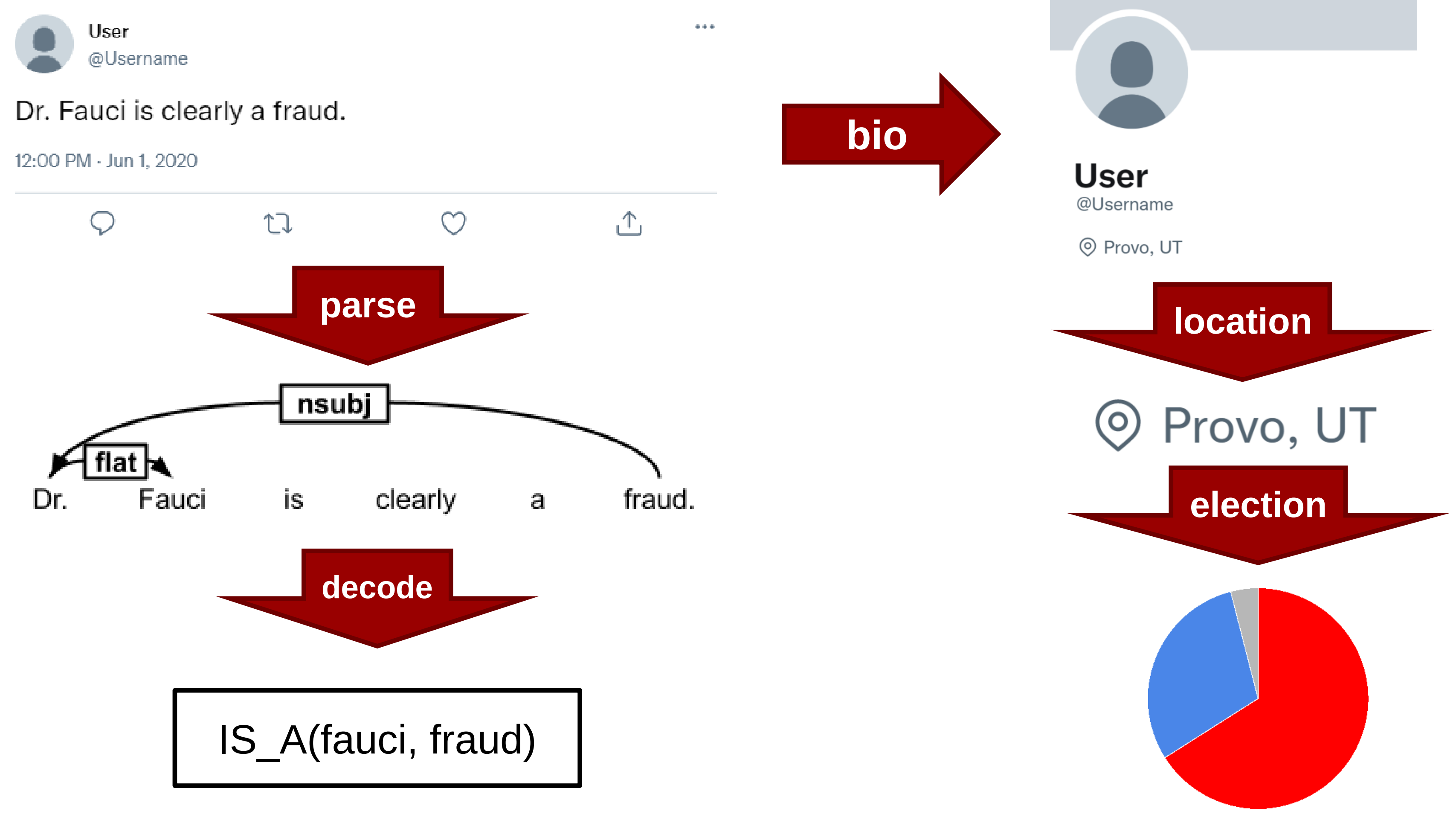
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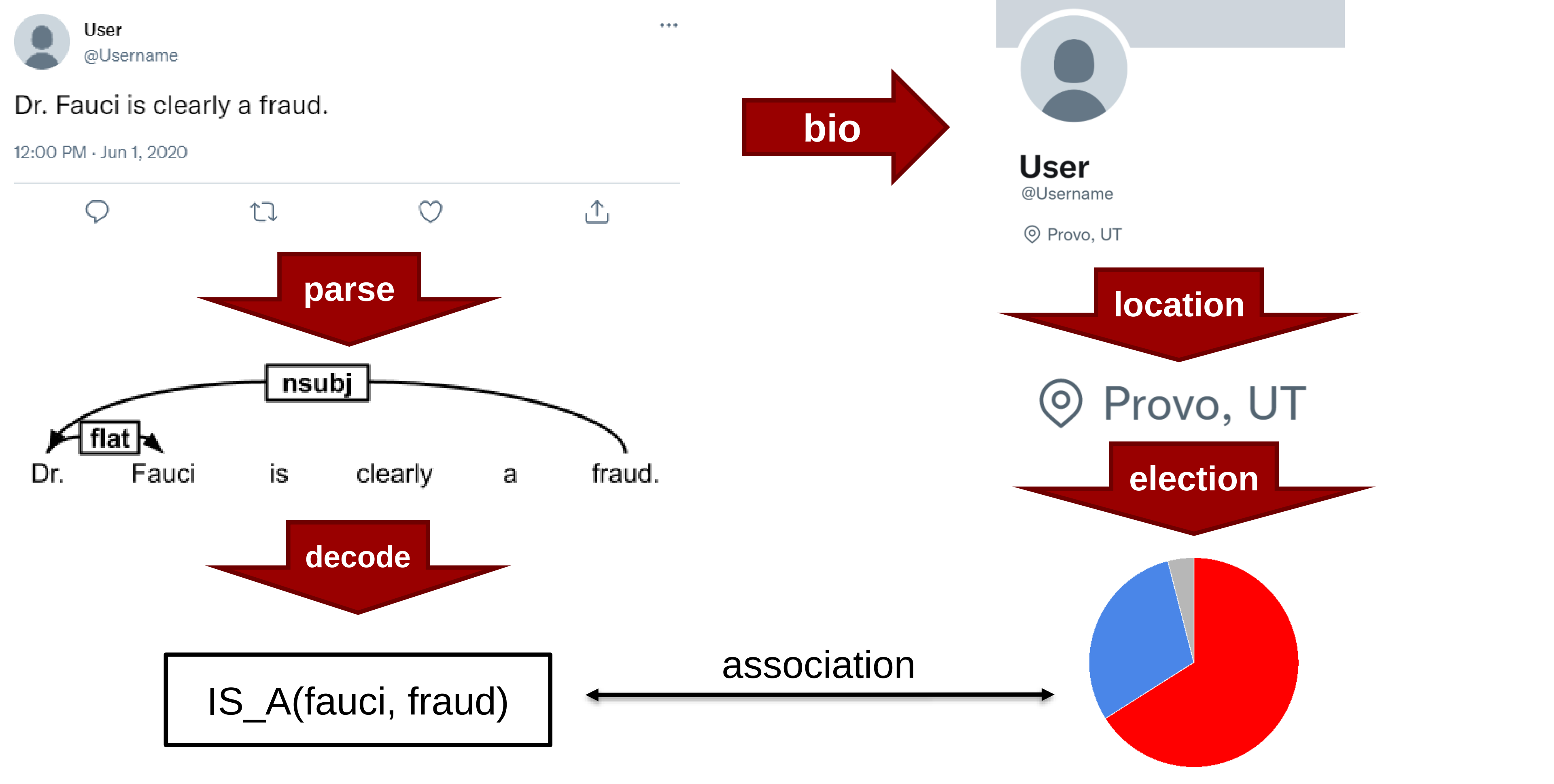
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association

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- This is done using a *t*-statistic.

  In this case, it is the deviation of a belief’s mean political valence from the population’s mean political valence, normalized with respect to the belief’s standard error.

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- This allows us to gather beliefs that should be disproportionately representative of Biden-leaning or Trump-leaning users.

Relation	**Trump-Leaning** ($t < -2$)	**Biden-Leaning** ($t > 2$)
IS_A(fauci, *property*$_{\text{nom}}$)	murderer**, joke**, hack*, fraud*, rat*, flip*, idiot, flop, state, prison, fake, jail	nih**, hero, md, director, president
IS_A(fauci, *property*$_{\text{adj}}$)	fake*, little*, deep, liberal, wrong, corrupt	beloved, optimistic, best
AS_AGENT(fauci, *verb*)	sweat**, force**, need*, help*, read*, lie*, know*, let*, not_fund*, not_understand*, flip, predict, write, make, stick, hold, prove, want, not_say, admit, not_get, demand, issue, laugh, state, put, spread, pull	speak**, join*, warn*, throw, not_recommend, offer, provide, respond, consider, debunk, fail, reveal
AS_PATIENT(fauci, *verb*)	not_trust***, screw, prosecute, grill, keep to, arrest, expose, lock, do to, remove, accord to, look like, mean, blast, read	know*, feature, discredit, threaten, worship, join, insult
HAS_A(fauci, *object*)	friend*, nih*, family, mind, hand, ex-employee, involvement, fraud, mask	guidance, time
AS_CONJUNCT(fauci, *conj.*)	gates***, obama**, bill gates*, biden*, brix, cdc, rest, covid, nih, company, government	director, experts

Table 5: TweetIE extractions with at least 20 unique users with a county-level political valence t-statistic outside of [-2, 2]. Results are reported in decreasing absolute value t-statistic. * $|t| > 3$, ** $|t| > 4$, *** $|t| > 5$.

Conclusion

We can extract the beliefs of communities through social media, and by doing so pursue a socially-aware form of information extraction.

Thank you for listening.

Paper Available at *github.com/slanglab/TweetIE_WNUT2022*.