Gauging the Behavioral Patterns of Voters Using a Unified Theory of Social Media Modeling

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Prof. Dr. Ram Mohana Reddy Guddeti (PhD)

Introduction

- ❖ Elections provide important opportunity to advance democratization!
- ❖ Now-a-days social media stands as an effective platform of self-expression, communication, and participation
    - ❖ Pitfalls of social media data*
    - ❖ Bots and sockpuppets?
    - ❖ Escaping filter bubbles?
    - ❖ Linguistic and temporal structure

* Kosinski, M., et al. "Facebook as a Research Tool for the Social Sciences." American Psychologist (2015): 543-556.

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- Can this carefully judged insight ever replace the traditional polling?

Social Media: Open Source to Privacy?

- Finding patterns and trends with time
  - Sources
  - Sentiments
  - Hashtags
  - Alliances

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  - Sentiments
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  - Alliances
- Sustainability and popularity on the social network
  - Temporal nature
  - User mentions

Social Media: Open Source to Privacy?

State	Political Party	Results
Telangana	BJP	1/119
	Congress+	21/119
	TRS	88/119
	Others	9/119
Chhattisgarh	BJP	22/90
	Congress+	68/90
Rajasthan	BJP	79/199
	Congress+	100/199
	Others	20/199
Madhya Pradesh	BJP	111/230
	Congress+	114/230
	Others	5/230
Mizoram	MLF	26/40
	Others	14/40

Opinion Polling: India 2018-19

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- Various polling strategies (e.g., open debates, allegations) must also be analyzed

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- Gender-based analytics – if social media mimics the real-world scenario, then should gender-based analytics be incorporated into the prediction model?

Problem Statement and Research Objectives

Mining and modeling users' digital footprints on social media (Twitter) to accurately predict the outcomes of the general elections in a nation (India)

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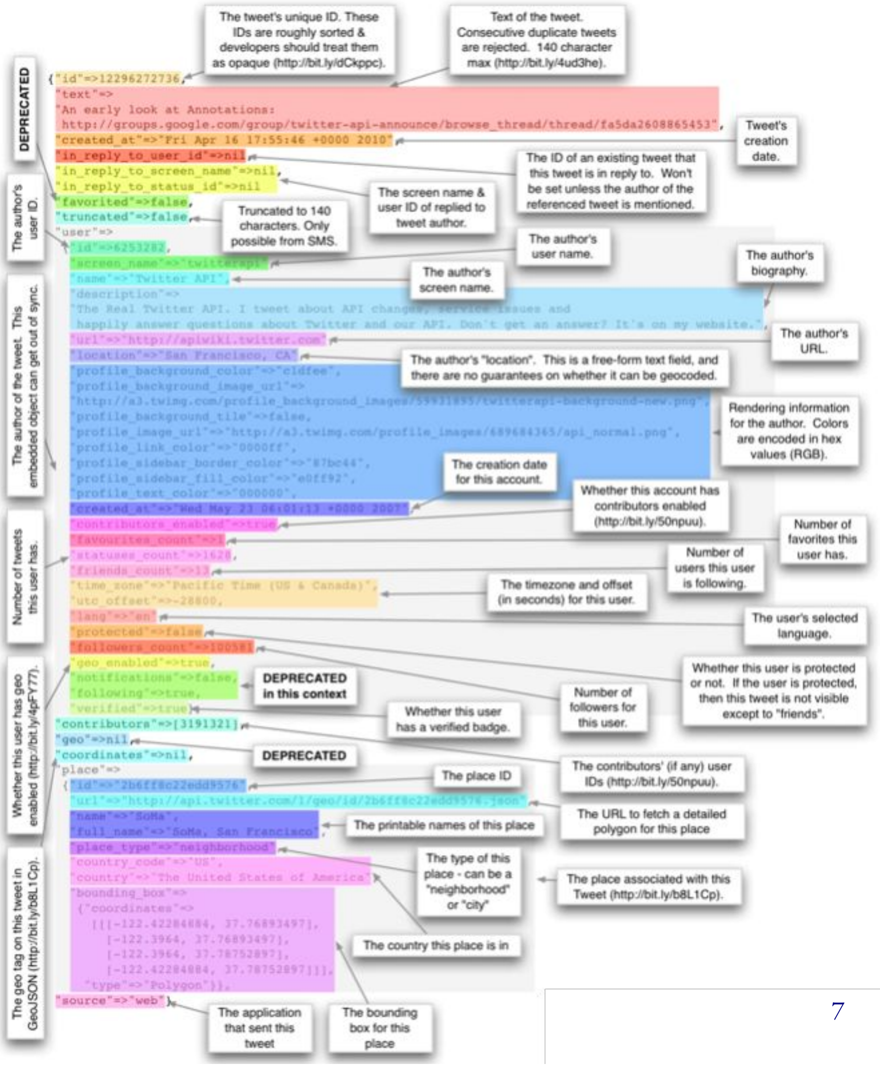
Twitter Mining: Parameters

- Followers count
- Friends count
- Listed count
- Retweet, Quote count
- Reply, Favorite count

reachability



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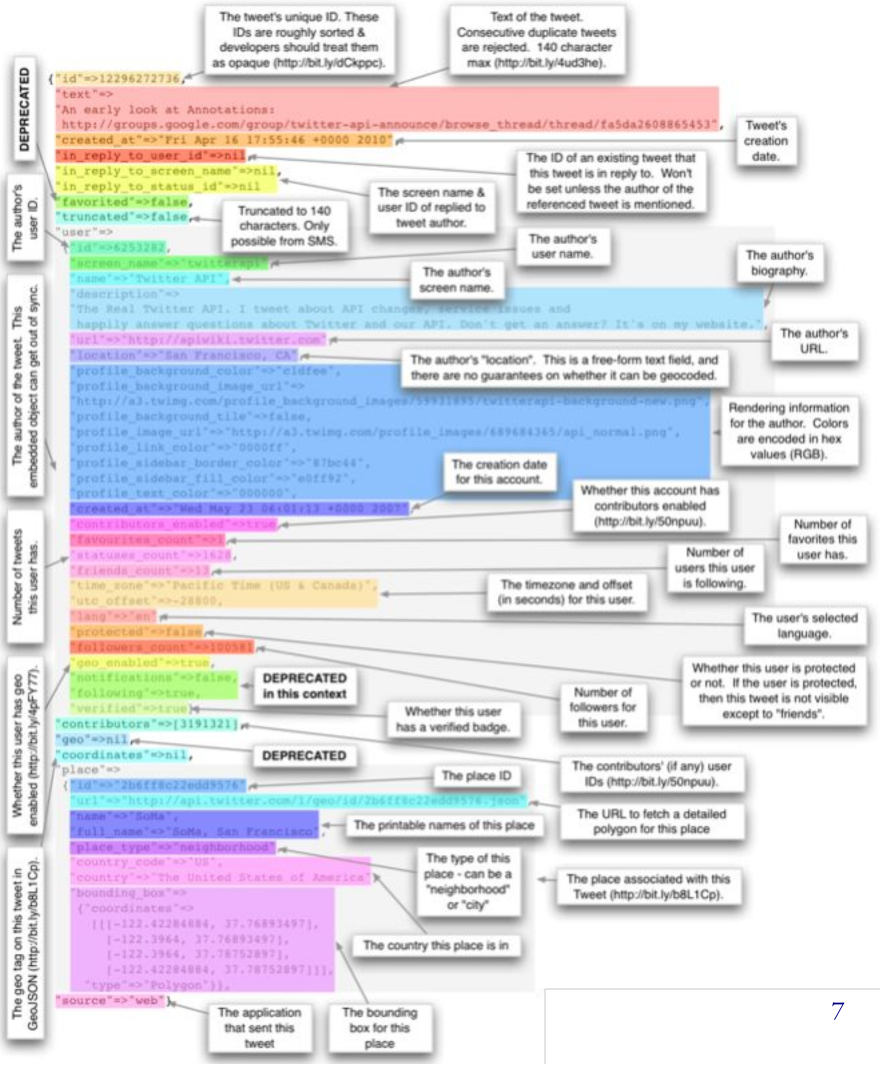

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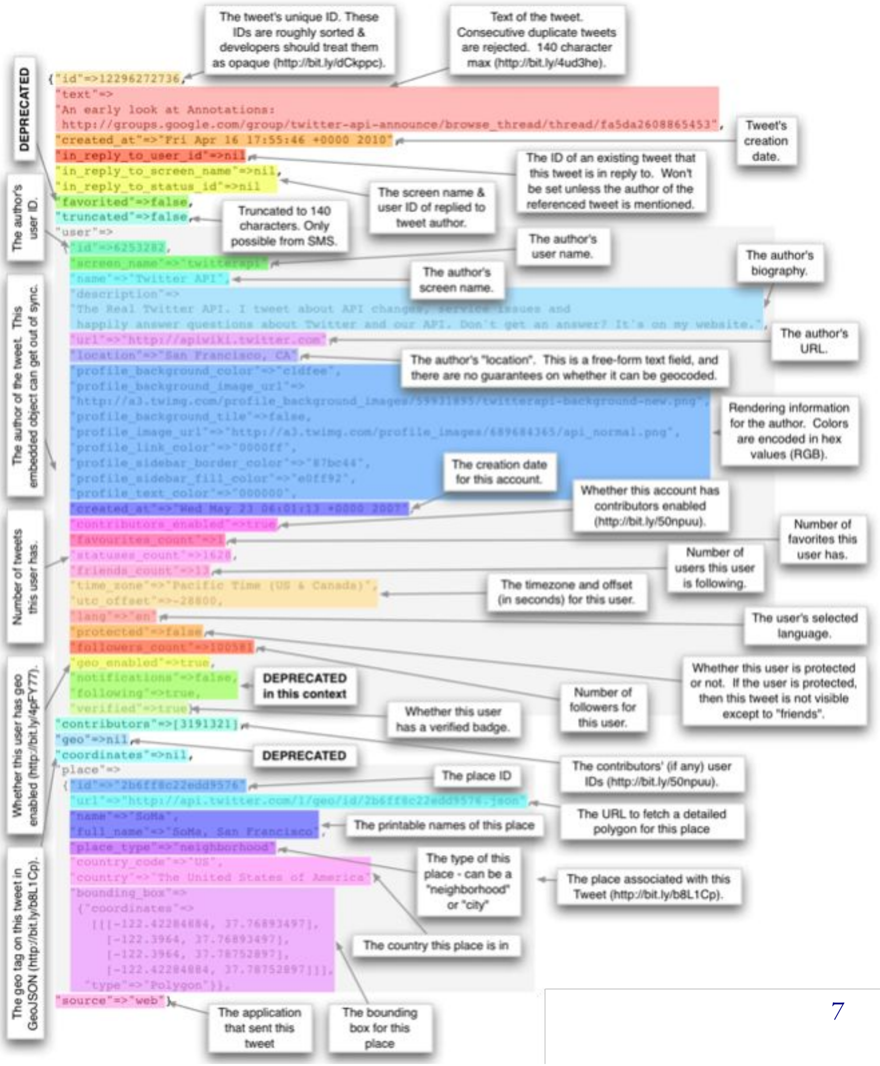
- Gender* – analysis



* Gender is not a Twitter parameter, it has to estimated separately

Challenges in Twitter Modeling

- Location – number of people posting their opinions vs. number of those people voting!

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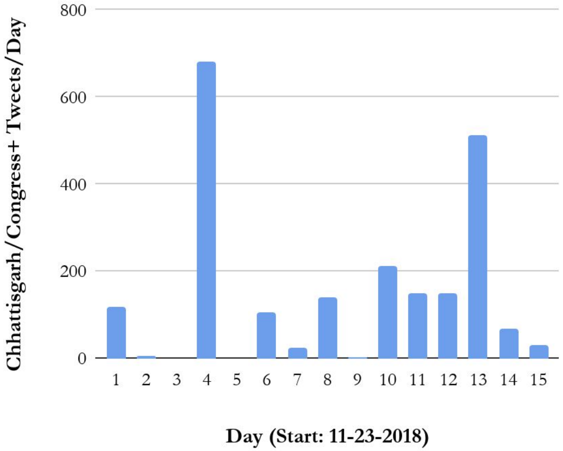

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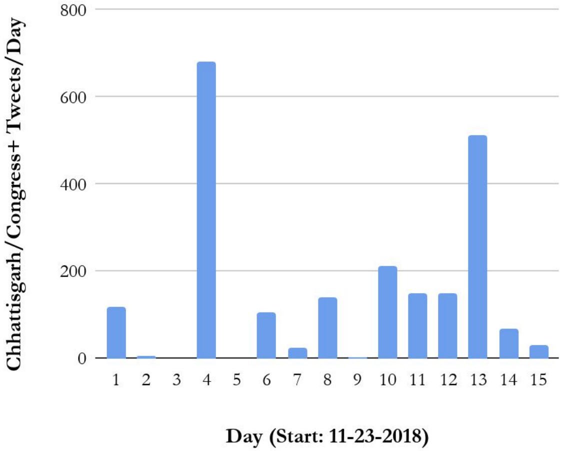

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- Language – discarding non-english tweets removes "48.2%" of the tweets (Hindi or Telugu)!

Theories of Social Media Modeling: Volume

- Measures the volume of attention or support, and is computed as the frequency of mentions online (e.g., retweets, supporters, likes, etc.)

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- Volumetric score is temporally weighted to assess the sustainability and popularity with time

$$\mathrm{Tem}_{t,t_e} = \frac{k}{t - t_e}$$

$$\boxed{\mathrm{Vol}^{(t)}_{p,T,t_e} = \frac{\sum_{t} \{\text{relevant social media mentions}\}_{p,t} \cdot \mathrm{Tem}_{t,t_e}}{\sum_{t} \sum_{i} \{\text{relevant social media mentions}\}_{i,t}} \ (\%)}$$

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- Sentiment score ($Sen_{p,T,t_e}^{(t,\ rch)}$) is weighted temporally and by the reachability of the footprint to assess the sustainability and popularity with time
  - User reachability index = *#followers* + *#friends* + *#listed*
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- We employ a hybrid of supervised and unsupervised approaches to effectively estimate the sentiment of the collected footprints
  - English tweets: SentiStrength
  - Non-English tweets: Deep Conv-LSTM architecture

Modeling the Sentiment: Challenges

- Complex linguistic structure
  - English + Native Language: దేశంపట్ల or ప్రజలపట్ల responsibility is not visible
  - Only Native Language: దేశంపట్ల కానీ ప్రజలపట్ల కానీ బాధ్యత కనిపించదు
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  - Telugu (5,410)[1], Hindi (5,228)[2], and code-mixed (Te-En*: 5,410 and Hi-En[3]: 3,879)

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	Telugu			Hindi		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Hand-annotated	250	250	250	250	250	250
Pure language	1,491	1,441	2,478	2,290	712	2,226
English code-mixed	1,491	1,441	2,478	1,352	570	1,957
Total	**3,232**	**3,132**	**5,206**	**3,892**	**1,532**	**4,433**

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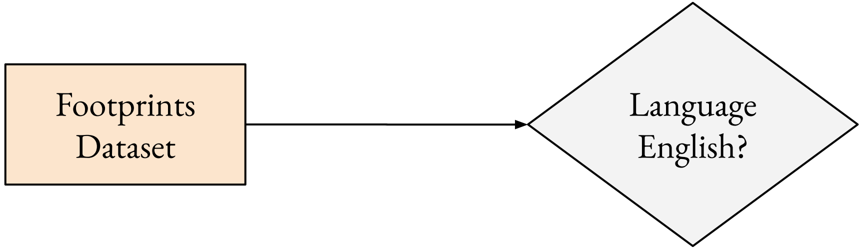

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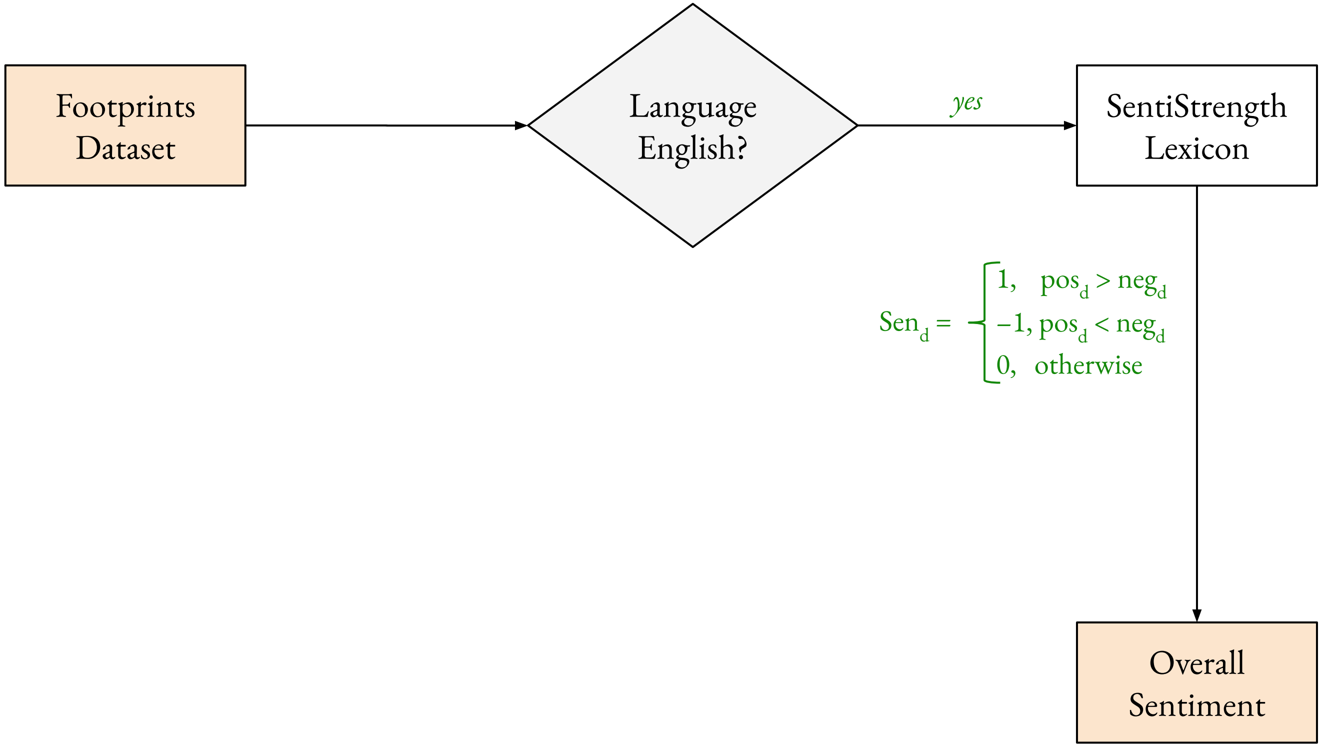

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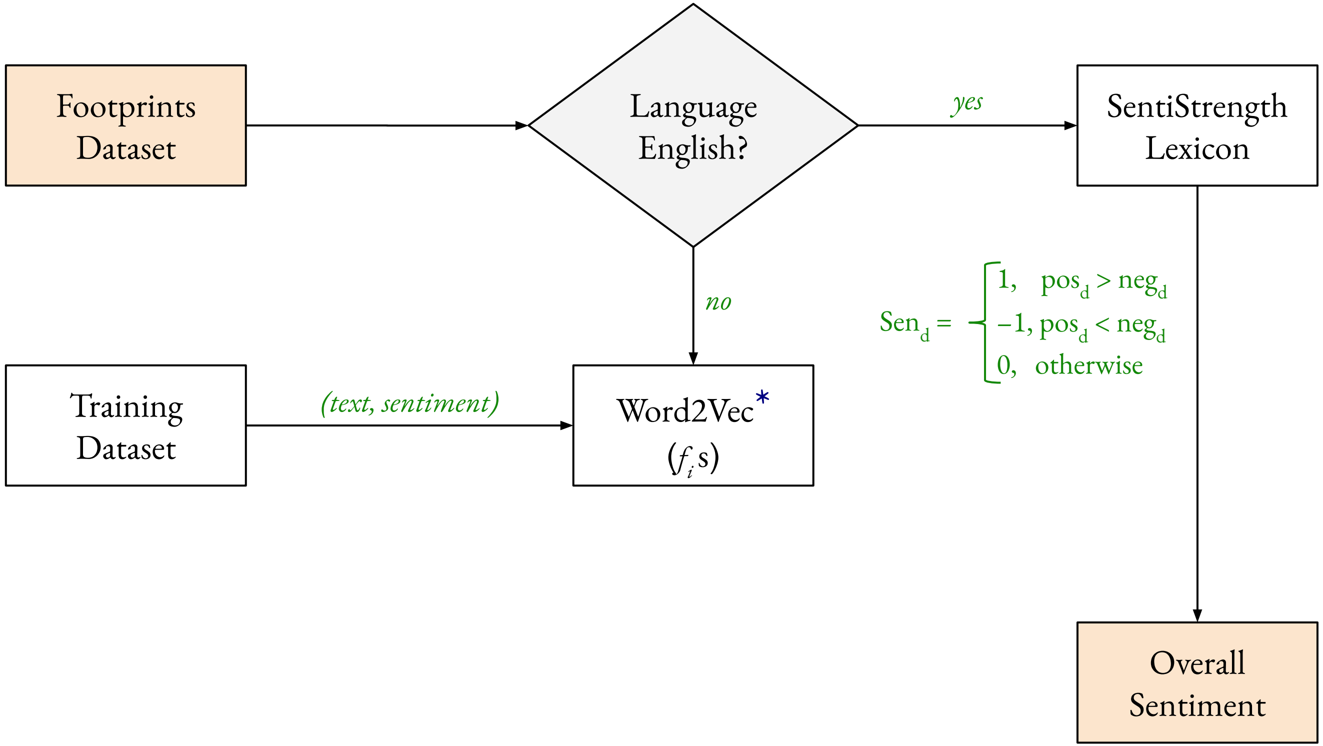

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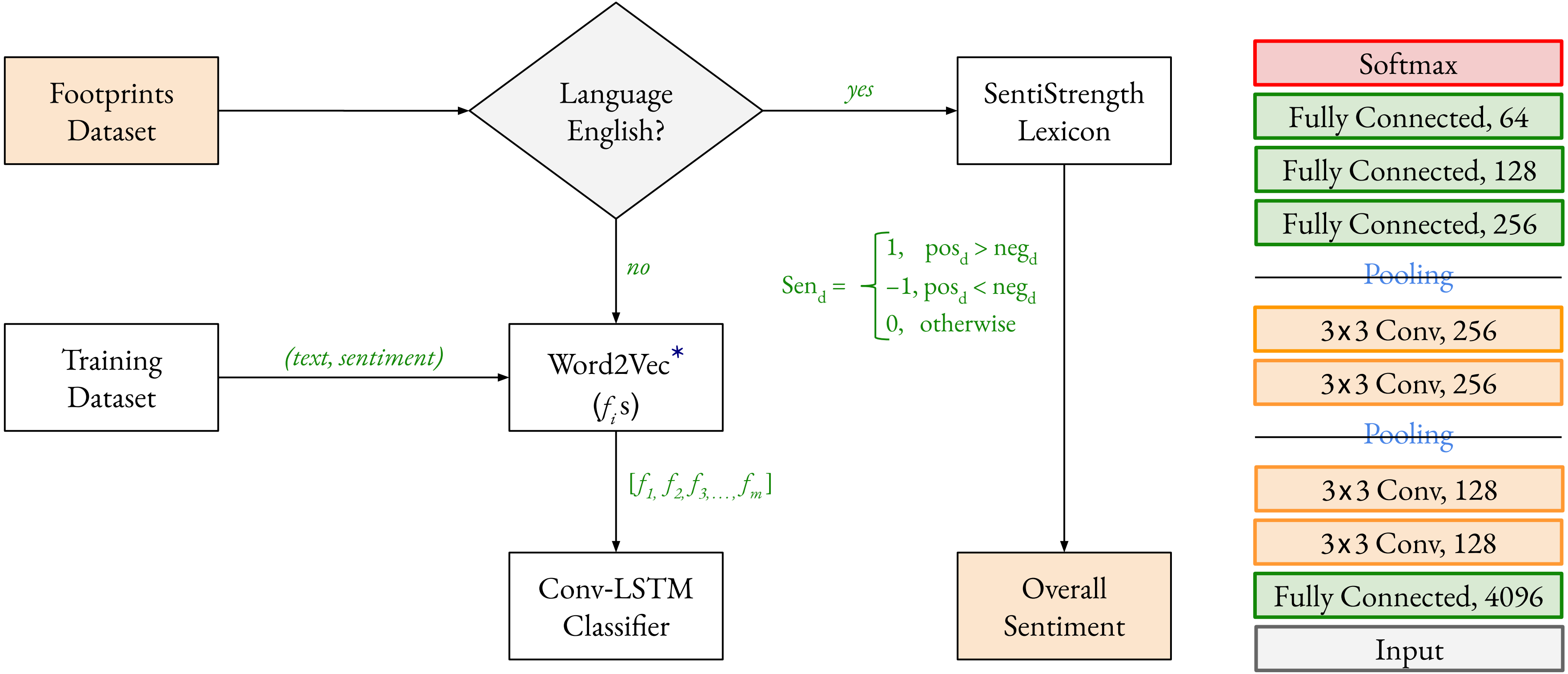

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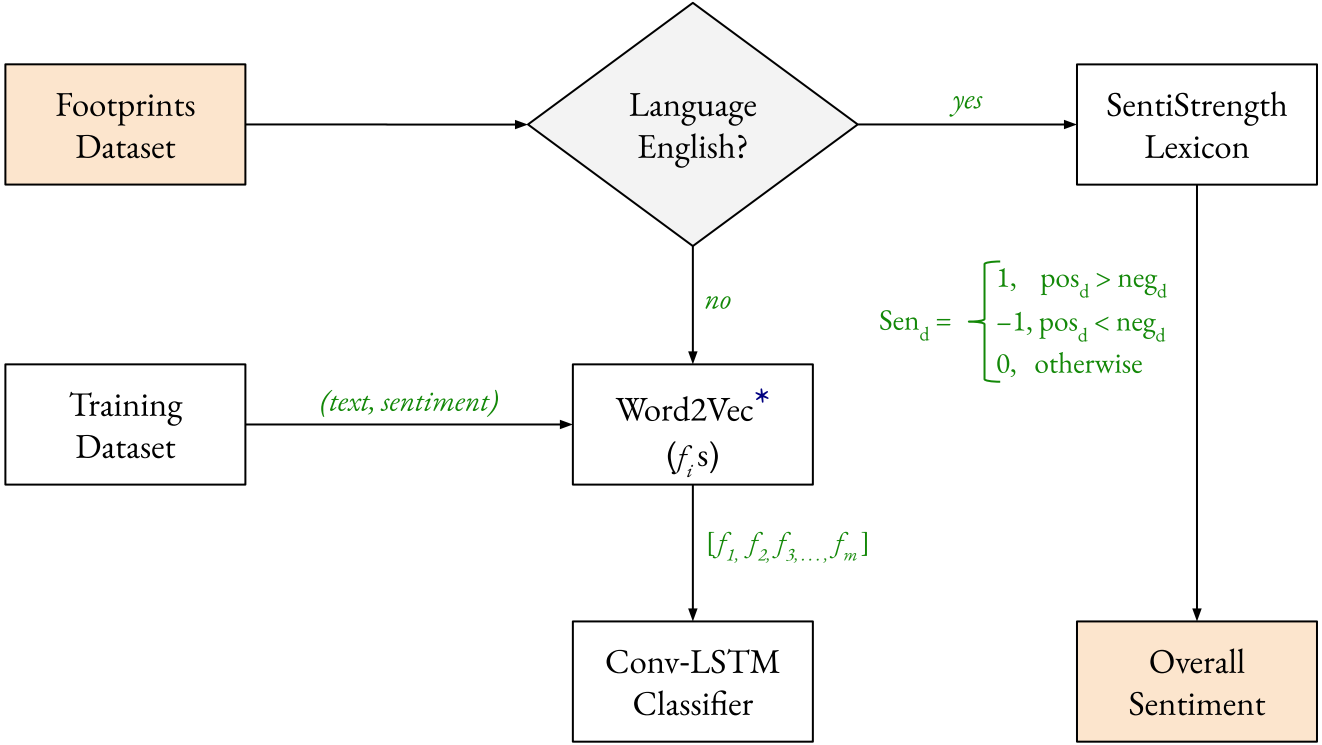

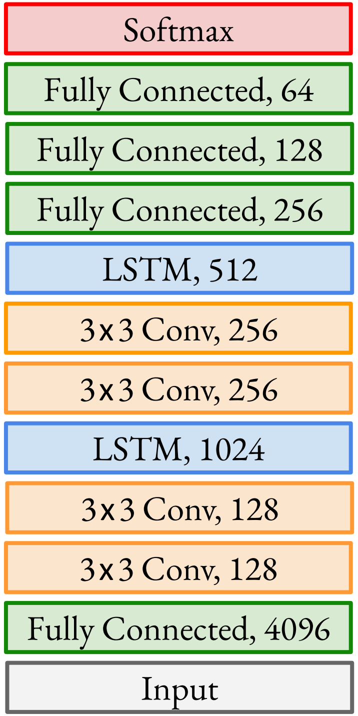

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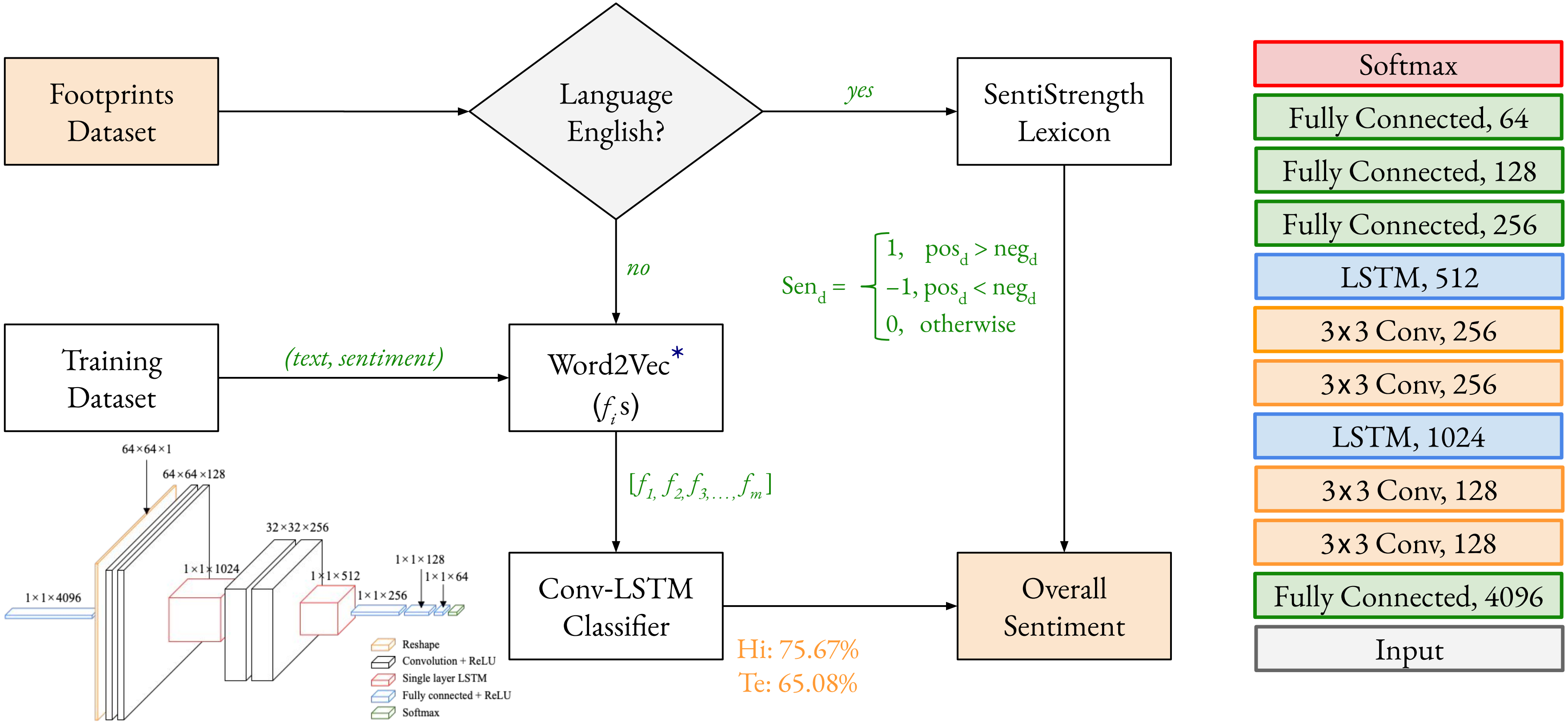

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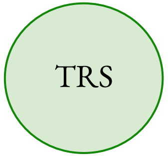

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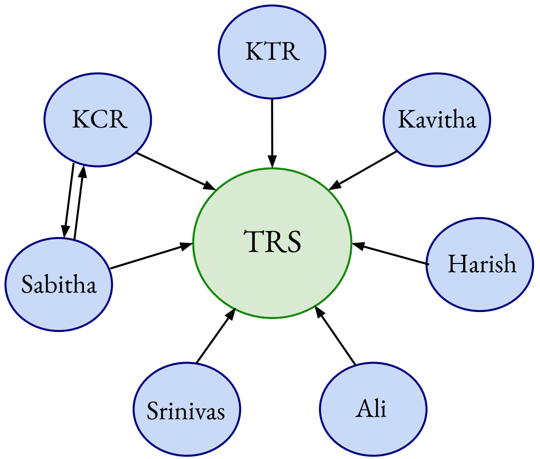

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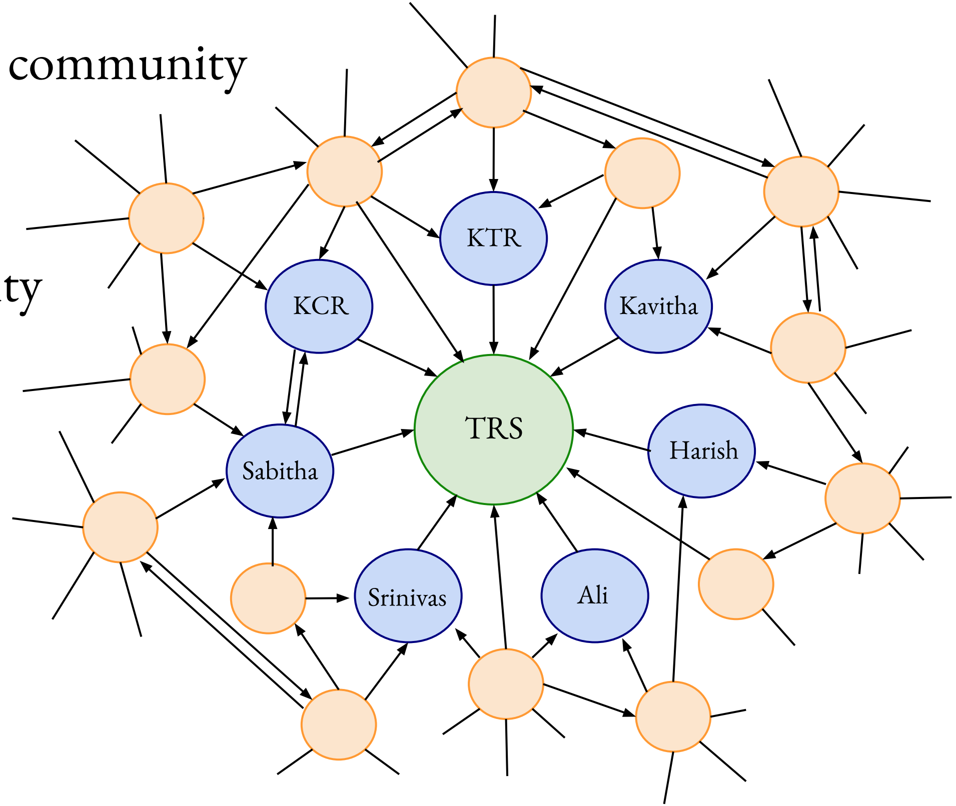

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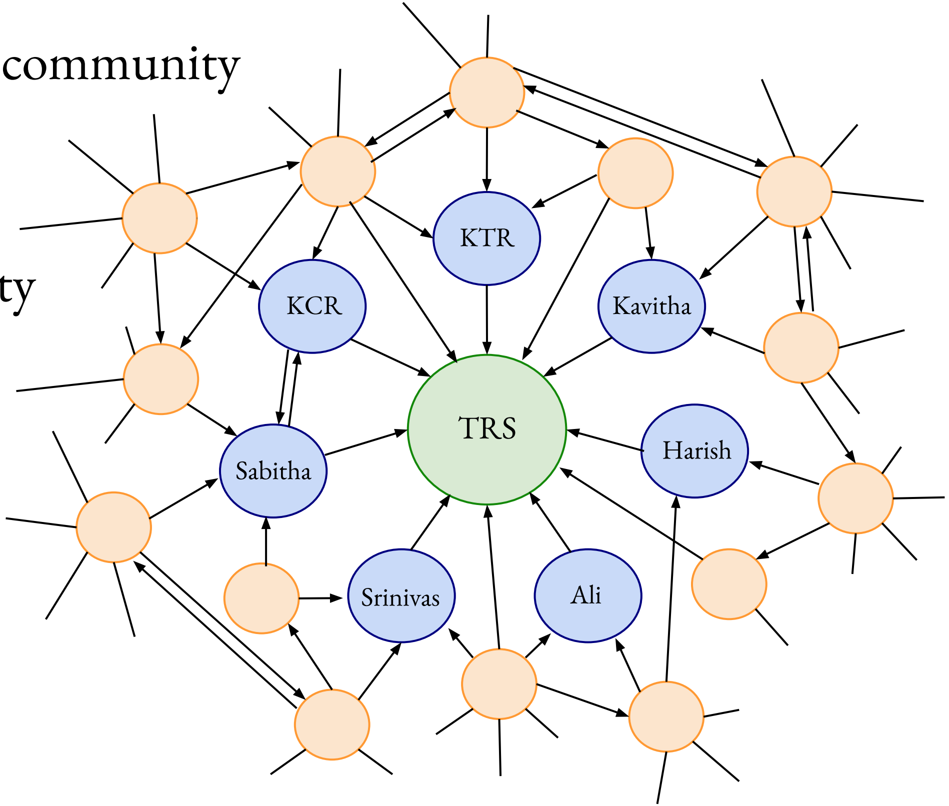
- Overall network score:

$$\frac{\#\text{edges}}{\text{possible }\#\text{edges}}$$

$$\boxed{Net^{(dens,\, betw)}_{p,T} = \frac{C_B(p) + (1/D(p))}{\sum_i C_B(i) + (1/D(p))}\ (\%)}$$

$$C_B(p) = \sum_{u \neq v \neq p \in V} \frac{\sigma(u, v \mid p)}{\sigma(u, v)}$$



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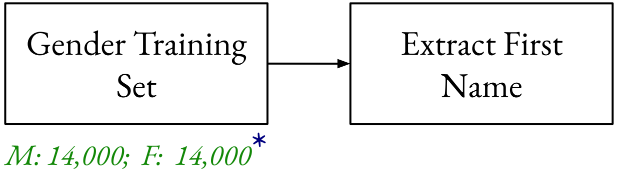

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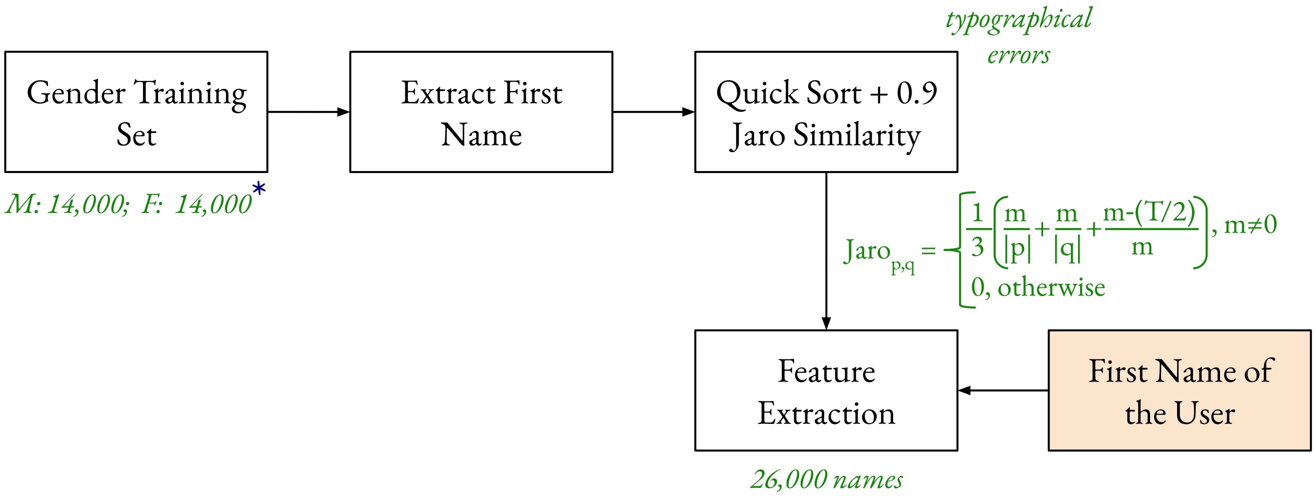

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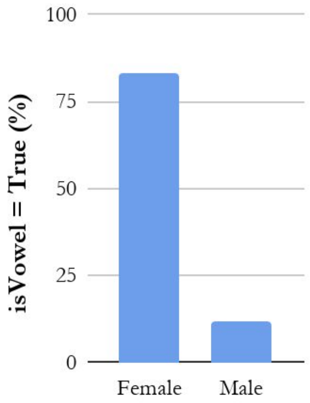

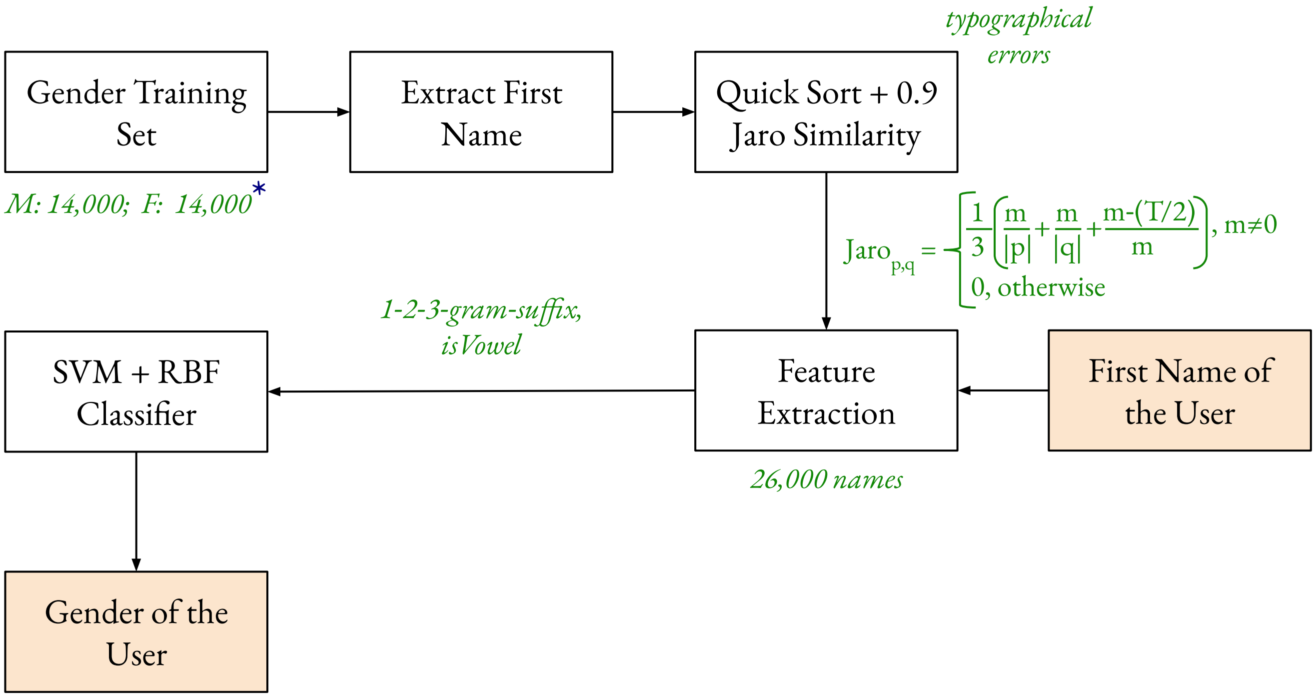

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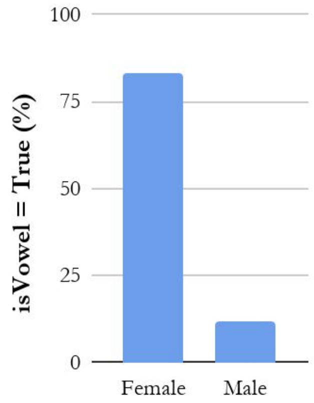

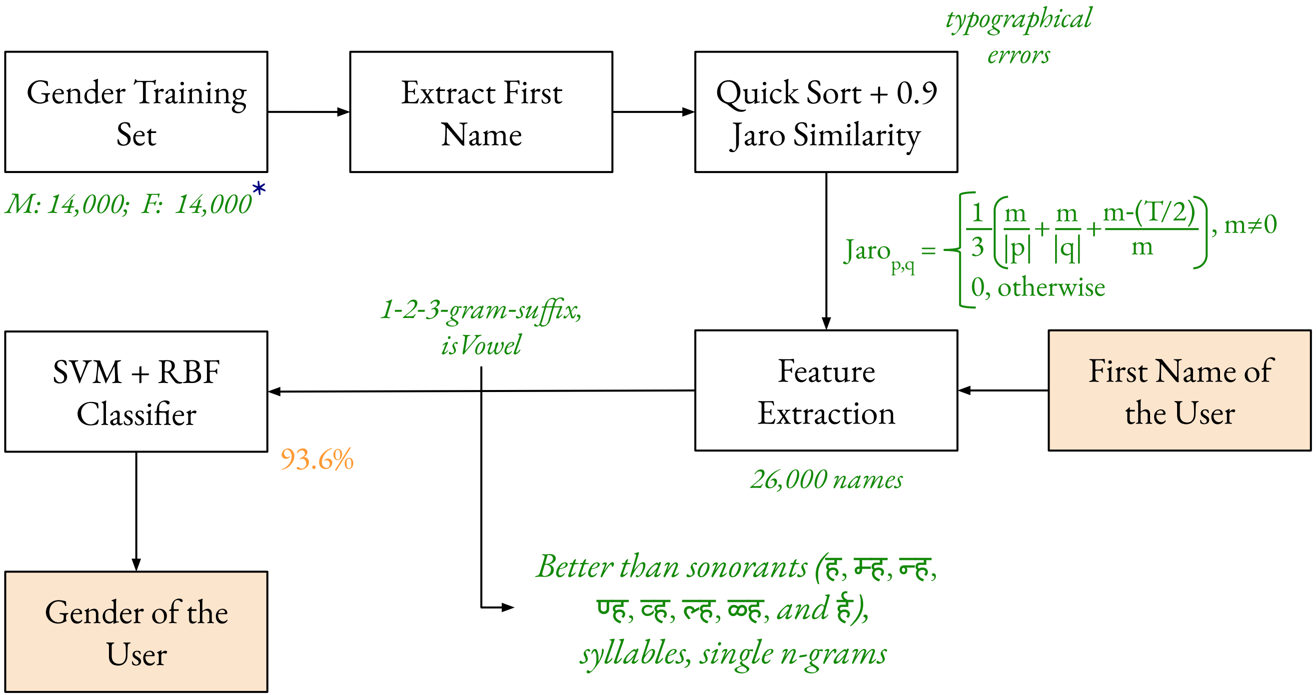

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Influential Parameter Mining: Issues and Biases

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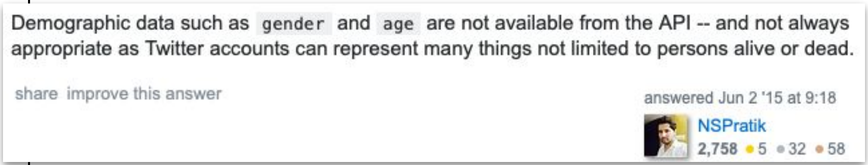
- Age and Experience
- Religion and Region (geo-tagging)
- Educational backgrounds

Twitter profile data?



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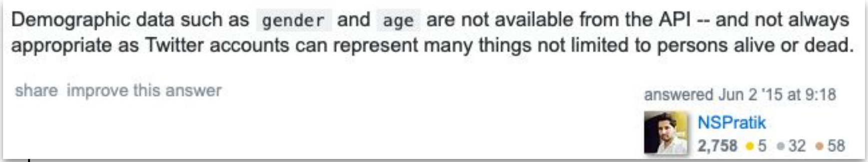
- Alliance loyalty (legacy data)
- Impact of political decisions –
  - Farm loan waiver, Minimum support price (agriculture), etc.
- Polling strategies and opposition speeches

Twitter profile data?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share improve this answer

answered Jun 2 '15 at 9:18

NSPratik

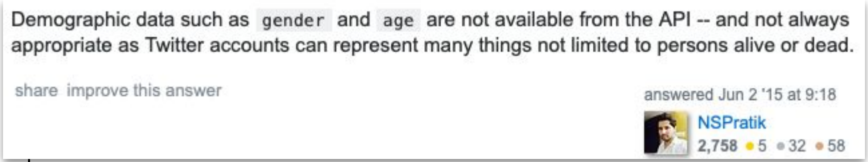
2,758 ●5 ●32 ●58

News articles

Influential Parameter Mining: Issues and Biases

- Gender and Related Reforms
- Age and Experience
- Religion and Region (geo-tagging)
- Educational backgrounds
- Alliance loyalty (legacy data)

Twitter profile data?



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NSPratik

2,758 ●5 ●32 ●58

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  - Farm loan waiver, Minimum support price (agriculture), etc.
- Polling strategies and opposition speeches

News articles

- Influence of money, liquor, gifts on elections!
- Financial backgrounds

Cannot be mined for!

Influential Parameter Mining: India

- Pulwama attack+
- Smart cities+
- SC/ST act+
- Ram mandir+
- Swachh Bharath+

Influential Parameter Mining: India

- Pulwama attack^{+}
- Smart cities^{+}
- SC/ST act^{+}
- Ram mandir^{+}
- Swachh Bharath^{+}
- GST^{-}
- Demonetization^{-}
- Black money^{-}
- Ganga clean^{-}

BJP

Influential Parameter Mining: India

- Pulwama attack^{+}
- Smart cities^{+}
- SC/ST act^{+}
- Ram mandir^{+}
- Swachh Bharath^{+}
- GST^{-}
- Demonetization^{-}
- Black money^{-}
- Ganga clean^{-}
- Save India^{+} – Congress+

} BJP

Unification of Modeling Theories: Linear Modeling

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* UToSMoV performs a temporal backtracking guided by influence

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$$\mathrm{UToSMoV}(p) = \begin{pmatrix} \beta_{1,m} \\ \beta_{1,f} \end{pmatrix} \cdot \begin{pmatrix} \mathrm{Vol}_m \\ \mathrm{Vol}_f \end{pmatrix}^T + \beta_{2,S} \cdot (\mathrm{Sen}_{pos} - \mathrm{Sen}_{neg}) + \beta_{2,I} \cdot (\mathrm{Inf}_{pos} - \mathrm{Inf}_{neg}) + \beta_3 \cdot (\mathrm{Net}) + \beta_0$$

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- Constants[1]: $\begin{cases} \beta_{2,S} \leq \beta_3 \leq \beta_{2,I} \cong (\beta_{1,m} + \beta_{1,f}), \text{ if } \beta_{1,m} \text{ and } \beta_{1,f} \text{ are known} \\ \beta_{2,S} \leq \beta_3 \leq \beta_{2,I} \text{ and } (\beta_{1,m} = \beta_{1,f} = 1), \text{ otherwise} \end{cases}$

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* $0 \leq \beta_{1,m}; \beta_{1,f}; \beta_{2,S}; \beta_{2,I}; \beta_3 \leq 1$

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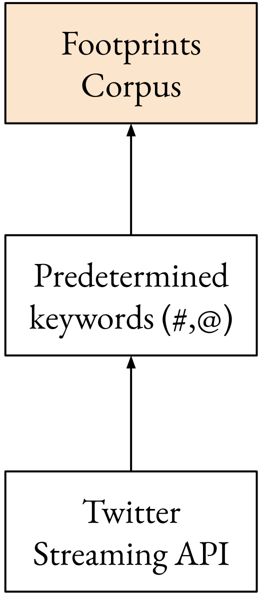
Unification of Modeling Theories: UToSMoV



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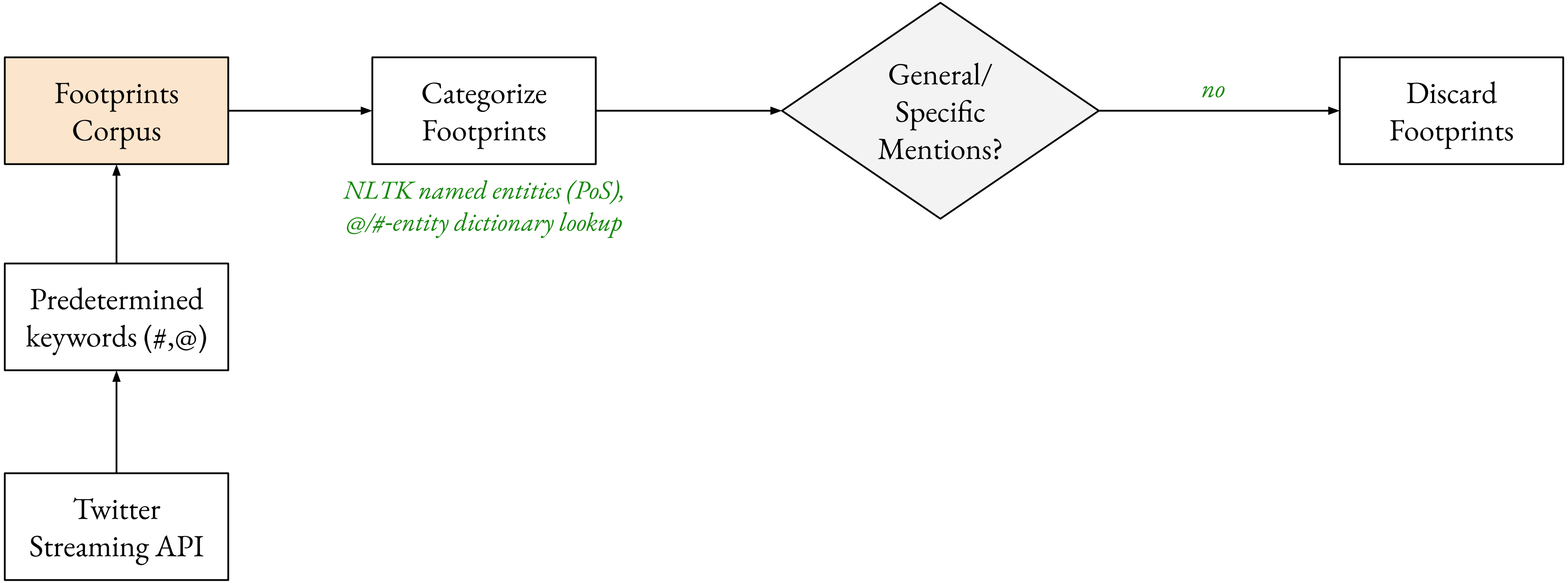

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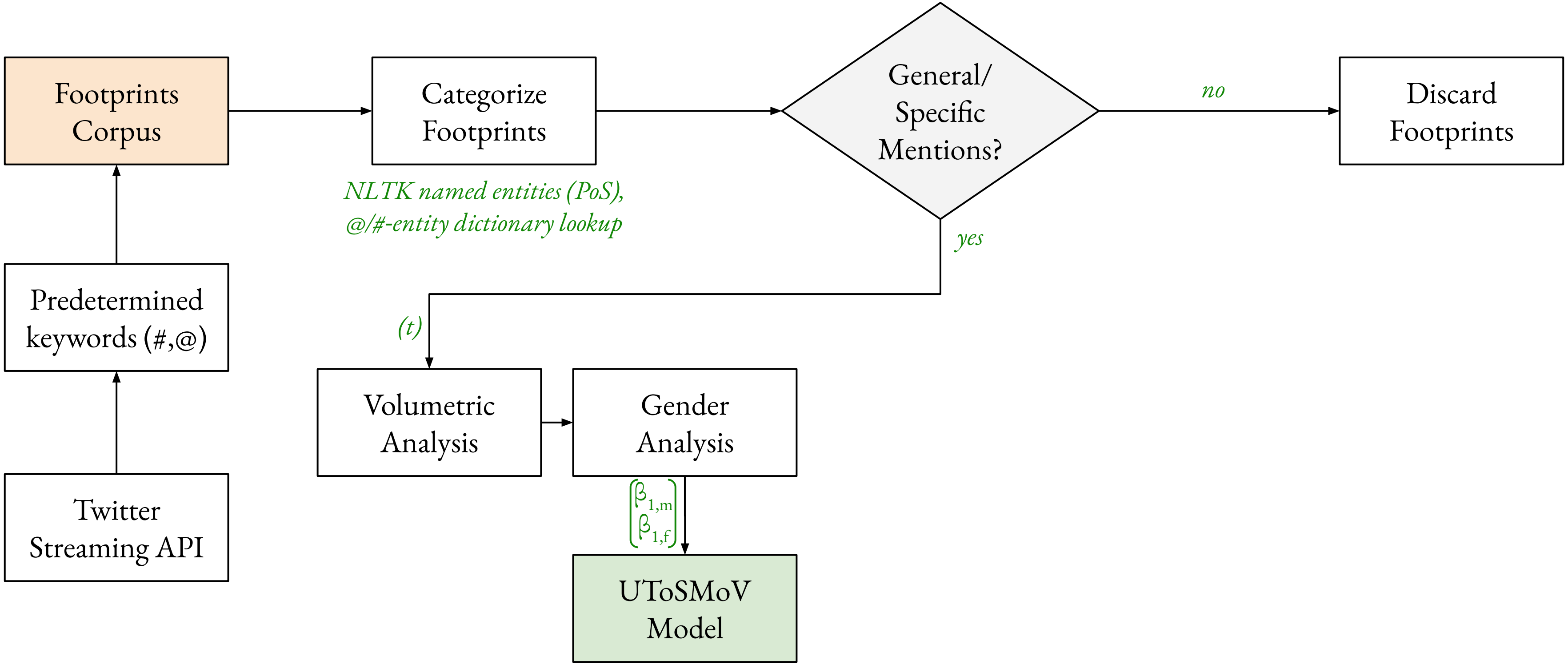

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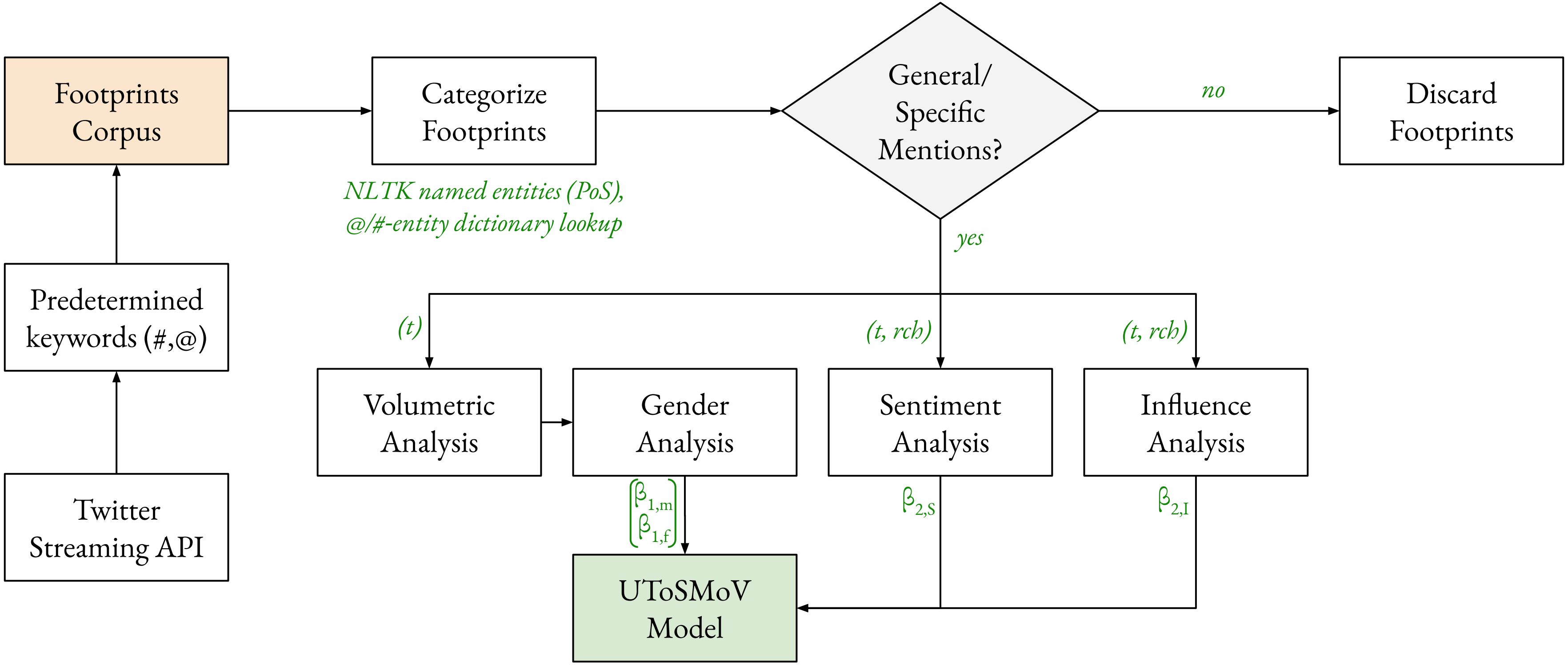
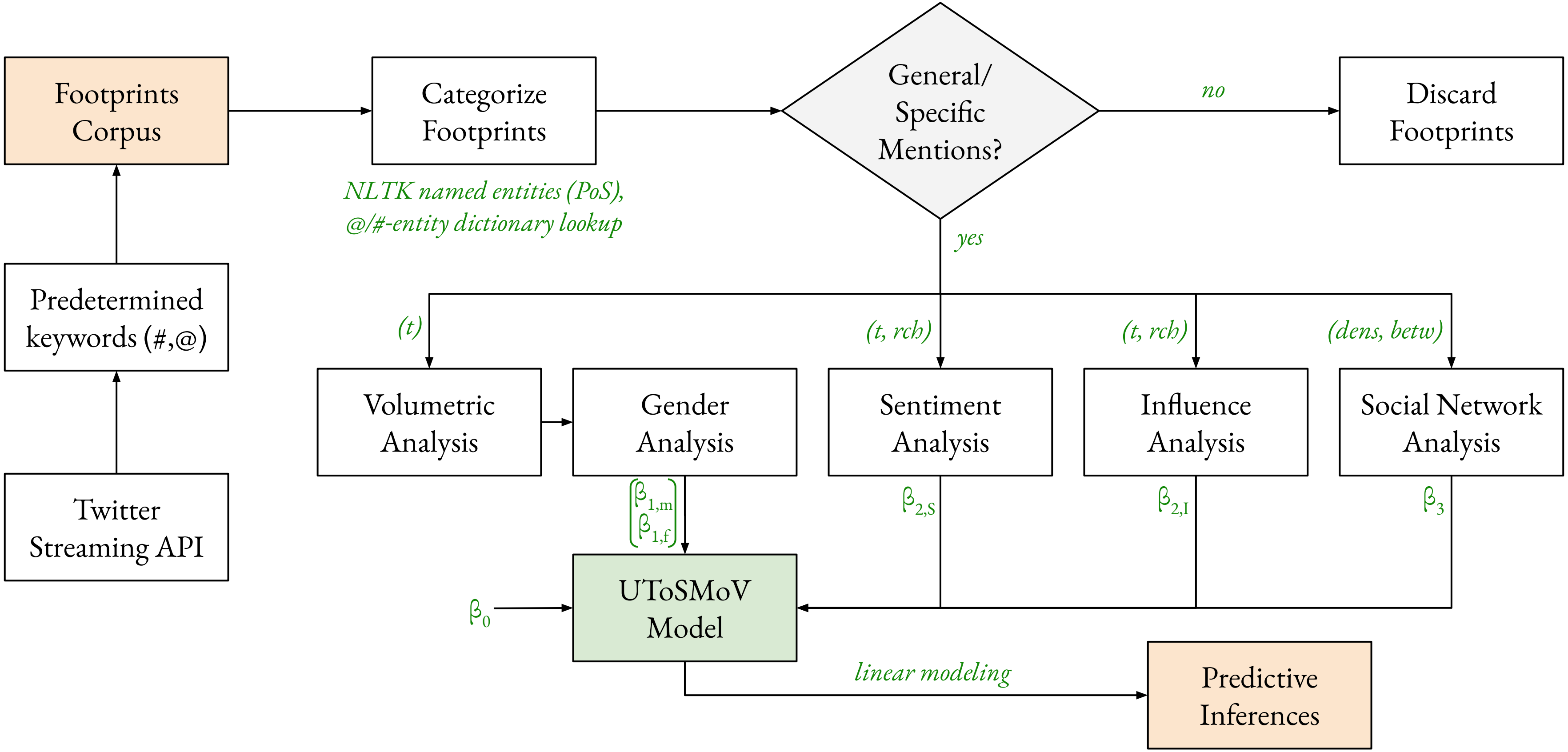


Unification of Modeling Theories: UToSMoV



Twitter Corpus Statistics

State	Political Party	Tweets Collected		Number of Handles*		Collection Time (days)
Telangana	BJP	23,642	241,489	4	19	~35
	Congress+	55,751		7		~35
	TRS	162,096		8		~35
Chhattisgarh	BJP	4,317	7,674	16	27	~25
	Congress+	3,357		11		~25
Rajasthan	BJP	101,040	168,228	28	55	~30
	Congress+	67,188		27		~30
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* Other generic handles were also used to collect the data and were then classified into a particular party based on the user mentions

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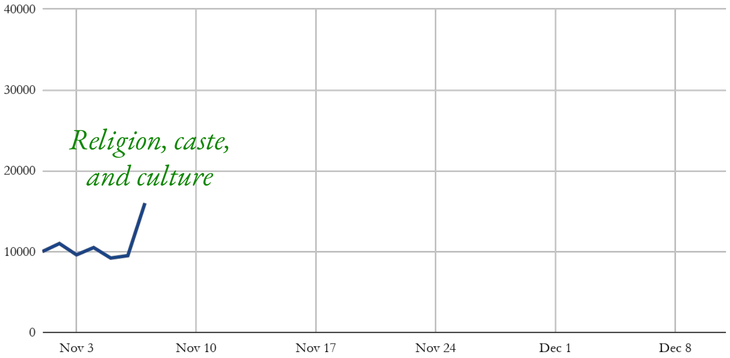

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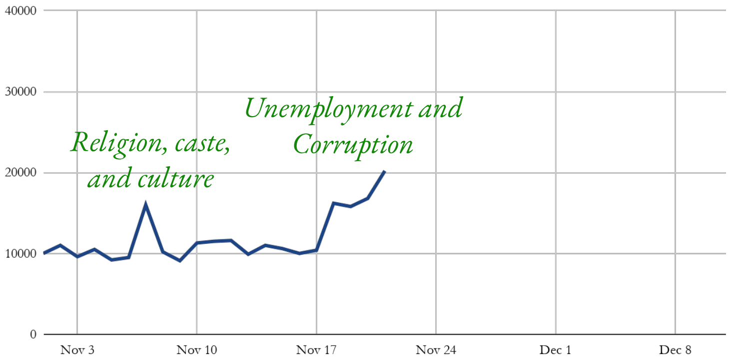

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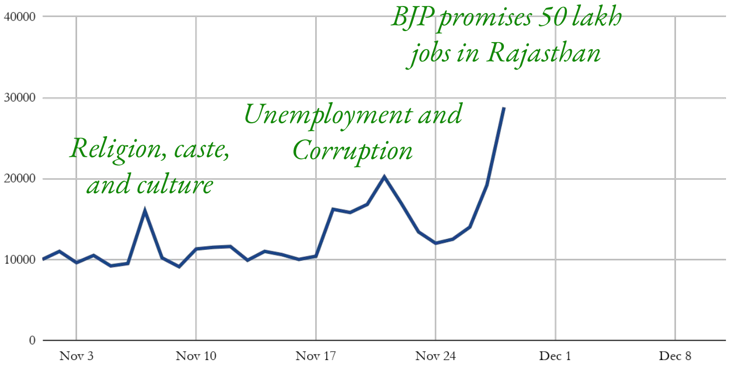

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- Top mentioned leaders:
  - @narendramodi
  - @RahulGandhi
  - @AmitShah
  - @myogiadityanath
  - @yadavakhilesh

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  - @AmitShah
  - @myogiadityanath
  - @yadavakhilesh
- Top conversations:
  - Rural economy
  - Religion and Caste
  - Vote tampering
  - Dynastic politics
  - Corruption

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UToSMoV: Data preprocessing

Repeated words (> 4)

Punctuations (>5)

Retweets

~~Word smoothing~~

Internet slang*

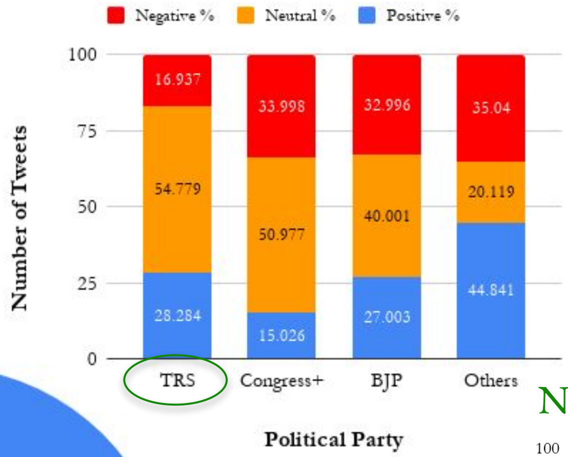
#	User Twitter ID	User Screen Name	User Gender	User Follow. Count	User Friends Count	User Listed Count	User Location	Tweet Created At	Tweet Lang.
4	1052824183866982400	Vinay Bhaskar	male	6	79	2	Andhra Pradesh India	Fri Nov 09 04:27:26 +0000 2018	te

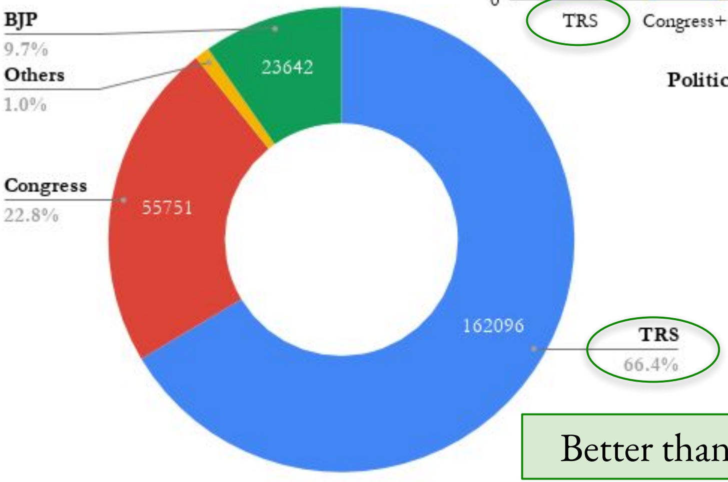
Tweet Hashtags	Tweet User Mentions	Tweet Retweet Count	Tweet Favorite Count	Tweet Quote Count	Tweet Reply Count	Tweet Text	Tweet Senti.	Tweet Alliance
#SaveTelangana #SaveDemocracy	@PTelangana @KTRTRS @RaoKavitha @trsharish @sushilrTOI	20	200	5	20	RT @PTelangana: KCR పార్టీ అరాచకాలు...@KTRTRS @RaoKavitha @trshar...	negative	TRS

* Abbreviation library can be found at: https://www.netlingo.com/acronyms.php

UToSMoV on Telangana: Results and Analysis

Sentiment Analysis ↦

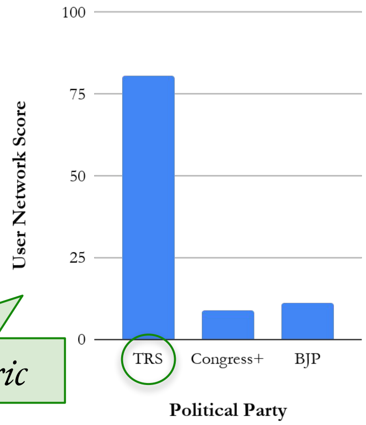


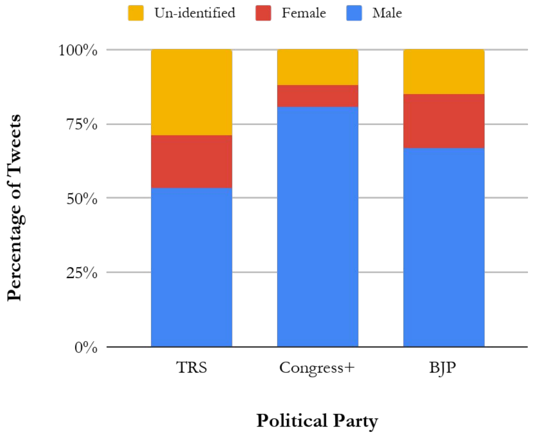


Volumetric Analysis ↥

Better than *Volumetric*

Network Analysis ↧





Gender Analysis ↥

Political engagement
Cognition *vs.* group thinking
Mass level voting behaviour

Male	: 50.3%
Female	: 48.0%
Others	: 01.7%

http://www.indiavotes.com/state/summary/61

UToSMoV on Telangana: Influential Parameters

- Kaleshwaram
- AP reorganisation act
- Mission Kakatiya
- Mission Bhagiratha
- Hyderabad metro rail
- Reservation bill act

TRS

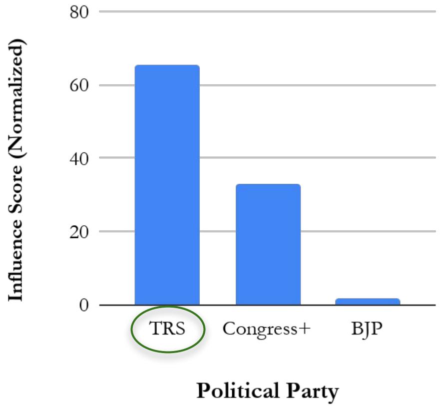
- Indiramma Illu
- One-lakh obs
- 30 Days 30 Questions

Congress+

- Cows distribution
- Renaming cities

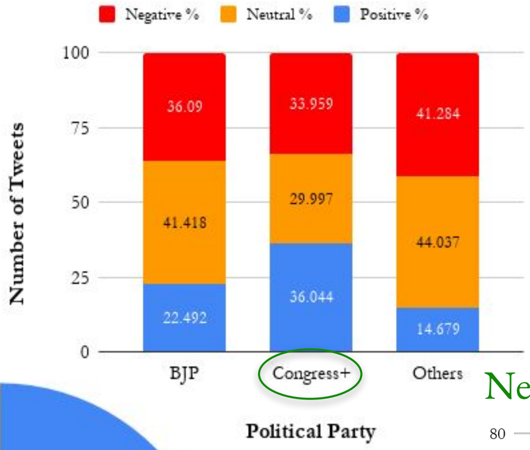
BJP

@KTRTRS,
@asadowaisi,
@UttamTPCC,
@drlaxmanbjp

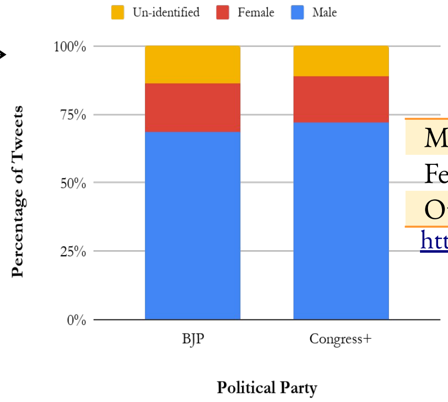


UToSMoV on Chhattisgarh: Results and Analysis

Sentiment Analysis ↦

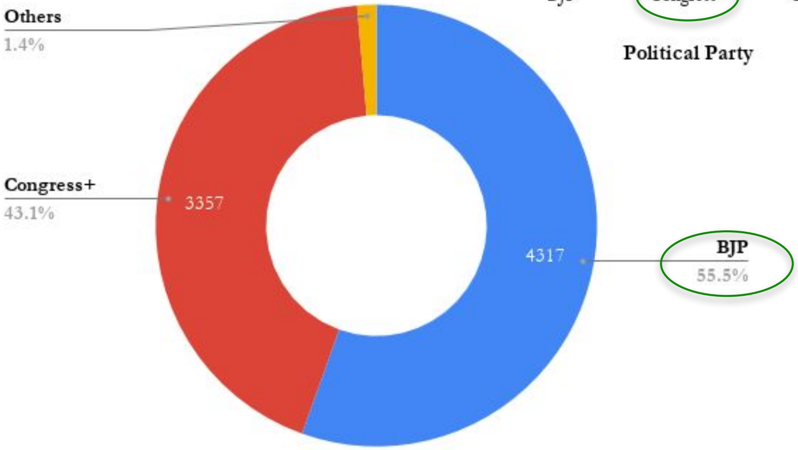


Gender Analysis ↦



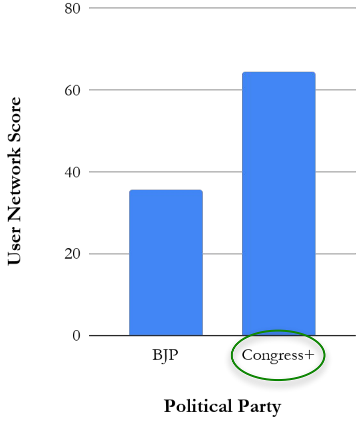
Male	: 50.5%
Female	: 49.5%
Others	: 00.0%

http://www.indiavotes.com/state/summary/54

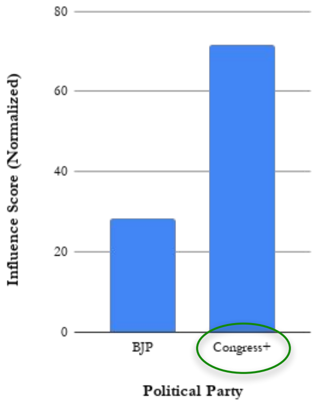


Volumetric Analysis ↥

Network Analysis ↧



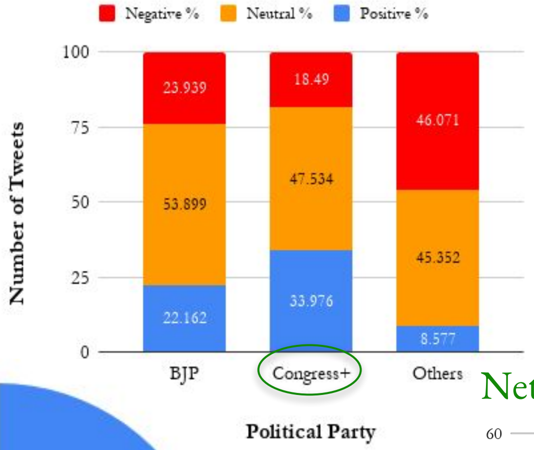
Influential Analysis ↧



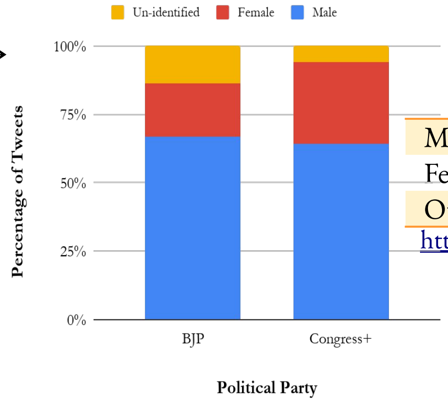
@drramansingh,
@Bhupesh_Baghel,
@ajitjogi_cg

UToSMoV on Rajasthan: Results and Analysis

Sentiment Analysis ↦

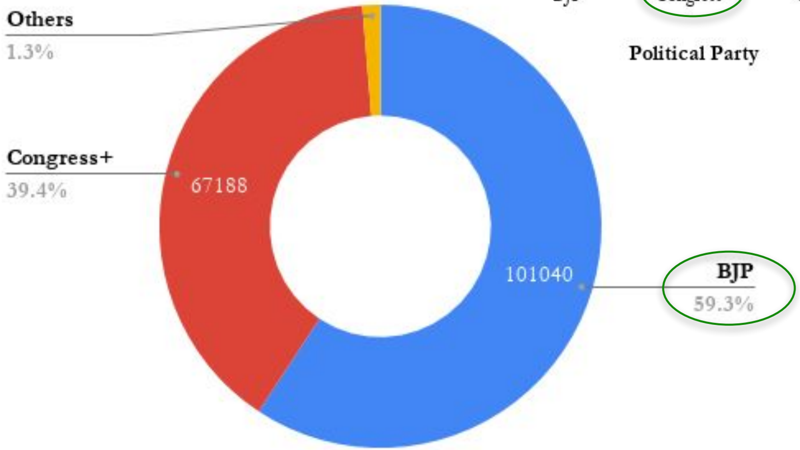


Gender Analysis ↦



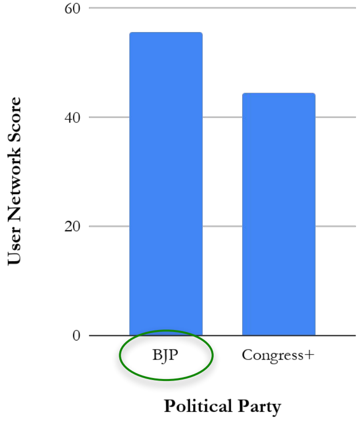
Male	: 52.7%
Female	: 47.3%
Others	: 00.0%

http://www.indiavotes.com/state/summary/14

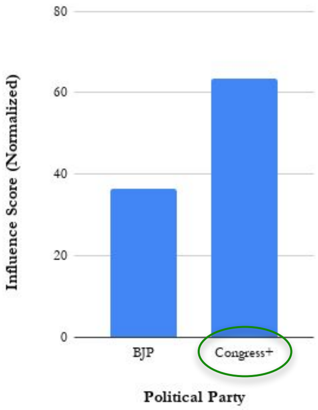


Volumetric Analysis ↥

Network Analysis ↧



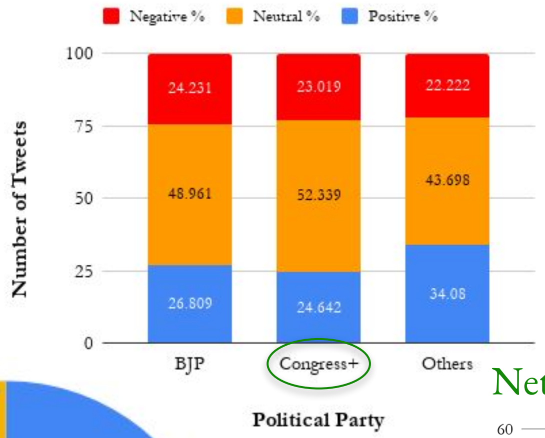
Influential Analysis ↧



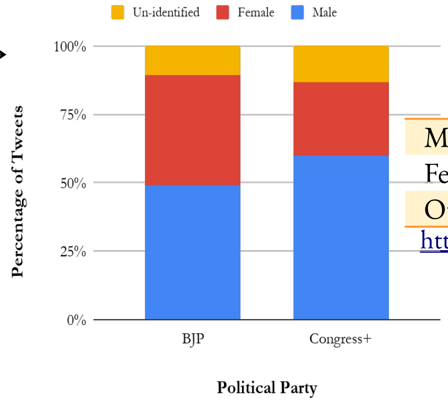
@VasundharaBJP,
@SachinPilot,
@ashokgehlot51,
@MPMadanSaini

UToSMoV on Madhya Pradesh: Results and Analysis

Sentiment Analysis ↦

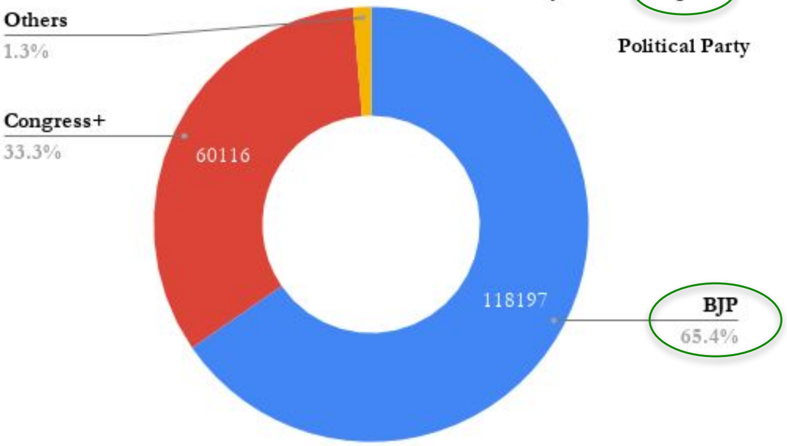


Gender Analysis ↦



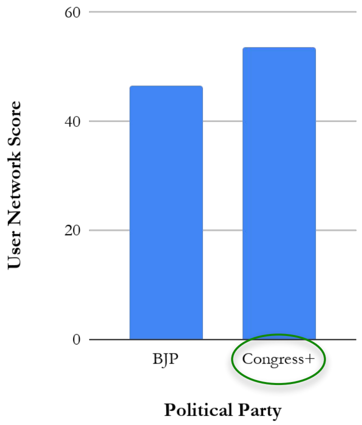
Male	: 52.7%
Female	: 47.3%
Others	: 00.0%

http://www.indiavotes.com/state/summary/59



Volumetric Analysis ↥

Network Analysis ↧



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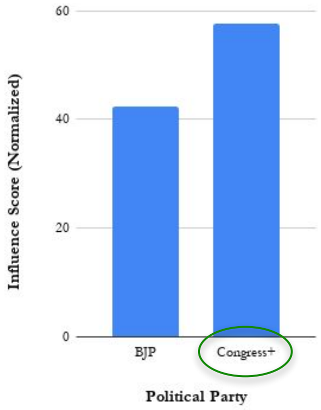
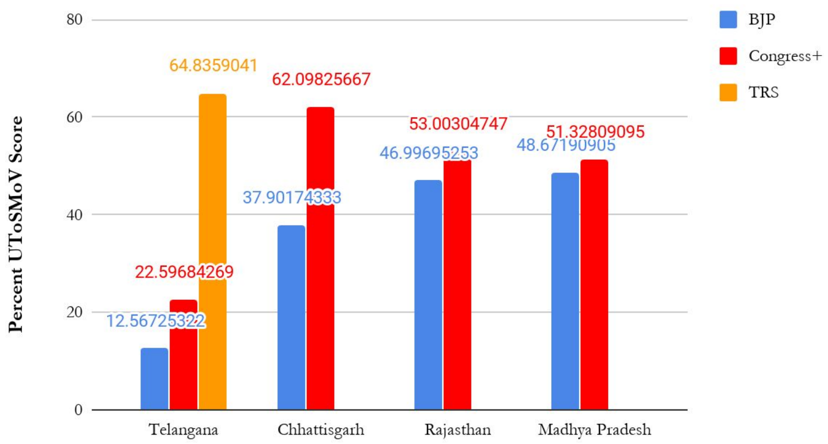


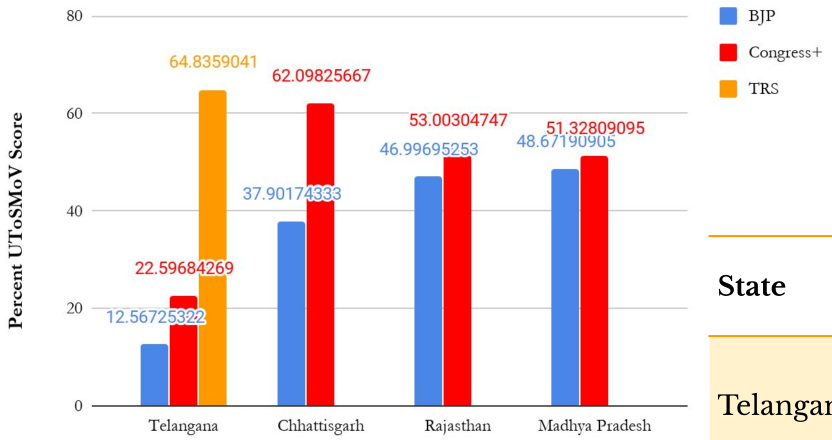
@ChouhanShivraj,
@JM_Scindia,
@OfficeOfKNath,
@ChitnisArchana

Unification of Various Theories: Predictions



- Telangana: TRS
- Chhattisgarh: Congress
- Rajasthan: Congress
- Madhya Pradesh: Congress

Unification of Various Theories: Quantified Selfie



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State	Political Party	Times Now CNX Exit Poll	C-Voter Exit Poll	UToSMoV	Actual Result
Telangana	BJP	05.88%	04.20%	12.57%	00.84%
	Congress+	31.09%	37.82%	22.60%	17.64%
	TRS	55.46%	48.74%	64.84%	73.95%
Chhattisgarh	BJP	51.11%	41.60%	37.90%	24.44%
	Congress+	38.89%	42.20%	62.10%	75.55%
Rajasthan	BJP	42.71%	39.70%	47.00%	39.69%
	Congress+	52.76%	47.90%	53.00%	50.25%
Madhya Pradesh	BJP	54.78%	41.50%	48.67%	48.26%
	Congress+	38.70%	42.30%	51.33%	49.56%

Conclusions and Future Work

- Unified framework that models volumetric, sentiment, social network, gender, and influence outperforms the baseline predictions
- Temporal backtracking guided by influence accounts for a change in the user's opinion due to the political party's influence
- Fact checking and fake-news detection modules are to be incorporated to enable more accurate predictions
- An effective strategy for bot and sockpuppet identification must be developed
- Develop a parameter self-adaptive model to learn the unification parameters
- Post-election alliances to be found using legacy data via monte-carlo simulations
- Polling strategies such as opposition speeches are to be analyzed

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