

TIMME: Twitter Ideology-detection via Multi-task Multi-relational Embedding



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KDD'20 Applied Data Science Track



TIMME

Motivation

Data

Preliminaries

Contribution

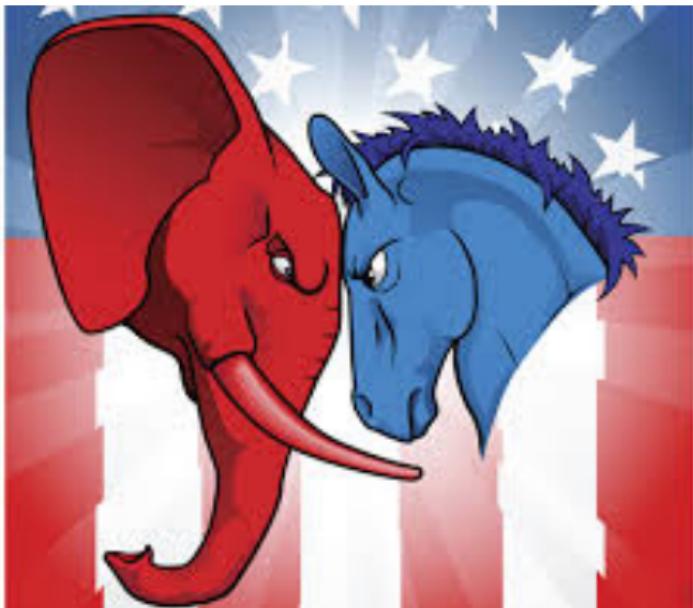
Model

Highlighted Results

Resources

TIMME





The picture comes from <http://www.marekrei.com/blog/political-ideology-detection/>.

Motivation: Ideology Detection

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The screenshot shows a web browser displaying the [congress.gov/congressional-record](https://www.congress.gov/congressional-record) page. The URL is visible in the address bar. The page title is "CONGRESS.GOV". The search bar contains the query "homeland security", "medicare". The search results page for the June 26, 2020, issue of the Congressional Record is shown, with results for "homeland security" and "medicare". The results include links to the full issue and specific sections like the Daily Digest.

congress.gov/congressional-record

CONGRESS.GOV Advanced Searches | Browse

Congressional Record MORE OPTIONS ▾

Search Tools | Support ▾ | Sign In ▾

Legislation | Congressional Record | Committees | Members

Home > Congressional Record (Most Recent Issue) > Daily Digest

Print | Subscribe | Share/Save | Give Feedback

The Congressional Record dated June 25th, 2020 is not yet available. To receive an email when the issue becomes available on Congress.gov, [subscribe to alerts](#).

Congressional Record

Proceedings and Debates of the U.S. Congress

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June 26, 2020

116th Congress (2019 - 2020), 2nd Session
Issue: Vol. 166, No. 118 — Daily Edition

[Entire Issue \(PDF\)](#)

Find an issue of the Record (1995-Present)

Date: [Calendar icon](#)

Or enter year and page number.

Sections in This Issue: [Daily Digest](#) House of Representatives Extensions of Remarks

Daily Digest

[Daily Digest Section \(PDF\)](#)

<https://www.congress.gov/congressional-record>

UCLA

Motivation: Ideology Detection on Twitter

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Barack Obama 

@BarackObama

Dad, husband, President, citizen.

⌚ Washington, DC  obama.org ⌚ Born August 4, 1961
📅 Joined March 2007

604.2K Following 120.2M Followers

Not followed by anyone you're following

Tweets	Tweets & replies	Media	Likes
★ Pinned Tweet			
 Barack Obama  @BarackObama - Jun 1	I wrote out some thoughts on how to make this moment a real turning point to bring about real change—and pulled together some resources to help young activists sustain the momentum by channeling their energy into concrete action.		



Donald J. Trump 

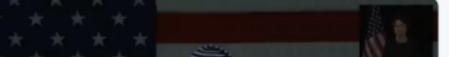
@realDonaldTrump

45th President of the United States of America 

⌚ Washington, DC  Instagram.com/realDonaldTrump
📅 Joined March 2009

46 Following 82.5M Followers

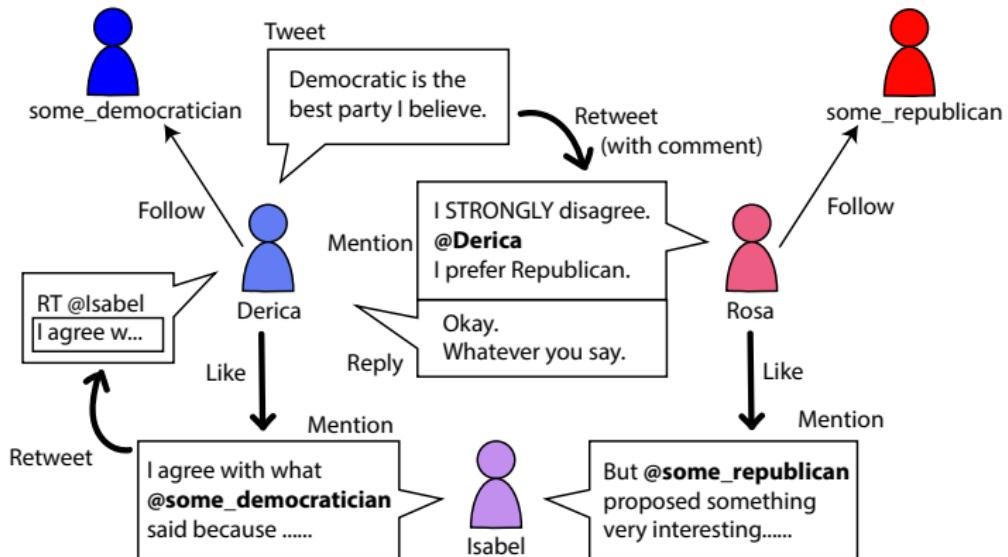
Not followed by anyone you're following

Tweets	Tweets & replies	Media	Likes
Donald J. Trump Retweeted			
 Dan Scavino  @DanScavino - Jun 21			

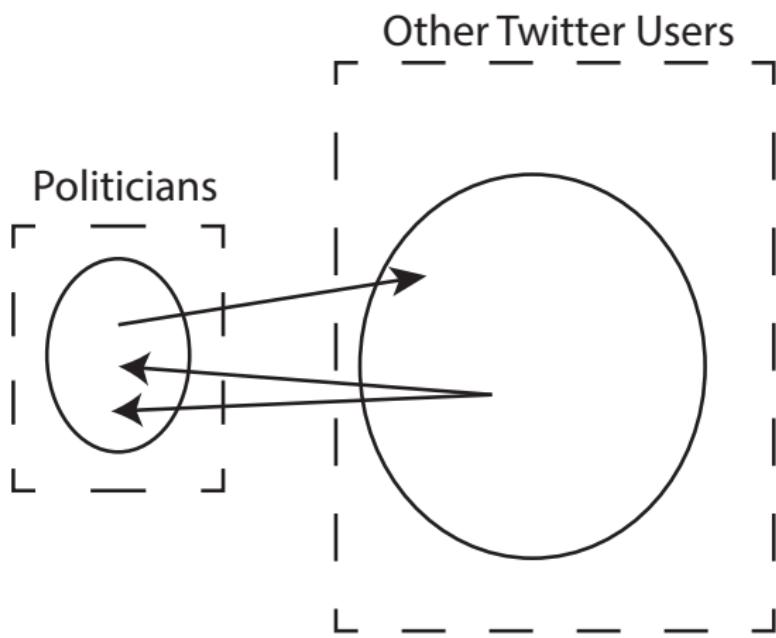
Example: US Presidents on Twitter

Motivation: Ideology Detection on Twitter

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Problem: Ideology Classification on Twitter



	PureP	P50	P20~50	P+all
# User	583	5,435	12,103	20,811
# Link	122,347	1,593,721	1,976,985	6,496,107
# Labeled User	581	759	961	1,206
# Featured User	579	5,149	11,725	19,418
# Follow-Link	59,073	529,448	158,746	915,438
# Reply-Link	1,451	96,757	121,133	530,598
# Retweet-Link	19,760	311,359	595,030	1,684,023
# Like-Link	14,381	302,571	562,496	1,794,111
# Mention-Link	27,682	353,586	539,580	1,571,937

Political-Centered Social Network Dataset

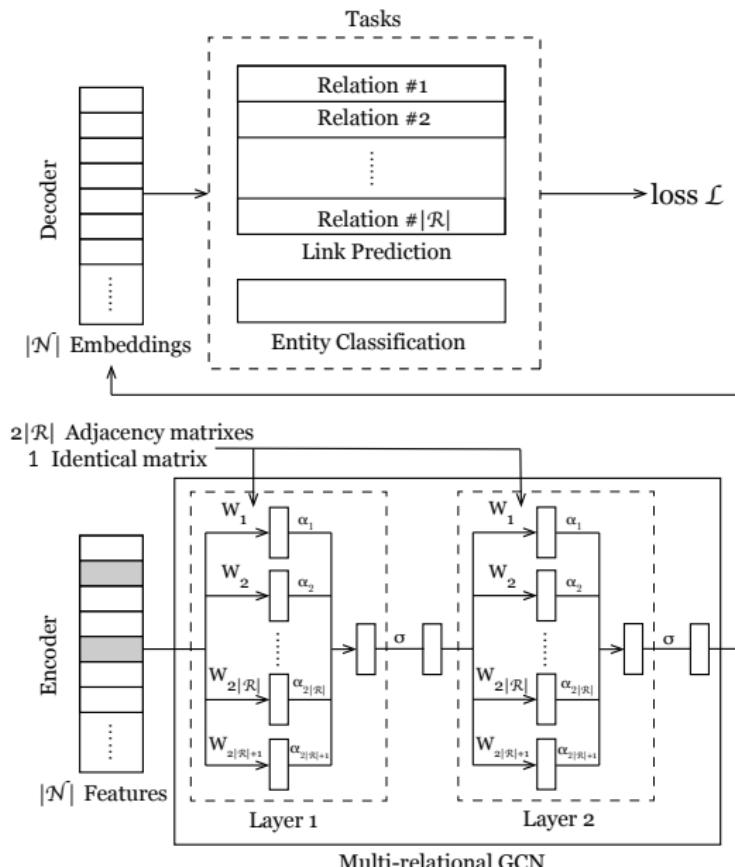
Literature Review:

- ▶ GCN (Graph Convolutional Network)
[http://web.cs.ucla.edu/~patricia.xiao/files/
Reading_Group_20181204.pdf](http://web.cs.ucla.edu/~patricia.xiao/files/Reading_Group_20181204.pdf)
- ▶ MTL (Multi-Task Learning)
[http://web.cs.ucla.edu/~patricia.xiao/files/
Reading_Group_20200121.pdf](http://web.cs.ucla.edu/~patricia.xiao/files/Reading_Group_20200121.pdf)

- ▶ Political-Centered Social Network Dataset
 - ▶ Described in Appendix, released with code

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- ▶ TIMME: learning embeddings on sparsely-labeled heterogeneous graph
 - ▶ MTL: handles the sparsity of labels
 - ▶ *Optionally* handles incomplete input features



In homogeneous GCN layers:

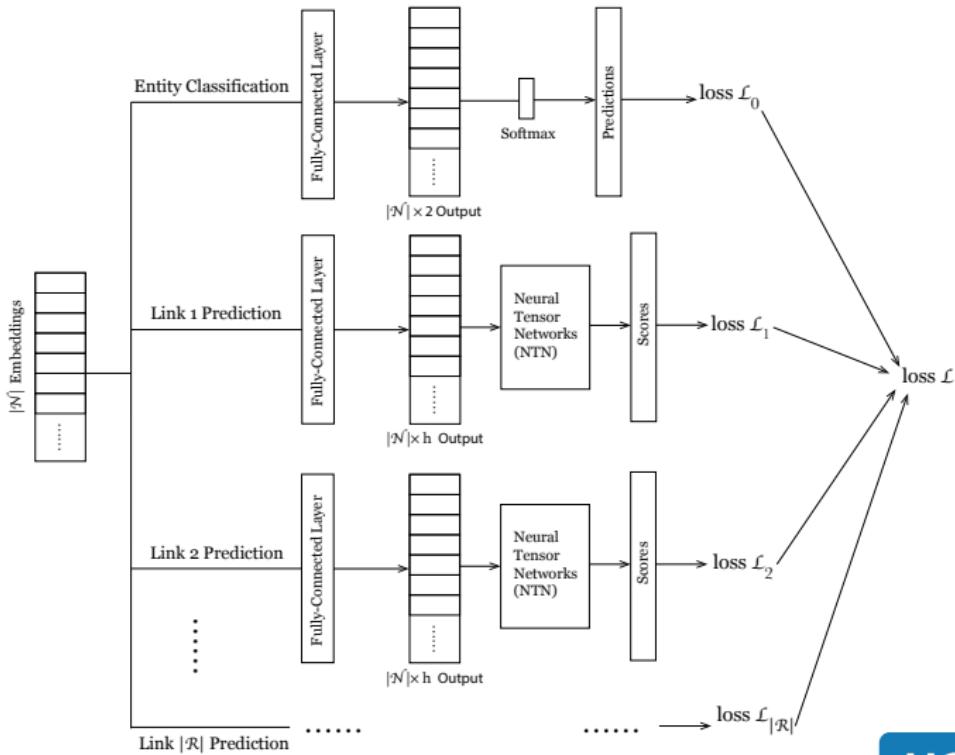
$$H^{(l+1)} = \sigma(\hat{A}H^{(l)}W^{(l)})$$

\hat{A} : the normalized adjacency matrix; $H^{(l+1)}$: layer- l output;
 $H^{(l)}$: layer- l input; $W^{(l)}$: layer- l weight.

In our heterogeneous design:

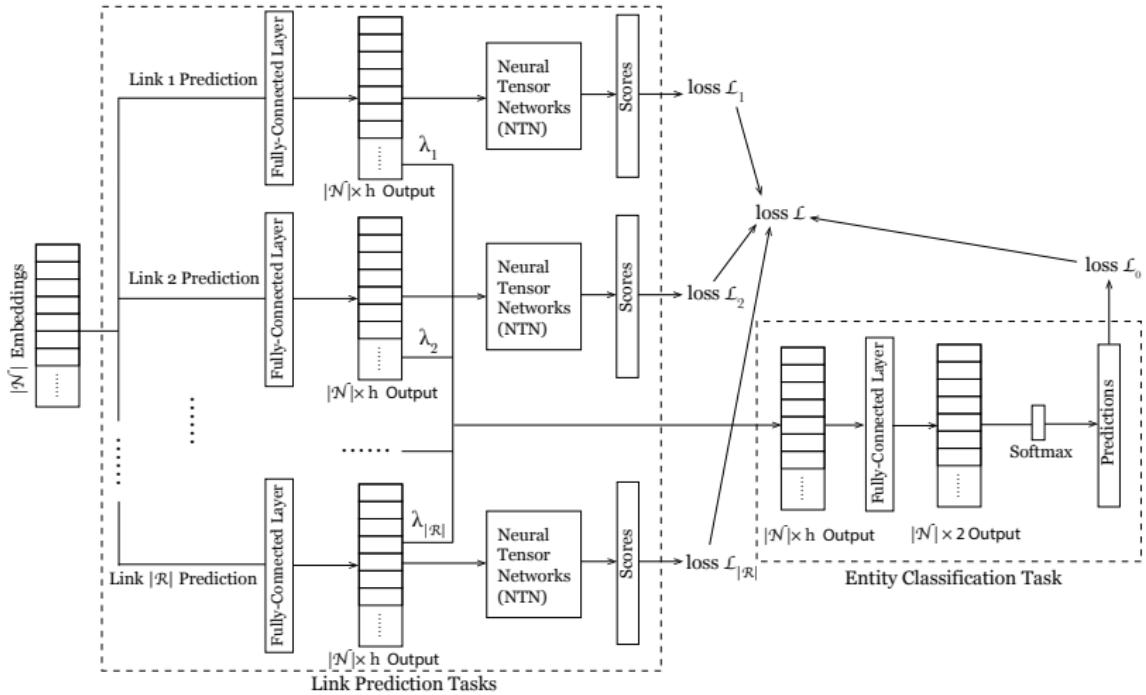
$$H^{(l+1)} = \sigma\left(\sum_{r \in \hat{R}} \alpha_r \hat{A}_r H^{(l)} W_r^{(l)}\right)$$

α_r : attention weight; $|\hat{R}| = 2R + 1$ includes R relations, R reversed relations, 1 identical matrix I .



Model: TIMME-hierarchical Decoder

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TIMME and **TIMME-hierarchical**:

$$\mathcal{L} = \sum_{i=0}^{|\mathcal{R}|} \mathcal{L}_i$$

loss is the sum of losses from all $|\mathcal{R}| + 1$ tasks.

- ▶ **TIMME-hierarchical** gives us clues on each relation's importance to ideology classification via λ .

TIMME-single:

$$\mathcal{L} = \mathcal{L}_i$$

for a single task i , $i \in \{0, 1, 2, \dots, |\mathcal{R}|\}$.

- ▶ **TIMME-single** proves that multi-task version is better.

Results Compared with Baselines

Model	PureP	P50	P20~50	P+all
GCN	1.0000/1.0000	0.9600/0.9600	0.9895/0.9895	0.9076/0.9083
r-GCN	1.0000/1.0000	0.9733/0.9733	0.9895/0.9895	0.9327/0.9333
HAN	0.9825/0.9824	0.9466/0.9467	0.9789/0.9789	0.9238/0.9250
TIMME-single	1.0000/1.0000	0.9733/0.9733	0.9895/0.9895	0.9333/0.9324
TIMME	0.9825/0.9824	0.9867/0.9867	1.0000/1.0000	0.9495/0.9500
TIMME-hierarchical	1.0000/1.0000	0.9733/0.9780	0.9895/0.9895	0.9580/0.9583

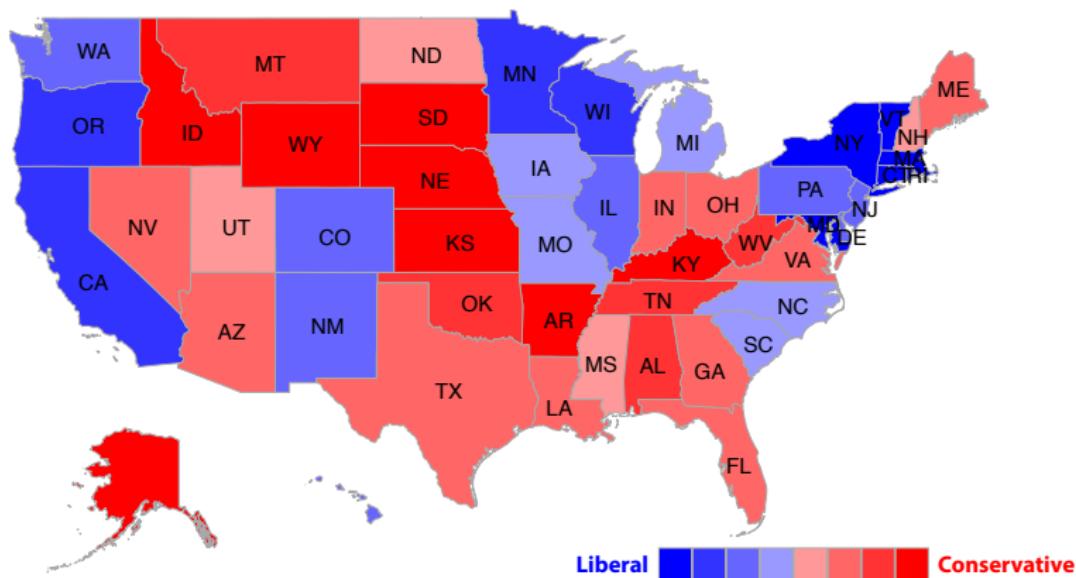
Table 2: Node classification measured by F1-score/accuracy.

Model	PureP	P50	P20~50	P+all
Follow Relation				
GCN+	0.8696/0.6167	0.9593/0.8308	0.9870/0.9576	0.9855/0.9329
r-GCN	0.8596/0.6091	0.9488/0.8023	0.9872/0.9537	0.9685/0.9201
HAN+	0.8891/0.7267	0.9598/0.8642	0.9620/0.8850	0.9723/0.9256
TIMME-single	0.8809/0.6325	0.9717/0.8792	0.9920/0.9709	0.9936/0.9696
TIMME	0.8763/0.6324	0.9811/0.9154	0.9945/0.9799	0.9943/0.9736
TIMME-hierarchical	0.8812/0.6409	0.9809/0.9145	0.9984/0.9813	0.9944/0.9739
Reply Relation				
GCN+	0.8602/0.7306	0.9625/0.9022	0.9381/0.8665	0.9705/0.9154
r-GCN	0.7962/0.6279	0.9421/0.8714	0.8868/0.7815	0.9640/0.9085
HAN+	0.8445/0.6359	0.9598/0.8616	0.9495/0.8664	0.9757/0.9210
TIMME-single	0.8685/0.7018	0.9695/0.9307	0.9939/0.9070	0.9775/0.9508
TIMME	0.9077/0.8004	0.9781/0.9417	0.9747/0.9347	0.9849/0.9612
TIMME-hierarchical	0.9224/0.8152	0.9766/0.9409	0.9737/0.9341	0.9854/0.9629
Retweet Relation				
GCN+	0.8955/0.7145	0.9574/0.8493	0.9351/0.8408	0.9724/0.9303
r-GCN	0.8865/0.6895	0.9411/0.8084	0.9063/0.7728	0.9735/0.9326
HAN+	0.7646/0.6139	0.9658/0.9213	0.9478/0.8962	0.9750/0.9424
TIMME-single	0.9015/0.7206	0.9754/0.9127	0.9673/0.9073	0.9824/0.9424
TIMME	0.9094/0.7285	0.9779/0.9181	0.9772/0.9291	0.9858/0.9511
TIMME-hierarchical	0.9105/0.7344	0.9780/0.9196	0.9766/0.9275	0.9869/0.9543
Like Relation				
GCN+	0.9007/0.7259	0.9527/0.8499	0.9349/0.8400	0.9690/0.9032
r-GCN	0.8924/0.7161	0.9343/0.7966	0.9038/0.7681	0.9510/0.8945
HAN+	0.8606/0.6176	0.9733/0.8851	0.9611/0.9062	0.9894/0.9481
TIMME-single	0.9113/0.7654	0.9725/0.9119	0.9655/0.9069	0.9796/0.9374
TIMME	0.9249/0.7926	0.9753/0.9171	0.9759/0.9292	0.9846/0.9504
TIMME-hierarchical	0.9278/0.7945	0.9752/0.9175	0.9752/0.9271	0.9851/0.9518
Mention Relation				
GCN+	0.8480/0.6233	0.9602/0.8617	0.9261/0.8170	0.9665/0.8910
r-GCN	0.8312/0.6023	0.9382/0.7963	0.8938/0.7563	0.9640/0.8902
HAN+	0.9000/0.7206	0.9573/0.8616	0.9574/0.8891	0.9724/0.9119
TIMME-single	0.8587/0.6502	0.9713/0.8981	0.9614/0.8923	0.9725/0.9096
TIMME	0.8684/0.6689	0.9730/0.9035	0.9730/0.9185	0.9839/0.9446
TIMME-hierarchical	0.8643/0.6597	0.9732/0.9046	0.9723/0.9166	0.9846/0.9463

Table 3: Link-prediction measured by ROC-AUC/PR-AUC.

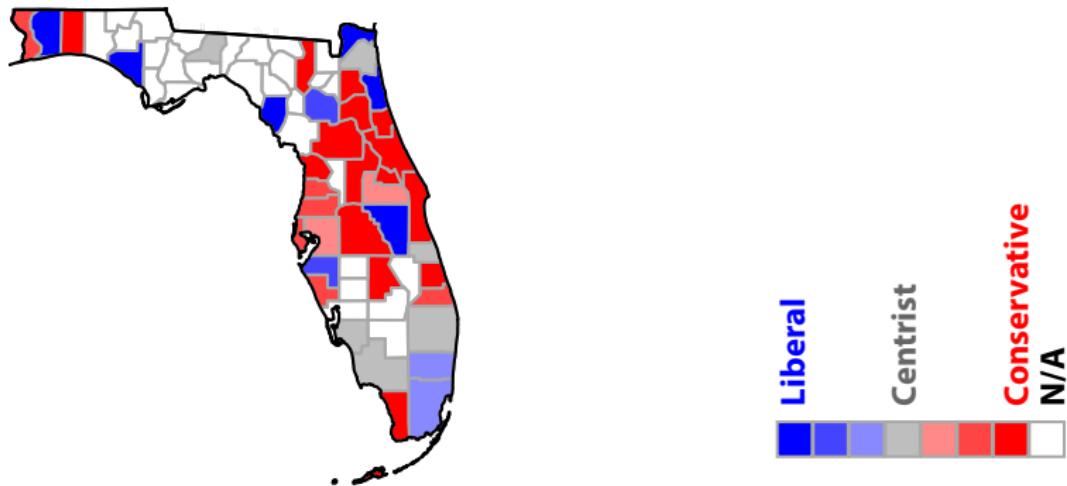
State-Level Ideology on Twitter

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County-Level Ideology on Twitter: Florida

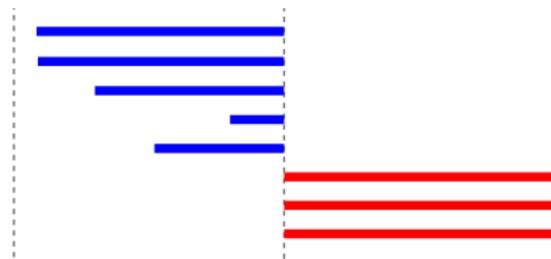
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Entity-Level Ideology on Twitter: News Agencies

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New York Times (@nytimes)
Guardian News (@guardiannews)
CBC News (@cbcnews)
CNN (@CNN)
Christian Science Monitor (@csmonitor)
The American Spectator (@amspectator)
Fox News Opinion (@FoxNewsOpinion)
National Review (@NRO)



Resources



Code with data available on Github:

- ▶ <https://github.com/PatriciaXiao/TIMME>

Presentation etc. on my personal website:

- ▶ <http://web.cs.ucla.edu/~patricia.xiao/timme.html>

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