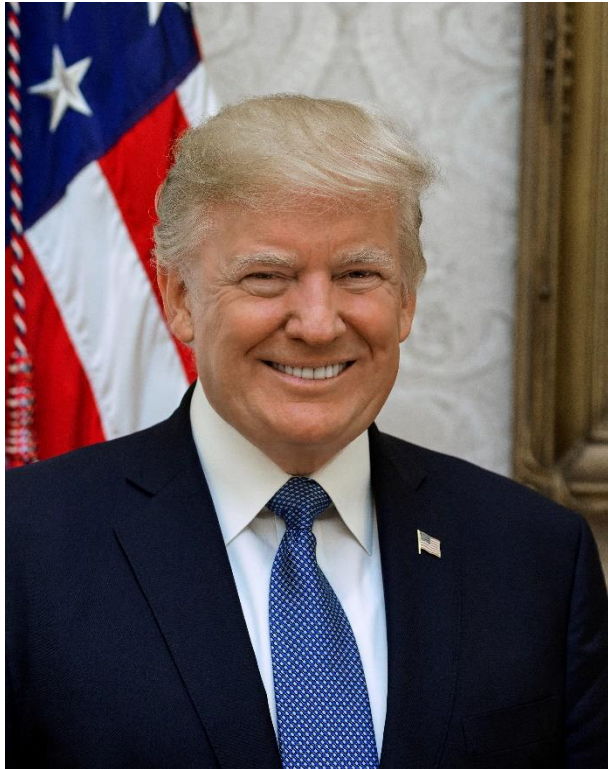


# We Don't Speak the Same Language: Interpreting Polarization through Machine Translation

Joint work with Rupak Sarkar\*, Mark S. Kamlet and Tom M.  
Mitchell

Presenter: Ashique KhudaBukhsh  
School of Computer Science  
Carnegie Mellon University (CMU)  
Pittsburgh, PA, USA

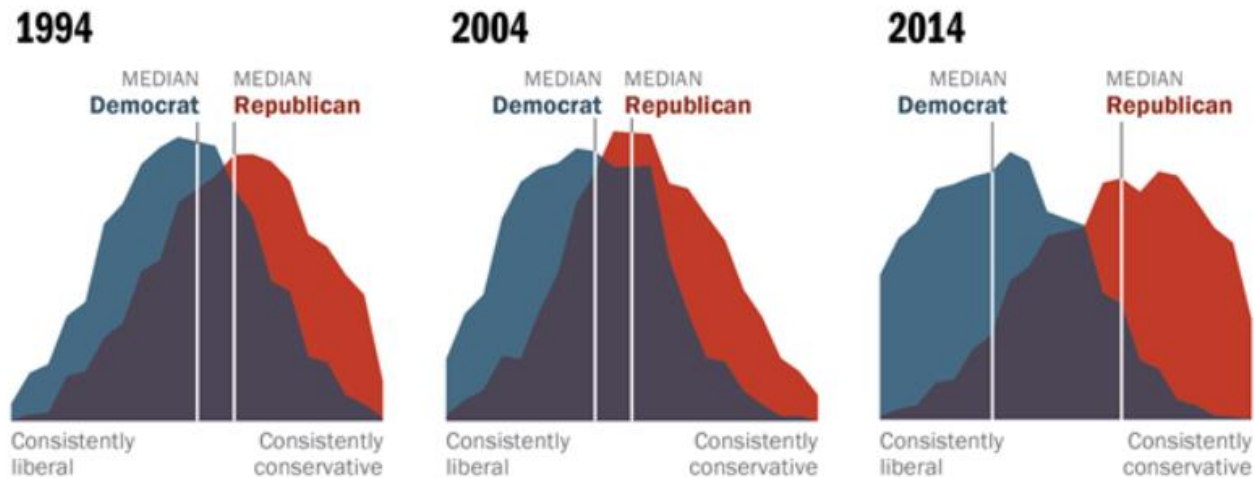
# US Political Landscape: 2020 Election



# Deepening Political Divide?

## Democrats and Republicans More Ideologically Divided than in the Past

*Distribution of Democrats and Republicans on a 10-item scale of political values*



Source: 2014 Political Polarization in the American Public

Notes: Ideological consistency based on a scale of 10 political values questions (see Appendix A). The blue area in this chart represents the ideological distribution of Democrats; the red area of Republicans. The overlap of these two distributions is shaded purple. Republicans include Republican-leaning independents; Democrats include Democratic-leaning independents (see Appendix B).

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# Hyper-Partisan News Media

- *Partisan and ideological divergence in both content and audience* [Bozell 2004, Hyun and Moon 2016]
- *Four major US news networks*



# The Big Three on YouTube



MSNBC ✓

3.4M subscribers



Fox News ✓

5.94M subscribers



CNN ✓

10.5M subscribers

# The Rising Star



One America News Network ✓

791K subscribers



Donald J. Trump ✓

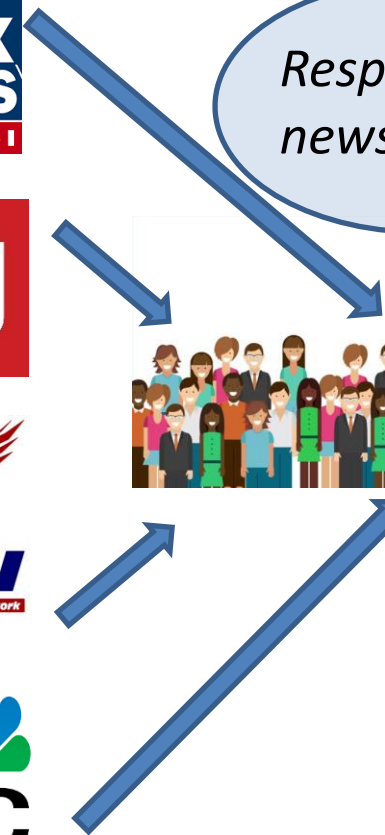
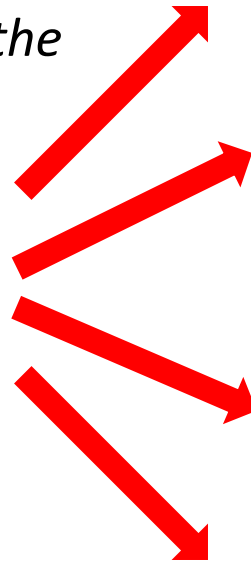
@realDonaldTrump

.@FoxNews is not watchable during weekend afternoons. It is worse than Fake News @CNN. I strongly suggest turning your dial to @OANN. They do a really "Fair & Balanced" job!

1:31 PM · Aug 16, 2020 · [Twitter for iPhone](#)

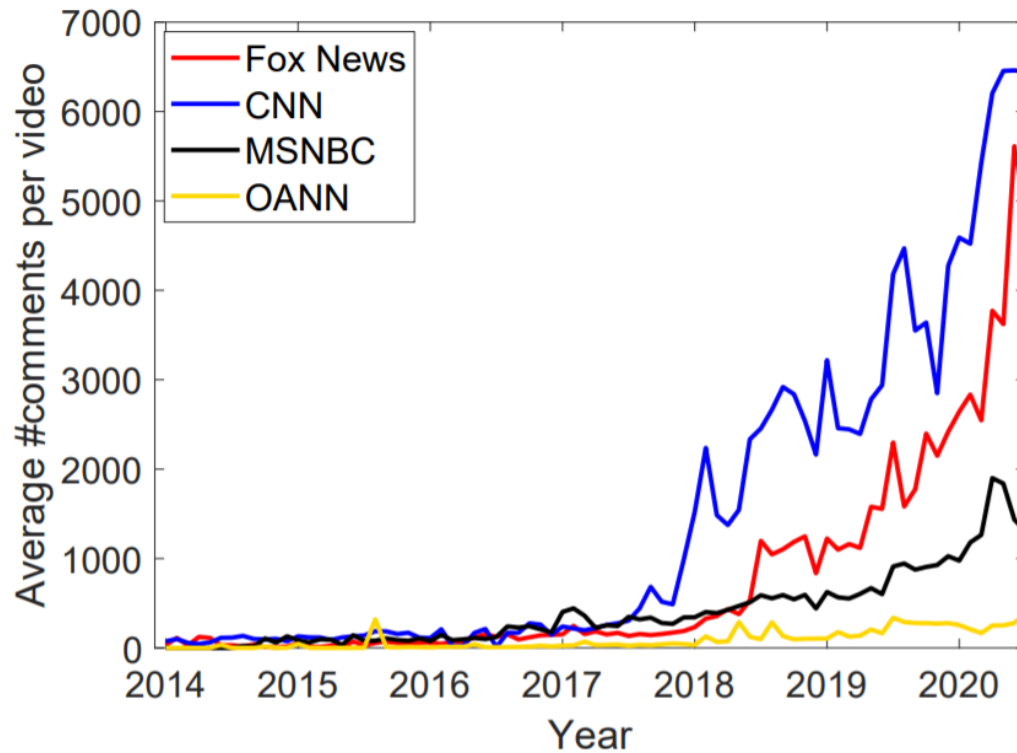
# Newsworthy Events, Topics, and Discussions

*Events interesting to the United States*



*Everything that is going on in the universe*

# A Novel, Rich Data Set: Text Response to News Events



*More than 85 million comments posted on 200K+ videos*



# How Do We Shed Light on Polarization?

- *Open research challenge: How can we quantify differences between these large-scale social media discussion data sets?*

# Polarization

- *Widely studied in social science*
- *Seminal work in political science that has used congressional votes to measure polarization*  
[McCarty, Poole, Rosenthal; 2006]
- *Research in computational linguistics focusing on mass-shootings*  
[Demszky, Garg, Voigt, Zou, Shapiro, Gentzkow, Jurafsky; 2019]
- *No prior work on quantifying polarization on large scale discussion data sets discussing a multitude of issues*

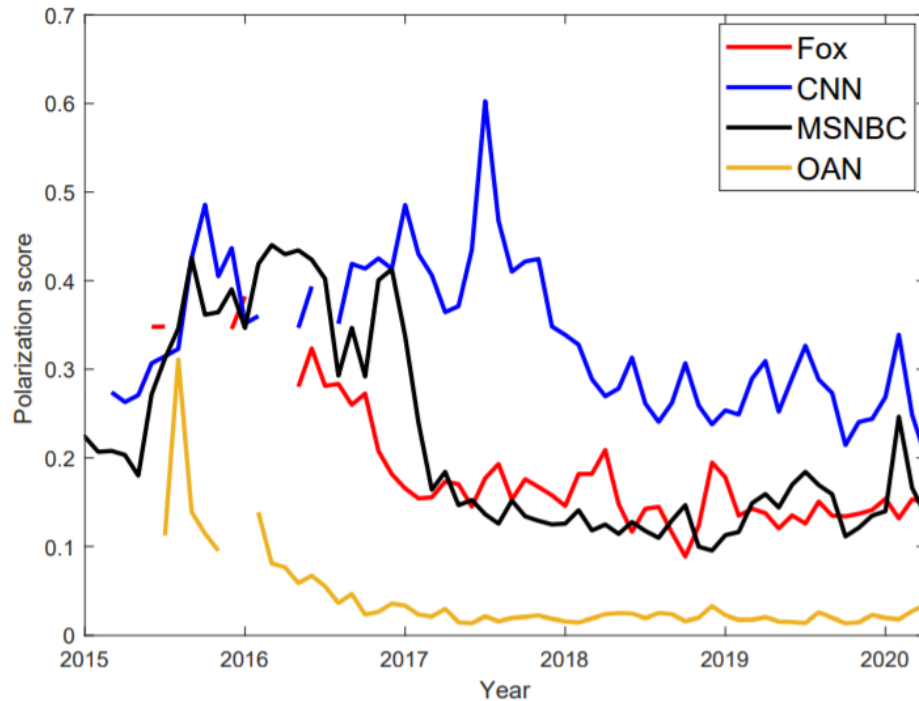
# Step 1: A Simple Measure to Track Polarization from Video Engagement

- *A simple measure*
  - Compute  $\frac{\text{dislike}}{\text{like} + \text{dislike}}$  of a given video
- *Take average of this value over all videos uploaded in a month for any given news network*
- *Interpretation: values closer to 0.5 indicate viewership has divided opinion*

# Advantages

- *Advantages*
  - $0 \leq \frac{\text{dislike}}{\text{like} + \text{dislike}} \leq 1$ , *mean of bounded variables is also bounded*
  - *One arbitrarily heavily liked or disliked video doesn't influence the overall trend by much*

# Temporal Trends



## Step 1: A Simple Measure to Track Polarization from Video Engagement

- A simple measure
  - Compute  $\frac{\text{dislike}}{\text{like} + \text{dislike}}$  of a given video
- Take average of this value over all videos uploaded in a month
- Interpretation: values closer to 0.5 indicate viewership has divided opinion

# How To Quantify Disagreement in Text Data?

*One mans meate is another mans poyson.*

– Thomas Draxe; *Bibliotheca Scholastica*; 1616.

- *Can we focus on one of the most basic units of language – the **words**?*
- *Count the number of words that mean **different things** to two communities?*
- *The larger this number the higher the disagreement*

# The Idea

- Assume two sub-communities are speaking in two *different* languages:  $L_{cnn}$  and  $L_{fox}$
- Translate each word belonging to  $L_{cnn}$  to  $L_{fox}$ 
  - Ideally, *apple* should translate to *apple*
  - *tree* should translate to *tree*

# What if it Doesn't?

- $w_1$  in  $L_{cnn}$  and  $w_2$  in  $L_{fox}$  are used in very similar contexts

Republicans are the greatest threat to America	Democrats are the greatest threat to America
Republicans are the greatest threat to America that this nation has ever seen. They have willingly enabled a tyranny and wannabe dictator. . .	. . . Had Trump placed more restrictions on travel sooner, Democrats would have cried "racism". Democrats are the greatest threat to America today.
Republicans are traitors	Democrats are traitors
The Republicans are traitors. Period, full stop. All good and patriotic Americans must see this, realize it for what it is, and then begin to act accordingly. . .	The DEMOCRATS are TRAITORS to our country and should be rounded up and exiled to a island.
I will never vote Republican again	I will never vote Democrat again
What a liar! I have always voted for the man not the party but after the way the republicans have acted I will NEVER vote republican again. . . .	I used to vote for the democrats because they cared about poor people. Now they only care about exploitable non-american poor people, talk about being un-american. I will never vote Democrat again.
Democrats are patriots	Republicans are patriots
Democrats are patriots just holding on to our constitution ! McConnell and trump must have their crowns slapped off their tyranny heads	Republicans are patriots, demoRats are traitors.
Democrats are fighting for	Republicans are fighting for
WE ARE A NATION OF IMMIGRANTS. THAT'S WHAT MAKES AMERICA GREAT!!!...DIVERSITY IS THE CORNERSTONE OF WESTERN DEMOCRACY. THE DEMOCRATS ARE FIGHTING FOR EQUALITY AND ECONOMIC STABILITY. . .	Democrats are doing everything in their power to take away your power as a citizen to make choices. The Republicans are fighting for YOU as an individual. Come on Americans! Wake up! . . .
Vote all Democrats in	Vote all Republicans in
. . .Regardless of whether or not our candidates win in the primaries or whether we even like the Democrats we must be prepared to vote all Democrats in and all Republicans out. . .	We the American people are tired of these crazy dems.Hope we vote all republicans in office.



# Machine Translation Meets Polarization

- *Assume two sub-communities are speaking in two different languages:  $L_{cnn}$  and  $L_{fox}$*
- *Translate each word belonging to  $L_{cnn}$  to  $L_{fox}$* 
  - *Count the number of misaligned pairs (i.e., words that do not translate to themselves)*
  - *The fewer this number, the greater is the similarity between the two sub-communities*

# Word Embeddings

- *A continuous representation of words in high-dimensional space*
- *Words that appear in similar contexts are (typically) placed close to each other*
- *Skip-gram embeddings: predicts an input word's context*  
[Mikolov, Chen, Corrado, Dean 2013]
- *Two words having similar embeddings imply they are used in similar contexts*

# Few Examples

- *Nearest neighbors of the word **amazing***
  - *incredible*
  - *wonderful*
  - *fantastic*
  - *awesome*
  - *phenomenal*
  - *remarkable*
  - *great*
  - *amazingly*
  - *brilliant*
  - *outstanding*

# Few Examples

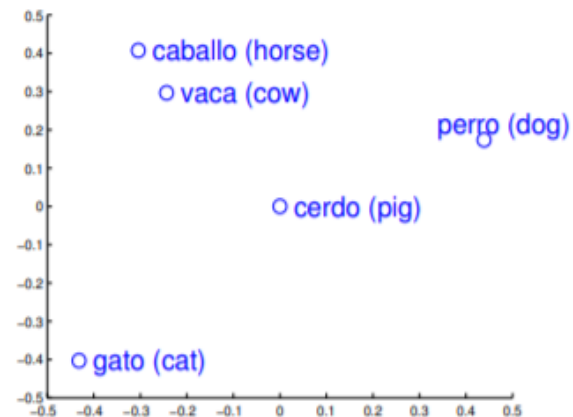
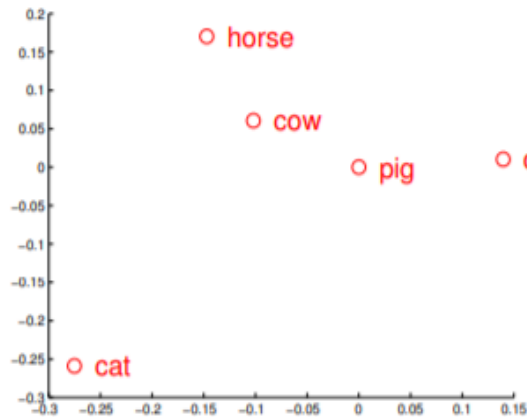
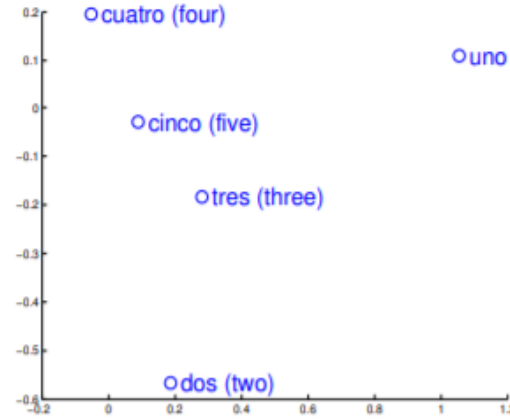
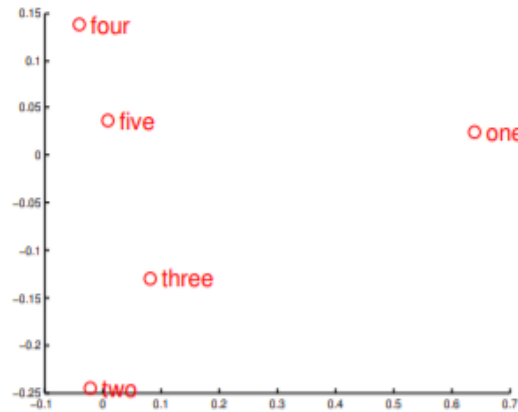
- *Nearest neighbors of the word **car***
  - *vehicles*
  - *cars*
  - *truck*
  - *accidents*
  - *driver*
  - *motor*
  - *bike*
  - *ambulance*
  - *driving*
  - *crashes*

# Alignment Based Machine Translation

- *Word embeddings of two (monolingual) corpora of two different languages*
- *A set of anchor words (bilingual dictionary)*
  - *<hola, hello>*
  - *<pescado, fish>*
  - *<gracias, thanks>*
  - *<lucha, fight>*
  - *<gato, cat>*
- *Learn a transformation  $W$  such that embedding of source word  $w_{source}$  when multiplied by  $W$  yields  $w_{target}$*

# A Classic Paper on This Idea

[Mikolov, Le, Sutskever ArXiv2013]



# Formally

- Let  $L_{source}$  and  $L_{target}$  be two languages with vocabularies  $V_{source}$  and  $V_{target}$ , respectively
- The translation scheme  $L_{source} \rightarrow L_{target}$  computes a transformation  $W$  and takes a word  $w_{source} \in V_{source}$  as input and outputs a single-word translation  $w_{target}$  such that
  - $w_{target} \in V_{target}$
  - $\forall w \in V_{target}, dist(w_{source}^e W, w^e) \geq dist(w_{source}^e W, w_{target}^e)$
- Cosine distance is used as  $dist(.)$

# Our Process

- *Sub-sample to create two corpora of equal size*
  - *Why? Embedding quality may vary with corpus size*
- *Two sets of word embeddings (say Fox and CNN)*
- *Stop-words (e.g., and, about, or ...) as anchor words*
- *Align them using a well-known method*

[Smith, Turban, Hamblin, Hammerla; 2017]



# $V_{source}$ , $V_{target}$ and Evaluation

- $V_{source}$  set to most frequent 5K words of the combined corpora
- $V_{target}$  set to most frequent 10K words of the combined corpora
- Compute the percentage of  $V_{source}$  that translates to itself
- Higher the value, better agreement

# Misaligned Pairs from CNN to Fox

Category	Misaligned pairs
Political entities	⟨democrats, republicans⟩, ⟨nunes, schiff⟩, ⟨dem. republican⟩, ⟨dnc, gop⟩, ⟨kushner, burisma⟩, ⟨gop, democrats⟩, ⟨flynn, hillary⟩
News entities	⟨fox, cnn⟩, ⟨hannity, cuomo⟩, ⟨tapper, hannity⟩, ⟨tucker, cuomo⟩
Derogatory	⟨trumptards, snowflakes⟩, ⟨chump, trump⟩, ⟨liberals, libtards⟩, ⟨pelosi, pelousy⟩, ⟨obamas, obummer⟩, ⟨cooper, giraffe⟩, ⟨biden, creep⟩, ⟨schiff, schitt⟩, ⟨barr, weasel⟩
(Near) synonyms	⟨lmao, lol⟩, ⟨allegations, accusations⟩, ⟨puppet, stooge⟩, ⟨bs, bullshit⟩, ⟨potus, president⟩, ⟨hahaha, lol⟩
Spelling errors	⟨mueller, muller⟩, ⟨kavanaugh, cavanaugh⟩, ⟨hillary, hilary⟩, ⟨isreal, israel⟩
Ideological	⟨kkk, blm⟩, ⟨christianity, multiculturalism⟩, ⟨sham, impeachment⟩, ⟨antifa, nazi⟩, ⟨liberals, conservatives⟩, ⟨communism, nazism⟩, ⟨leftists, fascists⟩, ⟨liberalism, conservatism⟩, ⟨communists, nazis⟩, ⟨immigrants, illegals⟩

# <KKK, BLM>

KKK is a hate group	BLM is a hate group
... The kkk is a hate group. But drump will not call them that, he calls them very fine people...	... blm is a hate group. A group of black supremacy isn't any different than white supremacy. Defund the department of education.
KKK terrorists	BLM terrorists
REPUBLICANS HAVE ALWAYS BEEN NEO-NAZI'S AND KKK TERRORISTS	Step 1 - Leftist defund the police Step 2 - Antifa and BLM terrorists, looters and rioters invade neighborhoods Step 3 - Patriots (thanks to the 2nd amendment) respond to defend their families and light up the terrorists Step 4 - Anitfa and BLM call the police for help and get no answer, repeat step 3 as needed
KKK is nothing more than a	BLM is nothing more than a
kkk is nothing more than a low-life racist terrorist gang...	BLM is nothing more than a racist cult.

# “Big Three” News Channels

		$\mathcal{L}_{target}$		
		$\mathcal{L}_{cnn}$	$\mathcal{L}_{fox}$	$\mathcal{L}_{msnbc}$
$\mathcal{L}_{source}$	$\mathcal{L}_{cnn}$	-	90.20%	94.20%
	$\mathcal{L}_{fox}$	89.60%	-	88.70%
	$\mathcal{L}_{msnbc}$	94.10%	88.50%	-

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- CNN is closer to MSNBC than Fox

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- Fox is closer to CNN than MSNBC

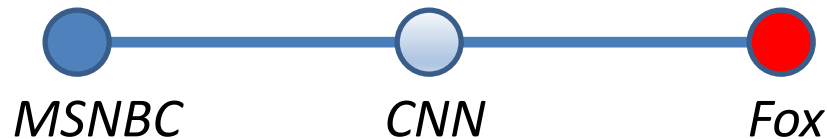
# “Big Three” News Channels

		$\mathcal{L}_{target}$		
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	$\mathcal{L}_{fox}$	89.60%	-	88.70%
	$\mathcal{L}_{msnbc}$	94.10%	88.50%	-

- MSNBC is closer to CNN than Fox

# “Big Three” News Channels

		$\mathcal{L}_{target}$		
		$\mathcal{L}_{cnn}$	$\mathcal{L}_{fox}$	$\mathcal{L}_{msnbc}$
$\mathcal{L}_{source}$	$\mathcal{L}_{cnn}$	-	90.20%	94.20%
	$\mathcal{L}_{fox}$	89.60%	-	88.70%
	$\mathcal{L}_{msnbc}$	94.10%	88.50%	-





# All Four News Networks

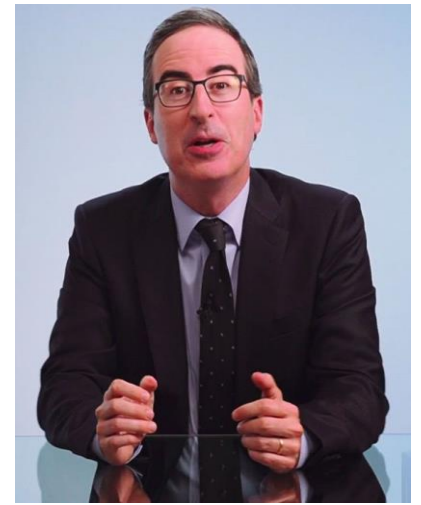
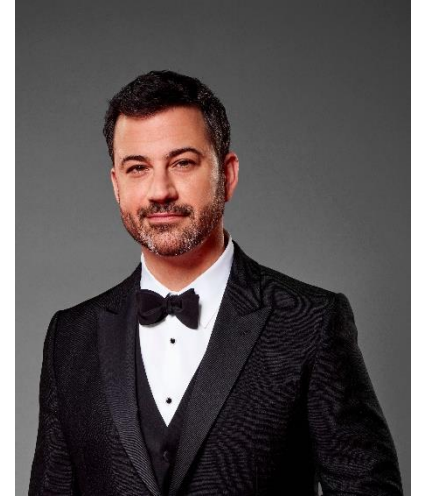


		$\mathcal{L}_{target}$			
		$\mathcal{L}_{cnn}$	$\mathcal{L}_{fox}$	$\mathcal{L}_{msnbc}$	$\mathcal{L}_{oann}$
$\mathcal{L}_{source}$	$\mathcal{L}_{cnn}$	-	61.1%	62.0%	42.2%
	$\mathcal{L}_{fox}$	60.1%	-	53.2%	52.7%
	$\mathcal{L}_{msnbc}$	63.0%	52.8%	-	41.9%
	$\mathcal{L}_{oann}$	43.3%	54.8%	42.5%	-

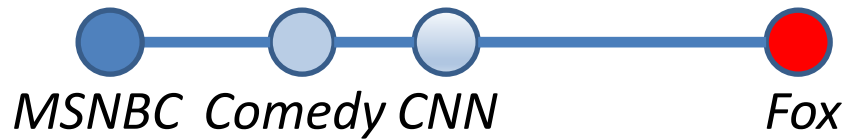
# The Other Sources of News



# Primetime Comedies



# Placing Comedy Along the Political Spectrum



# The Efficiency Argument

- *Solar* ( $L_{cnn}$ ) translates to *fossil* ( $L_{fox}$ )
- *Mask* ( $L_{fox}$ ) translates to *muzzle* ( $L_{oann}$ )



# Beyond Single Word

- *Black lives matter* in  $L_{cnn}$  is closer to *all lives matter* in  $L_{fox}$  than *black lives matter*

# The Big Picture

- *Different words may be used in near-identical contexts in different communities*
- *Such words may inform us about fundamental differences between the communities*
- *Machine translation methods provide a powerful, interpretable, and quantifiable framework*

# Collaborators



*Rupak Sarkar*



*Mark S. Kamlet*



*Tom M. Mitchell*



# Questions 😊

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 *khudabukhsh*