Controversy Detection and Analysis



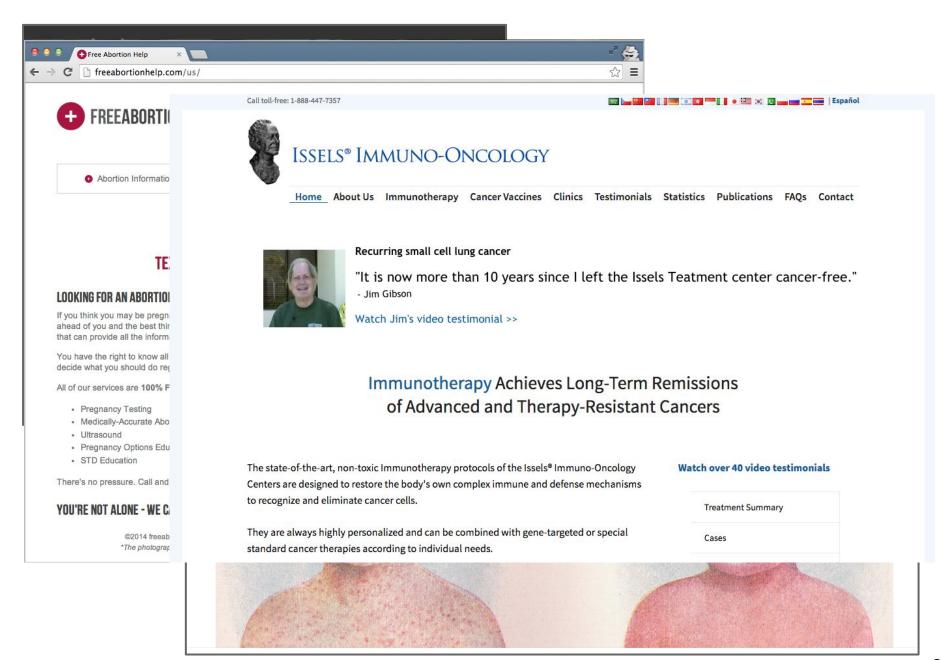
Dr. Shiri Dori-Hacohen AuCoDe

(+ University of Massachusetts Amherst)



Signal Media - December 2017

Presenting joint work with James Allan, David Jensen, Elad Yom-Tov, Myung-ha Jang, John Foley

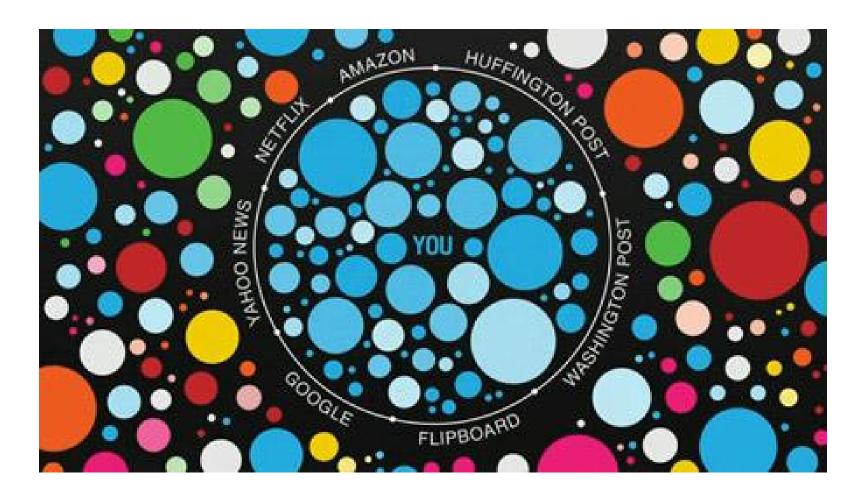




Growing interest in detecting controversy computationally

The Concerns

The Concerns



The Filter Bubble

The Concerns



Misinformation

Overview

- Motivation
- Related Work
- Controversy Detection in Wikipedia Using Collective Classification
- Contributions to Controversy Detection
 - On the web (using Wikipedia, language models)
 - Position paper (social, ethical, technical challenges)
 - Contention (population-based mathematical model)
- Startup AuCoDe

Controversy on the Web & search

- Only in domain-specific areas
 - News (Choi et al., 2010, Awadallah et al. 2011, Mejova et al., 2014)
 - Twitter (Popescu & Pennacchiotti, 2010)
- Controversial query detection (Gyllstrom & Moens, 2011)
- Controversy detection problem in the web didn't exist
 - Only specific sub-instances of it
 - Wasn't treated as a general issue
- Prior work focused almost exclusively on political controversies (using Debatepedia)

Sentiment Analysis vs. Controversy

- Sentiment analysis seen as a step towards detecting varying opinions/controversy
 - o cf. Choi et al., 2010; Cartright et al., 2009
- Other work shows sentiment & controversy are overlapping, but not identical, constructs
 - Dori-Hacohen & Allan, 2013; Mejova et al., 2014
- Sentiment analysis may be more effective when considering its variance in analyzing online conversations, rather than when examining individual webpages

Controversy Detection in Wikipedia

- Where everything started
- Kittur et al., 2007 First classifier for controversy in Wikipedia articles
- Sumi et al., 2011; Yasseri et al., 2012 Using the concept of edit wars and reverts; Heuristic approach
- Sepehri Rad & Barbosa, Sepehri Rad et al. 2012 Using collaboration networks between authors; Algorithm was computationally intensive, impractical
- Jankowski-lorek et al., 2015 article feedback tool
- Jesus et al., 2009 Clusters of controversial pages (anecdotally)
- Either machine learning or heuristic approaches
- Generally classify each page in isolation

Overview

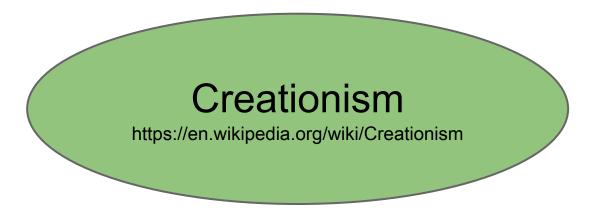
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Controversy Detection in Wikipedia Using Collective Classification

Published in SIGIR 2016

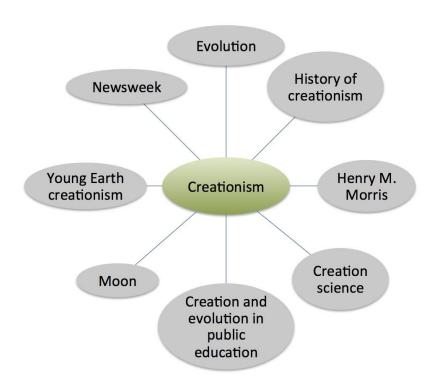
Joint work with David Jensen & James Allan

Controversy Detection in Wikipedia Using Collective Classification



Prior work on automated controversy detection in Wikipedia has focused on pages in isolation

Controversy Detection in Wikipedia Using Collective Classification



Hypothesis: related Wikipedia pages might have similar amount of controversy (homophily)

Collective & Stacked Classification

- Collective Inference is a technique which leverages homophily between related instances for inference
- However, it generally requires availability of labeled data for neighbors
- In our case, labeled data is sparse
- Stacked inference is an ensemble method which predicts labels for neighbors and then uses them

Approach

Intrinsic Classifier:

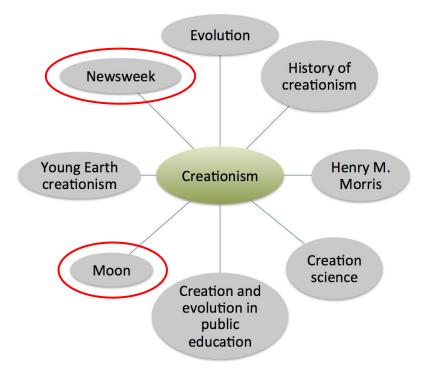
Training and inference on features of each WP page as a standalone page

(e.g. Creationism)

Leveraging the graph structure of WP to make the inference better

Bridging knowledge discovery and IR: A Subnetwork of Neighbors

- Traditionally: neighbors = relational database
- Hypothesis: not all links created equal



Use text similarity to select neighbors (TF-IDF)

Experimental conditions

Name	Description		
Stacked-	Proposed stacked inference system with a		
Ranked- k	similarity-based subnetwork		
Stacked-	A stacked inference system which uses k		
Random- k	randomly selected neighbors		
Neighbors-	A classifier based only on the neigh-		
Only-k	bor predictions (as in a regular stacked		
	model), without using the intrinsic fea-		
	tures of the center page		
Intrinsic	A classifier using only intrinsic features		
Stacked-	A stacked inference system, as above, but		
All	which uses all Wikipedia neighbors		
Prior work	See Sepehri Rad & Barbosa [12] for details		

Cross Validation Procedure

Algorithm 1 Cross-validation stacked training procedure

```
for fold i = 1..k, Set_i = A \setminus fold_i do

Train IM_i, an intrinsic model on Set_i

Select subneighbors(Set_i) \subseteq neighbors(Set_i)

Apply IM_i on subneighbors(Set_i)

Aggregate predictions of subneighbors(Set_i) to create an extended feature set, Set'_i

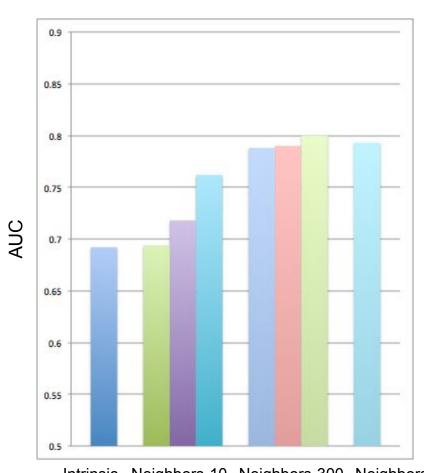
Train SM_i, a stacked collective model on Set'_i

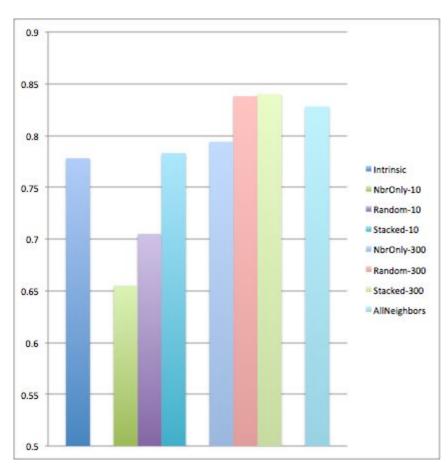
end for
```

Datasets

Set	Articles	Controversial
DHA [5]	1926	293 (15.2%)
SRMRB [12]	480	240 (50%)

Results - AUC



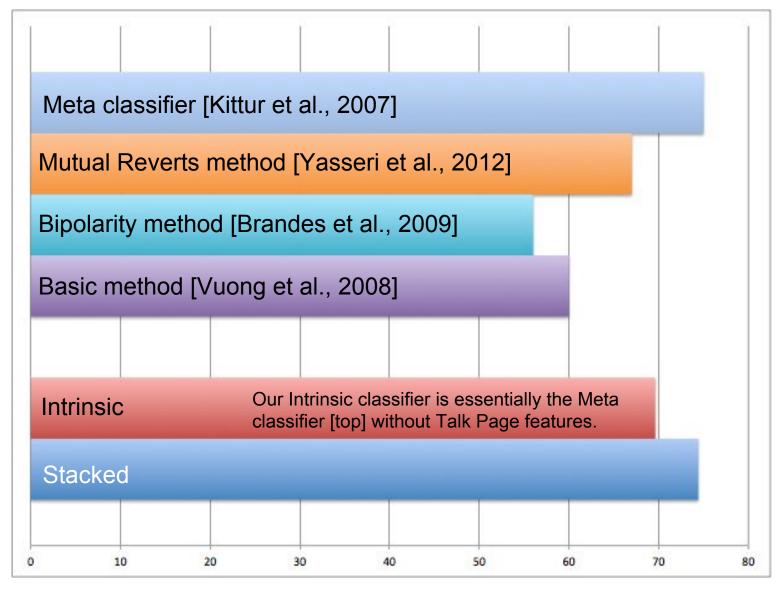


ntrinsic Neighbors-10 Neighbors-300 Neighbors-All

Intrinsic Neighbors-10 Neighbors-300 Neighbors-All

DHA dataset SRMRB dataset 21

Results - Accuracy (vs. prior work)



Results - summary

- Similar Neighbors improve results
 - Results increase substantially for first 25 neighbors
 - Stacked classifier outperforms both the Intrinsic and Neighbor-only models
 - Similar is better than Random, esp. w/small # of neighbors; converging as # approaches all neighbors
- Neighbors Provide Quality Inference Without Intrinsic Features
- Stacked Models Outperform Prior Work

So What?

- Leveraging the graph structure in Wikipedia
- Allows one to extend labels to a wider page set
 - Short edit history, no talk pages, low popularity, etc.
- Improved upon state-of-the-art methods
- Agnostic to the choice of intrinsic classifier
 - Any intrinsic classifier for controversy in Wikipedia can be enhanced by applying stacked classifier

Future Directions

- Subnetwork approach can be generalized to other semi-structured problem domains
- Study tradeoff between similarity and inference costs
- Explore other similarity constructions
- Automated detection of controversy holds promise for a variety of applications

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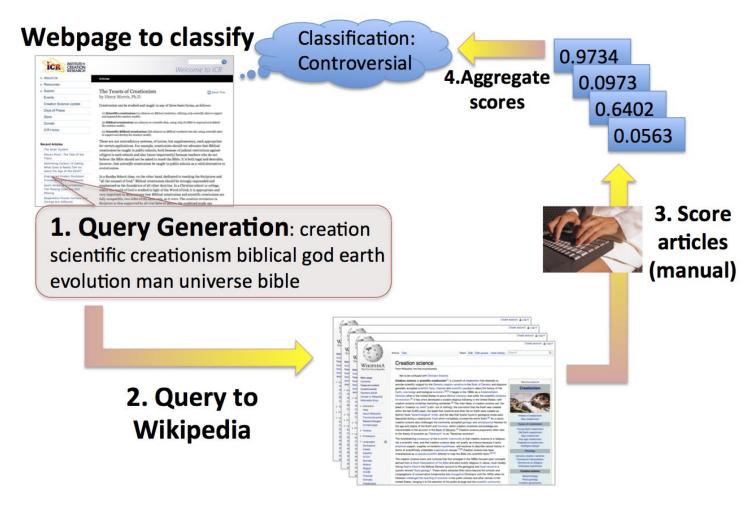
Our work so far

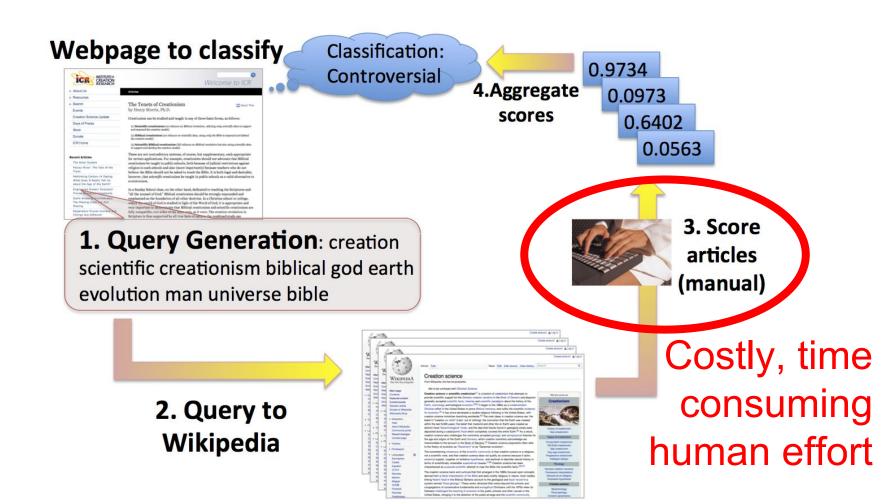
- Improving Controversy Detection in Wikipedia (Dori-Hacohen, Jensen & Allan; SIGIR 2016)
- Controversy Detection on the Web (Dori-Hacohen & Allan; CIKM 2013, ECIR 2015)
- Probabilistic Approaches to Controversy
 Detection (Jang, Foley, Dori-Hacohen & Allan; CIKM 2016)
- Navigating Controversy as a Complex Search
 Task (Dori-Hacohen, Yom-Tov & Allan; SCST workshop, ECIR 2015)
- Modeling Controversy as Contention Within Populations (Jang, Dori-Hacohen & Allan; ICTIR 2017)

Wikipedia is great, Web is better

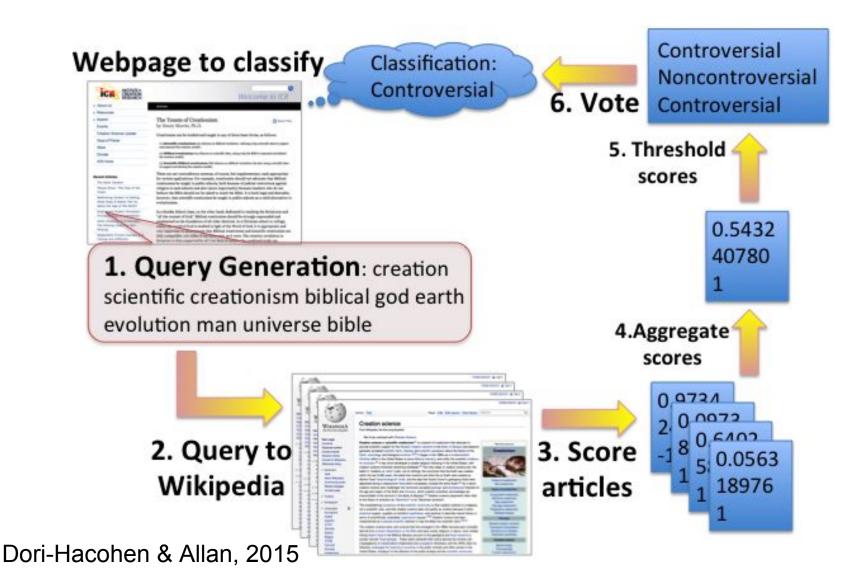
- We wanted to extend the work to the web
- But, the rich metadata from Wikipedia is non-existent on the web
- How can we bridge the gap?

Controversy Detection on the Web





Automated Controversy Detection on the web

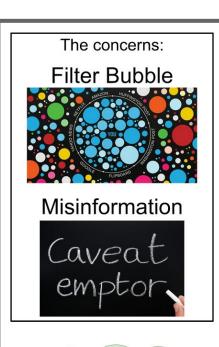


Language Models of Controversy

Jang, Foley, Dori-Hacohen, & Allan, CIKM 2016

A theoretical and empirical framework for Language Models of Controversy

$$P(D|C) \approx P(D|L_C) = \prod_{w \in D} (\lambda P(w|L_C) + (1 - \lambda)P(w|L_G))$$
$$\log P(D|L_C) = \sum_{w \in D} \log \left[\lambda P(w|L_C) + (1 - \lambda)P(w|L_G)\right]$$
$$P(D|L_{NC}) \approx P(D|L_{NC}) = \prod_{w \in D} P(w|L_{NC})$$
$$\log P(D|L_{NC}) = \sum_{w \in D} \log P(w|L_{NC})$$





(?) Strong disagreement among large groups of people.

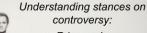
(?) Like relevance, define operationally.

Inter-annotator agreement is tough

Supporting users with controversial queries? CHALLENGE ACCEPTED.

Detecting controversial topics:

- Prior work on Wikipedia, Twitter, and the web
- From doc, query perspectives
- Goal of informing users



- Prior work on automated stance extraction
- Argumentation frameworks
- Sentiment ≠ controversy





Open questions:

- Concerns for democracy, diversity
- Bias regardless of personalization
- Slippery slope? Censorship??
- Effect on users?
- Ethical, civic duty? (to whom?)



Navigating Controversy as a Complex Search Task

Dori-Hacohen, Yom-Tov & Allan, SCST Workshop, ECIR 2015

Discussing technical, social and ethical challenges of helping users with controversy in search

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Definition of Controversy

- "controversial topics are those that generate strong disagreement among large groups of people."
 - Operational definition (à la relevance)
- Intuition suggests sentiment (incorrectly!)
- Problematic controversy definitions/datasets (by others)
 - Confounding Wiki vandalism and controversy (Vuong et al., 2008)
 - Using "lamest edit wars" as a controversy dataset (Bykau et al., 2015)

Towards a computational definition

- We were looking for a better definition that could be clearly understood & reproducible
- Inspired by "there is no controversy" arguments (e.g. vaccines/autism)
- How is it possible?

Contention, based on populations

- The big "a-ha" moment: we have to talk about populations
- We define a new term: contention
- Which is a function of topic, AND population
- What's the probability that two people, randomly selected from the population, will hold conflicting opinions?

Mathematical model for Contention

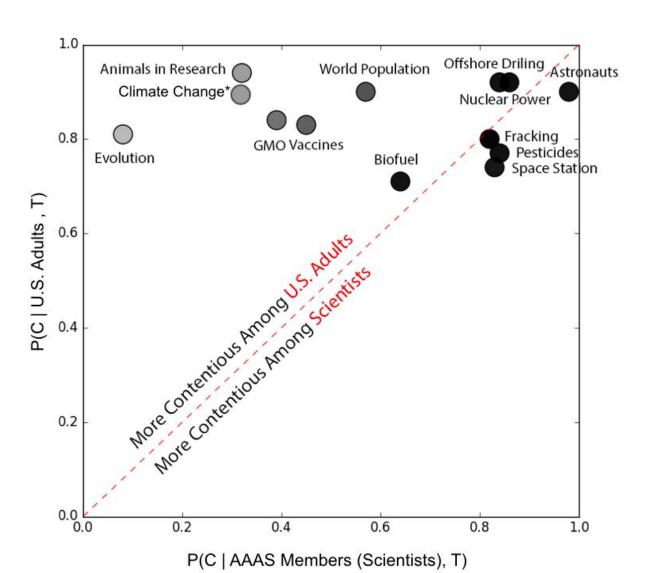
$$P(c|\Omega,T) = P(p_1,p_2 \text{ selected randomly from } \Omega, \exists s_i, s_j \in S,$$

s.t. $holds(p_1,s_i,T) \land holds(p_2,s_j,T) \land conflicts(s_i,s_j))$

We define **stance groups** in the population, which are groups of people that hold the same stance. For $i \in \{0..k\}$, let $G_i = \{p \in \Omega | holds(p, s_i, T)\}$. By construction, $\Omega = \bigcup_i G_i$.

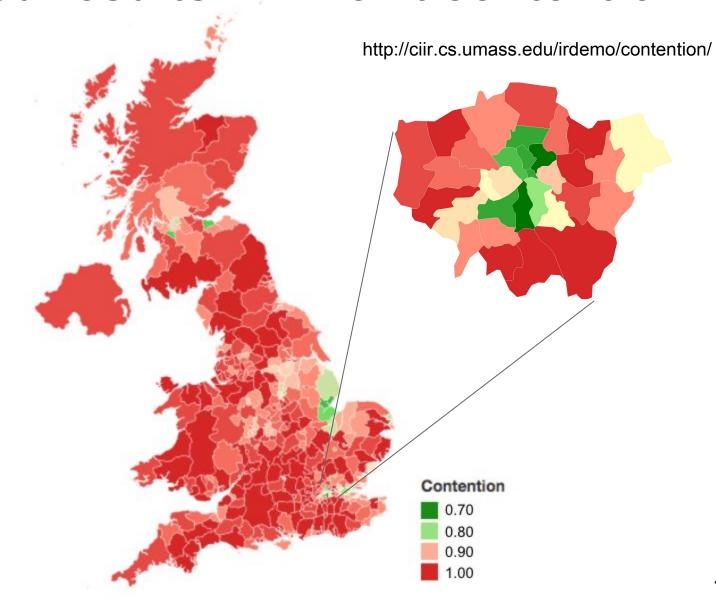
$$P(c|\Omega,T) = \frac{\sum_{i \in \{2..k\}} \sum_{j \in \{1..i-1\}} (2|G_i||G_j|)}{|\Omega|^2}$$

Selected results - scientists vs. U.S.



Selected results

Brexit contention

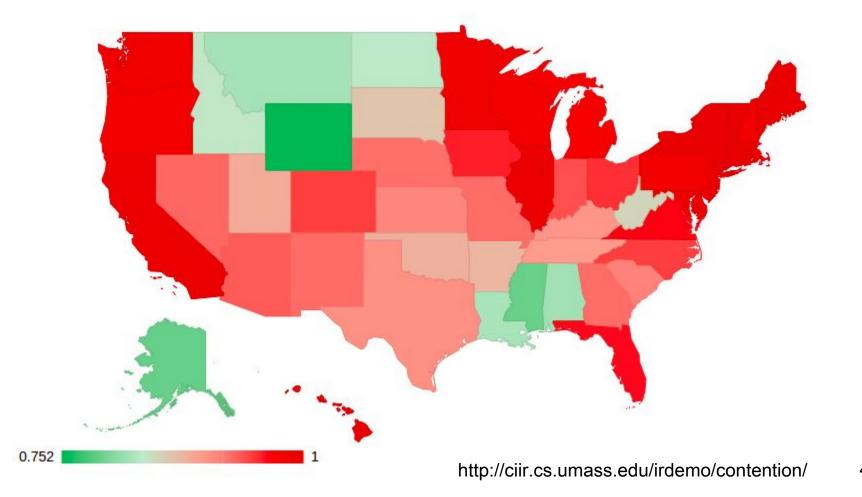


Outlier: 0.15



Selected results - Gun control in U.S.

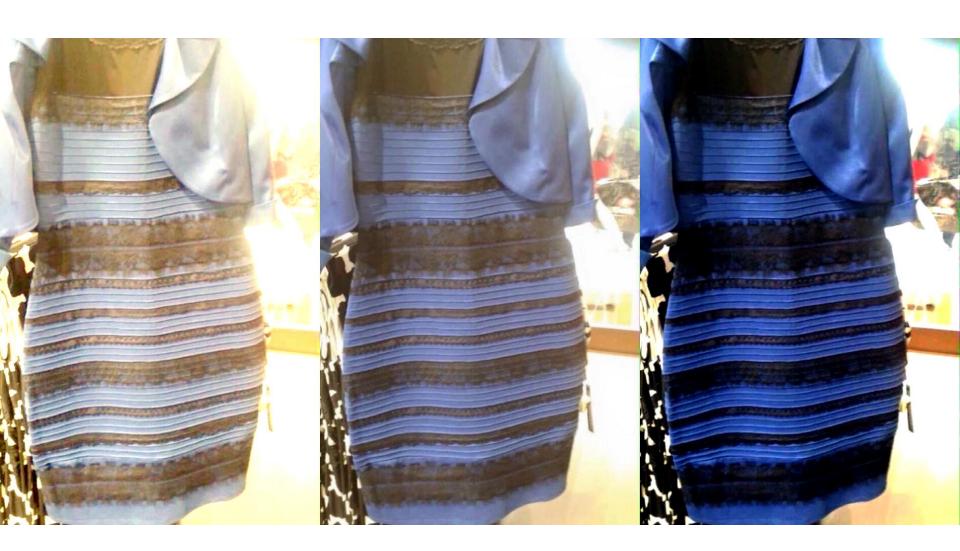
Do you support increased gun control?



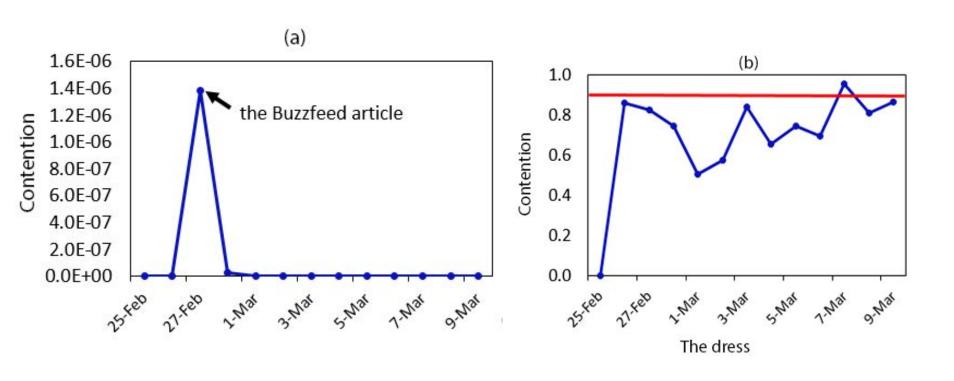
What colors are this dress?



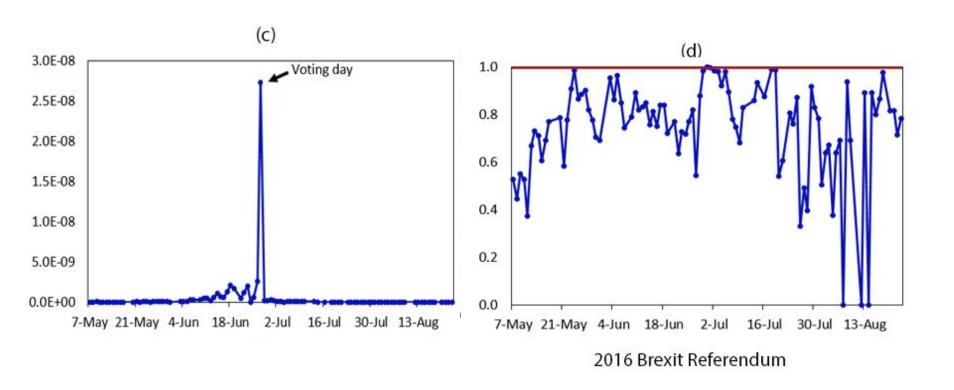
What colors are this dress?



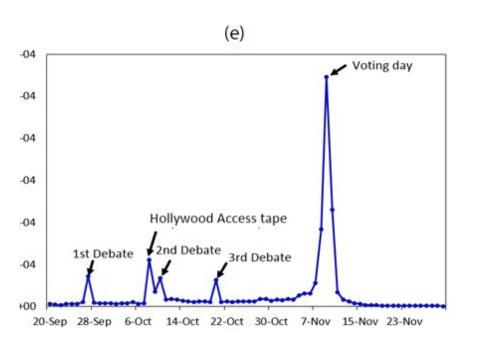
The Dress on Twitter

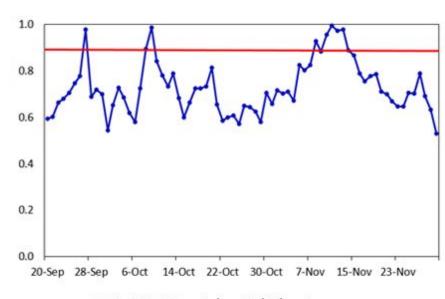


Brexit on Twitter



US Election on Twitter

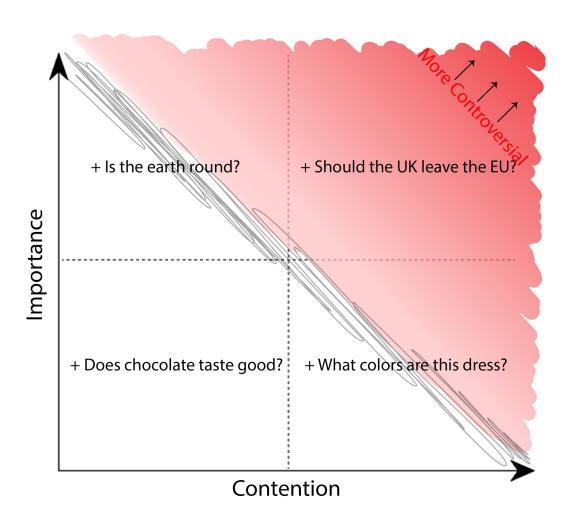




2016 U.S. Presidential Election

Hypothesized model for controversy

Contention is one dimension of controversy



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Startup -



 In April '16, I founded a startup to bring our controversy technology to market

 Won first place and non-equity grant in the UMass Innovation Challenge



Startup -



- Went through a couple of pivots (news, PR)
- Constructing an alternative data PoC (backtest)
- Looking into social good applications
- Patent application through UMass
- \$95K non-equity funding raised to date
- Recently applied for NSF SBIR funding

Thank you!

Questions, comments?

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