The shades and shapes of the pink wave: Visual perspectives of the Women's March

Jonathan Homola
Michelle Torres
Rice University
Washington University in St. Louis

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ONE MARCH…

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Estimated 3.3m - 5.6m in the U.S.

Over 200,000 in Washington D.C.

Largest protests since the 70's

...DIFFERENT PERSPECTIVES

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Relevance of visual frames

Women and politics in the media

- Quantity → more or less coverage for female candidates? (Bystrom et al. 2001; Hooghe et al. 2015; Kahn 1994; Smith 1997)
- Information and facts → shift to broader issue coverage (Atkeson and Krebs 2008)
- Style → focus personal issues vs leadership, positive vs negative coverage (Aaldering and Van Der Pas 2018; Bystrom et al. 2001; Devitt 2002; Kahn 1994)
- Visual content → campaigns and appearance (Bauer and Carpinella 2018; Hayes et al. 2014)

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Framing social movements

- Mobilization
- Formation of attitudes and opinions (e.g. inclusiveness, evaluations of success, identification)
- Impact on policy change

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  - GoogleVision API

Data and methods

Data: Women's March (January 2019)

- Getty: 2,492 images
- U.S. Newspaper covers (*Newseum*): 469 covers → 2,948 images (w/o publicity)
- Women's March Instagram: 82 images
- Women's March protests location: Wikipedia
- Ideology of newspapers: slant (Gentzkow and Shapiro 2010) and Twitter (Barberá 2018)
- Public: Clinton's vote share (county)

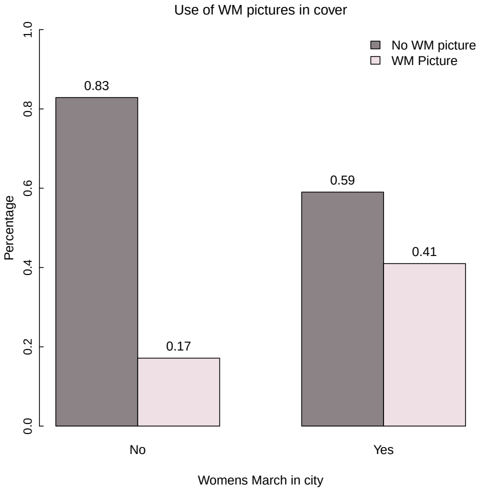
Methods

- Human coding
- Bag of Visual Words (Torres 2019)
- Content retrieval with GoogleVision API

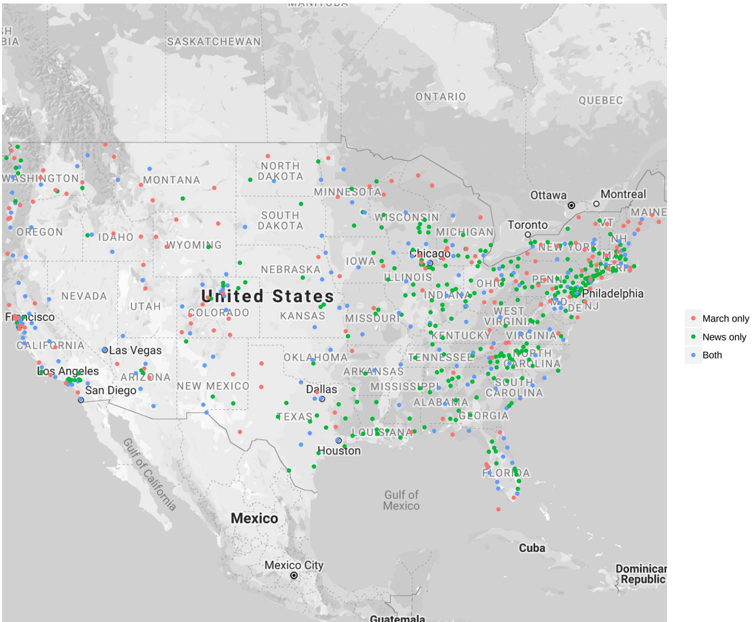
Coverage: the basics

COVERAGE: THE BASICS

- Focus: (1) is there a picture, (2) if so, how many, and (3) was there a protest in the city where the newspaper is from?
- 124 (26.4%) out of 469 have an image of the WM
- 183 (39.0%) out of 469 had a WM protest
- Mean number of pictures among those publishing at least one picture: 1.37



COVERAGE: THE BASICS (CONT.)



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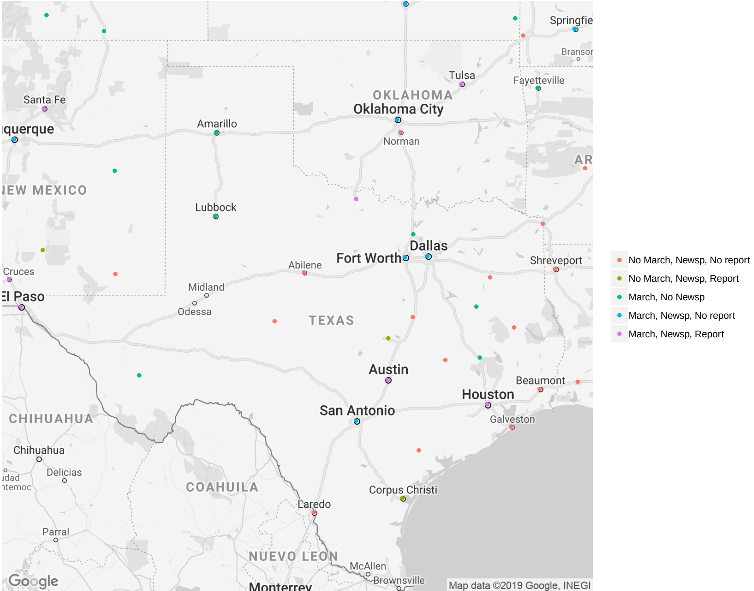
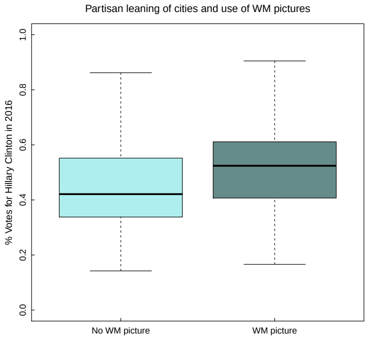


COVERAGE: FACTORS

Public's political leanings



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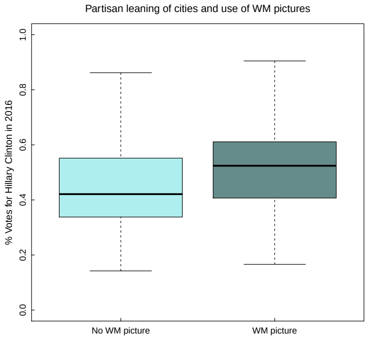
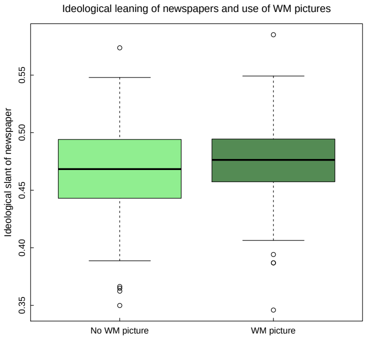


Newspapers' political leanings



COVERAGE: FACTORS (CONT.)

	WM Picture	Number of WM pictures
	Logit	*Poisson*
	(1)	(2)
March in the city	0.090	0.274
	(0.053)	(0.210)
Vote for Clinton	0.499*	2.731*
	(0.220)	(0.828)
Ideological slant	0.982	5.928
	(0.855)	(3.248)
Northeast	0.052	0.119
	(0.076)	(0.352)
South	0.002	−0.073
	(0.070)	(0.366)
West	0.410*	1.141*
	(0.073)	(0.289)
Constant	−0.567	−5.731*
	(0.478)	(1.856)
N	273	273
AIC	297.799	409.915

Content of the covers

- GoogleVision: `https://cloud.google.com/vision/`
- Labels found in each picture

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Only WM images

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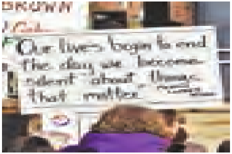
  - Model 2: ideology public, ideology newspaper, protest in city, and region

Examples of Visual Words

Three topics: Representative Images

Small group w/ signs



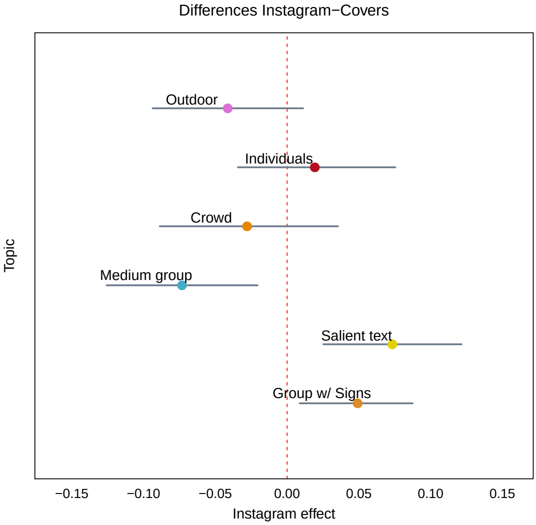
Medium group

Dense Crowd

THREE TOPICS: REPRESENTATIVE IMAGES

Women w/ hats

MOVEMENT VS. MEDIA



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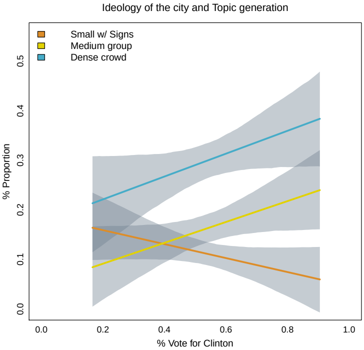

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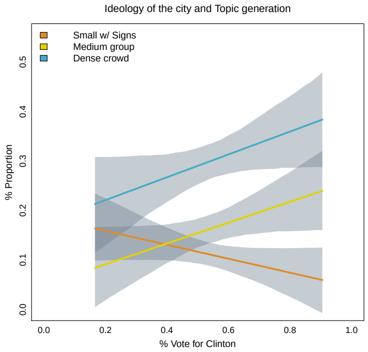

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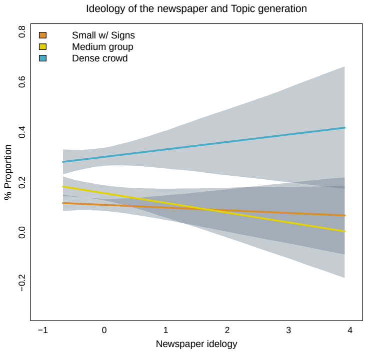
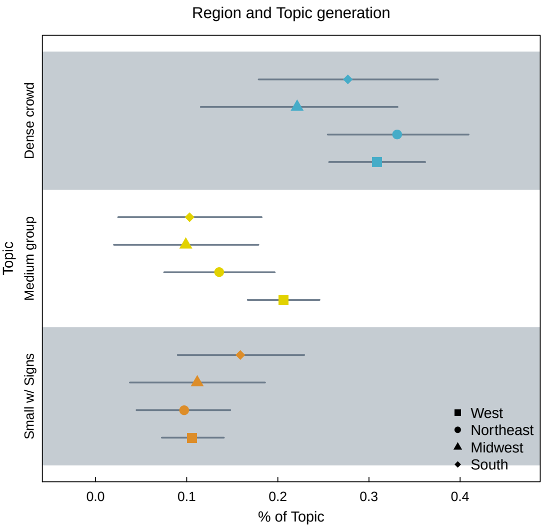


Regional focus



Emotional content

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- Face and emotion detection

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Conclusion

- Significant variation in newspaper coverage
- Ideology of public $>$ newspaper ideology
- $\rightarrow$ Newspapers as opinion shapers vs followers?

Further research

- Include text
- Use images from Twitter
- More factual data on protests
- Color-emotions
- Code newspaper presidential endorsements (?)

Feedback / questions

- What is the most interesting aspect?

Thank you!

smtorres@wustl.edu
homola@rice.edu