Recounts and Audits 2016

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Outline

Wisconsin

Using Twitter to Observe Election Incidents

Wisconsin data

- ▶ counts of votes for each presidential candidate in each ward (at each polling station)
  - ▶ both original counts and recounted counts
- ▶ counts of registered voters in each ward
  - ▶ most but not all voting wards are matched
- ▶ type of technology (and vendor) used in each municipality in the election
  - ▶ both tech used by most voters and accessibility technologies
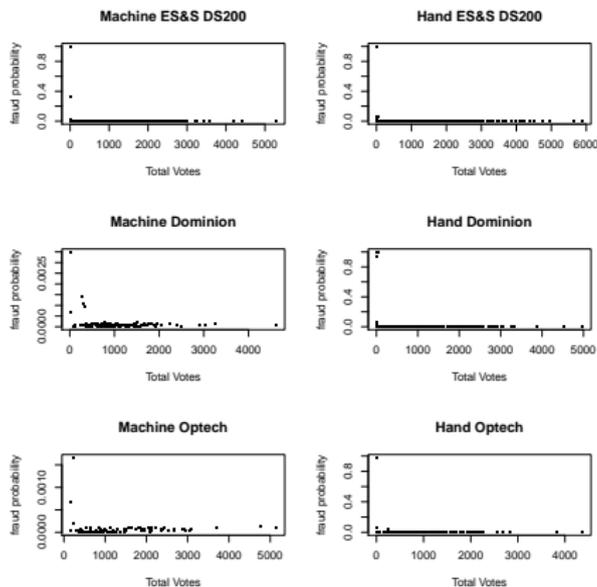- ▶ type of technology (and vendor) used for each ward in the recount

Wisconsin vote-registration anomalies

- ▶ nine "wards" have votes but no voter registration data
- ▶ seven "wards" have more votes than registered voters

Reporting Unit	Registered	Total Votes	
		Original	Recount
CITY OF STANLEY Ward 8		0	6
CITY OF MADISON Ward 130		1	1
CITY OF MADISON Ward 138		1	1
CITY OF HORICON Ward 7		1	1
CITY OF EAU CLAIRE Ward 60		1	1
CITY OF LA CROSSE Ward 30		0	17
CITY OF ABBOTSFORD Ward 6		7	0
TOWN OF MENASHA Wards 8-10		1877	1875
TOWN OF MENASHA Wards 11-13		1744	1746
CITY OF MADISON Ward 101	616	823	824
CITY OF MADISON Ward 121	6	7	7
CITY OF EAU CLAIRE Ward 65	11	14	13
TOWN OF SOMERS Ward 1	28	28	30
CITY OF STEVENS POINT Wards 35,40,43	3	4	2
TOWN OF BUENA VISTA Ward 4	2	5	5
TOWN OF OCONOMOWOC Ward 10	22	24	24

estimated (finite mixture model) fraud probabilities

▶ seven "wards" have high probabilities of "frauds" in the recounted vote totals, but the number of votes potentially affected in each instance is small

differences between recounted and original vote counts

▶ Trump: recounted votes minus original votes

	-25	-18	-16	-11	-10	-9	-7	-6	-5	-4	-3	-2	-1	0
Hand	1	1	0	0	1	1	2	2	5	9	15	43	167	1457
Machine	0	0	1	1	0	0	2	1	2	4	9	18	58	810
Mixed	0	0	0	0	0	0	0	0	0	2	3	3	21	199

	1	2	3	4	5	6	7	8	9	10	11	14	23	29
Hand	199	57	39	11	7	4	3	2	1	1	1	2	1	2
Machine	100	27	7	7	3	2	2	0	1	2	0	1	0	0
Mixed	31	8	3	1	2	0	0	1	0	0	0	0	0	0

	31	32	39	50	65	246
Hand	0	1	1	1	1	0
Machine	1	0	0	0	0	1
Mixed	0	0	0	0	0	0

differences between recounted and original vote counts

- ▶ Clinton: recounted votes minus original votes

	-30	-18	-17	-14	-12	-10	-8	-7	-6	-5	-4	-3	-2	-1
Hand	1	0	1	0	1	0	0	1	0	5	6	17	52	161
Machine	0	1	0	1	0	1	2	2	1	4	6	8	15	82
Mixed	0	0	0	0	0	0	0	0	1	0	1	4	6	25

	0	1	2	3	4	5	6	7	8	9	10	11	13	14
Hand	1457	187	79	22	10	9	5	8	4	0	2	1	1	1
Machine	734	126	31	18	6	4	6	5	2	1	0	0	0	1
Mixed	199	23	6	1	3	3	1	0	0	1	0	0	0	0

	15	17	19	22	24	33	68	79
Hand	1	1	1	1	1	0	1	1
Machine	0	1	1	0	0	1	0	0
Mixed	0	0	0	0	0	0	0	0

recount-original differences vary by candidate by machine

- ▶ reduce recount-original differences to increases and decreases
- ▶ 3-way interaction is statistically significant ($p < .0001$)

Trump			
	decrease	same	increase
Accuvote-OS	16	105	29
DS200	122	1154	183
Eagle	38	112	137
ImageCast Evolution	36	213	32
Insight	24	138	53
M100	27	142	28
None	110	621	68

Clinton			
	decrease	same	increase
Accuvote-OS	16	116	18
DS200	144	1031	284
Eagle	37	117	133
ImageCast Evolution	45	211	25
Insight	24	150	41
M100	39	129	29
None	98	653	48

using Twitter to observe election incidents

- ▶ we captured 4,566,333 unique Tweet texts during October 1–November 8, 2016
  - ▶ Tweets that matched keywords or contained election officials' handles were captured (in all 6,163,892 non-retweet Tweets)
- ▶ human labeling of an initial sample suggests about one percent of the Tweets contain observations of "incidents"
  - ▶ the initial sample shows incidents being observed from all 50 states (and the Virgin Islands)
- ▶ we're using machine learning techniques (with Tweet texts and linked images) to help find incident observations
- ▶ it's too early to say what are the relative frequencies of different type of incidents, but
  - ▶ mentions of line lengths and waiting times often occur
  - ▶ also of voter registration, absentee ballot or polling place issues
  - ▶ and mentions of voting machines or early voting