Questions of accuracy and fairness in radicalisation research

what should we do about terrorism online?

'Data Science in Action' Lecture

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Problems of a barrier-free internet

- \rightarrow The internet has reduced barriers to communication for everyone.
- \rightarrow Deviant groups are empowered to advertise and recruit online.
- → Black-box algorithmic detection regimes can inadvertently spread bias against similar but unrelated peoples.

→Unbiased, reliably coded data is particularly important to prevent biases in automated decisions, e.g., image classification









Harvesting Cross-media Data



In 2018: Tweets – 8,181,302 Web pages – 48,297 Images - ~1.5 mil



What should we do about terrorism online?



Number of violent acts by different VEOs from 1994 until 2016.





Do groups have a 'tell' in their destruction pattern?









Selected and unselected feature sets informs on aspects of attacks that are wellplanned and the aspects that are more of random consequences.





Feature selection techniques support more robust analyses





Number of hidden layers	Number of nodes in each hidden layer	Average test error	Std 10x CV
1	25	61.56%	2.05
1	50	61.53%	2.52
2	25	61.50%	2.43
2	50	61.80%	1.64
3	25	62.52%	1.58
3	50	62.39%	2.34

Multilayer perceptron accuracy based select features of the violent act reached 39%; 43% for all features; 42% with PCA generated-features



What should we do about terrorism online?

Removal options are still manually intensive.

- Freedom of speech
- Whack a mole problem
- Big data problem
- Burn out



How reliable are benchmark solutions of human coders taken from radical content on the open web?



The Approach(1)

- Four-person team in jury format
- 4 main categories
 - 4 categories were added in initial QA round
 - 1 category change in final QA round





The Approach(2)

	Second Round Classification									
		Training Materials	*Hard	Non-ISIS	*None	0.C.	*Soft	*S.P.	Useless	
	Flags of ISIS	0	0	0	36	0	0	0	0	36
ation	*Hard Propaganda	0	35511	268	723	13	96	40	0	36651
ific	Non-ISIS Groups	0	17	1291	31	0	4	6	2	1351
ass ass	*None	452	520	586	18522	946	242	102	76	21446
nd Cla	Official Communications	0	0	1	23	4411	0	0	0	4435
First Roui	*Soft Propaganda	0	123	739	4392	1	4163	40	0	9458
	*Symbolic Propaganda	0	193	10	134	4	249	933	0	1523
	Useless	0	6	4	18	0	6	1	20307	20342
Total		452	36370	2899	23879	5375	4760	1122	20385	95242



Images





Tweets





Pages





Typical Max Pooling Layer







Proposed Initial Layer of a Combined Model





Stylized CNN



Convolutional layers:

$$f_1 = 42 \times 42 \times 2, \ s_1 = 3, \ n_1 = 74$$

 $f_2 = 15 \times 15 \times 5, \ s_2 = 3, \ n_2 = 26$
 $f_3 = 13 \times 13 \times 24, \ s_3 = 2, \ n_3 = 46$
 $f_4 = 12 \times 12 \times 84, \ s_4 = 2, \ n_4 = 89$
 $f_5 = 5 \times 5 \times 15, \ s_5 = 2, \ n_5 = 62$

where f_m , s_m , and n_m denote the stride, size, and number of windows of the *m*-th layer, respectively.

The first two fully-connected layers have 4096 neurons each and the third fully-connected layer has as many neurons as the number of classes (8 here).



How well do machines identify extremist propaganda?



Class	Hard Propaganda	Soft Propaganda	Symbolic Propaganda	Organizational Communications	Landscapes	ISIS-other	Other Groups	None
Absolute size	38,460	9,933	1,605	5,960	1,569	26,360	2,151	34,597
Relative size	31.88%	8.23%	1.33%	4.94%	1.30%	21.85%	1.78%	28.68%
			Above: Label	led Images; Below: Al	l Images			
Absolute size	97964	25611	6886	16906	2532	91277	6330	941820
Relative size	8.24%	2.15%	0.58%	1.42%	0.21%	7.67%	0.53%	79.19%



Visual propaganda from OSM can be reliably detected

Binary Classifier	8-way Classifier (intent-based)
Overall generalization accuracy 97.02%	Overall generalization accuracy 86.08%
Overall generalization <i>F1</i>	Overall generalization <i>F1</i>
97.89%	85.76%

Class	Hard Propaganda	Soft Propaganda	Symbolic Propaganda	Organizational Communications	Landscapes	ISIS-other	Other Groups	None
Precision	84.47%	73.50%	66.80%	98.86%	75.00%	79.56%	94.43%	93.84%
Recall	92.78%	61.12%	57.79%	95.50%	61.56%	73.50%	77.40%	96.01%
F1	88.43%	66.74%	61.97%	97.67%	67.62%	76.41%	85.07%	94.91%



Evaluation of Approach

• Two **k** measurements in use

- Cohen's **ĸ**
- Fleiss' ĸ

	Cohen's Kappa		Asymptotic	Asymptotic 95% Confidence Interval		
	e chien e happa	Standard Error	z	Sig.	Lower Bound	Upper Bound
Overall Agreement	0.857	0.002	483.591	0.000	0.854	0.860



Fleiss' ĸ

	Conditional			Asymptotic	Asymptotic 95% Confidence Interval			
Rating Category	Probability	Карра	Standard Error	Z	Sig.	Lower Bound	Upper Bound	
Flags of ISIS	0.000	0.000	0.003	-0.058	0.953	-0.007	0.006	
General Training Materials	0.000	-0.002	0.003	-0.734	0.463	-0.009	0.004	
Hard Propaganda	0.973	0.956	0.003	294.913	0.000	0.949	0.962	
Non-ISIS Groups	0.608	0.599	0.003	184.727	0.000	0.592	0.605	
None	0.817	0.760	0.003	234.623	0.000	0.754	0.767	
Official Communications	0.899	0.894	0.003	275.844	0.000	0.887	0.900	
Soft Propaganda	0.586	0.552	0.003	170.407	0.000	0.546	0.559	
Symbolic Propaganda	0.705	0.701	0.003	216.441	0.000	0.695	0.708	
Useless	0.997	0.996	0.003	307.524	0.000	0.990	1.003	
a. Sample data contains 95242 effective subjects and 2 raters.								



Reliable and Explainable Detection						
Machines can detect terror propaganda	It is possible to separate religious, cultural, and co-opted messaging					
Generalizable Lessons and Future Research Directions						
Machines can learn nuance	Low-bias management regimes are possible but un(der) developed					



Discussion

How reliable are benchmark solutions of human coders taken from radical content on the open web?



→ Soft propaganda is hard to define.

→ Good performance on frequent samples; lesser performance on the margins.

 \rightarrow Necessary tradeoff between accuracy and scale.



How reliable are benchmark solutions of human coders taken from radical content on the open web?

- → Transfer learning to pre-sort Hard Propaganda.
- → Separation/further refinement of Soft Propaganda.
- → Overarching need for method to combine text and images (Crowe, Ricks & Hall, 2024).



Questions?



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(Digital) Participation theory can address individual online extremism





Li & Bernoff, 2011; Ligon, Hall, & Braun, 2018

(Digital) Participation theory can address individual online extremism





Li & Bernoff, 2011; Ligon, Hall, & Braun, 2018