



# Understanding and Discovering Deliberate Self-harm Content in Social Media

**Yilin Wang**<sup>1</sup> Jiliang Tang<sup>2</sup> Jundong Li<sup>1</sup> Baoxin Li<sup>1</sup> Yali Wan<sup>3</sup> Clayton  
Mellina<sup>4</sup> Neil O'Hare<sup>4</sup> Yi Chang<sup>5</sup>

<sup>1</sup>Arizona State University   <sup>2</sup>Michigan State University

<sup>3</sup>University of Washington   <sup>4</sup>Yahoo Research

<sup>5</sup> Huawei Research

WWW 2017

YAHOO!



## Self harm: What is it about ?



#self injure

#blithe

#olive

**Self harm**

#secret society 123



#svv

**Self  
mutilation**

#ana mia

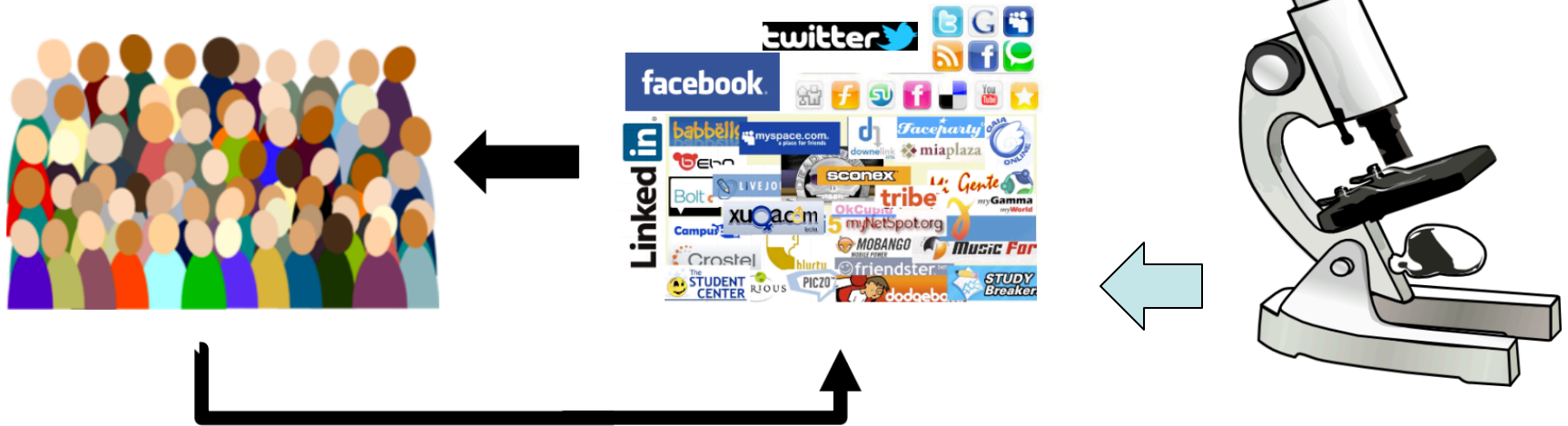


## Self harm: How common?

- 2 Million cases reported annually (US)
- 2<sup>nd</sup> leading cause of teenage deaths (world wide)
- Existing efforts only relied on self and friends/families reports, but most of self harm symptom is very difficult to discover.
- The relatively rare occurrence of completed self-harm treatment and the rare population made the studies expensive to conduct.



## Why Social Media?



- Monitoring human behavior
- A better place for young adolescents

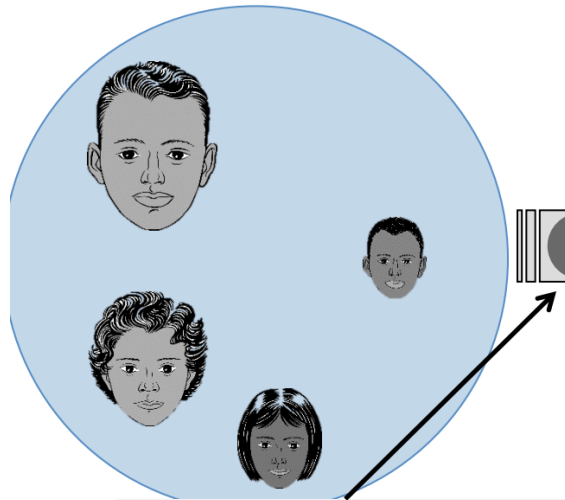
Social stigma exists for people who engaged in self harm

*“I swear to god, I got worse panic attack ever when adults talk about cutting and force you to show the wrist”*



## Motivation

The World

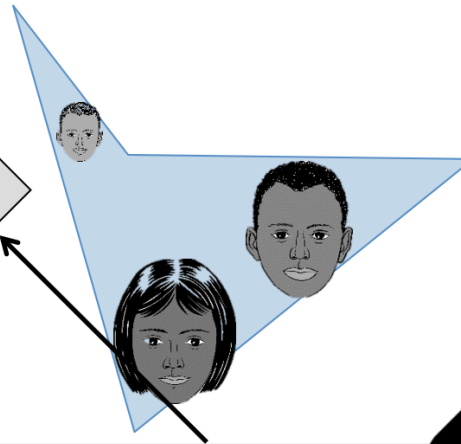


**31% of online adults (26% of all Americans) use Pinterest**

*% of online adults who use Pinterest*

All online adults	31%
Men	17
Women	45

Social Media

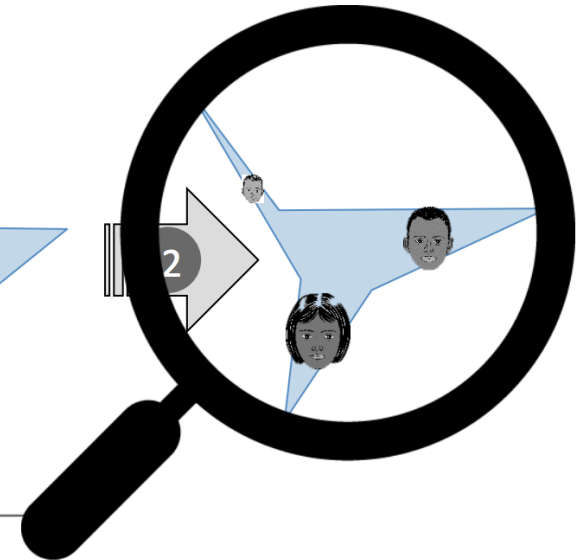


**24% of online adults (21% of all Americans) use Twitter**

*% of online adults who use Twitter*

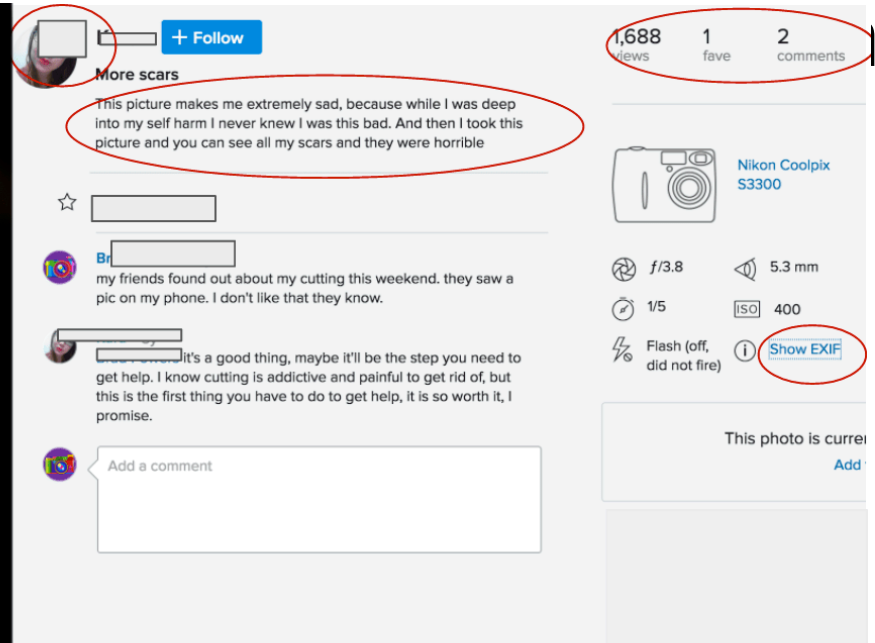
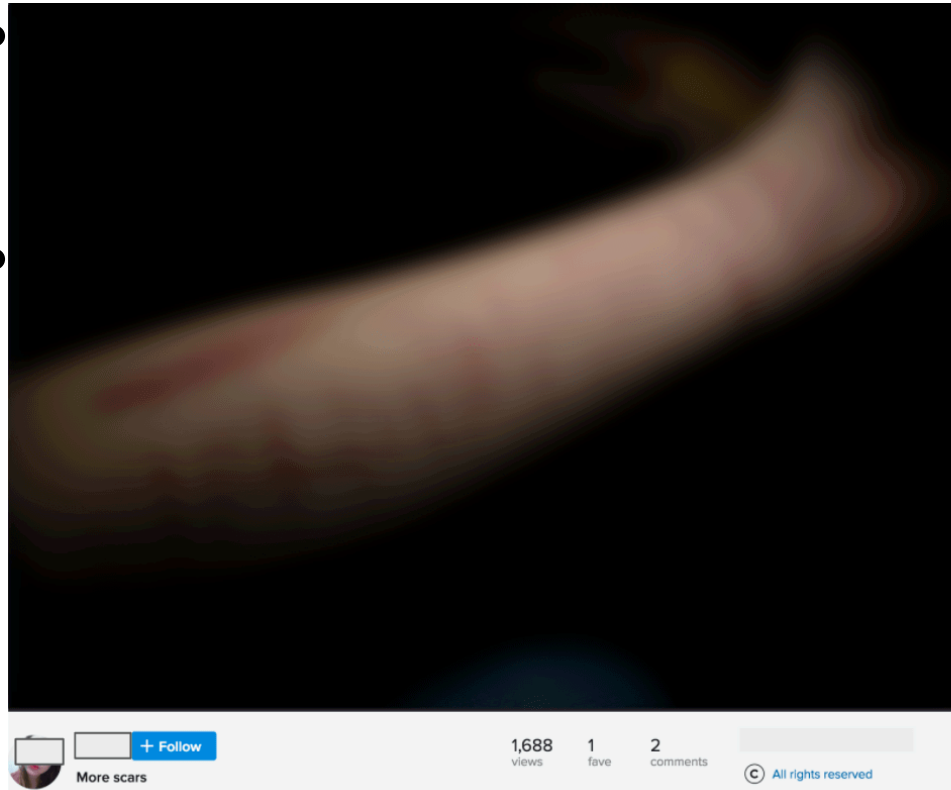
All online adults	24%
Men	24
Women	25

Sampled Social Data





## Research Questions





## Data Collection

Flickr: 10 Billion posts with 50 Million users

- Self-harm Content: “#selfharm” “#selfinjury”  
1B-> 15,792 posts

eatingdisorder	suicide	anxious	anorexia
mental-illness	depressed	killme	depression
selfhate	anamia	anxious	addiction
bruised	bulimia	bleeding	

Refine 383,614 posts and 63,949 users

- Normal User drawn from YFCC 19720 users and 93286 posts for each group





# Data Analysis

- Textual Analysis
- User Analysis
- Temporal Analysis
- Visual Content Analysis





## Textual Analysis

	Self-harm	Normal
<b>Linguistic</b>		
Nouns	0.158	0.268
Verbs	0.127	0.021
Adjective	0.035	0.084
Adverbs	0.032	0.023
readability	0.41	0.69
<b>Sentiment</b>		
Positive	0.06	0.29
Neutral	0.15	0.53
Negative	0.79	0.18

Theme	Token
Expression/ Symptom	anamia, anorexia, suicide, alone, stress, pretty, harms, stress, pain, angry, addiction, failure, beautiful, peace, illness, bulimic, individual, depressive, disorder
Disclosure	cuts, help, kill, live, die, plans, inflicted, treatments, eating, celebrates, suffer, saveme, triggers
Relationship/Noun	365days, razor, scar , blood, arms, wrist, band, knife, bathroom, bath, tattoo, girls, woman, boyfriend, people, body, night

- self-harm content tends to include more verbs and adjectives/adverbs than nouns which is very consistent with suicidal word usage.
- The poor linguistic structure usage and language suggest the decreased cognitive functioning and coherence.
- A large portion of negative sentiment words are used in self-harm content.





## User Analysis

	Volume	% of reply	# favorite	# friends
Self-harm	7.76	0.51	0.56	296.89
Normal	3.79	0.11	0.23	477.57

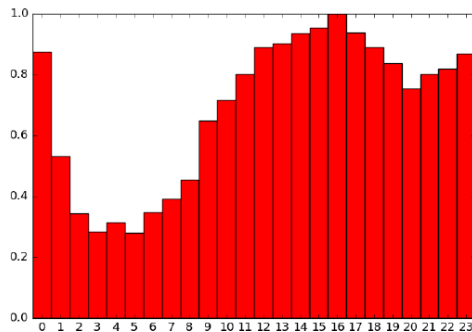
More Active: average post from create account to last login in.

High proportion of reply and number of favorites indicate that self harm content receives more social response.

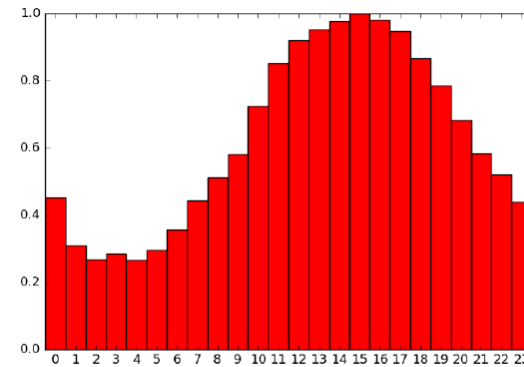
Self harm users has less friends shows that it could be berried by the large portion of normal users.



# Temporal Analysis



(a) Self-harm related Content



(b) Normal Content.

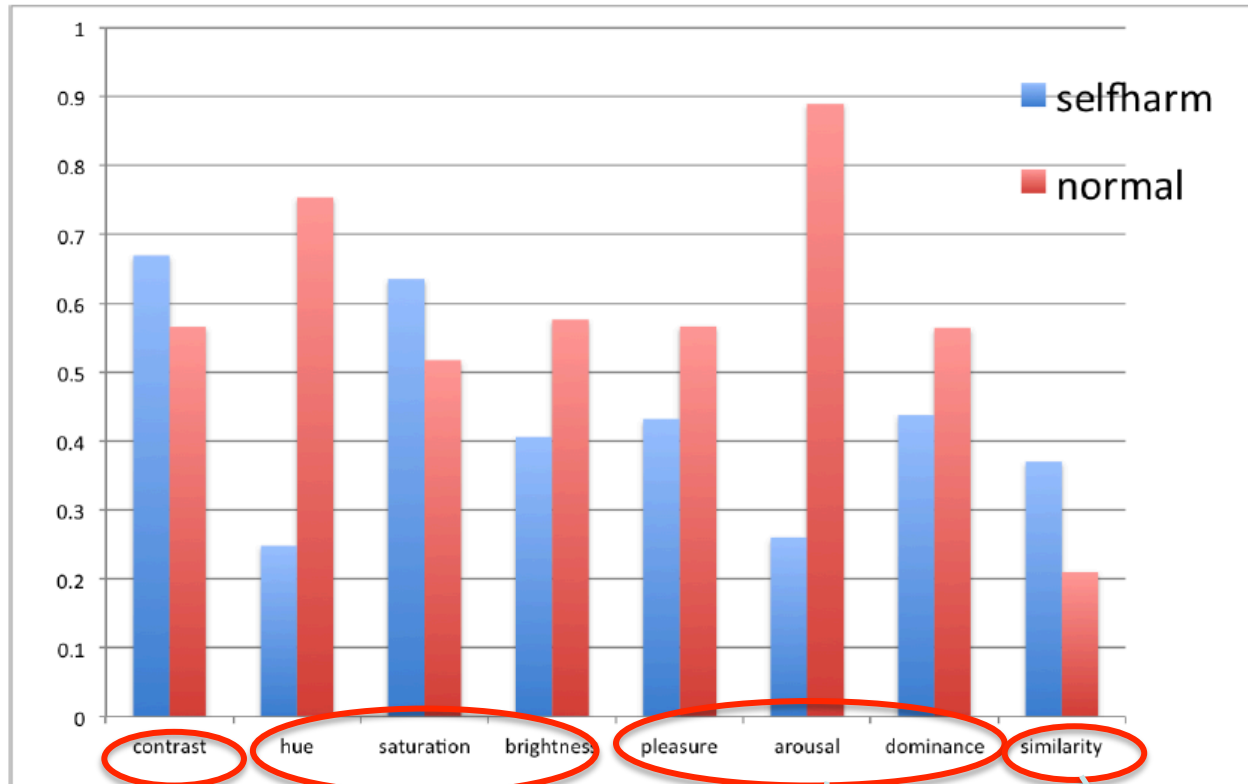
Normal users:

- fewer number is published later in the night and early morning.
- the number generally increases through the day (peaks in 3pm )

Such reason could be the mental issues related insomnia.



# Visual Content Analysis



saliency

Image Style

Image emotion

patterns



# The importance of our finding

- Let self harm post to be heard.

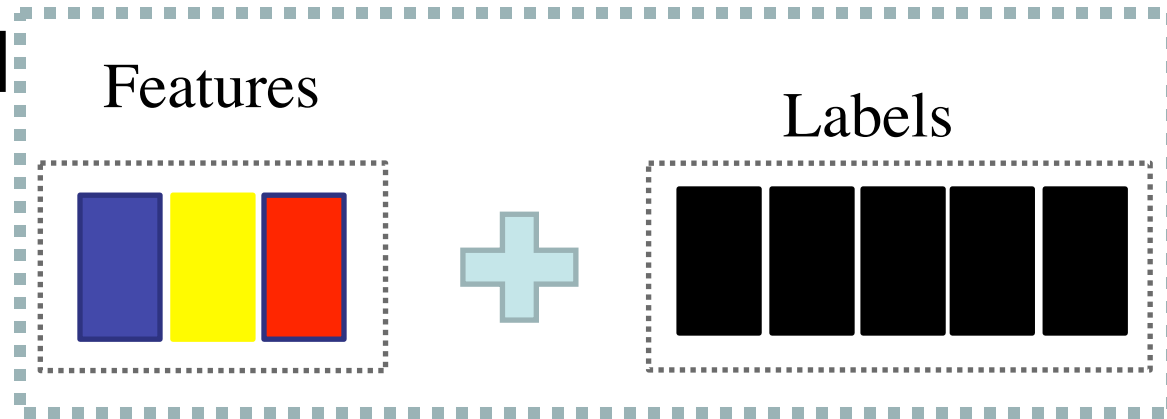
Common feature: visual feature and textural feature (CNN+WE)

Our findings: language usage, sentiment and lexicon, temporal, user information and visual patterns



# How to utilize the findings?

- supervised



Training the classifier



$$\min_{\mathbf{W}} \|\mathbf{X}\mathbf{W} - \mathbf{Y}\|_F^2 + \alpha \|\mathbf{W}\|_{2,1}$$



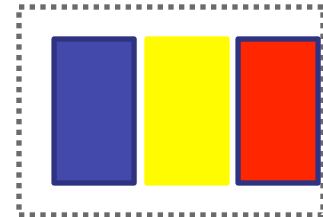
- unsupervised



textual information



## Our findings



# Model Learning

$$\begin{aligned} & \min_{\mathbf{W}, \mathbf{Z}} \quad \sum_{i=1}^m \lambda_i (Tr(\mathbf{Z}^T \mathbf{L}_i \mathbf{Z})) + \alpha \|\mathbf{XW} - \mathbf{Z}\|_F^2 + \beta \|\mathbf{W}\|_{2,1} \\ & \text{subject to} \quad \mathbf{Z}^T \mathbf{Z} = \mathbf{I}, \quad \mathbf{Z} \geq 0 \end{aligned}$$



## Experiments

### Dataset:

- Balanced dataset: equal size of self harm content and normal content. (150k)
- Imbalanced dataset : 1:10 with self harm to normal content. (150k and 850k)

### Metric:

- Supervised: F1 and precision
- Unsupervised: accuracy and NMI

Parameter analysis : alpha from 0.0001 to 10



# Results of Supervised Method

Visual

Algorithm	Balanced		Imbalanced	
	F1	precision	F1	precision
Word-embedding	57.9%	63.7%	37.9%	30.1 %
↓ CNN-image	61.8%	64.5%	48.6%	44.7%
CNN+WE	68.3%	72.3%	53.1%	46.7%
SCP-lite	68.4%	73.1%	54.5%	47.9%
SCP	<b>72.1%</b>	<b>75.2%</b>	<b>56.7%</b>	<b>49.8%</b>

Textual



# Results of Unsupervised Method

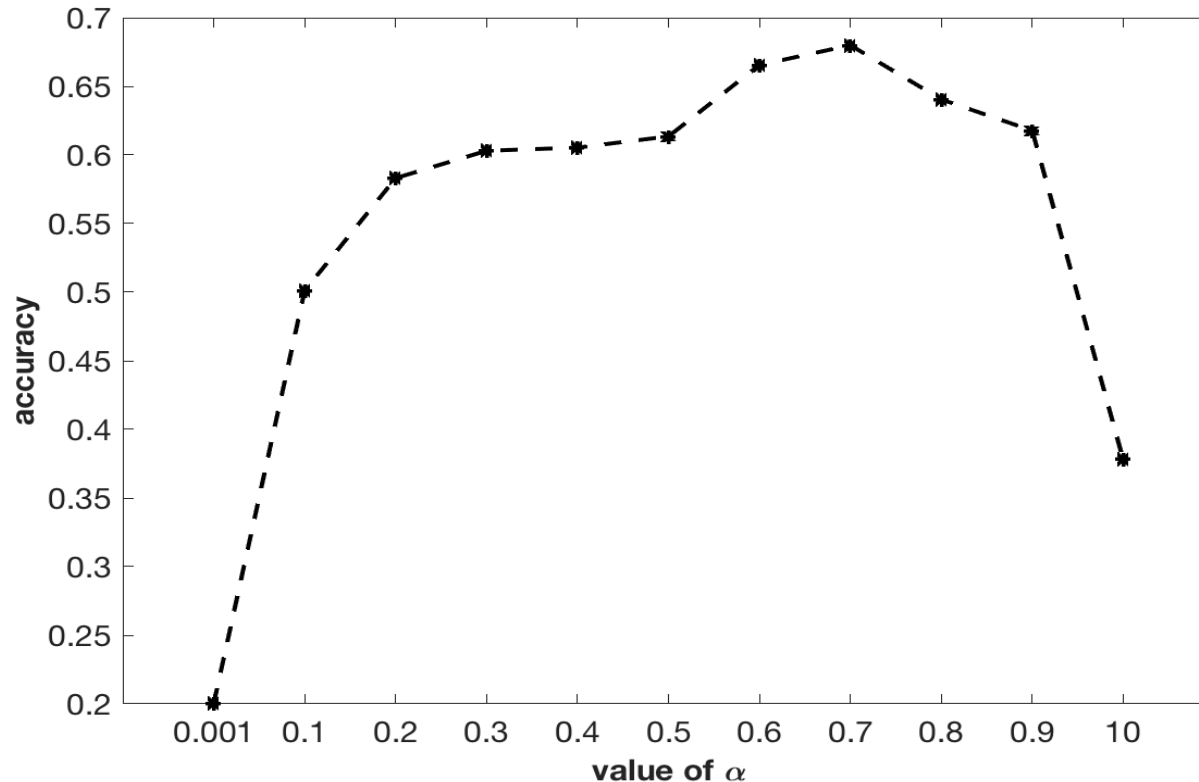
Visual

Algorithm	Balanced		Imbalanced	
	NMI	ACC	NMI	ACC
CNN+kmean	0.36	47.3%	0.15	15.3%
WE+kmeans	0.08	33.8%	0.04	10.3 %
CNN+WE+kmeans	0.46	56.2%	0.23	23.1%
USCP-lite	0.48	58.3%	0.26	24.3%
USCP	0.51	61.2%	0.31	27.4%

Textual



# Parameter



$$\min_{\mathbf{W}, \mathbf{Z}} \quad \sum_{i=1}^m \lambda_i (\text{Tr}(\mathbf{Z}^T \mathbf{L}_i \mathbf{Z})) + \alpha \|\mathbf{XW} - \mathbf{Z}\|_F^2 + \beta \|\mathbf{W}\|_{2,1}$$

subject to  $\mathbf{Z}^T \mathbf{Z} = \mathbf{I}, \quad \mathbf{Z} \geq 0$



## Conclusion

- Our analysis suggest that the characteristic of self harm content is very different with normal content.
- Features inspired by our findings improve detection of identify self harm content.
- We can extend our work to a semi supervised learning problem for real-world data.
- We will explore the network influences to self harm users.