Computer Assisted Qualitative Content Analysis

Topic Modeling + Curation = Scalability + Trustworthiness

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SurvAl Day, 7 October 2024

Suicide prevention resources

- National Suicide Prevention Lifeline: 988 / 1-800-273-8255 (TALK)
 - Veterans please press 1 to reach specialized support
 - Spanish: 1-888-628-9454
 - Deaf + Hard of Hearing: 1-800-799-4889
- Crisis Text Line: Text "HOME" to 741-741
- Online chat
 - https://suicidepreventionlifeline.org/chat/
- U.S. and worldwide
 - https://www.reddit.com/r/SuicideWatch/wiki/hotlines
 - This page provides information about phone and chat hotlines and online resources in the U.S. and worldwide

The challenge

- **Open-ends are a well-known problem in survey research:** language can yield extremely rich responses, including bringing to the surface aspects of a question or issue that the researcher might not have known to look for, but content analysis of text is *costly and labor-intensive*.
- **Computational methods are efficient and scalable**, but they are less widely used because it's hard to know if computational results are *trustworthy*.

How can you get an efficient and scalable analysis of open ends that produces categories you can trust?

Top down: looking for evidence through the lens of known categories/constructs/patterns

"[Despair], owing to some evil trick played upon the sick brain by the inhabiting psyche, comes to resemble the diabolical **discomfort** of being **imprisoned** in a fiercely **overheated** room. And because no breeze stirs this cauldron, because there is no escape from this **smothering confinement**, it is entirely natural that the victim begins to think ceaselessly of oblivion."

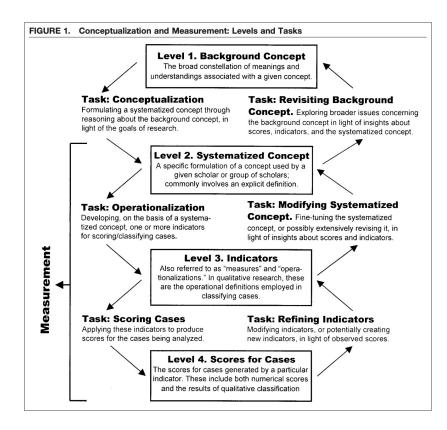
- Dr. Kay Redfield Jamison, Night Falls Fast: Understanding Suicide

Schuck, Allison; Calati, Raffaella; Barzilay, Shira; Bloch-Elkouby, Sarah; Galynker, Igor (May 2019). "Suicide Crisis Syndrome: A review of supporting evidence for a new suicide-specific diagnosis". Behavioral Sciences & the Law. 37 (3): 223–239. doi:10.1002/bsl.2397.

Entrapment

Measurement Validity: A Shared Standard for Qualitative and Quantitative Research

ROBERT ADCOCK and DAVID COLLIER University of California, Berkeley



Working bottom-up

Linehan et al. (1983): Discovering implicit categories using principal components analysis



I care enough about myself to live.

I believe I can find other solutions to my problems. I still have many things left to do.

I have hope that things will improve and the future will be happier.

I have the courage to face life.

It would hurt my family too much and I would not want them to suffer.

I would not want my family to feel guilty afterwards. I would not want my family to think I was selfish or a coward,

My family depends upon me and needs me.

I love and enjoy my family too much and could not leave them.

I am afraid of the actual "act" of killing myself (the pain, blood, violence).

I am a coward and do not have the guts to do it. I am so inept that my method would not work.

Linehan, M. M., Goodstein, J. L., Nielsen, S. L., & Chiles, J. A. (1983). Reasons for staying alive when you are thinking of killing yourself: The Reasons for Living Inventory. Journal of Consulting and Clinical Psychology, 51, 276–286. https://doi.org/10.1037/0022-006X.51.2.276

...

I	Feature 1	Feature 2	Feature N
item 1 item 2 item 3 item 4 	value 1 value 1 value 1 value 1	value 2 value 2 value 2 value 2	 value N value N value N value N

PRINCIPAL COMPONENT ANALYSIS OF THE REASONS FOR LIVING INVENTORY (VARIMAX ROTATION)†

Factor	Item Number	Loading (Range)
1	5, 11, 1, 9, 2, 6, 3, 10, 15, 21, 17, 8, 18, 19, 24, 22, 7, 20, 4, 12, 14, 13, 23	.77—.45
2	38, 35, 36, 37, 41, 44*, 43*, 42*, 39	.7957
3	25, 29, 26, 28, 30, 31, 27	.7648
4	32, 33, 34	.86—.67
5	47, 45, 46, 48	.80—.41

Osman, Augustine, et al. "Factor structure and reliability of the Reasons for Living Inventory." *Psychological reports* 70.1 (1992): 107-112.

Working bottom-up

COLLEGE IS GREAT AS LONG AS I DO NOT HAVE TO GO TO CLASS OR LEAVE MY ROOM. I DO NOT LIKE GOING OUT ANYMORE EVEN THOUGH I USED TO LOVE IT. NOW I JUST WANT TO SIT IN MY ROOM AND PLAY ON MY COMPUTER OR SLEEP. I DO NOT EVEN LIKE TALKING ON THE PHONE. THINGS I USED TO ENJOY, LIKE PEOPLE, I DO NOT ANYMORE. THEN THERE ARE THE CLASSES. I HATE ALL OF MINE. I FEEL LIKE SUCH A FAILURE. EVERYONE TOLD ME THEY WOULD BE HARD, BUT THIS IS RIDICULOUS. I CANNOT BELIEVE ANYONE CAN PASS THESE. I TRY MY HARDEST BUT THAT NEVER SEEMS TO BE ENOUGH. I KNOW I COULD SPEND MORE TIME ON MY HOMEWORK BUT WHEN I AM WORKING ON IT I GET SO WORN OUT I CANNOT THINK ANYMORE. THEN I REGRET NOT DOING IT. BUT IT IS LIKE A VICIOUS CYCLE. I AM SO EXHAUSTED I CANNOT THINK SO I SLEEP, THEN I WAKE UP EXHAUSTED AND I DO NOT HAVE ENOUGH ENERGY TO GO TO CLASS. THEN I DO NOT KNOW HOW TO DO MY HOMEWORK AND I GET DISCOURAGED AND IT TAKES ME TWICE AS LONG TO DO, SO I GET SO EXHAUSTED THAT I CANNOT THINK! THIS IS SO FRUSTRATING I FEEL LIKE THERE IS NO ONE IN THIS UNIVERSITY THAT CARES THAT I HATE IT HERE. ...

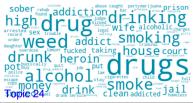
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Working bottom-up with topic models

Discovering implicit categories using topic modeling (Blei et al. 2003)

1	word 1	word 2		word N	
item 1 item 2 item 3 item 4	value 1 value 1 value 1 value 1	value 2 value 2 value 2 value 2 value 2		value N value N value N value N	
		exans V		high school states	
selor about college	s that I'd be able to get	into ar	emely graduate major	girlfriendpressure highschool	
-	ly called me worthless. I	graduated	ersity elementary s	chool courses schools exam due grade	,
		teacher	failure pare	ents ^{age} elementary sports test academic senior class	
· ,	eeing the negative side t	good senio	r_year startedfall	teachers graduation middle_school stress	
	om my senior year I migh	dropped s		failing hated middle home math freshman play	2
hing but stress. My	physical health is falling a	apart. terrib	le C finish faile	d program L bullied grades	'
m decently happy.I	just dropped out of colle	ge, be Topic	munity_college depre	junior triends community	



Topic 11 text

0.48050353 So, I'm a poor student (~2.8 GPA) at a good school. I've been talking to my college guidance counselor about colleges that I'd be able to get into a 0.47767672 Today I skipped school.....Got yelled at by my parents. Got compared to one of my actual friends..... My dad basically called me worthless. I start 0.45305499 Now matter how hard I try I don't think I can escape this depression. It all started over a fucking girl. Now I'm just seeing the negative side to eve 0.43119257 and I don't know what to, everyone including me expects me to go to college and now thanks to my shitty grades from my senior year I might not 0.39189101 I just feel like every area of my life is falling apart. My personal and professional life leads to nothing but stress. My physical health is falling apart 0.38730073 I'm considering suicide. I have struggled with depression and anxiety in the past, but right now I'm decently happy. I just dropped out of college, b

Example: Inferring population-specific categories from language

Notes	Valence	Regression value	Top 20 words
social engagement	р	-1.593	gar
social engagement	р	-1.122	game play football team watch win
social engagement	р	-0.89	na
social engagement	р	-0.694	music song listen play band sing hear
high emotional valence	e	-0.507	hor
somatic complaints	n	-0.205	party night girl time fun sorority meet
poor ego control; immature	n	0.177	yean wow minute name type runny suck minin guess oran oore gosh ugn stupit oad for ney :
relationship issues	n	0.234	call talk miss phone hope mom mad love stop tonight glad dad weird stupid matt email any
homesick; emotional distress	n	0.34	home miss friend school family leave weekend mom college feel parent austin stay visit lo
social engagement	р	0.51	friend people meet lot hang roommate join college nice fun club organization stay social to
negative affect*	n	0.663	suck damn stupid hate hell drink shit fuck doe crap smoke piss bad kid drug freak screw cr
high emotional valence	e	0.683	life change live person future dream realize mind situation learn goal grow time past enjoy
sleep disturbance*	n	0.719	sleep night tire wake morning bed day hour late class asleep fall stay nap tomorrow leave n
high emotional valence	e	0.726	love the happy person heart cry sad day feel world hard scar perfect feeling smile care stro
memories	n	0.782	weird talk use a search ti
somatic complaints*	n	0.805	hurt type head stop
anxiety*	n	1.111	feel worry stress study time sleep night tire wake morning bed day
emotional discomfort	n	1.591	feel time reason depress m hour loto close coloop fall story non
homesick; emotional distress*	n	2.307	hate doe sick feel bad hurt hour late class asleep fall stay nap

Supervised LDA topics from undergraduate stream-of-consciousness essays identified by a clinician as most relevant for assessing depression. Supervision (regression) is based on Z-scored Big-5 scores for emotional instability (neuroticism).

Resnik et al., Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language in Twitter. NAACL Workshop on Computational Linguistics and Clinical Psychology, Denver, CO, June 2015.

Example: Inferring population-specific categories from language

Notes	Valence	Regression value	Top 20 words
social engagement	р	-1.593	game play football team watch win sport ticket texas season practice run basketball lose so
social engagement	р	-1.122	music song listen play band sing hear sound guitar change remind cool rock concert voice
social engagement	р	-0.89	party night girl time fun sorority meet school house tonight lot rush drink excite fraternity
social engagement	р	-0.694	god die church happen day death lose doe bring care pray live plan close christian control 1
high emotional valence	e	-0.507	hope doe time bad wait glad nice happy worry guess lot fun forget bet easy finally suck fin
somatic complaints	n	-0.205	cold hot hair itch air light foot nose walk sit hear eye rain nice sound smell freeze weather
poor ego control; immature	n	0.177	yeah wow minute haha type funny suck hmm guess blah bore gosh ugh stupid bad lol hey
relationship issues	n	0.234	iny in the second se
homesick; emotional distress	n	0.34	hurt type head stop eye hand start tire
social engagement	р	0.51	
negative affect*	n	0.663	feel time finger arm neck move chair a
high emotional valence	e	0.683	OV OV
sleep disturbance*	n	0.719	stomach
high emotional valence	e	0.726	iro
memories	n	0.782	weird to crazy time sad stuff funny haven happen bad remember day hate lot sca
somatic complaints*	n	0.805	hur type head stop eye hand start tire feel time finger arm neck move chair stomach bother
anxiety*	n	1.111	feel worry stress study time hard lot relax nervous test focus school anxious concentrate pr
emotional discomfort	n	1.591	feel une reason depress
homesick; emotional distress*	n	2.307	hate doe sick

Supervised LDA topics from undergraduate stream-of-consciousne relevant for assessing depression. Supervision (regression) is base instability (neuroticism).

feel worry stress study time hard lot relax nervous test focus school anxious

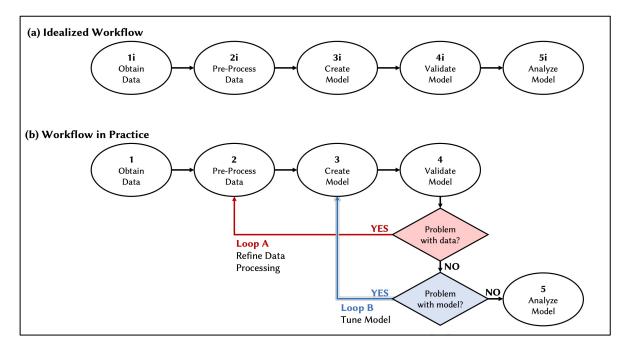
Resnik et al., Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language in Twitter. NAACL Workshop on Computational Linguistics and Clinical Psychology, Denver, CO, June 2015.

Problem: *All* computational models can produce garbage

"My Very Subjective Human Interpretation": Domain Expert Perspectives on Navigating the Text Analysis Loop for Topic Models

ALEXANDRA SCHOFIELD, Harvey Mudd College, USA SIQI WU, Massachusetts Institute of Technology, USA THEO BAYARD DE VOLO, Pitzer College, USA ALFREDO GOMEZ, Carnegie Mellon University, USA TATSUKI KUZE, Harvey Mudd College, USA SHARIFA SULTANA, University of Illinois, Urbana-Champaign, USA

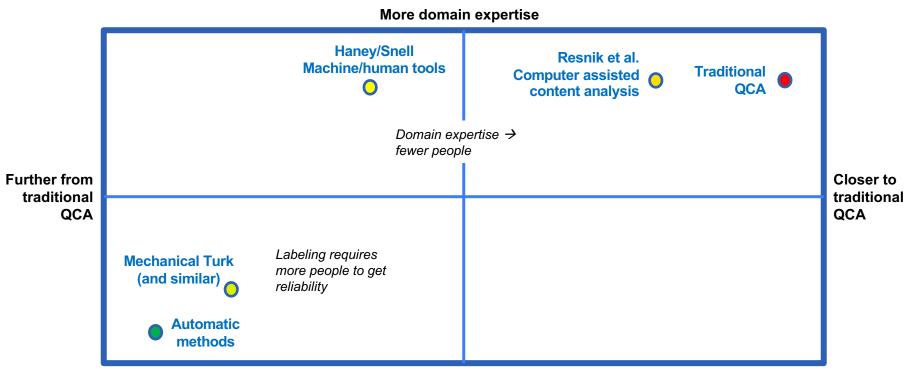




Automatically deciding if categories are good is hard: the case of topic models (LDA; Blei, Ng, and Jordan 2003)

- Good models of categories should predict observed documents!
 - Blei et al., 2003; Wallach, et al., ICML, 2009
- Uh oh: that approach does a bad job matching human judgments.
 - Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J., & Blei, D. (NeurIPS 2009). Reading tea leaves: How humans interpret topic models.
- Ok, here's an automated metric that correlates with human judgments!
 - Lau, J. H., Newman, D., & Baldwin, T. (EACL 2014). Machine reading tea leaves: Automatically evaluating topic coherence and topic model quality. [NPMI]
- Um, bad news: those fancy new neural topic models? Not really progress.
 - Hoyle, A., Goel, P., Hian-Cheong, A., Peskov, D., Boyd-Graber, J., & Resnik, P. (NeurIPS 2021).
 Is automated topic model evaluation broken? the incoherence of coherence.
 - Hoyle, A., Goel, P., Sarkar, R., & Resnik, P. (EMNLP Findings, 2022). Are Neural Topic Models Broken?

A (partial) landscape of approaches



Less domain expertise

For NLP, encouraging longer responses matters a lot!

A. How did your activities change during the COVID-19 pandemic? How have your activities changed, if at all, since lockdowns have eased?

B. Please write a few sentences, or more if you'd like, telling us how you have managed the COVID-19 pandemic and associated lockdown measures. Include discussion of how your activities have changed, if at all, before, during, and since the pandemic.

Device	Question	Responses_A	Average_length_A	Responses_B	Average_length_B	Difference (chars) Est di	fference (words)
Laptop or desktop computer	activities	437	151.99	420	274.62	122.63	20
Laptop or desktop computer	work	425	60.1	409	134.26	74.17	12
Laptop or desktop computer	symptoms	7	148.71	10	152.3	3.59	1
Laptop or desktop computer	vaccination	230	116.07	194	168.72	52.64	9
Laptop or desktop computer	needle_fear	439	72.17	437	78.94	6.77	1
Laptop or desktop computer	finances	437	95.41	375	124.97	29.56	5
Laptop or desktop computer	feedback	120	49.24	112	52.79	3.54	1
Mobile phone	activities	76	144.36	76	190.78	46.42	8
Mobile phone	work	74	64.57	72	110.5	45.93	8
Mobile phone	vaccination	39	100.03	45	101.73	1.71	0
Mobile phone	needle_fear	79	59.77	77	51.05	-8.72	-1
Mobile phone	finances	74	85.26	62	82.71	-2.55	0
Mobile phone	feedback	13	41.85	12	29.42	-12.43	-2
Tablet (with no separate keyboard)	activities	15	152.2	11	259.27	107.07	18
Tablet (with no separate keyboard)	work	15	63.4	10	79.4	16	3
Tablet (with no separate keyboard)	vaccination	9	193.11	4	76.25	-116.86	-19
Tablet (with no separate keyboard)	needle_fear	16	46.88	11	68.82	21.94	4
Tablet (with no separate keyboard)	finances	16	52.13	8	64.25	12.13	2
Tablet (with no separate keyboard)	feedback	4	84.75	1	14	-70.75	-12
Tablet (using a separate keyboard for typing)	activities	3	218.67	3	215.33	-3.33	-1
Tablet (using a separate keyboard for typing)	work	3	46.67	4	96	49.33	8
Tablet (using a separate keyboard for typing)	needle_fear	3	58	4	88.5	30.5	5
Tablet (using a separate keyboard for typing)	finances	3	105	3	106.67	1.67	0

TOPCAT Topic-Oriented Protocol for Content Analysis of Text

Scalable codebook development guided by topic modeling

Minimal technological requirements:

MALLET: See Graham, S., Weingart, S., & Milligan, I. (2012). Getting started with topic modeling and MALLET. The Editorial Board of the Programming Historian. <u>https://programminghistorian.org/en/lessons/topic-modeling-and-mallet</u>

Excel

A PDF viewer

TOPCAT: Topic modeling



Construct candidate models at multiple granularities Fast-pass or more rigorous manual rating of topic quality Selection of "starting point" model for curation

*Work in progress: automatic ranking of candidate models

docID	Topic 12	text										
4888	0.639	Decades a	go I swore I w	ould not mak	e my parents	look at me in a	a coffin. And I	swore I would	d never leave r	my son father	less. That is wl	hat kee
11853	0.632	I promised r	ny dad I woul	d never make	him cry when	n I was like 3 y	ears old. I am	now 28 and v	vill never brea	k that promis	e.	
8811	0.598	My best frie	nd. We had ju	ust lost our mo	other (her birt	h mom, who t	reated me as	her own), I kr	ew she could	n't handle losi	ng her and me	e too. S
13763	0.598	The though	of my mother	r having to los	e her younges	st child. She is	a strong wom	an but it wou	d break her. N	/ly friend had	only recently	died ag
312	0.596	My mother	lost a son 3 ye	ears ago I don	't want her to	lose another.						
13453	0.561	My burning	desire to not	have my mon	n lose both he	r father and o	ne of her sons	to suicide. Th	at woman has	lost enough.	I don't want h	ier to tl
8937	0.554	I watched m	y best friend'	s mother had	to be carried	out of her son	's funeral afte	r he killed him	self. I couldn't	t imagine doir	ng that to my n	nom. I
1976	0.553	My little sist	er being left a	lone with my	abusive parer	nts						
6558	0.553	Single mom	here. Didn't v	want to leave	my daughter a	alone.						

TOPCAT: Curation by subject matter experts

Specific family members

People were VERY specific about which family members kept them alive. They said things like, "I did not want my MOM, SISTER, DAD, ETC., to blame themselves." "I did not want to leave my grandmother, kids, or siblings, etc. to be without care."

sad extremely^{sick} MOT her grandma left single raised abus abusive attack kidchild promise brother siste worried break wife wife s live er daughter her daughter kids stave stay trailige daughter kids stave stay trailige daughter kids stave stay trailige daughter her daughter trailige daughter dad growing cancer grandmother young hell abuse man died parents passed topicerlest assed topic father step topicerlest assed topic father step topic father

The UB III

Protect my parents	Empathy for how this will impact one's
	parents, desire to spare them
	pain/devastation. "I couldn't do that to
	my mom/dad."

TOPCAT Curation by subject matter experts

- 4. Treating the column names of the document-topic spreadsheet (e.g. *Topic 1*, *Topic 2*, etc.) as a checklist, go through each one completing the following steps:
 - a. Sort the spreadsheet by that topic's column in descending (largest-to-smallest) order.
 - b. Set a timer for 120 seconds. This is simply to keep you from reading all the text responses in case they're interesting. You can use a cell phone, web browser or other timer. ("Siri [or Alexa], set a timer for two minutes!")
 - c. Skim the text column for the top documents to get a sense of what kinds of responses are strong on this particular topic. Also look at this topic's cloud in the PDF. Jot down common words or ideas under Description in the notes spreadsheet (discussed in Step 3, above).
 - d. You may find that documents you're looking at are about more than one topic. That's ok: you're not labeling documents here, you're looking at the documents to get a clearer understanding in your mind about what this column's topic is about.
 - e. Consolidate the notes you took in the Description column and give the theme a brief label or name in the Name column. Replace the original column header in the document-topic spreadsheet (e.g. *Topic 1*) with your new label.

f. If the tonic you are reviewing contains responses that are consistently similar to another

A	D	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	
docID	Topic 3	text											
3422	0.74	New comic	books came o	ut every week	, and series'	like Batman ar	nd Spider-Mar	will never en	d. So I might a	s well wait u	ntil after Wedn	esday.	
4529	0.735	I'm looking	forward to ne	ew episodes of	my favorite	tv shows. Nev	movies I liked	d. When I was	at the lowest	in my life my	favorite book s	eries hadn't f	finis
12473	0.72	Honestly it.	ââ,¬â"¢s wha	tever hobby I	had coming	up I could lool	k forward to. Å	Á¢â,⊸Å"AwIw	anna play tha	t video game	I have to stick	around to pla	ay it,
7195	0.679	Movies and	l Video games.	I lived in thes	e fantasy wo	rlds and alway	s wanted to s	ee the next ad	dition to come	e out. Its seen	ns silly but it wa	is my thing	
8181	0.679	It sounds st	tupid, but wait	ing for movies	or books to	come out. I'm	waiting for W	W84 and The	Winds of Win	ter, are helpi	ng. Plus I have	many books t	that
5330	0.677	star wars a	nd books. boo	ks are just a ni	ce way escap	pe from reality	. star wars is o	one of the few	things that ar	e making me	go forward.		
10188	0.651	Not wantin	g to miss Zelda	a breath of the	wild on Nint	endo Switch b	asically when	I heard about	that game fro	om the switch	I was basically	doing everyt	hing
5467	0.635	Sometimes	, the only thin	g you feel like	ou're hangi	ng around for	is a video gam	e that's comir	ng out or a mo	vie you wanr	a see. That's no	ot a good long	gter
2492	0.634	As stupid a	s it sounds, The	e Flash season	2 ended on a	a cliffhanger. I	wanted to stin	k around and	see how it pa	nned out			
16032	0.626	Sounds due	mb but I wante	ed to watch the	e last season	of Rick and M	orty						
4346	0.618	It sounds d	umb, but Dun	geons and Dra	gons (or tabl	etop RPGs in g	general). It wa	s always an ac	tivity I could le	ook forward	to, and a social	one to boot.	
8745	0.607	Not being a	ble to play the	e new video ga	mes. Sounds	silly, but I do	nââ,⊸â"¢t wa	nna miss out	on my passion				
15145	0.607	I gotta see	the ending of E	Berserk, One P	iece mayb	e a few more l	nxh chapters a	nd 2b like sex	bots.				
4553	0.605	I know it's	dumb, but find	ling out how s	ome TV show	vs, manga and	books plot we	ould unroll. Fu	inny thing mo	st of them ha	d shitty ending	s	
8353	0.605	Man, every	one has these	cool, noble re	asons, and h	ere I am just n	ot wanting to	miss out on n	ew seasons of	my favorite a	mimes That's	what's so coo	ab اد
11601	0.605	Waiting for	a good video	game to come	. Started wit	h Rainbow Six	Siege/Fallout	4, later Mode	rn Warfare. So	ometimes the	distractions wa	as all I really v	wan
14290	0.602	Sometimes	itââ,¬â,,¢s th	e littlest thing	that keep y	ou around. Fo	r me, it was ne	w books, mo	vies, and tv. I	would keep a	list of new boo	ks I wanted t	o re
6515	0.593	Iââ,¬â"¢n	too much of	a nerd. Before	i would thin	k, ââ,¬Å"I ha	ve to see wha	t happens in t	he next Star W	ars movieâ	â,¬. Ironically I	now hate tho	ose r
11635	0.593	I just wante	ed to see the a	vengers fight 1	hanos in the	MCU. It soun	ds silly but hav	ing something	g to look forwa	ard to at all ca	an be invaluabl	e when youÃ	¢â,-
10050							· ·	· · · · ·	• • • • • • • • • • • • • • • • • • •				





TOPCAT: Consensus step

Specific family members	People were VERY specific about which family members kept ther alive. They said things like, "I did want my MOM, SISTER, DAD, ET to blame themselves." "I did not want to leave my grandmother, kids, or siblings, etc. to be withou care."	pt them Sad working , "I did not attack kidniskow DAD, ETC., break wife did not cancer other, man kindis,		stowe child billing with the killed knew of the stowe alive put son leave blave friend yourg hell son bill betty mum reason	TML1 TML 0.0011 The interpretation of 2.500 (as a product on the sector) of 2.000 (b)	concerning the set of
	Prot	ect my parents		Empathy for how this will parents, desire to spare th pain/devastation. "I could my mom/dad."	em	
"Consensus" SMEs		Not wanting to family members	5.	ecific		

Time for some fun!

• Let's get dirty with some real data

https://tinyurl.com/topcat-tutorial