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LING 413

Final Project and Extra Credit

Term Project: Topic Models for Healthcare

Problem #1:

Gender	Sentiment (count and %)		Total (count and %)
	Positive	Negative	
Female	2953, 61.44%	1853, 38.56%	4806, 100%
Male	10616, 67.99%	4999, 32.01%	15615, 100%

The length of the smallest review was 0 tokens, and the length of the largest review was 4948 tokens. The average length of reviews was 341 tokens.

Problem #2:

No.	Questions	RateMD corpus	Healthcare company's corpus (i.e., reference corpus)
1	What is the language variety of the corpus (i.e., genre)?	Reviews written by RateMD users	Reviews written by patients of the company's clinics
2	What is the size of the corpus?	20,421 reviews	500,000 reviews
3	What meta-data is provided with the reviews?	Doctor's name, gender, clinic location, specialization, review sentiment	Doctor's name, gender, clinic location; review sentiment
4	What socio-demographic information is provided about the patients who wrote the reviews?	None	Gender, age, economic and educational status
5	Is the corpus balanced along the meta-data	No; there are more reviews for male doctors, and more	No (the dimensions are not uniformly distributed; they

	dimensions considered? (look only at sentiment and gender)	positive reviews than negative reviews	exhibit a natural distribution)
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One important disadvantage is that the reviews by RateMD users are anonymous, so there is no information about the patients who wrote the reviews. In fact, there is no proof that the review writers were patients. Assuming that the large majority of reviews are legitimate, this dataset can still be very useful due to its large size.

Task #2a

When cleaning the corpus, I chose to remove punctuation and numbers, lowercase everything, and remove stopwords. I also removed “doctor” and “dr” from the result, since those words appeared often and wouldn’t be a satisfactory result.

Without lemmatization

Without lemmatization, pre-processing took 0.5 seconds. The term dictionary contained 31,087 tokens.

With Set 1, the runtime was 2m57s. With Set 2, the runtime was 3m7s.

My results for Set 1, as well as an attempt at a manual label for each topic, are below:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Ambiguous	Ambiguous	Surgery	Children	Good service
would told never go back get see said even didnt	manner bedside patel good cardiologist tooth date listener heart annoyed	surgery pain surgeon cancer life procedure performed went back years	daughter son us child baby pregnancy children delivered old first	staff great feel made experience office professional friendly comfortable amazing

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Ambiguous	Recommended	Appointment	Treatment	Ambiguous
time always best great years	recommend would highly anyone excellent	office staff wait time appointment	medical treatment patient patients care	pediatrician weight stuff gyn pulled

patients patient staff feel like	staff caring knowledgeable care helpful	waiting rude get phone minutes	health condition years problem doctors	migraines theyre card environment welcoming
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There were a few vague topics such as Topic 1. For Topic 6, it feels like it could be positive, but there were not enough positive words for me to make a decision.

My results for Set 2:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Good service	High blood pressure	Recommended	Recovery	Ambiguous
smart lucky brain punctual average hearing forget considerate non cure	mother high blood pressure risk highest attack responded medicare denied	manner would bedside recommend feel great made anyone staff first	surgery pain went hospital procedure back cancer months vegas performed	years best life ever one doctors many patel ive would

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Ambiguous	Ambiguous	Good service	Ambiguous	Surgery
would told never office back get see said even time	billing super respectful annoyed prepared stupid price single corrected offers	staff recommend caring knowledgeable excellent great highly always helpful professional	time patients always wait like patient get really good never	surgery surgeon results happy knee excellent performed satisfied done procedure

Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
Bad service	Ambiguous	Ambiguous	Ambiguous	Costs

medical md clinic mean terrible thyroid agree practice across cold	ear drugs referrals w med diabetes reschedule anyway trained correctly	skin finding u anxiety lee pm dermatologist depression incredibly disorder	top guy broken ankle turn house stating whats demeanor nasty	insurance bill company teeth pay polite receive oral group smile
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Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
Treatment	Children	Ambiguous	Bad service	Ambiguous
daughter treatment diagnosis therapy condition options medicine pediatrician treatments conditions	son great feel children us makes kids comfortable knows love	god earth dealing bless town small retire switch delivering everytime	staff office rude front patients service good unprofessional worst poor	eye brown weight watch expert eyes quack smith loss please

I was not sure about labeling some topics even though I felt like there might be a loose correlation between words. Topic 20 had three eye-related words, but I didn't feel like it was enough.

Noun lemmatization

With noun lemmatization using WordNetLemmatizer, pre-processing took 3.1 seconds.

The term dictionary contained 28,950 tokens.

With Set 1, the runtime was 2m56s. With Set 2, the runtime was 3m6s.

My results for Set 1, as well as an attempt at a manual label for each topic:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Ambiguous	Ambiguous	Recommended	Ambiguous	Appointment
life saved dentist tooth teeth dismissed	informative father trained root whenever cavity	staff recommend would great highly excellent	manner bedside side bed sense sinus	office time never staff get see

uncaring glyman car pap	hormone avoided approachable rx	caring knowledgeable professional helpful	humor utmost recomend le	patient would appointment call
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Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Great service	Surgery	Ambiguous	Pregnancy	Family
time patient always care best take year feel great like	surgery surgeon procedure went result cancer performed breast done day	pain problem year told back would went month insurance said	baby pregnancy first pregnant medical child second life woman made	u daughter husband son heart child year hospital old mother

It was difficult to manually label many topics. For example, Topic 1 had both negative words (“uncaring”) and positive words (“saved”). I was not sure if I should label some topics as “ambiguous” if there were only about three words that seemed to fit. So, even though I labeled a few as “ambiguous”, the terms under that topic were not completely irrelevant.

For 20 topics:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Pregnancy	Great service	Fun	Recommended	Ambiguous
baby pregnancy delivered birth first made child ob high teeth	time feel always question take make patient care like great	sense dermatologist humor diabetes oral considerate afford complex mayo cured	recommend would highly anyone definitely friend knowledgeable wonderful recommended extremely	mark surgical smith gp reviewed removal shoe repair addiction nature

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Ambiguous	Appointment	Treatment	Ambiguous	Great service
year life husband son many old ago saved since month	time wait appointment hour patient see always minute waiting get	treatment patient problem medical condition health diagnosis concern issue year	told said would back went didn't never time see could	care excellent physician patient family caring compassionate knowledgeable staff friend

Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
Ambiguous	Surgery	Bad service	Ambiguous	Ambiguous
breast cancer face skin look result nose removed sinus antibiotic	surgery surgeon pain performed procedure went back knee great foot	mother front rude attitude desk tooth unprofessional away arrogant horrible	procedure hospital charge letter stated would completely caused also insurance	ever best ive one seen worst met far life illness

Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
Ambiguous	Ambiguous	Good service	Staff	Good service
u daughter child ear funny cardiologist annoyed	know don't patient care help go want	manner bedside good great pediatrician bed parent	office staff call patient rude insurance never	staff helpful great friendly office professional knowledgeable

dangerous husband born	doesnt like pain	kid listener allergy	get phone would	caring always knowledgable
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These results seemed to have more relevant results, especially related to good service. So, I think that Set 2 with 20 topics generates better topics.

Verb Lemmatization

Verb lemmatization using WordNetLemmatizer took 3.4 seconds. The term dictionary contained 27,234 tokens.

With Set 1, the runtime was 2m45s. With Set 2, the runtime was 3m16s.

My results for Set 1, as well as an attempt at a manual label for each topic:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Dentist	Recommended	Ambiguous	Treatment	Emotions
dentist teeth mom weight root tube wisdom gain sincere cavity	care staff great time recommend best always take years would	go tell would husband say hospital daughter baby could look	medical treatment patient condition diagnose test diagnosis patients treat health	informative luck disorder happier expectations utmost augmentation reccomend emotional strongly

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Surgery	Medication	Appointment	Costs	Good service
surgery surgeon procedure perform recommend would pain glyman result knee	pain help prescribe vegas meds cause medication back life drug	time get office go see call wait staff never tell	insurance pay bill charge company cost cover receive ear service	manner bedside outstanding manners timely genuine respectful ankle lack focus

These topics could be manually labeled effectively, except for Topic 3.

My results for Set 2:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Pain	Ambiguous	Ambiguous	Ambiguous	Recommended
pain vegas suffer back help severe las complain cause meds	heart mother father cardiologist hospital speak family brain die medical	go get tell call office see time say never wait	poor lack md communicate retire routine improve lee communication doubt	recommend would make highly feel anyone comfortable staff great go

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
Ambiguous	Good service	Treatment	Good service	Family
prescribe review drug sign comment look read medication bad negative	staff office time helpful wait always great friendly good son	explain treatment procedure detail options procedures result receive experience give	care excellent manner bedside patients patient physician knowledgeable great staff	us daughter wife nose old husband pediatrician earth ms bear

Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
Ambiguous	Surgery	Thankful	Thankful	Service
surgery work breast go result back years surgeon	surgery hospital surgeon go perform husband eye procedure	cancer god skin thank daughters thyroid scar remove	life save say side cant enough doc years	question answer ask time concern baby call always

look pain	months days	bless incredible	bed thank	rush phone
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Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
Good	Ambiguous	Ambiguous	Costs	Bad experience
best care know ever time take like see really always	young glad spot face w assistants house whats botox wall	years care time see take patient many find health issue	insurance bill pay company cover charge extra cost receive accept	rude ever worst arrogant experience awful horrible terrible attitude condescend

For k=20, the topics were slightly easier to label, and there seemed to be many with a general narrative.

Problem #3:

Lemmatization does not take much time compared to the runtime of the LDA models, so at least for this amount of data, the runtime is not an issue. Compared to no lemmatization, I did not see a significant difference in the goodness of topics for k=10, although verb lemmatization may have been slightly better for both k=10 and k=20. The comparison is complicated by manual labeling of each topic, which was very difficult because there is often no clear answer. So, if I labeled everything again, I would likely end up with different results. There were very rarely topics that were as clear as Topic 20 for verb lemmatization, where almost all words are negative. It may be possible that adding more words to the list of stopwords could change this outcome.

Task#2b

The runtime of cclDA for 10 topics and 2000 iterations was 36 minutes, far longer than the previous runtimes. The results were impressive, with the positive reviews (Collections 0 and 2) clearly showing positive terms, and the negative reviews (Collections 1 and 3) having mostly negative terms. For that reason, these results were better than the ones I had obtained in Task #2a. The overall top 10 words were not always as clear, such as in Topic 2, so those were much noisier. This might be fixed in the pre-processing with more stopwords and names removed. The results are in the table below:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
patients	like	dreher	years	surgery

<p>dreher care patient medical health one physician ever practice doctors knowledge well needs person find medicine treatment seems may -Collection 0 caring best excellent compassionate cares truly knowledgeable listens kind difficult personable competent outstanding genuinely intelligent rare physician lucky wonderful thoughtful -Collection 1 unprofessional poor lack license malpractice appears zero impatient inappropriate careless decision patronizing ego lawsuit abuse files revoked disrespectful physical confidentiality -Collection 2 best caring cares truly listens well compassionate</p>	<p>dreher dont go know im ever want doesnt going say one never child people see think baby even need -Collection 0 always love shes best amazing delivered awesome children pregnancy obgyn baby fantastic kids knows sweet honest pregnancies top high delivery -Collection 1 worst rude horrible shes money attitude insensitive dog weight yelled basically lose whatsoever disrespectful hodges rudest afraid hurry zyrtec nahra -Collection 2 hes love best always great wonderful amazing</p>	<p>would staff recommend manner bedside anyone helpful good extremely experience great family friendly patient caring care ever best nice -Collection 0 highly great knowledgeable excellent wonderful recommend professional friends caring understanding smart personable amazing recommended jacobson pleasant gentle courteous informative reassuring -Collection 1 rude worst uncaring horrible stories rawls lacks judgemental horror changing sarcastic nasty lacked futrell bonakdar abortion misdiagnoses snippy anger blau -Collection 2 great highly excellent caring knowledgeable kind recommend</p>	<p>doctors dreher problem ive seen one problems issues found many several find since times treatment ever specialist seeing help -Collection 0 years best great ive shes family love knowledgable well helped seeing listens many concerns gyn drive addressed obgyns overall weiss -Collection 1 cold awful test shes worse condescending arrogant wrong incompetent basic gyno sometimes refuses harwer bother false questioned cutlip sesslar swamy -Collection 2 dreher years recommend many always would problems</p>	<p>pain dreher would procedure back went surgeon done left one months breast two removed look performed knee second work -Collection 0 skin dermatologist happy pleased cancer lee treatments friend recently beautiful bonakdar dermatologists skilled dermatology javan happier melanoma sister implants annual -Collection 1 skin woman cancer routine please insisted mri gmitter fibroids suppose cost pulled supposed yearly iud levy hanging kolb responsibility formal -Collection 2 surgery surgeon amazing performed recommend recovery happy</p>
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always excellent physician kind outstanding knowledgeable trust top takes understanding really family dreher -Collection 3 doesnt man lack license opinion instead life unprofessional beware board alone lacks seems ego rudest total towards angry zero comes	really years family children delivered son knows awesome ive daughter guy kids obgyn -Collection 3 hes guy money horrible dont bad worst stay man wrong please believe life jerk heard basically maybe place treat drug	wonderful professional knowledgable thorough personable manner compassionate pleasant friends concerns definitely efficient awesome -Collection 3 rude terrible worst arrogant poor uncaring horrible awful condescending unhelpful cold attitude enemy whatsoever inconsiderate wish abrupt lazy shame warn	best anyone recommended highly care patient extremely thorough friends helped seeing say need -Collection 3 worse worst go failed dismissive opinion response arrogant something idea agree seeking disappointed cost someone expensive notes favor pompous wasted	highly shakiba excellent results surgeries rivadeneira job schwartz thank ago procedure plastic explained -Collection 3 surgery never still nothing worse bad mistake fix spine away spinal side mri xrays cut bone causing disc show nerve
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Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
time wait office appointment see get minutes waiting room dreher long staff never seen hours patients hour one even late -Collection 0 always helpful great thorough takes knowledgeable spends	office staff call insurance get phone never even calls rude new back called results would service patient make appointment medical -Collection 0 dreher staff efficient helpful mccormack able nice	dreher us husband hospital life son medication daughter help old could care years mother year would meds heart took take -Collection 0 life helped thank saved kolb grateful thanks	dreher time questions feel made like felt concerns answer sure never really experience make also always care listen rushed explain -Collection 0 takes caring thorough feel comfortable professional friendly	didnt back went told said would see even could came got asked first go called get wanted wasnt blood another -Collection 0 really time took found good everything wish

friendly wonderful sometimes doctors lot needed need worth though willing quickly within answers -Collection 1 waited unprofessional hour money pm left unfortunately avoid neither dermatologist unacceptable reschedule apology dirty arnold terms finally flu unorganized products -Collection 2 time dreher always takes questions good nice doctors patient patients also needed easy sometimes helpful knowledgeable lot need worth wait -Collection 3 another hours left room waited hour back minutes got finally reschedule anything thing	hollie use working satisfied appreciate clean taylor calls continue welcoming available busy glazer -Collection 1 refused terrible stay week later unless cancelled cash months melissa disorganized paid requested leaving hollie code messed yu kristensen welch -Collection 2 dreher staff office good great helpful care see friendly work personally doc person everyone nurse nurses clean people impressed needs -Collection 3 unprofessional called paid refused money wife company incompetent sent pay unless months charged	daughter pediatrician expertise incredible daughters miller world wonderful impressed woman today wife women -Collection 1 let ignored pills report nasty cough fluid misdiagnosed spinal needless mri mistakes quack means fine file legal lazy stated warning -Collection 2 life thank pain years saved helped grateful man cancer treatment best god back treated referred today free quality knowledge thanks -Collection 3 pain man refused even told wrong misdiagnosed er med pills though ignored caused	kind makes ease easy explains explained attentive warm listened trust confident answered punctual -Collection 1 unhelpful waste seem angry disappointed impersonal acted dismissive speaking lost whitney supposedly probst unfriendly uninterested thorough value another bad gliksman -Collection 2 staff feel comfortable great friendly takes professional ease everything helpful wonderful makes answered experience explained thorough explains took everyone well -Collection 3 didnt rude like seemed waste unprofessional acted interested seem difficult return cold became	right hope personally beyond glad weight knew barry sure little bit plan hamersley -Collection 1 told said pap refill control l asked desk medicine pill pelvic records birth seconds diet despite ridiculous obgyn mccormack wasted -Collection 2 first like one better took right time able day could hospital husband way going every much sure well problem listened -Collection 3 told said asked mri test nurse telling tried stated report later already neurologist
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trying walked dirty obviously pm paperwork explain	avoid billing correct script reason elsewhere billed	addict body second turned records meds complained	seems little uncomfortable comment wasting communication behavior	comp insisted saying letter medicine complete thats
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The runtime for cclDA for 20 topics and 2000 iterations was 40m45s. These results were noticeably not as good as the previous output, such as in Topic 1 Collection 0 where the results are very vague. However, the terms under each collection were mostly very good, with most of them being positive for positive reviews, and negative for negative reviews. The results are in the following table:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
dreher ever one ive doctors seen years far never met since many dentist going absolutely seeing times gone around come -Collection 0 best mclaughlin remembers gentle piper thoughtful notch elle de la kaye adore et doyle trs en specialty shah que je -Collection 1 worst flu mistake swamy	time questions dreher concerns answer always patient listen explain ask things question everything rushed answers answered issues talk understand took -Collection 0 takes caring thorough listens explains spends extra attentive punctual thoroughly loved gives eubanks wonderfully intelligent perfect easy types allen kakoulas -Collection 1 waste uncaring impersonal hodges	feel made like make felt dreher sure really makes going much well never better im making feeling way every understand -Collection 0 amazing comfortable great ease easy listened earth taylor polite incredible young fortunate soviero awesome salzman understands truly smiling dreher wonderful -Collection 1 worst probst sesslar privacy	go never see like else need want even someone would know back dont work wouldnt people treated get anything way -Collection 0 love kind sweet koster amazing beyond miss weiss area little compared upbeat previous kemp searched yu gyns beer busy montgomery -Collection 1 unprofessional rude stories careless	dreher care patient physician years family professional well doctors health many found issues practice kind find extremely several primary compassionate -Collection 0 knowledgeable thorough personable compassionate knowledgable smart recommended intelligent pleasure woman considerate understanding approachable responsive thoughtful use block diagnostician greatly ages -Collection 1 dismissive rawls handle indifferent

gyno gum fault uninterested mouth mis fitzgerald tonya excess thinks infact could prescription chipped eskam harwer -Collection 2 best hes gentle always fantastic ive need amazing teeth drs professional dental davis job smile understanding incredible newman respectful man -Collection 3 worst stay away rudest well lies sloppy reputation disability sucks temper simple difficulty cavities misfortune type inappropriate sedated unfounded relative	incredibly preached unresponsive leopold adofo hallway assuming results unkind demeaning hell incomplete overheard compensated unprofessionalism insufficient -Collection 2 takes always caring listens questions knowledgeable explains took kind answers thorough answered explain spends thoroughly available professional gives detail every -Collection 3 rude doesnt waste seemed interested wasted wasting response annoyed defensive distracted seem argumentative internet snow sign wo business smoke intake	messed offensive litleton barkan encounter frustrating another julia mahon customers ptsd dnc kulkarni runny men obviously -Collection 2 feel comfortable staff great wonderful ease everything love happy easy hands confident explained makes calm taken visits appreciated explaining positive -Collection 3 bad worse didnt arrogant problem jerk cold mistake bother sarcastic listen ok communication creepy condescending humiliated attempted prepared gun vulnerable	barclay please hudson inappropriate ten messed idiot inexperienced joykutty falling helpless disgrace caterson recommend abusive hateful -Collection 2 dreher anyone would wonderful kind caring friend humor cant sense treats trust everyone respect whole good else helps anywhere love -Collection 3 rude horrible condescending didnt please nasty shouldnt enemy yelled told word horribly rudely unless loud report mean hateful repeated badly	ira practitioner sarcastic michaelson exploring january liability warranted inaccurate lying factory guinea un interrogated alnief roomdid -Collection 2 caring excellent knowledgeable compassionate thorough kind also extremely skilled outstanding exceptional top intelligent warm lucky considerate notch fortunate personable diagnostician -Collection 3 opinion another ego mckay impossible negligence levine oxygen disrespect downright catheter notified partner turns unwilling factory disease language unreliable outpatient
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Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
time wait appointment	staff office dreher	call get called	test tests results	first baby went

room minutes see waiting long hours hour waited visit late office times seen another get exam least -Collection 0 knowledgeable always sometimes wonderful worth quickly quick within addressed rawls yearly available emergencies checkup quite mind though seeing kirsten efficiently -Collection 1 unprofessional unhelpful worse chart arnold yearly unfriendly vegan whitaker barry sojourner pelvic canceled diet dingy showed apologies shell slice shouldnt -Collection 2 time patient dreher see get wait always need long	nice rude always front nurse great experience extremely friendly good desk service knowledgeable also practice needs helpful -Collection 0 friendly helpful professional pleasant efficient courteous jacobson welcoming prompt machado knowledgeable fantastic easy organized midwife hill accommodate samuels accomodating wagner -Collection 1 rude incompetent hollie disorganized nasty pincus nahra gliksman gulati blackburn glazer petok wedlow slightly strictly snippy cap worthless dated neither -Collection 2 helpful friendly professional knowledgeable everyone experience pleasant courteous efficient	office appointment phone back calls day new days next return appt never nurse see even make would -Collection 0 always personally great promptly glazer fit wonderful kim sick allan though booked wedlow smile croft jensen female hope alexander cool -Collection 1 terrible desk requested oh ignored elsewhere excuse werner insensitive accepting didnt serious derm nath asking clerk mammogram impatient bruscato skip -Collection 2 dreher staff day office one right personally quickly see	blood diagnosis problem saw diagnosed opinion condition went needed second specialist found wrong symptoms treatment another took -Collection 0 caring warm explained able rare terrific impressed detailed suggestions provided schoenberg improvement carefully small morgan style walker pipan hamilton checks -Collection 1 awful pap condescending yu lost wasted stated lazy tap goldhaber cutlip dosage doshi smears steer varhola cdc misinformed means untreated -Collection 2 treatment problem thorough problems condition recommended explained doctors aviv	pregnancy pregnant going would weeks also due saw months even got birth everything second high every experience -Collection 0 delivered obgyn pregnancy babies helped supportive beautiful pregnancies hamersley calm deliver evans fantastic delivery throughout takoudes hope encouraging feigel adofo -Collection 1 told I died stay suppose levy iud placed smell pull easily besson unsympathetic bc depo dose table mistreatment weeks dilated -Collection 2 amazing delivered shakiba dreher obgyn helped wonderful first well
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needed worth sometimes little doctors spent every though much within drive -Collection 3 back finally got didnt obviously walked ask showed place reschedule gross consultation appeared slow acted martinez outrageous waited wife hallway	personable kind polite knowledgable overall tye super informative prompt nurses punctual -Collection 3 rude unprofessional incompetent unhelpful uncaring dirty disorganized unfriendly training hippa unpleasant unresponsive inconsiderate type late employees trash okay clueless system	follow issue home hospital kind work night etc used following de -Collection 3 told asked go stated still unprofessional refused letter saying telling manager goodman canceled apt needless practitioner paperwork med stand screamed	diagnosed cancer kakani immediately options treated diagnosis several found knew impressed -Collection 3 done nothing chart dismissive requested refused failed send arrogant idea mris tried incorrect advised insisted grua prostate frustrated incompetence fatigue	healthy happy pregnancy awesome brown around husband little throughout mind pregnancies -Collection 3 told blood apparently mess signs alone hit threatened insensitive jabara dx iui back induce moruzzi ivey listen steroids allergic mistake
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Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
insurance office visit money medical pay would even refused bill billing work paid company records service could information told cost -Collection 0 pleased mccormack trust hollie knowledgeable continue awesome plan	surgery pain back hospital went months knee two left surgeon still neck able later weeks surgeries year foot performed much -Collection 0 excellent awesome friend skilled arnold nicely healing painless	would recommend dreher anyone surgery procedure results happy definitely breast experience look done looking great surgeon work extremely well recommended -Collection 0 highly professional family friends everyone reassuring lot javan	told said didnt went back asked got could came even left see wanted took another go never wasnt right gave -Collection 0 found skin happy dermatologist lee glad barry dermatologists	patients care patient medical dreher needs health practice cares knowledge trust concern compassion best treatment personal person respect medicine many -Collection 0 caring excellent truly cares outstanding satisfied provides genuinely

brilliant issue informative confidence sarah cigna til holistic tattoo superb real monique -Collection 1 worst license melissa supposed kristensen welch straw nexium neither incorrectly refuses revoked refund note errors lawsuit notify oath besides vanessa -Collection 2 dreher care staff pleased satisfied received without team every happy clinic attention continue services necessary service impressed procedures unlike detailed -Collection 3 wife dollars lied paid charged refund fraud request refuses sorry dishonest accident explanation thousands	levy littleton reccomend docs colyer rather pros cons mohs barclay system understand -Collection 1 hysterectomy iv fluid kolb experiencing appalled urine vaginal vagina bags discover woo watching contacted hired chastised intimidate liters discuss rely -Collection 2 surgery surgeon recovery performed first free ago recommended replacement fusion hand thank surgeries job surgeons also yoon team outcome orthopedic -Collection 3 mri cut comp nothing fusion disc please bone er nerve pa screws xrays denied	happier understanding confidence expert recommendations chun fantastic cooper mary conservative dallas jones -Collection 1 disrespect ruined pezzello bonakdar autistic nausea heartless toxicity puss wessman scam snappy intake torment honey k dermatology disfigured traumatized jawline -Collection 2 highly recommend staff amazing surgeon pleased friends excellent results happier nose plastic expectations augmentation greco needing natural talented clark surgeries -Collection 3 awful nose fix mistakes correct scar worse mistake revision favor uneven tip crooked stomach	bonakdar dermatology melanoma treatments trehan products laser acne ensure sun annual spots -Collection 1 rude horrible refused seconds mccormack beware gmitter dirty medication pill enemy loud blamed insisted harwer angry upset wed disorganized werent -Collection 2 done procedure could surgery rivadeneira better schwartz found exactly met everything skin glad days concerned schlessinger made brain detail surgical -Collection 3 said get kept nurse upset man throat brain cold door reason thats let dismissed	exceptional received harwer puts mile kindness stays difficult genuine matter hammack mensah -Collection 1 lack zero rudest confidentiality pathetic files whatsoever unpleasant patronizing futrell paycheck screamed trubish krosi woman instructed wing carried genital discriminated -Collection 2 well cares truly listens physician compassionate family outstanding understanding excellent field beyond attentive physicians genuinely expertise caring extra genuine mile -Collection 3 lack man license attitude unprofessional board empathy pompous revoked retire choi impatient lacks public
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dropped exact demanded dare minute big	messed screwed complaining complained second ignored	botched promised lipson button schlessinger chin	buy stupid reply lie cruel raised	anger danger privacy provides verbally wonder
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Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
life dreher years one would enough could say help every way cannot still cant cancer much believe doctors god thank -Collection 0 kolb thank saved grateful needed thankful expertise implants women fountis drive illness gulati blessed closely angel weight reddoch breast explant -Collection 1 woman whitney garrett overweight kelly ray dey uba ending pass worse susan ford truth	help medication problem treatment get meds problems medications find take better medicine also prescribed pain seeing taking without treat give -Collection 0 years really helped listens compassionate willing helps whole natural welch proactive nancy steen emails insightful nahas peers lukawski humor scheinost -Collection 1 cough malpractice mistakes unknowledgeable zyrtec sells sued confusing ryan label trinh hurried duties hound	dreher good manner bedside job person experience really seems talk doc side knowledgeable kind problems best helpful skills caring bed -Collection 0 great excellent wonderful understanding listener lisa straightforward accurate nonsense andrews importantly regularly carol stein sincere communications role gyno appreciation fitting -Collection 1 poor taylor judgemental rudeness madoff step roland insane randak lunder bluntly defensive borderline accused	us dreher husband son daughter old year hospital family child mother going took care also heart wife well never see -Collection 0 love great wonderful children kids thanks pediatrician miller loves fabulous born fantastic nahra gentle lucky team blessing anna ray amorapanth -Collection 1 cold incompetence prescribed throat quack similar breastfeeding ramer inserts warning apology carla heads siudmak	dont know doesnt like im think people get want take say going good cant tell thats reviews bad doc wants -Collection 0 shes ive nice knows appreciate honest stuff straight forward approach bit nonsense blum retires arent busy surprised wright respectful condescending -Collection 1 shes money avoid disrespectful yelled unfortunately dollars per conclusion value tag furious unacceptable means

messed meshe germano recorded koster accusing -Collection 2 life thank man saved grateful best thanks knowledge thankful god better confidence quality brilliant skill team husband found forever bless -Collection 3 man arrogant avoid angry stop ruined beware zero malpractice shocked excuse add oath warning nightmare sued x convinced actions witness	sporn caught forbid insurer interrogating assumptions -Collection 2 years helped dreher many able issues willing seeing worked right others listened approach helping gone treatments hard hope past since -Collection 3 drug simply addict believe head another supposed legal real mg iv basically smith self floor failure spouse sports hell including	looked brained navarro traditional rather authorities -Collection 2 great excellent wonderful manner knowledgable awesome easy knowledgeable smart fantastic listener earth personable fabulous terrific puts around internist depth bedside -Collection 3 poor horrible terrible uncaring unhappy run whatsoever appears abrupt demeaning impersonal disinterested einbinder vet adjei timson behavioral wannabe staffing impolite	ineffective teasley rakovshik breastmilk curry decides -Collection 2 years always love family children great wonderful kids son loves referred pediatrician caring friends seen since patel trust born members -Collection 3 months died infection father turned flu supposed chest er dad yelling ended spoke caused misdiagnosed questioned wheelchair nasal careless insulting	cancelling samuels cancels malkin unorganized allen -Collection 2 hes good really nice knows like things guy one lot say make work sure forward honest busy stuff straight important -Collection 3 hes guy money wrong meds elsewhere quack touch basically horrible hed ignorant act copy hell hot luck violation shame cuz
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Extra-credit problem:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
fisher unfriendly diagnostician complain root understands trained average	worth spend skilled walked paid ordered father pediatrician	vegas las recomend comeau turn stent responsive students	uncaring earth end throat foot mean ent husbands	couple dad calm certified non retired till arthritis

mental sympathetic	personally comments	greatful single	insensitive unless	credit pusher
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Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
disorder theres aloof avoided texas rushing hasnt reccommend calming weakness	staff great time office would good best recommmend always care	dental price helpfull class pains feet lift trustworthy language drop	highest appropriate superb gp effective meticulous thompson twenty west contacting	punctual brown efficient informative tooth mind considerate gentle ankle alive

For 20 topics:

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
greatest dismissed jerk plenty theres j definatly lived till allows	satisfied good intelligent willing punctual shows children ease conditions spends	extra mile puts charge whenever price samples request reads staffing	informative dental involved smith lets gp liver notch upper medicines	vegas las foot skin half mark including body comforting allow

Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
broken root understands environment trained sharp pains break pas signed	fisher manor pulled faith hernia unwilling advance tummy obnoxious injured	spot manage nightmare proved greatful payment impersonal tonsils appeared judgmental	smart quite throat nose receptionist agree current customer tells manager	staff great time office would best recommmend always care years

Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
recomend solve students hurried medicaid slow individuals food perhaps valued	rushes ankle ego partner trustworthy mayo greedy impression taylor acomodating	lee dad father ms sucks miller recieved feet thompson license	pediatrician pushed class happens texas feelings accommodating injuries friday permanent	considerate migraines sincere annoyed via sleep forget hysterectomy sympathetic impatient

Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
town difficult whats end refill idea zero provider stars school	ensure bladder losing meticulous qualified professionals language adult relative contacting	cosmetic leaves reschedule dermatologist page talented knowlegable cancelled ears rudest	son appt kids breast listened check meds due children fantastic	visiting changes saver cyst welcoming aloof importantly professionally encouraging recommends

The output isn't totally irrelevant, but it does seem like many topics are noisier than without tf-idf. So, the output topics from Task #2a appear to be better.

b) In my opinion, tf-idf might be useful on its own for topic modeling, but with LDA, there is no need to give weights to words because it does not just take the top 10 most frequent words.