Text Mining

A sentiment analysis of Amazon book reviews

Team Autodesk Adoption

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The dataset

reviewTime	unixReviewTime	summary	overall	reviewText	reviewerName	asin	reviewerID
02 26, 2010	1267142400	"With Wings Like Eagles" Soars!	5	Michael Korda's hi	Gurman Singh Bal	61125369	A1UBELZ7KJCE4Z
06 27, 2010	1277596800	Scarpetta on the case	4	I really thought Sc	Janet M. Gruen "bookworm51"	006112740X	A1EVO3EVXEQTMC

	reviewTime	STRING
machinelearning-196501:machineLearningDataset.amazonBooks	unixReviewTime	INTEGER
7.78 GB	summary	STRING
8,898,041	overall	FLOAT
Feb 27, 2018, 3:10:32 PM	reviewText	STRING
Feb 27, 2018, 3:10:32 PM	reviewerName	STRING
Never	helpful	INTEGER
US	asin	STRING
None	reviewerID	STRING
	7.78 GB 8,898,041 Feb 27, 2018, 3:10:32 PM Feb 27, 2018, 3:10:32 PM Never Edit US	machinelearning-196501:machineLearningDataset.amazonBooks 7.78 GB summary 8,898,041 overall Feb 27, 2018, 3:10:32 PM reviewText Feb 27, 2018, 3:10:32 PM Rever Edit helpful US None

Sentiment Analysis

Steps:

- 1. Tokenize documents
- 2. Stem words and remove stop words
- 3. Join a dictionary that includes sentiment scores
- 4. Calculate score

Step 1: Tokenize Documents

	asin ‡	reviewerID ‡	overall ‡	reviewText
54751	1935627880	A3E2ET9QG1723S	5	What I loved about this book was the way that Chris has bo
43237	0966398130	A2F92M62KN324B	5	I liked it so much I bought a copy for one of my buddies. O
17312	0802723527	A1ZVELOA9LU4MR	4	Disclaimers: I received an e-galley of this book in exchange f
37938	061566069X	A25OT2WVEKP6HR	5	I am going to keep this review short I wasn't planning on r
26588	0062316869	A2IRQY7MU5RTZ8	5	I enjoyed the book very much and have told several of my r
725	0345485920	A3OS2OTE09QOOX	2	I bought this book thinking it would be something that wou
33265	0380804204	A3GG2QNXWFA3EK	5	I just found Ford two weeks ago, and I can say with a big sm
39482	0739458213	A1IPN9RNZGJ4BP	5	This book grabs your attention starting on page one, plus it
47208	1449361323	A30B0G0ClOOSQ2	5	As the authors discuss in the preface to this text, the conten
57146	B009THFEVA	A17DSQRFTCMRQ3	5	I enjoyed puzzles and quizzes, works my brain and is fun! Gr
21284	1494400626	A1SH3H8CWM8ECA	4	Now I see why this was my sister's favorite book when we w
26988	0131576070	A1K9IW99EFBZ52	5	I recommend this book with two others: Ed Brodow'sNegoti
46174	1416912045	A24EON2HWZJVN8	5	Neal SHusterman is such an underrated author, UNWIND w
7345	1450590497	ASJ3RS87GL3VD	3	This story rambled about a young Christian woman who lea
3498	0142410705	A28GMX5NXCV4OT	3	I love John Green, and probably have tremendously high ex
39568	0739458213	A3IKTWWTPQJNOF	5	This book was recommended to me by a professor. I was pr

asin 💠	reviewerID ‡	overall ‡	word ‡
1935627880	A3E2ET9QG1723S	5	what
1935627880	A3E2ET9QG1723S	5	
1935627880	A3E2ET9QG1723S	5	loved
1935627880	A3E2ET9QG1723S	5	about
1935627880	A3E2ET9QG1723S	5	this
1935627880	A3E2ET9QG1723S	5	book
1935627880	A3E2ET9QG1723S	5	was
1935627880	A3E2ET9QG1723S	5	the
1935627880	A3E2ET9QG1723S	5	way
1935627880	A3E2ET9QG1723S	5	that
1935627880	A3E2ET9QG1723S	5	chris
1935627880	A3E2ET9QG1723S	5	has
1935627880	A3E2ET9QG1723S	5	bound
1935627880	A3E2ET9QG1723S	5	together
1935627880	A3E2ET9QG1723S	5	two
1935627880	A3E2ET9QG1723S	5	love
	1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880 1935627880	1935627880 A3E2ET9QG1723S	1935627880 A3E2ET9QG1723S 5

Step 2: Stem Words and Remove Stop Words

*	asin ‡	reviewerID ‡	overall ‡	word ‡
1	1935627880	A3E2ET9QG1723S	5	love
2	1935627880	A3E2ET9QG1723S	5	book
3	1935627880	A3E2ET9QG1723S	5	chris
4	1935627880	A3E2ET9QG1723S	5	bind
5	1935627880	A3E2ET9QG1723S	5	love
6	1935627880	A3E2ET9QG1723S	5	story
7	1935627880	A3E2ET9QG1723S	5	separate
8	1935627880	A3E2ET9QG1723S	5	generation
9	1935627880	A3E2ET9QG1723S	5	bring
10	1935627880	A3E2ET9QG1723S	5	overlay
11	1935627880	A3E2ET9QG1723S	5	ellie
12	1935627880	A3E2ET9QG1723S	5	central
13	1935627880	A3E2ET9QG1723S	5	character.ellie
14	1935627880	A3E2ET9QG1723S	5	raconteur
15	1935627880	A3E2ET9QG1723S	5	diary
16	1935627880	A3F2FT9OG1723S	5	agony

	word ‡	lexicon ‡
1	a	SMART
2	a's	SMART
3	able	SMART
4	about	SMART
5	above	SMART
6	according	SMART
7	accordingly	SMART
8	across	SMART
9	actually	SMART
10	after	SMART
11	afterwards	SMART
12	again	SMART
13	against	SMART
14	ain't	SMART
15	all	SMART
16	allow	SMART

•	*	stem ‡	term ÷
	182	abolish	abolishes
	183	abolish	abolishing
	184	abolition	abolitions
	185	abolitionist	abolitionists
	186	A-bomb	A-bombs
	187	abominate	abominated
	188	abominate	abominates
	189	abominate	abominating
	190	abomination	abominations
	191	aboriginal	aboriginals
	192	Aborigine	Aborigines
	193	abort	aborted
	194	abort	aborting
	195	abort	aborts
	196	abortifacient	abortifacients
	197	abortion	abortions
	Showin	g 183 to 199 of 41	1,760 entries

Step 3: Join a Dictionary (lexicon) with Sentiment Score

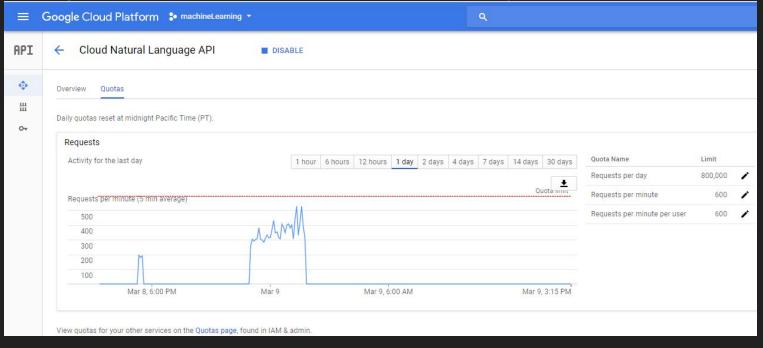
									word ‡	sentiment ‡	lexicon ‡	score ‡
*	asin ‡	reviewerID ‡	overall ‡	word ‡	sentiment ‡	lexicon ‡	score ‡	1	abandon	NA	AFINN	-2
1	1935627880	A3E2ET9QG1723S	5	love	NA	AFINN	3	2	abandoned	NA	AFINN	-2
2	1935627880	A3E2ET9QG1723S	5	book	NA	NA	NA	3	abandons	NA	AFINN	-2
3	1935627880	A3E2ET9QG1723S	5	chris	NA	NA	NA	4	abducted	NA	AFINN	-2
4	1935627880	A3E2ET9QG1723S	5	bind	NA	NA	NA	5	abduction	NA	AFINN	-2
5	1935627880	A3E2ET9QG1723S	5	love	NA	AFINN	3	6	abductions	NA	AFINN	-2
6	1935627880	A3E2ET9QG1723S	5	story	NA	NA	NA	7	abhor	NA	AFINN	-3
7	1935627880	A3E2ET9QG1723S	5	separate	NA	NA	NA	8	abhorred	NA	AFINN	-3
8	1935627880	A3E2ET9QG1723S	5	generation	NA	NA	NA	9	abhorrent	NA	AFINN	-3
9	1935627880	A3E2ET9QG1723S	5	bring	NA	NA	NA	10	abhors	NA	AFINN	-3
10	1935627880	A3E2ET9QG1723S	5	overlay	NA	NA	NA	11	abilities	NA	AFINN	2
11	1935627880	A3E2ET9QG1723S	5	ellie	NA	NA	NA	12	ability	NA	AFINN	2
12	1935627880	A3E2ET9QG1723S	5	central	NA	NA	NA	13	aboard	NA	AFINN	1
13	1935627880	A3E2ET9QG1723S	5	character.ellie	NA	NA	NA	14	absentee	NA	AFINN	-1
14	1935627880	A3E2ET9QG1723S	5	raconteur	NA	NA	NA	15	absentees	NA	AFINN	-1
15	1935627880	A3E2ET9QG1723S	5	diary	NA	NA	NA	16	absolve	NA	AFINN	2
16	1935627880	A3F2FT9OG1723S	5	anony	NA	NA	NA		to 17 of 2,476	2000		

Step 4: Calculate Sentiment Score for Each Review

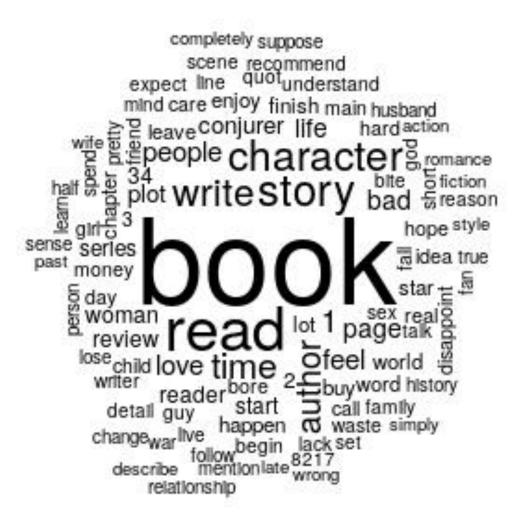
*	asin ‡	reviewerID ‡	sentiment_score ‡	overall ‡
1	0026009102	A2AYSFGUP5VTY3	1.6666667	4
2	0061730327	A3IFEXK0M52J2L	0.4166667	4
3	0061994316	A2FJ5NWS5LQ9LN	1.3076923	4
4	0061998974	A1AQDSTEBI8BB2	-1.2500000	5
5	0062026879	AHUT55E980RDR	2.3333333	5
6	006203619X	A3S0XEPOFOCB5W	1.4166667	5
7	0062316869	A2IRQY7MU5RTZ8	2.0000000	5
8	0131576070	A1K9IW99EFBZ52	0.1428571	5
9	0142410705	A28GMX5NXCV4OT	1.0000000	3
10	0143114808	A2ZQG435OSH2GZ	-0.2826087	4
11	0152010661	A1XUD5NNV5LOSH	2.5000000	5
12	0307594017	A19JA54QH6N041	2.0000000	4
13	0307712842	A310BJW6IJQNPK	1.6000000	5
14	0310330513	A34RH1RQBHK1P1	1.0000000	4
15	0312614578	A2MF4TISBBQT5A	1.1153846	4
16	0312890796	A3EX36SNRYD5VL	2.5000000	1

Google Natural Language and BigQuery API

- BigQuery: The dataset is too big to be analyzed on a PC
- Google Cloud NLP provides an automated way to calculate sentiment scores



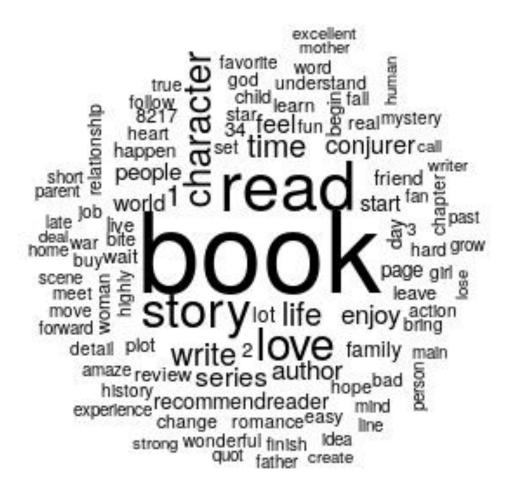
Negative single word



Neutral single words



Positive single words:



Negative bigram:

ayn rand michael moore science fiction love story book read stop read hard time sex scene star war dean koontz bad guy poorly write plot line character development main character story line brad thor 5 star entire book short story book start write style

star

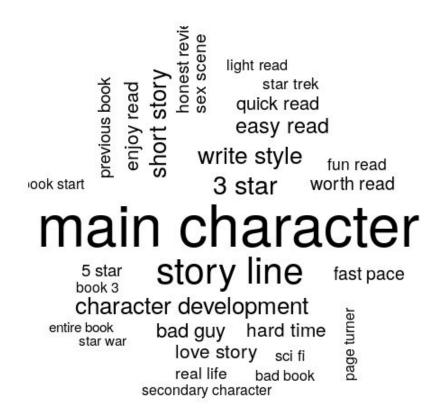
bad book

blood moon

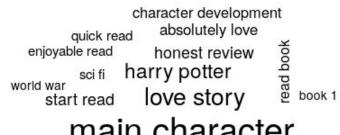
star review previous book

1 star

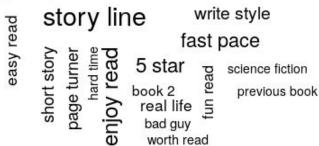
Neutral bigram:



Positive bigram:

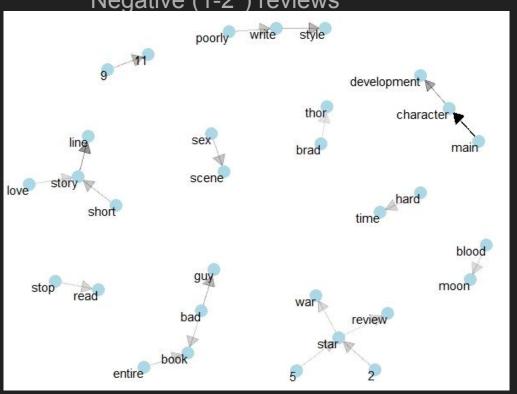


main character highly recommend



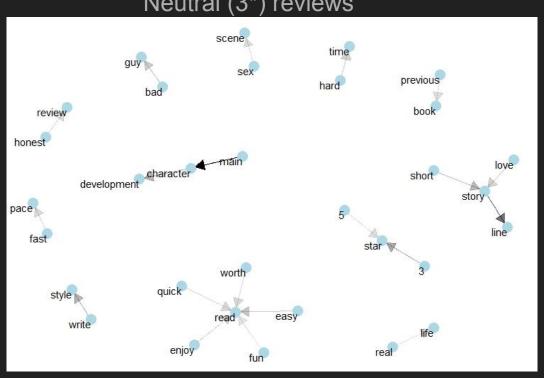
Word Network

Negative (1-2*) reviews



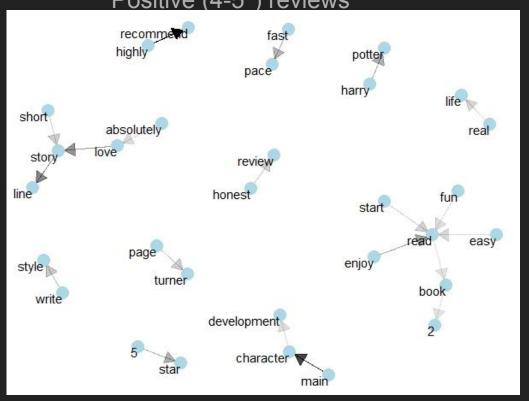
Word Network

Neutral (3*) reviews



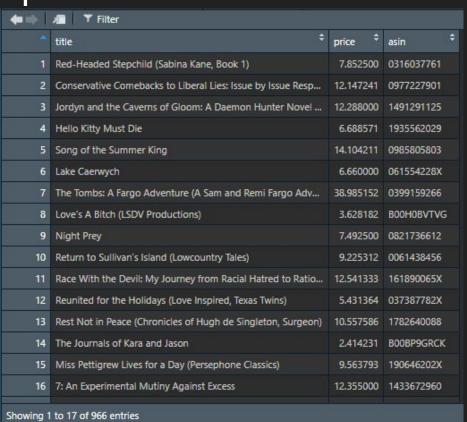
Word Network

Positive (4-5*) reviews



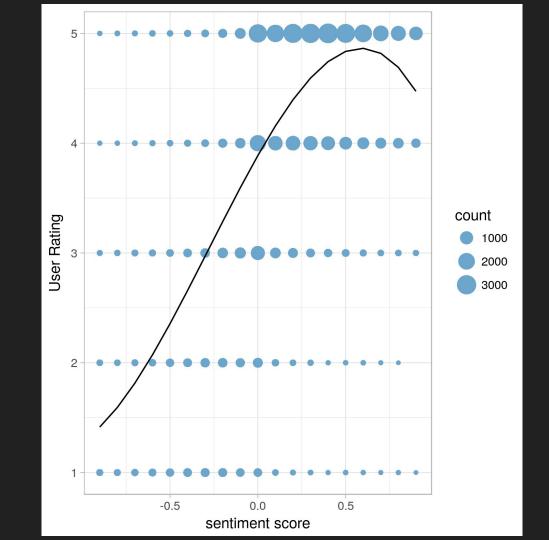
Web scraping Amazon for prices

We want check if we can use price of books in our model, so we scrapes books' price from Amazon.



A polynomial model

- 3rd degree polynomial model including to predict the rating a user will give a book
- Dependent variables tested: Sentiment score, Sentiment*Magnitude, Price
- Sentiment only gave us a better fit, so we dropped the other two.



Mean user and book rating "pull" factors

Inspired by the Netflix recommendation system prize winners
We apply two "pulling" factors on our prediction from the polynomial model:

- One pulls towards the existing mean rating for the book being reviewed
- One pulls towards the mean rating the reviewer has given to other books
- The more reviews we have for the book or the user in question, the greater the weight of the pull

```
y2 = y1 + bookPullWeight * (y1 - bookMeanRating) + userPullWeight * (y1 - userMeanRating)
```

Results on test data

- Mean residual: 0.625
- Our predicted rating is within 1 point from the actual rating 90.8% of the time

Applicability

 Gauge a rating score from text on book discussion forums which do not include star ratings

Thank You