# FIRST-PERSON NARRATIVE SENTIMENT CLASSIFICATION

Computational Content Analysis Week-3 Coding

Presenter: Linghui Wu



#### INTRODUCTION

- Reed, Lena, Jiaqi Wu, Shereen Oraby, Pranav Anand, and Marilyn Walker.
   "Learning lexico-functional patterns for first-person affect." arXiv preprint arXiv:1708.09789 (2017).
- People blogging about their day
  - NOT explicitly flag their affective state: *I am happy.*
  - INSTEAD describe situations that readers can readily infer: My friend brought me flowers.



#### DATA

- First-person narratives from **Spinn3r corpus**
- 15466 stories range from 225 to 375 words
- Mechanical Turkers annotated 2k random sentences
  - 498 positive
  - 754 negative



#### SETUP

- Tokenize and normalize text data
- Turn into tf-idf matrix and vectorize text data

train\_data\_df.sample(5)

	sentence	category	tokenized	normalized	vect
1078	Our regular insurance doesn't pay that.	0	[Our, regular, insurance, does, n't, pay, that]	[regular, insurance, pay]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
1018	We finally were able to send more Democrats to	0	[We, finally, were, able, to, send, more, Demo	[finally, able, send, democrat, congress]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.46784345097009256,
900	I'm just going to wait until they break up (if	0	[I, 'm, just, going, to, wait, until, they, br	[be, go, wait, break, fuck, know, give, chance]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
56	I came back home to take a gigantic broken-up	1	[I, came, back, home, to, take, a, gigantic, b	[come, home, gigantic, break, nap, perfect, ra	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
114	I had plans to put my bike in the back of the	1	[I, had, plans, to, put, my, bike, in, the, ba	[plan, bike, kia, bike, home, lot, ingenious,	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,

Split into training and testing sets



#### LOGISTIC REGRESSION

• Mean accuracy: 0.823 on train set, 0.648 on test set.

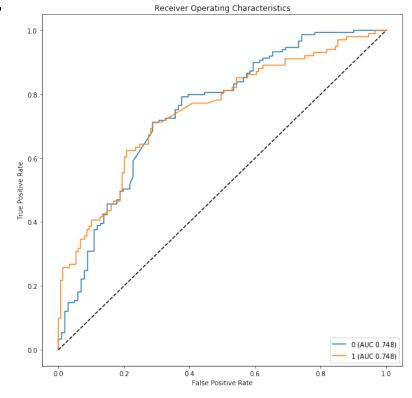
sentence

predict logistic

Category	Error Rate	AUC	Precision
0	0.308	0.643	0.684
1	0.308	0.643	0.722

Extrapolation on uncoded data

		<b></b>
2245	I ended up in some part of the Boondocks I've	0
1969	We found our seats before the concert started.	0
817	Don't mess with us mann!	0
26	So tonight we finally met.	1
1813	It was a lot of fun (yummy too.)	1





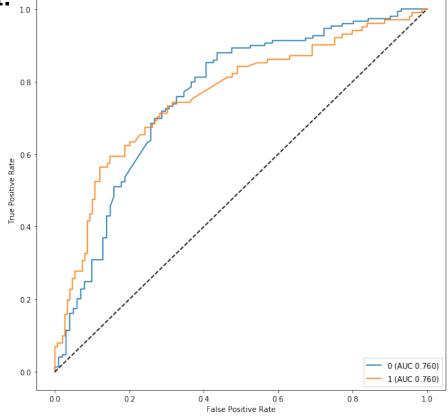
## NAÏVE BAYES

• Mean accuracy: 0.867 on train set, 0.732 on test set. 10

Category	Error Rate	AUC	Precision
0	0.268	0.694	0.723
1	0.268	0.694	0.758

Extrapolation on uncoded data

	sentence	predict_naive_bayes
1683	She found me roots of relish sweet, And honey	1
2453	If I didn't sit next to her in English, I woul	0
946	Today we are celebrating the life of one of So	1
628	You can imdb it yourselves, the movie is a com	0
120	I just always liked that quote.	0





#### **COMPARISON**

Classifier	Logistic Regression	Naïve Bayes
Training Set Accuracy	0.823	0.867
<b>Testing Set Accuracy</b>	0.648	0.732
Error Rate	0.308	0.268
AUC	0.643	0.694

- Naive Bayes reaches the asymptotic solution for fewer training sets than the Logistic Regression.
  - Ng, Andrew Y., and Michael I. Jordan. "On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes." In Advances in neural information processing systems, pp. 841-848. 2002.



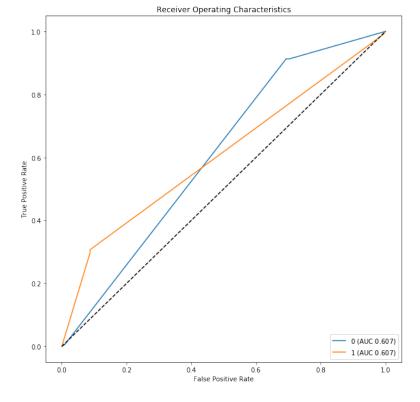
#### DECISION TREE

• Mean accuracy: 0.801 on train set, 0.624 on test set.

Category	Error_Rate	AUC	Precision
0	0.376	0.591	0.660
1	0.376	0.591	0.757

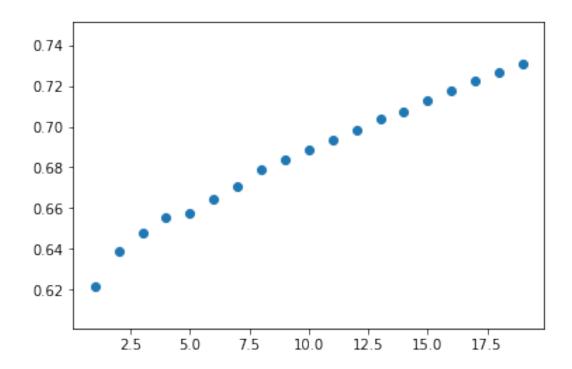
#### Extrapolation on uncoded data

	sentence	predict_decision_tree
1557	School stresses me more than anything.	0
2385	I was able to hike around and try to find a va	0
856	Today I was happily back at 193 lbs.	0
2123	I think Traci gets off on messing around with	1
772	I need it to go away.	1





#### TRIWMING THE TREE



• Improvement by bagging different trees?



#### RANDOM FOREST

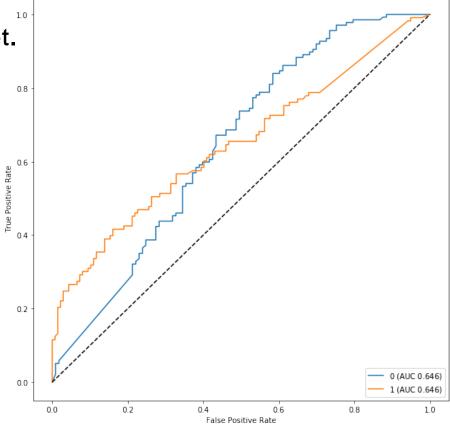
• Mean accuracy: 0.802 on train set, 0.636 on test set.

Category	Error Rate	AUC	Precision
0	0.364	0.602	0.601
1	0.364	0.606	0.823

Extrapolate on uncoded data

	Sentence	predict_random_lorest
2263	So I don't know why he called me Aly.	0
1683	She found me roots of relish sweet, And honey	1
2422	I meant it when I said it but in actuality it'	0
1217	Interesting weekend.	0
2104	So im thinking I need to pick up a second job	1

sentence predict random forest





#### **COMPARISON**

Classifier	<b>Decision Tree</b>	Random Forest
Training Set Accuracy	0.801	0.802
<b>Testing Set Accuracy</b>	0.624	0.636
Error Rate	0.376	0.364
AUC	0.591	0.601

- Improvement using ensemble methods?
- Yes, but only slightly better!



#### K-NEAREST NEIGHBORS

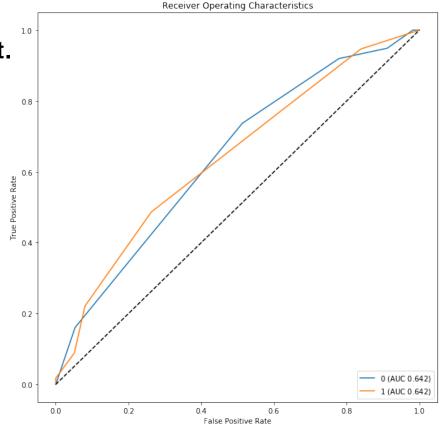
• Mean accuracy: 0.619 on train set, 0.556 on test set.

Category	Error Rate	AUC	Precision
0	0.444	0.509	0.552
1	0.444	0.509	1.000

Extrapolate on uncoded data

	Sentence	predict_knearest
2582	All in all I've taught or helped to teach mah	0
2517	But we've never met	0
641	Score one for me ?? But I am pretty sure it	0
2550	like in my title: WAAAAAAAAAAAAAAAAAAAAAAA	0
1694	"I was really nervous."	0

sentence predict knearest





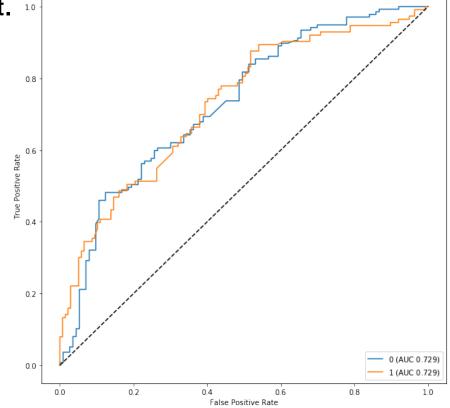
#### SVM

• Mean accuracy: 0.894 on train set, 0.660 on test set. 10

Category	<b>Error Rate</b>	AUC	Precision
0	0.340	0.634	0.633
1	0.340	0.634	0.759

Extrapolate on uncoded data

	sentence	predict_svm
1304	I'd go further into detail on this matter, but	0
2550	like in my title: WAAAAAAAAAAAAAAAAAAAAAAA	0
1277	Hey mom, I know I'm a baby, but I think I know	0
1947	I was up late last night writing the worst pap	0
1929	Forgive me.	0





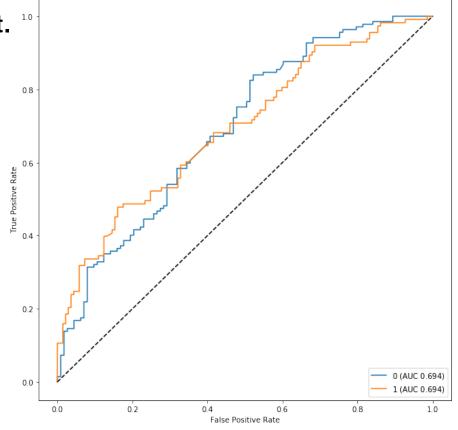
#### NEURAL NETWORKS

• Mean accuracy: 0.993 on train set, 0.636 on test set. 10

Category	Error Rate	AUC	Precision
0	0.364	0.624	0.644
1	0.364	0.624	0.622

Extrapolate on uncoded data

	sentence	predict_neural_net
2190	Again, I couldn't be happier.	1
938	I hate writing negatively about something that	0
1319	As you may have noticed, I didn't post anythin	0
953	When we were talking she said she ends up with	0
415	Other celebrity encounters: I squeezed in a hu	1





#### COMPARISON AMONG ALL MODELS

Classifier0.	Logistic Regression	Naïve Bayes	Decision Tree	Random Forest	K-nearest Neighbor	SVM	Neural Networks
Training Set Accuracy	0.823	0.867	0.801	0.802	0.619	0.894	0.993
Testing Set Accuracy	0.648	0.732	0.624	0.636	0.556	0.660	0.636
Error Rate	0.308	0.268	0.376	0.364	0.444	0.340	0.364
AUC	0.643	0.694	0.591	0.601	0.509	0.634	0.624

- Best algorithm: Naïve Bayes
- Neural Nets: High accuracy in training set but low in testing set -> Overfitting?
- Still not satisfying results



#### ALGORITHMS IN THE PAPER

- Baseline First-Person Classifiers
  - SVM with unigram features
  - NRC-Canada sentiment classifier
  - Stanford Sentiment Classifier
- AutoSlog First-Person Sentence-Level Classifier
  - Uses syntactic templates to define linguistic expressions
  - Verb-particle constructions: cry
  - Verb-head-of-preposition constructions: cheated on, care for



### ALGORITHMS IN THE PAPER

	Classifier	Pos	Neg	Macro
		<b>F</b> 1	<b>F1</b>	$\mathbf{F}$
1	SVM	0.66	0.60	0.64
2	NRC	0.58	0.69	0.64
3	Stanford	0.54	0.73	0.67
4	AutoSlog (ASlog)	0.11	0.68	0.53
5	<b>Retrained Stanford</b>	0.53	0.73	0.67
6	NRC, ASlog	0.60	0.78	0.71
7	Stanford, ASlog	0.55	0.76	0.70
8	NRC, ASlog, Stanford	0.64	0.79	0.74
9	NRC, ASlog, SVM	0.70	0.78	0.75

Table 4: Test Set Results



#### RESULTS FROM THE PAPER

- AutoSlog enhances the performance of current sentiment classifiers.
- Linguistic functions indicating positivity and negativity are different.
  - Positivity Active Participation: head for, ...
  - Negativity Private State: need, want, ...



#### MY CONCLUSIONS

- Larger number of hand-coded data enhances accuracy
- Ensemble methods improves performance
- Consider lexico-functional linguistic patterns



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