Twitter Writing Style Analysis

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Introduction

Final Goal

To detect the plagiarism of text on the internet from intellectuals/copywriters.

Current Status

Twitter analysis in order to correctly recognize the tweets from different authors.

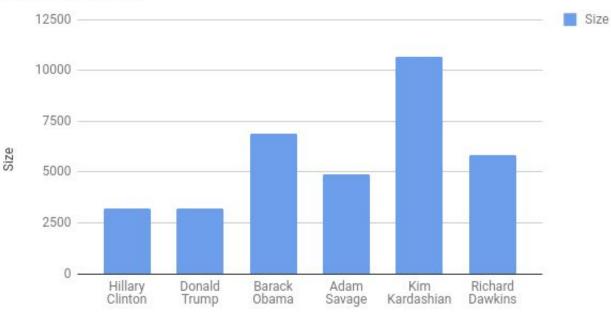






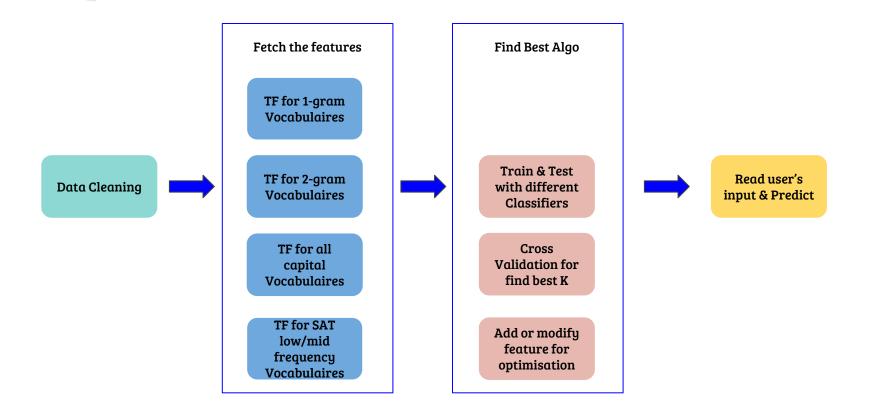




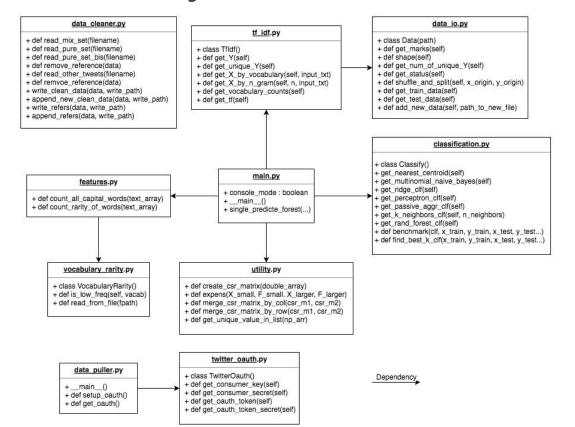


Resource

Implementations



Modularized Python Code



Data Cleaning

- 1. Replace the retweets or reference by " __QUOTE__ "
- 2. Replace the links "https:\\" by " __URL__ "
- 3. Replace the breakline "\n" with blank.
- 4. Save the reference content to the other file for future analysis.

Format of the clean data [Name Text] Some exemples DonaldTrump New national Bloomberg poll just released - thank you! Join the MOVEMENT: __URL__ #TrumpTrain... __URL__ DonaldTrump TONIGHT! NORTH CAROLINA: __URL__ WEDNESDAY! GEORGIA: __URL__ SATURDAY! NEVADA: __URL__ HillaryClinton .@realdonaldtrump: Attacking Muslim Americans is wrong, and it makes it harder for us to defeat terrorism. __URL__ KimKardashian East coast turn to E NOW!!!!! Keeping Up With The Kardashian's is on!!!!!! who's excited?

Parameters Optimisations

<u>Cross validation for parameter n_estimators / neighbors</u>

- Number of partition: 5
- Random Forest from 50 ~350 (jump by 50) K=200:80.71%
- K-Nearest-Neighbors from 5~ 55 (jump by 10) K=5: 64.72%

Parameters for other classifiers (Mostly Defaults)

- NearestCentroid()
- MultinomialNB(alpha=.01)
- RidgeClassifier(tol=1e-2, solver="auto")
- Perceptron(max_iter=50, tol=None)
- PassiveAggressiveClassifier(max_iter=50, tol=None)
- KNeighborsClassifier(n_neighbors=5)
- RandomForestClassifier(n_estimators=200)

3003 Features

- Term frequency of 1500 (from total: 15488) 1-gram vocabularies. (Tf-idf + ANOVA variant)
- Term frequency of 1500 (from total: 50485) 2-gram vocabularies. (Tf-idf + ANOVA variant)
- Term frequency of all capital vocabularies.
- 4. Term frequency of very difficult 5348 SAT vocabularies. (+ stemmer.stem)
- 5. Term frequency of medium difficult 2698 SAT vocabularies. (+ stemmer.stem)

pythoning -> python
vocabularies -> vocabulary

Top 100 Important Features Sorted (By Random Forest)

[Capital Words] [__url__] [__quote__] [bo] [president obama] [http ofa] [ofa bo] [obama] [ofa] [president] [Difficult Vocabs] [my] [mythbusters] [hillary] [trump] [twitter] [twitter] com] [__quote__ president] [rt] [ly] [and] [net] [so] [bit] [bit ly] [Med-difficult Vocabs] [by] [richarddawkins] [is] [love] [net http] [richarddawkins net] [it] [pic] [that] [for] [this] [www] [pic twitter] [http bit] [you] [we] [instagr] [not] [me] [thank you] [kimkardashian] [thank] [http instagr] [at] [http www] [http instagram] [great] [am] [but] [lol] [instagram com] [instagram] [trump2016] [will] [if] [religion] [instagr am] [from] [with] [just] [jamienotweet] [donald] [be] [up] [quys] [can] [twitpic] [today] [our] [twitpic com] [are] [tonight] [khloekardashian] [was] [all] [as] [jamie] [makeamericagreatagain] [awesome] [amp] [donald trump] [http twitpic] [health] [cruz] [what] [now] [here] [romney] [of the] [uk] [an] [__quote__ hillary] [out] [new]

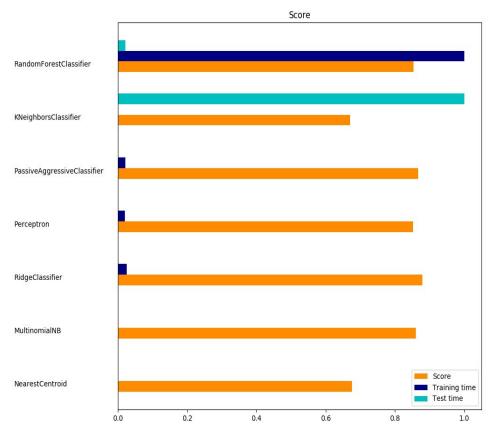


The Worst

Nearest Centroid Classifier - 68.3%

Top 3 Best

Ridge Classifier - 87.9%
Passive Aggressive - 86.9%
Multinomial NB - 86.4%



Prediction Accuracy Improvement

Change	Improved?
Add another 1000 3-gram features.	0%
Increase 1-gram and 2-gram features from 1000 to 1500.	+1-2%
From "sum of counts" to "sum of counts/total words count" for all capital words and SAT vocabularies.	+2-3% (+22% for Nearest Centroid)
Use sklearn.feature_selection.f_classif to select the most variant Tf-idf of 1-gram & 2-gram features.	+2%
	+6% (88% Best)

Demo!

Difficulties

- 1. Transformer the feautres fetched from one user-input tweet to 3003 features from training data.
- 2. Manipulate the sparse matrices correctly to add new features manually (to merge our new matrices into Tf-idf matrices).
- 3. To find and understand the best parameters for each classifier.
- 4. To increase prediction accuracy.





Generalization?

Training by M	ultinomial	MR/alpha	0 01 01-0	nrior-None	, fit_prior=True)
Training by: M Training time:		NB (a Lpna=	0.01, Clas	s_prior=wone	, fit_prior=(rue)
Predict time:					
Accuracy:	0.825				
Classification	report:				
р	recision	recall	f1-score	support	
EAP	0.82	0.81	0.82	1989	
HPL	0.84	0.83	0.84	1438	
MWS	0.81	0.84	0.82	1468	
avg / total	0.83	0.83	0.83	4895	
Confusion matr					
[[1616 155 2					
	68]				
175 67 12					
Dimensionality					
Density: 1.000					
					ne, copy_X=True, fit_intercept=Tru
max_it		ormalize=	False, ran	dom_state=No	ne, solver='auto',
	a1)				
tol=0.					
Training time:	0.679s				
Training time: Predict time:	0.679s 0.002s				
Training time: Predict time: Accuracy:	0.679s 0.002s 0.827				
Training time: Predict time: Accuracy: Classification	0.679s 0.002s 0.827 report:				
Training time: Predict time: Accuracy: Classification	0.679s 0.002s 0.827	recall	f1-score	support	
Training time: Predict time: Accuracy: Classification	0.679s 0.002s 0.827 report:	0.86	0.83	support 1989	
Training time: Predict time: Accuracy: Classification P EAP HPL	0.679s 0.002s 0.827 report: recision 0.80 0.88	0.86 0.80	0.83 0.84	1989 1438	
Training time: Predict time: Accuracy: Classification P EAP	0.679s 0.002s 0.827 report: recision 0.80	0.86	0.83	1989	
Training time: Predict time: Accuracy: Classification P EAP HPL	0.679s 0.002s 0.827 report: recision 0.80 0.88	0.86 0.80	0.83 0.84	1989 1438	
Training time: Predict time: Accuracy: Classification p EAP HPL MWS avg / total	0.679s 0.002s 0.827 report: recision 0.80 0.88 0.83	0.86 0.80 0.81	0.83 0.84 0.82	1989 1438 1468	
Training time: Predict time: Accuracy: Classification p EAP HPL MWS avg / total	0.679s 0.002s 0.827 report: recision 0.80 0.88 0.83	0.86 0.80 0.81	0.83 0.84 0.82	1989 1438 1468	
Training time: Predict time: Accuracy: Classification p EAP HPL MWS avg / total Confusion matr. [[1707 101 1]	0.679s 0.002s 0.827 report: recision 0.80 0.88 0.83	0.86 0.80 0.81	0.83 0.84 0.82	1989 1438 1468	
Training time: Predict time: Accuracy: Classification p EAP HPL MWS avg / total Confusion matr. [1707 101 1	0.679s 0.002s 0.827 report: recision 0.80 0.88 0.83 0.83	0.86 0.80 0.81	0.83 0.84 0.82	1989 1438 1468	
Training time: Predict time: Accuracy: Classification p EAP HPL MWS avg / total Confusion matr [[1707 101 1] [219 1150	0.679s 0.002s 0.827 report: recision 0.80 0.88 0.83 0.83 ix: 81] 69] 91]]	0.86 0.80 0.81	0.83 0.84 0.82	1989 1438 1468	

Overview	Data	Kernels Discussion Leaderboard Rules Te	am My Submissions	Late Submissi
835	→ 70	Neural Nut	0.526	29 6
836	▼ 23	Fabia	0.527	63 2
837	- 3	BoBdec	0.529	90 1
838	-7	Fisher	0.532	90 7
839	1 07	Miles Hill	0.533	54 1 2
840	- 5	Suresh	0.536	72 1
841	▼ 13	EnriqueSantos	0.542	28 8 2
842	- 11	Aleksandr Shatilov	0.543	25 7
843	▲ 20	Quincy	0.544	99 2
844	2 0	haoeric	0.545	59 1
845	- 2	ShahMuzaffarBashir	0.546	20 1
846	▼ 5	Robert Sobolewski	0.547	84 2 2



Clinton-trump-tweets.csv

https://www.kaggle.com/benhamner/clinton-trump-tweets/data

Trump-tweets.csv

https://www.kaggle.com/doughersak/donald-trump-tweet-statistics/data

Trump-tweets-bis.csv

https://www.kaggle.com/austinvernsonger/donaldtrumptweets/data

Others' tweets:

https://www.kaggle.com/adhok93/president-obama/data

Tutorial:

 $\frac{\text{http://scikit-learn.org/stable/auto}}{\text{nt-classification-20}} = \frac{\text{20} \text{newsgroups.html} \# \text{sphx-glr-auto-examples-text-docume}}{\text{1}} = \frac{\text{20} \text{newsgroups.html} \# \text{sphx-glr-auto-examples-text-docume}}{\text{2}} = \frac{\text{20} \text{newsgroups-pu}}{\text{2}} = \frac{\text{20} \text{newsgroups-html} \# \text{sphx-glr-auto-examples-text-docume}}{\text{2}} = \frac{\text{20} \text{newsgroups-html} \# \text{sphx-glr-auto-examples-text-docume}}}{\text{2}} = \frac{\text{20} \text{newsgroups-html$

Spooky Author Identification

https://www.kaggle.com/c/spooky-author-identification

