A comparative analysis of various machine learning techniques for trend prediction on social media

Application oriented project

CSI5155

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Motivation

What?

- Online content - rich source of information
- Detect changes in behaviours, trends, predict popularity

Why?

- Inform people, business, and authorities
- Help individuals prepare and act accordingly
  (high sales growth, major events, strikes)

Objectives

- Draw insights from data
- Find the most promising features
- Research ML techniques and best practices
- Binary classification of Twitter instances

How?

- Analyze the dataset
- Preprocessing techniques
- Perform experiments using ML algorithms from 4 categories:
  - Linear models
  - Tree-based
  - Distance-based
  - Rule-based
  - Ensemble

Dataset

- 11 attributes measured over a 7 days period (total of 77 attributes)
- Binary relative labeled data (increment by 500 of popularity level before and after the observed time frame)
- Class ratio:
  - 97.5% negative instances
  - 2.5 % positive instances (BUZZ)

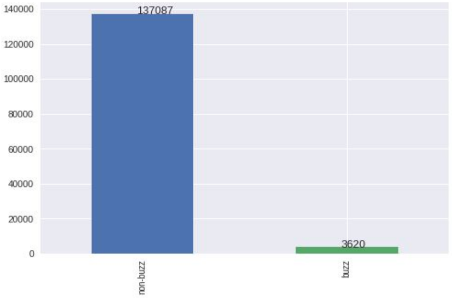

Figure 1: Dataset imbalance

Attributes

1. Number of Created Discussions (NCD)
2. Author increase (AI)
3. Number of atomic containers (NAC)
4. Number of Authors (NA)
5. Attention Level
    - AS(NA) - based on the number of authors (users)
    - AS(NAC) - measure with number of contributions
6. Burstiness Level (BL)
7. Contribution Sparseness (CS)
8. Author Interaction (AT)
9. Average Discussions Length (ADL)
10. Number of Active Discussions (NAD)

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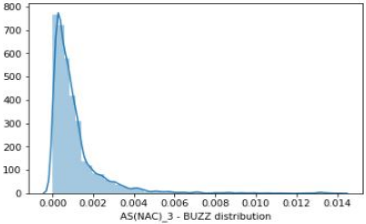

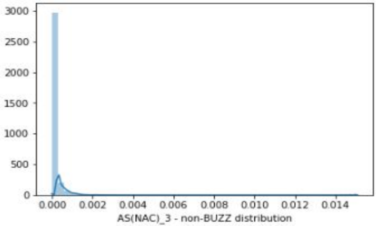

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4. **Rowwise normalization to unit norm**
    - preserves the distribution rowwise
    - helps normalizing the values of features with very different ranges (eg. [0,1] and [0,12000])
    - L2 normalization improves the F1 score

Feature selection

Principal Component Analysis

- 95% of the data is explained by 17 features
- 35 of the features have the most prominent influence on the generated principal components
- assumptions: data is zero centered $=>$ standardization needed

Evaluation metrics

- **F1 score**
- AUC weighted by support (the number of true instances for each label)
- **TPR (recall)**
- **Precision**
- TNR

Results

	F1	AUC	**TPR (recall)**	**Precision**	TNR
DT_IG	0.456540	0.7210	0.456233		0.9857
KNN_st_sc _norm_L2	**0.553923**	0.7317	0.469306	0.676864	0.9941
NC_mahalanobis	0.488551	0.7755	0.572034	0.432421	0.9791
LinSVC_minmax (0,37505)	0.473080	0.6761	0.356028	0.731774	0.9962
LinSVC_minmax (-300,300)	**0.338376**	**0.9015**	0.892426	0.208842	0.9106
LogReg_unitvar	0.493299	0.6848	0.373457	0.735563	0.9963
SVM_SGD _L2_norm_unitvar	0.516521	0.7605	0.535105	0.514327	0.9859
RF_st	**0.570278**	0.7239	0.451403	0.776747	0.9965
BAG+RF	0.548917	0.7087	0.420316	0.794784	0.9971

Comparisons

Table 1: T-Test - F1

Algotrithm pair	p-value	Statistical difference (95% conf)
BAG_DT - BAG_KNN	0.05712	yes
BAG_DT - BAG+KNN_stsc_norm_L2	1.17e-05	yes
BAG_KNN - BAG+KNN_stsc_norm_L2	5.12e-06	yes
KNN_stsc_L2 - BAG_DT	1.55e-05	yes
KNN_stsc_L2 - BAG+KNN_stsc_norm_L2	1.93e-05	yes
KNN_stsc_L2 - BAG+KNN_stsc_norm_L2	0.2565	no

Key learnings

1. Evaluation metrics importance
2. Testing the generalization power
3. Comparing multiple algorithms
4. The class-imbalance problem needs to be addressed using techniques suitable for the data set on discussion
5. Important features
6. Dependent features (NAC vs Attention Level)

Future work

- Neural networks and deep learning
- Addressing the class imbalance problem with different techniques
  - Learn the minority class itself instead of by comparing it with the non-BUZZ class
  - Oversampling and undersampling
  - Improve the models learning on each mini-dataset
- Other methods of feature selection (e.g. univariate selection)
- Inhance the dataset with the text of the posts
- Regression task and comparisons with other datasets
- Use only the most important features extracted from the PCA into the weak classifiers ensemble

References

- Dataset: http://archive.ics.uci.edu/ml/datasets/Buzz+in+social+media+#


THANK YOU FOR YOUR
ATTENTION
ANY QUESTIONS?