# Sports Articles Objectivity

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Skolkovo Institute of Science and Technology, "Introduction to Data Science"

Moscow, 2018

#### Task

- Binary classification of sports articles: objective vs subjective
- Betting is biased towards irrelevant information
- However, it is hard to identify (probably harder then semantic amalysis)
- Here is where ML comes to the rescue!

# Examples

#### Objective:

'Einalists in the Apertura play-offs, Toluca had drawn their first two Clausura games but got off to a good start when Edgar Be nitez put them ahead in the 16th minute. NyMatias Britso elvelled 20 minutes later but Lucas Silva netted 14 minutes from the end to ensure the visitors took all three points.\n\terms \text{tranco Arizala scored 13 minutes from time to ensure Jaguares claimed their r first point with a 1-1 draw against Monterrey, who had opened the scoring through Aldo De Nigris (14)\n Hosts Jaguares also had Jorge Rodriguez sent off in the closing moments.'

#### Subjective:

## Label distribution



### Wordclouds

Season gotwoway time will be the steven of t

Objective:



• Subjective:

# Text preprocessing

#### Before:

'Einalists in the Apertura play-offs, Toluca had drawn their first two Clausura games but got off to a good start when Edgar Be nitez put them ahead in the 16th minute.\nMatias Britos levelled 20 minutes later but Lucas Silva netted 14 minutes from the end to ensure the visitors took all three points.\n\text{tranco Arizala scored 13 minutes from time to ensure Jaguares claimed their first point with a 1-1 drawn against Monterrey, who had opened the scoring through Aldo De Nigris (14).\n Hosts Jaguares also had Jorge Rodriguez sent off in the closing moments.'

#### After:

'finalist apertura toluca drawn first two clausura game got good start edgar benitez put ahead minut matia brito level minut la ter luca silva net minut end ensur visitor took three point franco arizala score minut time ensur jaguar claim first point draw monterrey open score aldo de nigri host jaguar also jong rodriguez sent close momemat'

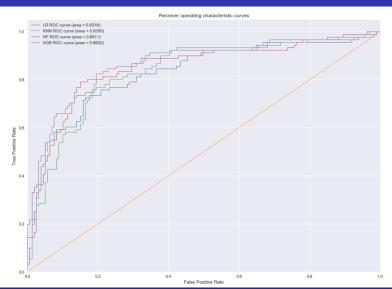
'barcelona star dani alv claim ansemal jack wilsher good superstar xavi andr iniesta the brazilian recent play wilsher friend c lash england and alv impress midfield perform ung barca chief bid summer he great player met play arsenal without doubt reach h eight player barcelona like xavi iniesta said arsenal lost star cesc fabrega alex song spanish leagu leader past two summer and boss ansene wenger brace new attempt barca nick latest midfield linchpin wilsher lot qualiti great person if i given chanc choo s player i would sign barcelona ad alv'

# Deep Learning

Layer (type)	Output	Shape	Param #
input_3 (InputLayer)	(None,	500)	0
embedding_3 (Embedding)	(None,	500, 50)	500000
bidirectional_3 (Bidirection	(None,	500, 100)	40400
conv1d_3 (Conv1D)	(None,	498, 50)	15050
global_max_pooling1d_3 (Glob	(None,	50)	0
dense_5 (Dense)	(None,	50)	2550
dense_6 (Dense)	(None,	1)	51

Total params: 558,051 Trainable params: 558,051 Non-trainable params: 0 troduction **ML on texts** ML on tabular data Results Conclusic

# TF-IDF ROCs



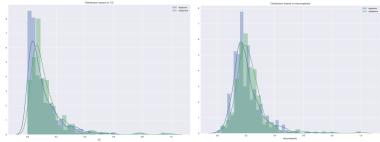
troduction ML on texts **ML on tabular data** Results Conclusion

#### Feature extraction

- . symbols total number of symbols in raw text
- sentences total number of sentences
- unique\_words\_count number of unique words
- unique\_words\_share ratio between number of unique words and number of total words
- word\_average\_len average word length in text
- stopwords count total number of stopwords
- stopwords\_share ratio between number of stopwords and number of total words
- polarity\_raw , polarity\_preprocessed polarity in raw and preprocessed text respectively using textblob
- subjectivity\_raw, subjectivity\_preprocessed subjectivity in raw and preprocessed text respectively using textblob

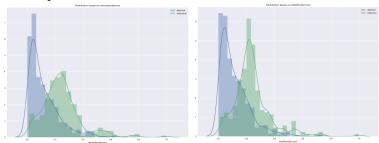
# Feature distributions

### Bad separation:



# Feature distributions

### Good separation:



### Low variance

WRB 0.000000 NNP 0.000000 ellipsis 0.000000 sentencelast 0.002663 JJS 0.002814 colon 0.006744 semicolon 0.006916 pronouns1st 0.007173 T0s 0.009206 exclamationmarks 0.010101 dtype: float64

### Low variance

X\_train[']35'].value\_counts()

0.0 744

0.2 3

0.6 1

0.8 1

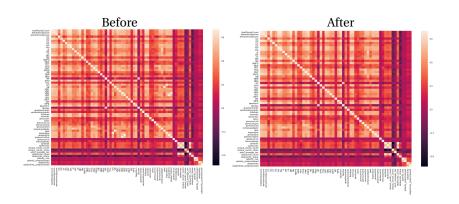
1.0 1

New 135 divers int64

Good to exclude: Name: JJS, dtype: int64

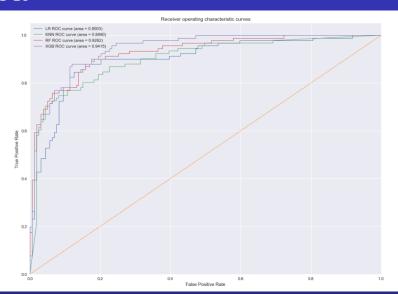
<pre>X_train['colon'].value_counts()</pre>			
0.000000	349		
0.026316	169		
0.052632	80		
0.078947	51		
0.105263	32		
0.131579	20		
0.157895	13		
0.184211	8		
0.236842	7		
0.210526	7		
0.315789	3		
0.289474	2		
0.605263	1		
0.421053	1		
0.368421	1		
0.710526	1		
0.394737	1		
0.263158	1		
0.868421	1		
0.342105	1		

# High correlation (1.0)



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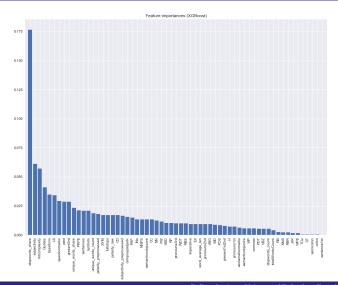
# ROCs



# Results

Model	Data	AUC-ROC
XGBoost	tabular	0.9415
Random Forest	tabular	0.9282
Logistic Regression	tabular	0.9003
KNN	tabular	0.8990
XGBoost	TF-IDF	0.8622
Random Forest	TF-IDF	0.8511
LSTM + Conv	texts	0.8460
KNN	TF-IDF	0.8350
Logistic Regression	TF-IDF	0.8316
LSTM	texts	0.8269

# Feature importances



troduction ML on texts ML on tabular data Results **Conclusion** 

#### Conclusion

- Different approaches were compared
  - DL on texts
    - LSTM+Conv was better than LSTM
    - The worst results though
    - Probably model architecture should be more complex
  - ML on TF-IDF matrix
    - Best: XGBoost
  - ML on tabular data
    - Best: XGBoost
    - The best approach
- EDA was performed
  - Low variance, high correlation features were excluded
- Feature extraction from texts
  - Golden feature: stopwords share
- Model is applicable to a real-life scenario
  - It is interpretable, the quality is good
  - But better to train it on larger dataset