

# Machine learning for rhetorical figure detection

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# Agenda

- Characteristics of rethorical figures
- Extract potential candidates and features
- Selection of classifier
- Generation of tranings data
- Results
- Conclusion

# Characteristics of rethorical figures

Alliteration

"<u>D</u>an's <u>d</u>og <u>d</u>ove <u>d</u>eep in the <u>d</u>am, <u>d</u>rinking <u>d</u>irty water as he <u>d</u>ove."

Adnomination

"He is <u>no</u>body from <u>no</u>where and he knows <u>no</u>thing."

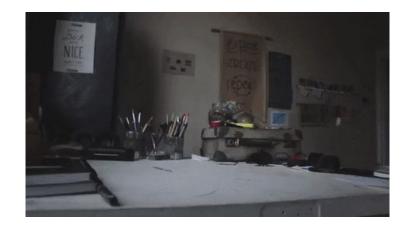
### 1. <u>Selection of the corpora</u>

### Problems:

- Nearly no good german sources
- Multiple formats
- No good generic search engines to find texts

### Solutions:

- Stick with those provided by nltk
- Train with the Guttenberg Corpus "austen-emma.txt"



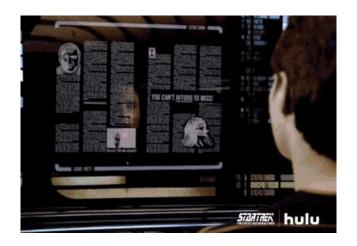
### 2. Preprocessing

### Problems:

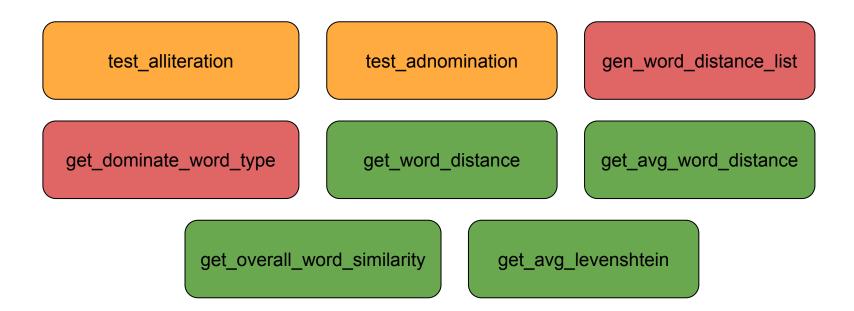
- How to determine a "good" sentence from a "bad" one
- What metrics should be gained

### Solutions:

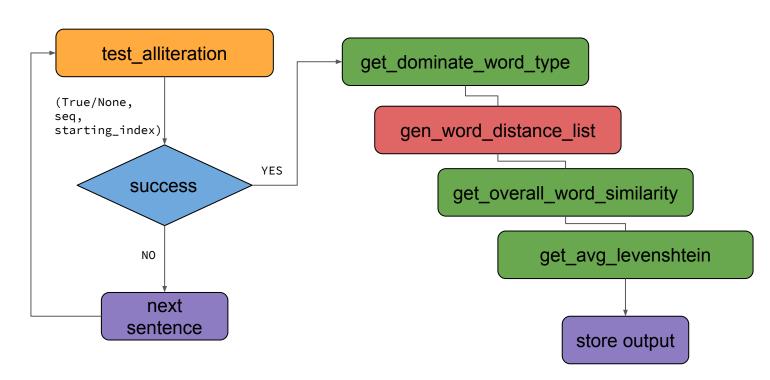
- Use test functions
- Creative selection of some typical text metrics (e.g. distance, similarity, type, levenshtein ...)



### Preprocessing



### 3. Feature function chaining



### 4. <u>Data organisation/generation</u>

### Example of a alliteration tuple:

count	word type	dist	similarity	levenshtein
4	1	1	0.059259259259259255	6.0

- count: Words with the same start
- word type: Maximum of repeated word type ('VB', 'NN', 'AT', ...)
- <u>dist:</u> Distance from one word to the next "important" word
- <u>similarity:</u> Overall word similarity based on *synset wup\_similarity*
- <u>levenshtein:</u> The popular Levenshtein distance

# Selection of classifier

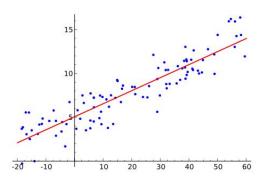
### 1. Logistic Regression

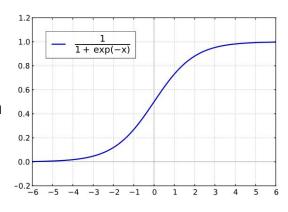
- data free of missing values
- predicting variable is binary or ordinal
- predictors independent from each other

### **Logistic Regression > Linear regression**

both: show influence of each feature on result

but: feature behaviour were more aligned with sigmoid function





## Selection of classifier

### Decision Tree Classifier

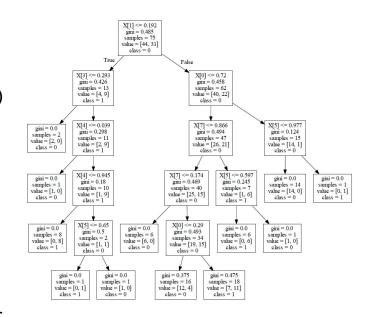
- predicts binary ANDOR multiclass (here: rethorical device)
- allows multiple classifications based on similar features

### Advantages:

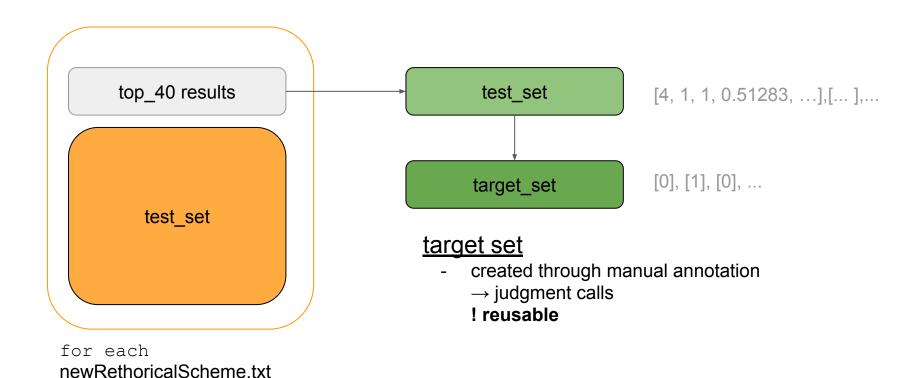
- accommodates multiple schemes
- easy to follow decision tree

### Disadvantages:

- increase in features → decrease in performance
- increase in features → importance of selection order



# Generation of trainings data



# Results

### 1. Reviewed Operations

- model.score score

```
- model.predict prediction prediction
     -model.predict prob probability
In [7]: tree model al.predict proba(test al)
Out[7]: array([[0., 1.],
             [1., 0.],
             [1., 0.],
             [1., 0.],
             [1., 0.],
             [1., 0.],
             [1., 0.],
             [0.5, 0.5],
```

```
Out[6]: array([1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0,
             1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
             1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0,
             0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0,
             0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1,
             0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
             1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1,
             1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0,
             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1,
             0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1,
             1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
             1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1,
             0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1,
             0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1,
             1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1,
             0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
             0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
             1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0,
             1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1,
             0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0])
  In [10]: reg model al.predict proba(test al
  Out[10]: array([[0.57138704, 0.42861296],
                           [0.62562396, 0.37437604].
                           [0.62562396, 0.37437604],
                            [0.55198214, 0.44801786],
                            [0.49567669, 0.50432331].
                           [0.55751147, 0.44248853],
                           [0.55751147, 0.44248853],
                           [0.41578677, 0.58421323].
```

# Results

### 2. Observations

### Alliteration

- common scheme when pattern matches
- in Regression Model: often 0.3 0.6 probability of being match

### Adnomination

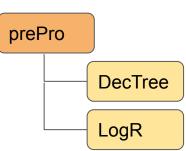
- needle-in-a-haystack problem
- in Regression Model: typically 0.8 0.9 probability of no match

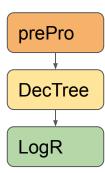
# **Tuning**

especially interesting for decision tree selection algorithm

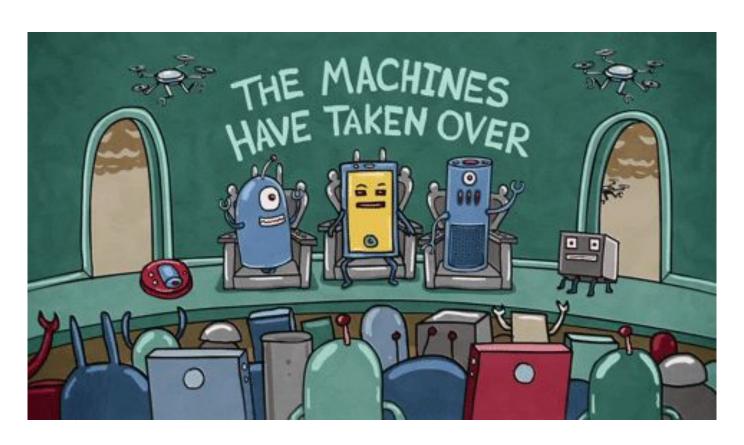
### other tuning options:

- improved: target set
- cross-validation
- improved feature selection
- Stacking of machine learning algorithms





# Conclusion



# Conclusion

- surface look on how rhetorical figures/schemes
- mining and analysing with the help of nltk toolkit/scikit-learn lib
- technical execution without specialised knowledge about data is limited

# Conclusion



# Q&A