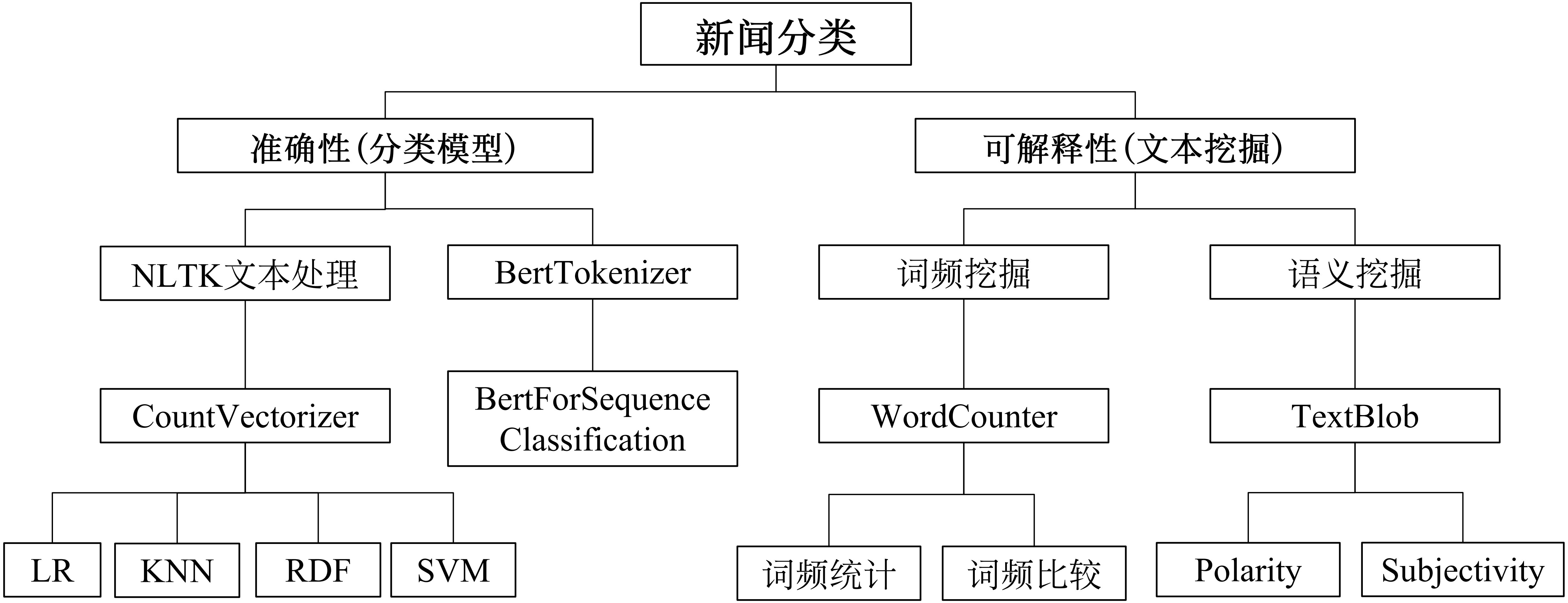
Real & Fake News Classification:
How & Why

To Begin With…

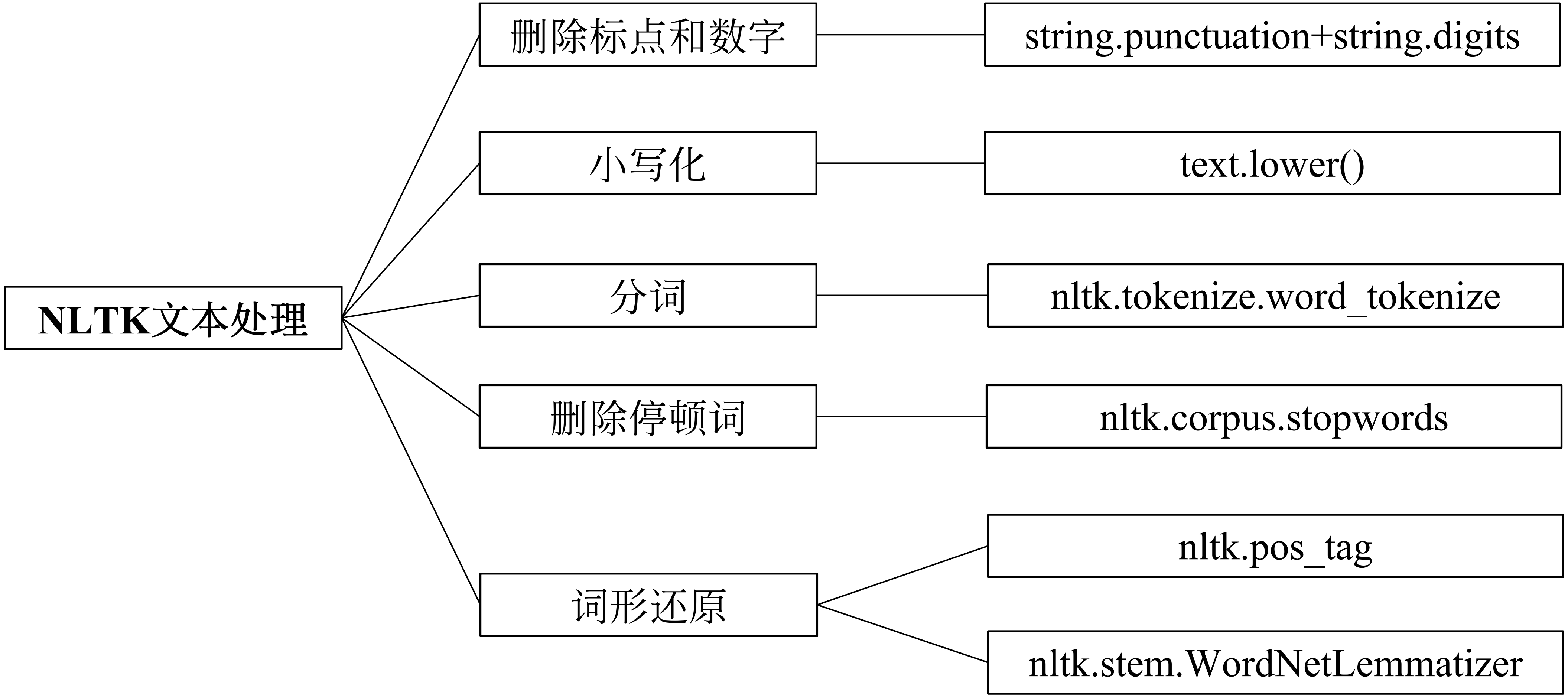
分类准确性 vs 可解释性?

My Framework



如何分类?——How

NLTK文本处理



NLTK文本处理
删除标点和数字
string.punctuation+string.digits
小写化
text.lower()
分词
nltk.tokenize.word_tokenize
删除停顿词
nltk.corpus.stopwords
词形还原
nltk.pos_tag
nltk.stem.WordNetLemmatizer

CountVectorizer

功能：先拟合提取出样本的整体特征，再进行降维等操作将文本向量化。

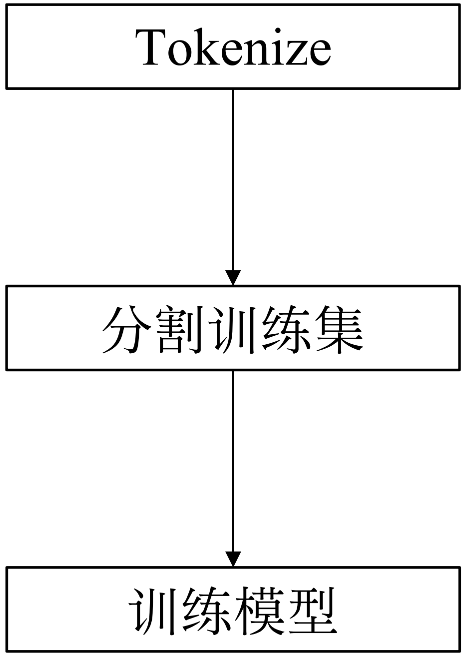
```
[25]: from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer()

corpus = [
      'This is the first document.',
      'This document is the second document.',
      'And this is the third one.',
      'Is this the first document?',
]

X = vectorizer.fit_transform(corpus)

print(X.toarray())
```

```
[[0 1 1 1 0 0 1 0 1]
 [0 2 0 1 0 1 1 0 1]
 [1 0 0 1 1 0 1 1 1]
 [0 1 1 1 0 0 1 0 1]]
```

Classification Model

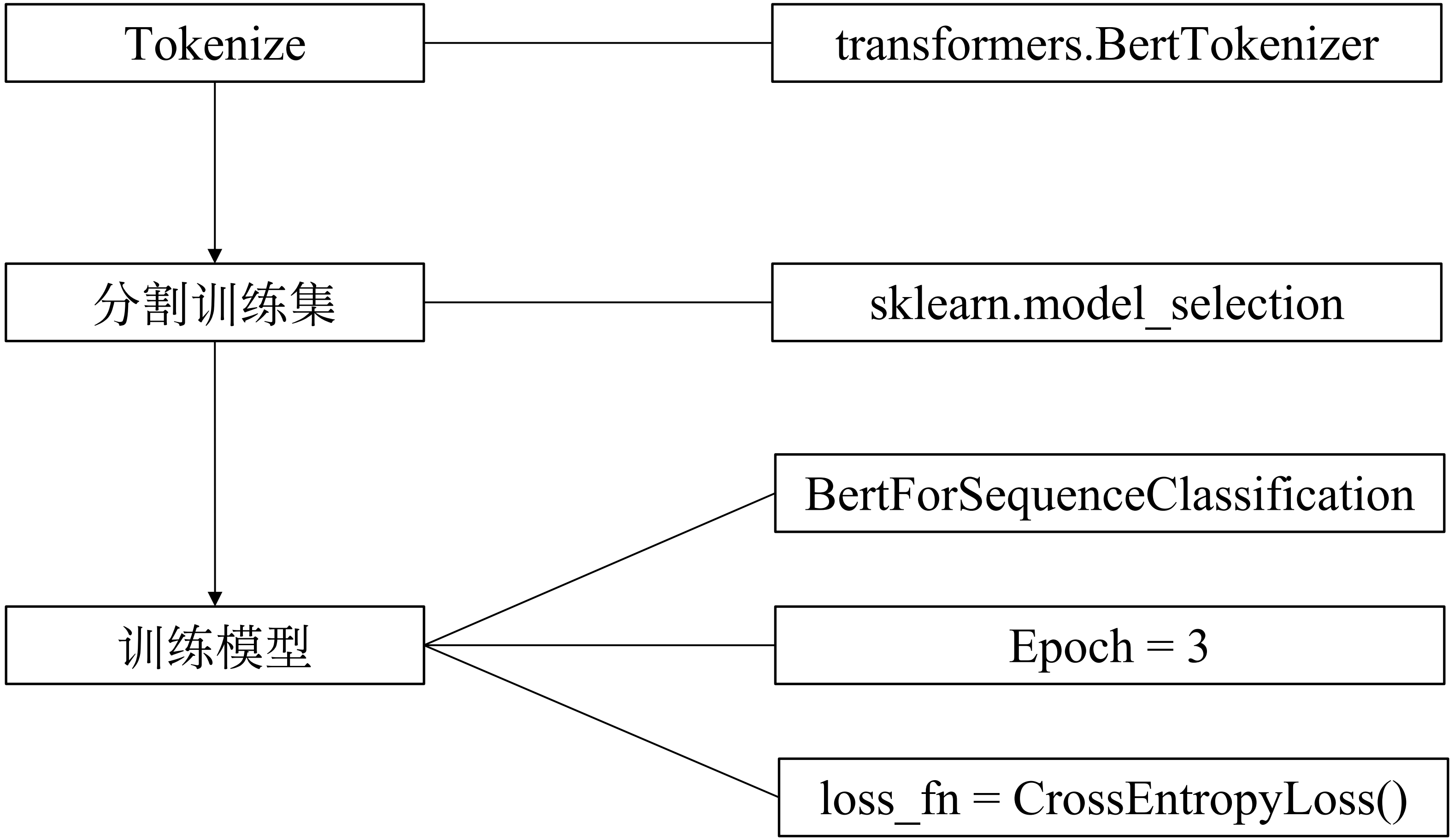
	Model	Avg_Accuracy	Avg_Precision	Avg_Recall	Avg_F1Score
0	Logistic Regresstion	0.995	0.994	0.995	0.995
1	Random Forest	0.991	0.991	0.991	0.990
2	SVM	0.995	0.993	0.995	0.995
3	KNN	0.617	0.563	0.719	0.719

Bert




```
[7]: from transformers import BertTokenizer
     tokenizer = BertTokenizer.from_pretrained('bert-base-cased')#选用large-cased版本

     tokenized_text = tokenizer('This document is the second document.',
                                padding='max_length', truncation=True,
                                max_length=16, return_tensors='pt')

     print(tokenized_text['input_ids'])

     tensor([[ 101, 1188, 5830, 1110, 1103, 1248, 5830,  119,  102,    0,    0,    0,
                 0,    0,    0,    0]])
```

Bert


Tokenize
transformers.BertTokenizer
分割训练集
sklearn.model_selection
训练模型
BertForSequenceClassification
Epoch = 3
loss_fn = CrossEntropyLoss()

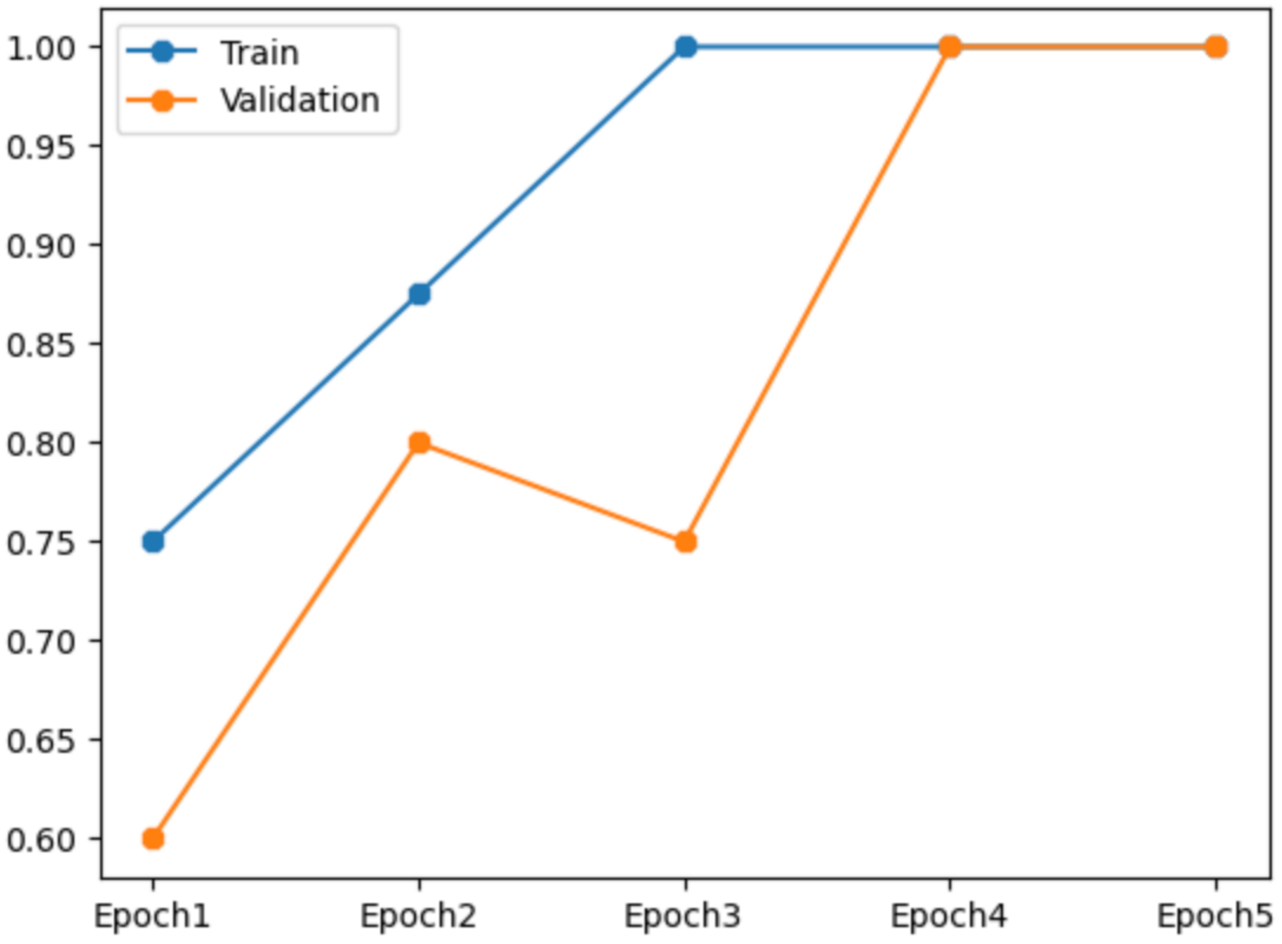
Bert-MiniSample

样本大小：50条真、50条假

训练集：80　　测试集：20

训练轮数：5

训练时间：约10分钟



Bert-LargeSample

样本大小：1000条真、1000条假

训练集：1600　　测试集：400

训练轮数：3

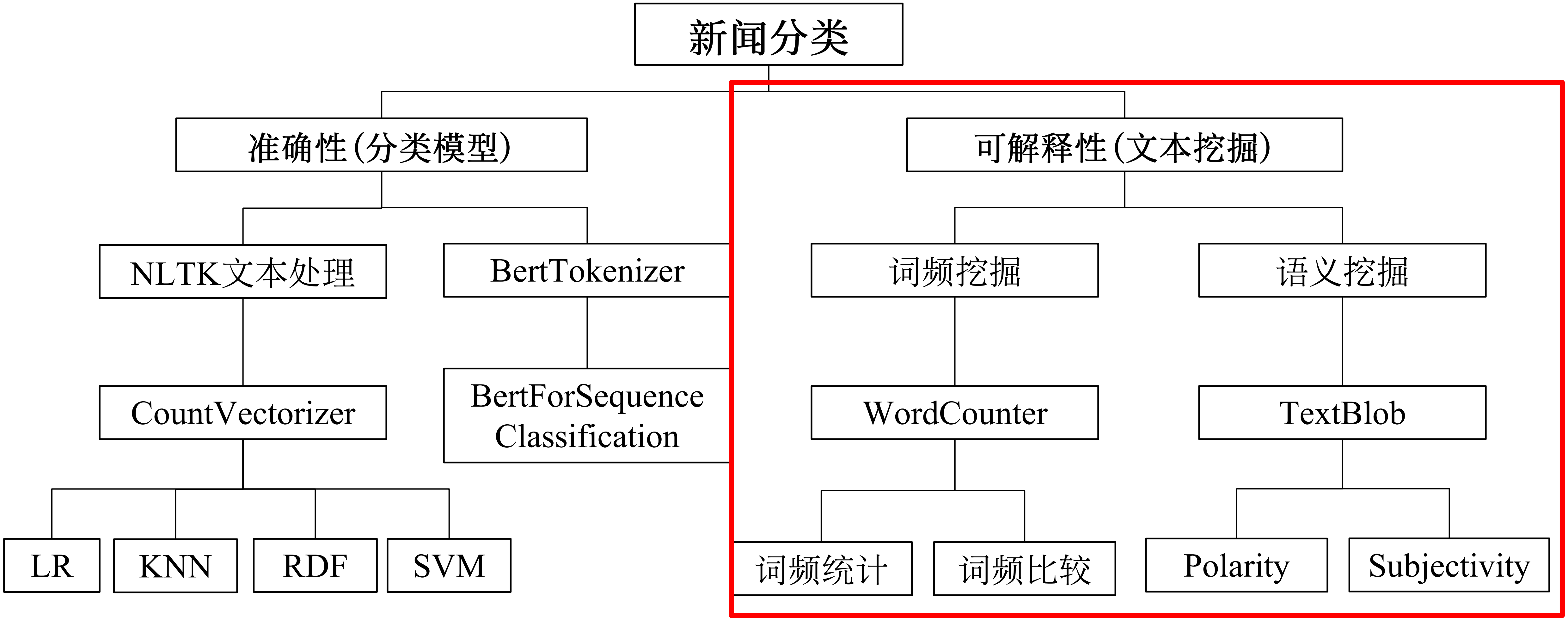
训练时间：约7.5小时

```
Epoch 1/3: 100%|██████████| 50/50 [2:38:47<00:00, 190.54s/it]
Epochs: 1
             | Train Accuracy:  1.000
             | Train Precision:  1.000
             | Train Recall:  1.000
             | Train F1Score:  1.000
             | Val Accuracy:  1.000
             | Val Precision:  1.000
             | Val Recall:  1.000
             | Val F1Score:  1.000
Epoch 2/3: 100%|██████████| 50/50 [2:38:58<00:00, 190.76s/it]
Epochs: 2
             | Train Accuracy:  1.000
             | Train Precision:  1.000
             | Train Recall:  1.000
             | Train F1Score:  1.000
             | Val Accuracy:  1.000
             | Val Precision:  1.000
             | Val Recall:  1.000
             | Val F1Score:  1.000
Epoch 3/3: 100%|██████████| 50/50 [2:37:58<00:00, 189.57s/it]
Epochs: 3
             | Train Accuracy:  1.000
             | Train Precision:  1.000
             | Train Recall:  1.000
             | Train F1Score:  1.000
             | Val Accuracy:  1.000
             | Val Precision:  1.000
             | Val Recall:  1.000
             | Val F1Score:  1.000
```

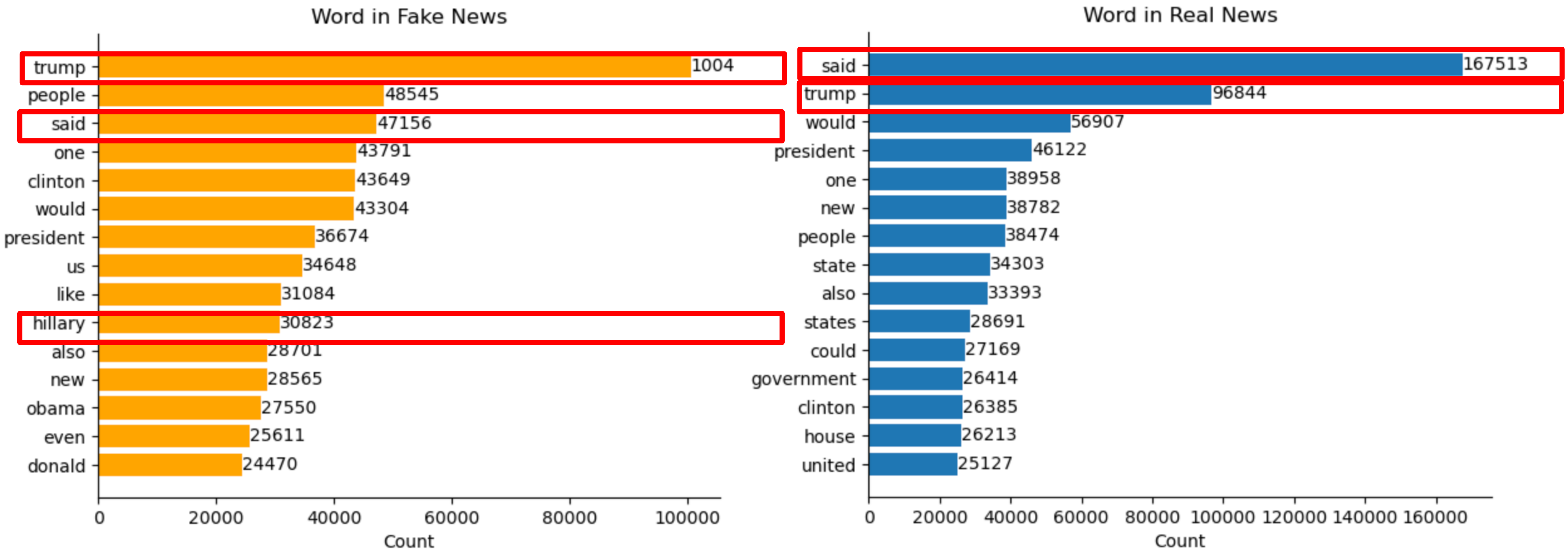
But…

为什么分类准确性这么高?——Why

My Framework



词频挖掘



Word in Fake News
trump
people
said
one
clinton
would
president
us
like
hillary
also
new
obama
even
donald
1004
48545
47156
43791
43649
43304
36674
34648
31084
30823
28701
28565
27550
25611
24470
0
20000
40000
60000
80000
100000
Count
Word in Real News
said
trump
would
president
one
new
people
state
also
states
could
government
clinton
house
united
167513
96844
56907
46122
38958
38782
38474
34303
33393
28691
27169
26414
26385
26213
25127
0
20000
40000
60000
80000
100000
120000
140000
160000
Count

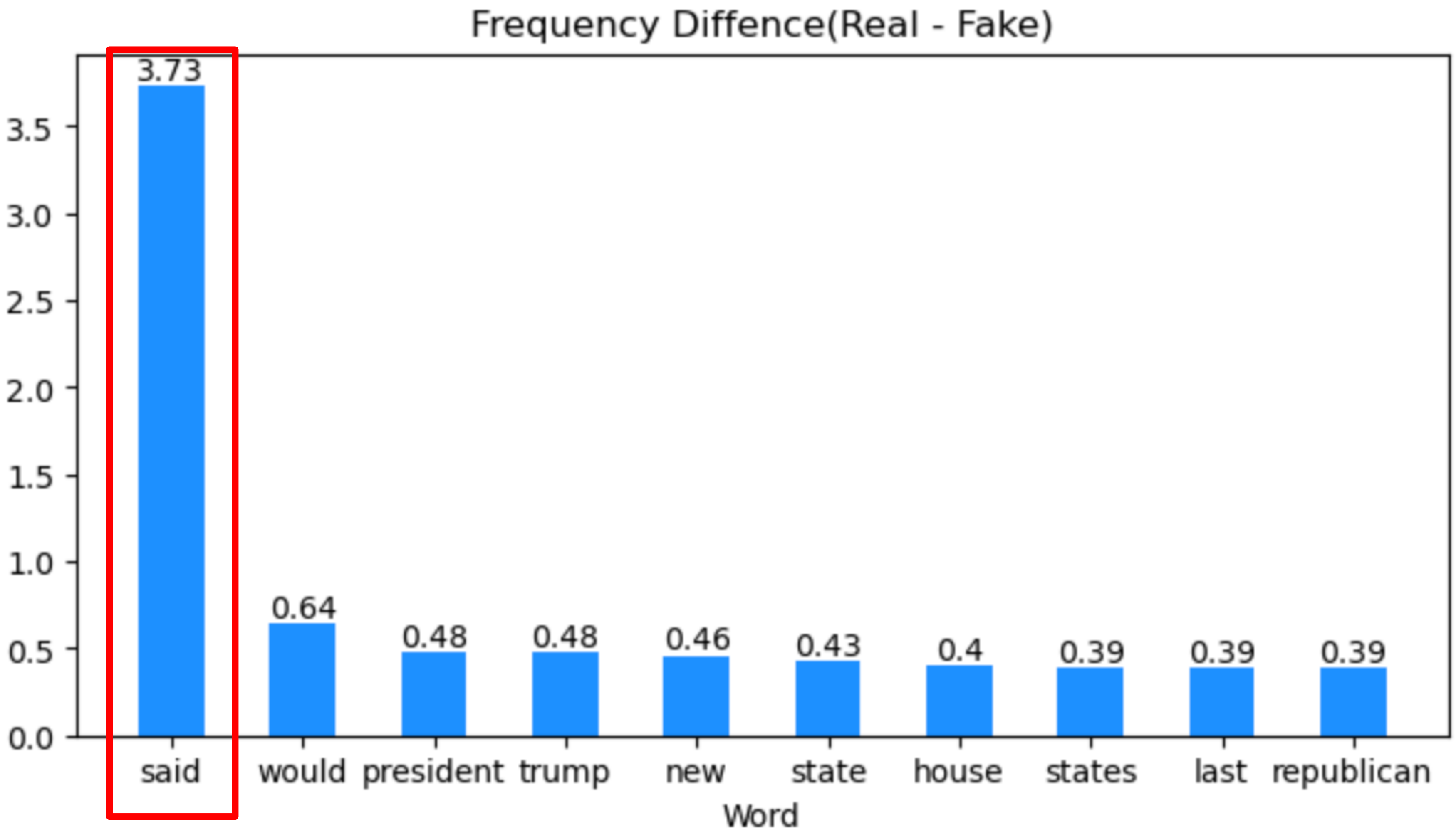
But…

真新闻：34806条　　　假新闻：43642条

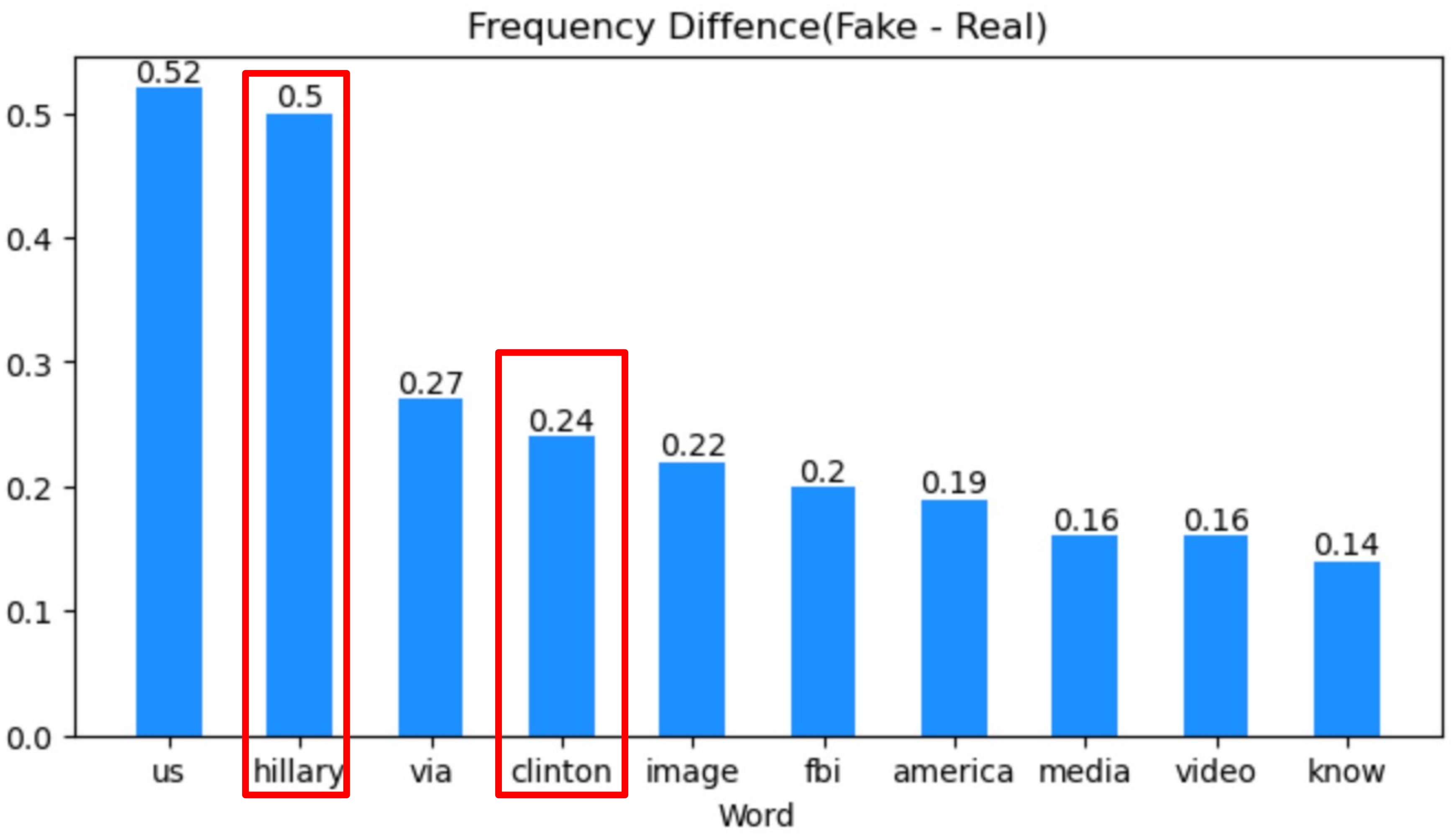
比较词语出现频率差距可能更有意义

$$frequency = \frac{Word\_count}{len(category)}$$

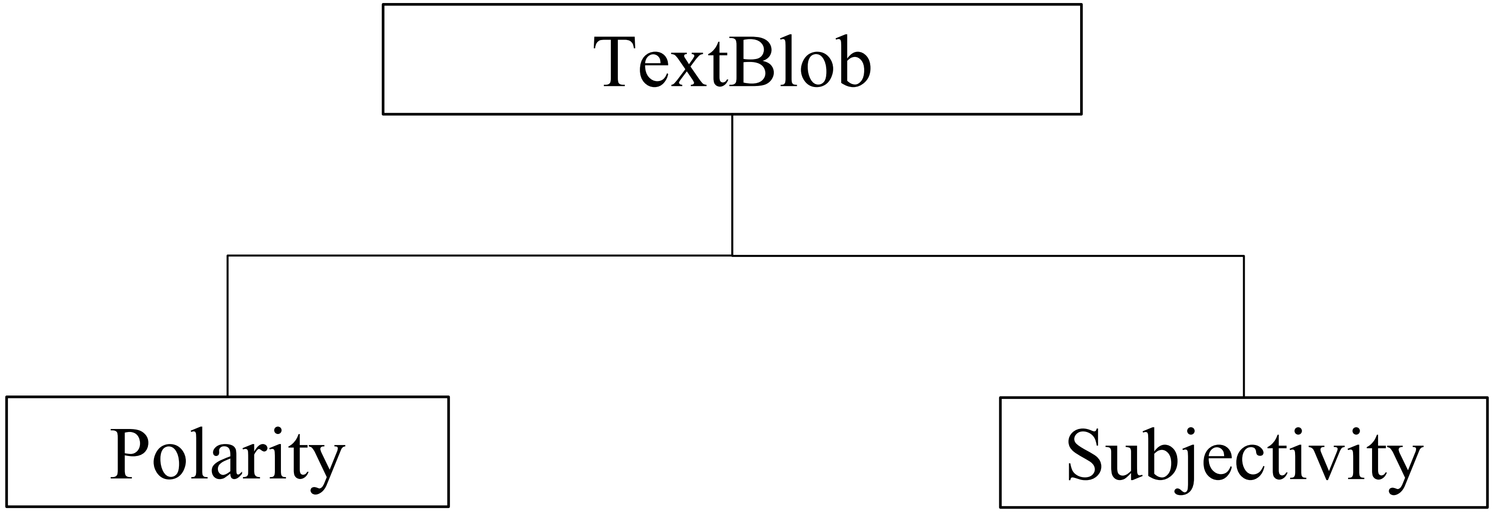
词频挖掘


Frequency Diffence(Real - Fake)
3.73
0.64
0.48
0.48
0.46
0.43
0.4
0.39
0.39
0.39
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
said
would
president
trump
new
state
house
states
last
republican
Word

词频挖掘


Frequency Diffence(Fake - Real)
0.52
0.5
0.27
0.24
0.22
0.2
0.19
0.16
0.16
0.14
0.5
0.4
0.3
0.2
0.1
0.0
us
hillary
via
clinton
image
fbi
america
media
video
know
Word

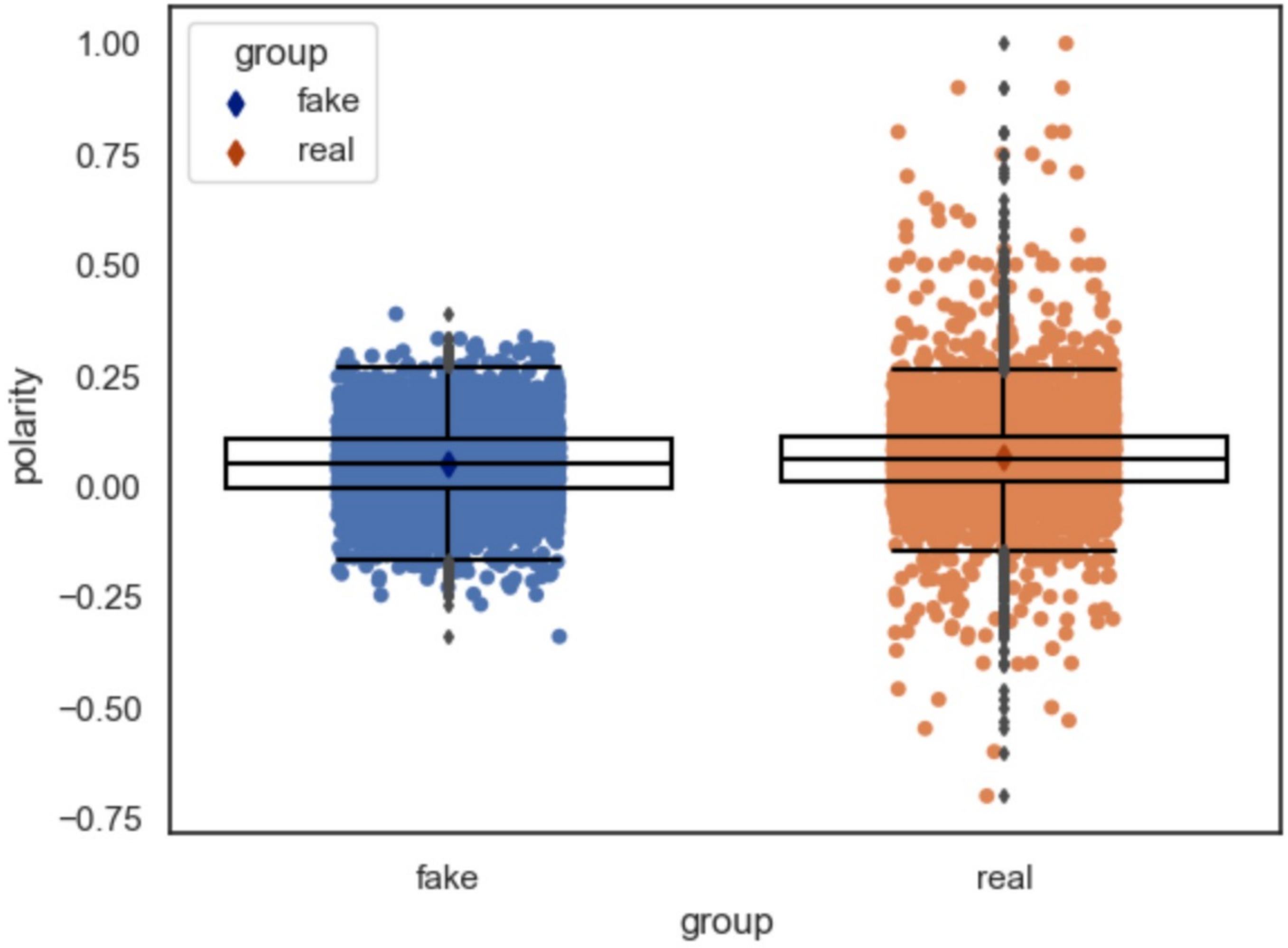
语义挖掘



文本极性：[-1:1]
越接近于1越积极

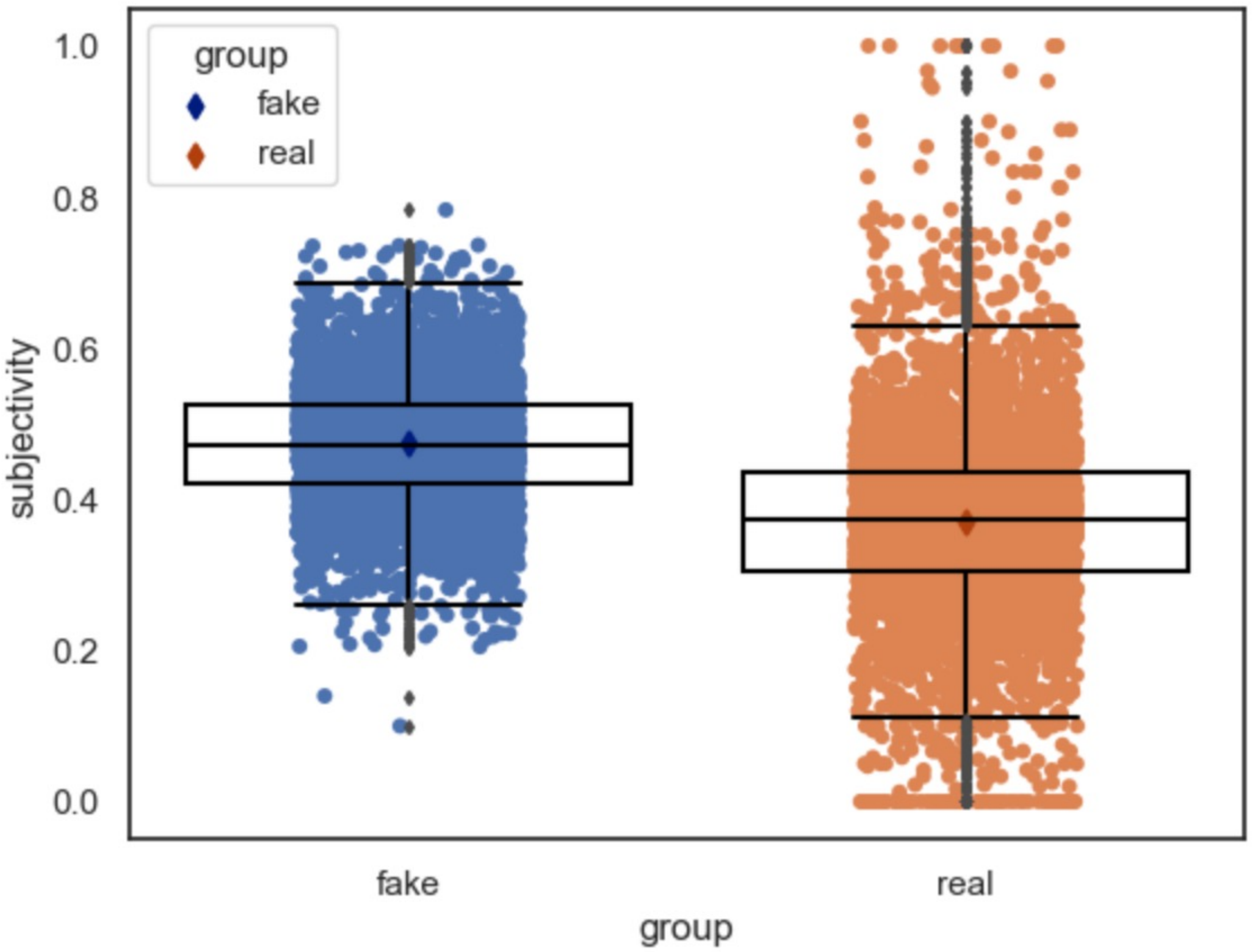
文本主观性：[0:1]
越接近于1越主观

语义挖掘——极性



group
fake
real
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
polarity
fake
real
group

语义挖掘——主观性



group
fake
real
1.0
0.8
0.6
0.4
0.2
0.0
subjectivity
fake
real
group

语义挖掘——主观性

eb08c12 TextBlob / textblob / en / en-sentiment.xml

Go to file

sloria Update English sentiment corpus 3079699 · 9 years ago

Code Blame 2932 lines (2932 loc) · 528 KB Raw

```
<?xml version="1.0" encoding="utf-8"?>
<!--
SUBJECTIVITY LEXICON FOR ENGLISH ADJECTIVES.
Adjectives have a polarity (negative/positive, -1.0 to +1.0) and a subjectivity (objective/subjective, +0.0 to +1.0).
The reliability specifies if an adjective was hand-tagged (1.0) or inferred (0.7).
Words are tagged per sense, e.g., ridiculous (pitiful) = negative, ridiculous (humorous) = positive.
The Cornetto id (lexical unit id) and Cornetto synset id refer to the Cornetto lexical database for Dutch.
The WordNet id refers to the WordNet3 lexical database for English.
The part-of-speech tags (pos) use the Penn Treebank || tag set: NN = noun, JJ = adjective, ...
For English movie reviews (Pang & Lee polarity dataset v2.0), the accuracy is 75% (P 0.76, R 0.75, F1 0.75).
-->
<sentiment language="en" version="1.3" author="Tom De Smedt, Walter Daelemans" license="PDDL">
<word form="13th" wordnet_id="a-02203763" pos="JJ" sense="coming next after the twelfth in position" polarity="0.0" subjectivity="0.0" inte
<word form="20th" cornetto_synset_id="n_a-531612" wordnet_id="a-02204716" pos="JJ" sense="coming next after the nineteenth in position" po
<word form="21st" wordnet_id="a-02204823" pos="JJ" sense="coming next after the twentieth in position" polarity="0.0" subjectivity="0.0" i
<word form="2nd" wordnet_id="a-02202146" pos="JJ" sense="coming next after the first in position in space or time or degree or magnitude"
<word form="3rd" cornetto_synset_id="n_a-530634" wordnet_id="a-02202307" pos="JJ" sense="coming next after the second and just before the
<word form="abhorrent" wordnet_id="a-1625063" pos="JJ" sense="offensive to the mind" polarity="-0.7" subjectivity="0.8" intensity="1.0" re
<word form="able" cornetto_synset_id="n_a-534450" wordnet_id="a-01017439" pos="JJ" sense="having a strong healthy body" polarity="0.5" sub
<word form="able" wordnet_id="a-00001740" pos="JJ" sense="(usually followed by 'to') having the necessary means or skill or know-how or au
```

Summary

1. 无论是常用的特征提取+分类模型还是Bert都能够很好地分类。

2. 两类新闻在文本上有一定的特征:

（1）假新闻的主观性更强，可能是由于编写中杜撰成分更多

（2）真新闻的“Said”词汇明显更多，可能由于真新闻更敢于引用

（3）假新闻的“Hilary”词汇明显更多，可能由于数据集所属时间问题

后续方向

1. 基于TextBlob词表，进一步挖掘主观的词汇（假新闻特征）。

2. 试着将可视化做的更美观（比如左右柱状图）。

3. 将Bert模型在全样本上进行预测检验。

感谢聆听

敬请批评指正

赵煜东

12月22日