Supervised sentiment analysis: Feature representation

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CS224u: Natural language understanding

N-gram feature functions

- Unigrams: the basis for “bag-of-words” models
- Easily generalized to “bag of-ngrams”
- Highly dependent on the tokenization scheme
- Can be combined with preprocessing steps like ‘_NEG’ marking
- Creates very large, very sparse feature representations
- Generally fails to directly model relationships between features

Feature functions vs. features

[1]:
```python
from collections import Counter
import numpy as np
import pandas as pd
from sklearn.feature_extraction import DictVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.utils.extmath import softmax
import sst
```

[2]:
```python
def unigrams_phi(text):
    return Counter(text.lower().split())
```

[3]:
```python
example_texts = ["a a a", "a a b", "a b b", "b b b"]
```

[4]:
```python
feats = [unigrams_phi(text) for text in example_texts]
```

[5]:
```python
vec = DictVectorizer(sparse=False)
```

[6]:
```python
X = vec.fit_transform(feats)
```

[7]:
```python
pd.DataFrame(X, columns=vec.get_feature_names())
```

[7]:

	a	b
0	3.0	0.0
1	2.0	1.0
2	1.0	2.0
3	0.0	3.0

Feature functions vs. features

```
[7]: pd.DataFrame(X, columns=vec.get_feature_names())

[7]:      a    b
     0  3.0  0.0
     1  2.0  1.0
     2  1.0  2.0
     3  0.0  3.0

[8]: y = ['C1', 'C1', 'C2', 'C3']

[9]: mod = LogisticRegression()

[10]: mod.fit(X, y)

[10]: LogisticRegression()

[11]: pd.DataFrame(mod.coef_, index=mod.classes_, columns=vec.get_feature_names())

[11]:            a          b
      C1  0.567932 -0.567932
      C2 -0.071105  0.071103
      C3 -0.496827  0.496829

[12]: softmax(X.dot(mod.coef_.T) + mod.intercept_)

[12]: array([[0.90606849, 0.08182458, 0.01210693],
             [0.69610577, 0.22566175, 0.07823248],
             [0.32165061, 0.37430625, 0.30404314],
             [0.07617433, 0.31820816, 0.60561751]])

[13]: mod.predict_proba(X)
```

Other ideas for hand-built feature functions

- Lexicon-derived features
- Negation marking
- Modal adverbs:
  - "It is quite possibly a masterpiece."
  - "It is totally amazing."
- Length based features
- Thwarted expectations: ratio of positive to negative words
  - "Many consider the movie bewildering, boring, slow-moving or annoying."
  - "It was hailed as a brilliant, unprecedented artistic achievement worthy of multiple Oscars."
- Non-literal language:
  - "Not exactly a masterpiece."
  - "Like 50 hours long."
  - "The best movie in the history of the universe."

Assessing individual feature functions

1. `sklearn.feature_selection` offers functions to assess how much information your feature functions contain with respect to your labels.
2. Take care when assessing feature functions individually; correlations between them will make these assessments hard to interpret:

X_1	X_2	X_3	y
1	1	0	T
1	0	1	T
1	0	0	T
0	1	1	T
0	1	0	F
0	0	1	F
0	0	1	F
0	0	1	F

$\text{chi2}(X_1, y) = 3$

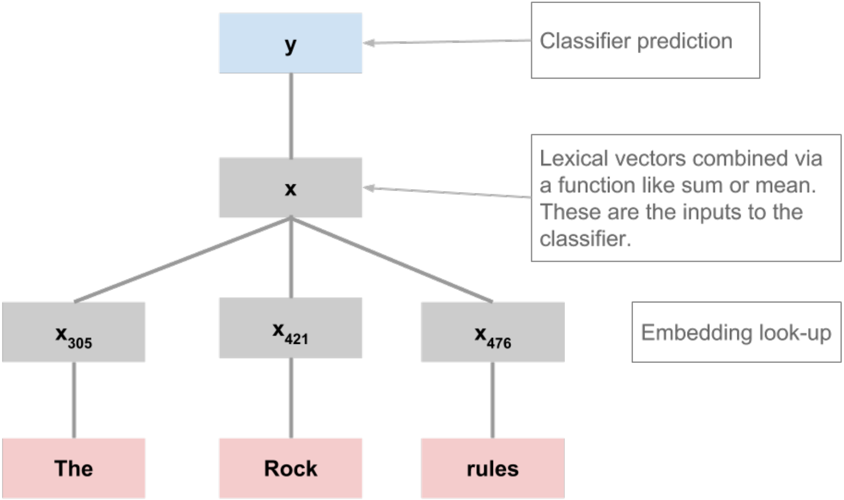
$\text{chi2}(X_2, y) = 0.33$

$\text{chi2}(X_3, y) = 0.2$

What do the scores tell us about the best model? In truth, a linear model performs best with just X_1, and including X_2 hurts.

3. Consider more holistic assessment methods: systematically removing or disrupting features in the context of a full model and comparing performance before and after.

Distributed representations as features



Distributed representations as features

```
[1]: import numpy as np
     import os
     from sklearn.linear_model import LogisticRegression
     import sst
     import utils

[2]: GLOVE_HOME = os.path.join('data', 'glove.6B')
     SST_HOME = os.path.join('data', 'sentiment')

[3]: glove_lookup = utils.glove2dict(os.path.join(GLOVE_HOME, 'glove.6B.300d.txt'))

[4]: def vsm_leaves_phi(text, lookup, np_func=np.mean):
         allvecs = np.array([lookup[w] for w in text.lower().split() if w in lookup])
         if len(allvecs) == 0:
             dim = len(next(iter(lookup.values())))
             feats = np.zeros(dim)
         else:
             feats = np_func(allvecs, axis=0)
         return feats

[5]: def glove_leaves_phi(text, np_func=np.mean):
         return vsm_leaves_phi(text, glove_lookup, np_func=np_func)

[6]: def fit_softmax(X, y):
         mod = LogisticRegression(
             fit_intercept=True, solver='liblinear', multi_class='auto')
         mod.fit(X, y)
         return mod

[7]: glove_sum_experiment = sst.experiment(
         sst.train_reader(SST_HOME),
         glove_leaves_phi,
         fit_softmax,
         vectorize=False) # Tell `experiment` it needn't use a DictVectorizer.
```