W4995 Applied Machine Learning

Working with Text Data

04/03/19

Andreas C. Müller

More kinds of data

- So far:
  - Fixed number of features
  - Contiguous
  - Categorical

More kinds of data

- So far:
  - Fixed number of features
  - Contiguous
  - Categorical
- Next up:
  - No pre-defined features
  - Free text
  - Images
  - (Audio, video, graphs, ...: not this class)

Typical Text Data

May Contain Spoilers

A dude in a dopey-looking Kong suit (the same one used in KING KONG VS. GODZILLA in 1962) provides much of the laffs in this much-mocked monster flick. Kong is resurrected on Mondo Island and helps out the lunkhead hero and other good guys this time around. The vampire-like villain is named Dr. Who-funny, he doesn't look like Peter Cushing! Kong finally dukes it out with Who's pride and joy, a giant robot ape that looks like a bad metal sculpture of Magilla Gorilla. Like many of Honda's flicks this may have had some merit before American audiences diddled around with it and added new footage. The Rankin/Bass animation company had a hand in this mess. They should have stuck to superior children's programs like The Little Drummer Boy.

... than this ;-) What would happen if Terry Gilliam and Douglas Adams would have worked together on one movie? This movie starts with a touch of Brazil... when, at a certain point, the story moves straight into the twilight zone... bringing up nothing new, but just nothing... and nothing is great fun! When Dave and Andrew starts to explore their new environment the movie gets really enjoyable... bouncing heads? well... yes ;-)

anyway... this movie was, imho, the biggest surprise at this year's FantasyFilmFest...

Just like in Cube and Cypher Natali gave this one a minimalistic, weird but very special design, which makes it hard to locate the place of the story or its time... timeless somehow...

Other Types of text data

Free string – but not “words”

Bag of Words

"This is how you get ants."

Toy Example

```
malory = ["Do you want ants?",
          "Because that's how you get ants."]
```

```
from sklearn.feature_extraction.text import CountVectorizer
vect = CountVectorizer()
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'because', 'do', 'get', 'how', 'that', 'want', 'you']
```

```
X = vect.transform(malory)
print(X.toarray())
```

```
array([[1, 0, 1, 0, 0, 0, 1, 1],
       [1, 1, 0, 1, 1, 1, 0, 1]])
```

"bag"

```
print(malory)
print(vect.inverse_transform(X)[0])
print(vect.inverse_transform(X)[1])
```

```
['Do you want ants?', 'Because that’s how you get ants.']
['ants' 'do' 'want' 'you']
['ants' 'because' 'get' 'how' 'that' 'you']
```

Text classification example: IMDB Movie Reviews

Data loading

```
from sklearn.datasets import load_files
reviews_train = load_files("../data/aclImdb/train/")

text_trainval, y_trainval = reviews_train.data, reviews_train.target
print("type of text_train: ", type(text_trainval))
print("length of text_train: ", len(text_trainval))
print("class balance: ", np.bincount(y_trainval))
```

```
type of text_trainval: <class 'list'>
length of text_trainval: 25000
class balance: [12500 12500]
```

Data loading

```
print("text_train[1]:")
print(text_trainval[1].decode())
```

```
text_train[1]:
'Words can't describe how bad this movie is. I can't explain it by
writing only. You have too see it for yourself to get at grip of how
horrible a movie really can be. Not that I recommend you to do that.
There are so many clichés, mistakes (and all other negative things
you can imagine) here that will just make you cry. To start with the
technical first, there are a LOT of mistakes regarding the airplane. I
won't list them here, but just mention the coloring of the plane. They
didn't even manage to show an airliner in the colors of a fictional
airline, but instead used a 747 painted in the original Boeing livery.
Very bad. The plot is stupid and has been done many times before, only
much, much better. There are so many ridiculous moments here that i
lost count of it really early. Also, I was on the bad guys' side all
the time in the movie, because the good guys were so stupid. "Executive
Decision" should without a doubt be you're choice over this one, even the
"Turbulence"-movies are better. In fact, every other movie in the world is
better than this one.'
```

Vectorization

```
text_train_val = [doc.replace(b"<br />", b" ")
                  for doc in text_train_val]
text_train, text_val, y_train, y_val = train_test_split(
    text_trainval, y_trainval, stratify=y_trainval, random_state=0)
vect = CountVectorizer()
X_train = vect.fit_transform(text_train)
X_val = vect.transform(text_val)
X_train
```

```
<18750x66651 sparse matrix of type '<class 'numpy.int64'>'
  with 2580448 stored elements in Compressed Sparse Row format>
```

Vocabulary

```
feature_names = vect.get_feature_names()
print(feature_names[:10])
```

```
['00', '000', '0000000000001', '00001', '00015', '000s', '001', '003830', '006', '007']
```

```
print(feature_names[20000:20020])
```

```
['eschews', 'escort', 'escorted', 'escorting', 'escorts', 'escpecially', 'escreve',
 'escrow', 'esculator', 'ese', 'eser', 'esha', 'eshaan', 'eshley', 'esk', 'eskimo',
 'eskimos', 'esmerelda', 'esmond', 'esophagus']
```

```
print(feature_names[::2000])
```

```
['00', 'ahoy', 'aspects', 'belting', 'bridegroom', 'cements', 'commas', 'crowds',
 'detlef', 'druids', 'eschews', 'finishing', 'gathering',  'gunrunner', 'homesickness',
 'inhumanities', 'kabbalism', 'leech', 'makes', 'miki', 'nas', 'organ', 'pesci',
 'principally', 'rebours', 'robotnik', 'sculptural', 'skinkons', 'stardom', 'syncer',
 'tools', 'unflagging', 'waaaay', 'yanks']
```

Classification

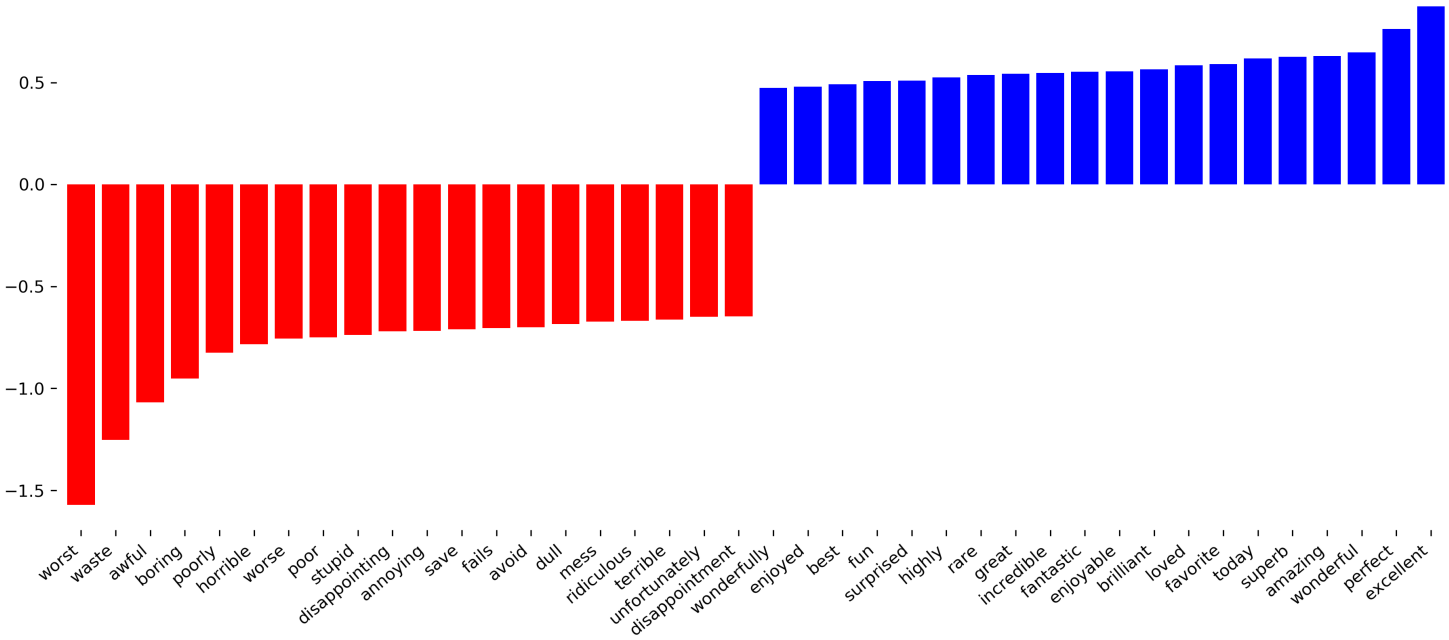
```
from sklearn.linear_model import LogisticRegressionCV
lr = LogisticRegressionCV().fit(X_train, y_train)
```

```
lr.C_
```

```
array([ 0.046])
```

```
lr.score(X_val, y_val)
```

```
0.882
```


0.5
0.0
−0.5
−1.0
−1.5
worst
waste
awful
boring
poorly
horrible
worse
poor
stupid
disappointing
annoying
save
fails
avoid
dull
mess
ridiculous
terrible
unfortunately
disappointment
wonderfully
enjoyed
best
fun
surprised
highly
rare
great
incredible
fantastic
enjoyable
brilliant
loved
favorite
today
superb
amazing
wonderful
perfect
excellent

Soo many options!

- How to tokenize?
- How to normalize words?
- What to include in vocabulary?

Tokenization

- Scikit-learn (very simplistic):
  - `re.findall(r"\b\w\w+\b")`
  - Includes numbers
  - discards single-letter words
  - `-` or `'` break up words

Changing the token pattern regex

```
vect = CountVectorizer(token_pattern=r"\b\w+\b")
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'because', 'do', 'get', 'how', 's', 'that', 'want', 'you']
```

Changing the token pattern regex

```
vect = CountVectorizer(token_pattern=r"\b\w+\b")
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'because', 'do', 'get', 'how', 's', 'that', 'want', 'you']
```

```
vect = CountVectorizer(token_pattern=r"\b\w[\w’]+\b")

vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'because', 'do', 'get', 'how', 'that’s', 'want', 'you']
```

Normalization

- Correct spelling?
- Stemming: reduce to word stem
- Lemmatization: smartly reduce to word stem

Normalization

- Correct spelling?
- Stemming: reduce to word stem
- Lemmatization: smartly reduce to word stem

"Our meeting today was worse than yesterday,
I'm scared of meeting the clients tomorrow."

Stemming:

```
['our', 'meet', 'today', 'wa', 'wors', 'than', 'yesterday', ',', 'i', "'m",
'scare', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
```

Lemmatization:

```
['our', 'meeting', 'today', 'be', 'bad', 'than', 'yesterday', ',', 'i', 'be',
'scar', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
```

Normalization

- Correct spelling?
- Stemming: reduce to word stem
- Lemmatization: smartly reduce to word stem

"Our meeting today was worse than yesterday,
I'm scared of meeting the clients tomorrow."

Stemming:

```
['our', 'meet', 'today', 'wa', 'wors', 'than', 'yesterday', ',', 'i', "'m",
'scare', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
```

Lemmatization:

```
['our', 'meeting', 'today', 'be', 'bad', 'than', 'yesterday', ',', 'i', 'be',
'scar', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
```

- scikit-learn:
  - Lower-case it
  - Configurable, use nltk or spacy

Restricting the Vocabulary

Stop Words

```
vect = CountVectorizer(stop_words='english')
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'want']
```

```
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
print(list(ENGLISH_STOP_WORDS))
```

```
['former', 'above', 'inc', 'off', 'on', 'those', 'not', 'fifteen', 'sometimes', 'too', 'is', 'move', 'much', 'own', 'until', 'wherein',
'which', 'over', 'thru', 'whoever', 'this', 'indeed', 'same', 'three', 'whatever', 'us', 'somewhere', 'after', 'eleven', 'most', 'de', 'full',
'into', 'being', 'yourselves', 'neither', 'he', 'onto', 'seems', 'who', 'between', 'few', 'couldnt', 'i', 'found', 'nobody', 'hereafter',
'therein', 'together', 'con', 'ours', 'an', 'anyone', 'became', 'mine', 'myself', 'before', 'call', 'already', 'nothing', 'top', 'further',
'thereby', 'why', 'here', 'next', 'these', 'ever', 'whereby', 'cannot', 'anyhow', 'thereupon', 'somehow', 'all', 'out', 'ltd', 'latterly',
'although', 'beforehand', 'hundred', 'else', 'per', 'if', 'afterwards', 'any', 'since', 'nor', 'thereafter', 'it', 'around', 'them',
'alone', 'up', 'sometime', 'very', 'give', 'elsewhere', 'always', 'cant', 'due', 'forty', 'still', 'either', 'was', 'beyond', 'fill',
'hereupon', 'no', 'might', 'by', 'everyone', 'five', 'often', 'several', 'and', 'something', 'formerly', 'she', 'him', 'become', 'get',
'could', 'ten', 'below', 'had', 'how', 'back', 'nevertheless', 'namely', 'herself', 'none', 'be', 'himself', 'becomes', 'hereby',
'never', 'along', 'while', 'side', 'amoungst', 'toward', 'made', 'their', 'part', 'everything', 'his', 'becoming', 'a', 'now', 'am',
'perhaps', 'moreover', 'seeming', 'themselves', 'name', 'etc', 'more', 'another', 'whither', 'see', 'herein', 'whom', 'among', 'un', 'via',
'every', 'cry', 'me', 'should', 'its', 'again', 'co', 'itself', 'two', 'yourself', 'seemed', 'under', 'then', 'meanwhile', 'anywhere',

'beside', 'seem', 'please', 'behind', 'sixty', 'were', 'in', 'upon', 'than', 'twelve', 'when', 'third', 'to', 'though', 'hence',
'done', 'other', 'where', 'someone', 'of', 'whose', 'during', 'many', 'as', 'except', 'besides', 'for', 'within', 'mostly', 'but',
'nowhere', 'we', 'our', 'through', 'both', 'bill', 'yours', 'less', 'well', 'have', 'therefore', 'one', 'last', 'throughout', 'can',
'mill', 'against', 'anyway', 'at', 'system', 'noone', 'that', 'would', 'only', 'rather', 'wherever', 'least', 'are', 'empty', 'almost',
```

Infrequent Words

- Remove words that appear in less than 2 documents:

```
vect = CountVectorizer(min_df=2)
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'you']
```

- Restrict vocabulary size to max_features most frequent words:

```
vect = CountVectorizer(max_features=4)
vect.fit(malory)
print(vect.get_feature_names())
```

```
['ants', 'because', 'do', 'you']
```

```
vect = CountVectorizer(min_df=2)
X_train_df2 = vect.fit_transform(text_train)

vect = CountVectorizer(min_df=4)
X_train_df4 = vect.fit_transform(text_train)
X_val_df4 = vect.transform(text_val)

print(X_train.shape)
print(X_train_df2.shape)
print(X_train_df4.shape)
```

```
(18750, 66651)
(18750, 39825)
(18750, 26928)
```

```
lr = LogisticRegressionCV().fit(X_train_df4, y_train)
lr.C_
```

```
array([ 0.046])
```

```
lr.score(X_val_df4, y_val)
```

```
0.881
```

Tf-idf rescaling

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \cdot \text{idf}(t)$$

$$\text{idf}(t) = \log \frac{1 + n_d}{1 + \text{df}(d, t)} + 1$$

n_d = total number of documents
$df(d, t)$ = number of documents containing term t

Tf-idf rescaling

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \cdot \text{idf}(t)$$

$$\text{idf}(t) = \log \frac{1 + n_d}{1 + \text{df}(d, t)} + 1$$

n_d = total number of documents
$df(d, t)$ = number of documents containing term t

- In sklearn: by default also L2 normalisation!

TfidfVectorizer, TfidfTransformer

```
from sklearn.feature_extraction.text import TfidfVectorizer, TfidfTransformer
```

```
malory_tfidf = TfidfVectorizer().fit_transform(malory)
malory_tfidf.toarray()
```

```
array([[ 0.41 ,  0.   ,  0.576,  0.   ,  0.   ,  0.   ,  0.576,  0.41 ],
       [ 0.318,  0.447,  0.   ,  0.447,  0.447,  0.447,  0.   ,  0.318]])
```

```
malory_tfidf = make_pipeline(CountVectorizer(),
                             TfidfTransformer()).fit_transform(malory)
malory_tfidf.toarray()
```

```
array([[ 0.41 ,  0.   ,  0.576,  0.   ,  0.   ,  0.   ,  0.576,  0.41 ],
       [ 0.318,  0.447,  0.   ,  0.447,  0.447,  0.447,  0.   ,  0.318]])
```

N-grams: Beyond single words

- Bag of words completely removes word order.
- "didn't love" and "love" are very different!

N-grams: Beyond single words

- Bag of words completely removes word order.
- "didn't love" and "love" are very different!

“This is how you get ants.”

Bigrams toy example

```
cv = CountVectorizer(ngram_range=(1, 1)).fit(malory)
print("Vocabulary size: ", len(cv.vocabulary_))
print("Vocabulary:\n", cv.get_feature_names())
```

```
Vocabulary size: 8
Vocabulary:
['ants', 'because', 'do', 'get', 'how', 'that', 'want', 'you']
```

```
cv = CountVectorizer(ngram_range=(2, 2)).fit(malory)
print("Vocabulary size: ", len(cv.vocabulary_))
print("Vocabulary:\n", cv.get_feature_names())
```

```
Vocabulary size: 8
Vocabulary:
['because that', 'do you', 'get ants', 'how you', 'that how', 'want ants', 'you get', 'you want']
```

```
cv = CountVectorizer(ngram_range=(1, 2)).fit(malory)
print("Vocabulary size: ", len(cv.vocabulary_))
print("Vocabulary:\n", cv.get_feature_names())
```

```
Vocabulary size: 16
Vocabulary:
['ants', 'because', 'because that', 'do', 'do you', 'get', 'get ants', 'how', 'how you', 'that', 'that how', 'want', 'want ants',
'you', 'you get', 'you want']
```

N-grams on IMDB data

```
Vocabulary Sizes
1-gram (min_df=4): 26928
2-gram (min_df=4): 128426
1-gram & 2-gram (min_df=4): 155354
1-3gram (min_df=4): 254274
1-4gram (min_df=4): 289443
```

```
cv = CountVectorizer(ngram_range=(1, 4)).fit(text_train)
print("Vocabulary size 1-4gram: ", len(cv.vocabulary_))
```

```
Vocabulary size 1-4gram (min_df=1): 7815528
```

- More than 20x more 4-grams!

Stop-word impact on bi-grams

```
cv = CountVectorizer(ngram_range=(1, 2), min_df=4)
cv.fit(text_train)
print("(1, 2), min_df=4: ", len(cv.vocabulary_))
cv = CountVectorizer(ngram_range=(1, 2), min_df=4,
                     stop_words="english")
cv.fit(text_train)
print("(1, 2), stopwords, min_df=4: ", len(cv.vocabulary_))
```

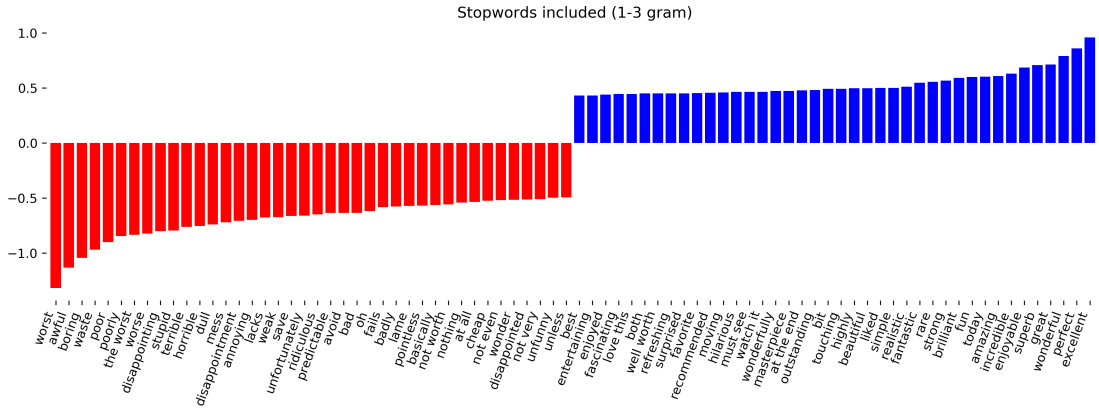
```
(1, 2), min_df=4: 155354
(1, 2), stopwords, min_df=4: 81085
```

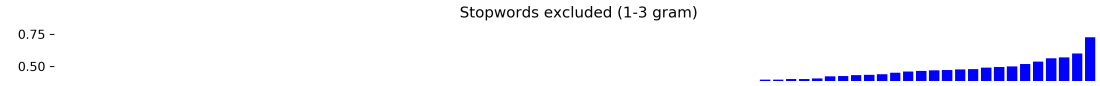
Stop-word impact on 4-grams

```
cv4 = CountVectorizer(ngram_range=(4, 4), min_df=4)
cv4.fit(text_train)
cv4sw = CountVectorizer(ngram_range=(4, 4), min_df=4,
                        stop_words="english")
cv4sw.fit(text_train)
print(len(cv4.get_feature_names()))
print(len(cv4sw.get_feature_names()))
```

```
31585
369
```

```
['worst movie ve seen' '40 year old virgin' 've seen long time'
'worst movies ve seen' 'don waste time money'
'mystery science theater 3000' 'worst film ve seen'
'lose friends alienate people' 'best movies ve seen'
'don waste time watching' 'jean claude van damme'
'really wanted like movie' 'best movie ve seen' 'rock roll high school'
'don think ve seen' 'let face music dance' 'don say didn warn'
'worst films ve seen' 'fred astaire ginger rogers' 'ha ha ha ha'
'la maman et la' 'maman et la putain' 'left cutting room floor'
've seen ve seen' 'just doesn make sense' 'robert blake scott wilson'
'late 70 early 80' 'crouching tiger hidden dragon' 'low budget sci fi'
'movie ve seen long' 'toronto international film festival'
'night evelyn came grave' 'good guys bad guys' 'low budget horror movies'
'waste time watching movie' 'vote seven title brazil' 'bad bad bad bad'
'morning sunday night monday' '14 year old girl' 'film based true story'
'don make em like' 'silent night deadly night'
'rating saturday night friday' 'right place right time'
'friday night friday morning' 'night friday night friday'
'friday morning sunday night' 'don waste time movie'
'saturday night friday night' 'really wanted like film']
```

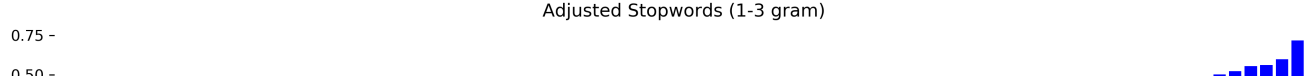

Stopwords included (1-3 gram)
1.0
0.5
0.0
−0.5
−1.0
worst
awful
boring
waste
poor
poorly
the worst
worse
disappointing
stupid
terrible
horrible
dull
mess
disappointment
annoying
lacks
weak
save
unfortunately
ridiculous
predictable
avoid
bad
oh
fails
badly
lame
pointless
basically
not worth
nothing
at all
cheap
not even
wonder
disappointed
not very
unfunny
unless
best
entertaining
enjoyed
fascinating
love this
both
well worth
refreshing
surprised
favorite
recommended
moving
hilarious
must see
watch it
wonderfully
masterpiece
at the end
outstanding
bit
touching
highly
beautiful
liked
simple
realistic
fantastic
rare
strong
brilliant
fun
today
amazing
incredible
enjoyable
superb
great
wonderful
perfect
excellent


Stopwords excluded (1-3 gram)
0.75
0.50

```
my_stopwords = set(ENGLISH_STOP_WORDS)
my_stopwords.remove("well")
my_stopwords.remove("not")
my_stopwords.add("ve")
```

```
vect3msw = CountVectorizer(ngram_range=(1, 3), min_df=4, stop_words=my_stopwords)
X_train3msw = vect3msw.fit_transform(text_train)
lr3msw = LogisticRegressionCV().fit(X_train3msw, y_train)
X_val3msw = vect3msw.transform(text_val)
lr3msw.score(X_val3msw, y_val)
```

```
0.883
```



Character n-grams

Principle

```
Do␣you␣want␣ants?
```

Principle

Do␣you␣want␣ants?

Principle

Principle

Do␣you␣want␣ants?

Principle

Do␣you␣want␣ants?

Applications

- Be robust to misspelling / obfuscation
- Language detection
- Learn from Names / made-up words

Toy example

- "Naive"

```
cv = CountVectorizer(ngram_range=(2, 3), analyzer="char").fit(malory)
print("Vocabulary size: ", len(cv.vocabulary_))
print("Vocabulary:\n", cv.get_feature_names())
```

```
Vocabulary size: 73
Vocabulary:
[' a', ' an', ' g', ' ge', ' h', ' ho', ' t', ' th', ' w', ' wa', ' y', ' yo', 'an', 'ant', 'at', 'at’', 'au', 'aus', 'be', 'bec', 'ca',
'cau', 'do', 'do ', 'e ', 'e t', 'ec', 'eca', 'et', 'et ', 'ge', 'get', 'ha', 'hat', 'ho', 'how', 'nt', 'nt ', 'nts', 'o ', 'o y', 'ou',
'ou ', 'ow', 'ow ', 's ', 's h', 's.', 's?', 'se', 'se ', 't ', 't a', 'th', 'tha', 'ts', 'ts.', 'ts?', 't’', 't’s', 'u ', 'u g', 'u w',
'us', 'use', 'w ', 'w y', 'wa', 'wan', 'yo', 'you', '’s', '’s ']
```

- Respect word boundaries

```
cv = CountVectorizer(ngram_range=(2, 3), analyzer="char_wb").fit(malory)
print("Vocabulary size:", len(cv.vocabulary_))
print("Vocabulary:\n", cv.get_feature_names())
```

```
Vocabulary size: 74
Vocabulary:
[' a', ' an', ' b', ' be', ' d', ' do', ' g', ' ge', ' h', ' ho', ' t', ' th', ' w', ' wa', ' y', ' yo', '. ', '? ', 'an', 'ant', 'at', '
at’', 'au', 'aus', 'be', 'bec', 'ca', 'cau', 'do', 'do ', 'e ', 'ec', 'eca', 'et', 'et ', 'ge', 'get', 'ha', 'hat', 'ho', 'how', 'nt', 'nt ',
'nts', 'o ', 'ou', 'ou ', 'ow', 'ow ', 's ', 's.', 's. ', 's?', 's? ', 'se', 'se ', 't ', 'th', 'tha', 'ts', 'ts.', 'ts?', 't’', 't’s',
'u ', 'us', 'use', 'w ', 'wa', 'wan', 'yo', 'you', '’s', '’s ']
```

IMDB Data

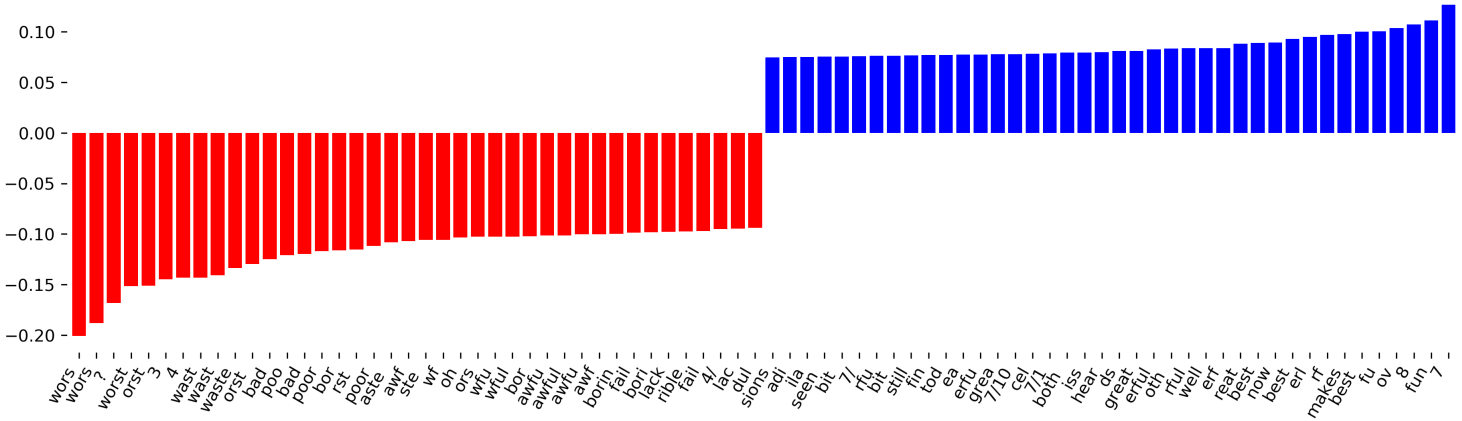
```
char_vect = CountVectorizer(ngram_range=(2, 5), min_df=4, analyzer="char_wb")
X_train_char = char_vect.fit_transform(text_train)
```

```
len(char_vect.vocabulary_)
```

```
164632
```

```
lr_char = LogisticRegressionCV().fit(X_train_char, y_train)
X_val_char = char_vect.transform(text_val)
lr_char.score(X_val_char, y_val)
```

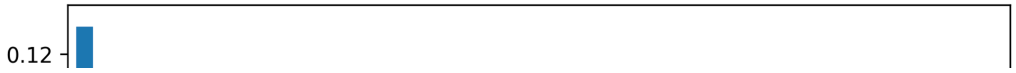
```
0.881
```


0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
wors
wors
?
worst
orst
3
4
wast
wast
waste
orst
bad
poo
bad
poor
bor
rst
poor
aste
awf
ste
wr
oh
ors
wfu
wful
bor
awru
awful
awfu
awr
borin
fail
bori
lack
rible
fail
4/
lac
dul
sions
adj
ila
seen
bit
7/
rfu
bit
still
fin
tod
ea
eru
grea
7/10
cel
7/1
both
iss
hear
ds
great
erful
oth
rful
well
erf
reat
best
now
best
eri
rf
makes
best
fu
ov
8
fun
7

48 / 60

Predicting Nationality from Name

	country	fullName	id	nationalPoliticalGroup	politicalGroup
0	Sweden	Lars ADAKTUSSON	124990	Kristdemokraterna	Group of the European People's Party (Christia...
1	Italy	Isabella ADINOLFI	124831	Movimento 5 Stelle	Europe of Freedom and Direct Democracy Group
2	Italy	Marco AFFRONTE	124797	Movimento 5 Stelle	Group of the Greens/European Free Alliance
3	Italy	Laura AGEA	124811	Movimento 5 Stelle	Europe of Freedom and Direct Democracy Group
4	United Kingdom	John Stuart AGNEW	96897	United Kingdom Independence Party	Europe of Freedom and Direct Democracy Group



Comparing words vs chars

```
bow_pipe = make_pipeline(CountVectorizer(), LogisticRegressionCV())
cross_val_score(bow_pipe, text_mem_train, y_mem_train, cv=5, scoring='f1_macro')
```

```
array([ 0.231,  0.241,  0.236,  0.28 ,  0.254])
```

```
char_pipe = make_pipeline(CountVectorizer(analyzer="char_wb"), LogisticRegressionCV())
cross_val_score(char_pipe, text_mem_train, y_mem_train, cv=5, scoring='f1_macro')
```

```
array([ 0.452,  0.459,  0.341,  0.469,  0.418])
```

Grid-search parameters

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import Normalizer

param_grid = {"logisticregression__C": [100, 10, 1, 0.1, 0.001],
              "countvectorizer__ngram_range": [(1, 1), (1, 2), (1, 5), (1, 7),
                                               (2, 3), (2, 5), (3, 8), (5, 5)],
              "countvectorizer__min_df": [1, 2, 3],
              "normalizer": [None, Normalizer()]
             }
grid = GridSearchCV(make_pipeline(CountVectorizer(analyzer="char"), Normalizer(), LogisticRegression(),
                                  memory="cache_folder"),
                    param_grid=param_grid, cv=10, scoring="f1_macro"
                   )
```

```
grid.fit(text_mem_train, y_mem_train)
```

```
grid.best_score_
```

```
0.58255198397046815
```

```
grid.best_params_
```

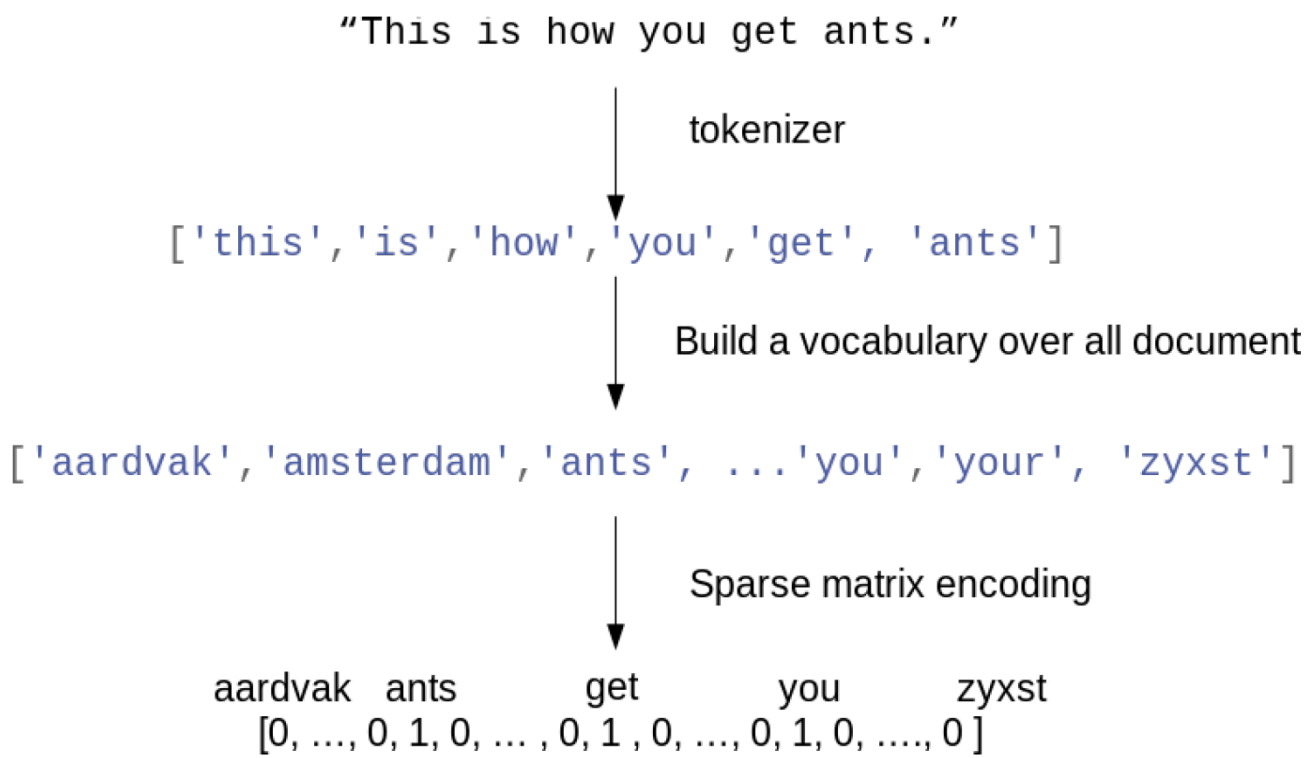
```
{'countvectorizer__min_df': 2,
 'countvectorizer__ngram_range': (1, 5),
 'logisticregression__C': 10}
```

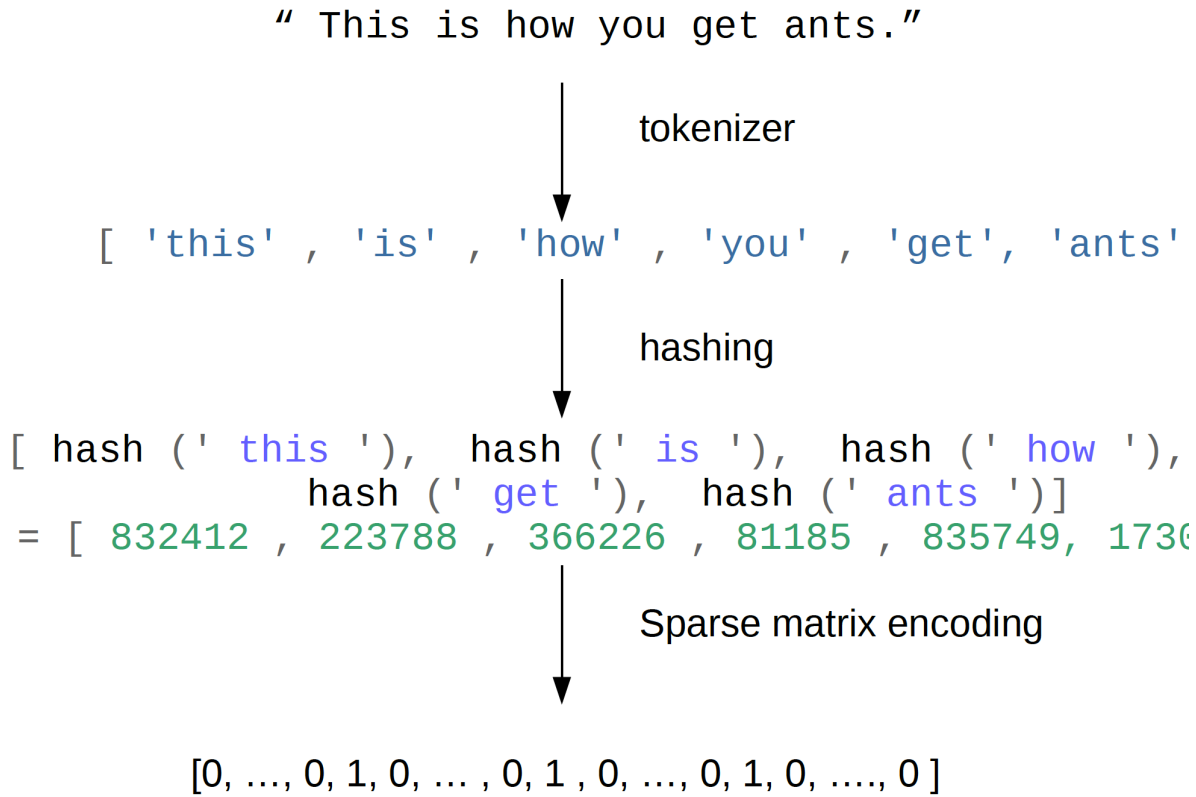
	param_countvectorizer__ngram_range	(1, 1)	(1, 2)	(1, 5)	(1, 7)	(2, 3)	(2, 5)	(3, 8)	(5, 5)
min_df	C								
1	0.001	0.141167	0.216887	0.266306	0.267246	0.325938	0.349475	0.281929	0.0653852
	0.1	0.44827	0.520445	0.551024	0.544649	0.475185	0.507482	0.428376	0.249614
	1.0	0.480549	0.545256	0.565362	0.554272	0.515928	0.517898	0.434622	0.333195
	10.0	0.499625	0.529781	0.575243	0.548367	0.495087	0.511727	0.432281	0.360981
	100.0	0.481605	0.515618	0.569864	0.547449	0.497854	0.505122	0.440256	0.383315
2	0.001	0.141167	0.211798	0.251195	0.253522	0.310884	0.341462	0.242935	0.0576071
	0.1	0.441997	0.523296	0.560686	0.552423	0.487937	0.500663	0.440686	0.184905
	1.0	0.482002	0.531615	0.573458	0.570961	0.50686	0.523805	0.455477	0.293757
	10.0	0.498945	0.534128	0.582552	0.574385	0.494141	0.522637	0.409354	0.279838
	100.0	0.469252	0.52665	0.581839	0.577626	0.488827	0.517176	0.427836	0.267407
3	0.001	0.141167	0.212785	0.24461	0.248863	0.309673	0.336444	0.214413	0.0576071
	0.1	0.437624	0.520559	0.564124	0.556022	0.497634	0.507008	0.430714	0.167934
	1.0	0.483502	0.534692	0.564548	0.559782	0.508479	0.526124	0.441994	0.232509
	10.0	0.499686	0.525823	0.577809	0.579871	0.497012	0.510214	0.432801	0.224545
	100.0	0.481043	0.512089	0.572186	0.574859	0.490168	0.491294	0.417196	0.224545

Other features

- Length of text
- Number of out-of-vocabularly words
- Presence / frequency of ALL CAPS
- Punctuation...!? (somewhat capturedd by char ngrams)
- Sentiment words (good vs bad)
- Whatever makes sense for the task!

Large Scale Text Vectorization


“This is how you get ants.”
tokenizer
['this','is','how','you','get', 'ants']
Build a vocabulary over all document
['aardvak','amsterdam','ants', ...'you','your', 'zyxst']
Sparse matrix encoding
aardvak ants get you zyxst
[0, ..., 0, 1, 0, ... , 0, 1 , 0, ..., 0, 1, 0, ..., 0]


“ This is how you get ants.”
tokenizer
['this' , 'is' , 'how' , 'you' , 'get', 'ants'
hashing
[hash (' this '), hash (' is '), hash (' how '),
hash (' get '), hash (' ants ')]
= [832412 , 223788 , 366226 , 81185 , 835749, 173
Sparse matrix encoding
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

Near drop-in replacement

- Careful: Uses l2 normalization by default!

```
from sklearn.feature_extraction.text import HashingVectorizer
hv = HashingVectorizer()
X_train = hv.transform(text_train)
X_val = hv.transform(text_val)
```

```
lr.score(X_val, y_val)
```

```
from sklearn.feature_extraction.text import HashingVectorizer
hv = HashingVectorizer()
X_train = hv.transform(text_train)
X_val = hv.transform(text_val)
```

```
X_train.shape
```

```
(18750, 1048576)
```

```
lr = LogisticRegressionCV().fit(X_train, y_train)
lr.score(X_val, y_val)
```

Trade-offs

Pro:

- Fast
- Works for streaming data
- Low memory footprint

Con:

- Can't interpret results
- Hard to debug
- (collisions are not a problem for model accuracy)

Questions ?