BASIC TEXT FEATURES FOR NLP: COUNTVECTORIZER

Introduction to NLP
Session 2

2023

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BASIC DEFINITIONS

- Definition: A corpus is a set of documents (usually an Iterable of strings).
- Definition: A vocabulary is a hash map (Dict) that maps words to positions.
- Definition: A vocabulary extracted from a corpus Dict of words containing the atomic symbols used to represent the corpus.
- Vocabularies are usually extracted tokenizing a corpus. A token is a substring from a document with 'atomic' meaning (usually tokens refer to words).

BASIC TEXT REPRESENTATION

- In order to input text to a machine learning algorithm we need to convert the string representation to vectors.
- The most basic way to encode text is a bag of words representation.
  - A bag-of-words describes the occurrence of words within a text.
  - A bag of words representation involves:
    - A vocabulary of known words.
    - A measure of the presence of known words (such as word counts).

BAG OF WORDS REPRESENTATION

- The vocabulary is usually stored as a dictionary (`Dict` or `OrderedDict`) that we will call `word_to_pos`.
    - keys in `word_to_pos` are the words in the vocabulary.
    - values in `word_to_pos` are the positions assigned to the words.
- The bag of words feature vector `x` for a document `d` is constructed using the counts of the words in `d`. Coordinate `k` in `x` contains the number of times the k'th word from `word_to_pos` appears in `d`.
    - `word_to_pos = {‘the’:0, ‘man’:1, ‘that’:2, ‘went’:3, ‘to’:4, ‘moon’:5}`
    - “`The man that went to the moon`”
    - $$\begin{array}{lcccccc} & \textit{the} & \textit{man} & \textit{that} & \textit{went} & \textit{to} & \textit{moon} \\ x = & [2, & 1, & 1, & 1, & 1, & 1] \end{array}$$

EXAMPLES BAG OF WORDS REPRESENTATION

- Consider the corpus:
  - “The cat sat on the mat”
  - “the cat and the dog sat on the mat”

```
word_to_pos ={The:0,
             cat:1,
             sat:2,
             on:3,
             the:4,
             mat:5,
             and: 6,
             dog:7}
```

Notice word_to_pos contains "the" and “The”.
Unless we do something to each token that is what will happen.

- Bag of words feature descriptor
  - “the cat sat on the mat” → [0, 1, 1, 1, 2, 1, 0, 0]
  - “the cat and the dog sat on the mat” → [0, 1, 1, 1, 3, 1, 1, 1]

Positions	0	1	2	3	4	5	6	7
“the cat sat on the mat”	0	1	1	1	2	1	0	0
“the cat and the dog sat on the mat”	0	1	1	1	3	1	1	1

BASIC DICTIONARIES FOR BAG OF WORDS REPRESENTATION

Standard dict (keys have no order)

```
normal_dict = {}

normal_dict['1'] = "A"
normal_dict['2'] = "B"
normal_dict['3'] = "C"
normal_dict['4'] = "D"
normal_dict['5'] = "E"

print("Printing normal Dictionary : ")

for k,v in normal_dict.items():
    print("key : {0}, value : {1}".format(k,v))
```

```
Printing normal Dictionary :
key : 3, value : C
key : 1, value : A
key : 2, value : B
key : 4, value : D
key : 5, value : E
```

OrderedDic (keys have order)

```
import collections

ordered_dict = collections.OrderedDict()

ordered_dict['1'] = "A"
ordered_dict['2'] = "B"
ordered_dict['3'] = "C"
ordered_dict['4'] = "D"
ordered_dict['5'] = "E"

print("Printing Ordered Dictionary : ")

for k,v in ordered_dict.items():
    print("key : {0},value : {1}".format(k,v))
```

```
Printing Ordered Dictionary :
key : 1,value : A
key : 2,value : B
key : 3,value : C
key : 4,value : D
key : 5,value : E
```

TEXT REPRESENTATION

- How can we apply machine learning techniques when the input is a text description?
  - We need to transform strings to vectors
- Challenges when working with text:
  - The feature vector dimensionality can be huge.
  - Words outside the vocabulary (such as misspelled words) might bring problems.

CREATING FEATURE VECTORS

- Given a corpus, how do we define a vocabulary?
  - We need to iterate over words, but raw data is usually not provided with words.

- There are several decisions that impact vocabulary creation:
  - I) How do we generate tokens? (Preprocessing)
  - II) Do we need to clean tokens? (Preprocessing)
  - III) Do we create combinations of tokens? (Feature extraction)
  - IV) Do we select combinations of tokens? (Feature selection/Feature pruning)

CONSTRUCTING A VOCABULARY

- In order to build feature descriptors we need to create a `word_to_pos.`
- `word_to_pos` depends on
  - How we generate tokens from strings.
  - How we clean the tokens.
- Many packages contain classes build to create vectorizer with a `.fit` method
- Scikit-learn has the `CountVectorizer` class during fit
  - Receives as input an iterable of strings.
  - For each string the class finds the tokens (or words) in the string.
  - Words are stored in `word_to_pos`.

COUNTVECTORIZER FROM SKLEARN

- `.fit(X)` Learns a vocabulary from raw data `X`.
- `.transform(x)` Generates an array with the feature descriptor for `x`.
- How should be store `.transform(x)` ?
  - Numpy array
  - List
  - Pandas dataframe
  - **Scipy csr matrix**

HIGH DIMENSIONAL FEATURE VECTORS

- In the context of document descriptors feature vectors can contain millions of words.
- Storing such vectors using lists of Numpy arrays is very inefficient.

COMPRESSED SPARSE ROW MATRIX (CSR MATRIX)

- A CSR matrix is constructed from 3 arrays:
  - `data`: contains the coordinate values of the array.
  - `ind_col`: contains the column indices of the elements in the matrix.
  - `ind_ptr`: contains the pointers that define which elements belong to to each row.
- In this example memory usage decreases from 30 numbers to 18.

```
X = np.array([[0,5,7,6,0,0,0,0,0,0],
              [0,0,0,0,0,0,0,0,0,1],
              [7,0,4,9,0,0,0,0,0,0]])
X
```

executed in 3ms, finished 12:25:55 2021-02-22

```
array([[0, 5, 7, 6, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [7, 0, 4, 9, 0, 0, 0, 0, 0, 0]])
```

```
data    = [5, 7, 6, 1, 7, 4, 9]
ind_col = [1, 2, 3, 9, 0, 2, 3]
ind_ptr = [0, 3, 4, 7]
```

executed in 2ms, finished 12:26:55 2021-02-22

```
X_csr = sp.csr_matrix((data, ind_col, ind_ptr))
X_csr.toarray()
```

executed in 3ms, finished 12:27:29 2021-02-22

```
array([[0, 5, 7, 6, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],
       [7, 0, 4, 9, 0, 0, 0, 0, 0, 0]])
```

TRANSFORMING AN ITERABLE OF STRINGS TO A SPARSE MATRIX

- How can we transform a sequence of strings to a sparse matrix?
- One approach would be:
  - I) Iterate over the data to create a vocabulary
  - II) Iterate over the data to generate the feature vectors for the elements in the vocabulary
  - can we improve this?
    - Maybe we can iterate over text and learn vocabulary and counts in a single iteration over the data.

GENERATING A FEATURE DESCRIPTOR FOR A LIST OF DOCUMENTS

```
docs = [['hello', 'world', 'hello'], ['goodbye', 'cruel', 'teacher', 'goodbye']]

def prepare_word_counts_with_dict(docs: Iterable[str], verbose=False):
    ind_ptr = [0]
    ind_col = []
    data = []
    vocabulary = {}
    # Let us use an auxiliary dict to keep track of counts

    return (data, ind_col, ind_ptr)

sp.csr_matrix(prepare_word_counts_with_dict(docs)).toarray()
```

```
array([[2, 1, 0, 0, 0],
       [0, 0, 2, 1, 1]])
```

GENERATING A FEATURE DESCRIPTOR FOR A LIST OF DOCUMENTS

```python
docs = [['hello', 'world', 'hello'], ['goodbye', 'cruel', 'teacher', 'goodbye']]

def prepare_word_counts_with_dict(docs: Iterable[str], verbose=False):
    ind_ptr = [0]
    ind_col = []
    data = []
    vocabulary = {}

    for m, doc in enumerate(docs):
        word_ind_counter = defaultdict(int)  # document counter for each doc in X
        for word in doc:
            vocabulary.setdefault(word, len(vocabulary))
            word_ind_counter[word] += 1

        data.extend(word_ind_counter.values())
        ind_ptr.append(ind_ptr[-1] + len(word_ind_counter))
        ind_col.extend([vocabulary[w] for w in word_ind_counter.keys()])

    return (data, ind_col, ind_ptr)

sp.csr_matrix(prepare_word_counts_with_dict(docs)).toarray()
```

```
array([[2, 1, 0, 0, 0],
       [0, 0, 2, 1, 1]])
```

GENERATING A FEATURE DESCRIPTOR FOR A LIST OF DOCUMENTS

```
docs = [['hello','world','hello'],['goodbye','cruel','teacher']]

ind_ptr = [0]
ind_col = []
data = []
vocabulary = {}
```

Let us do it WITHOUT auxiliary dict to keep track of counts

```
sp.csr_matrix((data, ind_col, ind_ptr)).toarray()
```

executed in 3ms, finished 12:34:07 2021-02-22

```
array([[2, 1, 0, 0, 0],
       [0, 0, 1, 1, 1]])
```

GENERATING A FEATURE DESCRIPTOR FOR A LIST OF DOCUMENTS

```
docs = [['hello','world','hello'],['goodbye','cruel','teacher']]

ind_ptr = [0]
ind_col = []
data = []
vocabulary = {}

for d in docs:
    for term in d:
        index = vocabulary.setdefault(term, len(vocabulary))
        ind_col.append(index)
        data.append(1)
    ind_ptr.append(len(ind_col))
```

executed in 3ms, finished 12:34:02 2021-02-22

```
sp.csr_matrix((data, ind_col, ind_ptr)).toarray()
```

executed in 3ms, finished 12:34:07 2021-02-22

```
array([[2, 1, 0, 0, 0],
       [0, 0, 1, 1, 1]])
```

DIFFERENT METHODOLOGIES TO DEFINE A LEARNING TASK

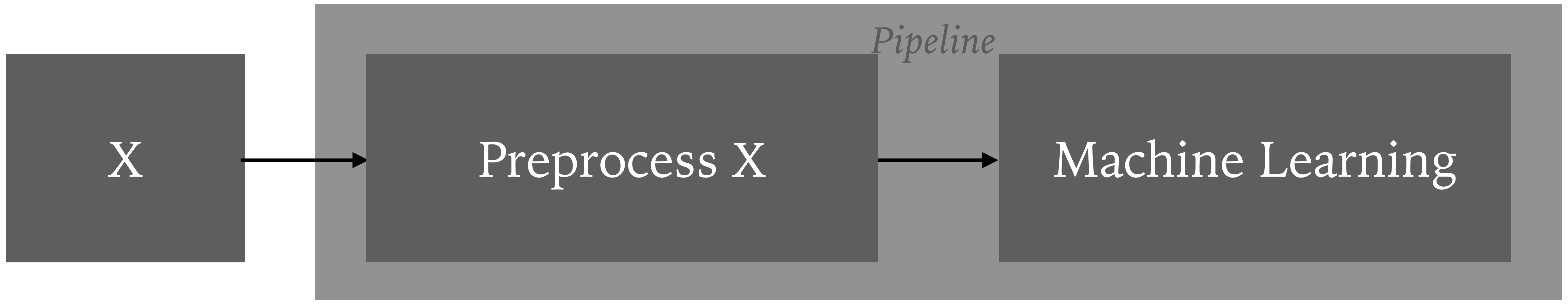
Scale, clean,

select features…

Fit a model,

do cross validation ..

➤ Composable/Composite models



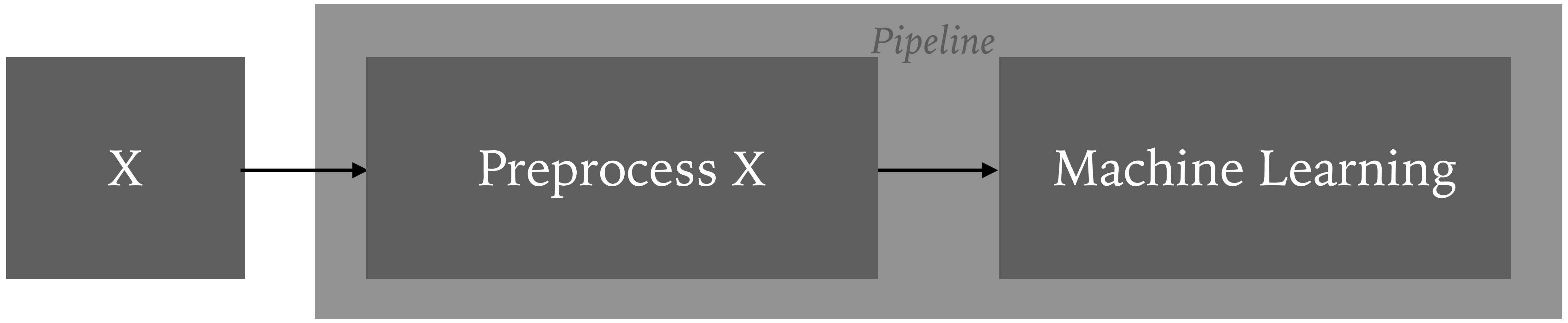
➤ Examples composite model implementations: *Sklearn Pipelines* *MLJ Learning Networks*

Scikit-learn *MLJ*

EXAMPLES


```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
logistic = sklearn.linear_model.LogisticRegression(C=0.1)

X_train_feature_vec = count_vectorizer.fit_transform(X_train)
logistic.fit(X_train_feature_vec, y_train)
```




```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
logistic = sklearn.linear_model.LogisticRegression(C=0.1)

model_pipe_3 = sklearn.pipeline.Pipeline([("countvectorizer", count_vectorizer),
                                          ("logisticregression", logistic)],
                                          )# memory='/Users/Shared/sklearn_mem/')

model_pipe_3.fit(X_train,y_train)
```

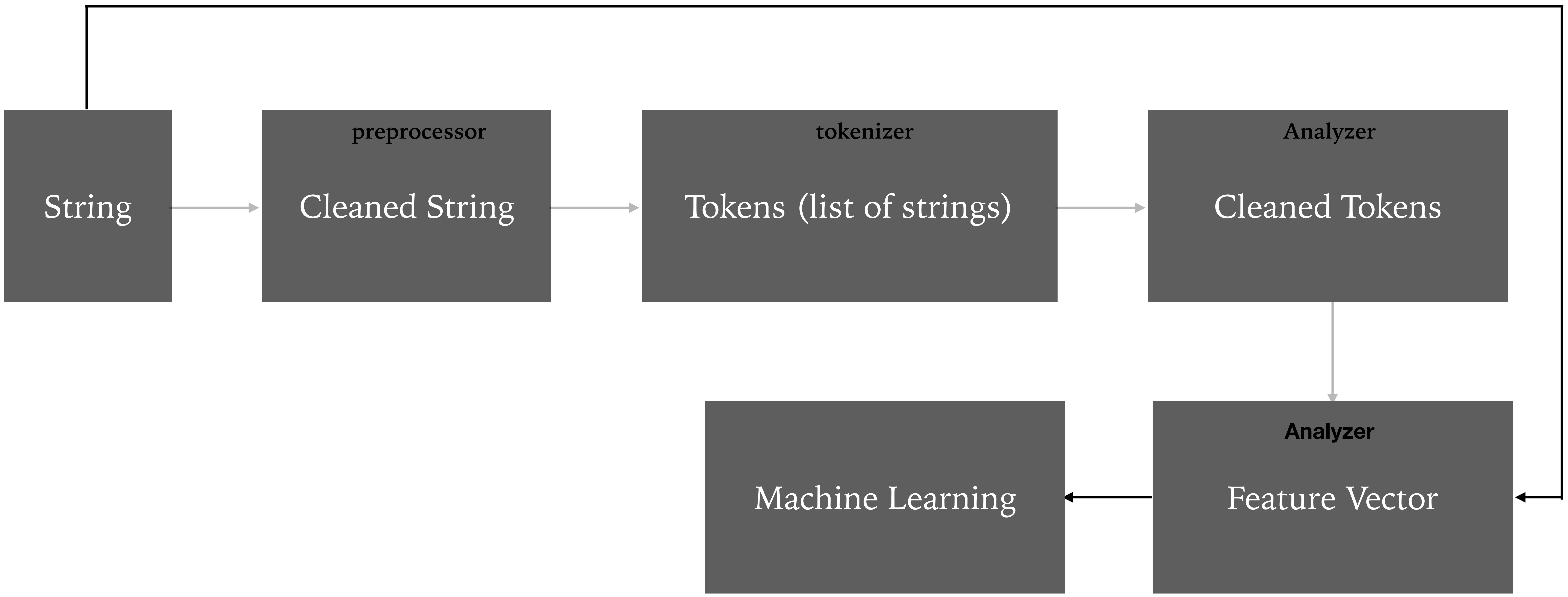
PIPLELINES OR COMPOSITE MODELS

- The purpose of the Pipeline is to assemble a composite model which consist on several steps that can be cross-validated together.
- Pipelines allow practitioners to easily compose and validate decisions made during training, instead of relying on pre-processing steps with ‘hand crafted’ decisions.
- Some of this decisions might include:
  - Type of tokenizer
  - Removing stop words
  - Using only words or bigram, trigrams etc..
  - Regularization parameters

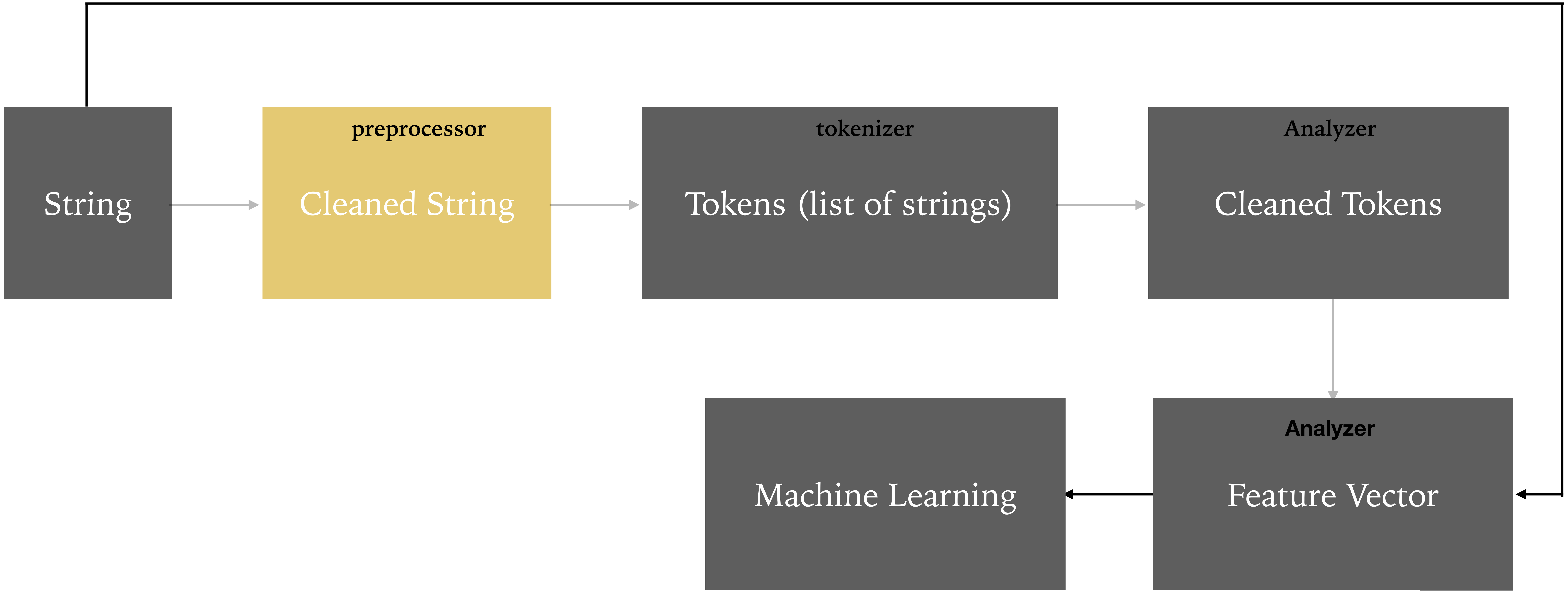
COUNTVECTORIZER

- A CounVectorizer is one of the most straight forward methods to generate descriptors for documents.

```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
```



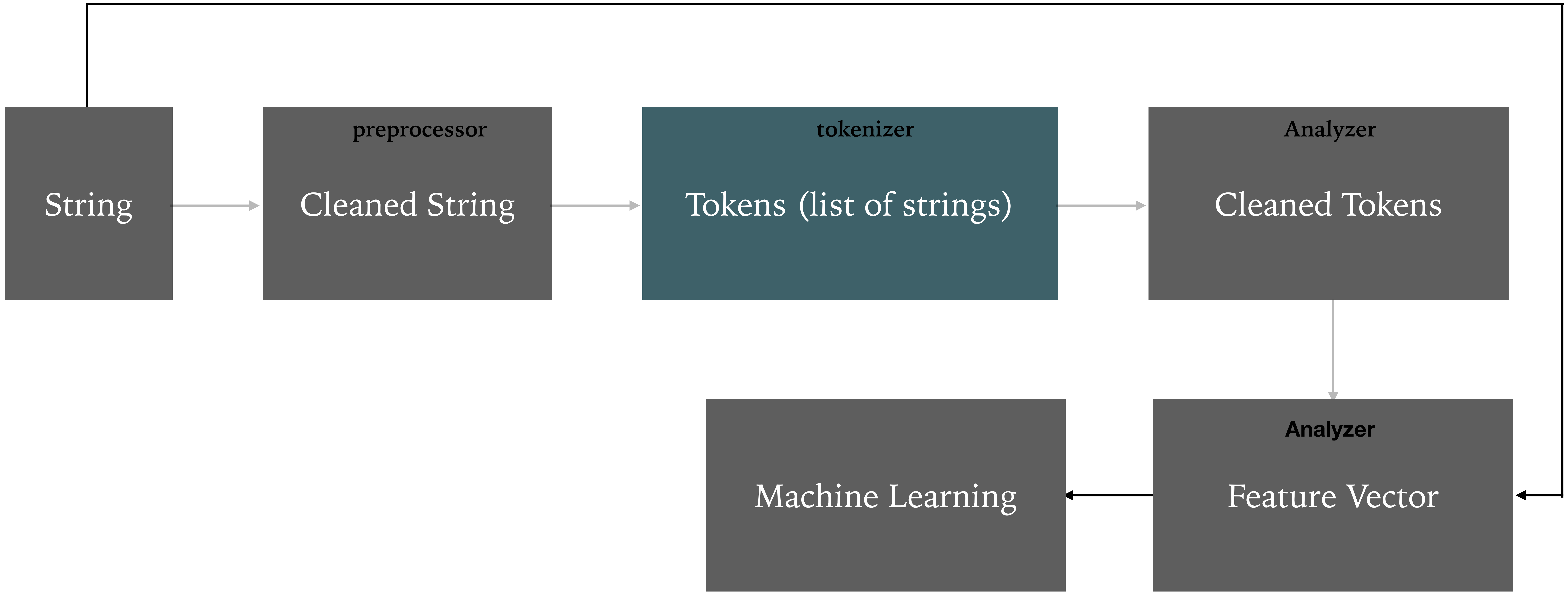
COUNTVECTORIZER: PREPROCESSOR




```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
count_vectorizer.fit(X_train)
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

COUNTVECTORIZER: TOKENIZER




```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
count_vectorizer.fit(X_train)
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

The \w\w+ ensures tokenized words have at least 2 symbols

TOKENIZER LIMITATIONS

- Tokenizer limitations
  - Single letter words such as `I` are ignored

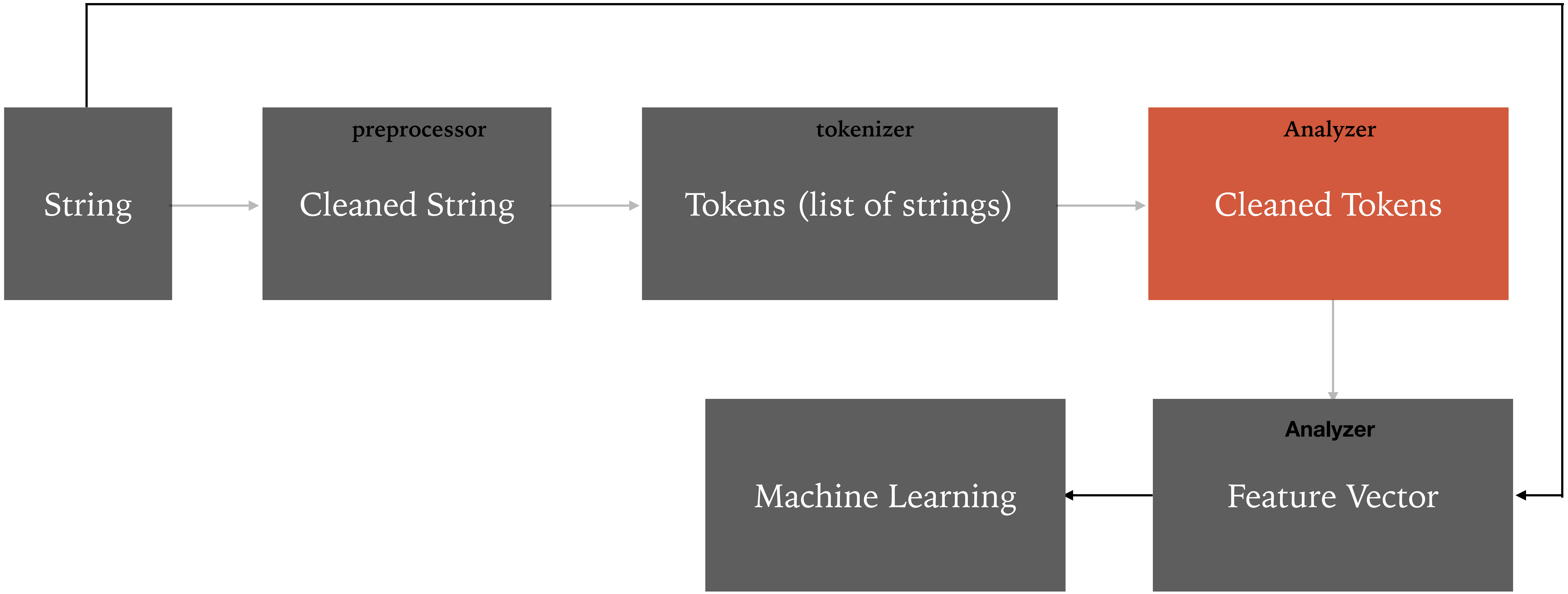
    re.findall(r'(?u)\b\w\w+\b', "I can't wait to go there!”)

    ['can', 'wait', 'to', 'go', ‘there’]
  - Expressions such as `can’t` are modified and might even change meaning!

    re.findall(r"\w+\'\w+", "I can't wait but I won't go there”)

    ["can't", “won't"]

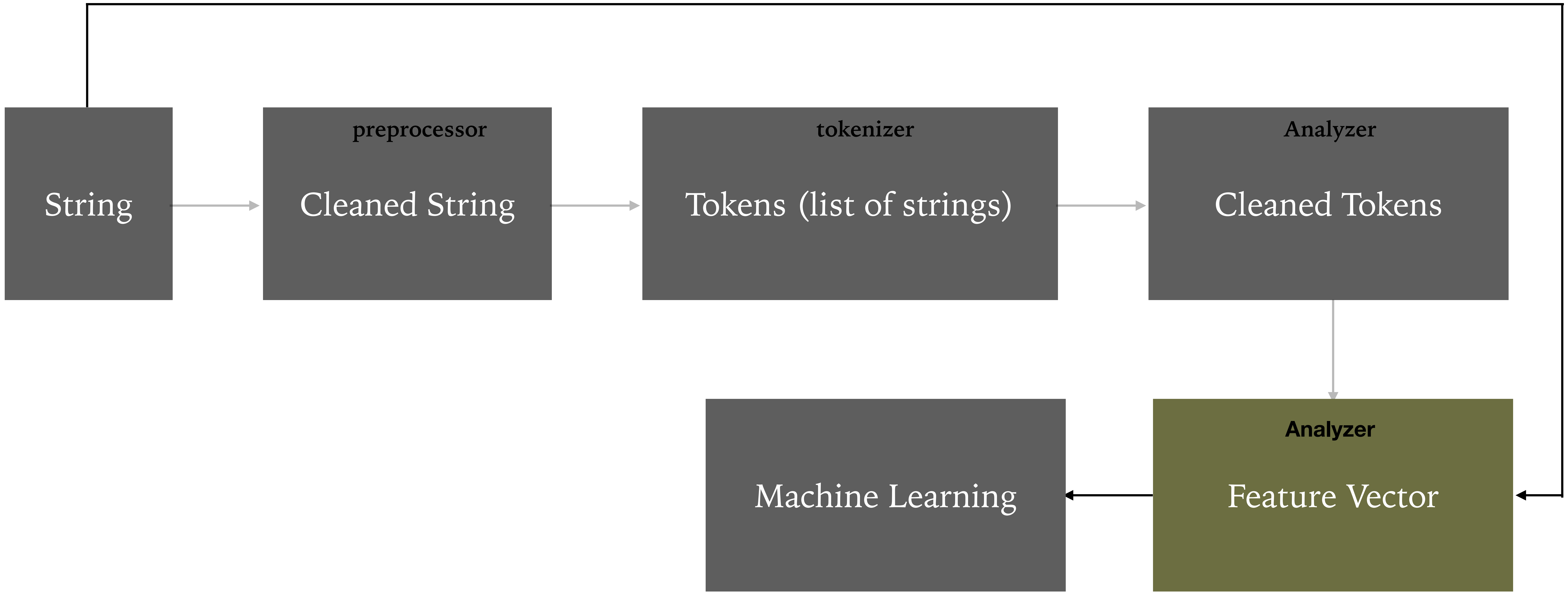
COUNTVECTORIZER: ANALYZER




```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
count_vectorizer.fit(X_train)
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

COUNTVECTORIZER: FEATURE VECTOR




```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
count_vectorizer.fit(X_train)
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

SUMMARY: CUSTOMISING VECTORIZER CLASSES

- **preprocessor**: a callable that takes an entire document as input (as a single string), and returns a possibly transformed version of the document, still as an entire string. This can be used to remove HTML tags, lowercase the entire document, etc.
- **tokenizer**: a callable that takes the output from the preprocessor and splits it into tokens, then returns a list of these.
- **analyzer**: a callable that replaces the preprocessor and tokenizer. The default analyzers all call the preprocessor and tokenizer, but custom analyzers will skip this. N-gram extraction and stop word filtering take place at the analyzer level, so a custom analyzer may have to reproduce these steps.

WHY IT IS IS IMPORTANT TO TUNE VECTORIZERS

➤ Many times vocabulary can be too rare that is not worth storing it.

```
count_vectorizer = sklearn.feature_extraction.text.CountVectorizer()
count_vectorizer.fit(X_train)
vocabulary = count_vectorizer.vocabulary_.keys()
vocabulary = list(vocabulary)
vocabulary.sort()
```

```
vocabulary
```

```
['00',
 '000',
 '0000',
 '00000',
 '00000000',
 '0000000004',
 '0000000005',
 '00000000b',
 '00000001',
 '00000001b',
 '00000010',
 '00000010b',
 '00000011',
 '00000011b',
 '0000001200',
 '00000074',
 '00000093',
 '000000e5',
 '00000100',
 '00000100b',
```

WORD TRANSFORMATIONS: STEMMING

- Stemming consist on removing the suffixes or prefixes used in word.
- The returned string from a stemmer might not be a valid word from the language.
- Example:
  - Stem(saw) = saw
  - Stem(destabilize) = destabil

WORD TRANSFORMATIONS: LEMMATIZATION

- Lemmatization consist on properly use of a vocabulary and morphological analysis of words, aiming to remove inflectional endings only with the goal of returning any word to a set of base (or dictionary form) words.
- The returned string from a lemmatizer should be a valid word from the language.
- Example:
  - Lemmatize(saw) = see
  - Lemmatize(destabilize) = destabilize

OPTIONAL: WHY DO WE REALLY NEED TO UNDERSTAND HOW CSR WORKS

- Sometimes custom implementations using underlying stored data can be better than build in methods:
- This will not be in the exam
- github issue

```python
import scipy.sparse as sp
import numpy as np
np.random.seed(123)
n_features = 100_000
n_samples = 100

X = sp.random(n_samples, n_features, density=0.01, format='csr')
```

```python
X
```

```
<100x100000 sparse matrix of type '<class 'numpy.float64'>'
	with 100000 stored elements in Compressed Sparse Row format>
```

```python
X.sum(axis=0).shape, type(X.sum(axis=0))
```

```
((1, 100000), numpy.matrix)
```

```python
%%timeit
s = sp.csr_matrix(X.sum(axis=0, dtype=np.int32))
```

```
1.11 ms ± 2.7 µs per loop (mean ± std. dev. of 7 runs, 1,000 loops each)
```

```python
s = sp.csr_matrix(X.sum(axis=0, dtype=np.int32))
s.nnz, s.shape
```

```
(16072, (1, 100000))
```

ENH: Allow reduction over sparse matrix to return sparse matrix #17389

Edit New issue

Open **davidbp** opened this issue on Nov 10, 2022 · 1 comment

davidbp commented on Nov 10, 2022 • edited

Is your feature request related to a problem? Please describe.

I am selecting rows in an sparse matrix and computing the mean over the selection (`X_sparse[row_indices, :].mean(axis=0)`). This process generates a `np.matrix` object that I store for further processing, but it is array is almost all zero. To use less memory, since the matrices are very sparse (and the result of the reduction is also very sparse), it might be benefitial to keep the result of the mean still sparse.

Describe the solution you'd like.

Have an input to the method, such as `X_sparse[row_indices,:].mean(axis=0, keep_sparse=False)`. If set to true, the method would return the same type of sparse matrix of the same type as `X_sparse`. Otherwise keep the current behaviour. Nothing would break.

Describe alternatives you've considered.

Simply cast the result back to sparse for every selection, that is, `scipy.sparse.csr_matrix(X_sparse[row_indices,:].mean(axis=0))` (but this takes a long time if the operation is repated many times and requires storing the dense array and then cast it to sparse).

Additional context (e.g. screenshots, GIFs)

No response

👍 1

Assignees

No one assigned

Labels

enhancement scipy.sparse

Projects

None yet

Milestone

No milestone

Development

No branches or pull requests

Notifications Customize

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3 participants

OPTIONAL: WHY DO WE REALLY NEED TO UNDERSTAND HOW CSR WORKS

We can do the sum over rows in a more intelligent way, using the nonzero indices

```
aux = sp.csr_matrix([[1,0,0,0,2],[3,0,0,2,0]])
```

```
aux.toarray()
```

```
array([[1, 0, 0, 0, 2],
       [3, 0, 0, 2, 0]])
```

```
aux.data
```

```
array([1, 2, 3, 2])
```

```
aux.indices
```

```
array([0, 4, 0, 3], dtype=int32)
```

```
aux.indptr
```

```
array([0, 2, 4], dtype=int32)
```

OPTIONAL: WHY DO WE REALLY NEED TO UNDERSTAND HOW CSR WORKS

Note that the resulting matrix of aggregating the nonzero values will have at index K the sum of all values in `.data` that have index K.

```
unique_indices = np.unique(aux.indices)
unique_indices
```

```
array([0, 3, 4], dtype=int32)
```

We can simply sum the values of the nonzero indices and create a sparse array with those sums

```
new_data = []
for k in unique_indices:
    val = aux.data[aux.indices==k].sum()
    new_data.append(val)
```

```
new_data
```

```
[4, 2, 2]
```

```
#csr_matrix((data, indices, indptr), [shape=(M, N)])
aux_mean = sp.csr_matrix((new_data, unique_indices, [0,len(new_data)]))
aux_mean
```

```
<1x5 sparse matrix of type '<class 'numpy.int64'>'
	with 3 stored elements in Compressed Sparse Row format>
```

```
aux_mean.toarray()
```

```
array([[4, 0, 0, 2, 2]])
```

OPTIONAL: WHY DO WE REALLY NEED TO UNDERSTAND HOW CSR WORKS

```python
def efficient_mean_over_rows(X_sparse):
    new_data = []
    unique_indices = np.unique(X_sparse.indices)
    for k in unique_indices:
        val = X_sparse.data[aux.indices==k].sum()
        new_data.append(val)

    X_sum = sp.csr_matrix((new_data, unique_indices, [0,len(new_data)]))
    return X_sum
```

```python
%%timeit
efficient_mean_over_rows(aux)
```

```
51 µs ± 1.46 µs per loop (mean ± std. dev. of 7 runs, 10,000 loops each)
```

```python
%%timeit
s = sp.csr_matrix(X.sum(axis=0, dtype=np.int32))
```

```
1.21 ms ± 7.51 µs per loop (mean ± std. dev. of 7 runs, 1,000 loops each)
```