Paraphrase Identification; Numpy; Scikit-Learn

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Paraphrase Identification

Paraphrase Identification

- Is a sentence (A) a paraphrase of another sentence (B)?
- Do two tweets contain the same information?
- This is a difficult problem
  - What is a paraphrase?
  - Do two **exact** paraphrases even exist?
    paraphrase $\Leftrightarrow$ strong similarity, approximately equal meaning
  - Linguistic variation
  - Even more difficult in twitter: abbreviations, spelling errors, ...
- Examples:

(A) I hate Mario Chalmersdont know why
(B) idc idc chalmers be making me mad

(A) It fits the larger iPhone 5
(B) Should I get the iPhone 5 or an Android

SemEval-2015 Task 1: Paraphrase Similarity in Twitter

- ca. 19000 tweet pairs annotated with Amazon Mechanical Turk
- Binary classification: Pair is paraphrase (True) or not (False)
- Brainstorming: good features for recognizing paraphrases?

Strong baseline features[1]

- Word overlap.
  - Most simple form: Number of common words that occur in both tweets (ignore frequency).
    "overlap"
  - Needs some normalization (so that there is no bias for longer tweets).
  - Simple solution: Extra feature for number of unique tokens in text1 and text2.
    "union"
- Word-Ngram overlap.
  - Accounts for some ordering information.
  - Otherwise same approach as for word overlap.
  - 3-grams perform well for this task
- Word-pair features
  - What if paraphrases use different, but semantically similar words?
  - Learn equivalences from tweets in training data!
  - Features for combinations: Word from text1 with word from text2.

[1] Thanks to Kevin Falkner for providing extensive feature analysis.

Example: feature representation

(A) happy Memorial Day have a happy weekend
(B) wishing everyone a happy Memorial Day

```
{"word_overlap":4,
"three_gram_overlap":1,
"word_union":8,
"threegram_union":8,
"happy#wishing":1,
"memorial#everyone":1,
"happy#happy":1,
...}
```

Implementation

- What is the result of the follwing list comprehension?

```
l=["wishing", "everyone", "a", "happy", "memorial", "day"]
n=2
[l[i:i+n] for i in range(len(l)-n+1)]
```

- How to implement word-pair features?

Data Representation for Machine Learning

Data Representation

- Dataset: collection of instances
- Design matrix

$$\mathbf{X} \in \mathbb{R}^{n \times m}$$

  - n: number of instances
  - m: number of features (also called *feature space*)
  - For example:
    $X_{i,j}$ count of feature j (e.g. a stem form) in document i.
- Unsupervised learning:
  - Model $\mathbf{X}$, or find interesting properties of $\mathbf{X}$.
  - Training data: only $\mathbf{X}$.
- Supervised learning:
  - Predict *specific* additional properties from $\mathbf{X}$.
  - Training data: Label vector $\mathbf{y} \in \mathbb{R}^n$ (or label matrix $\mathbf{Y} \in \mathbb{R}^{n \times k}$) together with $\mathbf{X}$

- Use matrix **X** and vector **y** to stack instances on top of each other.

$$\mathbf{X} = \begin{bmatrix} x_{12} & x_{13} & \dots & x_{1n} \\ x_{22} & x_{23} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m2} & x_{m3} & \dots & x_{mn} \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

- Binary classification:

$$\mathbf{y} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} \text{ ... or ... } \begin{bmatrix} -1 \\ 1 \\ \vdots \\ -1 \end{bmatrix}$$

- Multi-class classification (*one-hot-encoding*):

$$\mathbf{Y} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ \vdots \\ 0 & 1 & 0 \end{bmatrix}$$

Data Representation

- For performance reasons, machine-learning toolkits (scikit-learn, Keras, ...) use matrix representations (rather than e.g. string-to-count dictionaries).
- These matrix classes usually contain efficient implementations of
  - mathematical operations (matrix multiplication, vector addition ...)
  - data access and transformation (getting a certain row/column, inverting a matrix)
- What would be an appropriate underlying data-structures for the following feature sets:
  - Each feature is the grey-scale value of a pixel in a 100×100 gray-scale image?
  - Each feature is the indicator whether a particular word (vocab size 10000) occurs in a document or not?

Data Representation

- What would be an appropriate underlying data-structures for the following feature sets:
  - Each feature is the grey-scale value of a pixel in a 100×100 gray-scale image?

    Most of the features have a distinct value $\neq 0$. The appropriate data structure is similar to a nested list (list-of-lists). $\Rightarrow$ **Numpy Arrays**
  - Each feature is the indicator whether a particular word (vocab size 10000) occurs in a document or not?

    Most of the features have a value equal to 0. The appropriate data structure only stores those entries that are different than 0. (E.g with a dictionary: (row, col) $\rightarrow$ value.) $\Rightarrow$ **SciPy Sparse Matrices**

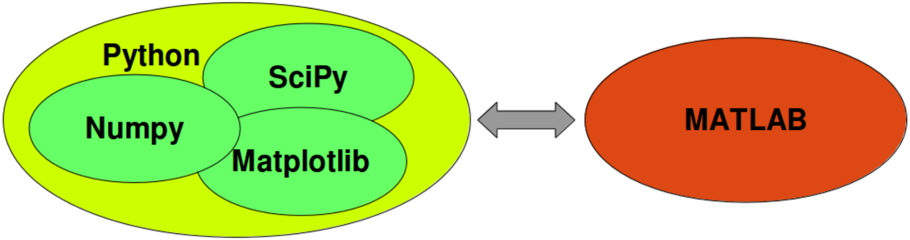
Introduction to Numpy

What is NumPy?

- Acronym for “Numeric Python”
- Open source extension module for Python.
- Powerful data structures for efficient computation of multi-dimensional arrays and matrices.
- Fast precompiled functions for mathematical and numerical routines.
- Used by many scientific computing and machine learning packages. For example
  - *Scipy* (Scientific Python): Useful functions for minimization, regression, Fourier-transformation and many others.
  - Similar datastructures exist in *Tensorflow, Pytorch*: Deep learning, mimimization of custom objective functions, auto-gradients.
- Downloading and installing numpy: `www.numpy.org`

The Python Alternative to Matlab

- Python in combination with Numpy, Scipy and Matplotlib can be used as a replacement for MATLAB.
- Matplotlib provides MATLAB-like plotting functionality.



Comparison between Core Python and Numpy

- *"Core Python"*: Python without any special modules, i.e. especially without NumPy.
- Advantages of Core Python:
  - high-level number objects: integers, floating point
  - containers: lists with cheap insertion and append methods, dictionaries with fast lookup
- Advantages of using Numpy with Python:
  - array oriented computing
  - efficiently implemented multi-dimensional arrays
  - designed for scientific computation

A simple numpy Example

- NumPy needs to be imported. Convention: use short name `np`

```
import numpy as np
```

- Turn a list of temperatures in Celsius into a one-dimensional numpy array:

```
>>> cvalues = [25.3, 24.8, 26.9, 23.9]
>>> np.array(cvalues)
[ 25.3  24.8  26.9  23.9]
```

- Turn temperature values into degrees Fahrenheit:

```
>>> C * 9 / 5 + 32
[ 77.54  76.64  80.42  75.02]
```

- Compare to using core python only:

```
>>> [ x*9/5 + 32 for x in cvalues]
[77.54, 76.64, 80.42, 75.02]
```

Creation of evenly spaced values (given stepsize)

- Useful for plotting: Generate values for x and compute $y = f(x)$
- Syntax:

```
arange([start,] stop[, step,], dtype=None)
```

- Similar to core python `range`, but returns `ndarray` rather than a `list iterator`.
- Defaults for `start` and `step`: 0 and 1
- `dtype`: If it is not given, the type will be automatically inferred from the other input arguments.
- Don't use non-integer step sizes (use `linspace` instead).
- Examples:

```
>>> np.arange(3.0)
array([ 0.,  1.,  2.])
>>> np.arange(1,5,2)
array([1, 3])
```

Creation of evenly spaced values (given number of values)

```
linspace(start, stop, num=50, endpoint=True, \
    retstep=False)
```

- Creates ndarray with num values equally distributed between start (included) and stop).
- If endpoint=True (default), the end point is included, otherwise (endpoint=False) it is excluded.

```
>>> np.linspace(1, 3, 5)
array([ 1. ,  1.5,  2. ,  2.5,  3. ])
>>> np.linspace(1, 3, 4, endpoint=False)
array([ 1. ,  1.5,  2. ,  2.5])
```

- If retstep=True, the stepsize is returned additionally:

```
>>> np.linspace(1, 3, 4, endpoint=False, \
    retstep=True)
(array([ 1. ,  1.5,  2. ,  2.5]), 0.5)
```

Exercise

- Compare the speed of vector addition in core Python and Numpy

Multidimensional Arrays

- NumPy arrays can be of arbitrary dimension.
- 0 dimensions (scalar):
  `np.array(42)`
- 1 dimension (vector):
  `np.array([3.4, 6.9, 99.8, 12.8])`
- 2 dimensions (matrix):

```
np.array([ [3.4, 8.7, 9.9],
    [1.1, -7.8, -0.7],
    [4.1, 12.3, 4.8]])
```

- 3 or more dimensions (tensor):

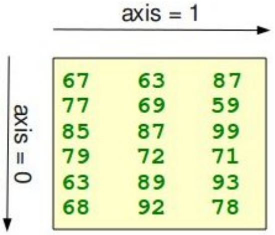
```
np.array([ [[111, 112], [121, 122]],
    [[211, 212], [221, 222]],
    [[311, 312], [321, 322]] ])
```

Question

- When can a 3 dimensional array be an appropriate representation?

Shape of an array

```
>>> x = np.array([ [67, 63, 87],
...                [77, 69, 59],
...                [85, 87, 99],
...                [79, 72, 71],
...                [63, 89, 93],
...                [68, 92, 78]])
>>> np.shape(x)
(6, 3)
```



Changing the shape

- `reshape` creates new array:

```
>>> a = np.arange(12).reshape(3, 4)
>>> a
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

- Changing `shape` value (for existing array):

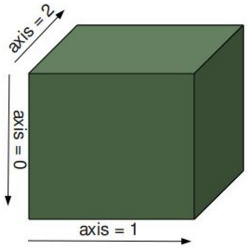
```
>>> a.shape = (2, 6)
>>> a
array([[ 0,  1,  2,  3,  4,  5],
       [ 6,  7,  8,  9, 10, 11]])
```

- Obviously, product of shape sizes must match number of elements!
- If a dimension is given as -1 in a reshaping operation, the other dimensions are automatically calculated.

Shape of 3D Array

```
>>> a = np.arange(24).reshape(2,3, 4)
>>> a
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]]])
```



Transposing an Array

- 2D case:

```
>>> a = np.arange(6).reshape(2,3)
array([[0, 1, 2],
       [3, 4, 5]])
>>> a.T
array([[0, 3],
       [1, 4],
       [2, 5]])
```

- Multidimensional case:
  - `a.transpose(...)` takes tuple of indices, indicating which axis of the old (input) array is used for each axis of the new (output) array.
  - 3D example:
    `b = a.transpose(1,0,2)`
  - ⇒ axis 1 in *a* is used as axis 0 for *b*, axis 0 (*a*) becomes 1 (*b*), and axis 2 (*a*) stays axis 2 (*b*).

Basic Operations

- By default, arithmetic operators on arrays apply *elementwise*:

```
>>> a = np.array( [20,30,40,50] )
>>> b = np.array( [0,1,2,3] )
>>> c = a-b
array([20, 29, 38, 47])
>>> b**2
array([0, 1, 4, 9])
>>> a<35
array([ True, True, False, False], dtype=bool)
```

- In particular, the *elementwise multiplication* ...

```
>>> a * b
array([ 0,  30, 80, 150])
```

- ... is not to be confused with the *dot product*:

```
>>> a.dot(b)
260
```

Unary Operators

- Numpy implements many standard unary (elementwise) operators:

```
>>> np.exp(b)
>>> np.sqrt(b)
>>> np.log(b)
```

- For some operators, an axis can be specified:

```
>>> b = np.arange(12).reshape(3,4)
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

>>> b.sum(axis=0)
array([12, 15, 18, 21])

>>> b.min(axis=1)
array([0, 4, 8])
```

Indexing elements

- Indexing single elements:

```
>>> B = np.array([ [[111, 112], [121, 122]],
...                [[211, 212], [221, 222]],
...                [[311, 312], [321, 322]] ])
>>> B[2][1][0]
321
>>> B[2,1,0]
321
```

- Indexing entire sub-array:

```
>>> B[1]
array([[211, 212],
       [221, 222]])
```

- Indexing starting from the end:

```
>>> B[-1,-1]
array([321, 322])
```

Indexing with Arrays/Lists of Indices

```
>>> a = np.arange(12)**2
>>> i = np.array( [ 1,1,3,8,5 ] )
>>> # This also works:
>>> # i = [ 1,1,3,8,5 ]
>>> a[i]
array([ 1,  1,  9, 64, 25])
```

Indexing with Boolean Arrays

Boolean indexing is done with a boolean matrix of the *same shape* (rather than of providing a list of integer indices).

```
>>> a = np.arange(12).reshape(3,4)
>>> b = a > 4
array([[False, False, False, False],
       [False,  True,  True,  True],
       [ True,  True,  True,  True]], dtype=bool)

>>> a[b]
array([ 5,  6,  7,  8,  9, 10, 11])

>>> a[b] = 0
array([[0, 1, 2, 3],
       [4, 0, 0, 0],
       [0, 0, 0, 0]])
```

Slicing

- Syntax for slicing lists and tuples can be applied to multiple dimensions in NumPy.
- Syntax:

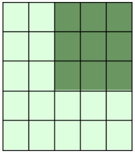
```
A[start0:stop0:step0, start1:stop1:step1, ...]
```

- Example in 1 dimension:

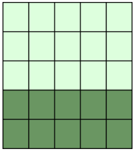
```
>>> S = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> S[3:6:2]
array([3, 5])
>>> S[:4]
array([0, 1, 2, 3])
>>> S[4:]
array([4, 5, 6, 7, 8, 9])
>>> S[:]
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

Slicing 2D

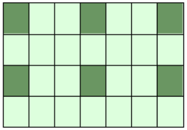
```
A = np.arange(25).reshape(5,5)
B = A[:3,2:]
```



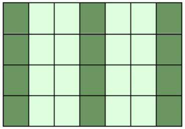
```
B = A[3:,:]
```



```
X = np.arange(28).reshape(4,7)
Y = X[::2, ::3]
```



```
Y = X[:, ::3]
```



Slicing: Caveat

- Slicing only creates a new **view**: the underlying data is shared with the original array.

```
>>> A = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> S = A[2:6]
>>> S[0] = 22
>>> S[1] = 23
>>> A
array([ 0,  1, 22, 23,  4,  5,  6,  7,  8,  9])
```

- If you want a deep copy that does not share elements with A, use: `A[2:6].copy()`

Quiz

- What is the value of `b`?

```
>>> a = np.arange(4)
>>> b = a[:]
>>> a *= b
```

Arrays of Ones and of Zeros

```
>>> np.ones((2,3))
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])

>>> a = np.ones((3,4),dtype=int)
array([[1, 1, 1, 1],
       [1, 1, 1, 1],
       [1, 1, 1, 1]])

>>> np.zeros((2,4))
array([[ 0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.]])

>>> np.zeros_like(a)
array([[0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0]])
```

Creating Random Matrices

- Array of floats uniformly drawn from the interval $[0, 1)$:

```
>>> np.random.rand(2,3)
array([[ 0.53604809,  0.54046081,  0.84399025],
       [ 0.59992296,  0.51895053,  0.09988041]])
```

- Generate floats drawn from standard normal distribution $\mathcal{N}(0, 1)$:

```
>>> np.random.randn(2,3)
array([[-1.28520219, -1.02882158, -0.20196267],
       [ 0.48258382, -0.2077209 , -2.03846176]])
```

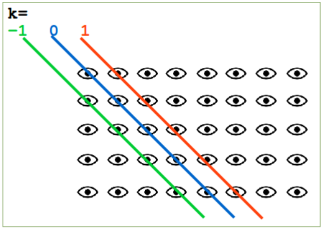
- For repeatability of your experiment, initialize the seed at the beginning of your script:
  - `>>> np.random.seed = 0`
  - Otherwise, it will be initialized differently at every run (from system clock).
  - If you use core python random numbers, also initialize the seed there:

```
>>> import random
>>> random.seed(9001)
```

Creating Diagonal Matrices

- `eye(N, M=None, k=0, dtype=float)`

N	Number of rows.
M	Number of columns.
k	Diagonal position. 0: main diagonal, starting at $(0, 0)$ $+n, -n$: move diagonal n up/down
dtype	Data type (e.g. `int` or `float`)



- $\Rightarrow$ To create an identity matrix (symmetric $N = M$, $k = 1$) the size N is the only argument.

Iterating

- Iterating over rows:

```
>>> for row in b:
...         print(row)
...
[0  1  2  3]
[10  11  12  13]
[20  21  22  23]
[30  31  32  33]
[40  41  42  43]
```

- ⇒ but (!) prefer matrix operations over iterating, if possible.

Stacking of arrays

- Vertical stacking:

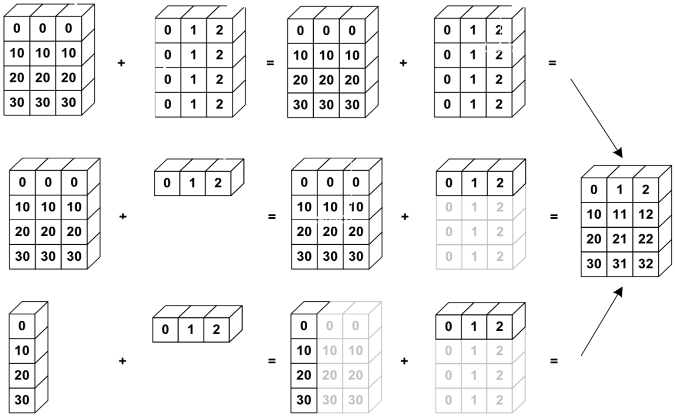
```
>>> a = np.array([[1,2],[3,4]])
>>> b = np.array([[11,22],[33,44]])
>>> np.vstack((a,b))
array([[ 1,  2],
       [ 3,  4],
       [11, 22],
       [33, 44]])
```

- Horizontal stacking:

```
>>> np.hstack((a,b))
array([[ 1,  2, 11, 22],
       [ 3,  4, 33, 44]])
```

Broadcasting

Operations can work on arrays of different sizes if Numpy can **transform** them so that they all have the **same size**!

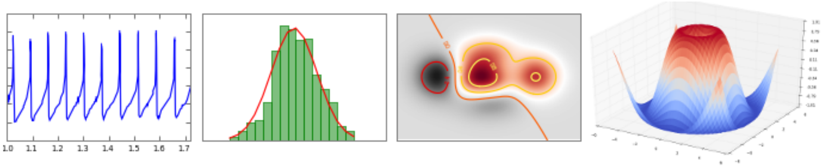


Plotting data

- Often it is a good idea to plot some properties of the data.
  - Verify expectations that you have about the data.
  - Spot trends, maxima/minima, (ir-)regularities and outliers.
  - similiratities / dissimilarities between two data sets.
- Recommended package: Matplotlib/Pyplot

Pyplot

- Plotting data and functions with Python.

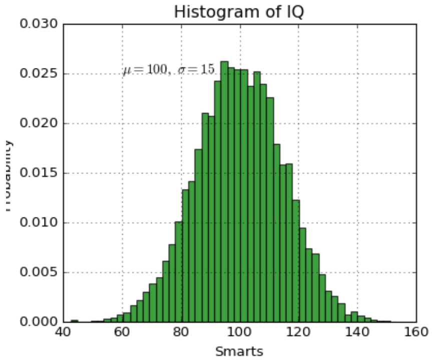


- Package of the `matplotlib` library.
- Uses `numpy` data structures
- Inspired by the `matlab` plotting commands
- Import pyplot as:

```
import matplotlib.pyplot as plt
```

Example: Histograms

- Show the empirical distribution of one variable.
- Frequency of values with equally-spaced intervals.



```
x = 100 + 15 * np.random.randn(10000)
plt.hist(x, 50)
```

Ressources

- NumPy Quickstart:
  `http://docs.scipy.org/doc/numpy-dev/user/quickstart.html`
- `http://www.python-course.eu/numpy.php`

Scipy Sparse Matrices

Scipy Sparse Matrices

- **SciPy** is another package of the Python scientific computing stack. (NumPy+SciPy+Matplotlib∼Matlab)
- `scipy.sparse` contains a range of sparse matrix implementations
  - Different underlying datastructures
  - slightly different use-cases
- All implementations
  - inherit from the same base class
  - provide basic matrix operations, e.g.:

`get_shape()`	Get shape of a matrix.
`getnnz()`	Number of stored values, including explicit zeros.
transpose([axes, copy])	Reverses the dimensions of the sparse matrix.
+, __add__(other)	Add two matrices.
∗, __mul__(other), dot(other)	Matrix (vector) multiplication
...	

Types of Sparse Matrices

scipy . sparse . csr_matrix	Compressed Sparse Row matrix (default). Very efficient format for arithmetic operations. (Less efficient for column slicing or inserting/removing values)
scipy . sparse . lil_matrix	Row-based linked list sparse matrix. Efficient changes to matrix structure. (Less efficient for column slicing or arithmetic)
scipy . sparse .coo_matrix	A sparse matrix in COOrdinate format. Triples of row, column and value. Good (only) for building matrices from coordinates. For any operations convert to CSR or LIL.
scipy . sparse . dia_matrix	Sparse matrix with DIAgonal storage
...	

What is the result?

```
import numpy as np
from scipy.sparse import csr_matrix
A = csr_matrix([[1, 2, 0], [0, 0, 3], [4, 0, 5]])
v = np.array([1, 0, -1])
A.dot(v)
```

Memory Saving

- Given:
  - 1000 docs
  - 100 unique words per doc
  - 10000 vocabulary size
- What is the expected percentage of memory used by sparse matrix (compared to dense)?

Time Saving

```
from timeit import default_timer as timer
from scipy import sparse
import numpy as np
rnd = np.random.RandomState(seed=123)

X = rnd.uniform(low=0.0, high=1.0, size=(200000, 1000))
v = rnd.uniform(low=0.0, high=1.0, size=(1000,1))
X[X<0.99]=0
v[v<0.99]=0
X_csr = sparse.csr_matrix(X)
v_csr = sparse.csr_matrix(v)

start = timer()
X_2 = X.dot(v)
time_dense = timer() - start

start = timer()
X_2 = X_csr.dot(v_csr)
time_sparse = timer() - start
```

⇒ **0.16 seconds (time_dense) vs. 0.01 seconds (time_sparse)**

Scikit-learn Data Structures

- Now that we know about Numpy (dense) matrices, and Scipy (sparse) matrices, let's see how we can use them for machine learning with Scikit-learn.

Scikit-learn Vectorizers

- For efficiency, Scikit-learn uses matrices for its algorithms.
- However, data is often present in different forms (text; dictionaries: feature $\rightarrow$ count; ...)
- Scikit-learn provides **Vectorizers** to convert other data-types into matrices.
- A vectorizer object provides a mapping (e.g. from vocabulary to column indices): it is important that the same mapping is used for training, test and dev data!
- For most vectorizers, one can choose whether Dense or Sparse representation is preferred.

Loading features from dicts

- `DictVectorizer` can be used to convert feature arrays represented as **lists of dict objects** to the NumPy/SciPy representation
- **Input:** one dict per instance (feature counts)
  - key: feature
  - value: observed value of that feature
- **Output:** Design matrix
- The vectorizer constructs a feature map - use the same feature map for new data! (I.e. do not create a new feature map).
- Values of the dictionary can be:
  - **Numerical**: the numerical value is stored in the resulting matrix in the column for that feature.
  - **Boolean**: two columns are created in the matrix for that feature.
  - **String**: several columns are created in the matrix, one for each possible value for that feature.

DictVectorizer: Example

```
>>> measurements = [
...     {'city': 'Dubai', 'temperature': 33.},
...     {'city': 'London', 'temperature': 12.},
...     {'city': 'San Fransisco', 'temperature': 18.},
... ]

>>> from sklearn.feature_extraction import DictVectorizer
>>> v = DictVectorizer()

>>> v.fit_transform(measurements).toarray()
array([[  1.,   0.,   0.,  33.],
       [  0.,   1.,   0.,  12.],
       [  0.,   0.,   1.,  18.]])

>>> v.get_feature_names()
['city=Dubai', 'city=London', 'city=San Fransisco', 'temperature']
```

DictVectorizer

- Creates sparse matrices by default, can be changed to dense.
- `v.fit(list_of_dicts)`: Creates and stores a mapping from features to matrix columns.
- `v.transform(list_of_other_dicts)`: Applies the stored mapping to (potentially new) dictionaries.
- `v.fit_transform(list_of_dicts)`: fit and transform in one step.

```
>>> v = DictVectorizer(sparse=False)
>>> D = [{'foo': 1, 'bar': 2}, {'foo': 3, 'baz': 1}]
>>> X = v.fit_transform(D)
>>> X
array([[ 2.,  0.,  1.],
       [ 0.,  1.,  3.]])
>>> v.inverse_transform(X) == [{'bar': 2.0, 'foo': 1.0}, \
    {'baz': 1.0, 'foo': 3.0}]
True
>>> v.transform({'foo': 4, 'unseen_feature': 3})
array([[ 0.,  0.,  4.]])
```

Feature hashing

- Hash function (not a rigorous definition, but sufficient for our purposes):
  - Function that maps every object from input space to an integer in pre-specified range
  - Regularities (e.g. sequential order) from input space are not preserved in output space, assignment looks random (for properties of interest)
- Hash collision: Two different values from input space are mapped to same output
- Applications of hash functions?

Feature hashing

- Large amounts of features also means many model parameters to learn and store (no sparsity here)
- One way of fighting amount of features: sort and take most frequent.
- Another way: use hash function to “randomly” group features together
- Hashing trick:
  - Input space: features
  - Output space: columns in design matrix
- `FeatureHasher`: Vectorizer that uses the hashing trick.
  $\Rightarrow$ inverse_transform is not possible

CountVectorizer: Transforming text into a design matrix

- SciPy CountVectorizer provides some functionality to create feature matrices from raw text
  - tokenization
  - lowercasing
  - ngram creation
  - occurrence counting
  - filtering by minimum word length (default=2)
  - filtering by minimum and maximum document frequency.
  - ...
- Use cases:
  - **CountVectorizer:** Very convenient for standard usage!
  - **DictVectorizer:** You have more control if you create the features (dictionaries) yourself and use DictVectorizer

CountVectorizer

```
>>> from sklearn.feature_extraction.text import CountVectorizer
>>> corpus = [
...     'This is the first document.',
...     'This is the second second document.',
...     'And the third one.',
...     'Is this the first document?',
... ]
>>> vectorizer = CountVectorizer()
>>> X = vectorizer.fit_transform(corpus)
>>> vectorizer.get_feature_names()
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third',
 'this']
>>> X.toarray()
array([[0, 1, 1, 1, 0, 0, 1, 0, 1],
       [0, 1, 0, 1, 0, 2, 1, 0, 1],
       [1, 0, 0, 0, 1, 0, 1, 1, 0],
       [0, 1, 1, 1, 0, 0, 1, 0, 1]], dtype=int64)
```

CountVectorizer: unigrams, bigrams, document frequency

```
>>> vectorizer = CountVectorizer(min_df=2, ngram_range=(1, 2))
>>> X = vectorizer.fit_transform(corpus)
>>> vectorizer.get_feature_names()
['document', 'first', 'first document', 'is', 'is the', 'the',
 'the first', 'this', 'this is']
>>> X.toarray()
array([[1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 0, 0, 1, 1, 1, 0, 1, 1],
       [0, 0, 0, 0, 0, 1, 0, 0, 0],
       [1, 1, 1, 1, 0, 1, 1, 1, 0]], dtype=int64)
```

Summary

- Features for Paraphrase identification
  - Number of overlapping words and ngrams
  - Normalization for tweet length
  - Word pair features
- Dense and Sparse Matrices
  - Numpy arrays
    `docs.scipy.org/doc/numpy-dev/user/quickstart.html`
  - Scipy sparse matrices
    `docs.scipy.org/doc/scipy-0.18.1/reference/sparse.html`
- Scikit-learn Vecorizers
  `http://scikit-learn.org/stable/modules/feature_extraction.html`
- Questions?