DEPAUL UNIVERSITY

DSC478: Programming Machine Learning Applications

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Text Categorization

- Assigning documents to a fixed set of categories
- Applications:
  - Web pages
    - Recommending pages
    - Classification hierarchies
    - Categorizing bookmarks
  - Newsgroup Messages /News Feeds / Micro-blog Posts
    - Recommending messages, posts, tweets, etc.
    - Message filtering
  - News articles
    - Personalized news
    - Sentiment analysis
  - Email messages
    - Routing
    - Folderizing
    - Spam filtering

Learning for Text Categorization

- Text Categorization is an application of classification

- Typical Learning Algorithms:
  - **Bayesian (naïve)**
  - **Relevance Feedback (Rocchio)**
  - **Nearest Neighbor**
  - **Neural network**
  - **Support Vector Machines (SVM)**

Recall … Similarity Metric

- Nearest neighbor method depends on a similarity (or distance) metric
- Simplest for continuous *m*-dimensional instance space is *Euclidean distance*
- Simplest for *m*-dimensional binary instance space is *Hamming distance* (number of feature values that differ)
- For text, cosine similarity of **TF-IDF** weighted vectors is typically most effective

Basic Text Processing

- Parse documents to recognize structure and meta-data
  - e.g., title, date, other fields, html tags, etc.
- Scan for word tokens
  - lexical analysis to recognize keywords, numbers, special characters, etc.
- Stopword removal
  - common words such as “the”, “and”, “or” which are not semantically meaningful in a document
- Stem words
  - morphological processing to group word variants (e.g., “compute”, “computer”, “computing”, “computes”, … can be represented by a single **stem** “comput” in the index)
- Assign weight to words
  - using frequency in documents and across documents
- Store Index
  - Stored in a Term-Document Matrix (“inverted index”) which stores each document as a vector of keyword weights

Basic Text Representation

- **Bag-of-words**: represent a document as a "bag-of-the-words" within it with their corresponding frequency
- Used for feature engineering in text data
  - Use 0 for words from the corpustvhat do not appear in a doc.
  - Corpus: all the text data/words in all your documents

"**John**","likes","to","watch","movies","Mary","likes","**movies**","**too**"
"Mary","**also**","likes","to","watch","**football**","**games**"

BoW1 = {"John":**1**,"likes":**2**,"to":**1**,"watch":**1**,"movies":**2**,"Mary":**1**,"too":**1**};
BoW2 = {"Mary":1,"also":1,"likes":1,"to":1,"watch":1,"football":1,"games":1};

(1) [**1**, **2**, **1**, **1**, **2**, **1**, **1**, **0**, **0**, **0**]
(2) [**0**, 1, 1, 1, **0**, 1, **0**, **1**, **1**, **1**]

also, *football* and games dot not appear in 1st doc.
John, *movies* and too dot not appear in 2nd doc.

Zipf Law & Why the Log Function?

- Zipf's law is an empirical law that states that frequency distribution of data in social and physical sciences (e.g., some corpus* of natural language utterances) often follows a Power-law distribution. More specifically, **the frequency of a term is inversely proportional to some power of its rank**.
  - **Most frequent word will occur approximately twice as often as the second most frequent word, three times as often as the third most frequent word, etc**.
  - In practice, this means less frequent data are lumped together at one end of the frequency spectrum, whose frequencies aren't too distinguishable. Applying log to the frequencies, "smooths" out the lumping
- It's often desirable to have scoring functions that are **additive**.

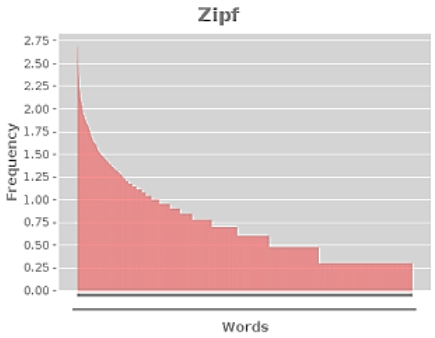
*** corpus: body of text you are analyzing**

Zipf Law & Why the Log Function?

- Zipf's law is an empirical law that states that frequency distribution of data in social and physical sciences (e.g., some corpus* of natural language utterances) often follows a Power-law distribution. More specifically, the frequency of a term is inversely proportional to some power of its rank.
- It's often desirable to have scoring functions that are additive.

- *N* be the number of elements;
- *k* be their rank;
- *s* be the value of the exponent characterizing the distribution.
- S=1 English Language

$$f(k; s, N) = \frac{1/k^s}{\sum_{n=1}^{N} (1/n^s)}$$



*** corpus: body of text you are analyzing**

TF*IDF Weights

- tf x idf measure:
  - term frequency (tf)
  - inverse document frequency (idf) -- a way to deal with the problems of the Zipf distribution
    - There are always a few very frequent tokens that are not good discriminators ("**stopwords**").
      - English examples: *to, from, on, and, the, ...*
    - There are always a large number of tokens that occur once and can mess up algorithms.
    - **Medium frequency words most descriptive**
  - Want to weight terms highly if they are
    - frequent in relevant documents … **BUT**
    - infrequent in the collection as a whole
- Goal: assign a tf x idf weight to each term in each document

TF*IDF Weights

$$w_{ik} = tf_{ik} * \log(N / n_k)$$

$T_k = \text{term } k \text{ in document } D_i$

$tf_{ik} = \text{frequency of term } T_k \text{ in document } D_i$

$idf_k = \text{inverse document frequency of term } T_k \text{ in } C$

$N = \text{total number of documents in the collection } C$

$n_k = \text{the number of documents in } C \text{ that contain } T_k$

$$idf_k = \log\left(\frac{N}{n_k}\right)$$

Inverse Document Frequency

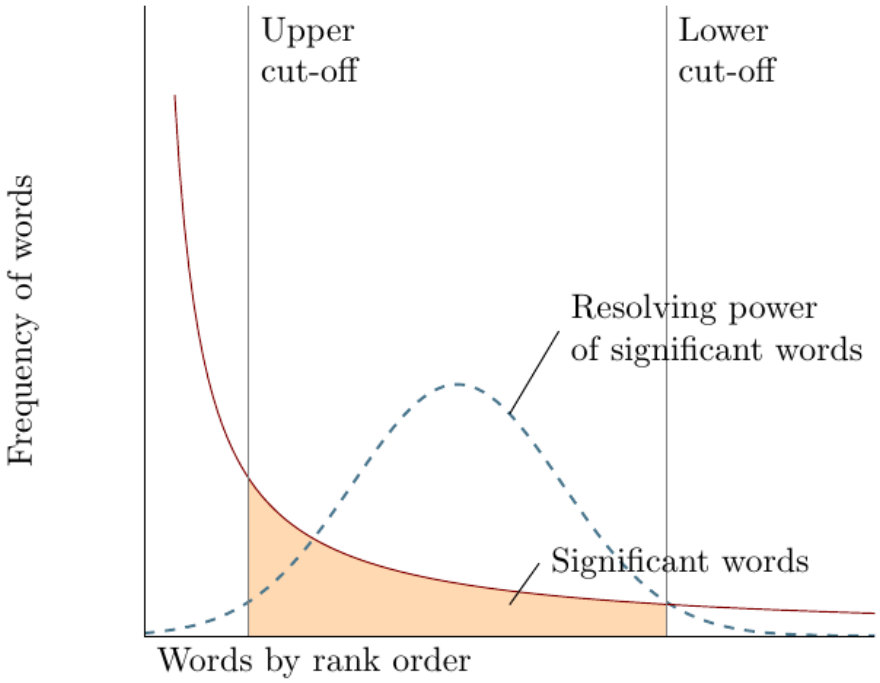
IDF provides high values for rare words and low values for common words

$$\log\left(\frac{10000}{10000}\right) = 0$$

$$\log\left(\frac{10000}{5000}\right) = 0.301$$

$$\log\left(\frac{10000}{20}\right) = 2.698$$

$$\log\left(\frac{10000}{1}\right) = 4$$



TF * IDF Example

The initial Term x Doc matrix (Inverted Index)

	Doc 1	Doc 2	Doc 3	Doc 4	Doc 5	Doc 6
T1	0	2	4	0	1	0
T2	1	3	0	0	0	2
T3	0	1	0	2	0	0
T4	3	0	1	5	4	0
T5	0	4	0	0	0	1
T6	2	7	2	1	3	0
T7	1	0	0	5	5	1
T8	0	1	1	0	0	3

df	idf = log2(N/df)
3	1.00
3	1.00
2	1.58
4	0.58
2	1.58
5	0.26
4	0.58
3	1.00

Documents represented as vectors of words

tf x idf Term x Doc matrix

	Doc 1	Doc 2	Doc 3	Doc 4	Doc 5	Doc 6
T1	0.00	2.00	4.00	0.00	1.00	0.00
T2	1.00	3.00	0.00	0.00	0.00	2.00
T3	0.00	1.58	0.00	3.17	0.00	0.00
T4	1.74	0.00	0.58	2.90	2.32	0.00
T5	0.00	6.34	0.00	0.00	0.00	1.58
T6	0.53	1.84	0.53	0.26	0.79	0.00
T7	0.58	0.00	0.00	2.92	2.92	0.58
T8	0.00	1.00	1.00	0.00	0.00	3.00

TF*IDF Limitations

- TF-IDF comes with some limitations and the biggest one is that it relies on a **clean set of data** (eg. minimal spelling errors, acronyms etc.) that is large enough, and that your dataset adheres to *Zipf's Law*.
- Its a huge assumption which doesn't really hold all the time, because real world data is complex
  - e.g., in scientific data, some rare words are the most important even though they appear only once, have "weird" characters and are easy to misspell etc.
  - e.g., what about tweets?

Using Rocchio Method

- Rocchio method is typically used for relevance feedback in information retrieval
  - **Relevance feedback** is a feature of some information retrieval systems. The idea behind relevance feedback is to take the results that are initially returned from a given query, to gather user feedback, and to use information about whether or not those results are relevant to perform a new query.

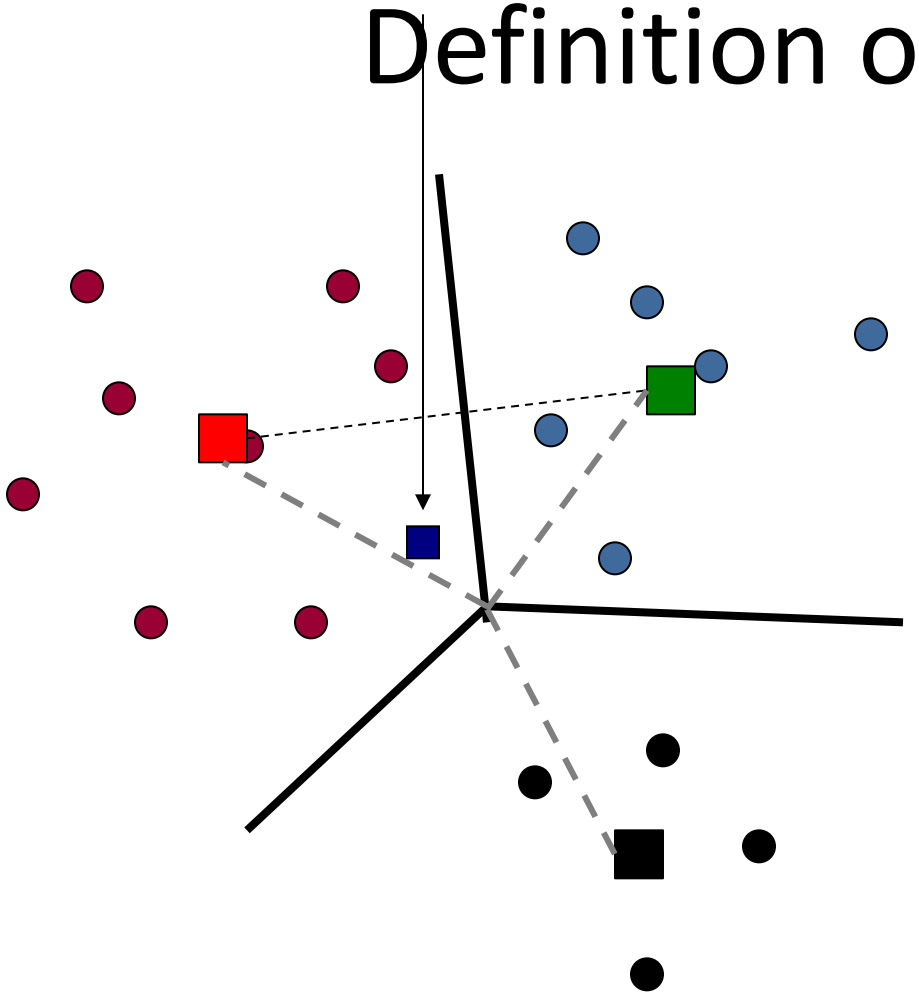
$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

- q_m = modified query vector; q_0 = original query vector; α,β,γ: weights (hand-chosen or set empirically); D_r = set of known relevant doc vectors; D_{nr} = set of known irrelevant doc vectors
- New query moves toward relevant documents and away from irrelevant documents

Using Rocchio Method

- Rocchio method can be adapted for text categorization
- Use standard TF/IDF weighted vectors to represent text documents
- For each category, compute a ***prototype*** vector by summing the vectors of the training documents in the category
- Assign test documents to the category with the closest prototype vector based on cosine similarity.

Definition of a Centroid



$$\vec{\mu}(c) = \frac{1}{|D_c|} \sum_{d \in D_c} \vec{v}(d)$$

Government

Science

Arts

- Where Dc is the set of all documents that belong to class c and v(d) is the vector space representation of d.
- Note that centroid will in general not be a unit vector even when the inputs are unit vectors.

Rocchio Text Categorization Algorithm (Training)

Assume the set of categories is $\{c_1, c_2, \ldots c_n\}$

For i from 1 to n let $\mathbf{p}_i = <0, 0, \ldots, 0>$ (*init. prototype vectors*)

For each training example $<x, c(x)> \in D$

Let $\mathbf{d}$ be the TF/IDF term vector for doc x

Let $i = j$ where $c_j = c(x)$

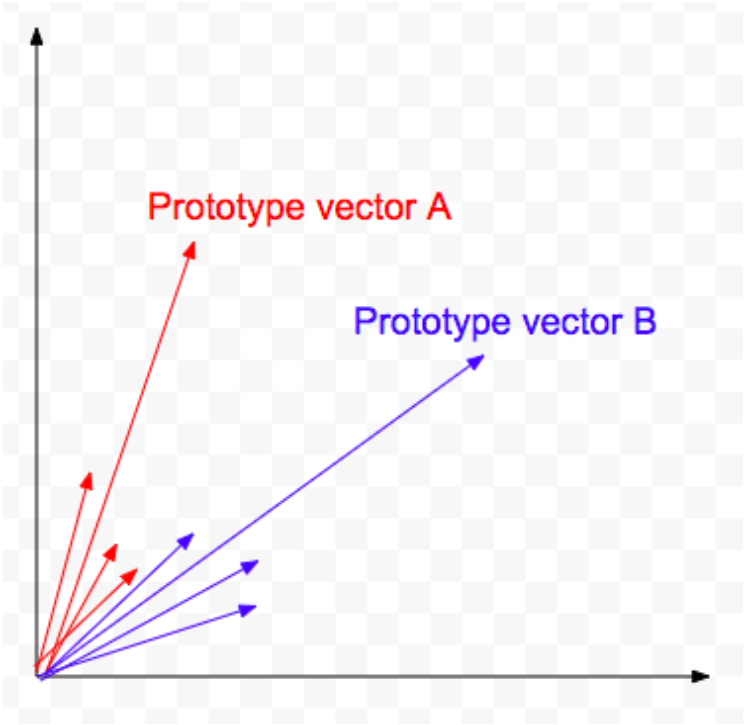
(*sum all the document vectors in c_i to get $\boldsymbol{p}_i$*)

Let $\mathbf{p}_i = \mathbf{p}_i + \mathbf{d}$

Rocchio Text Categorization Algorithm (Testing)

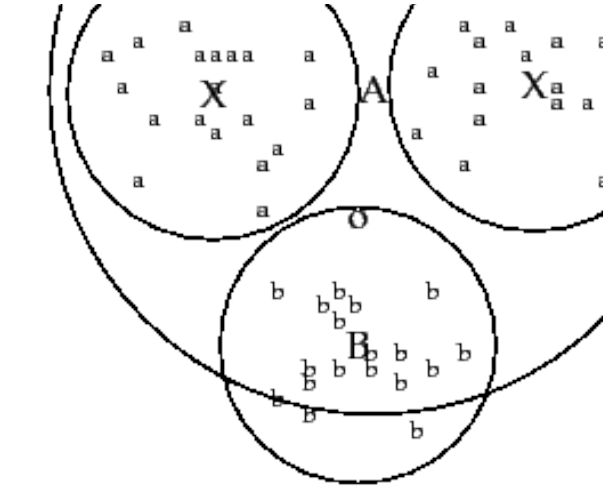
Given test document *x*

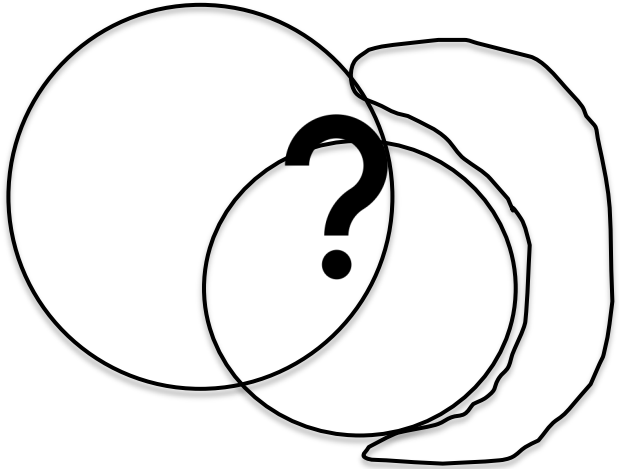
Let **d** be the TF/IDF term vector for *x*
Let *m* = –2 (*init. maximum cosSim*)
For *i* from 1 to *n*:
    (*compute similarity to prototype vector*)
    Let *s* = cosSim(**d**, $\mathbf{p}_i$)
    if *s* > *m*
        let *m* = *s*
        let *r* = c_i (*update most similar class prototype*)
Return class *r*



Rocchio Properties

- Does not guarantee a consistent hypothesis
  - Why? **Example maybe equally close to either prototype**.
- Forms a simple generalization of the examples in each class (a *prototype*)
- Prototype vector does not need to be averaged or otherwise normalized for length since cosine similarity is insensitive to vector length
- Classification is based on similarity to class prototypes
- Rocchio classification is simple and efficient, but inaccurate if classes are not approximately spheres with similar radii
- Rocchio also struggle with polymorphic (disjunctive categories see image)





Top figure: https://nlp.stanford.edu/IR-book/html/htmledition/rocchio-classification-1.html

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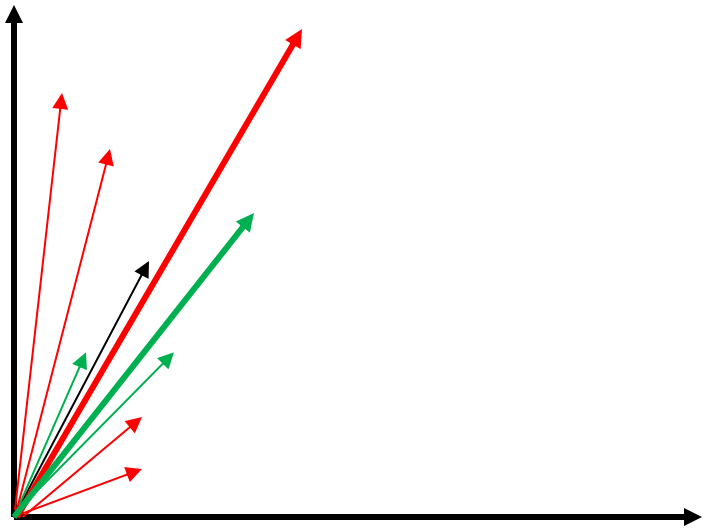


In this example, the category for the new document (in black will be red instead of green based on cosine similarity to the prototypes (big red and green arrows))

Scikit-Learn Example

Examples

```
>>> from sklearn.neighbors.nearest_centroid import NearestCentroid
>>> import numpy as np
>>> X = np.array([[-1, -1], [-2, -1], [-3, -2], [1, 1], [2, 1], [3, 2]])
>>> y = np.array([1, 1, 1, 2, 2, 2])
>>> clf = NearestCentroid()
>>> clf.fit(X, y)
NearestCentroid(metric='euclidean', shrink_threshold=None)
>>> print(clf.predict([[-0.8, -1]]))
[1]
```

KNN for Text

Training:

For each each training example $\langle x, c(x) \rangle \in D$

Compute the corresponding TF-IDF vector, $\mathbf{d}_x$, for document x

Test instance *y*:

Compute TF-IDF vector **d** for document *y*

For each $\langle x, c(x) \rangle \in D$

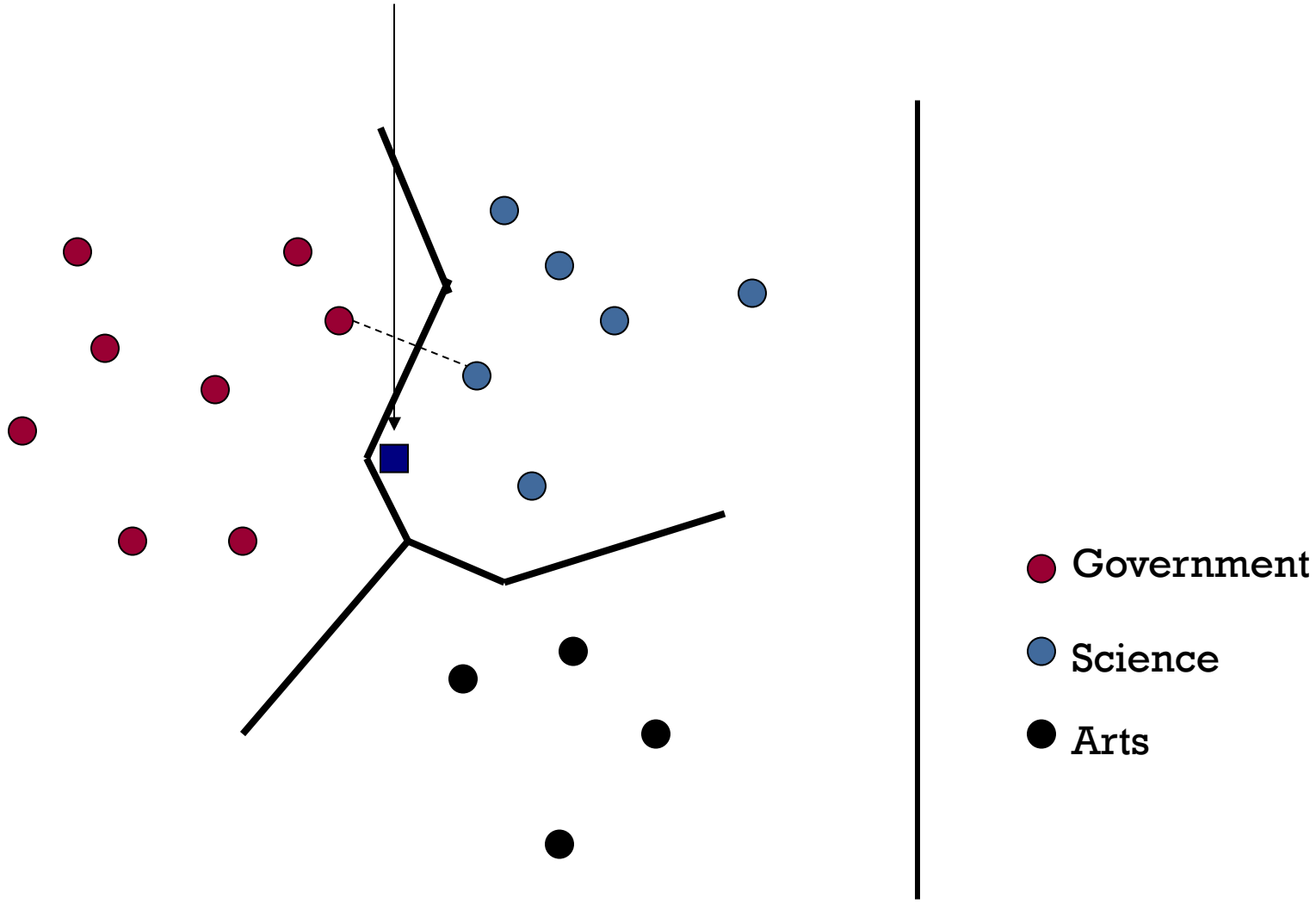
Let $s_x = \text{cosSim}(\mathbf{d}, \mathbf{d}_x)$

Sort examples, *x*, in *D* by decreasing value of s_x

Let *N* be the first *k* examples in D. (*get most similar neighbors*)

Return the majority class of examples in *N*

KNN for Text



KNN Discussion

- No feature selection necessary
- No training necessary
- Scales well with large number of classes
  - Don't need to train n classifiers for n classes
- Done naively, very expensive at test time
- In most cases it's more accurate than Rocchio/ KNN can handle non-spherical and other complex classes better than Rocchio.

Scikit-Learn Example

Examples

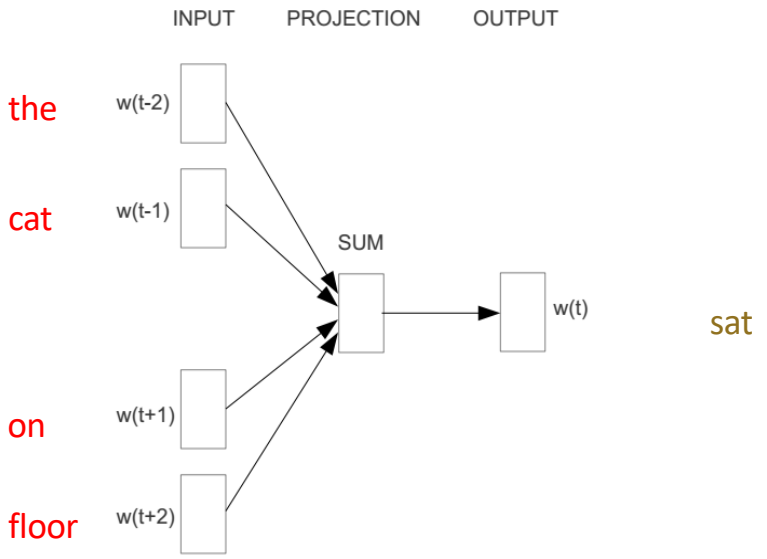
```
>>> X = [[0], [1], [2], [3]]
>>> y = [0, 0, 1, 1]
>>> from sklearn.neighbors import KNeighborsClassifier
>>> neigh = KNeighborsClassifier(n_neighbors=3)
>>> neigh.fit(X, y)
KNeighborsClassifier(...)
>>> print(neigh.predict([[1.1]]))
[0]
>>> print(neigh.predict_proba([[0.9]]))
[[0.66666667 0.33333333]]
```

Word Embedding (Neural Network)

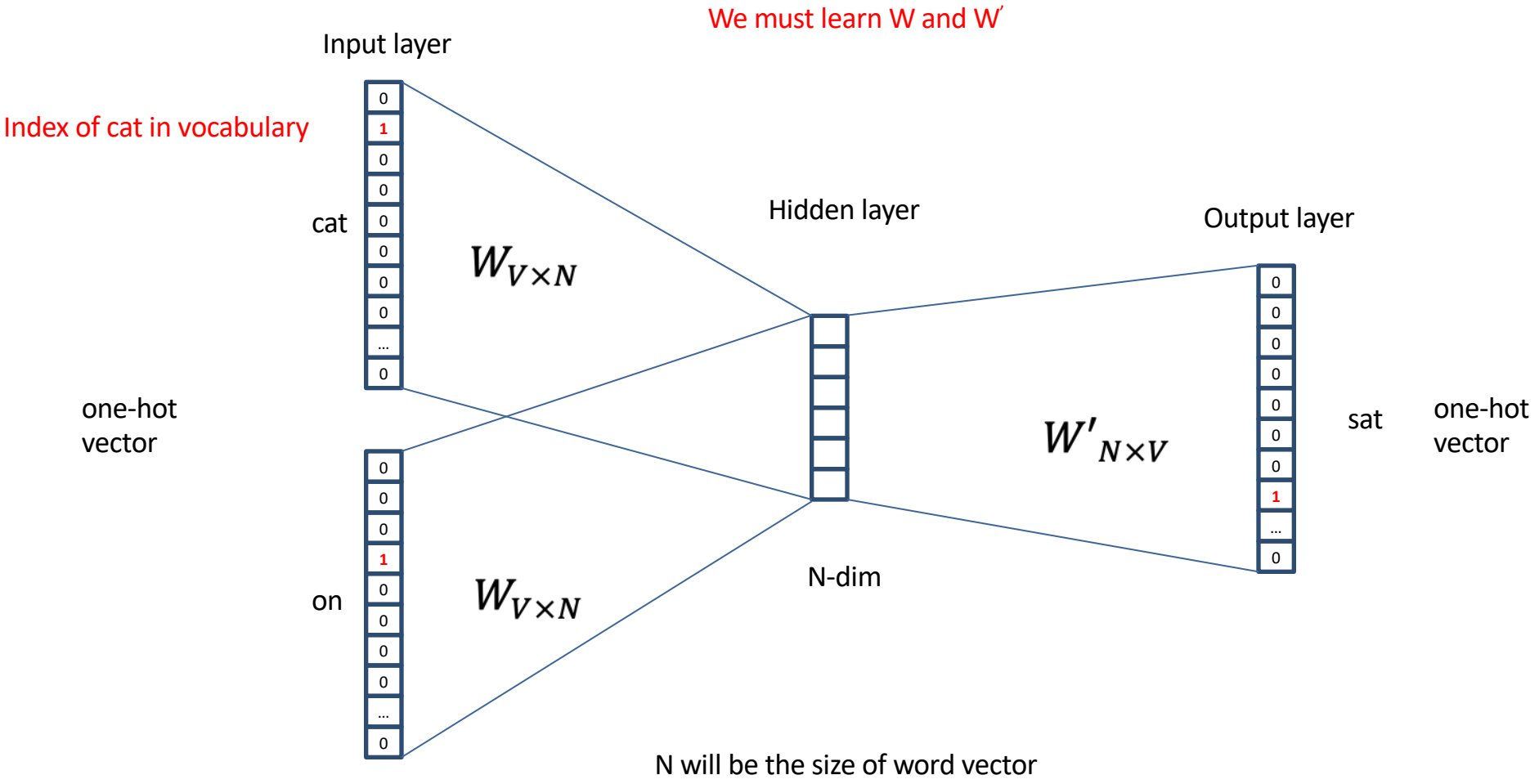
- Represent each word with a low-dimensional vector
- Word similarity = vector similarity
- Key idea: **Predict surrounding words of every word**
- Faster and can easily incorporate a new sentence/document or add a word to the vocabulary

e.g., “The cat sat on floor”

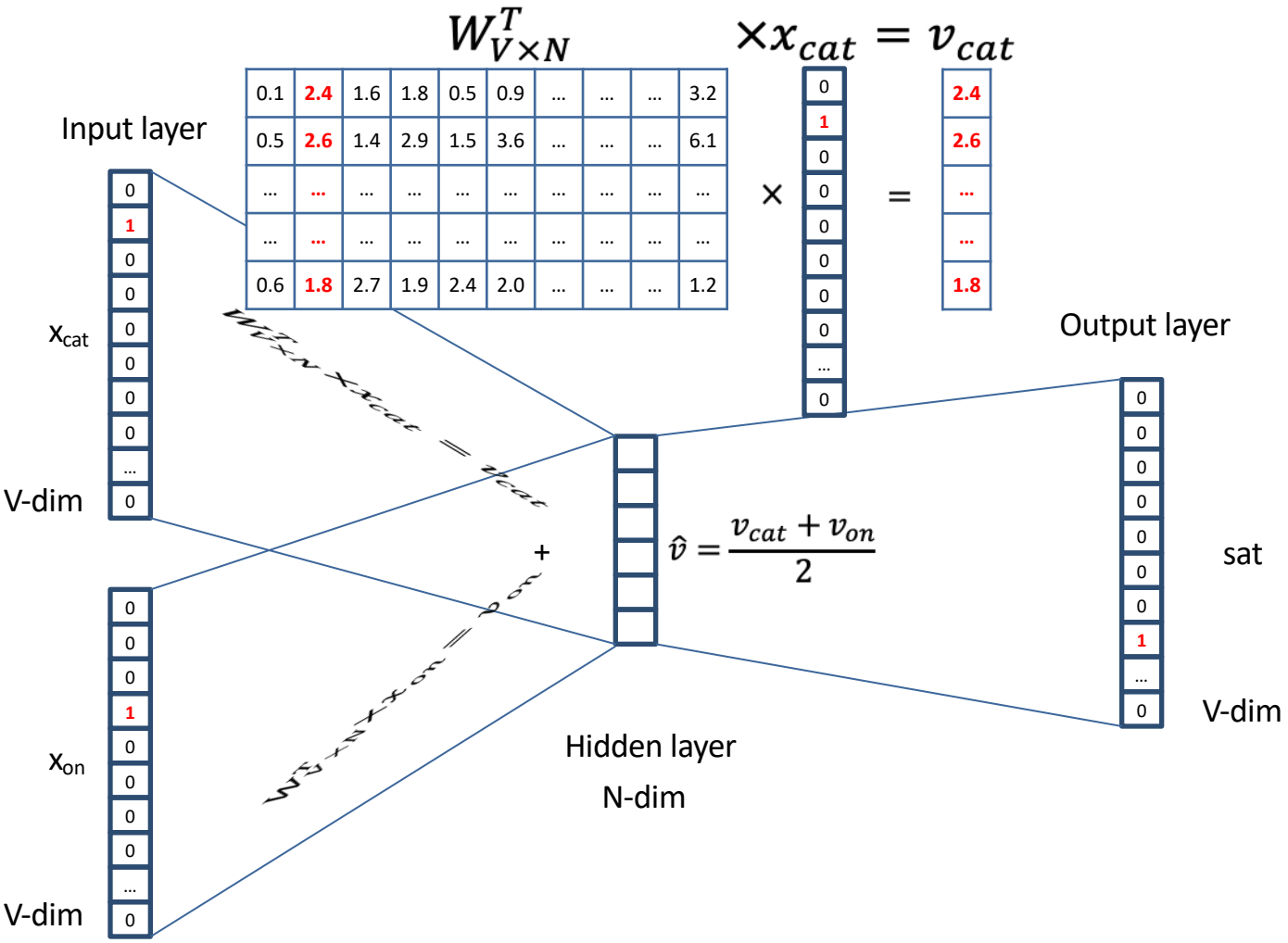
Window size = 2



Word2Vec


We must learn W and W′
Input layer
Index of cat in vocabulary
cat
one-hot vector
on
$W_{V\times N}$
$W_{V\times N}$
Hidden layer
N-dim
$W'_{N\times V}$
Output layer
sat
one-hot vector
N will be the size of word vector

Word2Vec


$W^T_{V\times N}$
$\times x_{cat} = v_{cat}$
Input layer
x_{cat}
V-dim
x_{on}
V-dim
Hidden layer
N-dim
$\hat{v} = \frac{v_{cat} + v_{on}}{2}$
Output layer
sat
V-dim

Applications

Word Analogies

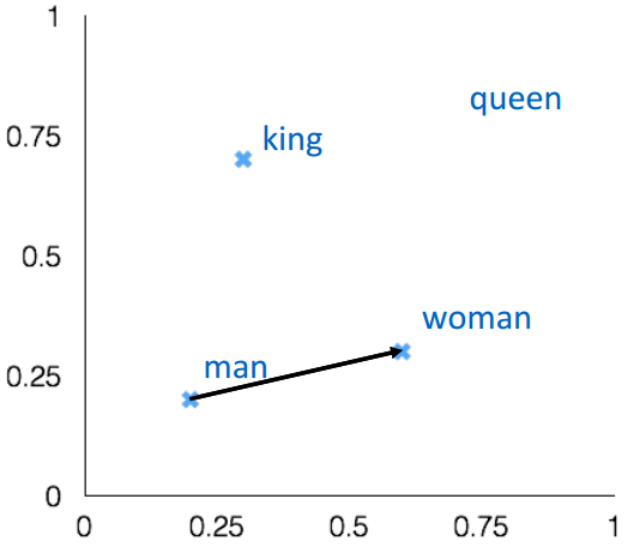
Test for linear relationships, examined by Mikolov et al. (2014)

a:b :: c:?

$$d = \arg\max_x \frac{(w_b - w_a + w_c)^T w_x}{||w_b - w_a + w_c||}$$

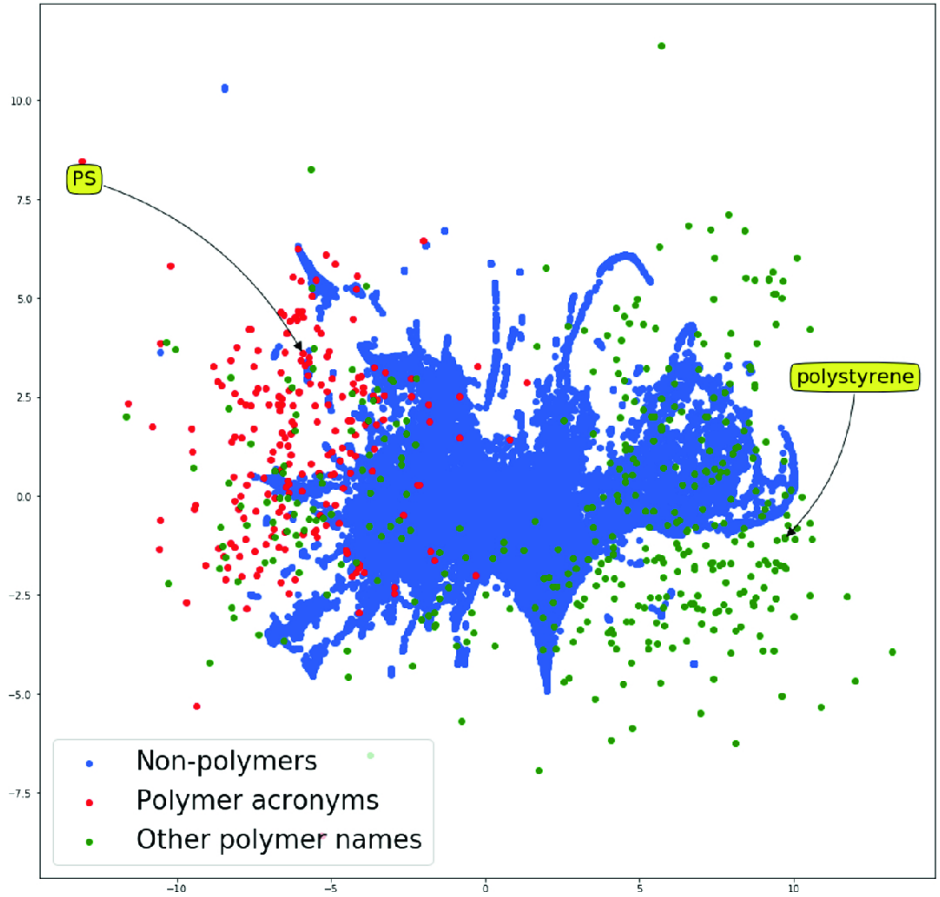
man:woman :: king:?

+	king	[0.30 0.70]
-	man	[0.20 0.20]
+	woman	[0.60 0.30]
	queen	[0.70 0.80]



Applications

- Visualizing polymer names, acronyms and all the other words in 100 documents
- Visualization done with tsne
  - https://projector.tensorflow.org/



Tchoua, Roselyne B., et al. "Creating training data for scientific named entity recognition with minimal human effort." *International Conference on Computational Science*. Springer, Cham, 2019.

Word Embedding to Sentences & Paragraphs

- Simple approach: take avg of the word2vecs of its words
- Another approach: Paragraph vector (2014, Quoc Le, Mikolov)
  - Extend word2vec to text level
  - Also, two models: add paragraph vector as the input
- Other Applications:
  - Search, e.g., query expansion
  - Sentiment analysis
  - Classification
  - Clustering

Gensim and FastText

- Easiest way to use it is via the Gensim libarary for Python

  https://radimrehurek.com/gensim/models/word2vec.html

Word2vec supports several word similarity tasks out of the box:

```
model.most_similar(positive=['woman', 'king'], negative=['man'], topn=1)
[('queen', 0.50882536)]
model.doesnt_match("breakfast cereal dinner lunch";.split())
'cereal'
model.similarity('woman', 'man')
0.73723527
```

- FastText in Python (and C):
  https://github.com/facebookresearch/fastText/tree/master/python

More NN-Based Word Representation

- Word2Vec: 2 basic neural network models:
  - Continuous Bag of Word (CBOW): use a window of word to predict the middle word
  - Skip-gram (SG): use a word to predict the surrounding ones in window. Usually better at predicting rare words
- FastText improves Word2Vec with integration of character n-gram embedding
- (Large) Pretrained word vectors:
  - Glove: https://nlp.stanford.edu/projects/glove/
  - ElMo: https://allennlp.org/elmo
  - BERT: https://github.com/google-research/bert
  - …

Limitations

- Can take a long time to train
- Needs a lot of (labelled) data to get insight
  - Easier to get for “regular” corpus
  - Not so simple for scientific text
- Hard to understand (recall black box)
  - OpenAI GPT-2 language model
  - https://openai.com/blog/better-language-models/
  - **Read their “*Release Strategy*” for more info**
    - **Ethical concerns**