# Naïve Bayes in Numpy

CS114B Lab 1

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January 27, 2022

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  - Learn about Numpy arrays and operations
  - Learn how to represent documents/machine learning inputs in general as vectors

# Naïve Bayes

**function** TRAIN NAIVE BAYES(D, C) **returns** log $P(c)$ and log $P(w|c)$

**for each** class $c \in C$ # Calculate $P(c)$ terms
  $N_{doc}$ = number of documents in D
  $N_c$ = number of documents from D in class c
  $logprior[c] \leftarrow \log \frac{N_c}{N_{doc}}$
  $V \leftarrow$ vocabulary of D
  $bigdoc[c] \leftarrow$ **append**(d) **for** d $\in$ D **with** class $c$
  **for each** word $w$ in V # Calculate $P(w|c)$ terms
    $count(w,c) \leftarrow$ # of occurrences of $w$ in $bigdoc[c]$
    $loglikelihood[w,c] \leftarrow \log \frac{count(w,c) + 1}{\sum_{w' \text{ in } V} (count(w',c) + 1)}$
**return** *logprior*, *loglikelihood*, $V$

**function** TEST NAIVE BAYES(*testdoc*, *logprior*, *loglikelihood*, C, V) **returns** best $c$

**for each** class $c \in C$
  $sum[c] \leftarrow logprior[c]$
  **for each** position $i$ in *testdoc*
    $word \leftarrow testdoc[i]$
    **if** $word \in V$
      $sum[c] \leftarrow sum[c] + loglikelihood[word,c]$
**return** $\text{argmax}_c\ sum[c]$

**Figure 4.2** The naive Bayes algorithm, using add-1 smoothing. To use add-$\alpha$ smoothing instead, change the $+1$ to $+\alpha$ for loglikelihood counts in training.

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- Use dictionaries (`self.class_dict` and `self.feature_dict`) to translate between class/feature names and indices
  - `self.class_dict` is given to you, while you will need to fill in `self.feature_dict` yourself

# Training Naïve Bayes

- Training data:

| document | class |
|---|---|
| just plain boring | negative |
| entirely predictable and lacks energy | negative |
| no surprises and very few laughs | negative |
| very powerful | positive |
| the most fun film of the summer | positive |

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- `self.class_dict = {'neg': 0, 'pos': 1}`
- `self.feature_dict = {'predictable': 0,`
  `'no': 1,`
  `'fun': 2,`
  `'very': 3`
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- Suppose we observe a movie review $d =$ "very very fun". Is the review positive or negative?

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- Compare:
  - $\log(P(-)) + \log(P(\text{very}|-)) + \log(P(\text{very}|-)) + \log(P(\text{fun}|-))$
  - $\log(P(+)) + \log(P(\text{very}|+)) + \log(P(\text{very}|+)) + \log(P(\text{fun}|+))$

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  - Features are words, values are counts
- `vector =` $\begin{bmatrix} 0 \\ 0 \\ 1 \\ 2 \\ \vdots \end{bmatrix}$

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$$= \begin{bmatrix} 0\log(1/17) + 0\log(1/17) + 1\log(1/34) + 2\log(1/17) \\ 0\log(1/29) + 0\log(1/29) + 1\log(2/29) + 2\log(2/29) \end{bmatrix}$$

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- This computes the log-likelihood of the document given each class
  - All we need is `self.prior`

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- $$\begin{bmatrix} \log(3/5) \\ \log(2/5) \end{bmatrix} + \begin{bmatrix} \log(1/34) + 2\log(1/17) \\ 3\log(2/29) \end{bmatrix}$$

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- Take the argmax: positive