Regular Expressions

Pattern	Matches
\s	whitespace
\d	any digit
{N}	exactly N of the previous item
\w	any "word" characters (includes numbers)
\S, \D, \W	anything NOT in the lowercase version of that pattern
\b	word boundary
^	start of the string
$	end of the string
A|B	A or B
[a − z], [abcde],[0 − 9]	any character in the brackets of specified range of characters
.	any character
?	0 or 1 of the preceding character
*	0 or more of the preceding character
+	1 or more of the preceding character
.*?	not greedy

Example of Not Greedy

```
text = "<tag>I have something here</tag> <tag>but other
    ↪ stuff here</tag>"
my_regex = r"<tag>.*?<\/tag>"
re.findall(my_regex, text) = ['<tag>I have something here
    ↪ </tag>', '<tag>but other stuff here</tag>']
```

Levenshtein Distance

	#	h	e	a	r
#	0	1	2	3	4
h	1	0	1	2	3
e	2	1	0	1	2
r	3	2	1	2	1
e	4	3	2	3	2

Operation	Cost per char
Insert	1
Delete	1
Replace	2

row i column j = the number of operations required from convert first i characters of source to first j characters of target.
1. the top left cell: 0 operations **2.** top row/first column: increment by 1 because it takes n inserts **3.1.** if characters in row i and column j are the same character, then $= c(i-1, j-1)$ **3.2.** otherwise $= 1 + \min(c(i, j-1), c(i, j-1), c(i-1, j-1))$

Text Normalization/Pre-Processing

1. Lowercasing **2.** True-casing **3.** Punctuation Removal **4.** Stopword (funciton words such as articles, prepositions, conjunctions and pronouns) Removal **5.** Stemming (takes the stem of the word - hacky e.g. policy and police become the same word) **6.** Lemmatization (map all morphologically equivalent words)

N-Gram Language Model

$P(w|h) = \prod_{k=1}^{n} P(w_k|w_{1:k-1})$ This solution suffers from **Data Sparsity**. The exact history h might not be present in the dataset we're using. Instead we can use the **Markov Assumption** and consider only the N prior words in the past.

Unigram Model
$\approx P(w_n)$

Bigram Model
$\approx P(w_n|w_{n-1})$

N-gram Model
$\approx P(w_n|w_{n-N+1:n-1})$

Calculating Probabilties
$P(w|h) = \frac{C(hw)}{C(h\star)} = \frac{C(hw)}{C(h)}$ where $C(hw)$ is the count of the history followed by the word and $C(h*) = C(h)$ is the count of the history followed by any word
with Laplace (Add-One) Smoothing $P^L(w|h) = \frac{C(hw)+1}{C(h)+|V|}$

Text Generation
Chose a starting point randomly on the line of most probable n-grams. **Unigram model:** continue sampling words randomly **Bigram model:** continue sampling bigrams conditioned on previously generated word

Limitations

N-grams don't do well at modeling long-term dependencies b.c. we forget old context, and N-grams don't do well with new sequences with similar meaning

Advantages

A clear paradigm to introduce - training and test sets - Perplexity as a metric for evaluation - Sampling to generate sentences - Other modifications to improve the model

Naive Bayes Text Classification

$P(c|W) = \frac{P(W|c)P(c)}{P(W)} \approx P(W|c)P(c)$ where $P(c)$ is the prior probability of class c i.e. $\frac{\text{Count}(c)}{\text{Count}(D)}$, number of docs with class c divided by count of all docs D

- $P(W)$ we *could* use a language model to get the probability of this sequence of words, but it doesn't change with respect to c so it's not required to get **relative** probabilities between classes

- $P(W|c)$ is a bit more complicated so we make the two following assumptions

Assumptions

Order of the words doesn't matter:
$P(W|c) = P(w_1, \ldots, w_n|c)$ such that the likelihood of the sequence given c uses a Bag of Words

Words are conditionally independent:
$P(W|c) = P(w_1, \ldots, w_n|c) = P(w_1|c) \cdot \cdots \cdot P(w_n|c)$ such that the probability of observing word A does not affect the probability of observing word B

Solution Derivation

$\hat{c} = \arg\max_{c \in C} P(c|W) = \arg\max_{c \in C} P(c) \prod_{i=1}^{N} P(w_i|c)$

it's better to operate in log space to avoid **underflow** $= \arg\max_{c \in C} \log P(c) + \sum_{i=1}^{n} \log P(w_i|c)$ this is considered a **Linear Classifier**!

To avoid division be zero, smoothing $P(w_i|c) = \frac{\text{count}(w_i,c)+1}{\sum_{w \in V}(\text{count}(w,c)+1)} = \frac{\text{count}(w_i,c)+1}{\left(\sum_{w \in V} \text{count}(w,c)\right)+|V|}$

Logistic Regression Text Classification

Binary

Supervised learning method where X is our TF-IDF counts, $Y \in \{0, 1\}$ our binary class.

Our model is $P(y=1|x) = \sigma\left(\left(\sum_{i=1}^{n} w_i x_i\right) + b\right) = \sigma(w \cdot x + b)$ where z is our score i.e. $P(y=1|x)$, w are our weights, x is our features, b is our bias, σ is sigmoid function

Example

Variable	x1	x2	x3	x4	x5	x6
Meaning	Count positive lexicon words	Count negative lexicon words	"No" is in document	Count 1st/2nd person pronouns	"!" is in document	log(word count)
Value	3	2	1	3	0	4.19
Weight	1.2	-4	2.4	0.1	3.3	-0.3

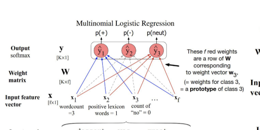
and **Bias** $= 0.1$

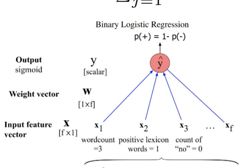
Multinomial

Represent Y as One-Hot Encoding and use SoftMax to map values to a Probability Distribution. Now, we will have separate weights for each class! For predections, we pick the class with the highest probability.

SoftMax

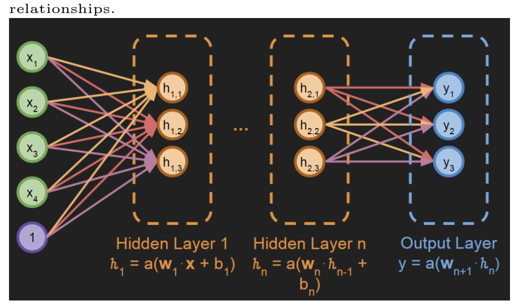
For each element $1 \le i \le K$, $\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$



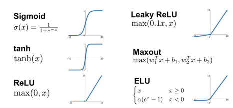


Neural Network

Our activation functions allow us to model non-linear relationships.

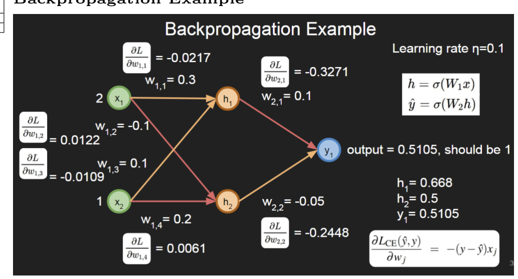


Activation Functions



Function Type	Equation	Derivative
Linear	f(x) = ax + c	f'(x) = a
Sigmoid	$f(x) = \frac{1}{1+e^{-x}}$	f'(x) = f(x) (1- f(x))
TanH	$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ReLU	f(x) = { 0 for x<0; x for x ≥0	f'(x) = { 0 for x<0; 1 for x ≥0
Parametric ReLU	f(x) = { αx for x<0; x for x ≥0	f'(x) = { α for x<0; 1 for x ≥0
ELU	f(x) = { $\alpha(e^x - 1)$ for x<0; x for x ≥0	f'(x) = { f(x) + α for x<0; 1 for x ≥0

Backpropagation Example



Feature Selection

For example, given sentence 1 (S1) and sentence 2 (S2), does S1 entail S2? **1.** BLEU Score: The number of overlapping n-grams between two strings **2.** Difference in length **3.** Overlap of words: absolute count, percentage overlap, over: all words, nouns, verbs, adjectives, adverbs **4.** Indicator for every unigram and bigram in S2 **5.** Count of each unigram pair between S1 and S2 that have same POS **6.** Count of each bigram pair between S1 and S2 that have the same POS in the second word

Gradient Descent

Let y be correct label for input x, $\hat{y}$ be output of $\sigma(w \cdot x + b)$, $L(\hat{y}, y) = -[y \log \hat{y} + (1-y)\log(1-\hat{y})]$ be the loss function (the negative log-likelihood)
Then we update our parameters such that we find our optimal $\hat{\theta}$ $\hat{\theta} = \arg\min_{\theta} \frac{1}{m} \sum_{i=1}^{m} L_{CE}(f(x^{(i)}; \theta), y^{(i)})$ where L_{CE} is the loss of the true label and model prediction given θ and $x^{(i)}$ and $\frac{1}{m}\sum_{i=1}^{m}$ gives the average overall points in the dataset

Updated a single parameter
$w^{t+1} = w^t - \eta \frac{d}{dw} L(f(x; w), y)$ where η is the learning rate

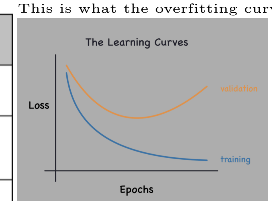
Update all parameters
$\theta^{t+1} = \theta^t - \eta \nabla L(f(x; \theta), y)$

Parallelization

Pack everything into matrices. Modern compilers and GPUs can do matrix operations in parallel!!

Overfitting

For example, using the wrong features (e.g. model relies on the count of the word "Jalapenos" when trying to differentiate between positive and negative statements because in the corpus, people had good things to say about Jalapenos)
This is what the overfitting curve looks like



Regularization

L2
$\hat{\theta} = \arg\max_{\theta} \left[\sum_{i=1}^{m} \log P(y^{(i)}|x^{(i)})\right] - \alpha \sum_{j=1}^{n} \theta_j^2$ penalty is much higher for large values

L1
$\hat{\theta} = \arg\max_{\theta} \left[\sum_{i=1}^{m} \log P(y^{(i)}|x^{(i)})\right] - \alpha \sum_{j=1}^{n} |\theta_j|$

Hyperparameter Tuning

Grid Search

```
import numpy as np
for lr in np.linspace(0.01, 0.1, num=5):
  for bs in np.linspace(8, 32, num=4):
    # train model, eval on validation
```

Random Search

```
import numpy as np
trials = 20
for i in range(trials):
  lr = np.random.uniform(0.01, 0.1)
  bs = np.random.randint(8, 32)
  # train model, eval on validation
```

Cross Validation

K-Fold
1. split into k equal parts **2.** test one part and train on the ohers **3.** do this for each fold **4.** average performance metric across all folds

Leave One Out
If you have very little data, set K to the number of instances (e.g. train on all instances except one test on that one instance.

Clustering

K-Means
1. randomly add k cluster centroids **2.** assign points to nearest centroid **3.** update the centroids based on the points **4.** reassign points to centroids **5.** move the centroids **6.** repeat until convergence

Jaccard Similarity

Similarity between phrases or sentences. Mentioning something more often does not matter. (It does not take into account frequency). $J = \frac{|A \cap B|}{|A \cup B|}$

Term Frequency Representation (TDM)

Each element in the vector represents the number of times the corresponding word appears in the document. Unlike Jaccard Similarity, frequency of terms plays into our similarity calculations. However, sometimes, stop words are a way of telling our models which words are important!

Similarity

Euclidian Distance

$d(x_i, x_i) = \sqrt{\sum_{m=1}(x_{im} - x_{jm})^2}$

Co-sine Distance

$1 - \frac{A \cdot B}{|A||B|}$ the difference between angles

Term Frequency Inverse Document Frequency (TF-IDF)

Term Frequency (TF)

The number of timers a term (token) appears in the document

Type	Description
Binary	1 if present, else 0
Count	Number of times it appears
Frequency	$\frac{extcount}{\text{total terms in document}}$
Log normalized count	$\log(1 + \text{count})$

Inverse Document Frequency (IDF)

The inverse of term popularity in the overall corpus.

$\text{IDF}(w, c) = \log\left(\frac{|c|}{|d \in c : w \in d|}\right)$ i.e. for word w and corpus c = for each document in the corpus, how many documents have the word

- the intuition between the log is that at some point, if the word is soo frequent, we aren't really getting that much information by the word being repeated again - the intuition behind the denominator is that if this word appears in all the documents, it is not important at all

Example

Doc	Content
1	Jalapenos have seeds
2	Donuts are great
3	Jalapenos have flavor

words = [jalapenos, have, seeds, donuts, are, great, flavor]

$\text{TF} = \begin{bmatrix}1 & 1 & 1 & 0 & 0 & 0 & 0\end{bmatrix}$

$\text{IDF} = \begin{bmatrix}\log\frac{3}{2} & \log\frac{3}{2} & \log 3 & 0 & 0 & 0 & 0\end{bmatrix}$

Limitations

TF-IDF still doesn't capture semantic similarity well. Our matrix if very sparse, which can be inefficient for memory and computation.

Latent Dirichlet Allocation (LDA)

Assume each document has a probability of belonging to a topic, each word has a probability of belonging to a topic, words in the same document are more likely to be in the same topic

Let c_t be the number of topics, c_w be the number of words, z the word by document array (randomly initialized topics), n_d doc by topic matrix of counts, n_w topic by word matrix of counts, n_t vector of counts by topics

```
repeat N times:
    for each word w in document d:
        remove w's topic z[d][w] from nd, nw, nt
        pz = \frac{nw[:,w] + \beta}{nt + cw \times \beta}
            ↪ * \frac{nd[d,:] + \alpha}{\text{len}(d)
            ↪ + ct \times a}
        p = pz \times \text{sum}()
        new topic z[d][w] sampled from pz
        add count for new topic back to nd, nw, nt
```

where β is Laplace Smoothing over words, α is Laplace Smoothing over topics, $\frac{n_w[:,w]}{n_t}$ is the count of words in a topic over the number of words in a topic, $\frac{n_d[d,:]}{\text{len}(d)}$ is the count of words in a document over the number of words in a document

Classification Evaluation

Accuracy

$\frac{TP+TN}{P+N}$

Precision

$\frac{TP}{TP+FP}$

Macro Precision

The average precision amongst all N classes $c_1, \ldots, c_n$

$\frac{1}{N}\sum \text{Precision}(c_i)$

Recall

$\frac{TP}{TP+FN}$

Macro Recall

The average recall amongst all N classes $c_1, \ldots, c_n$

$\frac{1}{N}\sum \text{Recall}(c_i)$

F1 Score

$= 2 \times \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$

Comparing Classifiers

Assume Null Hypothesis/H0 (both of our models come from the *same* distribution) is true and determine the range of probable results. Compute probability that the actual (observed) result is in that range. If low, there is evidence to reject H0 in favor of H1.

Using a **T-Test** would require many samples and assumes we are working with a normal distribution.

Non-Parametric Tests

Bootstrapped

sample with replacement

Let s be the number of times the difference of new test set is ≥ 0 i.e. $s = \delta(x_i) - \delta(x) \geq 0$ the number of times we sampled a difference at least as large as the observed difference

The p-value is defined as $p = \frac{s}{b}$ i.e. the probability of an observation at least as large as the observed one is happening under the H0 (where H0 = B is actually not better than A, in general).

However, we are sampling from our test set which does not have mean 0. The mean is $\delta(x)$, so instead we should check $\delta(x_i) - \delta(x) \geq \delta(x) \Rightarrow \delta(x_i) \geq 2\delta(x)$

Language Model Evaluation

Perplexity

It's the inverse of the probability that the model assigns to the held out data (lower is better). Shows what is the probability that it will be in the right bin

$\text{Perplexity}(W) = P(w_1 w_2 \ldots w_n)^{-\frac{1}{N}} = \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_n)}}$

N-Gram

Then for an n-gram language model

$= \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$

$= e^{\frac{1}{N}\sum_{i=1}^{N} - \log(P(w_i|w_1 \ldots w_{i-1}))}$

Unigram

$= \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i)}}$

Bigram

$= \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$

Topic Model Evaluation: Intrusion Methods

Using, for example, Amazon mechanical Turk

Word Intrusion

Are topics meaningful, interpretable, coherent, useful? **e.g.** take the highest probability words from a topic, take a high-probability word form another topic and add it, *hypothesis* if the topics are interpretable, users with consistency choose the correct intruder

Topic Intrusion

Is assignment of topics to documents meaningful, appropriate, useful? **e.g** display document title and first 500 characters, show the three topics with highest probability and one topic chosen randomly, have the user click on the set of words that is out of place, *hypothesis* if the association of topics to a document is interpretable, users with consistently choose the true intruding topic

Topic Coherence (Umass Version)

$C(t; V^{(t)}) = \sum_{m=2}^{M}\sum_{l=1}^{m-1} \log \frac{D(v_m^{(t)}, v_l^{(t)})+1}{D(v_t^{(t)})}$ where

$C(t; V(t))$ is the coherence of topic t given $V(t)$, the M most probable words in t, $D(v)$ how many documents contain word v, $D(v, v')$ how many documents contain both words (co-document frequency)

Discriminative vs Generative

Method	Generative	Discriminative
Learns	Estimate $P(x\|y)$ to then deduce $P(y\|x)$	Directly estimate $P(y\|x)$

Q&A

the set of all alphabetic strings [a-zA-Z]+

the set of all lower case alphabetic strings ending in a b
\b[a-z]*b\b

the set of all strings from the alphabet a, b such that each a is immediately preceded by and immediately followed by a b \b b+ (ab+)+ \b

the set of all strings with two consecutive repeated words (e.g., "Humbert Humbert" and "the the" but not "the bug" or "the big bug") (.+)\b \1

all strings that start at the beginning of the line with an integer and that end at the end of the line with a word
^[0-9]+.*[A-Za-z]+$

all strings that have both the word grotto and the word raven in them (but not, e.g., words like grottos that merely contain the word grotto) \b grotto \b .* \b raven \b |\b raven \b .* \b grotto \b

ELIZA-like program

```
s/.* YOU ARE (depressed|sad) .*/I AM SORRY TO HEAR YOU ARE
    ↪ \1/ s/.*
YOU ARE (depressed|sad) .*/WHY DO YOU THINK YOU ARE \1/ s
    ↪ /.*
all .*/IN WHAT WAY/ s/.*
always .*/CAN YOU THINK OF A SPECIFIC EXAMPLE/
```

Edit distance of "leda" to "deal".

		D	E	A	L
	0	1	2	3	4
L	1	1	2	3	3
E	2	2	1	2	3
D	3	2	2	2	3
A	4	3	3	2	3

All the non-zero trigram probabilities.

```
<s> I am Sam </s>
<s> Sam I am </s>
<s> I do not like green eggs and ham </s>
```

$P(w_n|w_{n-2}w_{n-1}) = \frac{C(w_{n-2}, w_{n-1}, w_n)}{C(w_{n-2}, w_{n-1})}$

$P(\text{am}|\langle s\rangle, I) = \frac{1}{2}$ $P(\text{Sam}|\text{I, am}) = \frac{1}{2}$

probability of `i want chinese food`. One using regular table, another using the add-1 smoothed table.

$P(\text{i want chinese food}) =$
$P(\text{i}|)P(\text{want}|\text{i})P(\text{chinese}|\text{want})P(\text{food}|\text{chinese})P(\langle/s\rangle|\text{food}) =$ 0.0001896 using add-1 smoothing = 0.000002406

Which is higher? Why?

Unsmoothed is higher because the bigrams used in the sentence are common in the corpus. However, with add-1 smoothing, the probability mass is redistributed to account for unseen n-grams, reducing the probabilities of frequent bigrams.

Using a bigram language model with add-one smoothing, what is $P(\text{Sam}|\text{am})$?

```
add <s> I am Sam </s> to line 3
```

$P(\text{Sam}|\text{am}) = \frac{C(am,\text{Sam})+1}{C(\text{am})+V} = \frac{2+1}{3+11} = 0.214$

What class will Naive Bayes assign to the sentence "I always like foreign films."? (assume equal prior probabilities for each class)

Word	Pos	Neg
I	0.09	0.16
always	0.07	0.06
like	0.29	0.06
foreign	0.04	0.15
films	0.08	0.11

For positive $P(s|\text{pos}) = P(\text{I}|\text{pos})P(\text{always}|\text{pos})$ $P(\text{like}|\text{pos})P(\text{foreign}|\text{pos})$ $P(\text{films}|\text{pos})$
$= 0.09 \times 0.07 \times 0.29 \times 0.04 \times 0.08 = 0.00005846$

For negative
$P(s|\text{neg}) = P(I|\text{neg})P(\text{always}|\text{neg})$ $P(\text{like}|\text{neg})P(\text{foreign}|\text{neg})$ $P(\text{films}|\text{neg}) = 0.16 \times 0.06 \times 0.06 \times 0.15 \times 0.11 = 0.00009504$

Since $P(s|\text{neg}) > P(s|\text{pos})$
the Naive Bayes classifier assigns the negative class to the sentence.

Compute the most likely class for **"fast, coup, shoot, fly"** Assume a naive Bayes and add-1 smoothing.

Rev.	Cat.
fun, coup, love, love	com
fast, fur, shoot	act
coup, fly, fast, fun	com
fur, shoot, shoot, fun	act
fly, fast, shoot, love	act

First, priors $P(\text{com}) = \frac{2}{5} = 0.4, P(\text{act}) = \frac{3}{5} = 0.6$

Vocab size $|V| = 7$

Likelihoods for each word where
$P(w|\text{class}) = \frac{C(w,\text{class})+1}{\sum C(w,\text{class})+|V|}$

Computed Likelihoods:

$P(\text{fast}|\text{com}) = \frac{1+1}{9+7} = \frac{2}{16}, P(\text{fast}|\text{act}) = \frac{2+1}{11+7} = \frac{3}{18}$

$P(\text{coup}|\text{com}) = \frac{2+1}{9+7} = \frac{3}{16}, P(\text{coup}|\text{act}) = \frac{0+1}{11+7} = \frac{1}{18}$

$P(\text{shoot}|\text{com}) = \frac{0+1}{9+7} = \frac{1}{16}, P(\text{shoot}|\text{act}) = \frac{4+1}{11+7} = \frac{5}{18}$

$P(\text{fly}|\text{com}) = \frac{1+1}{9+7} = \frac{2}{16}, P(\text{fly}|\text{act}) = \frac{1+1}{11+7} = \frac{2}{18}$

Using Naive Bayes assumption:
$P(D|\text{com}) = P(\text{fast}|\text{com})$ P(coup — com) P(shoot — com)
$P(\text{fly}|\text{com})P(\text{com}) = \frac{2}{16} \times \frac{3}{16} \times \frac{1}{16} \times \frac{2}{16} \times \frac{2}{5} = 0.000073242$
$P(D|\text{act}) = P(\text{fast}|\text{act})P(\text{coup}|\text{act})P(\text{shoot}|\text{act})$
$P(\text{fly}|\text{act})P(\text{act}) = \frac{3}{18} \times \frac{1}{18} \times \frac{5}{18} \times \frac{2}{18} \times \frac{3}{5} = 0.000171468$
Since $P(D|\text{act}) > P(D|\text{com})$ the document D is classified as act

Train two models, multinomial vs binary naive Bayes, both with add-1 smoothing.

Classify **"A good, good plot and great characters, but poor acting."**

Do the two models agree or disagree?

Doc	"Good"	"Poor"	"Great"	Class
d1	3	0	3	pos
d2	0	1	2	pos
d3	1	3	0	neg
d4	0	2	0	neg
d5	0	2	0	neg

Priors $P(\text{pos}) = \frac{2}{4} = 0.5, P(\text{neg}) = \frac{2}{4} = 0.5$

Vocab $|V| = 3$

Likelihoods $P(w|\text{class}) = \frac{C(w,\text{class})+1}{\sum C(w,\text{class})+|V|}$

$P(\text{good}|\text{pos}) = \frac{3+1}{9+3} = \frac{4}{12}, \quad P(\text{good}|\text{neg}) = \frac{2+1}{14+3} = \frac{3}{17}$

$P(\text{poor}|\text{pos}) = \frac{1+1}{9+3} = \frac{2}{12}, \quad P(\text{poor}|\text{neg}) = \frac{10+1}{14+3} = \frac{11}{17}$

$P(\text{great}|\text{pos}) = \frac{5+1}{9+3} = \frac{6}{12}, \quad P(\text{great}|\text{neg}) = \frac{2+1}{14+3} = \frac{3}{17}$

Multinomial:
$P(D|\text{pos}) = P(\text{good}|\text{pos})^2 P(\text{poor}|\text{pos})P(\text{great}|\text{pos})P(\text{pos})$
$= \left(\frac{4}{12}\right)^2 \times \frac{2}{12} \times \frac{6}{12} \times 0.5 = 0.000055$
For negative
$P(D|\text{neg}) = P(\text{good}|\text{neg})^2 P(\text{poor}|\text{neg})P(\text{great}|\text{neg})P(\text{neg})$
$= \left(\frac{3}{17}\right)^2 \times \frac{11}{17} \times \frac{3}{17} \times 0.5 = 0.00014$
since $P(D|\text{neg}) > P(D|\text{pos})$ the document D is classified as negative

Binarized
$P(D|\text{pos}) = P(\text{good}|\text{pos})P(\text{poor}|\text{pos})P(\text{great}|\text{pos})P(\text{pos})$
$= \frac{2}{7} \times \frac{3}{7} \times \frac{2}{7} \times 0.5 = 0.0139$
$P(D|\text{neg}) = P(\text{good}|\text{neg})P(\text{poor}|\text{neg})P(\text{great}|\text{neg})P(\text{neg})$
$= \frac{3}{9} \times \frac{2}{9} \times \frac{4}{9} \times 0.5 = 0.0197$
Since $P(D|\text{neg}) > P(D|\text{pos})$
Therefore, both models classify the document as negative, meaning they agree on the classification.

Credits

- Sarah for initial Overleaf version