

Creating features for machine learning from text

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"Aardvarks are small pig-like mammals that are found inhabiting a wide range of different habitats throughout Africa, south of the Sahara. They are mostly solitary and spend their days sleeping in underground burrows to protect them from the heat of the African sun, emerging in the cooler evening to search for food. Their name originates from the Afrikaans language in South Africa and means Earth Pig, due to their long snout and pig-like bo..."

##	a	able	african	after	all	along	also	although	an	and	animal	animals	are	areas	around	as	at	be	being	body	both	but	by	can	diet	different	due	eat	female	food
## 1	13	7	1	1	3	2	9	1	2	40	3	5	40	2	3	10	5	11	4	1	5	4	10	9	2	4	4	2	1	7
## 2	10	0	1	1	1	0	1	1	0	18	1	2	4	0	0	8	0	8	1	1	0	0	3	1	0	1	0	0	0	0
## 3	18	4	0	2	3	6	5	2	4	36	2	0	16	0	2	11	4	3	3	1	3	3	4	2	2	0	2	1	1	7
## 4	13	0	0	1	0	2	3	1	1	23	0	0	8	0	1	8	2	4	3	1	0	4	3	2	0	1	1	0	0	1
## 5	12	2	0	0	1	3	1	3	1	24	0	1	7	0	2	8	2	5	2	1	1	2	1	0	0	0	1	0	0	0
## 6	14	3	67	5	1	2	8	5	5	57	1	2	23	2	3	5	4	11	3	1	2	8	3	9	3	1	3	0	2	5
## 7	17	1	55	2	1	4	4	2	6	38	7	5	17	3	3	6	2	8	3	1	3	3	8	2	3	1	0	0	2	2
## 8	19	2	51	2	2	3	8	4	2	42	2	3	12	1	3	11	4	4	4	0	1	4	6	6	2	0	3	1	3	4
## 9	12	3	59	2	0	2	4	3	6	44	1	2	18	1	1	5	1	5	1	0	2	4	2	2	1	1	4	1	3	2
## 10	22	2	44	1	3	2	4	3	4	48	3	4	21	3	1	11	3	8	3	1	2	2	7	1	3	0	2	0	1	4
## 11	27	0	47	1	1	3	7	2	1	45	2	0	16	1	5	11	5	12	1	2	4	5	12	4	3	0	4	1	4	9
## 12	14	1	45	0	1	1	2	2	0	30	2	1	14	3	0	4	1	4	0	1	2	4	3	0	1	0	1	1	2	2
## 13	17	1	51	2	1	1	7	3	2	48	2	2	19	2	2	12	2	2	1	0	1	1	7	2	2	1	4	0	2	4
## 14	16	0	0	0	0	0	3	2	2	21	0	2	9	0	2	4	0	6	2	0	2	1	5	3	0	0	4	0	1	1
## 15	17	3	0	1	1	0	2	2	4	29	0	2	10	0	1	4	3	10	2	2	3	2	3	1	0	0	2	0	0	0
## 16	19	0	0	1	0	1	4	4	1	31	0	3	12	0	1	4	0	5	0	1	1	1	3	0	0	0	0	0	0	
## 17	17	0	0	0	1	0	4	0	4	25	1	1	13	0	0	10	1	3	1	1	1	0	0	3	0	0	4	0	0	1
## 18	20	2	0	1	1	0	2	1	3	19	0	3	6	1	1	12	2	3	1	1	2	7	4	2	0	1	1	0	0	0
## 19	18	4	0	1	3	1	4	2	5	29	2	3	26	0	1	10	4	8	3	1	3	1	6	7	2	5	3	1	1	0
## 20	11	1	0	2	3	0	9	3	8	38	3	7	17	2	0	4	2	7	4	1	4	1	6	1	1	1	3	2	3	6
## 21	20	1	0	1	1	1	4	0	6	45	2	4	31	0	1	9	2	8	1	2	1	11	4	3	1	2	0	1	3	0
## 22	16	3	0	0	0	0	4	1	3	24	3	1	5	0	0	7	1	4	1	3	1	2	6	0	0	0	1	0	0	0
## 23	10	2	0	1	1	1	3	2	2	27	0	0	10	1	0	8	1	9	3	0	0	2	2	4	0	1	0	0	0	0
## 24	15	0	0	0	0	0	3	2	1	31	0	1	10	0	2	9	0	4	0	0	3	4	0	1	0	2	0	0	0	0
## 25	9	0	0	0	0	0	6	3	2	31	0	2	8	0	0	3	2	3	1	1	1	2	4	4	0	1	0	0	0	0
## 26	16	0	0	3	0	1	1	1	4	22	0	0	9	0	0	10	2	4	1	1	1	5	1	3	0	2	1	0	0	0
## 27	20	0	0	1	1	0	1	1	3	27	2	4	8	0	0	3	1	4	3	1	3	3	8	2	0	0	2	0	0	0
## 28	10	0	0	0	1	0	0	0	0	10	0	0	2	0	0	1	0	0	0	0	0	0	2	1	0	0	0	0	0	
## 29	3	0	0	0	0	1	1	0	2	5	1	0	3	0	0	1	1	3	0	0	0	1	1	3	0	0	0	0	0	
## 30	2	0	0	0	0	0	3	0	1	4	0	0	0	0	0	2	0	2	0	0	0	1	1	0	0	0	0	0	0	0

The screenshot shows a web browser window with the title bar "Tidymodels". The address bar displays the URL "https://www.tidymodels.org". The main content area features the "Tidymodels" logo in pink. Below the logo is a hexagonal grid of colored hexagons, each containing a package icon: "tidymodels" (dark purple), "rsample" (green, featuring a white boot icon), "parsnip" (yellow-green, featuring a green leaf icon), "recipes" (cyan, featuring a cupcake icon), "TUNE" (black, featuring a colorful bar chart icon), and "yardstick" (red, featuring a ruler icon). To the right of the grid, the word "TIDYMODELS" is written in bold capital letters. Below it, a paragraph explains the framework: "The tidymodels framework is a collection of packages for modeling and machine learning using **tidyverse** principles." Further down, instructions for installation are provided: "Install tidymodels with:" followed by the R code "install.packages("tidymodels")".

Tidymodels

PACKAGES GET STARTED LEARN HELP CONTRIBUTE

TIDYMODELS

The tidymodels framework is a collection of packages for modeling and machine learning using **tidyverse** principles.

Install tidymodels with:

```
install.packages("tidymodels")
```

```
library(tidymodels)
```

```
## — Attaching packages —————— tidymodels 0.1.4 —
```

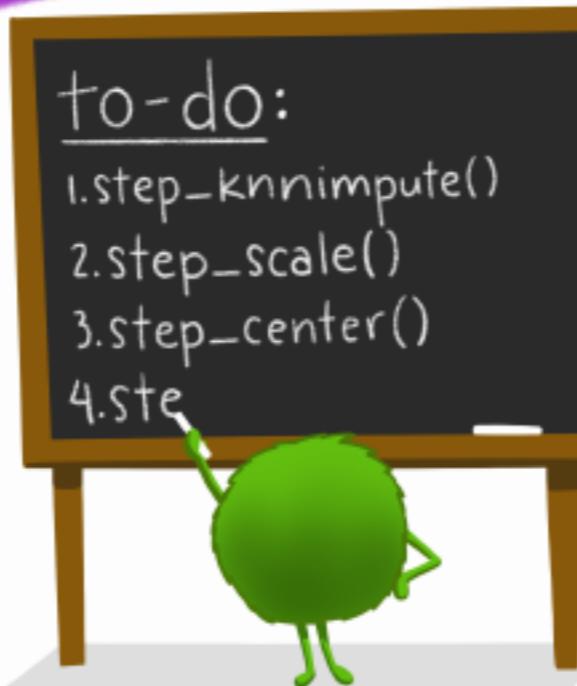
## ✓ broom	0.7.10	✓ rsample	0.1.0
## ✓ dials	0.0.10	✓ tune	0.1.6
## ✓ infer	1.0.0	✓ workflows	0.2.4
## ✓ modeldata	0.1.1	✓ workflowsets	0.1.0
## ✓ parsnip	0.1.7	✓ yardstick	0.0.8
## ✓ recipes	0.1.17		



I. SPECIFY VARIABLES
`recipe(y~a+b+..., data=pantry)`

recipes:

STREAMLINED DATA PRE-PROCESSING FOR
STATISTICAL + MACHINE LEARNING MODELS



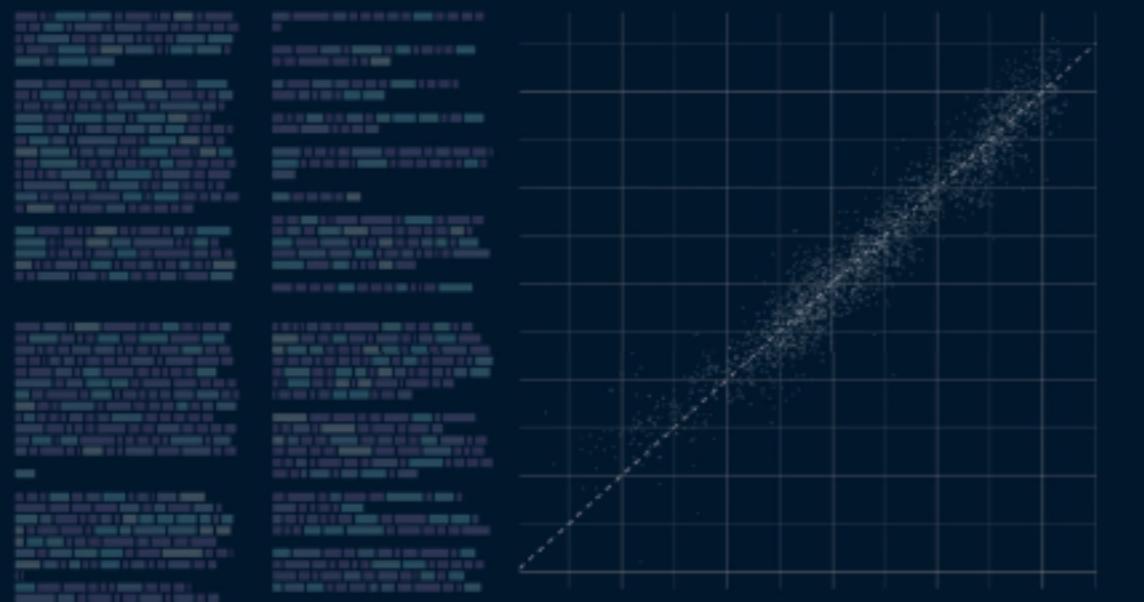
→ 2. DEFINE
PRE-PROCESSING
STEPS (`step_*`)

3. PROVIDE
DATASET(S) FOR
RECIPE STEPS
`prep()`

→ 4. APPLY
PRE-PROCESSING!
`bake()`

DATA SCIENCE SERIES

SUPERVISED MACHINE LEARNING FOR TEXT ANALYSIS IN R



EMIL HVITFELDT
JULIA SILGE



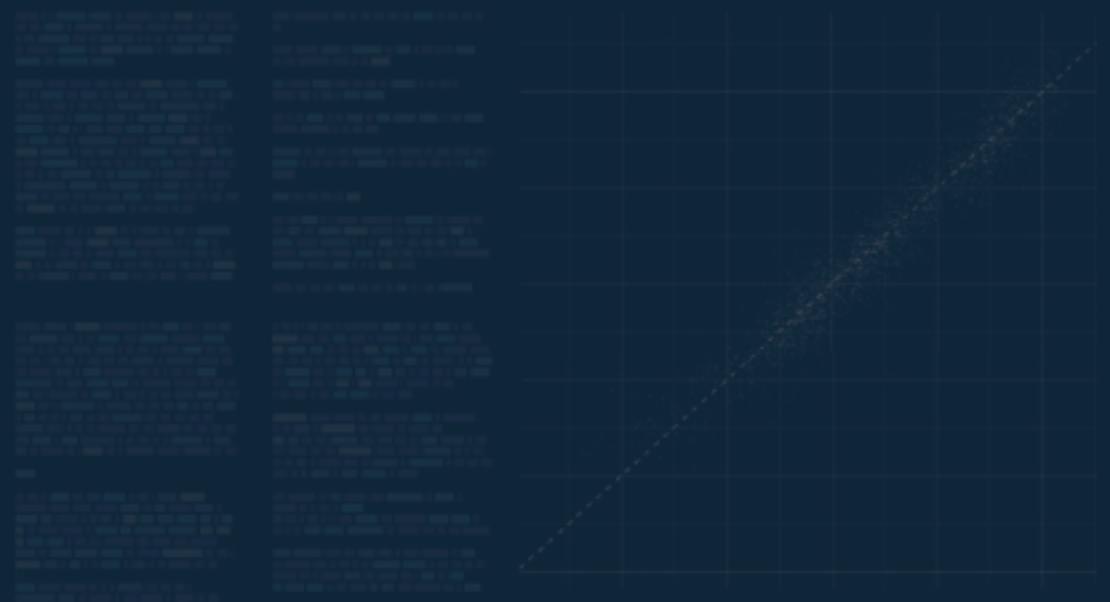
CRC Press
Taylor & Francis Group

A CHAPMAN & HALL BOOK



DATA SCIENCE SERIES

SUPERVISED MACHINE LEARNING FOR TEXT ANALYSIS IN R



EMIL HVITFELDT
JULIA SILGE

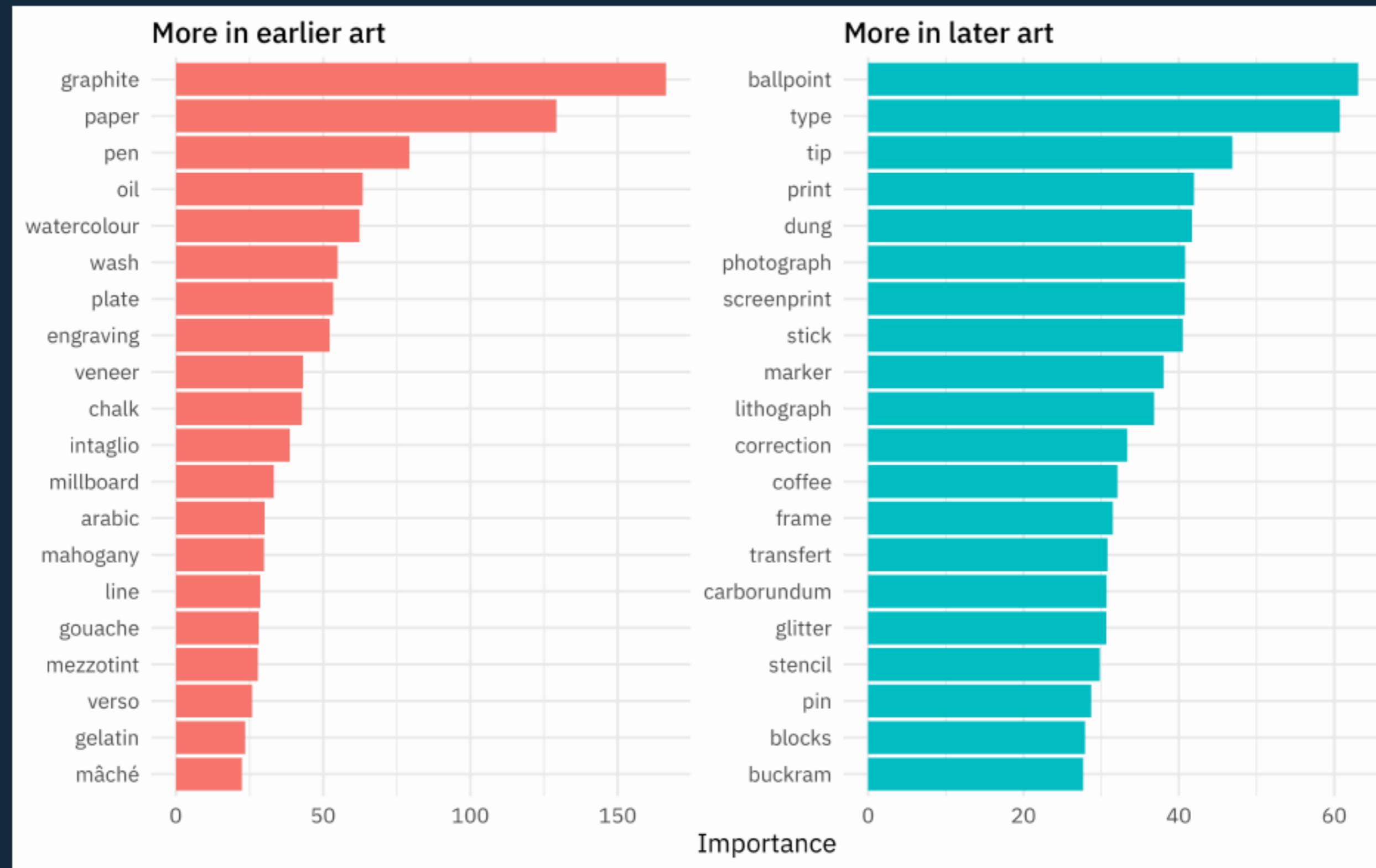
smltar.com



A CHAPMAN & HALL BOOK

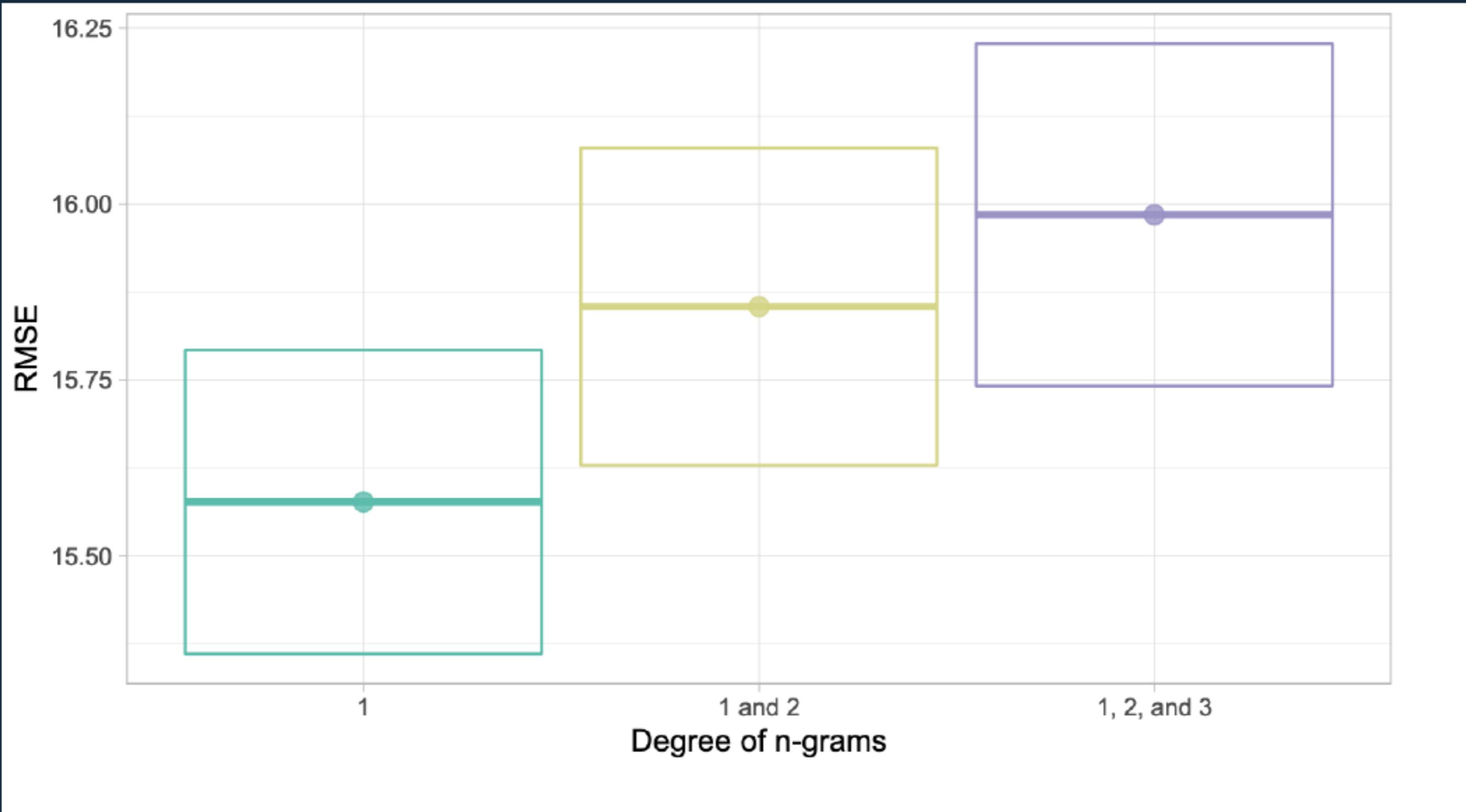
tokenization

```
## [1] "the"          "collared"      "peccary"       "also"
## [5] "referred"     "to"           "as"           "a"
## [9] "javelina"      "or"           "musk"         "hog"
## [13] "may"          "resemble"     "a"            "pig"
## [17] "however"      "peccaries"    "belong"       "to"
## [21] "a"            "completely"   "different"   "family"
## [25] "than"          "true"         "pigs"         "the"
## [29] "collared"     "peccary"      "belongs"      "to"
## [33] "the"          "tayassuidae" "family"       "while"
## [37] "pigs"          "belong"       "to"           "the"
## [41] "suidae"
```



```
## [1] "the collared"          "collared peccary"      "peccary also"
## [4] "also referred"         "referred to"           "to as"
## [7] "as a"                   "a javelina"            "javelina or"
## [10] "or musk"                "musk hog"              "hog may"
## [13] "may resemble"           "resemble a"             "a pig"
## [16] "pig however"            "however peccaries"    "peccaries belong"
## [19] "belong to"               "to a"                  "a completely"
## [22] "completely different"   "different family"     "family than"
## [25] "than true"               "true pigs"              "pigs the"
## [28] "the collared"            "collared peccary"      "peccary belongs"
## [31] "belongs to"               "to the"                 "the tayassuidae"
## [34] "tayassuidae family"     "family while"          "while pigs"
## [37] "pigs belong"              "belong to"              "to the"
## [40] "the suidae"
```

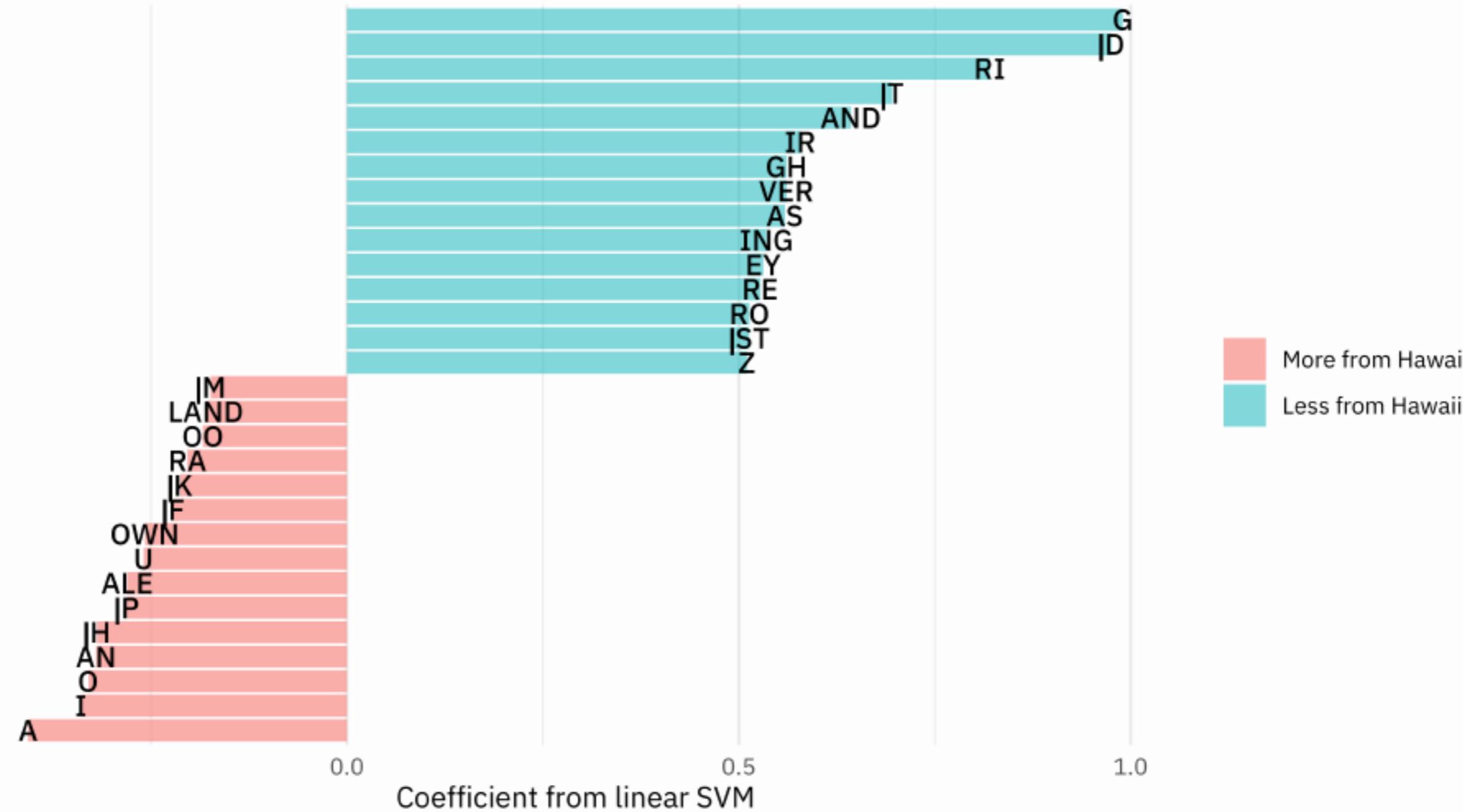
```
## [1] "the collared peccary"  
## [4] "also referred to"  
## [7] "as a javelina"  
## [10] "or musk hog"  
## [13] "may resemble a"  
## [16] "pig however peccaries"  
## [19] "belong to a"  
## [22] "completely different family"  
## [25] "than true pigs"  
## [28] "the collared peccary"  
## [31] "belongs to the"  
## [34] "tayassuidae family while"  
## [37] "pigs belong to"  
  
"collared peccary also"  
"referred to as"  
"a javelina or"  
"musk hog may"  
"resemble a pig"  
"however peccaries belong"  
"to a completely"  
"different family than"  
"true pigs the"  
"collared peccary belongs"  
"to the tayassuidae"  
"family while pigs"  
"belong to the"  
  
"peccary also referred"  
"to as a"  
"javelina or musk"  
"hog may resemble"  
"a pig however"  
"peccaries belong to"  
"a completely different"  
"family than true"  
"pigs the collared"  
"peccary belongs to"  
"the tayassuidae family"  
"while pigs belong"  
"to the suidae"
```



```
## [1] "the" "hec" "eco" "col" "oll" "lla" "lar" "are" "red" "edp" "dpe" "pec"
## [13] "ecc" "cca" "car" "ary" "rya" "yal" "als" "lso" "sor" "ore" "ref" "efe"
## [25] "fer" "err" "rre" "red" "edt" "dto" "toa" "oas" "asa" "saj" "aja" "jav"
## [37] "ave" "vel" "eli" "lin" "ina" "nao" "aor" "orm" "rmu" "mus" "usk" "skh"
## [49] "kho" "hog" "ogm" "gma" "may" "ayr" "yre" "res" "ese" "sem" "emb" "mbl"
## [61] "ble" "lea" "eap" "api" "pig" "igh" "gho" "how" "owe" "wev" "eve" "ver"
## [73] "erp" "rpe" "pec" "ecc" "cca" "car" "ari" "rie" "ies" "esb" "sbe" "bel"
## [85] "elo" "lon" "ong" "ngt" "gto" "toa" "oac" "aco" "com" "omp" "mpl" "ple"
## [97] "let" "ete" "tel" "ely" "lyd" "ydi" "dif" "iff" "ffe" "fer" "ere" "ren"
## [109] "ent" "ntf" "tfa" "fam" "ami" "mil" "ily" "lyt" "yth" "tha" "han" "ant"
## [121] "ntr" "tru" "rue" "uep" "epi" "pig" "igs" "gst" "sth" "the" "hec" "eco"
## [133] "col" "oll" "lla" "lar" "are" "red" "edp" "dpe" "pec" "ecc" "cca" "car"
## [145] "ary" "ryb" "ybe" "bel" "elo" "lon" "ong" "ngs" "gst" "sto" "tot" "oth"
## [157] "the" "het" "eta" "tay" "aya" "yas" "ass" "ssu" "sui" "uid" "ida" "dae"
## [169] "aef" "efa" "fam" "ami" "mil" "ily" "lyw" "ywh" "whi" "hil" "ile" "lep"
## [181] "epi" "pig" "igs" "gsb" "sbe" "bel" "elo" "lon" "ong" "ngt" "gto" "tot"
## [193] "oth" "the" "hes" "esu" "sui" "uid" "ida" "dae"
```

Which subwords in a US Post Office name are used more in Hawaii?

Subwords like A, I, O, and AN are the strongest predictors of a post office being in Hawaii



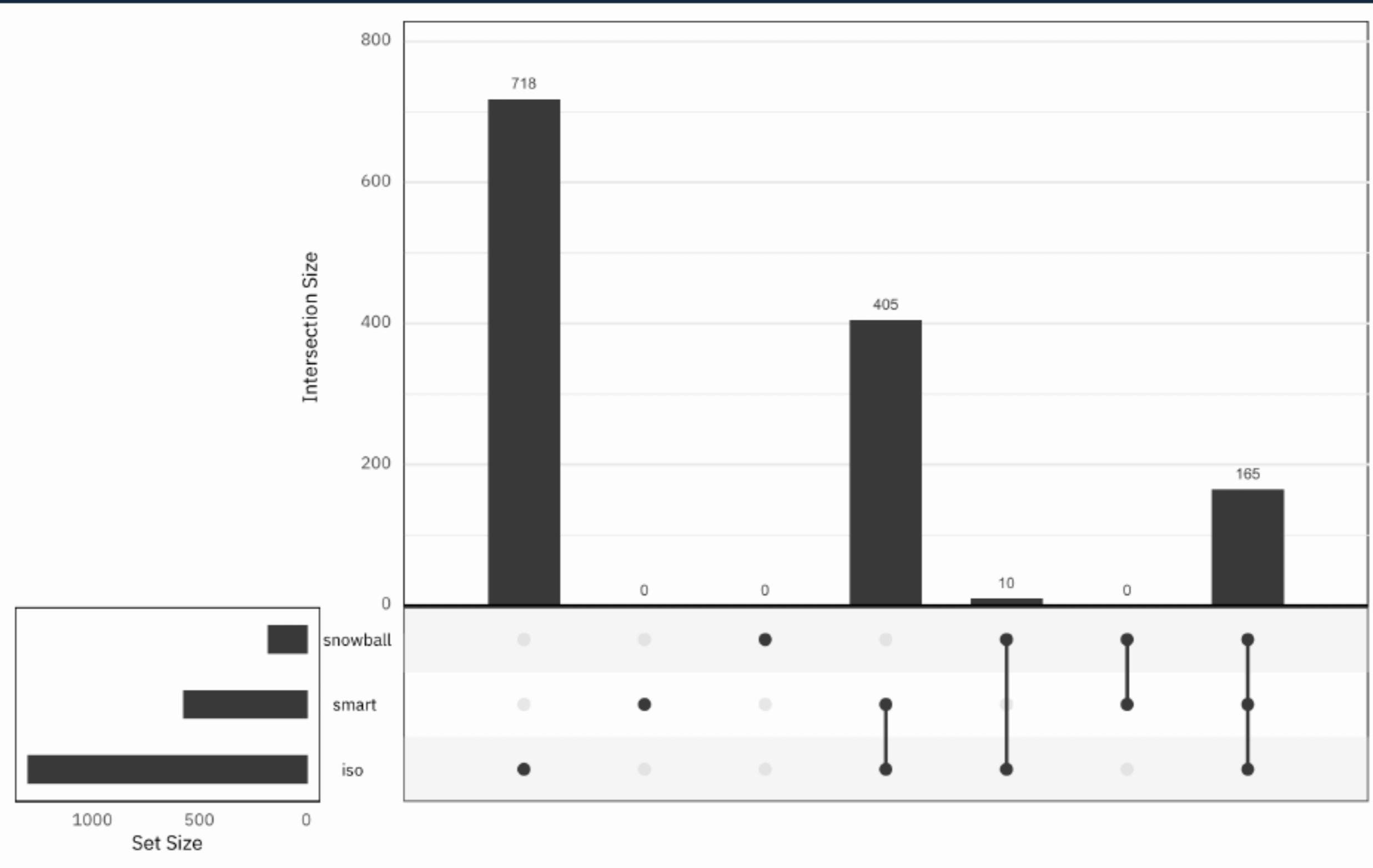
```
library(textrecipes)
recipe(diet ~ text, data = animal_train) %>%
  step_tokenize(
    text,
    token = "ngrams",
    options = list(n = 3, n_min = 1)
)
```

```
## Recipe
##
## Inputs:
##   role #variables
##     outcome      1
##     predictor    1
##
## Operations:
##   Tokenization for text
```

stop words

## [1] "가"	"가까스로"	"가령"	"각"	"각각"	"각자"	"각종"	"갖고말하자면"	"같다"	"같이"	"개의치않고"	"거니와"
## [13] "거바"	"거의"	"것"	"것과 같이"	"것들"	"게다가"	"겨우"	"견지에서"	"결과에 이르다"	"결국"	"결론을 낼 수 있다"	
## [25] "겸사겸사"	"고려하면서"	"고로"	"곧"	"공동으로"	"과연"	"관계가 있다"	"관계없이"	"관련이 있다"	"관하여"	"관한"	
## [37] "관해서는"	"구"	"구체적으로"	"구도하다"	"그"	"그들"	"그때"	"그래"	"그래도"	"그래서"	"그러나"	"그러니"
## [49] "그러니까"	"그러면"	"그러므로"	"그러한즉"	"그런데"	"그런 깨닭에"	"그런즉"	"그럼"	"그럼에도 불구하고"	"그렇게 함으로써"	"그렇지 않다면"	
## [61] "그렇지 않으면"	"그렇지만"	"그렇지않으면"	"그리고"	"그리하여"	"그만이다"	"그에 따르는"	"그위에"	"그저"	"그중에서"	"그치지 않다"	"근거로"
## [73] "근거하여"	"기대여"	"기점으로"	"기준으로"	"기타"	"까닭으로"	"까지"	"까지 미치다"	"까지도"	"화당"	"끙끙"	
## [85] "끼만"	"나"	"나마지는"	"남들"	"남짓"	"너"	"너희들"	"네"	"넷"	"년"	"는하지 않다"	
## [97] "놀라다"	"누가 알겠는가"	"누구"	"다른"	"다른 방면으로"	"다만"	"다섯"	"다수"	"다시 말하자면"	"다시말하면"	"다음"	
## [109] "다음에"	"다음으로"	"단지"	"답다"	"당신"	"당장"	"대로 하다"	"대하던"	"대해 말하자면"	"대해서"	"댕그"	
## [121] "더구나"	"데고다나"	"더라도"	"더불어"	"더욱이"	"더욱이든"	"도달하다"	"도착하다"	"동시에"	"동안"	"된바에야"	"된이상"
## [133] "두번째로"	"둘"	"둘째"	"뒤따라"	"뒤이어"	"두간에"	"둘"	"등등"	"딩동"	"따라"	"따라서"	
## [145] "따위"	"따지지 않다"	"때"	"때가 되어"	"때문에"	"또"	"또한"	"똑똑"	"라 해도"	"랑"	"로"	
## [157] "로, 위하여"	"로부터"	"로써"	"를"	"마음대로"	"마저"	"마저도"	"마치"	"막론하고"	"만 못하다"	"만약"	
## [169] "만약에"	"만은 아니다"	"만이 아니다"	"만큼"	"말하자면"	"말할것도 없고"	"매"	"매번"	"매쓰겁다"	"맞"	"모"	
## [181] "모두"	"무렵"	"무를쓰고"	"무슨"	"무엇때문에"	"물론"	"및"	"바꾸어말하자면"	"바꾸어서 말하면"	"바꾸어서 한다면"		
## [193] "바꿔 말하면"	"바로"	"바꿔같이"	"밖에 안된다"	"반대로"	"반대로 말하자면"	"버금"	"보는데서"	"보다더"	"보드록"	"본대로"	
## [205] "봐"	"봐라"	"부류의 사람들"	"부터"	"불구하고"	"불문하고"	"비교적"	"비길수 없다"	"비로소"	"비록"		
## [217] "비슷하다"	"비추어 보아"	"비해면"	"뿐만 아니라"	"분이니라"	"분이다"	"빼거리다"	"사"	"삼"	"상대적으로 말하자면"	"생각대로"	
## [229] "설령"	"설마"	"설사"	"셋"	"소생"	"쇠"	"쇳"	"습니까"	"습니다"	"시간"		
## [241] "시작하여"	"시초에"	"시기다"	"실로"	"심지어"	"아니"	"아니다를가"	"아니면"	"아니었다면"	"아래햇"		
## [253] "마무거나"	"마무도"	"아야"	"아틀라"	"아이고"	"아이구"	"아이야"	"아이쿠"	"아하"	"마톱"	"안 그려만"	
## [265] "많기 위해서"	"많기 위해서"	"알 수 있다"	"알았어"	"앗"	"말에서"	"앞의것"	"야"	"액간"	"영자"	"머"	"머기여차"
## [277] "어느"	"어느 난도"	"어느것"	"어느곳"	"어느때"	"어느쪽"	"어느해"	"어디"	"어때"	"어떠한"	"어판"	"어떤것"
## [289] "어떤것들"	"어떻게"	"어떻해"	"어이"	"어빠져"	"어랫든"	"어쩔수 없다"	"어찌"	"어찌됐든"	"어찌해든지"	"어찌하여"	
## [301] "언제"	"언젠가"	"얼마"	"얼마 안 되는 것"	"얼마간"	"얼마나"	"얼마만큼"	"얼마큼"	"殃殃"	"에"	"에 가서"	
## [313] "에 달려 있다"	"에 대해"	"에 있다"	"에 한하다"	"에게"	"에서"	"여기"	"여덟"	"여러분"	"여보시오"	"여부"	
## [325] "여섯"	"여진히"	"여자"	"연관되다"	"연에서"	"영"	"영차"	"열사람"	"예"	"예를 들면"	"예컨대"	
## [337] "예하연"	"오"	"오로지"	"오자마자"	"오직"	"오후"	"오히려"	"와"	"와 같은 사람들"	"와글로"	"와아"	
## [349] "왜"	"왜냐하면"	"외에도"	"요엔큼"	"요만한 것"	"요만한걸"	"요컨대"	"우르르"	"우리들"	"우선"	"무에 종합한것과같이"	
## [361] "운운"	"될"	"위에서 서술한바와같이"	"위하여"	"위해서"	"윙윙"	"욱"	"으로"	"으로 인하여"	"으로서"	"으로써"	"풀"
## [373] "응"	"응당"	"의"	"의거하여"	"의지하여"	"의해되다"	"의해"	"의해서"	"이"	"이 되다"	"이 밖에"	
## [385] "이 외에"	"이 정도의"	"이것"	"이곳"	"이미"	"이리언"	"이미래"	"미리아리하되"	"이러한"	"이런"	"이럴정도로"	"미렇게 많은 것"
## [397] "이렇게되면"	"이렇게말하자면"	"이행구나"	"이로 인하여"	"이르기까지"	"이리하여"	"이만큼"	"이번"	"이파"	"이상"	"이어서"	"이었다"
## [409] "이와 같다"	"이와 같은"	"이와 반대로"	"이와같다면"	"이외에도"	"이용하여"	"이유만으로"	"이벤"	"이자민"	"이쪽"	"이천구"	"이천육"
## [421] "이천칠"	"이천풀"	"인 듯하다"	"인펜"	"일"	"일것이다"	"밀금"	"밀단"	"밀때"	"밀반적으로"	"밀자라도"	"밀에 풀림없다"
## [433] "입각하여"	"입장에서"	"잇따라"	"잇다"	"자"	"자기"	"자기집"	"자마자"	"자신"	"잠한"	"잠시"	"제"
## [445] "제것"	"제것만큼"	"제것"	"제기"	"제쪽"	"전부"	"전자"	"전후"	"점에서 보아"	"정도에 이르다"	"제자기"	
## [457] "제외하고"	"조금"	"조차"	"조차도"	"줄줄"	"줄"	"줄마"	"착륙"	"주특주특"	"주저하지 않고"	"줄은 풀맞다"	"줄은모른다"
## [469] "증에서"	"증의하나"	"증음하여"	"즉"	"즉시"	"지든지"	"지안"	"지알고"	"진짜로"	"쪽으로"	"차라리"	"참"
## [481] "참나"	"첫번째로"	"첫"	"총적으로"	"총적으로 말하면"	"총적으로 보면"	"칠"	"킬킬"	"쿵쾅"	"쿵"	"타다"	"타인"
## [493] "탕탕"	"토하다"	"통하며"	"통"	"통타"	"막"	"팔"	"막"	"밀렁"	"밀렁"	"하"	"하게될것이다"
## [505] "하기하다"	"하기는가"	"하고 있다"	"하고 있다"	"하고하였다"	"하구나"	"하기 때문에"	"하기 위하여"	"하기는한데"	"하기만 하면"	"하기보다는"	"하기에"
## [517] "하나"	"하느니"	"하는 감에"	"하는 만이 낫다"	"하는것도"	"하는것만 못하다"	"하는것이 낫다"	"하는바"	"하더라도"	"하도다"	"하도록시키다"	"하도록해다"
## [529] "하든지"	"하려고하다"	"하마터면"	"하먼 할수록"	"하먼된다"	"하먼서"	"하물며"	"하여금"	"하여아"	"하자마자"	"하지 않는다면"	"하지 않도록"
## [541] "하지마"	"하지마라"	"하지만"	"하하"	"한 까닭에"	"한 이유는"	"한 후"	"한다면"	"한다면 끌라도"	"한데"	"한마디"	"한적이있다"
## [553] "한번으로는"	"한번도록"	"할 때마다"	"할 생각이다"	"할 줄 안다"	"할 지경이다"	"할 힘이 있다"	"할때"	"할만하다"	"할망정"	"할뿐"	"할수있다"
## [565] "할수있어"	"할줄알다"	"할지라도"	"할증인정"	"함께"	"해도된다"	"해도좋다"	"해봐요"	"해서는 안된다"	"해야한다"	"했어요"	"했어요"
## [577] "향하다"	"향하여"	"향해서"	"희"	"희적"	"희희"	"희희"	"희희"	"힐떡힐떡"	"형식으로 쓰여"	"혹시"	"혹은"
## [589] "흔자"	"훨씬"	"휘익"	"휴"	"흐흐"	"흐"	"흐흐"					

```
## [1] "i"          "me"          "my"          "myself"       "we"          "our"         "ours"
## [8] "ourselves"  "you"          "your"         "yours"        "yourself"    "yourselves"  "he"
## [15] "him"         "his"          "himself"     "she"          "her"          "hers"        "herself"
## [22] "it"          "its"          "itself"      "they"         "them"        "their"      "theirs"
## [29] "themselves" "what"         "which"       "who"          "whom"        "this"        "that"
## [36] "these"        "those"        "am"          "is"           "are"          "was"         "were"
## [43] "be"           "been"         "being"       "have"        "has"         "had"         "having"
## [50] "do"           "does"         "did"          "doing"        "would"       "should"     "could"
## [57] "ought"        "i'm"          "you're"      "he's"         "she's"       "it's"        "we're"
## [64] "they're"      "i've"         "you've"      "we've"        "they've"     "i'd"         "you'd"
## [71] "he'd"         "she'd"        "we'd"        "they'd"       "i'll"        "you'll"     "he'll"
## [78] "she'll"        "we'll"        "they'll"     "isn't"        "aren't"      "wasn't"      "weren't"
## [85] "hasn't"        "haven't"     "hadn't"      "doesn't"     "don't"       "didn't"     "won't"
## [92] "wouldn't"     "shan't"       "shouldn't"   "can't"        "cannot"      "couldn't"   "mustn't"
## [99] "let's"         "that's"        "who's"        "what's"       "here's"      "there's"     "when's"
## [106] "where's"      "why's"        "how's"        "a"            "an"          "the"         "and"
## [113] "but"          "if"           "or"          "because"     "as"          "until"      "while"
## [120] "of"           "at"           "by"          "for"          "with"        "about"      "against"
## [127] "between"      "into"         "through"    "during"      "before"      "after"       "above"
## [134] "below"         "to"           "from"        "up"           "down"        "in"          "out"
## [141] "on"           "off"          "over"        "under"       "again"       "further"    "then"
## [148] "once"          "here"         "there"       "when"        "where"       "why"         "how"
## [155] "all"           "any"          "both"        "each"        "few"         "more"        "most"
## [162] "other"         "some"         "such"        "no"          "nor"         "not"         "only"
## [169] "own"           "same"         "so"          "than"        "too"         "very"        "will"
```



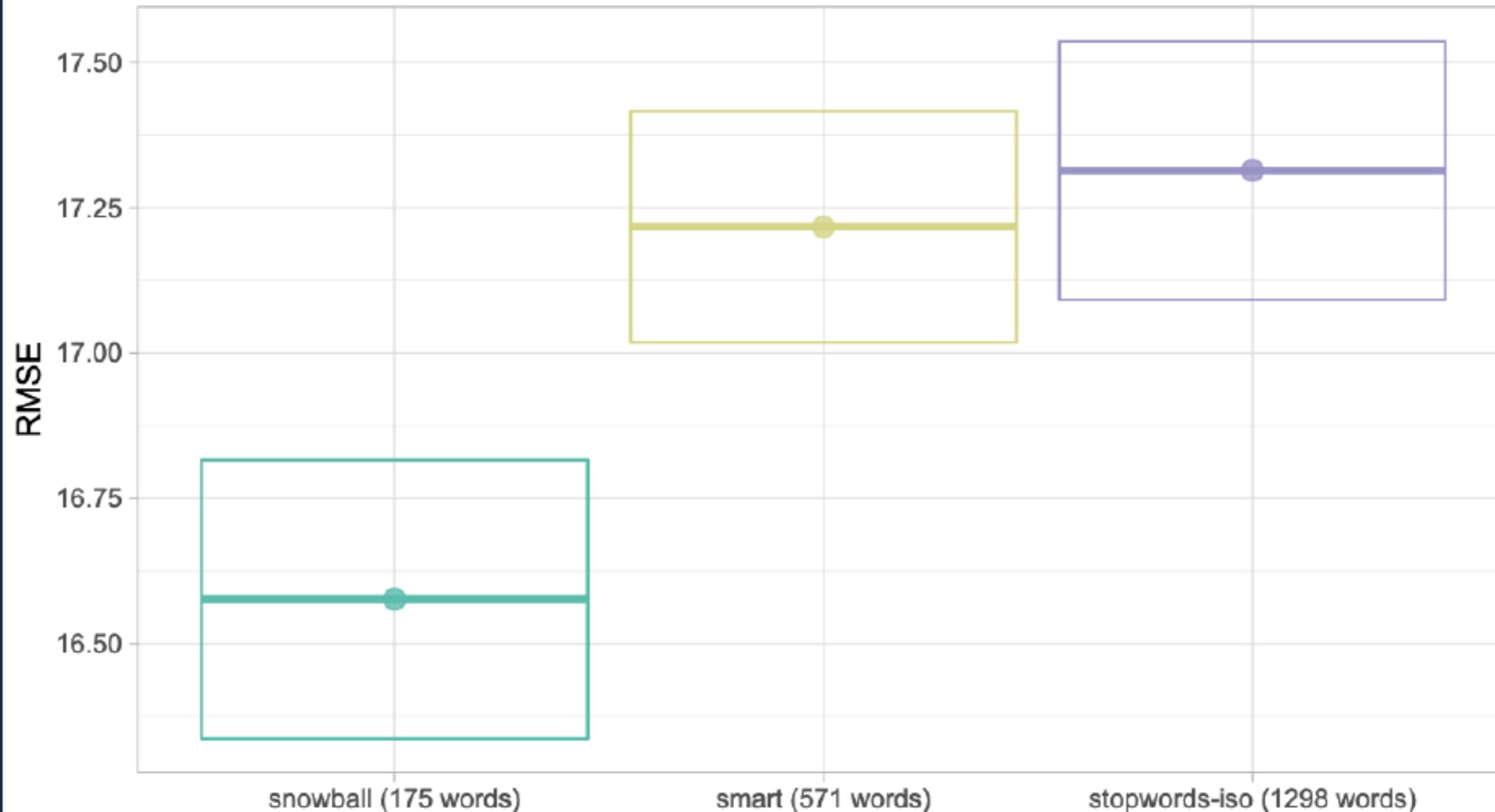
```
## [1] "she's"    "he'd"  
## [3] "she'd"    "he'll"  
## [5] "she'll"   "shan't"  
## [7] "mustn't"  "when's"  
## [9] "why's"    "how's"
```

```
recipe(diet ~ text, data = animal_train) %>%  
  step_tokenize(text) %>%  
  step_stopwords(text)
```

```
## Recipe  
##  
## Inputs:  
##  
##      role #variables  
##      outcome      1  
##      predictor     1  
##  
## Operations:  
##  
## Tokenization for text  
## Stop word removal for text
```

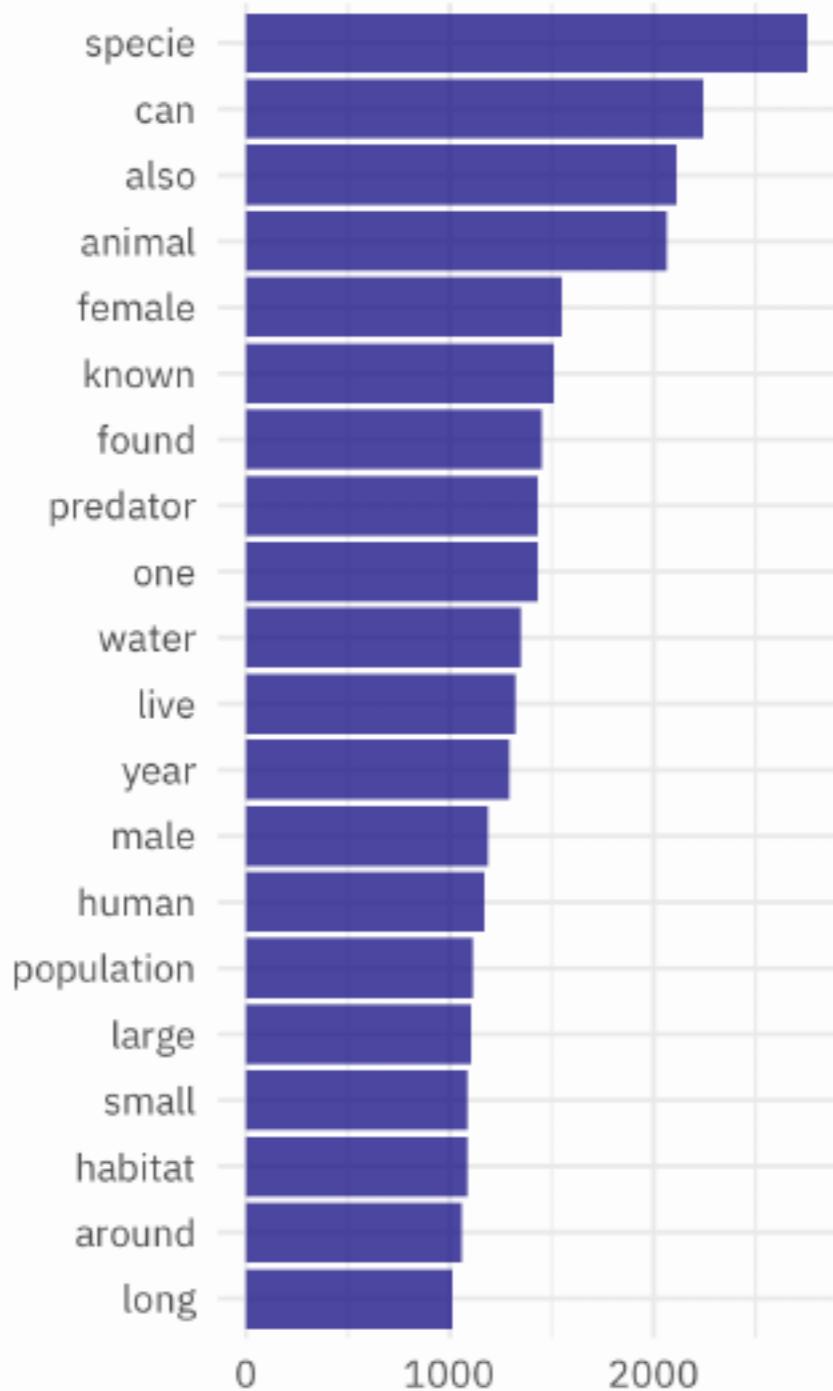
Model performance for three stop word lexicons

For this data set, the Snowball lexicon performed best

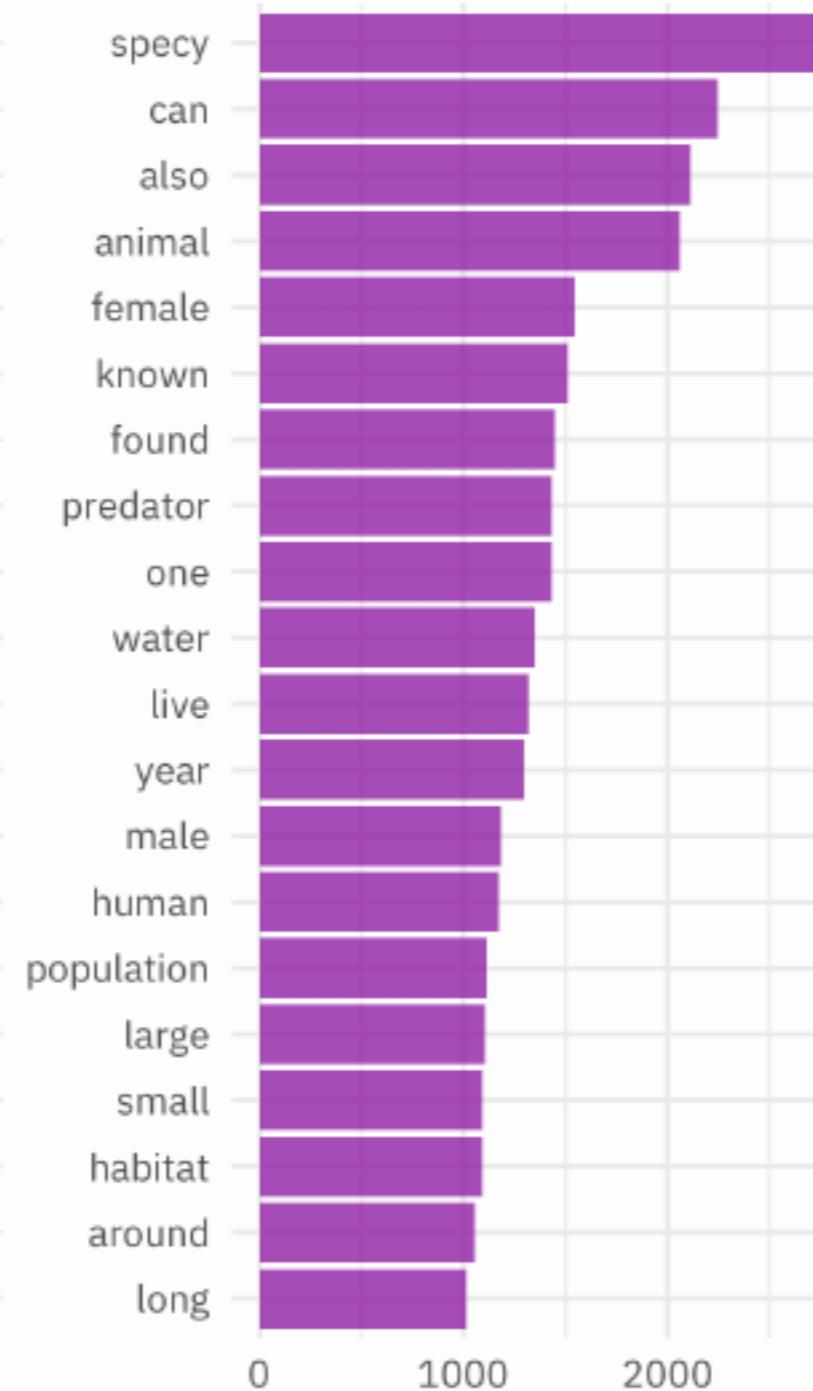


stemming

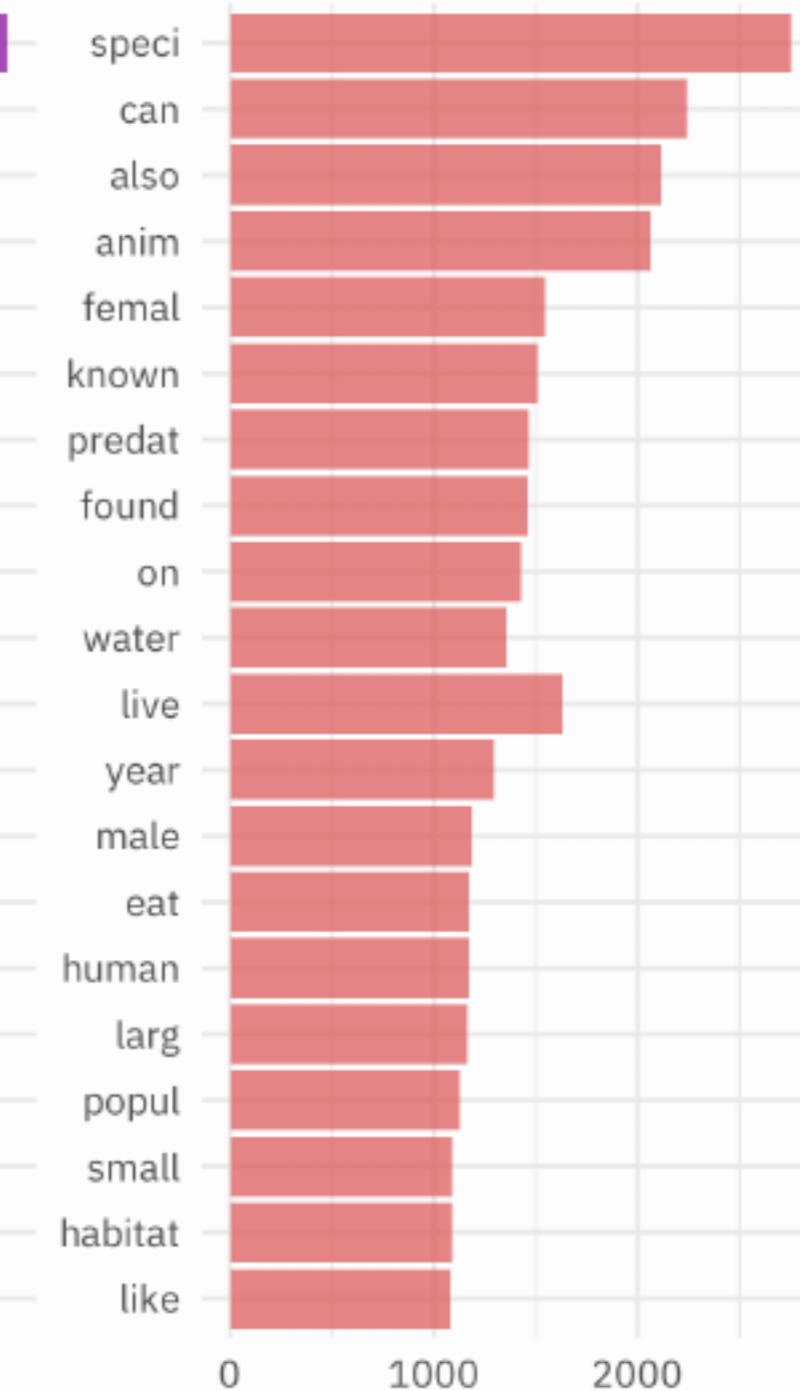
Remove S



Plural endings



Porter stemming



```
tidy_animals %>%  
  count(animal, word) %>%  
  cast_dfm(animal, word, n)
```

```
## Document-feature matrix of: 610 documents, 16,840 features (98.13% sparse) and 0 docvars.
```

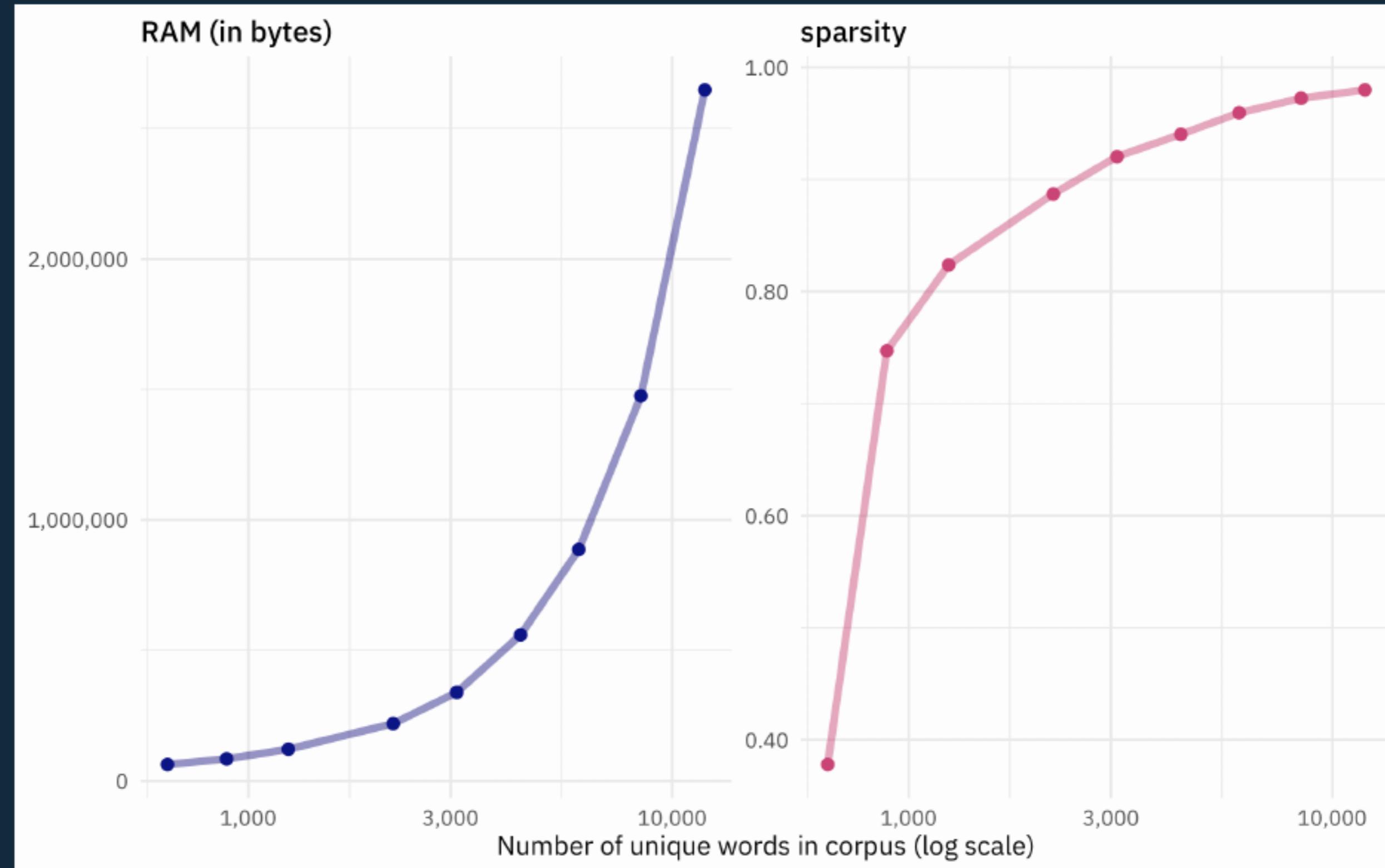
```
tidy_animals %>%  
  mutate(stem = wordStem(word)) %>%  
  count(animal, stem) %>%  
  cast_dfm(animal, stem, n)  
  
## Document-feature matrix of: 610 documents, 12,045 features (97.62% sparse) and 0 docvars.
```

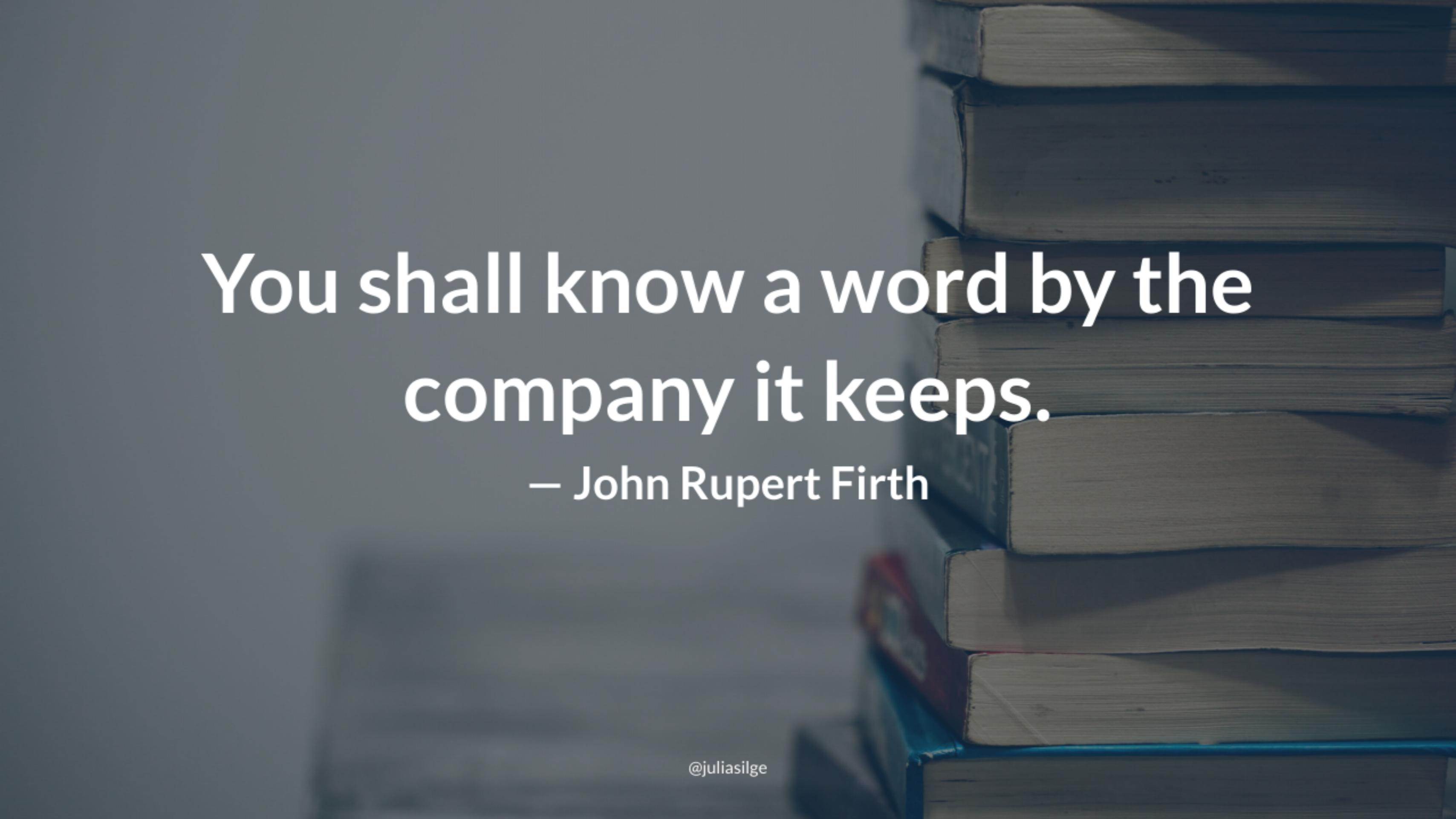
recall
true positive rate

precision
true negative rate

```
recipe(diet ~ text, data = animal_train) %>%
  step_tokenize(
    text,
    token = "ngrams",
    options = list(
      n = 2, n_min = 1,
      stopwords = stopwords::stopwords(source = "snowball")
    )
  ) %>%
  step_tokenfilter(text, max_tokens = tune()) %>%
  step_tfidf(text)
```

```
## Recipe
##
## Inputs:
##   role #variables
##   outcome      1
##   predictor     1
##
## Operations:
##   Tokenization for text
##   Text filtering for text
##   Term frequency-inverse document frequency with text
```



A dark, moody photograph of a stack of old books. The spines of the books are visible, showing various colors like blue, red, and brown, and some wear and tear. The lighting is dramatic, coming from the side, which creates strong highlights on the edges of the books and deep shadows on the left side.

You shall know a word by the company it keeps.

– John Rupert Firth

<i>word</i>	<i>distance</i>
month	1
year	0.607
months	0.593
monthly	0.454
installments	0.446
payment	0.429
week	0.406
weeks	0.400
85.00	0.399
bill	0.396

<i>word</i>	<i>distance</i>
error	1
mistake	0.683
clerical	0.627
problem	0.582
glitch	0.580
errors	0.571
miscommunication	0.512
misunderstanding	0.486
issue	0.478
discrepancy	0.474

<i>word</i>	<i>distance</i>
error	1
errors	0.792
mistake	0.664
correct	0.621
incorrect	0.613
fault	0.607
difference	0.594
mistakes	0.586
calculation	0.584
probability	0.583

Fairness and word embeddings

- African American first names are associated with more unpleasant feelings than European American first names
- Women's first names are more associated with family and men's first names are more associated with career
- Terms associated with women are more associated with the arts and terms associated with men are more associated with science

Features from text machine learning in the real world

@juliasilge

Thank you!

Julia Silge

juliasilge.com | smltar.com

Photo by Sharon McCutcheon on Unsplash