#### **Test**

```
rm(list=ls(all=T))
# uncomment this if running first time on local
# To rum on AWS, always uncomment this
# install.packages(c( "tidyverse", "readxl", "tm", "topicmodels", "NLP"))
library(tm)
## Warning: package 'tm' was built under R version 3.6.3
## Loading required package: NLP
## Warning: package 'NLP' was built under R version 3.6.3
library(topicmodels)
## Warning: package 'topicmodels' was built under R version 3.6.3
library(NLP)
library(readxl)
## Warning: package 'readxl' was built under R version 3.6.3
# options(stringsAsFactors = F)
```

## Loading statements

```
docs <- readxl::read_excel("E:/Projects/modern_slavery_registry/data/sheets/subset_data.xlsx")
docs <- docs[["final_statement_cleaned"]]
# https://stackoverflow.com/questions/47406555/error-faced-while-using-tm-packages-vcorpus-in-r
docs <- data.frame(doc_id=c(1:length(docs)), text=docs)</pre>
```

# Preparing document-term matrix for n-grams [1-n]

```
# https://stackoverflow.com/questions/45697840/custom-tokenizer-in-tm-package-r-not-working
corpus <- VCorpus(DataframeSource(docs))

# https://stackoverflow.com/questions/52207021/r-how-to-apply-terms-from-training-document-term-
matrix-dtm-to-test-dtm-bot
custom_tokenizer <- function(x) unlist(lapply(NLP::ngrams(words(x), 1:2), paste, collapse = " "), use.names = FALSE)

MIN_DF <- 10
MAX_DF <- 1000
dtm <- DocumentTermMatrix(
    corpus,
    control = list(
        tokenize=custom_tokenizer,
        bounds = list(global = c(MIN_DF, MAX_DF))))</pre>
```

#### Document-term dimension

```
cat("docs:", dim(dtm)[1], "vocab-size:", dim(dtm)[2])
```

```
## docs: 9993 vocab-size: 47987
```

## Pre-process document-term matrix

```
# due to vocabulary pruning, we have empty rows in our DTM
# LDA does not like this. So we remove those docs from the
# DTM and the metadata
sel_idx <- slam::row_sums(dtm) > 0
dtm <- dtm[sel_idx, ]</pre>
```

## Running LDA model

```
# number of topics
NUM_TOPICS <- 10
# set random number generator seed
set.seed(40)
NUM_ITER = 500
# compute the LDA model, inference via 500 iterations of Gibbs sampling
topicModel <- LDA(
    x=dtm,
    k=NUM_TOPICS,
    method="Gibbs",
    control=list(iter = NUM_ITER, verbose = 25))</pre>
```

```
## K = 10; V = 47987; M = 9993
## Sampling 500 iterations!
## Iteration 25 ...
## Iteration 50 ...
## Iteration 75 ...
## Iteration 100 ...
## Iteration 125 ...
## Iteration 150 ...
## Iteration 175 ...
## Iteration 200 ...
## Iteration 225 ...
## Iteration 250 ...
## Iteration 275 ...
## Iteration 300 ...
## Iteration 325 ...
## Iteration 350 ...
## Iteration 375 ...
## Iteration 400 ...
## Iteration 425 ...
## Iteration 450 ...
## Iteration 475 ...
## Iteration 500 ...
## Gibbs sampling completed!
```

# Getting top n words for each topic

```
NUM_TOP_WORDS = 10
terms(topicModel, NUM_TOP_WORDS)
```

```
Topic 3
##
         Topic 1
                              Topic 2
                                                             Topic 4
                              "2015 set"
                                                             "potential risk"
    [1,] "2015 act"
                                                 "germany"
##
    [2,] "procure"
                              "traffic take"
                                                 "france"
                                                             "reputable"
    [3,] "plc"
                              "within business" "ireland"
                                                             "circumstance"
##
   [4,] "asset"
                              "place within"
                                                 "australia" "statement set"
##
                                                 "usa"
                                                             "vehicle"
##
   [5,] "outsource"
                              "eligibility"
##
   [6,] "clause"
                              "commit act"
                                                 "africa"
                                                             "commit prevent"
   [7,] "regulate"
                              "continue take"
                                                 "canada"
                                                             "put place"
##
   [8,] "wholly"
                              "minimum wage"
                                                 "japan"
                                                             "retaliation"
##
                                                             "easy"
   [9,] "executive officer" "reprisal"
                                                 "spain"
##
##
   [10,] "bank"
                              "31st"
                                                 "italy"
                                                             "aim ensure"
##
         Topic 5
                               Topic 6
                                            Topic 7
                                                          Topic 8
   [1,] "identity"
                               "award"
                                             "store"
                                                          "target"
##
                               "investor"
                                             "shop"
##
   [2,] "physical"
                                                          "strengthen"
   [3,] "threat"
                               "charity"
                                            "return"
                                                          "compact"
##
   [4,] "sedex"
                               "research"
                                             "accessory"
                                                          "embed"
##
                               "school"
   [5,] "recruit"
                                             "send"
                                                          "align"
##
   [6,] "knowingly"
                               "innovation" "click"
                                                          "launch"
##
   [7,] "sexual"
                               "vision"
                                            "notice"
                                                          "channel"
##
                                                          "goal"
##
   [8,] "permanent"
                               "study"
                                             "gift"
   [9,] "equal opportunity"
##
                               "tender"
                                             "collection"
                                                          "collaboration"
## [10,] "accordance section" "energy"
                                             "card"
                                                          "map"
##
         Topic 9
                                   Topic 10
   [1,] "whistle blower"
                                   "chain act"
##
   [2,] "control ensure"
                                   "transparency supply"
##
   [3,] "high level"
                                   "california transparency"
##
   [4,] "level understand"
                                   "disclose"
##
   [5,] "initiative identify"
                                   "involuntary"
##
   [6,] "exploit"
                                   "among"
##
## [7,] "organization structure"
                                   "inc"
##
   [8,] "understand risk"
                                   "corrective"
   [9,] "anti policy"
                                   "comply applicable"
##
                                   "prison"
## [10,] "policy reflect"
# have a look a some of the results (posterior distributions)
tmResult <- posterior(topicModel)</pre>
# format of the resulting object
attributes(tmResult)
## $names
## [1] "terms" "topics"
# topics are probability distribtions over the entire vocabulary
```

```
## [1] 10 47987
```

# K distributions over nTerms(DTM) terms

# get beta from results

beta <- tmResult\$terms</pre>

dim(beta)

```
# aggregated beta distribution rowSums(beta)
```

```
## 1 2 3 4 5 6 7 8 9 10
## 1 1 1 1 1 1 1 1 1
```

## Computing perplexity for trained model

```
perplexity(topicModel, dtm)
```

```
## K = 10; V = 47987; M = 9993
## Sampling 500 iterations!
## Iteration 25 ...
## Iteration 50 ...
## Iteration 75 ...
## Iteration 100 ...
## Iteration 125 ...
## Iteration 150 ...
## Iteration 175 ...
## Iteration 200 ...
## Iteration 225 ...
## Iteration 250 ...
## Iteration 275 ...
## Iteration 300 ...
## Iteration 325 ...
## Iteration 350 ...
## Iteration 375 ...
## Iteration 400 ...
## Iteration 425 ...
## Iteration 450 ...
## Iteration 475 ...
## Iteration 500 ...
## Gibbs sampling completed!
```

```
## [1] 13157
```