Text Analysis of Aviation Safety Data

Predict 453 – Final Project Report

Rahul Sangole

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Northwestern

Contents

Data Source

- This is the dataset used for the SIAM 2007 Text Mining competition[1].
- This competition focused on developing text mining algorithms for document classification.
- The documents in question were aviation safety reports that documented one or more problems that occurred during certain flights.
- The goal was to label the documents with respect to the types of problems that were described. This is a subset of the Aviation Safety Reporting System (ASRS) dataset, which is publicly available.

[1] https://c3.nasa.gov/dashlink/resources/138/

Approach

Explore the data
- Text Corpus (Xs)
- Labels (Y)

How can I use the labels / categories?
- What level of aggregation should I consider my DSIDs?
- Identify non-unique categories

Text Preparation
- Eliminate non-unique categories
- Case to lower
- Handle period separation
- Remove punctuation
- Remove stopwords

Text Preparation
- Remove too common words
- Remove taxiway designations
- Remove airport IATA codes
- Strip whitespaces

Tidy Text
- One row per "category + dsid + word + count"

TF-IDF calculations upon category

tSNE investigation into underlying structures of term-document-matrix
- How many structures show up? These could indicate # of topics

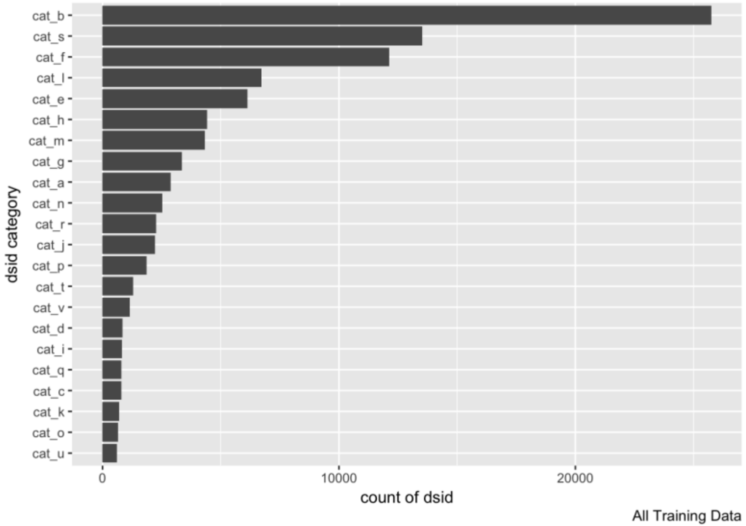
Structural Topic Models
- Use tSNE to identify # of topic models
- Specify # of topic models

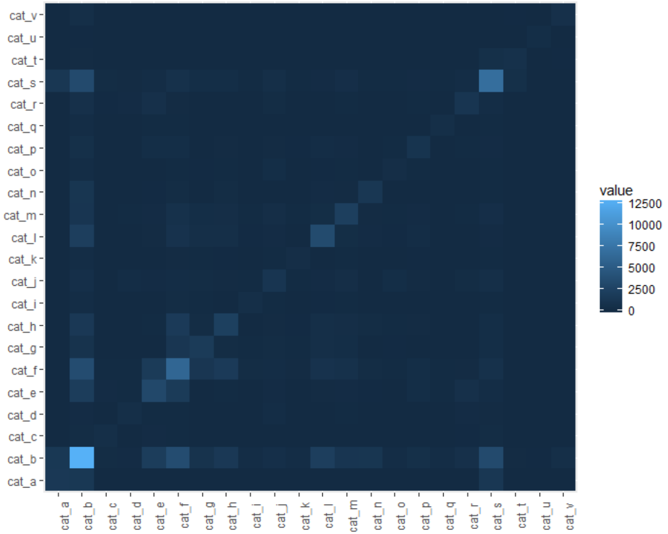
Post process STM models
- Plots
- Quantitative results

Interpret the model results

Input Data

- This is a very large dataset: [21519, 24]
- Each of the 21519 DSI is an aviation safety report
- There are a total of 22 categories. The categories aren't labeled. Does each category correspond to a topic? Or are there multiple topics within each category?
- Each DSID can belong to more than 1 category. [If this was false, all off diagonal cells would be dark].





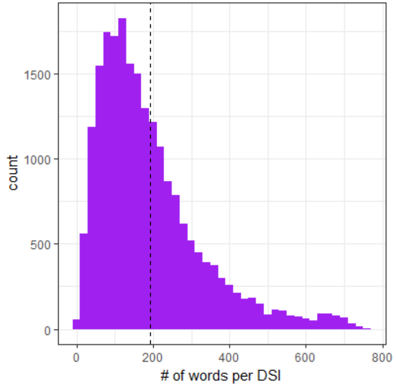
Exploratory Data Analysis

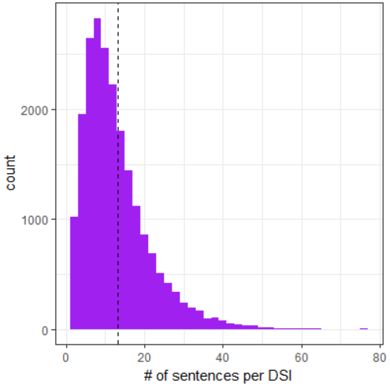
```
AND AILERON LOCKOUT
engineindicationandcrewalertingsystemmessage
occur.near LEVELOFF captain south ALTIMETER fail
AND UNWOUND TO _ feet.WE level OFF us firstofficer
south ALTIMETER AFTER A deviate OF _ feet.left
centralairdatacomputer
```

```
ON taxiout AT bos airport I miss A TURN AND CAME
INTO CONFLICT WITH AN aircraft _.WE BOTH CAME TO
A STOP AND I realize MY MISTAKE.THERE WAS NEVER
ani DANGER OF hit EACH OTHER.I WASWAY.humanfactor
give OTHER taxiinstruction BY ground AND WENT ON
MY DURING taxiout THE firstofficer IS frequent
OUT OF THE LOOP get LOAD DATA AND takeoff
perform.BOTH set OF eye ARE need DURING
TAXI.AFTER EVENT OF _ IT HAS BEEN hard TO FOCUS
AND CONCENTRATE.firstofficer south HAVE TOLD ME
THIS ALSO.WE NOW MORE THAN EVER FORCE OURSELVES
TO BE mind OF THE TASK AT HAND "
```

Interesting artifacts

- There is a mixture of lowercase and UPPERCASE words
- Some lowercase words seem to be pre-processed tokens (bi / tri grams)
- Sentences are separated by a period with no adjacent spaces
- Numbers have been replaced by _
- Stemming seems to have been done
- Airport IATA codes show up in lowercase





Word Cloud


flightlevel
without
normal
also
final
climb
direct
area
give
passenger
maintain
traffic
ground
pass
light
back
approach
left
crew
call
fail
receive
upon
taxi
flap
mile
turn
land
clear
start
state
hear
right
report
gate
close
hold
feet
feel
flight
time
told
return
hour
advise
runway
south
inform
check
fuel
take
contact
head
knot
stop
pilot
tower
just
control
captain
number
depart
posit
arrive
firstofficer

Data Processing

1. Remove non-unique categories
2. Case to lower
3. Handle period separation
4. Remove punctuation
5. Remove stopwords
6. Remove too common words
7. Remove taxiway designations
8. Remove airport IATA codes
9. Strip whitespaces

```
approximate _ ON september _ captain call ask WHERE HI
CLOSEOUT WAS.THE loadagent work THE flight inform ME THAT
THE FINAL CARGO number WERE NOT enter YET AND THERE WAS A
CHANCE THE flight MIGHT BE OVER THE maximum RAMP weigh.WHEN
THE FINAL CARGO number WERE final receive BY THE loadagent
SHE BECAME suspicion AS TO THE FIGURE
```

```
approximate september captain call closeout loadagent work
flight inform final cargo number enter yet chance flight
might maximum ramp weigh final cargo number final receive
loadagent became suspicion figure…
```

```r
vs <- VectorSource(training_data_uniques$text)
docs <- Corpus(vs)
meta(docs, 'doc_id') <- training_data_uniques$doc_id

stopwords_w_spaces <- stopwords('english') %>% gsub(pattern = '\'', replacement = ' ')
taxiway_designations <- unlist(c(letters, map(letters,  ~ paste0(.x, letters))))
remove_fullstop <- function(x) gsub(pattern = '\\.', replacement = ' ', x = x)
remove_too_common_words <- c('aircraft','airport')

docs %<>%
    tm_map(content_transformer(tolower)) %>%
    tm_map(content_transformer(remove_fullstop)) %>%
    tm_map(removePunctuation) %>%
    tm_map(removeNumbers) %>%
    tm_map(removeWords, stopwords_w_spaces) %>%
    tm_map(removeWords, remove_too_common_words) %>%
    tm_map(removeWords, taxiway_designations) %>%
    tm_map(removeWords, airport_iata_codes[1:7000]) %>%
    tm_map(removeWords, airport_iata_codes[7000:7800]) %>%
    tm_map(stripWhitespace)

tdm <- TermDocumentMatrix(docs)
```

Modeling

Modeling Approaches

- TF-IDF Based
- tSNE Based
- STM Based

Using existing *known* categories and TF-IDF, can we identify patterns in the categories?

Using only the term-document-matrix, can we identify any patterns? How many topics exist in the corpus?

Using only the term-document-matrix, can we identify topics in the corpus? How many topics? What are the topics? How do they agree with the *known* categories?

How I’m defining a DSI

For TF-IDF Analysis

- All the individual safety reports are grouped into the 22 *known* categories
- Thus, this is equivalent to a total of 22 DSIs in the corpus, each containing thousands of sentences

For STM Analysis

- Started with the TF-IDF approach
- Switched to defining each safety report as it’s own DSI
- Thus, total DSIs = 5949

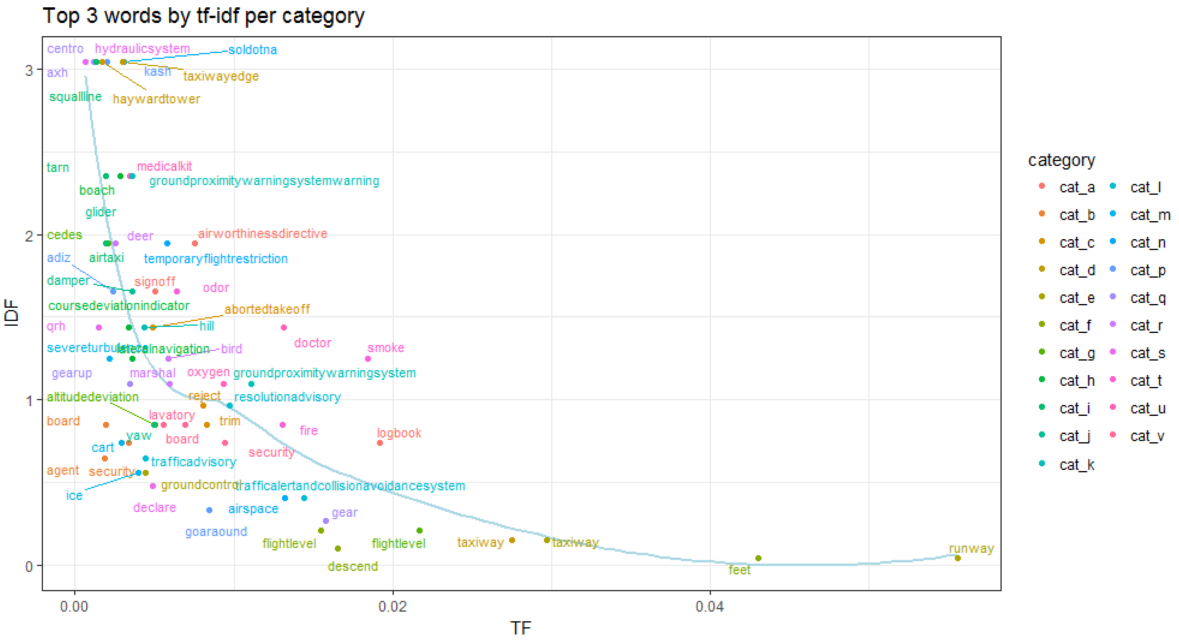
Equivalence Classes, Reference Term Vectors, Document Term Matrix

- Manually read through 10s of safety reports
- I could not find any obvious terms which I would group together into ECs
- The RTV is thus the remainder of the terms after pre-processing
- `tidytext` is used to create the RTV which is fed into a TermDocumentMatrix generation function
- The definition of ‘documents’ depends on if I’m doing a TF-IDF or STM

```
> inspect(tdm)
<<TermDocumentMatrix (terms: 13620, documents: 5949)>>
Non-/sparse entries: 355806/80669574
Sparsity           : 100%
Maximal term length: 70
Weighting          : term frequency (tf)
Sample             :
           Docs
Terms       1520 2733 2959 3039 3758 380 4938 5432 5867 5920
  approach     2    0    0    5    4   1    0    0    5    3
  call         1    1    0    0    1   0    0    0    4    4
  clear        1    0    2    2    5   0    1    7    1    0
  control      2    1    4    0    0   0    4    5    1    4
  feet         1    0    0    4    7   1    1   13    8   12
  flight       2    1    2    2    0   1    3    2    1    1
  land         3    2    7    9    0   6    1    1    3    1
  passenger    0    0    0    1    0   3    0    1    0    2
  report       0    0    0    3    2   1    1    2    1    4
  runway       2    3    3    3    0   4    0    1    8    1
```

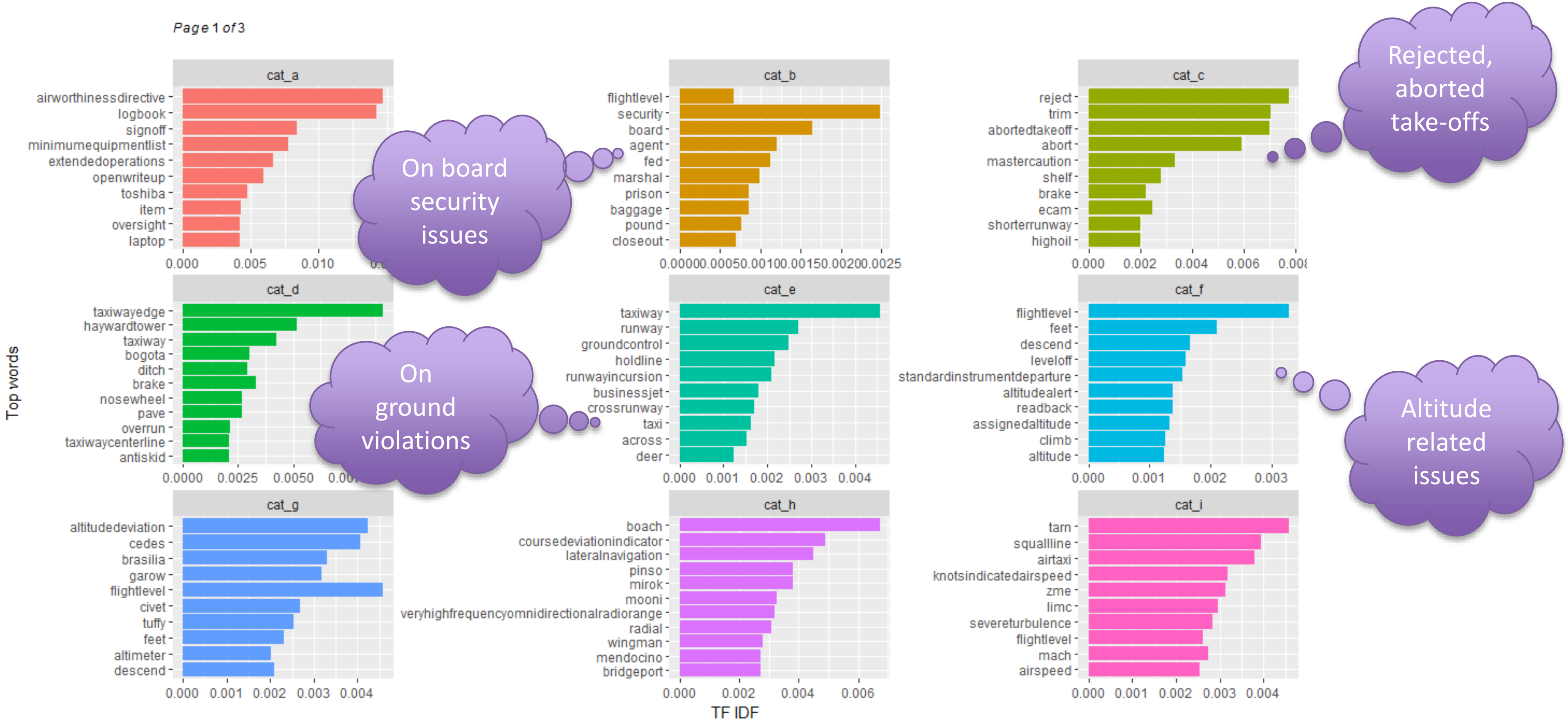
TF-IDF Based Analysis

	category	word	n	tf	idf	tf_idf
	<fct>	<chr>	<int>	<dbl>	<dbl>	<dbl>
1	cat_f	feet	1323	0.0430	0.0488	0.00210
2	cat_e	runway	876	0.0556	0.0488	0.00271
3	cat_s	declare	751	0.00491	0.480	0.00235
4	cat_l	trafficalertandcollisionavoidancesystem	749	0.0145	0.405	0.00586
5	cat_f	descend	508	0.0165	0.100	0.00165
6	cat_l	resolutionadvisory	503	0.00971	0.965	0.00937
7	cat_f	flightlevel	477	0.0155	0.211	0.00328
8	cat_b	security	475	0.00335	0.742	0.00248
9	cat_e	taxiway	468	0.0297	0.154	0.00458
10	cat_b	board	276	0.00195	0.847	0.00165



- Some terms are very exclusive to certain categories, with high values of IDF and low values of TF. Ex: *hydraulicsystem* for *cat_s*
- Others terms like *runway* show up in a lot more documents, yet have high TF values for certain categories like *cat_d*
- Both these instances result in high TF-IDF values within the respective categories

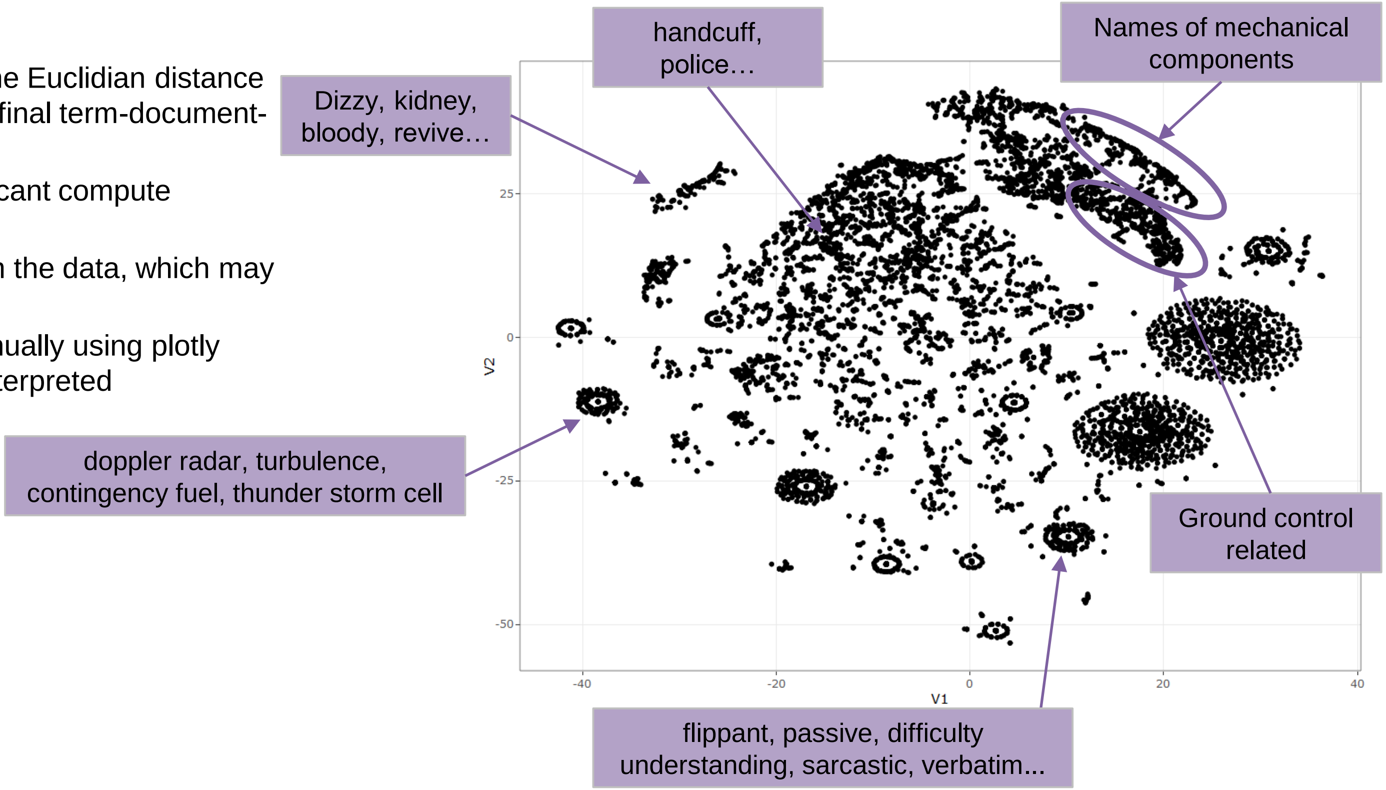
TF-IDF Based Analysis



[1] Remainder of the plots in the appendix

Structural Investigation using tSNE

- tSNE analysis is performed on the Euclidian distance matrix between the words in the final term-document-matrix
- The Rtsne package offers significant compute efficiency vs the tsne package
- We can see very clear clusters in the data, which may point to topics in the corpus
- Investigation of these points manually using plotly reveals patterns which can be interpreted

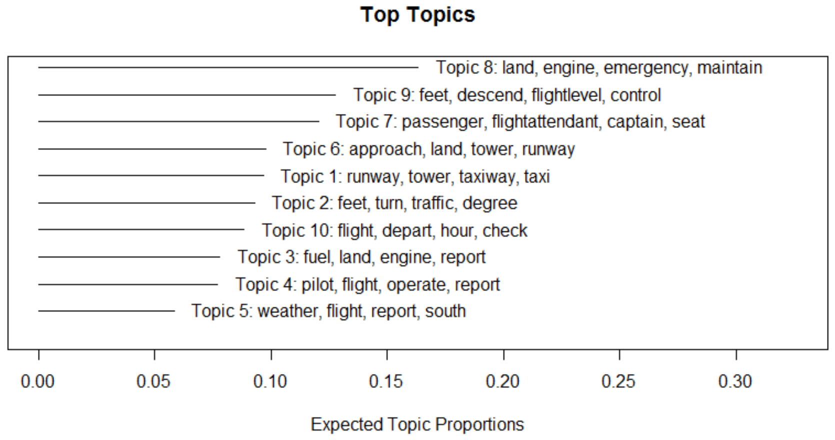


Structural Topic Modeling

- STMs allow researchers to flexibly estimate a topic model
- STMs are like LDA models, except they extend the capability to include document-level metadata into the topic model. This allows researchers to not only estimate topics but also relationships to document metadata.
- The `stm` package in R is quite powerful with many features which work well with the `tidyverse`, `tm`, `quanteda` and other major R packages

- Using `stm`, there are two main approaches towards deciding how many topics (K) are contained in the corpus:
  - Define the value(s) of K yourself
  - Use tsne to perform a dimension reduction on the TDM followed by some geometric calculations to estimate the number of “groupings”
    - This method resulted in 116 topics!
- To begin with, I’m assuming K=10

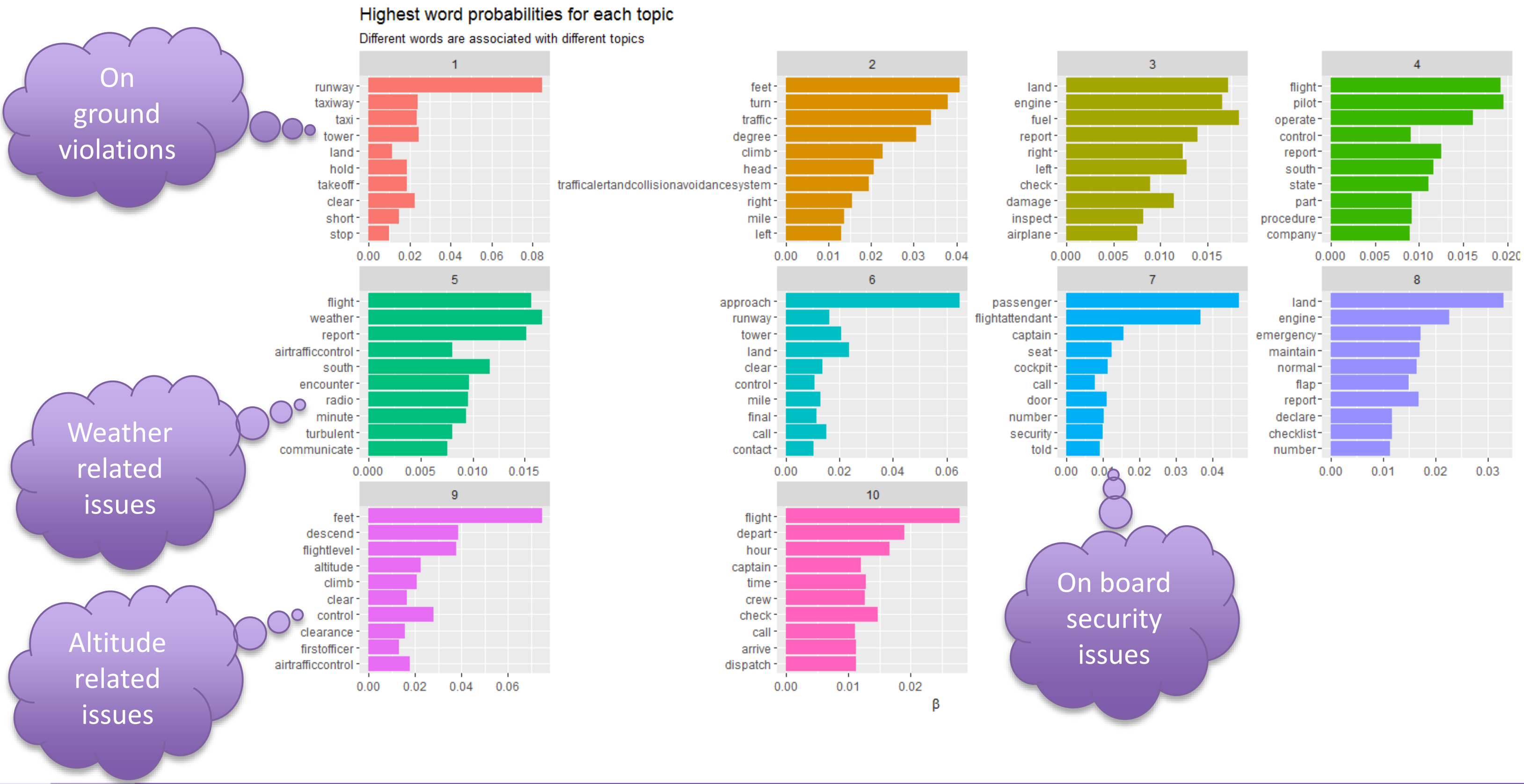
STM Results, K=10



- For each topic,
  - Highest probability terms
  - FREX: How exclusive terms are to this topic?
  - Lift: Higher weight to words which appear less frequently in other topics

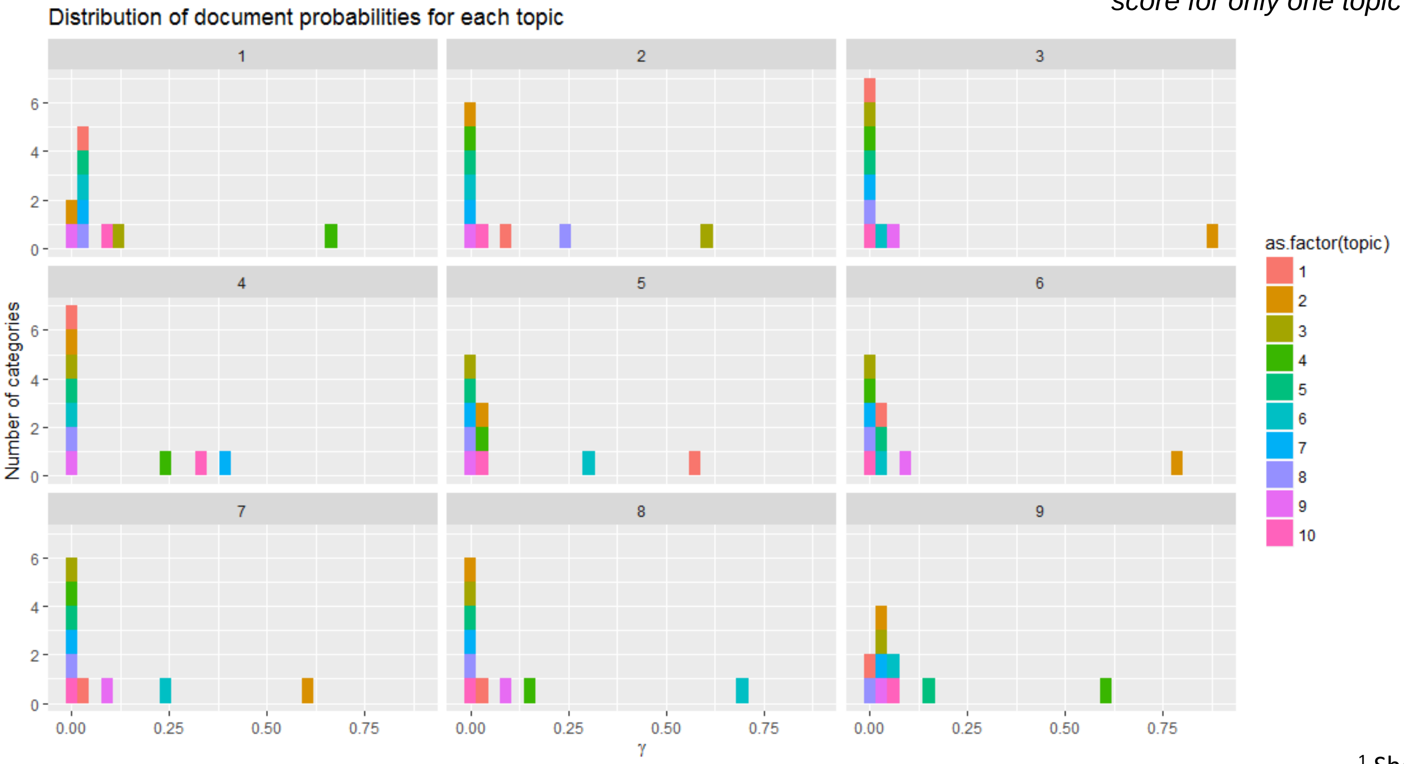
```
A topic model with 10 topics, 5949 documents and a 8515 word dictionary.
Topic 1 Top Words:
         Highest Prob: runway, tower, taxiway, taxi, clear, hold, takeoff
         FREX: taxiway, crossrunway, groundcontrol, takeoffclearance, taxi, hold, taxiins
         Lift: accessroad, airportlight, airportvehicle, apron, blowingsnow, breakaway, c
         Score: taxiway, runway, taxi, tower, groundcontrol, crossrunway, clearance
Topic 2 Top Words:
         Highest Prob: feet, turn, traffic, degree, climb, head, trafficalertandcollision
         FREX: resolutionadvisory, oclock, target, trafficalertandcollisionavoidancesyste
         Lift: arrivalcorridor, collisioncourse, computerfailure, conflictresolution, fal
         Score: trafficalertandcollisionavoidancesystem, resolutionadvisory, traffic, tra
Topic 3 Top Words:
         Highest Prob: fuel, land, engine, report, left, right, damage
         FREX: tank, revolutionsperminute, mixture, magneto, propel, fuelleak, deer
         Lift: accesspanel, airintake, airstrip, amplitude, automotive, auxiliarytank, bo
         Score: fuel, engine, tank, damage, gear, propel, brake
Topic 4 Top Words:
         Highest Prob: pilot, flight, operate, report, south, state, part
         FREX: federalaviationregulation, airman, federalaviationadministration, violate,
         Lift: causeconfusion, coupler, disapproved, eggx, flightdatacenter, furnish, hun
         Score: temporaryflightrestriction, federalaviationadministration, airman, violat
Topic 5 Top Words:
         Highest Prob: weather, flight, report, south, encounter, radio, minute
         FREX: thunderstorm, encounter, windshear, windshield, forecast, navigate, turbul
         Lift: aerobaticmaneuver, basicvisualflightrules, coldfront, contactor, dispense,
         Score: turbulent, weather, cloud, sector, ice, severeturbulence, encounter
Topic 6 Top Words:
         Highest Prob: approach, land, tower, runway, call, clear, mile
         FREX: adiz, finalapproachfix, potomac, instrumentflightrules, glideslope, classb
         Lift: adiz, angling, arlington, assignedtranspondercode, authoritarian, awo, bet
         Score: tower, approach, runway, airspace, downwind, adiz, visualflightrules
Topic 7 Top Words:
         Highest Prob: passenger, flightattendant, captain, seat, cockpit, door, number
         FREX: galley, doctor, lavatory, paramedic, firstclass, aisle, jetbridge
         Lift: abrasion, assault, auditor, beverage, bloody, boardingprocess, breath
         Score: flightattendant, passenger, security, door, board, doctor, agent
Topic 8 Top Words:
         Highest Prob: land, engine, emergency, maintain, report, normal, flap
         FREX: qrh, hydraulicsystem, trailingedge, overheat, flap, compressorstall, exhau
         Lift: hydraulicsystem, abnormalprocedure, aircyclemachine, allison, amberlight,
         Score: engine, flap, emergency, declare, trim, qrh, gear
Topic 9 Top Words:
         Highest Prob: feet, descend, flightlevel, control, altitude, climb, airtrafficco
         FREX: autopilot, flightlevel, altimeter, descend, assignedaltitude, altitude, al
         Lift: alertwindow, altitudeawareness, altitudecallout, altitudepreselect, altitu
         Score: flightlevel, feet, descend, climb, altitude, autopilot, clearance
Topic 10 Top Words:
         Highest Prob: flight, depart, hour, check, time, crew, captain
         FREX: schedule, load, release, logbook, cargo, paperwork, minimumequipmentlist
         Lift: accuload, airtrafficcontroldelay, magazines, maintenancediscrepancy, maint
         Score: schedule, dispatch, logbook, pound, paperwork, hour, minimumequipmentlist
```

Word Probabilities Per Topic



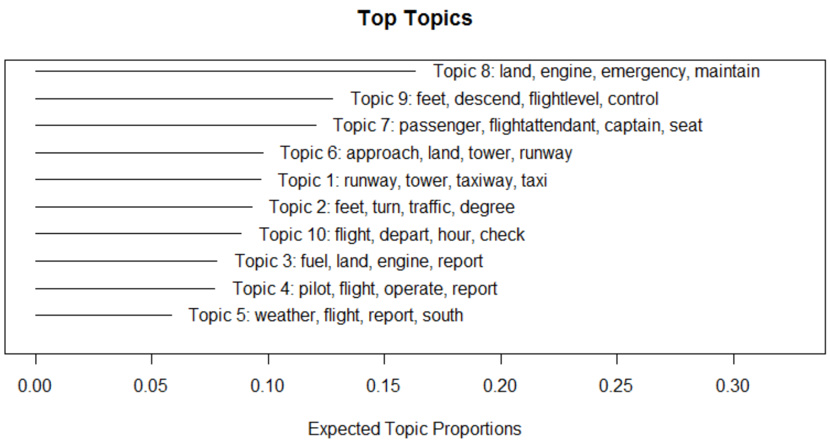
Document Distribution among Topics

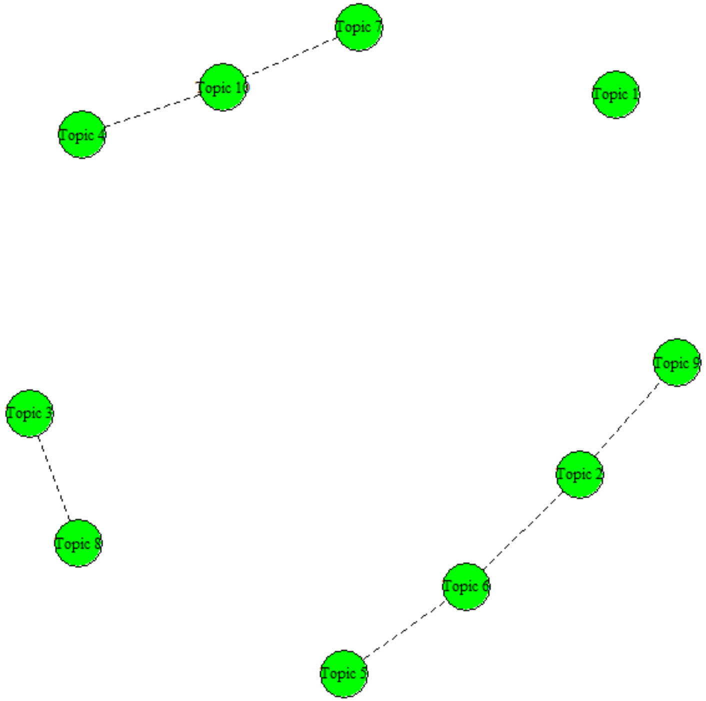
Each document should have a high gamma score for only one topic



[1] Showing 9 of 5949 DSIs

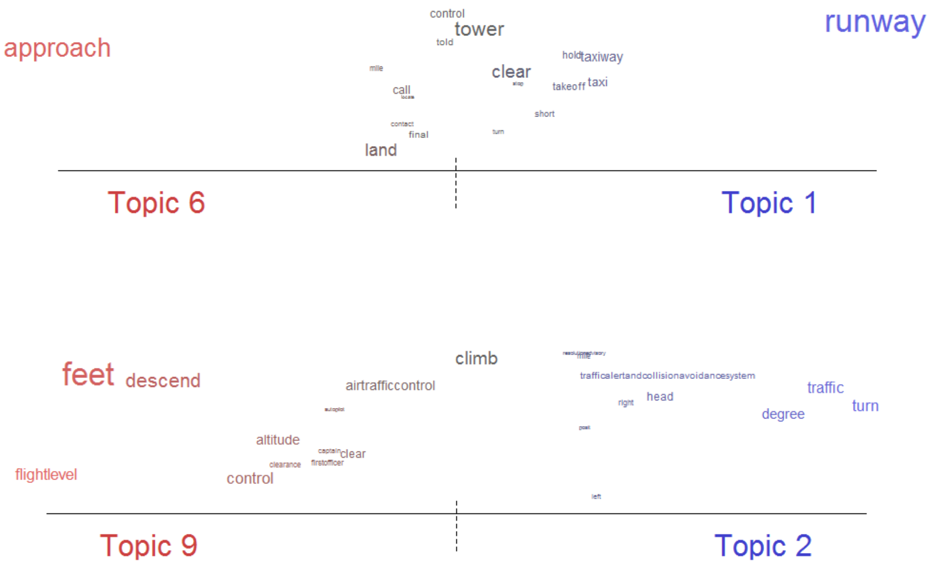
Topic Model Correlation

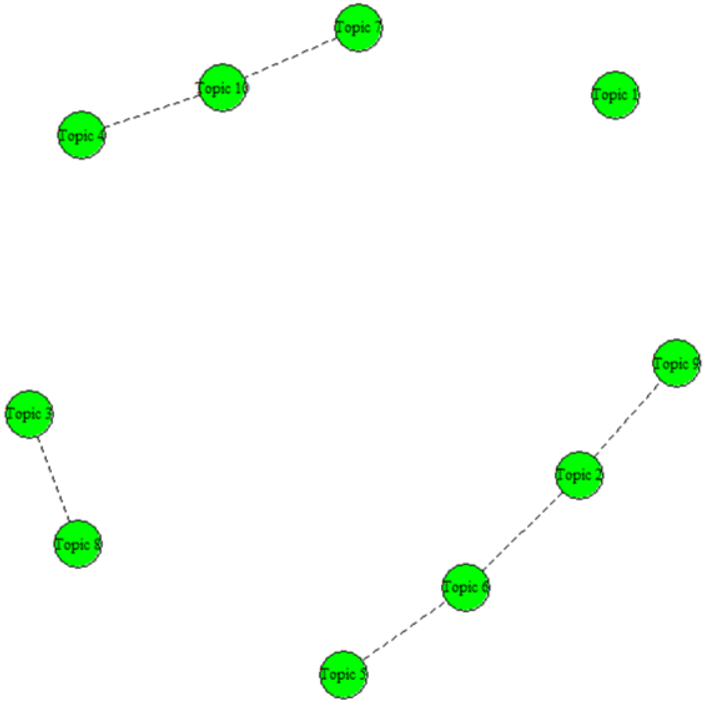




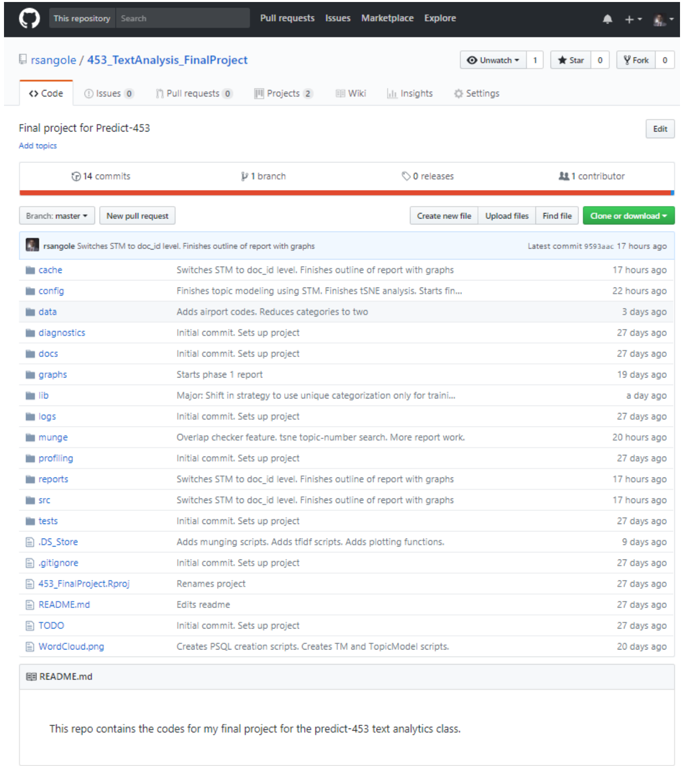
- Some topics are closer together, others seem further apart
- For example:
  - Topic 8 and Topic 3 both refer to engine and damage. While Topic 8 references hydraulic systems and flaps, Topic 3 references fuel & fuel leaks
  - Topic 1 is quite different from all the rest – it speaks about runway / taxiway / ground control clearance issues
- We can model this using ‘topic correlations’. Positive correlations indicates that both topics are likely to be discussed in a document.

Topic Model Correlation





Codebase



https://github.com/rsangole/453_TextAnalysis_FinalProject

```
 [1] bindrcpp_0.2        ggplus_0.1         stm_1.3.3          topicmodels_0.2-7
 [5] ggrepel_0.7.0       SnowballC_0.5.1    dbplyr_1.2.1       RPostgreSQL_0.6-2
 [9] DBI_0.8             doMC_1.3.5         iterators_1.0.9    foreach_1.4.4
[13] wordcloud2_0.2.1    magrittr_1.5       assertive_0.3-5    tidytext_0.1.7
[17] tm_0.7-3            NLP_0.1-11         corrplot_0.84      lattice_0.20-35
[21] lubridate_1.7.3     forcats_0.3.0      stringr_1.3.0      dplyr_0.7.4
[25] purrr_0.2.4         readr_1.1.1        tidyr_0.8.0        tibble_1.4.2
[29] ggplot2_2.2.1       tidyverse_1.2.1    plyr_1.8.4         reshape2_1.4.3
[33] ProjectTemplate_0.8
```

Lessons Learnt

- Text analytics is a deep subject with many rabbit holes to get lost in
- It’s a nascent field with a large number of analytics packages in R developed within the last 5 years
- More non-quantitative work involved than any other course
- Stability of results seem asymptotic and sensitive to pre-processing
- Long way to go

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Appendix

TF-IDF Based Analysis