Top_2023_Fashion_Trends

Eva Nikolai

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Top 2023 Fashion Trends

As fashion weeks are underway, it is always fun to get an idea of what trends we will see hitting the runways.

To get a better idea of key trends consumers can expect to see more frequently from designers, I decided to run a topic model on the top 10 results of 2023 fashion trends.

Load in necessary libraries:

```
library(rvest)
library(stringr)
```

To start, I scraped in 10 different fashion articles.

Refinery29:

```
refinery <- read_html("https://www.refinery29.com/en-us/fashion-trends-2023")|>
  html_elements("h2") |> html_text()

## clean refinery

refinery1 <- gsub("2023", "", refinery)

refinery2 <- gsub("Fashion\\sTrend", "", refinery1)

refinery3 <- gsub("Refinery.*", "", refinery2)
```

Hello!:

```
hello <- read_html("https://www.hellomagazine.com/hfm/20221017154410/2023-fashion-trends-to-have-on-you

## clean Hello

hello1 <- gsub("\\s\\s+", "", hello)

hello2 <- gsub("SHOP\\sNOW", "", hello1)

hello3 <- gsub("^RELATED.*|^READ.*|^MORE.*|^Hello!.*|^More\\son.*|^HELLO.*", "", hello2)

hello4 <- gsub("^READ.*", "", hello3)

hello <- gsub("Spring\\s2023\\s[Tt]rends", "", hello4)
```

```
hello <- gsub("Summer\\s2023\\s[Tt]rends", "", hello)

hello <- hello[-c(64)]
```

Vogue:

```
vogue <- read_html("https://www.vogue.com/article/spring-2023-trends-editors-picks")|> html_elements("h

## clean Vogue:

vogue1 <- gsub("^By\\s[A-Z].*", "", vogue)

vogue2 <- gsub("revist.*|Vogue.*|commerce.*|editor", "", vogue1)

vogue <- gsub("[Ss]ign\\sup.*|[Ss]igning\\sup.*", "", vogue2)
```

Glamour:

```
glamour <- read_html("https://www.glamour.com/story/2023-style-trends") %>%  html_elements("strong") %>%

glamour1 <- gsub("^By\\s[A-Z].*|Courtesy.*", "", glamour)

glamour2 <- gsub("revisit.*", "", glamour1)

glamour <- gsub("2023\\sStyle\\sTrend:", "", glamour2)
```

Insider:

```
insider <- read_html("https://www.insider.com/fashion-clothing-trends-coming-this-year-2023#lug-sole-lo
```

Elle:

```
elle <- read_html("https://www.elle.com/fashion/trend-reports/a41340278/spring-2023-fashion-trends/") %
```

Woman and Home:

```
womanhome <- read_html("https://www.womanandhome.com/fashion/fashion-trends-2023/") %>% html_elements("

womanhome1 <- gsub("opens.*", "", womanhome)

wh2 <- gsub("Sign.*", "", womanhome1)

wh3 <- gsub("[(]", "", wh2)

wh4 <- gsub("^\\d+\\.\\s", "", wh3)

womanhome <- wh4[-c(1:41)]

womanhome <- womanhome[-c(184:219)]
```

Forbes:

```r
forbes <- read_html("https://www.forbes.com/sites/sboyd/2023/01/28/the-9-fashion-trends-youre-about-to-s

forbes <- gsub("^\\d+\\)\\s", "", forbes)
```

Glamour UK:

```r
glamour_UK <- read_html("https://www.glamourmagazine.co.uk/gallery/spring-summer-2023-fashion-trends") %

glamour_UK1 <- glamour_UK[-c(92:131)]

glamour_UK1 <- gsub("^By\\s.*", "", glamour_UK1)

glamour_UK1 <- glamour_UK1[-c(1:36)]

glamour_UK <- gsub("([A-Z][a-z]+).*", "", glamour_UK1)
```

```r
bazaar <- read_html("https://www.harpersbazaar.com/fashion/trends/a41247745/spring-2023-fashion-trends/

bazaar1 <- bazaar[-c(1:2)]

bazaar <- bazaar1[-c(7:24)]
```

Combine articles:

```r
all_articles <- c(hello, vogue, glamour, insider, elle, womanhome, forbes, glamour_UK, bazaar)

all_articles2 <- gsub("-", "", all_articles)
```

Load in necessary libraries:

```r
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.2.3

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(quanteda)
```

```
## Warning: package 'quanteda' was built under R version 4.2.2
```

```
## Package version: 3.2.4
## Unicode version: 13.0
## ICU version: 69.1

## Parallel computing: 12 of 12 threads used.

## See https://quanteda.io for tutorials and examples.
```

```
library(stm)
```

```
## Warning: package 'stm' was built under R version 4.2.2

## stm v1.3.6 successfully loaded. See ?stm for help.
##  Papers, resources, and other materials at structuraltopicmodel.com
```

```
library(tm)
```

```
## Warning: package 'tm' was built under R version 4.2.2

## Loading required package: NLP

##
## Attaching package: 'NLP'

## The following objects are masked from 'package:quanteda':
##
##     meta, meta<-

##
## Attaching package: 'tm'

## The following object is masked from 'package:quanteda':
##
##     stopwords
```

```
library(textstem)
```

```
## Warning: package 'textstem' was built under R version 4.2.2

## Loading required package: koRpus.lang.en

## Warning: package 'koRpus.lang.en' was built under R version 4.2.2

## Loading required package: koRpus

## Warning: package 'koRpus' was built under R version 4.2.2

## Loading required package: sylly
```

```
## Warning: package 'sylly' was built under R version 4.2.2

## For information on available language packages for 'koRpus', run
##
##   available.koRpus.lang()
##
## and see ?install.koRpus.lang()

##
## Attaching package: 'koRpus'

## The following object is masked from 'package:tm':
##
##     readTagged

## The following objects are masked from 'package:quanteda':
##
##     tokens, types
```

Text cleaning & prep of combined articles

```
articles_lowered <- tolower(all_articles2)

df <- data.frame(articles_lowered)

articles_df <- df[!apply(df==""|df==" ", 1, all),]

articles_df <- articles_df[-c(5:6)]

articles_df <- gsub("[Ff]ashion|[Tt]rend|[Tt]rends|[Pp]aris|[Ss]pring|[Ss]tory|[Rr]unway|[Rr]unways|[Ll

articles_df <- gsub("([[:punct:]])", "", articles_df)

articles_df <- gsub("[Nn]ew\\s[Yy]ork|[Ww]eek|[Ss]eason", "", articles_df)

removed_words <- tm::removeWords(tolower(articles_df), words = stopwords("en"))


lemma_dictionary <- make_lemma_dictionary(removed_words,
                                          engine = 'hunspell')

articles_lemmatized <- lemmatize_strings(removed_words,
                                          lemma_dictionary)
```

Create the corpus with document variables

```
fashion_corpus <- corpus(articles_lemmatized)

fashion_token <- quanteda::tokens(fashion_corpus, remove_punct = TRUE, remove_symbols = TRUE, remove_nu

fashion_dfm <- dfm(fashion_token)
```

```
fashion_dfm <- dfm_trim(fashion_dfm, sparsity = 0.990)

fashion_stm <- convert(fashion_dfm, to = "stm")
```

```
## Warning in dfm2stm(x, docvars, omit_empty = TRUE): Dropped empty document(s):
## text1, text2, text5, text7, text9, text11, text13, text14, text15, text17,
## text18, text19, text21, text23, text25, text28, text29, text30, text32, text34,
## text35, text36, text38, text39, text40, text42, text43, text44, text46, text47,
## text48, text49, text51, text53, text54, text55, text62, text68, text74, text77,
## text92, text110, text119, text121, text122, text132, text134, text149, text164,
## text170, text188, text194, text196, text201, text202, text203, text204, text205,
## text206, text207, text208, text217, text219, text222, text226, text229, text230,
## text232, text233, text234, text235, text236, text237, text238, text239, text240,
## text241, text242, text243, text244, text246, text247, text248, text250, text252,
## text253, text254, text256, text257, text258, text259, text260, text262, text263,
## text264, text265, text266, text267, text268, text269, text271, text272, text273,
## text274, text276, text277, text278, text279, text281, text282, text283, text284,
## text285, text287, text288, text289, text290, text292, text293, text294, text295,
## text296, text297, text298, text299, text300, text301, text302, text303, text304,
## text305, text307, text308, text309, text311, text314, text315, text316, text321,
## text323, text324, text326
```

```
docs_stm <- fashion_stm$documents
vocab_stm <- fashion_stm$vocab
meta_stm <- fashion_stm$meta

fashionPrep <- prepDocuments(documents = docs_stm,
                             vocab = vocab_stm,
                             meta = meta_stm)
```

Evaluate Term Frequency

Out of curiosity, let's see what the most frequent terms are in each article:

```
term_frequency <- tm::termFreq(articles_lemmatized)

head(sort(term_frequency, decreasing = TRUE),20)
```

```
##   skirt   dress leather    midi  jacket   shirt   blaze   denim   getty   image
##      26      16      15      13      12      12      10      10      10      10
##    jean   photo   sheer     top     bag  cotton    maxi    pant  tailor bottega
##      10      10      10      10       7       7       7       7       7       6
```

From conducting the term frequency, we see that skirts, dresses, leather, denim, and sheer are the most used terms. This indicates that all 10 fashion articles believe these clothing articles/ styles will be particularly relevant in 2023 trends.

Let's keep this in mind when evaluating topics of scraped fashion articles.

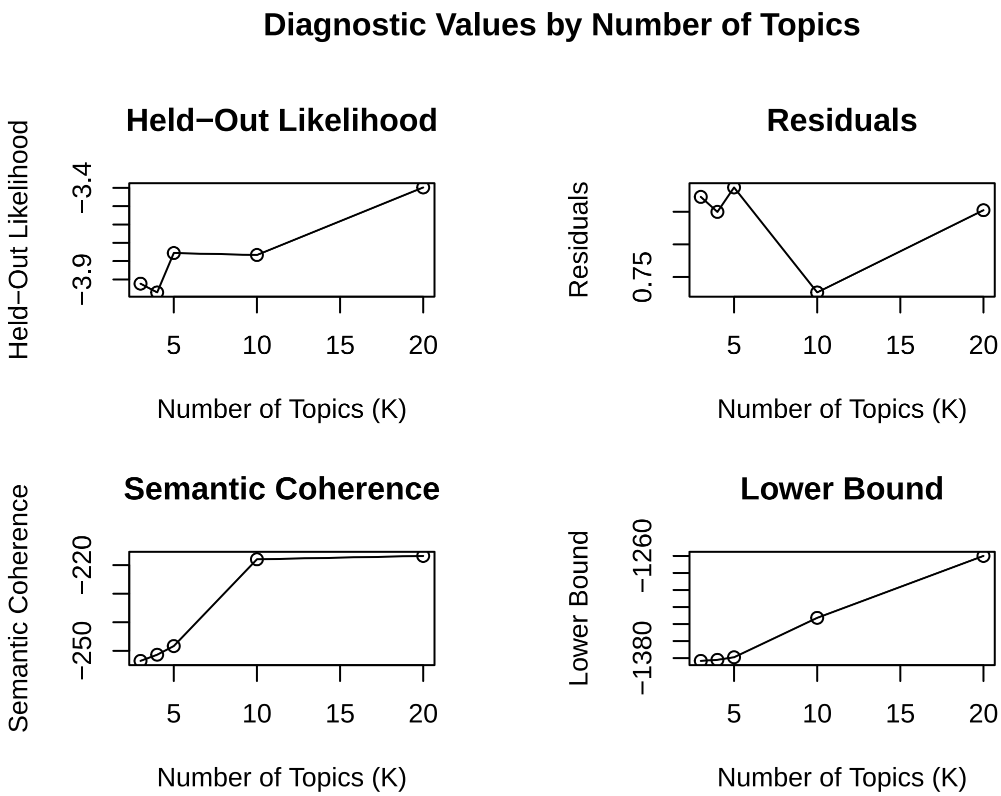
Ideally, these results will be able to identify the most popular trends for the 2023 fashion year.

Topic Model:

Perform kTest to choose topic count

```
kTest <- searchK(documents = fashionPrep$documents,
                 vocab = fashionPrep$vocab,
                 K = c(3, 4, 5, 10, 20), verbose = FALSE)

plot(kTest)
```



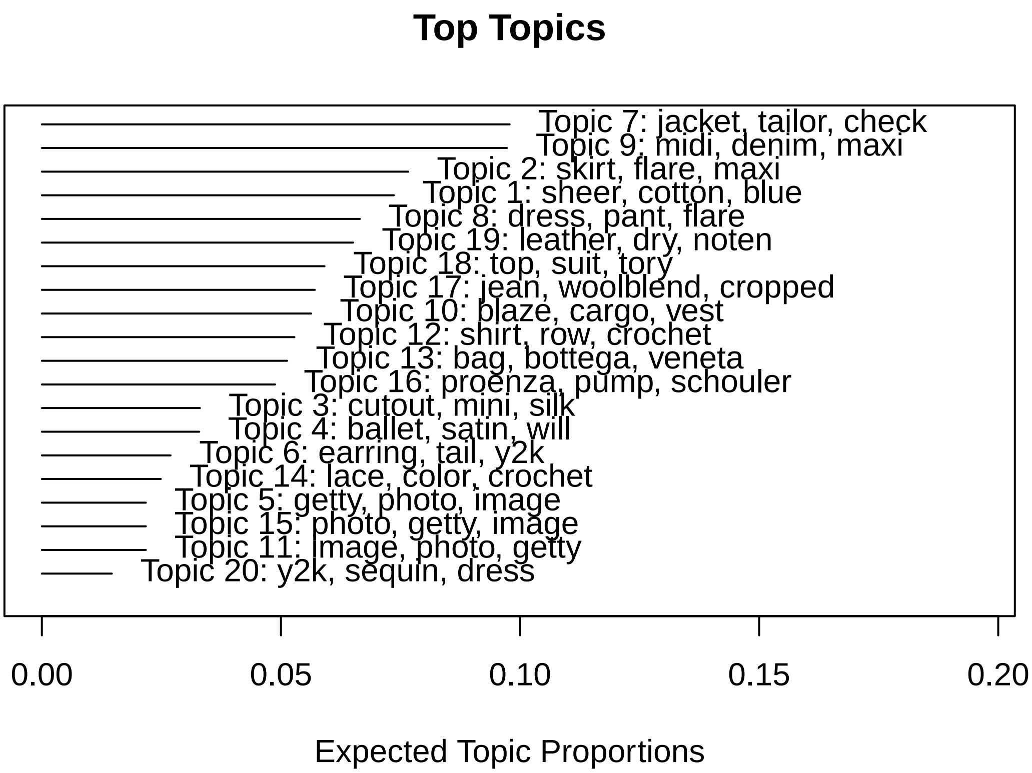
After viewing the results of the kTest, the results are fairly interesting. Specifically, it is interesting to see the semantic coherence be so high with 20 topics. As the ideal topic selection would be the number of topics with highest semantic coherence and lowest residuals, we see the model suggests to select 20 topics. However, as this is a very high number of topics, I also tested using the next highest topics, 5.

Option 1 - Test 20 Topics:

```
topics20 <- stm(documents = fashionPrep$documents,
                vocab = fashionPrep$vocab, seed = 1001,
                K = 20, verbose = FALSE)
```

Topic proportions plot at 20 topics:

```
plot(topics20)
```



See what emerges from each topic by evaluating high prob & FREX words

```r
top20_topic_list <- labelTopics(topics20)

print(top20_topic_list)
```

```
## Topic 1 Top Words:
##       Highest Prob: sheer, cotton, blue, oversized, crochet, row, shirt
##       FREX: sheer, blue, cotton, oversized, crochet, sequin, dress
##       Lift: blue, sheer, oversized, cotton, crochet, row, shirt
##       Score: sheer, cotton, blue, oversized, crochet, row, shirt
## Topic 2 Top Words:
##       Highest Prob: skirt, flare, maxi, midi, sequin, denim, prada
##       FREX: flare, skirt, sequin, maxi, crochet, midi, dress
##       Lift: flare, skirt, maxi, midi, sequin, denim, prada
##       Score: skirt, flare, maxi, midi, sequin, denim, prada
## Topic 3 Top Words:
##       Highest Prob: cutout, mini, silk, dress, sequin, midi, woolblend
##       FREX: cutout, mini, silk, sequin, dress, crochet, flare
##       Lift: cutout, mini, silk, dress, sequin, midi, woolblend
##       Score: cutout, silk, mini, dress, sequin, midi, woolblend
## Topic 4 Top Words:
##       Highest Prob: ballet, satin, will, prada, pump, midi, row
##       FREX: ballet, satin, will, skirt, sequin, midi, flare
##       Lift: ballet, satin, will, prada, pump, midi, row
##       Score: will, ballet, satin, prada, pump, midi, row
```

```
## Topic 5 Top Words:
##       Highest Prob: getty, photo, image, y2k, pant, dress, sheer
##       FREX: getty, photo, image, sequin, dress, cotton, crochet
##       Lift: getty, photo, image, y2k, pant, dress, sheer
##       Score: getty, photo, image, veneta, bottega, schouler, dry
## Topic 6 Top Words:
##       Highest Prob: earring, tail, y2k, denim, sequin, flare, midi
##       FREX: earring, tail, sequin, flare, skirt, crochet, dress
##       Lift: earring, tail, y2k, denim, sequin, flare, pant
##       Score: earring, tail, y2k, denim, flare, midi, pant
## Topic 7 Top Words:
##       Highest Prob: jacket, tailor, check, prada, saint, wool, pant
##       FREX: jacket, tailor, check, prada, saint, wool, sequin
##       Lift: check, jacket, prada, saint, tailor, wool, pant
##       Score: jacket, tailor, wool, check, saint, prada, pant
## Topic 8 Top Words:
##       Highest Prob: dress, pant, flare, midi, sequin, row, saint
##       FREX: dress, pant, sequin, flare, crochet, cotton, midi
##       Lift: pant, dress, flare, midi, sequin, row, saint
##       Score: dress, pant, flare, midi, sequin, row, saint
## Topic 9 Top Words:
##       Highest Prob: midi, denim, maxi, rise, sequin, skirt, flare
##       FREX: denim, midi, rise, maxi, sequin, skirt, flare
##       Lift: denim, rise, midi, maxi, sequin, skirt, flare
##       Score: midi, denim, maxi, rise, sequin, skirt, flare
## Topic 10 Top Words:
##       Highest Prob: blaze, cargo, vest, jean, woolblend, cropped, oversized
##       FREX: blaze, cargo, vest, flare, oversized, dress, sequin
##       Lift: blaze, cargo, vest, jean, woolblend, cropped, oversized
##       Score: blaze, cargo, vest, jean, woolblend, cropped, oversized
## Topic 11 Top Words:
##       Highest Prob: image, photo, getty, y2k, pant, dress, sheer
##       FREX: image, photo, getty, sequin, dress, cotton, crochet
##       Lift: image, photo, getty, y2k, pant, dress, sheer
##       Score: image, photo, getty, veneta, bottega, schouler, dry
## Topic 12 Top Words:
##       Highest Prob: shirt, row, crochet, cotton, oversized, blue, silk
##       FREX: shirt, row, crochet, cotton, sequin, oversized, dress
##       Lift: row, shirt, crochet, cotton, oversized, blue, silk
##       Score: shirt, row, crochet, cotton, oversized, blue, silk
## Topic 13 Top Words:
##       Highest Prob: bag, bottega, veneta, sequin, row, prada, leather
##       FREX: bag, bottega, veneta, sequin, crochet, dress, maxi
##       Lift: bag, bottega, veneta, sequin, row, prada, leather
##       Score: veneta, bottega, bag, sequin, row, prada, leather
## Topic 14 Top Words:
##       Highest Prob: lace, color, crochet, pink, sequin, top, y2k
##       FREX: lace, color, crochet, sequin, pink, skirt, cotton
##       Lift: color, lace, crochet, pink, sequin, top, y2k
##       Score: lace, color, crochet, pink, sequin, top, y2k
## Topic 15 Top Words:
##       Highest Prob: photo, getty, image, y2k, pant, dress, sheer
##       FREX: photo, getty, image, sequin, dress, cotton, crochet
##       Lift: photo, getty, image, y2k, pant, dress, sheer
```

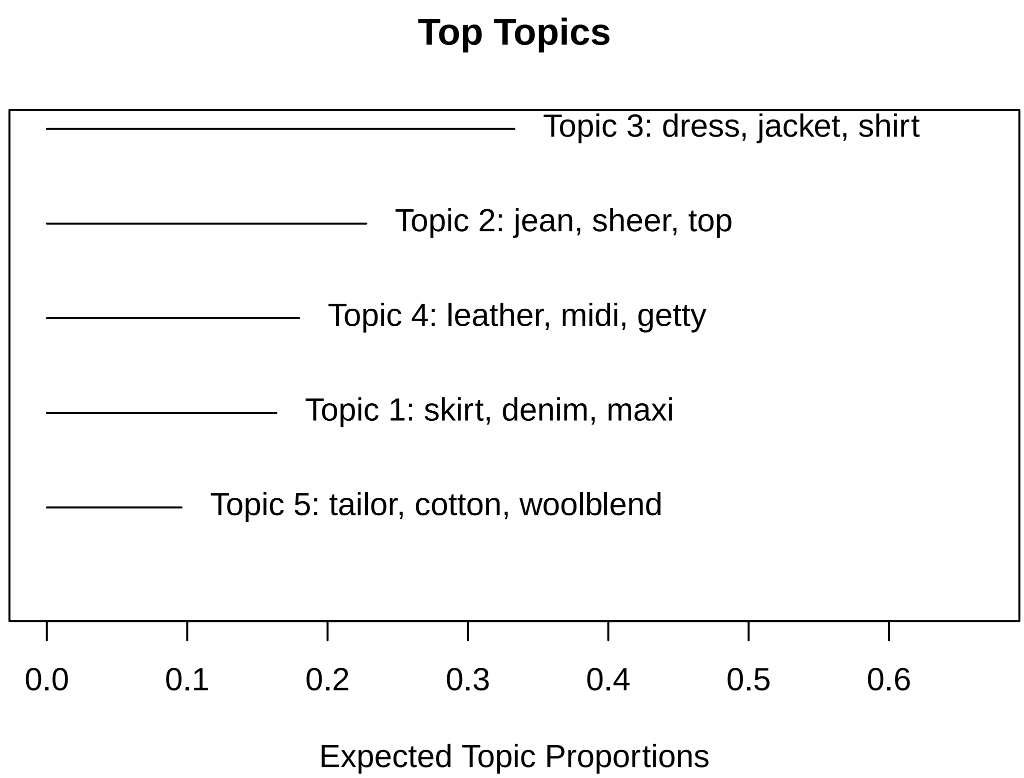
```
##       Score: photo, getty, image, veneta, bottega, schouler, dry
## Topic 16 Top Words:
##       Highest Prob: proenza, pump, schouler, mule, crochet, cropped, leather
##       FREX: proenza, pump, schouler, mule, crochet, sequin, skirt
##       Lift: mule, proenza, pump, schouler, crochet, cropped, leather
##       Score: schouler, proenza, pump, mule, crochet, cropped, leather
## Topic 17 Top Words:
##       Highest Prob: jean, woolblend, cropped, vest, cargo, jacket, blaze
##       FREX: jean, woolblend, cropped, vest, flare, oversized, cargo
##       Lift: cropped, jean, woolblend, vest, cargo, jacket, blaze
##       Score: jean, woolblend, cropped, vest, cargo, jacket, blaze
## Topic 18 Top Words:
##       Highest Prob: top, suit, tory, pink, jacket, dress, crochet
##       FREX: top, suit, tory, pink, crochet, sequin, dress
##       Lift: suit, tory, top, pink, jacket, dress, crochet
##       Score: top, suit, pink, tory, jacket, dress, crochet
## Topic 19 Top Words:
##       Highest Prob: leather, dry, noten, van, crochet, sequin, top
##       FREX: leather, dry, noten, van, crochet, sequin, cotton
##       Lift: dry, leather, noten, van, crochet, sequin, top
##       Score: leather, dry, noten, van, crochet, sequin, top
## Topic 20 Top Words:
##       Highest Prob: y2k, sequin, dress, flare, skirt, pant, crochet
##       FREX: y2k, sequin, crochet, skirt, flare, dress, midi
##       Lift: y2k, sequin, dress, flare, skirt, crochet, pant
##       Score: y2k, sequin, dress, flare, skirt, pant, crochet
```

Option 2 - Test 5 Topics:

```r
topics5 <- stm(documents = fashionPrep$documents,
             vocab = fashionPrep$vocab, seed = 1001,
             K = 5, verbose = FALSE)
```

Topic proportions plot at 4 topics:

```r
plot(topics5)
```



See what emerges from each topic by evaluating high prob & FREX words

```
top5_topic_list <- labelTopics(topics5)

print(top5_topic_list)
```

```
## Topic 1 Top Words:
##       Highest Prob: skirt, denim, maxi, earring, blue, check, rise
##       FREX: denim, earring, skirt, blue, check, rise, satin
##       Lift: blue, check, earring, rise, satin, denim, maxi
##       Score: denim, skirt, earring, maxi, rise, blue, check
## Topic 2 Top Words:
##       Highest Prob: jean, sheer, top, bag, bottega, veneta, proenza
##       FREX: sheer, jean, proenza, schouler, bottega, veneta, top
##       Lift: proenza, schouler, jean, sheer, bottega, veneta, flare
##       Score: jean, sheer, top, bottega, veneta, proenza, schouler
## Topic 3 Top Words:
##       Highest Prob: dress, jacket, shirt, blaze, pant, sequin, lace
##       FREX: sequin, dress, dry, noten, van, jacket, tory
##       Lift: dry, noten, van, tory, sequin, mini, suit
##       Score: dress, jacket, shirt, blaze, sequin, mini, lace
## Topic 4 Top Words:
##       Highest Prob: leather, midi, getty, image, photo, will, oversized
##       FREX: leather, getty, image, photo, will, midi, oversized
##       Lift: will, getty, image, photo, leather, oversized, ballet
##       Score: image, photo, getty, leather, midi, will, oversized
```

```
## Topic 5 Top Words:
##       Highest Prob: tailor, cotton, woolblend, cargo, saint, y2k, cropped
##       FREX: tailor, cotton, saint, cargo, woolblend, y2k, cropped
##       Lift: saint, tailor, cargo, cotton, y2k, woolblend, cropped
##       Score: tailor, cotton, woolblend, cargo, saint, y2k, cropped
```

When comparing both topic models results to one another, there are clear similarities. It seems that in 2023, consumers can anticipate to see popularity of a variation of skirts and dresses, all utilizing many different fabrics. Specifically, we will see fashion retailers producing many crochet/ fringe looks, using sheer design elements, silk and leather fabrics, and the resurgence of denim and jean.

Thank you for your interest in my analysis of the most relevant 2023 anticipated Fashion trends.