Text Analysis Workshop

Hello and welcome to tidy text analytics!

This Quarto document covers an example workflow of how to process and analyze open ended text data.

In our first section we'll be load the main libraries we'll need to start and load in our data

```
# A tibble: 6 x 6
  record_id date_and_time notification_type        notification_title email_body
      <dbl> <chr>         <chr>                    <chr>              <chr>
1       209 5/11/09 10:00 zINAC * Aerial (Fly-Ove~ [blank]            This is a~
2       210 5/15/09 8:00  zINAC * Drills / Exerci~ [blank]            This is a~
3       211 5/16/09 17:00 zINAC * Drills / Exerci~ [blank]            This is a~
4       212 5/17/09 17:00 zINAC * Drills / Exerci~ [blank]            This is a~
5       213 5/19/09 9:45  zINAC * Aerial (Fly-Ove~ [blank]            This is a~
6       214 5/20/09 9:30  zINAC * Aerial (Fly-Ove~ [blank]            This is a~
# i 1 more variable: cleaned_text <chr>
```

Next we'll convert our data into a tidy format with one row per word per message

```
tidy_words <- data |>
  select(record_id, date_and_time, notification_type, cleaned_text) |>
  unnest_tokens(word, cleaned_text) |>
  anti_join(stop_words)
```

```
Joining with `by = join_by(word)`
```

```
head(tidy_words)
```

```
# A tibble: 6 x 4
  record_id date_and_time notification_type          word
      <dbl> <chr>         <chr>                      <chr>
1       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  faa
2       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  planned
3       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  military
4       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  flyover
5       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  cancelled
6       210 5/15/09 8:00  zINAC * Drills / Exercises starting
```

```
tidy_words
```

```
# A tibble: 564,149 x 4
   record_id date_and_time notification_type          word
       <dbl> <chr>         <chr>                      <chr>
 1       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  faa
 2       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  planned
 3       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  military
 4       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  flyover
 5       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  cancelled
 6       210 5/15/09 8:00  zINAC * Drills / Exercises starting
 7       210 5/15/09 8:00  zINAC * Drills / Exercises 9
 8       210 5/15/09 8:00  zINAC * Drills / Exercises 00
 9       210 5/15/09 8:00  zINAC * Drills / Exercises morning
10       210 5/15/09 8:00  zINAC * Drills / Exercises continuing
# i 564,139 more rows
```

Here we can start to explore the most common words that show up in our corpus

```
tidy_words |>
  count(word, sort = TRUE) |>
  top_n(20)
```

```
Selecting by n
```

```
# A tibble: 20 x 2
   word          n
   <chr>     <int>
 1 expect     9796
 2 delays     9545
```

```
 3 due          9027
 4 alternate    7997
 5 street       7945
 6 routes       7705
 7 time         7658
 8 travel       7367
 9 service      7321
10 additional   7208
11 avenue       5761
12 00           5733
13 traffic      5733
14 pm           5432
15 brooklyn     5165
16 queens       5142
17 manhattan    4657
18 1            4514
19 vehicle      4376
20 issued       4299
```

Given that we have categories of interest in our data set, we can also filter per category to see common words across categories of interest

```r
tidy_words |>
  filter(notification_type == "Planned Events") |>
  count(word, sort =  TRUE) |>
  top_n(20)
```

```
Selecting by n
```

```
# A tibble: 20 x 2
   word              n
   <chr>         <int>
 1 pm              243
 2 approximately   131
 3 00              119
 4 street          100
 5 30               99
 6 6                90
 7 9                89
 8 nypd             83
 9 10               79
```

```
10 activity        79
11 7               75
12 brooklyn        74
13 manhattan       71
14 aircraft        68
15 emergency       68
16 occur           66
17 1               64
18 12              64
19 fdny            64
20 11              63
```

```
data |> count(notification_type)
```

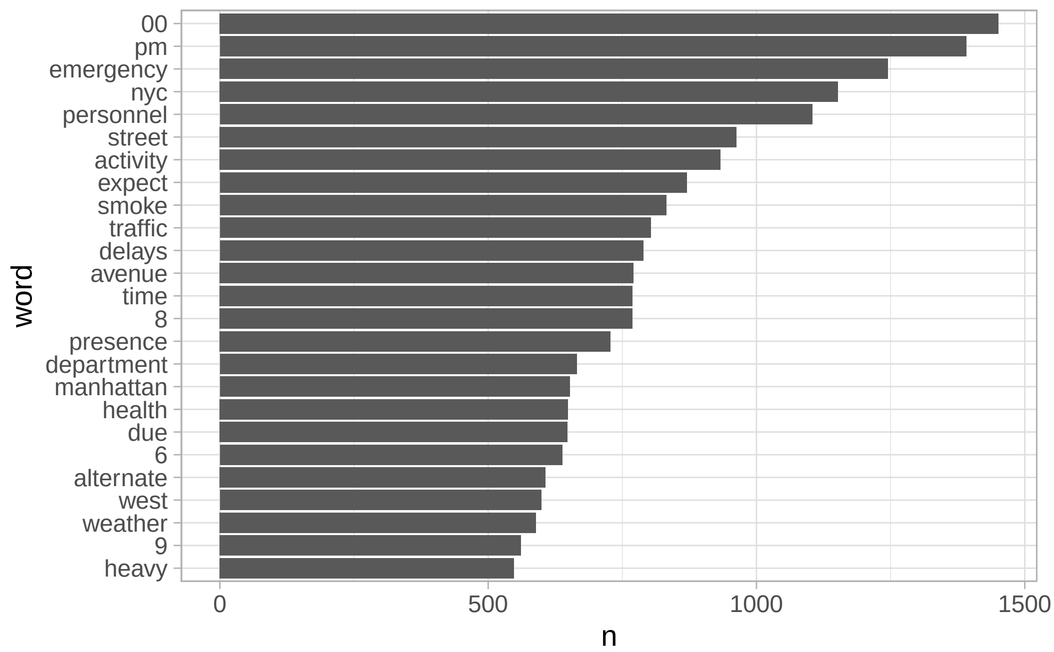
```
# A tibble: 18 x 2
   notification_type               n
   <chr>                       <int>
 1 Emergency Activity           1778
 2 Local Mass Transit           2734
 3 Mass Transit Restoration      907
 4 Missing Person               2154
 5 Nixle                         434
 6 Planned Events                338
 7 Public Health                1057
 8 Regional Mass Transit          43
 9 School Notification           210
10 Transportation               9013
11 Utility                      1895
12 Weather                      2540
13 zINAC * Aerial (Fly-Over)     559
14 zINAC * Drills / Exercises    316
15 zINAC * Environmental         937
16 zINAC * Fire                  557
17 zINAC * Parking               137
18 <NA>                           68
```

Tables are great but we can also present this information graphically

```
tidy_words |>
  filter(notification_type %in% c("Emergency Activity", "Public Health")) |>
  count(word, sort =  TRUE) |>
```

```
  top_n(25) |>
  mutate(word = fct_reorder(word, n)) |>
  ggplot(aes(n, word)) +
  geom_col()
```

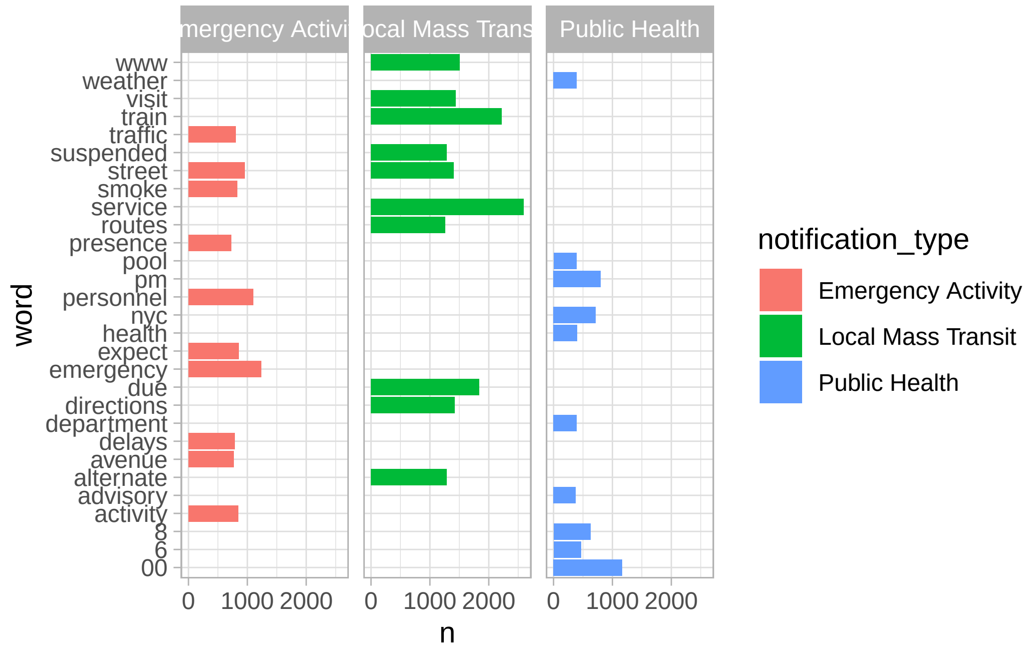
```
Selecting by n
```



Another example where we split our plot of common words by categories of interest

```
tidy_words |>
  filter(notification_type %in% c("Emergency Activity", "Public Health",
                                  "Local Mass Transit")) |>
  group_by(notification_type) |>
  count(word, sort = TRUE) |>
  top_n(10) |>
  ggplot(aes(n, word, fill = notification_type)) +
  geom_col() +
  facet_wrap(~ notification_type)
```

```
Selecting by n
```



Let's move into some sentiment analyses where we can examine the emotional valence of our text data. To do that we can leverage existing sentiment lexicons (validated dictionaries) that categorize words by specific emotions or quantify them by means of polarity (e.g negative to positive).

The tidytext package provides a few sentiment dictionaries which are useful. However, don't feel limited. Other lexicons exist in the form of data frames that can be added on to your data of interest. In certain instances it may be useful to customize a lexicon, or create one of your own.

```
head(get_sentiments("nrc"))
```

```
# A tibble: 6 x 2
  word      sentiment
  <chr>     <chr>
1 abacus    trust
2 abandon   fear
3 abandon   negative
4 abandon   sadness
5 abandoned anger
6 abandoned fear
```

```r
head(get_sentiments("afinn"))
```

```
# A tibble: 6 x 2
  word       value
  <chr>      <dbl>
1 abandon       -2
2 abandoned     -2
3 abandons      -2
4 abducted      -2
5 abduction     -2
6 abductions    -2
```

```r
head(get_sentiments("bing"))
```

```
# A tibble: 6 x 2
  word        sentiment
  <chr>       <chr>
1 2-faces     negative
2 abnormal    negative
3 abolish     negative
4 abominable  negative
5 abominably  negative
6 abominate   negative
```

Let's first explore the NRC lexicon which categorizes words across a series of emotions (e.g positive, negative, fear, trust, anticipation, etc).

We can take our tidy words data frame and inner join the nrc lexicon onto our data. Now our data-set has an additional feature categorizing each word by a particular emotion

```r
nrc_text <- tidy_words |>
  inner_join(get_sentiments("nrc"), by = "word")
```

```
Warning in inner_join(tidy_words, get_sentiments("nrc"), by = "word"): Detected an unexpected
i Row 16 of `x` matches multiple rows in `y`.
i Row 4308 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.
```

```r
nrc_text
```

```
# A tibble: 185,398 x 5
   record_id date_and_time notification_type          word      sentiment
       <dbl> <chr>         <chr>                      <chr>     <chr>
 1       209 5/11/09 10:00 zINAC * Aerial (Fly-Over)  military  fear
 2       210 5/15/09 8:00  zINAC * Drills / Exercises county    trust
 3       210 5/15/09 8:00  zINAC * Drills / Exercises emergency fear
 4       210 5/15/09 8:00  zINAC * Drills / Exercises emergency negative
 5       210 5/15/09 8:00  zINAC * Drills / Exercises emergency sadness
 6       210 5/15/09 8:00  zINAC * Drills / Exercises emergency surprise
 7       211 5/16/09 17:00 zINAC * Drills / Exercises trade     trust
 8       211 5/16/09 17:00 zINAC * Drills / Exercises center    positive
 9       211 5/16/09 17:00 zINAC * Drills / Exercises center    trust
10       211 5/16/09 17:00 zINAC * Drills / Exercises emergency fear
# i 185,388 more rows
```

Let's explore the proportion of emotion words in our data set.

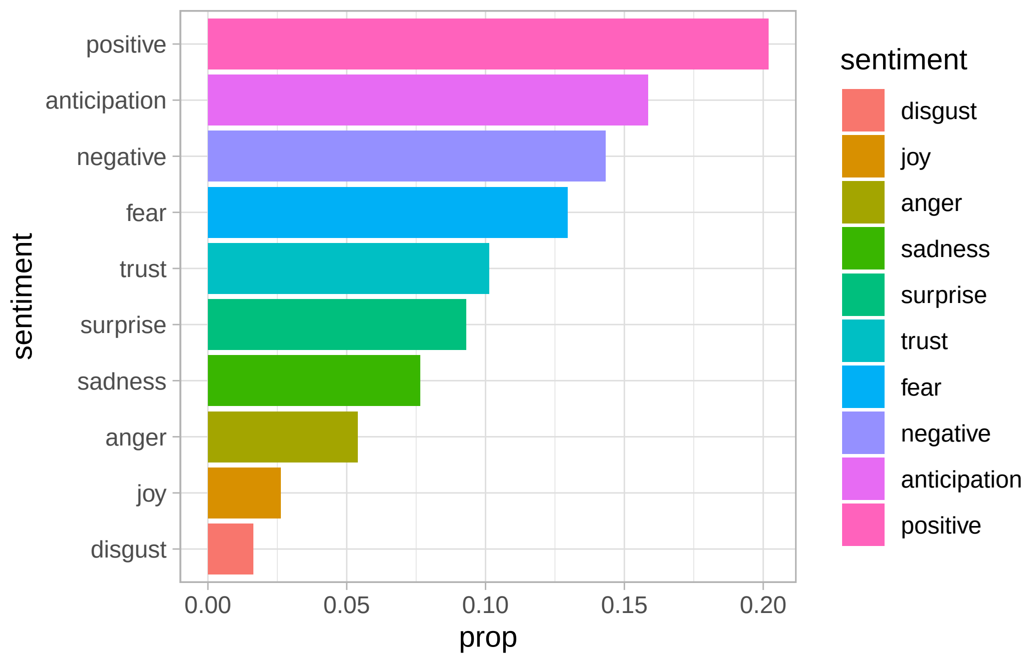
First via a table

```r
emotion_prop <- nrc_text |>
  count(sentiment, sort = TRUE) |>
  mutate(prop = n / sum(n))


emotion_prop
```

```
# A tibble: 10 x 3
   sentiment        n   prop
   <chr>        <int>  <dbl>
 1 positive     37430 0.202
 2 anticipation 29375 0.158
 3 negative     26541 0.143
 4 fear         24015 0.130
 5 trust        18780 0.101
 6 surprise     17224 0.0929
 7 sadness      14158 0.0764
 8 anger         9994 0.0539
 9 joy           4856 0.0262
10 disgust       3025 0.0163
```

And now by a graph

```
emotion_prop |>
  mutate(sentiment = fct_reorder(sentiment, prop)) |>
  ggplot(aes(prop, sentiment, fill = sentiment)) +
  geom_col()
```



Let's see if we can see some differences across categories. For this example we'll focus on Local Mass Transit and Transportation

```
nrc_text |>
  filter(notification_type == "Local Mass Transit") |>
  count(sentiment, sort = TRUE) |>
  mutate(prop = n / sum(n)) |>
  mutate(sentiment = fct_reorder(sentiment, prop)) |>
  ggplot(aes(prop, sentiment, fill = sentiment)) +
  geom_col()
nrc_text |>
  filter(notification_type == "Transportation") |>
  count(sentiment, sort = TRUE) |>
  mutate(prop = n / sum(n)) |>
```

```
  mutate(sentiment = fct_reorder(sentiment, prop)) |>
  ggplot(aes(prop, sentiment, fill = sentiment)) +
  geom_col()
```

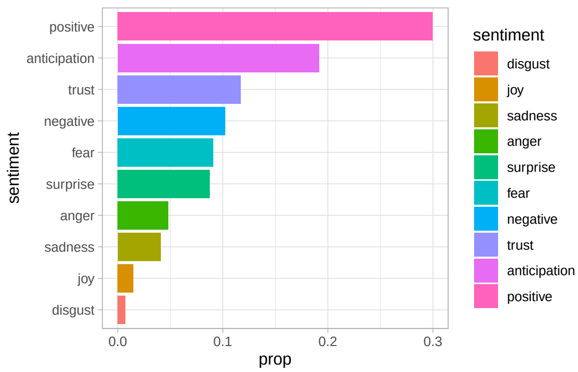


Figure 1: Local Transit

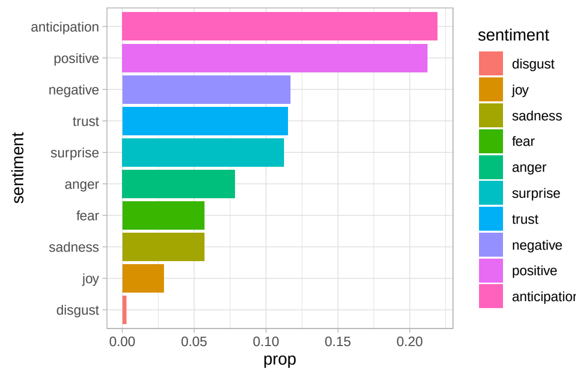


Figure 2: Transportation

We're not limited to a mere categorical analysis - for example one approach we can use is examining the frequency or count of words tied to certain emotions across groups.

As we see in our comparison between transportation and local mass transit it would appear that transportation has a higher frequency of words related to anticipation. Let's see if this difference is statistically significant.

To do this we can process our data to count the number of emotion based words per approach

```
nrc_counts <- nrc_text |>
  group_by(record_id) |>
  count(sentiment) |>
  ungroup() |>
  pivot_wider(names_from = sentiment,
              values_from = n,
              values_fill = 0) |>
  left_join(data, by = "record_id")

nrc_counts
```

```
# A tibble: 23,142 x 16
   record_id anticipation  fear negative sadness surprise trust positive   joy
       <dbl>        <int> <int>    <int>   <int>    <int> <int>    <int> <int>
 1         1            1     1        1       1        1     1        0     0
 2         2            1     0        0       0        0     0        0     0
```

```
 3          3            1     0       0       0       0     0       0     0
 4          4            2     2       2       2       2     0       1     0
 5          5            1     0       0       0       0     0       0     0
 6          6            1     1       1       0       0     1       1     0
 7          7            1     1       1       1       2     2       1     1
 8          9            0     0       0       0       1     0       1     0
 9         10            0     1       1       1       0     0       1     0
10         11            0     3       3       2       1     0       1     0
# i 23,132 more rows
# i 7 more variables: disgust <int>, anger <int>, date_and_time <chr>,
#   notification_type <chr>, notification_title <chr>, email_body <chr>,
#   cleaned_text <chr>
```

Now we can build a statistical model. Since we're working with count data we'll build a Poisson regression model.

```r
anticipation_model <- nrc_counts |>
  filter(notification_type %in% c("Local Mass Transit", "Transportation")) |>
  mutate(notification_type = as.factor(notification_type)) %$%
  glm(anticipation ~ notification_type, family = poisson)


anticipation_model
```

```

Call:  glm(formula = anticipation ~ notification_type, family = poisson)

Coefficients:
                    (Intercept)  notification_typeTransportation
                        0.09865                          0.39180

Degrees of Freedom: 11408 Total (i.e. Null);  11407 Residual
Null Deviance:      4959
Residual Deviance: 4561     AIC: 29680
```

We see the relative to local mass transit, transportation has a higher count of anticipation words and that this difference is statistically significant

```r
summary(anticipation_model)
```

```
Call:
glm(formula = anticipation ~ notification_type, family = poisson)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8072  -0.5340   0.2773   0.2773   2.6233

Coefficients:
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                      0.09865    0.01872   5.269 1.37e-07 ***
notification_typeTransportation  0.39180    0.02049  19.120  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 4958.7  on 11408  degrees of freedom
Residual deviance: 4560.6  on 11407  degrees of freedom
AIC: 29682

Number of Fisher Scoring iterations: 5
```

Taking the exponent our coefficient we see this is pretty sizable difference!

```r
exp(anticipation_model$coefficients[2])
```

```
notification_typeTransportation
                       1.479644
```

Let's take a dive into the type of anticipation words that exist across these two categories

```r
nrc_text |>
  filter(sentiment == "anticipation",
         notification_type %in% c("Transportation", "Local Mass Transit")) |>
  count(word, sort = TRUE)
```

```
# A tibble: 91 x 2
   word             n
   <chr>        <int>
```

```
 1 expect         7054
 2 time           6680
 3 closure        1610
 4 approaching     408
 5 rail            262
 6 tomorrow        172
 7 investigation   166
 8 track            95
 9 church           67
10 parade           55
# i 81 more rows
```

We're not limited to a frequency count. As we saw when we were exploring other sentiment lexicons we can leverage dictionaries that quantify words by polarity. This allows us to take the sum or average sentiment score across a particular text.

```
afinn_text <- tidy_words |>
  inner_join(get_sentiments("afinn"), by = "word") |>
  group_by(record_id) |>
  summarise(avg_val = mean(value, na.rm = TRUE)) |>
  ungroup() |>
  left_join(data, by = "record_id")

afinn_text
```

```
# A tibble: 16,809 x 7
   record_id avg_val date_and_time notification_type          notification_title
       <dbl>   <dbl> <chr>         <chr>                      <chr>
 1         1   -2    5/22/09 15:23 Utility                    Blank
 2         2    1    5/22/09 17:56 Utility                    [blank]
 3         4   -2    5/30/09 17:00 zINAC * Drills / Exercises [blank]
 4         6   -2    6/2/09 16:30  Public Health              [blank]
 5         7   -2    6/3/09 18:45  Emergency Activity         [blank]
 6        10   -2    6/21/09 0:00  <NA>                       [blank]
 7        11   -1.67 6/21/09 15:20 <NA>                       [blank]
 8        12   -2    6/25/09 0:00  Utility                    [blank]
 9        13    1.5  6/25/09 0:00  Utility                    [blank]
10        14   -2    7/1/09 0:00   Local Mass Transit         [blank]
# i 16,799 more rows
# i 2 more variables: email_body <chr>, cleaned_text <chr>
```

Let's see if we see a difference in overall emotional valence between transportation and local mass transit

```r
afinn_val_model <- afinn_text |>
  filter(notification_type %in% c("Transportation", "Local Mass Transit")) %$%
  lm(avg_val ~ notification_type)

summary(afinn_val_model)
```

```

Call:
lm(formula = avg_val ~ notification_type)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2923 -0.5290 -0.5290 -0.2923  5.4710 

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     -0.70765    0.02672  -26.48   <2e-16 ***
notification_typeTransportation -0.76335    0.03109  -24.55   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.155 on 7151 degrees of freedom
Multiple R-squared:  0.07776,	Adjusted R-squared:  0.07763 
F-statistic: 602.9 on 1 and 7151 DF,  p-value: < 2.2e-16
```

```r
afinn_text |>
  filter(notification_type %in% c("Transportation", "Local Mass Transit")) %$%
  t.test(avg_val ~ notification_type)
```

```

	Welch Two Sample t-test

data:  avg_val by notification_type
t = 25.894, df = 3627.3, p-value < 2.2e-16
alternative hypothesis: true difference in means between group Local Mass Transit and group T
95 percent confidence interval:
 0.7055496 0.8211473
```

```
sample estimates:
mean in group Local Mass Transit     mean in group Transportation 
                      -0.7076504                       -1.4709989 
```

Using both a linear regression and t-test approach we see that this is in fact the case. Let's wrap our analysis up in a quick summary reporting our findings using the report package

```r
require(report)
```

```
Loading required package: report
```

```r
afinn_text |>
  filter(notification_type %in% c("Transportation", "Local Mass Transit")) %$%
  t.test(avg_val ~ notification_type) |>
  report::report()
```

```
Warning: Unable to retrieve data from htest object.
  Returning an approximate effect size using t_to_d().

Effect sizes were labelled following Cohen's (1988) recommendations.

The Welch Two Sample t-test testing the difference of avg_val by
notification_type (mean in group Local Mass Transit = -0.71, mean in group
Transportation = -1.47) suggests that the effect is positive, statistically
significant, and large (difference = 0.76, 95% CI [0.71, 0.82], t(3627.31) =
25.89, p < .001; Cohen's d = 0.86, 95% CI [0.79, 0.93])
```

We have some other data of interest instead of notification type, like date and time of each emergency report.

Let's explore average emotional valence by time of day

```r
afinn_by_hour <- tidy_words |>
  filter(notification_type %in% c("Transportation", "Local Mass Transit")) |>
  inner_join(get_sentiments("afinn"), by = "word") |>
  mutate(hr = hour(mdy_hm(date_and_time))) |>
  group_by(notification_type, hr) |>
  summarise(avg_val = mean(value, na.rm = TRUE),
            sd_val = sd(value, na.rm = TRUE),
            n_count = n(),
```

```r
              sem = sd_val / sqrt(n_count))
```

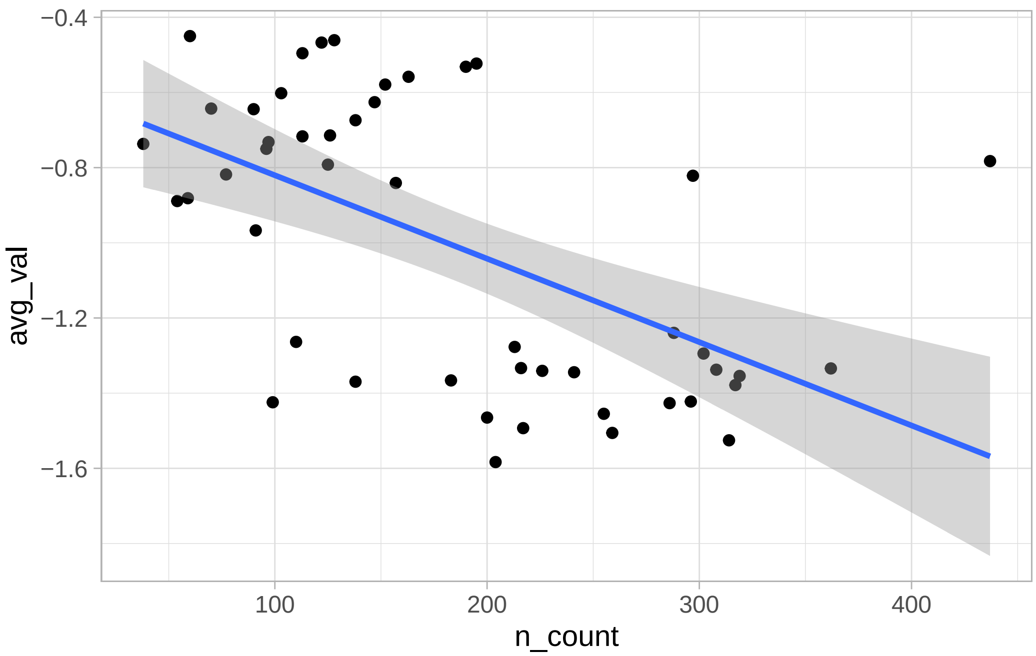
```
`summarise()` has grouped output by 'notification_type'. You can override using
the `.groups` argument.
```

```r
afinn_by_hour
```

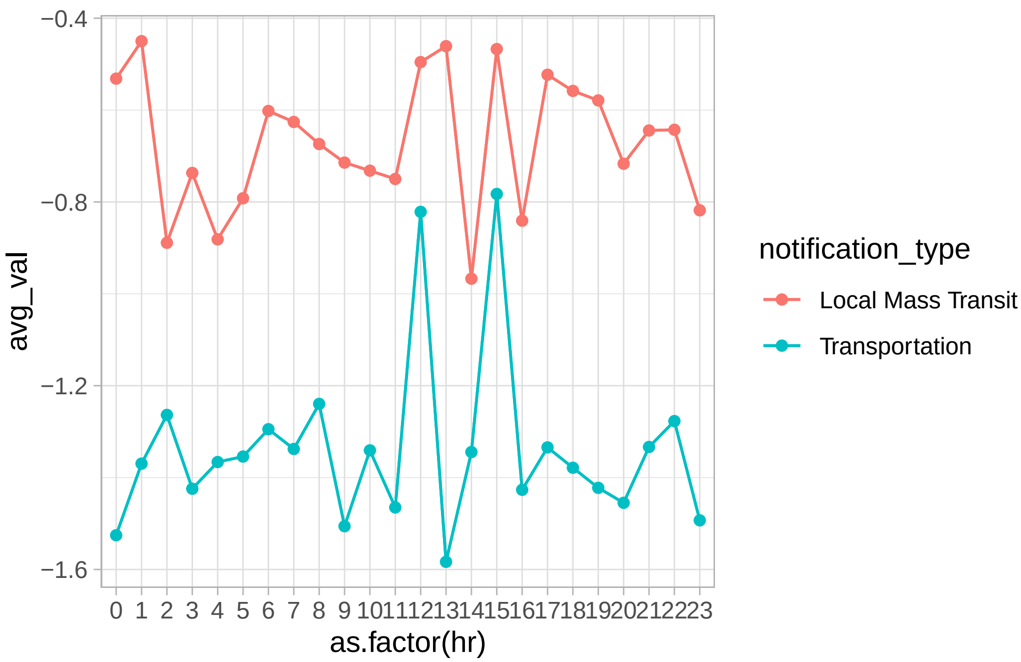
```
# A tibble: 48 x 6
# Groups:   notification_type [2]
   notification_type      hr avg_val sd_val n_count    sem
   <chr>               <int>   <dbl>  <dbl>   <int>  <dbl>
 1 Local Mass Transit      0  -0.532  1.37      190 0.0992
 2 Local Mass Transit      1  -0.45   1.52       60 0.197
 3 Local Mass Transit      2  -0.889  1.06       54 0.144
 4 Local Mass Transit      3  -0.737  1.08       38 0.176
 5 Local Mass Transit      4  -0.881  0.790      59 0.103
 6 Local Mass Transit      5  -0.792  1.29      125 0.115
 7 Local Mass Transit      6  -0.602  1.48      103 0.146
 8 Local Mass Transit      7  -0.626  1.23      147 0.101
 9 Local Mass Transit      8  -0.674  1.27      138 0.108
10 Local Mass Transit      9  -0.714  1.32      126 0.118
# i 38 more rows
```

```r
afinn_by_hour |>
  ggplot(aes(n_count, avg_val)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
`geom_smooth()` using formula = 'y ~ x'
```




```
afinn_by_hour |>
  ggplot(aes(as.factor(hr), avg_val, group = notification_type,
             color = notification_type)) +
  geom_point() +
  geom_line() +
  geom_path()  #+ geom_errorbar(mapping =  aes(ymin = avg_val - sem,  ymax = avg_val + sem
```



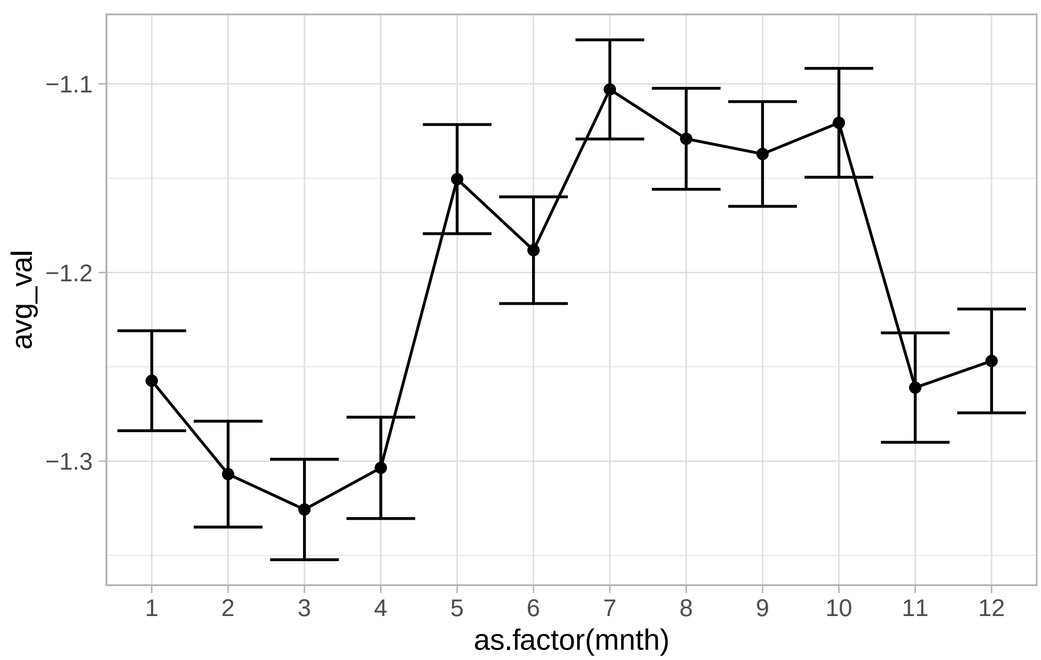

```r
afinn_mnth <- tidy_words |>
  inner_join(get_sentiments("afinn"), by = "word") |>
  mutate(mnth = month(mdy_hm(date_and_time))) |>
  group_by(mnth) |>
  summarise(avg_val = mean(value, na.rm = TRUE),
            sd_val = sd(value, na.rm = TRUE),
            n_count = n(),
            sem = sd_val / sqrt(n_count))

afinn_mnth
```

```
# A tibble: 12 x 5
    mnth avg_val sd_val n_count    sem
   <dbl>   <dbl>  <dbl>   <int>  <dbl>
 1     1   -1.26   1.32    2475 0.0265
 2     2   -1.31   1.28    2092 0.0281
 3     3   -1.33   1.28    2291 0.0266
 4     4   -1.30   1.30    2339 0.0269
 5     5   -1.15   1.43    2432 0.0289
 6     6   -1.19   1.37    2333 0.0283
 7     7   -1.10   1.47    3147 0.0263
 8     8   -1.13   1.38    2672 0.0268
```

```
 9     9   -1.14   1.38    2486 0.0278
10    10   -1.12   1.37    2238 0.0289
11    11   -1.26   1.32    2065 0.0290
12    12   -1.25   1.33    2325 0.0275
```

```
afinn_mnth |>
  ggplot(aes(as.factor(mnth), avg_val)) +
  geom_point() +
  geom_line() +
  geom_path(group = 1) +
  geom_errorbar(mapping =  aes(ymin = avg_val - sem,
                               ymax = avg_val + sem))
```

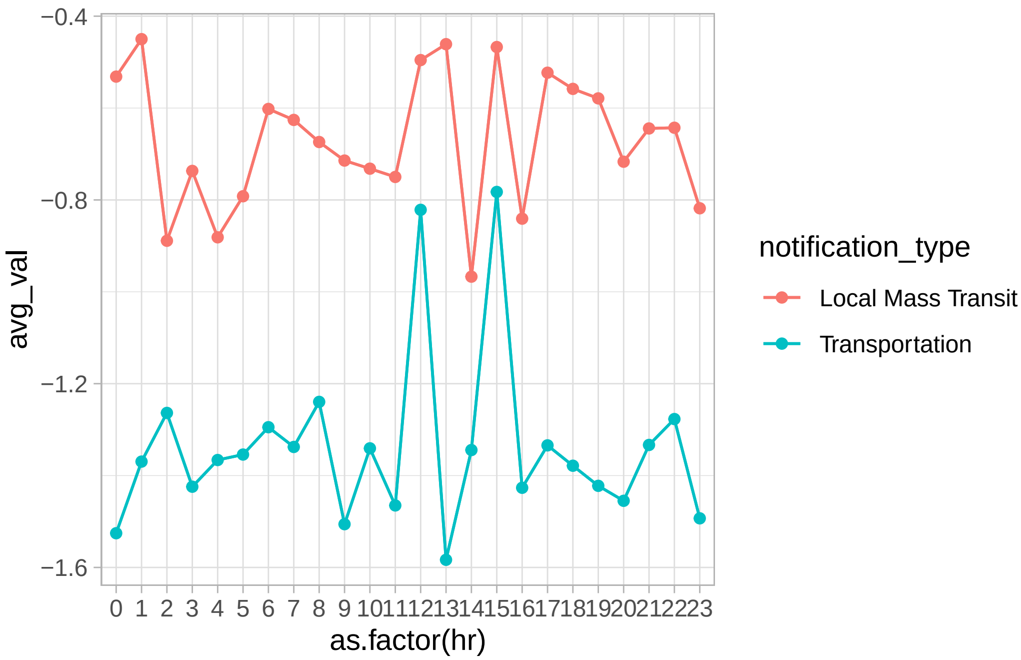
```
`geom_line()`: Each group consists of only one observation.
i Do you need to adjust the group aesthetic?
```




```
tidy_words |>
  filter(notification_type %in% c("Transportation", "Local Mass Transit")) |>
  inner_join(get_sentiments("afinn"), by = "word") |>
  mutate(hr = hour(mdy_hm(date_and_time))) |>
```

```
group_by(notification_type, hr) |>
summarise(avg_val = mean(value, na.rm = TRUE)) |>
ggplot(aes(as.factor(hr), avg_val, group = notification_type,
           color = notification_type)) +
geom_point() +
geom_line() +
geom_path()
```

```
`summarise()` has grouped output by 'notification_type'. You can override using
the `.groups` argument.
```



We've asked a lot of quant based questions of our data but let's start to search for some themes. One approach is to examine the clusters of words that are correlated with each other using the phi correlation coefficient. To accomplish this we'll add a few more packages that allow us to compute word correlations and graph a node map of our text data

```
require(ggraph)
```

```
Loading required package: ggraph
```

```r
require(widyr)
```

```
Loading required package: widyr
```

```r
require(igraph)
```

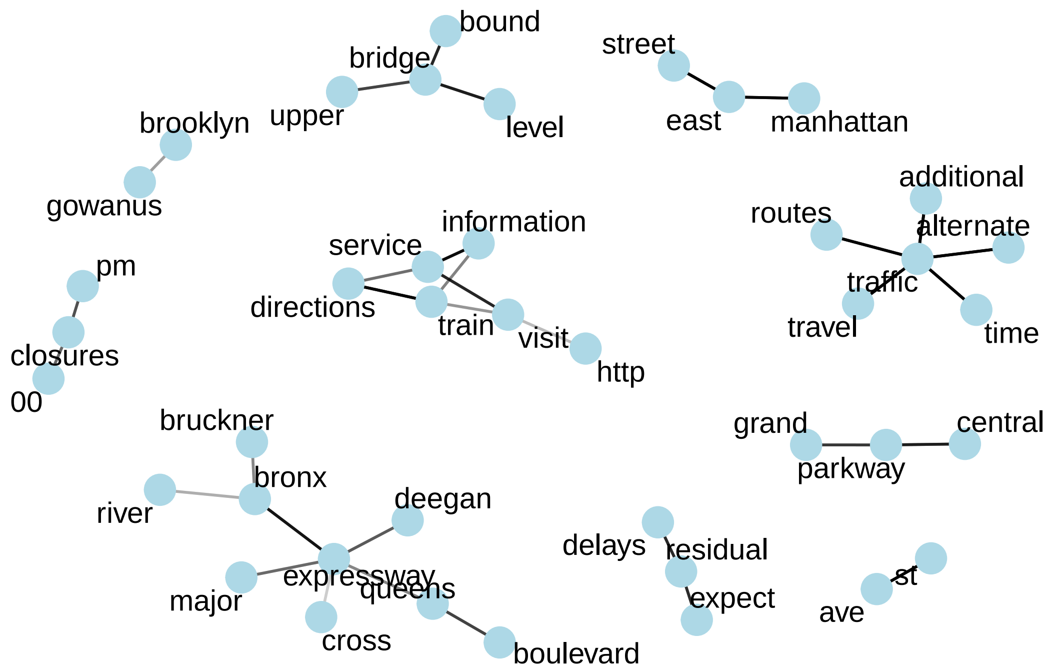
```
Loading required package: igraph


Attaching package: 'igraph'

The following objects are masked from 'package:lubridate':

    %--%, union

The following objects are masked from 'package:dplyr':

    as_data_frame, groups, union

The following objects are masked from 'package:purrr':

    compose, simplify

The following object is masked from 'package:tidyr':

    crossing

The following object is masked from 'package:tibble':

    as_data_frame

The following objects are masked from 'package:stats':

    decompose, spectrum

The following object is masked from 'package:base':

    union
```

```r
word_cors <- tidy_words |>
  filter(notification_type == "Transportation") |>
  add_count(word) |>
  filter(n > 200) |>
  pairwise_cor(word, record_id, sort = TRUE) |>
  filter(correlation >= .30 & correlation <= .40)

word_cors
```

```
# A tibble: 66 x 3
   item1      item2      correlation
   <chr>      <chr>            <dbl>
 1 additional traffic          0.398
 2 traffic    additional       0.398
 3 routes     traffic          0.396
 4 traffic    routes           0.396
 5 time       traffic          0.395
 6 traffic    time             0.395
 7 alternate  traffic          0.394
 8 traffic    alternate        0.394
 9 street     east             0.393
10 east       street           0.393
# i 56 more rows
```

We can now create a node map that will show us clusters of words. Play around with the data itself (filtering across notification types, or specifying correlation bounds) to see what clusters of words pop up.

```r
word_cors |>
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation), show.legend = FALSE) +
  geom_node_point(color = "lightblue", size = 5) +
  geom_node_text(aes(label = name), repel = TRUE) +
  theme_void()
```



If you want to highlight certain text patterns and identify that in the data.

Let's say we want to identify messages that start with "This is a message…". We can create a case statement using case_when() and grepl()

```
data |>
  mutate(says_the_thing = case_when(grepl("This is a message", email_body) ~ "Yup",
                                    TRUE ~ "Nope")) |>
         select(email_body, says_the_thing)
```

```
# A tibble: 25,677 x 2
   email_body                                                   says_the_thing
   <chr>                                                        <chr>
 1 This is a message from Notify NYC. Notification 2 issued 05/1~ Yup
 2 This is a message from Notify NYC. Notification 1 issued 5/15~ Yup
 3 This is a message from Notify NYC. Notification 1 issued 05/1~ Yup
 4 This is a message from Notify NYC. Notification 1 issued 05/1~ Yup
 5 This is a message from Notify NYC. Notification 1 issued 5/19~ Yup
 6 This is a message from Notify NYC. Notification 1 issued 5/20~ Yup
 7 This is a message from Notify NYC. Notification 1 issued 5/20~ Yup
 8 This is a message from Notify NYC. Notification 1 issued 5/21~ Yup
 9 This is a message from Notify NYC. Notification 1 issued 5/22~ Yup
```

```
10 Notification 2 issued on 12/04/2009 at 5 PM. All lane closure~ Nope
# i 25,667 more rows
```

Feel free to use this notebook and or the code in it to get started and further explore this data!

Thank you for attending the workshop!