The Power of Text and R

Using Call Center Transcripts to Train Financial Aid Counselors

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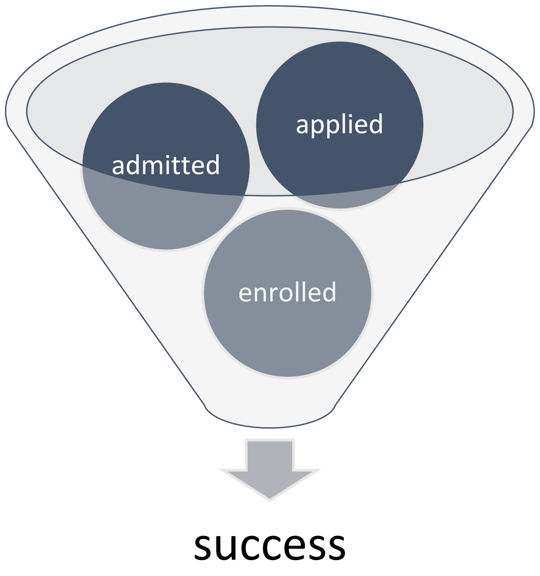
Objectives:

1. Understand the applications of text analytics in Institutional Research.
2. Demonstrate the utilization of R packages and processes for text analytics.
3. Show use cases for text analytics in financial aid counseling training.

Institutional research and student success in our department

A well-trained financial aid counselor is less of a barrier to student success in enrolling into the university. Enrolled students are successful students in our department. This is how we measure student success in the following scenarios.



How can we apply text analytics to institutional research?

1. One way is to do a classic open-ended Qualtrics survey and deploy it on a large scale. This gives structure to qualitative, institutional research.
2. A second way is to capture interactions or dialogues happening organically that pertain to institutional concerns which are recorded for training purposes.

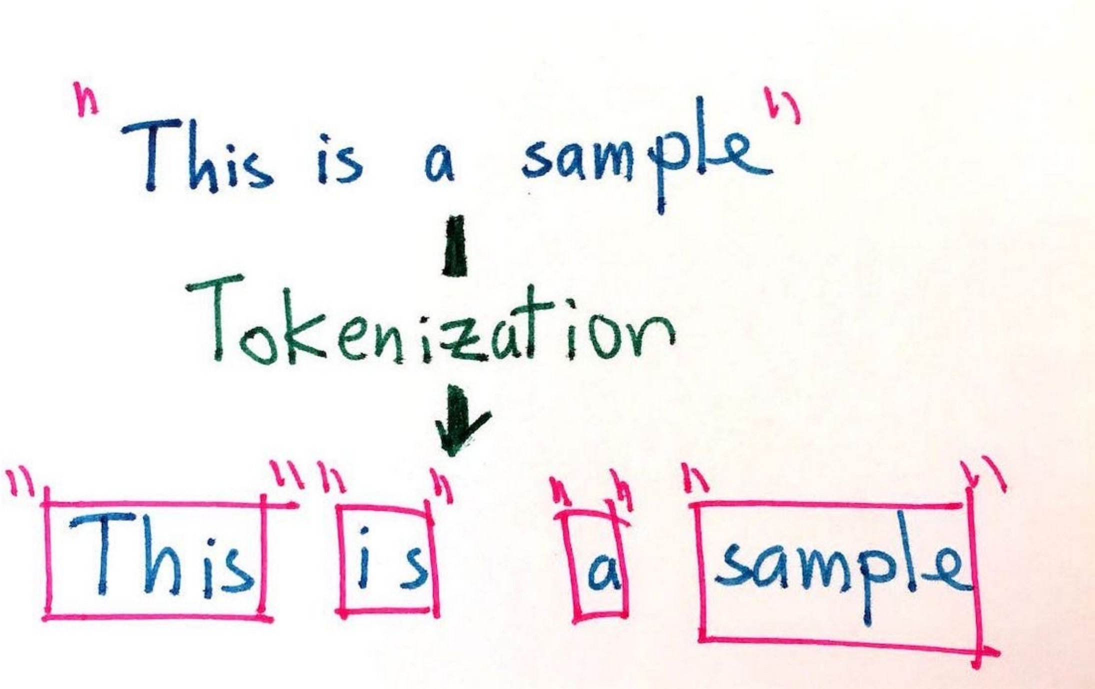
Why choose R to do this work?

Why not python, for example?

1. The main reason for using R is because R has caught up to python in topic modeling and sentiment analysis with the ‘quanteda’ and related libraries.
2. R can perform parallel computing, and even work on top of python (viz. spacy) to perform tokenization, part-of-speech tagging, and other functions.
3. Together with its native strengths in statistical libraries, R is chosen to perform the workload of text analytics and modeling because of its new speed, its efficiency, and its robust statistics.

What is tokenization?

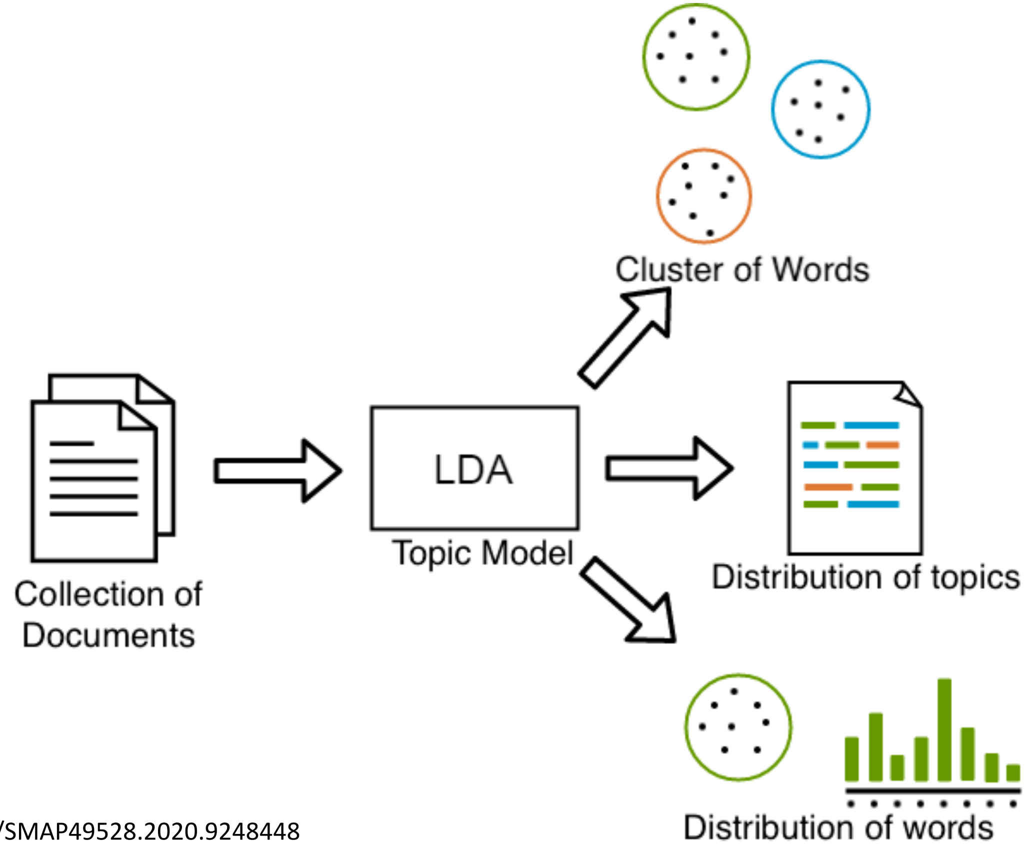
Tokenization is the process of breaking down long strings of texts into smaller parts. A sentence read into the computer can be tokenized so that the words are separated out and they become smaller, and statistical and other operations can be performed on those tokens.



Source: https://medium.com/data-science-in-your-pocket/tokenization-algorithms-in-natural-language-processing-nlp-1fceab8454af

What is topic modeling?

Topic modeling is the approach of finding related words from topics in a body of written work that has been read into the computer.



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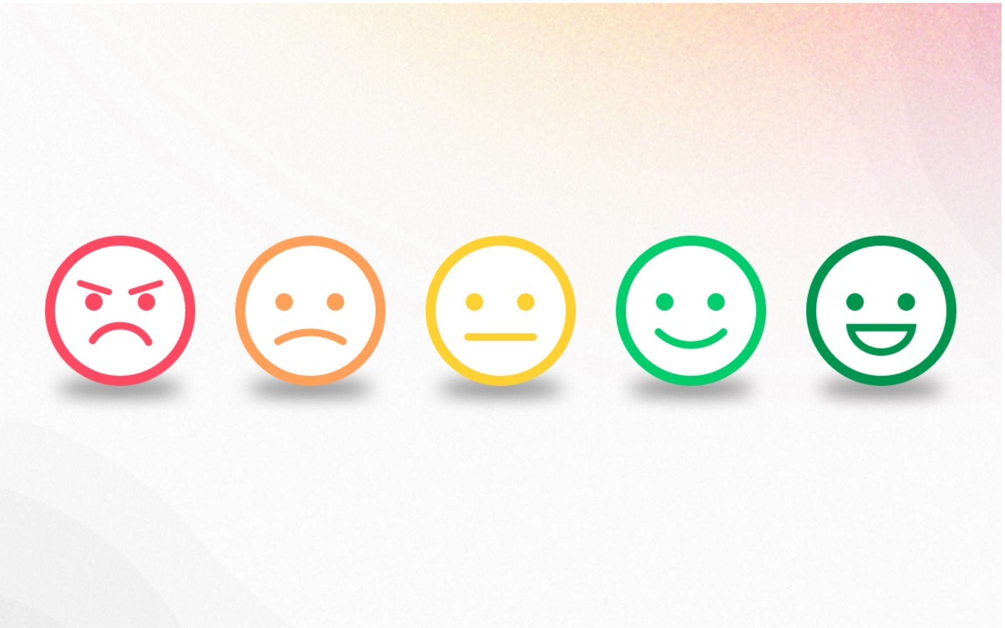
What is sentiment analysis?

Sentiment analysis is an analytical method by which a tagged body of computer readable text is marked with a numerical value that evaluates the text along an emotional valence, such as positive/negative, anger, joy, or other emotions. The marks given are usually per token (word) and are summed up to give a total score to the piece of writing.



Source: https://www.superannotate.com/blog/sentiment-analysis-explained

What is parallel computing?

Parallel computing is where many actions are performed by the computer at the same time. Parallel computing can cut the time of performing functions when compared to regular computing.

Enrollment Services Call Center

Daily Metrics: as of 5:00 pm, Tuesday, August 22, 2023

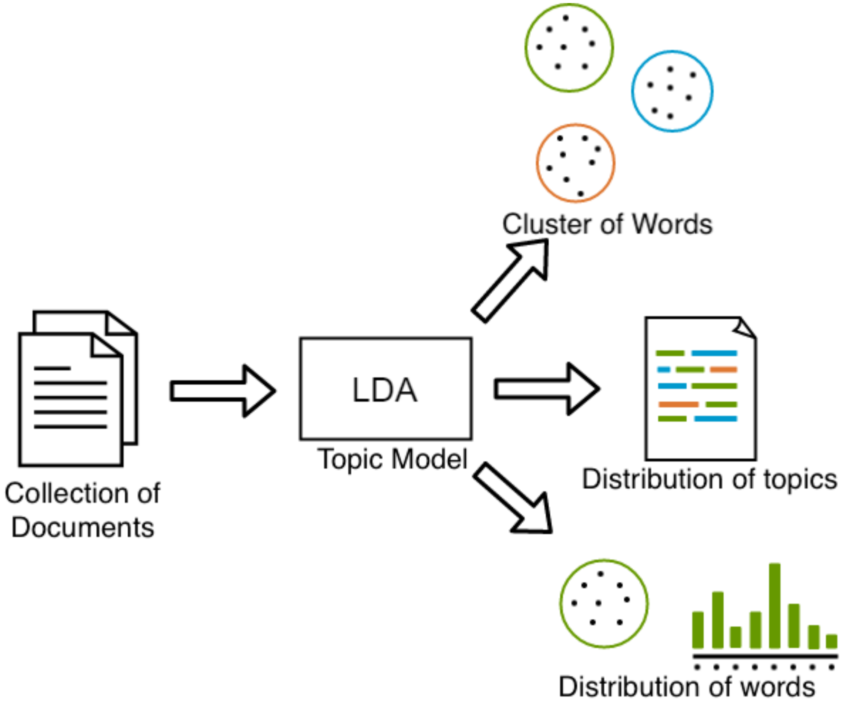
Dept.	Calls Presented	Avg. Hold Time	Calls Handled	Avg. Talk Time	Calls Missed	Avg. Time to Abandon
ADM	163	0:01:08	149	0:06:15	14	0:03:56
OUR	243	0:01:20	233	0:06:00	10	0:02:16
SBS	338	0:01:33	322	0:06:02	16	0:04:37
SFA	570	0:11:28	379	0:07:08	191	0:07:12

Weekly Metrics: Reflects weekly total, 8/14-8/18

Dept.	Calls Presented	Avg. Hold Time	Calls Handled	Avg. Talk Time	Calls Missed	Avg. Time to Abandon
ADM	1291	0:02:29	1073	0:05:13	218	0:04:59
OUR	1926	0:01:17	1604	0:05:46	322	0:01:52
SBS	3094	0:09:18	2584	0:05:07	510	0:05:52
SFA	3370	0:16:15	2120	0:07:08	1250	0:09:55

What is a latent Dirichlet allocation model?

A latent Dirichlet allocation model (LDA) is a statistical model that is probabilistic and pertains to bodies of text. Topic probabilities represent the body of documents, and are used in document classification, document modeling, and related functions (Blei, Ng, Jordan, 2003).



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Let’s get started

So you have some data ☺…

Topic Modeling

Use case 1

Financial Aid Counseling

RQ- What are the main topics in the large body of texts?

You are the financial aid counseling manager, and you want to know the main ideas happening in the past month during high call volume to set the post mortem for training.

R packages and R studio

```
library(tidyverse)
library(readtext)
library(quanteda)
library(quanteda.sentiment)
library(topicmodels)
library(tidytext)
```

Order of operations

1. Ingestion of text into the computer (N = 1,599 texts)
2. Create the corpus
3. Tokenize texts
4. Create the document feature matrix
5. Remove stopwords and other meaningless features
6. Create the Latent Dirichlet Allocation model (or related model)
7. Visualize with top terms

Here we use a public data frame from Kaggle to demonstrate use.

source: https://www.kaggle.com/datasets/brajeshmohapatra/consumer-complaint-resolution-data-set

Raw Data in Excel CSV

doc_id	consumer_complaint_narrative	sub_issue
313	This company Atlantic Credit and Finance is calling me up to 5 times a day on my	Frequent or repeated calls
367	I entered into a payment plan with XXXX XXXX on XX XX XXXX I received regular	Sued w o proper notification of suit
540	I rec d a letter from Ally XXXX for a debt that is NOT ours I verified this with my	Debt is not mine
671	I received a message from a family member that XXXX associates were trying to	Not disclosed as an attempt to collect
938	After retaining counsel in XXXX of XXXX due to contact by Javitch Co a collection	Contacted me instead of my attorney
1459	Threatened me on the phone that they were going to arrest my wife if she did pay a	Threatened arrest jail if do not pay
2265	Checked my credit report and have a derogatory remark against my credit score	Debt is not mine
2533	I have been receiving repeated calls XXXX to XXXX times daily for about two	Frequent or repeated calls
2945	This organization claims that they do not have written authorization to cease comm	Called after sent written cease of comm

Ingest Texts with ‘readtext’

```
> readtext('narr_subissues_cc.csv',
+          text_field = 'consumer_complaint_narrative',
+          docid_field = 'doc_id')
readtext object consisting of 1599 documents and 1 docvar.
# A data frame: 1,599 × 3
  doc_id text                 sub_issue
  <chr>  <chr>                <chr>
1 313    "\"This compa\"..." Frequent or repeated calls
2 367    "\"I entered \"..." Sued w o proper notification of suit
3 540    "\"I rec   d a\"..." Debt is not mine
4 671    "\"I received\"..." Not disclosed as an attempt to collect
5 938    "\"After reta\"..." Contacted me instead of my attorney
6 1459   "\"Threatened\"..." Threatened arrest jail if do not pay
# ℹ 1,593 more rows
# ℹ Use `print(n = ...)` to see more rows
```

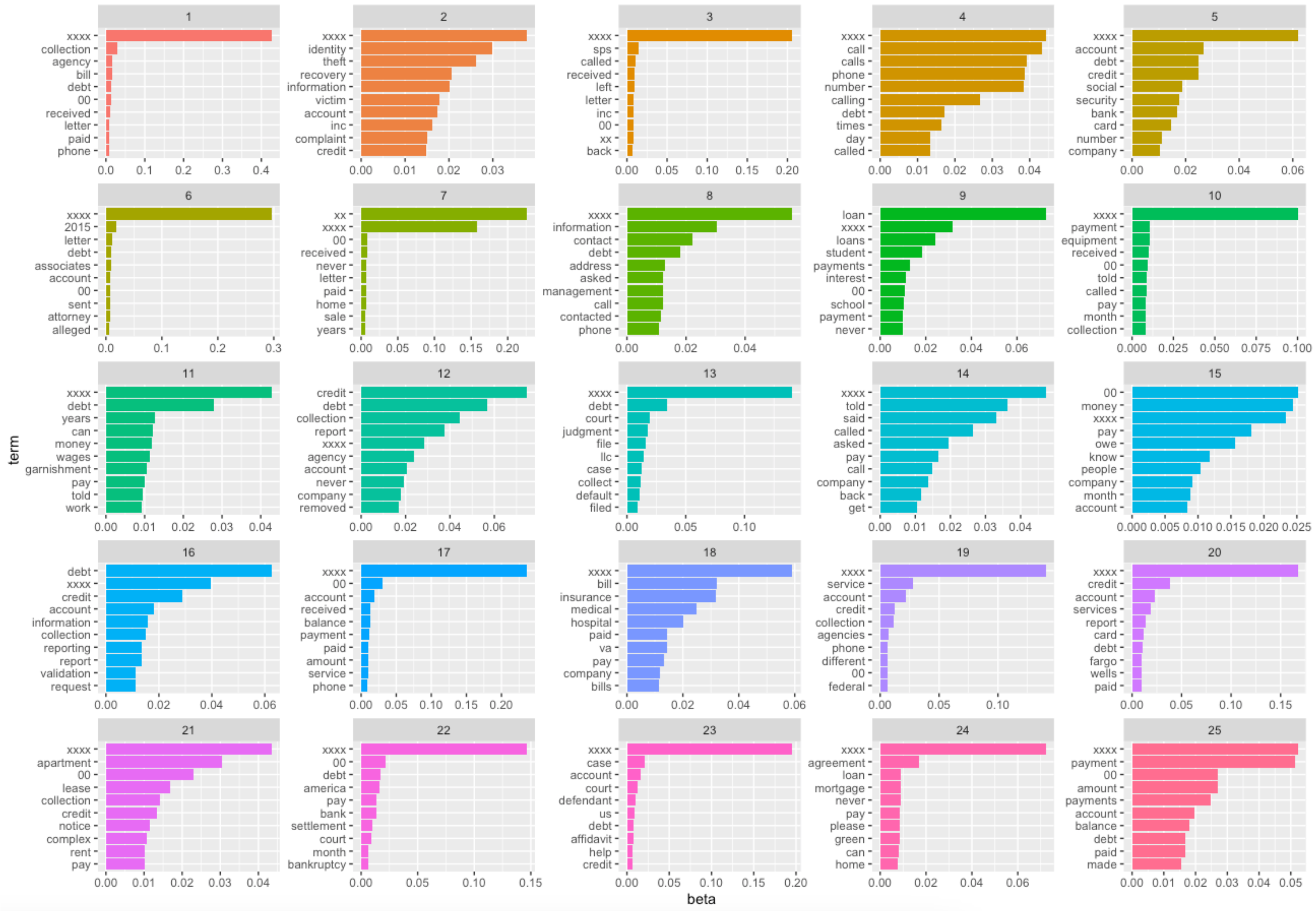
From corpus to latent Dirichlet allocation

```
text_object <- my_text |>
  corpus() |>
  tokens() |>
  dfm() |>
  dfm_remove(stopwords("english"))


mydfm <- quanteda::convert(text_object, to = "tm")

mylda <- LDA(mydfm, k = 25)
```

Where my_text = dataframe ingested into R studio by the readtext package, piped through using the quanteda package. This object is then passed to the 'tm' (text mining) package to be read into the LDA algorithm.

- Corpus– A body of text. The computer calls many documents into a single group of texts based on an algorithm or principle.
- Tokenizing– making human readable text computer readable.
- Document Feature Matrix – Preparatory structure that helps to perform a wide variety of data analysis forms downstream from this step.
- Latent Dirichlet Allocation– A statistical model that is laid on the text. Similar to clustering.
- Kappa- Greek symbol representing the number of topics that we want to see.

Topic Modeling with tidytext, ggplot2 packages



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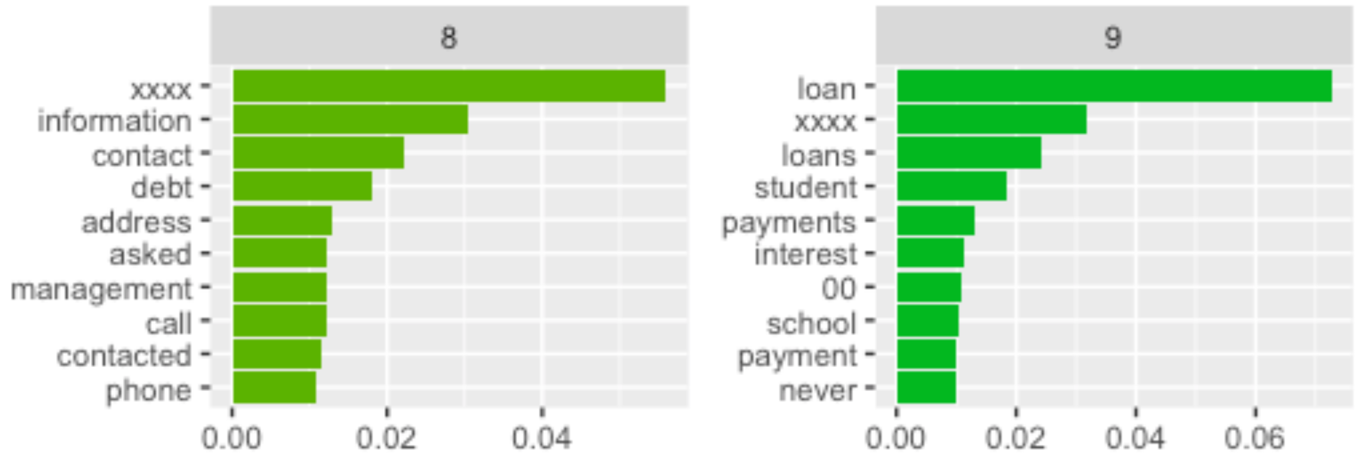
Topic Modeling- A breakdown

- With topics, the reader is left to infer topic names from the terms that come together under the heading.
- Beta scores represent the probability of term presence within each topic.
- In this case XXXXs represent masked information that would indicate personal information. This data set has been sanitized.

A close-up of Topics 8 and 9



Before…

```
# A tibble: 1,599 × 2
   doc_id consumer_complaint_narrative
    <dbl> <chr>
 1    313 "This company Atlantic Credit and Finance is calling me up to 5 times…
 2    367 "I entered into a payment plan with XXXX XXXX on XX XX XXXX  I receiv…
 3    540 "I rec  d a letter from Ally XXXX for a debt that is NOT ours  I veri…
 4    671 "I received a message from a family member that XXXX associates were …
 5    938 "After retaining counsel in XXXX of XXXX due to contact by Javitch   …
 6   1459 "Threatened me on the phone that they were going to arrest my wife if…
 7   2265 "Checked my credit report and have a derogatory remark against my cre…
 8   2533 "I have been receiving repeated calls  XXXX to XXXX times daily for a…
 9   2945 "This organization claims that they do not have written authorization…
10   3662 "I call XXXX customer service and told them my address XXXX  TX XXXX …
# ℹ 1,589 more rows
```

Sentiment Analysis

Use case scenario 2

Working Assumptions

- Negative associations found in sentiment analysis can provide opportunities to reflect on the context of dialogue.
- It can be somewhat normal for there to be ups and downs in the customer’s emotions during a service call.
- Sentiment analysis is a single tool to identify emotion and should be used judiciously in training.
- Sentiment analysis works based on word connotations that are converted to numerical value.

Fin Aid Counseling

1. RQ– Are there different sentiment scores in calls taken from nontraditional students, parents, and traditional students?

You are the call center manager and need to decide if there is a need for training based on the differences between sentiment scores between groups of people.

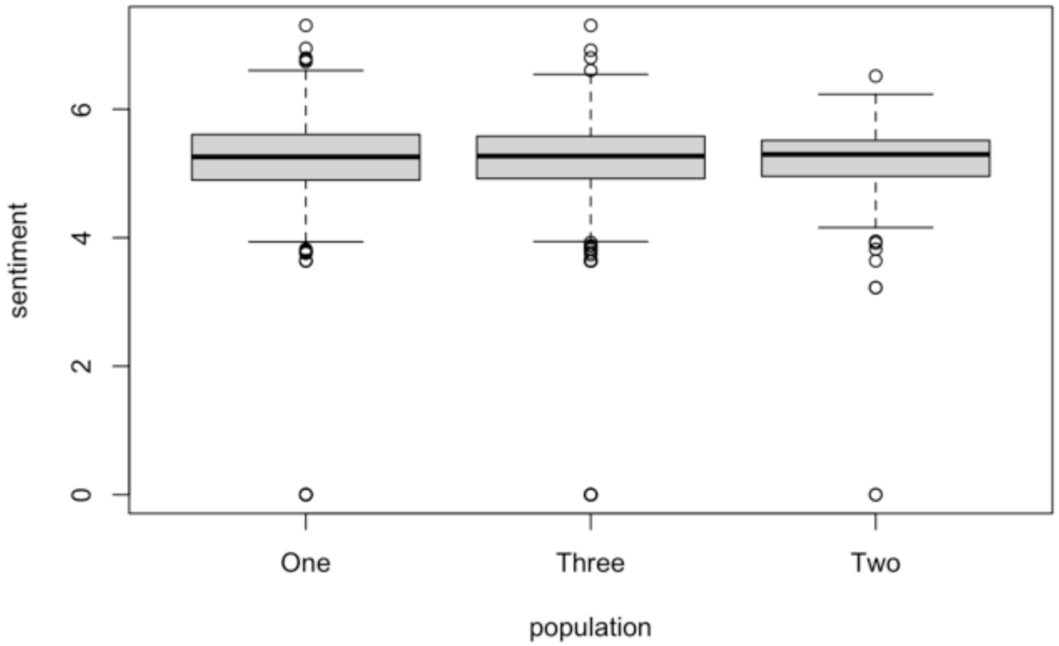
A nonparametric ANOVA can possibly answer this question

1. Rationale for training purposes-- If there are differences between groups, we may need to have special training for handling those groups to take their differences into consideration (viz. traditional, non-traditional, parents). In this nonparametric ANOVA, there are three groups: One, Two, Three.
2. Alternatively, cases below a particular threshold in sentiment scoring may be used for case studies in training.

```
# A tibble: 1,599 × 2
   population sentiment
   <chr>          <dbl>
 1 Three           5.39
 2 Three           5.89
 3 One             5.65
 4 Three           5.91
 5 One             5.30
 6 Three           5.78
 7 Three           4.44
 8 One             5.45
 9 Three           5.55
10 One             5.57
# ℹ 1,589 more rows
```

Are there differences between groups

Outliers can be used as case studies!




```
    Kruskal-Wallis rank sum test

data:  sentiment by population
Kruskal-Wallis chi-squared = 0.22169, df = 2, p-value = 0.8951
```

Results from the Kruskal-Wallis rank sum test indicates that there are not significant differences in the medians between the three groups.

Yes, but how does this help the individual financial aid counselor?

A case-by-case selection can be examined for text and sentiment scoring for training purposes by selecting the text, running it through the syuzhet pipe, and plotting it for highly granular analysis. The breakdown of this code happens in the next two slides.

```
library(syuzhet)

a <- "I have asked One Main Financial not to call my place of employment and yet they h


d <- a |>
  get_sentences() |>
  get_sentiment() |>
  print()
```

```
[1]  0.40  0.25 -0.75
```

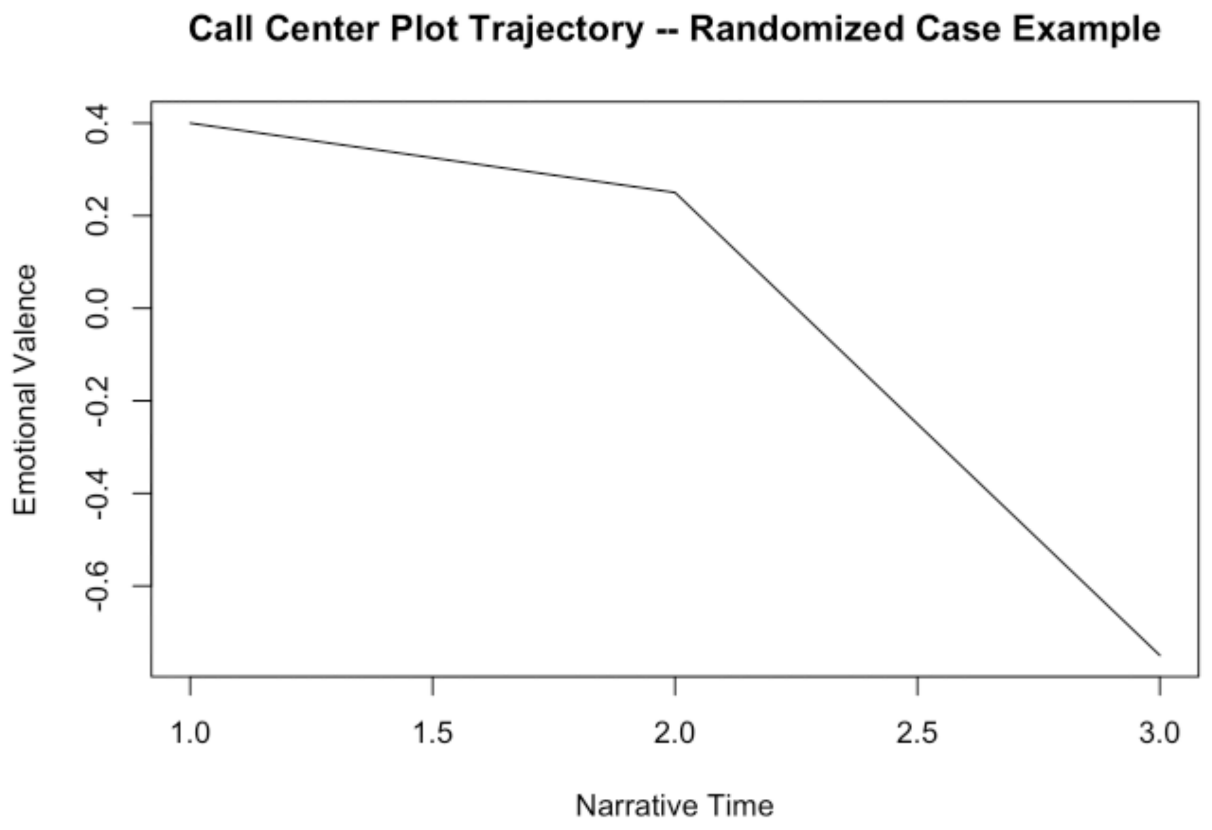
```
plot(
  d,
  type="l",
  main="Example Plot Trajectory",
  xlab = "Narrative Time",
  ylab= "Emotional Valence"
  )
```

Text Up Close Example 1

```
a <- "I have asked One Main Financial not to call my place of
employment and yet they have on three separate occasions. The most
recent was on XXXX when my coworker again informed them that I could
not receive calls at work. It is embarrassing and allows other people
to know my personal business."
```

Visualization for case produced by syuzhet library

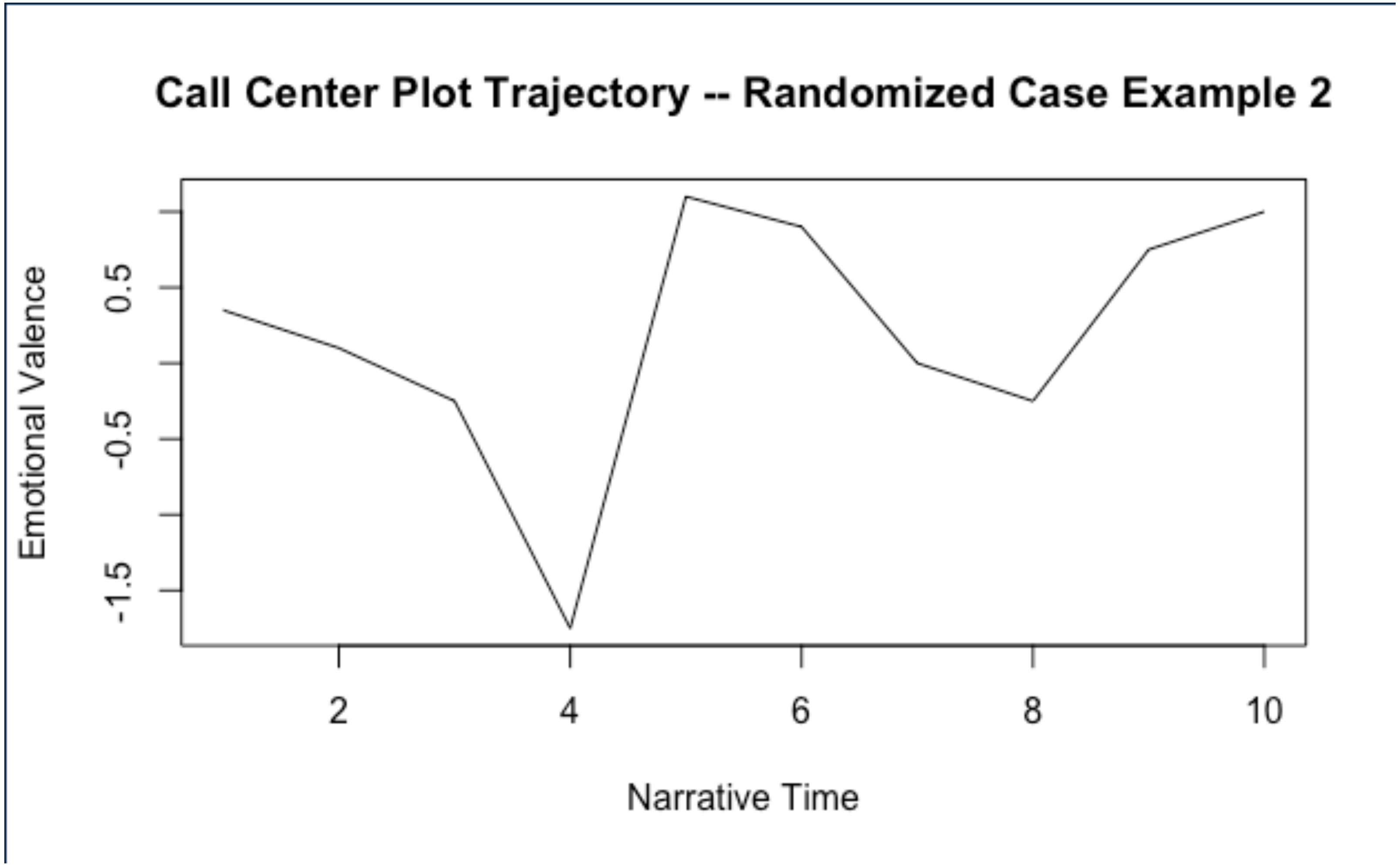
The following visualization plots three points, one for each sentence. Narrative time is produced from beginning of discussion to the end. Emotional valence is calculated based on word valences, concatenated and summed. The higher the emotional valence, the more positive the sentiment according to the syuzhet dictionary.



Case Use Example 2 - Text

```
b <- "My Loan balance is incorrect, and I would like to request a
hearing. This is a legal request that has to be given to me by the
creditor of my student loan balance in which my account manager
XXXX XXXX denied me. I will be speaking to my attorney on this
matter. Also, his collection tactics were extremely rude, and
unprofessional. I am being charged 13.12 % interest on an original
balance that was not even specified to me with the form I will
attach to this message. All that was specified to me is that I
paid {$4500.00} in interest, and {$680.00} on my principal. My
loan was around $4500.00 when I initially started the loan. I know
Navient collection agency is trying to rip me off because they say
the loan is in default. I have proof that I have been paying the
loan pretty much every month since 2010. Please help me. "
```

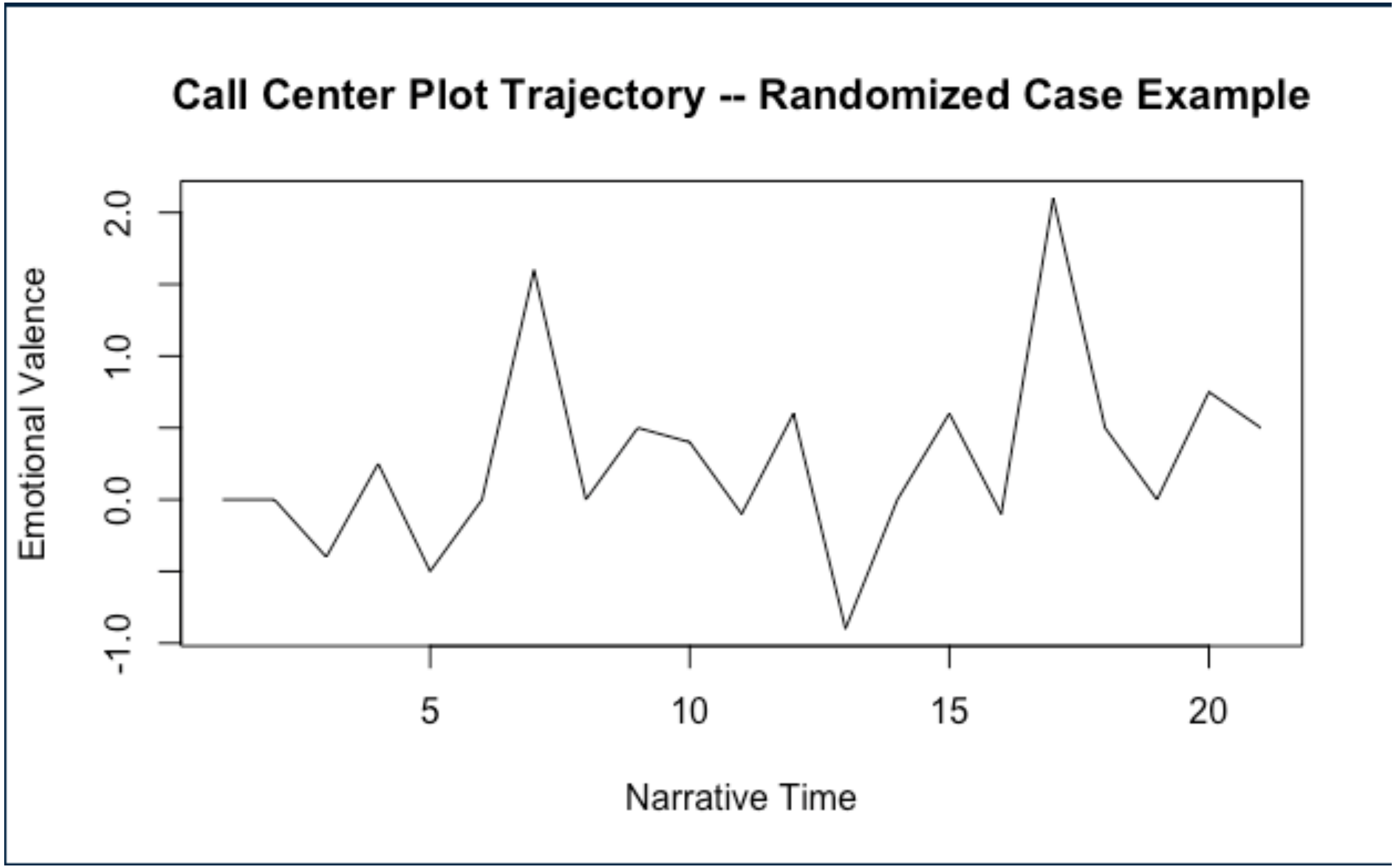
Sentiment Analysis visualization Example 2



Case Use Example 3 - Text

```
f <- 'I took out XXXX loans in XXXX and XXXX to supplement my
federal loans. The total was {$8100.00}. My Dad helped me out and
paid the set payment fee for two years ; this was approximately
{$80.00} a month split between the XXXX loans. The interest rate
has constantly changes around XXXX depending on which loan. It has
now been 10 years and I have barely made a dent on the loan. As of
XXXX XXXX I was told I would have XXXX more months of
repayments-14.5 more years at {$65.00} a month. I am not the best
at math but with an interest rate at 4 % I would have {$230.00} in
interest a year, {$19.00} a month and yet, when I have been paying
{$100.00} a month ( recently ) only {$43.00} knocked off the
balance. Where does the other {$57.00} go to? 29.6 % interest? As
of XXXX XXXX they started combining the loan information onto XXXX
statement. Then I noticed that my payment statement shows the
{$100.00} payments but that only {$55.00} has been applied each
month. I dont know where the rest of the money is going to. When
you call AES you get mysterious hang ups/long wait hold times over
an hour, etc. A person is given the run around. my loan balance is
{$5700.00} from {$8100.00} in 10 years of payments! That was
{$7200.00} ( at least because multiple payments over the monthly
payment due ) in that time period. If my calculations are correct,
interest at 4 % on the principal balance to start would have been
{$320.00} a year which of course decreases with payments. Even
with that, that would be {$3200.00} in interest over 10 years
meaning I have paid ( at least ) {$3900.00} off on my loan. Yet,
according to my statement I have only paid off {$2300.00}. Please
help, I am doing all I can to be responsible but this is
disheartening on top of the federal loans I have to shoulder.
Thank you!'
```

Sentiment Analysis visualization Example 3



NRC sentiment—an array of emotional content found in text (Example 2)

```
b |>
  get_sentences() |>
  get_nrc_sentiment()
```

```
b <- "My Loan balance is incorrect, and I would like to request a
hearing. This is a legal request that has to be given to me by the
creditor of my student loan balance in which my account manager
XXXX XXXX denied me. I will be speaking to my attorney on this
matter. Also, his collection tactics were extremely rude, and
unprofessional. I am being charged 13.12 % interest on an original
balance that was not even specified to me with the form I will
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loan was around $4500.00 when I initially started the loan. I know
Navient collection agency is trying to rip me off because they say
the loan is in default. I have proof that I have been paying the
loan pretty much every month since 2010. Please help me. "
```

A lexicon of emotions found within the 10 sentences (Example 2)

The previous code provides a data frame of various sentiment scores that can be broken down to assess

Description: df [10 × 10]

anger <dbl>	anticipation <dbl>	disgust <dbl>	fear <dbl>	joy <dbl>	sadness <dbl>	surprise <dbl>	trust <dbl>	negative <dbl>	positive <dbl>
0	0	0	1	0	0	0	0	2	1
0	0	0	0	0	1	0	2	1	2
1	0	0	1	0	0	0	1	0	1
0	0	0	1	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	2
0	0	0	0	0	0	0	1	0	2
0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	1	0	0	1	0
0	1	0	0	1	0	0	2	0	1
0	0	0	0	0	0	0	0	0	0

1–10 of 10 rows

Here is a close-up of some of the scores

disgust <dbl>	fear <dbl>	joy <dbl>	sadness <dbl>	surprise <dbl>	trust <dbl>
0	1	0	0	0	0
0	0	0	1	0	2
0	1	0	0	0	1
0	1	0	0	0	1
0	0	0	0	0	0
0	0	0	0	0	1
0	0	0	0	0	0
1	1	0	1	0	0
0	0	1	0	0	2
0	0	0	0	0	0

Thoughts about how to train..

1. Call center employees can retain negative memories of customer mistreatment and carry it over into the next day (Wang et al., 2013).
2. Call center employees suffering from customer mistreatment can suffer from poor sleep quality and next day recovery (Park and Kim, 2018).
3. High emotional intelligence is related to low turnover intentions and high job satisfaction in call center work (Feyerabend, Herd, and Choi, 2018).

How we can use sentiment analysis…Emotional Intelligence and Emotional Regulation (Feyerabend, Herd, and Choi, 2018).

1. Use the sentiment visualization and scores along with the text to notice when in the conversation emotion levels drop.
2. Discuss how to handle persistent negative sentiment scores in customer discussions (viz. how can you “lift” the conversation?)
3. Identify the source of negative sentiment, learn to de-internalize it.
4. Merge sentiment analysis with the rest of training as an add-on for quality enhancement (viz. ‘turn-at-talk’ work).
5. Think large scale and whether there are sentiment patterns between groups of people handled by customer service (viz. financial aid office).

Take home message

- It is normal for there to be spikes and dips in the emotional valence of the conversation.
- However, persistent, low emotional valences could be a flag.
- Analysis could focus on when in the conversation emotional valences drop (viz. is it right after the service provider talks?).
- Care should be taken to interpret the meaning of sentiment, and sentiment scores should frequently refer back to the text for appropriate context.

Next Steps…

Where we are now at Enrollment Services.

- We have different call centers in the Welcome Center
- We are currently in between call center services.
- As a result we cannot provide our own data to show here today.
- However, these methods will be used going forward.

Works Cited

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