



world**usability**day

## A Gold Mining Adventure

Using Natural Language Processing, Machine Learning, and Human-Centered Design to Find Gold in Unstructured Data

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November 12, 2020



# AGENDA

## Interpreting Unstructured Listening Session Data

- Project Goals and Objectives
- Listening Session Process
- Find Gold in Unstructured Data
- Optimize NLP Visualizations With HCD
- HCD Project Outcomes
- Additional HCD Considerations/Puzzles

# PROJECT GOALS AND OBJECTIVES

Improve the review process of unstructured listening session data by leveraging Artificial Intelligence and Human-Centered Design.

## Goals:

- Use HCD, Machine Learning (ML) and Natural Language Processing (NLP) to:
  - Achieve high reliability (>80%) accuracy for review of listening session data
  - Minimize/manage opportunities for human bias

## Objectives:

- Derive Themes
- Determine Sentiment

| Listening Session Topic | Data Set  |
|-------------------------|---|
| Prior Authorization     | Data from several transcribed, national listening sessions summarized into one data set |

# LISTENING SESSION PROCESS

## Without AI

Conduct listening sessions with stakeholders

Transcribe recorded audio into text

**Manually** sort text snippets into thematic groups

**Manually** identify the sentiment of themes

**Retype** findings into a management summary

## With AI

Conduct listening sessions with stakeholders

Transcribe recorded audio into text

Use **NLP** to categorize data into thematic groups

Use **ML** to assign sentiment to themes

Visualize themes/sentiment; **automate reporting**

# USE HCDD AND NLP TO Find Gold In Unstructured Data

# FIND GOLD IN UNSTRUCTURED DATA THEMES

## Themes

- Derive themes within unstructured data using Natural Language Processing
- Themes are scored and ranked by Tf-Idf\* within the unstructured data

## Sub-themes

- Derive sub-themes within themes through verb/adverb/adjective proximity and word frequency
- Sub-themes are scored and ranked by frequency

\***Tf-Idf** = **Term frequency**, **Inverse document frequency** – an algorithm used to evaluate how relevant or important a term is within a data set. The importance of a word increases proportionally to the number of times that word appears in the data set but is offset by the frequency of the words in the data set.

See [Wikipedia](https://en.wikipedia.org/wiki/Tf%E2%80%93idf) at <https://en.wikipedia.org/wiki/Tf%E2%80%93idf>.

# FIND GOLD IN UNSTRUCTURED DATA HCD FOR THEMES

- Replace manual derivation of themes, which is highly prone to bias, with NLP-driven, numerically-based derivation of themes
  - Automates/accelerates the speed of extracting themes
  - Reduces bias



# FIND GOLD IN UNSTRUCTURED DATA SENTIMENT

Derive the Sentiment of unstructured data  
using machine learning instead of manual sentiment assignment,  
thereby reducing bias.

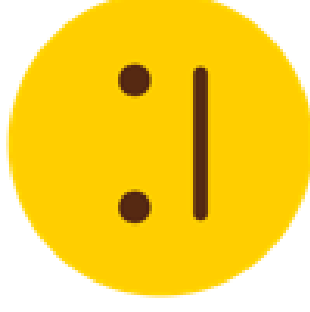
Positive



Negative

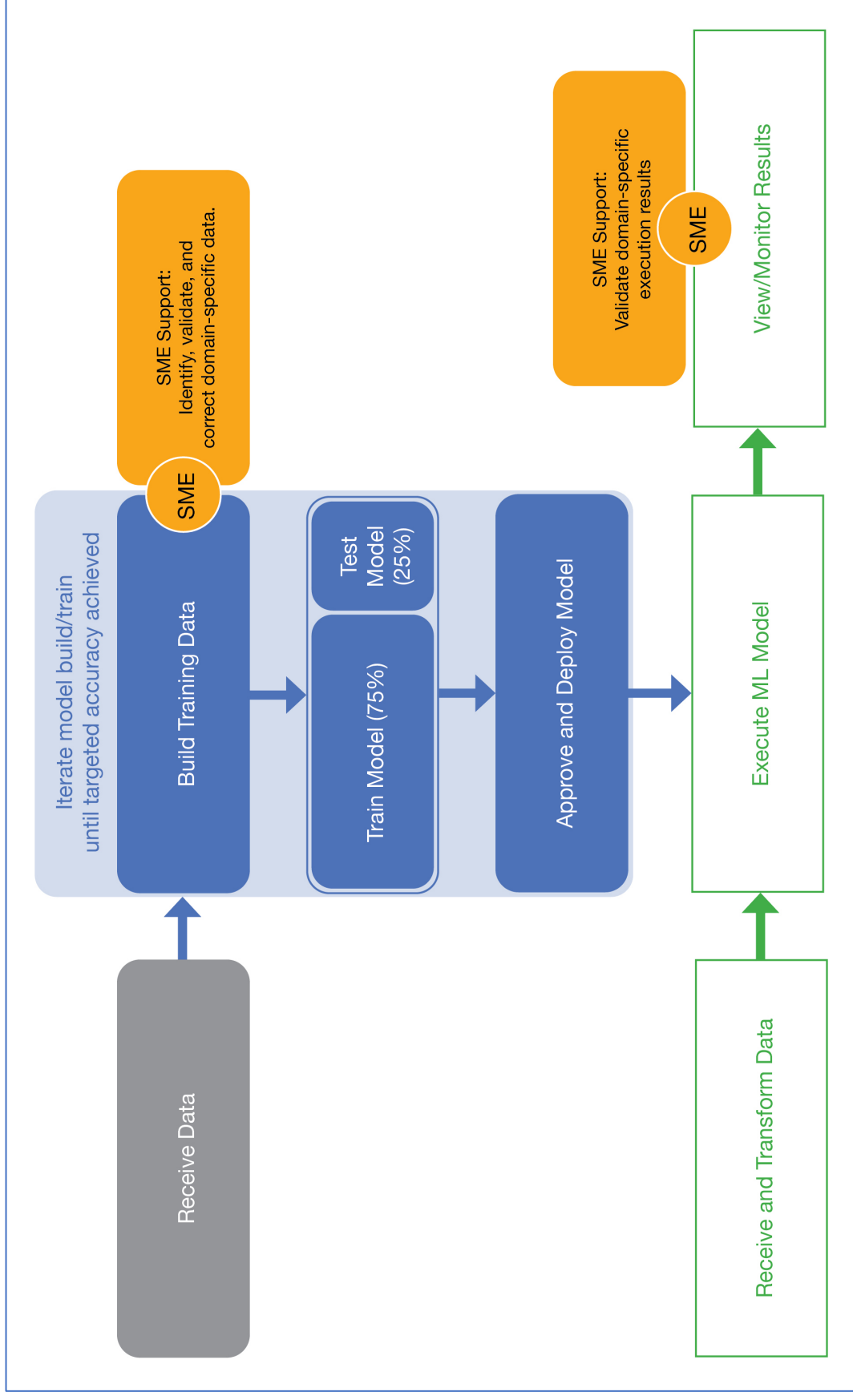


Neutral





# FIND GOLD IN UNSTRUCTURED DATA USING ML TO FIND SENTIMENT



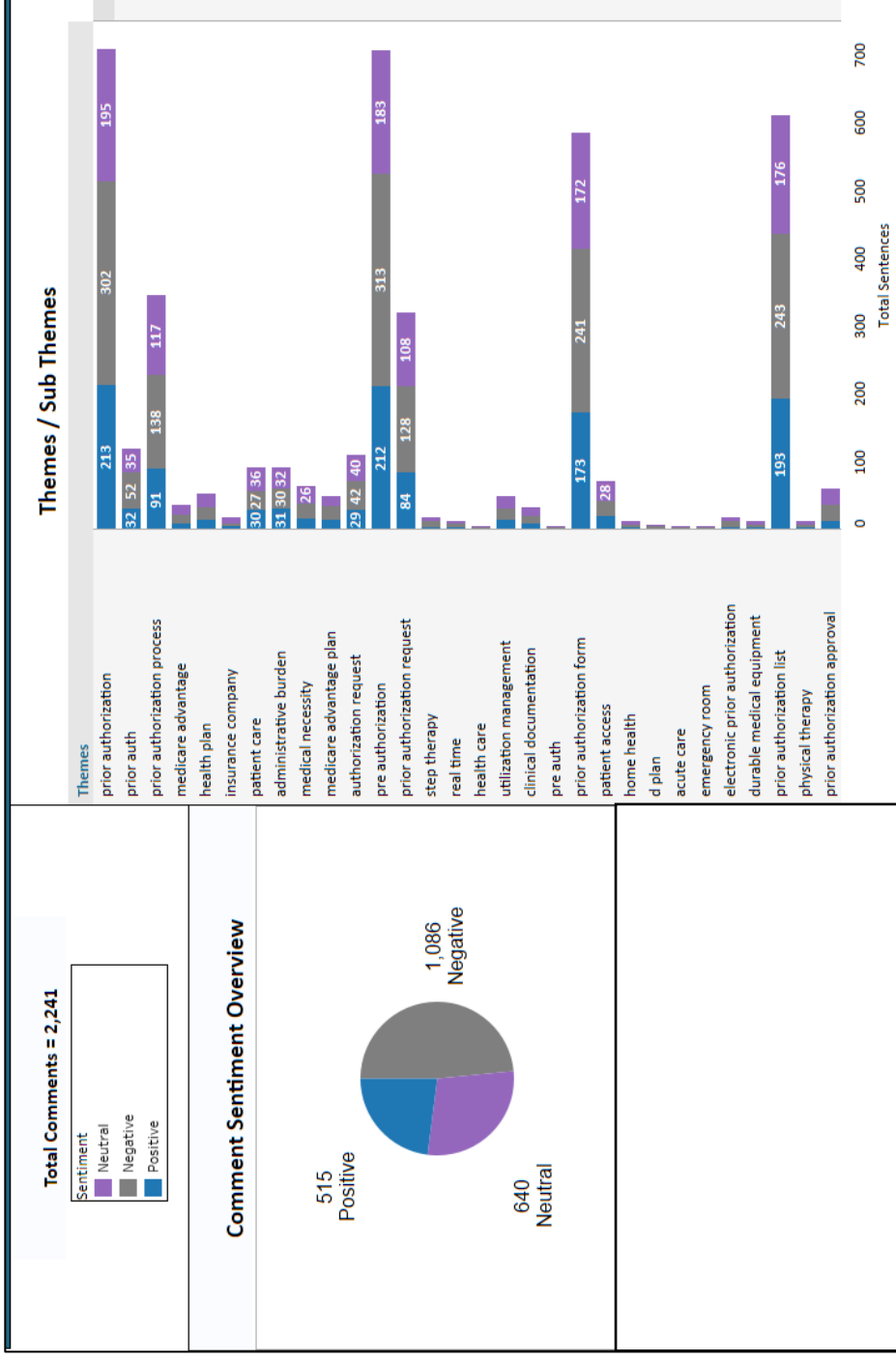
# FIND GOLD IN UNSTRUCTURED DATA

## AI MODEL ACCURACY

- Trained and executed the following models to compare results
  - BERT (Google)
  - RoBERTa (Facebook)
  - DistilBERT (A smaller and lighter version of the BERT model)
- A pre-trained model with 150 Gb of data
- Results – RoBERTa produced superior results

| Model      | Creator            | Accuracy      | F1 Score      | MCC           | Eval_Loss     |
|------------|--------------------|---------------|---------------|---------------|---------------|
| RoBERTa    | Facebook           | <b>0.8210</b> | <b>0.8210</b> | <b>0.6746</b> | <b>0.5046</b> |
| DistilBERT | Cornell University | 0.7354        | 0.7354        | 0.4932        | 0.7595        |
| BERT       | Google             | 0.7310        | 0.7310        | 0.6282        | 0.5615        |

# FIND GOLD IN UNSTRUCTURED DATA LISTENING SESSION THEMES WITH SENTIMENT



# PROJECT GOALS AND OBJECTIVES ATTAINED

## Goals achieved:

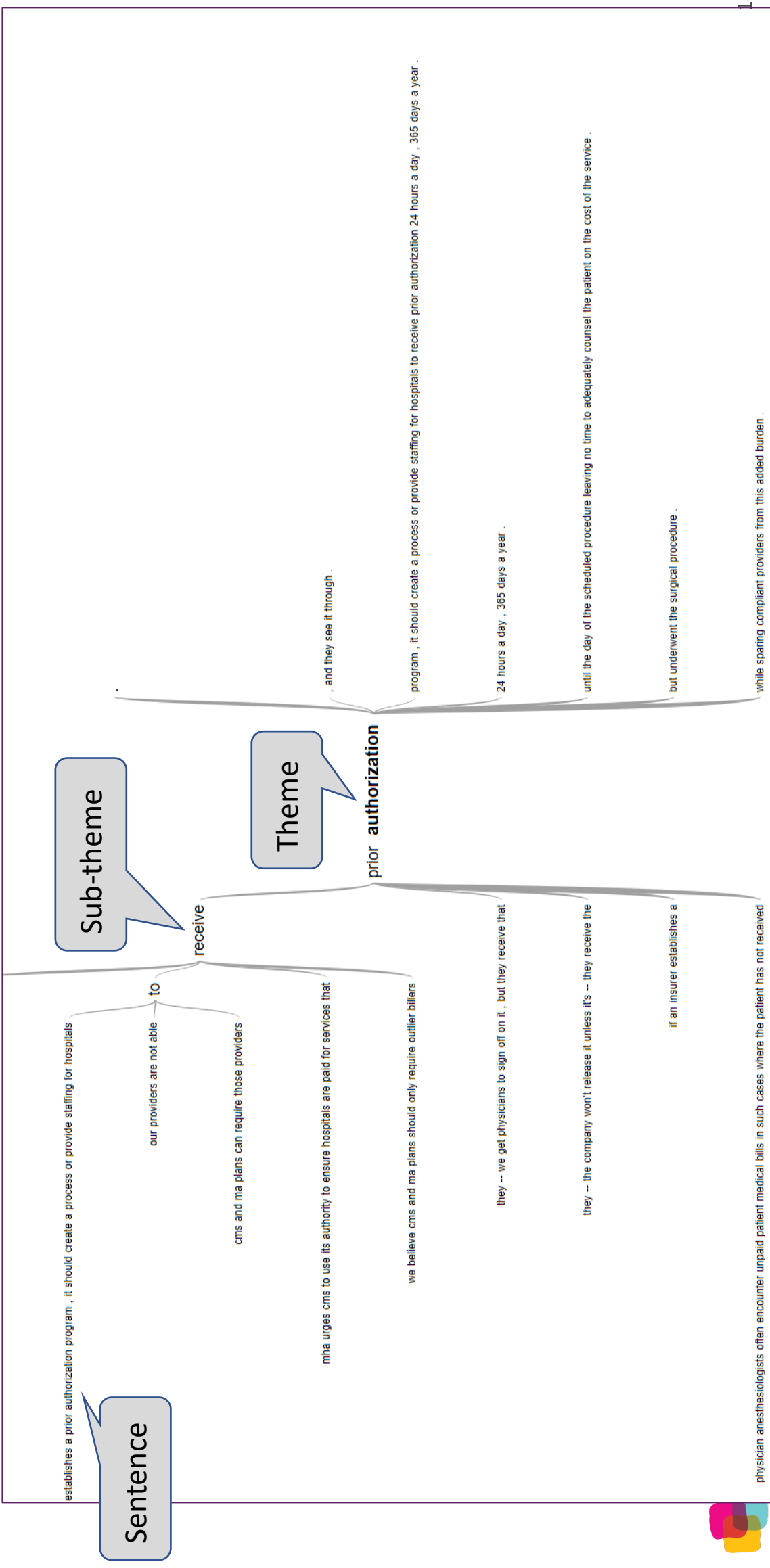
- Achieved high reliability (>80%) accuracy for sentiment assignment of listening session data
- Minimized human bias by utilizing ML and NLP modeling

| Objectives                      | Results  |
|---------------------------------|--|
| <b>Derive Themes/sub-themes</b> | <ul style="list-style-type: none"><li>• Deep learning algorithms determine the themes based on prevalence of text content and determine sub-themes based on theme proximity and frequency</li></ul>  |
| <b>Determine Sentiment</b>      | <ul style="list-style-type: none"><li>• Achieved &gt;80% accuracy</li><li>• Machine learning algorithms determine sentiment at multiple levels:<ul style="list-style-type: none"><li>• Overall sentiment</li><li>• Sentiment by themes</li><li>• Sentiment by stakeholders</li></ul></li></ul> |

# Optimize NLP Visualizations With HCD

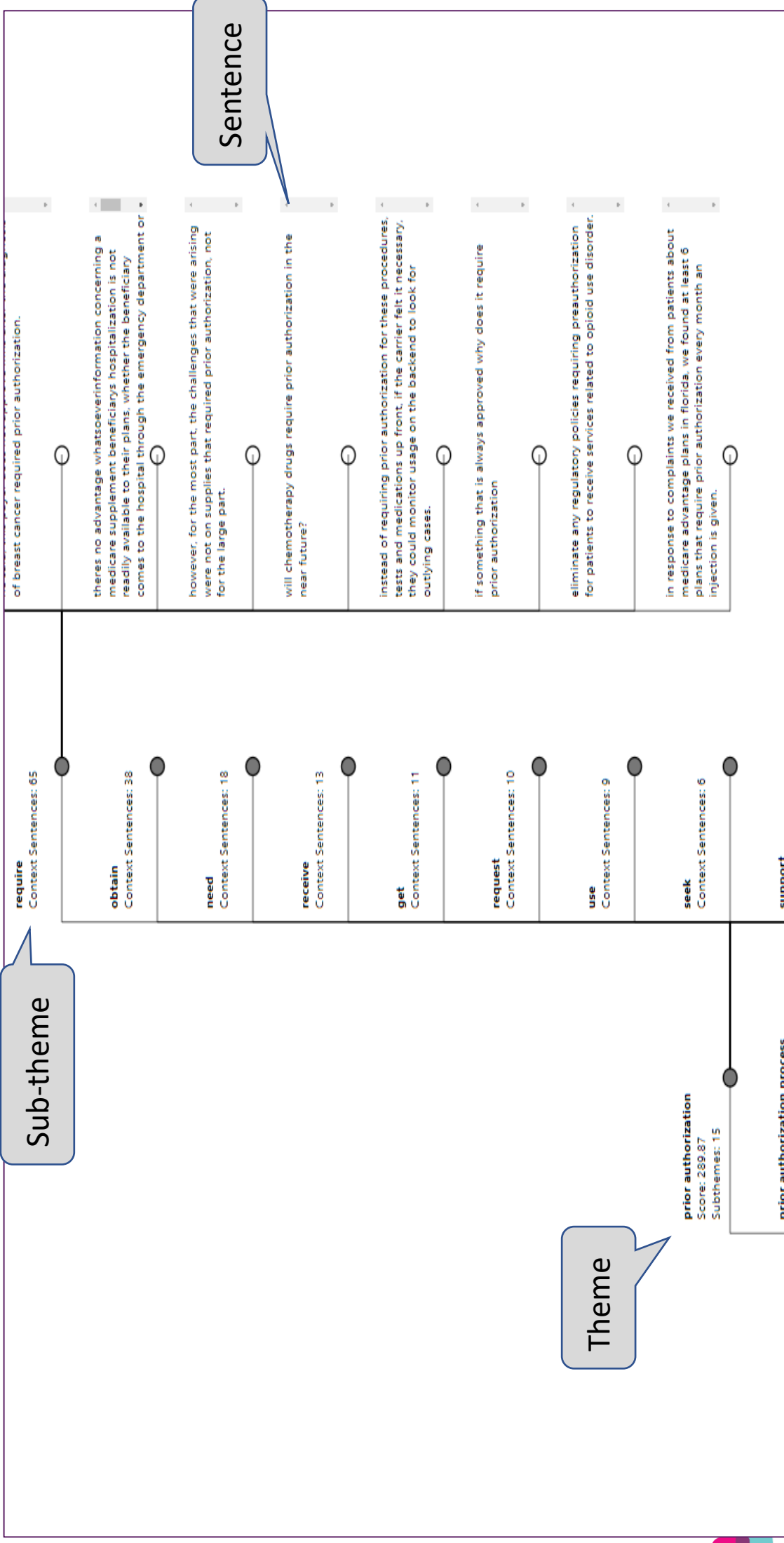
# OPTIMIZING NLP VISUALIZATIONS – ATTEMPT 1

## Themes and Sub-themes Tree View (Sentence-driven)



# OPTIMIZING NLP VISUALIZATIONS – ATTEMPT 2

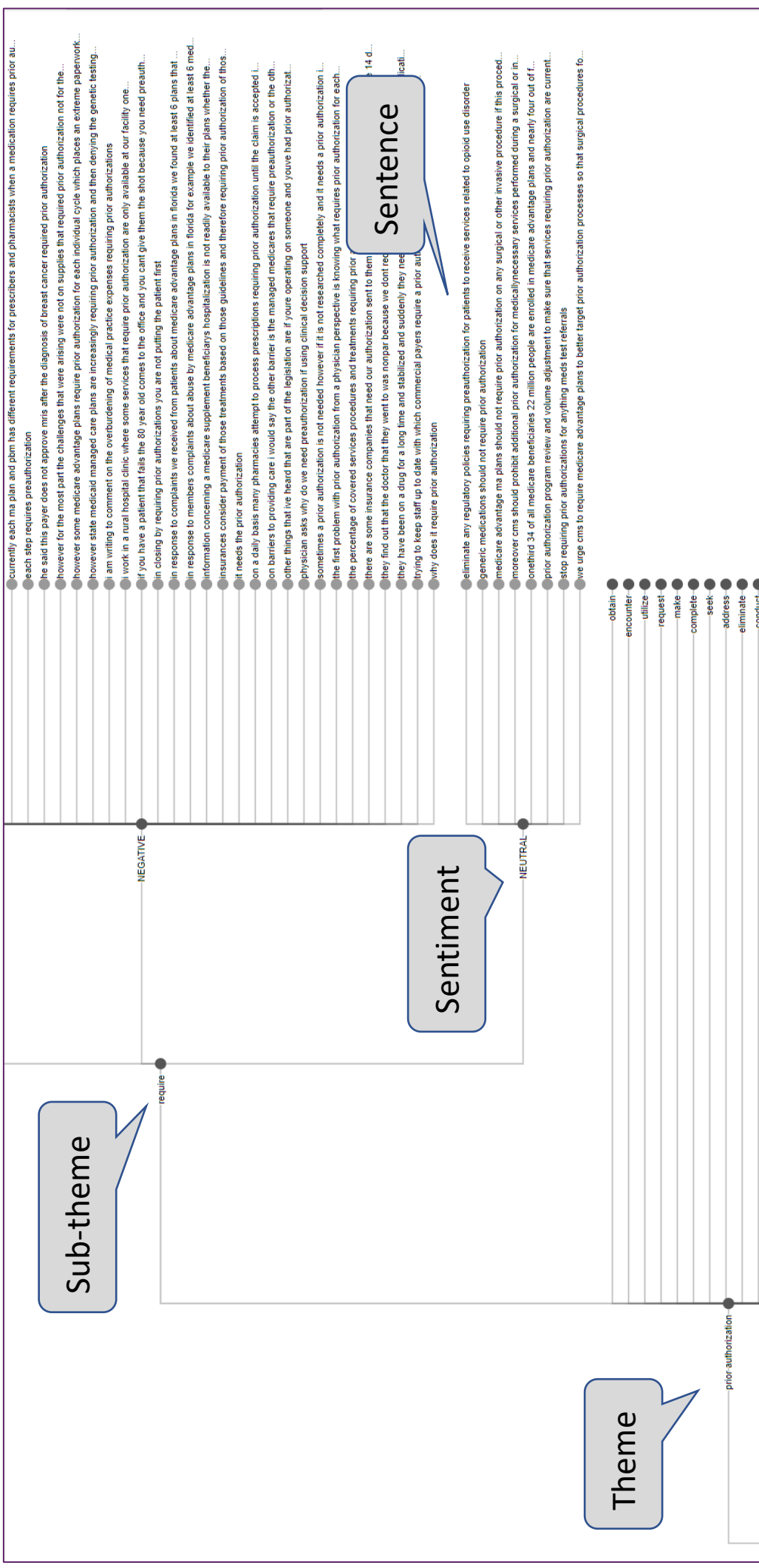
## Themes and Sub-themes (Theme-driven View)





# OPTIMIZING NLP VISUALIZATIONS -- ATTEMPT 3

## Themes and Sub-themes with Sentiment (Theme-driven View)





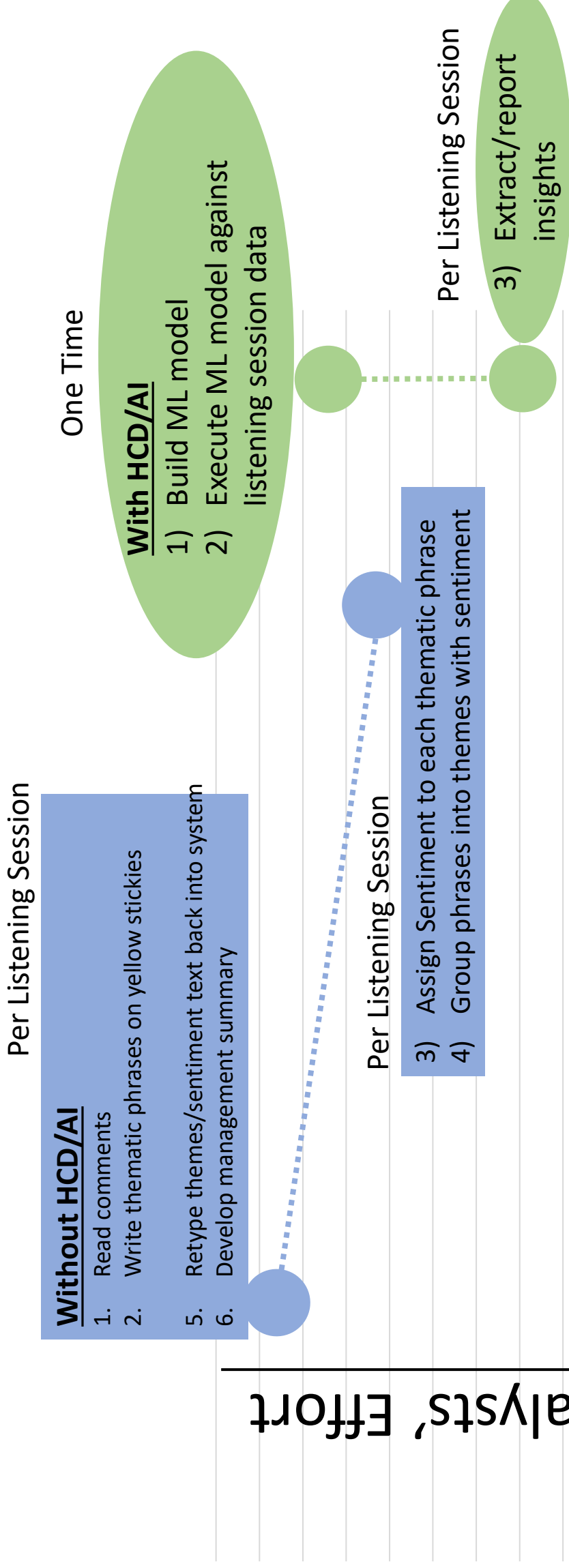
# ATTAINED PROJECT GOALS AND OBJECTIVES

## Goals achieved:

- Identified a visualization technique that made it possible to interpret listening session data with a large number of themes/sub-themes and their associated sentiment by using an interactive dashboard.

# HCD Project Outcomes

# HCD/AI MOVES ANALYSTS FROM LOW-VALUE TO HIGH-VALUE WORK



# HCD HELPS TO FIND GOLD IN UNSTRUCTURED DATA

- Artificial Intelligence automates previously manual tasks which:
  - Achieve high reliability (>80%) accuracy
  - Minimize human bias
  - Accelerate the speed of review for each listening session
  - Move analysts from low-value to high-value work
- Interactive visualizations are far superior to static visualizations by maximizing human-centered design to target insights, including:
  - Numerous filters
  - Drill-down capability (theme->sub-theme->sentiment)
- Accurate, SME-driven labelling of machine learning training data is crucial to modeling success

# ADDITIONAL HCD CONSIDERATIONS/PUZZLES

## Themes/Sentiment

- Static Data Set vs Changing Data Set
  - Changing data sets increase complexity and tracking overhead
- Subject Matter Expert Data Labelling

## Visualizations

- Multiple Months of Listening Session Data
  - Increases visualization complexity
  - How to track the review process as data changes over months



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THANK YOU

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