# Understanding the International Space Station Crew Perspective following Long Duration Missions through Data Analytics & Visualization of Crew Feedback

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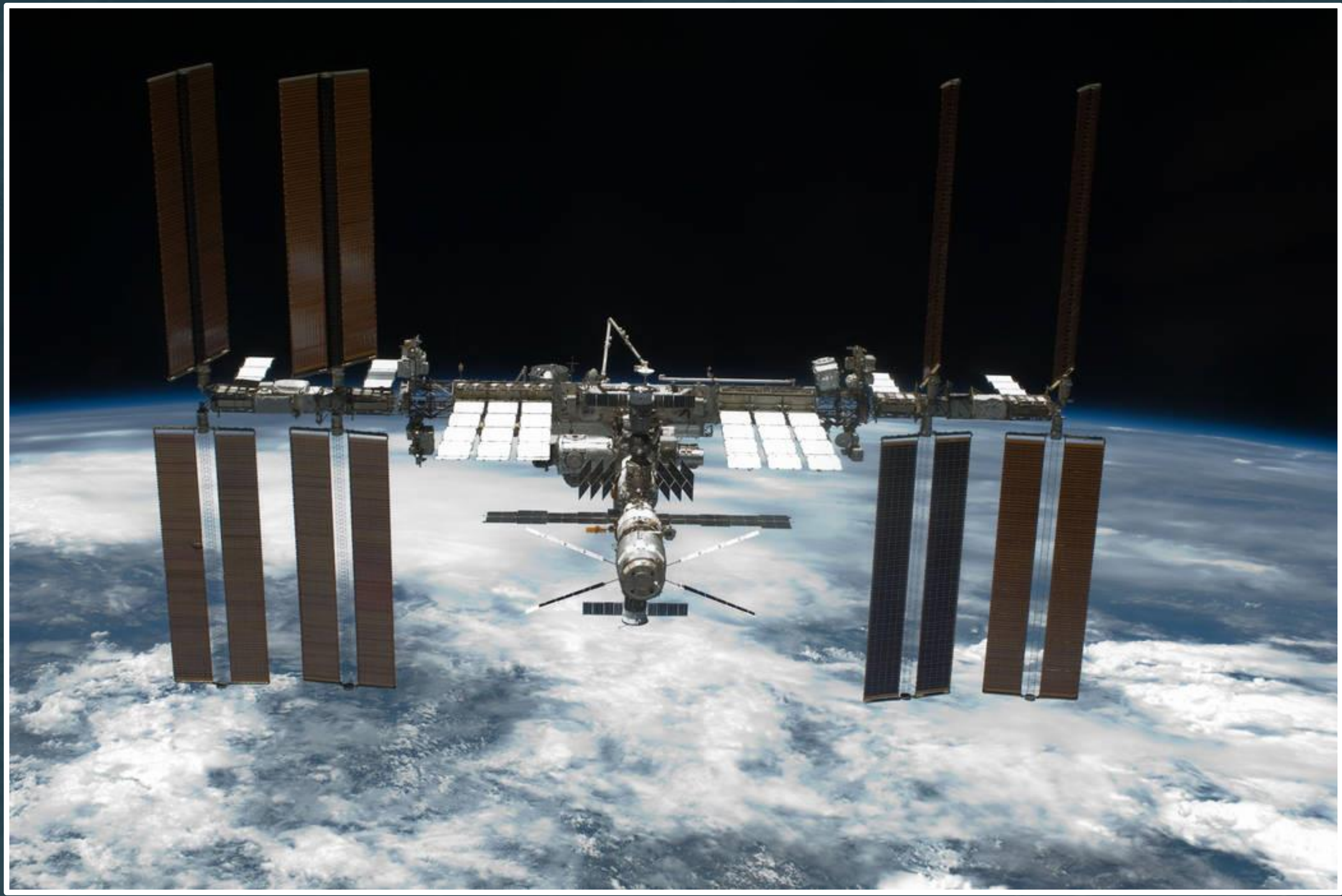


*The International Space Station as viewed by the Space Shuttle Endeavour STS-134 Crew Photo credit: www.nasa.gov*

# Background

- The International Space Station (ISS) became a home and research laboratory for NASA and International Partner crewmembers over 16 years ago.
- Currently, each ISS mission lasts about 6 months and consists of 3 to 6 crewmembers.
- At the completion of each mission, a series of 40+ debriefs are conducted with returning U.S. and International Partner crewmembers to obtain crew perspective feedback regarding working and living on board the ISS.
  - Debriefs encompass topics such as: habitability and human factors, dining, payload science, scheduling, planning, maintenance, health and safety.

# Background

- ISS postflight debrief data is governed under the Privacy Act of 1974 to allow crewmembers to speak without constraint regarding their time onboard the orbiting research laboratory.

- This protected debrief data is available only to select NASA personnel with a need to know and is collected and maintained at the Johnson Space Center by the Flight Crew Integration (FCI) Operational Habitability (OpsHab) team in the FCI ISS Crew Comments Database.

- The FCI OpsHab team works diligently to cultivate the database (which has almost 77,000 comments and is the only known ISS operations data resource of its kind) as a searchable record of life and work on board ISS and the ISS crew perspective.

This exceptionally unique collection of data is an invaluable human space flight resource for understanding how ISS crews live and work in space.

# Solving the Crew Perspective Problem

- Over the years, several attempts have been made, with limited results, to assess ISS crew perspective trends in this data in a more automated fashion:
  - Natural language processing, custom algorithms and software, and the use of basic visualizations such as word clouds.

- In June 2016, the FCI OpsHab team began collaborating with the Chief Knowledge Office (CKO).
  - The CKO team's initial efforts to develop a knowledge architecture theoretical framework have resulted in successful analysis and visualization of 75,000 ISS crew comments.
  - The initial results significantly improve on current methods and continue to evolve as the teams collaborate further.

# Challenges

- Raw text formats and the conversational nature of debriefs means the data is primarily unstructured.
- The quantity of data makes systematic human comprehension and manual assemblage of  knowledge difficult and labor intensive.
- With roughly 77,000 comments averaging 115 words, the quantity of text is roughly equivalent to over 90 copies of *To Kill a Mockingbird*.

Photo by Alec Soth

# Exploration

- How do the astronauts collectively view various topics and systems?
- What are the most important issues affecting space habitability and human factors?
- How have perceptions on various topics and systems changed over time?
- Can we automatically summarize content?
- Can we search and extract specific content or recommendations?

# Sentiment Analysis

- Sentiment analysis (sometimes known as opinion mining, polarity analysis, or emotion AI) refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information.

- Generally speaking, sentiment analysis aims to determine the attitude of a speaker, writer, or other subject with respect to some topic or the overall contextual polarity or emotional reaction to a document, interaction, or event.

# Theory

$$\delta = \frac{x_i^T}{\sqrt{n}}$$

$$x_i^T = \sum \left( \left( 1 + c\left( x_i^A - x_i^D \right) \right) * w \; (-1)^{\sum x_i^n} \right)$$

$$x_i^A = \sum (w_{neg} * \; x_i^a)$$

$$x_i^D = max(x_i^{D'}, -1)$$

$$x_i^{D'} = \sum (-w_{neg} * \; x_i^a + x_i^d)$$

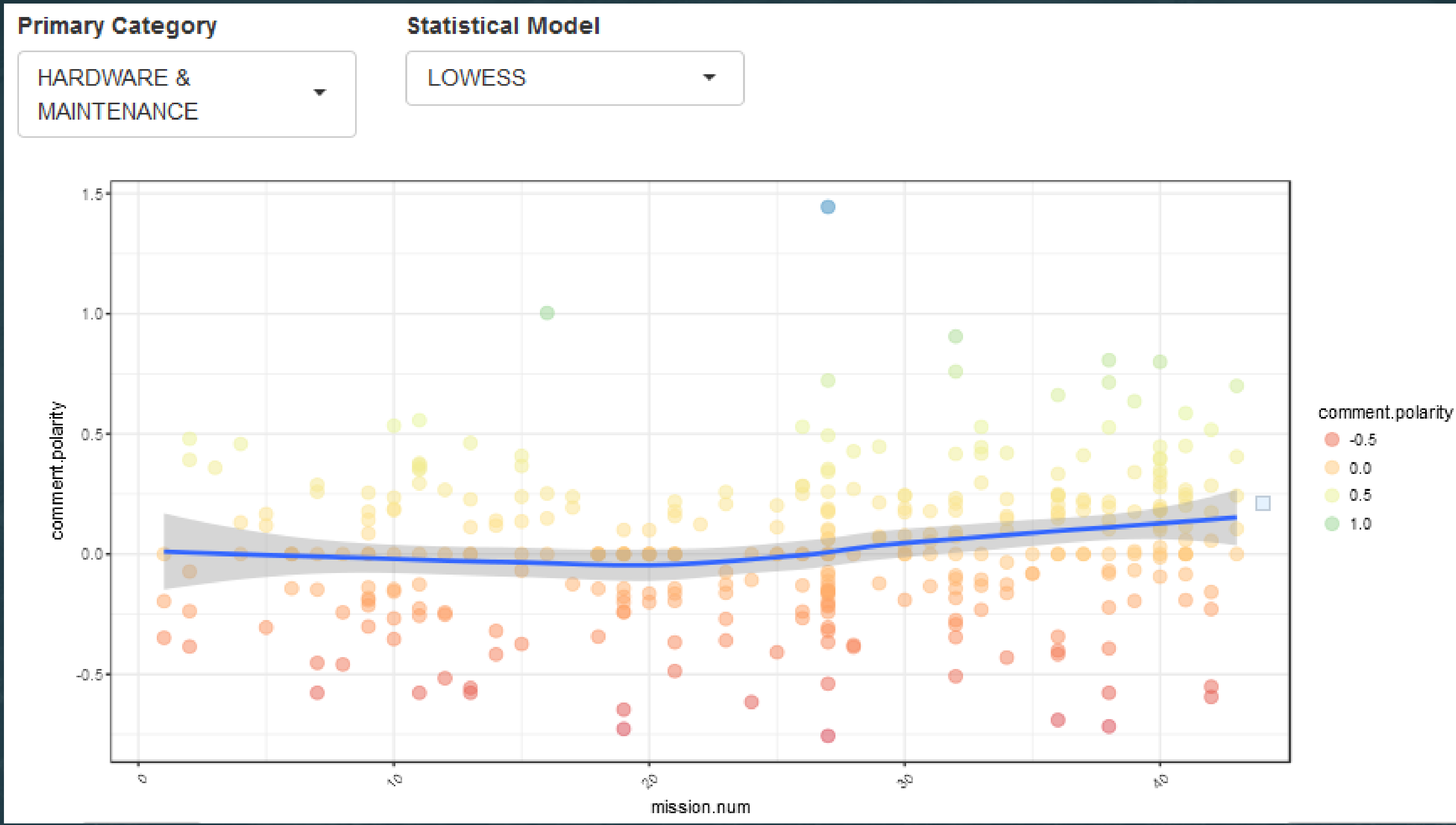
$$w_{neg} = (\sum x_i^N) \; mod \; 2$$

The algorithm utilizes a sentiment dictionary to tag polarized words. A context cluster of words is pulled from around this polarized word and are tagged as neutral, negator, amplifier, or de-amplifier. Each polarized word is then weighted by the number and position of the valence shifters directly surrounding the positive or negative word. Last, these context clusters are summed and divided by the square root of the word count, yielding an unbounded polarity score.

# Theory

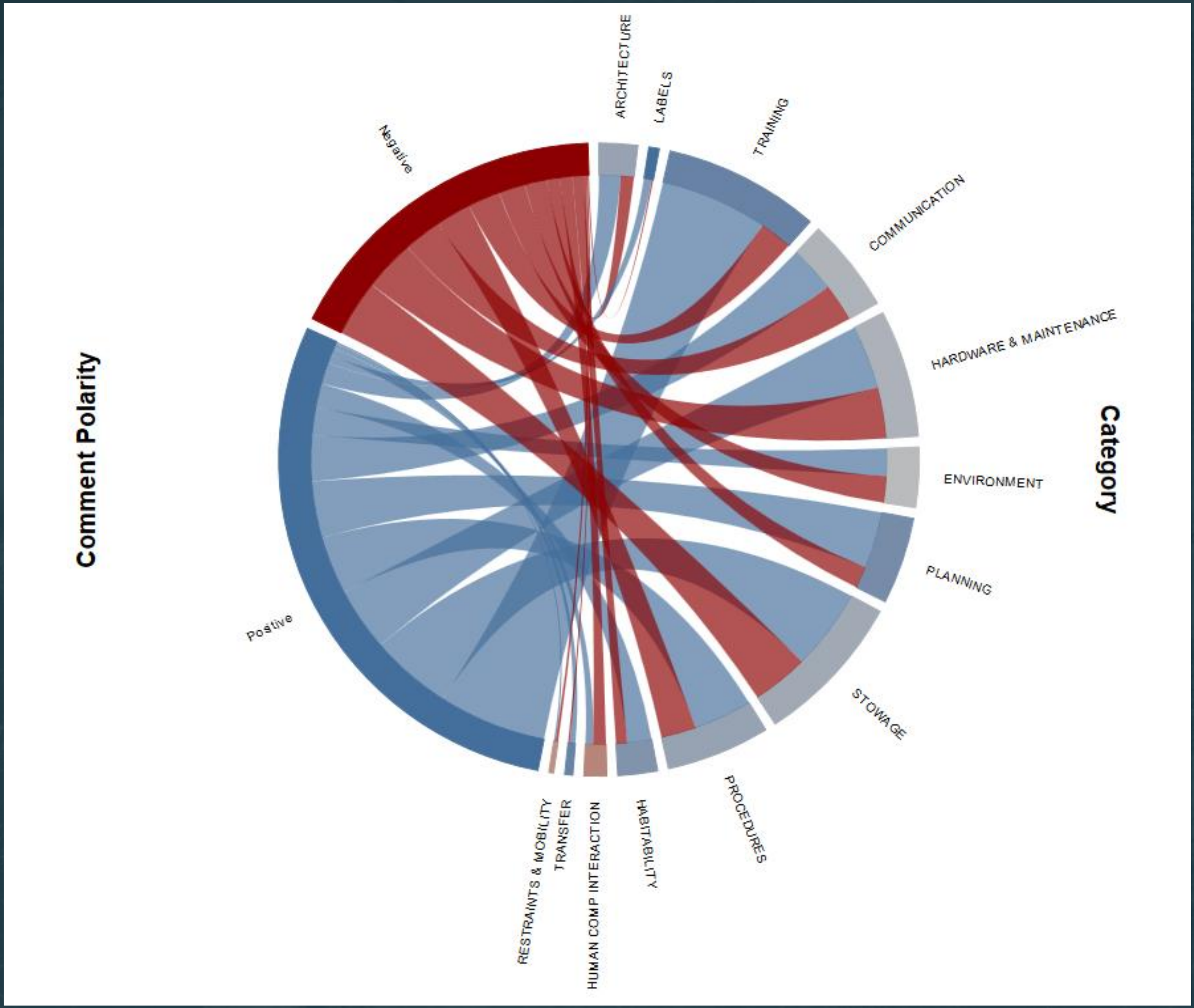
| Sentence | Word Demonstration | Score |
|---|---|---|
| I love ISS | positive polarized word | 0.577 |
| I hate ISS | negative polarized word | -0.577 |
| I barely love ISS | de-amplifier & polarized word | 0.100 |
| I really love ISS | amplifier & polarized word | 0.900 |
| I am the ISS | neutral | 0.000 |
| I don’t love ISS | negator & polarized word | -0.500 |
| I don't not love ISS | negator & negator & polarized word | 0.447 |
| I love ISS and I hate Monday | polarized word & polarized word | 0.000 |

# Polarity



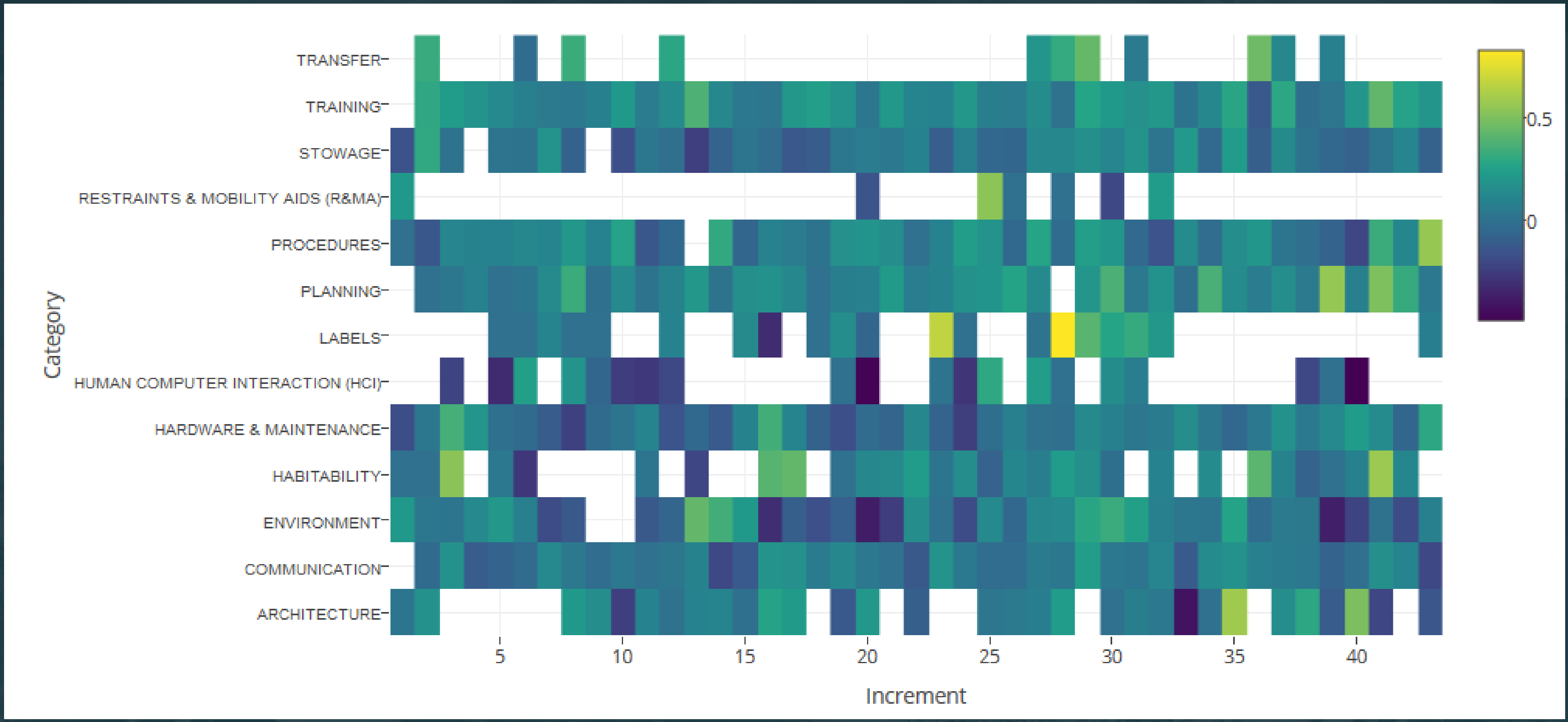
Primary Category
HARDWARE & MAINTENANCE
Statistical Model
LOWESS
comment.polarity
mission.num
1.5
1.0
0.5
0.0
-0.5
0
10
20
30
40
comment.polarity
-0.5
0.0
0.5
1.0

# Polarity



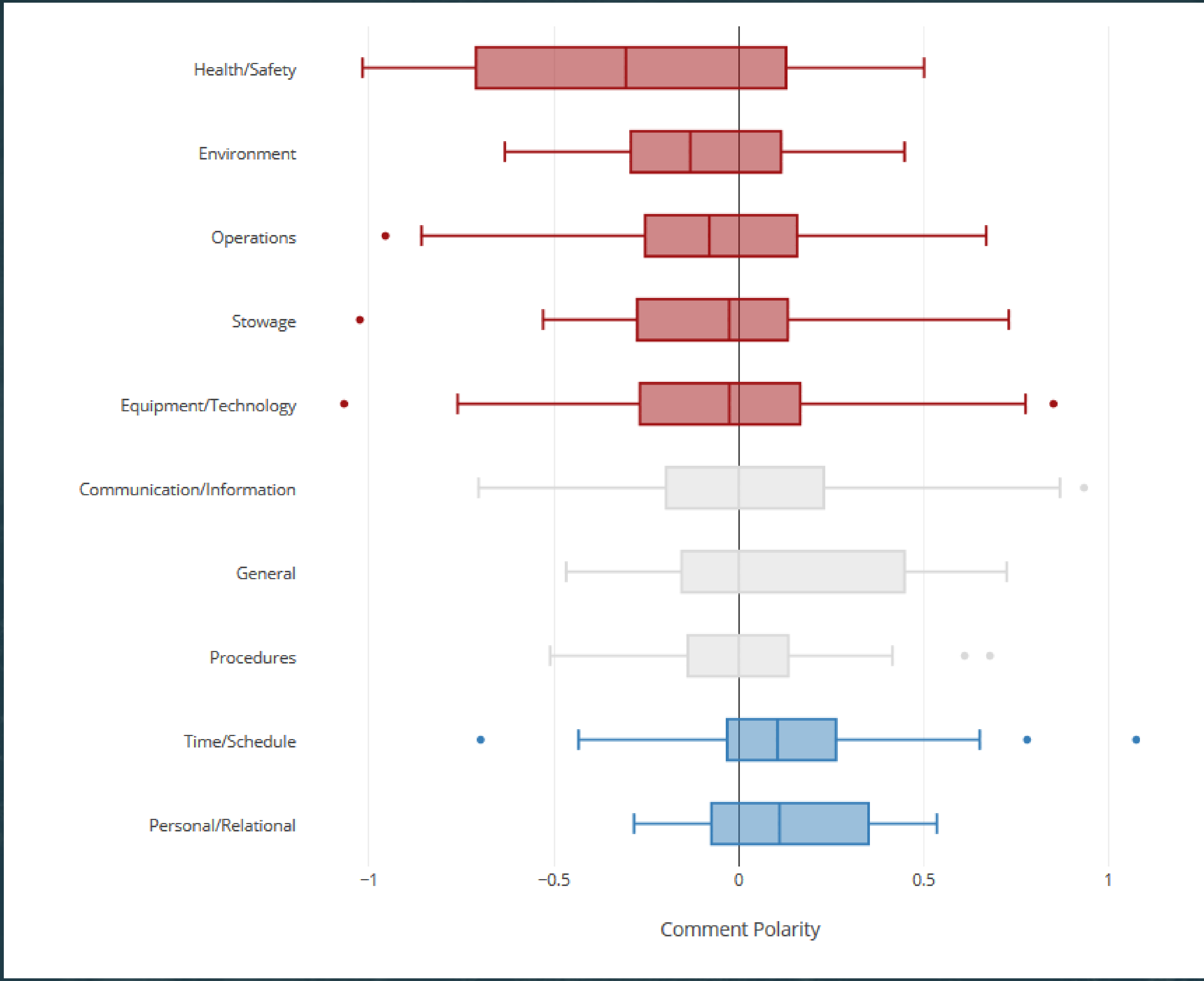
Comment Polarity
Negative
Positive
Category
ARCHITECTURE
LABELS
TRAINING
COMMUNICATION
HARDWARE & MAINTENANCE
ENVIRONMENT
PLANNING
STOWAGE
PROCEDURES
HABITABILITY
HUMAN COMP INTERACTION
TRANSFER
RESTRAINTS & MOBILITY

# Polarity



TRANSFER
TRAINING
STOWAGE
RESTRAINTS & MOBILITY AIDS (R&MA)
PROCEDURES
PLANNING
LABELS
HUMAN COMPUTER INTERACTION (HCI)
HARDWARE & MAINTENANCE
HABITABILITY
ENVIRONMENT
COMMUNICATION
ARCHITECTURE
Category
5
10
15
20
25
30
35
40
Increment
0.5
0

# Polarity



Health/Safety
Environment
Operations
Stowage
Equipment/Technology
Communication/Information
General
Procedures
Time/Schedule
Personal/Relational
−1
−0.5
0
0.5
1
Comment Polarity

# Search & Extraction

| Comment | "I" | "like" | "hate" | "ISS" |
|---|---|---|---|---|
| $X_1$ | 1 | 1 | 0 | 1 |
| $X_2$ | 1 | 0 | 1 | 1 |

We can weight comments or documents:

$$tfidf(t,d,D) = tf(t,d) * idf(t,D)$$

Where:

$tf(t,d)$ is the raw frequency of a term in a documents

$idf(t,d) = \log\left[\frac{N}{1+d\epsilon D:t\epsilon d}\right]$

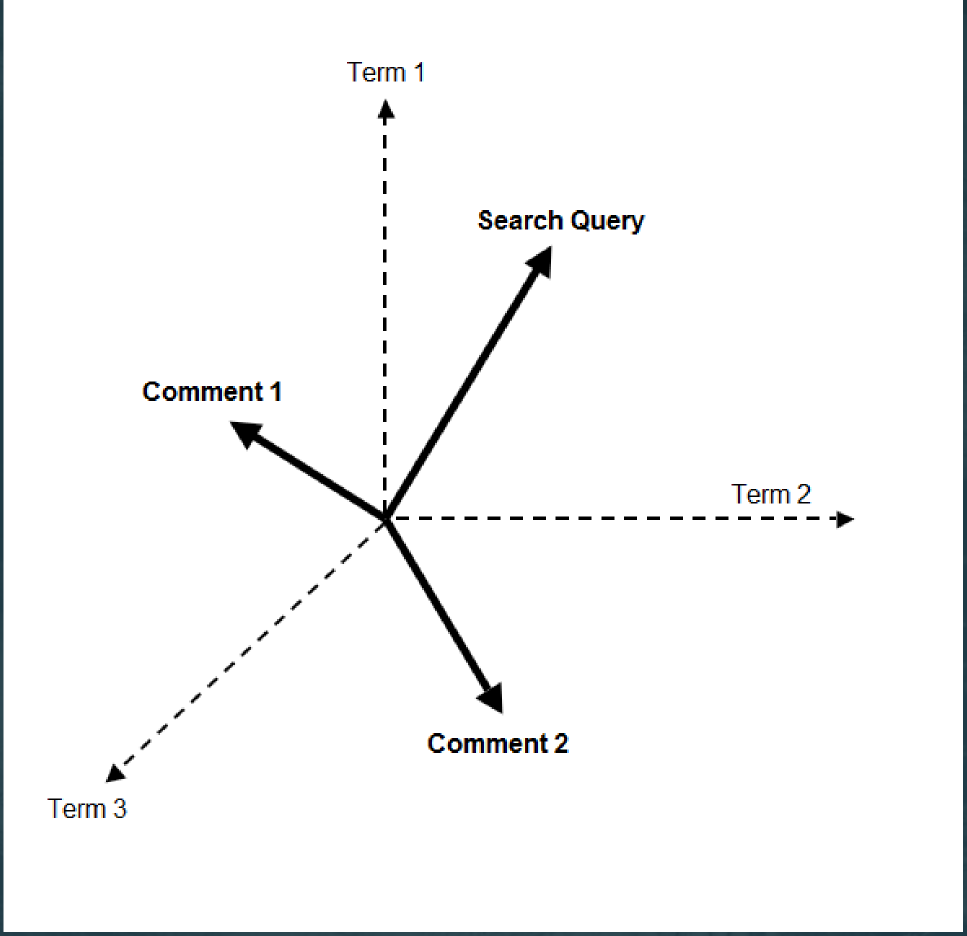
$N$: total number of comments

$|d \epsilon D : t \epsilon d|$ is the number of documents where the term $t$ appears

# Search & Extraction

Once the weightings have been established, we can compare the similarity of the vectors in the document term vector space. The way we compare the similarity of the vectors is by using the cosine similarity:

$$\cos(\theta) = \frac{\vec{A} * \vec{B}}{\|\vec{A}\| * \|\vec{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$



# Search & Extraction

## Search for “Food”

[illegible] food warmer [illegible] food [illegible]

[illegible] food [illegible] food warmer [illegible]

[illegible] food was great. [illegible] ate well [illegible] eat everything [illegible] food [illegible] eat [illegible] food [illegible] food.

# Classification

Another way to learn from the data is through the use of classification.

Consider the two very brief comments:

1) $X_1$ = I like ISS

2) $X_2$ =I hate ISS

We can encode this information in a matrix as follows:

| Comment | "I" | "like" | "hate" | "ISS" |
|---|---|---|---|---|
| $X_1$ | 1 | 1 | 0 | 1 |
| $X_2$ | 1 | 0 | 1 | 1 |

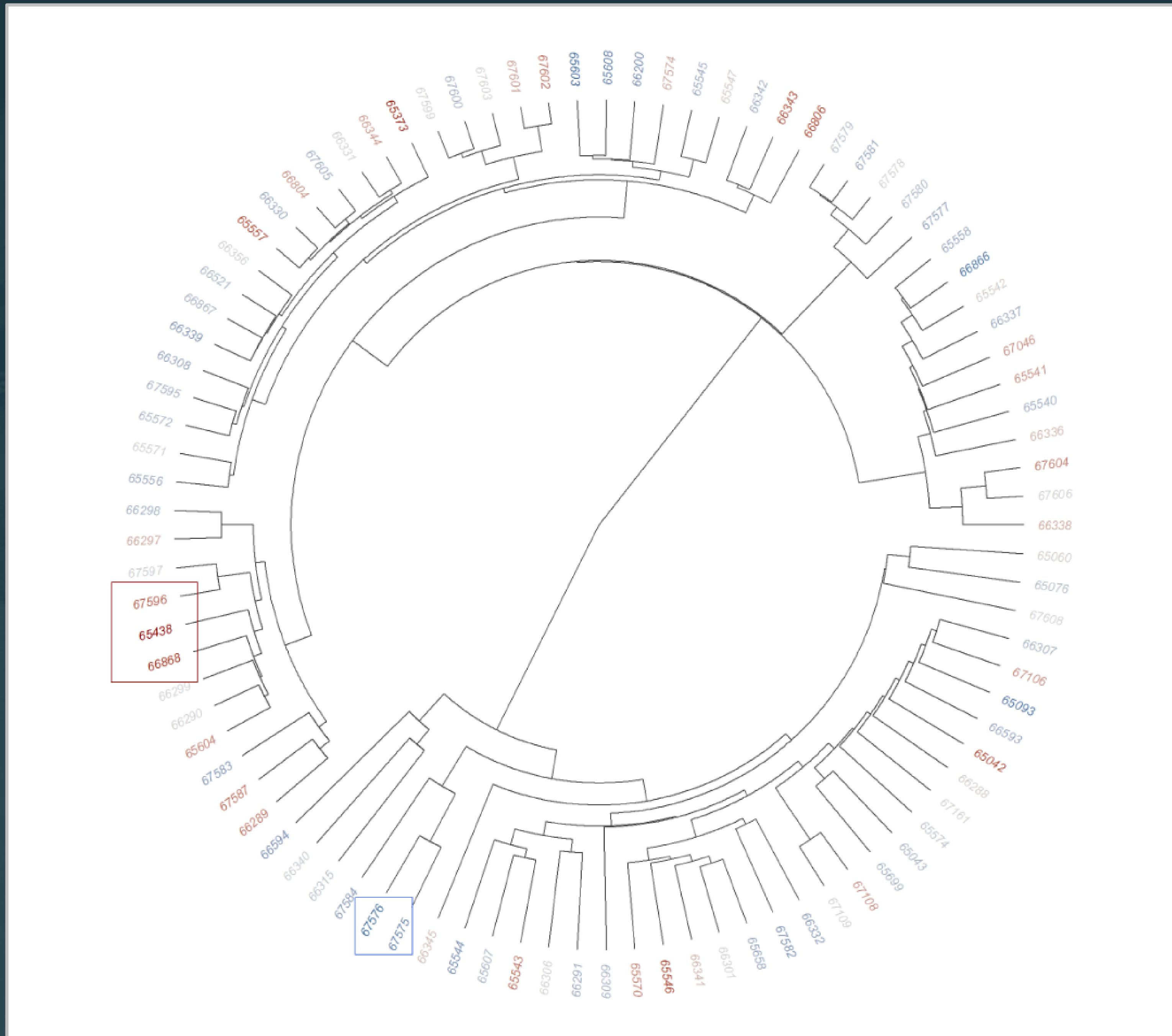
# Classification

Ward's method begins with all clusters as a singletons. A recursive algorithm is applied to minimize the total within-cluster variance. The initial cluster distances in Ward's minimum variance method are therefore defined to be the squared Euclidean distance between points:

$$d_{ij} = d(\{X_i\}, \{X_j\}) = \|X_i - X_j\|^2$$

See “Lance–Williams algorithms” for implementation details

A dendrogram is used to visualize the cluster. The horizontal axis (or arm length of the radial lines) represents the distance or dissimilarity between clusters. The vertical axis (or radial circumference) represents the objects and clusters. Each joining (fusion) of two clusters is represented on the graph by the splitting of a radial. The horizontal position of the split, shown by the angle, gives the distance (dissimilarity) between the two clusters.




# Classification

# Classification

[illegible] experienced high noise levels [illegible] noise behind the SM panels [illegible]

[illegible] WHC fan noise [illegible] resident tone. [illegible] grinding noise [illegible] hum [illegible]

[illegible] noise constraint [illegible] noise clock running [illegible] noise in the Lab [illegible] absorbs sound [illegible] silent. [illegible] noise [illegible] making noise.

# Future Work

This initial effort could take many directions to provide tangible benefits to human spaceflight programs:

- Use of readability measurements or keyword density of a crewmember's transcript and/or speech patterns.
- Assessment of other crew perspective data sources.
- Further automation of Data Science processes via the development of applications that facilitate their reuse, and by making many of the techniques used more accessible to other professionals.
- Improvement of the performance for the models used to determine sentiment, identification of various issues, and trends.

# Conclusions

- The ISS postflight debrief data is critical for current and future designs (e.g. hardware and software) and emphasizes the importance of applying data analytic and visualization methods to determine important crew perspective findings, over time.

- Efficiencies gained from the CKO-provided analysis and visualization methods include time savings and error minimization, thorough knowledge capture and useful summarization of key findings. This also allows ~~for~~ optimized information presentation and utilization.

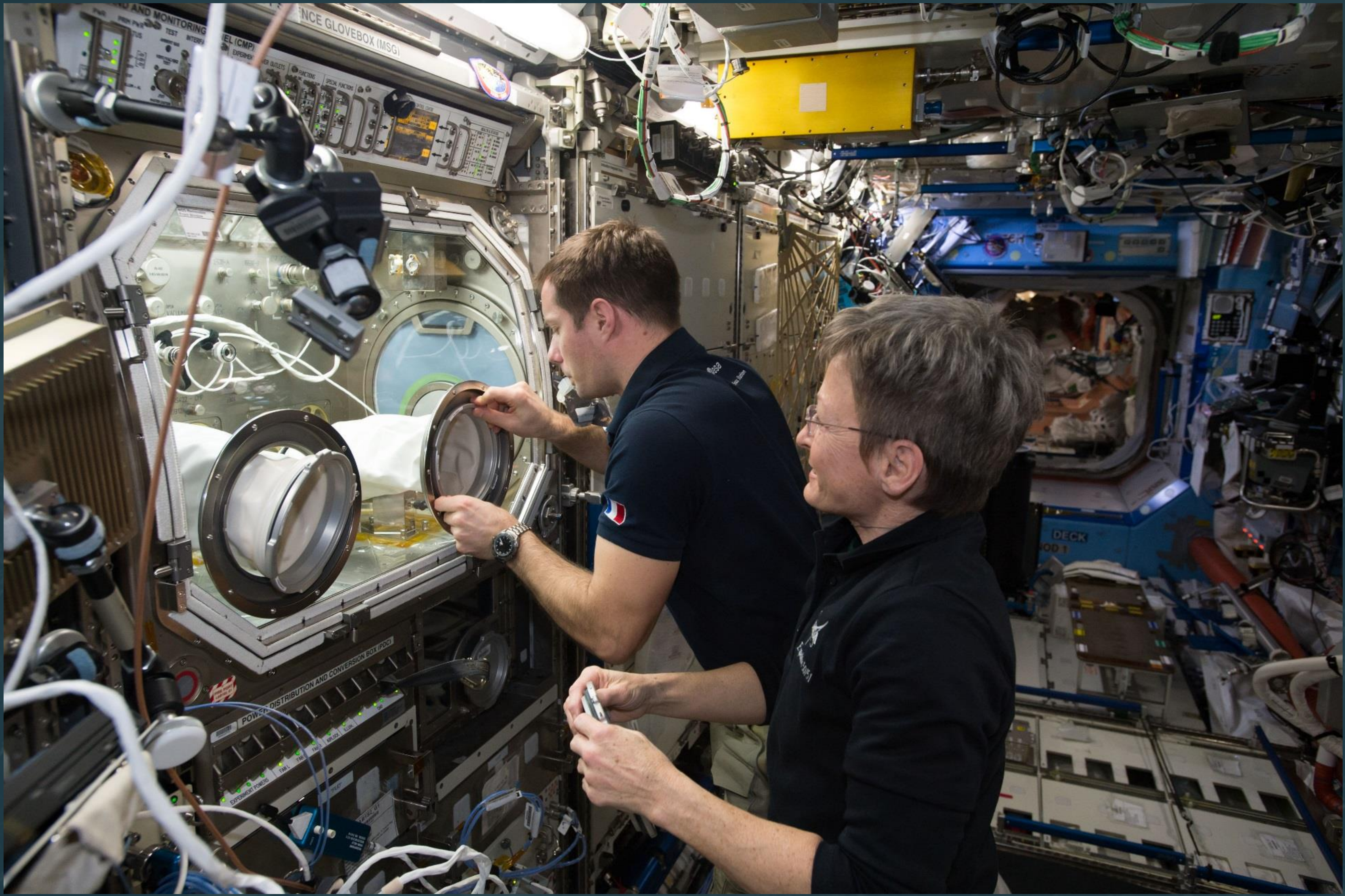
- Potential biases are also minimized ~~when compared~~ relative to manually reading all available comments and maintaining vigilance.

# Conclusions

- These data analytic and visualization methods can be used with other qualitative data sets developed from task analysis, workload analysis or other knowledge elicitation methods that yield large amounts of qualitative data.

- This collaborative effort between the FCI OpsHab team and the CKO is beneficial in many ways including:
  - Cultivating a customized solution to support human spaceflight design and development with Habitability & Human Factors and Knowledge Management expertise.
  - Improving upon an emergent history of ISS crew perspective feedback for reference and use in current and future spaceflight programs.

# Questions?



*The ISS US Operating Segment (USOS) Expedition 50 crew works in the Microgravity Science Glovebox in the US Lab. Photo credit: www.nasa.gov*

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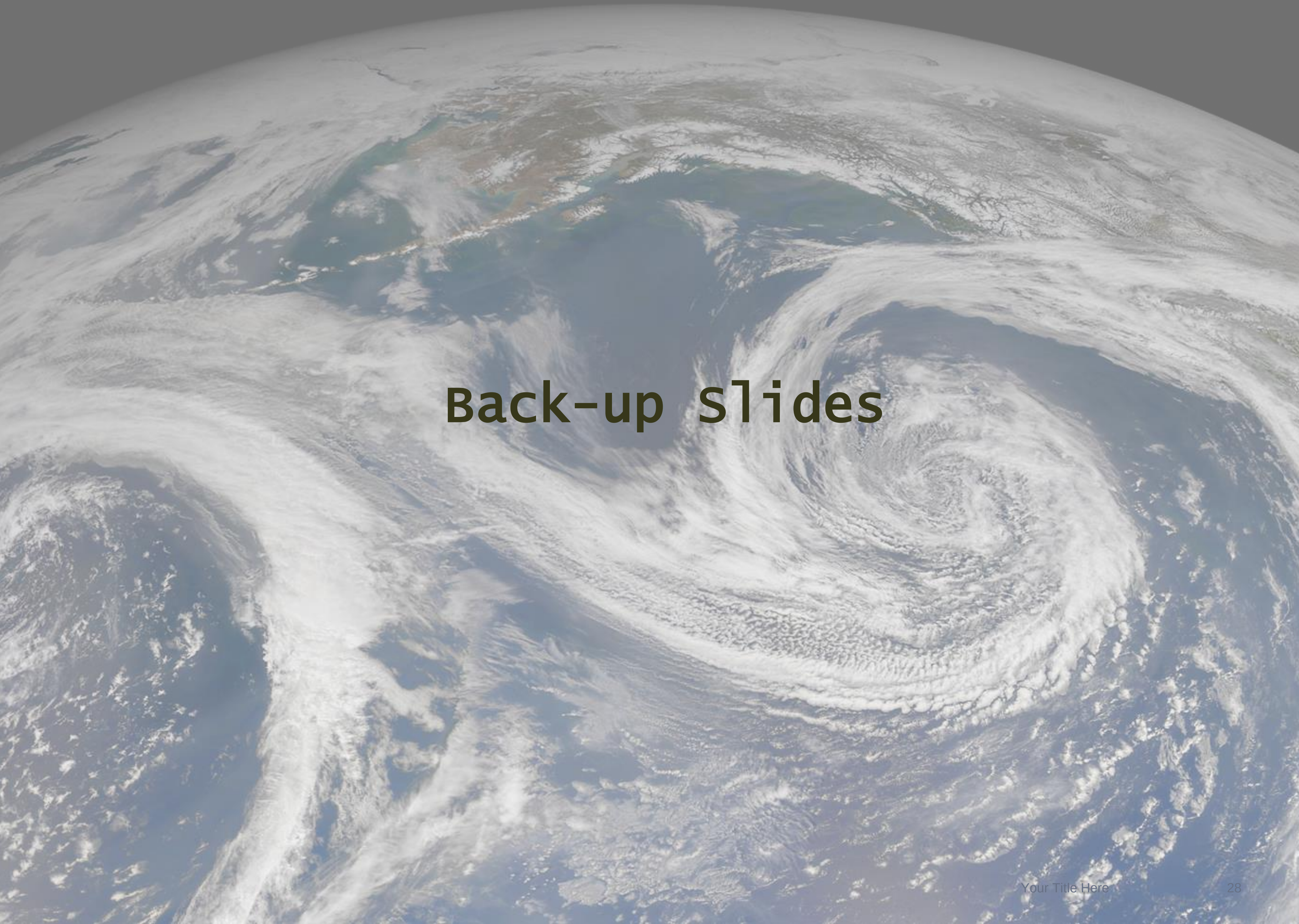

# Back-up Slides

# Example Implementation

```r
# Load libraries
library(qdap)

# Define a comment (Anders during Apollo 8 Debrief)
comment <- c("Chlorine procedure was a pain in the neck and I
think a dangerous one in that you might squirt chlorine around.
There was some chlorine on our hands. It is unfortunate we have
to do this. The injection port adapter seems to be loose in the
pipe neck and was tightened once by the LMP.")

# Extract Sentences
sentences <- sent_detect(comment)

# Apply polarity algorithm to each sentence
scores <- lapply(sentences, function(x){polarity(x)$group[,4]})
```

```
[1] -0.44  0.00 -0.35 -0.23
```

# Example Implementation

```r
# Load libraries
library(tm)
library(ape)

# Create Corpus
docs <- Corpus(VectorSource(documents))

# Clean up documents
docs <- tm_map(docs, content_transformer(tolower))
docs <- tm_map(docs, removePunctuation)
docs <- tm_map(docs, removeNumbers)
docs <- tm_map(docs, removeWords, tm::stopwords("english"))
docs <- tm_map(docs, stripWhitespace)
docs <- tm_map(docs, stemDocument)

# Perform Clustering
dtm <- DocumentTermMatrix(docs)
m <- as.matrix(dtm)
d <- dist(m)
groups <- hclust(d, method="ward.D")

# plot
plot(as.phylo(groups), type="fan")
```

# Natural Language Search

- Rather than only searching for documents with specific key words and morphological variations of these words, Natural Language Search looks for sentences where the query words are in a specific *relationship* – one that conveys the query meaning
- The *semantic structures* (i.e. the Subject, the Action, and the Object) determine if sentences and text have matching meanings, regardless of the numerous grammatical variations in sentences

The query ***apply pulse laser*** on a technical database might return:

*…the semiconductor film is heated and molten in a short time by **applying** an excimer **pulse laser** to the amorphous semiconductor film…*

But would devalue a return like:

…the **pulse laser** project's schedule **applied** a lot of pressure on management to bypass important testing requirements…

Because the project schedule is applying pressure, as opposed to the pulse laser itself. This reduction in irrelevant search results increases precision of what is returned

# Emotion Detection

- There have been some efforts to capture crew comments and feedback in the form of video responses.
- This presents a number of challenges for quantitative analysis.
- There are numerous algorithms and approaches to identifying both faces and facial landmarks (see geometric methods, eigenface methods, Gabor wavelets, discrete cossinus transforms, local binary patterns).
- This demonstration uses the Project Oxford algorithms (Microsoft Cognitive Services). The emotion classification is performed using supervised machine learning on facial landmark data, and a confidence score is given for each emotion.