STAT325: Analysis of Frankenstein

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Introduction

Frankenstein; or, The Modern Prometheus (Shelley 1818), written by Mary Shelley in 1818, is a groundbreaking work in the literary world that interweaves elements of Gothic literature with early ideas of science fiction. The novel tells the cautionary tale of Victor Frankenstein, a scientist who creates a sentient being, only to reject it which leads to tragic consequences for both the creator and the creature. The novel explores themes of ambition, responsibility, and the search for identity. *Frankenstein* has become an important dialogue about the limits of scientific exploration, the responsibilities of creators, and the societal implications of isolation and rejection. It raises essential questions about the nature of humanity, the pursuit of knowledge, and the consequences of ambition unhindered by ethical considerations. Additionally, *Frankenstein* has had an enduring influence on popular culture and media. The narrative unfolds through the perspectives of three distinct narrators: Captain Robert Walton, Victor Frankenstein, and The Creature. The use of multiple narrators allows Shelley to explore different viewpoints and layer the narrative with complex emotions and ethical questions, providing a rich tapestry of human experience and moral contemplation. Each narrative reflects each individual's experiences, biases, and emotional states, contributing to a many different perspectives of the same story. For this analysis, I would like to see if the sections told by different narrators vary from each other. An short example of the first couple of lines of each narrator's first section is shown in Table 1.

```
get_first_n_lines <- function(section_number, letter_or_chapter, n) {
  # Filter data for the specific section and section type

  section_data <- Frankenstein |>
    filter(section == section_number, section_type == letter_or_chapter)

  # Extract the first n lines of text, if there are at least n lines available
  if (nrow(section_data) >= n) {
    lines <- section_data$text[1:n]
  } else {
    lines <- section_data$text[1:nrow(section_data)]
  }
  combined_lines <- paste(lines, collapse = " ")
  combined_lines <- paste0(combined_lines, " ...")
  return(combined_lines)
}
```

```
example_text <- tibble(
  Narrator = c("Captain Robert Walton", "Victor Frankenstein", "The Creature"),
  `Example Text` = c(get_first_n_lines(1, "letter", 15), # Walton's first POV
                    get_first_n_lines(1, "chapter", 15), # Victor's first POV
                    get_first_n_lines(11, "chapter", 15)) # Creature's first POV
)

# Create the table
example_text |>
  kableExtra::kable(booktabs = TRUE, format = "latex",
                    linesep = "\\addlinespace",
                    caption = "Example Narrative Sections in Frankenstein") |>
  kableExtra::column_spec(1, width = "3cm") |>
  kableExtra::column_spec(2, width = "12cm") |>
  kableExtra::kable_styling(latex_options = "scale_down")
```

Methods

The novel is told using a framing device which is basically a story within a story within a story. More specifically, the narrators for each section are as follows:

Table 1: Example Narrative Sections in Frankenstein

Narrator	Example Text
Captain Robert Walton	Letter 1 _To Mrs. Saville, England._ St. Petersburgh, Dec. 11th, 17—. You will rejoice to hear that no disaster has accompanied the commencement of an enterprise which you have regarded with such evil forebodings. I arrived here yesterday, and my first task is to assure my dear sister of my welfare and increasing confidence in the success of my undertaking. I am already far north of London, and as I walk in the streets of ...
Victor Frankenstein	Chapter 1 I am by birth a Genevese, and my family is one of the most distinguished of that republic. My ancestors had been for many years counsellors and syndics, and my father had filled several public situations with honour and reputation. He was respected by all who knew him for his integrity and indefatigable attention to public business. He passed his younger days perpetually occupied by the affairs of his country; a variety of circumstances had prevented his marrying early, nor was it until the decline of life that he became a husband and the father of a family. As the circumstances of his marriage illustrate his character, I cannot refrain from relating them. One of his most intimate friends was a ...
The Creature	Chapter 11 “It is with considerable difficulty that I remember the original era of my being; all the events of that period appear confused and indistinct. A strange multiplicity of sensations seized me, and I saw, felt, heard, and smelt at the same time; and it was, indeed, a long time before I learned to distinguish between the operations of my various senses. By degrees, I remember, a stronger light pressed upon my nerves, so that I was obliged to shut my eyes. Darkness then came over me and troubled me, but hardly had I felt this when, by opening my eyes, as I now suppose, the light poured in upon me again. I walked and, I believe, descended, but I presently found a great alteration in my sensations. Before, dark and opaque bodies had surrounded me, impervious to my touch or sight; but I now found that I could wander on at liberty, with ...

- Walton: *Letters 1-4*
- Frankenstein: *Chapters 1-10*
- The Creature: *Chapters 11-16*
- Frankenstein: *Chapters 17-24.5*
- Walton: *Rest of Chapter 24*

For this part of my analysis, I use Latent Dirichlet Allocation (LDA) which was first used in machine learning by David Blei, Andrew Ng and Michael I. Jordan (Blei, Ng, and Jordan 2003). It is a method of topic modelling to try that I will use to see if there is evidence of the framing device within the novel. In other words, I would like to see if LDA can detect the parts of the story that are written by the same narrator. To do this in R, I will utilize methods explained in "tidytext" (Silge and Robinson 2016), as well as the `topicmodels` package (Grün and Hornik 2024) and the `stringr` package (Wickham 2023)

Initial Wrangling

To begin, the novel is pre-processed to remove common stop words, numbers, and other miscellaneous words. To create a unique label for each chapter, I combined the section and the section type as well as removed "section 0" which was the table of contents. Then, I created the document-word matrix and an LDA model using a value of `k`=12 which means that the LDA model will isolate topics. I decided to separate the novel into 12 topics because since the novel is long and there are many plot lines, this greater number of topics will help identify distinct topics.

```
# Pre-processing
other_stop_words <- tibble(
     word = paste(c(0:24, "Chapter", "11th", "_to")))

section_names <- c("letter 1", "letter 2", "letter 3", "letter 4", "chapter 1",
              "chapter 2", "chapter 3", "chapter 4", "chapter 5", "chapter 6",
              "chapter 7", "chapter 8", "chapter 9", "chapter 10", "chapter 11",
              "chapter 12", "chapter 13", "chapter 14", "chapter 15",
              "chapter 16", "chapter 17", "chapter 18", "chapter 19",
              "chapter 20", "chapter 21", "chapter 22", "chapter 23",
              "chapter 24", "letter 24.5")



narrators <-
  tibble(section_names) |>
```

```r
  mutate(
    section_number = readr::parse_number(section_names),
    narrator = case_when(
      str_detect(section_names, "letter") ~ "Captain Walton",
      str_detect(section_names, "chapter")
      & section_number <= 10 ~ "Victor Frankenstein",
      str_detect(section_names, "chapter")
      & between(section_number, 11, 16) ~ "The Creature",
      str_detect(section_names, "chapter")
      & section_number >= 17 ~ "Victor Frankenstein"
    )
  ) |>
  rename(document = "section_names")

# Clean and tokenize novel
# note: line 6854 is where Walton's POV starts back up in chapter 24
Frankenstein_LDA <- Frankenstein |>
  mutate(section = ifelse(line >= 6854, 24.5, section),
         section_type = ifelse(line >= 6854, "letter", section_type)) |>
  filter(section != 0) |>
  mutate(section_label = paste(section_type,section)) |>
  select(-section,-section_type) |>
  unnest_tokens(word, text) |>
  anti_join(stop_words) |>
  anti_join(other_stop_words) |>
  mutate(section_label = factor(section_label, levels = section_names))

# Create the document-word matrix
dtm <- Frankenstein_LDA |>
  count(section_label, word) |>
  cast_dtm(section_label, word, n)

# Create LDA model using value of k and seed
lda_model <- LDA(dtm, k = number_of_topics, control = list(seed = 1))
```

Beta Analysis

First, I looked at the per-topic-per-word probabilities to extract the top words that are used in each of the topics. Then I created a model to show the most common words in each of the topics.

```r
# Per-topic-per-word probabilities
topics_beta <- tidy(lda_model, matrix = "beta")

# Get the top terms
top_terms <- topics_beta |>
  group_by(topic) |>
  slice_max(beta, n = 5) |>
  ungroup() |>
  arrange(topic, -beta)

topic_names <- c("1: \"The Creature's birth\"", "2: \"Frankenstein's Studies\"",
                 "3: \"Justine's Trial\"", "4: \"Walton in Antarctica\"",
                 "5: \"Frankenstein's Guilt\"",
                 "6: \"Frankenstein on the Run\"",
                 "7: \"Frankenstein at Home\"", "8: \"Creating the Creature\"",
                 "9: \"Frankenstein in Antarctica\"",
                 "10: \"Frankenstein's Love\"", "11: \"The Creature Learning\"",
                 "12: \"The Creature Betrayed\"")

# Create visual
top_terms |>
  mutate(term = reorder_within(term, beta, topic),
         topic = factor(topic, levels = 1:12, labels = topic_names)) |>
  ggplot(aes(beta, term, fill = factor(topic, levels = topic_names))) +
  theme_minimal() +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free", ncol = 2) +
  scale_y_reordered() +
  labs(x = "Beta-value", y = "Words", fill = "Topic",
       title = "Most Common Words by Topic") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

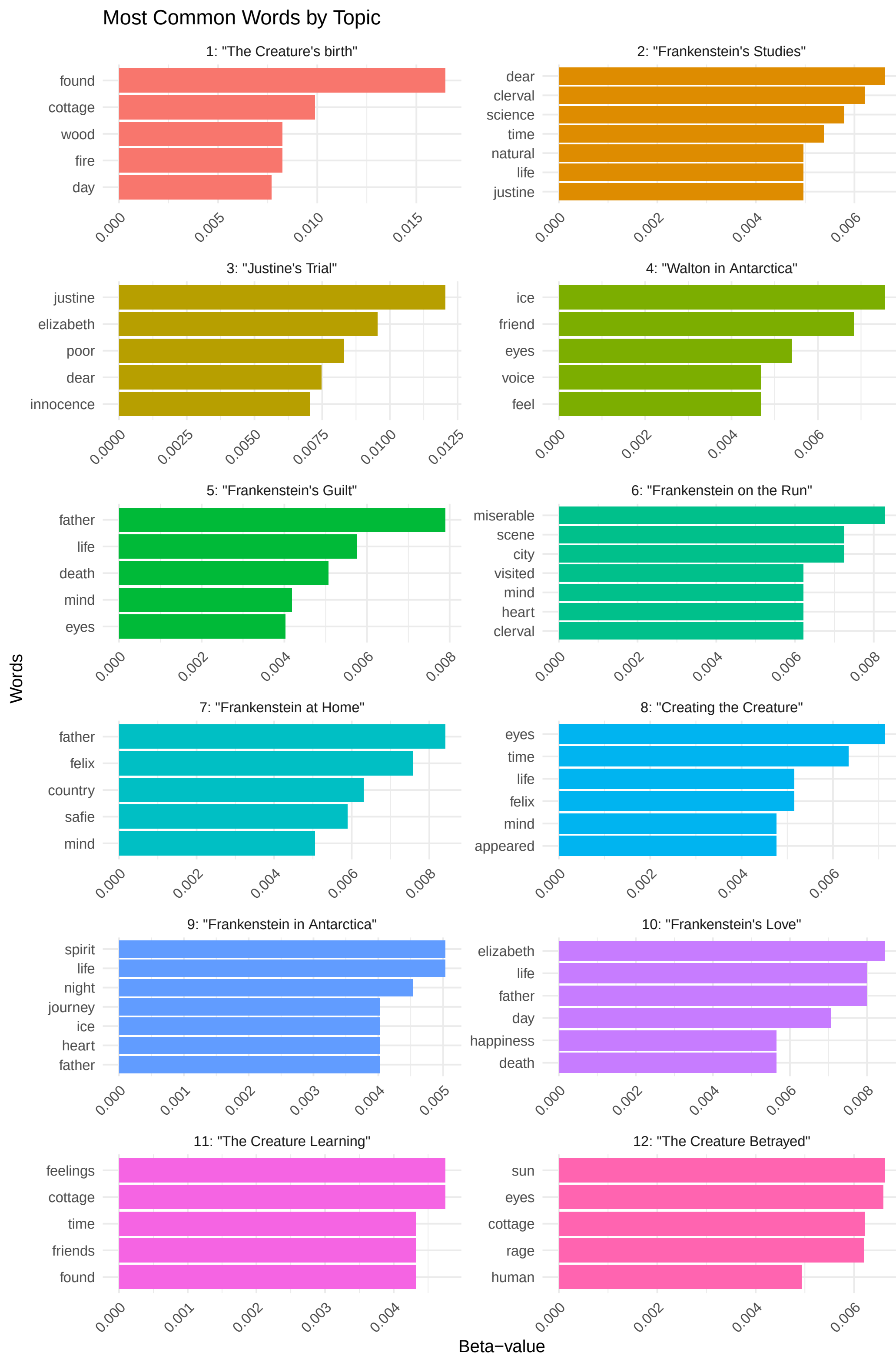

Figure 1: Figure of most common words in each topic

In particular, I chose to focus on three of the topics: 1: The Creature's Birth, 4: Walton in Antarctica, and 10: Frankenstein's Love.

Topic 1 shows that the most common words are found, cottage, wood, fire, and day. This topic gives very simple words that seem to be when The Creature is telling his story and thus has a limited knowledge of the world and talks of basic utilities and needs. He is talking about the day that he was born and first experienced the world.

Topic 4's most common words were ice, friend, eyes, voice, feel. This most likely represents Captain Robert Walton who was on an expedition to Antarctica when he met Victor Frankenstein and the The Creature. These words all seem ominous and make sense with all the death that occurs in the frozen landscape at the culmination of the novel.

Topic 10's most common words were Elizabeth, life, father, day, happiness, and death. This seems to be Victor Frankenstein's narration because one of his main devotions in life was towards his adopted sister, Elizabeth. His father was also an important figure in his life. He also "gave life" to his creation: The Creature.

Gamma Analysis

After, that, I examined the per-document-per-topic probabilities ("gamma") which gives the estimated proportion of words from that document that are generated from that topic. For example, this model predicts that a large portion of the words from Chapter 11 and Chapter 12 are generated from Topic 1. Looking back, we can see that this topic (The Creature's Birth) corresponded to the beginning of The Creature's life/narration which is true since The Creature's narration spans from Chapter 11 to Chapter 16. Using our other example chapters, we can see that Letter 4 and Letter 24.5 both are estimated to be generated from Topic 4 (Walton in Antarctica) which corresponds to Captain Robert Walton's narration! And finally, Chapter 4 and Chapter 22 are estimated to be generated from Topic 10 (Frankenstein's Love) which we had decided was Victor Frankenstein's narration.

```r
# Per-document-per-topic probabilities
topics_gamma <- tidy(lda_model, matrix = "gamma") |>
  mutate(document = factor(document, levels = section_names))

gamma_with_narrator <- topics_gamma |>
  pivot_wider(names_from = topic, values_from = gamma) |>
  inner_join(narrators, by = "document") |>
  pivot_longer(cols = 2:13, names_to = "topic", values_to = "gamma") |>
  mutate(document = factor(document, levels = section_names))

# Create visual
gamma_with_narrator |>
```

```r
mutate(topic = factor(topic, levels = 1:12, labels = topic_names)) |>
ggplot(aes(x = document, y = gamma, fill = factor(narrator))) +
geom_bar(stat ="identity") +
facet_wrap(~ topic, scales = "free_y", ncol = 2) +
theme_minimal() +
labs(x = "Section", y = "Topic Proportion", fill = "Topic",
     title = "Gamma Topic Distribution Across Frankenstein") +
theme(axis.text.x = element_text(angle = 90, hjust = 1),
      legend.position = "bottom")
```

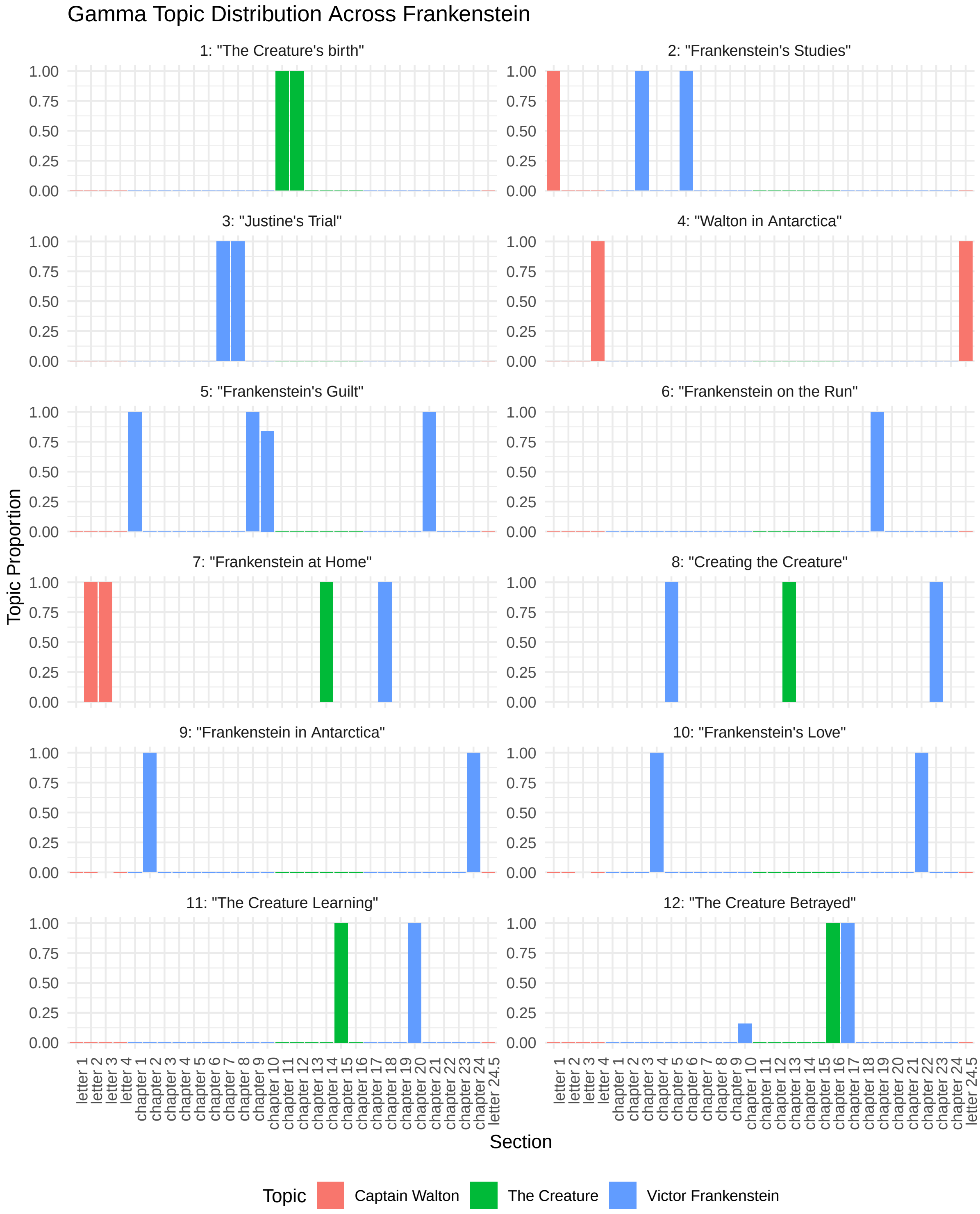

Figure 2: Per-section-per-topic probabilities

```r
gamma_with_narrator <- gamma_with_narrator |>
  mutate(topic_POV = case_when(topic %in% c(4) ~ "Walton Topic",
      topic %in% c(2,3,5,6,7,9,10)  ~ "Frankenstein Topic",
      topic %in% c(1,8,11,12)  ~ "Creature Topic"))

walton_pov <- gamma_with_narrator |>
  mutate(topic = factor(topic, levels = 1:12, labels = topic_names)) |>
  filter(topic_POV == "Walton Topic") |>
  ggplot(aes(x = document, y = gamma, group = topic, color = topic)) +
  geom_rect(xmin = 0, xmax = 4, ymin = 0, ymax = 2, alpha = 0.01, fill = 'lightblue', inhe
  geom_rect(xmin = 28.5, xmax = 29, ymin = 0, ymax = 2, alpha = 0.01, fill = 'lightblue',
  geom_point() + geom_smooth(se = FALSE, span = 0.5) + theme_minimal() +
  labs(x = "Section", y = "Topic Proportion", fill = "Topic",
       title = "Gamma Topic Distribution Across Frankenstein With Walton's Topics Highligh
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.position = "bottom") + coord_cartesian(ylim = c(0, 1))

frankenstein_pov <- gamma_with_narrator |>
  mutate(topic = factor(topic, levels = 1:12, labels = topic_names)) |>
  filter(topic_POV == "Frankenstein Topic") |>
  ggplot(aes(x = document, y = gamma, group = topic, color = topic)) +
  geom_rect(xmin = 4, xmax = 14, ymin = 0, ymax = 2, alpha = 0.01, fill = 'pink', inherit.
  geom_rect(xmin = 21, xmax = 28.5, ymin = 0, ymax = 2, alpha = 0.01, fill = 'pink', inher
  geom_point() + geom_smooth(se = FALSE, span = 0.5) + theme_minimal() +
  labs(x = "Section", y = "Topic Proportion", fill = "Topic",
       title = "Gamma Topic Distribution Across Frankenstein With Frankenstein's Topics Hi
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.position = "bottom") + coord_cartesian(ylim = c(0, 1))

creature_pov <- gamma_with_narrator |>
  mutate(topic = factor(topic, levels = 1:12, labels = topic_names)) |>
  filter(topic_POV == "Creature Topic") |>
  ggplot(aes(x = document, y = gamma, group = topic, color = topic)) +
  geom_rect(xmin = 14, xmax = 21, ymin = 0, ymax = 2, alpha = 0.01, fill = 'lightgreen', i
  geom_point() + geom_smooth(se = FALSE, span = 0.5) + theme_minimal() +
  labs(x = "Section", y = "Topic Proportion", fill = "Topic",
       title = "Gamma Topic Distribution Across Frankenstein With The Creature's Topics Hi
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.position = "bottom") + coord_cartesian(ylim = c(0, 1))

gridExtra::grid.arrange(walton_pov, frankenstein_pov, creature_pov, ncol = 1)
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```

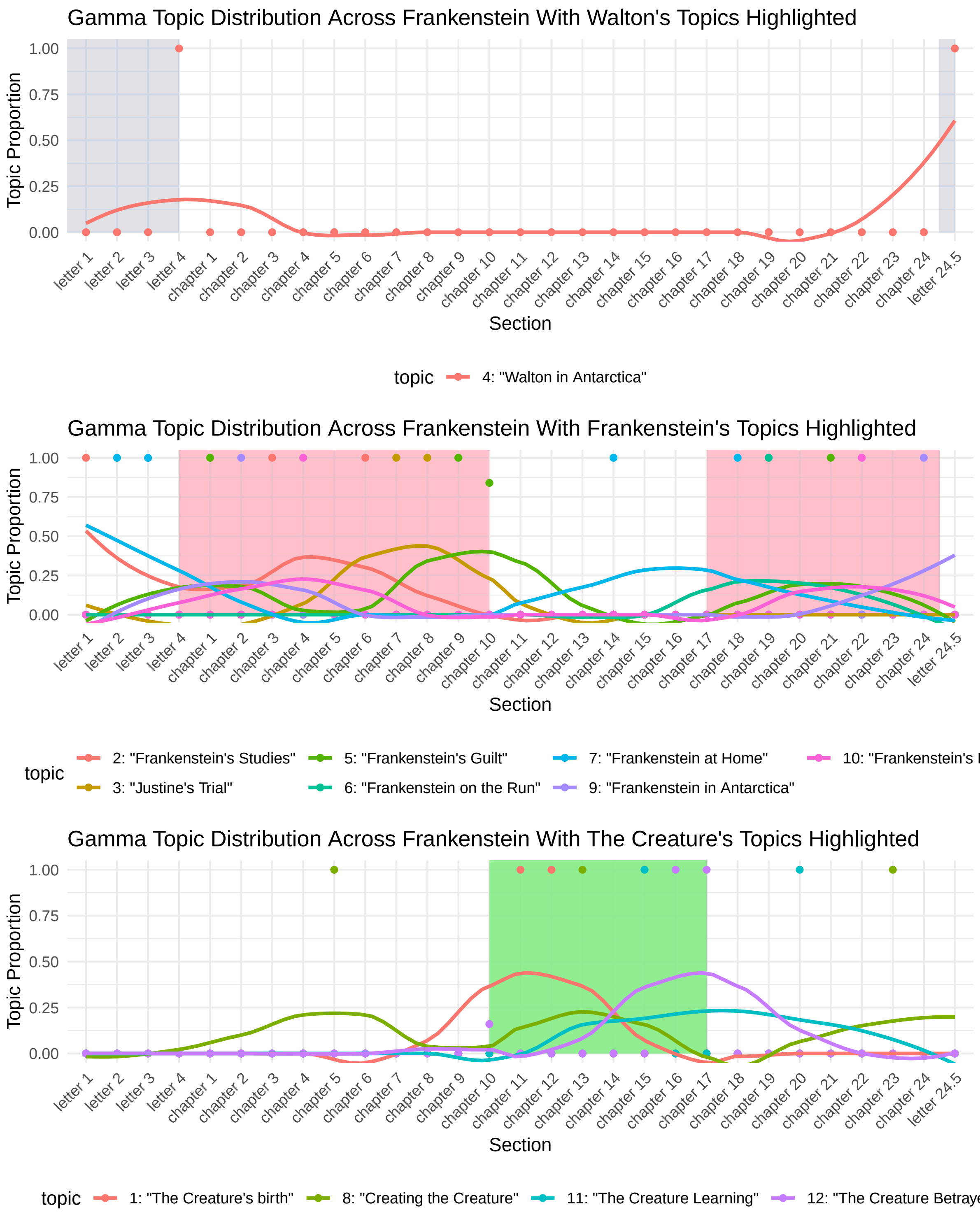

Figure 3: Per-section-per-topic probabilities

Results

Overall, the LDA topic modeling provided insights into the narrative structure within *Frankenstein* and was able to identify several elements of the framing device employed throughout the text. Although the model was not perfect as there were numerous topics with words dispersed across the entire book, refining the parameters could enhance its precision and effectiveness in distinguishing distinct narrative elements.

Shiny App

FIND WAY TO LINK SHINY APP HERE AND MAYBE GIVE A DESCRIPTION

Conclusion

WRAP UP THE WHOLE PROJECT

References

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. "Latent Dirichlet Allocation." *J. Mach. Learn. Res.* 3 (null): 993–1022.

Grün, Bettina, and Kurt Hornik. 2024. *Topicmodels: Topic Models*. https://CRAN.R-project.org/package=topicmodels.

Shelley, Mary Wollstonecraft. 1818. *Frankenstein; or, the Modern Prometheus*.

Silge, Julia, and David Robinson. 2016. "Tidytext: Text Mining and Analysis Using Tidy Data Principles in r." *JOSS* 1 (3). https://doi.org/10.21105/joss.00037.

Wickham, Hadley. 2023. *Stringr: Simple, Consistent Wrappers for Common String Operations*. https://stringr.tidyverse.org.