ABSTRACT

Storytelling has always been vital for human nature. From ancient times, humans have used stories for several objectives including entertainment, advertisement, and education. Various analyses have been conducted by researchers and creators to determine the way of producing good stories. The deep relationship between stories and emotions is a prime example. With the advancement in deep learning technology, computers are expected to understand and generate stories. This survey paper is intended to summarize and further contribute to the development of research being conducted on the relationship between stories and emotions. We believe creativity research is not to replace humans with computers, but to find a way of collaboration between humans and computers to enhance the creativity. With the intention of creating a new intersection between computational storytelling research and human creative writing, we introduced creative techniques used by professional storytellers.

Keywords Storytelling · Story Completion · Story Understanding · Creative Support · Natural Language Processing

1 Introduction

What makes a story a story? In this survey, we focus on “emotion” as an important keyword to get to the root of human creativity and to imitate and support it through computers.

The relationship between stories and emotions has been an essential part of research in the field of humanities, representing the cognitive and affective science of literature [Hogan, 2006, Pandit and Hogan, 2006, Johnson-Laird and Oatley, 2008, Hogan, 2010, 2019]. For creators, the practical knowledge of creative techniques stresses on the importance of being conscious of readers’ emotions in order to satisfy them. These findings have been introduced in computational linguistics (CL), Natural Language Processing (NLP), and Digital Humanities (DH). For example, in their book “The Emotion Thesaurus: A Writer’s Guide to Character Expression,” Ackerman and Puglisi [2012] insisted that a key component of every character is emotion. Referring to this, Kim and Klinger [2019a] analyzed how emotions are expressed non-verbally in a corpus of fan fiction short stories.

Lugmayr et al. [2017] insisted that a fundamental aspect of storytelling is the emotion, that allows the story to evoke cognitive aspects in its audience. With regard to serious storytelling, they referred to Denning’s book [Denning, 2005], which stated that having no emotional elements in presentations and applications can cause a failure in project funding. Therefore, numerous efforts have been made to disclose the mystery of the relationship between emotions and stories [Anderson and McMaster, 1982, Strapparava and Mihalcea, 2008, Abdul-Mageed and Ungar, 2017, Kim and Klinger, 2018, 2019b, Zad and Finlayson, 2020].

Mohammad [2012a] showed that sentiment analysis could be used along with effective visualizations to quantify and track emotions in mails and books. Referring to the talk by Kurt Vonnegut [Vonnegut, 1995], a famous American writer, attempts were made to classify stories by drawing their “emotional arcs” [Reagan et al., 2016, Chu and Roy, 2017, Somasundaran et al., 2020, Del Vecchio et al., 2020]. In Figure 1, we show an example of emotional arc.

Characters and their relationship are considered as essential for literary analysis [Bamman et al., 2014, Vala et al., 2015, Iyyer et al., 2016, Chaturvedi et al., 2017a]. In our previous work [Mori et al., 2019a], we investigated whether the emotional flow of a story is useful in predicting the reader’s interest. Moreover, there are some works that have tried to
Figure 1: A representative emotional arc, called “Man In Hole.” It starts a little above average. Somebody gets into trouble and gets out of it. This is a reproduction of a diagram drawn by Vonnegut [1995].

control story generation by considering emotions [Chandu et al., 2019, Luo et al., 2019, Brahman and Chaturvedi, 2020, Dathathri et al., 2020, Xu et al., 2020].

There are various terms which are interchangeably used with “emotion,” such as sentiment, feeling, and affect. Furthermore, the field of NLP uses “sentiment analysis” and “emotion analysis” differently. Referring to [Mayer et al., 2008, Liu, 2015], Kim and Klinger [2019c] defined emotion and sentiment as follows:

• **Emotion:** an integrated feeling state involving physiological changes, motor-preparedness, cognition about action, and inner experiences that emerges from an appraisal of the self or situation.

• **Sentiment:** positive or negative feeling underlying an opinion.

This definition is followed in this survey, but for simplicity, and unless otherwise noted, the two terms are used interchangeably as follows; “sentiment” refers to the positive-negative emotion axis (i.e., 1-dimensional expression), while “emotion” refers to the more diverse range of emotions.

In this paper, we discuss the results of our survey, conducted to verify the relationship between stories and emotions. Here, we introduce some remarkable recent survey papers on related topics.

Alhussain and Azmi [2021] surveyed on automatic story generation, especially focusing on non-interactive textual stories. They introduced three groups of such models: the structural models, planning-based models, and machine learning models. In their survey, they introduced MEXICA [Pérez y Pérez and Sharples, 2001], MINSTREL [Turner, 1993, 1994], and the analysis of emotional flow [Mori et al., 2019a] as the stream of understanding and generating stories that incorporate emotions.

Bae et al. [2021] conducted a preliminary survey on story interestingness, setting “how to measure story interestingness” as the research question. They insisted that there are two factors involved: the cognitive factor and the emotional factor.

Li et al. [2022] focused on the paradigm of pretrained language models (PLMs) and its application in text generation. They discussed the key factors for getting a desirable output.

Our survey is novel because in terms of creative writing support we include the findings of professional creative writers. Furthermore, computational story understanding and generation is an interdisciplinary field between humanities and the information sciences. Although this research is mainly based in the field of information science, it has a viewpoint associated with applications in humanities and practical knowledge to this field. Recent findings in neuroscience that examine the relationship between emotion and story is also presented. Although emotions are handled in various ways in story comprehension and generation, a more appropriate way to handle emotions in light of the latest findings is also presented in this study.
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Figure 2: Schematic diagram of story generation through human-computer interaction.

Figure 2 shows a schematic example of human-computer interactive story generation. In this system, the computer edits the text written by the human and then the human re-edits it to create the final version. To achieve this, computers are required to have various abilities such as understanding context, generating appropriate sentences, and explaining why the editing is done.

Now, our research question is; how can computers understand human creativity and enhance it with machine learning technologies?

The main contributions of our survey are as follows:

- We conducted our survey on the various elements of a story with particular attention to emotion. With the intention of creating a new intersection between computational storytelling research and human creative writing, we introduced creative techniques used by professional storytellers and examined how emotions are treated in these techniques.

- For a computer to support human creativity, it is necessary to solve the integrated task of understanding the story that a human is trying to write and supplementing it with appropriate story generation. This survey was conducted with the intention to accelerate the study on supporting creative writing based on research on story understanding and generation.

Note that our main focus is to understand human creativity with computers and to enhance it with machine learning technologies. We believe creativity research is not about replacing humans with computers but about finding a way in which humans and computers can collaborate to enhance creativity. We hope this survey on stories and emotions will serve as a material to proceed such research.

2 Structure of this Paper

As a guide to look through our survey, we briefly describe the significance of each section.

In Section 3, we introduce how professional storytellers consider the importance of emotions. For concrete examples, we cite some screenwriting techniques and show the relationship between story structure and emotions.
Section 4 introduces the research on the relationship between stories and emotions since the 1980s, mainly focusing on three popular views of emotions in computational analysis.

In Section 5, we outline recent rapid developments in language models. We present research on story generation; and also discuss text generation. This is to characterize story generation research, which can serve as a reference for future application in other domains to stories.

In Section 6, we introduce the tasks and methods useful in creative support. From the viewpoint of human story writing assistance, we believe in the possibility of a story completion approach.

Furthermore, we widen our survey to affective neuroscience in Section 7. We focus on emotions through the viewpoint of recent advances in affective neuroscience, to introduce an alternative perspective to the three popular views of emotions.

In this paper, we focus on emotion as an important element in a story; however, emotion alone does not make a story. Thus, in Section 8, we address other elements in a story and discuss their integration with research on emotion and their future direction.

Finally, we conclude our survey in Section 9.

3 Emotion in Screenwriting Theories

In research on the creation/co-creation of stories, the findings of those who actually create stories are helpful. A representative example is “emotional arcs.” This term is well-known to have been introduced by the American writer, Vonnegut[1995]. Based on the idea, Reagan et al.[2016] studied how stories could be clustered. In this section, we survey some practical creative writing techniques which we believe, will be helpful in conducting research on creative assistance.

Theories about creating stories emphasize the importance of being conscious of readers’ emotions in order to satisfy them. In particular, theories of screenplay writing are often considered to be practical, even by novelists[Brody, 2018]. This can be attributed to the fact that films require more people and money than novels, and have a restriction on how long a movie can run. Thus, there is a stronger need and merit to theorize how to “construct a structure of stories that sells well” than novels.

Our target is a novel, a story written in a text. We are aware that creating a novel is not the same as creating a film script. However, film screenplay writing has indeed been introduced into the practice of novelists and has proven useful in these different media. As a specific example, “SAVE THE CAT!”[Snyder, 2005], a technique originally proposed for screenplay writing, has been systematically applied to novel writing[Brody, 2018].

One of the most famous screenplay structures is the “three-act structure” proposed by Field[2006]. The first act sets up the situation, the second depicts the conflicts of the characters, and the third depicts the resolution. The entire screenplay is estimated to be 120 pages distributed as 30, 60, and 30 pages. The second act is particularly long; therefore, it is divided into the first and second halves with a central point. Figure 3 shows the overview of the three-act structure.

According to Gulino[2004,2019], “eight sequences” were proposed by Frank Daniel. While teaching screenwriting to students based on the three-act structure, he advised the students who were worried that each act was too long for the screenplay, to divide it into eight sequences of 15 pages each. Figure 3 shows the overview of this approach. This approach divides a story into eight equal lengths. Gulino[2004] explained that another reason for the number of sequences being eight was the physical limitation. When movies were shown on films, a 120-minute movie was divided into eight reels (rolls of film) due to capacity constraints. At 18 frames per second, the reels could contain between 10 and 15 minutes. The audience had to wait during the change of reel from the finished one to the next one by the projectionist. Filmmakers had to deal with this interval. Each reel needed its role in the movie, therefore, a 120-minute movie came to have eight meaningful units. Conversely, it can be said that physical constraint was one of the causes that shaped the composition of the film.

Another well-known theory about story structure is “Blake Snyder Beat Sheet” (BS2), introduced by “SAVE THE CAT!” by Snyder[2005]. While the author appreciated that Field’s book is helpful for screenwriters, he proposed a new structure with points in between, as the space between acts is too vast for a three-act structure. This is the division of a story into 15 “beats,” and is widely used. The overview of the BS2 is shown in Table 1.

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1Tetsuro Shimauchi, who translated Iglesias[2005] and Brody[2018] to Japanese, noted in his afterword as the translator in Brody[2018] that the response from those who write novels has been more noticeable than those who write screenplays, even though Iglesias[2005] is a book on screenwriting.
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Three-Act Structure

ACT 3
Resolution

ACT 2
Confrontation

ACT 1
Beginning

Mid Point

30 pages
60 pages
30 pages

Eight Sequences

H G F E D C B Sequence

A Finale That Soars “The Toys Are Alive!” The Big One Falling Without Style Double Prizes at Pizza Planet Buzz Takes A Hit Falling With Style The Unwanted Present

Example: “Toy Story” (1995)

The analysis was conducted by (Gulino, 2004).

Table 1: The overview of the Blake Snyder Beat Sheet.

| Beat               | Pages |
|--------------------|-------|
| 1 Opening Image    | 1     |
| 2 Theme Stated     | 5     |
| 3 Set-up           | 1-10  |
| 4 Catalyst         | 12    |
| 5 Debate           | 12-25 |
| 6 Break into Two   | 25    |
| 7 Sub Plot         | 30    |
| 8 Fun and Games    | 30-55 |
| 9 Midpoint         | 55    |
| 10 Bad Guys Close In | 55-75 |
| 11 All Is Lost     | 75    |
| 12 Dark Night of the Soul | 75-85 |
| 13 Break into Three | 85    |
| 14 Finale          | 85-110|
| 15 Final Image     | 110   |

Iglesias [2005] insisted the importance to distinguish between two types of emotions – character emotions and reader emotions. He gave the example of a comedy, where characters are stressed, but the viewers laugh at them. In a thriller, the characters may be calm and unaware, while the viewers may be on the edge of their seats because of a threat that the character is not aware of. He warned that screenwriters, who have a general inkling that emotions are important in a screenplay, put too much attention on the emotions of their characters. He wrote, “Whether your character cries or not is not as important as whether the reader cries.”
Table 2: The three popular viewpoints of emotions used in emotion analysis of text.

| Theory                        | Type          | Features                                                                                                                                 |
|-------------------------------|---------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Theory of basic emotions      | Categorical   | Emotions are universal and innate because they are perceived through facial expressions in the same way regardless of what culture one belongs to. There are six emotions: anger, disgust, fear, happiness, sadness, and surprise. |
| by Ekman 1993                 |               |                                                                                                                                          |
| Wheel of emotions             | Categorical   | A hybrid model that arranges emotions into concentric circles with the inner being the basic and the outer being more complex emotions.         |
| by Plutchik 1980              |               |                                                                                                                                          |
| Circumplex model of affect    | Dimensions    | Emotions are represented as vectors in a two-dimensional space and can be explained by a combination of two independent axes, Valence and Arousal. Valence means pleasantness–unpleasantness and Arousal means calmness–excitement. They are called “core affect”. As an extension, a third axis called Dominance can be added for a three-dimensional representation. Dominance means perceived control ranging from submissive to dominant. |
| by Russell 1980               |               |                                                                                                                                          |

4 Story Understanding and Emotions

In this section, we introduce the development of research in the field of story understanding, particularly in terms of understanding emotions. We also introduce datasets that handle the relationship between text and emotion and how they have been constructed with different intentions.

4.1 Understanding Emotion in Stories and Narratives

A story consists of three elements – character, event, and setting (i.e., location and temporal setting) [Park et al., 2020]. At the intersection of NLP and literary analysis, various studies have been conducted on these factors. Some analyze stories from the importance of characters and their relationships [Bamman et al., 2013, 2014; Massey et al., 2015; Vala et al., 2015; Chaturvedi et al., 2016; Srivastava et al., 2016]. To better comprehend stories, some studies considered stories to be collections of events. Using film scripts as a departure point for more general narrative research, Murtagh et al. [2009] analyzed their style and structure. They quantified various central perspectives, which have been discussed in McKee’s book, “Story” [McKee, 1997].

Referring to The Narrative Cloze Test [Chambers and Jurafsky, 2008] as a typical example of story understanding task considering events, Mostafazadeh et al. [2016] proposed the Story Cloze Test (SCT) as a more difficult task. SCT presents four sentences and the last sentence is excluded from a story composed of five sentences. The system must select an appropriate sentence from two choices that complement the missing last sentence. In addition to the task, the authors released a large-scale story corpus named ROCStories, which is a collection of non-fictional daily-life stories written by hundreds of workers of Amazon Mechanical Turk. The five-sentence stories contained varied common-sense knowledge.

Park et al. [2020] analyzed emotions in a story text using an emotion embedding model. In recent years, emotion estimation has been actively studied [Park et al., 2019; Demszky et al., 2020] using unsupervised pre-trained large neural models such as BERT [Devlin et al., 2019].

The number of characters in a story is not always one (protagonist) and research has been done in relation to this. Winston [2011] arranged for the simultaneous reading of stories by two separate personas, Dr. Jekyll and Mr. Hyde. Presenting NovelPerspective, a tool to subset digital literature based on the point of view (POV), White et al. [2018] showed many novels have multiple characters, each with their own storyline. We can refer to them and say that various perspectives should be considered when we consider emotions.

The importance of emotions in storytelling has long been pointed out and efforts to verify it using computers can be traced back to the 1980s. The pioneering work was done by Anderson and McMaster [1982]. Based on the 1,000 most frequently used English words for which Heise [1965] had presented semantic differential factor scores, they reported
the development of a computer program to assist the analysis and modeling of emotional tone in text by identifying those words in a passage of discourse. Emotion analysis in text is closely related to lexicons annotated with emotions, and in these annotations and analyses, psychological findings have been referred.

Kim and Klinger [2019c] stated that there are three theories of emotions popular in computational analysis of emotions: Ekman’s theory of basic emotions [Ekman 1993], Plutchik’s wheel of emotion [Plutchik 1980], and Russell’s circumplex model [Russell 1980].

These three views can be divided into categorical and dimensional emotions [Buechel and Hahn 2017a, Hakak et al. 2017]: Categorical emotions are represented by Ekman’s basic emotions and Plutchik’s wheel of emotions. Dimensional emotions are represented by Russell’s circumplex model. Categorical emotion theories divide emotions into discrete emotion labels. However, the dimensional emotion theory represents the emotion classes in a dimensional form. We summarize the three theories of emotions in Table 2.

Research on emotion and text strives to better understand human-written texts [Strapparava and Mihalcea 2008, Abdul-Mageed and Ungar 2017]. In the domain of story or narrative, Alm et al. [2005] provided children’s novels with positive/negative sentiment evaluations and a more complex set of eight classes of emotions based on Ekman’s basic emotions [Ekman 1993]. To predict emotions using machine learning, they classified the eight emotions again into three emotional valences: positive, negative, and neutral. Chaturvedi et al. [2017] proved that by considering emotional movement in a story, models could improve their performance on SCT. Studies have previously investigated the relationship between emotions and stories’ interestingness. As aforementioned in Section 3, Reagan et al. [2016] showed that stories collected from Project Gutenberg could be classified into six styles by considering their emotional arcs (i.e., the trajectory of average happiness in a story).

For reference, we would like to touch on research considering reader’s emotions in other text domain like news articles [Lin et al. 2007, Lin et al. 2008, Chang et al. 2015], microblogs [Tang and Chen 2012], Lin et al. [2007] studied the classification of news articles into emotions they invoke in their readers. Tang and Chen [Tang and Chen, 2012] classified microblogs into emotions based on the emotional arcs (i.e., the trajectory of average happiness in a story).

4 Russell noted in his paper that: “While this article was under editorial review, Plutchik (1980) published a specific circumplex model of affect and reported previously unpublished data from H. R. Conte’s (1975) doctoral dissertation supporting the model. Their model is similar, but not identical, to the one proposed here.” It is so impressive that the theories representing categorical emotions and those representing dimensional emotions were proposed at about the same time.

https://www.gutenberg.org
focused on a microblog conversation and insisted that the writer of the microblog and the reader who replies to it can both express their emotions. They named the process of changing from writer-emotion to reader-emotion as “a writer-reader emotion transition”, and examined the mined sentiment words. Based on recognizing, reader-emotion is different and maybe more complex than writer-emotion. Chang et al. [2015] worked on reader-emotion estimation and on writing assistance using template considering reader-emotion in the news article domain. The research of other domains also influences our research on stories and we hope this study influences them in the future.

4.2 Datasets of Text and Emotion

Many datasets have been proposed to deal with the relationship between text and emotion [De Bruyne et al., 2020]. There are lexicons that give emotional values to words and others that annotate emotions at the sentence level.

As noted in the previous subsection, models of emotion are commonly subdivided into categorical and dimensional ones. Datasets of text with emotion annotation are generally based on these emotional theories. Both the categorical and dimensional text-emotion datasets along with lexicons with emotions are presented below.

- **Categorical text-emotion datasets**: (children stories) [Alm et al., 2005], DENS [Liu et al., 2019], GoEmotions [Demszky et al., 2020]
- **Dimensional text-emotion datasets**: (Facebook posts) [Preotiuc-Pietro et al., 2016], EmoBank [Buechel and Hahn, 2017a,b], Shared-Character Stories [Mori et al., 2019a]
- **Lexicons**: the General Inquirer [Stone and Hunt, 1963], LIWC [Pennebaker et al., 2001], Tausczik and Pennebaker [2010], Pennebaker et al., ANEW [Bradley and Lang, 1999], SentiWordNet [Esuli and Sebastiani, Baccianella et al., 2010], SenticNet [Cambria et al., 2010, 2020], NRC Hashtag Emotion Lexicon [Mohammad, 2012b], Mohammad and Kiritchenko [2015], NRC Valence, Arousal, Dominance Lexicon [Mohammad, 2018a], NRC Affect Intensity Lexicon [Mohammad, 2018b]

For the three categories in the list above, we will mainly focus here on the first two, which are text datasets.

Alm et al. [2005] provided children’s novels with positive and negative sentiment evaluations and a more complex set of eight classes of emotions based on Ekman’s basic emotions [Ekman, 1993]. The goal of their annotation project was set to approximately 185 children’s stories, including Grimms’, H.C. Andersen’s, and B. Potter’s stories.

Liu et al. [2019] introduced the Dataset for Emotions of Narrative Sequences (DENS) for multi-class emotion analysis from long-form narratives in English. DENS was collected from both classic literature available on Project Gutenberg and modern online narratives available on Wattpad, annotated using Amazon Mechanical Turk. The dataset was annotated based on a modified Plutchik’s wheel of emotions [Plutchik, 1980]. They conducted an initial survey based on 100 stories with a significant fraction sampled from the romance genre. They asked readers to identify the major emotion exhibited in each story, from a choice of the original eight primary emotions: joy, sadness, anger, fear, anticipation, surprise, trust, and disgust. They found that readers have significant difficulty in identifying trust as an emotion associated with romantic stories. They modified the annotation scheme by removing Trust and adding Love. They also added the Neutral category to denote passages that do not exhibit any emotional content. The final annotation categories for DENS were: joy, sadness, anger, fear, anticipation, surprise, love, disgust, and neutral.

Demszky et al. [2020] proposed GoEmotions, the manually annotated dataset of 58,000 English Reddit comments, labeled for 27 emotion categories or neutral, with comments extracted from popular English subreddits.

Buechel and Hahn [2017a] explained that dimensional models consider affective states to be best described relative to a small number of independent emotional dimensions (often two or three): Valence (the degree of pleasantness or unpleasantness of an emotion), Arousal (the degree of calmness or excitement), and Dominance (the degree of perceived control ranging from submissive to dominant). Based on this idea, EmoBank is proposed as a text corpus, manually annotated with emotion according to the psychological VAD scheme [Buechel and Hahn, 2017a,b]. They claimed that the VAD model has a major advantage as the dimensions are designed as independent, so results remain comparable dimension-wise even in the absence of others (e.g., Dominance). Based on the findings of Katz et al. [2007] that annotations are done in vastly different ways depending on the viewpoint of the annotator, they did a

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5 Note that it is part of this dataset that is annotated with emotions.

6 In their paper, they used a preliminary annotated and tie-broken dataset of 1,580 sentences, or 22 of Grimms’ tales.

https://github.com/JULIELab/EmoBank

7 They noted that the Dominance dimension is sometimes omitted (as we did in [Mori et al., 2019a]).
pilot study [Buechel and Hahn, 2017b] on two samples (movie reviews and a genre-balanced corpus) to compare the inter-annotator agreement (IAA) resulting from different annotation perspectives—the writer’s and the reader’s perspective—in different domains. They had crowd workers annotate each of the 10,548 sentences from seven domains: news headlines, blogs, essays, fiction, letters, newspapers, and travel guides. They used the modified 5-point self-assessment manikin (SAM) scales for valence, arousal, and dominance. The original SAM was a 9-point scale [Bradley and Lang, 1994], but they changed the number to reduce the cognitive load during decision-making for crowd workers. From a psychological view, they filtered out highly improbable ratings, which were considered as fraudulent responses. Finally, they got a total of 10,062 sentences bearing VAD values for both perspectives.

We proposed Shared-Character Stories dataset (759 stories) and annotations for its subset (100 stories and 623 annotations) [Mori et al., 2019a]. The annotation was based on the psychological Valence-Arousal (VA) model and considered emotional changes in context. We also used SAM, but with the original 9-point scale. Our annotation procedure included emotions and other aspects—Storyness. Does the text seem to be a story? Fluency: Does the story read smoothly and fluently? Consistency: Is the story coherent from sentence to sentence? Clarity: Is the content of the stories easy to understand? Meaning: Does the story have a meaning/message?

We also asked crowd workers to tell us how interesting a story is and write a review. This made it possible to analyze the relationship between emotions and interestingness (and other aspects).

It is costly and time-consuming to manually annotate various information in texts. Annotating emotions is difficult because “emotions” vary from reader to reader (whether it is the reader’s own emotions or the understanding of the characters’ emotions), making it difficult to determine what is “correct emotion.” Here we show the examples by Katz et al. [2007]: while the headline “Hundreds killed in earthquake” would be universally accepted as negative, the headline “Italy defeats France in World Cup Final,” can be seen as positive, neutral, or even neutral depending on the viewpoint of the reader. They insisted that these types of problems made it very difficult for their annotators to provide consistent labels. Therefore, datasets of text and emotion are much smaller than tasks such as translation and summarization.

Regarding the relationships between categorical and dimensional emotions, Mohammad [2018b] stated that joy words have lower arousal scores on an average than sad words, which further have lower average arousal scores than anger and fear. Anger and fear have a very similar profile of average VAD scores.

Although the traditional basic emotions are an important way of thinking about emotions, the latest affective neuroscience findings deny that everyone has the same emotions regardless of culture or language. This will be discussed in detail in the Section 7. We believe that dimensional emotions can be used to handle a wider variety of emotions and we also emphasize the importance of “who is feeling.” In particular, in the case of stories, the reader’s emotions are important.

5 Recent Progress in Computational Storytelling

Although there are still issues to be considered such as coherence in long text generation, a transformer-based approach has shown to be able to generate sentences that look as if they were written by humans [Otter et al., 2020]. For example, Bena and Kalita [2019] confirmed that GPT-2 can generate high-quality poetry and stimulate the reader’s emotions.

The importance of emotions in stories is not underestimated and story generation with sentiment control (positive/negative) has been exceptionally well studied [Luo et al., 2019, Dathathri et al., 2020, Xu et al., 2020]. However, unlike the field of dialogue generation, where many studies tackled various emotion control [Ghosh et al., 2017, Zhou et al., 2018, Ma et al., 2020, Peng et al., 2020, Song et al., 2019], story generation with more variety of emotions was not addressed, up until quite recently. The control of emotions in story generation has focused on how to control positive-negative emotions. Moreover, categorical or dimensional emotions have not been well considered until recently, as per the best of our knowledge. Brahman and Chaturvedi [2020] did the first work on emotion-aware storytelling, which considers the emotional arc of the protagonist.

In this section, we introduce the brief history of story generation. Then, we introduce controllable story generation, which is essential for emotion-aware control of storytelling in Subsection. Finally, we discuss the works that tackled the task of evaluating story-like texts.

\[\text{https://github.com/mil-tokyo/SharedCharacterStories}\]

\[\text{We defined this as “Storyness”, as stated in [Mori et al., 2019a], but later an anonymous reviewer of our other paper pointed out that “Storylike-ness” would be more appropriate. We have retained the term “Storyness” because it is used in the published paper and we want to avoid confusion, but we thank the anonymous reviewer for the suggestion.}\]
5.1 Research on Story Generation

As we have discussed in the previous section, there is a significant relationship between story understanding (literary analysis) and emotions. Then, what about story generation?

Klein’s “automatic novel writer” [Klein et al., 1973], Meehan’s “TALE-SPIN” [Meehan, 1976, 1977], Lebowitz’s “Universe” [Lebowitz, 1984, 1985], and Turner’s MINSTREL [Turner, 1993, 1994] are often referred to as early efforts of automatic storytelling. From the perspective of computational creativity, Gervás [2009] stated that most systems were concerned with telling stories recognized as typical of the particular genre. He insisted the need to adopt evaluation practices introducing some measurement of novelty and quality.

McIntyre and Lapata [2009] published the pioneering work of the data-driven approach on story generation. Until then, story generation systems had relied on a large repository of background knowledge containing detailed information about the story plot and its characters. The information was usually handcrafted, but in their paper, McIntyre & Lapata introduced a data-driven approach.

Hermann et al. [2015] stated two approaches to solving automatic story generation: the symbolic and the neural (network) approaches. The above studies can be classified into these two and it seems that the former approach was taken at first. However, the latter became stronger due to the progress of deep learning.

Applying machine learning to human story writing assistance is an approach where interesting works were published in recent years [Roemmele, 2016, Peng et al., 2018, Yao et al., 2019, Goldfarb-Tarrant et al., 2019]. Referring to recurrent neural networks (RNN) as a promising machine learning framework for language generation tasks, Roemmele [2016] envisions the task of narrative auto-completion applied to helping an author write a story. Peng et al. [2018] proposed an analyze-to-generate framework for controllable story generation. They apply two types of generation control: 1) ending valence control (happy or sad ending), 2) storyline keywords.

Hou et al. [2019] categorized probabilistic story generation models into three categories: Theme-Oriented Models, Storyline-Oriented Models, and Human-Machine Interaction-Oriented Models. These models are different with respect to the user constraint, that is, the context given by a user to guide the generation probability of words. Theme-Oriented Models have static user constraint and no human-computer interaction exists. The representative examples of this category were proposed by Fan et al. [2018], Xu et al. [2018], Yao et al. [2019]. Storyline-Oriented Models have static user constraint. The constraint contains complete story plots, such as a set of pictures or an abstract description, or a specific story that needs an ending. Wang et al. [2018], Zhao et al. [2018], Wang and Wan [2019] proposed representative models. Human-Machine Interaction-Oriented Models have dynamic user constraints; the constraints vary through human-computer interaction. The models proposed by Clark et al. [2018a], Goldfarb-Tarrant et al. [2019] were considered representatives.

Xu et al. [2018] focused on the problem of narrative story generation. As a special kind of story generation [Li et al., 2013], their problem requires systems to generate a narrative story based on a short description of a scene or an event. They insisted that they eliminate external materials and consider the complete story generation task as McIntyre and Lapata [2009].

Hierarchical approaches, which divide story generation into some steps have been widely studied [Fan et al., 2019, Yao et al., 2019, Goldfarb-Tarrant et al., 2019, 2020, Fan et al., 2019] improved the performance of story generation by separating action and entity generation. Considering “Bilbo Baggins” as an example, they insisted on the difficulty of handling characters. They had rare names and were called in different ways: “he” and “hobbit” may refer to the same entity. Yao et al. [2019] proposed a two-step pipeline for open-domain story generation: 1) story planning, which generates a storyline, represented by an ordered list of words, and 2) surface realization, which composes a story based on the storyline. They proposed a hierarchical generation framework named plan-and-write that combines storyline planning and surface realization to generate stories from titles. Based on [Yao et al., 2019, Holtzman et al., 2018], Goldfarb-Tarrant et al. [2019] presented a neural narrative generation system named Plan-and-Revise in which humans and computers collaborate to generate stories.

In terms of the relationship with emotions, we should note that Bailey [1999] discussed story generation by considering reader emotion. The paper insisted that the reader’s expectations and questions are important for stories. The proposed cycle of story-generation consisted of four steps: 1) A search-space of possible next segments was generated from the reader’s knowledge-base. 2) The effects of each of these possible next segments, in conjunction with the assertions in the story-so-far, on the patterns of expectations and questions derived by the reader, were analyzed. 3) The segment which produced patterns of expectations and questions which best fit the patterns preferred by the abstract narration heuristics was chosen. 4) The chosen segment was asserted as the next segment of the story. The reader’s expectations and questions were updated to take account of the new segment. This paper proposed such a cycle; however the search-space becomes too large, which is a drawback. Time has passed since the cycle was proposed. We believe that it...
could be used more effectively. First, we believe that improvements in the performance of computational resources and the development of search methods have made it possible to search a large space more efficiently. It is also expected that the development of natural language generation methods improves the quality of the candidates generated and improves the segments of a story as a result of the search.

5.2 Controllable Story Generation with Transformers

The Transformer [Vaswani et al., 2017] is the basis of today’s significant improvement in NLP, and story generation is no exception. Here we give an overview of the Transformer and focus on efforts to control generation, which is essential in story generation.

With the advent of the sequence-to-sequence model (Seq2seq), neural networks have become common as a method for generating natural sentences. Seq2seq was first proposed for machine translation [Sutskever et al., 2014]; however, it has been widely applied to other tasks in NLP [Vinyals and Le, 2015]. There is a variant of Seq2seq, which uses convolutional neural networks (CNN) instead of RNNs [Gehring et al., 2017]. Then, by replacing the RNNs (or CNNs) in Seq2seq with self-attention, Transformer gets several advantages [ten. Last updated 2020-10-14 UTC.]: 1) Layer outputs can be calculated in parallel, instead of a series like RNN. 2) Distant items can affect each other’s output without passing through many RNN-steps, or convolution layers. 3) It can learn long-range dependencies.

Unsupervised pre-trained large neural models, such as BERT and GPT-2 [Radford et al., 2019], were proposed using the Transformer architecture, and soon became the mainstream in NLP. These pre-trained models were divided into two: the Transformer Encoder (bi-directional architecture) and the Transformer Decoder (left-to-right architecture). In sequence generation, models using left-to-right architecture [Radford et al., 2019; Yang et al., 2019] are more suitable. However, instead of using only one of the Transformer architectures, attempts to create Seq2seq (Encoder-Decoder) models using unsupervised pre-trained large neural models for initializing each of the encoders and the decoders are becoming the new mainstream [Lewis et al., 2020; Rothe et al., 2020; Lewis et al., 2020] proposed BART, which uses BERT as the encoder and GPT-2 as the decoder, and it showed high performance in tasks such as summarization. Rothe et al. [2020] proposed to use pre-trained checkpoints of BERT, GPT-2, and RoBERTa for initializing a large Transformer-based Seq2seq model. Raffel et al. [2020] proposed T5, which uses task-specific prefixes and can solve many text-to-text tasks in one model. There are also some papers that proposed new variations of Seq2Seq models based on the Transformer [Qi et al., 2020; Roller et al., 2020; Zhang et al., 2020a].

There are also works for controlling text generation in unsupervised pre-trained large neural models. CTRL [Keskar et al., 2019] is a pioneering work to control particular aspects of text generation with large-scale language models. Based on the large-scale language model MEGATRON [Shoeybi et al., 2020] and knowledge-enhanced story generation [Guan et al., 2020], MEGATRON-CNTRL [Xu et al., 2020] was proposed. Rashkin et al. [2020] proposed the task of outline-conditioned story generation. The input only provides a rough sketch of the plot, so models need to generate a story by interweaving the key points provided in the outline.

Inspired by Plug & Play Generative Networks (PPGN) [Nguyen et al., 2017] in computer vision, Dathathri et al. [2020] proposed Plug-and-Play Language Model (PPLM), an alternative approach for controlled text generation. Their approach uses the attachment models for pre-trained GPT-2 to control the word probability distribution during the word-by-word generation process. Optimization is performed ex post facto in the activation space, therefore no re-training or fine-tuning of the core language model is needed.

Following this trend, methods have been presented to control the output by adding modules for output control without modifying the core model: DELOREAN (DEcoding for nonmonotonic LOgical REAsoNing) [Qin et al., 2020], Side-tuning [Zhang et al., 2020b], Auxiliary tuning [Zeldes et al., 2020], and GeDi [Krause et al., 2021]. Qin et al. [2020] solved two tasks by their proposed DELOREAN: “Abductive Reasoning” and “Counterfactual Reasoning.”

Such controllable story generation is important in terms of taking emotions into account. Story generation with sentiment control (positive/negative) has been exceptionally well studied [Luo et al., 2019; Dathathri et al., 2020; Xu et al., 2020]. Although fine-grained emotion control of story ending generation was tackled by Luo et al. [2019], the control of emotions in story generation has been limited to positive-negative emotions. Categorical or dimensional emotions have not been well considered in this area until recently. Brahm and Chaturvedi [2020] did the pioneering work on emotion-aware storytelling, which considers the emotional arc of the protagonist. Their study was the first to model the emotional trajectory of the protagonist in neural storytelling. There are significant differences in their study and ours, with respect to task setting and the approach taken. We believe that the future direction should consider the reader’s emotion. The ultimate goal of story generation is to generate a story that satisfies readers as readers’ emotions are of utmost importance as suggested by Mori et al. [2019a].
As discussed in Subsection 4.1, the application of transformers in story understanding and generation has attracted attention in recent years. Transformer architecture’s impact is not only for story generation itself, but also for the evaluation of generated stories. In the next subsection, we will discuss the recent trend of evaluation metrics.

5.3 How to Evaluate Story-like Text

Evaluation of the generated stories (texts) is also a major topic in story (text) generation. Human evaluation is considered to be the gold standard; however, to evaluate all the texts generated by various models that contain various parameters is impossible. Human evaluation is costly, time-consuming, and dependent on individual abilities. Regarding Amazon Mechanical Turk, which is a crowdsourcing platform, Ippolito et al. [2019] pointed out that the evaluation by average workers is unreliable in the task of story infilling. They reported that their inserted honeypot question showed that performance on the question was close to random guessing. It was also stated by August et al. [2020] that human evaluation schemes tend to ignore the difference of perspectives, authors, and readers.

Therefore, automatic metrics to evaluate the day-by-day progress of natural language generation is strongly needed. However, traditional metrics have a poor correlation with human evaluation, so proper evaluation of NLG is difficult [Liu et al., 2016; Novikova et al., 2017; Chaganty et al., 2018; Gatt and Krahmer, 2018; Hashimoto et al., 2019]. In their survey of deep learning applied story generation, Hou et al. [2019] insisted that the inconsistency of datasets and the lack of effective automated evaluation metrics make it difficult to strictly compare the advantages and disadvantages of each model. Establishing automatic evaluation for various story generation tasks is so difficult that some papers have referred to this as “future work” [Chandu et al., 2019; Mori et al., 2019b].

In the field of creative assistance, it would be desirable to have humans participate in interactive evaluation owing to the nature of the task. However, it is impossible in terms of cost and time to have humans evaluate every candidate sentence that is generated. It is important to have an index of “good stories” to narrow down the number to a quantity that can be evaluated by humans.

6 Toward Creative Support

Cavazza et al. [2009] stressed the importance of emotions in an interactive storytelling system. At the time they published the paper, natural language processing was a bottleneck hampering the scalability of interactive storytelling systems. Therefore, they introduced their interaction technique based solely on emotional speech recognition. They have concentrated on a small set of five categories (each corresponding to combinations of valence/arousal): Negative Active, Negative Passive, Neutral, Positive Active, and Positive Passive.

Referring to [Cavazza et al., 2009; Chandu et al., 2019], adapted a personality trait that became crucial to capture and maintain the audience’s interest. They stressed that associating the narrative to a personality instigates a sense of empathy and relatedness. As there were no story datasets in which personality traits were annotated, they used Image Chat, a crowdsourced dataset of human-human conversations about an image with a given personality [Shuster et al., 2020]. An automatic evaluation of whether a story that reflects personality can be generated was left as future work. They also left human evaluation as an issue for the future.

From the viewpoint of human story writing assistance, we believe in the possibility of a story completion approach, wherein machines get an input of an unfinished story and return it in a completed form. Inspired by SCT, story ending generation (SEG) was designed as a subtask of story generation [Zhao et al., 2018]. Given an incomplete story, where the last sentence is excluded from the original five-sentence story, the objective of the task is to automatically generate the last sentence of this given incomplete story. Furthermore, based on SEG, Wang and Wan [2019] proposed a story completion task and investigated the problem of generating the missing story plot at any position in an incomplete story. If a middle sentence is missing, the task becomes more difficult, as the system must capture the context both before and after the missing sentence. In addition to this, research on text infilling has been actively conducted in recent years [Ippolito et al., 2019; Donahue et al., 2020; Huang et al., 2020; Wang et al., 2020], especially about stories. Ippolito et al. [2019] worked on the method to complement the gap between pre and post contexts, which they call story infilling. To understand and generate narrative/story, Wang et al. [2020] tackled controlled narrative/story generation where the model is guided to generate coherent narratives with user-specified target endings by interpolation.

Note: [Chandu et al., 2019] cited the preprint of [Shuster et al., 2020] on arXiv, 2018.

Note that the term “story completion” is also used in the area of Psychology [Clarke et al., 2019]. In this paper, we use the term as its definition in NLP, NLG.
Roemmele [2021] focused on an “inspiration through observation” paradigm for human interaction with generated text. Emphasizing “storiability” as a desirable feature of the result, Roemmele [2021] tackled story infilling task and concluded that automated models can intervene in the writing process without necessarily replacing human effort.

We should cite Abductive Reasoning as a task that is close to Story Completion. Bhagavatula et al. [2020] recently introduced Abductive Reasoning to the area of NLP [Qin et al., 2020] and explained, “Abductive Reasoning has long been considered to be at the core of understanding narratives [Hobbs et al., 1993], reading between the lines [Norvig 1987; Charniak and Shimoyama 1990], reasoning about everyday situations [Peirce et al. [1937]; Andersen 1973], and counterfactual reasoning [Pearl 2002; Pearl and Mackenzie 2018]. Despite the broad recognition of its importance, the study of abductive reasoning in narrative text has very rarely appeared in the NLP literature.” Then, they presented the first study that investigates the viability of language-based abductive reasoning. Abductive Reasoning is a task that focuses more on causality and common sense. Although it does not necessarily result in a story by itself, the methods and findings in this task can be fed back to Story Completion.

Below are some recent papers that deal with tasks that are close to (or almost equal to) story generation. Zhu et al. [2020] proposed an attention-based model called ScriptWriter. It is also in the context of story generation but is closer to dialogue generation with narrative consideration. Chakrabarty et al. [2020] focused on figurative language such as a simile to give readers new insights and inspirations. In the paper, they tackled the problem of simile generation. Kar et al. [2020] tackled story characterization from movie plot synopses and multi-view multi-labeled reviews. This study suggested the importance of considering that the different recipients of the story have their perspectives.

To develop Human-AI co-creation in the domain of story writing, we should not narrow our perspective to just NLP. Such a system has been studied in the collaborative area of NLP and Human Computer Interaction (HCI). Calderwood et al. [2020] explored how professional fiction writers use generative language models during their writing process. Osone et al. [2021] proposed “Buncho,” an AI supported story co-creation system in Japanese. With their system, users can generate titles and synopses from keywords. Yuan et al. [2022] sought to learn how people might use large neural language models, such as GPT-3 for creative writing. They proposed Wordcraft, a text editor which makes use of prompting techniques and UX patterns for the collaboration between users and large language models. We believe that the practical application of systems that are useful to creators will require the collective knowledge of various research areas, as well as knowledge outside of research (knowledge of practitioners).

7 Emotions in Cutting-edge Neuroscience

As discussed in Subsection 4.1, there are three popular views of emotions in computational analysis [Kim and Klinger 2019c]: Ekman’s theory of basic emotions, Plutchik’s wheel of emotion, and Russell’s circumplex model. However, from the viewpoint of affective neuroscience, there is still an ongoing debate about how emotions should be defined [Sander 2013]. We should mention here that cutting-edge neuroscientific findings provide us with a new perspective on emotions.

We begin this section by reviewing the classical theories. Darwin, famous for proposing the theory of evolution, is exclusively known for “The Origin of Species” [Darwin 1859]. He wrote several other books applying the theory. In “The Origin of Man and The Selection of His Sex” [Darwin 1871] and “On the Facial Expressions of Man and Animals” [Darwin 1872], Darwin stated that the criterion for an accurate assessment of emotion is the facial expression. During the 1960s, Tomkins and McCarter [1964] attempted to verify what they defined as basic emotions by linking them to facial expressions. Their experiment, called the basic emotion method, was designed to measure an ability called emotion recognition. Subjects were shown photographs of faces and asked to judge what emotions were indicated by the facial expressions. Ekman’s basic emotions are well known for their use in basic emotion experiments, with subjects from the Fore tribe in Papua New Guinea. It was concluded that emotions are universal and innate because they are perceived through facial expressions in the same way, regardless of what culture one belongs to. The results of this study still form the basis of much of the current research, as shown in Subsection 4.1 and 4.2.

The theory of basic emotions, established as described above, occupies an important position in affective computing of the text domain, as described in Subsection 4.1. However, in recent years, findings in cutting-edge neuroscience have cast doubt on the universality and innate nature of emotional cognition [Barrett 2017; 2020]. Referring to [Russell 1994], Barrett [2017] pointed out that Ekman’s theory, that is, emotions are universally recognized from facial expressions, has been questioned from a scientific point of view for more than 20 years. Barrett [2016] insisted that the last two decades of neuroscience research have brought us to the brink of a paradigm shift in understanding the workings of the brain and setting the stage to revolutionize our understanding of emotions. Based on the brain’s structure and function, Barrett proposed the “theory of constructed emotion,” which states that emotions should be modeled holistically as whole brain-body phenomena in context. The author developed an “emotional granularity” framework to understand and investigate individual differences in the valence-arousal circumplex model [Diab et al. 2011]. The framework...
The relationship between the two modes of expression is still an important subject of research. In his presentation slide, they also tried to directly use more than 500 unique emotional reactions from COMET, but failed because of the few training examples. If so, is “5” the best number? We think this is debatable. Controlling emotions using VAD is more complicated than using the four emotions; however, we believe it will be meaningful because of the potential for more diverse analysis.

In LREC 2018, Mohammad noted that the NRC AIL lexicon (i.e., lexicon of four basic emotions) is useful for studying the relationships between affect dimensions, especially when used in combination with the NRC VAD Lexicon. Other Aspects of Stories and Suggestions for Future Directions in this Area

In this paper, we focused on emotions, though we understand that emotions are not the only important aspects of stories. There are many other aspects to be considered: event, common sense, entity, and so on. These aspects have deep relationships with emotions, so we will tackle combining the approaches for these aspects with our emotional storytelling system as future work.

Events have been well-studied for story understanding and generation [Chambers and Jurafsky, 2008, Martin et al., 2018, Sims et al., 2019, Tambwekar et al., 2019], and the relationship between events and emotions have also been paid attention [Rashkin et al., 2018a]. Studies on common sense in stories/narratives have a strong relationship with those of events [Mostafazadeh et al., 2016, 2017], and the focus has been broadened to motivations and emotions [Rashkin et al., 2018b]. Mostafazadeh et al. [2020] proposed a neural model for text generation that incorporates context via entities. To support tasks in natural language processing and the computational humanities, Bamman et al. [2019], Sims et al. [2019], and Bamman et al. [2020] proposed LitBank, an annotated dataset of 100 different English literary texts annotated for entity categories (person, location, geo-political entity, facility, organization, and vehicle).

In future, it is conceivable to integrate various elements related to story generation, such as characters, emotions, and events, by Narratology. Narratology, founded on Propp’s folktale theory [Propp, 1968] as an origin [Imabuchi and Ogata, 2012], has been already shown as worth considering for story generation [Peinado and Gervás, 2005, Gervás et al., 2006, Imabuchi and Ogata, 2012]. Moreover, in recent years, Ogata and Akimoto [2019] introduced a new concept post-narratology, defined as “computational and cognitive approaches to narratology” which is closely related to story generation system.

How to handle “emotions” remains a big problem in computational linguistics. Which should we use, categorical emotions or dimensional emotions? If categorical, how many categories are suitable? Brahman and Chatturvedi [2020] used five (4 + 1) basic emotions of NRC AIL lexicon. They collected open-ended emotion-phrases from COMET [Bosselut et al., 2019], and mapped these phrases to one of the five basic emotions: anger, fear, joy, sadness, and neutral. They also tried to directly use more than 500 unique emotional reactions from COMET, but failed because of the few training examples. If so, is “5” the best number? We think this is debatable. Controlling emotions using VAD is more complicated than using the four emotions; however, we believe it will be meaningful because of the potential for more delicate emotional control.

The relationship between the two modes of expression is still an important subject of research. In his presentation slide in LREC 2018, Mohammad noted that the NRC AIL lexicon (i.e., lexicon of four basic emotions) is useful for studying the relationships between affect dimensions, especially when used in combination with the NRC VAD Lexicon.
As introduced in Section 7, “emotion” is an important subject of research in the field of neuroscience, especially in relation to the brain [Cowen and Keltner 2017]. How to incorporate cutting-edge knowledge in these fields into the treatment of language will also be important.

Although there are debates as to whether categorical or dimensional representations are better, it can be said that Arousal in dimensional emotion has an important meaning for human cognition and affection. Arousal expresses the rise and fall of emotions. A high Arousal level indicates that humans are excited by strong emotions, whereas Low Arousal means that the emotional stimulus is low and ineffective. These factors are closely related to humans’ raw emotions and feelings of liveliness. We [Mori et al. 2019a] hypothesized that human satisfaction with stories could be affected not only by pleasant and unpleasant feelings but also by high and low arousal, and confirmed it with dataset construction, experiment, and analysis.

9 Conclusion

Creativity is vital for humans, and writing and reading stories are essential aspects of creativity. Understanding how humans write and read stories has a tight relationship with understanding humans itself.

In this paper, we conducted extensive survey on stories and emotions. The novelty of this survey is that it included perspectives such as applications to creative writing support, professional techniques in storytelling, and findings in neuroscience. Our research question was: how computers can understand human creativity and enhance it with machine learning technologies? We believe creativity research is not to replace humans with computers, but to find a way of collaboration between humans and computers to enhance the creativity. We believe that this paper will lead to further development on story writing with the support of information science and technology and contribute to researchers and story writers.

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