Building a Story Dataset Based on Illustrated Cards

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***Abstract*—This paper introduces a crowdsourced text story dataset using the story card images of a commercial storytelling board game. We collect 705 text stories using illustrated story cards, where each story is classified with its ending type - either a happy ending or a sad ending. Then, the sentiment patterns for a series of illustrated story cards matching each text story are analyzed to explore possible emotional arcs present in each story. The most dominant sentiment pattern is Negative-Negative-Positive (N-N-P) in happy-ending stories; Negative-Negative-Negative (N-N-N) in sad-ending stories.**

***Index Terms*—Story Dataset, Illustrated Story Cards, Sentiment Analysis**

I. Introduction

Stories are an excellent tool for communication and a fundamental resource for literary works with various media, including text, film, video games, etc. While stories are essential and everywhere in our lives, story creation is a complicated and challenging task. Making a good story is even more demanding. For this reason, various storytelling board games have utilized either story cards such as Once Upon A Time (Atlas Games, 1993) and Dixit (Libellud, 2010) or story dices such as Rory's Story Cubes (2006) to leverage story writing.

In academia, several studies have focused on storytelling games for narrative generation. [1] presented a narrative generation system as a proof of concept, using tarot card images, to generate either a comedy-based story or a tragedy-based story. [2] developed a competitive storytelling game based on the word cards containing story elements such as order, love, and conflict. Recently, [3] suggested a grand AI challenge for creative captioning using the Dixit storytelling game card images.

The task of visual storytelling refers to creating stories with a sequence of images (typically consisting of five photos), whose primary goal is to create a human-like coherent story while maintaining the sequence (VIST: [4]). With the rapid progress of deep learning-based approaches, various attempts [5], [6] have been made to generate better (and more interesting) story descriptions using a photostream. Furthermore, [7] defined three qualities for visual storytelling - relevance, coherence, and expressiveness.

Story dataset is hard to collect as writing a good story requires time, effort, and inherent talent. In addition, labeling the story dataset is more demanding. In ROCStories, a crowdsourced text story dataset where a story consists of five sentences, the story ending (i.e., the last sentence) is connected with the characters and events in the previous sentences to evaluate the coherences of a story by choosing a proper ending from two options [8]. GLUCOSE (2020) is a large-scale story dataset incorporating commonsense causal knowledge based on ROCStories [9]. There is also a shared-character story dataset for evaluating story interestingness [10], containing annotations of the character's emotion and story interest.

To the best of our knowledge, there is no publicized text story dataset based on storytelling cards. Most of the previous visual storytelling story datasets use photostreams, which may constrain the user's creativity or imagination due to their direct interpretation. In this paper, we introduce a crowdsourced text story dataset using the story card images of a commercial storytelling board game.

The contributions of this paper are two-fold. First, we present a small-scale dataset including a set of story card images and matching text stories with the classification of ending types (either happy or sad). Second, we explore and analyze the possible sentiment patterns of the collected stories.

II. Dataset

A. Illustrated Story Cards

We employ a commercial storytelling board game named 'Storypic (YStory, 2014) [1]' under the permission of YStory. We posit that illustrated story cards can help the user create stories with less burden of story-making. The illustration in the story cards has two themes - emotion, and everyday life - consisting of 40 cards, respectively. Each illustrated story card is given a unique identification number from A_1 to A_40 (for daily themed illustration cards) and from B_1 to B_40 (for emotion themed illustration cards). We did not provide the user with specific words (e.g., baby, love, etc.), which might constrain the user's imagination.

B. Text Story Collection

To collect a crowdsourced text story dataset based on the illustrated story cards, we utilized Amazon's Mechanical Turk. The Turkers were given a story-building prompt to freely pick three out of eighty illustration cards and then make stories

[1] http://www.eeyagitalk.com/home/

(a) Example of happy ending story with positive-positive-positive pattern.

(b) Example of sad ending story with positive-positive-negative pattern.

Fig. 1. Examples of illustrated story cards-based text stories (Left: Happy-ending story; Right: Sad-ending story)

based on the selected cards. Specifically, the Turkers were requested to create two types of stories with different endings. One is to build a happy ending story, and the other is to make a story with a sad ending, such that the collected dataset has clear story endings for binary classification. In addition, the illustrated cards used in the story building are chronological, based on the three acts (1: Setup; 2: Development; 3: Ending). Finally, the Turkers were requested to write a sentence containing at least one event for each card.

Story collection proceeded for one month from April 2021. When choosing a crowdsourced story collection, we expected the overall story quality to be inconsistent depending on the Turkers. We finally collected 705 text stories, based on selected three cards out of eighty illustrated story cards, comprising 350 happy ending stories and 355 sad ending stories.

Figure 1 shows two types of collected story examples. The left exemplifies a simple happy ending story - a girl confesses to a boy she loves, and he accepts it. The right is an example of another simple story but with a sad ending this time - about a boy who wanted to be a pro soccer player but died young unexpectedly.

The collected whole story dataset consists of 2,182 sentences and 27,797 words, with an average of 12.7 words per sentence and 3.1 sentences per story. The number of words for a sentence ranges from just two words (e.g., "He worked.") to 43 words (e.g., "As Karen sees the soldiers in the streets after leaving the building of her former employer that she just got fired from for having a low social credit rating, it quickly dawns on her that maybe her friends were right the entire time."). The shortest story consists of 15 words (e.g., "Tom falls in love with Mary.", "Mary accepts Tom's love.", "After marriage, Mary got pregnant."), and the most extended story includes 130 words. Table I shows the overall statistics of the collected stories.

Table II and Table III shows the top 15 frequently used verbs, nouns, and adjectives in happy-ending and sad-ending stories, respectively. While most words are commonly used in both happy-ending and sad-ending stories, some interesting words are exclusively used in each story. For example, 'Baby,' 'Healthy,' and 'Beautiful' in happy-ending stories; 'Accident,' 'Military,' and 'Old' in sad-ending stories. Figure 2 shows word clouds using the top 20 frequently used words (noun and adjective only).

Ending Type	Word	Sentence	Story
Happy Ending	13,913	1,088	350
Sad Ending	13,884	1,094	355
Total	27,797	2,182	705

TABLE I
OVERALL STATISTICS OF THE COLLECTED STORY DATASET

Verb	Noun	Adjective
Get(116)	**Friend(82)**	**Happy(57)**
Go(111)	Day(80)	Good(43)
Become(71)	Boy(54)	New(40)
Play(63)	Doctor(50)	Long(20)
Decide(47)	Money(50)	Able(18)
Come(47)	John(47)	Healthy(18)
Start(45)	Lot(47)	Pregnant(17)
Find(45)	Baby(44)	Great(17)
Give(41)	Hospital(39)	Sad(16)
Make(41)	Life(39)	Many(15)
Want(37)	Home(38)	Beautiful(15)
Feel(35)	Time(37)	Big(14)
Meet(34)	Game(36)	Outside(11)
Take(30)	Love(33)	Late(10)
Tell(28)	Dream(32)	Due(10)

TABLE II
TOP 15 FREQUENTLY USED WORDS (VERB, NOUN, ADJECTIVE) IN HAPPY ENDING STORIES

C. Matching Words for Illustrated Cards

The same image can evoke different words in our minds. For this reason, we collected a list of representing words for each illustrated story card via crowdsourcing. Ten Amazon Turkers described matching words for eighty illustrated story cards. Figure 3 shows two samples of matching word lists for two illustrated story cards, where the bold fonts refer to common words described by more than five Turkers (i.e., agreed by more than 50% of annotators).

Verb	Noun	Adjective
Get(144)	**Day(90)**	**Sad(40)**
Go(121)	John(82)	Long(27)
Play(52)	Hospital(81)	Bad(26)
Become(41)	Car(77)	Due(18)
Come(40)	Friend(66)	Military(18)
Die(39)	Accident(55)	Old(17)
Start(39)	Time(44)	Happy(14)
Tell(39)	Boy(44)	New(13)
Make(35)	Home(43)	Homeless(13)
Meet(32)	Tom(42)	Good(13)
Lose(30)	School(41)	Little(12)
Run(28)	Money(39)	Able(11)
Admit(27)	Game(37)	Next(10)
Drive(27)	Doctor(33)	Late(10)
Take(26)	Work(33)	Pregnant(9)

TABLE III
TOP 15 FREQUENTLY USED WORDS (VERB, NOUN, ADJECTIVE) IN SAD ENDING STORIES

Fig. 2. Word Cloud for Happy-Ending Stories (Top) and Sad-Ending Stories (Bottom)

III. SENTIMENT PATTERNS

We analyzed sentiments for the eighty story cards using NLTK VADER sentiment analysis tool [11] about the list of matching words described in the previous section. The matching word list for the whole story cards contains 4,186 words, and the average word list length per card is 52.33. As a binary classification of sentiments, the sentiment of a story card is determined as positive if the average compound values for a list of matching words are greater than or equal to 0.1; otherwise, negative. Among the 80 story cards, there are 28 cards with positive emotions (positive cards, referred to as P) and 52 cards with negative emotions (negative cards, referred to as N). Of the collected cards for story creation, the proportions of P cards and N cards are 38.9%(822/2,115) and 61.1%(1,293/2,115), respectively.

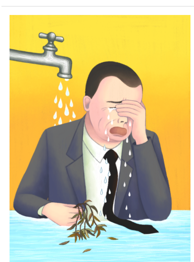
Identifying the emotional arcs of a story [12] is crucial to understanding a given story. After classifying the sentiment of each story card, we analyzed the emotional arcs (i.e., sentiment patterns) of three-card stories. As expected, the third (i.e., the last) card in the happy-ending stories tends to be a P card (75.7%). Similarly, the last card chosen in sad-ending stories tends to be an N card (93.5%). The figure 4) shows the distribution of eight possible types of sentiment patterns in the three-card stories.

As seen in Figure 4, the two most frequently appearing sentiment patterns in happy ending stories are N-N-P (31.4%) and N-P-P (20.3%). The frequency of N-P-P (20.3%) and P-P-P (11.1%) patterns are relatively low. Examples of the stories with these patterns are: ‘Living in a war zone - A bomb caused a fire - King invited to dinner for peace talks (N-N-P),’ ’Getting sick - Meeting a good doctor - Getting healthy (N-P-P).’ Based on this observation, we assume that N cards are preferably selected as the first card even for creating stories with a happy ending. P-P-N is the least frequently appearing pattern (3.4%).

As for sad ending stories, the two most frequently appearing sentiment patterns are N-N-N (32.4%) and P-N-N (32.1%). The second and the last cards’ sentiments are both negative in these two patterns. Story examples with these patterns are: ‘Feeling loneliness - Mentally disturbed - Get mental disorder (N-N-N)’ and ‘Hang out with friends - Accidents - Hospital (P-N-N).’ Naturally, P-P-P is the least frequently appearing pattern (0.8%).

gifting, giftbox, gift pack, **gift**, square box, box, generosity, **present**, thankful, thanks, birthday, loving, caring, wrap, tie, holding, ribbon, ribbon, offer, bow, green lace, red dress, white dots, dots, two hands, thoughtful, woman, surprise, love, smart, girl, give, gracious, handmade, special occasion, hostess

Total compound: 0.51819



crying, cry, cry a river, sad, sadness, **water**, man, tap, tap water, faucet, tears, plant, emotional, suit, wet, sobbing, upset, distraught, heartbreak, lost love, forlorn, face washing, waterworks, leak, black tie, tie, coat, white shirt, leaves, closed eyes, pain, agony, flowing

Total compound: -0.57812

Fig. 3. Matching Words List for Two Illustrated Story Cards (Above: Positive story card (VADER compound output = 0.51819); Below: Negative story card (VADER compound output = -0.57812)

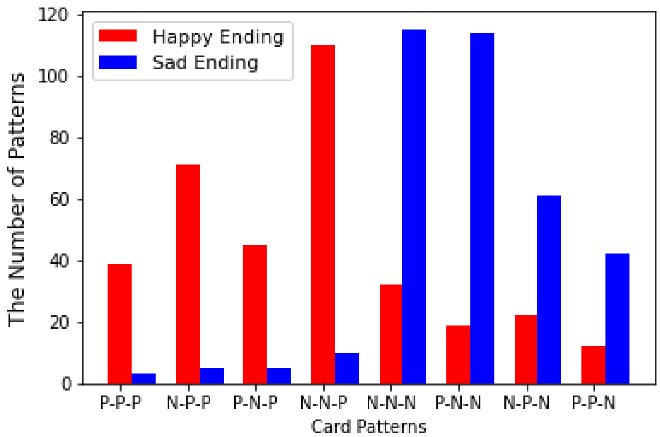


Fig. 4. Comparison of Sentiment Patterns of the Story's Three Story Cards According to Their Ending Types

IV. Conclusion

In this paper, we present an illustrated story cards-based text story dataset. We collect 705 text stories in which each story is associated with three illustrated story cards. In addition, all stories have annotated ending types - either happy (350) or sad (355). The sentiment patterns for a series of illustrated cards matching each text story are analyzed to explore possible emotional arcs. The most dominant sentiment pattern is Negative-Negative-Positive (N-N-P) in happy-ending stories; Negative-Negative-Negative (N-N-N) in sad-ending stories. While this work is yet at its early stage, we expect that analyzing sentiment patterns will be helpful for a computational narrative generation or understanding research. We are currently making annotations about story interestingness factors with the collected stories. After the annotations are done, we plan to investigate possible features that can explain interestingness in further work.

Acknowledgment

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Appendix