

# Towards Attribute-Entangled Controllable Text Generation: A Pilot Study of Blessing Generation

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## Abstract

Controllable Text Generation (CTG) has obtained great success due to its fine-grained generation ability obtained by focusing on multiple attributes. However, most existing CTG researches overlook *how to utilize the attribute entanglement to enhance the diversity of the controlled generated texts*. Facing this dilemma, we focus on a novel CTG scenario, i.e., **blessing generation** which is challenging because high-quality blessing texts require CTG models to comprehensively consider the entanglement between multiple attributes (e.g., objects and occasions). To promote the research on blessing generation, we present EBleT, a large-scale Entangled Blessing Text dataset containing 293K English sentences annotated with multiple attributes. Furthermore, we propose novel evaluation metrics to measure the quality of the blessing texts generated by the baseline models we designed. Our study opens a new research direction for controllable text generation and enables the development of attribute-entangled CTG models. Our dataset and source codes are available at <https://github.com/huangshulin123/Blessing-Generation>.

## 1 Introduction

Controllable Text Generation (CTG) aims to automatically generate the text under the restrictions of given conditions (Prabhumoye et al., 2020; Dong et al., 2021; Sun et al., 2022). As the mainstream, controlling multiple attributes enriches the information contained by generation and matches the demand of application scenarios, such as generating Chinese poetry (Yi et al., 2020), restaurant reviews (Chen et al., 2021), and product descriptions (Xu et al., 2019).

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Occasion	Object	Entanglemnet
Birthday		May <b>success</b> and happiness be with you every day, happy birthday to you.
Colleague		May your <b>career dreams</b> be <b>shining</b> like the <b>candles</b> on your cake. Happy birthday!
Christmas		Dear <b>boss</b> , I wish <b>God</b> shower you with his blessing this Christmas. Happy X-mas.
Boss		Merry <b>Christmas</b> to a <b>boss</b> who keeps the office <b>humming</b> along like <b>Santa's Workshop</b> !

Figure 1: Two groups of blessing examples. Each group contains blessing messages without (top) and with (bottom) the attribute entanglement. **Representative elements** of occasion/object attributes are marked.

Take the Chinese poetry generation task as an example, one beautiful poetry sentence should contain multiple attributes and reflect the entanglement (or mixture) of them through reasonable connection, e.g., in the sentence “胡马南来路已荒(The enemy’s warhorses march to the south, through destroyed roads)”, “胡马(enemy’s warhorses)” is a representative element of the military career, “南来(march to the south)” and “荒(destroyed)” represent the attribute of troubled times. This poetry sentence vividly depicts a picture of War in troubled times through the entanglement of attributes in just seven characters. Yi et al. (2020) also claim that considering the entanglement among attributes can effectively enhance the quality and diversity of generated poetry. Therefore, we believe that *better CTG models must focus on the effect of attribute entanglement, i.e., enhancing the reflection of multiple attributes through the use of various representative elements in the generated text*.

For Chinese CTG, with poetry generation as a typical scenario, researchers have conducted in-depth research on attribute entanglement, but in the English CTG field, the research on attribute entanglement has not been explored. Therefore, to promote research on attribute-entangled CTG in the English community, in this paper we focus on **blessing generation**, a new CTG task that

plays a key role in social scenarios. The automatically generated blessings will greatly promote interpersonal communication and enrich people’s daily life. More crucially, the blessing generation task is challenging due to its high requirement for entanglement between attributes, such as objects and occasions. As shown in Figure 1, “Santa’s Workshop” connects the occasion (Christmas) and object (Boss) into one phrase, making the blessing wonderful. A more vivid blessing embodies these two attributes in an intertwined manner, such as “keeps the office humming along like Santa’s Workshop”.

Facing the vacant of blessing generation, we construct EBleT, a large-scale **Entangled Blessing Text** dataset annotated with multiple attributes. Particularly, the EBleT is constructed with the following two features: (1) EBleT contains 23 occasions and 34 objects annotated on 293,403 blessing texts from 12 blessing websites. (2) As 92% of the blessing texts are personalized for the corresponding attributes, EBleT has at least 82% data containing the entanglement between attributes.

Additionally, the common generation evaluation metrics cannot reflect the characteristics of blessings clearly. To evaluate the generated blessings more comprehensively, we propose novel metrics to automatically calculate the degree of attribute entanglement and the quality of blessings. Our experiments demonstrate that mainstream CTG methods struggle to contain the entanglement. Moreover, existing methods can not balance the fluency, diversity, and entanglement between attributes. These results indicate that the blessing generation task we focus on is challenging and could serve as a useful benchmark for CTG research.

## 2 Task Definition

The blessing generation task aims to obtain a generation model  $\mathcal{G}(x_1, x_2; \theta)$  parameterized by  $\theta$ . Given the input attributes containing an object  $x_1 \in X_1$  and an occasion  $x_2 \in X_2$ , the model  $\mathcal{G}$  should output a blessing text  $y$  sent to  $x_1$  for  $x_2$ , where  $y = \{y_1, y_2, \dots, y_n\}$  is a sequence containing  $n$  words, and  $x_i (i = 1, 2)$  is a word or a phrase belonging to a collection of objects or occasions. The generated text  $y$  should reflect not only the language style of blessing, but also effective entanglement between both attributes. Additionally, the evaluation metrics for the language style of blessing and entanglement are described in Section 4.

## 3 EBleT Dataset

### 3.1 Dataset Construction

**Data Collection** We search blessing-related keywords (e.g., “send blessing”, “send wish”) via Google Search and obtain 12 blessing websites. We check the licences of those websites to ensure that data from these websites can be legally employed for our non-profit academic research. The occasions and objects are labeled by page headings and subheadings from these websites. Therefore, we obtain the headings and subheadings, as well as corresponding lists of blessing texts. The occasions and objects are extracted from the headings and subheadings. We totally collect about 1 million texts from the web as the raw corpus.

**Data Cleaning** After acquiring the original corpus, we remove completely duplicate sentences, delete all non-English text, and remove the sentences that do not reflect corresponding occasion/object attributes. Additionally, we observe that too long or too short sentences are mostly noise. Therefore, to further clean the dataset, we keep only sentences in the range of 10 to 200 words in length.

**Human Evaluation** To manually evaluate the quality of EBleT, we randomly select 20 data samples from each “object-occasion” pair except for the pairs related to the “General” object and finally obtain 5,520 data samples. Then we employ 3 college students who are English native speakers as annotators to manually assess the personalization and entanglement scores of these samples. As the annotation payment, we provide them 5 dollars for every 100 sentences they judged. Besides, to ensure the reliability of their scores, we carefully explain the concept of personalization and entanglement to them before the start of annotation. Specifically, **a blessing can be called personalized if the annotator can easily know its labeled occasion/object**. Moreover, **a blessing can be called entangled if it cleverly blends the characteristics of the labeled occasion/object, rather than combining the two so rigidly that it can be substituted for any other occasions or objects**. After being familiar with the concepts of personalization and entanglement, our annotators are asked to judge the sampled data and give the score (0 - common, 1 - personalized, 2 - both personalized and entangled). We take the majority vote as the annotation result for a data sample. The Fleiss’ kappa (Fleiss, 1971) of the annotations is 0.837,

which indicates the annotation results of our annotators can be regarded as “almost perfect agreement” (Landis and Koch, 1977). The results of human evaluation will be presented and analyzed in the “Dataset Quality” of Section 3.2.

### 3.2 Dataset Analysis

**Dataset Statistics** Table 1 describes statistics of EBleT. Compared with previous annotated CTG datasets, e.g., ROCStories (Mostafazadeh et al., 2016) with 50K stories, GYAFc (Rao and Tetreault, 2018) with 53K sentences and ToTTTo (Parikh et al., 2020) with 121K tables, our EBleT containing 293K blessing texts with corresponding occasion and object labels can be regarded as a sufficiently large-scale dataset. Moreover, our dataset consists of up to 276 pairs crossed by 23 categories of occasions and 34 categories of objects, which is challenging for models to learn the characteristics of each category of occasions and objects and to entangle them. More details and examples of EBleT are shown in Appendix A.1.

Property	Value
Dataset Size	293,403
Average Length	43.06
# Occasions	23
# Objects	34
# Occasion-object Pairs	276

Table 1: Dataset statistics of EBleT.

**Dataset Quality** Table 2 shows human evaluation results of EBleT. It indicates that about 92% of the blessing texts are personalized for the corresponding attributes, and about 82% data reflect the entanglement between attributes, which demonstrates the quality of EBleT.

		#Sample	#Per.	#Ent.
Occasion	Christmas	480	445	397
	Halloween	160	144	134
Object	Teacher	200	181	164
	Boss	140	126	118
Total		5,060	4,676	4,170

Table 2: Partial human evaluation results of EBleT. #Sample, #Per. and #Ent. denote the total number of sampled sentences, the number of personalized sentences and the number of entangled sentences respectively. The full list is presented in Table 7.

**Dataset Visualization** After removing the stop-words and the words related to specific occasions and objects, we plot the word cloud of EBlET as shown in Figure 2. We find out that some words (e.g., “wish”, “love”, and “happiness”) appear frequently. This phenomenon not only meets our common sense, i.e., blessing texts usually express wishes for each other, but also provides a class of words that need to be focused on for the development of future blessing generation models.



Figure 2: The word cloud visualization of EBLET.

## 4 Evaluation Metrics

#### 4.1 Blessing Score

To measure the quality of blessings, Blessing Score should reflect the extent to which a sentence fits the language style of the blessing. By counting word frequency, we observe that some words, e.g., “happy”, “merry”, and “heart”, frequently appear in blessing texts rather than in other texts. We obtain the 50 most frequently occurring words and remove the stopwords. These words are utilized to construct the bag-of-words of the blessing  $B$ .

For a sentence to be evaluated, to avoid the influence of irrelevant words, we use KeyBERT ([Grootendorst, 2020](#)) to extract 10 keywords to form a keyword list  $K$  as a representative of the sentence. All words in  $B$  and  $K$  are converted to word embeddings by Word2Vec ([Mikolov et al., 2013](#)) model  $E(\cdot)$ . For each keyword, we calculate its maximum similarity to all words in  $B$ , and then average the maximum similarity of all keywords to obtain the Blessing Score (BLE). It is formulated as follows:

$$\text{BLE} = \frac{1}{|K|} \sum_{w \in K} \max_{b \in B} \frac{E(w) \cdot E(b)}{\|E(w)\| \cdot \|E(b)\|}. \quad (1)$$

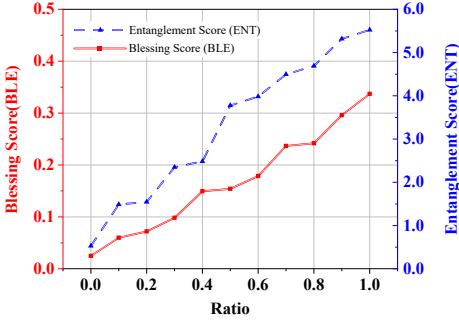


Figure 3: The correlation between human annotations and automatic metrics. The horizontal axis represents the proportion of the set that is manually annotated as blessing or entanglement.

## 4.2 Entanglement Score

To evaluate the degree of attribute entanglement, we assume that a blessing sentence with higher Entanglement Score should satisfy that the elements related to the occasions and objects appear simultaneously in more clauses. Further, occasion-related and object-related elements should alternate more times in one more entangled blessing sentence.

We construct two bags-of-words  $B_1, B_2$  to represent the occasion-related and object-related elements respectively. Specifically, the bags-of-words contain words directly related to the corresponding occasions and objects, which are listed in Table 8 and Table 9 of the Appendix.

For the Entanglement Score, we calculate whether words related to the two attributes occur simultaneously within each clause by cosine similarity, and add a bonus term  $O^1$  for the cases where related words occur alternately multiple times. Formally, for each sentence  $S$  to be evaluated, we split  $S$  into  $m$  clauses  $S = \{s_1, s_2, \dots, s_m\}$  and each clause  $s_i$  consists of  $n$  words  $s_i = \{w_{i1}, w_{i2}, \dots, w_{in}\}$ . The Entanglement Score (ENT) for  $S$  is calculated as follows:

$$\text{ENT} = \sum_{s_i \in S} I((\exists w_{ij}, w_{ik} \in s_i) C(w_{ij}, w_{ik})) + O, \quad (2)$$

$$C(w_1, w_2) = \text{sim}(w_1, B_1) > t \wedge \text{sim}(w_2, B_2) > t, \quad (3)$$

$$\text{sim}(w, B) = \max_{b \in B} \frac{E(w) \cdot E(b)}{\|E(w)\| \cdot \|E(b)\|}, \quad (4)$$

where  $I(c)$  is the indicator function, which has a value of 1 when the condition  $c$  is satisfied,  $t$  is a predetermined threshold.

<sup>1</sup>The specific implementation of our designed bonus is presented in the source code of the supplementary material.

## 4.3 Metric Verification

To verify the effectiveness of our proposed blessing and entanglement score, we conduct consistency analyses between automatic scores and human annotations. We extract 11 subsets and each of them has 100 pieces of data. Meanwhile, we make the proportion of blessings or entanglement (annotated by humans) in each set different, which is from 0.0 to 1.0. The average blessing score and entanglement score for the 11 subsets are calculated by our metrics. The results presented in Figure 3 demonstrate that our proposed metrics are highly consistent with the results of manual annotation.

## 5 Experiments

### 5.1 Experiment Setup

We set up experiments to evaluate the performance of existing models to generate entangled blessing texts. The full dataset is divided into a training set, a validation set and a test set in the ratio of 9:0.5:0.5 by stratified sampling.

To measure the consistency of generated outputs and reference blessing texts, we utilize BLEU (Papineni et al., 2002) and WMD (Kusner et al., 2015). WMD is a method to calculate the minimum embedded word distance required for a document to transfer to another one. In addition, we use Perplexity and Distinct-n( $n=1,2,3$ ) (Li et al., 2016) to evaluate the fluency and diversity of generated outputs. Specifically, GPT-Neo (Gao et al., 2020) is employed as the language model to obtain the perplexity. Furthermore, we use Blessing Score and Entanglement Score mentioned in Section 4 to evaluate the quality of blessings.

We evaluate two widely used generation models on EBLET for our proposed task:

**GPT-2** (Radford et al., 2019) is a Transformer-based decoder-only model (Liu et al., 2022) which achieves stable and excellent generation performance. For this task, we design a prompt: “Send this blessing to  $\langle object \rangle$  for  $\langle occasion \rangle$ ”, where  $\langle object \rangle$  and  $\langle occasion \rangle$  represent the object and occasion attributes, respectively. The prompt is utilized for the prefix input of GPT-2 model. Diverse Beam Search (Vijayakumar et al., 2016) is employed as the decoding method during the generation process to ensure diversity of generated blessings.

**T5** (Raffel et al., 2020) is a model of the encoder-decoder framework which is commonly used for

	BLEU↑	ROUGE-L↑	WMD↓	PPL↓	DIST-1↑	DIST-2↑	DIST-3↑	BLE↑	ENT↑
Common	-	-	-	-	0.609	0.953	0.998	0.022	-
GPT-2	0.225	0.382	1.018	20.12	0.176	0.327	0.405	0.308	3.52
T5	<b>0.247</b>	<b>0.393</b>	<b>1.015</b>	<b>13.47</b>	0.140	0.274	0.358	<b>0.334</b>	3.23
GPT-2 + CVAE	0.137	0.340	1.058	28.84	<b>0.409</b>	<b>0.788</b>	<b>0.907</b>	0.223	3.63
GPT-2 + Adv.	0.147	0.349	1.050	28.32	0.397	0.778	0.903	0.226	<b>3.78</b>
Reference	-	-	-	-	0.455	0.830	0.928	-	4.54

Table 3: Performance of different models on EBleT. **Common** represents the news texts collected from British Broadcasting Corporation which is used to make the comparison with blessings. "↑" represents higher is better for this metric and "↓" represents lower is better.

text-to-text generation tasks. The prompt mentioned above is utilized for the input of encoder side of T5 model.

Additionally, we consider applying CVAE (Sohn et al., 2015) for generation and using the latent variables to represent the entanglement of the two input attributes. Following the previous work (Fang et al., 2021), we employ pretrained GPT-2 as the backbone of CVAE to obtain higher quality generated results. Furthermore, we employ adversarial training (Adv.) (Yi et al., 2020) instead of minimizing KL divergence in CVAE to allow the model to learn more complex entangled representations.

## 5.2 Experiment Results

The results of Table 3 demonstrate that: (1) Models trained on EBleT can generate fluent blessing texts. The language style of generated texts is generally consistent with that of the blessing texts in the dataset. (2) The diversity and Entanglement Score of texts generated by GPT-2 and T5 are actually low. Meanwhile, employing CVAE or adversarial training architecture based on GPT-2 can effectively improve these two metrics but slightly reduce the quality of blessing. Additionally, the architecture of adversarial training outperforms CVAE in the entanglement and the quality of blessing, suggesting that the adversarial training architecture is more appropriate for entangling the attributes into generation. (3) There exists a gap of diversity and Entanglement Score between generated texts and references. It indicates that EBleT is a challenging benchmark for exploring the entanglement of attributes in CTG. Future work on this task should consider all the metrics of fluency, diversity, quality of blessings, and entanglement to generate blessings that are more in line with human expression.

## 6 Related Work

Controllable text generation (CTG) usually takes the controlled element and source text (which can be missing) as the input. Based on the input, the generation model produces the target text satisfying controlled elements. According to the core of CTG, i.e., the diversified controlled elements, we can divide CTG into the following two categories:

**Attribute Control:** Ghosh et al. (2017) add the sentiment information into the generator to control the sentiment of the generated sentences. Luo et al. (2019) explore a framework including sentiment analysis and sentiment generator to control the fine-grained sentiment of generation. Chen et al. (2021) introduce a mutual learning framework to generate emotionally controllable comments. In addition, Wang et al. (2019) control the style of the generated text to present a specific style of writing. Zhang et al. (2018) build a generation system to generate conversations with the specific persona.

**Content Control:** Cao et al. (2015) control the topic of generation, exploring the latent semantics of vocabularies and texts to get the distribution of the topic. Keskar et al. (2019) add different controlling code to realize topic control. Koncel-Kedziorski et al. (2016) use the generator to edit the articles written by humans, changing the theme without changing the original story. Additionally, Zheng et al. (2020) build LSTM and LSTMR to make sure the entities appear in the generated summary. Xu et al. (2020) incorporate keywords into each sentence of the story over the generation process. Kikuchi et al. (2016); Duan et al. (2020) introduce the methods for controlling the output sequence length.

However, existing research work on controlled generation doesn't include the work related to blessing and neglects the entanglement among attributes. Blessings can be used in many aspects of life, such

as e-cards, advertisements, and so on. Thus we introduce a new task - blessing generation and propose the corresponding dataset EBleT.

## 7 Conclusion

To explore the entanglement between attributes, we present EBleT, a blessing dataset that presents a new controllable generation task. We propose novel metrics to automatically measure attribute entanglement and the quality of blessings. We also provide several baselines and conduct experiments for blessing generation. Experimental results demonstrate that EBleT could serve as a useful benchmark for attribute entanglement in CTG.

## Limitations

In this paper, we conduct experiments on EBleT employing some representative mainstream models. Since our work is only a pilot study of attributed-entangled CTG, we do not conduct experiments on more controllable generation models. Because of the challenge of EBleT, we suggest that more complex models can be implemented for improving the performance of blessing generation.

## Ethical Considerations

In this paper, to facilitate the study of attribute-entangled CTG, we propose the blessing generation task which needs to pay attention to the attribute entanglement to obtain vivid blessings. We believe that the blessing generation task embodies humanistic care, and the various generated blessing texts can not only enrich people’s daily life, but also promote interpersonal relationships. We also present EBleT, a large-scale annotated blessing dataset. All the corpora used in EBleT come from freely available resources on public websites and do not involve any sensitive or illegal data. Additionally, we design new automatic evaluation metrics to measure the quality of blessings. We think that our designed metrics are instructive for future research on the CTG tasks. After all, in the current CTG field, how to conduct an effective evaluation is also an important and yet unsolved problem.

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## A Appendix

### A.1 Dataset Details

The size of each object/occasion category is shown in Table 4 and Table 5 respectively. It is worth noting that the “General” category refers to the case where the sending object of corresponding blessing is not acquired during the data collection process. In addition, there is mutual inclusion between some objects in our dataset. We consider this phenomenon is reasonable, e.g., we may write only one blessing message for elders, and send it to others, such as parents, uncles, and teachers, with a little modification.

Some examples of EBleT are shown in Table 6 which contain the blessings and the corresponding attributes (i.e., occasions and objects).

Object	Size	Object	Size
General	102,284	Customer	4,220
Friend	48,058	Parent	3,791
Lover	20,314	Newlywed	3,210
Teacher	14,092	Senior	2,785
Girlfriend	9,323	Daughter	2,614
Dad	8,871	Son	2,610
Kid	8,373	Employee	2,272
Wife	7,584	Grandma	427
Husband	7,478	Cousin	403
Boyfriend	6,603	Niece	319
Student	6,600	Granddaughter	238
Boss	5,592	Aunt	215
Sister	5,208	Grandson	210
Colleague	4,896	Nephew	160
Brother	4,884	Grandpa	155
Classmate	4,770	Uncle	135
Mom	4,602	Grandparent	107

Table 4: The data size of each object category.

Occasion	Size	Occasion	Size
New Year	55,162	Farewell	9,046
Birthday	36,329	Valentine’s Day	8,727
Christmas	27,713	Halloween	6,050
Wedding	21,039	Mother’s Day	4,132
Good Morning	18,197	Exam	3,659
Thanksgiving	15,245	Happy Weekend	3,506
Graduation	15,234	Good Afternoon	2,284
Father’s Day	14,344	Fool’s Day	2,074
Teacher’s Day	12,321	Easter	1,999
Good Night	11,667	Housewarming	1,810
Children’s Day	11,067	Women’s Day	1,239
Anniversary	10,559		

Table 5: The data size of each occasion category.

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**[Anniversary] [Aunt]** Happy Anniversary to the people I look up to whenever I am in doubt. Dear uncle and aunty, you guys are surely made for each other. Have a great year ahead.

---

**[Anniversary] [Parents]** You are the parents that all kids hope to have, you are the couple that all lovers hope to be and you both are the pillars of support that every family wishes it had. Happy anniversary to the best parents ever.

---

**[Birthday] [Daughter]** This day is truly a special day for us because this is the day when we first had a glimpse on our angel. Have a lovely birthday our dear daughter!

---

**[Birthday] [Colleague]** Ignite one candle, happiness will last forever. We work together for around one-third in a day, and it's more than we spend time with our family, and It means we are colleagues. Happy birthday, dear colleague!

---

**[Children's Day] [Kid]** My child, I bless you on this special day. You will never grow up, I wish you a happy Children's Day!

---

**[Children's Day] [Student]** We may be your teachers but we also have a lot more things to learn from you, especially how to laugh with all your hearts. Happy children's day!

---

**[Christmas] [Boss]** Merry Christmas to a boss who keeps the office humming along like Santa's Workshop!

---

**[Christmas] [Wife]** Precious wife, my heart hangs on your every breath, like lights hanging on a Christmas tree. Merry Christmas my dear love!

---

**[Easter] [Boyfriend]** One the beautiful Easter day, my boyfriend, let the prayers and fasting for Lord Jesus bring much love and happiness in our lives. I pray to the Lord to make our relationship fruitful and prosperous. Have a happy Easter.

---

**[Easter] [Teacher]** Dear teacher, you are my inspiration and I am happy to be under your guidance. It's such a hopeful time of year, I hope your heart gets filled with love, baskets with candies and Easter eggs this Easter.

---

**[Thanksgiving] [Boss]** It has always been a pleasure working with you because it has been great learning. Thanking you for playing a leading role in my happiness at work. Warm greetings on Thanksgiving!

---

**[Thanksgiving] [Wife]** Today, I want to say thanks so much for accepting to spend the rest of your life with me. Thanks so much for being my heart beat. I love you, dear wife. Happy Thanksgiving day!

Table 6: The examples of EBleT. The words related to the attribute **Occasion** and **Object** are highlighted(e.g. Happy Anniversary).

Object	#Sample	#Per.	#Ent.	Occasion	#Sample	#Per.	#Ent.
Aunt	80	73	66	Anniversary	260	239	214
Boss	140	126	118	Birthday	520	479	436
Boyfriend	240	223	197	Children's Day	120	112	104
Brother	220	199	180	Christmas	480	445	397
Classmate	220	206	183	Easter	100	92	81
Colleague	200	187	162	Exam	200	185	163
Cousin	60	55	48	Farewell	220	205	186
Customer	100	90	83	Father's Day	120	112	99
Dad	140	128	115	Fool's Day	40	38	35
Daughter	200	188	168	Good Afternoon	120	113	100
Employee	120	112	97	Good Morning	340	310	279
Friend	440	405	361	Good Night	260	239	213
Girlfriend	300	278	248	Graduation	300	285	243
Granddaughter	60	55	52	Halloween	160	144	134
Grandma	40	38	33	Happy Weekend	60	56	48
Grandpa	20	18	16	Housewarming	60	53	50
Grandparent	20	17	14	Mother's Day	140	131	114
Grandson	40	37	31	New Year	440	404	368
Husband	260	237	211	Teacher's Day	80	76	63
Kid	180	168	145	Thanksgiving	320	300	260
Lover	340	319	282	Valentine's Day	300	274	245
Mom	200	188	165	Wedding	320	289	262
Nephew	20	19	17	Women's Day	100	95	76
Newlywed	20	18	16				
Niece	60	56	51				
Parent	160	147	133				
Senior	80	73	69				
Sister	240	216	195				
Son	200	189	166				
Student	160	149	130				
Teacher	200	181	164				
Uncle	40	37	33				
Wife	260	244	221				

Table 7: Complete human evaluation results of EBleT. #Sample, #Per. and #Ent. denote the total number of sampled sentences, the number of personalized sentences and the number of entangled sentences respectively.

Object/Occasion	Related Words
Colleague	colleague, work, workplace, office, workshop, companion, workmate, coworker, mate, associate, helper, partner, hard, company, career, wealth, business
Boss	boss, work, workplace, office, workshop, chairman, chief, head, sir, supervisor, leader, charge, administrator, management, leadership, dictator, rule, thank, success, company, full, career, team, support, help, guidance, money, business, mentor, job, employees, create, development, professional, encouragement, achievements
Girlfriend	girlfriend, queen, love, addicted, kiss, sweetheart, mate, bestie, date, babe, baby, partner, forever, heart, beautiful, dear, sweet, forever, together, give, long, dreams, warm, sun, care, thank, future, moment, wind, bright, gift, remember, lovely, honey, promise, cherish, promise, shining, flower
Aunt	aunt, uncle, aunty, dear, sweet, family
Boyfriend	boyfriend, love, addicted, kiss, sweetheart, mate, bestie, date, babe, baby, partner, heart, forever, darling, honey, promise, charming, precious, hugs, accompany
Brother	brother, dear, forever, sister, sweet, heart, luck, joy, proud, engagement, health, family, harmony, thanks, handsome, follow, childhood, room
Classmate	classmate, friend, together, forever, long, sincere, graduation, cherish, youth, road, think, school, everyone, memory, success, grow, accompany
Cousin	cousin, grow, hand, family, forever
Customer	new, customer, work, health, joy, friendship, money, client, gifts
Dad	father, dad, love, thank, hard, warm, care, healthy, forever, family, dear, work, rain, give, young, strong, back, child, grow, son, daughter, support, parents, longevity, gratitude, kindness, umbrella, gentle, teaching, understand, journey, lamp, encouragement, illuminating, handsome, stalwart
Daughter	daughter, dear, sweet, baby, family, princess, enjoy, gift, lovely, parents, born, th
Employee	work, employee, thank, luck, future, success, career, dedication, together, forever, colleagues, team, success, appreciate, office
Friend	happiness, friend, forever, dear, joy, friendship, warm, work, smile, care, sun, miss, sincerely, reunion, help, grow, accompany, kind, cherish, sunshine, gratitude, drink, successful, buddy, embrace, invite, lonely
Granddaughter	granddaughter, dear, candies, sweet, grandpa, grandma, favorite, happy, trick, toy, beautiful
Grandma	grandma, health, longevity, dear, old, thank, grandmother, joy, beautiful, sweet, kind
Grandpa	grandpa, healthy, longevity, heart, smile, dear, old, thank, grandfather, joy, beautiful, sweet, kind, grandson, embrace
Grandparents	grandparents, healthy, longevity, heart, smile, dear, old, thank, joy, beautiful, sweet, kind, grandson, embrace
Grandson	grandson, cute, dear, candies, sweet, grandpa, grandma, favorite, happy, trick, toy, handsome, magic
Husband	love, husband, dear, heart, life, always, thank, only, father, special, sweet, everything, marriage, wife, honey, baby, children, grateful, family, kind, wedding, marriage, cherish, met, deep, promise, moments, engagement
Kid	children, kid, happy, childhood, childlike, innocence, child, little, heart, face, fun, growth, dreams, laugh, play, enjoy, haha, colorful, free, fly, lively
Lover	love, heart, life, dear, sweet, forever, dreams, together, sweetheart, thank, wife, husband, honey, moment, light, warm, babe, cherish, promise, sure, met, shining, angels, partner, hug, breath, important
Mom	mom, mother, love, thank, health, hard, forever, son, woman, daughter, grateful, parents, kindness
Nephew	nephew, success, future, dear, life, proud, achieve, niece, adult
Newlywed	newlywed, love, together, wedding, life, marriage, beautiful, new, congratulations, hundred, harmony, wife, pair, bridegroom, moment, phoenix, candles
Niece	success, future, dear, life, proud, achieve, niece, adult, hard, beauty
Parent	mom, parent, care, mother, family, father, life, thank, grateful, forever, children, warm, dear
Senior	health, senior, old, long, longevity, thank, care, wealth, give, sir
Sister	sister, dear, beautiful, heart, brother, old, little, gift, proud, family

Table 8: Bag-of-words related to objects and occasions.

Object/Occasion	Related Words
Son	son, dear, sweet, baby, family, prince, enjoy, follow, handsome, gift, pride, lovely, parents, born, th
Student	student, children, future, childhood, friends, innocence, childlike, smile, classmates, knowledge, grow, road, college, proud, career, study, wisdom, university, achieve, examination
Teacher	teacher, hard, students, full, knowledge, care, light, podium, gratitude, chalk, soul, sun, wisdom, thank, kindness, forward, tree, dreams, education, support, learning, accompany, class, illuminating, wings, guidance, watering
Uncle	uncle, old, aunt, dear, sweet, family
Wife	wife, love, life, beautiful, heart, dear, mother, woman, everything, family, darling, warm, sweetheart, moment, thanks, dream, children, married, accompany, sunshine, given, deserve, help
Christmas	Christmas, Xmas, merry, santa, card, tree, eve, stocking, humming, peace, claus, warm, night, gift, bell, snow, cold, deer, candlelight, chimney, elk, sled, shining, jesus
Thanksgiving	thanksgiving, thank, grateful, gratitude, care, give, warm, smile, kindness, bright, cherish
Graduation	graduation, congratulation, graduate, determination, dedication, achievement, life, future, success, proud, work, teacher, school, classmates, dreams, youth, journey, forward, college, leave, knowledge, continue, grow, study, society, examination
Anniversary	wedding, love, increase, darling, marriage, th, year, couple, life, together, best, believe, more, wonderful, always, heart, wife, husband, long, future, relationship, sweet
Birthday	birthday, happy, years, health, long, forever, special, gift, dreams
Children's Day	children, childhood, always, sweet, play, innocent, smile, june, forever, face, young, grow
Easter	easter, god, christ, lord, resurrection, new, eggs, spring, pray, basket, renewal, prosperity, bunny, rejoice, risen, holy
Exam	exam, success, luck, god, pray, comes, write, believe, sure, result, grades, final, proud, study, lord, pass, wisdom, efforts, questions, victory, preparation, excellent, paper, deserve, confidence
Farewell	farewell, life, goodbye, thank, friend, future, miss, luck, again, back, remember, memories, leaving, cherish, years
Father's Day	father, dad, love, thank, mountain, sea, deep, strong, support, son, shoulders, strength, light, parents, tired, accompany, busy, gentle, umbrella, teachings, given, heavy
Fool's Day	fool, april, happy, stupid, look, phone, money, really, smile, read, haha
Good Afternoon	afternoon, day, enjoy, everything, sunshine, lunch, midday, relaxing, breath
Good Morning	morning, face, new, smile, sun, start, light, mood, yesterday, embrace
Good Night	night, sleep, goodnight, dreams, tomorrow, sweet, stars, pray, today, bed, moon, close, asleep, sound, amen
Halloween	halloween, ghost, fun, pumpkin, afraid, lantern, candy, mask, witches, broom, moon, children, vampires, monster
Happy Weekend	weekend, work, fun, relax, saturday, busy, enjoy, rest, tired, sleep
Housewarming	new, house, housewarming, move, congratulations, come, neighbors, firecrackers, welcome
Mother's Day	mother, love, thank, children, women, daughter, son, giving, grow, sea, raising, sunshine, breeze, embrace
New Year	new, spring, coming, eve, change, warm, year, red, together, fireworks, welcome, forward, bright, prosperity, winter, busy, snow, cold, bloom, approaching, continue
Teacher's Day	teacher, thank, work, students, knowledge, full, flowers, light, chalk, podium, sun, warm, candle, dedication, school, september, growth, tree, garden, respect, illuminate, education, children, classroom, guidance, ignited
Valentine's Day	valentine, love, heart, dear, darling, together, sweet, promise, honey, share, romantic, handsome, beautiful, kiss, important, partner, babe
Wedding	love, wedding, life, forever, marriage, congratulations, sweet, future, bride, harmony, wife, always, year, fate, home, share, moment
Women's Day	women, beautiful, special, strength, wife, work, power, inspiration, proud, deserve, queen

Table 9: Bag-of-words related to objects and occasions.