EmojiLM: Modeling the New Emoji Language

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Abstract

With the rapid development of the internet, online social media welcomes people with different backgrounds through its diverse content. The increasing usage of emoji becomes a noticeable trend thanks to emoji's rich information beyond cultural or linguistic borders. However, the current study on emojis is limited to single emoji prediction and there are limited data resources available for further study of the interesting linguistic phenomenon. To this end, we synthesize a large text-emoji parallel corpus, Text2Emoji, from a large language model. Based on the parallel corpus, we distill a sequence-to-sequence model, EmojiLM, which is specialized in the text-emoji bidirectional translation. Extensive experiments on public benchmarks and human evaluation demonstrate that our proposed model outperforms strong baselines and the parallel corpus benefits emoji-related downstream tasks[1][2].

1 Introduction

These years have witnessed the boom of social media. Online messages, posts, and articles play indispensable roles in everyone's daily life. Compared with traditional media, social media nowadays provide a much more diverse platform for people all over the world. One noticeable improvement is the various content formats. The emergence of emoji is revolutionary but also foreseeable given their absolute necessity and rich information beyond the cultural or linguistic borders.

Emojis are a pre-defined set of pictograms, logograms, ideograms, or smileys and are usually embedded in electronic messages and web pages to fill in emotional cues otherwise missing from contexts[3]. With the increasing use of emojis, they are no longer a "nice-to-have" for an existing language,
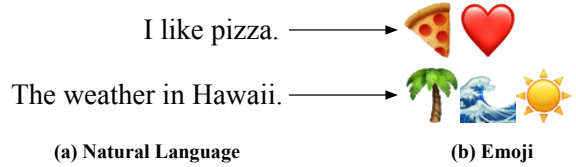

Figure 1: Examples of emoji translation from our Enlgish-Emoji parallel corpus, Text2Emoji.

but instead they act as an emerging "new language" that can be easily understood by users with diverse backgrounds. As reported, more and more people replace their redundant and bland pure-text posts with vivid emojis to deliver their complex semantics in a more witty way[4].

Considering the fascinating features of emojis, the existing emoji study is scarce and limited to single emoji predictions (Barbieri et al., 2018; Lee et al., 2022; Singh et al., 2022) which focuses on predicting a single emoji character according to the input sentence. While such experiment setting inspires the following research on the new type of data, it underestimates the expressing ability of emojis. Emojis are more than a substitute for emotion words (happy, sad, angry), but they can perform a similar role as natural language when people compose a sentence with multiple emojis, as shown in Figure 1. Little existing study pay enough attention to the formulation of the multi-emoji experiment setting.

To this end, we propose Text2Emoji, the first parallel corpus for emoji and text, and, EmojiLM, a distilled language model specialized in bidirectional English-Emoji translation. To the best of our knowledge, this is the first practice to go beyond rule-based or heuristic ways (e.g. string matching) and bring in the notion of Language Emoji translation for emoji studies. In addition, as shown in Figure 2, we build a website and implement a Chrome extension for users to use our service. They can

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enjoy the fun and convenience of English-Emoji translation as simply by visiting Google Translate. In comparison with directly querying online large language models services (e.g. ChatGPT[5], Bard[6]), our model is lighter and cheaper with weights accessible to the public community. Moreover, it is also feasible to fine-tune our proposed EmojiLM for relevant downstream tasks, including the aforementioned single-emoji prediction task.

To build the Text-Emoji parallel corpus, we synthesize data from large language models, which allows us to effortlessly create a corpus containing emojis that have 100 times larger emoji vocabulary size than prior work, such as TweetEval (Barbieri et al., 2020). We spend most of our effort on automatic and manual evaluation of the quality of the corpus and the derived distilled model. As aforementioned, there are little existing annotated data and it is infeasible to ask human laborers for annotation because of the high cost. We design prompts to trigger large language models to generate the corresponding emoji sequence according to the provided sentence. Next, similar to previous practices in neural machine translation, we train a sequence-to-sequence model on the parallel data as an English-Emoji translator. We package the pre-trained model and the I/O interfaces into a website and a Chrome extension for the public to use. To evaluate the performance of EmojiLM, we also compare it with strong baselines on three popular benchmarks, TweetEval, AG-News, and DBPdeia. Extensive experiments demonstrate the effectiveness of our proposed approach. Moreover, we conduct human evaluation on Text2Emoji and EmojiLM, where we compare our translation results with the ground truth in our parallel corpus. We observe that human annotators cannot distinguish the translation results from the ground truth, showing that our proposed model serves as an emoji translator of high quality.

We summarize our contribution as follows.

- We propose a parallel corpus for English-Emoji translation, Text2Emoji, which makes it possible to study the emoji usage as a new form of language and extends the scope of current emoji study from the single-Emoji prediction to the emoji translation.

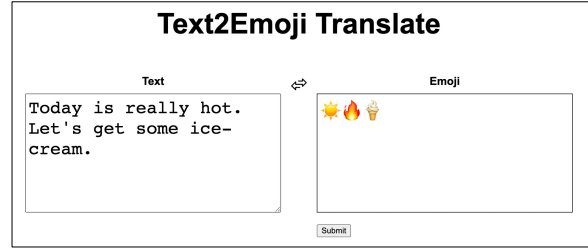- Based on Text2Emoji, we distill a sequence-

Figure 2: Screenshot from our implemented Text2Emoji translation website.

to-sequence model specialized in bidirectional English-Emoji translation, and implement a website and a chrome extension for public to use.

- Extensive experiments on public benchmark and human evaluation demonstrate the effectiveness of EmojiLM on three representative benchmarks.

2 Related Work

Research on Emoji As mentioned in Section 1, the current research on emojis mostly treats them as a symbol of emotion and creates the experiment setting, the single emoji prediction, which asks models to classify a given sentence into a given set of emojis. SemEval 2018 (Barbieri et al., 2018) proposes a multilingual emoji prediction task. The participants are asked to predict a single emoji for the given tweets either in English or Spanish. The emojis come from a fixed set of top 20 most popular emojis of each language. MultiEmo (Lee et al., 2022) proposes to use Bi-LSTM and attention mechanism to better solve the task. Singh et al. (2022) leverages the multi-task training and trains the model on emotion detection, sentiment analysis, and emoji prediction together.

Another research trend on emoji focuses on hate detection in online text with emojis (Kirk et al., 2021; Das et al., 2023). These works argue that existing methods fail to pay enough attention to the emoji characters in the online text, leading to their incapability to detect hateful language. While these works on hate detection emphasize the importance of emoji in online text, they are limited by the limited amount of existing online tweets or posts with emojis. Our work builds up a comprehensive parallel corpus for emoji so as to facilitate more future research on the emoji study.

Data Synthesis with LLMs Data synthesis is widely used to generate training data when it is difficult to obtain enough data for a specific task. Tang et al. (2023); Hämäläinen et al. (2023) leverage LLMs to generate synthetic data for the medical or HCI domains, and the synthesized data bring about improvement to the task thanks to the outstanding ability of LLMs.

3 EmojiLM

3.1 English-Emoji Parallel Corpus

We build a large English-Emoji parallel corpus, Text2Emoji, by prompting the LLM, `gpt-3.5-turbo` (OpenAI, 2023). To fully cover emojis in different domains, we ask the LLM to propose a sentence given a certain domain and then translate it into a series of emojis. We include 19 domains: "feeling", "career", "clothes", "animal", "plant", "weather", "food", "sports", "arts", "vehicle", "building", "tool", "country", "electrical appliance", "activity", "experience", "family member". We select these domains according to the categorization of emojis. Our prompt is presented as follows,

Write some sentences about a kind of <topic> and their pure emoji series translations in the following format: Text:... Emoji Translation:...

For the startup, we query the LLM 1000 times for each topic and collect the generated parallel sentences. We increase the diversity by setting the temperature of the generation to 1.5. However, the diversity is still limited since the sampling follows the probability distribution of a constant prompt. Thus, we utilize a property of the LLM to further increase the diversity that LLM inclines to generate something different given an instance for the instruction. Thus, with the startup data, we combine the prompt with an instance to encourage the LLM to generate more diverse sentences inside the topic.

User: *Write some sentences about a kind of <topic> and their pure emoji series translations in the following format: Text:... Emoji Translation:...*
System: *Text: <text> Emoji: <emoji>*

where we prompt the LLM to generate after a parallel instance, which is randomly sampled from the pool of generated instances. We further prompt with instances for 15000 times and thus build a large English-Emoji parallel corpus with $503.7K$ instances by filtering non-emoji tokens in the emoji series and instances with no emoji.

Attribute	Value
#Instance	$503.7K$
#Emoji Vocabulary	$2.3K$
#Text Average Length	15.18
#Emoji Average Length	7.97

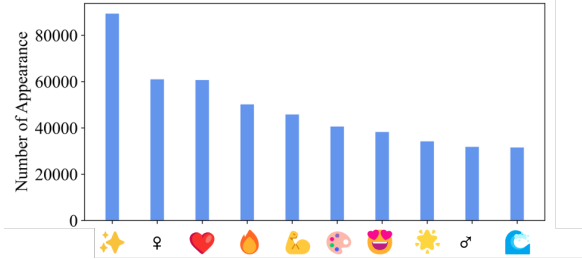Table 1: The statistics of our English-Emoji parallel.

Figure 3: Emoji tokens with the top 10 appearance in Text2Emoji.

Dataset Statistics In Table 1, we present the statistics of our English-Emoji parallel corpus. Our corpus covers a large ($2.3K$) emoji vocabulary, which is more than 100 times larger than the emoji class number (20) of the popular single emoji prediction dataset, TweetEval (Barbieri et al., 2020). The texts are in medium lengths, which is similar to the application scenario of emojis in reality. We also show the most popular emojis in Figure 3, which are also most commonly used in real-life social media. The gender symbols frequently appear in our corpus because there are composed emojis that are encoded as the combination of multiple emojis, joined with "\u200d". Gender symbols are generally combined with human emojis to switch the gender of them.

3.2 Learning Bidirectional Translation

Utilizing our comprehensive English-Emoji parallel corpus, we embark on the journey of training models that can seamlessly translate between texts and emojis in both directions. We adopted the encoder-decoder framework, a popular architecture for translation tasks, and implemented it with models like BART (Lewis et al., 2020) and T5 (Raffel et al., 2020).

However, it's important to note that emojis present unique tokenization challenges. The pre-existing vocabularies in models such as BART and T5 aren't optimized for emojis. As such, we enhanced the tokenizers by integrating the new emoji

	Text: Finding genuine happiness in pure moments of kindness and compassion from strangers. Small acts can make a big impact.
Choice1: 😊🌻👐	**Choice2:** 😊❤️👥🌟

Figure 4: An example in human evaluation.

	Model	B1	B2	B3	B4	BS
T→E	BART-B	32.2	20.0	14.2	10.8	-
	T5-B	32.6	20.4	14.5	11.0	-
	BART-L	34.8	21.9	16.1	12.0	-
E→T	BART-B	24.9	16.8	12.8	10.3	36.5
	T5-B	25.3	17.0	12.9	10.3	36.3
	BART-L	25.8	17.4	13.2	10.6	36.5

Table 2: The performance of bidirectional translation on the English-Emoji parallel corpus. (T5-B has the same scale as BART-L.)

vocabulary, ensuring they recognize and effectively process these symbols.

A distinct challenge in emoji translation is the concept of composed emojis. These emojis are encoded as a sequence, with different symbols joined using the "\u200d" separator. For instance, certain human emojis can switch genders by being combined with gender symbols. To ensure our translator is attuned to this nuance, we tokenize composed emojis into their constituent parts, separating them with the "\u200d" token. This strategy helps our translation models grasp the intricate relationships and compositions that emojis can present.

4 Experiment

4.1 Emoji Language Modeling

For both translation directions, we train a BART-Base (BART-B) model for 2 epochs with a 32 batch size. The learning rate is set to 5×10^{-5}. We set 2000 warmup steps for emoji-to-text translation.

We first evaluate the performance of learning on the English-Emoji parallel corpus. In this experiment, we split the whole corpus into train/dev/test datasets by 8/1/1. We train different language models on the training split and then translate the test split. In the generation step, we set the beam size to 4 and temperature to 1.0 to search for the sequence that maximizes the existence probability.

Human Evaluation To gain insight into how humans perceive the quality of our translation results, we engage human evaluators to assess our parallel corpus. Recognizing that directly judging the

	Dataset	#Train	#Test	#Domain	#Label
TweetEval	Emoji	45.0K	50.0K	Emoji	20
	Emoji-EX	47.4K	5.3K	Emoji	32
	Sentiment	45.6K	12.3K	Emotion	3
	Emotion	3.3K	1.4K	Emotion	4
	AG_News	120.0K	7.6K	Topic	4
	DBPedia	560.0K	70.0K	Topic	14

Table 3: The statistics of datasets used for task transferring.

correlation between a series of emojis and the corresponding text can be challenging and subjective, we adopt an indirect method of evaluation. Specifically, we present the evaluators with two potential translation outcomes, asking them to choose the one that seems more appropriate as shown in Figure 4. To eliminate biases linked to the order of presentation, the options are randomly switched. In this evaluation process, we sample 200 instances, with each instance being assessed by 3 different evaluators. This task is divided among 15 human evaluators, meaning that each evaluator provides feedback on 40 samples. After compiling the input from this substantial number of evaluators, we determine the final result by selecting the choice that has been favored by the majority.

1) **Text-to-emoji evaluation:** The human evaluator is given a sentence and is asked to select the better emoji series that represents the text between the generated emoji series by EmojiLM and one directly from the corpus. For 40% of the sample texts, participants favor the translation from our EmojiLM. This high proportion demonstrates that EmojiLM has a fair performance compared with the emoji from the corpus.

2) **Emoji-to-text evaluation:** This is a mirror test to the text-to-emoji evaluation. Given the emoji, the human evaluator selects the better-translated text from the emoji series. For 45% of the emojis, text from the corpus is selected as a better translation, further verifying the emoji-to-text ability of EmojiLM.

3) **Comparison w/ string-matching translator:** The evaluator is asked to compare the emoji generated by EmojiLM and an existing Emoji-Translate python package[7], which uses the string-matching strategy to map words into corresponding emojis. From 200 sample texts, EmojiLM is selected as a better emoji translator for 88% of them, verifying the absolute advantage of our translator.

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[7] pypi.org/project/emoji-translate

	Dataset	TweetEval				AG-News	DBPedia
		Emoji	Emoji-EX	Sentiment	Emotion		
	#Label	20	32	3	4	4	14
FULL SUP.	BERT	31.3	8.1	67.1	79.4	94.0	98.8
	BERTweet	33.6	10.1	70.1	79.9	**94.3**	98.9
	BART	30.8	12.1	69.8	79.8	93.4	**99.0**
	EmojiLM	**34.8**	**23.5**	**70.4**	**81.3**	93.6	**99.0**
FEW SUP.	BERT	10.3	5.1	36.3	27.0	54.9	95.1
	BERTweet	15.4	8.8	33.8	35.1	69.4	94.6
	BART	11.4	10.4	51.6	58.3	75.0	95.8
	EmojiLM	**23.8**	**13.6**	**55.7**	**61.3**	**84.0**	**96.4**

Table 4: Task transferring performances of different pre-trained language models.

Figure 5: The emojis used as labels for task transferring.

Overall, both emoji and text generated by EmojiLM hold a high level of quality in representing their respective input. EmojiLM consistently produces a higher quality of emojis when compared to the emojis generated by the existing Emoji-Translate python package.

Automatic Evaluation We involve more language models on automatic evaluation, including larger BART (BART-L) and T5 (T5-B, with the same parameter scale as BART-L). The learning rate is set to 3×10^{-4} for T5. The instruction for T5 is "translate text (emoji series) into emoji series (text): ". We use BLUE-n (Bn) (Papineni et al., 2002) and the BERTScore (BS, only for emoji-to-text evaluation) metric (Zhang et al., 2020) to automatically evaluate their performance on the test dataset. The translation performances are shown in Table 2. The bidirectional translator achieves high accuracy in emoji series generation considering the high diversity of emoji usage. For the emoji-to-text translation, the performance on BERTScore suggests our translator is able to capture the most semantics in the input emoji series.

4.2 Task Transferring

Datasets and Metrics We explore the transferability of emoji modeling to other tasks that are relevant to emojis. **TweetEval** (Barbieri et al., 2020) includes a popular subset (**Emoji**) for single emoji

prediction with 20 emojis as labels. **Emoji-EX**[8] is a dataset that extends the emoji number to 32 by incorporating negative emojis. **Emotion** (6 classes) and **Sentiment** (3 classes) are two subsets under **TweetEval** that can be formalized as emoji prediction by presenting the labels as emojis. To verify the generality of task transferring, we further incorporate two topic classification tasks: **AG-News** (4 classes) (Zhang et al., 2015) and **DBPedia** (14 classes) (Auer et al., 2007), also by presenting label names as emojis. We show the emojis formalization in Figure 5. More specific statistics of datasets in our experiments are shown in Table 3. Following the previous work (Barbieri et al., 2020), we use macro F1 score to evaluate performances on those text classification tasks.

Baselines and Setups As BART performs much better than T5 on translating text to emojis, we select BART for transferring to relevant tasks. We include different pre-trained language models as the baselines such as BERT (Devlin et al., 2019) and its variant, BERTweet (Nguyen et al., 2020), which is designed to be pre-trained on tweet texts. We also include BART without training on the English-Emoji parallel corpus to verify the benefit of further learning. For the BART baseline, we predict label texts instead of emojis, which is more consistent with the pre-training process of BART. We use models with the `large` size in the experiments for a fair comparison. For experiments in this part, we use a text-to-emoji translator that is pre-trained on the full corpus. We train models for 5 epochs for datasets without validation splits. All results in our experiments are averaged by 5 runs.

The model performances on task transferring

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[8]huggingface.co/datasets/adorkin/extended_tweet_emojis/viewer/adorkin–extended_tweet_emojis

are presented in Table 4. Our model shows the most significant advantage in emoji predictions, which outperforms all baselines, including the strong BERTweet. There is a definite gap between our EmojiLM and other baselines when the emoji classes increase to 32 in the Emoji-EX dataset. We attribute this to the understanding of emoji semantics of our EmojiLM, which enables it to handle the nuance between similar emojis. Our text-to-emoji pre-training also benefits emotion prediction as EmojiLM also achieves the best performances on Sentiment and Emotion subsets. This is also consistent with the fact that emojis are able to represent emotions efficiently, and thus the pre-training on emoji modeling benefits the emotion prediction task. On topic classification tasks, there is not a significant improvement under full supervision perhaps due to the large scale of those training splits. In comparison to the BART baseline, our EmojiLM always achieves a better performance, which suggests the potential of our model when labels can be formalized as emojis in text classification tasks.

Low-resource Situation Another advantage of training on our English-Emoji parallel corpus is improving the few-shot task transferring ability. As emoji prediction can be viewed as text-to-one-emoji translation, the consistency between the upstream and downstream tasks supports the potential for an efficient few-shot learning scenario. In Table 4, we present the performances of different language models using n-way 10-shot data as the supervision. We observe a large gap between our EmojiLM and other baselines. This phenomenon can be attributed to two factors: the translation scenario and the emoji understanding. The comparison between BART and BERT (BERTweet) reveals the first factor as BART performs much better with few data. The label names play an important role in task understanding when the supervision from the data scale decreases. Another factor is the concise nature of the emoji that summarizes a topic with a single token (emoji). Thus, our text-to-emoji EmojiLM significantly outperforms the text-to-text BART baseline.

4.3 Case Study

In Figure 6, we use specific cases to compare our EmojiLM translation results with those from the Emoji-Translate package, a string-matching baseline. The first two examples reveal a richer knowledge base of EmojiLM, as it accurately detects

Text: Yesterday, I climbed to the top of a mountain and saw an incredible sunset.
Emoji-Translate: 🏔️🎌
EmojiLM: 🏔️🌅👀💫
Text: The hospital down the street is newly renovated.
Emoji-Translate: 🏥
EmojiLM: 🏥🩹🔨🏗️👷👷🆕
Text: Watching the giants battle it out, while snacks and cheers fill the air. America's pastime at its finest
Emoji-Translate: 👕🦯
EmojiLM: ⚾🌭🌎🤩
Text: The stealthy snake coils up in its lair, waiting patiently for prey to approach.
Emoji-Translate: 🐍
EmojiLM: 🐍🐾🔍🌀💤👀🐰

Figure 6: Case study by comparing our translator (EmojiLM) with the Emoji-Translate package.

phrases like "incredible sunset" and "newly renovated," translating them into corresponding emojis. Unlike Emoji-Translate, EmojiLM also recognizes specific contexts. In the third example, it identifies "the Giants" as a baseball team, not literal giants, and outputs the emojis of relevant snacks such as "hotdog" and "beer."

In the fourth example, the power of our EmojiLM to create a narrative emoji series is clear. It crafts a story where a snake is patiently hunting, while Emoji-Translate merely returns a single snake emoji. This highlights the limitation of Emoji-Translate: it detects individual words and returns corresponding emojis but often misses the actual meaning within a specific context. On the other hand, EmojiLM offers a nuanced understanding of both the words and the overall sentence, utilizing a broader emoji knowledge base to provide more accurate and engaging translations.

5 Conclusion and Future Work

This paper introduces EmojiLM, an English-Emoji translator that goes beyond single emoji prediction to handle complex translations between texts and emojis. Utilizing a large corpus, EmojiLM outperforms existing baselines like BERTweet in text classification. This work represents a significant advancement in understanding and leveraging emojis in linguistic phenomena. Future work will delve into the intricate understanding of emojis by employing the embeddings derived from our model. Furthermore, we will explore the multifaceted association between textual and visual characteristics, with emojis serving as a connecting bridge.

Limitation

While the work presented herein demonstrates promising strides in the field of Emoji translation, certain limitations must be acknowledged. First and foremost, although we have successfully utilized LLMs to construct an English-Emoji parallel corpus, the source of this ability remains somewhat enigmatic. There is no publicly available training data specifically targeting this task, leading us to hypothesize that this ability stems from the LLM's understanding of emoji semantics and translation tasks. However, the exact mechanism remains unexplored and warrants further investigation. Secondly, the corpus itself might harbor biases towards popular emojis, reflecting the corpus used to train the LLMs rather than a balanced representation of Emoji usage across different cultures and communication contexts. This bias could lead to an overemphasis on commonly used emojis and potentially overlook the nuanced usage of lesser-known emojis, thus limiting the generalization and applicability of the derived models and tools. These challenges underline areas for future research and refinement in the pursuit of a more robust and comprehensive understanding of Emoji as a form of language.

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