ZEN 2.0: Continue Training and Adaption for N-gram Enhanced Text Encoders

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Abstract
Pre-trained text encoders have drawn sustaining attention in natural language processing (NLP) and shown their capability in obtaining promising results in different tasks. Recent studies illustrated that external self-supervised signals (or knowledge extracted by unsupervised learning, such as n-grams) are beneficial to provide useful semantic evidence for understanding languages such as Chinese, so as to improve the performance on various downstream tasks accordingly. To further enhance the encoders, in this paper, we propose to pre-train n-gram-enhanced encoders with a large volume of data and advanced techniques for training. Moreover, we try to extend the encoder to different languages as well as different domains, where it is confirmed that the same architecture is applicable to these varying circumstances and new state-of-the-art performance is observed from a long list of NLP tasks across languages and domains.

1 Introduction
The trend of pre-trained text encoders and decoders (language representations) has been featured in recent years with their effectiveness in performing different NLP tasks with a unified pre-training and fine-tuning paradigm (Devlin et al., 2019; Dai et al., 2019; Yang et al., 2019; Wei et al., 2019; Joshi et al., 2020; Liu et al., 2020). This paradigm, although in a “violent manner” with requiring huge computation cost, is nevertheless useful and provides both the academia and industry a new choice and ready-to-use resource to facilitate their NLP research and engineering. In this context, demanding on huge data is also accompanied with the computation needs, and particularly draws attention on data quality because the pre-trained models are often learned in a self-supervised manner so that the training objectives directly depend on the data nature. Yet, even though training data are often pre-processed and noise-filtered, some current models are restricted in learning adequate useful information from the data owing to their architecture limitations, such as applying vanilla BERT (Devlin et al., 2019) to Chinese, the important chunking information is omitted accordingly with the character-based encoder.

Therefore, many enhanced models are proposed to improve the model architecture for effective pre-training (Dai et al., 2019; Yang et al., 2019; Wei et al., 2019; Joshi et al., 2020; Liu et al., 2020), especially for particular language (i.e., Chinese). Of all models, ZEN (Diao et al., 2019) provides a flexible choice with an auxiliary encoder that learns n-gram information from the input text and uses such information to enhance the backbone character encoder. With this design, ZEN is able to not only take the advantage of text with larger granularity, which is highly important for languages such as Chinese, but also keep the effectiveness of the BERT architecture through its weakly supervised learning objectives. Compared to other models that use different masking strategies to learn information from larger granularity without improving the model architecture (Cui et al., 2019a; Sun et al., 2020), ZEN explicitly encodes n-gram information and combine it into character-based encoding from the input rather than back-propagated signals from output, and thus leads to a better text representation as well as easy-to-control knowledge insertion1.

In addition to the performance test in Diao et al. (2019), many other studies confirmed the effectiveness of ZEN, where the state-of-the-art performance is observed on Chinese word segmentation (Tian et al., 2020d), part-of-speech (POS) tagging (Tian et al., 2020a,b), parsing (Tian et al., 2020c), named entity recognition (Nie et al., 2020a,b), and conversation summarization (Song et al., 2020).

1One can manipulate the n-gram lexicon with desired n-gram/phrases to be learned during the pre-training process.
when ZEN is used as the encoder.

Although the performance of ZEN is proved on a series of Chinese NLP tasks, it still has room for improvement on many aspects. In doing so, there are several questions to be addressed for enhancing the current ZEN model: (1) whether n-gram representations are still useful when continue training the model especially with its size enlarged? e.g., from base to large version; (2) are there useful and widely applied adaptations that can be exploited by ZEN to further improve its representation ability? e.g., whole word masking; (3) whether texts in large granularity are also informative when their representations are used to train an encoder for languages other than Chinese? e.g., for those languages that are too different from Chinese. With such questions, we propose to update ZEN with the following improvements. First, we propose ZEN-large, increasing the amount of its parameters to the scale of BERT-large. Second, we refine n-gram representations with a weighting mechanism, apply whole n-gram masking and relative positional encoding during pre-training. Third, besides Chinese, we also apply the enhanced ZEN to Arabic, which is in a different language family and greatly varies from other languages that are intensively studied in NLP, e.g., English, French, etc.

To perform such pre-training, it is inevitable that larger models require more data and computing resources. With the aforementioned enhancements on ZEN, we use over eight and seven billion tokens in the training corpus for Chinese and Arabic, respectively. Especially for Arabic, to the best of our knowledge, this is the first model pre-trained exclusively for Arabic that uses such amount of data. For the pre-training process, we use a high-performance cluster with hundreds of GPUs² to perform model training and fine-tuning. The validity and effectiveness of the enhanced ZEN are evaluated by nine widely-used tasks (with ten datasets) for Chinese and six (with ten datasets) for Arabic, where the results confirm that a new state-of-the-art performance is achieved on these tasks. We also analyze the factors that affect the pre-training, including training steps, weighted n-gram representations, whole n-gram masking as well as adapted character encoding, which consistently indicate that the enhancements on ZEN are effective in helping its representation ability and training efficiency. To facilitate the research along this line and provide useful resources to the community, the enhanced ZEN is released at https://github.com/sinovation/ZEN2.

2 ZEN 2.0

Good text representations obtained from encoders often play an important role in many NLP tasks (Song and Shi, 2018; Song et al., 2017, 2018; Devlin et al., 2019). To improve character-based pre-trained encoders, ZEN 1.0 (Diao et al., 2019) provides a framework by leveraging important character-block (or text span) information with larger text granularity (i.e., n-grams) and representing such blocks with a specific encoder.³ In doing so, ZEN is structured with separate character and n-gram encoders. The character encoder is a Transformer (Vaswani et al., 2017) with multiple layers following the architecture of BERT to encode input characters; the n-gram encoder is also a similar Transformer structure without position encoding. When training, ZEN 1.0 follows BERT to mask several randomly selected characters in the input text. While in both training and fine-tuning, ZEN firstly finds the n-grams in the input text according to an n-gram lexicon, in which the n-grams are text spans that are likely to contain salient contents for representing important semantic information. Then, the model encodes these n-grams through its particular encoder and integrates their representations into the character encoder layer-wisely.

Based on the architecture of ZEN 1.0, we propose an update and adaptation for this model (ZEN 2.0) from three aspects, after which the model is upgraded into the same scale of BERT-large and applied to different languages (i.e., Chinese and Arabic). First, we refine the representations of n-grams by applying weights to the n-gram representations when integrating them into the character encoder. Second, in the training stage, we mask n-grams/words, rather than characters, in the input text of the character encoders. Third, we utilize relative positional encoding (Dai et al., 2019) for the character encoder to model direction and distance information from the input text. The details are illustrated in the following subsections.

2.1 Refined N-gram Representations

To encode n-grams, a Transformer with multi-head self-attention (MhA) are applied in ZEN 1.0. In the process of integrating the n-gram representations

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²All are NVidia Tesla V100 GPUs.

³We use “ZEN 1.0” to refer to its original version.
Figure 1: An illustration of the refined n-gram representations and their application to character encoder, where n-grams and their representations associated to the character “幻” (highlighted in blue) are weighted.

The weather on the sea is truly unpredictable. While blue skies, white clouds.

2.2 Whole N-gram Masking

The success of whole word masking (WWM) in BERT for English indicates that it is more appropriate to mask the whole words so as to preserve (as well as predict) important semantic information carried by words rather than sub-words/word-pieces or characters. Motivated by WWM and the fact that word is the smallest unit that can be used in isolation with objective or practical meaning, we propose to improve ZEN which follows Chinese BERT to mask characters in the training stage, by masking whole n-grams in the input text.

Because there is no natural word boundary between Chinese words in the raw text, we firstly use an off-the-shelf tokenizer to segment the input text into character n-grams and combine the adjacent ones into larger n-grams if they appear in the n-gram lexicon. Then, we randomly select some of the resulting n-grams and mask all characters in these selected n-grams, and ensure that 15% of the characters in the input text are masked.

Figure 2 illustrates the differences between character masking and n-gram masking in ZEN with an example input text, where the masked characters are represented by [M]. Compared with character masking, n-gram masking requires to mask all characters in the same n-gram. Afterwards, for the masked characters, we follow the conventional operation (Devlin et al., 2019; Dai et al., 2019; Wei et al., 2019; Sun et al., 2020) to (1) replace 80% of them by a special [MASK] token, (2) replace 10% of them by a random token, and (3) keep 10% of them the same. In the training stage, ZEN with whole n-gram masking tries to predict all characters in each masked n-gram based on its context and is thus optimized accordingly by larger text units.

2.3 Relative Positional Encoding

The original ZEN uses the same architecture (i.e., Transformer) of BERT to encode characters. Although such encoding process is effective in most cases, it still can be improved by modeling the distance and direction information for each input when encoding them, where Dai et al. (2019) proposed relative positional encoding that uses distance-
Figure 2: An illustration of the differences between character masking (ZEN 1.0) and n-gram masking (ZEN 2.0) with a given input text. Masked characters are represented by [M]. For ZEN 2.0, adjacent character n-grams obtained from an off-the-shelf tokenizer (segmenter) are combined into a new n-gram (highlighted in blue) if that n-gram appears in the n-gram lexicon. In the given example, to predict the masked character “儿” (son) highlighted in green, ZEN 1.0 relies more on its preceding characters “一” (one) and “会” (meeting) highlighted in yellow (because “一会儿” (a while) is a frequent phrase in Chinese), while ZEN 2.0 is designed to learn information from large text granularity (e.g., “一会儿” highlighted in yellow in the clause “一会儿乌云密布”) with all three characters masked together by whole n-gram masking.

Figure 3: The illustration of the process to model the relative positional information (i.e., $R^*$) in each head of the multi-head attention layer in the character encoder, where “MatMul” refers to matrix multiplication, Q, K, and V are the query, key, and value matrices, respectively, with $u$ and $v$ the trainable bias vectors.

and direction-aware attentions to further improve text representations, whose effectiveness is demonstrated by the decent improvement on many NLP tasks. Owing to its effectiveness, we adopt this adaptation to ZEN for character encoding.

Specifically, for the $i$-th character in the input and its context (whose indices are represented by $j$), its $d$-dimensional relative positional encoding vector is represented by $R_{i-j} \in \mathbb{R}^{1 \times d}$, where, according to the positional embedding of Vaswani et al. (2017), the $2t$-th value in $R_{i-j}$ is $\sin \left( \frac{i-j}{10000^{2t/d}} \right)$ and the $(2t+1)$-th value is $\cos \left( \frac{i-j}{10000^{2t/d}} \right)$. For each head of self-attention, whose input $H$ is a sequence of character representations, we apply three trainable matrices (i.e., $W_q$, $W_k$, and $W_v$) to each character representation $H_i$ and obtain the query vector $Q_i = W_q H_i$, the key vector $K_i = W_k H_i$, and the value vector $V_i = W_v H_i$. In addition, we also compute the relative positional representation $R^*_{i-j}$ by applying a trainable matrix $W_r$ to $R_{i-j}$:

$$R^*_{i-j} = W_r R_{i-j}$$ (4)

Then, we compute the attention $A_{i,j}^{rel}$ by (the process is illustrated in the dashed box in Figure 3):

$$A_{i,j}^{rel} = (Q_i + u) \cdot K_j + (Q_i + v) \cdot R^*_{i-j}$$ (5)

where $u$, $v$ are two different trainable bias vectors and “.” represents the inner product of two vectors. Afterwards, we compute the output of the particular head of self-attention by

$$head = \text{softmax}(A^{rel}) V$$ (6)

and apply it to other heads. Finally, we follow the standard Transformer to concatenate all heads and obtain the output of MhA.

3 Data and Training

3.1 Pre-training Corpora

In this work, we apply our enhancement of ZEN to two languages, namely, Chinese and Arabic, using
much more data than its original version (Diao et al., 2019) to ensure its generalization ability.

For Chinese, we follow the common practice in previous studies (Devlin et al., 2019; Cui et al., 2019a) to use Chinese Wikipedia dump as one of the corpora. To expand the generalization ability of ZEN, we use additional large-scale raw text from online resources, including (1) Chinese News Corpus, (2) Chinese Baike Corpus, (3) Chinese Webtext Corpus, (4) Chinese-English Parallel Corpus, (5) Chinese Comments Corpus, and (6) Zhihu Corpus, where the corpora (1)-(5) are obtained from CLUE and the corpus (6) is extracted from a well-known Chinese online question answering forum.

We follow Xu et al. (2020) to clean the data and perform more operations to improve their quality, such as filtering out sentences that contain bad words and non-text content (e.g., HTML mark-ups).

For Arabic, we collect Arabic News Corpus by crawling multiple Arabic online news websites and download existing resources including Arabic Wikipedia dump, AraCorpus, Tashkeela (Zerrouki and Balla, 2017), UN Parallel Corpus, Abu EI-Khair Corpus (El-Khair, 2016), and OSCAR (Suárez et al., 2019). We use BERT tokenizer to segment Arabic text into word-pieces and empirically regard the results as Arabic characters to facilitate character-based encoding in ZEN.

Overall, for the corpora in two languages, the statistics of them are reported in Table 1, with numbers of sentences and tokens presented.

### Table 1: The statistics of Chinese (a) and Arabic (b) corpora for pre-training ZEN 2.0, where number of total sentences (Sents #) and tokens (Tokens #) are reported.

| Corpora                                | Sents # | Tokens # | Corpora                                | Sents # | Tokens # |
|----------------------------------------|---------|----------|----------------------------------------|---------|----------|
| Chinese Wikipedia dump                 | 8.8M    | 287.6M   | Arabic Wikipedia dump                  | 6.3M    | 167.0M   |
| Chinese News Corpus                    | 52.3M   | 2,307.2M | Arabic News Corpus                     | 7.2M    | 168.3M   |
| Chinese Baike Corpus                   | 11.9M   | 335.0M   | AraCorpus                              | 10.6M   | 179.8M   |
| Chinese Webtext Corpus                 | 27.3M   | 892.3M   | Abu EL-Khair Corpus                    | 56.7M   | 1,927.3M |
| Chinese-English Parallel Corpus       | 5.5M    | 159.4M   | OSCAR                                  | 126.6M  | 4,153.0M |
| Chinese Comments Corpus               | 12.9M   | 327.0M   | Tashkeela                              | 0.5M    | 20.3M    |
| Zhihu Corpus                          | 149.5M  | 4,087.8M | UN Parallel Corpus                     | 23.2M   | 675.6M   |
| Total                                  | 268.2M  | 8,396.3M | Total                                  | 231.1M  | 7,291.3M |

For Chinese and Arabic, we train different ZEN models on the obtained large-scale raw text and follow previous studies (Devlin et al., 2019; Diao et al., 2019; Safaya et al., 2020) to optimize...
mize them by two semi-supervised tasks, namely, masked language model (MLM) and next sentence prediction (NSP). Following BERT, we use Adam optimizer with warmed-up during the first 36,000 steps and use the learning rate with a peak value of 1e-4 and linear decay. The batch size for ZEN-base is set to 24,576, and that for ZEN-large is 8,192. The total steps of training for Chinese and Arabic are 600K and 800K, respectively.

4 Fine-tune on Benchmark Tasks

4.1 Benchmark Tasks

To evaluate ZEN 2.0, we fine-tune the models on the benchmark datasets of several different tasks. For Chinese, we use Chinese word segmentation (CWS), Part-of-speech (POS) tagging, Named entity recognition (NER), Document classification (DC), Sentiment analysis (SA), Sentence pair matching (SPM)*, Natural language inference (NLI), Machine reading comprehension (MRC)*, and Question Answering (QA)*, where many of them are introduced in Diao et al. (2019) and we use the same datasets and settings in this work. Three (marked by *) tasks (datasets) are newly added for ZEN 2.0, with details illustrated below.

Table 2: The overall performance of ZEN 2.0 base (B) and large (L) for Chinese on nine NLP tasks with the comparison against existing representative pre-trained models (with both base and large version).

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For Arabic, we use the following tasks (datasets).

- **POS**: Part 1, 2, and 3 of the Penn Arabic Treebank (ATB)\(^{18}\) (Maamouri et al., 2004).
- **NER**: AQMAR (Mohit et al., 2012) and ANERC-Corp (Benajiba et al., 2007) containing articles from Wikipedia and newswire, respectively.
- **DC**: AR-5, AB-7, and KH-7 from the SANAD (Einea et al., 2019) dataset, containing 5, 7, and 7 unique document types, respectively.
- **SA**: The ASTD (Nabil et al., 2015) dataset that contains around 10,000 tweets.
- **NLI**: The Arabic part of the XNLI (Conneau et al., 2018) is used for this task.
- **MRC**: Arabic-SQuAD (Mozannar et al., 2019) and ARCD (Mozannar et al., 2019).

For all datasets used in the experiments, we follow previous studies to pre-process them and split them into train/dev/test sets. We follow the common practice to evaluate the performance of all models, i.e., we use F1 scores for CWS and NER, and use accuracy for POS tagging, DC, SA, SPM, and NLO; we use both exact match (EM) and F1 scores for MRC; and for QA, we use mean reciprocal rank (MRR) and F1 scores. For each dataset of a particular task, we fine-tune ZEN 2.0 on the training set and evaluate it on the test set\(^{19}\).

### 4.2 Overall Results

Table 2 reports the performance of base (B) and large (L) Chinese ZEN 2.0 on different tasks and the comparison with previous representative Chinese text encoders, including ERNIE 1.0 and 2.0 (Sun et al., 2019, 2020), RoBERTa-WWM (i.e., RoBERTa with whole word masking) (Cui et al., 2019a), NEZHA-WWM (i.e., NEZHA with whole word masking) (Wei et al., 2019), MWA (Li et al., 2020), MacBERT (Cui et al., 2020) as well as ZEN 1.0, where ZEN 2.0 achieves the highest performance.

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\(^{17}\)http://tcci.ccf.org.cn/conference/2016/didoc/evagline2.pdf

\(^{18}\)ATB part 1 is from https://catalog.ldc.upenn.edu/LDC2003T06, part 2 from https://catalog.ldc.upenn.edu/LDC2004T02, and part 3 from https://catalog.ldc.upenn.edu/LDC2005T20.

\(^{19}\)We follow previous studies (Wei et al., 2019; Sun et al., 2020) to evaluate Chinese ZEN 2.0 on the development set of CMRC2018 since it does not have an official test set.
performance on all tasks. Table 3 reports the performance of Arabic ZEN 2.0 (base and large version) compared with other widely used Arabic text encoders (some are from our runs), namely, multilingual BERT (Devlin et al., 2019), AraBERT 0.1 (Baly et al., 2020), and Arabic BERT (Safaya et al., 2020), where both versions of Arabic ZEN 2.0 outperform their corresponding baselines on all tasks.

A general summary from the results can be drawn that, n-gram information works well with ZEN 2.0 in different sizes (i.e., the base and large version), where refined n-gram representation, whole n-gram masking, and character encoding with relative positional information well collaborated with each other and improve the performance of ZEN 2.0 on different NLP tasks. Specifically, although directly upgrading ZEN 1.0 from base to large version improves its performance on many NLP tasks, ZEN 2.0 can be further boosted, demonstrating the necessity of the proposed enhancements. In addition, compared with previous pre-trained models that learn word (n-gram) information through different masking strategies, ZEN 2.0 is able to explicitly encode n-gram information in a more effective manner through both the refined n-gram representation and the whole n-gram masking, which leads ZEN 2.0 to outperform all previous studies as well as ZEN 1.0 on all tasks. Moreover, even though the languages are highly different between Chinese and Arabic, n-gram information is proved to be helpful for Arabic as well, although ZEN is not originally designed for it.

5 Analysis

5.1 The Effect of Training Steps

To analyze the effect of the enhancement on ZEN, we use two different tasks (i.e., NLI and MRC) to demonstrate the performance of ZEN 2.0 during the pre-training process. Specifically, we use

![Figure 4: The performance of different models on NLI (a) and MRC (b) with respect to the number of pre-training steps (in thousands), where the curves of BERT (L), ZEN 1.0 (L), and ZEN 2.0 (L) are illustrated in blue, orange, and green colors, respectively. The evaluation metric for NLI is accuracy and that for MRC is the F1 score.](image)

5.2 The Effect of N-gram Representations

N-grams are very useful features to represent contextual information and they are explicitly encoded in ZEN. We already show that in Table 2 and Table 3, with n-gram representations, the pre-trained models (both ZEN 1.0 and 2.0) outperform other

![Figure 5: Visualization of n-gram representations for some examples. The distance between two n-grams illustrates the similarity between their representations, where a low distance indicates the two n-grams have similar representations. N-grams in the same cluster are represented in the same color.](image)
Table 4: The performance of ZEN 2.0 large for Chinese with whole n-gram masking (WNM) when different off-the-shelf tokenizers (i.e., WMSeg and Jieba) are used. “N/A” standards for that the model with character masking.

| WNM          | CWS POS Tagging | NER | DC | SA |
|--------------|-----------------|-----|----|----|
|              | MSRA-CWS CTB5   | MSRA-NER | THUCNews | CHNSENtiCorp |
| ZEN 2.0 (L)  | 98.66 97.09     | 96.20 | 97.93 | 96.50 |
| WMSeg        | F1  | ACC | F1  | ACC |
| Jieba        | 98.57 | 96.99 | 96.18 | 97.90 | 96.33 |
| N/A          | 98.52 | 96.92 | 96.08 | 97.90 | 96.17 |

5.3 The Effect of Whole N-gram Masking

Whole word masking is proved to be useful in learning many previous pre-trained models. However, words are hard to be identified in Chinese (and Arabic in many cases), we therefore use n-gram masking instead in this work. Since we use a word segmenter to tokenize input text into pieces as the first step and then combine some pieces into larger n-grams for masking, the performance of the segmenter is vital for obtaining reasonable n-grams. To illustrate the effectiveness of using WMSeg as the segmenter, in this analysis, we compare ZEN 2.0 (large version) trained with whole n-gram masking (WNM) when a different segmenter, i.e., Jieba20, is applied with the same n-gram lexicon. Table 4 reports the comparison (ZEN 2.0 large) on all Chinese tasks. There are several observations. First, for all tasks, ZEN 2.0 with WNM obtains higher results than the models with character masking, which complies with the findings in previous studies (Sun et al., 2019; Cui et al., 2019a; Wei et al., 2019; Sun et al., 2020; Cui et al., 2020). Second, when using WNM, WMSeg outperforms Jieba and this option achieves the highest results on all tasks. This observation indicates that a better segmenter is of great importance for masking larger context, because WMSeg provides more accurate information of word boundaries so that the masked n-grams tend to be more reasonable semantic units.

5.4 Relative Positional Encoding Effect

To address the limitation of the vanilla Transformer in character encoding (which is used by ZEN 1.0), ZEN 2.0 applies the relative positional encoding technique to the character encoder. To explore the effect of this enhancement, we compare the performance of ZEN 2.0 with and without relative positional encoding (RPE) on two Chinese NLP tasks.

20https://github.com/fxsjy/jieba. We choose Jieba as the comparing segmenter for its widely usage as the conventional tool for Chinese word segmentation in many previous studies (Wei et al., 2019; Chen et al., 2020).
Figure 6: The performance histograms of ZEN 2.0 with (+) and without (-) relative positional encoding (RPE) on different Chinese (a) and Arabic (b) NLP tasks. The evaluation metric for NER and QA is F1 scores and that for NLI is the accuracy.

tasks (i.e., NLI and QA) and two Arabic NLP tasks (i.e., NER and NLI). Figure 6 shows the comparison between the models, in which the one with RPE (+RPE) consistently outperforms the one without RPE (-RPE) on all chosen tasks, demonstrating the effectiveness of modeling relative position information. Particularly, more than 2% improvement on the F1 score is observed on AQMAR dataset for Arabic NER task. It can be explained that the relative position information of Arabic texts is more important (in most cases the morphology of an Arabic word is different according to its position in a sentence); ZEN 2.0 with RPE is able to capture that information and thus generates high-quality text representations, which can further improve model performance on Arabic NLP tasks.

5.5 Case Study

To further examine how ZEN 2.0 leverages n-gram information to improve model performance, we conduct a case study on the NLI task, which is a difficult one requiring models to have a good understanding of contextual information in order to make correct predictions. Figure 7 shows two example (premise, hypothesis) pairs from Chinese (a) and Arabic (b). For both examples, ZEN 2.0 correctly predicts that the premise entails the hypothesis, while BERT fails to do so. The weight assigned to different n-grams in the n-gram encoder of ZEN 2.0 is visualized by different colors on the corresponding n-grams and their English translations, with deeper colors referring to higher weights.

Figure 7: A case study on the NLI task with two examples from Chinese (a) and Arabic (b). For both examples, ZEN 2.0 correctly predicts that the premise entails the hypothesis, while BERT fails to do so. The weight assigned to different n-grams in the n-gram encoder of ZEN 2.0 is visualized by different colors on the corresponding n-grams and their English translations, with deeper colors referring to higher weights.

6 Conclusion

We propose ZEN 2.0, an updated n-gram enhanced pre-trained encoder on Chinese and Arabic, with different improvements such as refined n-gram representations, whole n-gram masking and relative positional encoding applied to ZEN 1.0 and enlarged model size corresponding to BERT-large. Compared to its previous version, ZEN 2.0 outperforms it on all tested NLP tasks, including several new ones added to the fine-tune list. Moreover, for both Chinese and Arabic NLP tasks, ZEN 2.0 shows its superiority to other existing representative pre-trained models by achieving the state-of-the-art performance. Analyses are also conducted to investigate the effect of different improvements,
where the findings further demonstrate the effectiveness of them in improving the representation ability of ZEN 2.0. The case study conducted on Chinese and Arabic NLI task confirms that ZEN 2.0 appropriately leverages n-gram information to achieve a good understanding of the input text and thus obtain promising performance on this task.

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