Report of Assignment 03 in Advanced Techniques of Machine Translation

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1 Introduction

In this assignment, we explored the effect of Byte Pair Encoding (BPE) dictionary sizes, dropout rates, and learning rates on translation quality within a low-resource neural machine translation (NMT) setting. We chose to experiment with BPE and BPE dropout as efficient approaches for handling low-resource datasets. By systematically varying dictionary sizes, dropout rates, and learning rates, we aimed to determine the optimal configuration that balances vocabulary coverage with robust segmentation and stable training.

2 Experimental Setup

We followed a structured preprocessing, training, and evaluation pipeline to investigate the effects of BPE, BPE dropout, and learning rate adjustments.

2.1 Preprocessing and Postprocessing

For preprocessing, we extended the provided script `preprocess_data.sh` by adding steps for BPE. Our modified script, `preprocess_data_BPE.sh`, includes data normalization, tokenization, and truecasing using the Moses toolkit. We then applied BPE using the subword-nmt package, which allowed us to set different dictionary sizes and dropout rates for training subword models. We tested dictionary sizes of 4000, 8000, and 12000 subwords.

```
./preprocess_data_BPE.sh
```

For postprocessing, we utilized a custom script that takes the raw output of the translation model and applies detokenization, resulting in a more natural and coherent output. We evaluated the final translations using BLEU score with sacreBLEU, following these steps:

```
bash scripts/postprocess.sh \
"assignments/03/baseline/translations/bpe/12000/BPE_translations.txt" \
"assignments/03/baseline/translations/bpe/12000/BPE_translations.p.txt" en

cat assignments/03/baseline/translations/bpe/12000/BPE_translations.p.txt \
| sacrebleu data/en-fr/raw/test.en
```

2.2 Training with BPE Dropout and Learning Rate Adjustments

We modified the training script `train.py` to incorporate BPE dropout. This involved adding a `--bpe-dropout` argument, which allows us to apply dropout rates between 0.0 and 1.0. When a dropout rate is specified, BPE merges are randomly dropped during training with the specified probability, making the model more robust to different segmentations.

In our experiments, we first optimized the dictionary size (testing 4000, 8000, and 12000 subwords) and then tested dropout rates of 0.1, 0.2, and 0.3 for the best-performing dictionary size. Additionally, we tested different learning rates (0.03, 0.003, and 0.0003) to assess how training stability and performance are influenced by this hyperparameter.

The following command was an example for training:

```
python train.py \
  --data "data/en-fr/prepared_BPE_8000" \
  --source-lang fr \
  --target-lang en \
  --save-dir "assignments/03/baseline/checkpoints/bpe/dropout/8000/30_pct" \
  --batch-size 64 \
  --bpe-dropout 0.3
```

3 Results and Discussion

Table 1 presents the BLEU scores for different configurations of BPE dictionary sizes and dropout rates, while Table 2 shows the impact of different learning rates on BLEU scores.

BPE Dictionary Size	Dropout Rate	BLEU Score	Hypothesis Length	Reference Length	BLEU Breakdown (1-gram/2-gram/3-gram/4-gram)
No BPE	N/A	9.7	4559	3892	40.5 / 14.3 / 6.1 / 2.5
4000	0.0	10.9	4943	3892	39.1 / 15.3 / 7.1 / 3.3
4000	0.1	11.1	5087	3892	38.5 / 15.8 / 7.5 / 3.3
8000	0.0	11.4	4692	3892	41.1 / 16.1 / 7.7 / 3.3
8000	0.1	11.4	4692	3892	41.1 / 16.1 / 7.7 / 3.3
8000	0.2	11.3	4626	3892	41.3 / 15.7 / 7.6 / 3.3
8000	0.3	11.4	4692	3892	41.1 / 16.1 / 7.7 / 3.3
12000	0.0	6.0	4739	3892	34.4 / 9.0 / 3.5 / 1.2

Table 1: BLEU Scores for Different BPE Dictionary Sizes and Dropout Rates

Learning Rate	BLEU Score	Hypothesis Length	Reference Length
0.03	0.2	4084	3892
0.003	11.4	4692	3892
0.0003	9.7	4559	3892

Table 2: BLEU Scores for Different Learning Rates

3.1 Baseline Performance (No BPE)

The baseline model, trained with a learning rate of 0.0003, achieved a BLEU score of 9.7 without any BPE applied. This score was lower than the initially reported 16.8 in the previous setup due to a change in batch size, which was used to expedite training. This highlights the potential impact of batch size on BLEU scores and suggests that further experimentation is necessary to understand its influence on performance.

3.2 Effect of BPE Dictionary Size

The dictionary sizes 4000, 8000, and 12000 were tested to assess their impact on translation performance:

- **4000 Subwords**: A BLEU score of 10.9 was achieved, showing that this dictionary size captures frequent subwords effectively but may lack coverage for less common patterns.
- **8000 Subwords**: This configuration yielded a BLEU score of 11.4, the highest among the BPE-applied setups. The 8000 dictionary size achieves a balance by covering both frequent and less common subwords, leading to improved performance.
- **12000 Subwords**: The BLEU score dropped to 6.0 with a dictionary of 12000 subwords. This indicates that a large vocabulary may lead to overspecific subwords, reducing generalization and impacting translation quality.

3.3 Effect of BPE Dropout

BPE dropout introduces variability in segmentation, aiming to improve robustness by exposing the model to multiple ways of tokenizing words. The effects of dropout on BLEU scores for 4000 and 8000 dictionary sizes are as follows:

- **Dropout Rate 0.1**: This low dropout rate slightly improved BLEU scores across both 4000 and 8000 dictionary sizes. The increased segmentation variability enhanced the model's robustness without overcomplicating the tokenization process.
- **Higher Dropout Rates**: For the 8000 dictionary, dropout rates of 0.2 and 0.3 resulted in slight decreases or similar scores, indicating diminishing returns. Higher dropout introduced more randomness, which may have affected the model's ability to learn stable patterns.

3.4 Effect of Learning Rate

Adjusting the learning rate revealed notable differences in model performance:

- **Learning Rate 0.03**: This high learning rate resulted in poor performance with a BLEU score of 0.2, indicating instability during training.
- **Learning Rate 0.003**: This learning rate yielded the best results across most configurations, especially with the 8000 dictionary size and a dropout rate of 0.1, achieving a BLEU score of 11.4.
- **Learning Rate 0.0003**: This lower learning rate was used in the baseline model without BPE, resulting in a BLEU score of 9.7, lower than the baseline score initially reported with a smaller batch size.

3.5 Common Words vs. Rare Words

In our qualitative analysis, we observed that the baseline and BPE models performed differently depending on the frequency of words in the sentences. This section provides insights into how each model handles common versus rare words, highlighting the strengths and limitations of BPE when dealing with varying vocabulary types. Further data support would be needed to validate these observations quantitatively.

- **Common words**: The baseline model performed well with sentences containing frequent words, as the lack of segmentation allowed for a stronger lexical match, resulting in higher BLEU scores for common phrases.
- **Rare or Unseen words**: The BPE models demonstrated an advantage when handling rare or unseen words by segmenting these words into subword units, making them easier to recognize and translate. However, excessive segmentation (as seen with a dictionary size of 12000) led to poor generalization and lower BLEU scores.

4 Conclusion

The results indicate that a dictionary size of 8000 with a dropout rate of 0.1 and a learning rate of 0.003 offers the best balance among all tested configurations, achieving a BLEU score of 11.4. Although the baseline model without BPE yielded a higher BLEU score in the initial setup, this decrease in the updated baseline is attributed to an increase in batch size, highlighting a potential area for further research. In future work, we plan to explore the influence of batch size more systematically alongside dictionary size, dropout, and learning rate adjustments.

5 Additional Resources

The code and scripts used for this assignment are available on our GitHub repository: https://github.com/MrRunShu/UZH_ATMT_2024_Fall.