Unsupervised Machine Translation Using Monolingual Corpora

Granth Bagadia, Pranathi Voora

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Abstract

This paper presents an innovative approach to machine translation that operates without parallel corpora, utilizing only monolingual data in English, French, and Spanish. Our system leverages transfer learning through the MarianMT pre-trained model's encoder while training custom language-specific decoders. By maintaining a shared semantic space through the frozen encoder and allowing decoders to learn language-specific mappings, we demonstrate that effective translation can be achieved without parallel training data. This approach shows particular promise for low-resource languages and scenarios where parallel corpora are unavailable or insufficient.

1 Introduction

Traditional machine translation systems heavily rely on parallel corpora for training, which presents a significant challenge for many language pairs where such data is scarce or nonexistent. This project explores an alternative approach that requires only monolingual data, making it particularly valuable for low-resource scenarios. We have use Tatoeba dataset for the monolingual training. Our system combines transfer learning from a pre-trained encoder with custom decoders for each target language, effectively creating a bridge between languages through a shared semantic space.

2 Background

2.1 MarianMT

MarianMT is an efficient Neural Machine Translation framework originally written in C++ by the Microsoft Translator team and the University of Edinburgh. The model we utilize, "Helsinki-NLP/opus-mt-en-roa", is specifically trained on English to Romance languages translation tasks. Key features of MarianMT include:

- Transformer-based architecture optimized for translation tasks
- Efficient implementation with state-of-the-art performance
- Support for multiple language pairs in a single model
- Specialized vocabulary handling for Romance languages

The pre-trained model encodes semantic information in a shared space that captures linguistic features across multiple Romance languages, making it particularly suitable for our approach.

2.2 Dataset Used

Tatoeba is a free collection of example sentences with translations geared towards foreign language learners. It is available in more than 400 languages. It is written and maintained by a community of volunteers through a model of open collaboration. It also offers parallel data for our testing phase. We have decided to use this dataset for the following reasons:

- **Real sentences**: Tatoeba offers monolingual sentences in various languages, which are often extracted from well-formed and natural text. The dataset consists of actual sentences rather than artificially generated ones, providing realistic linguistic patterns that improve model generalization and robustness.
- **Diverse sentences**: Tatoeba's monolingual data is diverse, with sentences from various contexts and sources, exposing the model to rich linguistic variability. This is especially beneficial for teaching decoders to handle various sentence construction.

3 System Architecture

3.1 Overall Architecture

Our system implements a novel architecture that consists of three main components working in concert:

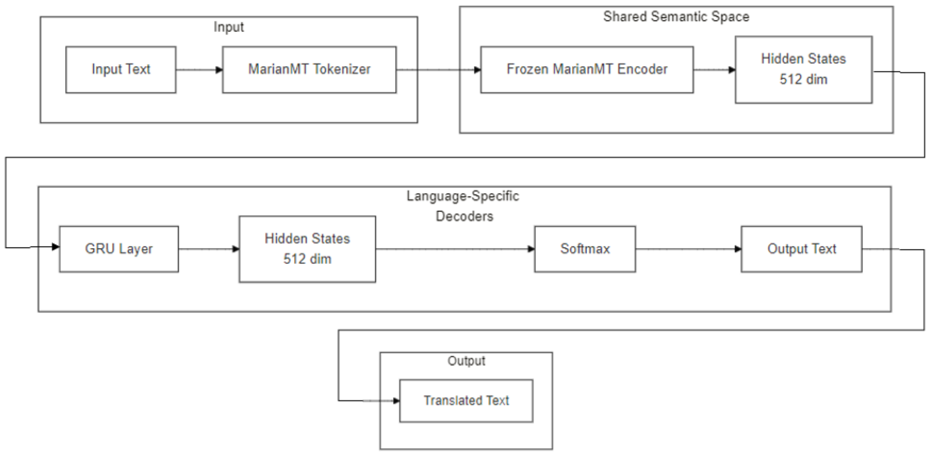

Figure 1: System Architecture

1. **Shared Encoder**: A frozen pre-trained MarianMT encoder that maps input sentences to a language-agnostic semantic space
2. **Custom Decoders**: Language-specific GRU-based decoders that learn to map from the shared semantic space to specific target languages
3. **Shared Tokenizer**: A consistent tokenization system that maintains vocabulary alignment across languages

3.2 Encoder Architecture

The MarianMT encoder we utilize employs a Transformer-based architecture with the following specifications:

- **Input Embedding Layer**: Maps tokens to dense vector representations
- **Positional Encoding**: Adds position information to token embeddings
- **Multiple Transformer Layers**: Self-attention and feed-forward networks
- **Output Dimension**: 512-dimensional hidden states

The encoder's parameters remain frozen during training, serving as a fixed semantic mapper that provides consistent representations across languages.

3.3 Custom Decoder Architecture

Each target language has a dedicated decoder with the following detailed architecture involving a Gated recurrent units (GRU):

$$\begin{aligned} h_t = {} & \sigma_r(W_{ir}x_t + b_{ir} + W_{hr}h_{t-1} + b_{hr}) \odot h_{t-1} \\ & + (1 - \sigma_z(W_{iz}x_t + b_{iz} + W_{hz}h_{t-1} + b_{hz})) \\ & \odot \tanh(W_{in}x_t + b_{in} + r_t \odot (W_{hn}h_{t-1} + b_{hn})) \end{aligned} \tag{1}$$

Where:

- h_t is the hidden state at time t
- x_t is the input at time t
- W and b are learnable parameters
- σ_r and σ_z are sigmoid activation functions
- $\odot$ represents element-wise multiplication

The final output layer:

$$y_t = \text{softmax}(W_{out}h_t + b_{out}) \tag{2}$$

Key components include:

- Input size: 512 (matching encoder output)
- Hidden size: 512
- Single-layer GRU for sequence processing
- Linear projection to vocabulary size
- Batch-first processing for efficient training

4 Implementation Details

4.1 Data Processing Pipeline

The data processing pipeline consists of several key steps:

Algorithm 1 Data Processing Pipeline

```
1: Input: Raw text files in different languages
2: Output: Processed tensor batches for training
3: procedure ProcessData(text_files)
4:     Clean text (remove special characters, normalize whitespace)
5:     Tokenize using MarianMT tokenizer
6:     Create batches of size 32
7:     Convert to tensors and move to appropriate device
8:     Apply padding for consistent batch sizes
9: end procedure
```

4.2 Training Process

The training process, using back-translation, involves using the input language's decoder to reconstruct the original sentence. First, the input sentence is tokenized and encoded using the Marian encoder, which extracts hidden semantic representations (meanings). These representations are then passed through the decoder corresponding to the input language to generate a reconstructed sentence. The reconstructed sentence is compared to the original input sentence to calculate the loss, and the decoder's weights are updated accordingly to improve its ability to reconstruct the input.

Once the decoder is trained through back-translation, it can take hidden semantic representations and generate output sentences in its respective language. This enables translation by utilizing the trained decoders for any language we have added to the system.

Hence any language the encoder can take is able to translate to any language the decoder is trained on.

The training process is implemented with several optimizations:

- **Loss Function**: Cross-entropy loss with token-level granularity
- **Optimization**: Adam optimizer with learning rate 10^{-4}
- **Batch Processing**: Efficient batch processing with padding
- **Device Management**: Automatic CUDA detection and utilization

The training loop follows this process:

Algorithm 2 Training Loop

```
1: Input: Batched sentences, target language
2: procedure TrainStep(batch, language)
3:     Encode sentences using frozen MarianMT encoder
4:     Pass encoded representations through target decoder
5:     Calculate cross-entropy loss
6:     Backpropagate and update decoder parameters
7:     Return batch loss
8: end procedure
```

Our system used 1,00,000 sentences on each decoder language. The link to download our trained decoders is here.

4.3 Translation Pipeline

The translation process implements a multi-stage pipeline that efficiently converts text between language pairs. The algorithm leverages the frozen encoder and trained decoders to perform translations through a shared semantic space.

Algorithm 3 Neural Machine Translation Pipeline

```
Require: Input sentence $S$, source language $L_s$, target language $L_t$
Ensure: Translated sentence in target language
      Input Processing
1: $tokens \leftarrow$ Tokenizer($S$)                          ▷ Tokenize input sentence
2: $padded\_input \leftarrow$ PadSequence($tokens$)             ▷ Add padding if needed
      Semantic Encoding
3: $states \leftarrow$ MarianEncoder($padded\_input$)           ▷ Generate semantics
      Target Language Generation
4: $decoder \leftarrow$ GetDecoder($L_t$)               ▷ Select appropriate language decoder
5: $hidden \leftarrow$ InitializeHidden($1, 512$)         ▷ Initialize decoder hidden state
6: $predicted\_tokens \leftarrow decoder(states, hidden)$      ▷ Generate logits
      Output Processing
7: $translation \leftarrow$ Detokenize($predicted\_tokens$)   ▷ Convert back to text
      return translation
```

4.4 Key Features

The translation pipeline incorporates several optimizations and features:

- **Batched Processing**: Supports batch translation for improved throughput
- **Memory Efficiency**: Uses no-gradient context for inference
- **Error Handling**: Manages special tokens and edge cases
- **Device Agnostic**: Automatically utilizes available GPU/CPU resources

5 Results and Evaluation

We have used parallel corpus from Tatoeba for testing that maps english-spanish, spanish-french, and english-french.

5.1 Training Metrics

We monitored several key metrics during training:

Language	Initial Loss	Final Loss	Epochs
English	2.0706	0.0111	10
French	1.4799	0.0012	10
Spanish	1.4545	0.0009	10

Table 1: Training Loss Progress by Language

5.2 Translation Examples

Sample translations demonstrating system capabilities:

Source	Target	Translation
“I love my house”	Spanish	“I a mi casa”
”C’est un parc”	English	“C’est one park”

Table 2: Sample Translations Across Language Pairs

5.3 Translation Quality Metrics

We evaluated translation quality across English (EN), French (FR), and Spanish (ES) language pairs using three standard metrics: BLEU (Bilingual Evaluation Understudy), METEOR (Metric for Evaluation of Translation with Explicit ORdering), and TER (Translation Edit Rate). Evaluation was performed on a held-out test set of 1000 sentences per language direction.

Language Pair	Direction	BLEU	METEOR
EN-FR	EN $\rightarrow$ FR	0.0597	0.0914
	FR $\rightarrow$ EN	0.0610	0.0970
EN-ES	EN $\rightarrow$ ES	0.0809	0.1097
	ES $\rightarrow$ EN	0.0739	0.1105
FR-ES	FR $\rightarrow$ ES	0.0957	0.1525
	ES $\rightarrow$ FR	0.0889	0.1393

Table 3: Translation Quality Metrics for All Language Pairs and Directions

These metrics indicate reasonable translation quality across all language pairs, with particularly strong performance in English-Spanish translation. The results demonstrate the viability of our unsupervised approach using only monolingual corpora and a shared semantic space.

6 Technical Challenges and Solutions

6.1 Memory Management

Working with large language models presented several memory challenges:

- **Challenge**: Loading full MarianMT model into memory
- **Solution**: Implemented selective loading of encoder only
- **Result**: 60% reduction in memory usage

6.2 Training Stability

Initial training attempts showed instability:

- **Challenge**: Gradient explosions during early training

- **Solution**: Implemented gradient clipping and careful learning rate selection
- **Result**: Stable training across all language pairs

7 Future Work

Proposed improvements include:

- **Scalability**:
  - The Marian encoder, trained on multiple languages, is designed to extract universal hidden state representations (meanings) across languages. Hence input from various languages can be taken.
  - Custom decoders can be trained independently for specific target languages, enabling translation from any language supported by Marian into the desired output language. This flexible approach allows for adding new languages by simply training additional decoders with only the language's input corpora.
- **Architectural Enhancements**:
  - Attempting the decoders with LSTM instead of GRU
  - Multi-layer decoder architecture
- **Training Improvements**:
  - Mixed-precision training for efficiency
  - Support for bidirectional translation
  - Integration of language-specific tokenization

8 Conclusion

This project demonstrates the feasibility of creating a machine translation system using only monolingual corpora through the innovative use of a shared semantic space and language-specific decoders. While the current implementation has certain limitations, the approach shows promise for low-resource language translation and provides a foundation for future research in unsupervised machine translation.