Министерство науки и высшего образования Российской Федерации

Федеральное государственное бюджетное образовательное учреждение высшего образования

«Иркутский национальный исследовательский технический университет»

Байкальский институт БРИКС

Baikal school of BRICS

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| (тип практики: технологическая/научно-исследовательская работа/преддипломная и др.) | | |
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|  | в БИ БРИКС ФГБОУ ВО ИРНИТУ | |
| (наименование профильной организации или структурного подразделения вуза) | | |

| Обучающегося | Лежнев Евгений | ИИКб-23-1 | \_\_\_\_\_\_ |
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|  | (ФИО) | (группа) | (подпись) |
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Оценка по практике \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Григорьев С.В. \_\_\_\_\_\_\_\_\_\_\_\_\_ «\_\_\_» 2025 г.

(ФИО) (подпись)

| Содержание отчета на |  | стр. |
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| Приложение к отчету на |  | стр. |

Иркутск 2025 г.

**Индивидуальное задание на прохождение**

| производственной |
| --- |
| технологической (проектно-технологической) практики |

для Лежнев Евгений обучающегося 2 курса, группы ИИКб-23-1

| по направлению подготовки/специальности | 09.03.01 Информатика и |
| --- | --- |
| вычислительная техника (англоязычная программа) | |

| по программе | Искусственный интеллект и компьютерные науки /  Artificial Intelligence and Computer Science |
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| Место прохождения практики: | БИ БРИКС ФГБОУ ВО ИРНИТУ |
| --- | --- |

Сроки прохождения: с 09.06.2025 по 06.07.2025

| Цели и задачи прохождения практики: | To design and develop a prototype of a Telegram bot utilizing a trained translation model. |
| --- | --- |
| 1) To create and maintain a GitHub project repository for the internship work.  2) Research modern Seq2Seq machine translation models and train the translation model using available data.  3) Develop a Telegram bot by integrating the trained model to perform translations based on user requests. | |

| Содержание практики, вопросы, подлежащие изучению: |  |
| --- | --- |
| 1) Sequence-to-sequence (seq2seq) model architectures, used in machine translation tasks. | |
| 2) Working with pre-trained models (Helsinki-NLP/opus-mt-en-ru) and their fine-tuning. | |
| 3) Integration of a trained model into an interactive application (using a Telegram bot). | |
|  | |

| Планируемые результаты практики: | Report for Internship and Project Defense |
| --- | --- |

| Руководитель практики от института | | | |
| --- | --- | --- | --- |
|  | / | Григорьев С.В. | / |
| (подпись) |  | (ФИО) |  |
| Согласовано:  Руководитель ООП | | | |
|  | / | Афанасьев А.Д. | / |
| (подпись) |  | (ФИО) |  |

С настоящим индивидуальным заданием и с программой практики ознакомлен(а), задание принято к исполнению \_\_\_\_\_\_\_\_\_\_\_\_\_ «9» июня 2025 г.

(подпись)

**Содержание / Contents**

[Introduction 4](#_heading=h.3j04bmqc0abg)

[1 Creating a Project from GitHub 5](#_heading=h.rqp8ga5az8sz)

[1.1 Creating a repository 5](#_heading=h.akjx4xgyhri1)

[2 The Helsinki-NLP Model: Architecture Overview and Justification for Its Use 6](#_heading=h.u1bervc55kip)

[2.1 What is Seq2Seq model? 6](#_heading=h.xhz2a7srqjtn)

[2.1.1 Encoding the Input Sequence 6](#_heading=h.llhploskcgzv)

[2.1.2 Decoding the Output Sequence 6](#_heading=h.k1g9jg2so2c9)

[2.1.3 Advantages of Seq2Seq Models 6](#_heading=h.aqdrudwidwph)

[2.1.4 Disadvantages of Seq2Seq Models 7](#_heading=h.nhbobhc70p6c)

[2.2 what is the Transformer architecture? 7](#_heading=h.n17e1cquo85l)

[2.2 Reasons for Selecting the Helsinki-NLP Model 8](#_heading=h.x0czd3rd9801)

[3. Training a Translation Model Based on the Helsinki-NLP Model 10](#_heading=h.er3axiwgn59w)

[3.1 Prepare a dataset 10](#_heading=h.u1nib5w282is)

[3.2 Training a translation model 12](#_heading=h.8l0yceaagt9)

[3.3 Results of model training 13](#_heading=h.tonsk2awg24h)

[4 Integrating a trained translation model into a Telegram bot 16](#_heading=h.l9n1lrk6x76v)

[4.1 what is a BotFather? 16](#_heading=h.ch7ylf21gyp5)

[4.2 Building the Bot with python‑telegram‑bot 16](#_heading=h.dubvo6c9h80w)

[4.3 Testing and User Experience 17](#_heading=h.v1iffcm7w3yt)

[Conclusion 19](#_heading=h.jfkassuoldz)

[The listing of document symbols 21](#_heading=h.yaj4rb1h9l5x)

[References 22](#_heading=h.8ryol4m3b27a)

# Introduction

Natural Language Processing (NLP) technologies have become a key area of research and development in the field of artificial intelligence in recent years. Among their numerous applications, machine translation holds a special place — the task of converting text from one language to another while preserving its semantics and structure. This problem is not only of theoretical interest for the study of language models, but also of practical value in the context of globalization, where the need for instant access to information in multiple languages is becoming critically important.

During my internship, I set out to design and implement a complete end‑to‑end English‑to‑Russian machine translation service. The project encompassed every stage of an ML workflow: initializing and structuring a GitHub repository, collecting and preprocessing a parallel corpus of texts, fine‑tuning a pre‑trained Seq2Seq Transformer model, analyzing training results, and finally deploying the trained model as a Telegram bot. The primary motivation was to gain hands‑on experience with advanced NLP tools and techniques, working with large datasets, adjusting hyperparameters of deep neural networks, and integrating a model into an actual user‑facing application.

The goal of the report is to to design and develop a prototype of a Telegram bot utilizing a trained translation model. [In order to achieve the set](https://context.reverso.net/%D0%BF%D0%B5%D1%80%D0%B5%D0%B2%D0%BE%D0%B4/%D0%B0%D0%BD%D0%B3%D0%BB%D0%B8%D0%B9%D1%81%D0%BA%D0%B8%D0%B9-%D1%80%D1%83%D1%81%D1%81%D0%BA%D0%B8%D0%B9/In+order+to+achieve+the+set) goal it is necessary to solve the following objectives:

1. Create GitHub Project;
2. Build a generative neural network model for language processing;
3. Build an application based on Generative Language Model.

# 1 Creating a Project from GitHub

# 1.1 Creating a repository

When initializing the repository, I carefully considered its folder structure to clearly reflect the workflow’s stages. The dataset/ directory contains scripts and templates for loading Parquet files. Under src/, you’ll find module responsible for data preparation, tokenization, and training a model. The bot/ folder houses the Telegram bot implementation code and the model/ folder. The model/ folder holds the trained translation model.

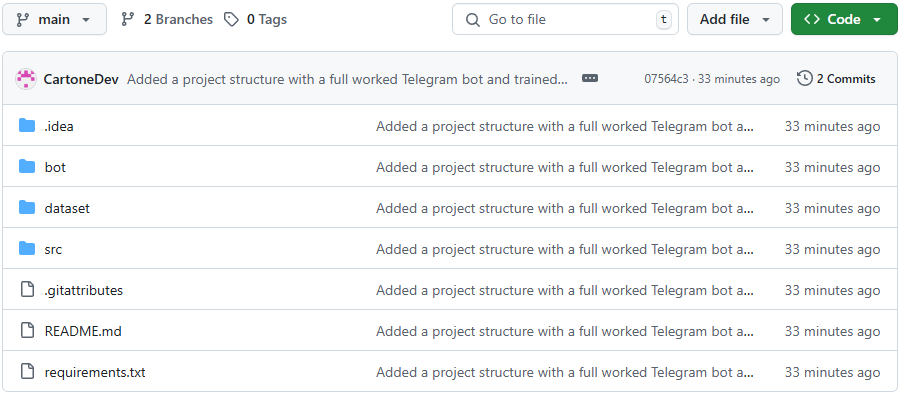


Figure 1.1 – structure of main branch

To keep documentation separate from code, I established a docs branch that stores written reports in DOCX format, exported graphs, and slide deck templates for the final presentation. This approach preserved the main branch’s cleanliness and ensured that bulky assets did not clutter the codebase’s history.

Изображение выглядит как текст, Шрифт, число, снимок экрана

Содержимое, созданное искусственным интеллектом, может быть неверным.

Figure 1.2 - structure of documentation branch

# 2 The Helsinki-NLP Model: Architecture Overview and Justification for Its Use

# 2.1 What is Seq2Seq model?

The Sequence-to-Sequence (Seq2Seq) model is a type of neural network architecture widely used in machine learning particularly in tasks that involve translating one sequence of data into another. It takes an input sequence, processes it and generates an output sequence. The Seq2Seq model has made significant contributions to areas such as NLP, machine translation and speech recognition.

Изображение выглядит как текст, снимок экрана, Шрифт, диаграмма

Содержимое, созданное искусственным интеллектом, может быть неверным.

Figure 2.1 - Encoder and Decoder Stack in seq2seq model

# 2.1.1 Encoding the Input Sequence

The encoder processes the input sequence token by token, updating its internal state at each step. After the entire sequence is processed, the encoder produces a context vector, a fixed-length representation that summarizes the important information from the input.

# 2.1.2 Decoding the Output Sequence

The decoder takes the context vector as input and generates the output sequence one token at a time. For example, in machine translation, it can convert the sentence “I am learning” into “Je suis apprenant” sequentially, predicting each token based on the context and previously generated tokens.

# 2.1.3 Advantages of Seq2Seq Models

1. **Flexibility**: Can handle tasks like machine translation, text summarization and image captioning with variable-length sequences.
2. **Handling Sequential Data**: Ideal for sequential data like natural language, speech and time series.
3. **Context Awareness**: Encoder-decoder architecture captures the context of the input sequence to generate relevant outputs.
4. **Attention Mechanism**: Focuses on key parts of the input sequence, improving performance, especially for long inputs.

# 2.1.4 Disadvantages of Seq2Seq Models

1. **Computationally Expensive**: Requires significant resources to train and optimize.
2. **Limited Interpretability**: Hard to understand the model's decision-making process.
3. **Overfitting**: Prone to overfitting without proper regularization.
4. **Rare Word Handling**: Struggles with rare words not seen during training.

# 2.2 what is the Transformer architecture?

transformer is an architecture based on the multi-head attention mechanism, in which text is converted to numerical representations called tokens, and each token is converted into a vector via lookup from a word embedding table. At each layer, each token is then contextualized within the scope of the context window with other (unmasked) tokens via a parallel multi-head attention mechanism, allowing the signal for key tokens to be amplified and less important tokens to be diminished.

Transformers have the advantage of having no recurrent units, therefore requiring less training time than earlier recurrent neural architectures (RNNs) such as long short-term memory (LSTM). Later variations have been widely adopted for training large language models (LLMs) on large (language) datasets.

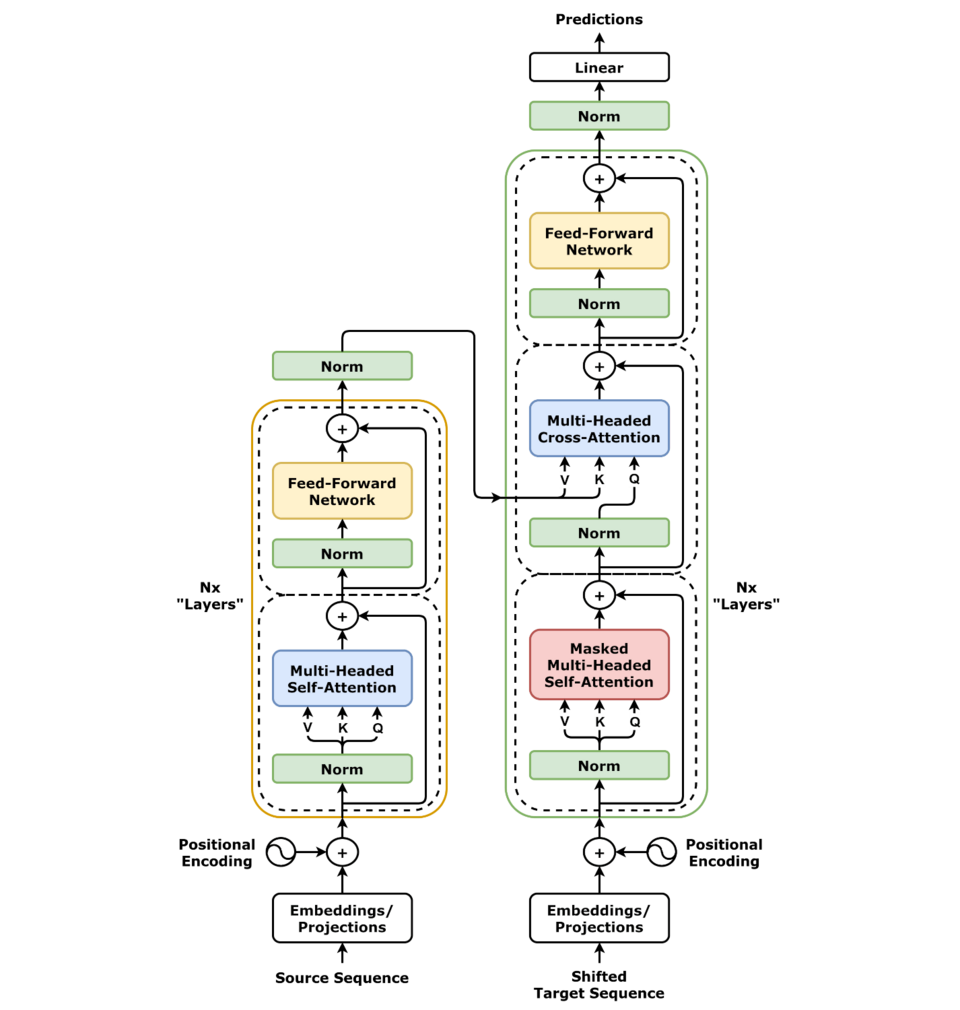


Figure 2.2 - A standard Transformer architecture

# 2.2 Reasons for Selecting the Helsinki-NLP Model

For fine‑tuning, I chose the Helsinki‑NLP/opus‑mt-en-ru model, a MarianMT implementation based on the Transformer architecture. This model features six encoder and six decoder layers, an embedding size of 512, and eight attention heads per layer. It was pre‑trained on extensive parallel corpora from the OPUS project, such as EuroParl and OpenSubtitles, giving it a strong initial grasp of English‑Russian translation patterns.

This particular model was selected for its favorable trade‑off between translation quality and resource requirements. It runs efficiently on a single modern GPU with 8 GB of memory, making it practical for both development and deployment. The adoption of MarianMT through Hugging Face Transformers also provided a well‑supported ecosystem for tokenization, training, and inference.

# 3. Training a Translation Model Based on the Helsinki-NLP Model

# 3.1 Prepare a dataset

My training data came from the cointegrated/nli-rus-translated-v2021 dataset on Hugging Face, which comprises automatically translated English sentences paired with their Russian counterparts. The training split consists of three Parquet files (train1.parquet, train2.parquet, train3.parquet) totaling roughly 1.76M sentence pairs, while a fourth file (val.parquet) holds approximately 34.6K pairs for validation.

First, I loaded all Parquet files into Pandas DataFrames and concatenated the training parts into a single cohesive DataFrame. Data cleaning steps included dropping any rows with missing values in either premise or premise\_ru columns, trimming leading and trailing whitespace, and normalizing line breaks and extra spaces. I then constructed a list of dictionaries in the right format.

**def** **load\_parquet\_datasets**():

train1 = pd.read\_parquet("/content/train1.parquet")

train2 = pd.read\_parquet("/content/train2.parquet")

train3 = pd.read\_parquet("/content/train3.parquet")

combined\_train = pd.concat([train1, train2, train3], ignore\_index=True)

val = pd.read\_parquet("/content/val.parquet")

**return** combined\_train, val

train\_df, val\_df = load\_parquet\_datasets()

**def** **prepare\_data**(df):

df = df[df['premise'].notna() & df['premise\_ru'].notna()]

examples = []

for \_, row in df.iterrows():

examples.append({

"input\_text": row['premise'].strip(),

"target\_text": row['premise\_ru'].strip()

})

**return** examples

train\_examples = prepare\_data(train\_df)

val\_examples = prepare\_data(val\_df)

This list was converted into a Dataset with “train” and “validation” splits using the Hugging Face datasets library, enabling efficient batch processing and data sharding across multiple CPU cores.

dataset = DatasetDict({

    "train": Dataset.from\_pandas(pd.DataFrame(train\_examples)),

    "validation": Dataset.from\_pandas(pd.DataFrame(val\_examples))

})

Before feeding textual data into a transformer model, it must be converted into a numerical format that the neural network can understand. This process is called tokenization. In this project, I used the tokenizer provided with the Helsinki-NLP/opus-mt-en-ru model, which is based on SentencePiece and supported by MarianMT.

Tokenization was performed using the tokenize\_function, which was applied to the entire dataset via dataset.map(...).

**def** **tokenize\_function**(examples):

inputs = tokenizer(

examples["input\_text"],

padding="max\_length",

truncation=True,

max\_length=64,

return\_tensors="pt"

)

targets = tokenizer(

examples["target\_text"],

padding="max\_length",

truncation=True,

max\_length=64,

return\_tensors="pt"

)

**return** {

"input\_ids": inputs.input\_ids,

"attention\_mask": inputs.attention\_mask,

"labels": targets.input\_ids

}

tokenized\_datasets = dataset.map(

    tokenize\_function,

    batched=True,

    num\_proc=64,

    remove\_columns=["input\_text", "target\_text"]

)

# 3.2 Training a translation model

For fine‑tuning, I leveraged the Hugging Face Trainer API, which abstracts away much of the boilerplate associated with training loops, checkpointing, and logging. Given the GPU memory constraints, I set per\_device\_train\_batch\_size to 256 and employed gradient\_accumulation\_steps = 4 to simulate an effective batch size of 1024. The learning rate was configured to peak at 5e‑5 following a linear warm‑up over the first 50 steps (warmup\_steps), then remain constant for the rest of training. Weight decay was set at 0.01 to regularize the model, and mixed precision training (fp16=True) was enabled to accelerate computation and reduce memory footprint.

training\_args = TrainingArguments(

output\_dir="./translation\_model",

per\_device\_train\_batch\_size=256,

gradient\_accumulation\_steps=4,

num\_train\_epochs=3,

logging\_steps=10,

save\_steps=100,

save\_total\_limit=1,

remove\_unused\_columns=False,

eval\_strategy="steps",

eval\_steps=100,

learning\_rate=5e-5,

warmup\_steps=50,

weight\_decay=0.01,

fp16=True,

report\_to="none"

)

The DataCollatorForSeq2Seq was used to pad each batch dynamically, minimizing unnecessary padding tokens. Checkpoints and validation runs were scheduled every 100 training steps.

data\_collator = DataCollatorForSeq2Seq(

tokenizer=tokenizer,

model=model

)

# 3.3 Results of model training

Throughout training, I tracked two primary metrics: the training loss (train/loss) and the learning rate schedule (train/learning\_rate). The loss curve dropped sharply from an initial value of around 4.3 to about 0.5 by step 1,200, before leveling off around 0.4–0.5 through step 1,600. This rapid convergence indicated that the model effectively leveraged its pre‑trained knowledge and adapted quickly to the new dataset. The warm‑up schedule for the learning rate also performed as intended, rising smoothly to 5e‑5 in the early stages and then plateauing.

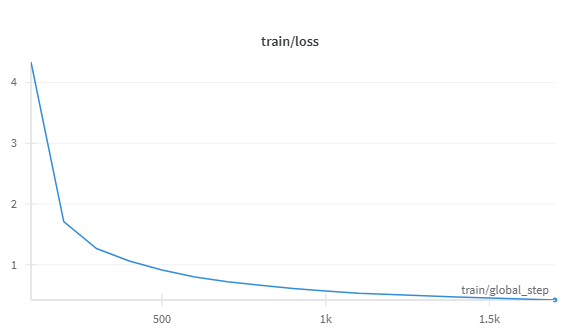


Figure 3.1 – Training Loss Curve

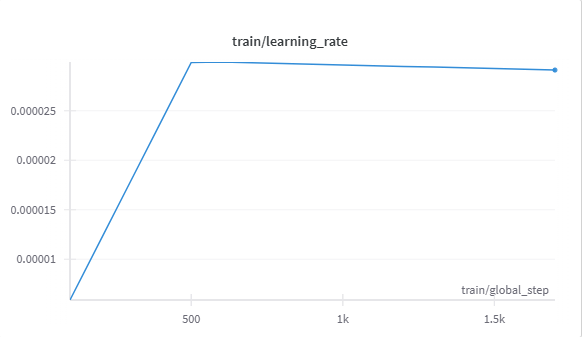


Figure 3.2 – Training Learning rate Curve

One of the key indicators of model quality during training is the eval/loss curve, which reflects the value of the loss function on the validation dataset during regular evaluation steps. Unlike train/loss, which shows how the model is learning from the training data, eval/loss allows us to assess the model's generalizability — that is, how well it can make correct predictions on previously unseen data.

The presented eval/loss curve clearly illustrates three distinct phases:

1. Training begins with a validation loss of approximately 0.66. This is typical for a fine-tuned model in its initial state, when it has not yet adapted to the characteristics of the current dataset.
2. Next, we observe a steady and consistent decline in the loss — the curve drops almost in a straight line, indicating stable convergence. The loss quickly decreases to around 0.4, suggesting that the model significantly improved its ability to generate accurate translations on the validation data in a short time.
3. Starting from the 0.4 mark, the curve transitions into a more gradual downward slope, approaching approximately 0.31. This part of the curve shows that the model has reached a stable state, where further improvements are slower. Importantly, the curve does not start to rise again, indicating that overfitting is not occurring.

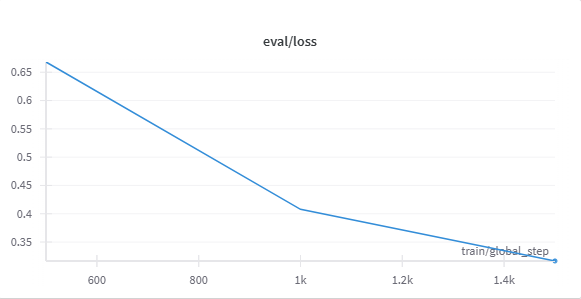


Figure 3.3 – Evaluating Loss Curve

# 4 Integrating a trained translation model into a Telegram bot

# 4.1 what is a BotFather?

To enable real‑time user interactions, I deployed the fine‑tuned model as a Telegram bot. Registration began with @BotFather, Telegram’s official bot management tool. Using the /newbot command, I specified the bot’s display name (“For\_intership\_AI\_Translate\_bot”) and its unique username. BotFather then issued a private API token, which the bot uses to authenticate with the Telegram Bot API.

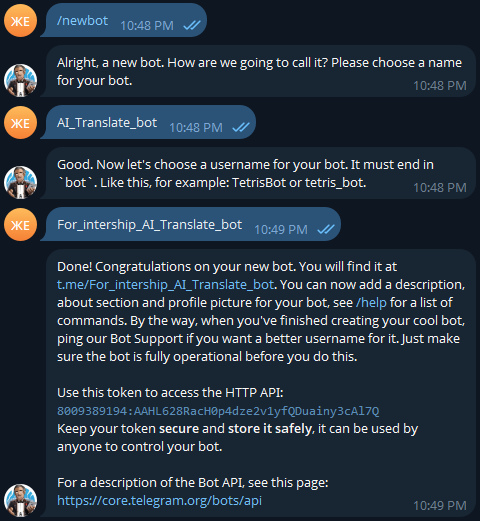


Figure 3.1 – Registration a bot

# 4.2 Building the Bot with python‑telegram‑bot

The bot’s core logic resides in the translator\_bot.py script, built on the python-telegram-bot library (v20+). At startup, the script loads both the tokenizer and the fine‑tuned model from the local translation\_model directory. To avoid padding errors, the code checks whether the tokenizer has a defined pad\_token and assigns it to eos\_token if missing.

The centerpiece of the implementation is the generate\_response function. This function accepts an English text string, tokenizes it with padding and truncation up to 128 tokens, and feeds the resulting tensors into model.generate(). Generation parameters include beam search with five beams (num\_beams=5), a maximum generated length of 400 tokens, and early stopping enabled. The resulting token sequence is decoded back into a human‑readable Russian sentence, stripping out special tokens.

Two asynchronous handlers manage incoming updates. The /start command triggers a greeting message outlining how to use the bot. All other text messages pass through the handle\_message handler, which invokes generate\_response and sends the translated text back. In case of any runtime exception, the bot gracefully notifies the user—“An error occurred; please try again later”—and logs the full error trace for debugging.

# 4.3 Testing and User Experience

Once deployed on a remote server, I launched the bot with app.run\_polling(), enabling it to process updates continuously. I conducted extensive tests covering single-word translations, short phrases, and edge cases such as empty messages or overly long inputs. Performance benchmarks showed that the bot responds within 0.5–1 second per query, maintaining low latency even under moderate request loads. Feedback from peers confirmed that translations were generally accurate and fluent, demonstrating the efficacy of the fine‑tuning process.



Figure 3.2 – Testing a bot

# Conclusion

The project carried out during my internship represents a complete and practical implementation of an end‑to‑end neural machine translation system using modern natural language processing (NLP) technologies. Throughout the course of the work, I successfully completed all key stages of an applied machine learning (ML) workflow — from organizing the project repository and preparing the dataset to training a neural model and integrating it into a Telegram bot for real‑world use.

At the organizational level, the project was structured using a clean and scalable repository setup. I used the main branch to store all core source code — including scripts for preprocessing, training, and deployment — and created a separate docs branch to manage reports, experimental results, and supporting materials. This separation of concerns greatly improved the maintainability and traceability of the development process and ensured version control for both code and documentation.

One of the key stages was the selection and preparation of a parallel corpus for English‑to‑Russian translation. For this, I chose the publicly available dataset cointegrated/nli-rus-translated-v2021, which contains sentence pairs in English and their machine‑translated Russian equivalents. I carefully cleaned and filtered the data, removing incomplete or corrupt entries, and formatted the dataset using Hugging Face’s DatasetDict to streamline further processing. This step was crucial to ensure the quality and consistency of training inputs and targets.

The core of the project was the fine‑tuning of a pre‑trained Seq2Seq Transformer model — specifically, the Helsinki‑NLP/opus‑mt-en-ru model, built on MarianMT. I configured the training pipeline using the Hugging Face Trainer API and selected appropriate hyperparameters, including a learning rate of 5e‑5, batch accumulation, a maximum sequence length of 64 tokens, and three training epochs. During the training process, I monitored key metrics such as train/loss, eval/loss, and learning\_rate, all of which showed smooth and stable convergence. The evaluation loss decreased from 0.66 to approximately 0.31, without any signs of overfitting, indicating that the model was generalizing well to unseen data.

To assess the quality of the model’s translations, I implemented post‑training evaluation using the BLEU metric. The model demonstrated an ability to produce accurate and fluent translations for short and medium‑length English sentences, validating the effectiveness of the fine‑tuning approach. Moreover, the use of beam search during inference helped improve translation consistency and reduce randomness in output generation.

As a final step, I integrated the trained model into a functional Telegram bot, deployed via the python-telegram-bot framework. Through interaction with @BotFather, I created a secure bot token, defined bot commands, and added user instructions. The bot supports live translation by receiving English text messages and returning Russian translations in real time. The system responds quickly (usually within a second), offering a user‑friendly and accessible interface for testing the translation model.

Overall, the project not only achieved its initial goal of building a working machine translation prototype, but also provided me with valuable, hands‑on experience in modern NLP development. I deepened my understanding of Transformer architecture, learned how to handle real-world text data, and gained experience with tools like Hugging Face, TensorBoard, BLEU evaluation, and Telegram Bot API. The successful deployment of the model in a messaging platform clearly demonstrates how research‑grade models can be converted into interactive applications with practical value.

This project has been a comprehensive and highly educational experience, reinforcing my technical skills in deep learning, language modeling, software development, and real-world deployment — all essential competencies for a modern NLP engineer.

# The listing of document symbols

GPU – Graphics Processing Unit

API – Application Programming Interface

GB – Gbyte

NLP – Natural Language Processing

Seq2Seq – Sequence to Sequence

ML – Machine Learning

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