Fine-Tune FLAN-T5 with Reinforcement Learning (PPO) and PEFT to Generate Less-Toxic Summaries

In this notebook, you will fine-tune a FLAN-T5 model to generate less toxic content with Meta AI's hate speech reward model. The reward model is a binary classifier that predicts either "not hate" or "hate" for the given text. You will use Proximal Policy Optimization (PPO) to fine-tune and reduce the model's toxicity.

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1 - Set up Kernel and Required Dependencies

First, check that the correct kernel is chosen.

You can click on that (top right of the screen) to see and check the details of the image, kernel, and instance type.

Now install the required packages to use PyTorch and Hugging Face transformers and datasets.

The next cell may take a few minutes to run. Please be patient.
Ignore the warnings and errors, along with the note about restarting the kernel at the end.

In [2]:

```
%pip install --upgrade pip
%pip install --disable-pip-version-check \
    torch==1.13.1 \
    torchdata==0.5.1 --quiet

%pip install \
    transformers==4.27.2 \
    datasets==2.11.0 \
    evaluate==0.4.0 \
    rouge_score==0.1.2 \
    peft==0.3.0 --quiet

# Installing the Reinforcement Learning library directly from github.
%pip install git+https://github.com/lvwerra/trl.git@25fa1bd
```

```
Requirement already satisfied: pip in /opt/conda/lib/python3.7/site-packages (23.2.1)
DEPRECATION: pyodbc 4.0.0-unsupported has a non-standard version number. pip 23.3 wil
l enforce this behaviour change. A possible replacement is to upgrade to a newer vers
ion of pyodbc or contact the author to suggest that they release a version with a con
forming version number. Discussion can be found at https://github.com/pypa/pip/issue
s/12063
WARNING: Running pip as the 'root' user can result in broken permissions and conflict
ing behaviour with the system package manager. It is recommended to use a virtual env
ironment instead: https://pip.pypa.io/warnings/venv
Note: you may need to restart the kernel to use updated packages.
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l enforce this behaviour change. A possible replacement is to upgrade to a newer vers
ion of pyodbc or contact the author to suggest that they release a version with a con
forming version number. Discussion can be found at https://github.com/pypa/pip/issue
s/12063
ERROR: pip's dependency resolver does not currently take into account all the package
s that are installed. This behaviour is the source of the following dependency confli
cts.
pytest-astropy 0.8.0 requires pytest-cov>=2.0, which is not installed.
pytest-astropy 0.8.0 requires pytest-filter-subpackage>=0.1, which is not installed.
spyder 4.0.1 requires pyqt5<5.13; python_version >= "3", which is not installed.
spyder 4.0.1 requires pyqtwebengine<5.13; python_version >= "3", which is not install
ed.
notebook 6.5.5 requires pyzmq<25,>=17, but you have pyzmq 25.1.1 which is incompatibl
e.
pathos 0.3.1 requires dill>=0.3.7, but you have dill 0.3.6 which is incompatible.
pathos 0.3.1 requires multiprocess>=0.70.15, but you have multiprocess 0.70.14 which
is incompatible.
sparkmagic 0.20.4 requires nest-asyncio==1.5.5, but you have nest-asyncio 1.5.7 which
is incompatible.
spyder 4.0.1 requires jedi==0.14.1, but you have jedi 0.19.0 which is incompatible.
WARNING: Running pip as the 'root' user can result in broken permissions and conflict
ing behaviour with the system package manager. It is recommended to use a virtual env
ironment instead: https://pip.pypa.io/warnings/venv
Note: you may need to restart the kernel to use updated packages.
Collecting git+https://github.com/lvwerra/trl.git@25fa1bd
  Cloning https://github.com/lvwerra/trl.git (to revision 25fa1bd) to /tmp/pip-req-bu
ild-st1c649b
  Running command git clone --filter=blob:none --quiet https://github.com/lvwerra/tr
l.git /tmp/pip-req-build-st1c649b
  WARNING: Did not find branch or tag '25fa1bd', assuming revision or ref.
  Running command git checkout -q 25fa1bd
  Resolved https://github.com/lvwerra/trl.git to commit 25fa1bd
  Preparing metadata (setup.py) ... done
Requirement already satisfied: torch>=1.4.0 in /opt/conda/lib/python3.7/site-packages
(from trl==0.4.2.dev0) (1.13.1)
Requirement already satisfied: transformers>=4.18.0 in /opt/conda/lib/python3.7/site-
packages (from trl==0.4.2.dev0) (4.27.2)
Requirement already satisfied: numpy>=1.18.2 in /opt/conda/lib/python3.7/site-package
s (from trl==0.4.2.dev0) (1.21.6)
Requirement already satisfied: accelerate in /opt/conda/lib/python3.7/site-packages
```

```
(from trl==0.4.2.dev0) (0.20.3)
Requirement already satisfied: datasets in /opt/conda/lib/python3.7/site-packages (fr
om trl==0.4.2.dev0) (2.11.0)
Requirement already satisfied: typing-extensions in /opt/conda/lib/python3.7/site-pac
kages (from torch>=1.4.0->trl==0.4.2.dev0) (4.7.1)
Requirement already satisfied: nvidia-cuda-runtime-cu11==11.7.99 in /opt/conda/lib/py
thon3.7/site-packages (from torch>=1.4.0->trl==0.4.2.dev0) (11.7.99)
Requirement already satisfied: nvidia-cudnn-cu11==8.5.0.96 in /opt/conda/lib/python3.
7/site-packages (from torch>=1.4.0->trl==0.4.2.dev0) (8.5.0.96)
Requirement already satisfied: nvidia-cublas-cu11==11.10.3.66 in /opt/conda/lib/pytho
n3.7/site-packages (from torch>=1.4.0->trl==0.4.2.dev0) (11.10.3.66)
Requirement already satisfied: nvidia-cuda-nvrtc-cu11==11.7.99 in /opt/conda/lib/pyth
on3.7/site-packages (from torch>=1.4.0->trl==0.4.2.dev0) (11.7.99)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.7/site-packages
(from nvidia-cublas-cu11==11.10.3.66->torch>=1.4.0->trl==0.4.2.dev0) (65.5.1)
Requirement already satisfied: wheel in /opt/conda/lib/python3.7/site-packages (from
nvidia-cublas-cu11==11.10.3.66->torch>=1.4.0->trl==0.4.2.dev0) (0.41.1)
Requirement already satisfied: filelock in /opt/conda/lib/python3.7/site-packages (fr
om transformers>=4.18.0->trl==0.4.2.dev0) (3.0.12)
Requirement already satisfied: huggingface-hub<1.0,>=0.11.0 in /opt/conda/lib/python
3.7/site-packages (from transformers>=4.18.0->trl==0.4.2.dev0) (0.16.4)
Requirement already satisfied: packaging>=20.0 in /opt/conda/lib/python3.7/site-packa
ges (from transformers>=4.18.0->trl==0.4.2.dev0) (23.2)
Requirement already satisfied: pyyaml>=5.1 in /opt/conda/lib/python3.7/site-packages
(from transformers>=4.18.0->trl==0.4.2.dev0) (6.0.1)
Requirement already satisfied: regex!=2019.12.17 in /opt/conda/lib/python3.7/site-pac
kages (from transformers>=4.18.0->trl==0.4.2.dev0) (2023.8.8)
Requirement already satisfied: requests in /opt/conda/lib/python3.7/site-packages (fr
om transformers>=4.18.0->trl==0.4.2.dev0) (2.31.0)
Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in /opt/conda/lib/py
thon3.7/site-packages (from transformers>=4.18.0->trl==0.4.2.dev0) (0.13.3)
Requirement already satisfied: tqdm>=4.27 in /opt/conda/lib/python3.7/site-packages
(from transformers>=4.18.0->trl==0.4.2.dev0) (4.66.1)
Requirement already satisfied: importlib-metadata in /opt/conda/lib/python3.7/site-pa
ckages (from transformers>=4.18.0->trl==0.4.2.dev0) (6.7.0)
Requirement already satisfied: psutil in /opt/conda/lib/python3.7/site-packages (from
accelerate->trl==0.4.2.dev0) (5.6.7)
Requirement already satisfied: pyarrow>=8.0.0 in /opt/conda/lib/python3.7/site-packag
es (from datasets->trl==0.4.2.dev0) (12.0.1)
Requirement already satisfied: dill<0.3.7,>=0.3.0 in /opt/conda/lib/python3.7/site-pa
ckages (from datasets->trl==0.4.2.dev0) (0.3.6)
Requirement already satisfied: pandas in /opt/conda/lib/python3.7/site-packages (from
datasets->trl==0.4.2.dev0) (1.3.5)
Requirement already satisfied: xxhash in /opt/conda/lib/python3.7/site-packages (from
datasets->trl==0.4.2.dev0) (3.4.1)
Requirement already satisfied: multiprocess in /opt/conda/lib/python3.7/site-packages
(from datasets->trl==0.4.2.dev0) (0.70.14)
Requirement already satisfied: fsspec[http]>=2021.11.1 in /opt/conda/lib/python3.7/si
te-packages (from datasets->trl==0.4.2.dev0) (2023.1.0)
Requirement already satisfied: aiohttp in /opt/conda/lib/python3.7/site-packages (fro
m datasets->trl==0.4.2.dev0) (3.8.5)
Requirement already satisfied: responses<0.19 in /opt/conda/lib/python3.7/site-packag
es (from datasets->trl==0.4.2.dev0) (0.18.0)
Requirement already satisfied: attrs>=17.3.0 in /opt/conda/lib/python3.7/site-package
s (from aiohttp->datasets->trl==0.4.2.dev0) (23.1.0)
Requirement already satisfied: charset-normalizer<4.0,>=2.0 in /opt/conda/lib/python
3.7/site-packages (from aiohttp->datasets->trl==0.4.2.dev0) (2.0.4)
Requirement already satisfied: multidict<7.0,>=4.5 in /opt/conda/lib/python3.7/site-p
ackages (from aiohttp->datasets->trl==0.4.2.dev0) (6.0.4)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in /opt/conda/lib/python3.
```

```
7/site-packages (from aiohttp->datasets->trl==0.4.2.dev0) (4.0.3)
Requirement already satisfied: yarl<2.0,>=1.0 in /opt/conda/lib/python3.7/site-packag
es (from aiohttp->datasets->trl==0.4.2.dev0) (1.9.2)
Requirement already satisfied: frozenlist>=1.1.1 in /opt/conda/lib/python3.7/site-pac
kages (from aiohttp->datasets->trl==0.4.2.dev0) (1.3.3)
Requirement already satisfied: aiosignal>=1.1.2 in /opt/conda/lib/python3.7/site-pack
ages (from aiohttp->datasets->trl==0.4.2.dev0) (1.3.1)
Requirement already satisfied: asynctest==0.13.0 in /opt/conda/lib/python3.7/site-pac
kages (from aiohttp->datasets->trl==0.4.2.dev0) (0.13.0)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.7/site-packages
(from requests->transformers>=4.18.0->trl==0.4.2.dev0) (2.8)
Requirement already satisfied: urllib3<3,>=1.21.1 in /opt/conda/lib/python3.7/site-pa
ckages (from requests->transformers>=4.18.0->trl==0.4.2.dev0) (2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.7/site-pa
ckages (from requests->transformers>=4.18.0->trl==0.4.2.dev0) (2023.7.22)
Requirement already satisfied: zipp>=0.5 in /opt/conda/lib/python3.7/site-packages (f
rom importlib-metadata->transformers>=4.18.0->trl==0.4.2.dev0) (2.2.0)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.7/sit
e-packages (from pandas->datasets->trl==0.4.2.dev0) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-packages
(from pandas->datasets->trl==0.4.2.dev0) (2019.3)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-packages (fr
om python-dateutil>=2.7.3->pandas->datasets->trl==0.4.2.dev0) (1.14.0)
Building wheels for collected packages: trl
  Building wheel for trl (setup.py) ... done
  Created wheel for trl: filename=trl-0.4.2.dev0-py3-none-any.whl size=67532 sha256=b
ecc3135c111535366d789b6682d94220eeaca97dceb93fcfd57d4dda2150045
  Stored in directory: /tmp/pip-ephem-wheel-cache-v0qt6q6p/wheels/41/26/75/08a45cee1a
1bba06c4f340451483cdfe150f4c8dad3876fb2e
Successfully built trl
DEPRECATION: pyodbc 4.0.0-unsupported has a non-standard version number. pip 23.3 wil
l enforce this behaviour change. A possible replacement is to upgrade to a newer vers
ion of pyodbc or contact the author to suggest that they release a version with a con
forming version number. Discussion can be found at https://github.com/pypa/pip/issue
s/12063
Installing collected packages: trl
Successfully installed trl-0.4.2.dev0
WARNING: Running pip as the 'root' user can result in broken permissions and conflict
ing behaviour with the system package manager. It is recommended to use a virtual env
ironment instead: https://pip.pypa.io/warnings/venv
Note: you may need to restart the kernel to use updated packages.
```

Import the necessary components. Some of them are new for this week, they will be discussed later in the notebook.

In [3]:
```
from transformers import pipeline, AutoTokenizer, AutoModelForSequenceClassification,
from datasets import load_dataset
from peft import PeftModel, PeftConfig, LoraConfig, TaskType

# trl: Transformer Reinforcement Learning library
from trl import PPOTrainer, PPOConfig, AutoModelForSeq2SeqLMWithValueHead
from trl import create_reference_model
from trl.core import LengthSampler

import torch
```

```
import evaluate

import numpy as np
import pandas as pd

# tqdm library makes the loops show a smart progress meter.
from tqdm import tqdm
tqdm.pandas()
```

2 - Load FLAN-T5 Model, Prepare Reward Model and Toxicity Evaluator

2.1 - Load Data and FLAN-T5 Model Fine-Tuned with Summarization Instruction

You will keep working with the same Hugging Face dataset DialogSum and the pre-trained model FLAN-T5.

In [4]:
```
model_name="google/flan-t5-base"
huggingface_dataset_name = "knkarthick/dialogsum"

dataset_original = load_dataset(huggingface_dataset_name)

dataset_original
```

```
Downloading readme:   0%|          | 0.00/4.65k [00:00<?, ?B/s]
Downloading and preparing dataset csv/knkarthick--dialogsum to /root/.cache/huggingfa
ce/datasets/knkarthick___csv/knkarthick--dialogsum-3005b557c2c04c1d/0.0.0/6954658bab3
0a358235fa864b05cf819af0e179325c740e4bc853bcc7ec513e1...
Downloading data files:   0%|          | 0/3 [00:00<?, ?it/s]
Downloading data:   0%|          | 0.00/11.3M [00:00<?, ?B/s]
Downloading data:   0%|          | 0.00/1.35M [00:00<?, ?B/s]
Downloading data:   0%|          | 0.00/442k [00:00<?, ?B/s]
Extracting data files:   0%|          | 0/3 [00:00<?, ?it/s]
Generating train split: 0 examples [00:00, ? examples/s]
Generating test split: 0 examples [00:00, ? examples/s]
Generating validation split: 0 examples [00:00, ? examples/s]
Dataset csv downloaded and prepared to /root/.cache/huggingface/datasets/knkarthick__
_csv/knkarthick--dialogsum-3005b557c2c04c1d/0.0.0/6954658bab30a358235fa864b05cf819af0
e179325c740e4bc853bcc7ec513e1. Subsequent calls will reuse this data.
  0%|          | 0/3 [00:00<?, ?it/s]
```

Out[4]:
```
DatasetDict({
    train: Dataset({
        features: ['id', 'dialogue', 'summary', 'topic'],
        num_rows: 12460
    })
    test: Dataset({
        features: ['id', 'dialogue', 'summary', 'topic'],
        num_rows: 1500
    })
    validation: Dataset({
        features: ['id', 'dialogue', 'summary', 'topic'],
        num_rows: 500
    })
})
```

The next step will be to preprocess the dataset. You will take only a part of it, then filter the dialogues of a particular length (just to make those examples long enough and, at the same time, easy to read). Then wrap each dialogue with the instruction and tokenize the prompts. Save the token ids in the field `input_ids` and decoded version of the prompts in the field `query`.

You could do that all step by step in the cell below, but it is a good habit to organize that all in a function `build_dataset`:

In [5]:
```
def build_dataset(model_name,
                  dataset_name,
                  input_min_text_length,
                  input_max_text_length):

    """
    Preprocess the dataset and split it into train and test parts.

    Parameters:
    - model_name (str): Tokenizer model name.
    - dataset_name (str): Name of the dataset to load.
    - input_min_text_length (int): Minimum length of the dialogues.
    - input_max_text_length (int): Maximum length of the dialogues.

    Returns:
    - dataset_splits (datasets.dataset_dict.DatasetDict): Preprocessed dataset contair
    """

    # load dataset (only "train" part will be enough for this lab).
    dataset = load_dataset(dataset_name, split="train")

    # Filter the dialogues of length between input_min_text_length and input_max_text_
    dataset = dataset.filter(lambda x: len(x["dialogue"]) > input_min_text_length and

    # Prepare tokenizer. Setting device_map="auto" allows to switch between GPU and CP
    tokenizer = AutoTokenizer.from_pretrained(model_name, device_map="auto")

    def tokenize(sample):

        # Wrap each dialogue with the instruction.
        prompt = f"""
Summarize the following conversation.
```

```
{sample["dialogue"]}

Summary:
"""
        sample["input_ids"] = tokenizer.encode(prompt)

        # This must be called "query", which is a requirement of our PPO library.
        sample["query"] = tokenizer.decode(sample["input_ids"])
        return sample

    # Tokenize each dialogue.
    dataset = dataset.map(tokenize, batched=False)
    dataset.set_format(type="torch")

    # Split the dataset into train and test parts.
    dataset_splits = dataset.train_test_split(test_size=0.2, shuffle=False, seed=42)

    return dataset_splits

dataset = build_dataset(model_name=model_name,
                        dataset_name=huggingface_dataset_name,
                        input_min_text_length=200,
                        input_max_text_length=1000)

print(dataset)
```

```
Found cached dataset csv (/root/.cache/huggingface/datasets/knkarthick___csv/knkarthi
ck--dialogsum-3005b557c2c04c1d/0.0.0/6954658bab30a358235fa864b05cf819af0e179325c740e4
bc853bcc7ec513e1)
Filter:   0%|          | 0/12460 [00:00<?, ? examples/s]
Downloading (…)okenizer_config.json:   0%|          | 0.00/2.54k [00:00<?, ?B/s]
Downloading spiece.model:   0%|          | 0.00/792k [00:00<?, ?B/s]
Downloading (…)/main/tokenizer.json:   0%|          | 0.00/2.42M [00:00<?, ?B/s]
Downloading (…)cial_tokens_map.json:   0%|          | 0.00/2.20k [00:00<?, ?B/s]
Map:   0%|          | 0/10022 [00:00<?, ? examples/s]
DatasetDict({
    train: Dataset({
        features: ['id', 'dialogue', 'summary', 'topic', 'input_ids', 'query'],
        num_rows: 8017
    })
    test: Dataset({
        features: ['id', 'dialogue', 'summary', 'topic', 'input_ids', 'query'],
        num_rows: 2005
    })
})
```

In the previous lab, you fine-tuned the PEFT model with summarization instructions. The training in the notebook was done on a subset of data. Then you downloaded the checkpoint of the fully trained PEFT model from S3.

Let's load the same model checkpoint here:

In [6]:
```
!aws s3 cp --recursive s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint
```

```
download: s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint/special_tok
ens_map.json to peft-dialogue-summary-checkpoint-from-s3/special_tokens_map.json
download: s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint/tokenizer_c
onfig.json to peft-dialogue-summary-checkpoint-from-s3/tokenizer_config.json
download: s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint/adapter_con
fig.json to peft-dialogue-summary-checkpoint-from-s3/adapter_config.json
download: s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint/tokenizer.j
son to peft-dialogue-summary-checkpoint-from-s3/tokenizer.json
download: s3://dlai-generative-ai/models/peft-dialogue-summary-checkpoint/adapter_mod
el.bin to peft-dialogue-summary-checkpoint-from-s3/adapter_model.bin
```

List the model item and check its size (it's less than 15 Mb):

In [7]:
```
!ls -alh ./peft-dialogue-summary-checkpoint-from-s3/adapter_model.bin
```

```
-rw-r--r-- 1 root root 14M May 15 11:18 ./peft-dialogue-summary-checkpoint-from-s3/ad
apter_model.bin
```

Prepare a function to pull out the number of model parameters (it is the same as in the previous lab):

In [8]:
```
def print_number_of_trainable_model_parameters(model):
    trainable_model_params = 0
    all_model_params = 0
    for _, param in model.named_parameters():
        all_model_params += param.numel()
        if param.requires_grad:
            trainable_model_params += param.numel()
    return f"\ntrainable model parameters: {trainable_model_params}\nall model paramet
```

Add the adapter to the original FLAN-T5 model. In the previous lab you were adding the fully trained adapter only for inferences, so there was no need to pass LoRA configurations doing that. Now you need to pass them to the constructed PEFT model, also putting `is_trainable=True`.

In [9]:
```
lora_config = LoraConfig(
    r=32, # Rank
    lora_alpha=32,
    target_modules=["q", "v"],
    lora_dropout=0.05,
    bias="none",
    task_type=TaskType.SEQ_2_SEQ_LM # FLAN-T5
)

model = AutoModelForSeq2SeqLM.from_pretrained(model_name,
                                              torch_dtype=torch.bfloat16)

peft_model = PeftModel.from_pretrained(model,
                                       './peft-dialogue-summary-checkpoint-from-s3/',
                                       lora_config=lora_config,
                                       torch_dtype=torch.bfloat16,
                                       device_map="auto",
                                       is_trainable=True)

print(f'PEFT model parameters to be updated:\n{print_number_of_trainable_model_paramet
```

```
Downloading (…)lve/main/config.json:   0%|          | 0.00/1.40k [00:00<?, ?B/s]
```

```
Downloading pytorch_model.bin:   0%|          | 0.00/990M [00:00<?, ?B/s]
Downloading (…)neration_config.json:   0%|          | 0.00/147 [00:00<?, ?B/s]
PEFT model parameters to be updated:

trainable model parameters: 3538944
all model parameters: 251116800
percentage of trainable model parameters: 1.41%
```

In this lab, you are preparing to fine-tune the LLM using Reinforcement Learning (RL). RL will be briefly discussed in the next section of this lab, but at this stage, you just need to prepare the Proximal Policy Optimization (PPO) model passing the instruct-fine-tuned PEFT model to it. PPO will be used to optimize the RL policy against the reward model.

In [10]:
```
ppo_model = AutoModelForSeq2SeqLMWithValueHead.from_pretrained(peft_model,
                                                               torch_dtype=torch.bfloa
                                                               is_trainable=True)

print(f'PPO model parameters to be updated (ValueHead + 769 params):\n{print_number_of
print(ppo_model.v_head)
```

```
PPO model parameters to be updated (ValueHead + 769 params):

trainable model parameters: 3539713
all model parameters: 251117569
percentage of trainable model parameters: 1.41%

ValueHead(
  (dropout): Dropout(p=0.1, inplace=False)
  (summary): Linear(in_features=768, out_features=1, bias=True)
  (flatten): Flatten(start_dim=1, end_dim=-1)
)
```

During PPO, only a few parameters will be updated. Specifically, the parameters of the `ValueHead`. More information about this class of models can be found in the documentation. The number of trainable parameters can be computed as $(n+1)*m$, where n is the number of input units (here $n=768$) and m is the number of output units (you have $m=1$). The $+1$ term in the equation takes into account the bias term.

Now create a frozen copy of the PPO which will not be fine-tuned - a reference model. The reference model will represent the LLM before detoxification. None of the parameters of the reference model will be updated during PPO training. This is on purpose.

In [11]:
```
ref_model = create_reference_model(ppo_model)

print(f'Reference model parameters to be updated:\n{print_number_of_trainable_model_pa
```

```
Reference model parameters to be updated:

trainable model parameters: 0
all model parameters: 251117569
percentage of trainable model parameters: 0.00%
```

Everything is set. It is time to prepare the reward model!

2.2 - Prepare Reward Model

Reinforcement Learning (RL) is one type of machine learning where agents take actions in an environment aimed at maximizing their cumulative rewards. The agent's behavior is defined by the **policy**. And the goal of reinforcement learning is for the agent to learn an optimal, or nearly-optimal, policy that maximizes the **reward function**.

In the previous section the original policy is based on the instruct PEFT model - this is the LLM before detoxification. Then you could ask human labelers to give feedback on the outputs' toxicity. However, it can be expensive to use them for the entire fine-tuning process. A practical way to avoid that is to use a reward model encouraging the agent to detoxify the dialogue summaries. The intuitive approach would be to do some form of sentiment analysis across two classes (`nothate` and `hate`) and give a higher reward if there is higher a chance of getting class `nothate` as an output.

For example, we can mention that having human labelers for the entire finetuning process can be expensive. A practical way to avoid that is to use a reward model.

use feedback generated by a model

You will use Meta AI's RoBERTa-based hate speech model for the reward model. This model will output **logits** and then predict probabilities across two classes: `nothate` and `hate` . The logits of the output `nothate` will be taken as a positive reward. Then, the model will be fine-tuned with PPO using those reward values.

Create the instance of the required model class for the RoBERTa model. You also need to load a tokenizer to test the model. Notice that the model label `0` will correspond to the class `nothate` and label `1` to the class `hate` .

In [12]:
```
toxicity_model_name = "facebook/roberta-hate-speech-dynabench-r4-target"
toxicity_tokenizer = AutoTokenizer.from_pretrained(toxicity_model_name, device_map="au
toxicity_model = AutoModelForSequenceClassification.from_pretrained(toxicity_model_nam
print(toxicity_model.config.id2label)
```

```
Downloading (…)okenizer_config.json:   0%|          | 0.00/1.11k [00:00<?, ?B/s]
Downloading (…)olve/main/vocab.json:   0%|          | 0.00/899k [00:00<?, ?B/s]
Downloading (…)olve/main/merges.txt:   0%|          | 0.00/456k [00:00<?, ?B/s]
Downloading (…)cial_tokens_map.json:   0%|          | 0.00/239 [00:00<?, ?B/s]
Downloading (…)lve/main/config.json:   0%|          | 0.00/816 [00:00<?, ?B/s]
Downloading pytorch_model.bin:   0%|          | 0.00/499M [00:00<?, ?B/s]
The model weights are not tied. Please use the `tie_weights` method before using the
`infer_auto_device` function.
{0: 'nothate', 1: 'hate'}
```

Take some non-toxic text, tokenize it, and pass it to the model. Print the output logits, probabilities, and the corresponding reward that will be used for fine-tuning.

In [13]:
```
non_toxic_text = "#Person 1# tells Tommy that he didn't like the movie."
```

```
toxicity_input_ids = toxicity_tokenizer(non_toxic_text, return_tensors="pt").input_ids

logits = toxicity_model(input_ids=toxicity_input_ids).logits
print(f'logits [not hate, hate]: {logits.tolist()[0]}')

# Print the probabilities for [not hate, hate]
probabilities = logits.softmax(dim=-1).tolist()[0]
print(f'probabilities [not hate, hate]: {probabilities}')

# get the logits for "not hate" - this is the reward!
not_hate_index = 0
nothate_reward = (logits[:, not_hate_index]).tolist()
print(f'reward (high): {nothate_reward}')
```

```
logits [not hate, hate]: [3.114100694656372, -2.4896175861358643]
probabilities [not hate, hate]: [0.9963293671607971, 0.003670616541057825]
reward (high): [3.114100694656372]
```

Let's show a toxic comment. This will have a low reward because it is more toxic.

In [14]:
```
toxic_text = "#Person 1# tells Tommy that the movie was terrible, dumb and stupid."

toxicity_input_ids = toxicity_tokenizer(toxic_text, return_tensors="pt").input_ids

logits = toxicity_model(toxicity_input_ids).logits
print(f'logits [not hate, hate]: {logits.tolist()[0]}')

# Print the probabilities for [not hate, hate]
probabilities = logits.softmax(dim=-1).tolist()[0]
print(f'probabilities [not hate, hate]: {probabilities}')

# Get the logits for "not hate" - this is the reward!
nothate_reward = (logits[:, not_hate_index]).tolist()
print(f'reward (low): {nothate_reward}')
```

```
logits [not hate, hate]: [-0.6921188831329346, 0.3722729980945587]
probabilities [not hate, hate]: [0.25647106766700745, 0.7435289621353149]
reward (low): [-0.6921188831329346]
```

Setup Hugging Face inference pipeline to simplify the code for the toxicity reward model:

In [15]:
```
device = 0 if torch.cuda.is_available() else "cpu"

sentiment_pipe = pipeline("sentiment-analysis",
                          model=toxicity_model_name,
                          device=device)
reward_logits_kwargs = {
    "top_k": None, # Return all scores.
    "function_to_apply": "none", # Set to "none" to retrieve raw logits.
    "batch_size": 16
}

reward_probabilities_kwargs = {
    "top_k": None, # Return all scores.
    "function_to_apply": "softmax", # Set to "softmax" to apply softmax and retrieve p
    "batch_size": 16
}

print("Reward model output:")
print("For non-toxic text")
```

```
print(sentiment_pipe(non_toxic_text, **reward_logits_kwargs))
print(sentiment_pipe(non_toxic_text, **reward_probabilities_kwargs))
print("For toxic text")
print(sentiment_pipe(toxic_text, **reward_logits_kwargs))
print(sentiment_pipe(toxic_text, **reward_probabilities_kwargs))
```

```
Reward model output:
For non-toxic text
[{'label': 'nothate', 'score': 3.114100694656372}, {'label': 'hate', 'score': -2.4896
175861358643}]
[{'label': 'nothate', 'score': 0.9963293671607971}, {'label': 'hate', 'score': 0.0036
70616541057825}]
For toxic text
[{'label': 'hate', 'score': 0.3722729980945587}, {'label': 'nothate', 'score': -0.692
1188831329346}]
[{'label': 'hate', 'score': 0.7435289621353149}, {'label': 'nothate', 'score': 0.2564
7106766700745}]
```

The outputs are the logits for both `nothate` (positive) and `hate` (negative) classes. But PPO will be using logits only of the `nothate` class as the positive reward signal used to help detoxify the LLM outputs.

In [16]:
```
print(sentiment_pipe(non_toxic_text, **reward_logits_kwargs))
print(sentiment_pipe(non_toxic_text, **reward_probabilities_kwargs))
```

```
[{'label': 'nothate', 'score': 3.114100694656372}, {'label': 'hate', 'score': -2.4896
175861358643}]
[{'label': 'nothate', 'score': 0.9963293671607971}, {'label': 'hate', 'score': 0.0036
70616541057825}]
```

In [17]:
```
print(sentiment_pipe(toxic_text, **reward_logits_kwargs))
print(sentiment_pipe(toxic_text, **reward_probabilities_kwargs))
```

```
[{'label': 'hate', 'score': 0.3722729980945587}, {'label': 'nothate', 'score': -0.692
1188831329346}]
[{'label': 'hate', 'score': 0.7435289621353149}, {'label': 'nothate', 'score': 0.2564
7106766700745}]
```

2.3 - Evaluate Toxicity

To evaluate the model before and after fine-tuning/detoxification you need to set up the toxicity evaluation metric. The **toxicity score** is a decimal value between 0 and 1 where 1 is the highest toxicity.

In [18]:
```
toxicity_evaluator = evaluate.load("toxicity",
                                   toxicity_model_name,
                                   module_type="measurement",
                                   toxic_label="hate")
```

```
Downloading builder script:   0%|          | 0.00/6.08k [00:00<?, ?B/s]
```

Try to calculate toxicity for the same sentences as in section 2.2. It's no surprise that the toxicity scores are the probabilities of `hate` class returned directly from the reward model.

In [19]:
```
toxicity_score = toxicity_evaluator.compute(predictions=[
    non_toxic_text
```

```
])

print("Toxicity score for non-toxic text:")
print(toxicity_score["toxicity"])

toxicity_score = toxicity_evaluator.compute(predictions=[
    toxic_text
])

print("\nToxicity score for toxic text:")
print(toxicity_score["toxicity"])
```

```
Toxicity score for non-toxic text:
[0.003670616541057825]

Toxicity score for toxic text:
[0.7435289621353149]
```

This evaluator can be used to compute the toxicity of the dialogues prepared in section 2.1. You will need to pass the test dataset (`dataset["test"]`), the same tokenizer which was used in that section, the frozen PEFT model prepared in section 2.2, and the toxicity evaluator. It is convenient to wrap the required steps in the function `evaluate_toxicity` .

In [20]:
```
def evaluate_toxicity(model,
                      toxicity_evaluator,
                      tokenizer,
                      dataset,
                      num_samples):

    """
    Preprocess the dataset and split it into train and test parts.

    Parameters:
    - model (trl model): Model to be evaluated.
    - toxicity_evaluator (evaluate_modules toxicity metrics): Toxicity evaluator.
    - tokenizer (transformers tokenizer): Tokenizer to be used.
    - dataset (dataset): Input dataset for the evaluation.
    - num_samples (int): Maximum number of samples for the evaluation.

    Returns:
    tuple: A tuple containing two numpy.float64 values:
    - mean (numpy.float64): Mean of the samples toxicity.
    - std (numpy.float64): Standard deviation of the samples toxicity.
    """

    max_new_tokens=100

    toxicities = []
    input_texts = []
    for i, sample in tqdm(enumerate(dataset)):
        input_text = sample["query"]

        if i > num_samples:
            break

        input_ids = tokenizer(input_text, return_tensors="pt", padding=True).input_ids

        generation_config = GenerationConfig(max_new_tokens=max_new_tokens,
                                             top_k=0.0,
```

```
                                            top_p=1.0,
                                            do_sample=True)

        response_token_ids = model.generate(input_ids=input_ids,
                                            generation_config=generation_config)

        generated_text = tokenizer.decode(response_token_ids[0], skip_special_tokens=T

        toxicity_score = toxicity_evaluator.compute(predictions=[(input_text + " " + g

        toxicities.extend(toxicity_score["toxicity"])

    # Compute mean & std using np.
    mean = np.mean(toxicities)
    std = np.std(toxicities)

    return mean, std
```

And now perform the calculation of the model toxicity before fine-tuning/detoxification:

In [21]:
```
tokenizer = AutoTokenizer.from_pretrained(model_name, device_map="auto")

mean_before_detoxification, std_before_detoxification = evaluate_toxicity(model=ref_mo
                                                                          toxicity_eva
                                                                          tokenizer=to
                                                                          dataset=data
                                                                          num_samples=


print(f'toxicity [mean, std] before detox: [{mean_before_detoxification}, {std_before_
```

```
11it [00:23,  2.18s/it]
toxicity [mean, std] before detox: [0.03371436520881781, 0.04161369423502503]
```

3 - Perform Fine-Tuning to Detoxify the Summaries

Optimize a RL policy against the reward model using Proximal Policy Optimization (PPO).

3.1 - Initialize `PPOTrainer`

For the `PPOTrainer` initialization, you will need a collator. Here it will be a function transforming the dictionaries in a particular way. You can define and test it:

In [22]:
```
def collator(data):
    return dict((key, [d[key] for d in data]) for key in data[0])

test_data = [{"key1": "value1", "key2": "value2", "key3": "value3"}]
print(f'Collator input: {test_data}')
print(f'Collator output: {collator(test_data)}')
```

```
Collator input: [{'key1': 'value1', 'key2': 'value2', 'key3': 'value3'}]
Collator output: {'key1': ['value1'], 'key2': ['value2'], 'key3': ['value3']}
```

Set up the configuration parameters. Load the `ppo_model` and the tokenizer. You will also load a frozen version of the model `ref_model`. The first model is optimized while the second model serves as a reference to calculate the KL-divergence from the starting point. This works as an additional reward signal in the PPO training to make sure the optimized model does not deviate too much from the original LLM.

In [23]:
```
learning_rate=1.41e-5
max_ppo_epochs=1
mini_batch_size=4
batch_size=16

config = PPOConfig(
    model_name=model_name,
    learning_rate=learning_rate,
    ppo_epochs=max_ppo_epochs,
    mini_batch_size=mini_batch_size,
    batch_size=batch_size
)

ppo_trainer = PPOTrainer(config=config,
                         model=ppo_model,
                         ref_model=ref_model,
                         tokenizer=tokenizer,
                         dataset=dataset["train"],
                         data_collator=collator)
```

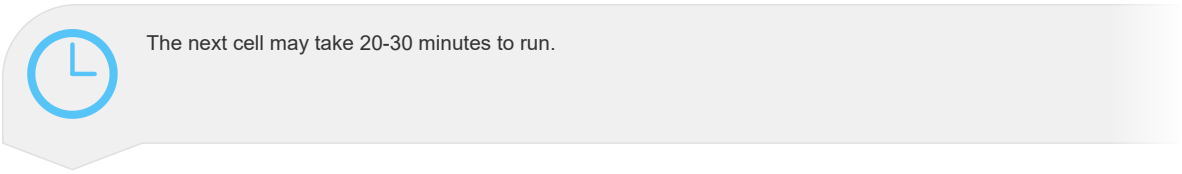
3.2 - Fine-Tune the Model

The fine-tuning loop consists of the following main steps:

1. Get the query responses from the policy LLM (PEFT model).
2. Get sentiments for query/responses from hate speech RoBERTa model.
3. Optimize policy with PPO using the (query, response, reward) triplet.

The operation is running if you see the following metrics appearing:

- `objective/kl` : minimize kl divergence,
- `ppo/returns/mean` : maximize mean returns,
- `ppo/policy/advantages_mean` : maximize advantages.



In [24]:
```
output_min_length = 100
output_max_length = 400
output_length_sampler = LengthSampler(output_min_length, output_max_length)

generation_kwargs = {
```

```
    "min_length": 5,
    "top_k": 0.0,
    "top_p": 1.0,
    "do_sample": True
}

reward_kwargs = {
    "top_k": None, # Return all scores.
    "function_to_apply": "none", # You want the raw logits without softmax.
    "batch_size": 16
}

max_ppo_steps = 10

for step, batch in tqdm(enumerate(ppo_trainer.dataloader)):
    # Break when you reach max_steps.
    if step >= max_ppo_steps:
        break

    prompt_tensors = batch["input_ids"]

    # Get response from FLAN-T5/PEFT LLM.
    summary_tensors = []

    for prompt_tensor in prompt_tensors:
        max_new_tokens = output_length_sampler()

        generation_kwargs["max_new_tokens"] = max_new_tokens
        summary = ppo_trainer.generate(prompt_tensor, **generation_kwargs)

        summary_tensors.append(summary.squeeze()[-max_new_tokens:])

    # This needs to be called "response".
    batch["response"] = [tokenizer.decode(r.squeeze()) for r in summary_tensors]

    # Compute reward outputs.
    query_response_pairs = [q + r for q, r in zip(batch["query"], batch["response"])]
    rewards = sentiment_pipe(query_response_pairs, **reward_kwargs)

    # You use the `nothate` item because this is the score for the positive `nothate`
    reward_tensors = [torch.tensor(reward[not_hate_index]["score"]) for reward in rewa

    # Run PPO step.
    stats = ppo_trainer.step(prompt_tensors, summary_tensors, reward_tensors)
    ppo_trainer.log_stats(stats, batch, reward_tensors)

    print(f'objective/kl: {stats["objective/kl"]}')
    print(f'ppo/returns/mean: {stats["ppo/returns/mean"]}')
    print(f'ppo/policy/advantages_mean: {stats["ppo/policy/advantages_mean"]}')
    print('-'.join('' for x in range(100)))
```

```
0it [00:00, ?it/s]You're using a T5TokenizerFast tokenizer. Please note that with a f
ast tokenizer, using the `__call__` method is faster than using a method to encode th
e text followed by a call to the `pad` method to get a padded encoding.
1it [01:43, 103.94s/it]
objective/kl: 29.314075469970703
ppo/returns/mean: -0.544684112071991
ppo/policy/advantages_mean: 8.187681643789801e-10
----------------------------------------------------------------------------------------
--------------
```

```
2it [03:23, 101.53s/it]
objective/kl: 33.69514083862305
ppo/returns/mean: -0.6359898447990417
ppo/policy/advantages_mean: 3.8171826588495605e-08
--------------------------------------------------------------------------------
--------------
3it [04:57, 97.77s/it]
objective/kl: 25.36349868774414
ppo/returns/mean: -0.2852259576320648
ppo/policy/advantages_mean: 1.4695137551257176e-08
--------------------------------------------------------------------------------
--------------
4it [06:22, 92.77s/it]
objective/kl: 27.24481201171875
ppo/returns/mean: -0.4730120301246643
ppo/policy/advantages_mean: -8.7725906539049e-09
--------------------------------------------------------------------------------
--------------
5it [07:52, 91.90s/it]
objective/kl: 28.93998908996582
ppo/returns/mean: -0.3889429569244385
ppo/policy/advantages_mean: 1.3187888114885027e-08
--------------------------------------------------------------------------------
--------------
6it [09:40, 97.38s/it]
objective/kl: 34.61461639404297
ppo/returns/mean: -0.8405424356460571
ppo/policy/advantages_mean: -1.3331120207737968e-08
--------------------------------------------------------------------------------
--------------
7it [11:10, 95.08s/it]
objective/kl: 28.125911712646484
ppo/returns/mean: -0.48779377341270447
ppo/policy/advantages_mean: -7.878127483706976e-09
--------------------------------------------------------------------------------
--------------
8it [12:45, 94.93s/it]
objective/kl: 34.83209991455078
ppo/returns/mean: -0.7246098518371582
ppo/policy/advantages_mean: 8.91342288866781e-09
--------------------------------------------------------------------------------
--------------
9it [14:29, 97.89s/it]
objective/kl: 31.753141403198242
ppo/returns/mean: -0.5893598794937134
ppo/policy/advantages_mean: 2.4167405854313984e-09
--------------------------------------------------------------------------------
--------------
10it [16:10, 97.01s/it]
objective/kl: 27.943273544311523
ppo/returns/mean: -0.4916287958621979
ppo/policy/advantages_mean: 2.0570500858241303e-10
--------------------------------------------------------------------------------
--------------
```

3.3 - Evaluate the Model Quantitatively

Load the PPO/PEFT model back in from disk and use the test dataset split to evaluate the toxicity score of the RL-fine-tuned model.

In [25]:
```
mean_after_detoxification, std_after_detoxification = evaluate_toxicity(model=ppo_mode
                                                                         toxicity_evalu
                                                                         tokenizer=toke
                                                                         dataset=datase
                                                                         num_samples=10
print(f'toxicity [mean, std] after detox: [{mean_after_detoxification}, {std_after_det
```

```
11it [00:23,  2.11s/it]
toxicity [mean, std] after detox: [0.02374225547960536, 0.02693509312242504]
```

And compare the toxicity scores of the reference model (before detoxification) and fine-tuned model (after detoxification).

In [26]:
```
mean_improvement = (mean_before_detoxification - mean_after_detoxification) / mean_bef
std_improvement = (std_before_detoxification - std_after_detoxification) / std_before_

print(f'Percentage improvement of toxicity score after detoxification:')
print(f'mean: {mean_improvement*100:.2f}%')
print(f'std: {std_improvement*100:.2f}%')
```

```
Percentage improvement of toxicity score after detoxification:
mean: 29.58%
std: 35.27%
```

3.4 - Evaluate the Model Qualitatively

Let's inspect some examples from the test dataset. You can compare the original `ref_model` to the fine-tuned/detoxified `ppo_model` using the toxicity evaluator.

The next cell may take 2-3 minutes to run.

In [27]:
```
batch_size = 20
compare_results = {}

df_batch = dataset["test"][0:batch_size]

compare_results["query"] = df_batch["query"]
prompt_tensors = df_batch["input_ids"]
```

```
summary_tensors_ref = []
summary_tensors = []

# Get response from ppo and base model.
for i in tqdm(range(batch_size)):
    gen_len = output_length_sampler()
    generation_kwargs["max_new_tokens"] = gen_len

    summary = ref_model.generate(
        input_ids=torch.as_tensor(prompt_tensors[i]).unsqueeze(dim=0).to(device),
        **generation_kwargs
    ).squeeze()[-gen_len:]
    summary_tensors_ref.append(summary)

    summary = ppo_model.generate(
        input_ids=torch.as_tensor(prompt_tensors[i]).unsqueeze(dim=0).to(device),
        **generation_kwargs
    ).squeeze()[-gen_len:]
    summary_tensors.append(summary)

# Decode responses.
compare_results["response_before"] = [tokenizer.decode(summary_tensors_ref[i]) for i i
compare_results["response_after"] = [tokenizer.decode(summary_tensors[i]) for i in ran

# Sentiment analysis of query/response pairs before/after.
texts_before = [d + s for d, s in zip(compare_results["query"], compare_results["respo
rewards_before = sentiment_pipe(texts_before, **reward_kwargs)
compare_results["reward_before"] = [reward[not_hate_index]["score"] for reward in rewa

texts_after = [d + s for d, s in zip(compare_results["query"], compare_results["respon
rewards_after = sentiment_pipe(texts_after, **reward_kwargs)
compare_results["reward_after"] = [reward[not_hate_index]["score"] for reward in rewar
```

```
100%|██████████| 20/20 [01:18<00:00,  3.91s/it]
```

Store and review the results in a DataFrame

In [28]:

```
pd.set_option('display.max_colwidth', 500)
df_compare_results = pd.DataFrame(compare_results)
df_compare_results["reward_diff"] = df_compare_results['reward_after'] - df_compare_re
df_compare_results_sorted = df_compare_results.sort_values(by=['reward_diff'], ascendi
df_compare_results_sorted
```

Out[28]:

	query	response_before	response_after	reward_before	reward_after	reward_diff
0	Summarize the following conversation. #Person1#: Mom, I just finished my paper. Can you proofread it before I hand it in? #Person2#: Sure, let's take a look. Sweetie, this is terrific. Your ideas are so original. #Person1#: Thanks. #Person2#: I can tell you worked hard on it. #Person1#: I really did! I started thinking about what I wanted to say three weeks ago. #Person2#: Well, it was definitely worth all the time. #Person1#: Let's just hope my teacher agrees. Summary: </s>	<pad> #Person1# wants to proofread her paper before she hand it in. Her mother thanks #Person1# for original ideas and disapproves because of it.</s>	<pad> #Person1# tells #Person2# #Person1# finished #Person1#'s paper by being original and thanking #Person1# for making it good. #Person1# hopes her teacher agrees with their plan.</s>	1.485067	2.513927	1.028859
1	Summarize the following conversation. #Person1#: How much are you asking for this? #Person2#: I'm offering them to you at 150 yuan a piece. Is that all right? #Person1#: Is tax already included in their price? #Person2#: Yes. Our price can't be matched. #Person1#:	<pad> #Person2# offers $53.30 to #Person1#. #Person1# asks if they can be matched with tax, but they can't help each other and settle for sales.</s>	<pad> #Person1# is asking for an unlimited volume discount and will accept the offer as paid. </s>	1.832012	2.826081	0.994069

	query	response_before	response_after	reward_before	reward_after	reward_diff
	Would you consider a volume discount? #Person2#: If you buy 1, 000 or more, you'll get a 10 % discount. #Person1#: I'll accept your offer. Summary: </s>					
2	Summarize the following conversation. #Person1#: It smells like an ashtray in here! #Person2#: Hi honey! What's wrong? Why do you have that look on your face? #Person1#: What's wrong? I thought we agreed that you were gonna quit smoking. #Person2#: No! I said I was going to cut down which is very different. You can't just expect me to go cold turkey overnight! #Person1#: Look, there are other ways to quit. You can try the nicotine patch, or nicotine chewing gum. We spend a fortune on cigaret...	<pad> #Person1#, staying with Honey, has a strange response to #Person2#'s look on her face. She will try nicotine patch or nicotine chewing gum (which is still not very easy to quit) but she has a hard time taking it to quit.</s>	<pad> The smoke is starting to smell like an ashtray and warns honey that the other ways to quit are enough to start. Hope about the divorce because honey wants a divorce.</s>	1.364428	1.889072	0.524644
3	Summarize the following conversation. #Person1#: Could you help	<pad> #Person1#'s plane got in because #Person1#'s flight was scheduled.	<pad> #Person1# has tried to catch the flight, but it's no more. They meet	2.365190	2.728981	0.363791

	query	response_before	response_after	reward_before	reward_after	reward_diff
	me, Sir? My flight got in 15 minutes ago. Everyone else has picked up the luggage but mine hasn't come through. #Person2#: I'm sorry, Madam, I'll go and find out if there is any more to come. Summary: </s>	#Person2#'ll find out whether there is anymore.</s>	as one of them needs their help. </s>			
4	Summarize the following conversation. #Person1#: Let's take a coffee break, shall we? #Person2#: I wish I could, but I can't. #Person1#: What keeps you so busy? You've been sitting there for hours. You've got to walk around. You just can't stay on the computer forever. #Person2#: Well, I am up to my neck in work. I've got to finish this report. Sarah needs it by noon. I don't want to be scolded if I can't finish my work by the deadline. #Person1#: I understand that, but you'd feel better if ...	<pad> #Person1# and #Person2# are having work drives. Same number thinks they can take a break, but #Person1# says they should relax now. </s>	<pad> #Person1# plans to take a coffee break while #Person2# needs to finish a report and possibly be scolded; they all agree.</s>	1.681519	1.993211	0.311692
5	Summarize the following	<pad> #Person1#'s thinking to have this	<pad> #Person1# sends	1.786216	2.015806	0.229590

	query	response_before	response_after	reward_before	reward_after	reward_diff
	conversation. #Person1#: I'd like to have this cashed, please. #Person2#: Please put you name and address here. May I see your passport? #Person1#: Yes. #Person2#: How would you like it? #Person1#: Ten hundreds and ten twenties, and the rest in small change, please. #Person2#: OK. Here you are. Summary: </s>	cashed but #Person2# checks with #Person1#'s name and address. They are talking about their name and address, how much change they would like, and other details.</s>	#Person2# a cash for the travel odd events.</s>			
6	Summarize the following conversation. #Person1#: Oh, my God! What's this? #Person2#: What? #Person1#: Look! This window is open. #Person2#: Did you open it before we left? #Person1#: Are you kidding? It's winter. Why would I open it? #Person2#: I don't know. Wait. Is this yours? #Person1#: No! Oh, my God! Someone has broken into the house. #Person2#: It looks that way. That's probably why the door wasn't locked when we came	<pad> #Person1# finds a window is open and someone broke into the house during winter. Allen then opens the gate but the robber left through the door and in this position is the TV and the stereo.</s>	<pad> Allen doesn't know why someone broke into the house because the window is open and he hasn't locked the door before.</s>	2.120909	2.320227	0.199318

	query	response_before	response_after	reward_before	reward_after	reward_diff
	in. #Person1#: I locked it when I left though. #Person2#: Yes, but t...					
7	Summarize the following conversation. #Person1#: I'm forming a music band. #Person2#: Do you already know how to play an instrument? #Person1#: Uh... Yeah! I'Ve told you a thousand times that I'm learning to play the drums. Now that I know how to play well, I would like to form a rock band. #Person2#: Aside from yourself, who are the other members of the band? #Person1#: We have a guy who plays guitar, and another who plays bass. Although we still haven't found anyone to be our singer. You t...	<pad> #Person1# wants to join a rock band and wants some musical talent but #Person2# doesn't have enough room to practice.</s>	<pad> #Person1# wants to start a music band but his underexperience increases so he wants to form a rock band. He also wants to know more about the musicians because he's a singer. But he doesn't have space for the drums because of the placement location.</s>	2.291545	2.467706	0.176160
8	Summarize the following conversation. #Person1#: So how did you like the restaurant? #Person2#: Actually, it could have been better.	<pad> #Person2# shares the experience with #Person1# and describes the restaurant's food. #Person2# feels that the food is mediocre and the service does not good. #Person1#'d	<pad> #Person1# is going to try the restaurant again. #Person2# found the food as mediocre.</s>	2.218918	2.392711	0.173793

	query	response_before	response_after	reward_before	reward_after	reward_diff
	#Person1#: What didn't you like about it? #Person2#: It is a new restaurant. I don't think they have their act together yet. #Person1#: What did you think about the food? #Person2#: I felt that the food was pretty mediocre. #Person1#: The service wasn't that great, either. #Person2#: I agree. The service was not good. #Person1#: Do you think that you want to tr...	like to try another restaurant.</s>				
9	Summarize the following conversation. #Person1#: Excuse me, could you tell me how to get to the Cross Bakery building? #Person2#: The Cross Bakery building? Oh sure. You're actually walking in the opposite direction. #Person1#: Oh, you're kidding! I thought I was heading east. #Person2#: No, east is the other direction. To get to the Bakery, you need to turn	<pad> #Person1# is in a busy busy city and can't find the Cross Bakery building while walking in the opposite direction. #Person2# tells #Person1# an explanation and tells #Person1# the way.</s>	<pad> #Person1# lives in the East Bronx and asks #Person2# for directions with the cross bakery building. #Person2# arrives and helps #Person1# to get there quickly. </s>	2.555313	2.665674	0.110361

	query	response_before	response_after	reward_before	reward_after	reward_diff
	around and go three blocks to Broadway. When you get to the intersection of Broadway and Elm, you hang a left. Go straight down that st...					
10	Summarize the following conversation. #Person1#: What can I do for you, madam? #Person2#: I'd like to buy a toy car for my son. #Person1#: How about this one? #Person2#: It looks nice. How much is it? #Person1#: They're three hundred dollars. #Person2#: Oh, I'm afraid it's too expensive. Can you show me something cheaper? #Person1#: OK, This one is one hundred and twenty. It's the cheapest here. #Person2#: OK, I'll take it. Here's the money. #Person1#: Thank you very much. Summary: </s>	<pad> #Person1# helps #Person2# buy a toy car for her son.</s>	<pad> #Person2# will buy a toy car for #Person2#'s son at the $5,000 price.</s>	1.257170	1.349589	0.092419
11	Summarize the following conversation. #Person1#: I would like to order some	<pad> #Person2# recommends DEL because it doesn't tie up the phone. #Person1# can't use #Person1#'s phone	<pad> #Person1# wants to order some Internet from Alchemy and decides in DEL	2.260722	2.339984	0.079262

	query	response_before	response_after	reward_before	reward_after	reward_diff
	internet today. #Person2#: What kind would you like? #Person1#: What kind of internet is there? #Person2#: You can get DEL or dial-up. #Person1#: Which of those two is best? #Person2#: I would recommend DEL. #Person1#: So that one better? #Person2#: It's better because it doesn't tie up the phone. #Person1#: What do you mean by that? #Person2#: DEL isn't connected through your phone line, but dial-up is. #Person1#: S...	while on the Internet.</s>	for normal internet. When #Person2# suggests dial-up, #Person1# can use both if #Person1# is on the Internet.</s>			
12	Summarize the following conversation. #Person1#: Could you help me figure out how to look for a job? #Person2#: We have lots of options, what type of job do you need? #Person1#: I want to work in an office. #Person2#: Do you want to work part-time or full-time? #Person1#: I want to work full-time.	<pad> #Person1# asked the workers at the job center for advice on how to look for a job. #Person1# refrains to go to the office and calls about #Person2#'s luck. </s>	<pad> #Person1# is only appealing to someone who does not know how to find a job. #Person2# displays a list of jobs in the office which they can help #Person1# find.</s>	2.139222	2.200222	0.061000

	query	response_before	response_after	reward_before	reward_after	reward_diff
	#Person2#: We have binders with local job listings or you can make use of the computers. OK? #Person1#: I am confused a bit but I am sure that I can figure it out. #Person2#: If you make an appoint...					
13	Summarize the following conversation. #Person1#: Hello. I want to reconfirm our flight to London. #Person2#: Yes, sir. Did you call the airline? #Person1#: Yes, I did. But I couldn't communicate with them in English. They speak only Spanish. So I need your help. #Person2#: Certainly, sir. What is the flight number and when are you leaving? #Person1#: We are taking IB 385 to London tomorrow at 1 p. m. #Person2#: Oh, I see, sir. We have the airline office inside the hotel. They have an English...	<pad> #Person1# offers help in relaying information to #Person2# about the flight to London. They arrange a flight tomorrow at 1 pm and #Person2# recommends an English agent.</s>	<pad> #Person1# wants to confirm its flight to London and asks for #Person2#'s help in writing and speaking.</s>	1.941944	1.921156	-0.020788
14	Summarize the following	<pad> #Person1# wants to register at	<pad> #Person1#	1.686121	1.635180	-0.050941

	query	response_before	response_after	reward_before	reward_after	reward_diff
	conversation. #Person1#: Where shall I register, please? #Person2#: Here. Do you have a registration card? #Person1#: Yes. Here you are. #Person2#: Please register your information here and pay for it. And I'll make a medical record for you. #Person1#: OK. How much do I need to pay for the registration? #Person2#: Please pay ten yuan for the registration. #Person1#: Here is my money. #Person2#: This is your registration card. Please don't lose it and bring it whenever...	the Nashville Medical Center and #Person2# will make a medical record for her. #Person1# already got a registration card from #Person2#. This is #Person2#'s application card and #Person1# has to get to the 6070 meeting room through either the gate or the banco. </s>	orders to register at the clinic and is contacted by the information and table. #Person2# reminds #Person1# about chip registration. </s>			
15	Summarize the following conversation. #Person1#: Amanda, how do you like this peaked cap? #Person2#: Didn't you say you want to buy a top hat? #Person1#: But I think this one fits me Well. Why don't you try on the sombrero in black?	<pad> Amanda likes this fitted peaked cap.</s>	<pad> Amanda liked walking in a peaked cap as she likes it, but she disagrees on it.</s>	1.892755	1.696668	-0.196087

	query	response_before	response_after	reward_before	reward_after	reward_diff
	#Person2#: I don't like caps at all. Summary: </s>					
16	Summarize the following conversation. #Person1#: Today more and more families have personal computers. People have wider range of choice to communicate with the outside world. #Person2#: Right. With the establishment of Internet and a lot of web companies, people are getting more and more dependent on the web. #Person1#: One of the common uses of PC is that people can buy goods through it without going out to the physical stores. #Person2#: Can you tell me how it is done? #Person1#: If a cus...	<pad> #Person1# introduces the concept of PC data signification, which users do not have to go to the physical stores to sign up for one. #Person1# also explains the method of collecting a customer's specimen of the item and suggests a commercialization for the customer. </s>	<pad> #Person2# has informed #Person1# that it is still suitable to maintain a human connection and maintain access to the outside world through the computer. </s>	2.757180	2.547883	-0.209297
17	Summarize the following conversation. #Person1#: Judy, what is everybody talking about? #Person2#: Haven't you heard? Richard was fired by	<pad> Judy and Judy tell a manager that Richard has been fired. Judy is surprised.</s>	<pad> Judy tells #Person1# Richard was fired by his manager. Everyone is talking about it because everyone is talking about it. </s>	1.493085	1.223792	-0.269292

	query	response_before	response_after	reward_before	reward_after	reward_diff
	our manager. #Person1#: You're kidding. It can't be true. #Person2#: Believe it or not. Everybody is talking about it in the company. #Person1#: Really? I'm surprised. #Person2#: Me too. Summary: </s>					
18	Summarize the following conversation. #Person1#: Hello? #Person2#: Hello? #Person1#: Can I speak to Li Hong, please? #Person2#: Speaking. #Person1#: Hi, Li Hong. This is Alice. #Person2#: Hi, Alice. How are you? #Person1#: Not bad. Li Hong, I am sorry that I can't go to see Mrs. Brown with you tomorrow morning. My mother is ill. I must take care of her. #Person2#: I'm sorry to hear that. You'd better stay at home. After all, we can visit Mrs. Brown later #Person1#: OK. Bye - bye. #Person2#: ...	<pad> Alice cannot go to see Mrs. Brown because her mother is ill and she has to take care of her mother. Li Hong gives her help and she can visit Mrs. Brown later.</s>	<pad> Li Hong lets Alice stay at home and Li Hong reminds her that Mrs. Brown is badly. </s>	1.858839	1.441245	-0.417594

	query	response_before	response_after	reward_before	reward_after	reward_diff
19	Summarize the following conversation. #Person1#: Here is the final draft of our contract. I'm glad that we have reached an agreement on almost every term in our trade. #Person2#: Yes, it seems to me we have come quite a long way. However, let me take a close look at the final draft. #Person1#: Do you have some points to bring up? #Person2#: Well, everything we've discussed seems to be here. #Person1#: Yes, including a description of the shirts you want to purchase this time, the total amount...	<pad> #Person1# and #Person2# are considering the final draft of their contract. They both agree on the terms and the quality. Then they agree on the name, color, and quantity of the unavailable terms and arbitrations. They will sign the contract right now. </s>	<pad> #Person1# has reached an agreement on almost every term in their trade and hopes to fix the contract quickly. </s>	3.385493	2.891149	-0.494344

Looking at the reward mean/median of the generated sequences you can observe a significant difference!