

# **ADL HW2**



### • Model (1%)

- Describe the model architecture and how it works on text summarization.
  - T5 is a transformer-based encoder-decoder architecture designed for various sequence-to-sequence tasks, including text summarization.
  - Key Components:
  - Encoder-Decoder Structure:
    - **Encoder:** Processes the input text (maintext) and encodes it into continuous representations.
    - **Decoder:** Generates the output text (title) by predicting one token at a time, using both the encoder's representations and its own previously generated tokens.

#### Self-Attention Mechanisms:

• Both the encoder and decoder use self-attention layers to capture dependencies between tokens in the input and output sequences.

### Cross-Attention:

• The decoder incorporates cross-attention layers to focus on relevant parts of the input sequence when generating each output token.

### **Function in Text Summarization:**

- **Input Processing:** The encoder transforms the main text into a context-aware representation.
- **Sequence Generation:** The decoder generates the summary by attending to the encoder's output and previously generated tokens.
- **Learning Objective:** The model is trained to minimize the difference between the generated summary and the reference summary, effectively learning to produce concise and informative summaries.

# • Preprocessing (1%)

• Describe your preprocessing (e.g. tokenization, data cleaning and etc.)

### **Data Preprocessing Steps**

### 1. Tokenization:

- Inputs ( maintext ):
  - Tokenized using the AutoTokenizer associated with the model.
  - Converts text into token IDs that the model can process.
- Targets (title):
  - Tokenized similarly, using tokenizer.as\_target\_tokenizer() to ensure correct handling.

### 2. Truncation and Padding:

- Inputs:
  - Truncated to a maximum length of **256 tokens** to handle long texts and fit GPU memory constraints.
  - Uses truncation=True to cut off sequences longer than the maximum length.

### Targets:

• Truncated to a maximum length of **64 tokens** to focus on concise summaries.

### 3. Label Preparation:

The tokenized target sequences are assigned to the "labels" key in the model inputs.

• Ensures the model computes the loss between its predictions and the actual summaries during training.

### 4. Data Cleaning:

- The code assumes that the dataset is already clean.
- No explicit steps for data cleaning like removing special characters or handling missing values are included.

#### 5. Dataset Column Removal:

- Original columns are removed after preprocessing to keep only the necessary tokenized data for training.
- Hyperparameter (1%)
  - Describe your hyperparameter you use and how you decide it.
    - 1. Number of Training Epochs ( num\_train\_epochs = 10 ):
      - Trains the model over 10 full passes of the training dataset.
      - Chosen to provide enough iterations for learning without overfitting.
    - 2. Batch Size (batch\_size = 8):
      - Small batch size to accommodate GPU memory limitations.
      - Effective batch size becomes batch\_size \* gradient\_accumulation\_steps = 64.

### 3. Gradient Accumulation Steps ( gradient\_accumulation\_steps = 8 ):

- Accumulates gradients over 8 steps before updating model weights.
- Allows for a larger effective batch size without exceeding memory limits.

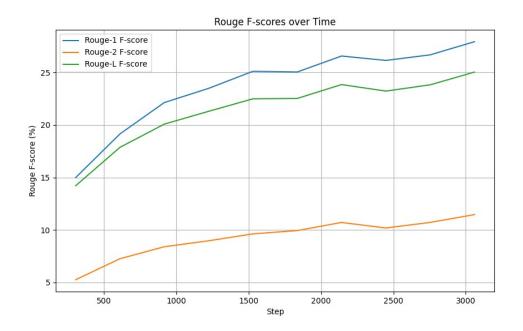
### 4. Maximum Sequence Lengths:

- **Inputs** ( max\_length=256 ): Captures sufficient context from the main text.
- Targets ( max\_length=64 ): Focuses on generating concise summaries.

### 5. Optimizer Settings:

- **Optimizer:** Adafactor, suitable for large models like T5.
- Learning Rate (1r=None):

- Relies on a relative learning rate with warmup (relative\_step=True, warmup\_init=True).
- Automatically adjusts learning rate based on training progress.
- Learning Curves (1%)
  - Plot the learning curves (ROUGE versus training steps)



# • Stratgies (2%)

• Describe the detail of the following generation strategies:

### 1. Greedy Search:

- Mechanism:
  - At each decoding step, selects the token with the highest probability.
- Characteristics:
  - **Deterministic Output:** Always produces the same summary for a given input.
  - **Limitations:** May lead to suboptimal summaries due to lack of exploration.

### 2. Beam Search:

Mechanism:

- Keeps track of the top k (beam width) most probable sequences at each step.
- Explores multiple hypotheses simultaneously.

#### Parameters:

• num\_beams: Number of beams (e.g., 5).

### Characteristics:

- **Balanced Exploration:** Increases the chance of finding a better overall summary.
- **Computational Cost:** More beams require more computation.

### 3. Top-k Sampling:

#### Mechanism:

• At each step, samples the next token from the top k most probable tokens.

#### Parameters:

• top\_k: Limits the number of tokens to sample from (e.g., 50).

### Characteristics:

- **Controlled Randomness:** Introduces diversity while limiting unlikely tokens.
- **Use Cases:** Creative tasks where variability is desired.

### 4. Top-p (Nucleus) Sampling:

#### Mechanism:

• Samples from the smallest possible set of tokens whose cumulative probability exceeds p.

#### Parameters:

• top\_p: Cumulative probability threshold (e.g., 0.9).

#### Characteristics:

- **Adaptive Sampling:** The size of the token pool varies dynamically.
- **Advantages:** Balances the need for diversity with maintaining coherence.

### 5. Temperature:

#### Mechanism:

• Adjusts the probability distribution by scaling logits before applying softmax.

#### Parameters:

• **temperature**: Controls the randomness (e.g., 0.7).

### Characteristics:

- **Lower Temperature (<1):** Makes the model more confident and outputs more common tokens.
- **Higher Temperature (>1):** Flattens the distribution, increasing randomness.

# • Hyperparameters (4%)

**Experiments with Different Generation Strategies** 

# 1. Greedy Search Experiments:

- Setting 1:
  - Parameters: num\_beams=1, do\_sample=False
  - **Results:** Lower ROUGE scores; summaries lacked depth.
- Setting 2:
  - Parameters: Adjusted max\_length=64
  - **Results:** Slight improvement but still inferior to beam search.

### 2. Beam Search Experiments:

- Setting 1: Beam Width 3
  - Parameters: num\_beams=3, do\_sample=False
  - **Results:** Improved ROUGE scores over greedy search.
- Setting 2: Beam Width 5
  - Parameters: num\_beams=5, do\_sample=False
  - **Results:** Best ROUGE scores: summaries were coherent and informative.

# 3. Top-k Sampling Experiments:

• Setting 1: **k=50** 

- Parameters: do\_sample=True , top\_k=50
- **Results:** Diverse but less coherent summaries; lower ROUGE scores.
- Setting 2: **k=100** 
  - **Parameters:** do\_sample=True , top\_k=100
  - **Results:** Increased diversity; slight improvement in ROUGE scores but still below beam search.

# 4. Top-p Sampling Experiments:

- Setting 1: p=0.9
  - **Parameters:** do\_sample=True , top\_p=0.9
  - **Results:** Summaries sometimes strayed off-topic; lower ROUGE scores.
- Setting 2: p=0.8
  - Parameters: do\_sample=True, top\_p=0.8
  - **Results:** Slightly more coherent; marginally better ROUGE scores.

### **5. Temperature Experiments:**

- Setting 1: temperature=0.7
  - **Results:** Summaries were more coherent; ROUGE scores improved.
- Setting 2: temperature=1.0
  - **Results:** Baseline: standard randomness.
- Setting 3: temperature=1.5
  - Results: Increased randomness; summaries were less coherent; ROUGE scores decreased.

## **Final Generation Strategy**

Based on the experimental results, the final generation strategy combines **Beam Search** with **Temperature Adjustment**:

- Parameters:
  - Beam Search:

- num\_beams=5
- do\_sample=False

# • Temperature:

• temperature=0.7

# • Additional Parameters:

- max\_length=64 (to ensure concise summaries)
- early\_stopping=True (to stop generation when an end-of-sequence token is
  generated)