ENVIRONMENT SETUP

```
!pip install -q torchmetrics
!pip install -q wandb
!pip install -q fastai
!pip install -q pytorch_lightning

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0:00:00
```

IMPORT LIBS

```python
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
from collections import defaultdict
import os
from torch.nn.utils.rnn import pad_sequence
import pandas as pd
import random
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```

```python
import torchvision
from torchvision import transforms as TT
from torchvision.models import resnet50, ResNet50_Weights
from torchvision.utils import make_grid

import torch
from torch import nn
from torch.utils.data import DataLoader, Dataset, random_split
from torch import optim
from torch.nn import functional as F
from torch import Tensor
from torch.nn.utils.rnn import pad_sequence

from tokenizers import Tokenizer, models, trainers, pre_tokenizers
import wandb
import tqdm
import torchmetrics as tm
from torchmetrics import Metric
from PIL import Image

from argparse import Namespace
from typing import List, Optional, Set

import editdistance
from pathlib import Path

from pytorch_lightning import Trainer, LightningModule
from pytorch_lightning.callbacks import Callback, EarlyStopping,
ModelCheckpoint, LearningRateMonitor
from torch.optim.lr_scheduler import ReduceLROnPlateau
from pytorch_lightning.loggers.wandb import WandbLogger

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

ARGUMENTS

```python
config = {
    "seed": 1234,

    "trainer": {
        "overfit_batches": 0.0,
        "check_val_every_n_epoch": 2,
        "fast_dev_run": False,
        "max_epochs": 100,
```

```
        "min_epochs": 1,
        "num_sanity_val_steps": 0,
    },

    "callbacks": {
        "model_checkpoint": {
            "save_top_k": 1,
            "save_weights_only": True,
            "mode": "min",
            "monitor": "val/loss",
            "dirpath":
"/content/drive/MyDrive/papersFolder/model_checkpoints",
            "filename": "{epoch}-{val/loss:.2f}-{val/cer:.2f}"
        },
        "early_stopping": {
            "patience": 3,
            "mode": "min",
            "monitor": "val/loss",
            "min_delta": 0.001
        },
        "LearningRateMonitor":{
            "logging_interval": "epoch"
        }
    },

    "data": {
        "batch_size": 16,
        "num_workers": 4,
        "pin_memory": True
    },

    "lit_model": {
        # Optimizer
        "lr": 0.0001,
        "weight_decay": 0.00001,

        # Scheduler
        "milestones": [10],
        "gamma": 0.5,

        # Model
        "d_model": 128,
        "dim_feedforward": 256,
        "nhead": 4,
        "dropout": 0,
        "num_decoder_layers": 3,
        "max_output_len": 200
    },

    "logger": {
```

```
        "project": "image-to-latex"
    }
}

path = '/content/drive/MyDrive/papersFolder/'
```

CUSTOM DATASET

```
#make latex_formulas.txt in order to make a custom tokenizer
df = pd.read_csv(os.path.join(path, 'merged_sorted.csv'))
latex_formulas = df.iloc[:, 1]
with open(os.path.join(path, 'latex_formulas.txt'), 'w',
encoding='utf-8') as f:
  for formula in latex_formulas:
    f.write(formula + '\n')

print('Done!')
```

```
Done!
```

```
#custom tokenizer

tokens = [
    '\\', '{', '}', '^', '+', '-', "'", '_', '!', '.', '/', '&', '%',
'*', '\\div', '\\geq',
    '\\leq', '\\frac', '\\times', '\\lim', '\\sin', '\\cos', '\\tan',
'\\csc', '\\sec',
    '\\sqrt', '\\sum', '\\rightarrow', '\\Rightarrow', '\\leftarrow',
'\\Leftarrow',
    '\\right', '\\left', '\\alpha', '\\beta', '|', '\\Delta', '\\
delta', '\\gamma', '\\lambda',
    '\\min', '\\max', '(', ')', '<', '>', '=', '\\pm', '\\mp', '\\
neq', '\\infty', 'matrix',
    '[', ']', '\\in', '\\notin', '\\cap', '\\cup', '\\begin', '\\end',
'\\dots', '\\int', ':',
    '\\ln', '\\pi', '\\theta', '\\to', '\\arctan', '\\arccot', '\\
arcsin', '\\arccos',
    '\\log', '\\sinh', '\\cosh', '\\coth', '\\tanh', '\\degree', '\\
sim',
    '\\forall', '\\emptyset', '\\buildrelF', '\\bar', '\\exists', '\\
varepsilon', '\\partial',
    '\\hat', '\\triangle', '\\mathbb', '\\simeq',
    'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm',
'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z',
    '0', '1', '2', '3', '4', '5', '6', '7', '8', '9'
]

tokenizer = Tokenizer(models.BPE())
```

```
special_tokens = ["<s>", "</s>", "<unk>", "<pad>"] + tokens
trainer = trainers.BpeTrainer(vocab_size=len(special_tokens),
special_tokens=special_tokens)

tokenizer.pre_tokenizer = pre_tokenizers.Whitespace()

files = ["/content/drive/MyDrive/papersFolder/latex_formulas.txt"]
tokenizer.train(files, trainer)

# ذخیره مدل
tokenizer.save("/content/drive/MyDrive/papersFolder/latex_tokenizer.js
on")

print("□Done")
```

```
□Done
```

```
def target_transform(label):
  tokenizer = Tokenizer.from_file(f"{path}/latex_tokenizer.json")
  encoded_label = tokenizer.encode(f'<s>{label}</s>')
  return torch.LongTensor(encoded_label.ids)

image_transform = TT.Compose([
    TT.Grayscale(num_output_channels=1),
    TT.Resize((256, 512)),
    TT.ToTensor(),
    TT.Normalize(mean=[0.5], std=[0.5])
])

class LatexImages(Dataset):
    _all_cropped_files = None

    def __init__(self, path, phase, image_transform=None,
target_transform=None):
        self.path = path
        self.image_transform = image_transform
        self.target_transform = target_transform
        self.phase = phase

        csv = pd.read_csv(os.path.join(self.path,
'merged_sorted.csv'))

        self.image_paths = []
        self.labels = []

        # پردازش پوشه‌ی "cropped"
        if LatexImages._all_cropped_files is None:
            cropped_folder = os.path.join(self.path, 'cropped')
            LatexImages._all_cropped_files =
os.listdir(cropped_folder)
            random.shuffle(LatexImages._all_cropped_files)
```

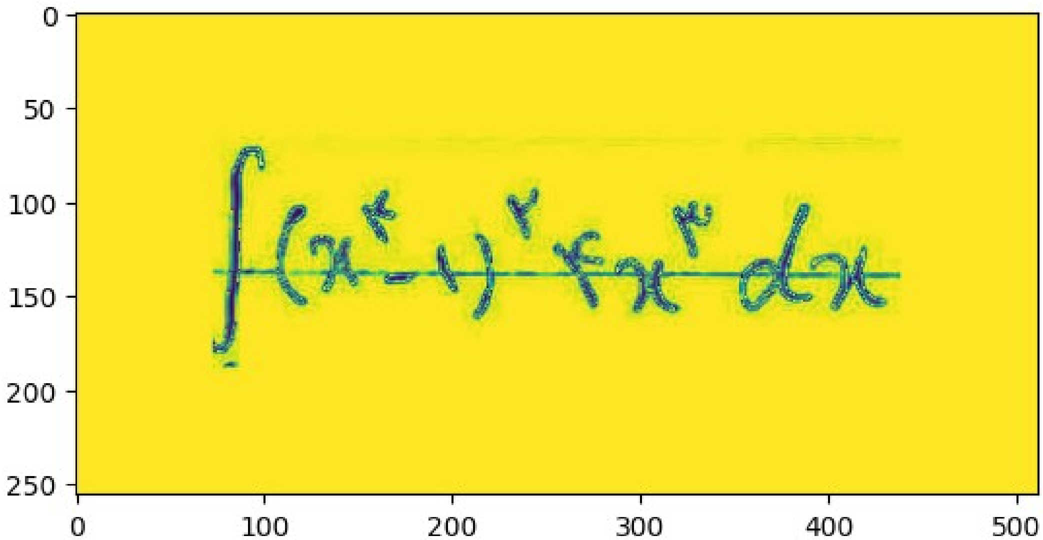
```
        if phase == 'train':
            start, end = 0, 5600
        elif phase == 'valid':
            start, end = 5600, 6600
        else:  # test
            start, end = 6600, 7000

        selected_files = LatexImages._all_cropped_files[start:end]

        for i in selected_files:
            image_path = fr'.\cropped\{i}'
            try:
                label = csv[csv['Image Path'] == image_path]['LaTeX 
Label'].values[0]
                self.image_paths.append(image_path)
                self.labels.append(label)
            except:
                print(f"Image not found in CSV: {image_path}")

        # پردازش سایر پوشه‌ها
        for folder in ['Symbols', 'EnglishAlphabet', 
'PersianNumbers']:
            folder_path = os.path.join(self.path, folder)
            extra_files = []  # لیست را در هر تکرار خالی می‌کنیم

            for subfolder in os.listdir(folder_path):
                subfolder_path = os.path.join(folder_path, subfolder)
                for fil in os.listdir(subfolder_path):
                    extra_files.append(fr'.\{folder}\{subfolder}\
{fil}')

            random.shuffle(extra_files)
            total_count = len(extra_files)
            train_count = int(0.8 * total_count)
            valid_count = int(0.2 * total_count)

            if phase == 'train':
                selected_files = extra_files[:train_count]
            elif phase == 'valid':
                selected_files = extra_files[train_count:train_count + 
valid_count]
            else:
                selected_files = extra_files[train_count + 
valid_count:]

            for image_path in selected_files:
                try:
                    label = csv[csv['Image Path'] == image_path]
['LaTeX Label'].values[0]
```

```
                    self.image_paths.append(image_path)
                    self.labels.append(label)
                except:
                    pass

    def __getitem__(self, index):
        try:
          image_path = os.path.join(self.path,
self.image_paths[index].split('\\')[1],
self.image_paths[index].split('\\')[2],
self.image_paths[index].split('\\')[3])
        except:
          image_path = os.path.join(self.path,
self.image_paths[index].split('\\')[1],
self.image_paths[index].split('\\')[2])
        if self.target_transform:
            label = self.target_transform(self.labels[index])
        else:
            label = self.labels[index]

        image = Image.open(image_path)
        if self.image_transform:
            image = self.image_transform(image)

        return image, label

    def __len__(self):
        return len(self.image_paths)

train_dataset = LatexImages(path=path, phase="train",
image_transform=image_transform, target_transform=target_transform)
valid_dataset = LatexImages(path=path, phase="valid",
image_transform=image_transform, target_transform=target_transform)
test_dataset = LatexImages(path=path, phase="test",
image_transform=image_transform, target_transform=target_transform)

print(len(train_dataset))  # 4000 + other folders
print(len(valid_dataset))  # 1500 + other folders
print(len(test_dataset))  # 1500
```

```
20943
4834
362
```

```
im, la = train_dataset.__getitem__(np.random.randint(0,
train_dataset.__len__()))

plt.imshow(TT.ToPILImage()(im))
print(im.shape, la.shape)
```

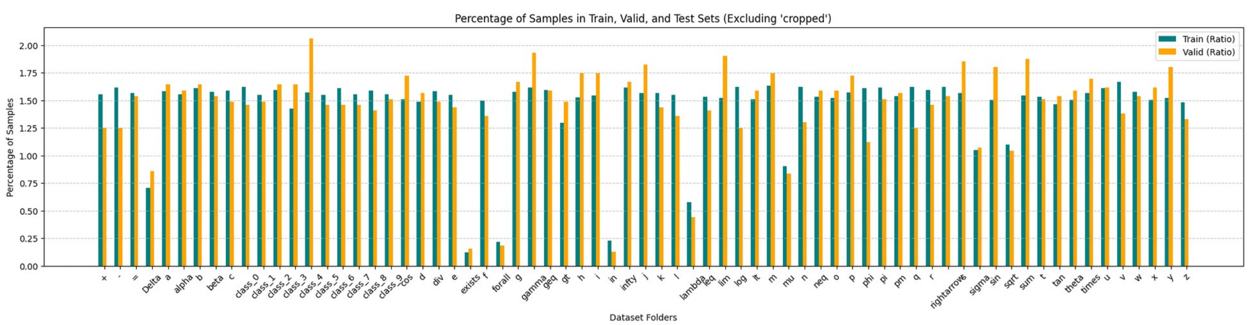
```
torch.Size([1, 256, 512]) torch.Size([20])
```



Analize the dataset

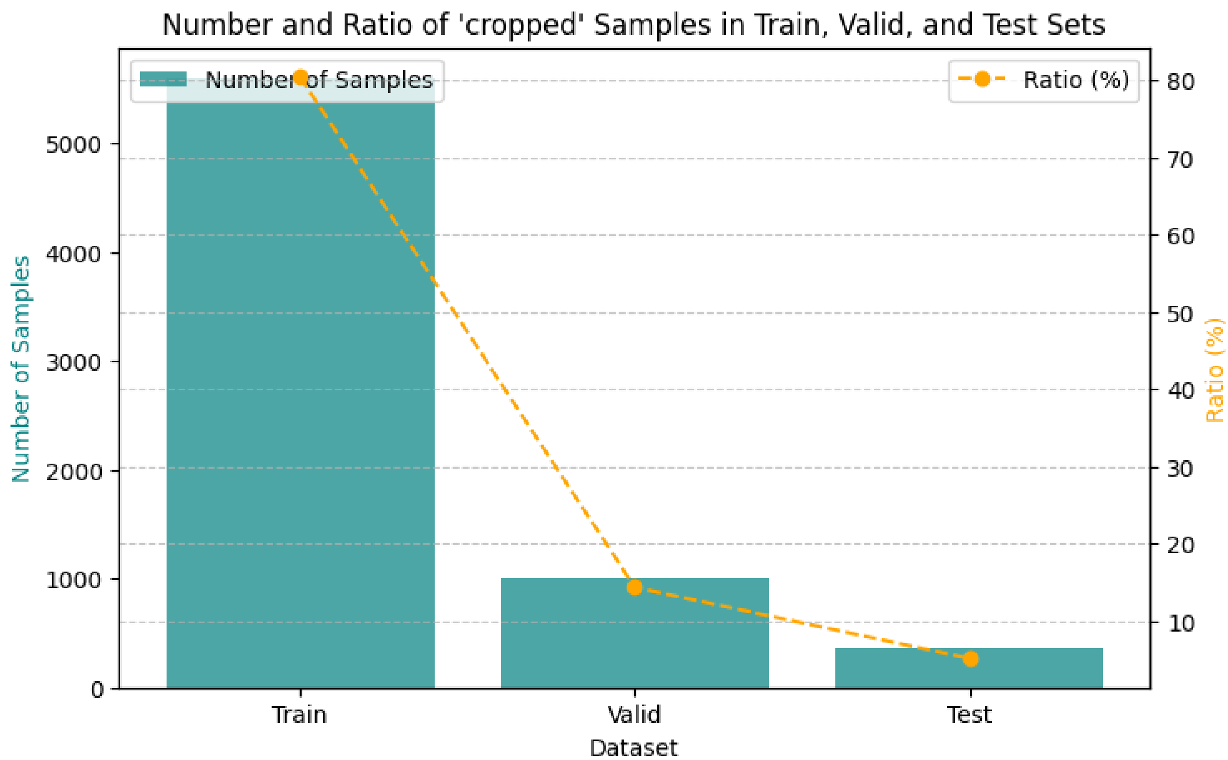
```
def count_samples(dataset):
    folder_counts = defaultdict(int)
    for image_path in dataset.image_paths:
        folder_name = image_path.split('\\')[-2]
        folder_counts[folder_name] += 1
    return folder_counts

# دریافت تعداد نمونه‌ها برای هر مجموعه
train_counts = count_samples(train_dataset)
valid_counts = count_samples(valid_dataset)

# حذف پوشه "cropped" از لیست پوشه‌ها
all_folders = sorted(set(train_counts.keys()) |
set(valid_counts.keys()))
all_folders = [folder for folder in all_folders if folder !=
"cropped"]

# استخراج تعداد نمونه‌ها و محاسبه نسبت‌ها (در صورت نبود مقدار برای یک پوشه، مقدار ۰ در
نظر گرفته می‌شود)
train_values = [train_counts.get(folder, 0) for folder in all_folders]
valid_values = [valid_counts.get(folder, 0) for folder in all_folders]
# محاسبه نسبت‌ها به صورت درصد
total_train = sum(train_values)
total_valid = sum(valid_values)
train_ratios = [count / total_train * 100 if total_train != 0 else 0
for count in train_values]
valid_ratios = [count / total_valid * 100 if total_valid != 0 else 0
for count in valid_values]
```

```
# تنظیمات نمودار
x = np.arange(len(all_folders))  # موقعیت برچسب‌های محورها
width = 0.25  # عرض هر میله

plt.figure(figsize=(25, 5))

# رسم میله‌ها برای نسبت‌ها فقط
plt.bar(x - width, train_ratios, width, label='Train (Ratio)', color='teal')
plt.bar(x, valid_ratios, width, label='Valid (Ratio)', color='orange')

# تنظیمات نمودار
plt.xlabel("Dataset Folders")
plt.ylabel("Percentage of Samples")
plt.title("Percentage of Samples in Train, Valid, and Test Sets (Excluding 'cropped')")
plt.xticks(ticks=x, labels=all_folders, rotation=45)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)

# نمایش نمودار
plt.show()
```




```
def count_cropped_samples(dataset):
    folder_counts = defaultdict(int)
    for image_path in dataset.image_paths:
        folder_name = image_path.split('\\')[-2]
        if folder_name == "cropped":  # فقط پوشه "cropped" را در نظر می‌گیریم
            folder_counts[folder_name] += 1
    return folder_counts

# دریافت تعداد نمونه‌ها برای پوشه "cropped"
train_cropped_counts = count_cropped_samples(train_dataset)
valid_cropped_counts = count_cropped_samples(valid_dataset)
test_cropped_counts = count_cropped_samples(test_dataset)
```

```
# تعداد نمونه‌ها
train_cropped_value = train_cropped_counts.get("cropped", 0)
valid_cropped_value = valid_cropped_counts.get("cropped", 0)
test_cropped_value = test_cropped_counts.get("cropped", 0)

# محاسبه نسبت‌ها
total_train = train_cropped_value + valid_cropped_value +
test_cropped_value
train_ratio = (train_cropped_value / total_train * 100) if total_train
!= 0 else 0
valid_ratio = (valid_cropped_value / total_train * 100) if total_train
!= 0 else 0
test_ratio = (test_cropped_value / total_train * 100) if total_train !
= 0 else 0

# تنظیمات نمودار
x = ['Train', 'Valid', 'Test']
values = [train_cropped_value, valid_cropped_value,
test_cropped_value]
ratios = [train_ratio, valid_ratio, test_ratio]

# رسم نمودار
fig, ax1 = plt.subplots(figsize=(8, 5))

# نمودار میله‌ای برای تعداد
ax1.bar(x, values, color='teal', alpha=0.7, label="Number of Samples")

# رسم نمودار میله‌ای برای نسبت‌ها
ax2 = ax1.twinx()  # ایجاد محور دوم برای نسبت‌ها
ax2.plot(x, ratios, color='orange', marker='o', label="Ratio (%)",
linestyle='--')

# تنظیمات نمودار
ax1.set_xlabel("Dataset")
ax1.set_ylabel("Number of Samples", color='teal')
ax2.set_ylabel("Ratio (%)", color='orange')
ax1.set_title("Number and Ratio of 'cropped' Samples in Train, Valid,
and Test Sets")

# نمایش لیجندها
ax1.legend(loc='upper left')
ax2.legend(loc='upper right')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Data Loader

```
def collate_fn(data):
    token = Tokenizer.from_file(f"{path}/latex_tokenizer.json")
    pad_value = token.get_vocab().get('<pad>', 3)
    tensors, targets = zip(*data)
    targets = [torch.tensor(t, dtype=torch.long) for t in targets]
    features = pad_sequence(targets, padding_value=pad_value,
batch_first=True)
    try:
        tensors = torch.stack(tensors)
    except RuntimeError as e:
        print(f"stack error: {e}")
        for i, t in enumerate(tensors):
            print(f"tensor shape error {i}: {t.shape}")

    return tensors, features

train_loader = DataLoader(train_dataset, shuffle=True,
collate_fn=collate_fn, **config['data'])
valid_loader = DataLoader(valid_dataset, shuffle=False,
collate_fn=collate_fn, **config['data'])
test_loader = DataLoader(test_dataset, shuffle=False,
collate_fn=collate_fn, **config['data'])
```

```
x, y = next(iter(train_loader))
x.shape, y.shape
```

```
(torch.Size([16, 1, 256, 512]), torch.Size([16, 25]))
```

Metric

```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
device
```

{"type":"string"}

```
class CharacterErrorRate(Metric):
    def __init__(self, ignore_indices: Set[int], *args):
        super().__init__(*args)
        self.ignore_indices = ignore_indices
        self.add_state("error", default=torch.tensor(0.0),
dist_reduce_fx="sum")
        self.add_state("total", default=torch.tensor(0),
dist_reduce_fx="sum")
        self.error: Tensor
        self.total: Tensor

    def update(self, preds, targets):
        N = preds.shape[0]
        for i in range(N):
            pred = [token for token in preds[i].tolist() if token not
in self.ignore_indices]
            target = [token for token in targets[i].tolist() if token
not in self.ignore_indices]
            distance = editdistance.distance(pred, target)
            if max(len(pred), len(target)) > 0:
                self.error += distance / max(len(pred), len(target))
        self.total += N

    def compute(self) -> Tensor:
        return self.error / self.total
```

Functions

```
class LitResNetTransformer(LightningModule):
    def __init__(
        self,
        d_model: int,
        dim_feedforward: int,
        nhead: int,
        dropout: float,
```

```
        num_decoder_layers: int,
        max_output_len: int,
        lr: float = 0.001,
        weight_decay: float = 0.0001,
        milestones: List[int] = [5],
        gamma: float = 0.1,
        save_path: str = path,  # مسیر ذخیره‌سازی پیش‌فرض
    ):
        super().__init__()
        self.save_hyperparameters()
        self.lr = lr
        self.weight_decay = weight_decay
        self.milestones = milestones
        self.gamma = gamma
        self.test_step_outputs = []  # ذخیره نتایج تست
        self.path = save_path  # ذخیره مسیر در کلاس
        self.tokenizer = 
Tokenizer.from_file(f"{self.path}/latex_tokenizer.json")
        self.model = ResNetTransformer(
            d_model=d_model,
            dim_feedforward=dim_feedforward,
            nhead=nhead,
            dropout=dropout,
            num_decoder_layers=num_decoder_layers,
            max_output_len=max_output_len,
            sos_index=self.tokenizer.get_vocab()["<s>"],
            eos_index=self.tokenizer.get_vocab()["</s>"],
            pad_index=self.tokenizer.get_vocab()["<pad>"],
            num_classes=self.tokenizer.get_vocab_size(),
        )
        self.loss_fn = 
nn.CrossEntropyLoss(ignore_index=self.tokenizer.get_vocab()["<pad>"])
        self.val_cer = CharacterErrorRate({self.tokenizer.get_vocab()
["<pad>"], self.tokenizer.get_vocab()["<s>"], 
self.tokenizer.get_vocab()["</s>"]})
        self.test_cer = CharacterErrorRate({self.tokenizer.get_vocab()
["<pad>"], self.tokenizer.get_vocab()["<s>"], 
self.tokenizer.get_vocab()["</s>"]})

    def training_step(self, batch, batch_idx):
        imgs, targets = batch
        logits = self.model(imgs, targets[:, :-1])  # گرفتن لاجیت‌ها
        loss = self.loss_fn(logits, targets[:, 1:])  # محاسبه‌ی لاس
        self.log("train/loss", loss)
        return loss

    def validation_step(self, batch):
        imgs, targets = batch
        logits = self.model(imgs, targets[:, :-1])
```

```
        loss = self.loss_fn(logits, targets[:, 1:])
        self.log("val/loss", loss, on_step=False, on_epoch=True,
prog_bar=True)

        preds = self.model.predict(imgs)
        val_cer = self.val_cer(preds, targets)
        self.log("val/cer", val_cer)

    def test_step(self, batch):
        imgs, targets = batch
        preds = self.model.predict(imgs)
        test_cer = self.test_cer(preds, targets)
        self.log("test/cer", test_cer)
        self.test_step_outputs.append(preds)
        return preds


    def on_test_epoch_end(self):
        with open(f"{path}/test_predictions.txt", "w") as f:
            for preds in self.test_step_outputs:
                for pred in preds:
                  decoded = []  # type: ignore
                  for j in pred.tolist():
                    if j!=3:
                      decoded.append(self.tokenizer.id_to_token(j))

                  decoded.append("\n")
                  decoded_str = " ".join(decoded)
                  f.write(decoded_str) # پاک کردن خروجی‌ها برای اجرای مجدد

    def configure_optimizers(self):
        optimizer = torch.optim.AdamW(self.model.parameters(),
lr=self.lr, weight_decay=self.weight_decay)
        scheduler = torch.optim.lr_scheduler.MultiStepLR(optimizer,
milestones=self.milestones, gamma=self.gamma)
        return [optimizer], [scheduler]
```

Model

```
class PositionalEncoding2D(nn.Module):
    """2-D positional encodings for the feature maps produced by the
encoder.

    Following https://arxiv.org/abs/2103.06450 by Sumeet Singh.

    Reference:
    https://github.com/full-stack-deep-learning/fsdl-text-recognizer-
2021-labs/blob/main/lab9/text_recognizer/models/transformer_util.py
```

```
    """

    def __init__(self, d_model: int, max_h: int = 2000, max_w: int =
2000) -> None:
        super().__init__()
        self.d_model = d_model
        assert d_model % 2 == 0, f"Embedding depth {d_model} is not
even"
        pe = self.make_pe(d_model, max_h, max_w)  # (d_model, max_h,
max_w)
        self.register_buffer("pe", pe)

    @staticmethod
    def make_pe(d_model: int, max_h: int, max_w: int) -> Tensor:
        """Compute positional encoding."""
        pe_h = PositionalEncoding1D.make_pe(d_model=d_model // 2,
max_len=max_h)  # (max_h, 1 d_model // 2)
        pe_h = pe_h.permute(2, 0, 1).expand(-1, -1, max_w)  # (d_model
// 2, max_h, max_w)

        pe_w = PositionalEncoding1D.make_pe(d_model=d_model // 2,
max_len=max_w)  # (max_w, 1, d_model // 2)
        pe_w = pe_w.permute(2, 1, 0).expand(-1, max_h, -1)  # (d_model
// 2, max_h, max_w)

        pe = torch.cat([pe_h, pe_w], dim=0)  # (d_model, max_h, max_w)
        return pe

    def forward(self, x: Tensor) -> Tensor:
        """Forward pass.

        Args:
            x: (B, d_model, H, W)

        Returns:
            (B, d_model, H, W)
        """
        assert x.shape[1] == self.pe.shape[0]  # type: ignore
        x = x + self.pe[:, : x.size(2), : x.size(3)]  # type: ignore
        return x


class PositionalEncoding1D(nn.Module):
    """Classic Attention-is-all-you-need positional encoding."""

    def __init__(self, d_model: int, dropout: float = 0.1, max_len:
int = 5000) -> None:
        super().__init__()
        self.dropout = nn.Dropout(p=dropout)
        pe = self.make_pe(d_model, max_len)  # (max_len, 1, d_model)
```

```
        self.register_buffer("pe", pe)

    @staticmethod
    def make_pe(d_model: int, max_len: int) -> Tensor:
        """Compute positional encoding."""
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len,
dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-
math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(1)
        return pe

    def forward(self, x: Tensor) -> Tensor:
        """Forward pass.

        Args:
            x: (S, B, d_model)

        Returns:
            (B, d_model, H, W)
        """
        assert x.shape[2] == self.pe.shape[2]  # type: ignore
        x = x + self.pe[: x.size(0)]  # type: ignore
        return self.dropout(x)

from typing import Union

class ResNetTransformer(nn.Module):
    def __init__(
        self,
        d_model: int,
        dim_feedforward: int,
        nhead: int,
        dropout: float,
        num_decoder_layers: int,
        max_output_len: int,
        sos_index: int,
        eos_index: int,
        pad_index: int,
        num_classes: int,
    ) -> None:
        super().__init__()
        self.d_model = d_model
        self.max_output_len = max_output_len + 2
        self.sos_index = sos_index
        self.eos_index = eos_index
        self.pad_index = pad_index
```

```
        # Encoder
        resnet = torchvision.models.resnet18(pretrained=False)
        self.backbone = nn.Sequential(
            resnet.conv1,
            resnet.bn1,
            resnet.relu,
            resnet.maxpool,
            resnet.layer1,
            resnet.layer2,
            resnet.layer3,
        )
        self.bottleneck = nn.Conv2d(256, self.d_model, 1)
        self.image_positional_encoder =
PositionalEncoding2D(self.d_model)

        # Decoder
        self.embedding = nn.Embedding(num_classes, self.d_model)
        self.y_mask =
generate_square_subsequent_mask(self.max_output_len)
        self.word_positional_encoder =
PositionalEncoding1D(self.d_model, max_len=self.max_output_len)
        transformer_decoder_layer =
nn.TransformerDecoderLayer(self.d_model, nhead, dim_feedforward,
dropout)
        self.transformer_decoder =
nn.TransformerDecoder(transformer_decoder_layer, num_decoder_layers)
        self.fc = nn.Linear(self.d_model, num_classes)

        # It is empirically important to initialize weights properly
        if self.training:
            self._init_weights()

    def _init_weights(self) -> None:
        """Initialize weights."""
        init_range = 0.1
        self.embedding.weight.data.uniform_(-init_range, init_range)
        self.fc.bias.data.zero_()
        self.fc.weight.data.uniform_(-init_range, init_range)

        nn.init.kaiming_normal_(
            self.bottleneck.weight.data,
            a=0,
            mode="fan_out",
            nonlinearity="relu",
        )
        if self.bottleneck.bias is not None:
            _, fan_out =
nn.init._calculate_fan_in_and_fan_out(self.bottleneck.weight.data)
            bound = 1 / math.sqrt(fan_out)
```

```
            nn.init.normal_(self.bottleneck.bias, -bound, bound)

    def forward(self, x: Tensor, y: Tensor) -> Tensor:
        """Forward pass.

        Args:
            x: (B, _E, _H, _W)
            y: (B, Sy) with elements in (0, num_classes - 1)

        Returns:
            (B, num_classes, Sy) logits
        """
        encoded_x = self.encode(x)  # (Sx, B, E)
        output = self.decode(y, encoded_x)  # (Sy, B, num_classes)
        output = output.permute(1, 2, 0)  # (B, num_classes, Sy)
        return output

    def encode(self, x: Tensor) -> Tensor:
        """Encode inputs and extract feature maps for visualization.

        Args:
            x: (B, C, _H, _W) - Input images

        Returns:
            encoded_x: (Sx, B, E) - Encoded sequence from ResNet
            feature_maps: (B, 256, H, W) - Feature maps from ResNet before bottleneck
        """
        if x.shape[1] == 1:
            x = x.repeat(1, 3, 1, 1)  # Convert grayscale to 3-channel if needed

        x = self.backbone(x)  # Extract features from ResNet backbone
        feature_maps = x.clone()  # Save feature maps before bottleneck
        x = self.bottleneck(x)  # Apply bottleneck layer
        x = self.image_positional_encoder(x)  # Apply positional encoding
        x = x.flatten(start_dim=2).permute(2, 0, 1)  # Reshape to (Sx, B, E)

        return x, feature_maps

    def decode(self, y: Tensor, encoded_x: Tensor) -> Tensor:
        """Decode encoded inputs with teacher-forcing.

        Args:
            encoded_x: (Sx, B, E)
            y: (B, Sy) with elements in (0, num_classes - 1)
```

```
        Returns:
            (Sy, B, num_classes) logits
        """
        y = y.permute(1, 0)  # (Sy, B)
        y = self.embedding(y) * math.sqrt(self.d_model)  # (Sy, B, E)
        y = self.word_positional_encoder(y)  # (Sy, B, E)
        Sy = y.shape[0]
        y_mask = self.y_mask[:Sy, :Sy].type_as(encoded_x)  # (Sy, Sy)
        output = self.transformer_decoder(y, encoded_x, y_mask)  #
(Sy, B, E)
        output = self.fc(output)  # (Sy, B, num_classes)
        return output

    def predict(self, x: Tensor) -> Tensor:
        """Make predctions at inference time.

        Args:
            x: (B, C, H, W). Input images.

        Returns:
            (B, max_output_len) with elements in (0, num_classes - 1).
        """
        B = x.shape[0]
        S = self.max_output_len

        encoded_x = self.encode(x)  # (Sx, B, E)

        output_indices = torch.full((B, S),
self.pad_index).type_as(x).long()
        output_indices[:, 0] = self.sos_index
        has_ended = torch.full((B,), False)

        for Sy in range(1, S):
            y = output_indices[:, :Sy]  # (B, Sy)
            logits = self.decode(y, encoded_x)  # (Sy, B, num_classes)
            # Select the token with the highest conditional
probability
            output = torch.argmax(logits, dim=-1)  # (Sy, B)
            output_indices[:, Sy] = output[-1:]  # Set the last output
token

            # Early stopping of prediction loop to speed up prediction
            has_ended |= (output_indices[:, Sy] ==
self.eos_index).type_as(has_ended)
            if torch.all(has_ended):
                break

        # Set all tokens after end token to be padding
        eos_positions = find_first(output_indices, self.eos_index)
        for i in range(B):
```

```
            j = int(eos_positions[i].item()) + 1
            output_indices[i, j:] = self.pad_index

        return output_indices


def generate_square_subsequent_mask(size: int) -> Tensor:
    """Generate a triangular (size, size) mask."""
    mask = (torch.triu(torch.ones(size, size)) == 1).transpose(0, 1)
    mask = mask.float().masked_fill(mask == 0, float("-
inf")).masked_fill(mask == 1, float(0.0))
    return mask


def find_first(x: Tensor, element: Union[int, float], dim: int = 1) ->
Tensor:
    """Find the first occurence of element in x along a given
dimension.

    Args:
        x: The input tensor to be searched.
        element: The number to look for.
        dim: The dimension to reduce.

    Returns:
        Indices of the first occurence of the element in x. If not
found, return the
        length of x along dim.

    Usage:
        >>> first_element(Tensor([[1, 2, 3], [2, 3, 3], [1, 1, 1]]),
3)
        tensor([2, 1, 3])

    Reference:
        https://discuss.pytorch.org/t/first-nonzero-index/24769/9

        I fixed an edge case where the element we are looking for is
at index 0. The
        original algorithm will return the length of x instead of 0.
    """
    mask = x == element
    found, indices = ((mask.cumsum(dim) == 1) & mask).max(dim)
    indices[(~found) & (indices == 0)] = x.shape[dim]
    return indices
```

Train

```
wandb.finish()

lit_model = LitResNetTransformer(**config['lit_model']).to(device)

callbacks: List[Callback] = []
callbacks.append(ModelCheckpoint(**config['callbacks']
['model_checkpoint']))
callbacks.append(EarlyStopping(**config['callbacks']
['early_stopping']))
callbacks.append(LearningRateMonitor(**config['callbacks']
['LearningRateMonitor']))

logger: Optional[WandbLogger] = None
if config['logger']:
  logger = WandbLogger(**config['logger'])

trainer = Trainer(**config['trainer'], callbacks=callbacks,
logger=logger)

if trainer.logger:
    trainer.logger.log_hyperparams(Namespace(**config))

trainer.fit(lit_model, train_dataloaders=train_loader,
val_dataloaders=valid_loader)
```

```
----------------------------------------------------------------------
-----
KeyboardInterrupt                         Traceback (most recent call
last)
<ipython-input-27-39d4e8d30b34> in <cell line: 0>()
----> 1 lit_model =
LitResNetTransformer(**config['lit_model']).to(device)
      2
      3 callbacks: List[Callback] = []
      4 callbacks.append(ModelCheckpoint(**config['callbacks']
['model_checkpoint']))
      5 callbacks.append(EarlyStopping(**config['callbacks']
['early_stopping']))

/usr/local/lib/python3.11/dist-packages/lightning_fabric/utilities/
device_dtype_mixin.py in to(self, *args, **kwargs)
     53         device, dtype = torch._C._nn._parse_to(*args,
**kwargs)[:2]
     54         _update_properties(self, device=device, dtype=dtype)
---> 55         return super().to(*args, **kwargs)
     56
     57     @override
```

```
/usr/local/lib/python3.11/dist-packages/torch/nn/modules/module.py in
to(self, *args, **kwargs)
   1338                     raise
   1339
-> 1340         return self._apply(convert)
   1341
   1342     def register_full_backward_pre_hook(

/usr/local/lib/python3.11/dist-packages/torch/nn/modules/module.py in
_apply(self, fn, recurse)
    898         if recurse:
    899             for module in self.children():
--> 900                 module._apply(fn)
    901
    902         def compute_should_use_set_data(tensor,
tensor_applied):

/usr/local/lib/python3.11/dist-packages/torch/nn/modules/module.py in
_apply(self, fn, recurse)
    898         if recurse:
    899             for module in self.children():
--> 900                 module._apply(fn)
    901
    902         def compute_should_use_set_data(tensor,
tensor_applied):

/usr/local/lib/python3.11/dist-packages/torch/nn/modules/module.py in
_apply(self, fn, recurse)
    986         for key, buf in self._buffers.items():
    987             if buf is not None:
--> 988                 self._buffers[key] = fn(buf)
    989
    990         return self

/usr/local/lib/python3.11/dist-packages/torch/nn/modules/module.py in
convert(t)
   1324                         memory_format=convert_to_format,
   1325                     )
-> 1326                 return t.to(
   1327                     device,
   1328                     dtype if t.is_floating_point() or
t.is_complex() else None,

KeyboardInterrupt:
```

Test on Test Loader

```
valid_loader = DataLoader(valid_dataset, batch_size=8, shuffle=True,
collate_fn=collate_fn)
test_loader = DataLoader(test_dataset, batch_size=8, shuffle=True,
collate_fn=collate_fn)

lit_model =
LitResNetTransformer.load_from_checkpoint('/content/drive/MyDrive/
papersFolder/model_checkpoints/epoch=17-val/loss=0.12-val/
cer=0.05_0.12_v_0_1.ckpt', map_location=device)
lit_model.eval()
```

```
LitResNetTransformer(
  (model): ResNetTransformer(
    (backbone): Sequential(
      (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2),
padding=(3, 3), bias=False)
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
      (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
      (4): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
        (1): BasicBlock(
          (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (5): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2),
```

```
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (downsample): Sequential(
            (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2),
bias=False)
            (1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          )
        )
        (1): BasicBlock(
          (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
        )
      )
      (6): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (downsample): Sequential(
            (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2),
bias=False)
            (1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          )
        )
        (1): BasicBlock(
          (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
```

```
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
        )
      )
    )
    (bottleneck): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1))
    (image_positional_encoder): PositionalEncoding2D()
    (embedding): Embedding(156, 128)
    (word_positional_encoder): PositionalEncoding1D(
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (transformer_decoder): TransformerDecoder(
      (layers): ModuleList(
        (0-2): 3 x TransformerDecoderLayer(
          (self_attn): MultiheadAttention(
            (out_proj):
NonDynamicallyQuantizableLinear(in_features=128, out_features=128,
bias=True)
          )
          (multihead_attn): MultiheadAttention(
            (out_proj):
NonDynamicallyQuantizableLinear(in_features=128, out_features=128,
bias=True)
          )
          (linear1): Linear(in_features=128, out_features=256,
bias=True)
          (dropout): Dropout(p=0, inplace=False)
          (linear2): Linear(in_features=256, out_features=128,
bias=True)
          (norm1): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (norm2): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (norm3): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (dropout1): Dropout(p=0, inplace=False)
          (dropout2): Dropout(p=0, inplace=False)
          (dropout3): Dropout(p=0, inplace=False)
        )
      )
    )
    (fc): Linear(in_features=128, out_features=156, bias=True)
  )
  (loss_fn): CrossEntropyLoss()
  (val_cer): CharacterErrorRate()
```

```
  (test_cer): CharacterErrorRate()
)
```

```python
trainer = Trainer(**config['trainer'])
valid_results = trainer.test(lit_model, dataloaders=valid_loader)

print(f"Valid CER: {valid_results[0]['test/cer']:.4f}")
```

```
INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda),
used: True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False,
using: 0 TPU cores
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False,
using: 0 HPUs
INFO:pytorch_lightning.utilities.rank_zero:You are using a CUDA device
('NVIDIA A100-SXM4-40GB') that has Tensor Cores. To properly utilize
them, you should set `torch.set_float32_matmul_precision('medium' |
'high')` which will trade-off precision for performance. For more
details, read
https://pytorch.org/docs/stable/generated/torch.set_float32_matmul_pre
cision.html#torch.set_float32_matmul_precision
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 -
CUDA_VISIBLE_DEVICES: [0]
```

{"model_id":"48657354bd814728ae423e1afa4efc94","version_major":2,"version_minor":0}

Test metric	DataLoader 0
test/cer	0.025387462228536606

```
Valid CER: 0.0254
```

```python
trainer = Trainer(**config['trainer'])
test_results = trainer.test(lit_model, dataloaders=test_loader)

print(f"Test CER: {test_results[0]['test/cer']:.4f}")
```

```
INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda),
used: True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False,
using: 0 TPU cores
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False,
using: 0 HPUs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 -
CUDA_VISIBLE_DEVICES: [0]
```

{"model_id":"ced6f41363e0419f83d4c4d894c61293","version_major":2,"version_minor":0}

Test metric	DataLoader 0
test/cer	0.06705634295940399

```
Test CER: 0.0671
```

test on loaded image

```
lit_model =
LitResNetTransformer.load_from_checkpoint('/content/drive/MyDrive/
papersFolder/model_checkpoints/epoch=17-val/loss=0.12-val/
cer=0.05_0.12_v_0_1.ckpt', map_location=device)
lit_model.eval()
```

```
LitResNetTransformer(
  (model): ResNetTransformer(
    (backbone): Sequential(
      (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2),
padding=(3, 3), bias=False)
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
      (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
      (4): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
        (1): BasicBlock(
          (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
        )
      )
      (5): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (downsample): Sequential(
            (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2),
bias=False)
            (1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          )
        )
        (1): BasicBlock(
          (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
        )
      )
      (6): Sequential(
        (0): BasicBlock(
          (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (downsample): Sequential(
            (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2),
bias=False)
            (1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          )
```

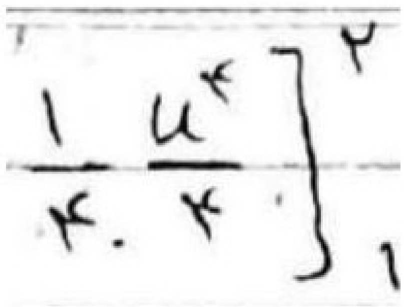
```
        )
        (1): BasicBlock(
          (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1,
affine=True, track_running_stats=True)
        )
      )
    )
    (bottleneck): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1))
    (image_positional_encoder): PositionalEncoding2D()
    (embedding): Embedding(156, 128)
    (word_positional_encoder): PositionalEncoding1D(
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (transformer_decoder): TransformerDecoder(
      (layers): ModuleList(
        (0-2): 3 x TransformerDecoderLayer(
          (self_attn): MultiheadAttention(
            (out_proj):
NonDynamicallyQuantizableLinear(in_features=128, out_features=128,
bias=True)
          )
          (multihead_attn): MultiheadAttention(
            (out_proj):
NonDynamicallyQuantizableLinear(in_features=128, out_features=128,
bias=True)
          )
          (linear1): Linear(in_features=128, out_features=256,
bias=True)
          (dropout): Dropout(p=0, inplace=False)
          (linear2): Linear(in_features=256, out_features=128,
bias=True)
          (norm1): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (norm2): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (norm3): LayerNorm((128,), eps=1e-05,
elementwise_affine=True)
          (dropout1): Dropout(p=0, inplace=False)
          (dropout2): Dropout(p=0, inplace=False)
          (dropout3): Dropout(p=0, inplace=False)
        )
      )
```

```
      )
      (fc): Linear(in_features=128, out_features=156, bias=True)
    )
    (loss_fn): CrossEntropyLoss()
    (val_cer): CharacterErrorRate()
    (test_cer): CharacterErrorRate()
)

import torch
import torchvision.transforms as TT
import matplotlib.pyplot as plt
from PIL import Image
from google.colab import files  # مخصوص Colab
from IPython.display import display, Math

# 1 آپلود تصویر
uploaded = files.upload()
image_path = list(uploaded.keys())[0]

# 2 پردازش تصویر
image = Image.open(image_path).convert("L")  # سیاه و سفید (Grayscale)
transform = TT.Compose([
    TT.Grayscale(num_output_channels=1),
    TT.Resize((256, 512)),
    TT.ToTensor(),
    TT.Normalize(mean=[0.5], std=[0.5])
])
img_tensor = transform(image).unsqueeze(0).to(device)

# 3 پردازش توسط مدل
with torch.no_grad():
    pred = lit_model.model.predict(img_tensor)[0]
# 4 تبدیل خروجی به متن LaTeX
decoded = []
for j in pred.tolist():
  if j!=1:
    decoded.append(lit_model.tokenizer.id_to_token(j))
  else:
    decoded.append(lit_model.tokenizer.id_to_token(j))
    break
decoded_str = "".join(decoded)

# 5 نمایش تصویر
plt.imshow(image, cmap="gray")
plt.axis("off")
plt.show()

print("□ **Predicted LaTeX Code:**")
print(decoded_str)
```

```
print("\n□ **Rendered LaTeX Formula:**")
display(Math(decoded_str))
```

```
<IPython.core.display.HTML object>
```

```
Saving im_ (1701).jpg to im_ (1701).jpg
```



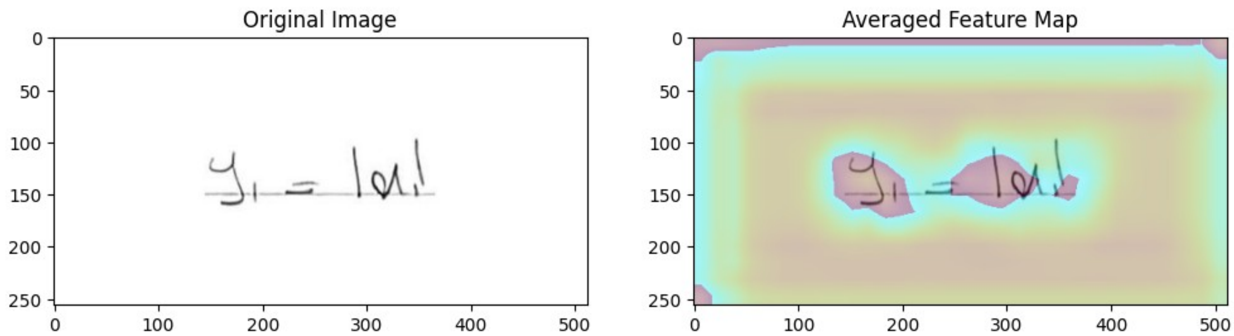
```
□ **Predicted LaTeX Code:**
<s>\frac{1}{4}\frac{u^4}{4}|_1^2</s>

□ **Rendered LaTeX Formula:**

<IPython.core.display.Math object>
```

□Feature map

```
test_loader = DataLoader(test_dataset, batch_size=1, shuffle=True,
collate_fn=collate_fn)

import cv2
import numpy as np
import matplotlib.pyplot as plt
import torch

def visualize_single_feature_map(image_tensor, feature_maps):
    """
    Display the input image alongside a single averaged feature map.

    :param image_tensor: The input test image from the DataLoader
(Tensor of shape 1, C, 256, 512).
    :param feature_maps: The feature maps from the intermediate layers
of ResNet (Tensor of shape B, 256, H, W).
```

```
    """
    # Convert Tensor to NumPy (shape: H, W, C)
    img = image_tensor.squeeze(0).permute(1, 2, 0).cpu().numpy()
    img = (img - img.min()) / (img.max() - img.min())  # Normalize for
visualization
    img = np.uint8(img * 255)
    img = cv2.cvtColor(img, cv2.COLOR_GRAY2BGR)  # Convert grayscale
to BGR for heatmap overlay

    # Compute the mean feature map across all channels to generate a
single visualization
    feature_map = feature_maps[0].mean(dim=0).detach().cpu().numpy()

    # Resize the feature map to match the input image size
    feature_map = cv2.resize(feature_map, (512, 256))
    # feature_map = (feature_map - feature_map.min()) /
(feature_map.max() - feature_map.min())  # Normalize

    # Generate a heatmap from the feature map
    heatmap = cv2.applyColorMap(np.uint8(255 * feature_map),
cv2.COLORMAP_VIRIDIS)
    overlayed = cv2.addWeighted(img, 0.6, heatmap, 0.4, 0)

    # Display the original image and the feature map overlay
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.imshow(img, cmap='gray')
    plt.title("Original Image")

    plt.subplot(1, 2, 2)
    plt.imshow(overlayed)
    plt.title("Averaged Feature Map")
    plt.show()

def process_one_test_image(model, test_dataloader, device="cuda"):
    """
    Run the model on a single test image and visualize a single
averaged feature map.

    :param model: The ResNetTransformer model.
    :param test_dataloader: The DataLoader containing test images.
    :param device: Run on 'cuda' or 'cpu'.
    """
    model.eval()
    with torch.no_grad():
        for batch in test_dataloader:
            image, _ = batch  # Fetch a single test image (labels not
needed)
            image = image.to(device)
```

```
            # Pass the image through the model and retrieve feature
maps
            _, feature_maps = model.encode(image)

            # Display only one averaged feature map
            visualize_single_feature_map(image.cpu(),
feature_maps.cpu())
            break  # Process only one image

process_one_test_image(lit_model.model, test_loader, device="cuda")
```




```

```