Assignment 2 C

May 1, 2025

ΕΠΕΞΕΡΓΑΣΙΑ ΦΥΣΙΚΗΣ ΓΛΩΣΣΑΣ - Ε Γ. Text Classification with RNNs Γ \mathbf{M} : E $\mathbf{\Sigma}$: I K \mathbf{E} : 2025-04-25 | v.0.0.1 $\mathbf{2}$ П П Т Apple Silicon (M1/M2/M3), GPU Neural Engine torch.backends.mps. Γ torchtext. H torch runtime conflicts. Apple-based [155]: %pip install datasets numpy matplotlib --quiet Note: you may need to restart the kernel to use updated packages. []: %pip install numpy==1.24.4 --force-reinstall --quiet Collecting numpy==1.24.4 Using cached numpy-1.24.4-cp311-cp311-macosx_11_0_arm64.whl.metadata (5.6 kB) Using cached numpy-1.24.4-cp311-cp311-macosx_11_0_arm64.whl (13.8 MB) Installing collected packages: numpy Attempting uninstall: numpy Found existing installation: numpy 1.24.4 Uninstalling numpy-1.24.4: Successfully uninstalled numpy-1.24.4 Successfully installed numpy-1.24.4 Note: you may need to restart the kernel to use updated packages.

Note: you may need to restart the kernel to use updated packages.

[156]: %pip install torch==2.1.0 torchtext==0.16.0 --quiet #

```
[158]: import torch
       if torch.backends.mps.is_available():
           device = torch.device("mps")
           print(" X
                                  : Apple Silicon GPU (MPS)")
       elif torch.cuda.is_available():
           device = torch.device("cuda")
           print(" X
                           : NVIDIA CUDA")
       else:
           device = torch.device("cpu")
           print(" X
                                   : CPU")
        Х
                      : Apple Silicon GPU (MPS)
      2.1
             \mathbf{E}
                    \mathbf{B}
      \mathbf{O}
         • torch, torchtext:
         • datasets:
                                  IMDB dataset
         • numpy, matplotlib, collections, re:
  []: import torch.nn as nn
       from torch.utils.data import DataLoader, Dataset
       from datasets import load_dataset
       import numpy as np
       from collections import Counter
       import re
       import random
             Φ
                            - AG News Dataset
      2.2
                    \Delta
      T AG News dataset
                                                   : Kaggle - AG News Classification Dataset
      Α
                       .csv: - train.csv 120.000
                                                       -test.csv 7.600
      K
                      : - K
                                (Class Index) - T
                                                           (Title) - \Sigma
                                                                                (Description)
      \mathbf{O}
                                       string
[194]: import pandas as pd
       # Ф
                  CSV
       train_data = pd.read_csv('train.csv')
       test_data = pd.read_csv('test.csv')
       # △
                 datasets (label,
```

```
train_dataset = [(label, train_data['Title'][i] + ' ' +__

¬train_data['Description'][i]) for i, label in enumerate(train_data['Class
□

¬Index'])]
       test_dataset = [(label, test_data['Title'][i] + ' ' +__
        otest_data['Description'][i]) for i, label in enumerate(test_data['Classu

¬Index'])]
       print(f"Training samples: {len(train_dataset)}")
       print(f"Test samples: {len(test_dataset)}")
      Training samples: 120000
      Test samples: 7600
      2.3
             Tokenization – Basic English Tokenizer
      Γ
                           tokens
                                                     tokenizer
                                                                       torchtext,
      basic english.
      Α
            tokenizer:

    M

         • A

    \( \Delta \)

[160]: | #device = torch.device("cpu")
       from torchtext.data import get_tokenizer
                                                               )
       # Basic English tokenizer (lowercase,
       tokenizer = get_tokenizer("basic_english")
      2.4
                      Λ
                              (Vocabulary)
      \sum_{i}
                                              (vocab)
         • O
                                      10
                                               training
                                                         test
         • T
                  tokens:
                        padding
             - <PAD>
             - <UNK>
                                  (out-of-vocabulary)
      Η
                                  build_vocab_from_iterator
                                                                        torchtext.
[161]: from torchtext.vocab import build_vocab_from_iterator
       # Σ
                            tokenized
       def build_vocabulary(datasets):
           for dataset in datasets:
               for _, text in dataset:
                   yield tokenizer(text)
```

Vocabulary size: 21254

2.5 Δ Σ collate_batch

- Tokenization
- M indices (vocab)
- Truncation Padding
- Optionally: -1 labels, 1 (... AGNews)

```
[162]: import torch
      MAX_WORDS = 25
      def collate_batch(batch, shift_labels=True):
          Y, X = list(zip(*batch))
          Y = torch.tensor(Y)
          if shift_labels:
              Y = Y - 1 #
                              datasets AGNews
          else:
              Y
          # Tokenization + indices
          X = [vocab(tokenizer(text)) for text in X]
          # Truncation/Padding MAX_WORDS
          X = [
              tokens + [vocab['<PAD>']] * (MAX_WORDS - len(tokens)) if len(tokens) <__
        →MAX_WORDS else tokens[:MAX_WORDS]
              for tokens in X
          ]
```

```
return torch.tensor(X, dtype=torch.int64).to(device), Y.to(device)
```

2.6

DataLoaders

```
Γ
                                                 DataLoader,
         • T
                    batches
         • T
                   custom
                                 collate_batch
                                                 tokenization
                                                               padding
         • Shuffle
                               training set
         • E
                     lazy-loading, batch-wise
                                                 GPU/MPS
             BATCH_SIZE
                               1024
                                                                  batch.
      Η
[163]: from torch.utils.data import DataLoader
       # HYPER-PARAMETERS
       BATCH_SIZE = 1024
       # DataLoader training set
       train_loader = DataLoader(
           train_dataset,
           batch_size=BATCH_SIZE,
           shuffle=True,
           collate_fn=collate_batch
       )
       # DataLoader
                       test set
       test_loader = DataLoader(
           test_dataset,
           batch_size=BATCH_SIZE,
           shuffle=False,
           collate_fn=collate_batch
       )
                           - RNNClassifier (AGNews & IMDB)
      2.7
             O
                   \mathbf{M}
      Η
            RNNClassifier
         • T
                               RNN (RNN, LSTM)
         • T
                                                  bidirectional)
                                   embeddings
         • T
         • T
                                    embeddings
                          " (freeze)
[164]: import torch.nn as nn
       import torch.nn.functional as F
       class RNNClassifier(nn.Module):
           def __init__(self,
```

```
vocab_size,
             embedding_dim,
             hidden_dim,
             output_dim,
             rnn_type="rnn",
                                     # "rnn" "lstm"
             num_layers=1,
             bidirectional=False,
             pretrained_embeddings=None,
             freeze_embeddings=False
    super(RNNClassifier, self).__init__()
    self.embedding = nn.Embedding(vocab_size, embedding_dim)
    if pretrained_embeddings is not None:
                                                                           Ш
        self.embedding.weight.data.copy_(pretrained_embeddings)
    if freeze_embeddings:
                                                                       5
        self.embedding.weight.requires_grad = False
                                                                       5
    if rnn_type == "rnn":
        self.rnn = nn.RNN(
            input_size=embedding_dim,
            hidden size=hidden dim,
            num_layers=num_layers,
            bidirectional=bidirectional,
            batch_first=True
    elif rnn_type == "lstm":
        self.rnn = nn.LSTM(
            input_size=embedding_dim,
            hidden_size=hidden_dim,
            num_layers=num_layers,
            bidirectional=bidirectional,
            batch_first=True
        )
    else:
        raise ValueError("Unsupported rnn_type. Choose 'rnn' or 'lstm'.")
    direction_factor = 2 if bidirectional else 1
    self.fc = nn.Linear(hidden_dim * direction_factor, output_dim)
def forward(self, x):
    x = self.embedding(x)
```

```
rnn_out, _ = self.rnn(x)
               out = self.fc(rnn_out[:, -1, :]) #
                                                                 output
                                                                           sequence
               return F.softmax(out, dim=1)
      2.8
            П
                      \mathbf{M}
      Α
                                                        RNNClassifier:
      2.8.1
             1-layer RNN
      Τ
                 : RNN
      Χ
             benchmarking
      2.8.2
              2-layer Bidirectional LSTM (BiLSTM)
      Ι
                : LSTM,
                                   (biLSTM), 2
                                                      . A
[165]: # 1-layer RNN
       model = RNNClassifier(
           vocab_size=len(vocab),
           embedding_dim=100,
           hidden_dim=64,
           output_dim=4,
           rnn_type="rnn",
           num_layers=1,
           bidirectional=False
       ).to(device)
       # 2-layer BiLSTM
       model = RNNClassifier(
           vocab_size=len(vocab),
           embedding_dim=100,
           hidden_dim=64,
           output_dim=4,
           rnn_type="lstm",
           num_layers=2,
           bidirectional=True
       ).to(device)
      2.9
            O
                   Υ
```

[]: $MAX_WORDS = 25$ # M token sequence (padding/truncation) EPOCHS = 15 # Π training set

O

```
# M
       BATCH_SIZE = 1024
                                        mini-batch (
       EMBEDDING_DIM = 100
                                            word embeddings
                                # △
       HIDDEN_DIM = 64
                                # △
                                            hidden states
                                                              RNN
      2.10
               \Sigma
                                  В
                        Α
      Γ
         • H
                                                    multi-class classification
                         CrossEntropyLoss,
         O
                       Adam,
[167]: loss_fn = nn.CrossEntropyLoss()
       optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING RATE)
      2.11
               \mathbf{\Sigma}
                       Α
                                - evaluate_model
               evaluate_model()
                                                          test set ( validation set),
      gradients.
      \mathbf{E}
         • T
                            dataset (total_loss / len(dataloader))
          • T
                     labels (true_labels)
         • T
                             (pred_labels)
[168]: def evaluate_model(model, dataloader, loss_fn):
           model.eval()
           total_loss = 0
           true_labels = []
           pred_labels = []
           with torch.no_grad():
                for X_batch, y_batch in dataloader:
                    outputs = model(X_batch)
                    loss = loss_fn(outputs, y_batch)
                    total_loss += loss.item()
                    preds = outputs.argmax(dim=1)
                    true_labels.append(y_batch.cpu())
                    pred_labels.append(preds.cpu())
           true_labels = torch.cat(true_labels)
           pred_labels = torch.cat(pred_labels)
           return total_loss / len(dataloader), true_labels.numpy(), pred_labels.
         →numpy()
      2.12
               \mathbf{\Sigma}
                      \mathbf{E}
                               - train_model
```

epochs

Η

train_model()

```
• E
                       training set

    A

                    test set
         • E
                            : train loss, val loss val accuracy
[169]: from tqdm import tqdm
       from sklearn.metrics import accuracy_score
       def train_model(model, train_loader, test_loader, optimizer, loss_fn, epochs):
           for epoch in range(1, epochs + 1):
               model.train()
               train_losses = []
               print(f"Epoch {epoch}")
               for X_batch, y_batch in tqdm(train_loader):
                   optimizer.zero_grad()
                   outputs = model(X_batch)
                   loss = loss_fn(outputs, y_batch)
                   loss.backward()
                   optimizer.step()
                   train_losses.append(loss.item())
               avg_train_loss = sum(train_losses) / len(train_losses)
               # Evaluation on test set
               val_loss, y_true, y_pred = evaluate_model(model, test_loader, loss_fn)
               val_acc = accuracy_score(y_true, y_pred)
               print(f"Train Loss: {avg_train_loss:.4f} | Val Loss: {val_loss:.4f} | __
        →Val Accuracy: {val_acc:.4f}\n")
      2.13
              \mathbf{E}
                      RNN M
                                    (1-Layer RNN)
      П
                                              1-layer RNN
                                                                   AGNews dataset:
         • RNN (LSTM)
                 (layer)
         • 1
                      (bidirectional)
         • M
                       (World, Sports, Business, Sci/Tech)
  []: # △
                1-layer RNN
       model = RNNClassifier(
           vocab_size=len(vocab),
           embedding_dim=EMBEDDING_DIM,
           hidden_dim=HIDDEN_DIM,
           output_dim=4,
                                                (World, Sports, Business, Sci/Tech)
                                     # 4
```

Γ

:

```
rnn_type="rnn",
                                          RNN
           num_layers=1,
                                     # 1 layer
           bidirectional=False
                                   # bidirectional
       ).to(device)
       # Loss
                 Optimizer
       loss_fn = nn.CrossEntropyLoss()
       optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
       train model(
           model=model.
           train_loader=train_loader,
           test_loader=test_loader,
           optimizer=optimizer,
           loss_fn=loss_fn,
           epochs=EPOCHS
       )
      2.14
              O
                    M
                              П
      O
                 Ε
                      1.
                                             RNN-based
         • T
               RNN: RNN LSTM
         • M
                                  (bidirectional)
         • E
                      (lavers)
      O
                         configurations
[173]: model_configs = [
           {"name": "1RNN",
                                  "rnn_type": "rnn", "num_layers": 1, "bidirectional":
        → False},
           {"name": "1Bi-RNN",
                                  "rnn_type": "rnn",
                                                       "num_layers": 1, "bidirectional":
        → True},
           {"name": "2Bi-RNN",
                                  "rnn_type": "rnn", "num_layers": 2, "bidirectional":
        → True},
           {"name": "1LSTM",
                                  "rnn_type": "lstm", "num_layers": 1, "bidirectional":
        → False},
           {"name": "1Bi-LSTM",
                                  "rnn_type": "lstm", "num_layers": 1, "bidirectional":
        → True},
           {"name": "2Bi-LSTM",
                                  "rnn type": "lstm", "num layers": 2, "bidirectional":
        → True}
       ]
      2.15
              \mathbf{\Sigma}
                     \mathbf{E}
                                \mathbf{K} \mathbf{M}
                                            - run_single_model()
              run single model()

    N

                               configuration (config)
         • N
                        EPOCHS
```

- N
- N

error analysis

2.15.1 E (Arguments):

```
П
                             П
config
                             Λ
                                                      , layers . .)
pretrained_embeddings
                             Embedding matrix (GloVe . .) None
                                            embeddings
freeze_embeddings
                             Α
                             \mathbf{T}
vocab_to_use
                             Α
                                            AGNews, 2
                                                          IMDB)
output_dim
                                       (4
train_loader
                             DataLoader
                                           training set
                             DataLoader
test_loader
                                           test set
```

```
[174]: import time
       def run_single_model(config,
                            pretrained_embeddings=None,
                            freeze_embeddings=False,
                                                                    5
                            vocab_to_use=vocab, #
                                                               6
                            output_dim=4,
                                                                     6
                            train_loader=train_loader,
                                                                              6
                            test_loader=test_loader
                            ):
           print(f"\n Training: {config['name']}")
           model = RNNClassifier(
               vocab size=len(vocab to use),
               embedding_dim=EMBEDDING_DIM,
               hidden_dim=HIDDEN_DIM,
               output_dim=output_dim,
               rnn_type=config["rnn_type"],
               num_layers=config["num_layers"],
               bidirectional=config["bidirectional"],
               pretrained_embeddings=pretrained_embeddings,
               freeze_embeddings=freeze_embeddings #
           ).to(device)
           optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
           loss_fn = nn.CrossEntropyLoss()
           start = time.time()
           train_model(model, train_loader, test_loader, optimizer, loss_fn,_u
        ⊶epochs=EPOCHS)
```

```
end = time.time()
          total_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
          val_loss, y_true, y_pred = evaluate_model(model, test_loader, loss_fn)
          val_acc = accuracy_score(y_true, y_pred)
          return {
              "Model": config['name'],
              "Accuracy": round(val_acc * 100, 2),
              "Parameters": total_params,
              "Time (sec)": round((end - start) / EPOCHS, 2),
              "y_pred": y_pred # <-- ∏
                                             predictions
          }
      2.16
                   O
             \mathbf{E}
                         {f M}
                                - run_experiments()
      Η
             run_experiments()
                                                                       model_configs,
        • E DataFrame
        • E dictionary
                        predicted labels (y_pred)
[175]: import pandas as pd
      def run_experiments(configs, pretrained_embeddings=None,__
       ofreeze_embeddings=False, vocab_to_use=vocab, output_dim=4,__
       otrain_loader=train_loader, test_loader=test_loader): # pretrained_embeddings_
                    4 | freeze_embeddings
          results = []
          preds_dict = {}
          for cfg in configs:
              result = run_single_model(cfg,_
       →pretrained_embeddings=pretrained_embeddings,

¬freeze_embeddings=freeze_embeddings,
              vocab_to_use=vocab_to_use,
              output_dim=output_dim,
              train_loader=train_loader,
              test_loader=test_loader
                  ) # pretrained_embeddings
                                                    4 | freeze_embeddings
              results.append(result)
          df_results = pd.DataFrame(results)
          return df_results, preds_dict
```

```
3 A
                 \mathbf{E}
                               \Pi & \Sigma
      3.1 E
                   \Gamma.1 - E
                                                  П
      \sum_{i}
         • T
                 RNN (RNN LSTM)
                              bidirectional
         • T
         • T
                          (layers): 1 	 2
[176]: results_table, preds_dict = run_experiments(model_configs)
        Training: 1RNN
      Epoch 1
      100%|
                 | 118/118 [00:03<00:00, 36.01it/s]
      Train Loss: 1.2895 | Val Loss: 1.1397 | Val Accuracy: 0.6053
      Epoch 2
      100%|
                 | 118/118 [00:03<00:00, 37.01it/s]
      Train Loss: 1.0579 | Val Loss: 1.0076 | Val Accuracy: 0.7370
      Epoch 3
      100%|
                 | 118/118 [00:03<00:00, 37.33it/s]
      Train Loss: 0.9659 | Val Loss: 0.9579 | Val Accuracy: 0.7862
      Epoch 4
      100%|
                 | 118/118 [00:03<00:00, 37.23it/s]
      Train Loss: 0.9256 | Val Loss: 0.9394 | Val Accuracy: 0.8026
      Epoch 5
                 | 118/118 [00:03<00:00, 30.15it/s]
      100%|
      Train Loss: 0.9030 | Val Loss: 0.9171 | Val Accuracy: 0.8253
      Epoch 6
      100%|
                 | 118/118 [00:03<00:00, 34.03it/s]
      Train Loss: 0.8868 | Val Loss: 0.9066 | Val Accuracy: 0.8346
      Epoch 7
```

| 118/118 [00:03<00:00, 36.72it/s]

100%|

```
Train Loss: 0.8743 | Val Loss: 0.8973 | Val Accuracy: 0.8449
Epoch 8
100%|
          | 118/118 [00:03<00:00, 36.43it/s]
Train Loss: 0.8661 | Val Loss: 0.8969 | Val Accuracy: 0.8443
Epoch 9
100%|
          | 118/118 [00:03<00:00, 36.89it/s]
Train Loss: 0.8579 | Val Loss: 0.8910 | Val Accuracy: 0.8503
Epoch 10
100%|
          | 118/118 [00:03<00:00, 37.28it/s]
Train Loss: 0.8529 | Val Loss: 0.8847 | Val Accuracy: 0.8574
Epoch 11
100%|
          | 118/118 [00:03<00:00, 37.08it/s]
Train Loss: 0.8477 | Val Loss: 0.8820 | Val Accuracy: 0.8596
Epoch 12
          | 118/118 [00:03<00:00, 36.94it/s]
100%|
Train Loss: 0.8437 | Val Loss: 0.8817 | Val Accuracy: 0.8603
Epoch 13
100%|
          | 118/118 [00:03<00:00, 35.07it/s]
Train Loss: 0.8398 | Val Loss: 0.8764 | Val Accuracy: 0.8646
Epoch 14
          | 118/118 [00:03<00:00, 36.79it/s]
Train Loss: 0.8356 | Val Loss: 0.8784 | Val Accuracy: 0.8650
Epoch 15
          | 118/118 [00:03<00:00, 35.67it/s]
100%|
Train Loss: 0.8329 | Val Loss: 0.8748 | Val Accuracy: 0.8664
 Training: 1Bi-RNN
Epoch 1
100% | 118/118 [00:04<00:00, 23.67it/s]
```

```
Train Loss: 1.2968 | Val Loss: 1.1575 | Val Accuracy: 0.5787
Epoch 2
100%|
          | 118/118 [00:04<00:00, 28.84it/s]
Train Loss: 1.0878 | Val Loss: 1.0124 | Val Accuracy: 0.7339
Epoch 3
100%|
          | 118/118 [00:04<00:00, 28.66it/s]
Train Loss: 0.9724 | Val Loss: 0.9546 | Val Accuracy: 0.7920
Epoch 4
100%|
          | 118/118 [00:04<00:00, 29.05it/s]
Train Loss: 0.9249 | Val Loss: 0.9286 | Val Accuracy: 0.8142
Epoch 5
100%|
          | 118/118 [00:05<00:00, 22.48it/s]
Train Loss: 0.9008 | Val Loss: 0.9130 | Val Accuracy: 0.8295
Epoch 6
          | 118/118 [00:04<00:00, 27.45it/s]
100%|
Train Loss: 0.8841 | Val Loss: 0.9030 | Val Accuracy: 0.8382
Epoch 7
100%|
          | 118/118 [00:04<00:00, 27.15it/s]
Train Loss: 0.8716 | Val Loss: 0.8920 | Val Accuracy: 0.8492
Epoch 8
100%|
          | 118/118 [00:04<00:00, 28.92it/s]
Train Loss: 0.8634 | Val Loss: 0.8890 | Val Accuracy: 0.8525
Epoch 9
100%|
          | 118/118 [00:04<00:00, 29.10it/s]
Train Loss: 0.8548 | Val Loss: 0.8870 | Val Accuracy: 0.8536
Epoch 10
100%|
          | 118/118 [00:04<00:00, 29.07it/s]
Train Loss: 0.8489 | Val Loss: 0.8838 | Val Accuracy: 0.8561
```

```
| 118/118 [00:04<00:00, 28.56it/s]
Train Loss: 0.8442 | Val Loss: 0.8770 | Val Accuracy: 0.8638
Epoch 12
100%|
          | 118/118 [00:04<00:00, 27.70it/s]
Train Loss: 0.8395 | Val Loss: 0.8821 | Val Accuracy: 0.8588
Epoch 13
100%|
          | 118/118 [00:04<00:00, 26.49it/s]
Train Loss: 0.8368 | Val Loss: 0.8732 | Val Accuracy: 0.8667
Epoch 14
100%|
          | 118/118 [00:04<00:00, 26.94it/s]
Train Loss: 0.8348 | Val Loss: 0.8709 | Val Accuracy: 0.8700
Epoch 15
100%|
          | 118/118 [00:04<00:00, 29.03it/s]
Train Loss: 0.8303 | Val Loss: 0.8731 | Val Accuracy: 0.8680
 Training: 2Bi-RNN
Epoch 1
       | 118/118 [00:06<00:00, 19.38it/s]
Train Loss: 1.2619 | Val Loss: 1.1031 | Val Accuracy: 0.6339
Epoch 2
100%|
          | 118/118 [00:06<00:00, 19.22it/s]
Train Loss: 1.0447 | Val Loss: 0.9992 | Val Accuracy: 0.7399
Epoch 3
100%
          | 118/118 [00:06<00:00, 18.37it/s]
Train Loss: 0.9715 | Val Loss: 0.9635 | Val Accuracy: 0.7784
Epoch 4
          | 118/118 [00:06<00:00, 19.28it/s]
Train Loss: 0.9361 | Val Loss: 0.9345 | Val Accuracy: 0.8072
Epoch 5
100% | 118/118 [00:06<00:00, 19.58it/s]
```

```
Train Loss: 0.9117 | Val Loss: 0.9255 | Val Accuracy: 0.8129
Epoch 6
100%|
          | 118/118 [00:06<00:00, 18.40it/s]
Train Loss: 0.8998 | Val Loss: 0.9091 | Val Accuracy: 0.8308
Epoch 7
          | 118/118 [00:06<00:00, 19.36it/s]
100%|
Train Loss: 0.8921 | Val Loss: 0.9082 | Val Accuracy: 0.8308
Epoch 8
100%|
          | 118/118 [00:06<00:00, 19.44it/s]
Train Loss: 0.8798 | Val Loss: 0.9030 | Val Accuracy: 0.8353
Epoch 9
100%|
          | 118/118 [00:07<00:00, 16.22it/s]
Train Loss: 0.8760 | Val Loss: 0.9025 | Val Accuracy: 0.8371
Epoch 10
          | 118/118 [00:08<00:00, 13.25it/s]
100%|
Train Loss: 0.8725 | Val Loss: 0.9068 | Val Accuracy: 0.8320
Epoch 11
100%|
          | 118/118 [00:08<00:00, 13.50it/s]
Train Loss: 0.8675 | Val Loss: 0.8929 | Val Accuracy: 0.8478
Epoch 12
          | 118/118 [00:06<00:00, 19.41it/s]
Train Loss: 0.8701 | Val Loss: 0.8934 | Val Accuracy: 0.8474
Epoch 13
          | 118/118 [00:06<00:00, 18.52it/s]
100%|
Train Loss: 0.8599 | Val Loss: 0.8854 | Val Accuracy: 0.8557
Epoch 14
          | 118/118 [00:06<00:00, 19.47it/s]
Train Loss: 0.8581 | Val Loss: 0.8798 | Val Accuracy: 0.8611
```

```
100%|
          | 118/118 [00:06<00:00, 16.89it/s]
Train Loss: 0.8622 | Val Loss: 0.8841 | Val Accuracy: 0.8567
 Training: 1LSTM
Epoch 1
          | 118/118 [00:04<00:00, 28.86it/s]
Train Loss: 1.2385 | Val Loss: 1.0363 | Val Accuracy: 0.7105
Epoch 2
100%|
          | 118/118 [00:04<00:00, 28.78it/s]
Train Loss: 0.9723 | Val Loss: 0.9350 | Val Accuracy: 0.8121
Epoch 3
          | 118/118 [00:03<00:00, 30.24it/s]
100%|
Train Loss: 0.9088 | Val Loss: 0.9013 | Val Accuracy: 0.8405
Epoch 4
100%|
          | 118/118 [00:04<00:00, 28.78it/s]
Train Loss: 0.8810 | Val Loss: 0.8861 | Val Accuracy: 0.8568
Epoch 5
100%|
          | 118/118 [00:04<00:00, 25.36it/s]
Train Loss: 0.8619 | Val Loss: 0.8808 | Val Accuracy: 0.8613
Epoch 6
100%|
          | 118/118 [00:04<00:00, 27.54it/s]
Train Loss: 0.8509 | Val Loss: 0.8725 | Val Accuracy: 0.8695
Epoch 7
100%
          | 118/118 [00:04<00:00, 28.62it/s]
Train Loss: 0.8412 | Val Loss: 0.8702 | Val Accuracy: 0.8716
Epoch 8
          | 118/118 [00:04<00:00, 28.48it/s]
Train Loss: 0.8345 | Val Loss: 0.8705 | Val Accuracy: 0.8718
Epoch 9
100%| | 118/118 [00:03<00:00, 31.00it/s]
```

```
Train Loss: 0.8287 | Val Loss: 0.8631 | Val Accuracy: 0.8787
Epoch 10
100%|
          | 118/118 [00:03<00:00, 29.91it/s]
Train Loss: 0.8231 | Val Loss: 0.8638 | Val Accuracy: 0.8792
Epoch 11
100%|
          | 118/118 [00:03<00:00, 29.57it/s]
Train Loss: 0.8206 | Val Loss: 0.8612 | Val Accuracy: 0.8805
Epoch 12
100%|
          | 118/118 [00:03<00:00, 30.24it/s]
Train Loss: 0.8167 | Val Loss: 0.8581 | Val Accuracy: 0.8833
Epoch 13
100%|
          | 118/118 [00:03<00:00, 30.61it/s]
Train Loss: 0.8135 | Val Loss: 0.8582 | Val Accuracy: 0.8846
Epoch 14
          | 118/118 [00:04<00:00, 27.96it/s]
100%|
Train Loss: 0.8113 | Val Loss: 0.8567 | Val Accuracy: 0.8843
Epoch 15
100%|
          | 118/118 [00:04<00:00, 29.11it/s]
Train Loss: 0.8095 | Val Loss: 0.8565 | Val Accuracy: 0.8859
 Training: 1Bi-LSTM
Epoch 1
100%|
       | 118/118 [00:04<00:00, 27.17it/s]
Train Loss: 1.2642 | Val Loss: 1.0614 | Val Accuracy: 0.6859
Epoch 2
          | 118/118 [00:04<00:00, 27.52it/s]
Train Loss: 0.9814 | Val Loss: 0.9370 | Val Accuracy: 0.8067
Epoch 3
100% | 118/118 [00:04<00:00, 28.45it/s]
```

```
Train Loss: 0.9100 | Val Loss: 0.9086 | Val Accuracy: 0.8332
Epoch 4
100%|
          | 118/118 [00:04<00:00, 27.64it/s]
Train Loss: 0.8801 | Val Loss: 0.8891 | Val Accuracy: 0.8522
Epoch 5
100%|
          | 118/118 [00:05<00:00, 20.07it/s]
Train Loss: 0.8622 | Val Loss: 0.8800 | Val Accuracy: 0.8622
Epoch 6
100%|
          | 118/118 [00:05<00:00, 23.15it/s]
Train Loss: 0.8502 | Val Loss: 0.8757 | Val Accuracy: 0.8651
Epoch 7
100%|
          | 118/118 [00:04<00:00, 27.40it/s]
Train Loss: 0.8420 | Val Loss: 0.8694 | Val Accuracy: 0.8728
Epoch 8
          | 118/118 [00:04<00:00, 28.36it/s]
100%|
Train Loss: 0.8348 | Val Loss: 0.8680 | Val Accuracy: 0.8739
Epoch 9
100%|
          | 118/118 [00:04<00:00, 27.71it/s]
Train Loss: 0.8288 | Val Loss: 0.8646 | Val Accuracy: 0.8755
Epoch 10
          | 118/118 [00:05<00:00, 19.97it/s]
Train Loss: 0.8248 | Val Loss: 0.8633 | Val Accuracy: 0.8783
Epoch 11
          | 118/118 [00:07<00:00, 15.27it/s]
100%|
Train Loss: 0.8202 | Val Loss: 0.8617 | Val Accuracy: 0.8797
Epoch 12
100%|
          | 118/118 [00:04<00:00, 27.56it/s]
Train Loss: 0.8171 | Val Loss: 0.8635 | Val Accuracy: 0.8772
```

```
| 118/118 [00:04<00:00, 28.32it/s]
Train Loss: 0.8148 | Val Loss: 0.8620 | Val Accuracy: 0.8793
Epoch 14
100%|
          | 118/118 [00:04<00:00, 24.84it/s]
Train Loss: 0.8118 | Val Loss: 0.8591 | Val Accuracy: 0.8812
Epoch 15
100%|
          | 118/118 [00:04<00:00, 28.04it/s]
Train Loss: 0.8092 | Val Loss: 0.8595 | Val Accuracy: 0.8812
 Training: 2Bi-LSTM
Epoch 1
          | 118/118 [00:10<00:00, 10.85it/s]
100%|
Train Loss: 1.1963 | Val Loss: 1.0044 | Val Accuracy: 0.7392
Epoch 2
100%|
          | 118/118 [00:07<00:00, 15.49it/s]
Train Loss: 0.9465 | Val Loss: 0.9130 | Val Accuracy: 0.8289
Epoch 3
100%|
          | 118/118 [00:06<00:00, 18.02it/s]
Train Loss: 0.8916 | Val Loss: 0.8974 | Val Accuracy: 0.8434
Epoch 4
100%|
          | 118/118 [00:06<00:00, 18.15it/s]
Train Loss: 0.8684 | Val Loss: 0.8800 | Val Accuracy: 0.8600
Epoch 5
100%
          | 118/118 [00:11<00:00, 10.17it/s]
Train Loss: 0.8528 | Val Loss: 0.8752 | Val Accuracy: 0.8658
Epoch 6
          | 118/118 [00:09<00:00, 12.58it/s]
Train Loss: 0.8421 | Val Loss: 0.8701 | Val Accuracy: 0.8709
Epoch 7
100%|
         | 118/118 [00:06<00:00, 18.19it/s]
```

```
Train Loss: 0.8342 | Val Loss: 0.8684 | Val Accuracy: 0.8730
Epoch 8
100%|
          | 118/118 [00:06<00:00, 18.00it/s]
Train Loss: 0.8283 | Val Loss: 0.8639 | Val Accuracy: 0.8779
Epoch 9
100%|
          | 118/118 [00:08<00:00, 14.27it/s]
Train Loss: 0.8228 | Val Loss: 0.8601 | Val Accuracy: 0.8799
Epoch 10
          | 118/118 [00:06<00:00, 17.86it/s]
100%|
Train Loss: 0.8191 | Val Loss: 0.8585 | Val Accuracy: 0.8841
Epoch 11
100%|
          | 118/118 [00:06<00:00, 18.22it/s]
Train Loss: 0.8174 | Val Loss: 0.8601 | Val Accuracy: 0.8808
Epoch 12
          | 118/118 [00:08<00:00, 13.80it/s]
100%|
Train Loss: 0.8134 | Val Loss: 0.8568 | Val Accuracy: 0.8837
Epoch 13
100%|
          | 118/118 [00:12<00:00, 9.47it/s]
Train Loss: 0.8107 | Val Loss: 0.8607 | Val Accuracy: 0.8804
Epoch 14
          | 118/118 [00:06<00:00, 18.06it/s]
Train Loss: 0.8101 | Val Loss: 0.8571 | Val Accuracy: 0.8838
Epoch 15
          | 118/118 [00:06<00:00, 18.29it/s]
100%|
```

Train Loss: 0.8068 | Val Loss: 0.8579 | Val Accuracy: 0.8841

3.1.1 K Π E Γ .1

```
[179]: # Transpose results to match the table format in the assignment
       df_transposed = results_table.set_index("Model").T
       # Round accuracy to 2 decimals, format numbers
       df_display = pd.DataFrame({
           col: [
                f"{df_transposed.loc['Accuracy', col]:.2f}",
                f"{int(df_transposed.loc['Parameters', col]):,}",
                f"{df_transposed.loc['Time (sec)', col]:.2f}"
           ]
           for col in df_transposed.columns
       }, index=["Accuracy", "Parameters", "Time cost"])
       df_display
[179]:
                         1RNN
                                  1Bi-RNN
                                              2Bi-RNN
                                                            1LSTM
                                                                     1Bi-LSTM
                                                                                2Bi-LSTM
                        86.64
                                                            88.59
                                    86.80
                                                85.67
                                                                        88.12
                                                                                   88.41
       Accuracy
       Parameters 2,136,284 2,147,164
                                            2,171,996
                                                                   2,210,908
                                                                               2,310,236
                                                        2,168,156
       Time cost
                         3.42
                                     4.47
                                                 6.84
                                                             4.27
                                                                         4.98
                                                                                     8.32
      3.1.2 E
                   \Gamma.1 – \Sigma
      Α
                                (RNN & LSTM, / bidirectionality 1 2
         • H
                                                                                          ). T
                2Bi-LSTM,
                                               accuracy
         • H
                                                85.88\%
                                                         88.59%). A
                 bidirectional
         • H
                                                                                       . O
           Bi-models
        \sum
      3.2
             \mathbf{E}
                   \Gamma.2 – E
                                  \mathbf{K}
                                        Λ
                                                 Π
      \sum
      3.2.1 \Delta
                     DataFrame O
                                          П
      Γ
            sample
                      test set,
                                          DataFrame
         • T
                       (Title + Description)
         • T ground truth label (0–3)
         • T
                                 (World, Sports, . .)
         • T
                             (1RNN, 1Bi-RNN, ...)
```

```
[180]: # Ground truth labels (0-3)
       y_true = test_data["Class Index"].values - 1
       # Map index → category
       label_names = ["World", "Sports", "Business", "Sci/Tech"]
       # △
                    DataFrame
       df_errors = pd.DataFrame({
           "text": test_data['Title'] + ' ' + test_data['Description'],
           "true_label": y_true
       })
       # П
       for model_name, preds in preds_dict.items():
           df_errors[model_name] = preds
       # A
                        (text)
       df_errors["true_category"] = df_errors["true_label"].apply(lambda i:__
        →label_names[i])
       for model_name in preds_dict:
           df_errors[model_name] = df_errors[model_name].apply(lambda i:__
        →label names[i])
```

3.2.2 E K Λ

0 :

```
from collections import Counter

def majority_vote(row):
    preds = [row[m] for m in preds_dict]
    return Counter(preds).most_common(1)[0][0]

# B

all_wrong_mask = df_errors.apply(
    lambda row: all(row[m] != row["true_category"] for m in preds_dict),
    axis=1
)

# #

df_all_wrong = df_errors[all_wrong_mask].copy()

# T majority vote
df_all_wrong["majority_vote"] = df_all_wrong.apply(majority_vote, axis=1)
```

```
print(f" * Σ
                                           : {len(df_all_wrong)}")
       print("\n * K
                                         :")
       print(df_all_wrong["true_category"].value_counts())
       * Σ
                                  : 333
       * K
      true_category
      Business
                   125
      World
                   116
      Sci/Tech
                   77
      Sports
                   15
      Name: count, dtype: int64
[183]: # E
                   10
       df_all_wrong[["text", "true category", *preds dict.keys(), "majority_vote"]].
        \rightarrowhead(10)
[183]:
                                                          text true category \
       79
            Live: Olympics day four Richard Faulds and Ste...
                                                                     World
            Intel to delay product aimed for high-definiti...
       83
                                                                  Business
            U.S. Misses Cut in Olympic 100 Free ATHENS, Gr...
                                                                     World
            Consumers Would Pay In Phone Proposal A propos...
       89
                                                                  Sci/Tech
           Stocks Climb on Drop in Consumer Prices NEW YO...
       106
                                                                     World
       110
            Yahoo! Ups Ante for Small Businesses Web giant...
                                                                  Business
       120
           Oil prices bubble to record high The price of ...
                                                                     World
       154
            Google Lowers Its IPO Price Range SAN JOSE, Ca...
                                                                     World
       196
            Stock Prices Climb Ahead of Google IPO NEW YOR...
                                                                     World
       200
            Strong Family Equals Strong Education Single m...
                                                                  Sci/Tech
                1RNN
                       1Bi-RNN
                                 2Bi-RNN
                                              1LSTM
                                                     1Bi-LSTM
                                                               2Bi-LSTM majority_vote
       79
                                                                 Sports
                                                                                Sports
              Sports
                        Sports
                                  Sports
                                             Sports
                                                       Sports
                                                               Sci/Tech
                                                                              Sci/Tech
       83
            Sci/Tech Sci/Tech Sci/Tech Sci/Tech Sci/Tech
       88
              Sports
                        Sports
                                  Sports
                                             Sports
                                                       Sports
                                                                 Sports
                                                                                Sports
       89
            Business Business Business
                                           Business Business
                                                               Business
                                                                              Business
       106 Business Business Business Business
                                                               Business
                                                                              Business
       110 Sci/Tech Sci/Tech Sci/Tech
                                           Sci/Tech Sci/Tech
                                                               Sci/Tech
                                                                              Sci/Tech
       120 Business Business Business Business Business
                                                                              Business
       154
           Sci/Tech Business Sci/Tech Business Business
                                                               Sci/Tech
                                                                              Sci/Tech
       196 Business Business Business
                                           Business Business
                                                               Business
                                                                              Business
       200
           Business
                         World
                                Business
                                              World Business
                                                                  World
                                                                              Business
      3.2.3
            \mathbf{E}
                  \Gamma.2 – \Sigma
                                       RNN-based
      Α
                      test set
            \mathbf{\Sigma}
                  333
            Η
```

```
- Business: 116
              - Sci/Tech: 77
              - Sports:
                           15
            Η
                     Sports

    Σ

              - \Sigma
                                                           "Business"
                                                                        "World").
              - H
                                 (majority vote)
                                                              label,
         • <u>\script{\sum}</u>
                              B'
                                    (Naive Bayes & SVM), :
              -\Pi
              - A
                                                World
                                                        Business.
        Γ
             :>\Pi
                             RNN-based
      3.3
             {f E}
                   \Gamma.3 – M
                                            MAX_WORDS
      \Sigma
                                  MAX_WORDS
                                               25
                                                    50,
      3.3.1
              oldsymbol{\Sigma}
      Ν
         • H
                          (accuracy)
         • O
         • H
                        input (
                                     sequences
                                                    )
[184]: MAX_WORDS = 50
       results_50, preds_50 = run_experiments(model_configs)
        Training: 1RNN
      Epoch 1
      100% | 118/118 [00:05<00:00, 23.46it/s]
      Train Loss: 1.3765 | Val Loss: 1.3508 | Val Accuracy: 0.3312
      Epoch 2
                 | 118/118 [00:04<00:00, 24.45it/s]
      100%|
      Train Loss: 1.3350 | Val Loss: 1.3147 | Val Accuracy: 0.3858
      Epoch 3
                 | 118/118 [00:04<00:00, 24.34it/s]
      100%|
```

- World: 125

```
Train Loss: 1.2998 | Val Loss: 1.3028 | Val Accuracy: 0.3853
Epoch 4
100%|
          | 118/118 [00:04<00:00, 24.14it/s]
Train Loss: 1.3022 | Val Loss: 1.2859 | Val Accuracy: 0.4058
Epoch 5
          | 118/118 [00:06<00:00, 19.14it/s]
100%|
Train Loss: 1.2738 | Val Loss: 1.2727 | Val Accuracy: 0.4218
Epoch 6
100%|
          | 118/118 [00:05<00:00, 23.14it/s]
Train Loss: 1.2611 | Val Loss: 1.2595 | Val Accuracy: 0.4397
Epoch 7
100%|
          | 118/118 [00:04<00:00, 25.26it/s]
Train Loss: 1.2739 | Val Loss: 1.2661 | Val Accuracy: 0.4355
Epoch 8
          | 118/118 [00:04<00:00, 24.16it/s]
100%|
Train Loss: 1.2829 | Val Loss: 1.2809 | Val Accuracy: 0.4300
Epoch 9
100%|
          | 118/118 [00:04<00:00, 24.88it/s]
Train Loss: 1.2629 | Val Loss: 1.2297 | Val Accuracy: 0.4874
Epoch 10
          | 118/118 [00:04<00:00, 25.74it/s]
Train Loss: 1.2789 | Val Loss: 1.2759 | Val Accuracy: 0.4339
Epoch 11
          | 118/118 [00:04<00:00, 25.69it/s]
100%|
Train Loss: 1.2644 | Val Loss: 1.2605 | Val Accuracy: 0.4328
Epoch 12
100%|
          | 118/118 [00:04<00:00, 25.76it/s]
Train Loss: 1.2490 | Val Loss: 1.2511 | Val Accuracy: 0.4408
```

```
| 118/118 [00:04<00:00, 25.29it/s]
Train Loss: 1.2091 | Val Loss: 1.1665 | Val Accuracy: 0.5518
Epoch 14
100%|
          | 118/118 [00:05<00:00, 22.15it/s]
Train Loss: 1.2429 | Val Loss: 1.2772 | Val Accuracy: 0.4596
Epoch 15
100%|
          | 118/118 [00:04<00:00, 23.94it/s]
Train Loss: 1.2618 | Val Loss: 1.3132 | Val Accuracy: 0.4203
 Training: 1Bi-RNN
Epoch 1
          | 118/118 [00:06<00:00, 18.36it/s]
100%|
Train Loss: 1.3781 | Val Loss: 1.3461 | Val Accuracy: 0.3393
Epoch 2
100%
          | 118/118 [00:06<00:00, 18.34it/s]
Train Loss: 1.3373 | Val Loss: 1.3376 | Val Accuracy: 0.3591
Epoch 3
100%|
          | 118/118 [00:06<00:00, 18.37it/s]
Train Loss: 1.3443 | Val Loss: 1.3420 | Val Accuracy: 0.3509
Epoch 4
100%|
          | 118/118 [00:09<00:00, 12.48it/s]
Train Loss: 1.2878 | Val Loss: 1.2828 | Val Accuracy: 0.3986
Epoch 5
100%|
          | 118/118 [00:09<00:00, 12.20it/s]
Train Loss: 1.2909 | Val Loss: 1.3102 | Val Accuracy: 0.3680
Epoch 6
100%|
          | 118/118 [00:09<00:00, 12.20it/s]
Train Loss: 1.2694 | Val Loss: 1.2621 | Val Accuracy: 0.4416
Epoch 7
100%|
          | 118/118 [00:07<00:00, 15.14it/s]
```

```
Train Loss: 1.2814 | Val Loss: 1.2778 | Val Accuracy: 0.4038
Epoch 8
100%|
          | 118/118 [00:06<00:00, 17.40it/s]
Train Loss: 1.2612 | Val Loss: 1.2576 | Val Accuracy: 0.4295
Epoch 9
100%|
          | 118/118 [00:06<00:00, 17.44it/s]
Train Loss: 1.2428 | Val Loss: 1.2683 | Val Accuracy: 0.4238
Epoch 10
100%|
          | 118/118 [00:07<00:00, 15.46it/s]
Train Loss: 1.2442 | Val Loss: 1.2363 | Val Accuracy: 0.4495
Epoch 11
100%|
          | 118/118 [00:06<00:00, 17.09it/s]
Train Loss: 1.2286 | Val Loss: 1.2635 | Val Accuracy: 0.4246
Epoch 12
          | 118/118 [00:06<00:00, 17.77it/s]
100%|
Train Loss: 1.2289 | Val Loss: 1.2349 | Val Accuracy: 0.4530
Epoch 13
100%|
          | 118/118 [00:07<00:00, 15.89it/s]
Train Loss: 1.2236 | Val Loss: 1.2420 | Val Accuracy: 0.4464
Epoch 14
          | 118/118 [00:09<00:00, 11.87it/s]
Train Loss: 1.2362 | Val Loss: 1.2527 | Val Accuracy: 0.4292
Epoch 15
          | 118/118 [00:06<00:00, 16.95it/s]
100%|
Train Loss: 1.2194 | Val Loss: 1.2312 | Val Accuracy: 0.4503
 Training: 2Bi-RNN
Epoch 1
```

100% | 118/118 [00:10<00:00, 10.84it/s]

```
Train Loss: 1.3570 | Val Loss: 1.3230 | Val Accuracy: 0.3995
Epoch 2
100%|
          | 118/118 [00:11<00:00, 10.00it/s]
Train Loss: 1.3243 | Val Loss: 1.3657 | Val Accuracy: 0.2954
Epoch 3
100%|
          | 118/118 [00:10<00:00, 10.81it/s]
Train Loss: 1.3132 | Val Loss: 1.2958 | Val Accuracy: 0.4029
Epoch 4
100%|
          | 118/118 [00:10<00:00, 10.86it/s]
Train Loss: 1.2746 | Val Loss: 1.2862 | Val Accuracy: 0.4105
Epoch 5
100%|
          | 118/118 [00:11<00:00, 10.35it/s]
Train Loss: 1.2756 | Val Loss: 1.2771 | Val Accuracy: 0.4204
Epoch 6
          | 118/118 [00:10<00:00, 10.91it/s]
100%
Train Loss: 1.2560 | Val Loss: 1.2965 | Val Accuracy: 0.4067
Epoch 7
100%|
          | 118/118 [00:12<00:00, 9.36it/s]
Train Loss: 1.2336 | Val Loss: 1.2454 | Val Accuracy: 0.4855
Epoch 8
100%|
          | 118/118 [00:11<00:00, 10.72it/s]
Train Loss: 1.2386 | Val Loss: 1.2708 | Val Accuracy: 0.4676
Epoch 9
          | 118/118 [00:10<00:00, 10.91it/s]
100%|
Train Loss: 1.2563 | Val Loss: 1.2393 | Val Accuracy: 0.4857
Epoch 10
          | 118/118 [00:15<00:00, 7.42it/s]
100%|
Train Loss: 1.3468 | Val Loss: 1.3730 | Val Accuracy: 0.3154
```

```
100%|
          | 118/118 [00:15<00:00, 7.49it/s]
Train Loss: 1.3598 | Val Loss: 1.3566 | Val Accuracy: 0.3339
Epoch 12
100%|
          | 118/118 [00:12<00:00, 9.24it/s]
Train Loss: 1.3031 | Val Loss: 1.3222 | Val Accuracy: 0.3782
Epoch 13
100%|
          | 118/118 [00:10<00:00, 10.85it/s]
Train Loss: 1.2819 | Val Loss: 1.2739 | Val Accuracy: 0.4483
Epoch 14
100%|
          | 118/118 [00:11<00:00, 10.37it/s]
Train Loss: 1.2575 | Val Loss: 1.2609 | Val Accuracy: 0.4637
Epoch 15
100%|
          | 118/118 [00:11<00:00, 10.54it/s]
Train Loss: 1.2495 | Val Loss: 1.2567 | Val Accuracy: 0.4487
 Training: 1LSTM
Epoch 1
       | 118/118 [00:04<00:00, 24.75it/s]
Train Loss: 1.3209 | Val Loss: 1.1462 | Val Accuracy: 0.6049
Epoch 2
100%|
          | 118/118 [00:04<00:00, 25.59it/s]
Train Loss: 1.0443 | Val Loss: 0.9873 | Val Accuracy: 0.7630
Epoch 3
100%|
          | 118/118 [00:04<00:00, 27.11it/s]
Train Loss: 0.9544 | Val Loss: 0.9408 | Val Accuracy: 0.8004
Epoch 4
          | 118/118 [00:04<00:00, 25.45it/s]
Train Loss: 0.9125 | Val Loss: 0.9155 | Val Accuracy: 0.8262
Epoch 5
100% | 118/118 [00:07<00:00, 16.31it/s]
```

```
Train Loss: 0.8979 | Val Loss: 0.9019 | Val Accuracy: 0.8395
Epoch 6
100%|
          | 118/118 [00:08<00:00, 14.59it/s]
Train Loss: 0.8901 | Val Loss: 0.9045 | Val Accuracy: 0.8370
Epoch 7
100%|
          | 118/118 [00:05<00:00, 20.05it/s]
Train Loss: 0.8742 | Val Loss: 0.8870 | Val Accuracy: 0.8539
Epoch 8
100%|
          | 118/118 [00:04<00:00, 27.25it/s]
Train Loss: 0.8619 | Val Loss: 0.8704 | Val Accuracy: 0.8701
Epoch 9
100%|
          | 118/118 [00:04<00:00, 27.20it/s]
Train Loss: 0.8624 | Val Loss: 0.8724 | Val Accuracy: 0.8676
Epoch 10
          | 118/118 [00:04<00:00, 26.82it/s]
100%|
Train Loss: 0.8540 | Val Loss: 0.8744 | Val Accuracy: 0.8678
Epoch 11
100%|
          | 118/118 [00:05<00:00, 20.63it/s]
Train Loss: 0.8474 | Val Loss: 0.8635 | Val Accuracy: 0.8780
Epoch 12
          | 118/118 [00:08<00:00, 14.69it/s]
Train Loss: 0.8433 | Val Loss: 0.8619 | Val Accuracy: 0.8789
Epoch 13
100%|
          | 118/118 [00:04<00:00, 27.13it/s]
Train Loss: 0.8402 | Val Loss: 0.8647 | Val Accuracy: 0.8758
Epoch 14
100%|
          | 118/118 [00:04<00:00, 26.83it/s]
Train Loss: 0.8456 | Val Loss: 0.8656 | Val Accuracy: 0.8747
```

```
| 118/118 [00:05<00:00, 23.59it/s]
Train Loss: 0.8427 | Val Loss: 0.8610 | Val Accuracy: 0.8801
 Training: 1Bi-LSTM
Epoch 1
          | 118/118 [00:08<00:00, 14.24it/s]
Train Loss: 1.3149 | Val Loss: 1.1649 | Val Accuracy: 0.5651
Epoch 2
100%|
          | 118/118 [00:13<00:00, 8.55it/s]
Train Loss: 1.0847 | Val Loss: 1.0248 | Val Accuracy: 0.7233
Epoch 3
          | 118/118 [00:13<00:00, 8.59it/s]
100%|
Train Loss: 0.9878 | Val Loss: 0.9648 | Val Accuracy: 0.7786
Epoch 4
100%|
          | 118/118 [00:13<00:00, 8.52it/s]
Train Loss: 0.9363 | Val Loss: 0.9441 | Val Accuracy: 0.7987
Epoch 5
100%|
          | 118/118 [00:09<00:00, 12.98it/s]
Train Loss: 0.9098 | Val Loss: 0.9160 | Val Accuracy: 0.8251
Epoch 6
100%|
          | 118/118 [00:08<00:00, 13.43it/s]
Train Loss: 0.8916 | Val Loss: 0.9051 | Val Accuracy: 0.8378
Epoch 7
100%
          | 118/118 [00:08<00:00, 13.19it/s]
Train Loss: 0.8769 | Val Loss: 0.8946 | Val Accuracy: 0.8468
Epoch 8
          | 118/118 [00:09<00:00, 12.45it/s]
Train Loss: 0.8655 | Val Loss: 0.8868 | Val Accuracy: 0.8550
Epoch 9
```

100%| | 118/118 [00:07<00:00, 16.36it/s]

```
Train Loss: 0.8611 | Val Loss: 0.8833 | Val Accuracy: 0.8574
Epoch 10
100%|
          | 118/118 [00:07<00:00, 15.98it/s]
Train Loss: 0.8619 | Val Loss: 0.8850 | Val Accuracy: 0.8575
Epoch 11
          | 118/118 [00:12<00:00, 9.28it/s]
100%|
Train Loss: 0.8608 | Val Loss: 0.8820 | Val Accuracy: 0.8599
Epoch 12
100%|
          | 118/118 [00:07<00:00, 16.25it/s]
Train Loss: 0.8536 | Val Loss: 0.8778 | Val Accuracy: 0.8637
Epoch 13
100%|
          | 118/118 [00:07<00:00, 16.22it/s]
Train Loss: 0.8586 | Val Loss: 0.8765 | Val Accuracy: 0.8643
Epoch 14
          | 118/118 [00:10<00:00, 11.61it/s]
100%|
Train Loss: 0.8444 | Val Loss: 0.8764 | Val Accuracy: 0.8649
Epoch 15
100%|
          | 118/118 [00:13<00:00, 8.54it/s]
Train Loss: 0.8404 | Val Loss: 0.8676 | Val Accuracy: 0.8730
 Training: 2Bi-LSTM
Epoch 1
100%|
       | 118/118 [00:12<00:00, 9.49it/s]
Train Loss: 1.2969 | Val Loss: 1.1574 | Val Accuracy: 0.5792
Epoch 2
          | 118/118 [00:13<00:00, 8.59it/s]
Train Loss: 1.1084 | Val Loss: 1.0865 | Val Accuracy: 0.6562
Epoch 3
100%|
          | 118/118 [00:19<00:00, 6.05it/s]
```

```
Train Loss: 1.0314 | Val Loss: 0.9964 | Val Accuracy: 0.7454
Epoch 4
100%|
          | 118/118 [00:19<00:00, 5.90it/s]
Train Loss: 0.9692 | Val Loss: 0.9531 | Val Accuracy: 0.7866
Epoch 5
          | 118/118 [00:16<00:00, 7.28it/s]
100%|
Train Loss: 0.9283 | Val Loss: 0.9252 | Val Accuracy: 0.8141
Epoch 6
100%|
          | 118/118 [00:12<00:00, 9.82it/s]
Train Loss: 0.9024 | Val Loss: 0.9067 | Val Accuracy: 0.8334
Epoch 7
100%|
          | 118/118 [00:15<00:00, 7.48it/s]
Train Loss: 0.8851 | Val Loss: 0.8942 | Val Accuracy: 0.8467
Epoch 8
          | 118/118 [00:17<00:00, 6.65it/s]
100%|
Train Loss: 0.8733 | Val Loss: 0.8890 | Val Accuracy: 0.8522
Epoch 9
100%|
          | 118/118 [00:12<00:00, 9.67it/s]
Train Loss: 0.8641 | Val Loss: 0.8798 | Val Accuracy: 0.8605
Epoch 10
          | 118/118 [00:14<00:00, 8.16it/s]
Train Loss: 0.8557 | Val Loss: 0.8723 | Val Accuracy: 0.8686
Epoch 11
          | 118/118 [00:19<00:00, 6.16it/s]
100%|
Train Loss: 0.8506 | Val Loss: 0.8671 | Val Accuracy: 0.8734
Epoch 12
          | 118/118 [00:19<00:00, 6.03it/s]
Train Loss: 0.8437 | Val Loss: 0.8655 | Val Accuracy: 0.8733
```

```
Train Loss: 0.8401 | Val Loss: 0.8577 | Val Accuracy: 0.8821
      Epoch 14
                 | 118/118 [00:14<00:00, 8.24it/s]
      100%|
      Train Loss: 0.8360 | Val Loss: 0.8612 | Val Accuracy: 0.8796
      Epoch 15
      100%|
                 | 118/118 [00:19<00:00, 6.03it/s]
      Train Loss: 0.8347 | Val Loss: 0.8627 | Val Accuracy: 0.8779
[185]: # Transpose results to match the table format in the assignment
       df_transposed_50 = results_50.set_index("Model").T
       # Round accuracy to 2 decimals, format numbers
       df_display_50 = pd.DataFrame({
           col: [
               f"{df_transposed_50.loc['Accuracy', col]:.2f}",
               f"{int(df_transposed_50.loc['Parameters', col]):,}",
               f"{df_transposed_50.loc['Time (sec)', col]:.2f}"
           for col in df_transposed_50.columns
       }, index=["Accuracy", "Parameters", "Time cost"])
       df_display_50
[185]:
                        1RNN
                                1Bi-RNN
                                           2Bi-RNN
                                                         1LSTM
                                                                 1Bi-LSTM
                                                                            2Bi-LSTM
       Accuracy
                       42.03
                                  45.03
                                             44.87
                                                         88.01
                                                                    87.30
                                                                               87.79
      Parameters 2,136,284 2,147,164 2,171,996 2,168,156 2,210,908
                                                                           2,310,236
                                             12.25
                                                                    10.44
       Time cost
                        5.10
                                   7.88
                                                          5.54
                                                                               16.42
                  \Gamma.3 -\Sigma
      3.3.2 E
      Α
                    MAX_WORDS
                                25
                                   50
      Т
         • T accuracies
                              RNN (1RNN, 1Bi-RNN, 2Bi-RNN)
             – ∏. .
                   1RNN
                               ~87%
                                           \sim 42\%.
         • T LSTM-based
                                (1LSTM, 1Bi-LSTM, 2Bi-LSTM)
           87–88%).
         • 0
         • Π. . 2Bi-LSTM
                                \sim 8 \text{ sec} \sim 16 \text{ sec} epoch.
```

| 118/118 [00:12<00:00, 9.54it/s]

```
* T
                  * T
                             embeddings
                  * T
                             hidden layer
             - K
                                    (MAX_WORDS).
       Γ
            \sum
                                 50 tokens:

    H

                           RNN
                                                   "vanishing gradient"
                     ).
                                LSTM
                                LSTM
                                                                                     context.
             \mathbf{E}
                   \Gamma.4 – E
                                    Π
                                               GloVe Embeddings
      3.4
      \Sigma
                                                (GloVe)
                                                                randomly initialized embeddings
      3.4.1 \Phi
                   GloVe Embeddings
      T GloVe vectors
                                     glove.6B.100d.txt,
                                                                   400.000
                                                                                      100.
[186]: # 🛭
       def load_glove_embeddings(glove_path):
           embeddings_index = {}
           with open(glove_path, encoding='utf8') as f:
                for line in f:
                    values = line.strip().split()
                    word = values[0]
                    vector = torch.tensor([float(x) for x in values[1:]], dtype=torch.
        ⊶float32)
                    embeddings_index[word] = vector
           return embeddings_index
       glove_embeddings = load_glove_embeddings('glove.6B.100d.txt')
       print(f"Loaded {len(glove_embeddings)} word vectors from GloVe.")
      Loaded 400000 word vectors from GloVe.
      3.4.2 \Delta
                     Pretrained Embedding Matrix
      Γ
                   vectors
                                          embedding matrix:
[187]: def create_embedding_matrix(vocab, glove_embeddings, embedding_dim):
           matrix = torch.zeros(len(vocab), embedding_dim)
```

:

• O

```
for word, idx in vocab.get_stoi().items():
               if word in glove_embeddings:
                   matrix[idx] = glove_embeddings[word]
               else:
                   matrix[idx] = torch.randn(embedding_dim) * 0.01 # random init_
           return matrix
[188]: embedding_matrix = create_embedding_matrix(vocab, glove_embeddings,__
        →EMBEDDING_DIM)
      3.4.3
              \Sigma
                         Υ
                                -\mathbf{T}
                                        Π
                                                \mathbf{E}
                                                       4
      Γ
                                GloVe embeddings,
                                                    inline
         • O
           "'python #
                                 4
      3.4.4 E
                            GloVe Embeddings
                   П
      Т
                     embedding\_matrix
  [ ]: MAX_WORDS = 25
       # E
                            GloVe embeddings
       results_glove, preds_glove = run_experiments(model_configs,_
        pretrained_embeddings=embedding_matrix)
       Training: 1RNN
      Epoch 1
                 | 118/118 [00:03<00:00, 30.60it/s]
      100%|
      Train Loss: 1.0526 | Val Loss: 0.9051 | Val Accuracy: 0.8411
      Epoch 2
      100%|
                 | 118/118 [00:03<00:00, 31.82it/s]
      Train Loss: 0.8857 | Val Loss: 0.8724 | Val Accuracy: 0.8705
      Epoch 3
                 | 118/118 [00:03<00:00, 31.62it/s]
      100%
      Train Loss: 0.8729 | Val Loss: 0.8904 | Val Accuracy: 0.8530
      Epoch 4
      100% | 118/118 [00:03<00:00, 31.19it/s]
```

```
Train Loss: 0.8719 | Val Loss: 0.8813 | Val Accuracy: 0.8632
Epoch 5
100%|
          | 118/118 [00:03<00:00, 30.53it/s]
Train Loss: 0.8731 | Val Loss: 0.8791 | Val Accuracy: 0.8620
Epoch 6
100%|
          | 118/118 [00:03<00:00, 29.52it/s]
Train Loss: 0.8750 | Val Loss: 0.8761 | Val Accuracy: 0.8663
Epoch 7
100%|
          | 118/118 [00:03<00:00, 31.22it/s]
Train Loss: 0.8606 | Val Loss: 0.8628 | Val Accuracy: 0.8789
Epoch 8
100%|
          | 118/118 [00:03<00:00, 30.44it/s]
Train Loss: 0.8558 | Val Loss: 0.8723 | Val Accuracy: 0.8707
Epoch 9
          | 118/118 [00:03<00:00, 31.49it/s]
100%|
Train Loss: 0.8501 | Val Loss: 0.8596 | Val Accuracy: 0.8818
Epoch 10
100%|
          | 118/118 [00:03<00:00, 32.43it/s]
Train Loss: 0.8495 | Val Loss: 0.8644 | Val Accuracy: 0.8780
Epoch 11
          | 118/118 [00:03<00:00, 31.74it/s]
Train Loss: 0.8921 | Val Loss: 0.9048 | Val Accuracy: 0.8387
Epoch 12
          | 118/118 [00:03<00:00, 30.58it/s]
100%|
Train Loss: 0.8826 | Val Loss: 0.8896 | Val Accuracy: 0.8513
Epoch 13
          | 118/118 [00:04<00:00, 27.21it/s]
Train Loss: 0.8577 | Val Loss: 0.8630 | Val Accuracy: 0.8789
```

```
| 118/118 [00:04<00:00, 28.31it/s]
Train Loss: 0.8488 | Val Loss: 0.8634 | Val Accuracy: 0.8775
Epoch 15
100%|
          | 118/118 [00:03<00:00, 32.33it/s]
Train Loss: 0.8532 | Val Loss: 0.8791 | Val Accuracy: 0.8633
 Training: 1Bi-RNN
Epoch 1
100%|
          | 118/118 [00:04<00:00, 23.72it/s]
Train Loss: 1.0482 | Val Loss: 0.8979 | Val Accuracy: 0.8536
Epoch 2
          | 118/118 [00:04<00:00, 26.83it/s]
100%|
Train Loss: 0.8860 | Val Loss: 0.8850 | Val Accuracy: 0.8600
Epoch 3
100%|
          | 118/118 [00:04<00:00, 26.49it/s]
Train Loss: 0.8712 | Val Loss: 0.8885 | Val Accuracy: 0.8562
Epoch 4
          | 118/118 [00:04<00:00, 26.86it/s]
100%|
Train Loss: 0.8695 | Val Loss: 0.8707 | Val Accuracy: 0.8725
Epoch 5
100%|
          | 118/118 [00:05<00:00, 22.80it/s]
Train Loss: 0.8604 | Val Loss: 0.8707 | Val Accuracy: 0.8709
Epoch 6
100%|
          | 118/118 [00:04<00:00, 25.24it/s]
Train Loss: 0.8612 | Val Loss: 0.8672 | Val Accuracy: 0.8745
Epoch 7
          | 118/118 [00:04<00:00, 27.41it/s]
Train Loss: 0.8560 | Val Loss: 0.8627 | Val Accuracy: 0.8789
Epoch 8
100% | 118/118 [00:04<00:00, 27.22it/s]
```

```
Train Loss: 0.8556 | Val Loss: 0.8752 | Val Accuracy: 0.8674
Epoch 9
100%|
          | 118/118 [00:04<00:00, 26.74it/s]
Train Loss: 0.8482 | Val Loss: 0.8586 | Val Accuracy: 0.8832
Epoch 10
          | 118/118 [00:05<00:00, 23.48it/s]
100%|
Train Loss: 0.8528 | Val Loss: 0.8646 | Val Accuracy: 0.8786
Epoch 11
100%|
          | 118/118 [00:04<00:00, 25.20it/s]
Train Loss: 0.8526 | Val Loss: 0.8876 | Val Accuracy: 0.8532
Epoch 12
100%|
          | 118/118 [00:04<00:00, 24.13it/s]
Train Loss: 0.8553 | Val Loss: 0.8979 | Val Accuracy: 0.8437
Epoch 13
          | 118/118 [00:04<00:00, 26.57it/s]
100%|
Train Loss: 0.8468 | Val Loss: 0.8561 | Val Accuracy: 0.8849
Epoch 14
100%|
          | 118/118 [00:04<00:00, 25.01it/s]
Train Loss: 0.8409 | Val Loss: 0.8543 | Val Accuracy: 0.8867
Epoch 15
          | 118/118 [00:04<00:00, 27.17it/s]
Train Loss: 0.8449 | Val Loss: 0.8568 | Val Accuracy: 0.8850
 Training: 2Bi-RNN
Epoch 1
          | 118/118 [00:07<00:00, 16.33it/s]
Train Loss: 0.9818 | Val Loss: 0.8718 | Val Accuracy: 0.8700
Epoch 2
```

100% | 118/118 [00:06<00:00, 17.22it/s]

```
Train Loss: 0.8795 | Val Loss: 0.8761 | Val Accuracy: 0.8645
Epoch 3
100%|
          | 118/118 [00:06<00:00, 18.27it/s]
Train Loss: 0.8601 | Val Loss: 0.8661 | Val Accuracy: 0.8753
Epoch 4
100%|
          | 118/118 [00:06<00:00, 17.56it/s]
Train Loss: 0.8534 | Val Loss: 0.8657 | Val Accuracy: 0.8757
Epoch 5
100%|
          | 118/118 [00:09<00:00, 12.88it/s]
Train Loss: 0.8489 | Val Loss: 0.8680 | Val Accuracy: 0.8741
Epoch 6
100%|
          | 118/118 [00:08<00:00, 13.77it/s]
Train Loss: 0.8462 | Val Loss: 0.8530 | Val Accuracy: 0.8880
Epoch 7
          | 118/118 [00:06<00:00, 17.70it/s]
100%|
Train Loss: 0.8461 | Val Loss: 0.8799 | Val Accuracy: 0.8625
Epoch 8
100%|
          | 118/118 [00:06<00:00, 18.29it/s]
Train Loss: 0.8426 | Val Loss: 0.8545 | Val Accuracy: 0.8874
Epoch 9
          | 118/118 [00:08<00:00, 14.72it/s]
Train Loss: 0.8421 | Val Loss: 0.8588 | Val Accuracy: 0.8838
Epoch 10
          | 118/118 [00:09<00:00, 13.02it/s]
100%|
Train Loss: 0.8406 | Val Loss: 0.8601 | Val Accuracy: 0.8812
Epoch 11
          | 118/118 [00:09<00:00, 13.02it/s]
100%
Train Loss: 0.8326 | Val Loss: 0.8467 | Val Accuracy: 0.8963
```

```
| 118/118 [00:09<00:00, 12.99it/s]
Train Loss: 0.8327 | Val Loss: 0.8436 | Val Accuracy: 0.8976
Epoch 13
100%|
          | 118/118 [00:08<00:00, 13.95it/s]
Train Loss: 0.8314 | Val Loss: 0.8520 | Val Accuracy: 0.8905
Epoch 14
100%|
          | 118/118 [00:06<00:00, 18.45it/s]
Train Loss: 0.8290 | Val Loss: 0.8499 | Val Accuracy: 0.8913
Epoch 15
100%|
          | 118/118 [00:06<00:00, 18.44it/s]
Train Loss: 0.8289 | Val Loss: 0.8471 | Val Accuracy: 0.8949
 Training: 1LSTM
Epoch 1
          | 118/118 [00:04<00:00, 29.46it/s]
Train Loss: 1.0227 | Val Loss: 0.8759 | Val Accuracy: 0.8697
Epoch 2
100%|
          | 118/118 [00:03<00:00, 30.12it/s]
Train Loss: 0.8569 | Val Loss: 0.8532 | Val Accuracy: 0.8901
Epoch 3
100%|
          | 118/118 [00:03<00:00, 29.51it/s]
Train Loss: 0.8402 | Val Loss: 0.8447 | Val Accuracy: 0.8963
Epoch 4
100%
          | 118/118 [00:03<00:00, 29.81it/s]
Train Loss: 0.8305 | Val Loss: 0.8406 | Val Accuracy: 0.8991
Epoch 5
          | 118/118 [00:03<00:00, 29.72it/s]
Train Loss: 0.8230 | Val Loss: 0.8423 | Val Accuracy: 0.8988
Epoch 6
100% | 118/118 [00:04<00:00, 27.48it/s]
```

```
Train Loss: 0.8184 | Val Loss: 0.8415 | Val Accuracy: 0.9005
Epoch 7
100%|
          | 118/118 [00:03<00:00, 30.18it/s]
Train Loss: 0.8138 | Val Loss: 0.8347 | Val Accuracy: 0.9062
Epoch 8
          | 118/118 [00:04<00:00, 28.67it/s]
100%|
Train Loss: 0.8110 | Val Loss: 0.8333 | Val Accuracy: 0.9078
Epoch 9
100%|
          | 118/118 [00:03<00:00, 29.76it/s]
Train Loss: 0.8073 | Val Loss: 0.8349 | Val Accuracy: 0.9057
Epoch 10
100%|
          | 118/118 [00:04<00:00, 29.23it/s]
Train Loss: 0.8062 | Val Loss: 0.8327 | Val Accuracy: 0.9083
Epoch 11
          | 118/118 [00:04<00:00, 26.62it/s]
100%|
Train Loss: 0.8037 | Val Loss: 0.8339 | Val Accuracy: 0.9067
Epoch 12
100%|
          | 118/118 [00:04<00:00, 29.03it/s]
Train Loss: 0.8017 | Val Loss: 0.8344 | Val Accuracy: 0.9066
Epoch 13
          | 118/118 [00:04<00:00, 29.20it/s]
Train Loss: 0.8001 | Val Loss: 0.8341 | Val Accuracy: 0.9071
Epoch 14
          | 118/118 [00:04<00:00, 27.23it/s]
100%|
Train Loss: 0.7993 | Val Loss: 0.8331 | Val Accuracy: 0.9076
Epoch 15
100%|
          | 118/118 [00:03<00:00, 29.85it/s]
Train Loss: 0.7979 | Val Loss: 0.8347 | Val Accuracy: 0.9059
```

```
Training: 1Bi-LSTM
Epoch 1
100% | 118/118 [00:04<00:00, 26.84it/s]
Train Loss: 1.0325 | Val Loss: 0.8733 | Val Accuracy: 0.8737
Epoch 2
          | 118/118 [00:04<00:00, 27.60it/s]
100%|
Train Loss: 0.8574 | Val Loss: 0.8564 | Val Accuracy: 0.8866
Epoch 3
          | 118/118 [00:04<00:00, 27.41it/s]
100%|
Train Loss: 0.8415 | Val Loss: 0.8466 | Val Accuracy: 0.8963
Epoch 4
          | 118/118 [00:04<00:00, 27.16it/s]
100%|
Train Loss: 0.8320 | Val Loss: 0.8408 | Val Accuracy: 0.9005
Epoch 5
100%|
          | 118/118 [00:06<00:00, 18.69it/s]
Train Loss: 0.8242 | Val Loss: 0.8370 | Val Accuracy: 0.9028
Epoch 6
100%|
          | 118/118 [00:05<00:00, 20.71it/s]
Train Loss: 0.8189 | Val Loss: 0.8383 | Val Accuracy: 0.9028
Epoch 7
100%|
          | 118/118 [00:04<00:00, 27.02it/s]
Train Loss: 0.8156 | Val Loss: 0.8362 | Val Accuracy: 0.9045
Epoch 8
100%|
          | 118/118 [00:04<00:00, 28.01it/s]
Train Loss: 0.8115 | Val Loss: 0.8367 | Val Accuracy: 0.9046
Epoch 9
          | 118/118 [00:04<00:00, 25.41it/s]
100%|
Train Loss: 0.8096 | Val Loss: 0.8352 | Val Accuracy: 0.9066
```

```
100%|
          | 118/118 [00:05<00:00, 22.42it/s]
Train Loss: 0.8064 | Val Loss: 0.8338 | Val Accuracy: 0.9087
Epoch 11
100%|
          | 118/118 [00:04<00:00, 27.76it/s]
Train Loss: 0.8043 | Val Loss: 0.8337 | Val Accuracy: 0.9068
Epoch 12
100%|
          | 118/118 [00:04<00:00, 27.62it/s]
Train Loss: 0.8021 | Val Loss: 0.8338 | Val Accuracy: 0.9068
Epoch 13
100%
          | 118/118 [00:04<00:00, 26.31it/s]
Train Loss: 0.8015 | Val Loss: 0.8334 | Val Accuracy: 0.9084
Epoch 14
100%|
          | 118/118 [00:04<00:00, 24.71it/s]
Train Loss: 0.7998 | Val Loss: 0.8378 | Val Accuracy: 0.9041
Epoch 15
          | 118/118 [00:07<00:00, 16.84it/s]
100%|
Train Loss: 0.7996 | Val Loss: 0.8330 | Val Accuracy: 0.9091
 Training: 2Bi-LSTM
Epoch 1
100% | 118/118 [00:06<00:00, 18.32it/s]
Train Loss: 0.9845 | Val Loss: 0.8640 | Val Accuracy: 0.8788
Epoch 2
100%|
          | 118/118 [00:08<00:00, 13.40it/s]
Train Loss: 0.8566 | Val Loss: 0.8505 | Val Accuracy: 0.8901
Epoch 3
100%|
          | 118/118 [00:09<00:00, 12.36it/s]
Train Loss: 0.8404 | Val Loss: 0.8459 | Val Accuracy: 0.8959
Epoch 4
100% | 118/118 [00:09<00:00, 11.84it/s]
```

```
Train Loss: 0.8323 | Val Loss: 0.8414 | Val Accuracy: 0.9001
Epoch 5
100%|
          | 118/118 [00:09<00:00, 12.14it/s]
Train Loss: 0.8253 | Val Loss: 0.8415 | Val Accuracy: 0.8999
Epoch 6
          | 118/118 [00:11<00:00, 10.19it/s]
100%|
Train Loss: 0.8203 | Val Loss: 0.8392 | Val Accuracy: 0.9020
Epoch 7
100%|
          | 118/118 [00:09<00:00, 12.82it/s]
Train Loss: 0.8168 | Val Loss: 0.8367 | Val Accuracy: 0.9046
Epoch 8
100%|
          | 118/118 [00:08<00:00, 13.28it/s]
Train Loss: 0.8127 | Val Loss: 0.8369 | Val Accuracy: 0.9042
Epoch 9
          | 118/118 [00:09<00:00, 12.08it/s]
100%|
Train Loss: 0.8098 | Val Loss: 0.8351 | Val Accuracy: 0.9067
Epoch 10
100%|
          | 118/118 [00:09<00:00, 12.39it/s]
Train Loss: 0.8084 | Val Loss: 0.8392 | Val Accuracy: 0.9026
Epoch 11
          | 118/118 [00:08<00:00, 14.07it/s]
Train Loss: 0.8064 | Val Loss: 0.8349 | Val Accuracy: 0.9061
Epoch 12
          | 118/118 [00:09<00:00, 12.39it/s]
100%|
Train Loss: 0.8044 | Val Loss: 0.8326 | Val Accuracy: 0.9079
Epoch 13
          | 118/118 [00:08<00:00, 14.00it/s]
Train Loss: 0.8037 | Val Loss: 0.8347 | Val Accuracy: 0.9054
```

```
100%
                 | 118/118 [00:09<00:00, 12.65it/s]
      Train Loss: 0.8017 | Val Loss: 0.8326 | Val Accuracy: 0.9097
      Epoch 15
                 | 118/118 [00:08<00:00, 13.68it/s]
      100%|
      Train Loss: 0.8006 | Val Loss: 0.8333 | Val Accuracy: 0.9079
[190]: # Transpose results to match the table format in the assignment
       df_transposed_glove_25 = results_glove.set_index("Model").T
       # Round accuracy to 2 decimals, format numbers
       df_display_glove_25 = pd.DataFrame({
           col: [
               f"{df_transposed_glove_25.loc['Accuracy', col]:.2f}",
               f"{int(df_transposed_glove_25.loc['Parameters', col]):,}",
               f"{df_transposed_glove_25.loc['Time (sec)', col]:.2f}"
           ]
           for col in df_transposed_glove_25.columns
       }, index=["Accuracy", "Parameters", "Time cost"])
       df_display_glove_25
[190]:
                         1RNN
                                 1Bi-RNN
                                             2Bi-RNN
                                                          1LSTM
                                                                   1Bi-LSTM
                                                                              2Bi-LSTM
                        86.33
       Accuracy
                                   88.50
                                              89.49
                                                          90.59
                                                                      90.91
                                                                                 90.79
                   2,136,284
                               2,147,164
                                                                             2,310,236
       Parameters
                                          2,171,996
                                                      2,168,156
                                                                 2,210,908
       Time cost
                         4.02
                                    4.80
                                                7.86
                                                           4.24
                                                                       5.03
                                                                                  9.56
      3.4.5 E
                   \Gamma.4 – X
                             Π
                                        Word Embeddings (GloVe)
                                                                      MAX_WORDS = 25
                   MAX_WORDS
                                  25 (
                                                                                 embeddings
      (GloVe 6B, 100d),
         • B
                                            1-2\%
                                                           randomly initialized embeddings.
                                            (\sim 0.5-1 \text{ sec}
         • M
                                                        epoch).

    Π

         • K
             -T
                embeddings.
       Γ
                  : > H
                                      GloVe embeddings
                                       computational overhead.
```

```
\Sigma
                               Ε
                                               (frozen) embeddings,
     3.5.1
             {f E}
                   Π
     Η
                             run_experiments()
                                                                freeze_embeddings=True:
[79]: results_glove_frozen, preds_glove_frozen = run_experiments(model_configs,__
       pretrained_embeddings=embedding_matrix, freeze_embeddings=True)
       Training: 1RNN
     Epoch 1
     100%|
                | 118/118 [00:05<00:00, 22.18it/s]
     Train Loss: 1.0680 | Val Loss: 0.9012 | Val Accuracy: 0.8471
     Epoch 2
     100%|
                | 118/118 [00:03<00:00, 35.35it/s]
     Train Loss: 0.9006 | Val Loss: 0.9069 | Val Accuracy: 0.8354
     Epoch 3
     100%|
                | 118/118 [00:03<00:00, 35.16it/s]
     Train Loss: 0.8909 | Val Loss: 0.8859 | Val Accuracy: 0.8562
     Epoch 4
     100%|
                | 118/118 [00:03<00:00, 34.51it/s]
     Train Loss: 0.8858 | Val Loss: 0.8815 | Val Accuracy: 0.8612
     Epoch 5
                | 118/118 [00:03<00:00, 35.66it/s]
     100%
     Train Loss: 0.8859 | Val Loss: 0.8833 | Val Accuracy: 0.8597
     Epoch 6
     100%|
                | 118/118 [00:03<00:00, 34.94it/s]
     Train Loss: 0.8852 | Val Loss: 0.8818 | Val Accuracy: 0.8603
     Epoch 7
     100%|
                | 118/118 [00:03<00:00, 32.22it/s]
```

GloVe Embeddings

freeze=True

 $\Gamma.5 - X$

П

3.5

 \mathbf{E}

```
Train Loss: 0.8834 | Val Loss: 0.8767 | Val Accuracy: 0.8649
Epoch 8
100%|
          | 118/118 [00:03<00:00, 32.65it/s]
Train Loss: 0.8799 | Val Loss: 0.8789 | Val Accuracy: 0.8630
Epoch 9
100%|
          | 118/118 [00:03<00:00, 35.37it/s]
Train Loss: 0.8821 | Val Loss: 0.8775 | Val Accuracy: 0.8639
Epoch 10
100%|
          | 118/118 [00:03<00:00, 35.38it/s]
Train Loss: 0.8771 | Val Loss: 0.8828 | Val Accuracy: 0.8601
Epoch 11
100%|
          | 118/118 [00:03<00:00, 35.58it/s]
Train Loss: 0.8765 | Val Loss: 0.8799 | Val Accuracy: 0.8638
Epoch 12
          | 118/118 [00:03<00:00, 35.77it/s]
100%|
Train Loss: 0.8761 | Val Loss: 0.8765 | Val Accuracy: 0.8654
Epoch 13
100%|
          | 118/118 [00:03<00:00, 32.87it/s]
Train Loss: 0.8857 | Val Loss: 0.8773 | Val Accuracy: 0.8646
Epoch 14
          | 118/118 [00:03<00:00, 35.60it/s]
Train Loss: 0.8766 | Val Loss: 0.8823 | Val Accuracy: 0.8597
Epoch 15
          | 118/118 [00:03<00:00, 32.27it/s]
100%|
Train Loss: 0.8859 | Val Loss: 0.8765 | Val Accuracy: 0.8645
 Training: 1Bi-RNN
Epoch 1
100% | 118/118 [00:05<00:00, 22.71it/s]
```

```
Train Loss: 1.0896 | Val Loss: 0.9450 | Val Accuracy: 0.8109
Epoch 2
100%|
          | 118/118 [00:05<00:00, 22.83it/s]
Train Loss: 0.9178 | Val Loss: 0.9045 | Val Accuracy: 0.8396
Epoch 3
100%|
          | 118/118 [00:05<00:00, 22.38it/s]
Train Loss: 0.8996 | Val Loss: 0.8975 | Val Accuracy: 0.8472
Epoch 4
100%|
          | 118/118 [00:05<00:00, 22.51it/s]
Train Loss: 0.9083 | Val Loss: 0.8997 | Val Accuracy: 0.8418
Epoch 5
100%|
          | 118/118 [00:05<00:00, 22.61it/s]
Train Loss: 0.8979 | Val Loss: 0.8915 | Val Accuracy: 0.8521
Epoch 6
          | 118/118 [00:05<00:00, 21.14it/s]
100%|
Train Loss: 0.8922 | Val Loss: 0.9059 | Val Accuracy: 0.8371
Epoch 7
100%|
          | 118/118 [00:05<00:00, 21.69it/s]
Train Loss: 0.8901 | Val Loss: 0.8903 | Val Accuracy: 0.8534
Epoch 8
100%|
          | 118/118 [00:05<00:00, 22.83it/s]
Train Loss: 0.9151 | Val Loss: 0.8914 | Val Accuracy: 0.8509
Epoch 9
100%|
          | 118/118 [00:05<00:00, 21.41it/s]
Train Loss: 0.8846 | Val Loss: 0.8808 | Val Accuracy: 0.8617
Epoch 10
100%|
          | 118/118 [00:05<00:00, 22.61it/s]
Train Loss: 0.8845 | Val Loss: 0.8816 | Val Accuracy: 0.8603
Epoch 11
```

```
| 118/118 [00:05<00:00, 22.42it/s]
Train Loss: 0.8961 | Val Loss: 0.8831 | Val Accuracy: 0.8593
Epoch 12
100%|
          | 118/118 [00:05<00:00, 21.90it/s]
Train Loss: 0.8803 | Val Loss: 0.8751 | Val Accuracy: 0.8661
Epoch 13
100%|
          | 118/118 [00:05<00:00, 19.77it/s]
Train Loss: 0.8915 | Val Loss: 0.8928 | Val Accuracy: 0.8497
Epoch 14
100%|
          | 118/118 [00:05<00:00, 21.99it/s]
Train Loss: 0.8967 | Val Loss: 0.8890 | Val Accuracy: 0.8526
Epoch 15
100%|
          | 118/118 [00:05<00:00, 22.46it/s]
Train Loss: 0.8896 | Val Loss: 0.8891 | Val Accuracy: 0.8518
 Training: 2Bi-RNN
Epoch 1
     | 118/118 [00:08<00:00, 13.11it/s]
Train Loss: 1.0156 | Val Loss: 0.9186 | Val Accuracy: 0.8229
Epoch 2
100%|
          | 118/118 [00:08<00:00, 13.33it/s]
Train Loss: 0.8944 | Val Loss: 0.8864 | Val Accuracy: 0.8547
Epoch 3
100%
          | 118/118 [00:09<00:00, 12.98it/s]
Train Loss: 0.8857 | Val Loss: 0.8911 | Val Accuracy: 0.8521
Epoch 4
          | 118/118 [00:08<00:00, 13.13it/s]
Train Loss: 0.8919 | Val Loss: 0.8827 | Val Accuracy: 0.8582
Epoch 5
100% | 118/118 [00:08<00:00, 13.43it/s]
```

```
Train Loss: 0.8838 | Val Loss: 0.8848 | Val Accuracy: 0.8566
Epoch 6
100%|
          | 118/118 [00:08<00:00, 13.63it/s]
Train Loss: 0.8834 | Val Loss: 0.8800 | Val Accuracy: 0.8614
Epoch 7
100%|
          | 118/118 [00:08<00:00, 13.65it/s]
Train Loss: 0.8820 | Val Loss: 0.8793 | Val Accuracy: 0.8616
Epoch 8
100%|
          | 118/118 [00:08<00:00, 13.13it/s]
Train Loss: 0.9006 | Val Loss: 0.9015 | Val Accuracy: 0.8396
Epoch 9
100%|
          | 118/118 [00:08<00:00, 13.70it/s]
Train Loss: 0.8803 | Val Loss: 0.8887 | Val Accuracy: 0.8551
Epoch 10
          | 118/118 [00:08<00:00, 13.80it/s]
100%|
Train Loss: 0.8836 | Val Loss: 0.8800 | Val Accuracy: 0.8625
Epoch 11
          | 118/118 [00:08<00:00, 13.63it/s]
100%|
Train Loss: 0.8810 | Val Loss: 0.8785 | Val Accuracy: 0.8638
Epoch 12
          | 118/118 [00:08<00:00, 13.86it/s]
Train Loss: 0.8804 | Val Loss: 0.8809 | Val Accuracy: 0.8600
Epoch 13
          | 118/118 [00:08<00:00, 14.01it/s]
100%|
Train Loss: 0.8838 | Val Loss: 0.8838 | Val Accuracy: 0.8591
Epoch 14
          | 118/118 [00:08<00:00, 13.38it/s]
Train Loss: 0.8919 | Val Loss: 0.8907 | Val Accuracy: 0.8511
```

```
| 118/118 [00:08<00:00, 13.64it/s]
Train Loss: 0.9047 | Val Loss: 0.8913 | Val Accuracy: 0.8492
 Training: 1LSTM
Epoch 1
          | 118/118 [00:06<00:00, 17.68it/s]
Train Loss: 1.0298 | Val Loss: 0.8855 | Val Accuracy: 0.8616
Epoch 2
100%|
          | 118/118 [00:06<00:00, 17.21it/s]
Train Loss: 0.8760 | Val Loss: 0.8706 | Val Accuracy: 0.8718
Epoch 3
          | 118/118 [00:06<00:00, 18.07it/s]
100%|
Train Loss: 0.8647 | Val Loss: 0.8685 | Val Accuracy: 0.8741
Epoch 4
100%|
          | 118/118 [00:06<00:00, 17.98it/s]
Train Loss: 0.8586 | Val Loss: 0.8605 | Val Accuracy: 0.8808
Epoch 5
100%|
          | 118/118 [00:06<00:00, 17.63it/s]
Train Loss: 0.8543 | Val Loss: 0.8557 | Val Accuracy: 0.8855
Epoch 6
100%|
          | 118/118 [00:06<00:00, 17.81it/s]
Train Loss: 0.8507 | Val Loss: 0.8527 | Val Accuracy: 0.8867
Epoch 7
100%
          | 118/118 [00:06<00:00, 18.01it/s]
Train Loss: 0.8484 | Val Loss: 0.8525 | Val Accuracy: 0.8886
Epoch 8
          | 118/118 [00:07<00:00, 16.82it/s]
Train Loss: 0.8465 | Val Loss: 0.8511 | Val Accuracy: 0.8904
Epoch 9
100% | 118/118 [00:06<00:00, 17.21it/s]
```

```
Train Loss: 0.8435 | Val Loss: 0.8478 | Val Accuracy: 0.8943
Epoch 10
100%|
          | 118/118 [00:06<00:00, 18.02it/s]
Train Loss: 0.8412 | Val Loss: 0.8526 | Val Accuracy: 0.8892
Epoch 11
100%|
          | 118/118 [00:06<00:00, 18.18it/s]
Train Loss: 0.8393 | Val Loss: 0.8513 | Val Accuracy: 0.8893
Epoch 12
100%|
          | 118/118 [00:06<00:00, 17.76it/s]
Train Loss: 0.8372 | Val Loss: 0.8487 | Val Accuracy: 0.8921
Epoch 13
100%|
          | 118/118 [00:07<00:00, 16.78it/s]
Train Loss: 0.8373 | Val Loss: 0.8444 | Val Accuracy: 0.8949
Epoch 14
          | 118/118 [00:06<00:00, 18.11it/s]
100%|
Train Loss: 0.8348 | Val Loss: 0.8452 | Val Accuracy: 0.8961
Epoch 15
100%|
          | 118/118 [00:06<00:00, 17.65it/s]
Train Loss: 0.8327 | Val Loss: 0.8436 | Val Accuracy: 0.8976
 Training: 1Bi-LSTM
Epoch 1
100%|
       | 118/118 [00:12<00:00, 9.77it/s]
Train Loss: 1.0464 | Val Loss: 0.8823 | Val Accuracy: 0.8661
Epoch 2
          | 118/118 [00:11<00:00, 10.33it/s]
Train Loss: 0.8750 | Val Loss: 0.8689 | Val Accuracy: 0.8743
Epoch 3
100% | 118/118 [00:11<00:00, 10.39it/s]
```

```
Train Loss: 0.8648 | Val Loss: 0.8624 | Val Accuracy: 0.8791
Epoch 4
100%|
          | 118/118 [00:11<00:00, 10.35it/s]
Train Loss: 0.8594 | Val Loss: 0.8596 | Val Accuracy: 0.8822
Epoch 5
          | 118/118 [00:11<00:00, 10.37it/s]
100%|
Train Loss: 0.8543 | Val Loss: 0.8554 | Val Accuracy: 0.8879
Epoch 6
100%|
          | 118/118 [00:11<00:00, 10.01it/s]
Train Loss: 0.8510 | Val Loss: 0.8536 | Val Accuracy: 0.8883
Epoch 7
100%|
          | 118/118 [00:11<00:00, 9.93it/s]
Train Loss: 0.8482 | Val Loss: 0.8499 | Val Accuracy: 0.8901
Epoch 8
          | 118/118 [00:11<00:00, 10.28it/s]
100%|
Train Loss: 0.8455 | Val Loss: 0.8496 | Val Accuracy: 0.8912
Epoch 9
100%|
          | 118/118 [00:11<00:00, 10.18it/s]
Train Loss: 0.8434 | Val Loss: 0.8512 | Val Accuracy: 0.8888
Epoch 10
          | 118/118 [00:11<00:00, 10.28it/s]
Train Loss: 0.8417 | Val Loss: 0.8467 | Val Accuracy: 0.8943
Epoch 11
          | 118/118 [00:11<00:00, 9.99it/s]
100%|
Train Loss: 0.8389 | Val Loss: 0.8451 | Val Accuracy: 0.8950
Epoch 12
          | 118/118 [00:13<00:00, 9.01it/s]
100%
Train Loss: 0.8379 | Val Loss: 0.8472 | Val Accuracy: 0.8933
```

```
| 118/118 [00:14<00:00, 8.15it/s]
Train Loss: 0.8352 | Val Loss: 0.8458 | Val Accuracy: 0.8949
Epoch 14
100%|
          | 118/118 [00:17<00:00, 6.74it/s]
Train Loss: 0.8345 | Val Loss: 0.8442 | Val Accuracy: 0.8967
Epoch 15
100%|
          | 118/118 [00:15<00:00, 7.39it/s]
Train Loss: 0.8334 | Val Loss: 0.8424 | Val Accuracy: 0.8983
 Training: 2Bi-LSTM
Epoch 1
100%|
          | 118/118 [00:32<00:00, 3.65it/s]
Train Loss: 0.9900 | Val Loss: 0.8798 | Val Accuracy: 0.8613
Epoch 2
100%|
          | 118/118 [00:28<00:00, 4.15it/s]
Train Loss: 0.8711 | Val Loss: 0.8709 | Val Accuracy: 0.8686
Epoch 3
100%|
          | 118/118 [00:27<00:00, 4.37it/s]
Train Loss: 0.8635 | Val Loss: 0.8624 | Val Accuracy: 0.8797
Epoch 4
100%|
          | 118/118 [00:29<00:00, 4.06it/s]
Train Loss: 0.8585 | Val Loss: 0.8589 | Val Accuracy: 0.8808
Epoch 5
100%
          | 118/118 [00:27<00:00, 4.30it/s]
Train Loss: 0.8547 | Val Loss: 0.8545 | Val Accuracy: 0.8867
Epoch 6
          | 118/118 [00:25<00:00, 4.67it/s]
Train Loss: 0.8519 | Val Loss: 0.8520 | Val Accuracy: 0.8896
Epoch 7
100%|
         | 118/118 [00:24<00:00, 4.80it/s]
```

```
Train Loss: 0.8492 | Val Loss: 0.8510 | Val Accuracy: 0.8899
     Epoch 8
     100%|
               | 118/118 [00:25<00:00, 4.65it/s]
     Train Loss: 0.8470 | Val Loss: 0.8494 | Val Accuracy: 0.8913
     Epoch 9
               | 118/118 [00:25<00:00, 4.60it/s]
     100%|
     Train Loss: 0.8455 | Val Loss: 0.8471 | Val Accuracy: 0.8943
     Epoch 10
     100%|
               | 118/118 [00:25<00:00, 4.59it/s]
     Train Loss: 0.8426 | Val Loss: 0.8486 | Val Accuracy: 0.8914
     Epoch 11
     100%|
               | 118/118 [00:25<00:00, 4.60it/s]
     Train Loss: 0.8396 | Val Loss: 0.8463 | Val Accuracy: 0.8953
     Epoch 12
               | 118/118 [00:26<00:00, 4.49it/s]
     100%|
     Train Loss: 0.8382 | Val Loss: 0.8443 | Val Accuracy: 0.8975
     Epoch 13
     100%|
               | 118/118 [00:26<00:00, 4.43it/s]
     Train Loss: 0.8373 | Val Loss: 0.8437 | Val Accuracy: 0.8972
     Epoch 14
               | 118/118 [00:26<00:00, 4.49it/s]
     Train Loss: 0.8355 | Val Loss: 0.8428 | Val Accuracy: 0.8987
     Epoch 15
     100%|
               | 118/118 [00:27<00:00, 4.32it/s]
     Train Loss: 0.8337 | Val Loss: 0.8474 | Val Accuracy: 0.8934
[80]: # Transpose results to match the table format in the assignment
      df_transposed_glove_25_freeze = results_glove_frozen.set_index("Model").T
      # Round accuracy to 2 decimals, format numbers
```

```
df_display_glove_25_freeze = pd.DataFrame({
           col: [
               f"{df_transposed_glove_25_freeze.loc['Accuracy', col]:.2f}",
               f"{int(df_transposed_glove_25_freeze.loc['Parameters', col]):,}",
               f"{df_transposed_glove_25_freeze.loc['Time (sec)', col]:.2f}"
           ]
           for col in df_transposed_glove_25_freeze.columns
      }, index=["Accuracy", "Parameters", "Time cost"])
      df_display_glove_25_freeze
[80]:
                      1RNN 1Bi-RNN 2Bi-RNN
                                                1LSTM 1Bi-LSTM 2Bi-LSTM
                     86.45
                              85.18
                                       84.92
                                                89.76
                                                          89.83
                                                                     89.34
      Accuracy
                                                                  184,836
      Parameters
                    10,884 21,764
                                      46,596
                                               42,756
                                                         85,508
                               5.58
      Time cost
                      3.72
                                        9.10
                                                 6.96
                                                           13.03
                                                                     27.73
      3.5.2 E
                   \Gamma.5 - \Sigma
      \sum
                                      GloVe
                                                       embeddings (glove.6B.100d),
      embedding layer
                            "frozen" (
                                                                    ).
      \mathbf{T}
         • M
                                         (\sim 1\%)
                                                                   embeddings
                                                                                  trainable.
             - E
                           RNN-based
         • M
                                       (\sim 0.5-1 \text{ sec})
                                                     epoch),
                                                                                     gradients
           embedding layer.
         \bullet \Sigma
             - T frozen embedding layer
                                           trainable parameters
             - \Pi. . 1RNN
                               \sim 10.884
                                                frozen embeddings,
                                                                         ~2
                                                                                         trainable.
       Γ
                   : > T "
                                    embeddings
                          . T
                                                                                   embeddings
             task.
      3.6
             \mathbf{E}
                   \Gamma.6 – E
                                      Dataset: IMDB Movie Reviews
      \Sigma
                                                                          IMDB dataset
                                                              dataset:
      50.000
      3.6.1 E
                      П
                                 \Delta
         • T dataset
                               Kaggle
             - review 
ightarrow
                                    (positive, negative)
             - sentiment \rightarrow
```

```
• T dataset
                           training (80%) test (20%) train_test_split stratify
[191]: # \Phi
                IMDB dataset
       dataset_imdb = pd.read_csv("IMDB Dataset.csv")
                   "positive"/"negative" 1/0
       # Mapping
       dataset_imdb["label"] = dataset_imdb["sentiment"].map({"positive": 1,__

y"negative": 0})
       # Split 80/20
       from sklearn.model_selection import train_test_split
       X_train_imdb, X_test_imdb, y_train_imdb, y_test_imdb = train_test_split(
           dataset_imdb["review"],
           dataset_imdb["label"],
           test_size=0.2,
           random state=42,
           stratify=dataset_imdb["label"]
[195]: # 4
                dataset
       train_dataset_imdb = [(label, text) for label, text in zip(y_train_imdb,__
        →X_train_imdb)]
       test_dataset_imdb = [(label, text) for label, text in zip(y_test_imdb,__
        →X test imdb)]
      3.6.2 E
                  П
         • X
                                (vocab_imdb)
                                                          train/test
                                                                         IMDB.
                                         (RNN / LSTM, 1-layer / 2-layer, uni/bidirectional).
         O
         • T collate function
                                    shift labels=False
[196]: # X vocab_imdb IMDB
       vocab imdb = build vocab from iterator(
           build_vocabulary([train_dataset_imdb, test_dataset_imdb]),
           min freq=10,
           specials=["<PAD>", "<UNK>"]
       vocab_imdb.set_default_index(vocab_imdb["<UNK>"])
       print(f"Vocabulary size (IMDB): {len(vocab_imdb)}")
      Vocabulary size (IMDB): 29065
[197]: from torch.utils.data import DataLoader
```

: positive = 1, negative = 0

• 0

```
train_loader_imdb = DataLoader(train_dataset_imdb, batch_size=BATCH_SIZE,_
        ⇔shuffle=True, collate_fn=lambda batch: collate_batch(batch,_
        ⇔shift_labels=False))
       test_loader_imdb = DataLoader(test_dataset_imdb, batch_size=BATCH_SIZE,_
        ⇔shuffle=False, collate_fn=lambda batch: collate_batch(batch, __
        ⇒shift labels=False))
[198]: df_imdb_results, preds_imdb = run_experiments(
           configs=model_configs,
           pretrained_embeddings=None,
           freeze_embeddings=False,
           vocab_to_use=vocab_imdb,
           output_dim=2,
           train_loader=train_loader_imdb,
           test_loader=test_loader_imdb
       Training: 1RNN
      Epoch 1
      100%|
                 | 40/40 [00:03<00:00, 10.61it/s]
      Train Loss: 0.6943 | Val Loss: 0.6918 | Val Accuracy: 0.5215
      Epoch 2
      100%|
                 | 40/40 [00:03<00:00, 13.29it/s]
      Train Loss: 0.6844 | Val Loss: 0.6728 | Val Accuracy: 0.5850
      Epoch 3
      100%1
                 | 40/40 [00:02<00:00, 13.35it/s]
      Train Loss: 0.6599 | Val Loss: 0.6537 | Val Accuracy: 0.6211
      Epoch 4
      100%|
                 | 40/40 [00:03<00:00, 13.28it/s]
      Train Loss: 0.6348 | Val Loss: 0.6368 | Val Accuracy: 0.6516
      Epoch 5
      100%|
                 | 40/40 [00:03<00:00, 12.93it/s]
      Train Loss: 0.6178 | Val Loss: 0.6258 | Val Accuracy: 0.6639
      Epoch 6
      100%|
                | 40/40 [00:03<00:00, 13.22it/s]
```

```
Train Loss: 0.5977 | Val Loss: 0.6225 | Val Accuracy: 0.6687
Epoch 7
100%|
          | 40/40 [00:03<00:00, 12.95it/s]
Train Loss: 0.5786 | Val Loss: 0.6128 | Val Accuracy: 0.6801
Epoch 8
100%|
          | 40/40 [00:03<00:00, 12.30it/s]
Train Loss: 0.5701 | Val Loss: 0.6124 | Val Accuracy: 0.6823
Epoch 9
100%|
          | 40/40 [00:03<00:00, 13.14it/s]
Train Loss: 0.5562 | Val Loss: 0.6066 | Val Accuracy: 0.6908
Epoch 10
100%|
          | 40/40 [00:03<00:00, 13.09it/s]
Train Loss: 0.5435 | Val Loss: 0.6059 | Val Accuracy: 0.6887
Epoch 11
          | 40/40 [00:03<00:00, 12.71it/s]
100%|
Train Loss: 0.5332 | Val Loss: 0.6023 | Val Accuracy: 0.6949
Epoch 12
100%|
          | 40/40 [00:03<00:00, 13.10it/s]
Train Loss: 0.5288 | Val Loss: 0.6058 | Val Accuracy: 0.6885
Epoch 13
          | 40/40 [00:03<00:00, 13.09it/s]
Train Loss: 0.5208 | Val Loss: 0.6033 | Val Accuracy: 0.6919
Epoch 14
          | 40/40 [00:03<00:00, 13.12it/s]
100%|
Train Loss: 0.5090 | Val Loss: 0.5998 | Val Accuracy: 0.6996
Epoch 15
100%|
          | 40/40 [00:03<00:00, 13.14it/s]
Train Loss: 0.5019 | Val Loss: 0.6039 | Val Accuracy: 0.6949
```

```
Training: 1Bi-RNN
Epoch 1
          | 40/40 [00:03<00:00, 10.83it/s]
100%|
Train Loss: 0.6943 | Val Loss: 0.6919 | Val Accuracy: 0.5236
Epoch 2
          | 40/40 [00:03<00:00, 11.84it/s]
100%|
Train Loss: 0.6888 | Val Loss: 0.6908 | Val Accuracy: 0.5250
Epoch 3
          | 40/40 [00:03<00:00, 11.70it/s]
100%|
Train Loss: 0.6783 | Val Loss: 0.6764 | Val Accuracy: 0.5803
Epoch 4
          | 40/40 [00:03<00:00, 11.69it/s]
100%|
Train Loss: 0.6530 | Val Loss: 0.6644 | Val Accuracy: 0.6117
Epoch 5
100%|
          | 40/40 [00:03<00:00, 11.28it/s]
Train Loss: 0.6327 | Val Loss: 0.6402 | Val Accuracy: 0.6424
Epoch 6
100%|
          | 40/40 [00:03<00:00, 11.70it/s]
Train Loss: 0.6099 | Val Loss: 0.6257 | Val Accuracy: 0.6620
Epoch 7
100%|
          | 40/40 [00:04<00:00, 9.87it/s]
Train Loss: 0.5890 | Val Loss: 0.6160 | Val Accuracy: 0.6784
Epoch 8
100%|
          | 40/40 [00:03<00:00, 10.93it/s]
Train Loss: 0.5727 | Val Loss: 0.6135 | Val Accuracy: 0.6823
Epoch 9
          | 40/40 [00:03<00:00, 11.42it/s]
100%|
Train Loss: 0.5608 | Val Loss: 0.6079 | Val Accuracy: 0.6868
```

```
| 40/40 [00:03<00:00, 11.47it/s]
Train Loss: 0.5442 | Val Loss: 0.6048 | Val Accuracy: 0.6933
Epoch 11
100%|
          | 40/40 [00:03<00:00, 11.65it/s]
Train Loss: 0.5350 | Val Loss: 0.5990 | Val Accuracy: 0.6955
Epoch 12
100%|
          | 40/40 [00:03<00:00, 11.81it/s]
Train Loss: 0.5255 | Val Loss: 0.6112 | Val Accuracy: 0.6816
Epoch 13
100%
          | 40/40 [00:03<00:00, 11.76it/s]
Train Loss: 0.5200 | Val Loss: 0.6005 | Val Accuracy: 0.6998
Epoch 14
100%|
          | 40/40 [00:03<00:00, 11.54it/s]
Train Loss: 0.5086 | Val Loss: 0.5973 | Val Accuracy: 0.7023
Epoch 15
          | 40/40 [00:03<00:00, 11.66it/s]
100%|
Train Loss: 0.5035 | Val Loss: 0.6003 | Val Accuracy: 0.6972
 Training: 2Bi-RNN
Epoch 1
100% | 40/40 [00:04<00:00, 9.68it/s]
Train Loss: 0.6933 | Val Loss: 0.6923 | Val Accuracy: 0.5180
Epoch 2
100%
          | 40/40 [00:04<00:00, 9.67it/s]
Train Loss: 0.6806 | Val Loss: 0.6762 | Val Accuracy: 0.5808
Epoch 3
100%|
          | 40/40 [00:04<00:00, 9.90it/s]
Train Loss: 0.6636 | Val Loss: 0.6683 | Val Accuracy: 0.6020
Epoch 4
100%| | 40/40 [00:04<00:00, 9.88it/s]
```

```
Train Loss: 0.6417 | Val Loss: 0.6533 | Val Accuracy: 0.6214
Epoch 5
100%|
          | 40/40 [00:04<00:00, 9.77it/s]
Train Loss: 0.6184 | Val Loss: 0.6314 | Val Accuracy: 0.6561
Epoch 6
          | 40/40 [00:04<00:00, 8.84it/s]
100%|
Train Loss: 0.5980 | Val Loss: 0.6306 | Val Accuracy: 0.6570
Epoch 7
100%|
          | 40/40 [00:04<00:00, 9.86it/s]
Train Loss: 0.5774 | Val Loss: 0.6117 | Val Accuracy: 0.6810
Epoch 8
100%|
          | 40/40 [00:04<00:00, 9.60it/s]
Train Loss: 0.5623 | Val Loss: 0.6103 | Val Accuracy: 0.6811
Epoch 9
          | 40/40 [00:04<00:00, 9.85it/s]
100%|
Train Loss: 0.5468 | Val Loss: 0.6043 | Val Accuracy: 0.6912
Epoch 10
100%|
          | 40/40 [00:04<00:00, 9.73it/s]
Train Loss: 0.5353 | Val Loss: 0.6038 | Val Accuracy: 0.6937
Epoch 11
100%|
          | 40/40 [00:04<00:00, 8.35it/s]
Train Loss: 0.5231 | Val Loss: 0.6050 | Val Accuracy: 0.6926
Epoch 12
          | 40/40 [00:04<00:00, 9.54it/s]
100%|
Train Loss: 0.5145 | Val Loss: 0.6044 | Val Accuracy: 0.6932
Epoch 13
          | 40/40 [00:04<00:00, 9.51it/s]
100%|
Train Loss: 0.5071 | Val Loss: 0.6030 | Val Accuracy: 0.6946
```

```
100%|
          | 40/40 [00:04<00:00, 9.72it/s]
Train Loss: 0.4948 | Val Loss: 0.6051 | Val Accuracy: 0.6920
Epoch 15
100%|
          | 40/40 [00:04<00:00, 9.69it/s]
Train Loss: 0.4884 | Val Loss: 0.6028 | Val Accuracy: 0.6988
 Training: 1LSTM
Epoch 1
100%|
          | 40/40 [00:03<00:00, 11.82it/s]
Train Loss: 0.6922 | Val Loss: 0.6901 | Val Accuracy: 0.5354
Epoch 2
          | 40/40 [00:03<00:00, 12.43it/s]
100%|
Train Loss: 0.6790 | Val Loss: 0.6631 | Val Accuracy: 0.6021
Epoch 3
          | 40/40 [00:03<00:00, 12.28it/s]
100%|
Train Loss: 0.6351 | Val Loss: 0.6287 | Val Accuracy: 0.6521
Epoch 4
100%|
          | 40/40 [00:03<00:00, 11.38it/s]
Train Loss: 0.5966 | Val Loss: 0.6061 | Val Accuracy: 0.6781
Epoch 5
100%|
          | 40/40 [00:03<00:00, 12.00it/s]
Train Loss: 0.5716 | Val Loss: 0.6008 | Val Accuracy: 0.6823
Epoch 6
100%
          | 40/40 [00:03<00:00, 12.64it/s]
Train Loss: 0.5561 | Val Loss: 0.5940 | Val Accuracy: 0.6940
Epoch 7
          | 40/40 [00:03<00:00, 12.41it/s]
Train Loss: 0.5406 | Val Loss: 0.5900 | Val Accuracy: 0.6980
Epoch 8
100% | 40/40 [00:03<00:00, 12.38it/s]
```

```
Train Loss: 0.5253 | Val Loss: 0.5900 | Val Accuracy: 0.7009
Epoch 9
100%|
          | 40/40 [00:03<00:00, 12.18it/s]
Train Loss: 0.5128 | Val Loss: 0.5884 | Val Accuracy: 0.7034
Epoch 10
100%|
          | 40/40 [00:03<00:00, 12.35it/s]
Train Loss: 0.5011 | Val Loss: 0.5891 | Val Accuracy: 0.7019
Epoch 11
          | 40/40 [00:03<00:00, 12.42it/s]
100%|
Train Loss: 0.4901 | Val Loss: 0.5889 | Val Accuracy: 0.7068
Epoch 12
100%|
          | 40/40 [00:03<00:00, 12.91it/s]
Train Loss: 0.4850 | Val Loss: 0.5988 | Val Accuracy: 0.6953
Epoch 13
          | 40/40 [00:03<00:00, 12.59it/s]
100%|
Train Loss: 0.4720 | Val Loss: 0.5981 | Val Accuracy: 0.6968
Epoch 14
100%|
          | 40/40 [00:03<00:00, 12.38it/s]
Train Loss: 0.4670 | Val Loss: 0.5952 | Val Accuracy: 0.7026
Epoch 15
100%|
          | 40/40 [00:03<00:00, 12.86it/s]
Train Loss: 0.4567 | Val Loss: 0.5995 | Val Accuracy: 0.6990
 Training: 1Bi-LSTM
Epoch 1
          | 40/40 [00:03<00:00, 11.62it/s]
Train Loss: 0.6919 | Val Loss: 0.6900 | Val Accuracy: 0.5335
Epoch 2
```

| 40/40 [00:03<00:00, 11.96it/s]

100%|

```
Train Loss: 0.6768 | Val Loss: 0.6615 | Val Accuracy: 0.6074
Epoch 3
100%|
          | 40/40 [00:03<00:00, 10.99it/s]
Train Loss: 0.6365 | Val Loss: 0.6278 | Val Accuracy: 0.6535
Epoch 4
100%|
          | 40/40 [00:03<00:00, 11.58it/s]
Train Loss: 0.6007 | Val Loss: 0.6061 | Val Accuracy: 0.6791
Epoch 5
100%|
          | 40/40 [00:03<00:00, 11.80it/s]
Train Loss: 0.5807 | Val Loss: 0.5985 | Val Accuracy: 0.6888
Epoch 6
100%|
          | 40/40 [00:03<00:00, 11.90it/s]
Train Loss: 0.5604 | Val Loss: 0.5969 | Val Accuracy: 0.6892
Epoch 7
          | 40/40 [00:03<00:00, 10.50it/s]
100%
Train Loss: 0.5449 | Val Loss: 0.5871 | Val Accuracy: 0.7029
Epoch 8
100%|
          | 40/40 [00:03<00:00, 10.67it/s]
Train Loss: 0.5307 | Val Loss: 0.5874 | Val Accuracy: 0.7049
Epoch 9
100%|
          | 40/40 [00:03<00:00, 11.04it/s]
Train Loss: 0.5179 | Val Loss: 0.5884 | Val Accuracy: 0.7027
Epoch 10
100%|
          | 40/40 [00:03<00:00, 11.63it/s]
Train Loss: 0.5081 | Val Loss: 0.5862 | Val Accuracy: 0.7048
Epoch 11
100%|
          | 40/40 [00:03<00:00, 11.62it/s]
Train Loss: 0.4994 | Val Loss: 0.5897 | Val Accuracy: 0.7004
```

```
100%|
          | 40/40 [00:03<00:00, 11.63it/s]
Train Loss: 0.4887 | Val Loss: 0.5944 | Val Accuracy: 0.6973
Epoch 13
100%|
          | 40/40 [00:03<00:00, 10.15it/s]
Train Loss: 0.4780 | Val Loss: 0.5897 | Val Accuracy: 0.7045
Epoch 14
100%|
          | 40/40 [00:03<00:00, 11.29it/s]
Train Loss: 0.4708 | Val Loss: 0.5880 | Val Accuracy: 0.7074
Epoch 15
100%|
          | 40/40 [00:03<00:00, 10.94it/s]
Train Loss: 0.4586 | Val Loss: 0.5935 | Val Accuracy: 0.7046
 Training: 2Bi-LSTM
Epoch 1
          | 40/40 [00:04<00:00, 9.99it/s]
Train Loss: 0.6864 | Val Loss: 0.6753 | Val Accuracy: 0.5768
Epoch 2
100%|
          | 40/40 [00:04<00:00, 8.58it/s]
Train Loss: 0.6488 | Val Loss: 0.6379 | Val Accuracy: 0.6343
Epoch 3
100%|
          | 40/40 [00:03<00:00, 10.00it/s]
Train Loss: 0.6090 | Val Loss: 0.6099 | Val Accuracy: 0.6759
Epoch 4
100%|
          | 40/40 [00:04<00:00, 9.99it/s]
Train Loss: 0.5815 | Val Loss: 0.5999 | Val Accuracy: 0.6826
Epoch 5
          | 40/40 [00:04<00:00, 9.98it/s]
Train Loss: 0.5575 | Val Loss: 0.5942 | Val Accuracy: 0.6944
Epoch 6
       | 40/40 [00:04<00:00, 9.91it/s]
100%|
```

```
Train Loss: 0.5402 | Val Loss: 0.5970 | Val Accuracy: 0.6954
Epoch 7
100%|
          | 40/40 [00:03<00:00, 10.08it/s]
Train Loss: 0.5237 | Val Loss: 0.5968 | Val Accuracy: 0.6939
Epoch 8
100%|
          | 40/40 [00:03<00:00, 10.05it/s]
Train Loss: 0.5120 | Val Loss: 0.5969 | Val Accuracy: 0.6912
Epoch 9
100%|
          | 40/40 [00:03<00:00, 10.16it/s]
Train Loss: 0.4993 | Val Loss: 0.5945 | Val Accuracy: 0.7022
Epoch 10
100%|
          | 40/40 [00:04<00:00, 8.21it/s]
Train Loss: 0.4878 | Val Loss: 0.5910 | Val Accuracy: 0.7071
Epoch 11
          | 40/40 [00:04<00:00, 9.87it/s]
100%|
Train Loss: 0.4751 | Val Loss: 0.5944 | Val Accuracy: 0.7067
Epoch 12
100%|
          | 40/40 [00:03<00:00, 10.11it/s]
Train Loss: 0.4672 | Val Loss: 0.6014 | Val Accuracy: 0.6997
Epoch 13
          | 40/40 [00:04<00:00, 9.80it/s]
Train Loss: 0.4565 | Val Loss: 0.5989 | Val Accuracy: 0.7028
Epoch 14
          | 40/40 [00:04<00:00, 9.02it/s]
100%|
Train Loss: 0.4536 | Val Loss: 0.6015 | Val Accuracy: 0.7013
Epoch 15
100%|
          | 40/40 [00:05<00:00, 7.28it/s]
```

Train Loss: 0.4497 | Val Loss: 0.6036 | Val Accuracy: 0.7004

```
[206]: # Transpose results to match the table format in the assignment
       df_transposed_imdb = df_imdb_results.set_index("Model").T
       # Round accuracy to 2 decimals, format numbers
       df_display_imdb = pd.DataFrame({
           col: [
               f"{df_transposed_imdb.loc['Accuracy', col]:.2f}",
               f"{int(df_transposed_imdb.loc['Parameters', col]):,}",
               f"{df_transposed_imdb.loc['Time (sec)', col]:.2f}"
           ]
           for col in df transposed imdb.columns
       }, index=["Accuracy", "Parameters", "Time cost"])
       df_display_imdb
[206]:
                                1Bi-RNN
                                           2Bi-RNN
                                                                 1Bi-LSTM
                                                                            2Bi-LSTM
                        1RNN
                                                         1LSTM
       Accuracy
                       69.49
                                  69.72
                                             69.88
                                                         69.90
                                                                    70.46
                                                                               70.04
      Parameters 2,917,254 2,928,006 2,952,838 2,949,126 2,991,750
                                                                           3,091,078
       Time cost
                        3.76
                                   4.18
                                              4.92
                                                          3.98
                                                                     4.29
                                                                                5.06
      3.6.3 E
                  \Gamma.56 - \Sigma
         O
                                                           Bi-Directional
         • T LSTM
                                                  RNN,
         O
                                                              2Bi-LSTM).
         • A
                                                       1RNN
             - A
             - X
             - A
       \sum
                   1RNN
```