a02-fnn_solution

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1 Work done by pair of students

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2 Deep Learning: Assignment 2

[ ]:
```
# Define imports & defaults
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import DataLoader, Dataset

# import helper functions
import os
import sys

sys.path.append(os.getcwd())
from a02helper import *

DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
torch.manual_seed(0)  # ensure reproducibility
np.random.seed(0)
MAX_SEQ_LEN = 200
BATCH_SIZE = 32
```

2.1 Task 1: Datasets

[ ]:
```
import string
from torchtext.data import get_tokenizer

class ReviewsDataset(Dataset):
    def __init__(
        self,
        reviews_file="data/reviews_small.txt",
        labels_file="data/labels_small.txt",
        use_vocab=False,
```

```python
    ):
        """
        A dataset of movie reviews and their labels.

        Args:
            reviews_file: the reviews file
            labels_file:  the labels file
            use_vocab: if True, yield reviews in a numerical representation
        """
        # Load data from filesystem
        with open(reviews_file) as f:
            raw_reviews = f.readlines()

        with open(labels_file) as f:
            raw_labels = f.readlines()

        # Preprocessing and store (in memory)
        self._reviews = self._preprocess_reviews(raw_reviews)
        self._labels = self._preprocess_labels(raw_labels)

        # Build vocabulary
        self.vocab = None
        if use_vocab:
            from torchtext.vocab import build_vocab_from_iterator

            self.vocab = build_vocab_from_iterator(
                self._reviews, specials=["<pad>"]  # will get token id 0
            )

    def __len__(self):
        """Returns the length of the dataset."""
        # YOUR CODE HERE
        return len(self._reviews)


    def __getitem__(self, idx):
        """
        Returns a tuple of a preprocessed review and the corresponding label.␣
↪If the
        vocabulary is enabled, returns a numerical representation of the review.

        Args:
            idx: a single index
        Returns: a (review, label) tuple
        """
        # YOUR CODE HERE
        review, label = self._reviews[idx], self._labels[idx]
```

```python
        # If vocabulary is enabled, convert review to numerical representation
        if self.vocab is not None:
            review = [self.vocab[token] for token in review]

        return review, label



    def tokenize_review(self, review):
        tokenizer = get_tokenizer("basic_english")
        return tokenizer(review)

    def _preprocess_reviews(self, raw_reviews):
        """
        Applies two kinds of preprocessing:

        (i) Apply the "basic_english" tokenizer from the torchtext library to
        transform every review into a list of normalized tokens (cf.
        https://pytorch.org/text/stable/data_utils.html#get-tokenizer).


        (ii) Remove punctuation (cf.
        https://docs.python.org/3/library/string.html#string.punctuation).


        Returns: list of tokenized reviews
        """
        # YOUR CODE HERE

        tokenized_reviews = list(map(self.tokenize_review, raw_reviews))
        cleaned_reviews = [[token for token in review if token not in string.
 ↪punctuation] for review in tokenized_reviews]

        return cleaned_reviews


    def _preprocess_labels(self, raw_labels):
        """
        Transform raw labels into integers, where 1="positive" and 0 otherwise.

        Returns: list of labels
        """
        # YOUR CODE HERE
        preprocessed_labels = [1 if label.strip() == 'positive' else 0 for␣
 ↪label in raw_labels]
```

```
        return preprocessed_labels
        # Hint: You can remove leading and trailing whitespace from the raw␣
↪labels using
        # the strip() method.
```

[ ]:
```
# Test your code (without vocabulary).
dataset = ReviewsDataset()
print(dataset[0])

# Should yield:
# (['bromwell', 'high', 'is', 'a', 'cartoon', 'comedy', ... ], 1)
```

```
(['bromwell', 'high', 'is', 'a', 'cartoon', 'comedy', 'it', 'ran', 'at', 'the',
'same', 'time', 'as', 'some', 'other', 'programs', 'about', 'school', 'life',
'such', 'as', 'teachers', 'my', 'years', 'in', 'the', 'teaching', 'profession',
'lead', 'me', 'to', 'believe', 'that', 'bromwell', 'high', 's', 'satire', 'is',
'much', 'closer', 'to', 'reality', 'than', 'is', 'teachers', 'the', 'scramble',
'to', 'survive', 'financially', 'the', 'insightful', 'students', 'who', 'can',
'see', 'right', 'through', 'their', 'pathetic', 'teachers', 'pomp', 'the',
'pettiness', 'of', 'the', 'whole', 'situation', 'all', 'remind', 'me', 'of',
'the', 'schools', 'i', 'knew', 'and', 'their', 'students', 'when', 'i', 'saw',
'the', 'episode', 'in', 'which', 'a', 'student', 'repeatedly', 'tried', 'to',
'burn', 'down', 'the', 'school', 'i', 'immediately', 'recalled', 'at', 'high',
'a', 'classic', 'line', 'inspector', 'i', 'm', 'here', 'to', 'sack', 'one',
'of', 'your', 'teachers', 'student', 'welcome', 'to', 'bromwell', 'high', 'i',
'expect', 'that', 'many', 'adults', 'of', 'my', 'age', 'think', 'that',
'bromwell', 'high', 'is', 'far', 'fetched', 'what', 'a', 'pity', 'that', 'it',
'isn', 't'], 1)
```

[ ]:
```
# Test your code (with vocabulary).
dataset = ReviewsDataset(use_vocab=True)
print(dataset[0])

# Should yield:
# ([10661, 307, 6, 3, 1177, 202, 8,  ... ], 1)
```

```
([10661, 307, 6, 3, 1177, 202, 8, 2248, 33, 1, 168, 56, 15, 49, 85, 8902, 43,
422, 122, 140, 15, 3234, 59, 144, 9, 1, 5504, 6267, 454, 72, 5, 260, 12, 10661,
307, 13, 2060, 6, 73, 2780, 5, 692, 76, 6, 3234, 1, 29527, 5, 1730, 7117, 1,
6161, 1726, 36, 52, 68, 212, 143, 63, 1409, 3234, 17974, 1, 28056, 4, 1, 221,
758, 31, 2748, 72, 4, 1, 6311, 10, 731, 2, 63, 1726, 54, 10, 208, 1, 321, 9, 64,
3, 1601, 4042, 743, 5, 2853, 187, 1, 422, 10, 1254, 10116, 33, 307, 3, 380, 322,
6162, 10, 135, 136, 5, 10172, 30, 4, 134, 3234, 1601, 2545, 5, 10661, 307, 10,
529, 12, 113, 1841, 4, 59, 676, 103, 12, 10661, 307, 6, 227, 4163, 48, 3, 2201,
12, 8, 231, 21], 1)
```

2.2 Task 2: Data Loaders

[ ]:
```
# Split dataset into training, validation, and test subsets
dataset = ReviewsDataset(use_vocab=True)
train_set, val_set, test_set = torch.utils.data.random_split(
    dataset, [0.8, 0.1, 0.1], generator=torch.Generator().manual_seed(123)
)
```

2.2.1 Task 2a

[ ]:
```
# Example usage of a data loader
dataloader = DataLoader(
    val_set,  # a dataset
    1,  # desired batch size
    False,  # whether to randomly shuffle the dataset
    num_workers=0,  # number of workers that construct batches in parallel
)
```

[ ]:
```
# Let's print the first batch
batch = next(iter(dataloader))
print(batch)

# [[tensor([11]), tensor([6]), tensor([1]), ...], tensor([0])]
```

```
[[tensor([11]), tensor([6]), tensor([1]), tensor([1037]), tensor([6578]),
tensor([4]), tensor([10]), tensor([89]), tensor([120]), tensor([48]),
tensor([163]), tensor([47]), tensor([6]), tensor([27]), tensor([342]),
tensor([4]), tensor([2228]), tensor([140]), tensor([3]), tensor([186]),
tensor([1466]), tensor([1]), tensor([771]), tensor([26]), tensor([78]),
tensor([1459]), tensor([200]), tensor([1101]), tensor([1]), tensor([66]),
tensor([26]), tensor([78]), tensor([5199]), tensor([5]), tensor([2288]),
tensor([1]), tensor([7861]), tensor([6591]), tensor([2]), tensor([83]),
tensor([2446]), tensor([25]), tensor([1]), tensor([182]), tensor([2756]),
tensor([2520]), tensor([34]), tensor([1]), tensor([145]), tensor([8]),
tensor([13]), tensor([39]), tensor([290]), tensor([25]), tensor([252]),
tensor([14480]), tensor([32]), tensor([52]), tensor([497]), tensor([9]),
tensor([223]), tensor([1]), tensor([3254]), tensor([25]), tensor([937]),
tensor([2]), tensor([153]), tensor([568]), tensor([5]), tensor([91]),
tensor([2]), tensor([30]), tensor([388]), tensor([1110]), tensor([17]),
tensor([80]), tensor([62]), tensor([1]), tensor([119]), tensor([255]),
tensor([14]), tensor([34]), tensor([2632]), tensor([1539]), tensor([133]),
tensor([28]), tensor([6]), tensor([31]), tensor([56]), tensor([33]),
tensor([27]), tensor([119]), tensor([413]), tensor([1]), tensor([230]),
tensor([4]), tensor([1036]), tensor([17]), tensor([3]), tensor([738]),
tensor([552]), tensor([1305]), tensor([11189]), tensor([14923]), tensor([6]),
tensor([88]), tensor([203]), tensor([3]), tensor([50]), tensor([283]),
tensor([19]), tensor([1]), tensor([27078]), tensor([44]), tensor([683]),
tensor([8])], tensor([0])]
```

2.2.2 Task 2b

[ ]:
```
from torch.nn.utils.rnn import pad_sequence

def review_collate_fn(raw_batch):
    """Prepare batches of reviews from a review dataset.

    Args:
        raw_batch: collection of (review, label)-tuples from a ReviewDataset

    Returns: a tuple (review x token id tensor, label tensor) of sizes
    batch_size*MAX_SEQ_LEN and batch_size, respectively.

    """

    reviews = [item[0] for item in raw_batch]
    labels = [item[1] for item in raw_batch]

    cropped_reviews = [review[:MAX_SEQ_LEN] for review in reviews]


    padded_reviews = pad_sequence([torch.tensor(review) for review in␣
 ↪cropped_reviews], batch_first=True, padding_value=0)

    label_tensor = torch.tensor(labels)

    return padded_reviews, label_tensor
```

[ ]:
```
# Test your function
review_collate_fn([([1, 2, 3], 1), (torch.arange(MAX_SEQ_LEN * 2) + 1, 0)])

# Should yield:
# (tensor([[  1,   2,   3,   0,   0,  ..., 0 ],
#          [  1,   2,   3,   4,   5,  ..., 200 ]]),
#  tensor([1, 0]))
```

```
/var/folders/t3/h38q5w_d36ncdxty42rj79mr0000gn/T/ipykernel_24909/2946447728.py:2
0: UserWarning: To copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  padded_reviews = pad_sequence([torch.tensor(review) for review in
cropped_reviews], batch_first=True, padding_value=0)
```

[ ]:
```
(tensor([[  1,   2,   3,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
```

```
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0],
        [  1,    2,    3,    4,    5,    6,    7,    8,    9,   10,   11,   12,   13,   14,
          15,   16,   17,   18,   19,   20,   21,   22,   23,   24,   25,   26,   27,   28,
          29,   30,   31,   32,   33,   34,   35,   36,   37,   38,   39,   40,   41,   42,
          43,   44,   45,   46,   47,   48,   49,   50,   51,   52,   53,   54,   55,   56,
          57,   58,   59,   60,   61,   62,   63,   64,   65,   66,   67,   68,   69,   70,
          71,   72,   73,   74,   75,   76,   77,   78,   79,   80,   81,   82,   83,   84,
          85,   86,   87,   88,   89,   90,   91,   92,   93,   94,   95,   96,   97,   98,
          99,  100,  101,  102,  103,  104,  105,  106,  107,  108,  109,  110,  111,  112,
         113,  114,  115,  116,  117,  118,  119,  120,  121,  122,  123,  124,  125,  126,
         127,  128,  129,  130,  131,  132,  133,  134,  135,  136,  137,  138,  139,  140,
         141,  142,  143,  144,  145,  146,  147,  148,  149,  150,  151,  152,  153,  154,
         155,  156,  157,  158,  159,  160,  161,  162,  163,  164,  165,  166,  167,  168,
         169,  170,  171,  172,  173,  174,  175,  176,  177,  178,  179,  180,  181,  182,
         183,  184,  185,  186,  187,  188,  189,  190,  191,  192,  193,  194,  195,  196,
         197,  198,  199,  200]]),
 tensor([1, 0]))
```

[ ]:
```python
# Create the data loaders (with shuffling for training data -> randomization)
train_loader = DataLoader(train_set, BATCH_SIZE, True,␣
 ↪collate_fn=review_collate_fn)
val_loader = DataLoader(val_set, BATCH_SIZE, False,␣
 ↪collate_fn=review_collate_fn)
test_loader = DataLoader(test_set, BATCH_SIZE, False,␣
 ↪collate_fn=review_collate_fn)
```

[ ]:
```python
# Let's print the first batch
batch = next(iter(val_loader))
print(batch)



# (tensor([[   11,     6,     1,  ...,     0,     0,     0],
#          [   11,   170,  2220,  ...,     0,     0,     0],
#          [   48,     3, 30376,  ...,     0,     0,     0],
#          ...,
#          [  176,    56,    10,  ...,     0,     0,     0],
#          [  239,   534,  1404,  ...,    44,   120,     1],
```

```
#          [ 2954, 15576,      6,  ...,  2678,     65,      1]]),
#  tensor([0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0,␣
↪1,
#          0, 0, 0, 1, 1, 1, 0, 0]))
```

```
(tensor([[   11,     6,     1,  …,     0,     0,     0],
        [   11,   170,  2220,  …,     0,     0,     0],
        [   48,     3, 30376,  …,     0,     0,     0],
        …,
        [  176,    56,    10,  …,     0,     0,     0],
        [  239,   534,  1404,  …,    44,   120,     1],
        [ 2954, 15576,     6,  …,  2678,    65,     1]]), tensor([0, 1, 0, 1,
0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1,
        0, 0, 0, 1, 1, 1, 0, 0]))
```

2.3 Task 3: Recurrent Neural Networks

[ ]:
```
class SimpleLSTM(nn.Module):
    def __init__(
        self, vocab_size, embedding_dim, hidden_dim, num_layers=1,␣
↪cell_dropout=0.0
    ):
        """
        Initializes the model by setting up the layers.

        Args:
            vocab_size: number of unique words in the reviews
            embedding_dim: size of the embeddings
            hidden_dim: dimension of the LSTM output
            num_layers: number of LSTM layers
            cell_dropout: dropout applied between the LSTM layers
                          (provide to LSTM constructor as dropout argument)
        """
        super().__init__()

        self.num_layers = num_layers
        self.hidden_dim = hidden_dim

        # YOUR CODE HERE
        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        self.lstm = nn.LSTM(
            embedding_dim, hidden_dim, num_layers=num_layers,␣
↪dropout=cell_dropout, batch_first=True
        )

        self.fc = nn.Linear(hidden_dim, 1)
```

```python
        self.sigmoid = nn.Sigmoid()



    def forward(self, x):
        """
        Performs a forward pass of the model on some input and hidden state.

        Parameters
        ----------
        x: batch as a (batch_size, sequence_length) tensor

        Returns
        -------
        Probability of positive class and the last output of the LSTM.
        """
        # init hidden layer, which is needed for the LSTM
        hidden = self.init_hidden(len(x))

        # YOUR CODE HERE

        # Embedding layer
        embedded = self.embedding(x)

        # LSTM layer
        lstm_out, hidden = self.lstm(embedded, hidden)

        # Take the last output of the LSTM
        last_output = lstm_out[:, -1, :]

        # Linear layer
        logits = self.fc(last_output)

        # Sigmoid activation
        prob = self.sigmoid(logits)

        return prob, last_output

    def init_hidden(self, batch_size):
        """Initialize hidden states.

        Returns a tuple of two num_layers x batch_size x hidden_dim tensors␣
↪(one for
        initial cell states, one for initial hidden states) consisting of all␣
↪zeros.
        """
```

```
        # YOUR CODE HERE
        # Note: ensure that the returned tensors are located on DEVICE.
        weight = next(self.parameters()).data
        hidden = (
            weight.new(self.num_layers, batch_size, self.hidden_dim).zero_().
 ↪to(DEVICE),
            weight.new(self.num_layers, batch_size, self.hidden_dim).zero_().
 ↪to(DEVICE)
        )
        return hidden


# Test constructor
model = SimpleLSTM(50, 10, 32, 2, 0.1).to(DEVICE)
print(model)

# Should give:
# SimpleLSTM(
#   (embedding): Embedding(50, 10)
#   (lstm): LSTM(10, 32, num_layers=2, batch_first=True, dropout=0.1)
#   (fc): Linear(in_features=32, out_features=1, bias=True)
#   (sigmoid): Sigmoid()
# )
```

```
SimpleLSTM(
  (embedding): Embedding(50, 10)
  (lstm): LSTM(10, 32, num_layers=2, batch_first=True, dropout=0.1)
  (fc): Linear(in_features=32, out_features=1, bias=True)
  (sigmoid): Sigmoid()
)
```

[ ]:
```
# Test forward pass
model = SimpleLSTM(50, 10, 32, 2).to(DEVICE)
dummy_data = torch.arange(30, dtype=torch.int, device=DEVICE).reshape(3, 10)

# fix model parameters
for key in model.state_dict():
    model.state_dict()[key][:] = 0.1
probs, states = model(dummy_data)
print(probs)
print(states)


# tensor([[0.9643],
#         [0.9643],
#         [0.9643]], device='cuda:0 or cpu', grad_fn=<SigmoidBackward0>)
```

```
# tensor([[0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985],
#         [0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985],
#         [0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.
 ↪9985,
#          0.9985, 0.9985, 0.9985, 0.9985, 0.9985]], device='cuda:0 or cpu',
#        grad_fn=<SliceBackward0>)
```

```
tensor([[0.9643],
        [0.9643],
        [0.9643]], grad_fn=<SigmoidBackward0>)
tensor([[0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985],
        [0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985],
        [0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985, 0.9985,
         0.9985, 0.9985, 0.9985, 0.9985, 0.9985]], grad_fn=<SliceBackward0>)
```

2.3.1 Task 3d

[ ]:
```
@torch.no_grad()  # Disables autograd for this function
def reviews_eval(
    model, eval_loader, label="val", loss_fn=torch.nn.functional.
 ↪binary_cross_entropy
):
    model.to(DEVICE)
```

```
    model.eval()  # sets model to evaluation mode (e.g., relevant for dropout)

    total_correct = total_loss = 0
    for reviews, labels in eval_loader:
        reviews, labels = reviews.to(DEVICE), labels.to(DEVICE)

        # Forward pass: Compute the model's output, reshape it to a vector, and
        # then run the provided loss function.
        # YOUR CODE HERE

        # Receive model output (probabilities)
        output, _ = model(reviews)
        output = output.view(-1)

        # Compute loss
        loss = loss_fn(output, labels.float())

        # Eval stats: Add loss to total_loss and number of correct predictions␣
↪to
        # total_correct.
        # YOUR CODE HERE

        # Add loss to total_loss
        total_loss += loss.item()

        # Add number of correct predictions to total_correct
        total_correct += ((output > 0.5) == labels).sum().item()

    print(
        f"            "
        f"{label} accuracy: {total_correct / len(eval_loader.dataset):.4f}\t"
        f"{label} loss: {total_loss / len(eval_loader):.4f}"
    )
```

[ ]:
```
# Test your implementation
model = SimpleLSTM(len(dataset.vocab), 10, 10, 1, 0).to(DEVICE)
reviews_eval(model, val_loader)

# Should yield with different but similar numbers:
#             val accuracy: 0.5100        val loss: 0.6928
```

```
            val accuracy: 0.5225        val loss: 0.6926
```

2.3.2 Task 3e

[ ]:
```python
def reviews_train(
    model,
    train_loader,
    val_loader,
    lr=0.01,
    epochs=3,
    max_norm=5,
    loss_fn=torch.nn.functional.binary_cross_entropy,
):
    """
    Train a network on the review data

    Args:
        model: Initialized model
        train_loader: Dataloader for the training data
        val_loader: Dataloader for the validation data
        lr: learning rate
        epochs: number of epochs
        max_norm: max norm of gradients for gradient clipping
        loss_fn: Loss function
    """
    # Send the model's parameters to your accelerator (cuda or cpu)
    model = model.to(DEVICE)

    # Define optimizer for the parameters which require gradients (cf. Task 5)
    optimizer = torch.optim.Adam(
        [param for param in model.parameters() if param.requires_grad], lr=lr
    )

    # Let's go
    for epoch in range(epochs):
        total_correct = total_loss = 0
        for reviews, labels in train_loader:
            model.train()

            # Send batch to your accelerator
            reviews, labels = reviews.to(DEVICE), labels.to(DEVICE)

            # Forward pass: Compute the model's output, reshape it to a vector,␣
↪and then
            # run the provided loss function.
            output, _ = model(reviews)
            output = output.view(-1)
            loss = loss_fn(output, labels.float())
```

```python
            # Backward pass:
            # (i)   Compute the gradients wrt. the loss
            loss.backward()
            # (ii)  Clip the gradients using
            # https://pytorch.org/docs/stable/generated/torch.nn.utils.
 ↪clip_grad_norm_.html to max_norm
            torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm)
            # (iii) Run the optimizer
            optimizer.step()
            # (iv)  Clear all accumulated gradients
            optimizer.zero_grad()

            # Compute epoch statistics:
            # (i)  Add the loss of this batch to the total_loss
            total_loss += loss.item()
            # (ii) Add the number of correct predictions (max prob) to␣
 ↪total_correct
            total_correct += ((output > 0.5) == labels).sum().item()

        print(
            f"Epoch {epoch + 1:2}\t"
            f"train accuracy: {total_correct / len(train_loader.dataset):.4f}\t"
            f"train loss: {total_loss / len(train_loader):.4f}"
        )

        # now validate
        reviews_eval(model, val_loader, loss_fn=loss_fn)
```

[ ]:
```python
# Test your implementation
model = SimpleLSTM(len(dataset.vocab), 10, 10, 1).to(DEVICE)
reviews_train(model, train_loader, val_loader, epochs=5)

# Should yield something like (note: numbers have high variance over runs):
# Epoch  1        train accuracy: 0.4994        train loss: 0.6953
#             val accuracy: 0.4875        val loss: 0.6922
# Epoch  2        train accuracy: 0.5319        train loss: 0.6885
#             val accuracy: 0.5275        val loss: 0.6861
# Epoch  3        train accuracy: 0.6059        train loss: 0.6443
#             val accuracy: 0.5400        val loss: 0.6902
# Epoch  4        train accuracy: 0.6863        train loss: 0.5438
#             val accuracy: 0.5925        val loss: 0.7453
# Epoch  5        train accuracy: 0.8334        train loss: 0.3875
#             val accuracy: 0.7300        val loss: 0.6310
```

```
Epoch  1        train accuracy: 0.5116  train loss: 0.6935
            val accuracy: 0.4850        val loss: 0.6951
Epoch  2        train accuracy: 0.5503  train loss: 0.6814
            val accuracy: 0.5175        val loss: 0.7005
```

```
Epoch  3        train accuracy: 0.6034  train loss: 0.6346
            val accuracy: 0.5000        val loss: 0.7338
Epoch  4        train accuracy: 0.7141  train loss: 0.5344
            val accuracy: 0.6625        val loss: 0.6996
Epoch  5        train accuracy: 0.8216  train loss: 0.4115
            val accuracy: 0.6650        val loss: 0.7808
```

2.4 Task 4: Pre-trained Embeddings & Visualization

2.4.1 Task 4b

[ ]:
```
# Load Glove embeddings into a plain embedding layer.
vocab = dataset.vocab
glove_embeddings = nn.Embedding(len(vocab), 100, device=DEVICE)
reviews_load_embeddings(glove_embeddings, vocab.get_stoi())
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
```

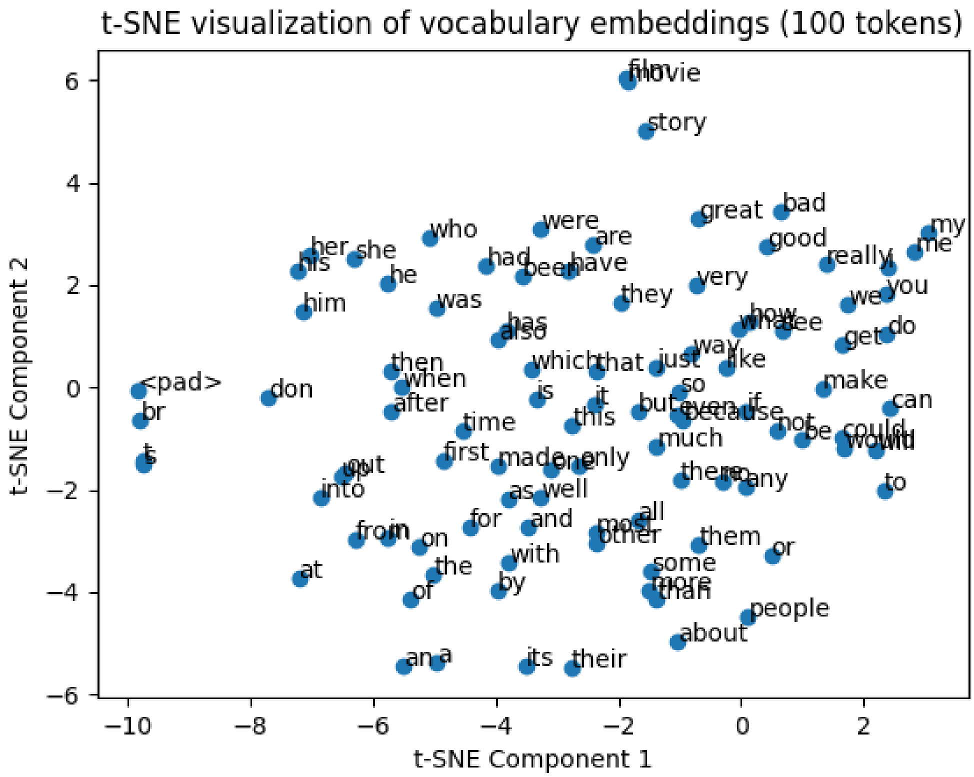
[ ]:
```
reviews_load_embeddings(glove_embeddings, vocab.get_stoi())
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
```

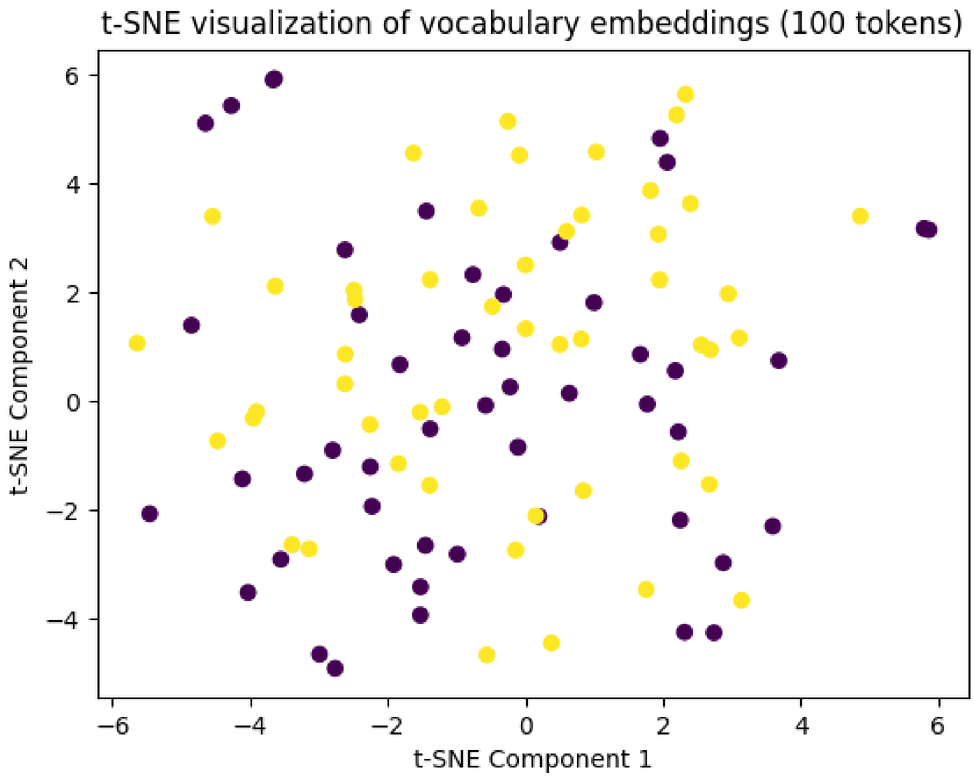
[ ]:
```
# Print one embedding
glove_embeddings(torch.tensor(vocab["movie"], device=DEVICE))
```

[ ]:
```
tensor([ 0.3825,  0.1482,  0.6060, -0.5153,  0.4399,  0.0611, -0.6272, -0.0254,
         0.1643, -0.2210,  0.1442, -0.3721, -0.2168, -0.0890,  0.0979,  0.6561,
         0.6446,  0.4770,  0.8385,  1.6486,  0.8892, -0.1181, -0.0125, -0.5208,
         0.7785,  0.4872, -0.0150, -0.1413, -0.3475, -0.2959,  0.1028,  0.5719,
        -0.0456,  0.0264,  0.5382,  0.3226,  0.4079, -0.0436, -0.1460, -0.4835,
         0.3204,  0.5509, -0.7626,  0.4327,  0.6175, -0.3650, -0.6060, -0.7962,
         0.3929, -0.2367, -0.3472, -0.6120,  0.5475,  0.9481,  0.2094, -2.7771,
        -0.6022,  0.8495,  1.2549,  0.0179, -0.0419,  2.1147, -0.0266, -0.2810,
         0.6812, -0.1417,  0.9925,  0.4988, -0.6754,  0.6417,  0.4230, -0.2791,
         0.0634,  0.6891, -0.3618,  0.0537, -0.1681,  0.1942, -0.4707, -0.1480,
        -0.5899, -0.2797,  0.1679,  0.1057, -1.7601,  0.0088, -0.8333, -0.5836,
        -0.3708, -0.5659,  0.2070,  0.0713,  0.0556, -0.2976, -0.0727, -0.2560,
         0.4269,  0.0589,  0.0911,  0.4728], grad_fn=<EmbeddingBackward0>)
```

[ ]:
```
# Plot embeddings of first 100 words using t-SNE
nextplot()
_ = tsne_vocab(glove_embeddings, torch.arange(100), vocab)
```



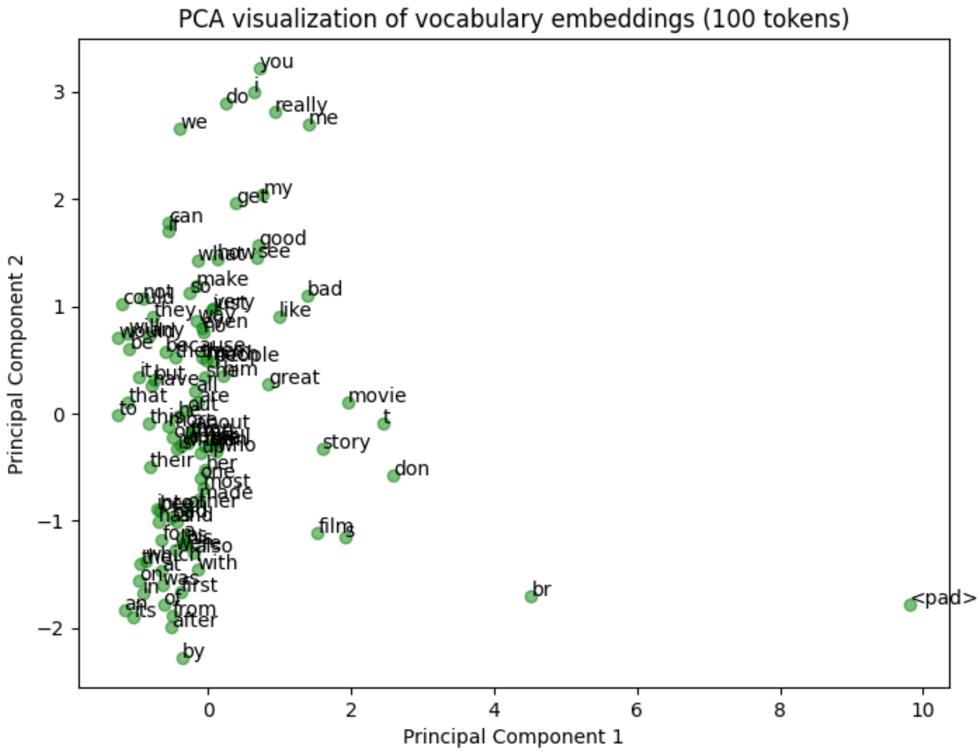

```
[ ]: # You can also specify colors and/or drop the item labels
nextplot()
_ = tsne_vocab(glove_embeddings, torch.arange(100), colors=[0] * 50 + [1] * 50)
```



2.4.2 Adding PCA

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

def PCA_embeddings(embeddings, tokens=None, vocab=None, colors=None,␣
↪n_components=2):
    """
    Visualize embeddings from an embedding module using PCA.

    Args:
        embeddings: embedding layer of the model
        tokens: limit to the provided embeddings (a tensor of indexes)
        vocab: a vocabulary to label dots in scatter plot with tokens
        colors: colors for each point in the scatter plot
        n_components: number of principal components to use for PCA
    """
    # Convert embeddings to numpy array
    embedding_matrix = embeddings.weight.data.numpy()[:100]
```

```
    if tokens is not None:
        embedding_matrix = embedding_matrix[tokens]
    else:
        tokens = torch.arange(len(embedding_matrix))

    # Perform PCA
    pca = PCA(n_components=n_components)
    principal_components = pca.fit_transform(embedding_matrix)

    # Plot PCA result
    plt.figure(figsize=(8, 6))
    plt.scatter(principal_components[:, 0], principal_components[:, 1],␣
 ↪c=colors, alpha=0.5)

    # Add token labels to points
    if vocab:
        for i in range(len(embedding_matrix)):
            plt.annotate(vocab.get_itos()[tokens[i]], (principal_components[i,␣
 ↪0], principal_components[i, 1]))

    plt.title(f'PCA visualization of vocabulary embeddings (100 tokens)')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.show()


PCA_embeddings(glove_embeddings, vocab=vocab, colors="green")
```



2.4.3 Task 4c

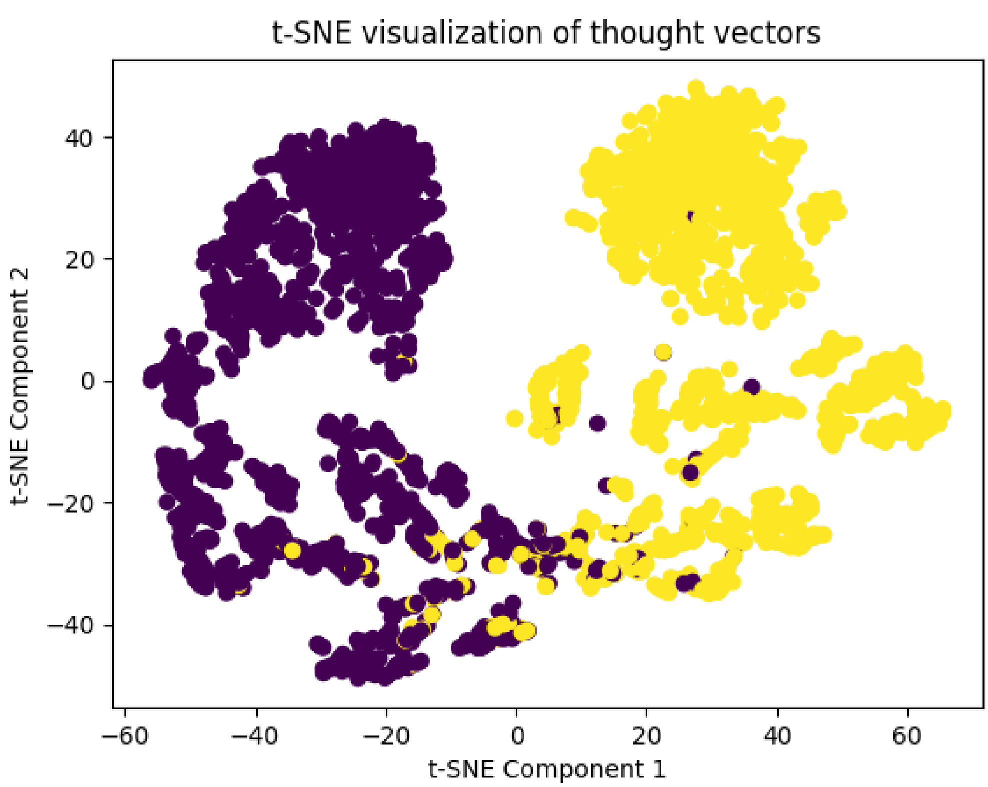
[ ]:
```
# hyperparameter settings for rest of task 4
vocab_size = len(dataset.vocab)
embedding_dim = 100
hidden_dim = 100
num_layers = 2
n_epochs = 10
cell_dropout = 0.0
```

[ ]:
```
# train a plain model
model = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪cell_dropout).to(
    DEVICE
)
reviews_train(model, train_loader, val_loader, epochs=n_epochs)

# Should reach a (train) accuracy of >0.9. If not, rerun.
```

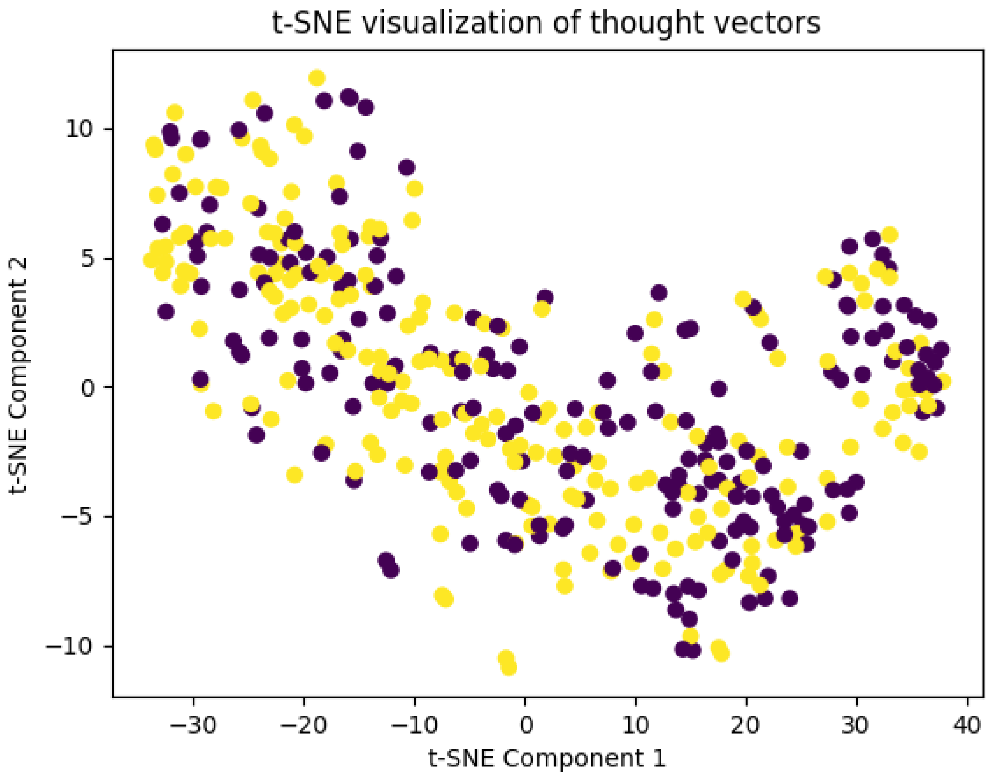
```
Epoch  1        train accuracy: 0.4841  train loss: 0.6972
            val accuracy: 0.5000        val loss: 0.6927
```

```
Epoch  2        train accuracy: 0.5537  train loss: 0.6813
            val accuracy: 0.4650        val loss: 0.7082
Epoch  3        train accuracy: 0.6194  train loss: 0.5905
            val accuracy: 0.5400        val loss: 0.7525
Epoch  4        train accuracy: 0.6759  train loss: 0.4895
            val accuracy: 0.5275        val loss: 0.8901
Epoch  5        train accuracy: 0.7666  train loss: 0.4141
            val accuracy: 0.5675        val loss: 1.0505
Epoch  6        train accuracy: 0.8378  train loss: 0.3466
            val accuracy: 0.5550        val loss: 1.1407
Epoch  7        train accuracy: 0.8819  train loss: 0.2769
            val accuracy: 0.5325        val loss: 1.3425
Epoch  8        train accuracy: 0.9119  train loss: 0.2207
            val accuracy: 0.5550        val loss: 1.3570
Epoch  9        train accuracy: 0.9297  train loss: 0.1852
            val accuracy: 0.5675        val loss: 1.1795
Epoch 10        train accuracy: 0.9475  train loss: 0.1463
            val accuracy: 0.5675        val loss: 1.5681
```

[ ]:
```
# Plot t-SNE embeddings of the thought vectors for training data
# point color = label
nextplot()
_ = tsne_thought(model, train_loader, DEVICE)
```



[ ]:
```
# Plot t-SNE embeddings of of the thought vectors for validation data
nextplot()
_ = tsne_thought(model, val_loader, DEVICE)
```



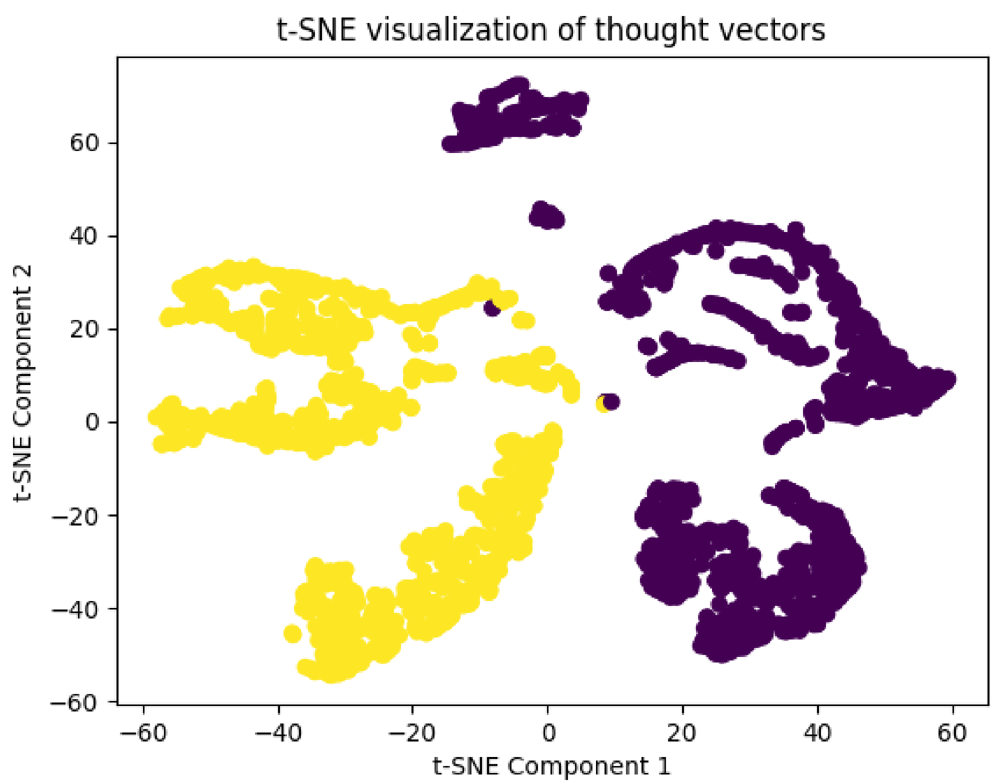
2.4.4 Task 4d

[ ]:
```
# Initialize the model with *p*re-trained embeddings with *f*inetuning, then␣
↪train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
↪cell_dropout)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

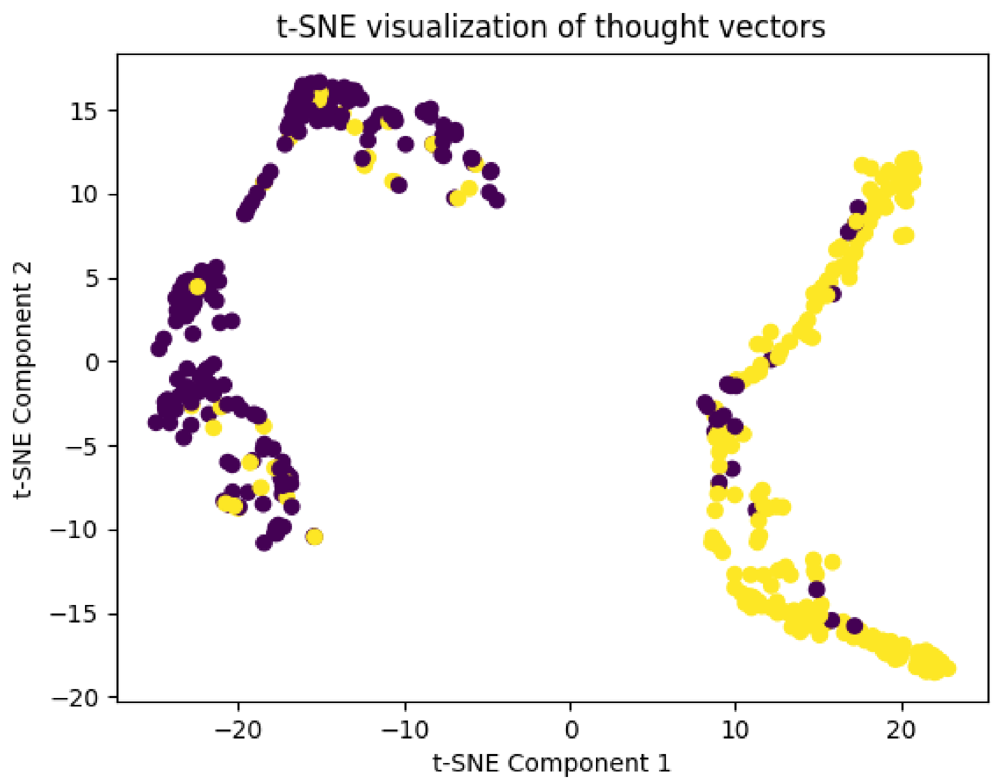
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4856  train loss: 0.6947
            val accuracy: 0.4900        val loss: 0.6933
Epoch  2        train accuracy: 0.5416  train loss: 0.6764
```

```
            val accuracy: 0.5300        val loss: 0.6979
Epoch  3        train accuracy: 0.7497  train loss: 0.4796
            val accuracy: 0.7050        val loss: 0.5697
Epoch  4        train accuracy: 0.8988  train loss: 0.2700
            val accuracy: 0.8100        val loss: 0.5045
Epoch  5        train accuracy: 0.9594  train loss: 0.1300
            val accuracy: 0.8375        val loss: 0.5846
Epoch  6        train accuracy: 0.9872  train loss: 0.0551
            val accuracy: 0.8075        val loss: 0.6754
Epoch  7        train accuracy: 0.9953  train loss: 0.0214
            val accuracy: 0.8250        val loss: 0.7818
Epoch  8        train accuracy: 0.9978  train loss: 0.0140
            val accuracy: 0.8150        val loss: 0.8342
Epoch  9        train accuracy: 0.9981  train loss: 0.0095
            val accuracy: 0.8225        val loss: 0.8304
Epoch 10        train accuracy: 0.9984  train loss: 0.0053
            val accuracy: 0.8100        val loss: 0.9343
```

[ ]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[ ]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



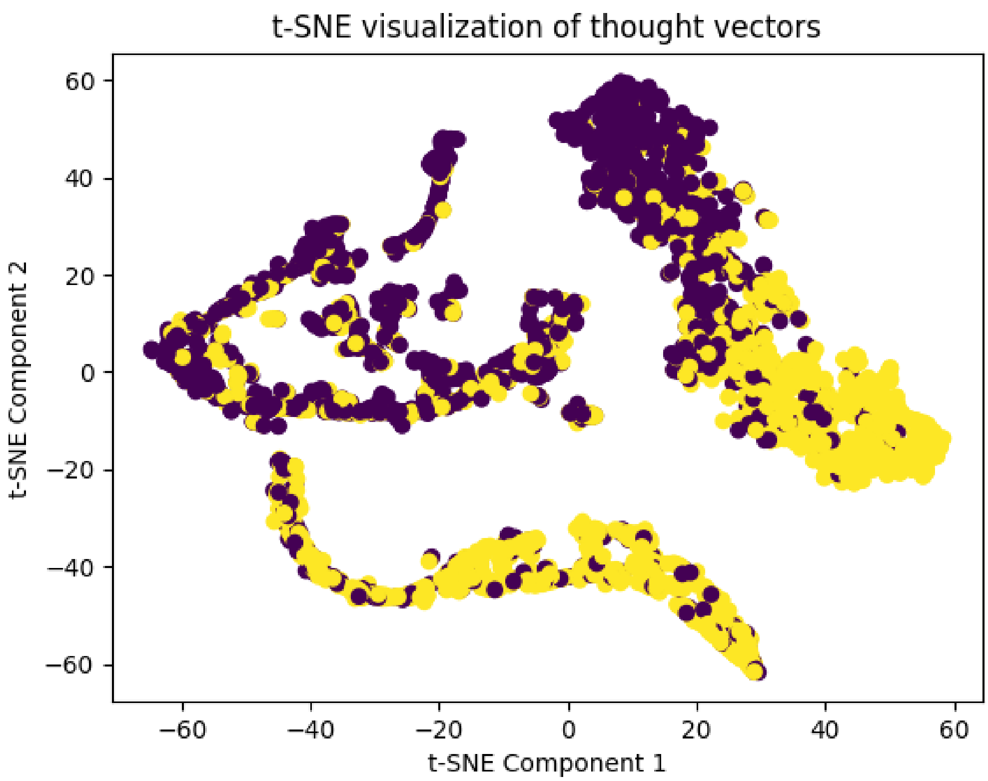
2.4.5 Task 4e

[ ]:
```
# Initialize the model with *p*re-trained embeddings without finetuning, then␣
 ↪train
model_p = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪cell_dropout)
reviews_load_embeddings(model_p.embedding, vocab.get_stoi())
model_p.embedding.weight.requires_grad = False
reviews_train(model_p, train_loader, val_loader, epochs=n_epochs)
```

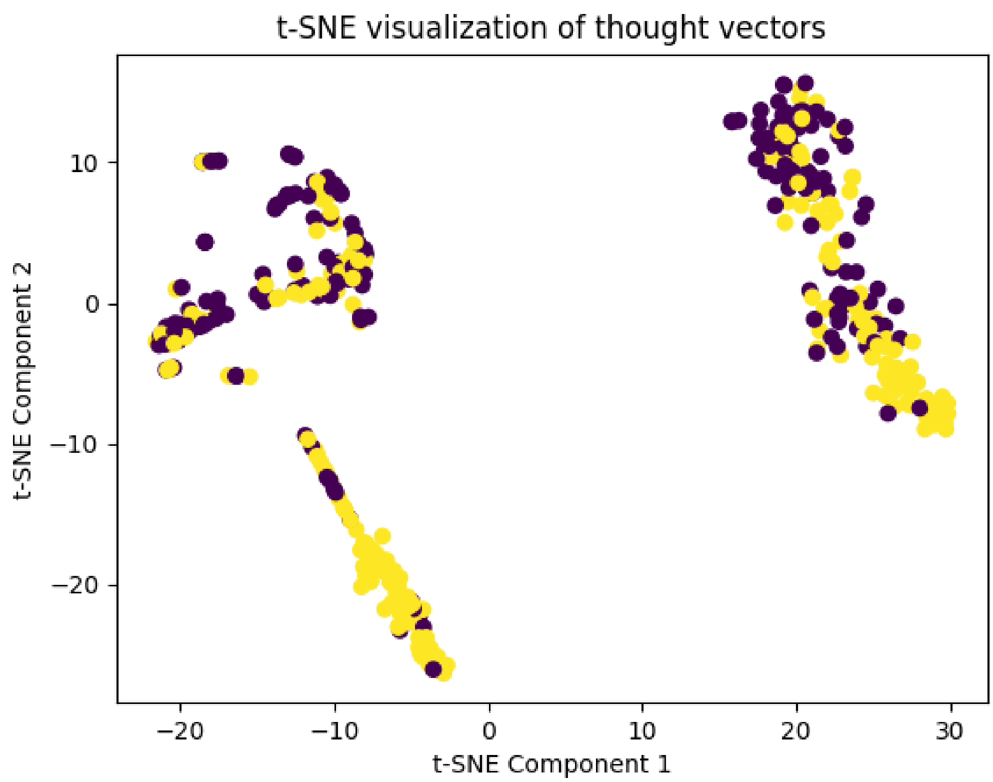
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4928  train loss: 0.6951
            val accuracy: 0.5125        val loss: 0.6931
Epoch  2        train accuracy: 0.5141  train loss: 0.6929
            val accuracy: 0.5200        val loss: 0.6919
Epoch  3        train accuracy: 0.5178  train loss: 0.6901
            val accuracy: 0.4850        val loss: 0.6932
```

```
Epoch  4        train accuracy: 0.5022  train loss: 0.6933
            val accuracy: 0.5175        val loss: 0.6928
Epoch  5        train accuracy: 0.5397  train loss: 0.6808
            val accuracy: 0.5175        val loss: 0.6922
Epoch  6        train accuracy: 0.5709  train loss: 0.6630
            val accuracy: 0.5425        val loss: 0.6798
Epoch  7        train accuracy: 0.5994  train loss: 0.6324
            val accuracy: 0.5225        val loss: 0.7071
Epoch  8        train accuracy: 0.7191  train loss: 0.5594
            val accuracy: 0.6525        val loss: 0.6325
Epoch  9        train accuracy: 0.7428  train loss: 0.5303
            val accuracy: 0.6750        val loss: 0.6083
Epoch 10        train accuracy: 0.7519  train loss: 0.5262
            val accuracy: 0.5825        val loss: 0.6507
```

[ ]:
```
nextplot()
_ = tsne_thought(model_p, train_loader, DEVICE)
```



[ ]:
```
nextplot()
_ = tsne_thought(model_p, val_loader, DEVICE)
```



2.5 Task 5: Exploration

2.5.1 Task 5a

Simple RNN class implementation

[ ]:
```
# YOUR CODE HERE
class SimpleRNN(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, num_layers=1,␣
 ↪cell_dropout=0.0, bidirectional=False, cell_type='lstm'):
        super().__init__()

        self.num_layers = num_layers
        self.hidden_dim = hidden_dim
        self.bidirectional = bidirectional
        self.cell_type = cell_type

        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        if self.cell_type == 'lstm':
```

```
            self.rnn = nn.LSTM(embedding_dim, hidden_dim,␣
↪num_layers=num_layers, dropout=cell_dropout, batch_first=True,␣
↪bidirectional=bidirectional)
        elif self.cell_type == 'gru':
            self.rnn = nn.GRU(embedding_dim, hidden_dim, num_layers=num_layers,␣
↪dropout=cell_dropout, batch_first=True, bidirectional=bidirectional)
        else:  # Elman
            self.rnn = nn.RNN(embedding_dim, hidden_dim, num_layers=num_layers,␣
↪dropout=cell_dropout, batch_first=True, bidirectional=bidirectional)

        self.fc = nn.Linear(hidden_dim * 2 if bidirectional else hidden_dim, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        hidden = self.init_hidden(len(x))

        embedded = self.embedding(x)
        rnn_out, hidden = self.rnn(embedded, hidden)
        last_output = rnn_out[:, -1, :]

        logits = self.fc(last_output)
        prob = self.sigmoid(logits)

        return prob, last_output

    def init_hidden(self, batch_size):
        weight = next(self.parameters()).data
        if self.cell_type == 'lstm':
            hidden = (
                weight.new(self.num_layers * (2 if self.bidirectional else 1),␣
↪batch_size, self.hidden_dim).zero_().to(DEVICE),
                weight.new(self.num_layers * (2 if self.bidirectional else 1),␣
↪batch_size, self.hidden_dim).zero_().to(DEVICE)
            )
        else:  # Elman RNN and GRU
            hidden = weight.new(self.num_layers * (2 if self.bidirectional else␣
↪1), batch_size, self.hidden_dim).zero_().to(DEVICE)
        return hidden
```

2.5.2 Train and evaluate the model

Simple RNN is trained and evaluated with the all possible combinations of the following parameters: - **Dropout**: 0, 0.8 - **RNN cell types**: Elman cell, GRU cell, LSTM cell - **Direction of RNN** : unidirectional, bidirectional.

[ ]:
```
# Dropout values
dropout_values = [0, 0.8]
```

```
# Cell types
cell_types = ['rnn', 'gru', 'lstm']

# Bidirectional values
bidirectional_values = [False, True]

for dropout in dropout_values:
    for cell_type in cell_types:
        for bidirectional in bidirectional_values:
            print(f"Training model with dropout={dropout},␣
↪cell_type={cell_type}, bidirectional={str(bidirectional)}")
            model = SimpleRNN(vocab_size, embedding_dim, hidden_dim,␣
↪num_layers, dropout, bidirectional, cell_type)
            reviews_load_embeddings(model.embedding, vocab.get_stoi())
            reviews_train(model, train_loader, val_loader, epochs=n_epochs)
```

```
Training model with dropout=0, cell_type=rnn, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5009  train loss: 0.7070
            val accuracy: 0.4900        val loss: 0.6977
Epoch  2        train accuracy: 0.5103  train loss: 0.7074
            val accuracy: 0.5225        val loss: 0.7022
Epoch  3        train accuracy: 0.5169  train loss: 0.7050
            val accuracy: 0.5175        val loss: 0.7030
Epoch  4        train accuracy: 0.5487  train loss: 0.6772
            val accuracy: 0.5300        val loss: 0.7158
Epoch  5        train accuracy: 0.6028  train loss: 0.6299
            val accuracy: 0.4775        val loss: 0.7776
Epoch  6        train accuracy: 0.6278  train loss: 0.5906
            val accuracy: 0.5075        val loss: 0.7360
Epoch  7        train accuracy: 0.6494  train loss: 0.5582
            val accuracy: 0.5400        val loss: 0.7344
Epoch  8        train accuracy: 0.6434  train loss: 0.5669
            val accuracy: 0.5425        val loss: 0.8228
Epoch  9        train accuracy: 0.6669  train loss: 0.5287
            val accuracy: 0.5375        val loss: 0.8146
Epoch 10        train accuracy: 0.6725  train loss: 0.5062
            val accuracy: 0.5000        val loss: 0.9907
Training model with dropout=0, cell_type=rnn, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4913  train loss: 0.7328
            val accuracy: 0.4900        val loss: 0.7192
Epoch  2        train accuracy: 0.5194  train loss: 0.7181
            val accuracy: 0.5025        val loss: 0.7603
```

```
Epoch  3        train accuracy: 0.5553  train loss: 0.6893
            val accuracy: 0.5100        val loss: 0.7046
Epoch  4        train accuracy: 0.5691  train loss: 0.6802
            val accuracy: 0.5100        val loss: 0.7298
Epoch  5        train accuracy: 0.5956  train loss: 0.6530
            val accuracy: 0.5350        val loss: 0.6974
Epoch  6        train accuracy: 0.5863  train loss: 0.6386
            val accuracy: 0.4950        val loss: 0.7366
Epoch  7        train accuracy: 0.6209  train loss: 0.6276
            val accuracy: 0.5275        val loss: 0.7529
Epoch  8        train accuracy: 0.6059  train loss: 0.6213
            val accuracy: 0.5150        val loss: 0.7597
Epoch  9        train accuracy: 0.6047  train loss: 0.6424
            val accuracy: 0.5275        val loss: 0.7577
Epoch 10        train accuracy: 0.6094  train loss: 0.6001
            val accuracy: 0.4775        val loss: 0.7557
Training model with dropout=0, cell_type=gru, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5828  train loss: 0.6696
            val accuracy: 0.7775        val loss: 0.4800
Epoch  2        train accuracy: 0.9053  train loss: 0.2511
            val accuracy: 0.8650        val loss: 0.2973
Epoch  3        train accuracy: 0.9944  train loss: 0.0242
            val accuracy: 0.8125        val loss: 0.7040
Epoch  4        train accuracy: 0.9984  train loss: 0.0058
            val accuracy: 0.8575        val loss: 0.6349
Epoch  5        train accuracy: 1.0000  train loss: 0.0003
            val accuracy: 0.8600        val loss: 0.7511
Epoch  6        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8600        val loss: 0.7970
Epoch  7        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8575        val loss: 0.8287
Epoch  8        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8575        val loss: 0.8556
Epoch  9        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8575        val loss: 0.8788
Epoch 10        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8575        val loss: 0.8993
Training model with dropout=0, cell_type=gru, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4988  train loss: 0.7147
            val accuracy: 0.4800        val loss: 0.7104
Epoch  2        train accuracy: 0.7197  train loss: 0.5031
            val accuracy: 0.8350        val loss: 0.4141
Epoch  3        train accuracy: 0.9681  train loss: 0.0965
            val accuracy: 0.8575        val loss: 0.4100
```

```
Epoch  4        train accuracy: 0.9969  train loss: 0.0125
            val accuracy: 0.8050        val loss: 0.6617
Epoch  5        train accuracy: 0.9991  train loss: 0.0019
            val accuracy: 0.8350        val loss: 0.9350
Epoch  6        train accuracy: 0.9997  train loss: 0.0005
            val accuracy: 0.8475        val loss: 0.8510
Epoch  7        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8550        val loss: 0.9483
Epoch  8        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8525        val loss: 0.9755
Epoch  9        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8525        val loss: 0.9997
Epoch 10        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8525        val loss: 1.0208
Training model with dropout=0, cell_type=lstm, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5012  train loss: 0.6943
            val accuracy: 0.5050        val loss: 0.6938
Epoch  2        train accuracy: 0.5337  train loss: 0.6898
            val accuracy: 0.4975        val loss: 0.6982
Epoch  3        train accuracy: 0.5934  train loss: 0.6467
            val accuracy: 0.5000        val loss: 0.7164
Epoch  4        train accuracy: 0.6931  train loss: 0.5581
            val accuracy: 0.7450        val loss: 0.5832
Epoch  5        train accuracy: 0.8628  train loss: 0.3542
            val accuracy: 0.7725        val loss: 0.5599
Epoch  6        train accuracy: 0.9534  train loss: 0.1525
            val accuracy: 0.7350        val loss: 0.7497
Epoch  7        train accuracy: 0.9791  train loss: 0.0654
            val accuracy: 0.7950        val loss: 0.6579
Epoch  8        train accuracy: 0.9906  train loss: 0.0383
            val accuracy: 0.7750        val loss: 0.7919
Epoch  9        train accuracy: 0.9950  train loss: 0.0209
            val accuracy: 0.7475        val loss: 0.8680
Epoch 10        train accuracy: 0.9947  train loss: 0.0131
            val accuracy: 0.7725        val loss: 0.9023
Training model with dropout=0, cell_type=lstm, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5006  train loss: 0.7016
            val accuracy: 0.4900        val loss: 0.6972
Epoch  2        train accuracy: 0.5181  train loss: 0.6920
            val accuracy: 0.4675        val loss: 0.7184
Epoch  3        train accuracy: 0.5559  train loss: 0.6782
            val accuracy: 0.5075        val loss: 0.7111
Epoch  4        train accuracy: 0.5750  train loss: 0.6254
            val accuracy: 0.5050        val loss: 0.7767
```

```
Epoch  5        train accuracy: 0.6016  train loss: 0.5927
            val accuracy: 0.4850        val loss: 0.8704
Epoch  6        train accuracy: 0.7056  train loss: 0.5238
            val accuracy: 0.5900        val loss: 0.9097
Epoch  7        train accuracy: 0.8125  train loss: 0.4097
            val accuracy: 0.6375        val loss: 0.7661
Epoch  8        train accuracy: 0.8878  train loss: 0.2655
            val accuracy: 0.7075        val loss: 0.7162
Epoch  9        train accuracy: 0.9494  train loss: 0.1424
            val accuracy: 0.7900        val loss: 0.6476
Epoch 10        train accuracy: 0.9812  train loss: 0.0601
            val accuracy: 0.7750        val loss: 0.8637
Training model with dropout=0.8, cell_type=rnn, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5141  train loss: 0.7134
            val accuracy: 0.4875        val loss: 0.7439
Epoch  2        train accuracy: 0.4791  train loss: 0.7135
            val accuracy: 0.5125        val loss: 0.7524
Epoch  3        train accuracy: 0.4891  train loss: 0.7167
            val accuracy: 0.5275        val loss: 0.6945
Epoch  4        train accuracy: 0.4947  train loss: 0.7103
            val accuracy: 0.5225        val loss: 0.6971
Epoch  5        train accuracy: 0.4844  train loss: 0.7118
            val accuracy: 0.5200        val loss: 0.6984
Epoch  6        train accuracy: 0.5081  train loss: 0.7048
            val accuracy: 0.5125        val loss: 0.7070
Epoch  7        train accuracy: 0.4859  train loss: 0.7154
            val accuracy: 0.5200        val loss: 0.7059
Epoch  8        train accuracy: 0.5234  train loss: 0.7087
            val accuracy: 0.4875        val loss: 0.7109
Epoch  9        train accuracy: 0.4856  train loss: 0.7153
            val accuracy: 0.5225        val loss: 0.6923
Epoch 10        train accuracy: 0.5022  train loss: 0.7036
            val accuracy: 0.5225        val loss: 0.6941
Training model with dropout=0.8, cell_type=rnn, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5050  train loss: 0.7461
            val accuracy: 0.4925        val loss: 0.7155
Epoch  2        train accuracy: 0.5081  train loss: 0.7196
            val accuracy: 0.4925        val loss: 0.7532
Epoch  3        train accuracy: 0.4941  train loss: 0.7296
            val accuracy: 0.5200        val loss: 0.8333
Epoch  4        train accuracy: 0.5288  train loss: 0.7074
            val accuracy: 0.4950        val loss: 0.7150
Epoch  5        train accuracy: 0.5553  train loss: 0.6820
            val accuracy: 0.5325        val loss: 0.7119
```

```
Epoch  6        train accuracy: 0.5925  train loss: 0.6562
            val accuracy: 0.5000        val loss: 0.7358
Epoch  7        train accuracy: 0.6062  train loss: 0.6292
            val accuracy: 0.5100        val loss: 0.8313
Epoch  8        train accuracy: 0.6034  train loss: 0.6463
            val accuracy: 0.5275        val loss: 0.8154
Epoch  9        train accuracy: 0.5984  train loss: 0.6204
            val accuracy: 0.5250        val loss: 0.7760
Epoch 10        train accuracy: 0.6069  train loss: 0.6278
            val accuracy: 0.4925        val loss: 0.7899
Training model with dropout=0.8, cell_type=gru, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5031  train loss: 0.7122
            val accuracy: 0.4825        val loss: 0.7708
Epoch  2        train accuracy: 0.6175  train loss: 0.6262
            val accuracy: 0.8000        val loss: 0.4122
Epoch  3        train accuracy: 0.9303  train loss: 0.1884
            val accuracy: 0.8600        val loss: 0.3518
Epoch  4        train accuracy: 0.9847  train loss: 0.0484
            val accuracy: 0.8300        val loss: 0.4822
Epoch  5        train accuracy: 0.9947  train loss: 0.0174
            val accuracy: 0.8450        val loss: 0.5877
Epoch  6        train accuracy: 0.9972  train loss: 0.0099
            val accuracy: 0.8575        val loss: 0.6636
Epoch  7        train accuracy: 0.9984  train loss: 0.0029
            val accuracy: 0.8325        val loss: 1.0184
Epoch  8        train accuracy: 0.9978  train loss: 0.0054
            val accuracy: 0.8550        val loss: 0.8904
Epoch  9        train accuracy: 0.9931  train loss: 0.0206
            val accuracy: 0.8450        val loss: 0.8110
Epoch 10        train accuracy: 0.9956  train loss: 0.0136
            val accuracy: 0.8475        val loss: 0.7808
Training model with dropout=0.8, cell_type=gru, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5056  train loss: 0.7162
            val accuracy: 0.4900        val loss: 0.7042
Epoch  2        train accuracy: 0.5309  train loss: 0.7044
            val accuracy: 0.5800        val loss: 0.6540
Epoch  3        train accuracy: 0.8516  train loss: 0.3546
            val accuracy: 0.8075        val loss: 0.4432
Epoch  4        train accuracy: 0.9781  train loss: 0.0676
            val accuracy: 0.8550        val loss: 0.3666
Epoch  5        train accuracy: 0.9925  train loss: 0.0308
            val accuracy: 0.8725        val loss: 0.4024
Epoch  6        train accuracy: 0.9950  train loss: 0.0179
            val accuracy: 0.8650        val loss: 0.4109
```

```
Epoch  7        train accuracy: 0.9953  train loss: 0.0220
            val accuracy: 0.8875        val loss: 0.3903
Epoch  8        train accuracy: 0.9962  train loss: 0.0132
            val accuracy: 0.8825        val loss: 0.3867
Epoch  9        train accuracy: 0.9969  train loss: 0.0115
            val accuracy: 0.8825        val loss: 0.4477
Epoch 10        train accuracy: 0.9969  train loss: 0.0098
            val accuracy: 0.8875        val loss: 0.5010
Training model with dropout=0.8, cell_type=lstm, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5000  train loss: 0.6980
            val accuracy: 0.4950        val loss: 0.6956
Epoch  2        train accuracy: 0.4894  train loss: 0.6950
            val accuracy: 0.5200        val loss: 0.6935
Epoch  3        train accuracy: 0.5047  train loss: 0.6944
            val accuracy: 0.4900        val loss: 0.6941
Epoch  4        train accuracy: 0.5138  train loss: 0.6939
            val accuracy: 0.4900        val loss: 0.6954
Epoch  5        train accuracy: 0.4959  train loss: 0.6949
            val accuracy: 0.4800        val loss: 0.6950
Epoch  6        train accuracy: 0.5084  train loss: 0.6953
            val accuracy: 0.5000        val loss: 0.6964
Epoch  7        train accuracy: 0.5503  train loss: 0.6843
            val accuracy: 0.5075        val loss: 0.7025
Epoch  8        train accuracy: 0.5906  train loss: 0.6552
            val accuracy: 0.5650        val loss: 0.6960
Epoch  9        train accuracy: 0.6228  train loss: 0.6114
            val accuracy: 0.5850        val loss: 0.7594
Epoch 10        train accuracy: 0.6416  train loss: 0.5660
            val accuracy: 0.5275        val loss: 0.8274
Training model with dropout=0.8, cell_type=lstm, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5066  train loss: 0.6989
            val accuracy: 0.4950        val loss: 0.6955
Epoch  2        train accuracy: 0.5050  train loss: 0.6947
            val accuracy: 0.5025        val loss: 0.6965
Epoch  3        train accuracy: 0.5309  train loss: 0.6899
            val accuracy: 0.5600        val loss: 0.6840
Epoch  4        train accuracy: 0.5856  train loss: 0.6422
            val accuracy: 0.4875        val loss: 0.7429
Epoch  5        train accuracy: 0.6234  train loss: 0.6057
            val accuracy: 0.5400        val loss: 0.7843
Epoch  6        train accuracy: 0.6575  train loss: 0.5550
            val accuracy: 0.5625        val loss: 0.7665
Epoch  7        train accuracy: 0.7472  train loss: 0.4787
            val accuracy: 0.5800        val loss: 0.7580
```

```
Epoch  8        train accuracy: 0.7844  train loss: 0.4494
            val accuracy: 0.6875        val loss: 0.8497
Epoch  9        train accuracy: 0.8550  train loss: 0.3500
            val accuracy: 0.7375        val loss: 0.6093
Epoch 10        train accuracy: 0.8741  train loss: 0.3255
            val accuracy: 0.6350        val loss: 0.8643
```

Simple RNN is trained and evaluated with the all possible combinations of the following parameters: - **Dropout**: 0.4 - **RNN cell types**: Elman cell, GRU cell, LSTM cell - **Direction of RNN** : unidirectional, bidirectional.

[ ]:
```
# Dropout values
dropout_values = [0.4]

# Cell types
cell_types = ['rnn', 'gru', 'lstm']

# Bidirectional values
bidirectional_values = [False, True]

for dropout in dropout_values:
    for cell_type in cell_types:
        for bidirectional in bidirectional_values:
            print(f"Training model with dropout={dropout},␣
 ↪cell_type={cell_type}, bidirectional={str(bidirectional)}")
            model = SimpleRNN(vocab_size, embedding_dim, hidden_dim,␣
 ↪num_layers, dropout, bidirectional, cell_type)
            reviews_load_embeddings(model.embedding, vocab.get_stoi())
            reviews_train(model, train_loader, val_loader, epochs=n_epochs)
```

```
Training model with dropout=0.4, cell_type=rnn, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4884  train loss: 0.7157
            val accuracy: 0.5175        val loss: 0.6949
Epoch  2        train accuracy: 0.5044  train loss: 0.7055
            val accuracy: 0.4850        val loss: 0.7427
Epoch  3        train accuracy: 0.5044  train loss: 0.7066
            val accuracy: 0.5200        val loss: 0.6956
Epoch  4        train accuracy: 0.5012  train loss: 0.7095
            val accuracy: 0.4900        val loss: 0.6954
Epoch  5        train accuracy: 0.5269  train loss: 0.6979
            val accuracy: 0.5200        val loss: 0.7268
Epoch  6        train accuracy: 0.5875  train loss: 0.6570
            val accuracy: 0.5000        val loss: 0.7310
Epoch  7        train accuracy: 0.6378  train loss: 0.5750
            val accuracy: 0.5475        val loss: 0.8477
Epoch  8        train accuracy: 0.6663  train loss: 0.5276
```

```
            val accuracy: 0.5450       val loss: 0.7639
Epoch  9        train accuracy: 0.6847  train loss: 0.4862
            val accuracy: 0.5275       val loss: 0.9407
Epoch 10        train accuracy: 0.6891  train loss: 0.4663
            val accuracy: 0.5025       val loss: 0.9573
Training model with dropout=0.4, cell_type=rnn, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5009  train loss: 0.7402
            val accuracy: 0.5175       val loss: 0.6968
Epoch  2        train accuracy: 0.5319  train loss: 0.7139
            val accuracy: 0.5200       val loss: 0.7179
Epoch  3        train accuracy: 0.5500  train loss: 0.6861
            val accuracy: 0.4850       val loss: 0.7048
Epoch  4        train accuracy: 0.5887  train loss: 0.6619
            val accuracy: 0.5300       val loss: 0.7248
Epoch  5        train accuracy: 0.6181  train loss: 0.6547
            val accuracy: 0.4975       val loss: 0.7630
Epoch  6        train accuracy: 0.6275  train loss: 0.5774
            val accuracy: 0.4925       val loss: 0.8133
Epoch  7        train accuracy: 0.6516  train loss: 0.5712
            val accuracy: 0.4875       val loss: 0.8403
Epoch  8        train accuracy: 0.6647  train loss: 0.5330
            val accuracy: 0.5050       val loss: 0.8799
Epoch  9        train accuracy: 0.6597  train loss: 0.5203
            val accuracy: 0.4975       val loss: 0.9422
Epoch 10        train accuracy: 0.6809  train loss: 0.5035
            val accuracy: 0.4975       val loss: 0.9562
Training model with dropout=0.4, cell_type=gru, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5384  train loss: 0.6938
            val accuracy: 0.6375       val loss: 0.6885
Epoch  2        train accuracy: 0.8878  train loss: 0.2898
            val accuracy: 0.9050       val loss: 0.2916
Epoch  3        train accuracy: 0.9941  train loss: 0.0238
            val accuracy: 0.8825       val loss: 0.4388
Epoch  4        train accuracy: 0.9991  train loss: 0.0049
            val accuracy: 0.8800       val loss: 0.5274
Epoch  5        train accuracy: 1.0000  train loss: 0.0004
            val accuracy: 0.8575       val loss: 0.7591
Epoch  6        train accuracy: 0.9988  train loss: 0.0038
            val accuracy: 0.8525       val loss: 0.6040
Epoch  7        train accuracy: 0.9994  train loss: 0.0026
            val accuracy: 0.8650       val loss: 0.8175
Epoch  8        train accuracy: 0.9931  train loss: 0.0201
            val accuracy: 0.8575       val loss: 0.7603
Epoch  9        train accuracy: 0.9975  train loss: 0.0067
```

```
            val accuracy: 0.8475        val loss: 0.7740
Epoch 10        train accuracy: 0.9981  train loss: 0.0065
            val accuracy: 0.7950        val loss: 1.1038
Training model with dropout=0.4, cell_type=gru, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5784  train loss: 0.6623
            val accuracy: 0.7625        val loss: 0.4825
Epoch  2        train accuracy: 0.8956  train loss: 0.2631
            val accuracy: 0.8300        val loss: 0.3866
Epoch  3        train accuracy: 0.9891  train loss: 0.0357
            val accuracy: 0.8450        val loss: 0.6082
Epoch  4        train accuracy: 0.9981  train loss: 0.0051
            val accuracy: 0.8325        val loss: 0.8242
Epoch  5        train accuracy: 1.0000  train loss: 0.0004
            val accuracy: 0.8050        val loss: 1.1303
Epoch  6        train accuracy: 1.0000  train loss: 0.0002
            val accuracy: 0.8250        val loss: 1.0451
Epoch  7        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8250        val loss: 1.0813
Epoch  8        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8250        val loss: 1.1199
Epoch  9        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8275        val loss: 1.1513
Epoch 10        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8275        val loss: 1.1752
Training model with dropout=0.4, cell_type=lstm, bidirectional=False
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4844  train loss: 0.6967
            val accuracy: 0.4900        val loss: 0.6932
Epoch  2        train accuracy: 0.5062  train loss: 0.6936
            val accuracy: 0.4825        val loss: 0.6946
Epoch  3        train accuracy: 0.5522  train loss: 0.6791
            val accuracy: 0.4975        val loss: 0.7008
Epoch  4        train accuracy: 0.6166  train loss: 0.6082
            val accuracy: 0.5200        val loss: 0.7357
Epoch  5        train accuracy: 0.6803  train loss: 0.5060
            val accuracy: 0.7425        val loss: 0.7125
Epoch  6        train accuracy: 0.8625  train loss: 0.3316
            val accuracy: 0.7950        val loss: 0.6042
Epoch  7        train accuracy: 0.9394  train loss: 0.1897
            val accuracy: 0.8200        val loss: 0.6369
Epoch  8        train accuracy: 0.9709  train loss: 0.1035
            val accuracy: 0.8500        val loss: 0.6389
Epoch  9        train accuracy: 0.9825  train loss: 0.0706
            val accuracy: 0.8550        val loss: 0.7070
Epoch 10        train accuracy: 0.9897  train loss: 0.0469
```

```
            val accuracy: 0.8575        val loss: 0.6696
Training model with dropout=0.4, cell_type=lstm, bidirectional=True
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4991  train loss: 0.7016
            val accuracy: 0.4875        val loss: 0.6948
Epoch  2        train accuracy: 0.5409  train loss: 0.6872
            val accuracy: 0.4775        val loss: 0.6972
Epoch  3        train accuracy: 0.5922  train loss: 0.6517
            val accuracy: 0.4825        val loss: 0.7022
Epoch  4        train accuracy: 0.6069  train loss: 0.6123
            val accuracy: 0.5375        val loss: 0.8028
Epoch  5        train accuracy: 0.6706  train loss: 0.5238
            val accuracy: 0.7400        val loss: 0.6853
Epoch  6        train accuracy: 0.8803  train loss: 0.3100
            val accuracy: 0.8025        val loss: 0.6851
Epoch  7        train accuracy: 0.9375  train loss: 0.1797
            val accuracy: 0.7975        val loss: 0.5517
Epoch  8        train accuracy: 0.9728  train loss: 0.0963
            val accuracy: 0.7300        val loss: 0.9135
Epoch  9        train accuracy: 0.9803  train loss: 0.0744
            val accuracy: 0.8350        val loss: 0.6508
Epoch 10        train accuracy: 0.9912  train loss: 0.0353
            val accuracy: 0.8125        val loss: 0.6955
```

2.5.3 Task 5b

According to our research, the model with the highest performance (val accuracy: 0.9050, val loss: 0.2916) has the following parameters:

- **Dropout**: 0.4
- **RNN cell type**: GRU cell
- **Direction of RNN** : unidirectional

P.s. the highest performance has been reached on the 2nd Epoch of training process.

2.5.4 Optimization of the best model

Here we fix aforementioned parameters of the model and try to discover the best set of hyper parameters for it

[ ]:
```python
# hyperparameter settings
hidden_dims = [50, 100]
num_layers_values = [1, 2]
n_epochs_values = [5]

for hidden_dim in hidden_dims:
    for num_layers in num_layers_values:
        for n_epochs in n_epochs_values:
```

```
        print(f"Training model with hidden_dim={hidden_dim},␣
↪num_layers={num_layers}, n_epochs={n_epochs}")
        model = SimpleRNN(vocab_size, embedding_dim, hidden_dim,␣
↪num_layers, 0.4, False, 'gru')
        reviews_load_embeddings(model.embedding, vocab.get_stoi())
        reviews_train(model, train_loader, val_loader, epochs=n_epochs)
```

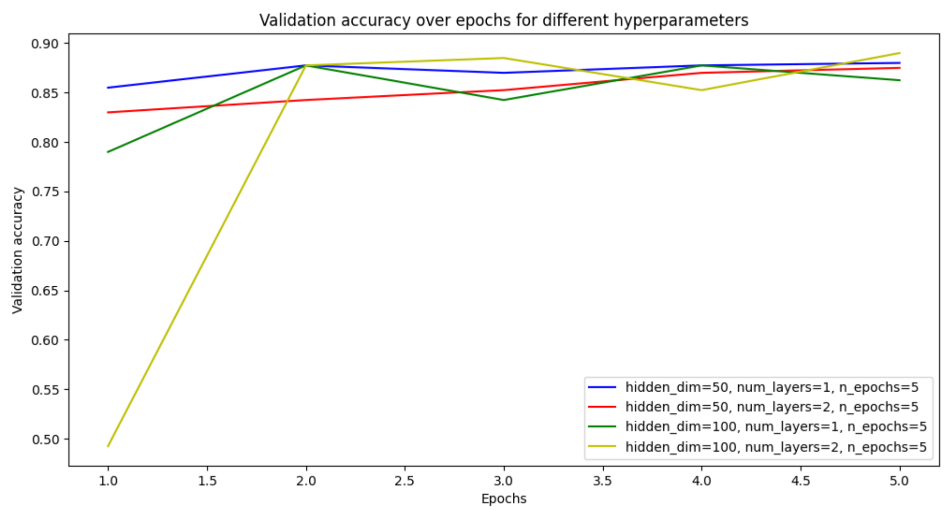
```
Training model with hidden_dim=50, num_layers=1, n_epochs=5
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.6428  train loss: 0.6044
            val accuracy: 0.8550        val loss: 0.3222
Epoch  2        train accuracy: 0.9519  train loss: 0.1377
            val accuracy: 0.8775        val loss: 0.3597
Epoch  3        train accuracy: 0.9981  train loss: 0.0090
            val accuracy: 0.8700        val loss: 0.5382
Epoch  4        train accuracy: 1.0000  train loss: 0.0016
            val accuracy: 0.8775        val loss: 0.5922
Epoch  5        train accuracy: 1.0000  train loss: 0.0008
            val accuracy: 0.8800        val loss: 0.6587
Training model with hidden_dim=50, num_layers=2, n_epochs=5
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5837  train loss: 0.6547
            val accuracy: 0.8300        val loss: 0.4110
Epoch  2        train accuracy: 0.9203  train loss: 0.2124
            val accuracy: 0.8425        val loss: 0.3869
Epoch  3        train accuracy: 0.9922  train loss: 0.0223
            val accuracy: 0.8525        val loss: 0.5517
Epoch  4        train accuracy: 0.9984  train loss: 0.0053
            val accuracy: 0.8700        val loss: 0.6525
Epoch  5        train accuracy: 1.0000  train loss: 0.0003
            val accuracy: 0.8750        val loss: 0.7324
Training model with hidden_dim=100, num_layers=1, n_epochs=5
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5600  train loss: 0.6861
            val accuracy: 0.7900        val loss: 0.5036
Epoch  2        train accuracy: 0.9103  train loss: 0.2391
            val accuracy: 0.8775        val loss: 0.3243
Epoch  3        train accuracy: 0.9888  train loss: 0.0382
            val accuracy: 0.8425        val loss: 0.5253
Epoch  4        train accuracy: 0.9984  train loss: 0.0102
            val accuracy: 0.8775        val loss: 0.4711
Epoch  5        train accuracy: 0.9997  train loss: 0.0030
            val accuracy: 0.8625        val loss: 0.5473
Training model with hidden_dim=100, num_layers=2, n_epochs=5
```

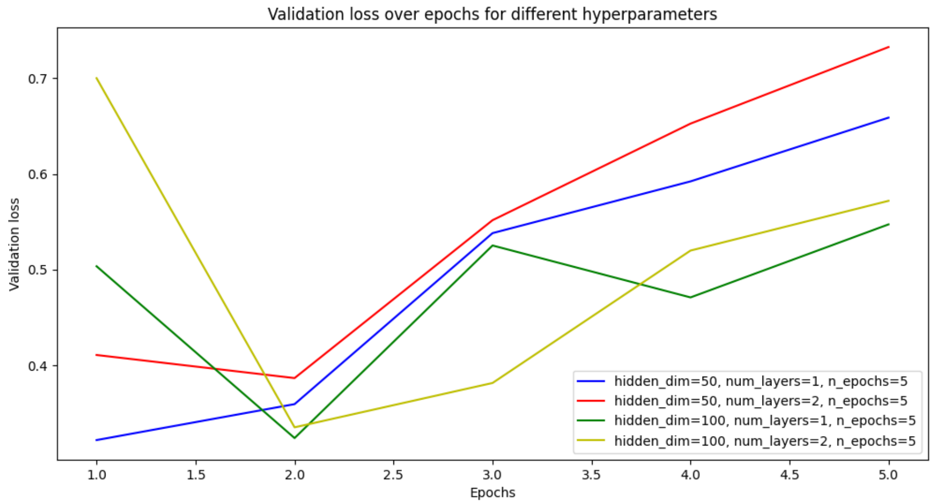
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5112  train loss: 0.7109
            val accuracy: 0.4925        val loss: 0.6999
Epoch  2        train accuracy: 0.7419  train loss: 0.4654
            val accuracy: 0.8775        val loss: 0.3355
Epoch  3        train accuracy: 0.9794  train loss: 0.0725
            val accuracy: 0.8850        val loss: 0.3818
Epoch  4        train accuracy: 0.9978  train loss: 0.0088
            val accuracy: 0.8525        val loss: 0.5200
Epoch  5        train accuracy: 1.0000  train loss: 0.0013
            val accuracy: 0.8900        val loss: 0.5719
```

Visualization of Model's Validation Accuracy and Loss Based on the Epoch Hyperparameter These visualizations reveal that the model achieves its peak validation accuracy and minimum validation loss during the second Epoch.

[ ]:
```
import matplotlib.pyplot as plt

# lists are returned from training function
# For simplicity, let's only consider validation accuracy here
val_accuracies_50_1_5 = [0.8550, 0.8775, 0.8700, 0.8775, 0.8800]
val_accuracies_50_2_5 = [0.8300, 0.8425, 0.8525, 0.8700, 0.8750]
val_accuracies_100_1_5 = [0.7900, 0.8775, 0.8425, 0.8775, 0.8625]
val_accuracies_100_2_5 = [0.4925, 0.8775, 0.8850, 0.8525, 0.8900]
epochs = range(1, len(val_accuracies_50_1_5) + 1)

# Plot validation accuracy
plt.figure(figsize=(12, 6))
plt.plot(epochs, val_accuracies_50_1_5, 'b', label='hidden_dim=50,␣
↪num_layers=1, n_epochs=5')
plt.plot(epochs, val_accuracies_50_2_5, 'r', label='hidden_dim=50,␣
↪num_layers=2, n_epochs=5')
plt.plot(epochs, val_accuracies_100_1_5, 'g', label='hidden_dim=100,␣
↪num_layers=1, n_epochs=5')
plt.plot(epochs, val_accuracies_100_2_5, 'y', label='hidden_dim=100,␣
↪num_layers=2, n_epochs=5')
plt.title('Validation accuracy over epochs for different hyperparameters')
plt.xlabel('Epochs')
plt.ylabel('Validation accuracy')
plt.legend()
plt.show()

# lists are returned from training function
val_losses_50_1_5 = [0.3222, 0.3597, 0.5382, 0.5922, 0.6587]
val_losses_50_2_5 = [0.4110, 0.3869, 0.5517, 0.6525, 0.7324]
val_losses_100_1_5 = [0.5036, 0.3243, 0.5253, 0.4711, 0.5473]
```

```
val_losses_100_2_5 = [0.6999, 0.3355, 0.3818, 0.5200, 0.5719]

# Plot validation loss
plt.figure(figsize=(12, 6))
plt.plot(epochs, val_losses_50_1_5, 'b', label='hidden_dim=50, num_layers=1,␣
  ↪n_epochs=5')
plt.plot(epochs, val_losses_50_2_5, 'r', label='hidden_dim=50, num_layers=2,␣
  ↪n_epochs=5')
plt.plot(epochs, val_losses_100_1_5, 'g', label='hidden_dim=100, num_layers=1,␣
  ↪n_epochs=5')
plt.plot(epochs, val_losses_100_2_5, 'y', label='hidden_dim=100, num_layers=2,␣
  ↪n_epochs=5')
plt.title('Validation loss over epochs for different hyperparameters')
plt.xlabel('Epochs')
plt.ylabel('Validation loss')
plt.legend()
plt.show()
```



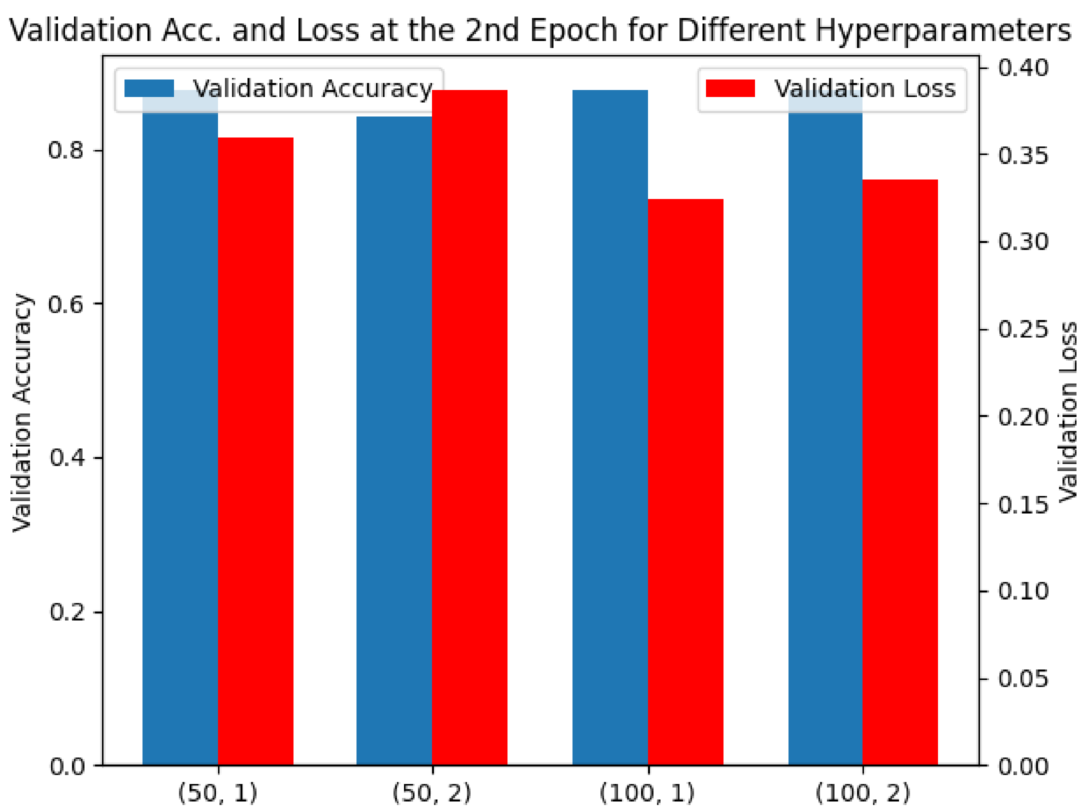


Visualization of Model's Validation Accuracy and Loss from the Second Epoch (Peak Performance) The plot reveals two optimal sets of hyperparameters:: 1. hidden_dim=100, num_layers=1: accuracy = 0.8775, loss = 0.3243 2. hidden_dim=100, num_layers=2: accuracy = 0.8775, loss = 0.3355

Given that the accuracy for both sets is identical, and the loss values are only marginally different, we need to consider other factors. We have a moderate n_epoch=2 value and a relatively high dropout=0.4 parameter, which introduces a higher level of regularization. Taking these into account, **we opt for the second set of hyperparameters (hidden_dim=100, num_layers=2)**. This choice enables the second layer of GRUs to detect more complex data patterns, counterbalancing the level of regularization introduced by the n_epoch and dropout hyperparameters.

[ ]:
```
import numpy as np

# Validation accuracy and loss at the second epoch for different hyperparameters
val_accuracies = [0.8775, 0.8425, 0.8775, 0.8775]
val_losses = [0.3597, 0.3869, 0.3243, 0.3355]
labels = ['(50, 1)', '(50, 2)', '(100, 1)', '(100, 2)']

x = np.arange(len(labels))  # the label locations
width = 0.35  # the width of the bars

fig, ax1 = plt.subplots()

# Plot validation accuracy
rects1 = ax1.bar(x - width/2, val_accuracies, width, label='Validation␣
 ↪Accuracy')
```

```
ax1.set_ylabel('Validation Accuracy')
ax1.set_title('Validation Acc. and Loss at the 2nd Epoch for Different␣
 ↪Hyperparameters')
ax1.set_xticks(x)
ax1.set_xticklabels(labels)
ax1.legend(loc='upper left')

ax2 = ax1.twinx()
# Plot validation loss
rects2 = ax2.bar(x + width/2, val_losses, width, label='Validation Loss',␣
 ↪color='r')
ax2.set_ylabel('Validation Loss')
ax2.legend(loc='upper right')

fig.tight_layout()
plt.show()
```



2.5.5 Evaluation of the optimized model

[ ]:
```
# Best hyperparameters
hidden_dim = 100
num_layers = 2
n_epochs = 2
dropout = 0.4
bidirectional = False
cell_type = 'gru'

print(f"Training model with hidden_dim={hidden_dim}, num_layers={num_layers},␣
↪n_epochs={n_epochs}")
model = SimpleRNN(vocab_size, embedding_dim, hidden_dim, num_layers, dropout,␣
↪bidirectional, cell_type)
reviews_load_embeddings(model.embedding, vocab.get_stoi())
reviews_train(model, train_loader, val_loader, epochs=n_epochs)

reviews_eval(model, test_loader, label="test")
```

```
Training model with hidden_dim=100, num_layers=2, n_epochs=2
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5900  train loss: 0.6332
            val accuracy: 0.8175        val loss: 0.4341
Epoch  2        train accuracy: 0.9353  train loss: 0.1697
            val accuracy: 0.8625        val loss: 0.3648
            test accuracy: 0.9025       test loss: 0.2814
```