a02

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[1]:
```
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```

1 Deep Learning: Assignment 2

[2]:
```
%matplotlib ipympl

# 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
```

```
Warning: Cannot change to a different GUI toolkit: notebook. Using ipympl
instead.
```

1.1 Task 1: Datasets

[3]:
```
import string
from torchtext.vocab import vocab
from torchtext.data import get_tokenizer
```

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

```
        """
        review = self._reviews[idx]
        label = self._labels[idx]
        if self.vocab is not None:
            #review_ids = self.vocab([token for token in review])
            review_ids = [self.vocab[token] for token in review if token in␣
↪self.vocab]
            return review_ids, label
        else:
            return review, label

    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
        """
        tokenizer = get_tokenizer("basic_english")
        punctuation = set(string.punctuation)

        processed_reviews = []
        for review in raw_reviews:
            processed_review = tokenizer(review.strip().lower())
            processed_review = [tok for tok in processed_review if tok not in␣
↪punctuation]
            processed_reviews.append(processed_review)
        return processed_reviews

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

        Returns: list of labels
        """
        # Hint: You can remove leading and trailing whitespace from the raw␣
↪labels using
        # the strip() method.
        preprocessed_labels_list = []
        for label in raw_labels:
            label = label.strip()
```

```python
            if label == "positive":
                preprocessed_labels_list.append(1)
            else:
                preprocessed_labels_list.append(0)
        return preprocessed_labels_list
```

[4]:
```python
# 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)
```

[5]:
```python
# 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)
```

1.2 Task 2: Data Loaders

[6]:
```python
# 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)
)
```

1.2.1 Task 2a

[7]:
```python
# 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
)
```

[8]:
```python
# 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])]
```

[9]:
```
print(len(val_set[0][0]))
print(len(val_set[1][0]))
print(len(val_set[2][0]))
```

```
116
158
131
```

[10]:
```
# explanation: for the Question 2a

# The current code in cell [7] treats each review (a row of input sequence␣
↪data) as an individual batch. This becomes problematic because reviews can␣
↪have different lengths. By default,
# PyTorch's DataLoader( ) expects all elements in a batch to be the same size.␣
↪When the batch size increases and we mix reviews of varying lengths, the␣
↪DataLoader( ) encounters errors.

# To overcome this challenge, we can define a maximum sequence length for the␣
↪input data. This essentially sets a cap on the length of each review. If a␣
↪review exceeds the limit, we can
# truncate it by keeping only the first words up to the maximum length.␣
↪Conversely, shorter reviews can be padded with a special token (like␣
↪"<PAD>", in our case we are using 0 instead of
# "<PAD>" based on the provided code setting within the ReviewDataset function)␣
↪to ensure all reviews within a batch have the same length without causing␣
↪error from DataLoader. This
# padding technique effectively increase the length of shorter reviews to match␣
↪the maximum, allowing the DataLoader to function smoothly.

# By defining a maximum sequence length and handling variable-length reviews␣
↪through truncation and padding, we ensure the DataLoader can efficiently␣
↪process batches of reviews during
# training.
```

1.2.2 Task 2b

[11]:
```
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, labels = zip(*raw_batch)
```

```python
    padded_reviews = torch.zeros(len(reviews), MAX_SEQ_LEN, dtype=torch.long)

    for i, review in enumerate (reviews):
        if len(review) <= MAX_SEQ_LEN:
            padded_reviews[i, :len(review)] = torch.tensor(review)
        else:
            padded_reviews[i, :] = torch.tensor(review[:MAX_SEQ_LEN])
    label_tensor = torch.tensor(labels, dtype=torch.long)
    return padded_reviews, label_tensor
```

[12]:
```python
# 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/2h/v65x911156j8d_r4wnykkqrw0000gn/T/ipykernel_3491/3521082536.py:18
: 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[i, :] = torch.tensor(review[:MAX_SEQ_LEN])
```

[12]:
```
(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]))
```

[13]:

```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)
```

[14]:

```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]))
```

1.3 Task 3: Recurrent Neural Networks

[15]:
```python
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
        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        self.cell_dropout = cell_dropout
        self.lstm = nn.LSTM(embedding_dim, hidden_dim, batch_first = True,␣
 ↪num_layers = num_layers, dropout = cell_dropout)
        self.fc = nn.Linear(hidden_dim, 1)
        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.
        """
        hidden = self.init_hidden(len(x))
        embeddings = self.embedding(x)
        outputs, (hidden_state, cell_state) = self.lstm(embeddings, hidden)
        thought_vector = hidden_state[-1, :, :]
        logits = self.fc(thought_vector)
        predictions = self.sigmoid(logits)
        return predictions, thought_vector
```

```python
    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.
        """
        # Note: ensure that the returned tensors are located on DEVICE.
        hidden = (torch.zeros(self.num_layers, batch_size, self.hidden_dim,␣
 ↪device = self.embedding.weight.device),
                  torch.zeros(self.num_layers, batch_size, self.hidden_dim,␣
 ↪device = self.embedding.weight.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()
)
```

[16]:
```python
# 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>)
```

1.3.1 Task 3d

[17]:
```
@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.
        prediction, _ = model(reviews)
        prediction = prediction.view(-1)
        loss = loss_fn(prediction, labels.float())

        # Eval stats: Add loss to total_loss and number of correct predictions␣
 ↪to
        # total_correct.
        total_loss = total_loss + loss.item()
        prediction_class = torch.round(prediction)
        correct = (prediction_class == labels).sum().item()
        total_correct = total_correct + correct

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

[18]:
```
# 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: 0.5375        val loss: 0.6925
```

1.3.2 Task 3e

[19]:
```
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.
            prediction, _ = model(reviews)
            prediction = prediction.view(-1)
            loss = loss_fn(prediction, labels.float())
```

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

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

        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)
```

[20]:
```
# 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: 0.5131  train loss: 0.6940
            val accuracy: 0.4800        val loss: 0.6956
Epoch  2        train accuracy: 0.5503  train loss: 0.6854
            val accuracy: 0.5650        val loss: 0.6881
Epoch  3        train accuracy: 0.5953  train loss: 0.6339
            val accuracy: 0.5475        val loss: 0.7067
Epoch  4        train accuracy: 0.6653  train loss: 0.5385
            val accuracy: 0.5225        val loss: 0.7984
Epoch  5        train accuracy: 0.7106  train loss: 0.4592
            val accuracy: 0.5975        val loss: 0.8588
```

1.4 Task 4: Pre-trained Embeddings & Visualization

1.4.1 Task 4b

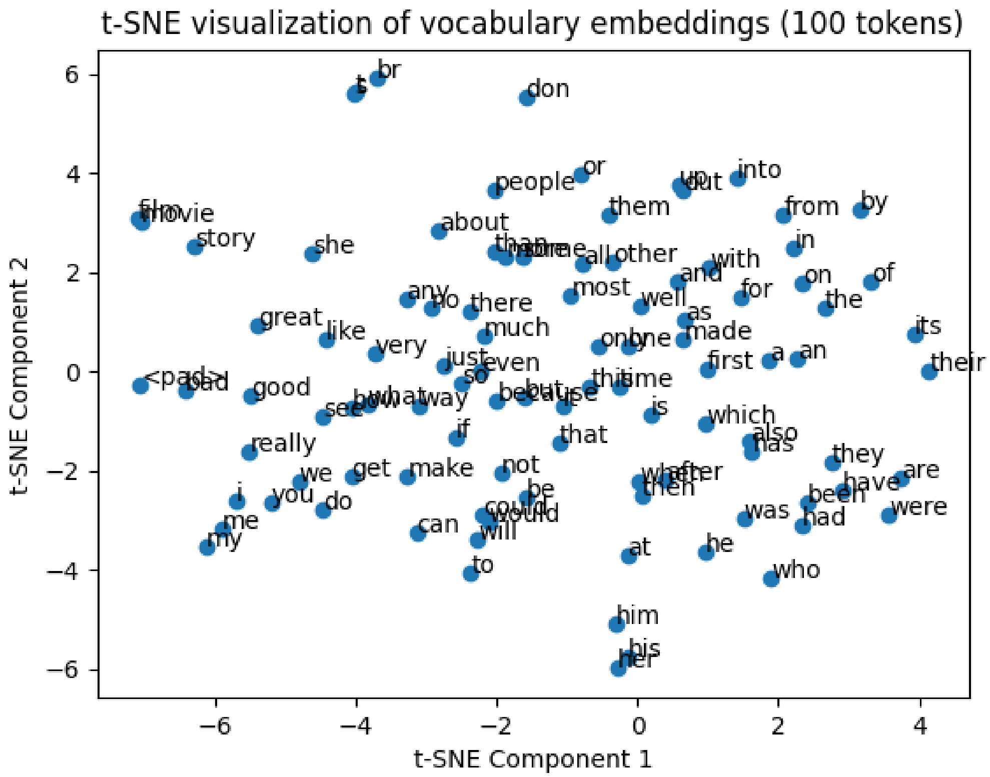
[21]:
```
# Load Glove embeddings into a plain embedding layer.
vocab = dataset.vocab
glove_embeddings = nn.Embedding(len(vocab), 100, device=DEVICE)
reviews_load_embeddings(glove_embeddings, vocab.get_stoi())
```

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

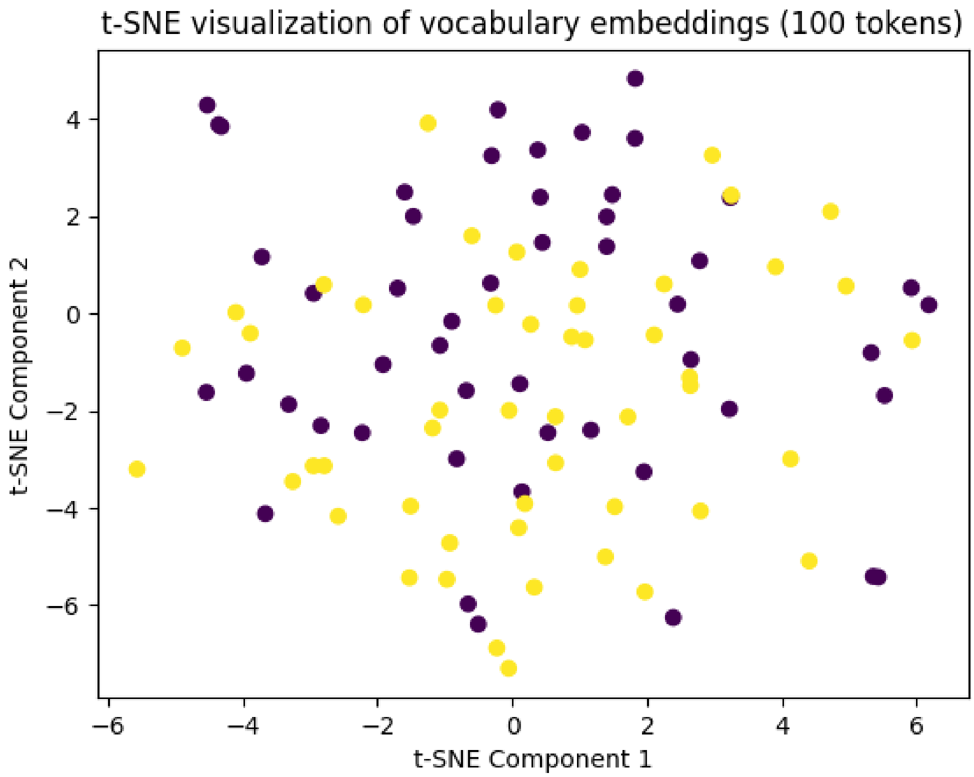
[22]:
```
# Print one embedding
glove_embeddings(torch.tensor(vocab["movie"], device=DEVICE))
```

[22]:
```
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>)
```

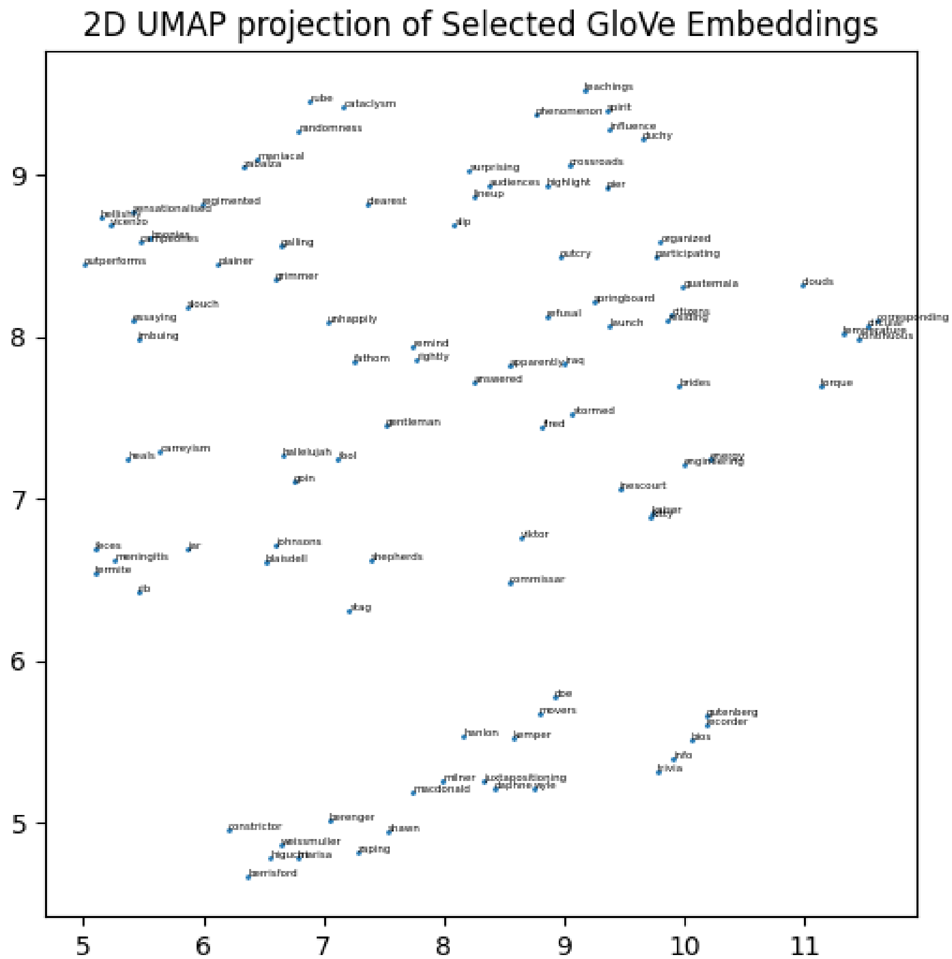
[23]:
```
# Plot embeddings of first 100 words using t-SNE
nextplot()
_ = tsne_vocab(glove_embeddings, torch.arange(100), vocab)
```




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



[25]:
```
import umap

embeddings = glove_embeddings.weight.detach().cpu().numpy()
indices = np.random.choice(range(len(vocab)), 100, replace=False)
selected_embeddings = embeddings[indices]
selected_words = [vocab.get_itos()[i] for i in indices]
reducer = umap.UMAP(n_neighbors=5, n_components=2, metric='cosine')
umap_embeddings = reducer.fit_transform(selected_embeddings)
plt.figure(figsize=(6, 6))

plt.scatter(umap_embeddings[:, 0], umap_embeddings[:, 1], s=1)
plt.title('2D UMAP projection of Selected GloVe Embeddings')
for i, word in enumerate(selected_words):
    plt.annotate(word, (umap_embeddings[i, 0], umap_embeddings[i, 1]),␣
 ↪fontsize=4)
plt.show()
```



1.4.2 Task 4c

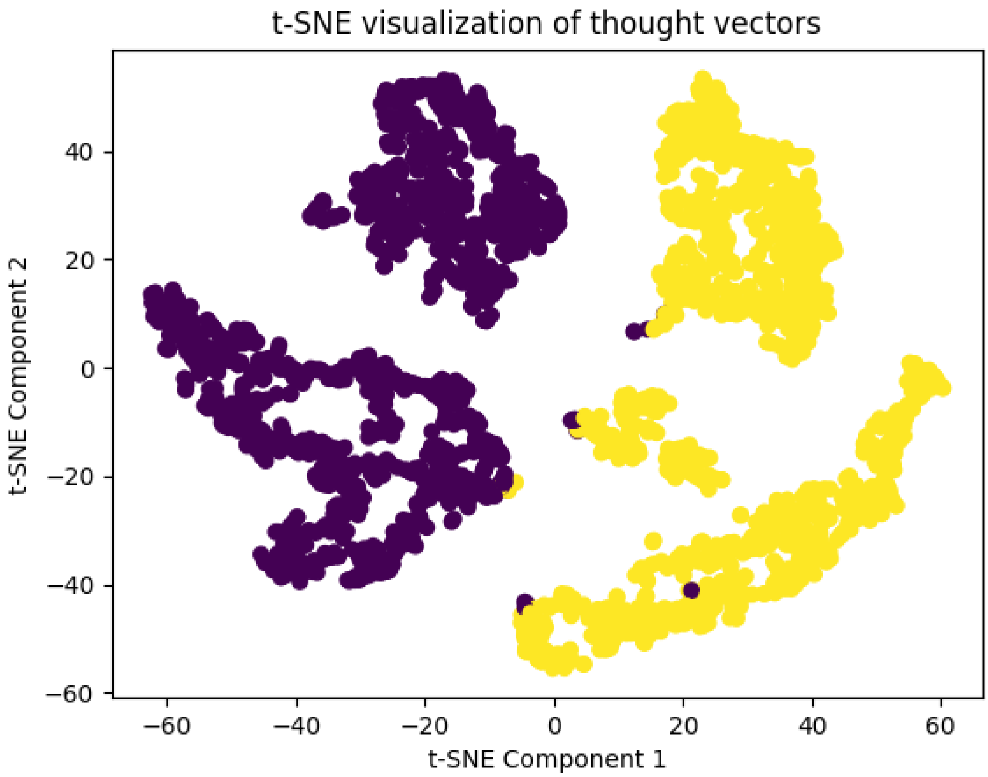
[26]:
```
# hyperparameter settings for rest of task 4
vocab_size = len(dataset.vocab)
embedding_dim = 100
hidden_dim = 100
num_layers = 2
n_epochs = 10
cell_dropout = 0.0
```

[27]:
```
# train a plain model
model = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
↪cell_dropout).to(
```

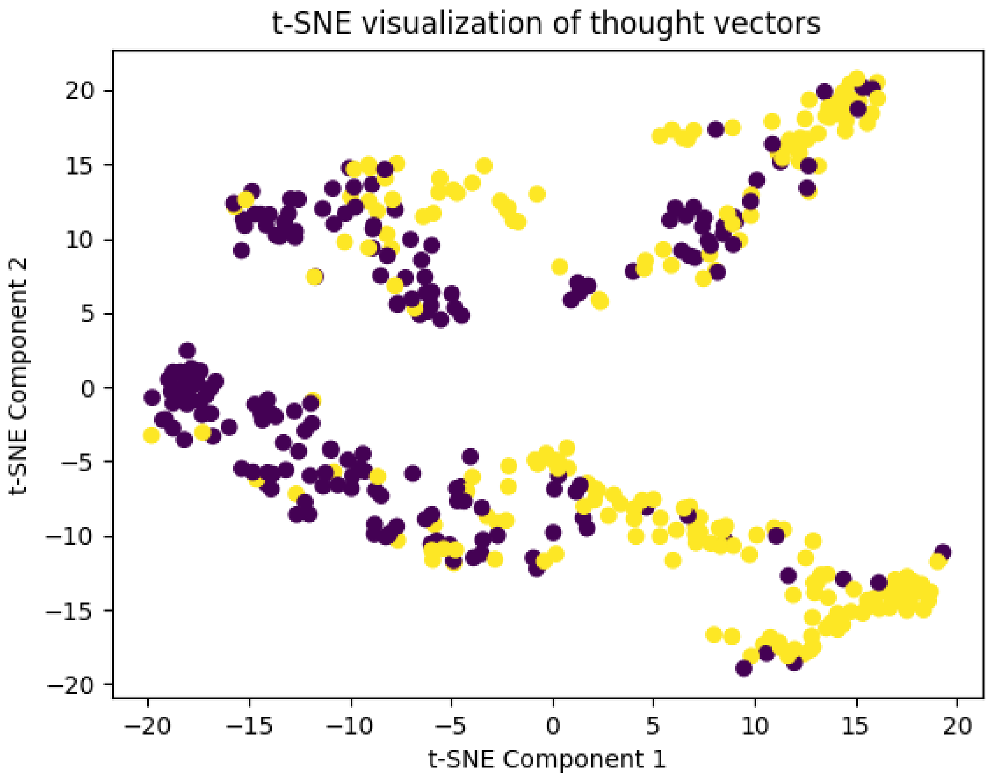
```
    DEVICE
)
reviews_train(model, train_loader, val_loader, epochs=n_epochs)

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

```
Epoch  1        train accuracy: 0.4928  train loss: 0.6999
            val accuracy: 0.4825        val loss: 0.6957
Epoch  2        train accuracy: 0.4928  train loss: 0.6938
            val accuracy: 0.4825        val loss: 0.6934
Epoch  3        train accuracy: 0.5106  train loss: 0.6929
            val accuracy: 0.4725        val loss: 0.6939
Epoch  4        train accuracy: 0.5316  train loss: 0.6897
            val accuracy: 0.5000        val loss: 0.6998
Epoch  5        train accuracy: 0.6009  train loss: 0.6364
            val accuracy: 0.5200        val loss: 0.7398
Epoch  6        train accuracy: 0.6500  train loss: 0.5464
            val accuracy: 0.4950        val loss: 0.8098
Epoch  7        train accuracy: 0.7472  train loss: 0.4570
            val accuracy: 0.6175        val loss: 0.8547
Epoch  8        train accuracy: 0.8853  train loss: 0.2865
            val accuracy: 0.6675        val loss: 0.8698
Epoch  9        train accuracy: 0.9500  train loss: 0.1435
            val accuracy: 0.7125        val loss: 0.8566
Epoch 10        train accuracy: 0.9812  train loss: 0.0560
            val accuracy: 0.7350        val loss: 0.9660
```

[28]:
```
# Plot t-SNE embeddings of the thought vectors for training data
# point color = label
nextplot()
_ = tsne_thought(model, train_loader, DEVICE)
```



[29]:
```
# Plot t-SNE embeddings of the thought vectors for validation data
nextplot()
_ = tsne_thought(model, val_loader, DEVICE)
```



1.4.3 Task 4d

[30]:
```
# Initialize the model with pre-trained embeddings with finetuning, 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: 0.4888  train loss: 0.6950
            val accuracy: 0.4850        val loss: 0.6932
Epoch  2        train accuracy: 0.5153  train loss: 0.6905
            val accuracy: 0.5200        val loss: 0.6928
Epoch  3        train accuracy: 0.5141  train loss: 0.6928
            val accuracy: 0.4850        val loss: 0.6932
Epoch  4        train accuracy: 0.5425  train loss: 0.6826
            val accuracy: 0.4950        val loss: 0.6943
Epoch  5        train accuracy: 0.6425  train loss: 0.5942
            val accuracy: 0.6900        val loss: 0.6207
Epoch  6        train accuracy: 0.8213  train loss: 0.3973
```

```
              val accuracy: 0.7550        val loss: 0.5638
Epoch  7          train accuracy: 0.9031  train loss: 0.2660
              val accuracy: 0.7825        val loss: 0.5483
Epoch  8          train accuracy: 0.9337  train loss: 0.1904
              val accuracy: 0.7950        val loss: 0.6733
Epoch  9          train accuracy: 0.9547  train loss: 0.1314
              val accuracy: 0.7650        val loss: 0.7809
Epoch 10          train accuracy: 0.9716  train loss: 0.0880
              val accuracy: 0.8000        val loss: 0.7238
```

1.4.4 Task 4e

[31]:
```
# Initialize the model with pre-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: 0.5162  train loss: 0.6896
              val accuracy: 0.4875        val loss: 0.8306
Epoch  4          train accuracy: 0.5262  train loss: 0.6957
              val accuracy: 0.4900        val loss: 0.6936
Epoch  5          train accuracy: 0.5509  train loss: 0.6783
              val accuracy: 0.5100        val loss: 0.6943
Epoch  6          train accuracy: 0.5766  train loss: 0.6511
              val accuracy: 0.5025        val loss: 0.7334
Epoch  7          train accuracy: 0.6075  train loss: 0.6163
              val accuracy: 0.5825        val loss: 0.7070
Epoch  8          train accuracy: 0.6972  train loss: 0.5623
              val accuracy: 0.7125        val loss: 0.6833
Epoch  9          train accuracy: 0.7309  train loss: 0.5567
              val accuracy: 0.6875        val loss: 0.6195
Epoch 10          train accuracy: 0.7503  train loss: 0.5176
              val accuracy: 0.6875        val loss: 0.6246
```

1.5 Task 5: Exploration

Task 5a

[32]:
```
class SimpleLSTM(nn.Module):
    def __init__(
```

```
        self, vocab_size, embedding_dim, hidden_dim, num_layers=1, cell_type = "lstm", cell_dropout=0.0, bidirectional=False
    ):
        super().__init__()
        self.num_layers = num_layers
        self.hidden_dim = hidden_dim
        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        self.cell_dropout = cell_dropout
        self.cell_type = cell_type
        self.bidirectional = bidirectional
        if self.cell_type == "lstm":
            self.rnn = torch.nn.LSTM(embedding_dim, hidden_dim, num_layers = num_layers, batch_first = True, dropout = cell_dropout, bidirectional=self.bidirectional)
        elif self.cell_type == "gru":
            self.rnn = torch.nn.GRU(embedding_dim, hidden_dim, num_layers = num_layers, batch_first = True, dropout = cell_dropout, bidirectional=self.bidirectional)
        elif self.cell_type == "elman":
            self.rnn = torch.nn.RNN(embedding_dim, hidden_dim, num_layers = num_layers, batch_first = True, dropout = cell_dropout, bidirectional=self.bidirectional)
        self.fc = nn.Linear(hidden_dim * 2 if self.bidirectional else hidden_dim, 1)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        hidden = self.init_hidden(len(x))
        embeddings = self.embedding(x)
        outputs, hidden_state = self.rnn(embeddings, hidden)
        if self.bidirectional:
            if self.cell_type == "lstm":
                hidden_state = torch.cat((hidden_state[0][-2,:,:], hidden_state[0][-1,:,:]), dim = 1)
            else:
                hidden_state = torch.cat((hidden_state[-2,:,:], hidden_state[-1,:,:]), dim = 1)
        else:
            if self.cell_type == "lstm":
                hidden_state = hidden_state[0][-1,:,:]
            else:
                hidden_state = hidden_state[-1,:,:]
        thought_vector = hidden_state
        logits = self.fc(thought_vector)
        predictions = self.sigmoid(logits)
        return predictions, thought_vector
```

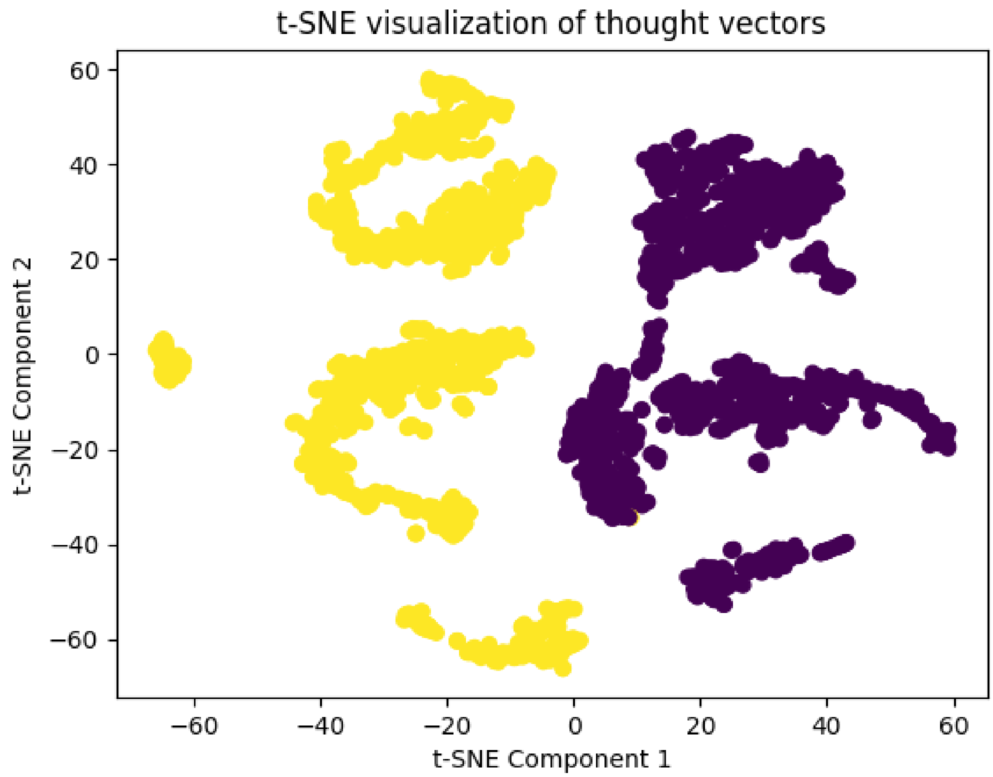
```
    def init_hidden(self, batch_size):
        num_directions = 2 if self.bidirectional else 1
        if self.cell_type == "lstm":
            hidden = (torch.zeros(self.num_layers * num_directions, batch_size,␣
↪self.hidden_dim, device = self.embedding.weight.device),
                    torch.zeros(self.num_layers * num_directions, batch_size,␣
↪self.hidden_dim, device = self.embedding.weight.device))
        else:
            hidden = torch.zeros(self.num_layers * num_directions, batch_size,␣
↪self.hidden_dim, device = self.embedding.weight.device)
        return hidden
```

dropout = 0.0 and Bidirectional LSTM

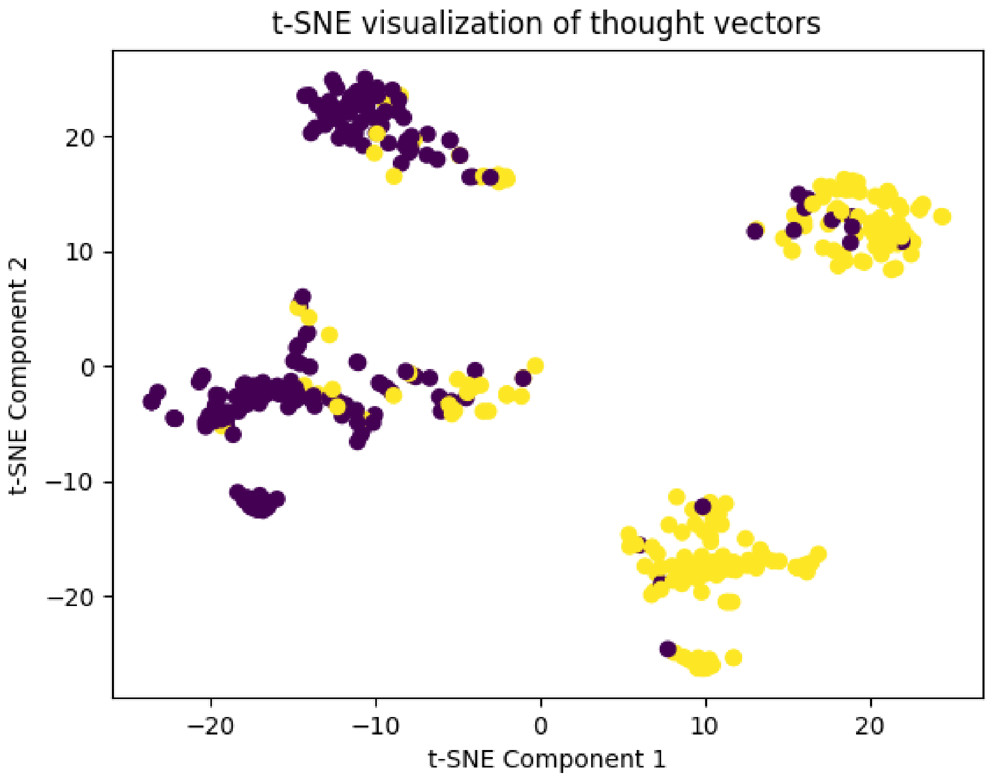
[33]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪"lstm", 0.0, True)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5153  train loss: 0.6936
            val accuracy: 0.5200        val loss: 0.6912
Epoch  2        train accuracy: 0.6497  train loss: 0.6190
            val accuracy: 0.6600        val loss: 0.6246
Epoch  3        train accuracy: 0.8825  train loss: 0.2839
            val accuracy: 0.8225        val loss: 0.4654
Epoch  4        train accuracy: 0.9825  train loss: 0.0585
            val accuracy: 0.8725        val loss: 0.4033
Epoch  5        train accuracy: 0.9975  train loss: 0.0158
            val accuracy: 0.8125        val loss: 0.7838
Epoch  6        train accuracy: 0.9991  train loss: 0.0060
            val accuracy: 0.8850        val loss: 0.5905
Epoch  7        train accuracy: 0.9997  train loss: 0.0026
            val accuracy: 0.8625        val loss: 0.6895
Epoch  8        train accuracy: 0.9997  train loss: 0.0022
            val accuracy: 0.8650        val loss: 0.7565
Epoch  9        train accuracy: 0.9997  train loss: 0.0028
            val accuracy: 0.8725        val loss: 0.6960
Epoch 10        train accuracy: 0.9997  train loss: 0.0023
            val accuracy: 0.8700        val loss: 0.7447
```

[34]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[35]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



dropout = 0.0 and Unidirectional LSTM

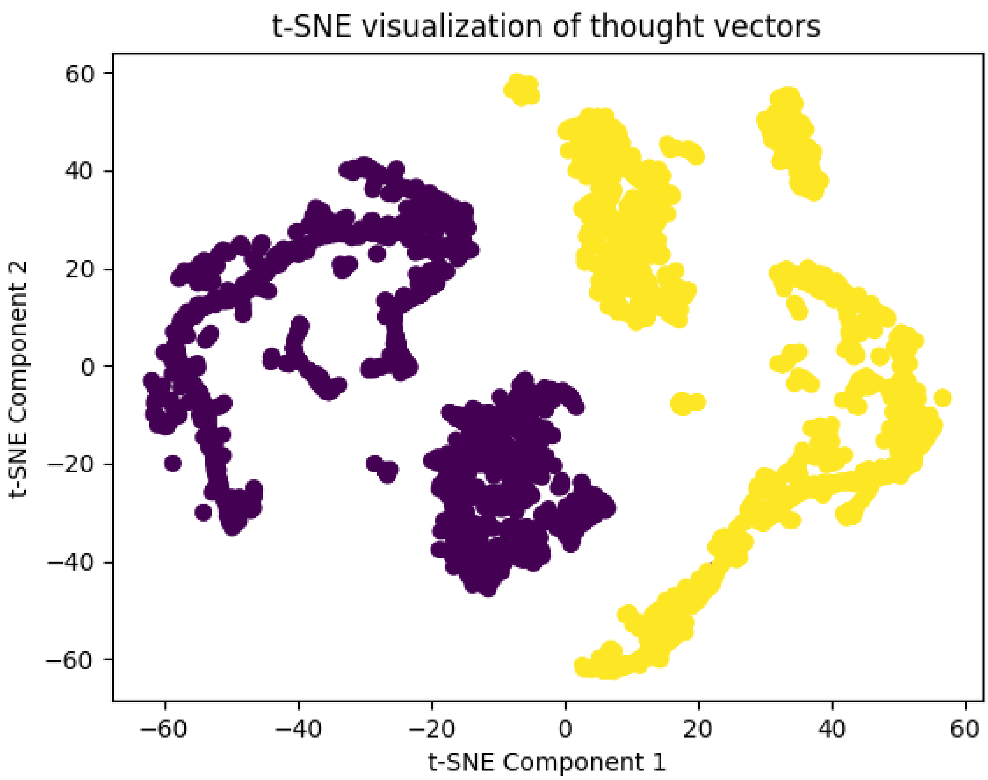
[36]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪"lstm", 0.0, False)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5059  train loss: 0.6947
            val accuracy: 0.4825        val loss: 0.6934
Epoch  2        train accuracy: 0.5587  train loss: 0.6769
            val accuracy: 0.5200        val loss: 0.7043
Epoch  3        train accuracy: 0.7847  train loss: 0.4528
            val accuracy: 0.7250        val loss: 0.5789
Epoch  4        train accuracy: 0.9453  train loss: 0.1758
            val accuracy: 0.8150        val loss: 0.5023
Epoch  5        train accuracy: 0.9825  train loss: 0.0616
            val accuracy: 0.7900        val loss: 0.6953
Epoch  6        train accuracy: 0.9944  train loss: 0.0234
            val accuracy: 0.8100        val loss: 0.7986
```

```
Epoch  7        train accuracy: 0.9950  train loss: 0.0162
            val accuracy: 0.8025        val loss: 0.8413
Epoch  8        train accuracy: 0.9984  train loss: 0.0065
            val accuracy: 0.8275        val loss: 0.8040
Epoch  9        train accuracy: 0.9994  train loss: 0.0037
            val accuracy: 0.8125        val loss: 1.0207
Epoch 10        train accuracy: 0.9997  train loss: 0.0028
            val accuracy: 0.8150        val loss: 1.1340
```

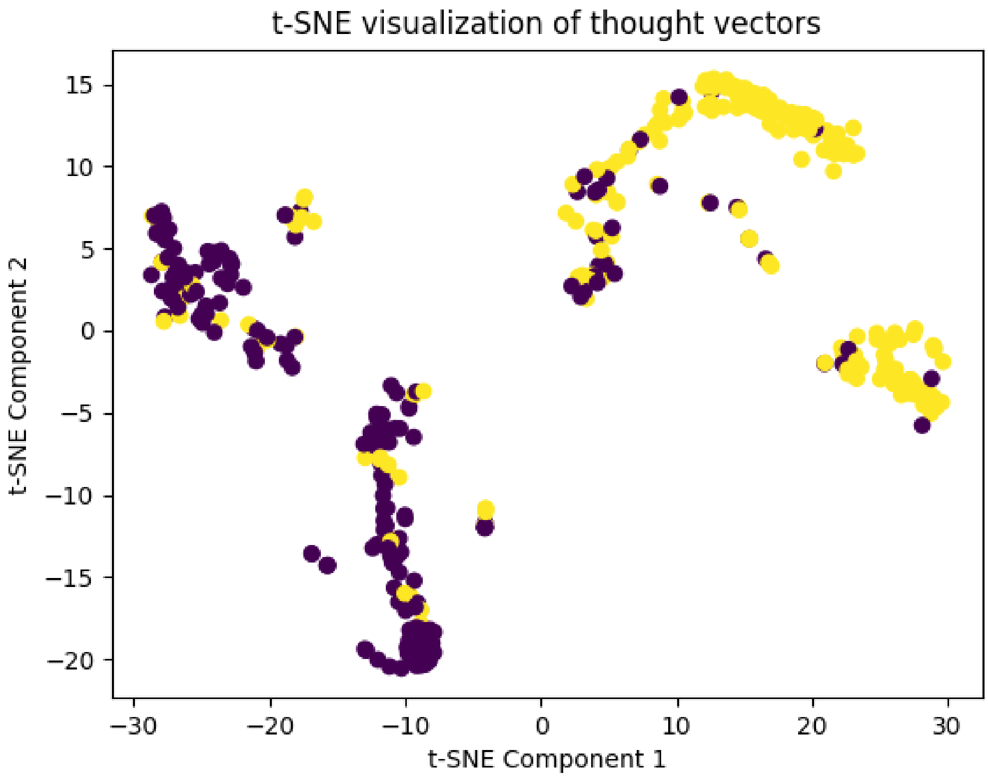
[37]:

```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[38]:

```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



dropout = 0.8 and Bidirectional LSTM

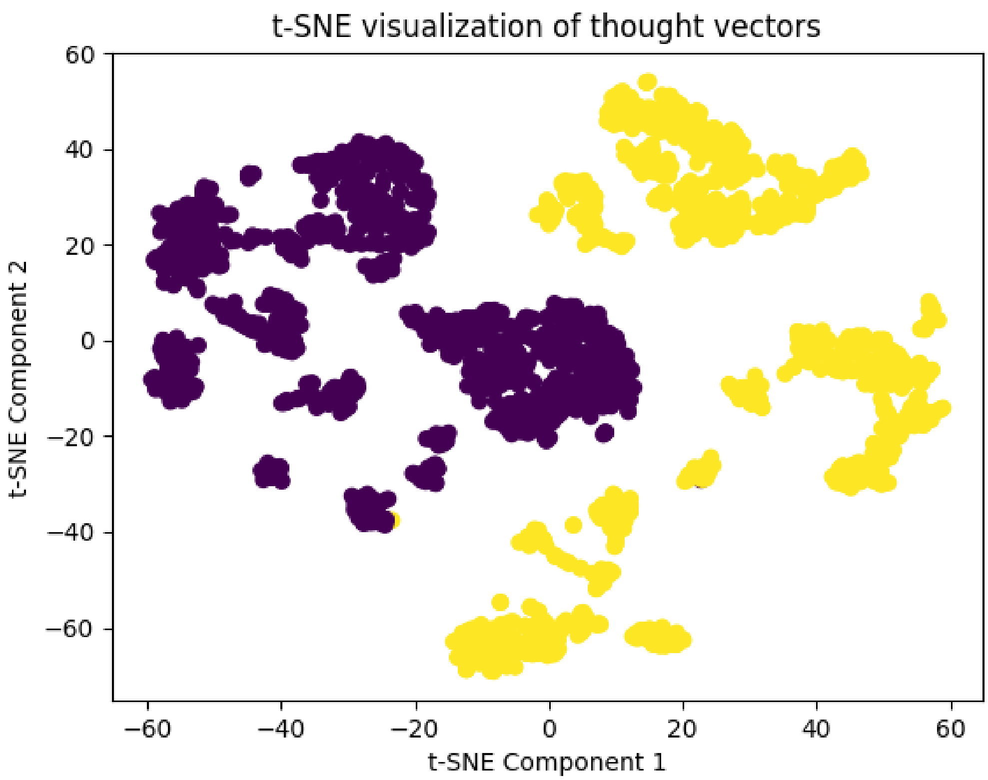
[39]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪"lstm", 0.8, True)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5094  train loss: 0.6977
            val accuracy: 0.5300        val loss: 0.6923
Epoch  2        train accuracy: 0.5559  train loss: 0.6848
            val accuracy: 0.5950        val loss: 0.6508
Epoch  3        train accuracy: 0.7547  train loss: 0.5102
            val accuracy: 0.8450        val loss: 0.4315
Epoch  4        train accuracy: 0.9403  train loss: 0.1704
            val accuracy: 0.8200        val loss: 0.6849
Epoch  5        train accuracy: 0.9803  train loss: 0.0611
            val accuracy: 0.8450        val loss: 0.4435
Epoch  6        train accuracy: 0.9938  train loss: 0.0248
            val accuracy: 0.8500        val loss: 0.7188
```

```
Epoch  7        train accuracy: 0.9959  train loss: 0.0162
            val accuracy: 0.8625        val loss: 0.7143
Epoch  8        train accuracy: 0.9931  train loss: 0.0218
            val accuracy: 0.8775        val loss: 0.5299
Epoch  9        train accuracy: 0.9966  train loss: 0.0112
            val accuracy: 0.8600        val loss: 0.5964
Epoch 10        train accuracy: 0.9981  train loss: 0.0081
            val accuracy: 0.8675        val loss: 0.5266
```

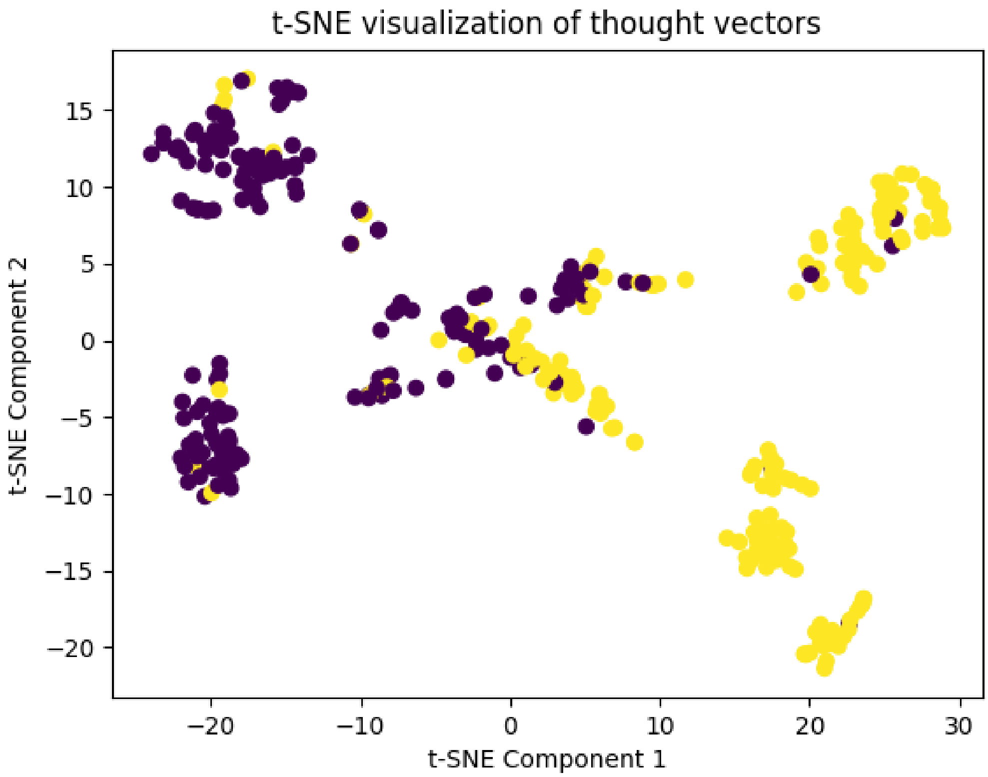
[40]:

```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[41]:

```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



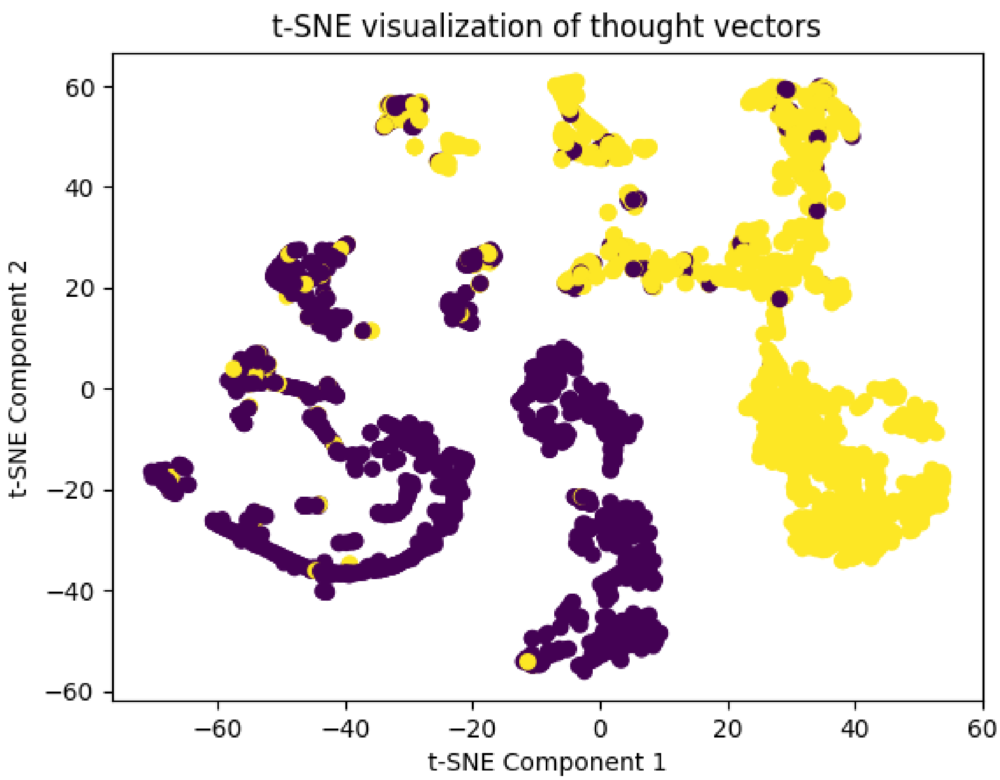
dropout = 0.8 and Unidirectional LSTM

[42]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪"lstm", 0.8, False)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

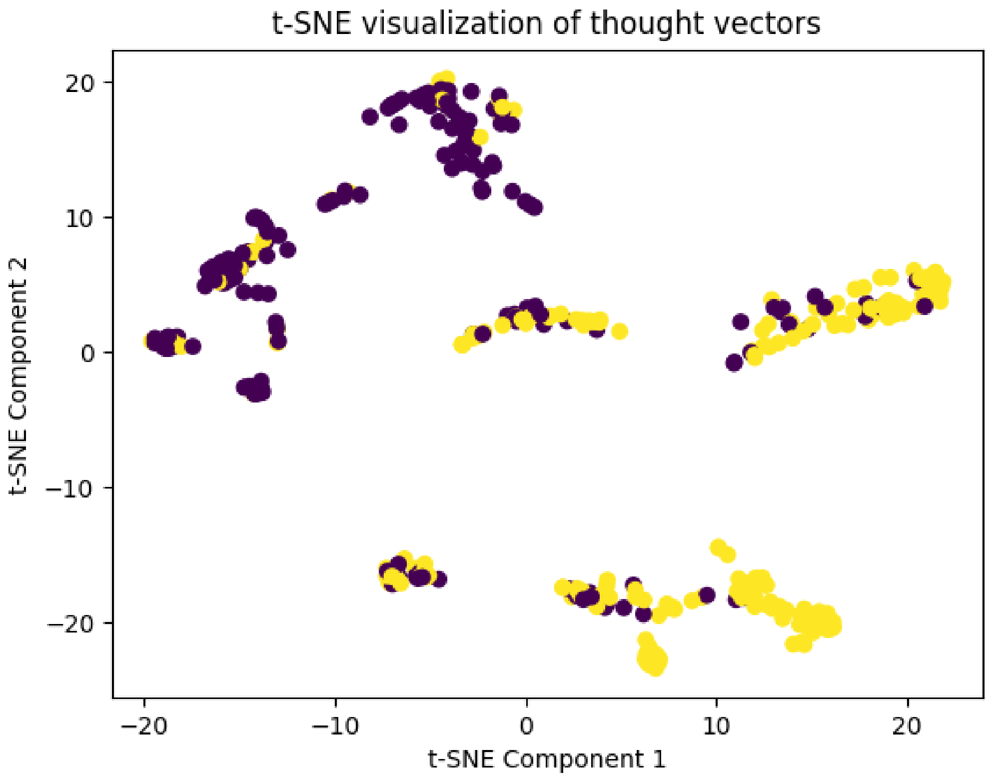
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5044  train loss: 0.6961
            val accuracy: 0.4825        val loss: 0.6964
Epoch  2        train accuracy: 0.5034  train loss: 0.6961
            val accuracy: 0.4875        val loss: 0.6954
Epoch  3        train accuracy: 0.5122  train loss: 0.6952
            val accuracy: 0.5350        val loss: 0.6921
Epoch  4        train accuracy: 0.5238  train loss: 0.6924
            val accuracy: 0.4900        val loss: 0.7053
Epoch  5        train accuracy: 0.5781  train loss: 0.6610
            val accuracy: 0.5075        val loss: 0.7048
Epoch  6        train accuracy: 0.6547  train loss: 0.5851
            val accuracy: 0.6300        val loss: 0.7208
```

```
Epoch  7        train accuracy: 0.7581  train loss: 0.4761
            val accuracy: 0.6900        val loss: 0.6710
Epoch  8        train accuracy: 0.8544  train loss: 0.3498
            val accuracy: 0.7350        val loss: 0.6609
Epoch  9        train accuracy: 0.8862  train loss: 0.2898
            val accuracy: 0.6250        val loss: 1.0919
Epoch 10        train accuracy: 0.9087  train loss: 0.2460
            val accuracy: 0.7675        val loss: 0.6516
```

[43]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[44]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



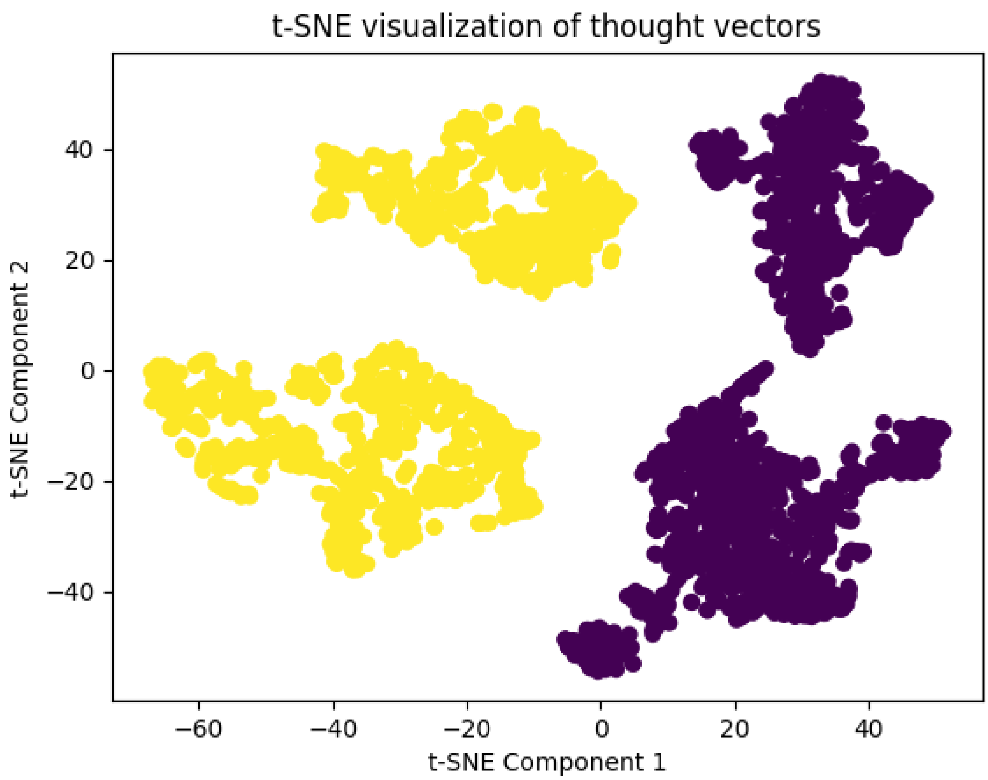
dropout = 0.0 and Unidirectional GRU cell

[45]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers, "gru",␣
↪0.0, False)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

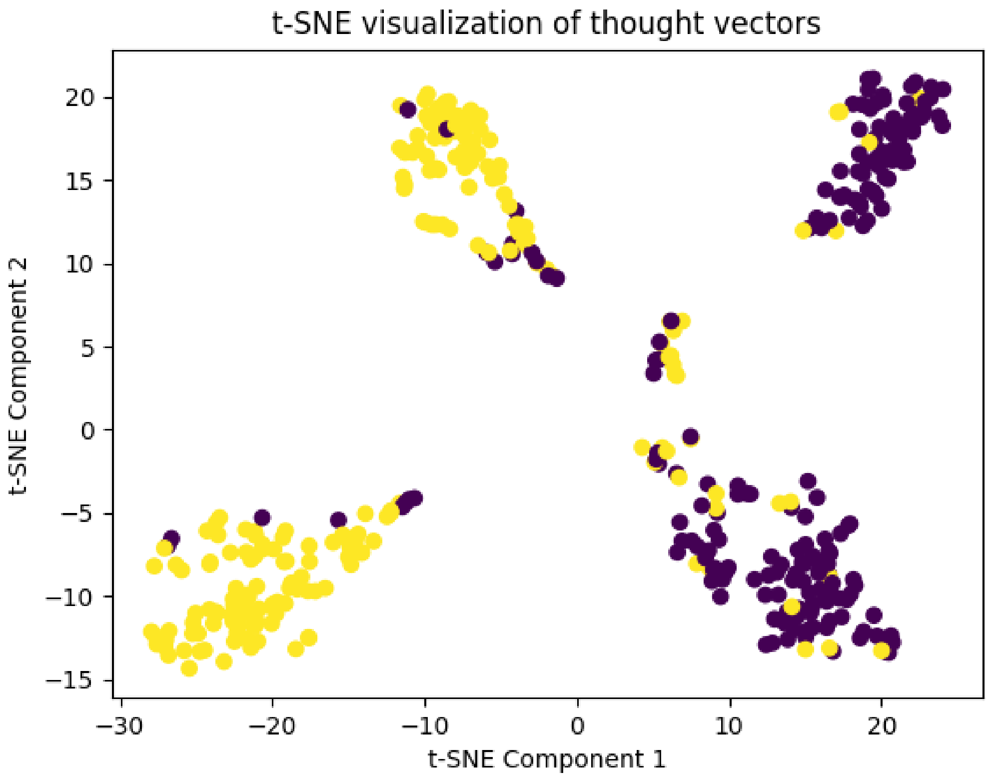
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.5766  train loss: 0.6873
            val accuracy: 0.4800        val loss: 0.8398
Epoch  2        train accuracy: 0.8137  train loss: 0.3855
            val accuracy: 0.8700        val loss: 0.3228
Epoch  3        train accuracy: 0.9819  train loss: 0.0645
            val accuracy: 0.8700        val loss: 0.3085
Epoch  4        train accuracy: 0.9962  train loss: 0.0185
            val accuracy: 0.8725        val loss: 0.4523
Epoch  5        train accuracy: 0.9997  train loss: 0.0039
            val accuracy: 0.8700        val loss: 0.5667
Epoch  6        train accuracy: 0.9997  train loss: 0.0017
            val accuracy: 0.8725        val loss: 0.6787
```

```
Epoch  7        train accuracy: 0.9994  train loss: 0.0021
            val accuracy: 0.8725        val loss: 0.6353
Epoch  8        train accuracy: 1.0000  train loss: 0.0003
            val accuracy: 0.8700        val loss: 0.6769
Epoch  9        train accuracy: 1.0000  train loss: 0.0002
            val accuracy: 0.8725        val loss: 0.7060
Epoch 10        train accuracy: 1.0000  train loss: 0.0002
            val accuracy: 0.8725        val loss: 0.7278
```

[46]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[47]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



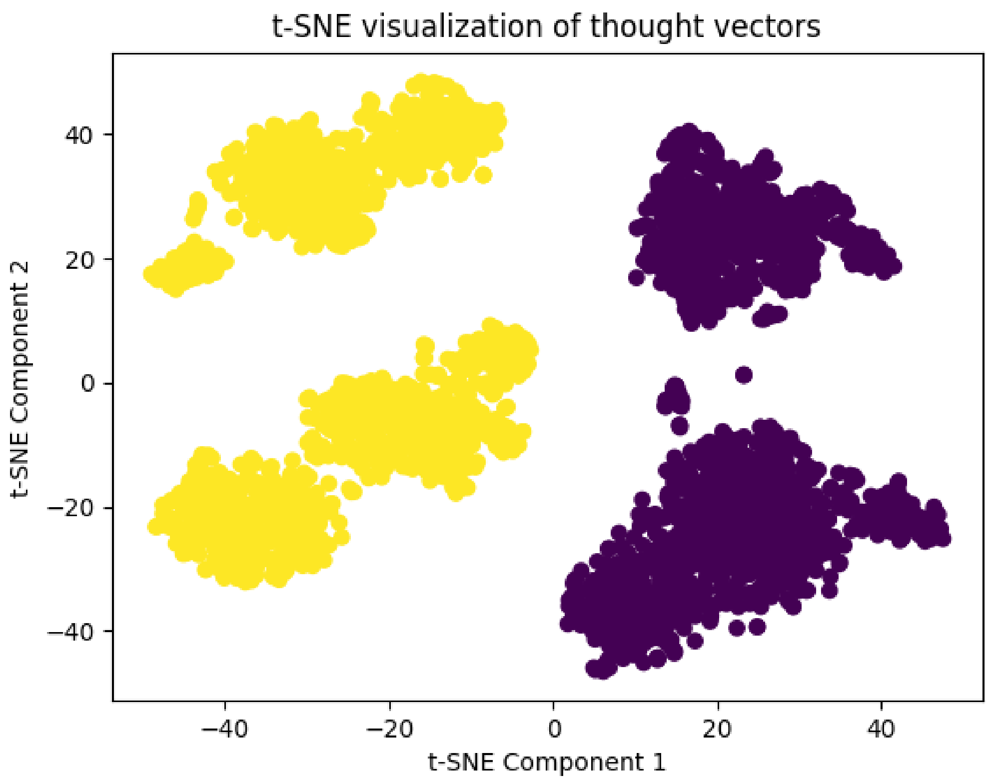
dropout = 0.8 and Bidirectional GRU cell

[48]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers, "gru",␣
↪0.8, True)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

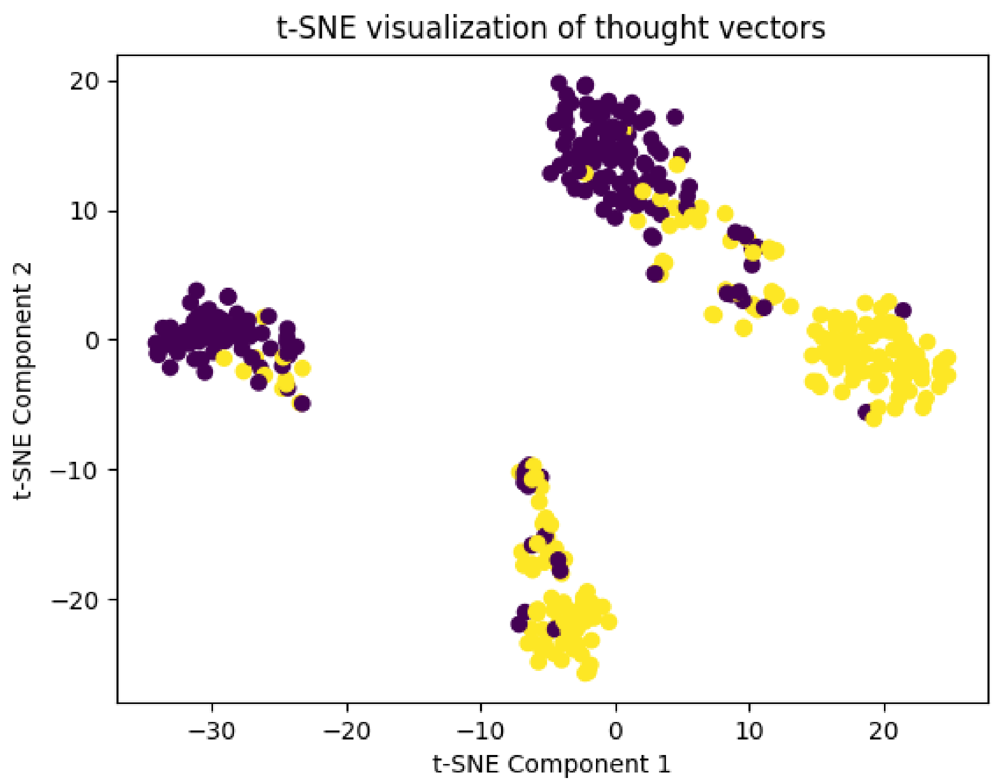
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.6166  train loss: 0.6434
            val accuracy: 0.8375        val loss: 0.3994
Epoch  2        train accuracy: 0.9216  train loss: 0.2040
            val accuracy: 0.8700        val loss: 0.3392
Epoch  3        train accuracy: 0.9928  train loss: 0.0248
            val accuracy: 0.8825        val loss: 0.4144
Epoch  4        train accuracy: 0.9994  train loss: 0.0017
            val accuracy: 0.8875        val loss: 0.4964
Epoch  5        train accuracy: 0.9994  train loss: 0.0027
            val accuracy: 0.8500        val loss: 0.8054
Epoch  6        train accuracy: 0.9997  train loss: 0.0017
            val accuracy: 0.8700        val loss: 0.5759
```

```
Epoch  7        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8675        val loss: 0.6222
Epoch  8        train accuracy: 1.0000  train loss: 0.0001
            val accuracy: 0.8700        val loss: 0.6641
Epoch  9        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8650        val loss: 0.7094
Epoch 10        train accuracy: 1.0000  train loss: 0.0000
            val accuracy: 0.8650        val loss: 0.7323
```

[49]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[50]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



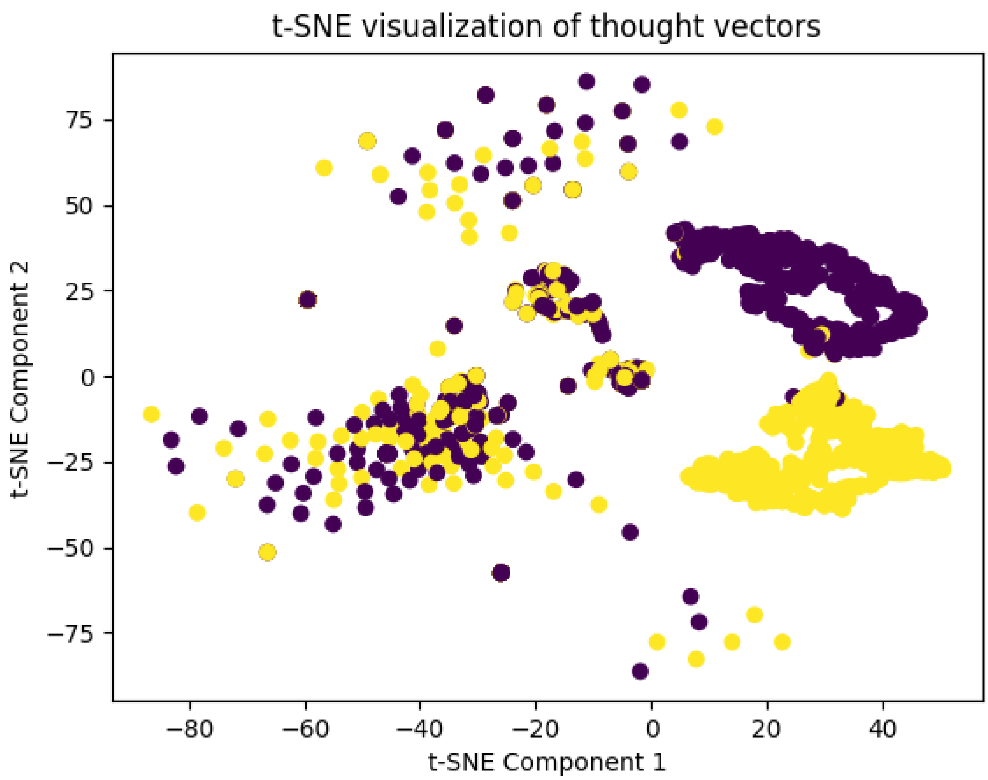
dropout = 0.0 and Unidirectional Elman cell

[51]:
```
# Initialize the model with pre-trained embeddings with finetuning, then train
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪"elman", 0.0, False)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

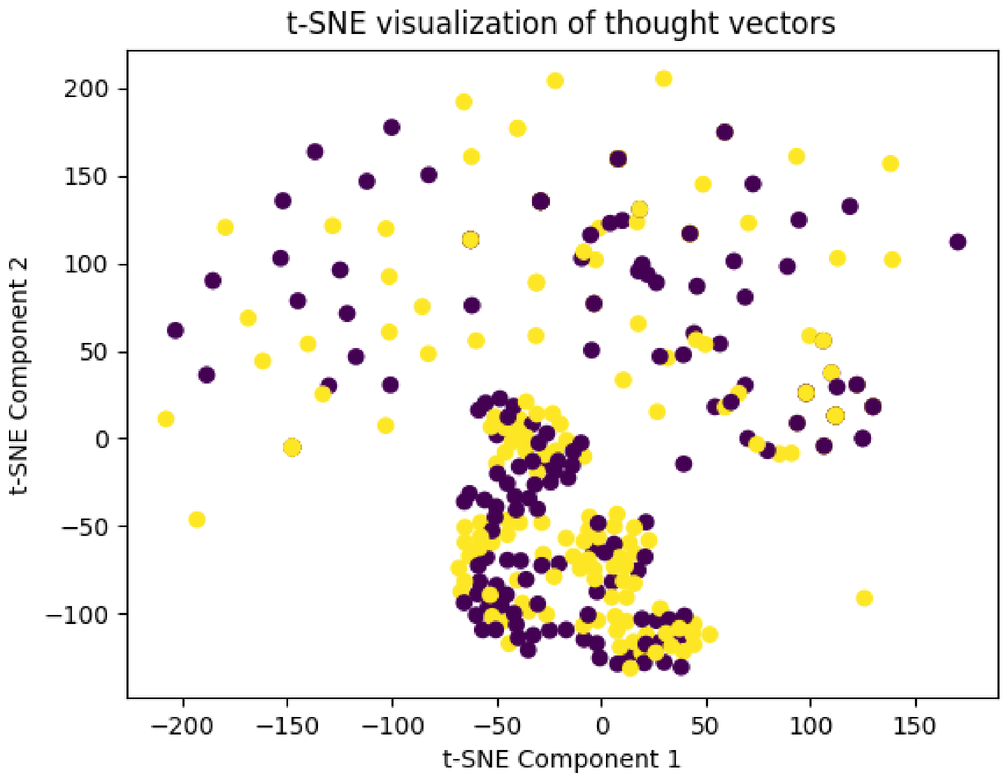
```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
Epoch  1        train accuracy: 0.4994  train loss: 0.7154
            val accuracy: 0.4900        val loss: 0.6986
Epoch  2        train accuracy: 0.5106  train loss: 0.7100
            val accuracy: 0.4900        val loss: 0.7114
Epoch  3        train accuracy: 0.5328  train loss: 0.6935
            val accuracy: 0.4850        val loss: 0.7275
Epoch  4        train accuracy: 0.5909  train loss: 0.6388
            val accuracy: 0.4850        val loss: 0.7406
Epoch  5        train accuracy: 0.6534  train loss: 0.5554
            val accuracy: 0.5100        val loss: 0.9516
Epoch  6        train accuracy: 0.6656  train loss: 0.5044
            val accuracy: 0.4700        val loss: 0.8663
```

```
Epoch  7        train accuracy: 0.6947  train loss: 0.4791
            val accuracy: 0.4825        val loss: 0.8753
Epoch  8        train accuracy: 0.6984  train loss: 0.4638
            val accuracy: 0.5025        val loss: 0.9274
Epoch  9        train accuracy: 0.7066  train loss: 0.4414
            val accuracy: 0.5025        val loss: 1.2211
Epoch 10        train accuracy: 0.6934  train loss: 0.4360
            val accuracy: 0.4800        val loss: 1.2877
```

[52]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[53]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



Task 5b

[54]:
```
@torch.no_grad()
def reviews_eval(
    model, eval_loader, label="val", loss_fn=torch.nn.functional.
 ↪binary_cross_entropy
):
    model.to(DEVICE)
    model.eval()

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

        prediction, _ = model(reviews)
        prediction = prediction.view(-1)
        loss = loss_fn(prediction, labels.float())

        total_loss = total_loss + loss.item()
        prediction_class = torch.round(prediction)
        correct = (prediction_class == labels).sum().item()
```

```
        total_correct = total_correct + correct

    val_loss = total_loss / len(eval_loader)
    val_accuracy = total_correct / len(eval_loader.dataset)

    print(
        f"              "
        f"{label} accuracy: {val_accuracy:.4f}\t"
        f"{label} loss: {val_loss:.4f}"
    )

    return val_loss
```

[55]:

```
def reviews_train(
    model,
    train_loader,
    val_loader,
    lr=0.01,
    epochs=3,
    max_norm=5,
    loss_fn=torch.nn.functional.binary_cross_entropy,
    patience = 3,
):
    model = model.to(DEVICE)

    optimizer = torch.optim.Adam(
        [param for param in model.parameters() if param.requires_grad], lr=lr
    )

    best_val_loss = float("inf")
    patience_counter = 0
    for epoch in range(epochs):
        total_correct = total_loss = 0
        for reviews, labels in train_loader:
            model.train()

            reviews, labels = reviews.to(DEVICE), labels.to(DEVICE)

            prediction, _ = model(reviews)
            prediction = prediction.view(-1)
            loss = loss_fn(prediction, labels.float())

            loss.backward()
            torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm = max_norm)
            optimizer.step()
            optimizer.zero_grad()
```

```
            total_loss = total_loss + loss.item()
            prediction_class = torch.round(prediction)
            correct = (prediction_class == labels).sum().item()
            total_correct = total_correct + correct

        val_loss = reviews_eval(model, val_loader, loss_fn=loss_fn)

        if val_loss < best_val_loss:
            best_val_loss = val_loss
            torch.save(model.state_dict(), f"model_best_val_loss.pt")
            patience_counter = 0
        else:
            patience_counter += 1
        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}"
        )
        if patience_counter >= patience:
            print(f"Early stopping triggered after {patience} epochs with no␣
↪validation loss improvement.")
            break
    return best_val_loss
```

[56]:
```
vocab_size = len(dataset.vocab)
embedding_dim = 100
n_epochs = 10
cell_type = 'gru'
bidirectional = True
num_layers = 2
```

[57]:
```
import optuna

def objective(trial):
    hidden_dim = trial.suggest_int('hidden_dim', 64, 128)
    cell_dropout = trial.suggest_float('cell_dropout', 0.0, 0.5)
    model = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
↪cell_type, cell_dropout, bidirectional)
    reviews_load_embeddings(model.embedding, vocab.get_stoi())
    best_val_loss = reviews_train(model, train_loader, val_loader,␣
↪epochs=n_epochs)
    return best_val_loss
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=20)
```

```
[I 2024-05-03 18:32:07,226] A new study created in memory with name: no-
name-b769d2f6-87ce-4d57-8ff1-c4a9f0868e28
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8350       val loss: 0.4329
Epoch  1        train accuracy: 0.6653  train loss: 0.6229
            val accuracy: 0.8575       val loss: 0.3728
Epoch  2        train accuracy: 0.9378  train loss: 0.1713
            val accuracy: 0.8725       val loss: 0.4074
Epoch  3        train accuracy: 0.9941  train loss: 0.0209
            val accuracy: 0.8775       val loss: 0.5673
Epoch  4        train accuracy: 1.0000  train loss: 0.0010
```

```
[I 2024-05-03 18:34:38,980] Trial 0 finished with value: 0.37276275570576006 and
parameters: {'hidden_dim': 126, 'cell_dropout': 0.16898837483042878}. Best is
trial 0 with value: 0.37276275570576006.
```

```
            val accuracy: 0.8775       val loss: 0.5998
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8175       val loss: 0.4541
Epoch  1        train accuracy: 0.6328  train loss: 0.6255
            val accuracy: 0.8575       val loss: 0.3690
Epoch  2        train accuracy: 0.9278  train loss: 0.1860
            val accuracy: 0.8525       val loss: 0.5111
Epoch  3        train accuracy: 0.9953  train loss: 0.0152
            val accuracy: 0.8700       val loss: 0.6198
Epoch  4        train accuracy: 1.0000  train loss: 0.0007
```

```
[I 2024-05-03 18:37:12,413] Trial 1 finished with value: 0.368980552141483 and
parameters: {'hidden_dim': 111, 'cell_dropout': 0.357598769745876}. Best is
trial 1 with value: 0.368980552141483.
```

```
            val accuracy: 0.8625       val loss: 0.6881
Epoch  5        train accuracy: 1.0000  train loss: 0.0002
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.7700       val loss: 0.4559
Epoch  1        train accuracy: 0.6175  train loss: 0.6447
            val accuracy: 0.8800       val loss: 0.2979
Epoch  2        train accuracy: 0.9209  train loss: 0.1980
            val accuracy: 0.8925       val loss: 0.5393
Epoch  3        train accuracy: 0.9972  train loss: 0.0104
            val accuracy: 0.9025       val loss: 0.4824
Epoch  4        train accuracy: 0.9994  train loss: 0.0030
```

```
[I 2024-05-03 18:39:49,157] Trial 2 finished with value: 0.29790392288794887 and
parameters: {'hidden_dim': 106, 'cell_dropout': 0.3334983015769939}. Best is
trial 2 with value: 0.29790392288794887.
```

```
            val accuracy: 0.9050        val loss: 0.5177
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8725        val loss: 0.3068
Epoch  1        train accuracy: 0.6653  train loss: 0.5779
            val accuracy: 0.8775        val loss: 0.2906
Epoch  2        train accuracy: 0.9516  train loss: 0.1229
            val accuracy: 0.8425        val loss: 0.6517
Epoch  3        train accuracy: 0.9981  train loss: 0.0070
            val accuracy: 0.8675        val loss: 0.6400
Epoch  4        train accuracy: 0.9997  train loss: 0.0012

[I 2024-05-03 18:41:39,431] Trial 3 finished with value: 0.2906067268206523 and
parameters: {'hidden_dim': 81, 'cell_dropout': 0.31094170398776455}. Best is
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8625        val loss: 0.7101
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8425        val loss: 0.3641
Epoch  1        train accuracy: 0.6728  train loss: 0.5829
            val accuracy: 0.8475        val loss: 0.4024
Epoch  2        train accuracy: 0.9516  train loss: 0.1363
            val accuracy: 0.8575        val loss: 0.6535
Epoch  3        train accuracy: 0.9953  train loss: 0.0190

[I 2024-05-03 18:43:28,814] Trial 4 finished with value: 0.36414683094391453 and
parameters: {'hidden_dim': 95, 'cell_dropout': 0.09721499092775143}. Best is
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8600        val loss: 0.6309
Epoch  4        train accuracy: 0.9988  train loss: 0.0060
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8500        val loss: 0.3127
Epoch  1        train accuracy: 0.6866  train loss: 0.5487
            val accuracy: 0.8850        val loss: 0.3032
Epoch  2        train accuracy: 0.9603  train loss: 0.1237
            val accuracy: 0.8900        val loss: 0.4365
Epoch  3        train accuracy: 0.9972  train loss: 0.0101
            val accuracy: 0.8875        val loss: 0.5352
Epoch  4        train accuracy: 1.0000  train loss: 0.0004

[I 2024-05-03 18:45:46,833] Trial 5 finished with value: 0.3031991250239886 and
parameters: {'hidden_dim': 94, 'cell_dropout': 0.21773799554081363}. Best is
```

```
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8950       val loss: 0.5613
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8000       val loss: 0.4602
Epoch  1        train accuracy: 0.6291  train loss: 0.6357
            val accuracy: 0.8575       val loss: 0.3929
Epoch  2        train accuracy: 0.9341  train loss: 0.1671
            val accuracy: 0.8725       val loss: 0.4704
Epoch  3        train accuracy: 0.9959  train loss: 0.0185
            val accuracy: 0.8525       val loss: 0.5169
Epoch  4        train accuracy: 0.9991  train loss: 0.0023

[I 2024-05-03 18:48:23,340] Trial 6 finished with value: 0.39287095846465003 and
parameters: {'hidden_dim': 110, 'cell_dropout': 0.4919306658700668}. Best is
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8550       val loss: 0.5912
Epoch  5        train accuracy: 0.9997  train loss: 0.0020
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8625       val loss: 0.3172
Epoch  1        train accuracy: 0.6603  train loss: 0.5888
            val accuracy: 0.8625       val loss: 0.3585
Epoch  2        train accuracy: 0.9503  train loss: 0.1454
            val accuracy: 0.8900       val loss: 0.3525
Epoch  3        train accuracy: 0.9969  train loss: 0.0119

[I 2024-05-03 18:50:13,651] Trial 7 finished with value: 0.317195400595665 and
parameters: {'hidden_dim': 86, 'cell_dropout': 0.48071266281454306}. Best is
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8775       val loss: 0.6002
Epoch  4        train accuracy: 0.9988  train loss: 0.0053
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8825       val loss: 0.3173
Epoch  1        train accuracy: 0.6775  train loss: 0.5740
            val accuracy: 0.8625       val loss: 0.4030
Epoch  2        train accuracy: 0.9491  train loss: 0.1461
            val accuracy: 0.8575       val loss: 0.5100
Epoch  3        train accuracy: 0.9925  train loss: 0.0243

[I 2024-05-03 18:52:25,688] Trial 8 finished with value: 0.3173267187980505 and
parameters: {'hidden_dim': 119, 'cell_dropout': 0.12782325868286398}. Best is
trial 3 with value: 0.2906067268206523.
```

```
            val accuracy: 0.8850       val loss: 0.5306
Epoch  4        train accuracy: 0.9994  train loss: 0.0024
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8475       val loss: 0.3492
Epoch  1        train accuracy: 0.6381  train loss: 0.6063
            val accuracy: 0.8825       val loss: 0.3952
Epoch  2        train accuracy: 0.9403  train loss: 0.1601
            val accuracy: 0.8625       val loss: 0.6310
Epoch  3        train accuracy: 0.9953  train loss: 0.0130

[I 2024-05-03 18:53:54,522] Trial 9 finished with value: 0.34920736918082607 and
parameters: {'hidden_dim': 85, 'cell_dropout': 0.4157959216767957}. Best is
trial 3 with value: 0.2906067268206523.

            val accuracy: 0.8750       val loss: 0.6275
Epoch  4        train accuracy: 0.9997  train loss: 0.0017
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8650       val loss: 0.3193
Epoch  1        train accuracy: 0.6916  train loss: 0.5649
            val accuracy: 0.8950       val loss: 0.2687
Epoch  2        train accuracy: 0.9550  train loss: 0.1313
            val accuracy: 0.8800       val loss: 0.4207
Epoch  3        train accuracy: 0.9969  train loss: 0.0104
            val accuracy: 0.8850       val loss: 0.5276
Epoch  4        train accuracy: 1.0000  train loss: 0.0005

[I 2024-05-03 18:55:16,659] Trial 10 finished with value: 0.2687366845516058 and
parameters: {'hidden_dim': 64, 'cell_dropout': 0.004205943985287786}. Best is
trial 10 with value: 0.2687366845516058.

            val accuracy: 0.8850       val loss: 0.5521
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8725       val loss: 0.3056
Epoch  1        train accuracy: 0.6853  train loss: 0.5735
            val accuracy: 0.8525       val loss: 0.4082
Epoch  2        train accuracy: 0.9509  train loss: 0.1264
            val accuracy: 0.8700       val loss: 0.5304
Epoch  3        train accuracy: 0.9969  train loss: 0.0092

[I 2024-05-03 18:56:21,811] Trial 11 finished with value: 0.30563747653594386
and parameters: {'hidden_dim': 64, 'cell_dropout': 0.0007470956028043929}. Best
is trial 10 with value: 0.2687366845516058.

            val accuracy: 0.8900       val loss: 0.4971
```

```
Epoch  4        train accuracy: 0.9997  train loss: 0.0008
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8125        val loss: 0.4242
Epoch  1        train accuracy: 0.6681  train loss: 0.5680
            val accuracy: 0.8825        val loss: 0.3073
Epoch  2        train accuracy: 0.9522  train loss: 0.1203
            val accuracy: 0.8900        val loss: 0.3991
Epoch  3        train accuracy: 0.9975  train loss: 0.0066
            val accuracy: 0.8875        val loss: 0.4772
Epoch  4        train accuracy: 1.0000  train loss: 0.0003
```

[I 2024-05-03 18:57:48,143] Trial 12 finished with value: 0.30734442747556245 and parameters: {'hidden_dim': 65, 'cell_dropout': 0.2873650476734631}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8875        val loss: 0.4814
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8625        val loss: 0.3541
Epoch  1        train accuracy: 0.6309  train loss: 0.6173
            val accuracy: 0.8725        val loss: 0.3388
Epoch  2        train accuracy: 0.9350  train loss: 0.1659
            val accuracy: 0.8875        val loss: 0.3496
Epoch  3        train accuracy: 0.9959  train loss: 0.0172
            val accuracy: 0.9075        val loss: 0.4217
Epoch  4        train accuracy: 0.9997  train loss: 0.0015
```

[I 2024-05-03 18:59:29,910] Trial 13 finished with value: 0.3388075392979842 and parameters: {'hidden_dim': 74, 'cell_dropout': 0.02701841868838295}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8725        val loss: 0.6391
Epoch  5        train accuracy: 0.9997  train loss: 0.0004
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8725        val loss: 0.3334
Epoch  1        train accuracy: 0.6550  train loss: 0.6134
            val accuracy: 0.8700        val loss: 0.3543
Epoch  2        train accuracy: 0.9506  train loss: 0.1288
            val accuracy: 0.8775        val loss: 0.4464
Epoch  3        train accuracy: 0.9988  train loss: 0.0065
```

[I 2024-05-03 19:00:42,762] Trial 14 finished with value: 0.3333545235487131 and parameters: {'hidden_dim': 76, 'cell_dropout': 0.23069484476552762}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8850        val loss: 0.4821
Epoch  4        train accuracy: 0.9994  train loss: 0.0013
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8350        val loss: 0.3626
Epoch  1        train accuracy: 0.6684  train loss: 0.5816
            val accuracy: 0.8750        val loss: 0.3196
Epoch  2        train accuracy: 0.9469  train loss: 0.1469
            val accuracy: 0.8550        val loss: 0.5691
Epoch  3        train accuracy: 0.9962  train loss: 0.0137
            val accuracy: 0.8775        val loss: 0.5871
Epoch  4        train accuracy: 0.9994  train loss: 0.0018
```

[I 2024-05-03 19:02:18,873] Trial 15 finished with value: 0.319586476454368 and parameters: {'hidden_dim': 75, 'cell_dropout': 0.29610041223238853}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8725        val loss: 0.6029
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8875        val loss: 0.2882
Epoch  1        train accuracy: 0.6803  train loss: 0.5710
            val accuracy: 0.8800        val loss: 0.3472
Epoch  2        train accuracy: 0.9431  train loss: 0.1455
            val accuracy: 0.8650        val loss: 0.4676
Epoch  3        train accuracy: 0.9978  train loss: 0.0101
```

[I 2024-05-03 19:03:47,237] Trial 16 finished with value: 0.28817003736129176 and parameters: {'hidden_dim': 85, 'cell_dropout': 0.07497566875230444}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8725        val loss: 0.6357
Epoch  4        train accuracy: 0.9988  train loss: 0.0026
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8750        val loss: 0.2831
Epoch  1        train accuracy: 0.6719  train loss: 0.5681
            val accuracy: 0.8775        val loss: 0.3147
Epoch  2        train accuracy: 0.9519  train loss: 0.1321
            val accuracy: 0.8625        val loss: 0.4742
Epoch  3        train accuracy: 0.9981  train loss: 0.0075
```

[I 2024-05-03 19:05:08,547] Trial 17 finished with value: 0.2830975456879689 and parameters: {'hidden_dim': 70, 'cell_dropout': 0.07315598741137136}. Best is trial 10 with value: 0.2687366845516058.

```
            val accuracy: 0.8900        val loss: 0.5268
```

```
Epoch  4        train accuracy: 1.0000  train loss: 0.0005
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8500        val loss: 0.3432
Epoch  1        train accuracy: 0.6766  train loss: 0.5663
            val accuracy: 0.8925        val loss: 0.3098
Epoch  2        train accuracy: 0.9497  train loss: 0.1328
            val accuracy: 0.8800        val loss: 0.4782
Epoch  3        train accuracy: 0.9959  train loss: 0.0125
            val accuracy: 0.8800        val loss: 0.6038
Epoch  4        train accuracy: 0.9997  train loss: 0.0013
```

```
[I 2024-05-03 19:06:45,945] Trial 18 finished with value: 0.30981439695908475
and parameters: {'hidden_dim': 69, 'cell_dropout': 0.04854634791931167}. Best is
trial 10 with value: 0.2687366845516058.
```

```
            val accuracy: 0.8775        val loss: 0.6515
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8200        val loss: 0.4029
Epoch  1        train accuracy: 0.6778  train loss: 0.5658
            val accuracy: 0.8900        val loss: 0.3172
Epoch  2        train accuracy: 0.9487  train loss: 0.1415
            val accuracy: 0.8600        val loss: 0.4811
Epoch  3        train accuracy: 0.9969  train loss: 0.0128
            val accuracy: 0.8900        val loss: 0.5496
Epoch  4        train accuracy: 0.9991  train loss: 0.0036
```

```
[I 2024-05-03 19:08:24,215] Trial 19 finished with value: 0.3171897759804359 and
parameters: {'hidden_dim': 69, 'cell_dropout': 0.131424981943556}. Best is trial
10 with value: 0.2687366845516058.
```

```
            val accuracy: 0.8850        val loss: 0.6746
Epoch  5        train accuracy: 1.0000  train loss: 0.0002
Early stopping triggered after 3 epochs with no validation loss improvement.
```

[58]:
```
def reviews_train(
    model,
    train_loader,
    val_loader,
    lr=0.01,
    epochs=3,
    max_norm=5,
    loss_fn=torch.nn.functional.binary_cross_entropy,
    patience = 3,
):
```

```
    model = model.to(DEVICE)

    optimizer = torch.optim.Adam(
        [param for param in model.parameters() if param.requires_grad], lr=lr
    )

    best_val_loss = float("inf")
    patience_counter = 0
    for epoch in range(epochs):
        total_correct = total_loss = 0
        for reviews, labels in train_loader:
            model.train()

            reviews, labels = reviews.to(DEVICE), labels.to(DEVICE)

            prediction, _ = model(reviews)
            prediction = prediction.view(-1)
            loss = loss_fn(prediction, labels.float())

            loss.backward()
            torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm = max_norm)
            optimizer.step()
            optimizer.zero_grad()

            total_loss = total_loss + loss.item()
            prediction_class = torch.round(prediction)
            correct = (prediction_class == labels).sum().item()
            total_correct = total_correct + correct

        val_loss = reviews_eval(model, val_loader, loss_fn=loss_fn)

        if val_loss < best_val_loss:
            best_val_loss = val_loss
            torch.save(model.state_dict(), f"model_best_val_loss.pt")
            patience_counter = 0
        else:
            patience_counter += 1
        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}"
        )
        if patience_counter >= patience:
            print(f"Early stopping triggered after {patience} epochs with no validation loss improvement.")
            break
```

```
        reviews_eval(model, val_loader, loss_fn=loss_fn)
```

[59]:
```
vocab_size = len(dataset.vocab)
embedding_dim = 100
hidden_dim = 64
num_layers = 2
n_epochs = 10
cell_type = "gru"
bidirectional = True
cell_dropout = 0.004205943985287786
```

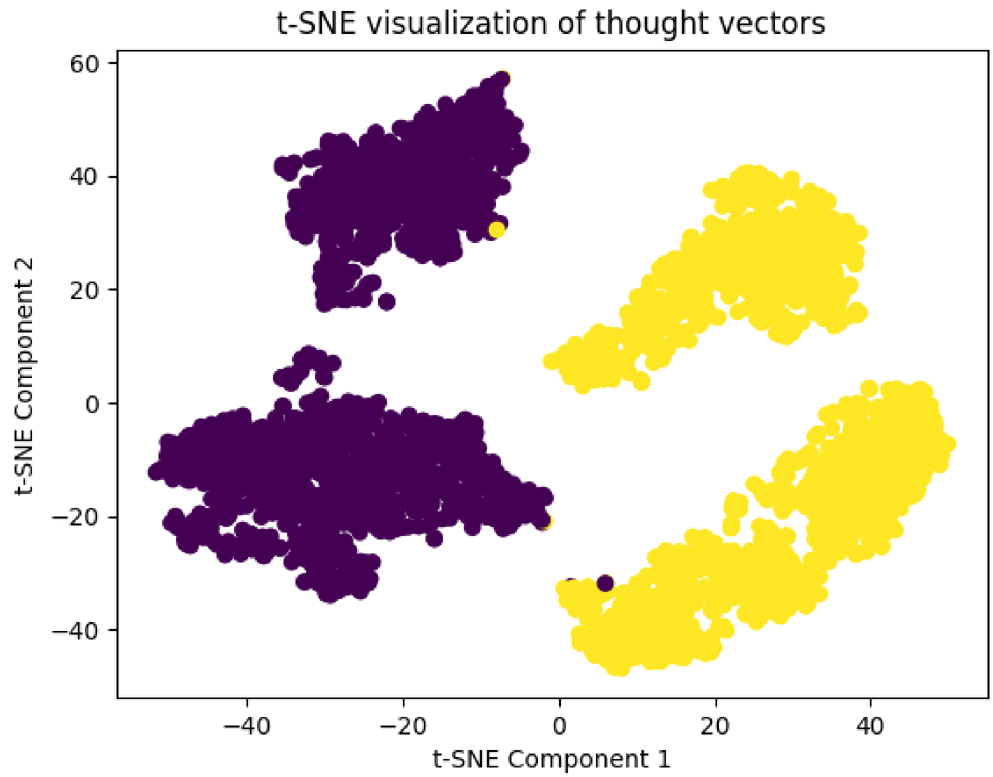
[64]:
```
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪cell_type, cell_dropout, bidirectional)
reviews_load_embeddings(model_pf.embedding, vocab.get_stoi())
reviews_train(model_pf, train_loader, val_loader, epochs=n_epochs)
```

```
Initializing embedding layer with pretrained word embeddings…
Initialized 29841/32363 word embeddings
            val accuracy: 0.8675        val loss: 0.3289
Epoch  1        train accuracy: 0.6916  train loss: 0.5717
            val accuracy: 0.8675        val loss: 0.3289
            val accuracy: 0.8950        val loss: 0.2899
Epoch  2        train accuracy: 0.9491  train loss: 0.1452
            val accuracy: 0.8950        val loss: 0.2899
            val accuracy: 0.8725        val loss: 0.5185
Epoch  3        train accuracy: 0.9988  train loss: 0.0059
            val accuracy: 0.8725        val loss: 0.5185
            val accuracy: 0.8950        val loss: 0.4998
Epoch  4        train accuracy: 0.9997  train loss: 0.0008
            val accuracy: 0.8950        val loss: 0.4998
            val accuracy: 0.8950        val loss: 0.5114
Epoch  5        train accuracy: 1.0000  train loss: 0.0001
Early stopping triggered after 3 epochs with no validation loss improvement.
```

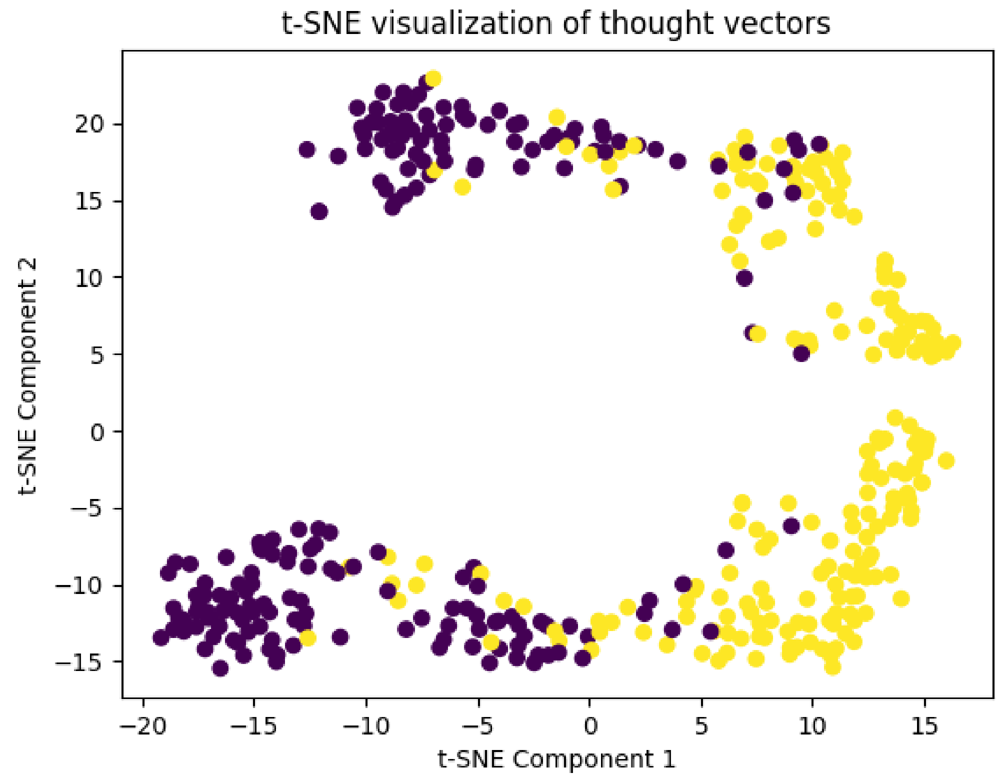
[65]:
```
model_pf = SimpleLSTM(vocab_size, embedding_dim, hidden_dim, num_layers,␣
 ↪cell_type, cell_dropout, bidirectional)
model_pf.load_state_dict(torch.load("model_best_val_loss.pt"))
print(" testing loss: ", reviews_eval(model_pf, test_loader, loss_fn = torch.nn.
 ↪functional.binary_cross_entropy))
```

```
            val accuracy: 0.8650        val loss: 0.3505
 testing loss:  0.3504867765765924
```

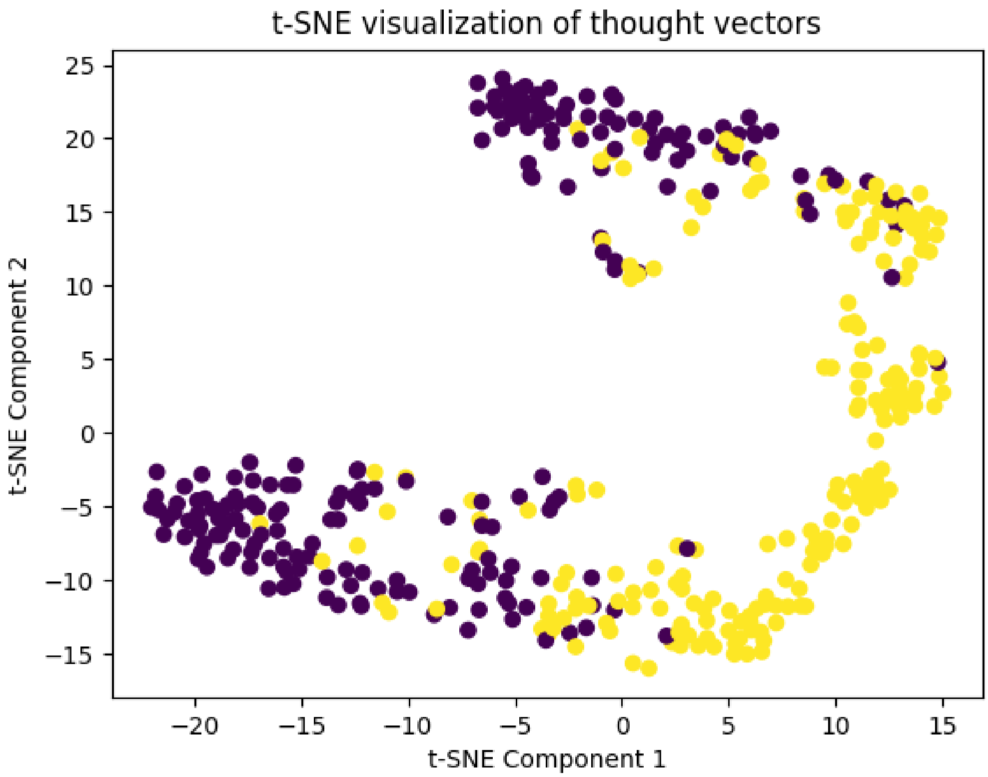
[66]:
```
nextplot()
_ = tsne_thought(model_pf, train_loader, DEVICE)
```



[67]:
```
nextplot()
_ = tsne_thought(model_pf, val_loader, DEVICE)
```



[68]:
```
nextplot()
_ = tsne_thought(model_pf, test_loader, DEVICE)
```


t-SNE visualization of thought vectors
t-SNE Component 2
t-SNE Component 1
25
20
15
10
5
0
−5
−10
−15
−20
−15
−10
−5
0
5
10
15