Sentiment Analysis for Marketing
PHASE -4

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TEAM ID	Proj-212173-Team-1
PROJECT NAME	Sentiment analysis for Marketing

Training and Testing:

Training and testing of sentiment analysis for marketing is a process used to build and evaluate machine learning or natural language processing models that can automatically classify text data, such as customer reviews or social media comments, into different sentiment categories (e.g., positive, negative, neutral). Sentiment analysis is a valuable tool for marketers as it helps them gauge public opinion, customer satisfaction, and overall brand perception.

Training and testing a sentiment analysis model for marketing using the BERT (Bidirectional Encoder Representations from Transformers) algorithm is a powerful approach due to BERT's ability to capture contextual information in text.

Sentiment analysis for marketing involves the process of training a model to automatically classify text data into sentiment categories and then testing the model's performance

BERT-based Model:

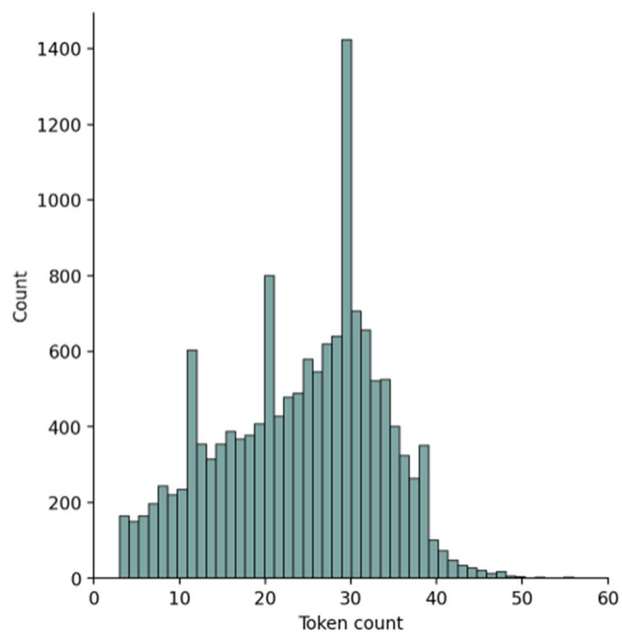
```
[13] MODEL = 'bert-base-uncased'
     tokenizer = BertTokenizer.from_pretrained(MODEL, do_lower_case=True)
```

```
Downloading (…)okenizer_config.json: 100% 28.0/28.0 [00:00<00:00, 664B/s]
Downloading (…)solve/main/vocab.txt: 100% 232k/232k [00:00<00:00, 819kB/s]
Downloading (…)/main/tokenizer.json: 100% 466k/466k [00:00<00:00, 12.5MB/s]
Downloading (…)lve/main/config.json: 100% 570/570 [00:00<00:00, 19.6kB/s]
```

The above code sets up a BERT-based model for tokenizing and processing text using the 'bert-base-uncased' model, which is a widely used variant of BERT for various NLP tasks. The tokenizer converts text to lowercase to ensure compatibility with the model's training data, as BERT models are typically trained on lowercase text.

Distribution plot:

```
[14] sns.displot(tokens)
     plt.xlim([0, 60]);
     plt.xlabel('Token count');
```



The above code calculates the token counts for text samples in a DataFrame, creates a distribution plot to visualize how token counts are distributed, and customizes the plot by setting the x-axis limits and labeling the x-axis.

To build Custom dataset:

```
from torch.utils.data import Dataset, DataLoader

# Define a custom dataset, more info on how to build custom dataset can be
# found at https://pytorch.org/tutorials/beginner/data_loading_tutorial.html
class CustomDataset(Dataset):

    def __init__(
        self,
        tweets,
        labels,
        tokenizer,
        max_length
    ):
        self.tweets = tweets
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_length = max_length

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

    def __getitem__(self, idx):
        tweet = self.tweets[idx]
        label = self.labels[idx]
```

```
        tokenize = self.tokenizer.encode_plus(
            tweet,
            add_special_tokens=True,
            max_length=self.max_length,
            return_token_type_ids=False,
            padding='max_length',
            return_attention_mask=True,
            return_tensors='pt'
        )
        return {
            'tweet': tweet,
            'input_ids': tokenize['input_ids'].flatten(),
            'attention_mask': tokenize['attention_mask'].flatten(),
            'targets': torch.tensor(label, dtype=torch.long)}
```

This custom dataset class is designed to be used with PyTorch's DataLoader to efficiently load and preprocess text data for BERT-based models, particularly for text classification tasks.

Sets up data loaders:

```python
MAX_LENGTH = 64
TEST_SIZE = 0.1
VALID_SIZE = 0.5
BATCH_SIZE = 16
NUM_WORKERS = 2

train_sampler, test_sampler = train_test_split(df, test_size=TEST_SIZE, random_state=RANDOM_STATE)
valid_sampler, test_sampler = train_test_split(test_sampler, test_size=VALID_SIZE, random_state=RANDOM_STATE)

train_set = CustomDataset(
    train_sampler['text'].to_numpy(),
    train_sampler['labels'].to_numpy(),
    tokenizer,
    MAX_LENGTH
)
test_set = CustomDataset(
    test_sampler['text'].to_numpy(),
    test_sampler['labels'].to_numpy(),
    tokenizer,
    MAX_LENGTH
)
valid_set = CustomDataset(
    valid_sampler['text'].to_numpy(),
    valid_sampler['labels'].to_numpy(),
    tokenizer,
    MAX_LENGTH
)
```

```python
train_loader = DataLoader(train_set, batch_size=BATCH_SIZE, num_workers=NUM_WORKERS)
test_loader = DataLoader(test_set, batch_size=BATCH_SIZE, num_workers=NUM_WORKERS)
valid_loader = DataLoader(valid_set, batch_size=BATCH_SIZE, num_workers=NUM_WORKERS)
```

The above code splits the data into training, validation, and testing sets, creates custom datasets for each set, and sets up data loaders to efficiently load and process the data in mini-batches for machine learning model training and evaluation.

Custom PyTorch Model for Sentiment Analysis:

```
from torch import nn
class AirlineSentimentClassifier(nn.Module):

    def __init__(self, num_labels):
        super (AirlineSentimentClassifier, self).__init__()
        self.bert = BertModel.from_pretrained(MODEL)
        self.dropout = nn.Dropout(p=0.2)
        self.classifier = nn.Linear(self.bert.config.hidden_size, num_labels)

    def forward(self, input_ids, attention_mask):
        outputs = self.bert(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
        pooled_output = outputs[1]
        pooled_output = self.dropout(pooled_output)
        out = self.classifier(pooled_output)
        return out
```

The above code defines a custom sentiment analysis model that uses a pre-trained BERT model for feature extraction and a linear layer for classification. The forward method outlines how the input data is processed through the model to make sentiment predictions.

Deep Learning Model Deployment on GPU:

```
[19] model = AirlineSentimentClassifier(len(labels_map))
     print(model)

     # Move tensors to GPU on CUDA enables devices
     if device:
         model.cuda()
```

```
Downloading model.safetensors: 100%  440M/440M [00:04<00:00, 33.2MB/s]
AirlineSentimentClassifier(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
  (dropout): Dropout(p=0.2, inplace=False)
  (classifier): Linear(in_features=768, out_features=3, bias=True)
)
```

The above code demonstrates an important aspect of deep learning, which is model deployment on GPUs. GPUs are well-suited for accelerating the training and inference of deep learning models due to their parallel processing capabilities.

Configuration and Training Setup for Deep Learning Model in PyTorch:

```
n_epochs = 10
learning_rate =2e-5

# Loss function
criterion = nn.CrossEntropyLoss()

# Optimizer
optimizer = AdamW(model.parameters(), lr=learning_rate, correct_bias=False)

# Define scheduler
training_steps = len(train_loader)*n_epochs
scheduler = get_linear_schedule_with_warmup(
    optimizer,
    num_warmup_steps=0,
    num_training_steps=training_steps
)
```

```
/usr/local/lib/python3.10/dist-packages/transformers/optimization.py:411: FutureWarning: This implementation of AdamW is de
  warnings.warn(
```

The above code prepares the training environment for the deep learning model. It sets the number of training epochs, the learning rate, the loss function, the optimizer (AdamW), and a learning rate scheduler. The scheduler is designed to gradually adjust the learning rate during training, which can help improve model convergence and performance.

Training,Validation and Model Checkpointing:

```
# Track changes in validation loss
valid_loss_min = np.Inf

for epoch in range(1, n_epochs+1):

    # Setting training and validation loss
    train_loss = []
    validation_loss = []
    tr_predictions = 0
    acc = 0
    val_predictions = 0

    ###################
    #  Train the model #
    ###################
    model = model.train()
    for data in train_loader:

        # Moving tensors to GPU on CUDA enabled devices
        if device:
            input_ids, attention_mask, targets = data["input_ids"].cuda(), data["attention_mask"].cuda(), data["targets"].cuda()
        # Clear the gradients of variables
        optimizer.zero_grad()
```

```
#### Forward pass
# Pass input through the model
output = model(
    input_ids=input_ids,
    attention_mask=attention_mask
)
# Compute batch loss
loss = criterion(output, targets)
# Convert output probabilities to class probabilities
_, pred = torch.max(output, 1)
# Track correct predictions
tr_predictions += torch.sum(pred == targets)

#### Backward Pass
# Compute gradients wrt to model parameters
loss.backward()
# To avoid exploding gradients, we clip the gradients of the model
nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)
# Perform parameter update
optimizer.step()
# Update learning rate
scheduler.step()
# Update loss per mini batches
train_loss.append(loss.item())
```

```python
# Validate the model #
######################
model.eval()
with torch.no_grad():
    for data in valid_loader:

        # Moving tensors to GPU on CUDA enabled devices
        if device:
            input_ids, attention_mask, targets = data["input_ids"].cuda(), data["attention_mask"].cuda(), data["targets"].cuda(

        #### Forward pass
        # Pass input through the model
        output = model(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
        # Compute batch loss
        loss = criterion(output, targets)
        # Convert output probabilities to class probabilities
        _, pred = torch.max(output, 1)
        # Update loss per mini batches
        validation_loss.append(loss.item())
        # Track correct predictions
        val_predictions += torch.sum(pred == targets)
```

```python
# Compute accuracy
train_accuracy = tr_predictions.double()/len(train_sampler)
val_accuracy = val_predictions.double()/len(valid_sampler)

# Print loss statistics
print('Epoch: {}/{} \n\tTraining Loss: {:.6f} \n\tValidation Loss: {:.6f} \n\tTrain Accuracy: {:.6f} \n\tVal Accuracy: {:.6f}'
.format(epoch,n_epochs, np.mean(train_loss), np.mean(validation_loss), train_accuracy, val_accuracy))

# Save model if validation loss is decreased
if val_accuracy > acc:
    print('Saving model...')
    torch.save(model.state_dict(), 'bert_base_fine_tuned.pt')
    acc = val_accuracy
```

The above code outlines the training and validation process for a deep learning model, monitoring metrics, and saving the best model based on validation accuracy.

Output:

```
Epoch: 1/10
	Training Loss: 0.478485
	Validation Loss: 0.426510
	Train Accuracy: 0.813221
	Val Accuracy: 0.848361
Saving model...
Epoch: 2/10
	Training Loss: 0.251598
	Validation Loss: 0.587404
	Train Accuracy: 0.912720
	Val Accuracy: 0.837432
Saving model...
Epoch: 3/10
	Training Loss: 0.147462
	Validation Loss: 0.694001
	Train Accuracy: 0.958333
	Val Accuracy: 0.848361
Saving model...
Epoch: 4/10
	Training Loss: 0.095958
	Validation Loss: 0.852052
	Train Accuracy: 0.976548
	Val Accuracy: 0.841530
Saving model...
Epoch: 5/10
	Training Loss: 0.062927
	Validation Loss: 0.967488
	Train Accuracy: 0.985504
	Val Accuracy: 0.842896
Saving model...
Epoch: 6/10
	Training Loss: 0.042360
	Validation Loss: 1.066000
	Train Accuracy: 0.990437
	Val Accuracy: 0.840164
Saving model...
Epoch: 7/10
	Training Loss: 0.032142
	Validation Loss: 1.132496
	Train Accuracy: 0.992410
	Val Accuracy: 0.833333
Saving model...
Epoch: 8/10
	Training Loss: 0.024429
	Validation Loss: 1.184951
	Train Accuracy: 0.993777
	Val Accuracy: 0.829235
Saving model...
Epoch: 9/10
	Training Loss: 0.018996
	Validation Loss: 1.230268
	Train Accuracy: 0.994991
	Val Accuracy: 0.831967
Saving model...
Epoch: 10/10
	Training Loss: 0.015075
	Validation Loss: 1.244014
	Train Accuracy: 0.995826
	Val Accuracy: 0.830601
Saving model...
```

Model Evaluation and Test Data Analysis:

```
# Track test loss
test_loss = 0.0
class_predictions = list(0. for i in range(3))
class_total = list(0. for i in range(3))
predictions = []
labels = []

model.eval()
with torch.no_grad():
    for data in test_loader:

        # Moving tensors to GPU on CUDA enabled devices
        if device:
            input_ids, attention_mask, targets = data["input_ids"].cuda(), data["attention_mask"].cuda(), data["targets"].cuda()

        #### Forward pass
        # Pass input through the model
        output = model(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
```

```
        # Compute batch loss
        loss = criterion(output, targets)
        # Update loss
        test_loss += loss.item()
        # convert output probabilities to predicted class
        _, pred = torch.max(output, 1)

        predictions.extend(pred)
        labels.extend(targets)

predictions = torch.stack(predictions) if not device else torch.stack(predictions).cpu()
labels = torch.stack(labels) if not device else torch.stack(labels).cpu()
```

The above code performs model evaluation on the test dataset. It computes the test loss and collects predictions and labels for further evaluation, such as accuracy calculation, confusion matrix, or any other performance metrics.

Classification Model Evaluation with a Classification Report:

```
print(classification_report(predictions, labels, target_names=['neutral', 'positive','negative']))
```

	precision	recall	f1-score	support
neutral	0.68	0.71	0.69	146
positive	0.79	0.81	0.80	118
negative	0.92	0.90	0.91	468
accuracy			0.85	732
macro avg	0.79	0.81	0.80	732
weighted avg	0.85	0.85	0.85	732

The above code is using the classification_report function to generate a report that summarizes the performance of a classification model, typically in the context of machine learning or deep learning

Confusion Matrix:

```
cm = confusion_matrix(labels, predictions)
heatmap = sns.heatmap(cm, annot=True, fmt='d', cmap='Greens')
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right')
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=30, ha='right')
plt.xlabel('True sentiment')
plt.ylabel('Predicted sentiment');
```

The above code is used to create a confusion matrix heatmap for visualizing the results of a classification model.

Output: