In [2]:
```
import os
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style='whitegrid')

#from wordcloud import WordCloud
import tensorflow as tf
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA, TruncatedSVD
from sklearn.metrics import classification_report,confusion_matrix
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Embedding, LSTM,Dense, SpatialDropout1D, Dropout
from keras.initializers import Constant

# Reset individual options to default
pd.reset_option('display.max_columns')
pd.reset_option('display.max_rows')
pd.reset_option('display.max_colwidth')

# Set desired options
pd.set_option('display.max_columns', 100)
pd.set_option('display.max_rows', 900)
pd.set_option('display.max_colwidth', 200)

import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
train = pd.read_csv('training.csv',header=None)
validation = pd.read_csv('validation.csv',header=None)

train.columns=['Tweet ID','Entity','Sentiment','Tweet Content']
validation.columns=['Tweet ID','Entity','Sentiment','Tweet Content']

print("Training DataSet: \n")
train = train.sample(2000)
display(train.head())
```

```
Training DataSet:
```

	Tweet ID	Entity	Sentiment	Tweet Content
55500	2329	CallOfDuty	Positive	Good little session on COD earlier - absolutely beaming folks
73023	8910	Nvidia	Positive	Just hang out
63515	7685	MaddenNFL	Positive	One of my favorite rappers to all-time is narrating one of my upcoming video ads with his all-time favorite Louisville player on their cover. Please don't pinch me
23630	4450	Google	Irrelevant	I definitely miss being with this amazing group of student athletes and coaches every day. I loved the positivity and work ethic that these girls still bring every day!
66766	7032	johnson&johnson	Neutral	But Johnson & Johnson says its

In [4]:
```
print("Validation DataSet: \n")
display(validation.head())
```

```
Validation DataSet:
```

	Tweet ID	Entity	Sentiment	Tweet Content
0	3364	Facebook	Irrelevant	I mentioned on Facebook that I was struggling for motivation to go for a run the other day, which has been translated by Tom's great auntie as 'Hayley can't get out of bed' and told to his grandma...
1	352	Amazon	Neutral	BBC News - Amazon boss Jeff Bezos rejects claims company acted like a 'drug dealer' bbc.co.uk/news/av/busine…
2	8312	Microsoft	Negative	@Microsoft Why do I pay for WORD when it functions so poorly on my @SamsungUS Chromebook?
3	4371	CS-GO	Negative	CSGO matchmaking is so full of closet hacking, it's a truly awful game.
4	4433	Google	Neutral	Now the President is slapping Americans in the face that he really did commit an unlawful act after his acquittal! From Discover on Google vanityfair.com/news/2020/02/t…

In [5]:
```
train = train.dropna(subset=['Tweet Content'])

display(train.isnull().sum())
print("*****"* 5)
display(validation.isnull().sum())
```

```
Tweet ID         0
Entity           0
Sentiment        0
Tweet Content    0
dtype: int64
*************************
Tweet ID         0
Entity           0
Sentiment        0
Tweet Content    0
dtype: int64
```

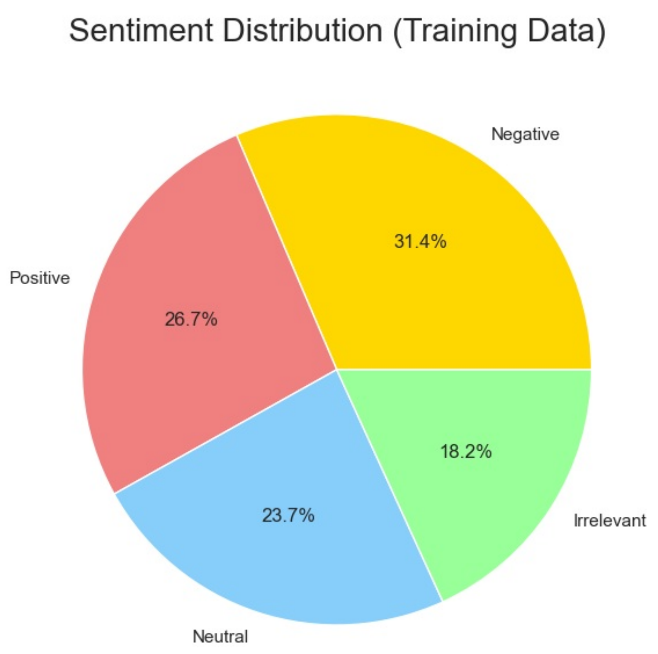
In [6]:
```
duplicates = train[train.duplicated(subset=['Entity', 'Sentiment', 'Tweet Content'], keep=False)]
train = train.drop_duplicates(subset=['Entity', 'Sentiment', 'Tweet Content'], keep='first')

duplicates = validation[validation.duplicated(subset=['Entity', 'Sentiment', 'Tweet Content'], keep=False)]
validation = validation.drop_duplicates(subset=['Entity', 'Sentiment', 'Tweet Content'], keep='first')
```

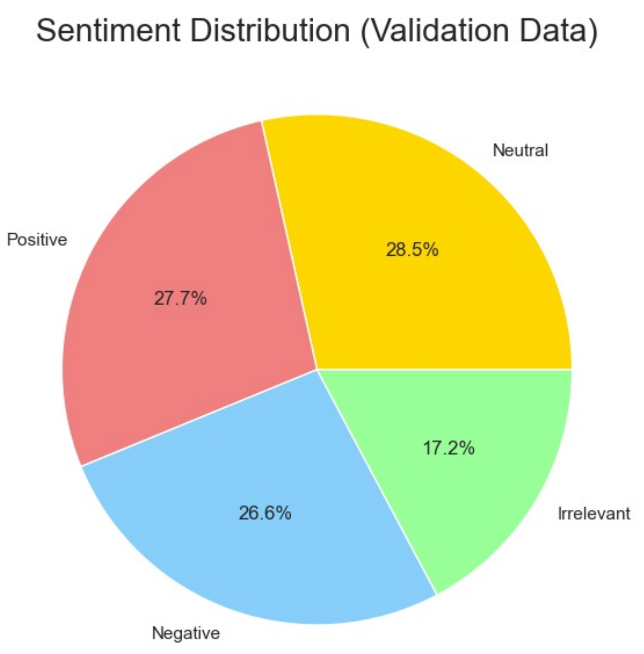
In [7]:
```
import pandas as pd

# Assuming 'train' and 'validation' are your DataFrames

# Calculate sentiment counts for train and validation data
sentiment_counts_train = train['Sentiment'].value_counts()
sentiment_counts_validation = validation['Sentiment'].value_counts()

# Combine counts into a single DataFrame
combined_counts = pd.concat([sentiment_counts_train, sentiment_counts_validation], axis=1)

# Fill missing values (if any) with 0
combined_counts.fillna(0, inplace=True)

# Rename columns
combined_counts.columns = ['Test Data', 'Validation Data']  # Set desired column names

combined_counts
```

Out[7]:

	Test Data	Validation Data
Sentiment		
Negative	625	266
Positive	530	277
Neutral	472	285
Irrelevant	361	172

In [8]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming 'train' and 'validation' are your DataFrames

# Calculate sentiment counts
sentiment_counts_train = train['Sentiment'].value_counts()
sentiment_counts_validation = validation['Sentiment'].value_counts()

# Create subplots for side-by-side comparison
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))  # Adjust figsize for better view

# Create pie chart for training data
ax1.pie(sentiment_counts_train, labels=sentiment_counts_train.index, autopct='%1.1f%%', colors=['gold', 'lightc
ax1.set_title('Sentiment Distribution (Training Data)', fontsize=20)

# Create pie chart for validation data
ax2.pie(sentiment_counts_validation, labels=sentiment_counts_validation.index, autopct='%1.1f%%', colors=['gold
ax2.set_title('Sentiment Distribution (Validation Data)', fontsize=20)

# Adjust layout for better visualization
plt.tight_layout()
plt.show()
```





In [9]:

```
# Calculate the value counts of 'Entity'
entity_counts = train['Entity'].value_counts()

# Get the top 9 names
top_names = entity_counts.head(19)

# Aggregate the tenth name as 'Other'
other_count = entity_counts[19:].sum()
top_names['Other'] = other_count

# Display the top 19 names and 'Other'
top_names.to_frame()
```

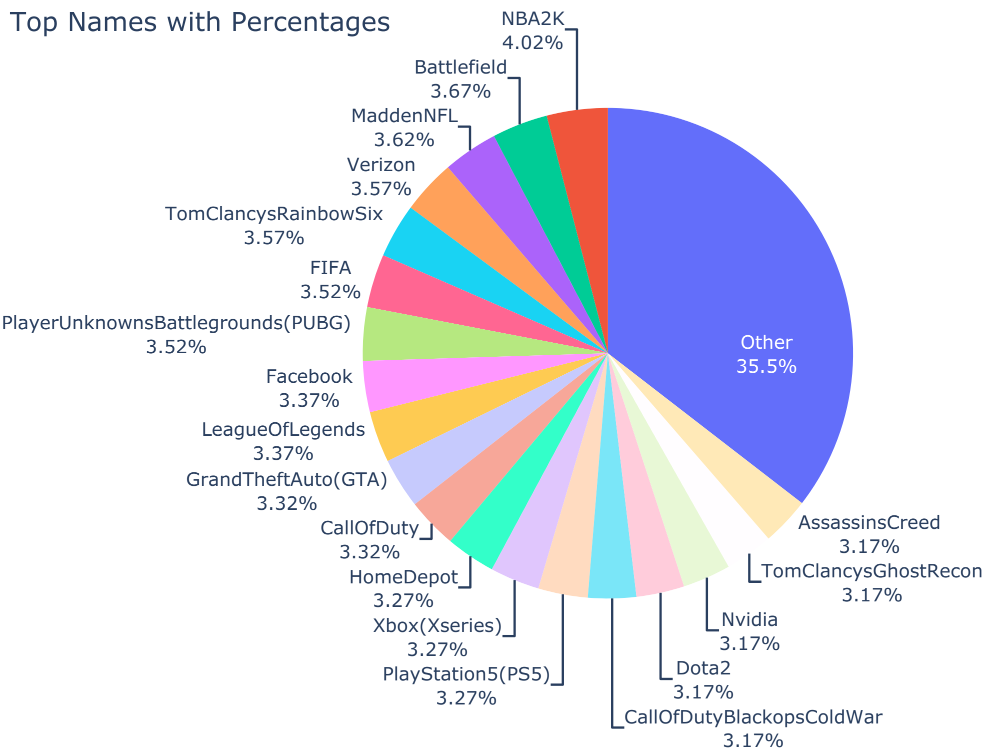
Out[9]:

Entity	count
NBA2K	80
Battlefield	73
MaddenNFL	72
Verizon	71
TomClancysRainbowSix	71
FIFA	70
PlayerUnknownsBattlegrounds(PUBG)	70
Facebook	67
LeagueOfLegends	67
GrandTheftAuto(GTA)	66
CallOfDuty	66
HomeDepot	65
Xbox(Xseries)	65
PlayStation5(PS5)	65
CallOfDutyBlackopsColdWar	63
Dota2	63
Nvidia	63
TomClancysGhostRecon	63
AssassinsCreed	63
Other	705

In [10]:

```
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio

# Calculate the percentages
percentages = (top_names / top_names.sum()) * 100

# Create the pie chart
fig = go.Figure(data=[go.Pie(
```

```
    labels=percentages.index,
    values=percentages,
    textinfo='label+percent',
    insidetextorientation='radial'
)])

# Update layout
fig.update_layout(
    title_text='Top Names with Percentages',
    showlegend=False
)

# Show the plot
fig.show()
```



In [11]:
```
from tensorflow.keras.layers import Input, Dropout, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.initializers import TruncatedNormal
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.metrics import CategoricalAccuracy
from tensorflow.keras.utils import to_categorical

import pandas as pd
from sklearn.model_selection import train_test_split
```

In [12]:
```
import pandas as pd
import plotly.graph_objects as go

# Assuming you've already run the data preprocessing steps
data = train[['Tweet Content', 'Sentiment']]

# Set your model output as categorical and save in new label col
data['Sentiment_label'] = pd.Categorical(data['Sentiment'])

# Transform your output to numeric
data['Sentiment'] = data['Sentiment_label'].cat.codes

# Use the entire training data as data_train
data_train = data

# Use validation data as data_test
data_test = validation[['Tweet Content', 'Sentiment']]
data_test['Sentiment_label'] = pd.Categorical(data_test['Sentiment'])
data_test['Sentiment'] = data_test['Sentiment_label'].cat.codes

# Create a colorful table using Plotly
fig = go.Figure(data=[go.Table(
    header=dict(
        values=list(data_train.columns),
        fill_color='paleturquoise',
        align='left',
```

```
        font=dict(color='black', size=12)
    ),
    cells=dict(
        values=[data_train[k].tolist()[:10] for k in data_train.columns],
        fill_color=[
            'lightcyan',  # Tweet Content
            ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
              else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_train['Sentiment_label'][:10]
            ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
              else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_train['Sentiment_label'][:10]
            'lavender'  # Sentiment (numeric)
        ],
        align='left',
        font=dict(color='black', size=11)
    ))
])

# Update the layout
fig.update_layout(
    title='First 10 Rows of Training Data',
    width=1000,
    height=400,
)

fig.show()
```

First 10 Rows of Training Data

Tweet Content	Sentiment	Sentiment_label
Good little session on COD earlier - absolutely beaming folks	3	Positive
Just hang out	3	Positive
One of my favorite rappers to all-time is narratin one of my upcoming video ads with his all-time favorite Louisville player on their cover. Please do pinch me	3	Positive
I definitely miss being with this amazing group of student athletes and coaches every day. I loved t positivity and work ethic that these girls still brin	0	Irrelevant

```
In [15]: import plotly.graph_objects as go

# Create a colorful table using Plotly for the test data
fig = go.Figure(data=[go.Table(
    header=dict(
        values=list(data_test.columns),
        fill_color='paleturquoise',
        align='left',
        font=dict(color='black', size=12)
    ),
    cells=dict(
        values=[data_test[k].tolist()[:5] for k in data_test.columns],  # Show first 5 rows
        fill_color=[
            'lightcyan',  # Tweet Content
            ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
             else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_test['Sentiment_label'][:5]],
            ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
             else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_test['Sentiment_label'][:5]],
            'lavender'  # Sentiment (numeric)
        ],
        align='left',
        font=dict(color='black', size=11)
    ))
])

# Update the layout
fig.update_layout(
    title='First 5 Rows of Test Data',
    width=1000,
    height=500,
)

# Show the figure
fig.show()
```

First 5 Rows of Test Data

Tweet Content	Sentiment	Sentiment_label
I mentioned on Facebook that I was struggling fc motivation to go for a run the other day, which h been translated by Tom's great auntie as 'Hayley can't get out of bed' and told to his grandma, wh thinks I'm a lazy, terrible person	0	Irrelevant
BBC News - Amazon boss Jeff Bezos rejects claim company acted like a 'drug dealer' bbc.co.uk/news/av/busine…	2	Neutral
@Microsoft Why do I pay for WORD when it funct so poorly on my @SamsungUS Chromebook?	1	Negative
CSGO matchmaking is so full of closet hacking, it truly awful game.	1	Negative
Now the President is slapping Americans in the fa that he really did commit an unlawful act after hi acquittal! From Discover on Google	2	Neutral

BERT (Bidirectional Encoder Representations from Transformers)

BERT: Bidirectional Encoder Representations from Transformers

BERT is a groundbreaking language model that has significantly advanced the field of Natural Language Processing (NLP).

It stands for Bidirectional Encoder Representations from Transformers.

Key Concepts

- **Bidirectional:** Unlike previous models that processed text sequentially (left to right or right to left), BERT considers the entire context of a word, both preceding and following it. This enables a deeper understanding of language nuances.
- **Encoder:** BERT focuses on understanding the input text rather than generating new text. It extracts meaningful representations from the input sequence.
- **Transformers:** The underlying architecture of BERT is based on the Transformer model, known for its efficiency in handling long sequences and capturing dependencies between words.

How BERT Works

- **Pre-training:** BERT is initially trained on a massive amount of text data (like Wikipedia and BooksCorpus) using two unsupervised tasks:
  - **Masked Language Modeling (MLM):** Randomly masks some words in the input and trains the model to predict the masked words based on the context of surrounding words.

- **Next Sentence Prediction (NSP):** Trains the model to predict whether two given sentences are consecutive in the original document.
- **Fine-tuning:** After pre-training, BERT can be adapted to specific NLP tasks with minimal additional training. This is achieved by adding a task-specific output layer to the pre-trained model.

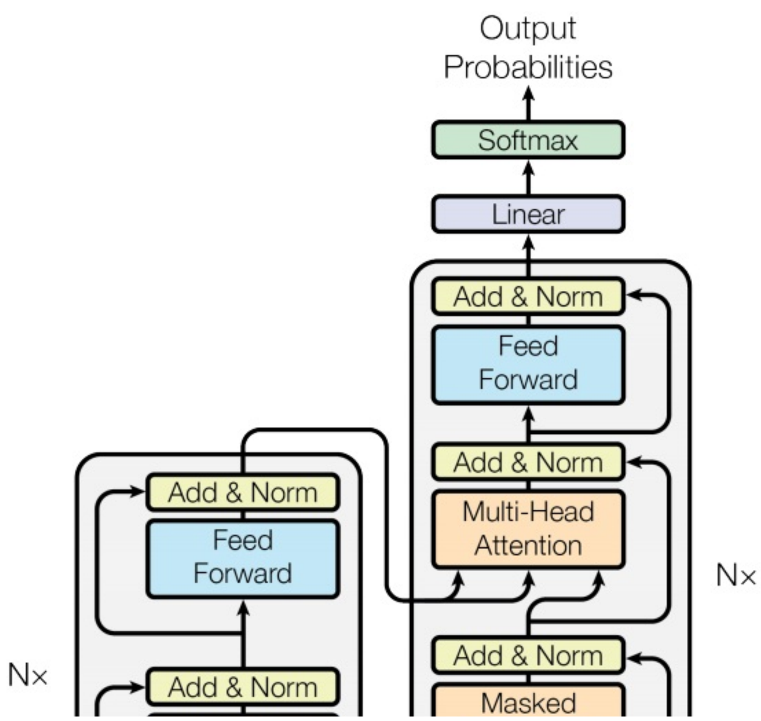
Advantages of BERT

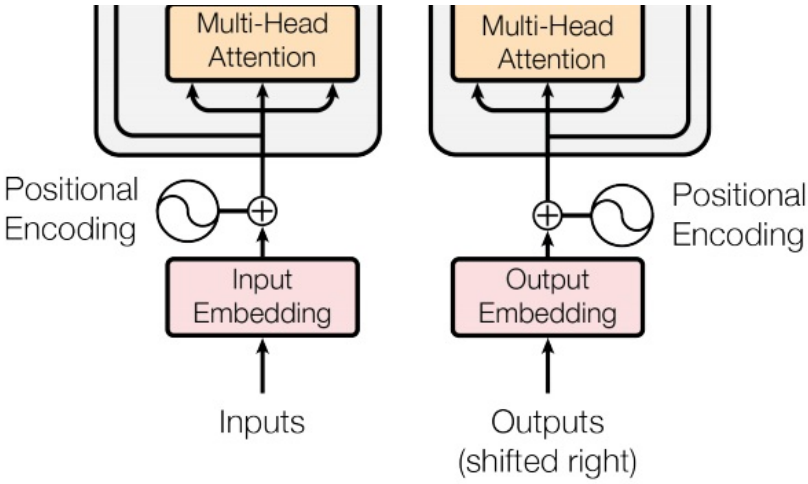
- **Strong performance:** BERT has achieved state-of-the-art results on a wide range of NLP tasks, including question answering, text classification, named entity recognition, and more.
- **Efficiency:** Fine-tuning BERT for new tasks is relatively quick and requires less data compared to training models from scratch.
- **Versatility:** BERT can be applied to various NLP problems with minimal modifications.

Applications of BERT

- **Search engines:** Improving search relevance and understanding user queries.
- **Chatbots:** Enhancing natural language understanding and generating more human-like responses.
- **Sentiment analysis:** Accurately determining the sentiment expressed in text.
- **Machine translation:** Improving the quality of translated text.
- **Text summarization:** Generating concise summaries of lengthy documents.

In essence, BERT is a powerful language model that has revolutionized NLP by capturing the bidirectional context of words and enabling efficient transfer learning for various tasks.





In [13]:

```
%%time

import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import BertTokenizer, BertForSequenceClassification, AdamW
from sklearn.metrics import accuracy_score, classification_report

# Preprocess the dataF
def preprocess_data(df):
    df['label'] = df['Sentiment_label'].map({'Positive': 2, 'Negative': 0, 'Neutral': 1, 'Irrelevant': 3})
    return df['Tweet Content'].tolist(), df['label'].tolist()

train_texts, train_labels = preprocess_data(data_train)
test_texts, test_labels = preprocess_data(data_test)

# Create a custom dataset
class SentimentDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self, idx):
        text = str(self.texts[idx])
        label = self.labels[idx]

        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            return_token_type_ids=False,
            padding='max_length',
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize tokenizer and create datasets
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
train_dataset = SentimentDataset(train_texts, train_labels, tokenizer)
test_dataset = SentimentDataset(test_texts, test_labels, tokenizer)

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

# Initialize the model_BERT
model_BERT = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=4)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model_BERT.to(device)

# Set up optimizer
optimizer = AdamW(model_BERT.parameters(), lr=2e-5)

# Training loop
```

```python
num_epochs = 3

for epoch in range(num_epochs):
    model_BERT.train()
    for batch in train_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)
        outputs = model_BERT(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        optimizer.step()

    # Evaluation on test set
    model_BERT.eval()
    test_preds = []
    test_true = []
    with torch.no_grad():
        for batch in test_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels']
            outputs = model_BERT(input_ids, attention_mask=attention_mask)
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            test_preds.extend(preds)
            test_true.extend(labels.numpy())

    accuracy = accuracy_score(test_true, test_preds)
    print(f'Epoch {epoch + 1}/{num_epochs}, Test Accuracy: {accuracy:.4f}')


# Save the model_BERT
torch.save(model_BERT.state_dict(), 'sentiment_model_BERT.pth')
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncas
ed and are newly initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Epoch 1/3, Test Accuracy: 0.5450
Epoch 2/3, Test Accuracy: 0.5600
Epoch 3/3, Test Accuracy: 0.6080
CPU times: user 1min 41s, sys: 52.3 s, total: 2min 33s
Wall time: 2min 38s
```

In [14]:
```python
# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant
```

```
              precision    recall  f1-score   support

    Negative       0.62      0.84      0.72       266
     Neutral       0.59      0.55      0.57       285
    Positive       0.61      0.74      0.67       277
  Irrelevant       0.55      0.13      0.21       172

    accuracy                           0.61      1000
   macro avg       0.59      0.57      0.54      1000
weighted avg       0.60      0.61      0.58      1000
```

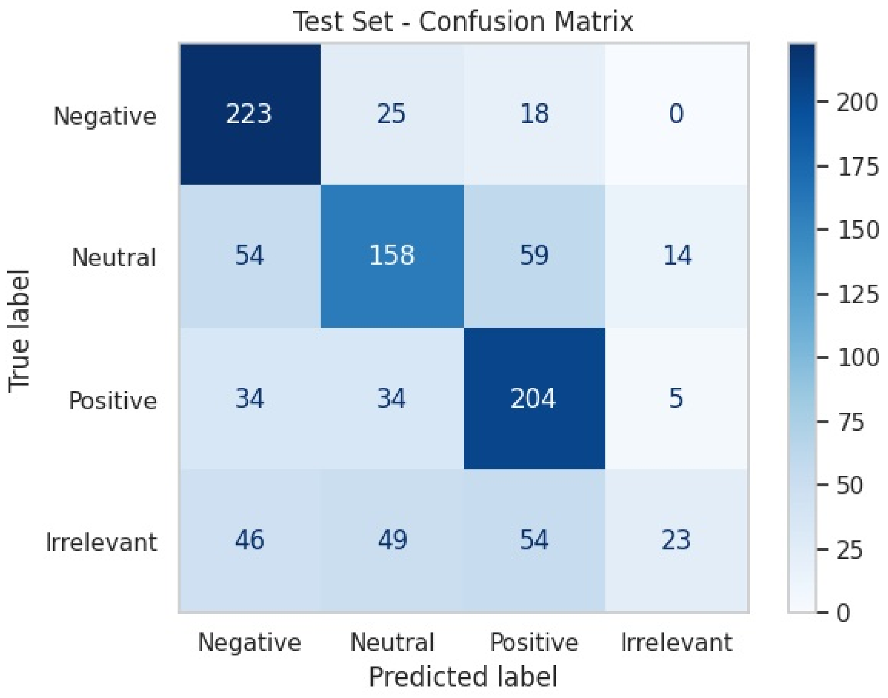
In [15]:
```python
# Assuming test_true and test_preds are defined
from sklearn.metrics import confusion_matrix

# Check if test_true labels need conversion (optional)
if not isinstance(test_true[0], str):  # If labels are not strings
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    test_true_encoded = encoder.fit_transform(test_true)  # Encode labels
    labels = [0, 1, 2, 3]  # Numerical labels
else:
    test_true_encoded = test_true
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels

# Calculate confusion matrix with consistent labels
confusion_matrix_BERT = confusion_matrix(test_true_encoded, test_preds, labels=labels)

print("Confusion matrix BERT \n")
confusion_matrix_BERT
```

```
Confusion matrix BERT
```

Out[15]:
```
array([[223,  25,  18,   0],
       [ 54, 158,  59,  14],
       [ 34,  34, 204,   5],
       [ 46,  49,  54,  23]])
```

In [16]:
```python
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
```

```python
labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels
test_display = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_BERT, display_labels=labels)
test_display.plot(cmap='Blues')
plt.title("Test Set - Confusion Matrix")
plt.grid(False)
plt.tight_layout()
plt.show()
```



RoBERTa (Robustly Optimized BERT Pretraining Approach)

RoBERTa: A Robustly Optimized BERT Approach

RoBERTa is an improved version of the BERT (Bidirectional Encoder Representations from Transformers) model. It builds upon BERT's architecture but incorporates several key modifications to enhance its performance.

Key Differences from BERT

- **Larger Training Dataset:** RoBERTa was trained on a significantly larger dataset compared to the original BERT, leading to a richer understanding of language.
- **Dynamic Masking:** Unlike BERT's static masking during pre-training, RoBERTa applies dynamic masking, where the masked tokens are changed multiple times for each training instance. This forces the model to learn more robust representations.
- **Longer Training:** RoBERTa undergoes a longer training process with larger batch sizes, allowing it to converge to a better optimum.
- **Removal of Next Sentence Prediction (NSP):** RoBERTa eliminates the NSP objective, focusing solely on Masked Language Modeling (MLM). This change simplifies the training process and improves performance on downstream tasks.
- **Increased Sequence Length:** RoBERTa can handle longer input sequences, enabling it to process more context-rich information.

Benefits of RoBERTa

- **Improved Performance:** RoBERTa consistently outperforms BERT on a wide range of NLP tasks, achieving state-of-the-art results.
- **Efficiency:** The modifications in RoBERTa lead to faster training and convergence.
- **Versatility:** Like BERT, RoBERTa can be fine-tuned for various NLP tasks, including text classification, question answering, and more.

Applications

- **Search Engines:** Enhancing search relevance and understanding user queries.
- **Chatbots:** Improving natural language understanding and generating more human-like responses.
- **Sentiment Analysis:** Accurately determining the sentiment expressed in text.
- **Machine Translation:** Enhancing the quality of translated text.
- **Text Summarization:** Generating concise summaries of lengthy documents.

In conclusion, RoBERTa is a powerful language model that builds upon the success of BERT by incorporating several refinements. Its improved performance and versatility make it a popular choice for various NLP applications.

In [17]:

```
%%time

import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import BertTokenizer, BertForSequenceClassification, AdamW
from transformers import RobertaTokenizer, RobertaForSequenceClassification, AdamW
from sklearn.metrics import accuracy_score, classification_report

# Preprocess the data
def preprocess_data(df):
    df['label'] = df['Sentiment_label'].map({'Positive': 2, 'Negative': 0, 'Neutral': 1, 'Irrelevant': 3})
    return df['Tweet Content'].tolist(), df['label'].tolist()

train_texts, train_labels = preprocess_data(data_train)
test_texts, test_labels = preprocess_data(data_test)

# Create a custom dataset
class SentimentDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self, idx):
        text = str(self.texts[idx])
        label = self.labels[idx]

        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            return_token_type_ids=False,
            padding='max_length',
```

```
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize tokenizer and create datasets
#tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
tokenizer = RobertaTokenizer.from_pretrained('roberta-base')
train_dataset = SentimentDataset(train_texts, train_labels, tokenizer)
test_dataset = SentimentDataset(test_texts, test_labels, tokenizer)

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

# Initialize the model
#model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=4)
model_RoBERTa = RobertaForSequenceClassification.from_pretrained('roberta-base', num_labels=4)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model_RoBERTa.to(device)

# Set up optimizer
optimizer = AdamW(model_RoBERTa.parameters(), lr=2e-5)

# Training loop
num_epochs = 3

for epoch in range(num_epochs):
    model_RoBERTa.train()
    for batch in train_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)
        outputs = model_RoBERTa(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        optimizer.step()

    # Evaluation on test set
    model_RoBERTa.eval()
    test_preds = []
    test_true = []
    with torch.no_grad():
        for batch in test_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels']
            outputs = model_RoBERTa(input_ids, attention_mask=attention_mask)
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            test_preds.extend(preds)
            test_true.extend(labels.numpy())

    accuracy = accuracy_score(test_true, test_preds)
    print(f'Epoch {epoch + 1}/{num_epochs}, Test Accuracy: {accuracy:.4f}')


# Save the model
torch.save(model_RoBERTa.state_dict(), 'sentiment_RoBERTa_model.pth')
```

```
Some weights of RobertaForSequenceClassification were not initialized from the model checkpoint at roberta-base
and are newly initialized: ['classifier.dense.bias', 'classifier.dense.weight', 'classifier.out_proj.bias', 'cl
assifier.out_proj.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Epoch 1/3, Test Accuracy: 0.5390
Epoch 2/3, Test Accuracy: 0.5790
Epoch 3/3, Test Accuracy: 0.5930
CPU times: user 1min 42s, sys: 54.8 s, total: 2min 36s
Wall time: 2min 38s
```

In [18]:

```
# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant
```

```
              precision    recall  f1-score   support

    Negative       0.62      0.80      0.70       266
     Neutral       0.69      0.37      0.48       285
    Positive       0.56      0.80      0.66       277
  Irrelevant       0.50      0.31      0.38       172

    accuracy                           0.59      1000
   macro avg       0.59      0.57      0.55      1000
weighted avg       0.60      0.59      0.57      1000
```

In [19]:

```python
# Assuming test_true and test_preds are defined
from sklearn.metrics import confusion_matrix

# Check if test_true labels need conversion (optional)
if not isinstance(test_true[0], str):  # If labels are not strings
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    test_true_encoded = encoder.fit_transform(test_true)  # Encode labels
    labels = [0, 1, 2, 3]  # Numerical labels
else:
    test_true_encoded = test_true
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels

# Calculate confusion matrix with consistent labels
confusion_matrix_RoBERTa = confusion_matrix(test_true_encoded, test_preds, labels=labels)

print("Confusion matrix RoBERTa \n")
confusion_matrix_RoBERTa
```

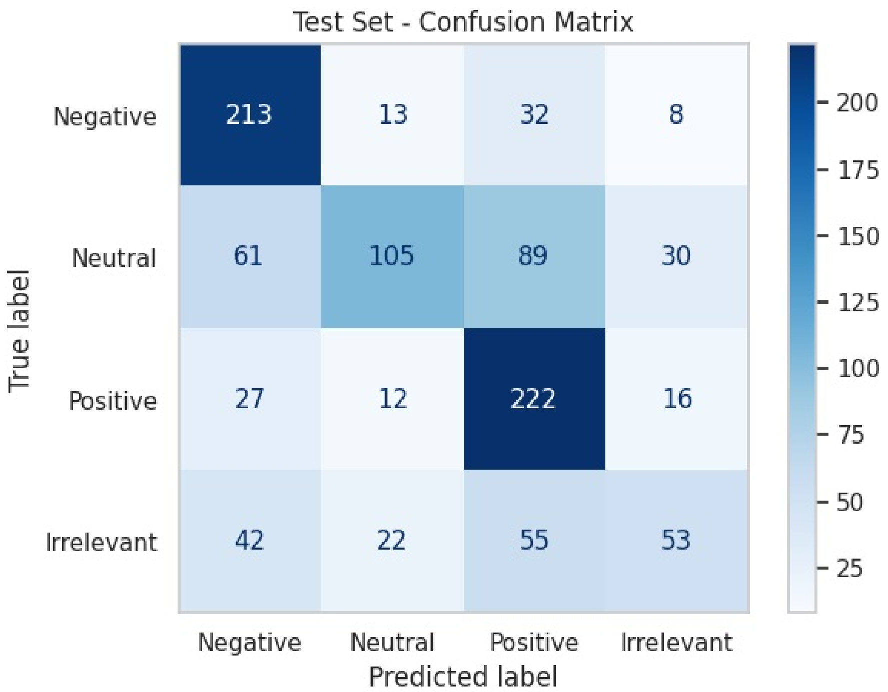
```
Confusion matrix RoBERTa
```

Out[19]:

```
array([[213,  13,  32,   8],
       [ 61, 105,  89,  30],
       [ 27,  12, 222,  16],
       [ 42,  22,  55,  53]])
```

In [20]:

```python
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels
test_display = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_RoBERTa, display_labels=labels)
test_display.plot(cmap='Blues')
plt.title("Test Set - Confusion Matrix")
plt.grid(False)
plt.tight_layout()
plt.show()
```



DistilBERT (Distilled version of BERT)

> **DistilBERT: A Smaller, Faster BERT**
>
> DistilBERT is a smaller and faster version of the BERT model. It's created

using a technique called knowledge distillation. This means that a smaller model (the student) learns to mimic the behavior of a larger, more complex model (the teacher). In this case, the teacher is BERT.

Key Features

- **Smaller size:** DistilBERT is about 40% smaller than BERT, making it more efficient in terms of memory and computation.
- **Faster:** It's also significantly faster than BERT, making it suitable for real-time applications.
- **Comparable performance:** Despite its smaller size, DistilBERT retains about 95% of BERT's language understanding capabilities.

How it Works

- **Knowledge Distillation:** The process involves training DistilBERT to predict the same outputs as BERT for a given input. However, instead of using hard labels (the correct answer), DistilBERT is trained on softened outputs from BERT. This allows the smaller model to learn more generalizable knowledge.
- **Architecture Simplification:** Some architectural elements of BERT, such as the token type embeddings, are removed to reduce complexity.

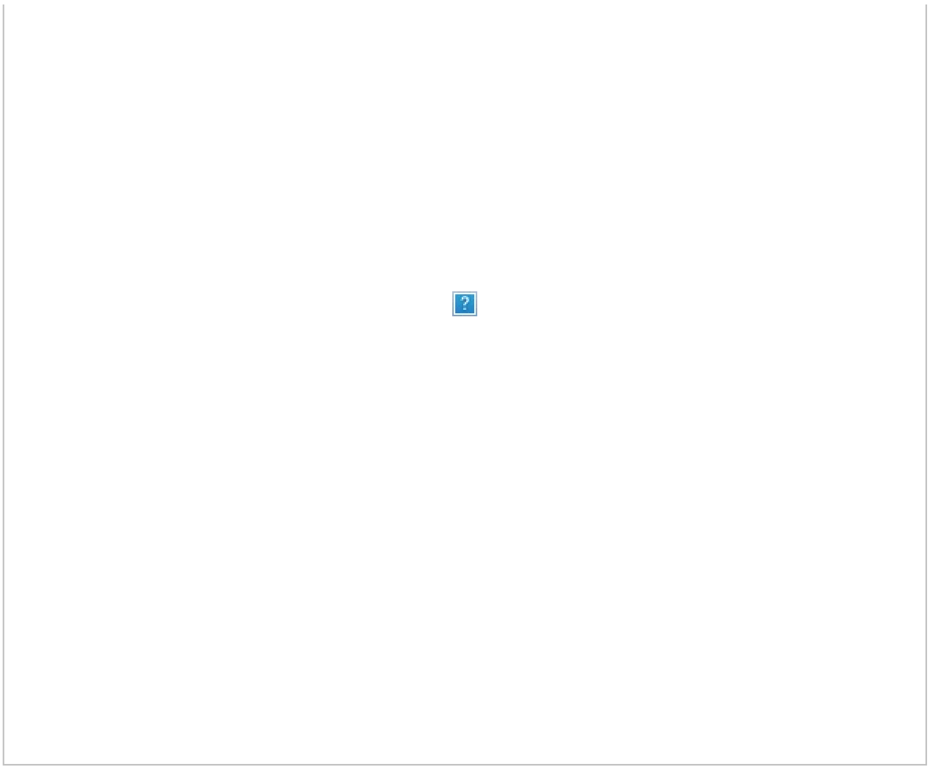
Advantages

- **Efficiency:** Smaller size and faster inference speed make it suitable for resource-constrained environments.
- **Cost-effective:** Lower computational requirements lead to reduced training and inference costs.
- **Good performance:** Despite its smaller size, it maintains a high level of performance on various NLP tasks.

Applications

- **Text classification:** Sentiment analysis, topic modeling
- **Named entity recognition:** Identifying entities in text (e.g., persons, organizations, locations)
- **Question answering:** Finding answers to questions based on given text
- **Text generation:** Summarization, translation

In summary, DistilBERT offers a compelling balance between model size, speed, and performance. It's a valuable tool for NLP practitioners looking to deploy models efficiently without sacrificing accuracy.



In [21]:

```
%%time

import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import DistilBertTokenizer, DistilBertForSequenceClassification, AdamW
from sklearn.metrics import accuracy_score, classification_report

# Preprocess the data
def preprocess_data(df):
    df['label'] = df['Sentiment_label'].map({'Positive': 2, 'Negative': 0, 'Neutral': 1, 'Irrelevant': 3})
    return df['Tweet Content'].tolist(), df['label'].tolist()

train_texts, train_labels = preprocess_data(data_train)
test_texts, test_labels = preprocess_data(data_test)

# Create a custom dataset
class SentimentDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self, idx):
        text = str(self.texts[idx])
        label = self.labels[idx]

        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            return_token_type_ids=False,
            padding='max_length',
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize tokenizer and create datasets
tokenizer = DistilBertTokenizer.from_pretrained('distilbert-base-uncased')
train_dataset = SentimentDataset(train_texts, train_labels, tokenizer)
test_dataset = SentimentDataset(test_texts, test_labels, tokenizer)

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)
```

```python
# Initialize the model DistilBERT
model_DistilBERT = DistilBertForSequenceClassification.from_pretrained('distilbert-base-uncased', num_labels=4)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model_DistilBERT.to(device)

# Set up optimizer
optimizer = AdamW(model_DistilBERT.parameters(), lr=2e-5)

# Training loop
num_epochs = 3

for epoch in range(num_epochs):
    model_DistilBERT.train()
    for batch in train_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)
        outputs = model_DistilBERT(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        optimizer.step()

    # Evaluation on test set
    model_DistilBERT.eval()
    test_preds = []
    test_true = []
    with torch.no_grad():
        for batch in test_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels']
            outputs = model_DistilBERT(input_ids, attention_mask=attention_mask)
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            test_preds.extend(preds)
            test_true.extend(labels.numpy())

    accuracy = accuracy_score(test_true, test_preds)
    print(f'Epoch {epoch + 1}/{num_epochs}, Test Accuracy: {accuracy:.4f}')


# Save the model_DistilBERT
torch.save(model_DistilBERT.state_dict(), 'sentiment_model_distilbert.pth')
```

```
Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilber
t-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight', 'pre_classifier.bias', 'pre_
classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Epoch 1/3, Test Accuracy: 0.5500
Epoch 2/3, Test Accuracy: 0.5660
Epoch 3/3, Test Accuracy: 0.6140
CPU times: user 1min 10s, sys: 9.6 s, total: 1min 19s
Wall time: 1min 21s
```

In [22]:

```python
# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant
```

```
              precision    recall  f1-score   support

    Negative       0.64      0.78      0.71       266
     Neutral       0.59      0.64      0.61       285
    Positive       0.65      0.69      0.67       277
  Irrelevant       0.45      0.20      0.27       172

    accuracy                           0.61      1000
   macro avg       0.58      0.58      0.57      1000
weighted avg       0.60      0.61      0.59      1000
```

In [23]:

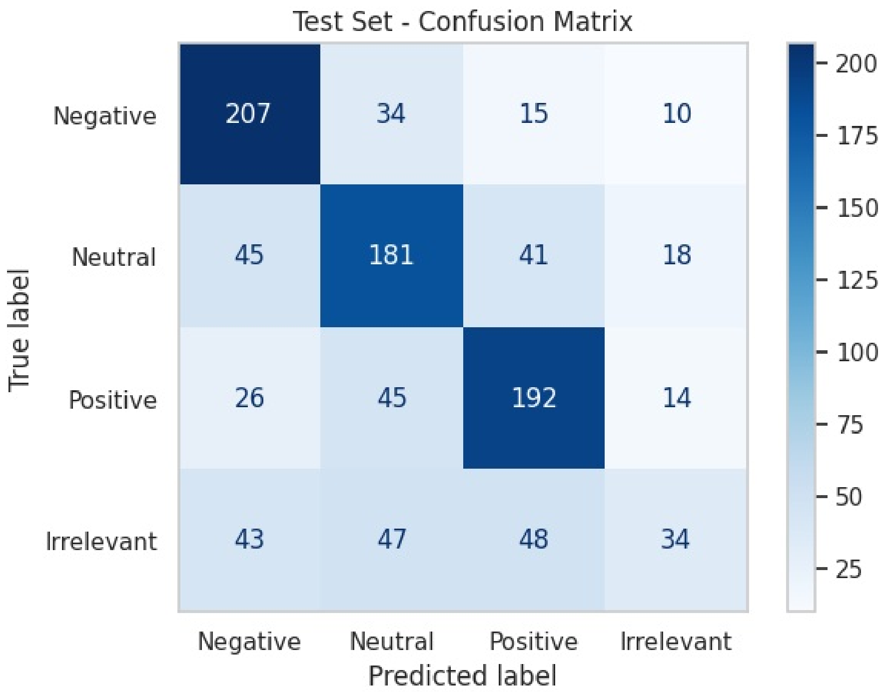
```python
# Assuming test_true and test_preds are defined
from sklearn.metrics import confusion_matrix

# Check if test_true labels need conversion (optional)
if not isinstance(test_true[0], str):  # If labels are not strings
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    test_true_encoded = encoder.fit_transform(test_true)  # Encode labels
    labels = [0, 1, 2, 3]  # Numerical labels
else:
    test_true_encoded = test_true
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels

# Calculate confusion matrix with consistent labels
confusion_matrix_DistilBERT = confusion_matrix(test_true_encoded, test_preds, labels=labels)
```

```
print("Confusion matrix DistilBERT \n")
confusion_matrix_DistilBERT
```

```
Confusion matrix DistilBERT
```

Out[23]:
```
array([[207,  34,  15,  10],
       [ 45, 181,  41,  18],
       [ 26,  45, 192,  14],
       [ 43,  47,  48,  34]])
```

In [24]:
```
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels
test_display = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_DistilBERT, display_labels=labels)
test_display.plot(cmap='Blues')
plt.title("Test Set - Confusion Matrix")
plt.grid(False)
plt.tight_layout()
plt.show()
```



ALBERT (A Lite BERT)

ALBERT: A Lite BERT for Self-Supervised Learning

ALBERT stands for A Lite BERT for Self-Supervised Learning. It's a language model developed by Google AI, designed to be more efficient and effective than the original BERT model.

Key Improvements Over BERT

- **Parameter Reduction:** ALBERT significantly reduces the number of parameters compared to BERT, making it more computationally efficient and faster to train. This is achieved by:
- **Factorized embedding parameterization:** Separating the embedding space into two smaller spaces, reducing the number of parameters.
- **Cross-layer parameter sharing:** Sharing parameters across different layers to reduce redundancy.
- **Sentence-Order Prediction (SOP):** Instead of the Next Sentence Prediction (NSP) task used in BERT, ALBERT employs SOP. This task is more challenging and helps the model better understand sentence

relationships.

Architecture

ALBERT maintains the overall transformer architecture of BERT but incorporates the aforementioned improvements. It consists of:

- **Embedding layer:** Converts input tokens into numerical representations.
- **Transformer encoder:** Processes the input sequence and captures contextual information.
- **Output layer:** Predicts the masked words and sentence order.

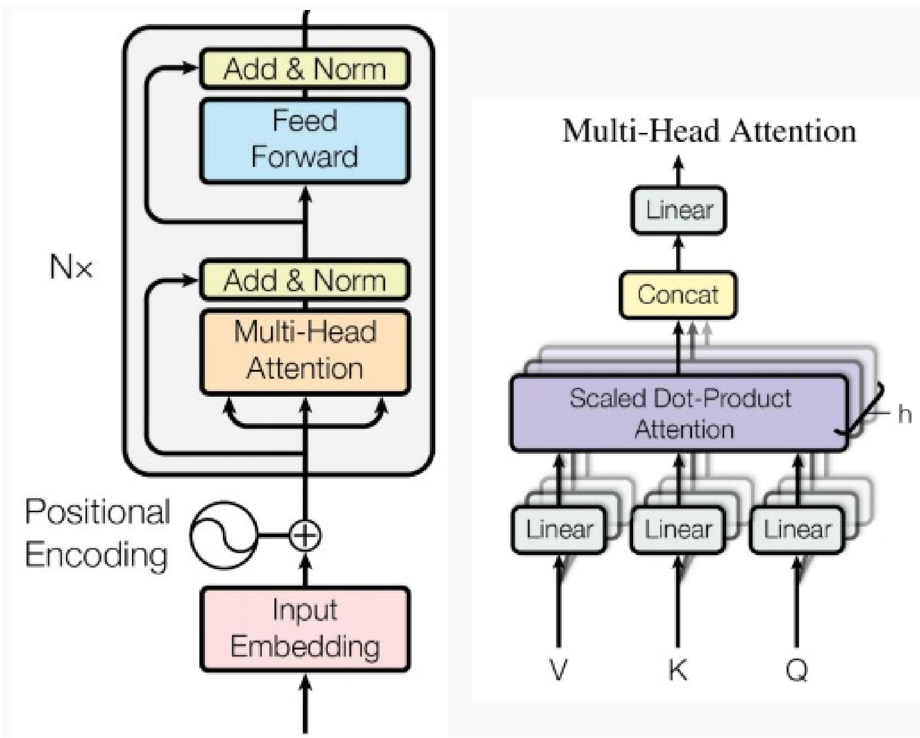
Benefits of ALBERT

- **Efficiency:** ALBERT is significantly smaller and faster to train than BERT.
- **Improved Performance:** Despite its smaller size, ALBERT often achieves better or comparable performance to BERT on various NLP tasks.
- **Versatility:** Like BERT, ALBERT can be fine-tuned for various NLP tasks.

Applications

- **Text classification:** Sentiment analysis, topic modeling
- **Question answering:** Answering questions based on given text
- **Named entity recognition:** Identifying entities in text (e.g., persons, organizations, locations)
- **Text summarization:** Generating concise summaries of lengthy documents

In summary, ALBERT is a powerful language model that addresses some of the limitations of BERT while maintaining its strengths. It offers a good balance between model size, speed, and performance, making it a popular choice for various NLP applications.



Inputs

In [25]:
```
%%time

import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import AlbertTokenizer, AlbertForSequenceClassification, AdamW
from sklearn.metrics import accuracy_score, classification_report

# Preprocess the data
def preprocess_data(df):
    df['label'] = df['Sentiment_label'].map({'Positive': 2, 'Negative': 0, 'Neutral': 1, 'Irrelevant': 3})
    return df['Tweet Content'].tolist(), df['label'].tolist()

train_texts, train_labels = preprocess_data(data_train)
test_texts, test_labels = preprocess_data(data_test)

# Create a custom dataset
class SentimentDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self, idx):
        text = str(self.texts[idx])
        label = self.labels[idx]

        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            padding='max_length',
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize tokenizer and create datasets
tokenizer = AlbertTokenizer.from_pretrained('albert-base-v2')
train_dataset = SentimentDataset(train_texts, train_labels, tokenizer)
test_dataset = SentimentDataset(test_texts, test_labels, tokenizer)

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

# Initialize the model
model_ALBERT = AlbertForSequenceClassification.from_pretrained('albert-base-v2', num_labels=4)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model_ALBERT.to(device)

# Set up optimizer
optimizer = AdamW(model_ALBERT.parameters(), lr=2e-5)

# Training loop
num_epochs = 3

for epoch in range(num_epochs):
    model_ALBERT.train()
    for batch in train_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)
        outputs = model_ALBERT(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        optimizer.step()

    # Evaluation on test set
    model_ALBERT.eval()
    test_preds = []
    test_true = []
    with torch.no_grad():
        for batch in test_loader:
```

```
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels']
            outputs = model_ALBERT(input_ids, attention_mask=attention_mask)
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            test_preds.extend(preds)
            test_true.extend(labels.numpy())

    accuracy = accuracy_score(test_true, test_preds)
    print(f'Epoch {epoch + 1}/{num_epochs}, Test Accuracy: {accuracy:.4f}')

# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant

# Save the model
torch.save(model_ALBERT.state_dict(), 'sentiment_model_albert.pth')
```

```
Some weights of AlbertForSequenceClassification were not initialized from the model checkpoint at albert-base-v
2 and are newly initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Epoch 1/3, Test Accuracy: 0.5680
Epoch 2/3, Test Accuracy: 0.5590
Epoch 3/3, Test Accuracy: 0.5760
              precision    recall  f1-score   support

    Negative       0.61      0.69      0.65       266
     Neutral       0.53      0.61      0.56       285
    Positive       0.66      0.66      0.66       277
  Irrelevant       0.40      0.22      0.28       172

    accuracy                           0.58      1000
   macro avg       0.55      0.54      0.54      1000
weighted avg       0.56      0.58      0.56      1000

CPU times: user 2min 15s, sys: 26.5 s, total: 2min 42s
Wall time: 2min 43s
```

In [26]:

```
# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant
```

```
              precision    recall  f1-score   support

    Negative       0.61      0.69      0.65       266
     Neutral       0.53      0.61      0.56       285
    Positive       0.66      0.66      0.66       277
  Irrelevant       0.40      0.22      0.28       172

    accuracy                           0.58      1000
   macro avg       0.55      0.54      0.54      1000
weighted avg       0.56      0.58      0.56      1000
```

In [27]:

```
# Assuming test_true and test_preds are defined
from sklearn.metrics import confusion_matrix

# Check if test_true labels need conversion (optional)
if not isinstance(test_true[0], str):  # If labels are not strings
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    test_true_encoded = encoder.fit_transform(test_true)  # Encode labels
    labels = [0, 1, 2, 3]  # Numerical labels
else:
    test_true_encoded = test_true
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels

# Calculate confusion matrix with consistent labels
confusion_matrix_ALBERT = confusion_matrix(test_true_encoded, test_preds, labels=labels)

print("Confusion matrix ALBERT \n")
confusion_matrix_ALBERT
```

```
Confusion matrix ALBERT
```

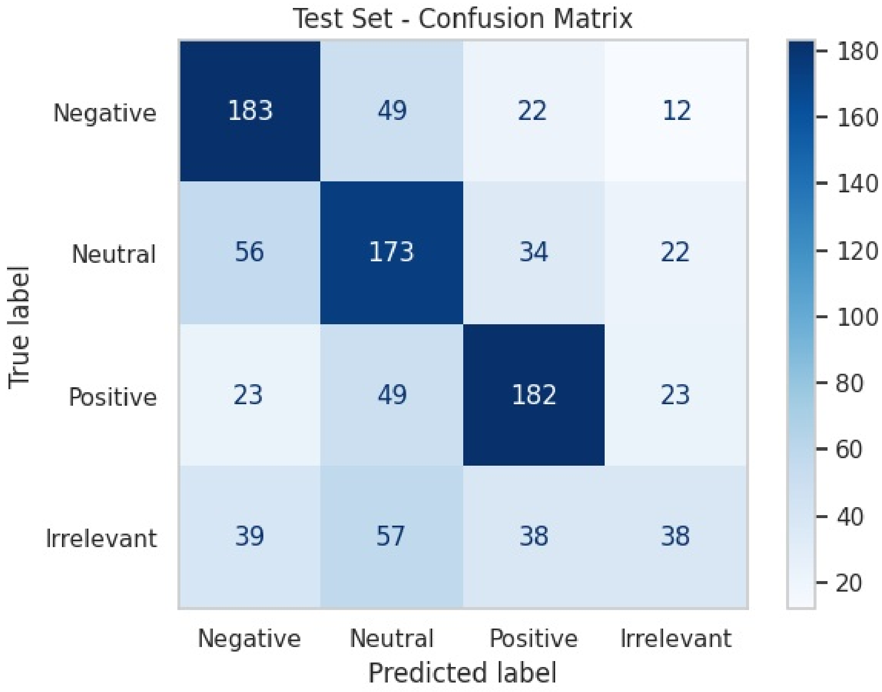
Out[27]:

```
array([[183,  49,  22,  12],
       [ 56, 173,  34,  22],
       [ 23,  49, 182,  23],
       [ 39,  57,  38,  38]])
```

In [28]:

```
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels
test_display = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_ALBERT, display_labels=labels)
test_display.plot(cmap='Blues')
plt.title("Test Set - Confusion Matrix")
plt.grid(False)
plt.tight_layout()
```

```
plt.show()
```



XLNet

XLNet: Going Beyond BERT

XLNet is a powerful language model that builds upon the successes of its predecessor, BERT, while addressing some of its limitations.

It stands for "Extreme Language Model".

Key Differences from BERT

- **Autoregressive vs. Autoencoding:** While BERT is an autoencoding model, XLNet is an autoregressive model. This means that XLNet predicts the next token in a sequence given the previous ones, similar to how we humans generate text. This approach allows XLNet to capture bidirectional context without the limitations of BERT's masked language modeling.
- **Permutation Language Model:** XLNet introduces the concept of a permutation language model. Instead of training on a fixed order of tokens, it considers all possible permutations of the input sequence. This enables the model to learn dependencies between any two tokens in the sequence, regardless of their position.

How XLNet Works

- **Permutation Language Modeling:** XLNet randomly permutes the input sequence and trains the model to predict the masked tokens in any position based on the context of the remaining tokens.
- **Attention Mechanism:** Similar to BERT, XLNet uses a self-attention mechanism to capture dependencies between different parts of the input sequence.

- **Two-Stream Self-Attention:** XLNet employs two streams of self-attention:
- **Content stream:** Focuses on the content of the tokens.
- **Query stream:** Focuses on the position of the tokens in the permutation.

Advantages of XLNet

- **Bidirectional Context:** XLNet can capture bidirectional context more effectively than BERT, leading to improved performance on various NLP tasks.
- **Flexibility:** The permutation language modeling approach allows for more flexible modeling of language.
- **Strong Performance:** XLNet has achieved state-of-the-art results on many NLP benchmarks.

Applications of XLNet

- *Text classification*
- *Question answering*
- *Natural language inference*
- *Machine translation*
- *Text summarization*

In summary, XLNet is a significant advancement in the field of natural language processing, offering improved performance and flexibility compared to previous models. Its ability to capture bidirectional context effectively makes it a powerful tool for various NLP applications.

In [29]:

```
%%time
import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import XLNetTokenizer, XLNetForSequenceClassification, AdamW
from sklearn.metrics import accuracy_score, classification_report

# Preprocess the data
def preprocess_data(df):
    df['label'] = df['Sentiment_label'].map({'Positive': 2, 'Negative': 0, 'Neutral': 1, 'Irrelevant': 3})
    return df['Tweet Content'].tolist(), df['label'].tolist()

train_texts, train_labels = preprocess_data(data_train)
test_texts, test_labels = preprocess_data(data_test)

# Create a custom dataset
class SentimentDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self, idx):
        text = str(self.texts[idx])
        label = self.labels[idx]

        encoding = self.tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=self.max_len,
            padding='max_length',
```

```
            truncation=True,
            return_attention_mask=True,
            return_token_type_ids=True,
            return_tensors='pt',
        )

        return {
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatten(),
            'token_type_ids': encoding['token_type_ids'].flatten(),
            'labels': torch.tensor(label, dtype=torch.long)
        }

# Initialize tokenizer and create datasets
tokenizer = XLNetTokenizer.from_pretrained('xlnet-base-cased')
train_dataset = SentimentDataset(train_texts, train_labels, tokenizer)
test_dataset = SentimentDataset(test_texts, test_labels, tokenizer)

# Create data loaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

# Initialize the model XLNet
model_XLNet = XLNetForSequenceClassification.from_pretrained('xlnet-base-cased', num_labels=4)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model_XLNet.to(device)

# Set up optimizer
optimizer = AdamW(model_XLNet.parameters(), lr=2e-5)

# Training loop
num_epochs = 3

for epoch in range(num_epochs):
    model_XLNet.train()
    for batch in train_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        token_type_ids = batch['token_type_ids'].to(device)
        labels = batch['labels'].to(device)
        outputs = model_XLNet(input_ids, attention_mask=attention_mask, token_type_ids=token_type_ids, labels=l
        loss = outputs.loss
        loss.backward()
        optimizer.step()

    # Evaluation on test set
    model_XLNet.eval()
    test_preds = []
    test_true = []
    with torch.no_grad():
        for batch in test_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            token_type_ids = batch['token_type_ids'].to(device)
            labels = batch['labels']
            outputs = model_XLNet(input_ids, attention_mask=attention_mask, token_type_ids=token_type_ids)
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            test_preds.extend(preds)
            test_true.extend(labels.numpy())

    accuracy = accuracy_score(test_true, test_preds)
    print(f'Epoch {epoch + 1}/{num_epochs}, Test Accuracy: {accuracy:.4f}')

# Save the model_XLNet
torch.save(model_XLNet.state_dict(), 'sentiment_model_xlnet.pth')
```

```
Some weights of XLNetForSequenceClassification were not initialized from the model checkpoint at xlnet-base-cas
ed and are newly initialized: ['logits_proj.bias', 'logits_proj.weight', 'sequence_summary.summary.bias', 'sequ
ence_summary.summary.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Epoch 1/3, Test Accuracy: 0.5400
Epoch 2/3, Test Accuracy: 0.5640
Epoch 3/3, Test Accuracy: 0.6170
CPU times: user 2min 27s, sys: 1min 9s, total: 3min 36s
Wall time: 3min 30s
```

In [30]:

```
# Final evaluation
print(classification_report(test_true, test_preds, target_names=['Negative', 'Neutral', 'Positive', 'Irrelevant
```

```
              precision    recall  f1-score   support

    Negative       0.61      0.79      0.69       266
     Neutral       0.62      0.59      0.60       285
    Positive       0.65      0.71      0.68       277
  Irrelevant       0.51      0.24      0.32       172

    accuracy                           0.62      1000
   macro avg       0.60      0.58      0.57      1000
weighted avg       0.61      0.62      0.60      1000
```

In [31]:

```
# Assuming test_true and test_preds are defined
from sklearn.metrics import confusion_matrix

# Check if test_true labels need conversion (optional)
if not isinstance(test_true[0], str):  # If labels are not strings
    from sklearn.preprocessing import LabelEncoder
    encoder = LabelEncoder()
    test_true_encoded = encoder.fit_transform(test_true)  # Encode labels
    labels = [0, 1, 2, 3]  # Numerical labels
else:
    test_true_encoded = test_true
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels

# Calculate confusion matrix with consistent labels
confusion_matrix_XLNet = confusion_matrix(test_true_encoded, test_preds, labels=labels)

print("Confusion matrix XLNet \n")
confusion_matrix_XLNet
```

```
Confusion matrix XLNet
```

Out[31]:

```
array([[211,  28,  18,   9],
       [ 50, 168,  44,  23],
       [ 40,  32, 197,   8],
       [ 43,  43,  45,  41]])
```

In [32]:

```
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']  # String labels
test_display = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_XLNet, display_labels=labels)
test_display.plot(cmap='Blues')
plt.title("Test Set - Confusion Matrix")
plt.grid(False)
plt.tight_layout()
plt.show()
```