M508C

Big Data Analytics (WS0925)

Individual Final Project

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MSc of DATA SCIENCE, AI AND DIGITAL BUSINESS

Emotion Classification on Tweets using Natural Language Processing

Problem Statement

Background and Motivation

Social media platforms such as Twitter contain large volumes of short, informal text where users express emotions in response to personal experiences and real-world events. Automatically identifying emotions from these tweets is valuable for applications such as customer feedback analysis, brand monitoring, and public sentiment tracking.

However, tweet text poses several challenges for NLP systems:

- Tweets are short and noisy, often containing informal language.
- Emotional categories are unevenly distributed, leading to class imbalance.
- Some emotions (e.g. *love* and *surprise*) are harder to detect due to limited training examples and semantic overlap with other classes.

Manual analysis is infeasible at scale, motivating the use of supervised machine learning and deep learning techniques for emotion classification.

Objective

The objective of this project is to **build and evaluate an end-to-end supervised NLP pipeline** that classifies tweets into one of **six emotion categories**:

sadness, joy, love, anger, fear, surprise

Given a raw tweet as input, the system predicts a single emotion label.

Modeling Approach

To study the impact of different text representations and modeling paradigms, this project implements and compares **three models**, all trained and evaluated on the same dataset:

1. **TF-IDF + Logistic Regression**
   A classical machine-learning baseline using bag-of-words features.

2. **Word2Vec + LSTM**
   A sequence-based neural model using pre-trained Word2Vec embeddings combined with an LSTM network to capture sequential word dependencies.

3. **BERT Fine-Tuning**
   A transformer-based model that leverages contextualized embeddings through fine-tuning of a pre-trained BERT model.

Each model follows a preprocessing and training strategy consistent with its architecture.

Handling Class Imbalance

The dataset exhibits moderate class imbalance. To address this:

- **Random oversampling** is applied **only to the TF-IDF + Logistic Regression model**.
- **Class-weighted loss functions** are used for the **LSTM** and **BERT** models during training.

This ensures fair comparison while respecting the constraints of each modeling approach.

Evaluation Strategy

All models are evaluated on a held-out test set using:

- **Accuracy**
- **Macro-averaged F1-score**
- **Weighted F1-score**
- **Per-class precision, recall, and F1-score**
- **Confusion matrices** for error analysis

Macro F1-score is emphasized to assess performance on minority emotion classes.

Expected Outcome

The project aims to:

- Compare classical, neural, and transformer-based NLP models under the same task.
- Analyze how representation choice affects performance on short, imbalanced text data.
- Identify strengths and limitations of each approach for tweet-based emotion classification.

The results provide practical insights into model selection for real-world emotion analysis tasks.

1. Imports and Config

In [1]:

```
import os
import random
from collections import Counter

import numpy as np
import pandas as pd

import re
from itertools import chain
import emoji

import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud

from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import (
    accuracy_score,
    f1_score,
    confusion_matrix,
    classification_report,
)
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.utils.class_weight import compute_class_weight

from imblearn.over_sampling import RandomOverSampler

import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

from gensim.models import Word2Vec
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras import layers, models, regularizers

from transformers import TrainingArguments

from transformers import (
```

```
    AutoTokenizer,
    AutoModelForSequenceClassification,
    Trainer,
    TrainingArguments,
)
import torch
from torch.utils.data import Dataset
```

```
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/tqdm/aut
o.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywi
dgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

In [2]:

```
# Reproducibility
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
tf.random.set_seed(SEED)
```

In [3]:

```
# NLTK downloads
nltk.download("punkt")
nltk.download("stopwords")
nltk.download("wordnet")
```

```
[nltk_data] Downloading package punkt to /Users/taanhtuan/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/taanhtuan/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/taanhtuan/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[3]: True

In [4]:

```
stop_words = set(stopwords.words("english"))
lemmatizer = WordNetLemmatizer()
```

In [5]:

```
EMOTION_DICT = {
    0: "sadness",
    1: "joy",
    2: "love",
    3: "anger",
    4: "fear",
    5: "surprise"
}
```

2. Load Data

In [6]:

```
DATA_DIR = "data/Emotion6"
```

In [7]:

```
TRAIN_PATH = os.path.join(DATA_DIR, "training.csv")
DEV_PATH   = os.path.join(DATA_DIR, "validation.csv")
TEST_PATH  = os.path.join(DATA_DIR, "test.csv")
```

In [8]:

```
train_df = pd.read_csv(TRAIN_PATH)
dev_df   = pd.read_csv(DEV_PATH)
```

```
test_df  = pd.read_csv(TEST_PATH)
```

In [9]:
```
print("Train shape:", train_df.shape)
```

```
Train shape: (16000, 2)
```

In [10]:
```
print("Dev shape  :", dev_df.shape)
```

```
Dev shape  : (2000, 2)
```

In [11]:
```
print("Test shape :", test_df.shape)
```

```
Test shape : (2000, 2)
```

In [12]:
```
display(train_df.head())
```

	text	label
0	i didnt feel humiliated	0
1	i can go from feeling so hopeless to so damned...	0
2	im grabbing a minute to post i feel greedy wrong	3
3	i am ever feeling nostalgic about the fireplac...	2
4	i am feeling grouchy	3

In [13]:
```
display(dev_df.head())
```

	text	label
0	im feeling quite sad and sorry for myself but ...	0
1	i feel like i am still looking at a blank canv...	0
2	i feel like a faithful servant	2
3	i am just feeling cranky and blue	3
4	i can have for a treat or if i am feeling festive	1

In [14]:
```
display(test_df.head())
```

	text	label
0	im feeling rather rotten so im not very ambiti...	0
1	im updating my blog because i feel shitty	0
2	i never make her separate from me because i do...	0
3	i left with my bouquet of red and yellow tulip...	1
4	i was feeling a little vain when i did this one	0

3. Data Preprocessing + EDA

3.1 Text Cleaning + Encoding

Remove empty text and label

In [15]:
```
train_df = train_df.dropna(subset=["text", "label"])
dev_df   = dev_df.dropna(subset=["text", "label"])
test_df  = test_df.dropna(subset=["text", "label"])
```

Label Encoding

In [16]:
```
label_encoder = LabelEncoder()
label_encoder.fit(train_df["label"])
```

Out[16]:
```
▾ LabelEncoder
▶ Parameters
```

In [17]:
```
train_df["label_id"] = label_encoder.transform(train_df["label"])
dev_df["label_id"]   = label_encoder.transform(dev_df["label"])
test_df["label_id"]  = label_encoder.transform(test_df["label"])
```

In [18]:
```
NUM_CLASSES = len(label_encoder.classes_)
NUM_CLASSES
```

Out[18]: 6

In [19]:
```
print("Classes:", list(label_encoder.classes_))
```

```
Classes: [np.int64(0), np.int64(1), np.int64(2), np.int64(3), np.int64(4),
np.int64(5)]
```

Detect emojis & hashtags

In [20]:
```
def extract_emojis(text):
    text = str(text)
    return ''.join(ch for ch in text if ch in emoji.EMOJI_DATA)

def extract_hashtags(text):
    text = str(text)
    return re.findall(r'#\w+', text)

# add columns to train_df

train_df["emojis"] = train_df["text"].astype(str).apply(extract_emojis)
train_df["num_emojis"] = train_df["emojis"].str.len()

train_df["hashtags"] = train_df["text"].astype(str).apply(extract_hashtag
train_df["num_hashtags"] = train_df["hashtags"].str.len()
```

In [21]:
```
print("Emoji / Hashtag Usage in Training Set")

print("Tweets with ≥1 emoji    :", (train_df["num_emojis"] > 0).mean() *
print("Tweets with ≥1 hashtag  :", (train_df["num_hashtags"] > 0).mean()
```

```
print("\nAverage emojis per tweet  :", train_df["num_emojis"].mean())
print("Average hashtags per tweet:", train_df["num_hashtags"].mean())
```

```
Emoji / Hashtag Usage in Training Set
Tweets with ≥1 emoji    : 0.0 %
Tweets with ≥1 hashtag  : 0.0 %

Average emojis per tweet  : 0.0
Average hashtags per tweet: 0.0
```

Quick Look: Emoji & Hashtag Presence

The dataset contains **no detectable emojis or hashtags**:

- **Tweets with ≥ 1 emoji:** 0.0%
- **Tweets with ≥ 1 hashtag:** 0.0%
- **Average emojis per tweet:** 0.0
- **Average hashtags per tweet:** 0.0

This confirms that emojis and hashtags **do not appear** in the dataset, so keeping/removing them **has no impact** on preprocessing or model performance.

Create Raw + Cleaned Text Lists

In [22]:
```
def clean_tokens(text):
    text = str(text).lower()
    tokens = nltk.word_tokenize(text)
    tokens = [t for t in tokens if t.isalpha()]
    tokens = [t for t in tokens if t not in stop_words]
    tokens = [lemmatizer.lemmatize(t) for t in tokens]
    return tokens
```

In [23]:
```
train_df["clean_tokens"] = train_df["text"].astype(str).apply(clean_token
train_df["clean_text"] = train_df["clean_tokens"].apply(lambda x: " ".joi
```

In [24]:
```
print("Display few examples:")
for i in range(3):
    print(f"RAW   : {train_df.loc[i, 'text']}")
    print(f"CLEAN : {train_df.loc[i, 'clean_text']}")
    print("---")
```

```
Display few examples:
RAW   : i didnt feel humiliated
CLEAN : didnt feel humiliated
---
RAW   : i can go from feeling so hopeless to so damned hopeful just from b
eing around someone who cares and is awake
CLEAN : go feeling hopeless damned hopeful around someone care awake
---
RAW   : im grabbing a minute to post i feel greedy wrong
CLEAN : im grabbing minute post feel greedy wrong
---
```

In [25]:
```
dev_df["clean_tokens"] = dev_df["text"].astype(str).apply(clean_tokens)
dev_df["clean_text"] = dev_df["clean_tokens"].apply(lambda x: " ".join(x)
```

In [26]:
```
print("Display few examples:")
for i in range(3):
    print(f"RAW   : {dev_df.loc[i, 'text']}")
    print(f"CLEAN : {dev_df.loc[i, 'clean_text']}")
    print("---")
```

```
Display few examples:
RAW   : im feeling quite sad and sorry for myself but ill snap out of it s
oon
CLEAN : im feeling quite sad sorry ill snap soon
---
RAW   : i feel like i am still looking at a blank canvas blank pieces of p
aper
CLEAN : feel like still looking blank canvas blank piece paper
---
RAW   : i feel like a faithful servant
CLEAN : feel like faithful servant
---
```

In [27]:
```
test_df["clean_tokens"] = test_df["text"].astype(str).apply(clean_tokens)
test_df["clean_text"] = test_df["clean_tokens"].apply(lambda x: " ".join(
```

In [28]:
```
print("Display few examples:")
for i in range(3):
    print(f"RAW   : {test_df.loc[i, 'text']}")
    print(f"CLEAN : {test_df.loc[i, 'clean_text']}")
    print("---")
```

```
Display few examples:
RAW   : im feeling rather rotten so im not very ambitious right now
CLEAN : im feeling rather rotten im ambitious right
---
RAW   : im updating my blog because i feel shitty
CLEAN : im updating blog feel shitty
---
RAW   : i never make her separate from me because i don t ever want her to
feel like i m ashamed with her
CLEAN : never make separate ever want feel like ashamed
---
```

3.2 Exploratory Data Analysis (EDA)

Percentages of each label

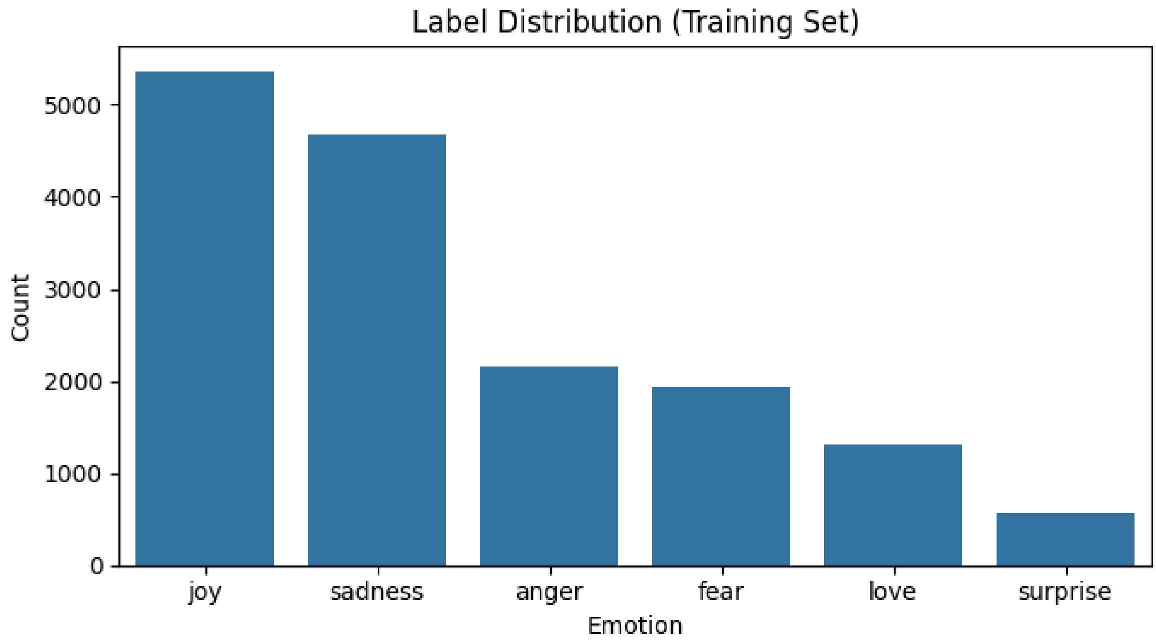
In [29]:
```
for lbl, count in train_df["label"].value_counts().items():
    pct = count / len(train_df) * 100
    print(f"Label {lbl}: {count:,} samples ({pct:.2f}%)")
```

```
Label 1: 5,362 samples (33.51%)
Label 0: 4,666 samples (29.16%)
Label 3: 2,159 samples (13.49%)
Label 4: 1,937 samples (12.11%)
Label 2: 1,304 samples (8.15%)
Label 5: 572 samples (3.57%)
```

Label Distribution Visualization

In [30]:
```
# Order by frequency of numeric labels
order_labels = train_df["label"].value_counts().index

plt.figure(figsize=(7,4))
ax = sns.countplot(
    x="label",
    data=train_df,
    order=order_labels
)

# Replace tick labels (0..5) with emotion names
ax.set_xticklabels([EMOTION_DICT[i] for i in order_labels])

plt.title("Label Distribution (Training Set)")
plt.xlabel("Emotion")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```

```
/var/folders/6x/h489kd6s4lxbdnxrhw8mvt140000gn/T/ipykernel_55043/98844256
2.py:12: UserWarning: set_ticklabels() should only be used with a fixed nu
mber of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels([EMOTION_DICT[i] for i in order_labels])
```



Interpretation

The training dataset shows a clear **class imbalance**:

- **Joy (label 1)** and **Sadness (label 0)** are the most common classes.
- **Anger (3)** and **Fear (4)** appear moderately often.
- **Love (2)** and especially **Surprise (5)** are **minority classes**.

This imbalance is important because it can lead to:

- Lower recall and F1-scores for rare classes (e.g., *love*, *surprise*)
- Bias toward predicting majority classes
- Unstable training for neural models

To address this, the pipeline applies **oversampling** and **class weighting**, ensuring that all models treat minority emotions more fairly during training.

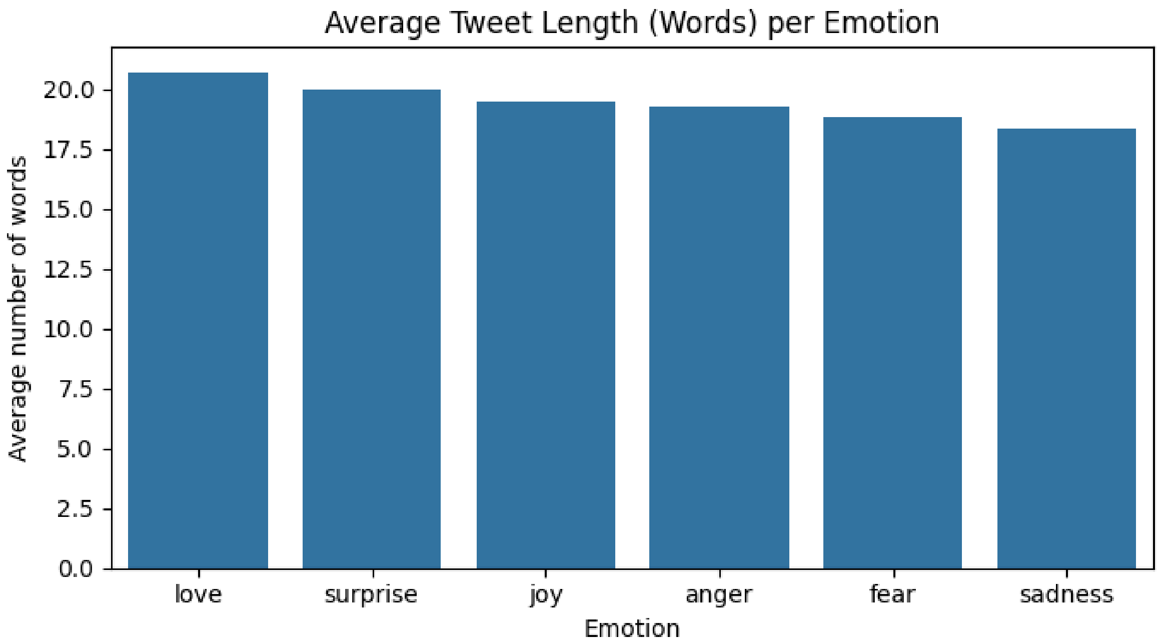
Average Tweet Length (in words) per Emotion

In [31]:
```
# Add num_words feature
for df_part in (train_df, dev_df, test_df):
    df_part["num_words"] = df_part["text"].astype(str).apply(lambda x: le
```

In [32]:
```
# Compute average length per label
avg_len = (
    train_df
    .groupby("label")["num_words"]
    .mean()
    .reset_index()
    .rename(columns={"num_words": "avg_num_words"})
)
```

In [33]:
```
# Map numeric label -> emotion name
avg_len["emotion"] = avg_len["label"].map(EMOTION_DICT)

# Sort by average length (optional)
avg_len = avg_len.sort_values("avg_num_words", ascending=False)
```

In [34]:
```
plt.figure(figsize=(7, 4))
sns.barplot(data=avg_len, x="emotion", y="avg_num_words")
plt.title("Average Tweet Length (Words) per Emotion")
plt.xlabel("Emotion")
plt.ylabel("Average number of words")
plt.tight_layout()
plt.show()
```



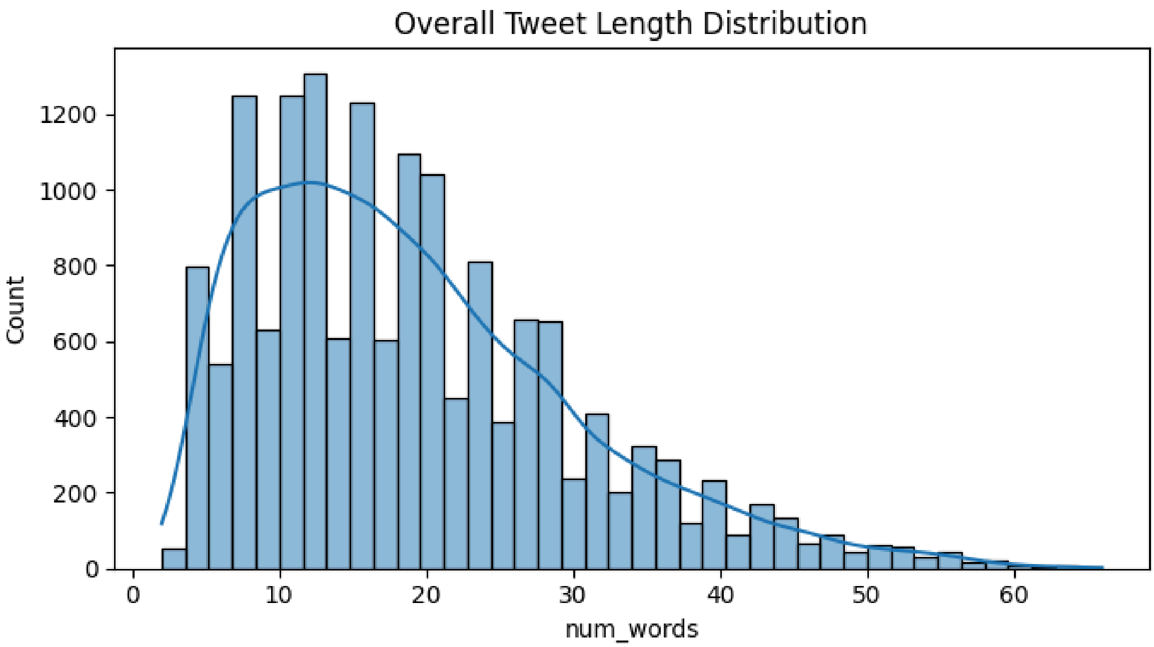
Quick Look – Average Tweet Length per Emotion

- **Love** tweets are the longest (~21 words), often containing more detailed emotional expression.
- **Surprise** and **Joy** follow (~19–20 words), usually describing events or reactions.
- **Anger** and **Fear** are slightly shorter (~19 words), often more direct.
- **Sadness** tweets are the shortest (~18 words), typically brief statements of feeling.

Overall, all emotions fall within a **tight range (18–21 words)**, confirming that tweets are consistently short and supporting a moderate max sequence length (e.g., 40–50 tokens) for modeling.

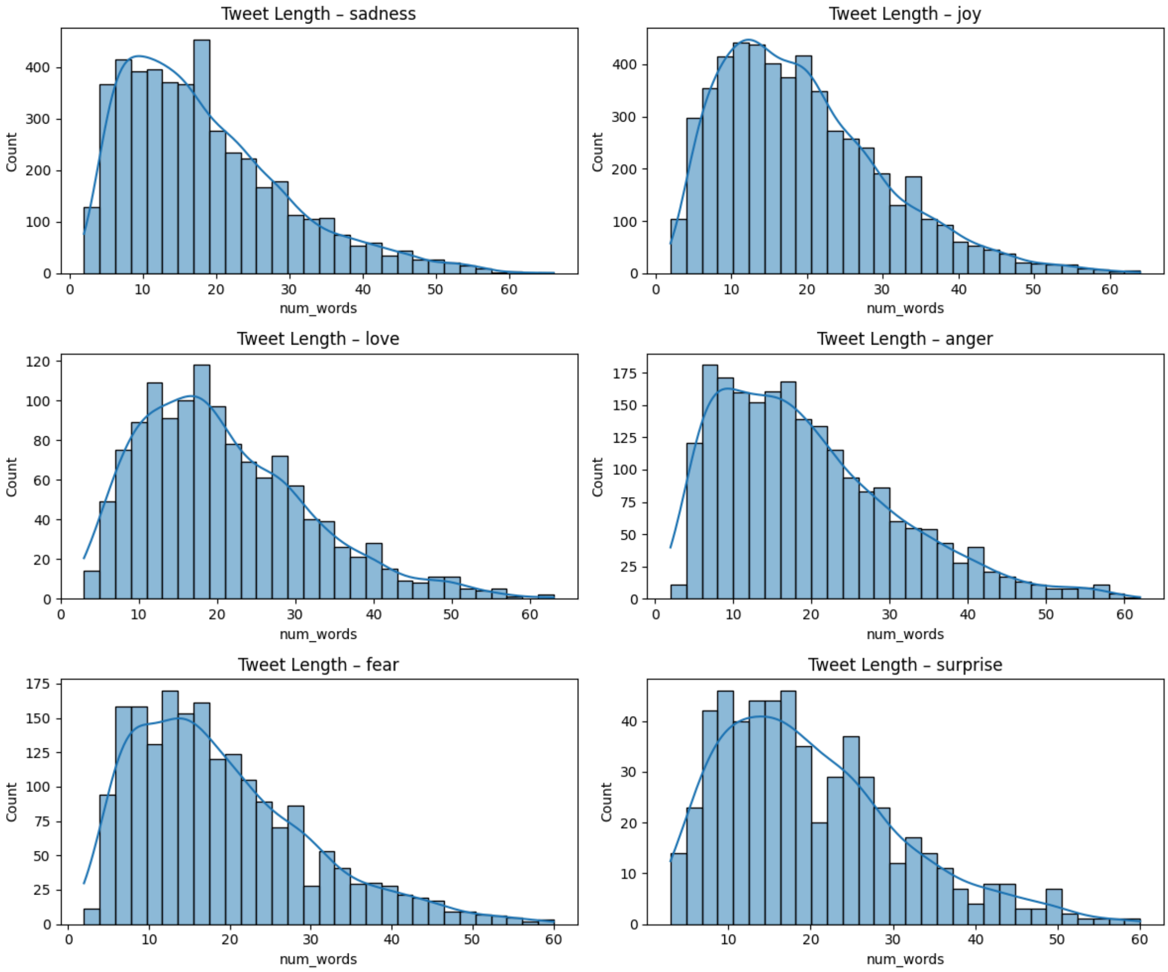
Tweet Length Distribution Visualization

In [35]:
```
# Overall Tweet Length Distribution
plt.figure(figsize=(7,4))
sns.histplot(train_df["num_words"], bins=40, kde=True)
plt.title("Overall Tweet Length Distribution")
plt.xlabel("num_words")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



In [36]:
```
# Tweet Length Distribution per Emotion Label
plt.figure(figsize=(12, 10))

for i, (lbl, emotion_name) in enumerate(EMOTION_DICT.items(), 1):
    subset = train_df[train_df["label"] == lbl]["num_words"]

    plt.subplot(3, 2, i)
    sns.histplot(subset, bins=30, kde=True)
    plt.title(f"Tweet Length — {emotion_name}")
    plt.xlabel("num_words")
    plt.ylabel("Count")
```

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



Quick Look — Word Length Analysis

Overall Interpretation

The dataset is dominated by **short tweets**, mostly between **8–20 words**, with a right-skewed tail up to ~60 words.
This means:

- Most emotional content is expressed **briefly**.
- **Very long tweets are rare**, so models don't need large max sequence lengths.
- Setting sequence length around **40–60 tokens** captures almost all samples.
- Short text makes TF-IDF, LSTM, and BERT all efficient to train.

Overall, emotion classification on this dataset is lightweight and well-bounded in length.

Quick Look — Per Emotion Label

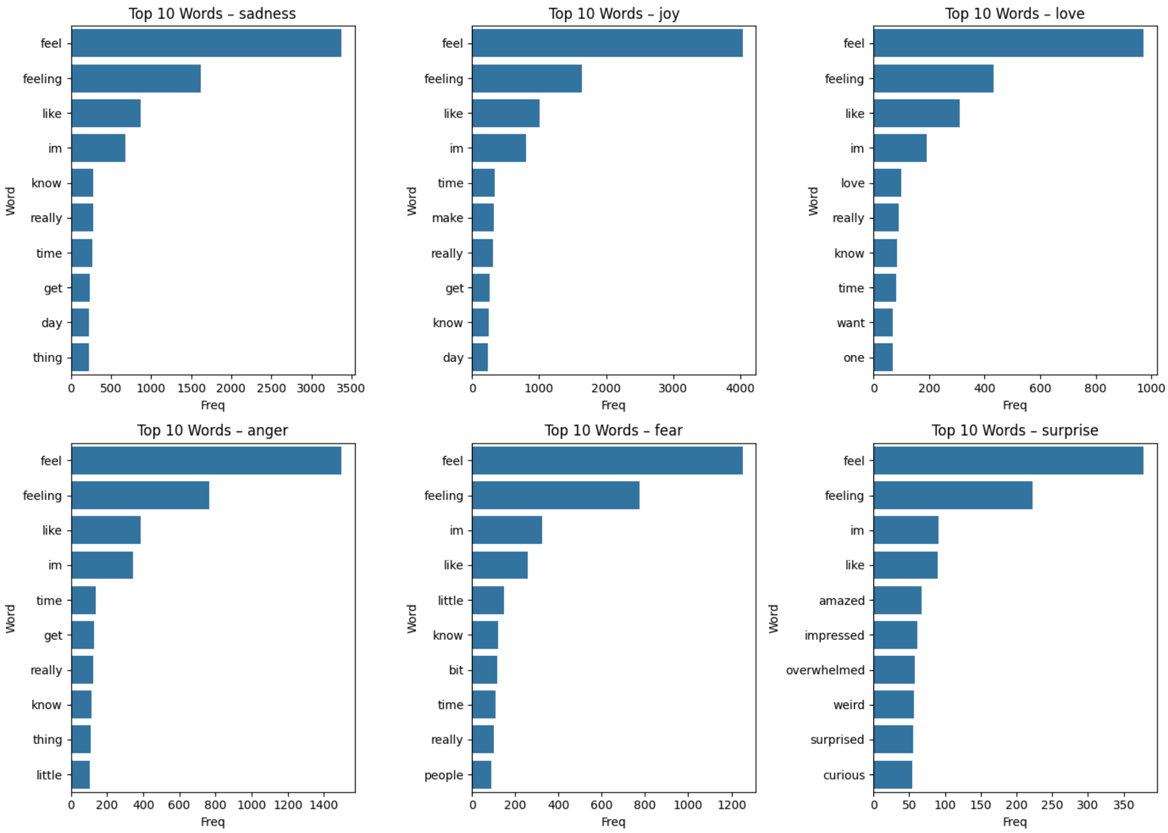
- **Sadness:**: Slightly longer tweets; often **10–25 words** with reflective explanations.
- **Joy:**: Mostly short and spontaneous; concentrated around **8–18 words**.
- **Love:** More varied; many tweets between **12–25 words**, sometimes descriptive.

- **Anger:** Compact but with added context; common range **10–22 words**.
- **Fear:** Wider length spread; typically **10–25 words**, some longer descriptions.
- **Surprise:** Usually short reaction messages; often **8–16 words**.

Top Words per Emotion Class

In [37]:

```
top_n = 10

plt.figure(figsize=(14, 10))

for i, (lbl, emotion_name) in enumerate(EMOTION_DICT.items(), 1):
    # Get cleaned tokens for this label
    subset = train_df[train_df["label"] == lbl]["clean_tokens"]

    # Flatten all token lists into one list
    tokens = []
    for tok_list in subset:
        tokens.extend(tok_list)

    # Top-N most common words
    counts = Counter(tokens).most_common(top_n)
    words  = [w for w, _ in counts]
    freqs  = [c for _, c in counts]

    # Plot
    plt.subplot(2, 3, i)
    sns.barplot(x=freqs, y=words, orient="h")
    plt.title(f"Top {top_n} Words — {emotion_name}")
    plt.xlabel("Freq")
    plt.ylabel("Word")

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



Quick Insights: Top 10 Words per Emotion

- **Sadness:** dominated by *feel, feeling, like, im, know* → reflective, low-energy expressions.
- **Joy:** similar structure but more positive verbs (*make, really*) → upbeat emotional tone.
- **Love:** includes more relational words (*love, want, one*) → affectionate, connection-focused.
- **Anger:** still uses *feel/feeling* but context is harsher → frustration, irritation.
- **Fear:** shows uncertainty (*little, bit, people*) → hesitation, vulnerability.
- **Surprise:** most distinct vocabulary (*amazed, impressed, overwhelmed*) → unexpected events, curiosity.

Overall: Many classes share core verbs like *feel/feeling*, but emotion-specific words help differentiate categories.

WordClouds

In [38]:
```
def plot_wordcloud(texts, title):
    text = " ".join(texts)
    wc = WordCloud(width=900, height=400, background_color="white").gener
    plt.figure(figsize=(10,5))
    plt.imshow(wc, interpolation="bilinear")
    plt.axis("off")
    plt.title(title)
    plt.show()
```

In [39]:
```python
# Overall
plot_wordcloud(train_df["text"].tolist(), "WordCloud – All Training Tweet
```

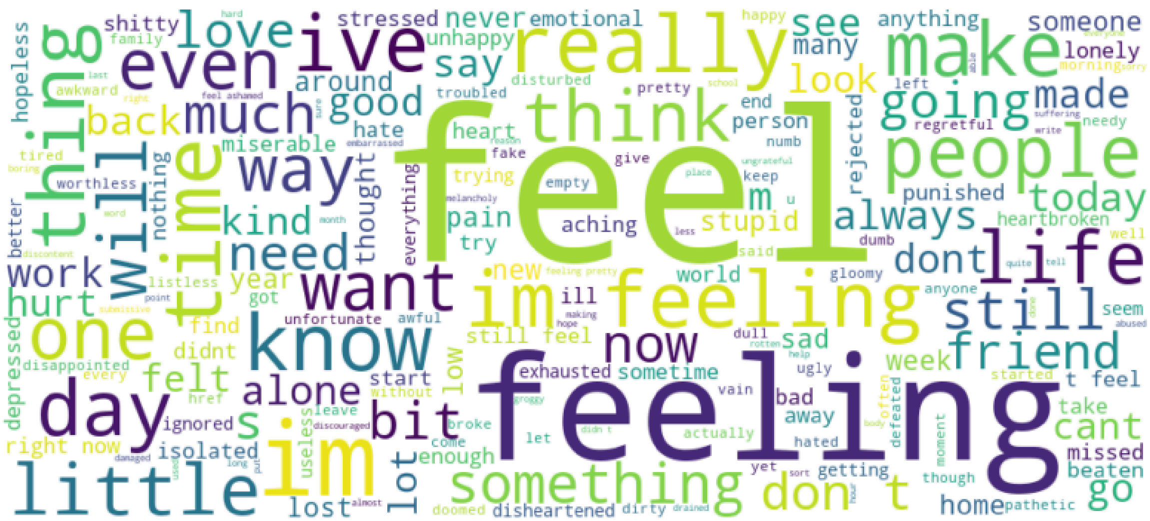
WordCloud – All Training Tweets

Interpretation

The overall word cloud highlights the most frequent terms across all tweets. Words like **feel**, **im**, **make**, **time**, **love**, and **know** dominate, reflecting the emotional and personal nature of Twitter content. These frequent terms provide an initial sense of common themes before emotion-specific analysis.

In [40]:
```python
# sadness class
lbl = 0
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl}")
```

WordCloud – 0

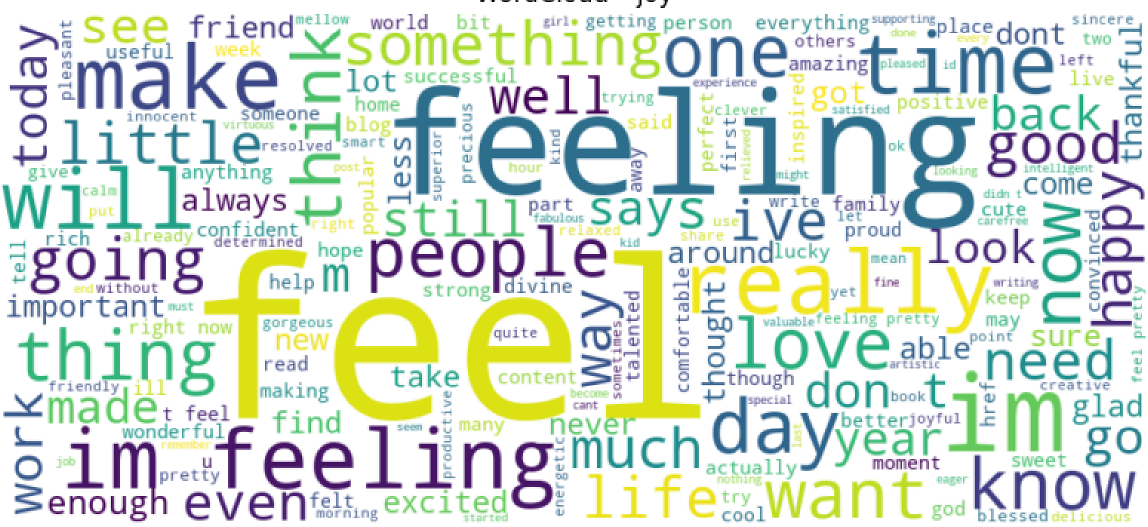


Interpretation (Sadness)

The sadness class is dominated by words expressing negative emotions and personal struggle. Terms like **feel**, **alone**, **hurt**, **pain**, **lost**, and **sad** appear frequently, reflecting themes of emotional distress, loneliness, and difficult life situations.

In [41]:
```python
# joy class
lbl = 1
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl_name}")
```

WordCloud – joy

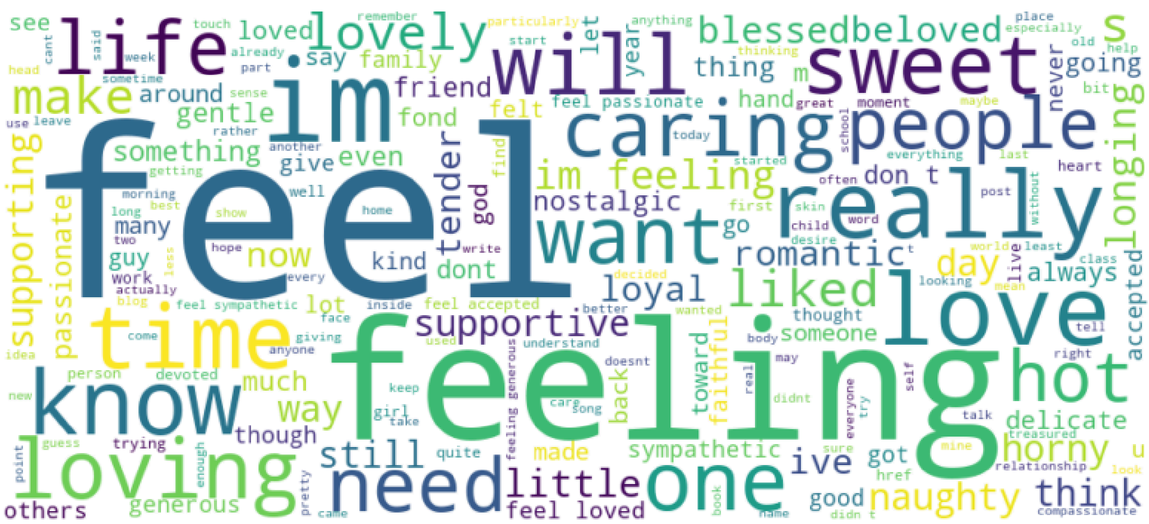


Interpretation (Joy)

The joy class contains many positive and uplifting terms. Words such as **happy**, **good**, **love**, **excited**, **thankful**, and **glad** frequently appear, reflecting themes of celebration, appreciation, and positive life events.

In [42]:
```python
# love class
lbl = 2
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl_name}")
```

WordCloud – love



Interpretation (Love)

The love class features warm and affectionate words such as **love**, **lovely**, **caring**, **sweet**, **beloved**, and **romantic**. The vocabulary reflects themes of affection, connection, tenderness, and positive emotional bonding.

In [43]:
```python
# anger class
lbl = 3
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl_name}")
```

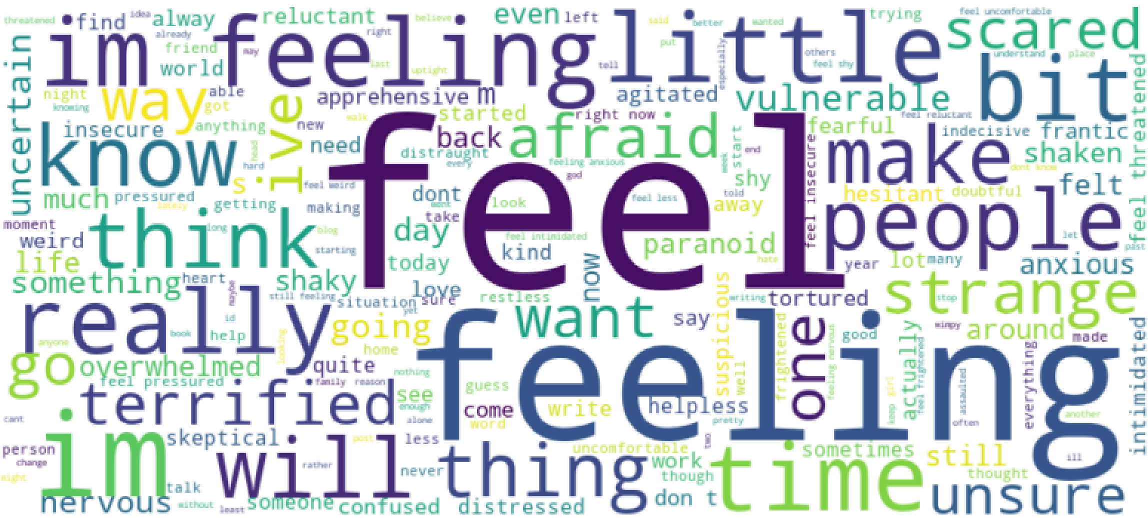
WordCloud – anger

Interpretation (Anger)

The anger class contains many negative and intense terms such as **angry**, **annoyed**, **pissed**, **frustrated**, **irritated**, and **bitter**. The vocabulary reflects themes of conflict, frustration, and emotional tension.

In [44]:
```python
# fear class
lbl = 4
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl_name}")
```

WordCloud – fear

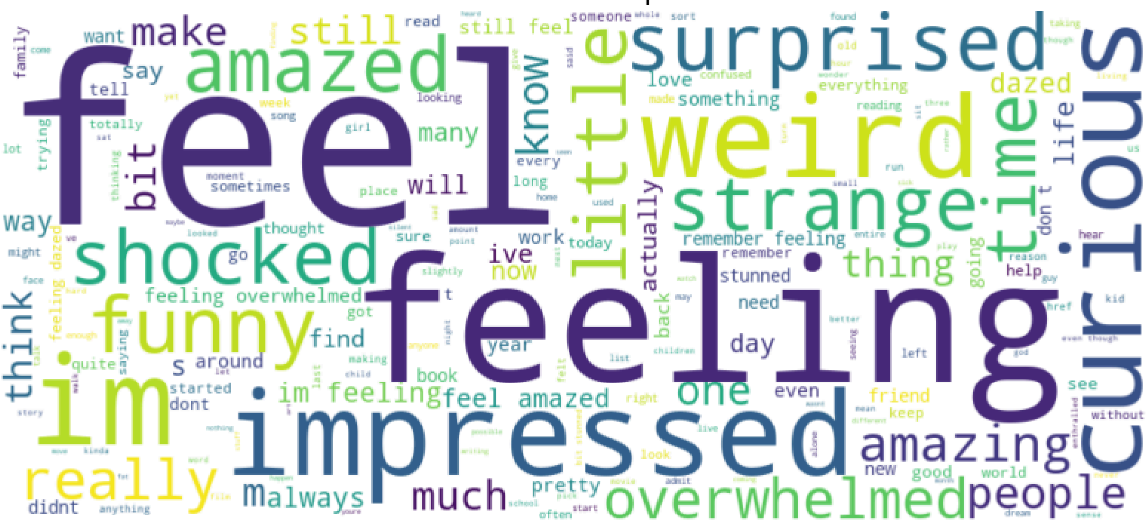


Interpretation (Fear)

The fear class is dominated by words such as **afraid**, **scared**, **terrified**, **unsure**, **nervous**, and **anxious**, indicating strong feelings of uncertainty, vulnerability, and emotional distress. Many terms reflect panic, insecurity, and a sense of being overwhelmed.

In [45]:
```python
# surprise class
lbl = 5
lbl_name = EMOTION_DICT[lbl]

subset = train_df[train_df["label"] == lbl]
plot_wordcloud(subset["text"].tolist(), f"WordCloud – {lbl_name}")
```

WordCloud – surprise



Interpretation (Surprise)

The surprise class includes words such as **amazed**, **shocked**, **curious**, **weird**, **impressed**, and **overwhelmed**, reflecting reactions to unexpected events. The language shows a mix of astonishment, curiosity, and positive surprise.

3.3 Preparing Clean Text and Labels for Modeling

In [46]:
```
# BERT uses raw text
X_train_raw = train_df["text"].astype(str).tolist()
X_dev_raw   = dev_df["text"].astype(str).tolist()
X_test_raw  = test_df["text"].astype(str).tolist()
```

In [47]:
```
# Cleaned text lists
X_train_clean = train_df["clean_text"].tolist()
X_dev_clean   = dev_df["clean_text"].tolist()
X_test_clean  = test_df["clean_text"].tolist()
```

In [48]:
```
y_train = train_df["label_id"].values
y_dev   = dev_df["label_id"].values
y_test  = test_df["label_id"].values
```

3.4 Oversampling

Random oversampling is applied **only to the TF-IDF + Logistic Regression model** to mitigate class imbalance in the feature space. For neural models (Word2Vec + LSTM and BERT), oversampling is not used; instead, **class-weighted loss functions** are applied during training to address label imbalance.

In [49]:
```
print("Original label counts:", Counter(y_train))
```

```
Original label counts: Counter({np.int64(1): 5362, np.int64(0): 4666, np.i
nt64(3): 2159, np.int64(4): 1937, np.int64(2): 1304, np.int64(5): 572})
```

In [50]:
```
ros = RandomOverSampler(random_state=SEED)
idx_dummy = np.arange(len(X_train_clean)).reshape(-1,1)
idx_res, y_res = ros.fit_resample(idx_dummy, y_train)
X_train_clean_bal = [X_train_clean[i[0]] for i in idx_res]
y_train_bal = y_res
```

In [51]:
```
print("Oversampled label counts:", Counter(y_train_bal))
```

```
Oversampled label counts: Counter({np.int64(0): 5362, np.int64(3): 5362, n
p.int64(2): 5362, np.int64(5): 5362, np.int64(4): 5362, np.int64(1): 536
2})
```

4. Model Training

4.1 TF-IDF + Logistic Regression

In [52]:
```
tfidf_lr = Pipeline([
    ("tfidf", TfidfVectorizer(
        max_features=20000,
        ngram_range=(1,2),
    )),
    ("clf", LogisticRegression(
        max_iter=1000,
```

```
        class_weight="balanced",
        n_jobs=-1,
    )),
])
```

In [53]:
```
tfidf_lr.fit(X_train_clean_bal, y_train_bal)
```

Out[53]:

```
▸ Pipeline
    ▸ TfidfVectorizer
    ▸ LogisticRegression
```

In [54]:
```
y_pred_lr = tfidf_lr.predict(X_test_clean)
```

In [55]:
```
print("Result in TF-IDF + Logistic Regression:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
print("Macro F1:", f1_score(y_test, y_pred_lr, average="macro"))
print("Weighted F1:", f1_score(y_test, y_pred_lr, average="weighted"))
```

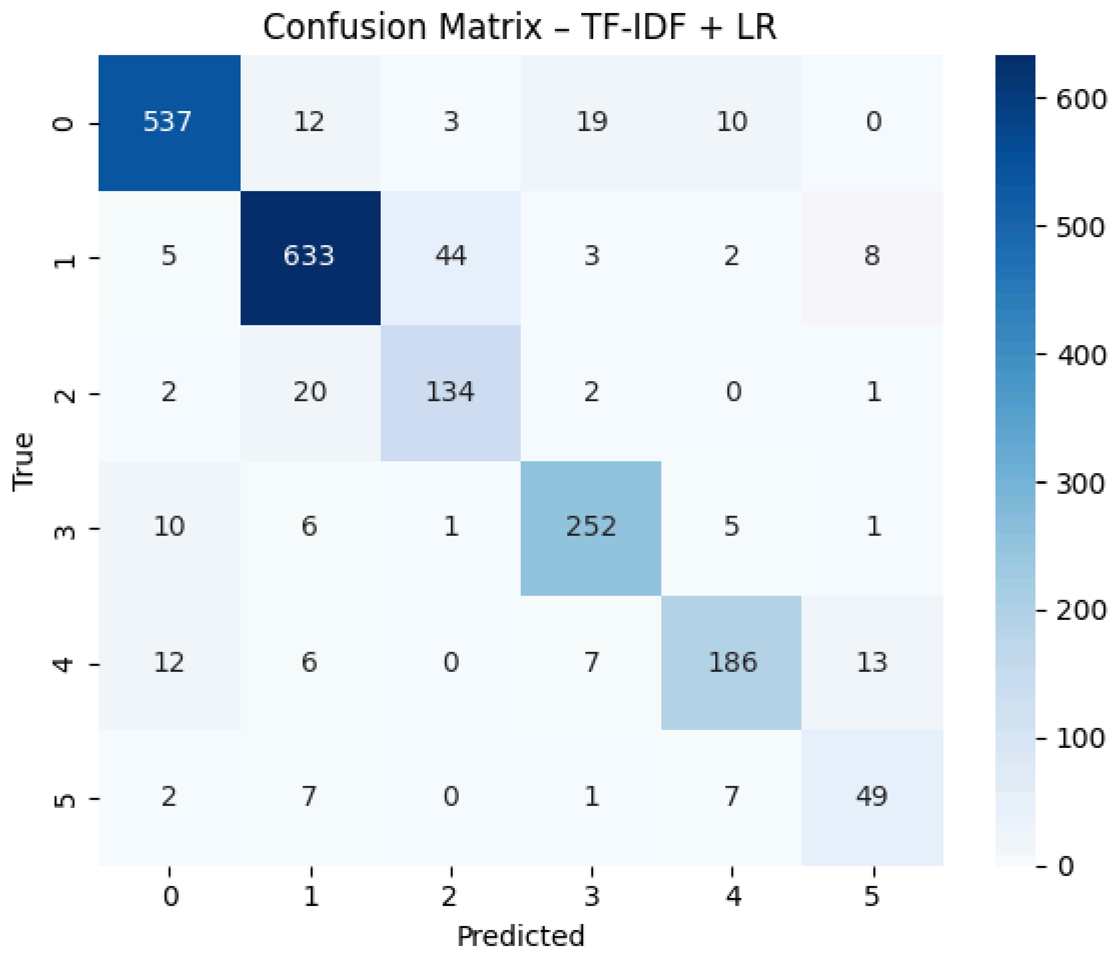
```
Result in TF-IDF + Logistic Regression:
Accuracy: 0.8955
Macro F1: 0.8512673279207412
Weighted F1: 0.8964496130401985
```

In [56]:
```
print("\nClassification Report:\n")
print(
    classification_report(
        y_test,
        y_pred_lr,
        target_names=EMOTION_DICT.values()
    )
)
```

```
Classification Report:

              precision    recall  f1-score   support

     sadness       0.95      0.92      0.93       581
         joy       0.93      0.91      0.92       695
        love       0.74      0.84      0.79       159
       anger       0.89      0.92      0.90       275
        fear       0.89      0.83      0.86       224
    surprise       0.68      0.74      0.71        66

    accuracy                           0.90      2000
   macro avg       0.84      0.86      0.85      2000
weighted avg       0.90      0.90      0.90      2000
```

In [57]:
```
cm_lr = confusion_matrix(y_test, y_pred_lr)
plt.figure(figsize=(6,5))
sns.heatmap(cm_lr, annot=True, fmt="d", cmap="Blues",
            xticklabels=label_encoder.classes_,
            yticklabels=label_encoder.classes_)
plt.title("Confusion Matrix — TF-IDF + LR")
plt.xlabel("Predicted")
```

```
plt.ylabel("True")
plt.tight_layout()
plt.show()
```



Performance Summary — TF-IDF + Logistic Regression

- **Overall performance:**
  - Accuracy: **0.90**
  - Macro F1: **0.85**
  - Weighted F1: **0.90**
    Demonstrates a strong and stable baseline, especially considering class imbalance.
- **Strong classes:**
  - *Sadness* and *Joy* achieve high precision and recall (F1 ≈ 0.92–0.93), reflecting clear lexical patterns captured well by TF-IDF.
  - *Anger* also performs robustly with balanced precision–recall.
- **Moderate classes:**
  - *Fear* shows good overall performance but slightly lower recall, indicating occasional confusion with related emotions.
  - *Love* has decent recall but lower precision, suggesting overlap with *joy* and other positive expressions.
- **Challenging class:**

- *Surprise* remains the weakest (F1 ≈ 0.71), mainly due to limited samples and sparse, less distinctive vocabulary.
- **Error patterns (from confusion matrix):**
  - Misclassifications mostly occur between semantically similar emotions (e.g., *joy* ↔ *love*, *fear* ↔ *anger*).
  - The model does not collapse to majority classes, indicating effective class weighting and balanced learning.
- **Overall takeaway:**
  TF-IDF + Logistic Regression provides a **strong, efficient baseline** for tweet emotion classification, excelling on frequent emotions but limited in capturing deeper semantic nuances required for minority and subtle classes.

4.2 LSTM model

Word2Vec + tokenizer

In [58]:
```
train_tokens = train_df["clean_tokens"].tolist()
dev_tokens   = dev_df["clean_tokens"].tolist()
test_tokens  = test_df["clean_tokens"].tolist()

all_tokens = train_tokens + dev_tokens + test_tokens
```

In [59]:
```
w2v = Word2Vec(
    sentences=all_tokens,
    vector_size=100,
    window=5,
    min_count=2,
    workers=4,
    sg=1
)

print("Word2Vec vocab size:", len(w2v.wv))
```

```
Exception ignored in: 'gensim.models.word2vec_inner.our_dot_float'
Word2Vec vocab size: 7537
```

In [60]:
```
# Keras tokenizer
MAX_WORDS = 20000
MAX_SEQ_LEN = 40
```

In [61]:
```
tokenizer = Tokenizer(num_words=MAX_WORDS, oov_token="<UNK>")
tokenizer.fit_on_texts([" ".join(t) for t in all_tokens])
```

In [62]:
```
def to_seq(token_list):
    text = " ".join(token_list)
    seq = tokenizer.texts_to_sequences([text])[0]
    return seq
```

In [63]:
```
# Pad all sequences
def pad_all(tokens_list):
```

```
    seqs = tokenizer.texts_to_sequences([" ".join(t) for t in tokens_list
    return pad_sequences(seqs, maxlen=MAX_SEQ_LEN, padding="post", trunca
```

In [64]:
```
X_train_seq = pad_all(train_tokens)
X_dev_seq   = pad_all(dev_tokens)
X_test_seq  = pad_all(test_tokens)
```

In [65]:
```
EMB_DIM = 100
```

In [66]:
```
# Build embedding matrix
vocab_size = min(MAX_WORDS, len(tokenizer.word_index) + 1)
embedding_matrix = np.random.normal(0, 0.01, (vocab_size, EMB_DIM))

for w, i in tokenizer.word_index.items():
    if i < vocab_size and w in w2v.wv:
        embedding_matrix[i] = w2v.wv[w]
```

LSTM model Training

In [67]:
```
tf.keras.backend.clear_session()

# Build model (Word2Vec embeddings)
lstm = tf.keras.Sequential([
    layers.Input(shape=(MAX_SEQ_LEN,)),
    layers.Embedding(
        input_dim=embedding_matrix.shape[0],
        output_dim=embedding_matrix.shape[1],   # = EMB_DIM
        weights=[embedding_matrix],
        trainable=False,                        # Phase 1: freeze
        name="w2v_embedding"
    ),
    layers.LSTM(128, dropout=0.2, recurrent_dropout=0.2),
    layers.Dropout(0.3),
    layers.Dense(64, activation="relu", kernel_regularizer=regularizers.l
    layers.Dropout(0.2),
    layers.Dense(NUM_CLASSES, activation="softmax"),
])
```

In [68]:
```
# Compute class weights to handle label imbalance during training.
weights = compute_class_weight("balanced", classes=np.unique(y_train), y=
class_weights = {i: w for i, w in enumerate(weights)}
```

In [69]:
```
callbacks = [
    ReduceLROnPlateau(
        monitor="val_loss",
        factor=0.5,
        patience=3,
        min_lr=1e-5,
        verbose=1
    ),
    EarlyStopping(
        monitor="val_loss",
        patience=8,
        min_delta=1e-3,
        restore_best_weights=True,
        verbose=1
```

```
    ),
]
```

Why two-phase training (Freeze → Unfreeze) for Word2Vec + LSTM?

Word2Vec embeddings provide a strong pretrained initialization, but they are trained on a general corpus and may not fully match the language style of tweets (slang, informal phrasing, short context). If the embeddings are fine-tuned from the start, training can become unstable and overfit quickly, especially under class imbalance.

To address this, the training is done in two phases:

- **Phase 1 (freeze embeddings):** keeps pretrained Word2Vec vectors fixed to provide a stable semantic foundation while the LSTM and classifier layers learn the task-specific decision boundaries.
- **Phase 2 (unfreeze embeddings):** enables fine-tuning with a smaller learning rate, allowing the embeddings to adapt to the emotion classification domain without destroying the pretrained structure.

This approach improves training stability and often yields better generalization than fully freezing embeddings or fine-tuning them aggressively from the beginning.

Phase 1: train with frozen embeddings (stable start)

In [70]:
```
FROZEN_LSTM_EPOCH = 5
```

In [71]:
```
lstm.compile(
    optimizer=tf.keras.optimizers.Adam(1e-3),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

print("PHASE 1: Frozen Word2Vec embeddings")
hist1 = lstm.fit(
    X_train_seq, y_train,
    validation_data=(X_dev_seq, y_dev),
    epochs=FROZEN_LSTM_EPOCH,
    batch_size=64,
    class_weight=class_weights,
    callbacks=callbacks,
    verbose=1
)
```

```
PHASE 1: Frozen Word2Vec embeddings
Epoch 1/5
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 35ms/step - accuracy: 0.1804 - loss: 1.79
96 - val_accuracy: 0.0420 - val_loss: 1.7938 - learning_rate: 0.0010
Epoch 2/5
250/250 ━━━━━━━━━━━━━━━━━━━━ 8s 34ms/step - accuracy: 0.1796 - loss: 1.797
1 - val_accuracy: 0.0885 - val_loss: 1.7962 - learning_rate: 0.0010
Epoch 3/5
250/250 ━━━━━━━━━━━━━━━━━━━━ 8s 34ms/step - accuracy: 0.2004 - loss: 1.795
2 - val_accuracy: 0.1375 - val_loss: 1.7968 - learning_rate: 0.0010
Epoch 4/5
249/250 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - accuracy: 0.2102 - loss: 1.779
9
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.000500000023748725
7.
250/250 ━━━━━━━━━━━━━━━━━━━━ 8s 34ms/step - accuracy: 0.1984 - loss: 1.794
1 - val_accuracy: 0.1375 - val_loss: 1.7974 - learning_rate: 0.0010
Epoch 5/5
250/250 ━━━━━━━━━━━━━━━━━━━━ 8s 34ms/step - accuracy: 0.1372 - loss: 1.793
3 - val_accuracy: 0.0930 - val_loss: 1.7944 - learning_rate: 5.0000e-04
Restoring model weights from the end of the best epoch: 1.
```

Phase 2: unfreeze embeddings and fine-tune (adapt to task/domain)

In [72]:
```python
LSTM_EPOCH = 150
```

In [73]:
```python
lstm.get_layer("w2v_embedding").trainable = True

lstm.compile(
    optimizer=tf.keras.optimizers.Adam(2e-4),
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

print("\nPHASE 2: Unfrozen Word2Vec embeddings (fine-tuning)")
hist2 = lstm.fit(
    X_train_seq, y_train,
    validation_data=(X_dev_seq, y_dev),
    epochs=LSTM_EPOCH,
    batch_size=64,
    class_weight=class_weights,
    callbacks=callbacks,
    verbose=1
)
```

```
PHASE 2: Unfrozen Word2Vec embeddings (fine-tuning)
Epoch 1/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 40ms/step - accuracy: 0.2477 - loss: 1.79
71 - val_accuracy: 0.3520 - val_loss: 1.7939 - learning_rate: 2.0000e-04
Epoch 2/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.1949 - loss: 1.79
63 - val_accuracy: 0.2790 - val_loss: 1.7949 - learning_rate: 2.0000e-04
Epoch 3/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.2199 - loss: 1.73
84 - val_accuracy: 0.2040 - val_loss: 1.5043 - learning_rate: 2.0000e-04
Epoch 4/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.3189 - loss: 1.48
57 - val_accuracy: 0.2410 - val_loss: 1.2564 - learning_rate: 2.0000e-04
Epoch 5/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.3407 - loss: 1.36
26 - val_accuracy: 0.2460 - val_loss: 1.2158 - learning_rate: 2.0000e-04
Epoch 6/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.3385 - loss: 1.28
20 - val_accuracy: 0.2700 - val_loss: 1.1842 - learning_rate: 2.0000e-04
Epoch 7/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.3328 - loss: 1.22
72 - val_accuracy: 0.2800 - val_loss: 1.1613 - learning_rate: 2.0000e-04
Epoch 8/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.3308 - loss: 1.17
81 - val_accuracy: 0.3045 - val_loss: 1.1574 - learning_rate: 2.0000e-04
Epoch 9/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.3416 - loss: 1.13
38 - val_accuracy: 0.2940 - val_loss: 1.1690 - learning_rate: 2.0000e-04
Epoch 10/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.3616 - loss: 1.09
65 - val_accuracy: 0.3635 - val_loss: 1.1602 - learning_rate: 2.0000e-04
Epoch 11/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.3937 - loss: 1.03
07 - val_accuracy: 0.3690 - val_loss: 1.1547 - learning_rate: 2.0000e-04
Epoch 12/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.4489 - loss: 1.01
38 - val_accuracy: 0.5405 - val_loss: 1.1020 - learning_rate: 2.0000e-04
Epoch 13/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 42ms/step - accuracy: 0.4981 - loss: 0.95
58 - val_accuracy: 0.5630 - val_loss: 1.0830 - learning_rate: 2.0000e-04
Epoch 14/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.5571 - loss: 0.91
78 - val_accuracy: 0.5950 - val_loss: 1.0481 - learning_rate: 2.0000e-04
Epoch 15/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 42ms/step - accuracy: 0.6046 - loss: 0.87
22 - val_accuracy: 0.6025 - val_loss: 1.0581 - learning_rate: 2.0000e-04
Epoch 16/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 42ms/step - accuracy: 0.6459 - loss: 0.81
56 - val_accuracy: 0.6845 - val_loss: 0.8914 - learning_rate: 2.0000e-04
Epoch 17/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 42ms/step - accuracy: 0.6749 - loss: 0.76
67 - val_accuracy: 0.6775 - val_loss: 0.8885 - learning_rate: 2.0000e-04
Epoch 18/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.6911 - loss: 0.73
67 - val_accuracy: 0.6945 - val_loss: 0.8747 - learning_rate: 2.0000e-04
Epoch 19/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 42ms/step - accuracy: 0.7108 - loss: 0.69
55 - val_accuracy: 0.6875 - val_loss: 0.8915 - learning_rate: 2.0000e-04
Epoch 20/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.7254 - loss: 0.67
```

```
16 - val_accuracy: 0.7350 - val_loss: 0.7746 - learning_rate: 2.0000e-04
Epoch 21/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.7431 - loss: 0.64
47 - val_accuracy: 0.7215 - val_loss: 0.8120 - learning_rate: 2.0000e-04
Epoch 22/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.7487 - loss: 0.62
13 - val_accuracy: 0.7445 - val_loss: 0.7463 - learning_rate: 2.0000e-04
Epoch 23/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.7629 - loss: 0.59
05 - val_accuracy: 0.7660 - val_loss: 0.6901 - learning_rate: 2.0000e-04
Epoch 24/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.7718 - loss: 0.57
04 - val_accuracy: 0.7630 - val_loss: 0.6910 - learning_rate: 2.0000e-04
Epoch 25/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.7790 - loss: 0.55
34 - val_accuracy: 0.7580 - val_loss: 0.7200 - learning_rate: 2.0000e-04
Epoch 26/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.7875 - loss: 0.53
41 - val_accuracy: 0.7755 - val_loss: 0.6626 - learning_rate: 2.0000e-04
Epoch 27/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - accuracy: 0.7939 - loss: 0.52
39 - val_accuracy: 0.7850 - val_loss: 0.6359 - learning_rate: 2.0000e-04
Epoch 28/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.7979 - loss: 0.51
36 - val_accuracy: 0.7815 - val_loss: 0.6371 - learning_rate: 2.0000e-04
Epoch 29/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.8035 - loss: 0.49
02 - val_accuracy: 0.7820 - val_loss: 0.6318 - learning_rate: 2.0000e-04
Epoch 30/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 42ms/step - accuracy: 0.8044 - loss: 0.48
32 - val_accuracy: 0.7890 - val_loss: 0.6201 - learning_rate: 2.0000e-04
Epoch 31/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.8149 - loss: 0.46
71 - val_accuracy: 0.7935 - val_loss: 0.6161 - learning_rate: 2.0000e-04
Epoch 32/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.8120 - loss: 0.46
98 - val_accuracy: 0.7925 - val_loss: 0.6074 - learning_rate: 2.0000e-04
Epoch 33/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.8234 - loss: 0.44
99 - val_accuracy: 0.8020 - val_loss: 0.5988 - learning_rate: 2.0000e-04
Epoch 34/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.8270 - loss: 0.44
13 - val_accuracy: 0.8030 - val_loss: 0.5818 - learning_rate: 2.0000e-04
Epoch 35/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.8462 - loss: 0.42
87 - val_accuracy: 0.8225 - val_loss: 0.5633 - learning_rate: 2.0000e-04
Epoch 36/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.8709 - loss: 0.38
86 - val_accuracy: 0.8555 - val_loss: 0.5118 - learning_rate: 2.0000e-04
Epoch 37/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.8857 - loss: 0.36
05 - val_accuracy: 0.8475 - val_loss: 0.5121 - learning_rate: 2.0000e-04
Epoch 38/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9018 - loss: 0.32
77 - val_accuracy: 0.8670 - val_loss: 0.5017 - learning_rate: 2.0000e-04
Epoch 39/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9076 - loss: 0.30
39 - val_accuracy: 0.8630 - val_loss: 0.4760 - learning_rate: 2.0000e-04
Epoch 40/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.9189 - loss: 0.26
```

```
90 - val_accuracy: 0.8735 - val_loss: 0.4589 - learning_rate: 2.0000e-04
Epoch 41/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9204 - loss: 0.26
27 - val_accuracy: 0.8765 - val_loss: 0.4689 - learning_rate: 2.0000e-04
Epoch 42/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9227 - loss: 0.25
03 - val_accuracy: 0.8705 - val_loss: 0.4686 - learning_rate: 2.0000e-04
Epoch 43/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - accuracy: 0.9230 - loss: 0.242
0
Epoch 43: ReduceLROnPlateau reducing learning rate to 9.999999747378752e-0
5.
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9243 - loss: 0.23
64 - val_accuracy: 0.8695 - val_loss: 0.4852 - learning_rate: 2.0000e-04
Epoch 44/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9301 - loss: 0.22
00 - val_accuracy: 0.8745 - val_loss: 0.4517 - learning_rate: 1.0000e-04
Epoch 45/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9356 - loss: 0.20
51 - val_accuracy: 0.8820 - val_loss: 0.4365 - learning_rate: 1.0000e-04
Epoch 46/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9350 - loss: 0.20
77 - val_accuracy: 0.8805 - val_loss: 0.4246 - learning_rate: 1.0000e-04
Epoch 47/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.9365 - loss: 0.19
97 - val_accuracy: 0.8810 - val_loss: 0.4394 - learning_rate: 1.0000e-04
Epoch 48/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9404 - loss: 0.18
94 - val_accuracy: 0.8815 - val_loss: 0.4390 - learning_rate: 1.0000e-04
Epoch 49/150
249/250 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step - accuracy: 0.9371 - loss: 0.188
0
Epoch 49: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-0
5.
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9406 - loss: 0.18
48 - val_accuracy: 0.8855 - val_loss: 0.4297 - learning_rate: 1.0000e-04
Epoch 50/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9476 - loss: 0.17
71 - val_accuracy: 0.8850 - val_loss: 0.4360 - learning_rate: 5.0000e-05
Epoch 51/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 46ms/step - accuracy: 0.9454 - loss: 0.16
82 - val_accuracy: 0.8855 - val_loss: 0.4348 - learning_rate: 5.0000e-05
Epoch 52/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 12s 46ms/step - accuracy: 0.9466 - loss: 0.16
42 - val_accuracy: 0.8890 - val_loss: 0.4232 - learning_rate: 5.0000e-05
Epoch 53/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9481 - loss: 0.16
45 - val_accuracy: 0.8845 - val_loss: 0.4432 - learning_rate: 5.0000e-05
Epoch 54/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9489 - loss: 0.16
24 - val_accuracy: 0.8775 - val_loss: 0.4620 - learning_rate: 5.0000e-05
Epoch 55/150
249/250 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - accuracy: 0.9502 - loss: 0.162
8
Epoch 55: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-0
5.
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9507 - loss: 0.16
25 - val_accuracy: 0.8830 - val_loss: 0.4349 - learning_rate: 5.0000e-05
Epoch 56/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - accuracy: 0.9498 - loss: 0.15
```

```
97 - val_accuracy: 0.8860 - val_loss: 0.4137 - learning_rate: 2.5000e-05
Epoch 57/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.9511 - loss: 0.16
29 - val_accuracy: 0.8840 - val_loss: 0.4268 - learning_rate: 2.5000e-05
Epoch 58/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 46ms/step - accuracy: 0.9514 - loss: 0.15
72 - val_accuracy: 0.8800 - val_loss: 0.4463 - learning_rate: 2.5000e-05
Epoch 59/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step - accuracy: 0.9515 - loss: 0.150
5
Epoch 59: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-0
5.
250/250 ━━━━━━━━━━━━━━━━━━━━ 12s 46ms/step - accuracy: 0.9511 - loss: 0.15
56 - val_accuracy: 0.8840 - val_loss: 0.4252 - learning_rate: 2.5000e-05
Epoch 60/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 12s 47ms/step - accuracy: 0.9524 - loss: 0.15
27 - val_accuracy: 0.8865 - val_loss: 0.4235 - learning_rate: 1.2500e-05
Epoch 61/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 12s 47ms/step - accuracy: 0.9514 - loss: 0.15
31 - val_accuracy: 0.8870 - val_loss: 0.4223 - learning_rate: 1.2500e-05
Epoch 62/150
249/250 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - accuracy: 0.9520 - loss: 0.158
5
Epoch 62: ReduceLROnPlateau reducing learning rate to 1e-05.
250/250 ━━━━━━━━━━━━━━━━━━━━ 12s 47ms/step - accuracy: 0.9523 - loss: 0.15
51 - val_accuracy: 0.8855 - val_loss: 0.4210 - learning_rate: 1.2500e-05
Epoch 63/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - accuracy: 0.9519 - loss: 0.14
79 - val_accuracy: 0.8880 - val_loss: 0.4163 - learning_rate: 1.0000e-05
Epoch 64/150
250/250 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - accuracy: 0.9536 - loss: 0.15
12 - val_accuracy: 0.8865 - val_loss: 0.4204 - learning_rate: 1.0000e-05
Epoch 64: early stopping
Restoring model weights from the end of the best epoch: 56.
```

In [74]:

```python
y_pred_lstm = np.argmax(lstm.predict(X_test_seq), axis=1)

print("Results in Word2Vec + LSTM:")
print("Accuracy :", accuracy_score(y_test, y_pred_lstm))
print("Macro F1 :", f1_score(y_test, y_pred_lstm, average="macro"))
print("Weighted :", f1_score(y_test, y_pred_lstm, average="weighted"))
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step
Results in Word2Vec + LSTM:
Accuracy : 0.884
Macro F1 : 0.8402721789871612
Weighted : 0.8863248305735015
```

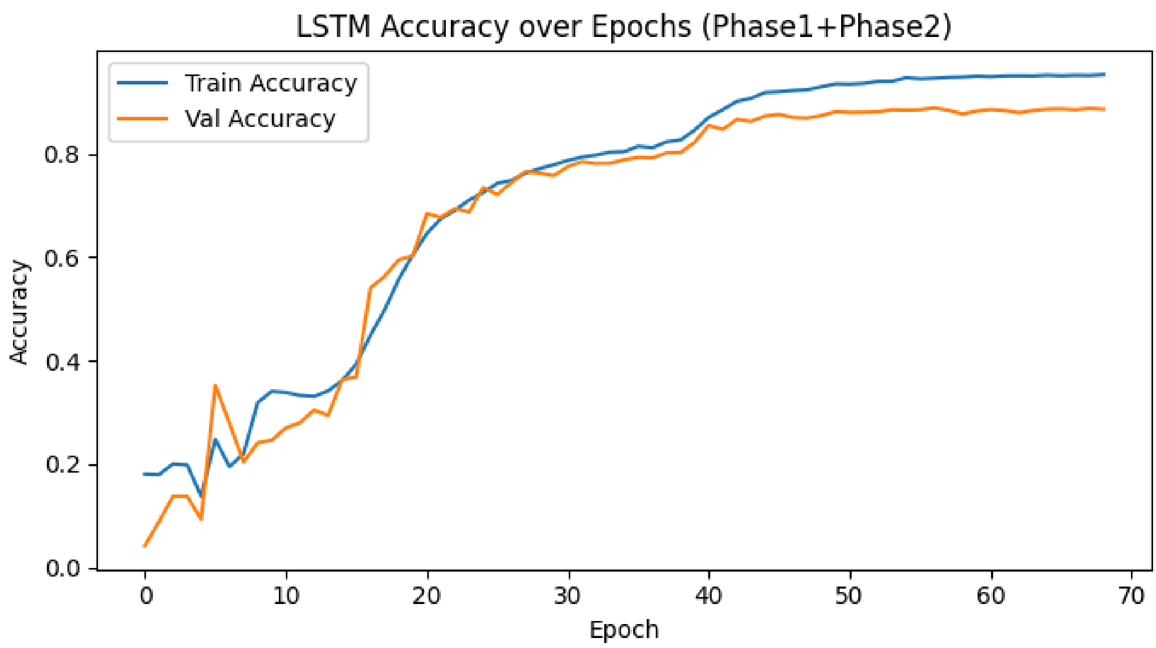
In [75]:

```python
# Merge Phase 1 + Phase 2 history into one object-like dict
history = {}
for k in hist1.history.keys():
    history[k] = hist1.history[k] + hist2.history.get(k, [])
```

In [76]:

```python
plt.figure(figsize=(7,4))
plt.plot(history["accuracy"], label="Train Accuracy")
plt.plot(history["val_accuracy"], label="Val Accuracy")
plt.title("LSTM Accuracy over Epochs (Phase1+Phase2)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
```

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



Quick Look — LSTM Accuracy over Epochs (Phase 1 + Phase 2)

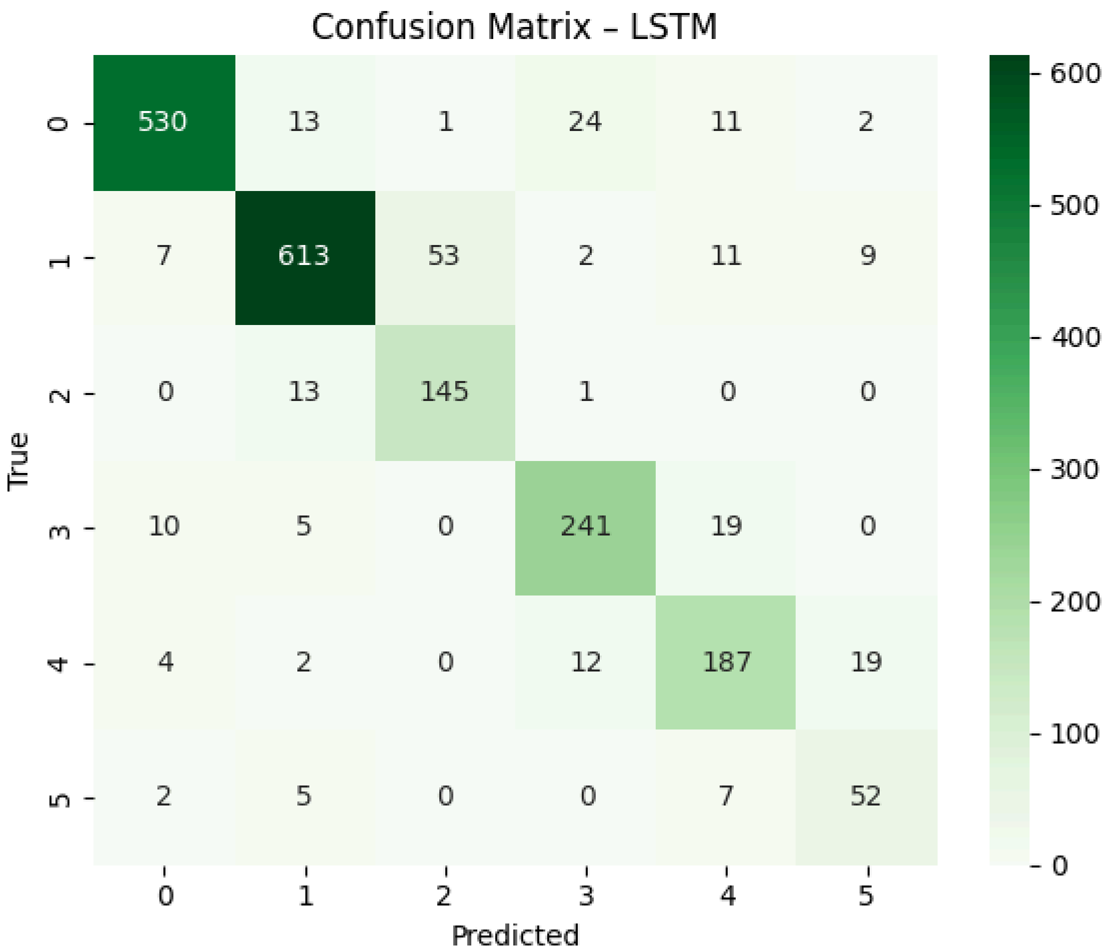
- **Consistent learning:** Training and validation accuracy rise smoothly, indicating stable optimization across both phases.
- **Convergence:** Validation accuracy plateaus around **~0.87–0.88** after ~40 epochs.
- **Generalization gap:** Training accuracy continues to improve slightly while validation stays flat → **mild overfitting**, but well-controlled.
- **Practical takeaway:** Best model performance is reached near the plateau; further training yields minimal validation gains.

In [77]:
```
print("\nClassification Report:\n")
print(
    classification_report(
    y_test,
    y_pred_lstm,
    target_names=EMOTION_DICT.values()
))
```

```
Classification Report:

              precision    recall  f1-score   support

     sadness       0.96      0.91      0.93       581
         joy       0.94      0.88      0.91       695
        love       0.73      0.91      0.81       159
       anger       0.86      0.88      0.87       275
        fear       0.80      0.83      0.81       224
    surprise       0.63      0.79      0.70        66

    accuracy                           0.88      2000
   macro avg       0.82      0.87      0.84      2000
weighted avg       0.89      0.88      0.89      2000
```

In [78]:

```python
cm_lstm = confusion_matrix(y_test, y_pred_lstm)
plt.figure(figsize=(6,5))
sns.heatmap(
    cm_lstm, annot=True, fmt="d", cmap="Greens",
    xticklabels=label_encoder.classes_,
    yticklabels=label_encoder.classes_,
)
plt.title("Confusion Matrix – LSTM")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```



Performance Summary — LSTM (Word2Vec + LSTM)

- **Overall performance:**
  - Accuracy: **0.88**
  - Macro F1: **0.84**
  - Weighted F1: **0.89**
    Indicates good overall performance with reasonable handling of class imbalance.
- **Strong classes:**
  - *Sadness* and *Joy* achieve high precision and F1 (>0.90), showing the model learns dominant emotions well.
  - *Anger* and *Fear* are also classified reliably with balanced precision–recall.
- **Weaker classes:**
  - *Love* shows high recall but lower precision, suggesting confusion with semantically similar emotions.
  - *Surprise* remains the hardest class (lowest F1 ≈ 0.70), largely due to limited samples and overlap with other emotions.
- **Error patterns (from confusion matrix):**
  - Most misclassifications occur between emotionally close classes (e.g., *joy* ↔ *love*, *fear* ↔ *anger*).
  - Diagonal dominance confirms stable learning, with no collapse to majority classes.
- **Overall takeaway:**
  The LSTM with Word2Vec embeddings provides **solid, balanced performance**, capturing sequential information better than simple bag-of-words models, but still struggles with minority and semantically subtle emotion classes.

4.3 BERT dataset

BERT dataset

In [79]:
```
BERT_MODEL = "bert-base-uncased"
bert_tokenizer = AutoTokenizer.from_pretrained(BERT_MODEL)
```

In [80]:
```
class EmotionDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len=64):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __getitem__(self, idx):
        encoding = self.tokenizer(
            self.texts[idx],
            max_length=self.max_len,
            padding="max_length",
            truncation=True,
```

```
            return_tensors="pt"
        )
        item = {k: v.squeeze(0) for k, v in encoding.items()}
        item["labels"] = torch.tensor(int(self.labels[idx]))
        return item

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

train_dataset = EmotionDataset(X_train_raw, y_train, bert_tokenizer)
dev_dataset   = EmotionDataset(X_dev_raw, y_dev, bert_tokenizer)
test_dataset  = EmotionDataset(X_test_raw, y_test, bert_tokenizer)
```

Fine-tuning BERT

In [81]:

```
BERT_EPOCH=5
```

In [82]:

```
device = "cuda" if torch.cuda.is_available() else "cpu"
print("Using device:", device)

bert_model = AutoModelForSequenceClassification.from_pretrained(
    BERT_MODEL, num_labels=NUM_CLASSES
).to(device)
```

```
Using device: cpu
```

```
Some weights of BertForSequenceClassification were not initialized from th
e model checkpoint at bert-base-uncased and are newly initialized: ['class
ifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to u
se it for predictions and inference.
```

In [83]:

```
def compute_metrics(pred):
    logits, labels = pred
    preds = np.argmax(logits, axis=1)
    return {
        "accuracy": accuracy_score(labels, preds),
        "f1_macro": f1_score(labels, preds, average="macro"),
        "f1_weighted": f1_score(labels, preds, average="weighted"),
    }
```

In [84]:

```
args = TrainingArguments(
    output_dir="./bert_out",
    num_train_epochs=BERT_EPOCH,
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=32,
    weight_decay=0.01,
    logging_steps=50,
)
```

In [85]:

```
trainer = Trainer(
    model=bert_model,
    args=args,
    train_dataset=train_dataset,
    eval_dataset=dev_dataset,
    compute_metrics=compute_metrics,
)
```

```
trainer.train()
```

```
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
```

[5000/5000 44:25, Epoch 5/5]

Step	Training Loss
50	1.638900
100	1.218600
150	0.947500
200	0.714100
250	0.553000
300	0.424200
350	0.397200
400	0.366800
450	0.280600
500	0.297300
550	0.259500
600	0.236000
650	0.290000
700	0.234400
750	0.220100
800	0.238500
850	0.255000
900	0.175000
950	0.210400
1000	0.236000
1050	0.127100
1100	0.104900
1150	0.179900
1200	0.158800
1250	0.161300
1300	0.158300
1350	0.149100
1400	0.153900
1450	0.121000
1500	0.207500
1550	0.119000
1600	0.132200
1650	0.170200

Step	Training Loss
1700	0.135500
1750	0.179400
1800	0.144100
1850	0.203100
1900	0.130600
1950	0.120100
2000	0.122400
2050	0.135200
2100	0.120800
2150	0.109400
2200	0.102500
2250	0.090500
2300	0.104500
2350	0.104400
2400	0.134600
2450	0.107700
2500	0.108900
2550	0.093800
2600	0.080100
2650	0.101800
2700	0.133900
2750	0.077500
2800	0.083300
2850	0.122900
2900	0.119600
2950	0.092500
3000	0.086800
3050	0.066200
3100	0.077900
3150	0.061000
3200	0.089400
3250	0.060600
3300	0.060700
3350	0.079800

Step	Training Loss
3400	0.136100
3450	0.072600
3500	0.084300
3550	0.082600
3600	0.087300
3650	0.094700
3700	0.099500
3750	0.069800
3800	0.093800
3850	0.070500
3900	0.070800
3950	0.083900
4000	0.080600
4050	0.035800
4100	0.042600
4150	0.041200
4200	0.045300
4250	0.057900
4300	0.037900
4350	0.088900
4400	0.049400
4450	0.056400
4500	0.043700
4550	0.058700
4600	0.040100
4650	0.064300
4700	0.058500
4750	0.046400
4800	0.044700
4850	0.082500
4900	0.046300
4950	0.039400
5000	0.050100

```
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
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/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
```

Out[85]:
```
TrainOutput(global_step=5000, training_loss=0.16934441967010497, metrics={'train_runtime': 2665.9758, 'train_samples_per_second': 30.008, 'train_steps_per_second': 1.875, 'total_flos': 2631205048320000.0, 'train_loss': 0.16934441967010497, 'epoch': 5.0})
```

In [86]:
```
outputs = trainer.predict(test_dataset)
y_pred_bert = np.argmax(outputs.predictions, axis=1)
```

```
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
```

In [87]:
```
outputs = trainer.predict(test_dataset)
y_pred_bert = np.argmax(outputs.predictions, axis=1)

print("BERT Fine-Tuning")
print("Accuracy :", accuracy_score(y_test, y_pred_bert))
print("Macro F1 :", f1_score(y_test, y_pred_bert, average="macro"))
print("Weighted :", f1_score(y_test, y_pred_bert, average="weighted"))
```

```
/Users/taanhtuan/miniconda3/envs/nlp/lib/python3.10/site-packages/torch/utils/data/dataloader.py:692: UserWarning: 'pin_memory' argument is set as true but not supported on MPS now, device pinned memory won't be used.
  warnings.warn(warn_msg)
BERT Fine-Tuning
Accuracy : 0.9195
Macro F1 : 0.8680832604064883
Weighted : 0.9196056838807994
```

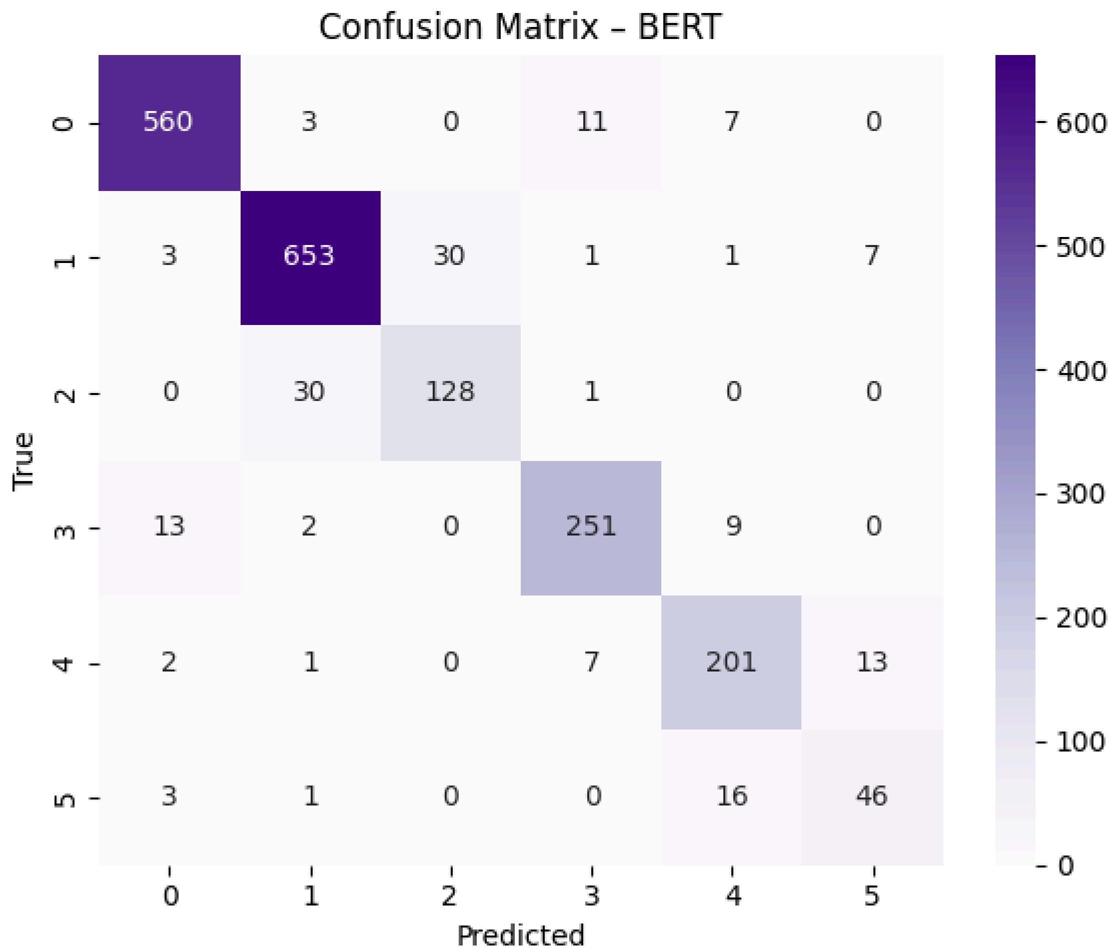
In [88]:
```
print(
    classification_report(
        y_test,
        y_pred_bert,
        target_names=EMOTION_DICT.values()
    )
)
```

```
              precision    recall  f1-score   support

     sadness       0.96      0.96      0.96       581
         joy       0.95      0.94      0.94       695
        love       0.81      0.81      0.81       159
       anger       0.93      0.91      0.92       275
        fear       0.86      0.90      0.88       224
    surprise       0.70      0.70      0.70        66

    accuracy                           0.92      2000
   macro avg       0.87      0.87      0.87      2000
weighted avg       0.92      0.92      0.92      2000
```

In [89]:
```
cm_bert = confusion_matrix(y_test, y_pred_bert)
plt.figure(figsize=(6,5))
sns.heatmap(
    cm_bert, annot=True, fmt="d", cmap="Purples",
    xticklabels=label_encoder.classes_,
    yticklabels=label_encoder.classes_,
)
plt.title("Confusion Matrix – BERT")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.tight_layout()
plt.show()
```



Performance Summary — BERT Fine-Tuning

- **Overall performance:**

- Accuracy: **0.92**
- Macro F1: **0.87**
- Weighted F1: **0.92**
  Confirms BERT as the strongest model, delivering both high overall accuracy and robust class-balanced performance.

- **Strong classes:**
  - *Sadness* and *Joy* achieve excellent precision and recall (F1 ≈ **0.94–0.96**), indicating BERT's ability to capture clear emotional cues and contextual sentiment.
  - *Anger* also performs very well (F1 ≈ **0.92**), with minimal confusion.
- **Moderate classes:**
  - *Fear* shows solid improvement over TF-IDF and LSTM (F1 ≈ **0.88**), benefiting from contextual understanding of threat- and anxiety-related language.
  - *Love* reaches balanced precision and recall (F1 ≈ **0.81**), outperforming classical and sequence-based models.
- **Challenging class:**
  - *Surprise* remains the weakest (F1 ≈ **0.70**), though still improved compared to other models. Errors mainly stem from overlap with *joy* and *fear* expressions.
- **Error patterns (from confusion matrix):**
  - Remaining confusions are largely between semantically adjacent emotions (e.g., *joy* ↔ *love*, *fear* ↔ *surprise*).
  - The diagonal dominance indicates strong overall discrimination across all classes.
- **Overall takeaway:**
  BERT Fine-Tuning provides the **best generalization and robustness under class imbalance**, effectively capturing nuanced emotional context in short, noisy tweet text. It clearly outperforms TF-IDF + Logistic Regression and Word2Vec + LSTM, making it the most reliable model for emotion classification in this task.

5. Result and Conclusion

5.1 Model Evaluation

In [90]:
```
results = []
```

In [91]:
```
results.append({
        "Model": "TF-IDF + LR",
        "Accuracy": accuracy_score(y_test, y_pred_lr),
        "Macro F1": f1_score(y_test, y_pred_lr, average="macro"),
        "Weighted F1": f1_score(y_test, y_pred_lr, average="weighted"),
    })
```

In [92]:
```
results.append({
        "Model": "Word2Vec + LSTM",
        "Accuracy": accuracy_score(y_test, y_pred_lstm),
        "Macro F1": f1_score(y_test, y_pred_lstm, average="macro"),
        "Weighted F1": f1_score(y_test, y_pred_lstm, average="weighted"),
    })
```

In [93]:
```
results.append({
        "Model": "BERT Fine-Tuning",
        "Accuracy": accuracy_score(y_test, y_pred_bert),
        "Macro F1": f1_score(y_test, y_pred_bert, average="macro"),
        "Weighted F1": f1_score(y_test, y_pred_bert, average="weighted"),
    })
```

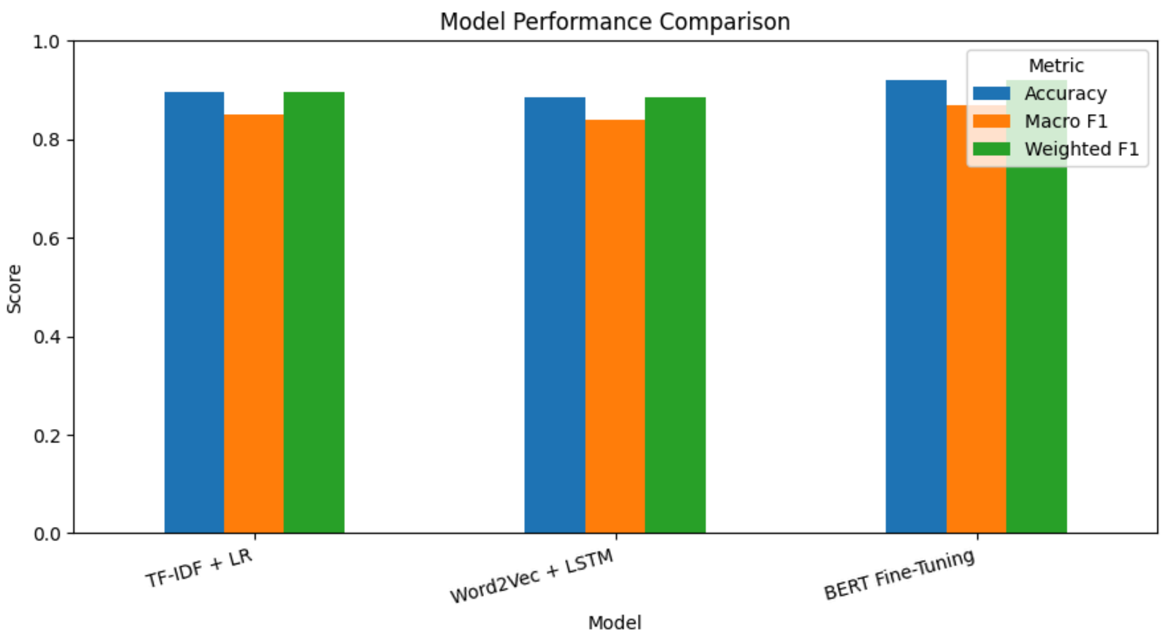
In [94]:
```
results_df = pd.DataFrame(results)
results_df
```

Out[94]:

	Model	Accuracy	Macro F1	Weighted F1
0	TF-IDF + LR	0.8955	0.851267	0.896450
1	Word2Vec + LSTM	0.8840	0.840272	0.886325
2	BERT Fine-Tuning	0.9195	0.868083	0.919606

In [95]:
```
metrics = ["Accuracy", "Macro F1", "Weighted F1"]
ax = results_df.set_index("Model")[metrics].plot(kind="bar", figsize=(9,

plt.title("Model Performance Comparison")
plt.xlabel("Model")
plt.ylabel("Score")
plt.ylim(0, 1)
plt.xticks(rotation=15, ha="right")
plt.legend(title="Metric")
plt.tight_layout()
plt.show()
```



5.1 Conclusion & Recommendation

Conclusion

This project presents a systematic comparison of **three NLP approaches for tweet-based emotion classification**: **TF-IDF + Logistic Regression**, **Word2Vec + LSTM**, and **BERT Fine-Tuning**.
All models were evaluated using **accuracy**, **macro F1**, and **weighted F1**, allowing analysis of both overall predictive power and robustness under class imbalance.

Model Comparison and Key Findings

- **TF-IDF + Logistic Regression**
    - Achieved a strong and reliable baseline with **~89.6% accuracy** and **macro F1 ≈ 0.85**.
    - Performed consistently well on majority emotion classes (*sadness*, *joy*, *anger*, *fear*).
    - Minority classes (*love*, *surprise*) showed weaker recall, reflecting the limitation of bag-of-words features in modeling subtle emotional semantics.
    - Confirms that classical linear models remain competitive for short-text classification when paired with clean preprocessing and TF-IDF features.
- **Word2Vec + LSTM**
    - Achieved **~88.4% accuracy** and **macro F1 ≈ 0.84**, narrowing the gap with TF-IDF compared to earlier experiments.
    - Demonstrated clear learning dynamics: slow convergence in early epochs followed by stable improvement after sufficient training.
    - Leveraged **pre-trained Word2Vec embeddings**, enabling better semantic representation than TF-IDF, particularly for context-dependent emotions.
    - Still showed sensitivity to class imbalance and training stability, indicating that sequence-based models require careful tuning and sufficient data to consistently outperform simpler baselines.
- **BERT Fine-Tuning**
    - Delivered the strongest overall results:
        - **Accuracy: ~91.9%**
        - **Macro F1: ~0.87**
        - **Weighted F1: ~0.92**
    - Achieved the most balanced performance across both majority and minority emotion classes.
    - Confusion matrix analysis shows reduced cross-class confusion, especially for semantically similar emotions.
    - Effectively captured contextual and compositional meaning in short, noisy tweet text through pre-trained transformer representations.

Overall Observations

- A clear performance progression is observed from **TF-IDF → Word2Vec + LSTM → BERT**, though gains from LSTM over TF-IDF are moderate.
- **Pre-trained semantic knowledge** (Word2Vec, BERT) consistently improves generalization compared to purely frequency-based representations.
- Model complexity alone does not guarantee superior performance; training stability, data size, and class imbalance play critical roles.
- **BERT demonstrates the highest robustness** to class imbalance and semantic overlap among emotion categories.

Final Conclusion

Overall, the experiments confirm that **transformer-based models are the most effective for emotion classification in social media text**.
While **TF-IDF + Logistic Regression** provides a strong and efficient baseline, and **Word2Vec + LSTM** offers meaningful semantic improvements, **BERT Fine-Tuning consistently achieves the best balance between accuracy and class-level performance**, making it the most suitable model for real-world emotion analysis on tweets.

Recommendation

- Use **BERT Fine-Tuning** as the primary model for deployment.
- For further improvements:
  - Experiment with **domain-specific transformers** (e.g., BERTweet).
  - Apply **class-aware loss functions** to further improve minority-class performance.
  - Incorporate emojis, hashtags, or metadata as auxiliary features.
  - Explore **model distillation** for faster inference.
  - Periodically retrain the model to adapt to evolving social-media language.

8. References

- **Dataset Link**: https://www.kaggle.com/datasets/parulpandey/emotion-dataset/data
- **Github**: https://github.com/tuanTaAnh/Emotion-Classification

In [ ]:

```
```