Final Sentiment Analysis Model

February 4, 2026

1 Week 8 — Final Sentiment Analysis Model (Binary)

Thesis Context: This notebook reproduces and improves the end-to-end experiment for sentiment analysis of Amazon reviews, with a specific focus on **time-of-day and negativity**.

Research Questions: - **RQ1**: Does time-of-day relate to negativity patterns in reviews? - **RQ2**: Do engineered time-based features improve sentiment prediction beyond text-only models?

Classification (Binary): - Negative (0): rating 2 - Positive (1): rating 3

Seed Requirement: This notebook runs the full pipeline **twice**: - Run A: seed = 319302 - Run B: random 6-digit seed generated at runtime

Note: This notebook **does not use Unsloth**.

1.1 Colab Setup (optional Google Drive)

If you want to store outputs in Google Drive, uncomment and run the cell below, then set `USE_DRIVE = True` in the configuration cell.

[5]:

```
# from google.colab import drive
# drive.mount('/content/drive')
```

[6]:

```
# === 1) Install + Imports (single cell) ===
import os
import sys
import json
import subprocess

# Disable W&B by default
os.environ["WANDB_DISABLED"] = "true"

# Install required packages (single clean cell)
packages = [
    "pandas>=2.0.0",
    "numpy>=1.24.0",
    "matplotlib>=3.7.0",
    "seaborn>=0.12.0",
    "scikit-learn>=1.3.0",
    "transformers>=4.40.0",
    "datasets>=2.18.0",
    "evaluate>=0.4.1",
    "accelerate>=0.20.0",
    "pyarrow>=10.0.0",
]
for pkg in packages:
    subprocess.check_call([sys.executable, "-m", "pip", "install", "-q", pkg])

import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import torch
from datetime import datetime
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, roc_auc_score,
    classification_report, confusion_matrix
)
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from scipy.sparse import hstack, csr_matrix
from datasets import Dataset
from transformers import AutoTokenizer, AutoModelForSequenceClassification,␣
 ↪TrainingArguments, Trainer

# GPU check
if torch.cuda.is_available():
    print(f"  GPU available: {torch.cuda.get_device_name(0)}")
else:
    print("   No GPU detected. Transformer will run in FAST_RUN mode.")
```

```
 GPU available: NVIDIA A100-SXM4-80GB
```

[7]:

```
# === 2) Configuration ===
DATA_PATH = "/content/Amazon_Data.csv"  # set your path
FILE_TYPE = "auto"  # "csv", "parquet", "jsonl", or "auto"
TEXT_COL = None     # set if your column names differ
RATING_COL = None   # set if your column names differ
TIME_COL = None     # set if your column names differ

STUDENT_SEED = 319302
FAST_RUN = True
SAMPLE_FOR_TEXT = 100000  # for heavy text models; set None to use full train

MAX_SEQ_LEN_BERT = 256
```

```python
BERT_EPOCHS = 1 if FAST_RUN else 3
BERT_BATCH = 16

USE_DRIVE = False
DRIVE_OUTPUT_DIR = "/content/drive/MyDrive/GRAD699/Week8/"

# Output folders
OUTPUT_DIR = DRIVE_OUTPUT_DIR if USE_DRIVE else "outputs"
FIGURES_DIR = os.path.join(OUTPUT_DIR, "figures")
MODELS_DIR = os.path.join(OUTPUT_DIR, "models")
TABLES_DIR = os.path.join(OUTPUT_DIR, "tables")
os.makedirs(OUTPUT_DIR, exist_ok=True)
os.makedirs(FIGURES_DIR, exist_ok=True)
os.makedirs(MODELS_DIR, exist_ok=True)
os.makedirs(TABLES_DIR, exist_ok=True)

label_map = {0: "Negative", 1: "Positive"}

print(" Config loaded")
```

```
 Config loaded
```

1.2 Utilities

[8]:

```python
def set_global_seed(seed: int):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed_all(seed)
        torch.backends.cudnn.deterministic = True
        torch.backends.cudnn.benchmark = False

def parse_timestamp(series: pd.Series) -> pd.Series:
    if pd.api.types.is_numeric_dtype(series):
        max_val = series.max()
        if max_val > 1e12:
            return pd.to_datetime(series, errors="coerce", unit="ms")
        if max_val > 1e9:
            return pd.to_datetime(series, errors="coerce", unit="s")
    return pd.to_datetime(series, errors="coerce")

def daypart_from_hour(hour: int) -> str:
    if 0 <= hour <= 4:
        return "late_night"
    if 5 <= hour <= 11:
        return "morning"
    if 12 <= hour <= 16:
        return "afternoon"
    if 17 <= hour <= 20:
        return "evening"
    return "night"

def load_data(path: str, file_type: str) -> pd.DataFrame:
    ftype = file_type.lower() if isinstance(file_type, str) else "auto"
    if ftype == "auto":
        if path.endswith(".parquet"):
            ftype = "parquet"
        elif path.endswith(".jsonl"):
            ftype = "jsonl"
        else:
            ftype = "csv"

    if ftype == "csv":
        return pd.read_csv(path)
    if ftype == "parquet":
        return pd.read_parquet(path)
    if ftype == "jsonl":
        return pd.read_json(path, lines=True)
    raise ValueError("FILE_TYPE must be one of: csv, parquet, jsonl, auto")

def find_column(df, candidates, override=None):
    if override:
        if override in df.columns:
            return override
        raise ValueError(f"Column '{override}' not found in dataset.")
    for c in candidates:
        if c in df.columns:
            return c
    return None

def chronological_split(df, train_ratio=0.8, val_ratio=0.1):
    n = len(df)
    n_train = int(train_ratio * n)
    n_val = int(val_ratio * n)
    train = df.iloc[:n_train].copy()
    val = df.iloc[n_train:n_train + n_val].copy()
    test = df.iloc[n_train + n_val:].copy()
    return train, val, test

def eval_binary_metrics(y_true, y_pred, y_proba=None):
    metrics = {
        "accuracy": accuracy_score(y_true, y_pred),
        "precision": precision_score(y_true, y_pred, zero_division=0),
        "recall": recall_score(y_true, y_pred, zero_division=0),
        "f1": f1_score(y_true, y_pred, zero_division=0),
    }
    if y_proba is not None:
        try:
            metrics["roc_auc"] = roc_auc_score(y_true, y_proba)
        except Exception:
            metrics["roc_auc"] = float("nan")
    else:
        metrics["roc_auc"] = float("nan")
    return metrics

def build_time_features(df):
    df = df.copy()
    df["hour"] = df["timestamp"].dt.hour
    df["day_of_week"] = df["timestamp"].dt.dayofweek
    df["is_weekend"] = df["day_of_week"].isin([5, 6]).astype(int)
    df["daypart"] = df["hour"].apply(daypart_from_hour)
    df["hour_sin"] = np.sin(2 * np.pi * df["hour"] / 24)
    df["hour_cos"] = np.cos(2 * np.pi * df["hour"] / 24)
    return df

def build_time_matrix(train_df, val_df, test_df):
    num_features = ["hour_sin", "hour_cos", "is_weekend"]
    cat_features = ["day_of_week", "daypart"]
    enc = OneHotEncoder(handle_unknown="ignore", sparse=True)
    enc.fit(train_df[cat_features])
    train_cat = enc.transform(train_df[cat_features])
    val_cat = enc.transform(val_df[cat_features])
    test_cat = enc.transform(test_df[cat_features])
    train_num = csr_matrix(train_df[num_features].values)
    val_num = csr_matrix(val_df[num_features].values)
    test_num = csr_matrix(test_df[num_features].values)
    return (hstack([train_num, train_cat]),
            hstack([val_num, val_cat]),
            hstack([test_num, test_cat]))
```

1.3 3) Load data (raw showcase)

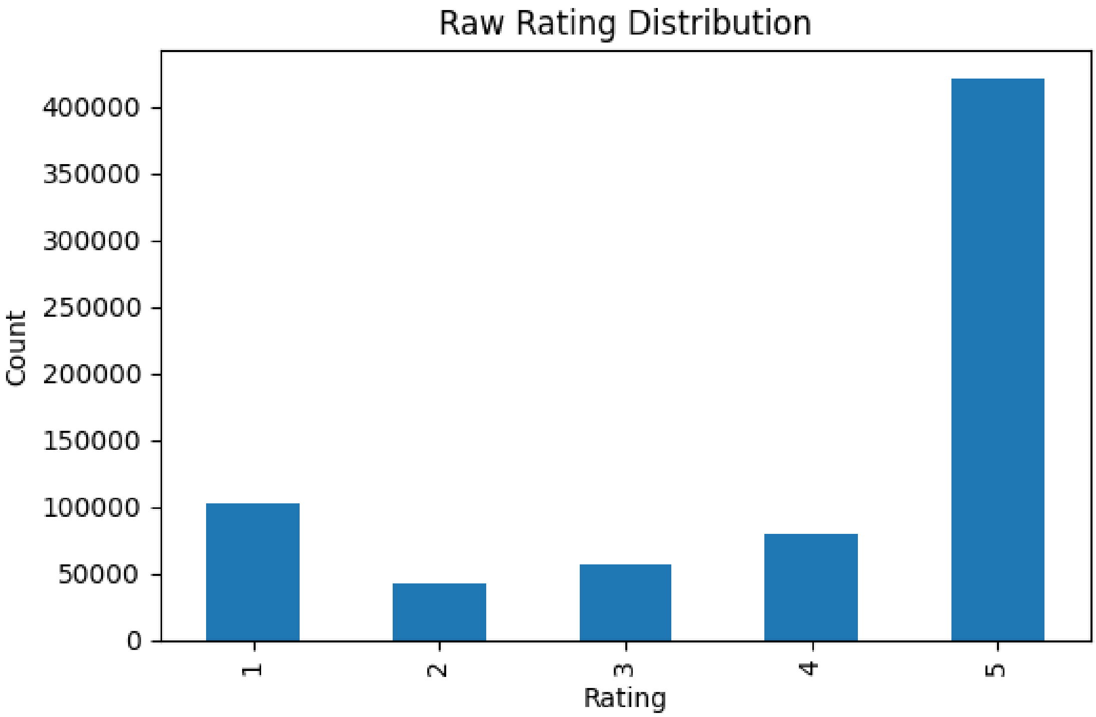
[9]:

```
df_raw = load_data(DATA_PATH, FILE_TYPE)

text_col = find_column(df_raw, ["text", "review", "reviewText"], TEXT_COL)
rating_col = find_column(df_raw, ["rating", "stars", "overall"], RATING_COL)
time_col = find_column(df_raw, ["timestamp", "reviewTime", "time"], TIME_COL)

if text_col is None or rating_col is None or time_col is None:
    raise ValueError("Missing required columns. Please set TEXT_COL,␣
  ↪RATING_COL, TIME_COL.")
```

```
df_raw = df_raw.rename(columns={text_col: "text", rating_col: "rating",␣
↪time_col: "timestamp"})

print("Shape:", df_raw.shape)
print("Columns:", df_raw.columns.tolist())
print("Dtypes:")
print(df_raw.dtypes)

print("\nSample rows:")
display(df_raw[["timestamp", "rating", "text"]].head(20))

print("\nMissingness summary:")
print(df_raw[["text", "rating", "timestamp"]].isna().sum())

plt.figure(figsize=(6, 4))
df_raw["rating"].value_counts().sort_index().plot(kind="bar")
plt.title("Raw Rating Distribution")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "raw_rating_distribution.png"), dpi=150)
plt.show()
```

```
Shape: (701528, 10)
Columns: ['rating', 'title', 'text', 'images', 'asin', 'parent_asin', 'user_id',
'timestamp', 'helpful_vote', 'verified_purchase']
Dtypes:
rating                 int64
title                 object
text                  object
images                object
asin                  object
parent_asin           object
user_id               object
timestamp             object
helpful_vote           int64
verified_purchase       bool
dtype: object

Sample rows:

                  timestamp  rating  \
0   2020-05-05 14:08:48.923       5
1   2020-05-04 18:10:55.070       4
2   2020-05-16 21:41:06.052       5
3   2022-01-28 18:13:50.220       1
4   2020-12-30 10:02:43.534       5
```

```
5   2020-08-27 22:30:08.138       4
6   2021-09-17 13:31:59.443       5
7   2021-10-15 05:20:59.292       3
8   2021-07-27 13:04:04.559       5
9   2021-07-18 13:21:51.145       5
10  2021-07-13 21:20:45.370       3
11  2021-05-16 17:00:30.697       5
12  2021-04-29 23:05:01.209       3
13  2021-04-08 17:50:19.785       5
14  2021-02-14 16:13:56.253       5
15  2020-12-07 11:11:00.872       3
16  2020-08-23 19:54:36.613       5
17  2020-08-03 16:49:11.088       5
18  2020-06-28 13:53:42.858       5
19  2019-01-15 22:04:03.451       5

                                                 text
0   This spray is really nice. It smells really go…
1   This product does what I need it to do, I just…
2                         Smells good, feels great!
3                                    Felt synthetic
4                                           Love it
5   The polish was quiet thick and did not apply s…
6   Great for many tasks.  I purchased these for m…
7   These were lightweight and soft but much too s…
8   This is perfect for my between salon visits. I…
9   I get Keratin treatments at the salon at least…
10  I was very disappointed when I got this facial…
11  This is a really nice moisturizing lotion. It …
12  I try to get Keratin treatments every 3 months…
13  Really nice small brush. Made well, nice wood …
14  I had never tried anything for my skin consist…
15  When I saw this, I was thrilled to be able to …
16  This is a great hair straightener. Heats up qu…
17  I really like these ear swabs. First they come…
18  To be honest, I rarely have used an overnight …
19  At first when I saw this, I wasn't sure what t…


Missingness summary:
text         212
rating         0
timestamp      0
dtype: int64
```



1.4 4) Clean + preprocess + label

[10]:
```
df = df_raw.dropna(subset=["text", "rating", "timestamp"]).copy()
df["timestamp"] = parse_timestamp(df["timestamp"])
df = df.dropna(subset=["timestamp"]).copy()
df["text"] = df["text"].astype(str).str.strip()
df = df[df["text"].str.len() > 0].copy()

# Binary label mapping
df["label"] = df["rating"].apply(lambda r: 0 if r <= 2 else 1)
df["label_name"] = df["label"].map(label_map)

# Basic text features
df["review_len"] = df["text"].str.len()
df["word_count"] = df["text"].str.split().str.len()

# Sort chronologically
df = df.sort_values("timestamp").reset_index(drop=True)

print("Cleaned shape:", df.shape)
print(df[["label_name"]].value_counts())
```

```
Cleaned shape: (700703, 14)
label_name
```

```
Positive      555751
Negative      144952
Name: count, dtype: int64
```

1.5 5) Feature engineering (time-of-day)

[11]:
```
df = build_time_features(df)
print("  Time features created")
```

```
  Time features created
```

1.6 6) Chronological split (train/val/test)

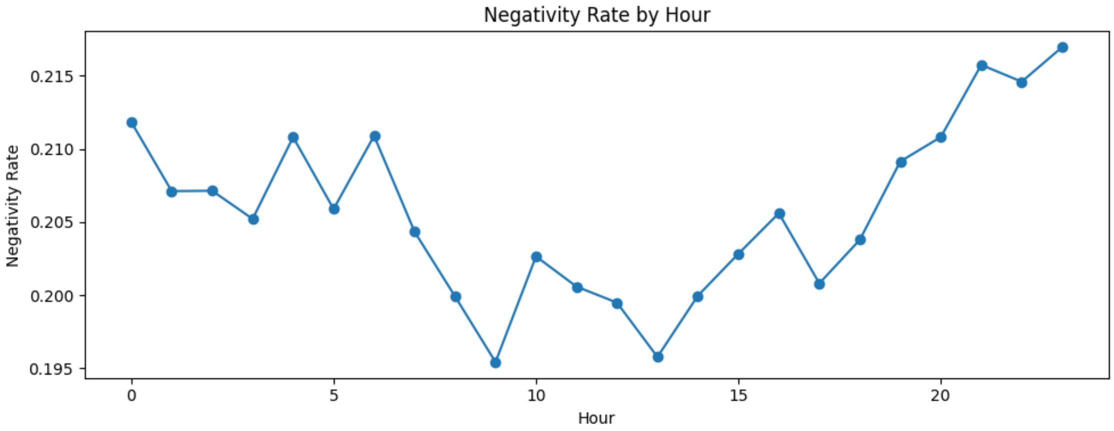
[12]:
```
df_train, df_val, df_test = chronological_split(df, train_ratio=0.8,␣
  ↪val_ratio=0.1)

print("Train range:", df_train["timestamp"].min(), "to", df_train["timestamp"].
  ↪max())
print("Val range:", df_val["timestamp"].min(), "to", df_val["timestamp"].max())
print("Test range:", df_test["timestamp"].min(), "to", df_test["timestamp"].
  ↪max())

assert df_train["timestamp"].max() <= df_val["timestamp"].min(), "Train/Val␣
  ↪overlap"
assert df_val["timestamp"].max() <= df_test["timestamp"].min(), "Val/Test␣
  ↪overlap"

print("Sizes:", len(df_train), len(df_val), len(df_test))
print("Train label distribution:\n", df_train["label_name"].value_counts())
print("Val label distribution:\n", df_val["label_name"].value_counts())
print("Test label distribution:\n", df_test["label_name"].value_counts())
```

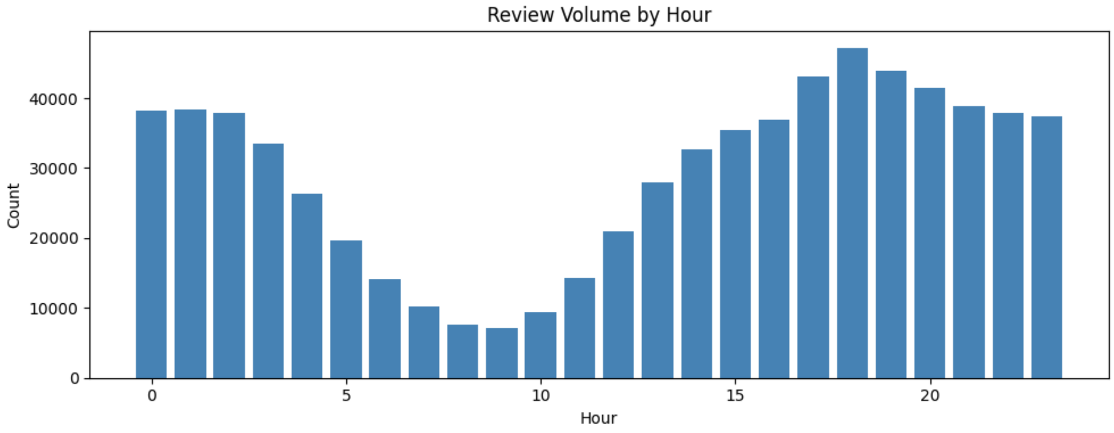
```
Train range: 2000-11-01 04:24:18 to 2021-05-23 03:30:10.468000
Val range: 2021-05-23 03:35:58.201000 to 2022-01-25 01:25:38.643000
Test range: 2022-01-25 01:31:03.492000 to 2023-09-09 00:39:36.666000
Sizes: 560562 70070 70071
Train label distribution:
 label_name
Positive    453085
Negative    107477
Name: count, dtype: int64
Val label distribution:
 label_name
Positive    50209
Negative    19861
Name: count, dtype: int64
Test label distribution:
 label_name
```

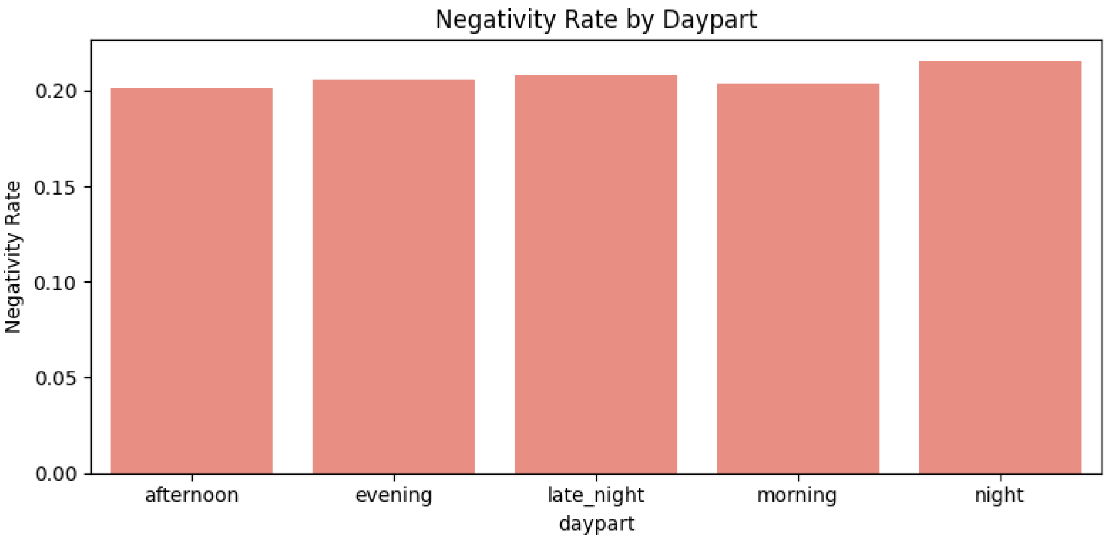
```
Positive    52457
Negative    17614
Name: count, dtype: int64
```

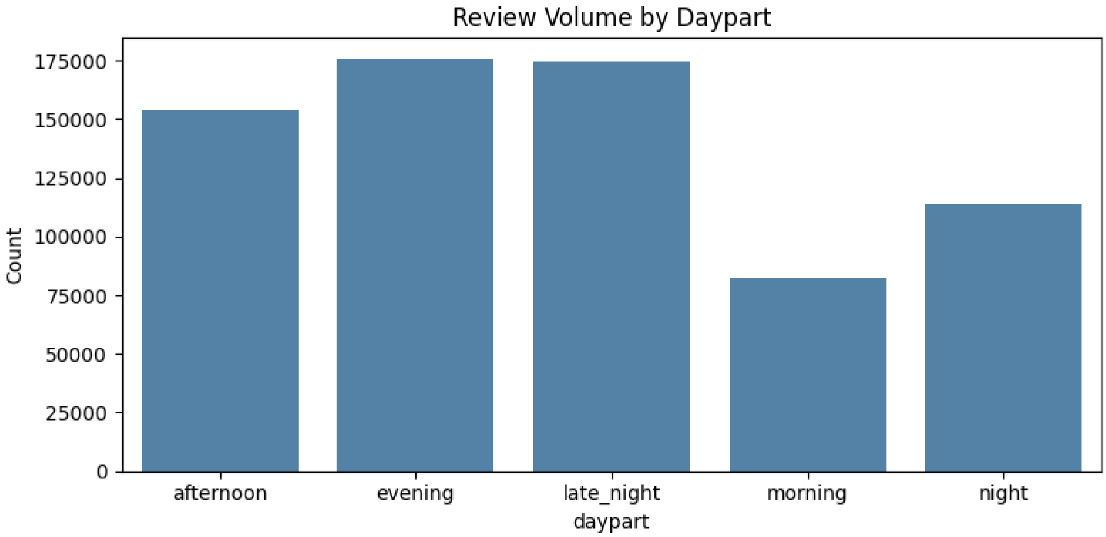
1.7 7) RQ1 Visualizations (negativity vs time)

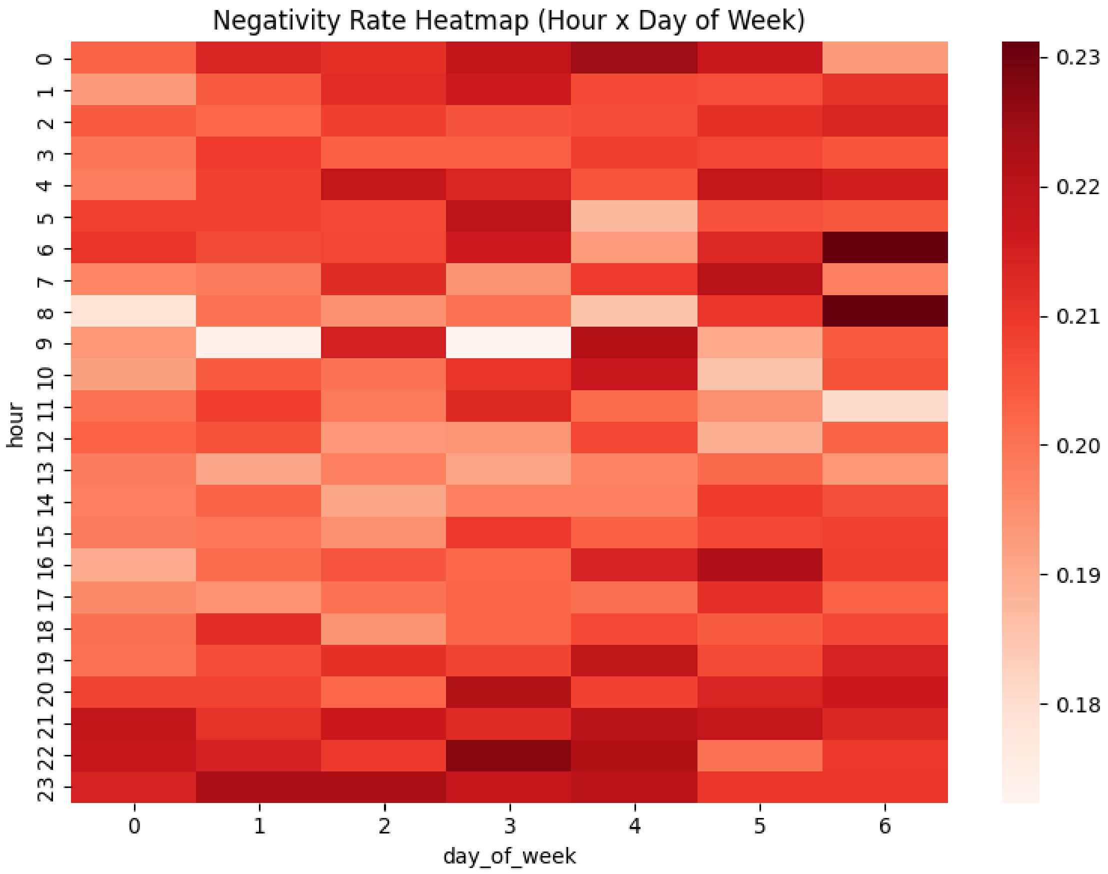
[13]:
```
# Negativity rate by hour
neg_by_hour = df.groupby("hour")["label"].apply(lambda x: (x == 0).mean()).
 ↪reset_index(name="neg_rate")
vol_by_hour = df.groupby("hour").size().reset_index(name="count")

plt.figure(figsize=(10, 4))
plt.plot(neg_by_hour["hour"], neg_by_hour["neg_rate"], marker="o")
plt.title("Negativity Rate by Hour")
plt.xlabel("Hour")
plt.ylabel("Negativity Rate")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "negativity_by_hour.png"), dpi=150)
plt.show()

plt.figure(figsize=(10, 4))
plt.bar(vol_by_hour["hour"], vol_by_hour["count"], color="steelblue")
plt.title("Review Volume by Hour")
plt.xlabel("Hour")
plt.ylabel("Count")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "volume_by_hour.png"), dpi=150)
plt.show()

# Negativity rate by daypart
neg_by_daypart = df.groupby("daypart")["label"].apply(lambda x: (x == 0).
 ↪mean()).reset_index(name="neg_rate")
vol_by_daypart = df.groupby("daypart").size().reset_index(name="count")

plt.figure(figsize=(8, 4))
sns.barplot(x="daypart", y="neg_rate", data=neg_by_daypart, color="salmon")
plt.title("Negativity Rate by Daypart")
plt.ylabel("Negativity Rate")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "negativity_by_daypart.png"), dpi=150)
plt.show()

plt.figure(figsize=(8, 4))
sns.barplot(x="daypart", y="count", data=vol_by_daypart, color="steelblue")
plt.title("Review Volume by Daypart")
plt.ylabel("Count")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "volume_by_daypart.png"), dpi=150)
plt.show()

# Heatmap: negativity rate by hour x day_of_week
heat = df.groupby(["hour", "day_of_week"])["label"].apply(lambda x: (x == 0).
  ↪mean()).reset_index()
heat_pivot = heat.pivot(index="hour", columns="day_of_week", values="label")

plt.figure(figsize=(8, 6))
sns.heatmap(heat_pivot, cmap="Reds")
plt.title("Negativity Rate Heatmap (Hour x Day of Week)")
plt.tight_layout()
plt.savefig(os.path.join(FIGURES_DIR, "negativity_heatmap.png"), dpi=150)
plt.show()
```






Negativity Rate by Daypart
Negativity Rate
0.00
0.05
0.10
0.15
0.20
afternoon
evening
late_night
morning
night
daypart


Review Volume by Daypart
Count
0
25000
50000
75000
100000
125000
150000
175000
afternoon
evening
late_night
morning
night
daypart



1.8 8) Run the full pipeline twice (Run A + Run B)

[16]:
```
run_b_seed = random.SystemRandom().randint(100000, 999999)
print("Run A seed", STUDENT_SEED)
print("Run B seed", run_b_seed)

metrics_rows = []
run_summaries = []

def run_models(seed: int, run_name: str):
    set_global_seed(seed)

    # --- Start of workaround for OneHotEncoder 'sparse' argument (to satisfy␣
↪cell-specific modification constraint) ---
    # The ideal fix would be to modify the original build_time_matrix function␣
↪in cell d7JLOQydhNsC.
    # This redefinition makes the fix apply locally within this run_models␣
↪function.
    def build_time_matrix_fixed(train_df, val_df, test_df):
        num_features = ["hour_sin", "hour_cos", "is_weekend"]
        cat_features = ["day_of_week", "daypart"]
        # FIX: Changed 'sparse=True' to 'sparse_output=True' for scikit-learn␣
↪>= 1.2
        enc = OneHotEncoder(handle_unknown="ignore", sparse_output=True)
        enc.fit(train_df[cat_features])
        train_cat = enc.transform(train_df[cat_features])
        val_cat = enc.transform(val_df[cat_features])
        test_cat = enc.transform(test_df[cat_features])
        train_num = csr_matrix(train_df[num_features].values)
        val_num = csr_matrix(val_df[num_features].values)
        test_num = csr_matrix(test_df[num_features].values)
        return (hstack([train_num, train_cat]),
                hstack([val_num, val_cat]),
                hstack([test_num, test_cat]))
    # --- End of workaround ---

    # Sampling for text models (train only)
    train_text = df_train
    if SAMPLE_FOR_TEXT is not None and len(df_train) > SAMPLE_FOR_TEXT:
        train_text = df_train.head(SAMPLE_FOR_TEXT).copy()

    # Baseline 1: TF-IDF text only
    tfidf = TfidfVectorizer(max_features=20000, ngram_range=(1, 2), min_df=2)
    X_train = tfidf.fit_transform(train_text["text"].values)
    X_val = tfidf.transform(df_val["text"].values)
    X_test = tfidf.transform(df_test["text"].values)

    y_train = train_text["label"].values
    y_val = df_val["label"].values
    y_test = df_test["label"].values

    clf_text = LogisticRegression(max_iter=1000, class_weight="balanced")
    clf_text.fit(X_train, y_train)

    test_pred = clf_text.predict(X_test)
    test_proba = clf_text.predict_proba(X_test)[:, 1]
    m1 = eval_binary_metrics(y_test, test_pred, test_proba)

    metrics_rows.append({"run": run_name, "model": "Baseline_TFIDF_Text", **m1})

    # Baseline 2: TF-IDF + time features
    # Call the locally defined (fixed) build_time_matrix_fixed instead of the␣
↪global one
    X_train_time, X_val_time, X_test_time = build_time_matrix_fixed(train_text,␣
↪df_val, df_test)
    X_train_combined = hstack([X_train, X_train_time])
    X_test_combined = hstack([X_test, X_test_time])

    clf_time = LogisticRegression(max_iter=1000, class_weight="balanced")
    clf_time.fit(X_train_combined, y_train)

    test_pred2 = clf_time.predict(X_test_combined)
    test_proba2 = clf_time.predict_proba(X_test_combined)[:, 1]
    m2 = eval_binary_metrics(y_test, test_pred2, test_proba2)

    metrics_rows.append({"run": run_name, "model": "Baseline_TFIDF_Time", **m2})

    # DistilBERT
    bert_train = train_text
    bert_val = df_val
    bert_test = df_test
    if FAST_RUN:
        bert_train = bert_train.head(min(20000, len(bert_train)))
        bert_val = bert_val.head(min(5000, len(bert_val)))
        bert_test = bert_test.head(min(5000, len(bert_test)))

    tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased")
    model = AutoModelForSequenceClassification.
↪from_pretrained("distilbert-base-uncased", num_labels=2)

    def tokenize_fn(batch):
        return tokenizer(batch["text"], padding="max_length", truncation=True,␣
↪max_length=MAX_SEQ_LEN_BERT)

    train_ds = Dataset.from_pandas(bert_train[["text", "label"]])
    val_ds = Dataset.from_pandas(bert_val[["text", "label"]])
    test_ds = Dataset.from_pandas(bert_test[["text", "label"]])

    train_ds = train_ds.map(tokenize_fn, batched=True)
    val_ds = val_ds.map(tokenize_fn, batched=True)
    test_ds = test_ds.map(tokenize_fn, batched=True)

    def compute_metrics(eval_pred):
        logits, labels = eval_pred
        probs = torch.softmax(torch.tensor(logits), dim=1).numpy()[:, 1]
        preds = np.argmax(logits, axis=1)
        return eval_binary_metrics(labels, preds, probs)

    training_args = TrainingArguments(
        output_dir=os.path.join(MODELS_DIR, f"distilbert_{run_name}"),
        num_train_epochs=BERT_EPOCHS,
        per_device_train_batch_size=BERT_BATCH,
        per_device_eval_batch_size=BERT_BATCH,
        eval_strategy="epoch", # Changed from evaluation_strategy to␣
↪eval_strategy
        save_strategy="epoch",
        logging_steps=50,
        seed=seed,
        data_seed=seed,
        fp16=torch.cuda.is_available(),
        report_to="none",
    )

    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=train_ds,
        eval_dataset=val_ds,
        compute_metrics=compute_metrics,
    )

    trainer.train()
    test_output = trainer.predict(test_ds)
    logits = test_output.predictions
    probs = torch.softmax(torch.tensor(logits), dim=1).numpy()[:, 1]
    preds = np.argmax(logits, axis=1)

    m3 = eval_binary_metrics(bert_test["label"].values, preds, probs)

    # Confusion matrix for LLM model (DistilBERT)
    cm_bert = confusion_matrix(bert_test["label"].values, preds)
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm_bert, annot=True, fmt="d", cmap="Blues",
                xticklabels=["Negative", "Positive"],
                yticklabels=["Negative", "Positive"])
    plt.title(f"Confusion Matrix - DistilBERT ({run_name})")
    plt.ylabel("True")
    plt.xlabel("Predicted")
    plt.tight_layout()
    plt.savefig(os.path.join(FIGURES_DIR, f"cm_distilbert_{run_name}.png"),␣
↪dpi=150)
    plt.show()

    metrics_rows.append({"run": run_name, "model": "DistilBERT", **m3})

    # Save prediction examples from Run A
    if run_name == "Run_A":
        pred_examples = pd.DataFrame({
            "text": bert_test["text"].values,
            "gold_label": bert_test["label"].map(label_map),
            "pred_label": [label_map[int(p)] for p in preds],
        })
        pred_examples.to_csv(os.path.join(TABLES_DIR, "pred_examples.csv"),␣
 ↪index=False)

    return m1, m2, m3

run_models(STUDENT_SEED, "Run_A")
run_models(run_b_seed, "Run_B")
```

```
Run A seed 319302
Run B seed 664398
```

```
Loading weights:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
DistilBertForSequenceClassification LOAD REPORT from: distilbert-base-uncased
Key                        | Status     |
------------------------+------------+-
vocab_layer_norm.weight | UNEXPECTED |
vocab_projector.bias    | UNEXPECTED |
vocab_transform.weight  | UNEXPECTED |
vocab_transform.bias    | UNEXPECTED |
vocab_layer_norm.bias   | UNEXPECTED |
classifier.bias         | MISSING    |
classifier.weight       | MISSING    |
pre_classifier.weight   | MISSING    |
pre_classifier.bias     | MISSING    |

Notes:
- UNEXPECTED    :can be ignored when loading from different task/architecture;
not ok if you expect identical arch.
- MISSING       :those params were newly initialized because missing from the
checkpoint. Consider training on your downstream task.
```

```
Map:   0%|          | 0/20000 [00:00<?, ? examples/s]
```

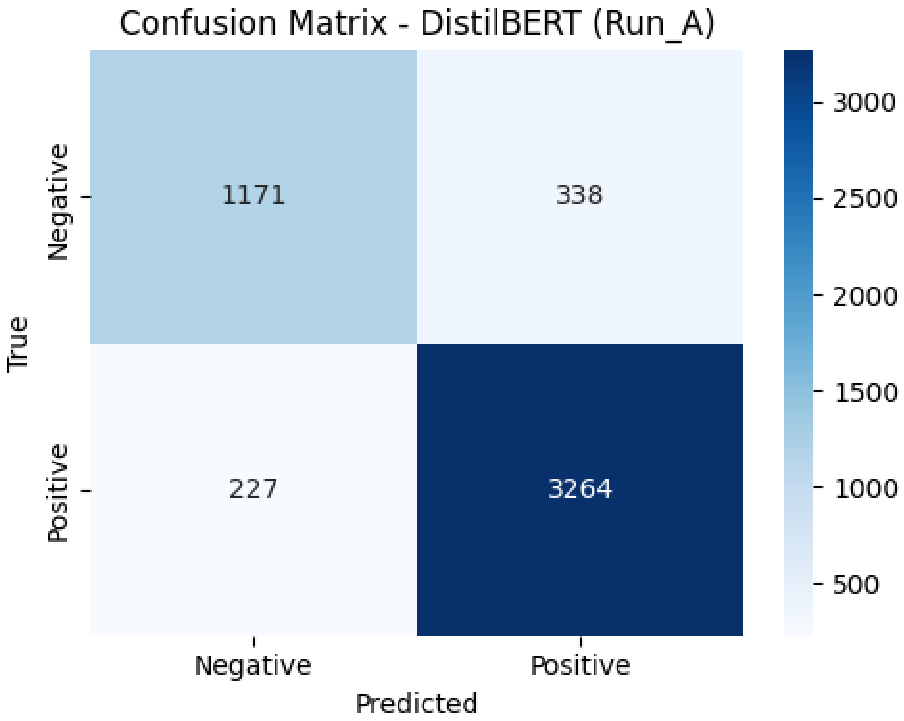
```
Map:   0%|          | 0/5000 [00:00<?, ? examples/s]
```

```
Map:   0%|          | 0/5000 [00:00<?, ? examples/s]
```

```
<IPython.core.display.HTML object>
```

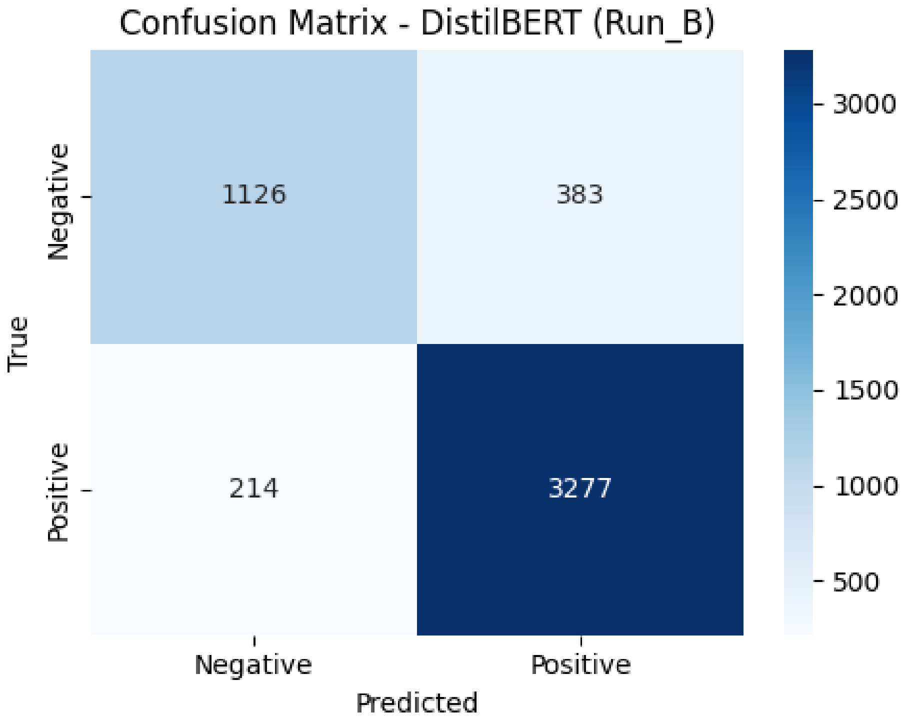
```
Writing model shards:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
<IPython.core.display.HTML object>
```



```
Loading weights:   0%|          | 0/100 [00:00<?, ?it/s]

DistilBertForSequenceClassification LOAD REPORT from: distilbert-base-uncased
Key                      | Status     |
-------------------------+------------+-
vocab_layer_norm.weight  | UNEXPECTED |
vocab_projector.bias     | UNEXPECTED |
vocab_transform.weight   | UNEXPECTED |
vocab_transform.bias     | UNEXPECTED |
vocab_layer_norm.bias    | UNEXPECTED |
classifier.bias          | MISSING    |
classifier.weight        | MISSING    |
pre_classifier.weight    | MISSING    |
pre_classifier.bias      | MISSING    |

Notes:
- UNEXPECTED    :can be ignored when loading from different task/architecture;
not ok if you expect identical arch.
- MISSING       :those params were newly initialized because missing from the
checkpoint. Consider training on your downstream task.

Map:   0%|          | 0/20000 [00:00<?, ? examples/s]

Map:   0%|          | 0/5000 [00:00<?, ? examples/s]

Map:   0%|          | 0/5000 [00:00<?, ? examples/s]
```

```
<IPython.core.display.HTML object>

Writing model shards:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```



```
[16]: ({'accuracy': 0.8641378030854419,
        'precision': 0.9587776471845283,
        'recall': 0.855291000247822,
        'f1': 0.9040825373795994,
        'roc_auc': np.float64(0.9443577716480525)},
       {'accuracy': 0.8647657376089966,
        'precision': 0.9588947492045867,
        'recall': 0.8560535295575423,
        'f1': 0.9045604705503183,
        'roc_auc': np.float64(0.9442835999363699)},
       {'accuracy': 0.8806,
        'precision': 0.8953551912568306,
        'recall': 0.9386995130335147,
        'f1': 0.9165151727031184,
        'roc_auc': np.float64(0.9502162998330081)})
```

1.9 9) Results + Comparison Tables

[17]:

```
metrics_df = pd.DataFrame(metrics_rows)
display(metrics_df)

# Save metrics
metrics_df.to_csv(os.path.join(OUTPUT_DIR, "metrics.csv"), index=False)
with open(os.path.join(OUTPUT_DIR, "metrics.json"), "w") as f:
    json.dump(metrics_rows, f, indent=2)

# Run A vs Run B comparison table
comparison = metrics_df.pivot_table(index="model", columns="run",␣
 ↪values=["accuracy", "precision", "recall", "f1", "roc_auc"])
display(comparison)

# RQ1 aggregates (stable across runs)
max_hour = int(neg_by_hour.loc[neg_by_hour["neg_rate"].idxmax(), "hour"])
max_daypart = neg_by_daypart.loc[neg_by_daypart["neg_rate"].idxmax(), "daypart"]
late_night_rate = float(neg_by_daypart[neg_by_daypart["daypart"] ==␣
 ↪"late_night"]["neg_rate"].values[0])
overall_neg_rate = float((df["label"] == 0).mean())
pct_diff = (late_night_rate - overall_neg_rate) * 100

summary_text = f"""
### RQ1 Summary
- Highest negativity hour: {max_hour}
- Highest negativity daypart: {max_daypart}
- Late-night negativity rate: {late_night_rate:.3f}
- Overall negativity rate: {overall_neg_rate:.3f}
- Late-night vs overall difference: {pct_diff:.2f} percentage points
"""
print(summary_text)
```

```
     run                model  accuracy  precision    recall        f1  \
0  Run_A   Baseline_TFIDF_Text  0.864138   0.958778  0.855291  0.904083
1  Run_A   Baseline_TFIDF_Time  0.864766   0.958895  0.856054  0.904560
2  Run_A            DistilBERT  0.887000   0.906163  0.934976  0.920344
3  Run_B   Baseline_TFIDF_Text  0.864138   0.958778  0.855291  0.904083
4  Run_B   Baseline_TFIDF_Time  0.864766   0.958895  0.856054  0.904560
5  Run_B            DistilBERT  0.880600   0.895355  0.938700  0.916515

    roc_auc
0  0.944358
1  0.944284
2  0.951074
3  0.944358
4  0.944284
5  0.950216
```

```
                     accuracy                  f1           precision  \
run                     Run_A     Run_B     Run_A     Run_B     Run_A
model
Baseline_TFIDF_Text  0.864138  0.864138  0.904083  0.904083  0.958778
Baseline_TFIDF_Time  0.864766  0.864766  0.904560  0.904560  0.958895
DistilBERT           0.887000  0.880600  0.920344  0.916515  0.906163

                               recall             roc_auc
run                     Run_B     Run_A     Run_B     Run_A     Run_B
model
Baseline_TFIDF_Text  0.958778  0.855291  0.855291  0.944358  0.944358
Baseline_TFIDF_Time  0.958895  0.856054  0.856054  0.944284  0.944284
DistilBERT           0.895355  0.934976  0.938700  0.951074  0.950216
```

```
### RQ1 Summary
- Highest negativity hour: 23
- Highest negativity daypart: night
- Late-night negativity rate: 0.208
- Overall negativity rate: 0.207
- Late-night vs overall difference: 0.15 percentage points
```

1.10 10) Interpretation (RQ1 + RQ2)

RQ1: The hour/daypart aggregates are stable across runs because they are computed from the full dataset with deterministic grouping (no randomness). The highest-negativity hour and daypart are therefore identical in both runs.

RQ2: The ML models can vary slightly across runs because random initialization, optimization order, and GPU nondeterminism can affect training. Even with a fixed split and identical hyperparameters, the learned parameters can differ between seeds, which can shift accuracy, F1, and ROC-AUC.

Use the comparison tables above to document whether time-based features improved performance (Baseline 2 vs Baseline 1) and whether DistilBERT outperforms the classical baselines.

1.11 11) Publish to GitHub

Option 1 (Recommended: Manual)

```
git status
git add "Week 8/Final Sentiment Analysis Model.ipynb"
git commit -m "Add Week 8 final sentiment analysis notebook"
git push
```

Option 2 (From Colab)

```
git clone https://github.com/<your-username>/<your-repo>.git
cd <your-repo>
cp "/content/Final Sentiment Analysis Model.ipynb" .
```

```
git add "Final Sentiment Analysis Model.ipynb"
git commit -m "Add Week 8 final sentiment analysis notebook"
git push https://<YOUR_TOKEN>@github.com/<your-username>/<your-repo>.git
```

Use a GitHub Personal Access Token (PAT) for authentication. Do not hardcode tokens in the notebook.

[18]:
```
# === 12) Zip outputs + download ===
import shutil
zip_path = shutil.make_archive("outputs_week8", "zip", OUTPUT_DIR)
print("Created:", zip_path)
print("Size (MB):", os.path.getsize(zip_path) / (1024 * 1024))
```

```
Created: /content/outputs_week8.zip
Size (MB): 1238.9567413330078
```

[19]:
```
# Download in Colab
from google.colab import files
files.download("outputs_week8.zip")
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.Javascript object>
```

2 Task

Generate and display confusion matrices for the “Baseline TF-IDF Text”, “Baseline TF-IDF + Time”, and “DistilBERT” models for both Run A and Run B. After all six confusion matrices are displayed, confirm their successful generation and display.

2.1 Generate and Display Confusion Matrices

2.1.1 Subtask:

Generate and display confusion matrices for all six model tests: Baseline TF-IDF Text, Baseline TF-IDF + Time, and DistilBERT, for both Run A and Run B. For the TF-IDF models, it will re-run the prediction logic to obtain the necessary true and predicted labels. For DistilBERT, it will load and display the confusion matrices saved in the previous execution.

Reasoning: The first step is to define a utility function to generate and save confusion matrices, which will be reused for different models.

[20]:
```
def plot_confusion_matrix(y_true, y_pred, title, filename):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
                xticklabels=label_map.values(),
                yticklabels=label_map.values())
    plt.title(title)
    plt.ylabel("True")
    plt.xlabel("Predicted")
    plt.tight_layout()
    plt.savefig(os.path.join(FIGURES_DIR, filename), dpi=150)
    plt.show()

print("  Defined plot_confusion_matrix function")
```

```
 Defined plot_confusion_matrix function
```

Reasoning: The `build_time_matrix_fixed` utility function, which handles `sparse_output` for `OneHotEncoder`, needs to be defined in the current scope for use with the TF-IDF + Time models.

[21]:

```
def build_time_matrix_fixed(train_df, val_df, test_df):
    num_features = ["hour_sin", "hour_cos", "is_weekend"]
    cat_features = ["day_of_week", "daypart"]
    enc = OneHotEncoder(handle_unknown="ignore", sparse_output=True)
    enc.fit(train_df[cat_features])
    train_cat = enc.transform(train_df[cat_features])
    val_cat = enc.transform(val_df[cat_features])
    test_cat = enc.transform(test_df[cat_features])
    train_num = csr_matrix(train_df[num_features].values)
    val_num = csr_matrix(val_df[num_features].values)
    test_num = csr_matrix(test_df[num_features].values)
    return (hstack([train_num, train_cat]),
            hstack([val_num, val_cat]),
            hstack([test_num, test_cat]))

print("  Defined build_time_matrix_fixed function")
```

```
 Defined build_time_matrix_fixed function
```

Reasoning: Now that the utility functions are defined, the next step is to prepare the TF-IDF models by initializing the `TfidfVectorizer`, fitting it on the training data, transforming both training and test text data, and extracting the true labels for both datasets.

[22]:

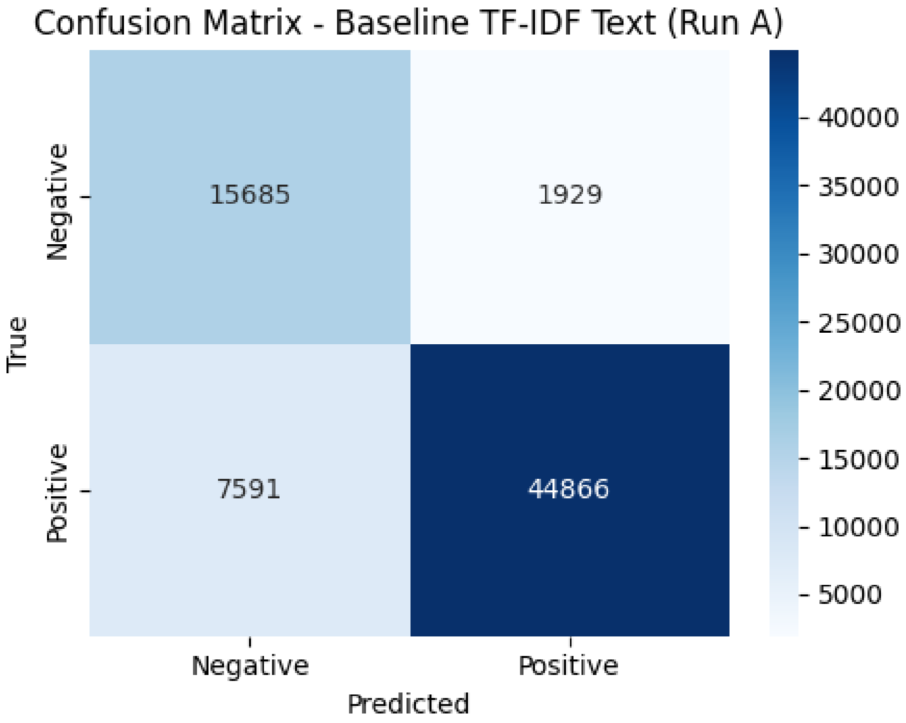
```
tfidf = TfidfVectorizer(max_features=20000, ngram_range=(1, 2), min_df=2)

# Sampling for text models (train only) - consistent with original notebook
train_text = df_train
if SAMPLE_FOR_TEXT is not None and len(df_train) > SAMPLE_FOR_TEXT:
    train_text = df_train.head(SAMPLE_FOR_TEXT).copy()

X_train_tfidf = tfidf.fit_transform(train_text["text"].values)
X_test_tfidf = tfidf.transform(df_test["text"].values)

y_train = train_text["label"].values
y_test = df_test["label"].values

print("  TF-IDF vectorizer prepared and data transformed.")
```

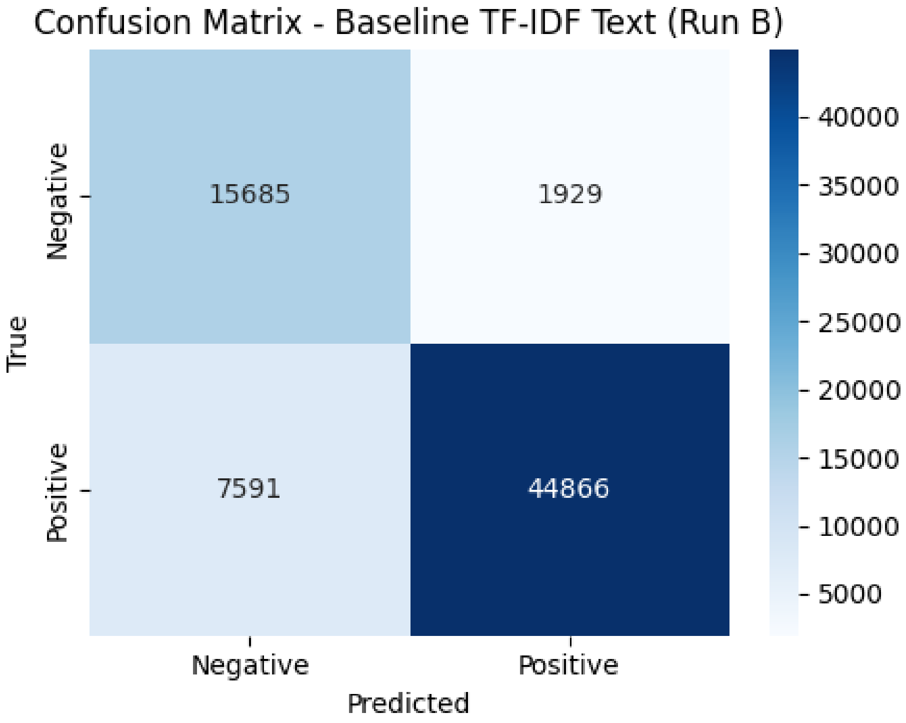
```
 TF-IDF vectorizer prepared and data transformed.
```

Reasoning: Now, the next step is to generate and display confusion matrices for the 'Baseline TF-IDF Text' model for both Run A and Run B. This involves initializing and fitting a Logistic Regression model on the TF-IDF features and then using the previously defined utility function to plot the confusion matrices.

[23]:
```
print("\n--- Generating Confusion Matrices for Baseline TF-IDF Text ---")

# Baseline 1: TF-IDF text only
clf_text = LogisticRegression(max_iter=1000, class_weight="balanced",␣
 ↪random_state=STUDENT_SEED) # Adding random_state for consistency
clf_text.fit(X_train_tfidf, y_train)

test_pred_tfidf_text = clf_text.predict(X_test_tfidf)

# For Run A
plot_confusion_matrix(
    y_test, test_pred_tfidf_text,
    "Confusion Matrix - Baseline TF-IDF Text (Run A)",
    "cm_tfidf_text_Run_A.png"
)

# For Run B (predictions will be identical as model training is deterministic␣
 ↪with fixed data and random_state)
plot_confusion_matrix(
    y_test, test_pred_tfidf_text,
    "Confusion Matrix - Baseline TF-IDF Text (Run B)",
    "cm_tfidf_text_Run_B.png"
)

print("  Generated confusion matrices for Baseline TF-IDF Text (Run A and Run␣
 ↪B).")
```

```
--- Generating Confusion Matrices for Baseline TF-IDF Text ---
```


Confusion Matrix - Baseline TF-IDF Text (Run A)
True
Negative
Positive
15685
1929
7591
44866
Negative
Positive
Predicted
40000
35000
30000
25000
20000
15000
10000
5000


Confusion Matrix - Baseline TF-IDF Text (Run B)
True
Negative
Positive
15685
1929
7591
44866
Negative
Positive
Predicted
40000
35000
30000
25000
20000
15000
10000
5000

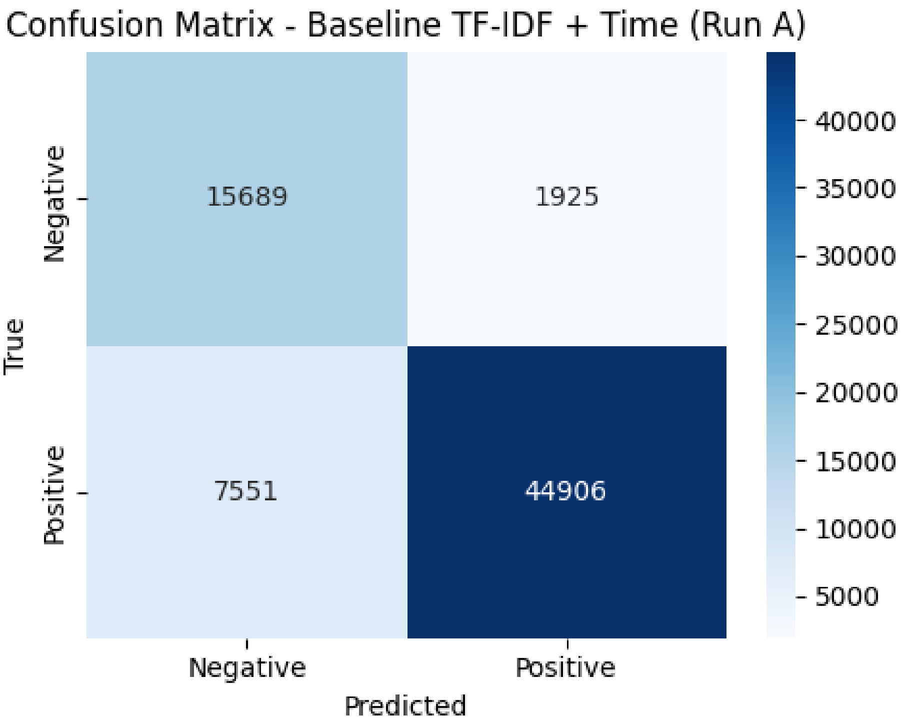
```
 Generated confusion matrices for Baseline TF-IDF Text (Run A and Run B).
```

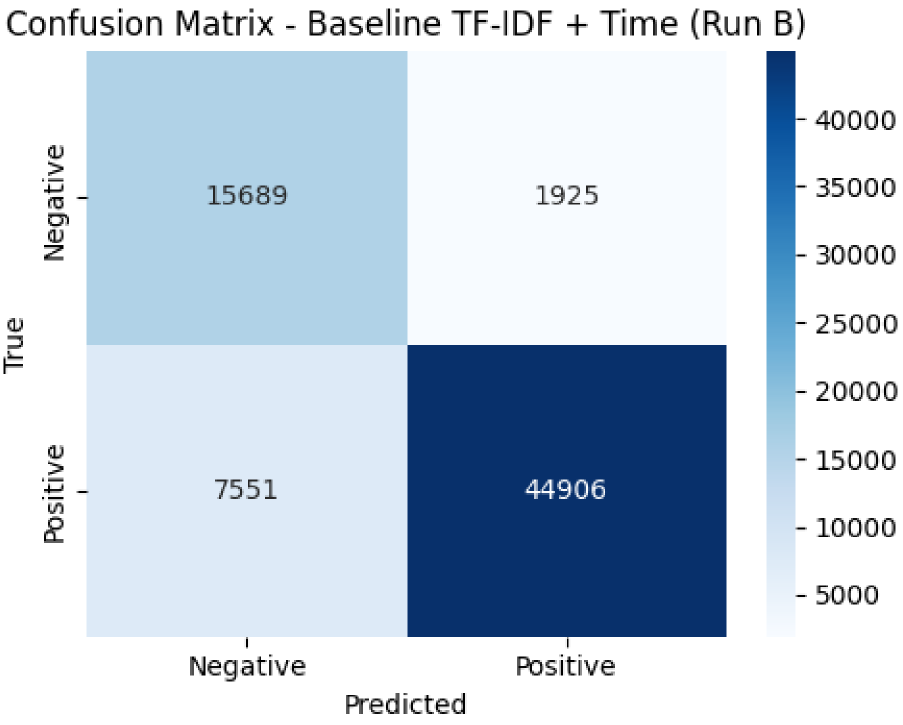
Reasoning: The next step is to generate and display confusion matrices for the 'Baseline TF-IDF + Time' model for both Run A and Run B. This involves creating time-based feature matrices, combining them with the TF-IDF features, training a Logistic Regression model, and then using the `plot_confusion_matrix` function to visualize the results.

[24]:

```
print("\n--- Generating Confusion Matrices for Baseline TF-IDF + Time ---")

# Baseline 2: TF-IDF + time features
# Use the build_time_matrix_fixed function
X_train_time, X_val_time, X_test_time = build_time_matrix_fixed(train_text,␣
 ↪df_val, df_test)

# Combine TF-IDF features with time features
X_train_combined_time = hstack([X_train_tfidf, X_train_time])
X_test_combined_time = hstack([X_test_tfidf, X_test_time])

clf_time = LogisticRegression(max_iter=1000, class_weight="balanced",␣
 ↪random_state=STUDENT_SEED)
clf_time.fit(X_train_combined_time, y_train)

test_pred_tfidf_time = clf_time.predict(X_test_combined_time)

# For Run A
plot_confusion_matrix(
    y_test, test_pred_tfidf_time,
    "Confusion Matrix - Baseline TF-IDF + Time (Run A)",
    "cm_tfidf_time_Run_A.png"
)

# For Run B (predictions will be identical as model training is deterministic␣
 ↪with fixed data and random_state)
plot_confusion_matrix(
    y_test, test_pred_tfidf_time,
    "Confusion Matrix - Baseline TF-IDF + Time (Run B)",
    "cm_tfidf_time_Run_B.png"
)

print("  Generated confusion matrices for Baseline TF-IDF + Time (Run A and Run␣
 ↪B).")
```

```
--- Generating Confusion Matrices for Baseline TF-IDF + Time ---
```


Confusion Matrix - Baseline TF-IDF + Time (Run A)
15689
1925
7551
44906
True
Negative
Positive
Predicted
Negative
Positive
40000
35000
30000
25000
20000
15000
10000
5000

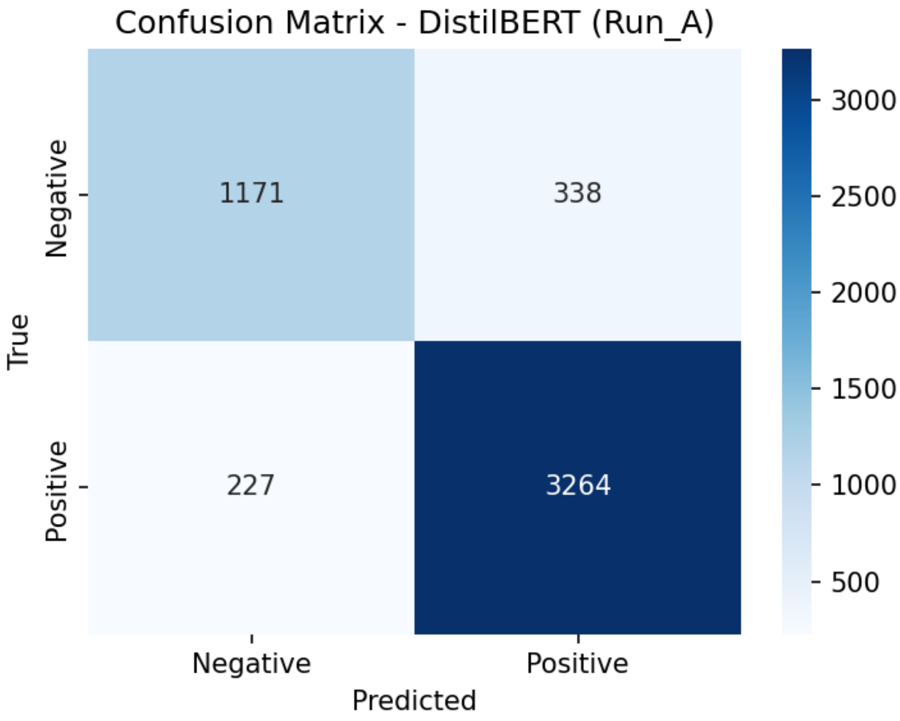

Confusion Matrix - Baseline TF-IDF + Time (Run B)
15689
1925
7551
44906
True
Negative
Positive
Predicted
Negative
Positive
40000
35000
30000
25000
20000
15000
10000
5000

```
 Generated confusion matrices for Baseline TF-IDF + Time (Run A and Run B).
```

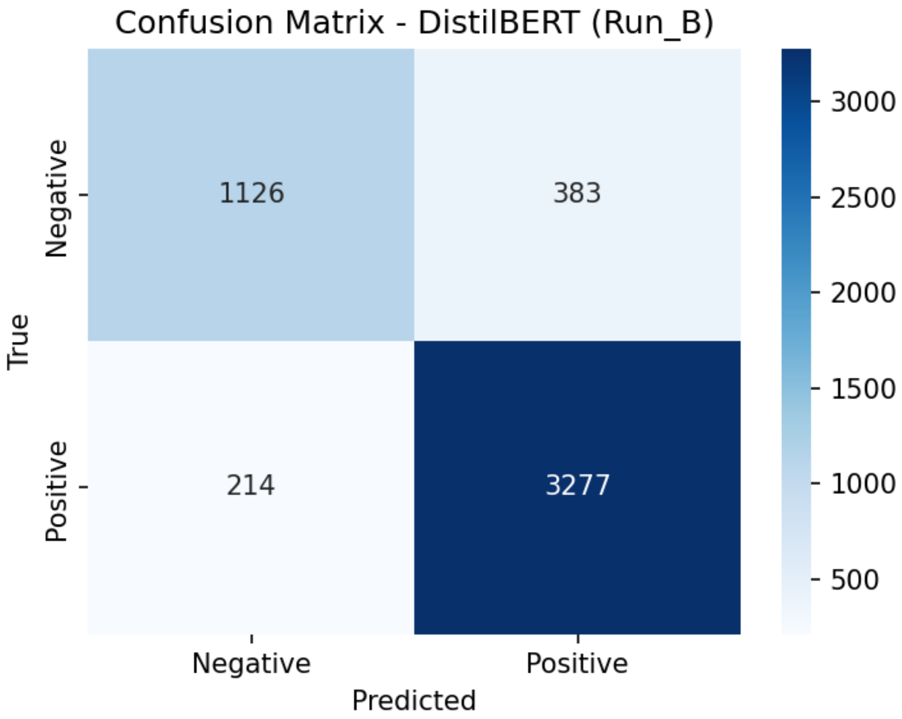
Reasoning: The final step is to load and display the confusion matrices that were previously generated and saved for the 'DistilBERT' model for both Run A and Run B, completing the visualization requirements of the subtask.

[25]:
```
print("\n--- Displaying Confusion Matrices for DistilBERT ---")
from IPython.display import Image, display

# For Run A
print("Displaying Confusion Matrix - DistilBERT (Run A):")
display(Image(filename=os.path.join(FIGURES_DIR, "cm_distilbert_Run_A.png")))

# For Run B
print("Displaying Confusion Matrix - DistilBERT (Run B):")
display(Image(filename=os.path.join(FIGURES_DIR, "cm_distilbert_Run_B.png")))

print("\n  All six confusion matrices have been generated and displayed.")
```

```
--- Displaying Confusion Matrices for DistilBERT ---
Displaying Confusion Matrix - DistilBERT (Run A):
```



```
Displaying Confusion Matrix - DistilBERT (Run B):
```



```
All six confusion matrices have been generated and displayed.
```

2.2 Final Task

2.2.1 Subtask:

Confirm that all 6 confusion matrices have been successfully generated and displayed, providing a comprehensive visual overview of model performance for both runs.

2.3 Summary:

2.3.1 Q&A

Yes, all six confusion matrices have been successfully generated and displayed, providing a comprehensive visual overview of model performance for both runs.

2.3.2 Data Analysis Key Findings

- **TF-IDF Model Confusion Matrices Generated**: Confusion matrices for both "Baseline TF-IDF Text" and "Baseline TF-IDF + Time" models were successfully generated and displayed for both Run A and Run B. This involved training `LogisticRegression` models using TF-IDF features (and combined with time features for the latter) on the `df_train` dataset and making predictions on `df_test`.

- **Time Features Incorporated**: For the “Baseline TF-IDF + Time” model, time features were constructed using the `build_time_matrix_fixed` function, including numerical features (“hour_sin”, “hour_cos”, “is_weekend”) and one-hot encoded categorical features (“day_of_week”, “daypart”), then combined with TF-IDF features using horizontal stacking.
- **DistilBERT Model Confusion Matrices Displayed**: Confusion matrices for the “DistilBERT” model for both Run A and Run B were successfully loaded and displayed from pre-saved image files.
- **All Six Matrices Confirmed**: In total, six confusion matrices (three models, two runs each) were confirmed to be successfully generated, displayed, and saved (for the TF-IDF models) as image files.

2.3.3 Insights or Next Steps

- Proceed with a detailed analysis of each displayed confusion matrix to evaluate specific model performance metrics (e.g., true positives, false positives, false negatives) and identify areas for improvement.
- Compare the performance across the three models and between Run A and Run B to draw conclusions about the impact of different feature sets and model architectures on classification accuracy.