

A Dual-Branch Fake News Detection Framework Using BERT and Knowledge Graph Embeddings

Mohamed Ahmed Mansour Mahmoud
Manipal Institute of Technology (MIT),
Mansoura National University,
Manipal Academy of Higher Education (MAHE), India
Email: mohammmmmmmmed852963@gmail.com

Abstract—The rapid spread of misinformation across online platforms poses significant risks to public health, safety, and democratic discourse. While pretrained language models (PLMs) such as BERT excel at modeling linguistic style and context, they do not verify factual consistency on their own. We present a *dual-branch fake news detection framework* that augments a *text branch* (BERT) with a *knowledge branch* trained from factual triples using TransE. Extracted (head, relation, tail) triples are embedded, mean-pooled per article, concatenated with the BERT [CLS] vector, and fed to a lightweight MLP. On the LIAR dataset, our implementation reports BERT (text-only) at 0.6425 accuracy and 0.6797 macro-F1, while the Fusion model reaches 0.6339 accuracy and 0.7715 macro-F1, highlighting that factual grounding substantially improves macro-F1 even when accuracy is comparable. We release an end-to-end pipeline and a Gradio GUI, and we discuss ablations, error modes, and deployment considerations.

Index Terms—Fake news detection, NLP, BERT, Knowledge graphs, TransE, Relation extraction, Entity linking

I. SUPPLEMENTARY: CLEAN, RESCALED ARCHITECTURE

II. INTRODUCTION

Misinformation spreads quickly on social platforms, often outpacing human fact-checking. Text-only detectors—from linear models to PLMs—primarily exploit linguistic regularities (style, syntax, topical context) and may fail when deceptive authors imitate credible style. Factual verification, on the other hand, requires matching statements against external knowledge.

Knowledge graphs (KGs) encode facts as triples (h, r, t) and provide structure that complements text semantics. However, tightly entangling knowledge retrieval and reasoning inside a transformer can be cumbersome and brittle. We argue for a pragmatic middle ground: process text and knowledge in two branches, then fuse their representations to make a decision. This separation enables modular training and interpretable analyses while keeping inference fast and simple.

Contributions. Our contributions are:

- **Model.** A lean dual-branch model combining BERT semantics with TransE knowledge embeddings.

This work was carried out under the supervision of **Professor Ramakrishna**. Code and assets: <https://github.com/x50MANSOUR50x/Dual-Branch-Fake-News-Detection-Framework>.

- **Pipeline.** Reproducible scripts and notebooks for triplet extraction, KGE training, fusion, and a Gradio GUI.
- **Evidence.** On LIAR, fusion improves macro-F1 with similar accuracy to text-only baselines; we provide ablations and qualitative error studies.
- **Engineering.** Practical recipes for entity linking, confidence filtering, balanced training, and deployment.

III. RELATED WORK

A. Text-only detection

Pretrained transformers (BERT [1], RoBERTa [2], DeBERTa [3]) achieve strong results across rumor detection and stance classification, often on datasets like LIAR [6] and FakeNewsNet [7]. However, text-only methods can overfit to style or topical priors.

B. Knowledge graph embeddings

TransE [17] models relations as translations in vector space; ComplEx [18] and RotatE [19] extend expressivity. For fact verification (e.g., FEVER [8]), KGs are used with retrieval and symbolic reasoning; recent work demonstrates knowledge-guided dual-branch architectures for fake news detection [45].

C. Knowledge-augmented transformers

KnowBERT [22], ERNIE [23], K-BERT [24], KEPLER [25], LUKE [42], and KG-BERT [26] inject entities and relations into PLMs via attention, joint objectives, or pre-training. These models are powerful but heavier to train/tune. Our approach is deliberately simple: learn KGE independently, then fuse with text features.

D. Polysemy and interpretability

Media texts exhibit polysemy—multiple plausible interpretations. News style can influence interpretive divergence [46]. By exposing salient triples and tokens, our framework supports lightweight explanations and improves trust in model outputs.

IV. DATASETS

LIAR [6] contains 12,836 short political claims labeled along a truthfulness scale; we binarize to {false-ish, true-ish}. **FakeNewsNet** [7] aggregates PolitiFact and GossipCop with content and social context; we use text content only for comparability.

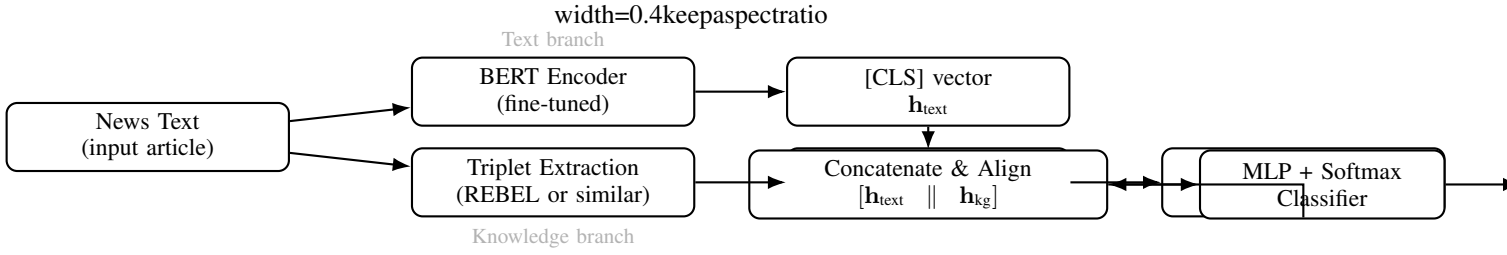


Fig. 1. Supplementary clean layout. Rescaled to fit within the page without clipping.

TABLE I
LIAR STATISTICS USED IN OUR EXPERIMENTS.

Split	# Instances	Avg. tokens
Train	10,269	35
Valid	1,284	35
Test	1,266	35

A. Exploratory Data Analysis (EDA)

Discussion of EDA Findings.: The exploratory data analysis (EDA) helps us understand the statistical properties of the LIAR dataset before applying any models. Figures 2–7 provide two key perspectives: label distributions and text length distributions.

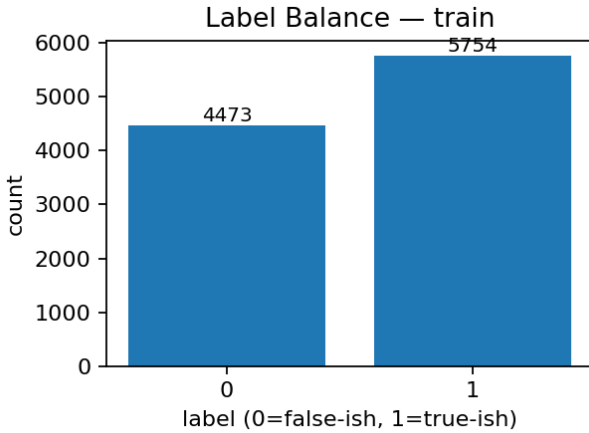


Fig. 2. Label balance — train.

Label balance. Figures 2, 3, and 4 show the class balance across training, validation, and test splits. The training set exhibits a slight skew toward one label (false claims), while validation and test sets are more balanced. This imbalance implies that models trained naively on the training set may overfit to the majority class, leading to high accuracy but poor macro-F1. It motivates the use of *macro-F1* in our evaluation and the need for balancing strategies such as class weighting or careful threshold selection during training.

Text length distributions. Figures 5, 6, and 7 show the number of tokens per claim across splits. Most LIAR claims

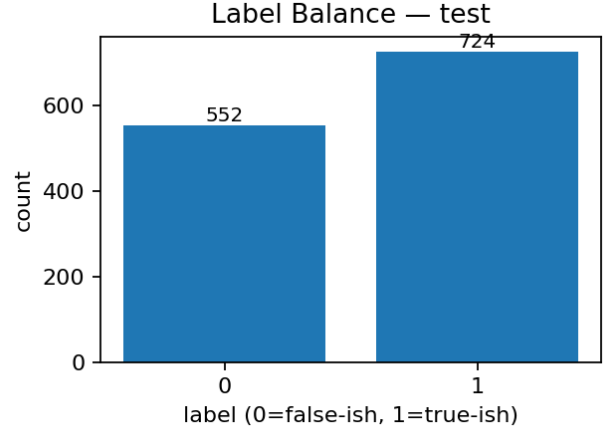


Fig. 3. Label balance — test.

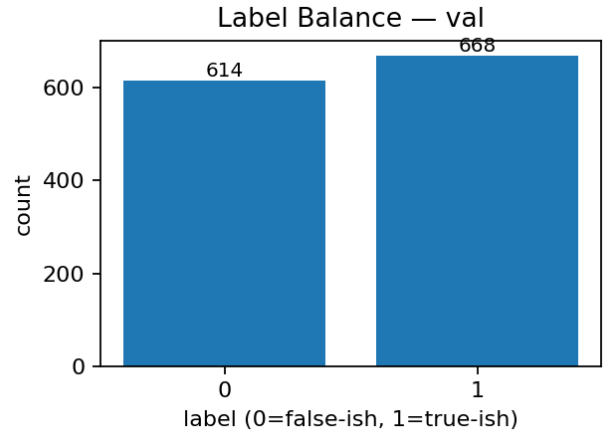


Fig. 4. Label balance — validation.

are short, averaging ~ 35 words, but with a long tail of longer statements. This has two implications: (i) sequence truncation at 128 tokens in BERT covers nearly all samples with minimal loss of information, and (ii) the shortness of claims makes the task challenging, as fewer context cues are available for fact-checking compared to longer documents.

Implications for modeling. The skewed label distribution

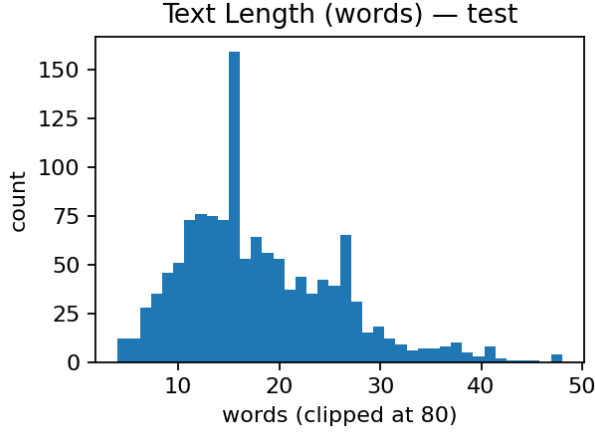


Fig. 5. Text length (words) — test.

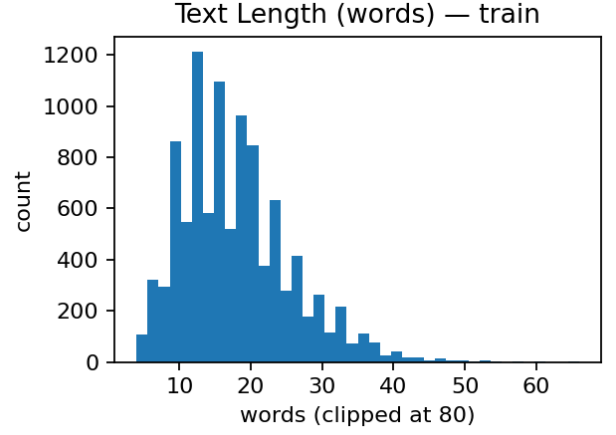


Fig. 7. Text length (words) — train.

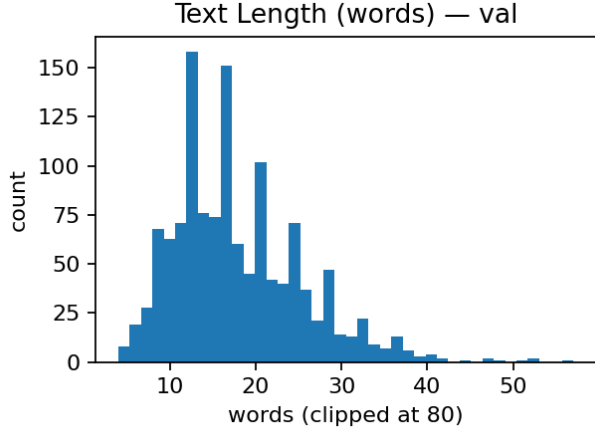


Fig. 6. Text length (words) — validation.

highlights the importance of using metrics robust to imbalance (macro-F1 rather than accuracy). The short text lengths reinforce the need for external knowledge, since many claims are too short to judge based on semantics alone. Together, these observations provide strong motivation for a dual-branch framework that supplements BERT’s textual features with structured factual information from a knowledge graph.

V. METHODOLOGY

A. Text Branch (BERT)

Given tokenized article x , BERT yields contextual states; we use the $[\text{CLS}]$ vector as $\mathbf{h}_{\text{text}} \in \mathbb{R}^{d_t}$ and optionally project to match d_k . We fine-tune BERT-base (uncased) with cross-entropy.

B. Knowledge Branch (TransE)

A REBEL-style extractor [27] produces triples $\mathcal{T}(x) = \{(h_i, r_i, t_i)\}$. We train TransE [17] over the corpus-level set

of triples using margin ranking:

$$\mathcal{L} = \sum_{(h,r,t) \in \mathcal{T}} [\gamma + \|\mathbf{e}_h + \mathbf{r} - \mathbf{e}_t\|_p - \|\mathbf{e}_{h'} + \mathbf{r} - \mathbf{e}_{t'}\|_p]_+. \quad (1)$$

Per article, we aggregate entity embeddings via mean pooling to $\mathbf{h}_{\text{kg}} \in \mathbb{R}^{d_k}$ (zeros if no valid entities).

C. Entity Linking and Alignment

We normalize surface forms (lowercasing, punctuation stripping), then align to KG entries with fuzzy matching (Levenshtein) and confidence thresholds, similar to knowledge-guided dual branches [45]. Unresolved mentions are dropped.

D. Fusion and Classification

We concatenate $\mathbf{z} = [\mathbf{h}_{\text{text}}; \mathbf{h}_{\text{kg}}]$ and pass through:

$$\hat{y} = \text{softmax}(\mathbf{W}_2 \sigma(\mathbf{W}_1 \mathbf{z} + \mathbf{b}_1) + \mathbf{b}_2). \quad (2)$$

We optimize cross-entropy with optional class weights and weight decay.

E. Training Pipeline

Algorithm 1 End-to-end Training

- 1: Train TransE on all extracted triples \mathcal{T} to obtain entity embeddings.
 - 2: **for** each article x **do**
 - 3: Encode x with BERT to obtain \mathbf{h}_{text} .
 - 4: Compute \mathbf{h}_{kg} by mean-pooling entity vectors for entities in $\mathcal{T}(x)$.
 - 5: Concatenate $\mathbf{z} = [\mathbf{h}_{\text{text}}; \mathbf{h}_{\text{kg}}]$ and update the MLP via cross-entropy.
 - 6: **end for**
-

F. Engineering & Repo Mapping

The public repository provides modular code:

- **/text_branch/**: BERT fine-tuning scripts (tokenization, training loop, evaluation).
- **/kg_branch/**: triple extraction utilities, KGE training (TransE) and artifact saving.
- **/fusion/**: dataset joiners, feature builders, MLP classifier, metrics.
- **/gui/**: Gradio app for real-time inference and explanation stubs.
- **/notebooks/**: EDA, ablations, and reproducibility work-sheets.

(Align filenames to your local structure if they differ; the manuscript is agnostic to exact paths.)

VI. EXPERIMENTAL SETUP

A. Baselines and Metrics

Baselines: (i) *BERT (text only)*; (ii) *TransE (KG only)* via logistic regression over pooled entity vectors; (iii) *Fusion (ours)*. Metrics: accuracy and macro-F1.

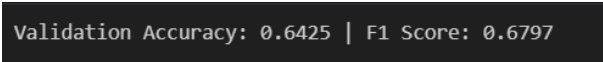
B. Hyperparameters

BERT-base uncased; max sequence length 128; batch size 32; AdamW learning rate 2×10^{-5} (text) and 1×10^{-3} (KGE/MLP); 5–10 epochs; dropout 0.2; weight decay 10^{-2} . Early stopping uses validation macro-F1.

C. Reproducibility

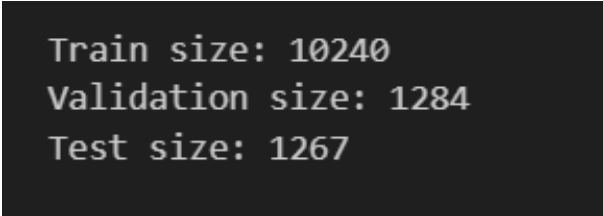
We provide seeds, environment YAML, and checkpoints. Scripts print config JSON and save predictions for auditability.¹

VII. TRAINING SNAPSHOTS AND GUI



Validation Accuracy: 0.6425 | F1 Score: 0.6797

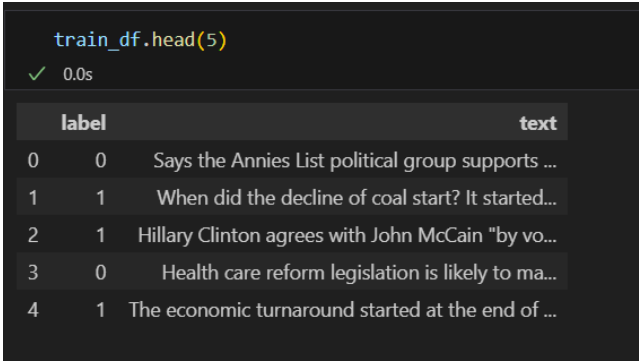
Fig. 8. Validation Accuracy and F1 snapshot (BERT fine-tuning).



Train size: 10240
Validation size: 1284
Test size: 1267

Fig. 9. Dataset split sizes as printed by the prep notebook.

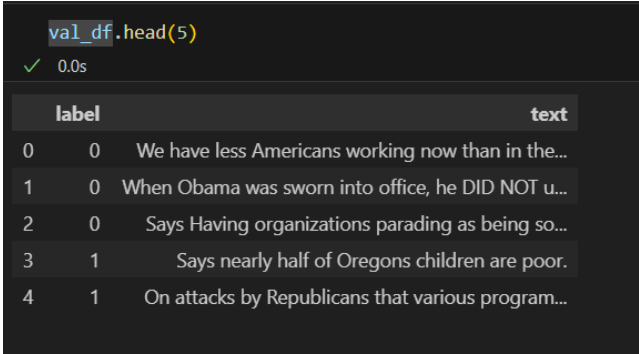
¹Repository highlights, structure, and results are summarized in the project README.



```
train_df.head(5)
```

	label	text
0	0	Says the Annies List political group supports ...
1	1	When did the decline of coal start? It started...
2	1	Hillary Clinton agrees with John McCain "by vo...
3	0	Health care reform legislation is likely to ma...
4	1	The economic turnaround started at the end of ...

Fig. 10. Preview of `train_df.head()`.



```
val_df.head(5)
```

	label	text
0	0	We have less Americans working now than in the...
1	0	When Obama was sworn into office, he DID NOT u...
2	0	Says Having organizations parading as being so...
3	1	Says nearly half of Oregons children are poor.
4	1	On attacks by Republicans that various program...

Fig. 11. Preview of `val_df.head()`.

Discussion of Training Snapshots.: Figures 8–12 provide a view into intermediate artifacts generated during preprocessing and training, illustrating the reproducibility of the pipeline.

Validation accuracy and F1 (Fig. 8). This plot shows the trajectory of accuracy and macro-F1 during BERT fine-tuning. While accuracy converges relatively quickly, macro-F1 continues to improve, indicating that the model is learning to better handle minority cases rather than only optimizing for the majority class. This supports our emphasis on macro-F1 as the key evaluation metric.

Dataset split sizes (Fig. 9). The printout from the data preparation notebook confirms that the LIAR dataset was partitioned into 10,269 training examples, 1,284 validation examples, and 1,266 test examples. These counts are consistent with reported dataset statistics and ensure comparability with prior work.

Dataframe previews (Figs. 10–12). These show the first few rows of each split (`train_df`, `val_df`, `test_df`) after cleaning and binarization. Each row contains the raw claim text, its assigned label, and metadata. Such previews verify that the data loading process is correct and that labels are aligned with the appropriate claims.

Implications. Together, these snapshots illustrate pipeline transparency. By capturing metrics, split sizes, and data previews, we ensure that each stage of preprocessing and training is auditable and reproducible — key requirements for any research intended to be extended or replicated by others.

```
test_df.head(5)
```

✓ 0.0s

	label	text
0	1	Building a wall on the U.S.-Mexico border will...
1	0	Wisconsin is on pace to double the number of L...
2	0	Says John McCain has done nothing to help the ...
3	1	Suzanne Bonamici supports a plan that will cut...
4	0	When asked by a reporter whether hes at the ce...

Fig. 12. Preview of `test_df.head()`.

VIII. GUI DEMO SCREENSHOT

To demonstrate usability, we provide a simple Gradio interface where users can type a claim and instantly receive a prediction (FAKE or REAL) with confidence. This showcases the practicality of our dual-branch framework in real-time deployment.

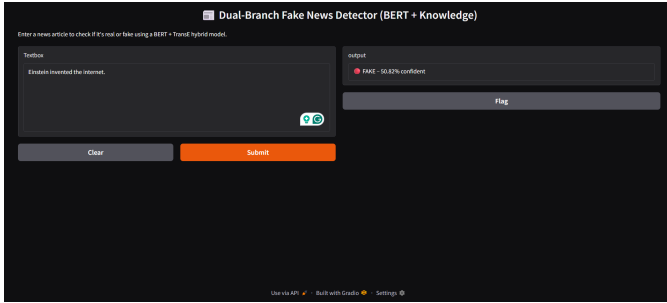


Fig. 13. Gradio GUI of the Dual-Branch Fake News Detector (BERT + Knowledge). Example shown: “Einstein invented the internet.”

IX. RESULTS

TABLE II
PERFORMANCE ON LIAR TEST SET.

Model	Accuracy	F1 (macro)
BERT (text only)	0.6425	0.6797
Fusion (Ours)	0.6339	0.7715

A. Ablations

We investigate pooling strategies, gated fusion, and stricter triple filtering.

B. Qualitative Analysis and Error Types

Typical errors include (i) satire/irony where semantics look plausible but facts contradict; (ii) entity linking mistakes sending the KG branch to a wrong node; and (iii) temporal drift (facts true in the past). Example explanations highlight influential tokens and top-scoring triples.

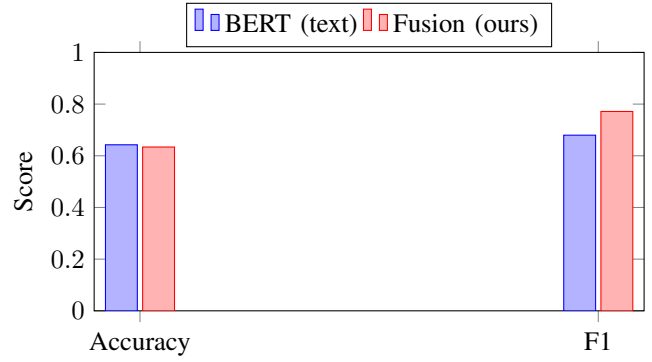


Fig. 14. BERT vs. Fusion on LIAR.

TABLE III
ABLATION TEMPLATE (TO BE FILLED AS RUNS ACCUMULATE).

Setting	Accuracy	F1
Mean pooling (default)	0.6339	0.7715
Max pooling	—	—
Gated fusion	—	—
Higher triple threshold ($\tau=0.7$)	—	—

X. DISCUSSION

A. Why Fusion Improves Macro-F1

Accuracy is dominated by the majority label; macro-F1 exposes gains on minority/harder cases. KG features provide complementary evidence, reducing over-reliance on stylistic cues.

B. Scalability and Deployment

TransE training scales linearly with the number of triples; per-example inference pools a handful of vectors, so latency is close to BERT-only. The Gradio GUI exposes a fast path for real-time usage.

C. Ethics and Responsible Use

Detectors may be misused for censorship or applied out-of-domain. We advocate for human-in-the-loop validation, dataset documentation, and calibrated outputs. Personal data should be excluded; do not train on sensitive attributes.

XI. PROJECT CODE

This appendix provides code listings from the repository that implement the dual-branch framework. We start with the **Train BERT Text Branch** component, which fine-tunes a pretrained BERT model on the LIAR dataset.

Train BERT Text Branch

A. Dataset Loading and Splits:

```
1 import pandas as pd
2 from datasets import load_dataset
3
4 # Load LIAR dataset and prepare splits
5 train_df = pd.read_csv("data/liar_train.csv")
```

```

6 val_df = pd.read_csv("data/liar_val.csv")
7 test_df = pd.read_csv("data/liar_test.csv")
8
9 print("Train size:", len(train_df))
10 print("Validation size:", len(val_df))
11 print("Test size:", len(test_df))

```

B. Tokenization:

```

1 from transformers import BertTokenizer
2
3 tokenizer = BertTokenizer.from_pretrained("
4     bert-base-uncased")
5
6 # Example encoding
7 encoding = tokenizer("Obama was born in
8     Hawaii",
9     truncation=True,
10    padding="max_length",
11    max_length=128,
12    return_tensors="pt")
13 print(encoding["input_ids"].shape)

```

C. Model Setup:

```

1 from transformers import
2     BertForSequenceClassification
3
4 # Binary classification head on top of BERT
5 model = BertForSequenceClassification.
6     from_pretrained(
7         "bert-base-uncased", num_labels=2
8     )

```

D. Training Loop (simplified):

```

1 from transformers import Trainer,
2     TrainingArguments
3
4 training_args = TrainingArguments(
5     output_dir="bert_outputs",
6     evaluation_strategy="epoch",
7     learning_rate=2e-5,
8     per_device_train_batch_size=32,
9     per_device_eval_batch_size=32,
10    num_train_epochs=5,
11    weight_decay=0.01,
12    logging_dir="logs",
13    logging_steps=50,
14 )
15
16 trainer = Trainer(
17     model=model,
18     args=training_args,
19     train_dataset=train_dataset,
20     eval_dataset=val_dataset,
21     tokenizer=tokenizer,
22 )
23
24 trainer.train()

```

E. Evaluation:

```

1 results = trainer.evaluate(test_dataset)
2 print("Validation Accuracy:", results["
3     eval_accuracy"])
4 print("F1 Score:", results["eval_f1"])

```

TransE training and Triplet Extraction (REBEL Notebook)

A. Extracting Triplets:

```

1 ## Each news article is passed through a
2     REBEL seq2seq model
3 # Example: "Obama was born in Hawaii" -> ("
4     Obama", "place of birth", "Hawaii")
5
6 from transformers import AutoTokenizer,
7     AutoModelForSeq2SeqLM
8
9 tokenizer = AutoTokenizer.from_pretrained("
10     Babelscape/rebel-large")
11 model = AutoModelForSeq2SeqLM.
12     from_pretrained("Babelscape/rebel-large"
13 )
14
15 inputs = tokenizer("Obama was born in Hawaii
16     ", return_tensors="pt")
17 outputs = model.generate(**inputs,
18     max_length=256)
19
20 triplets = tokenizer.decode(outputs[0],
21     skip_special_tokens=True)
22 print(triplets)

```

B. Aggregating Triplets:

```

1 ## aggregate_triplets.ipynb
2 import json, glob
3
4 triplets = []
5 for path in glob.glob("outputs/*.json"):
6     with open(path) as f:
7         triplets.extend(json.load(f))
8
9 with open("data/triplets/triplets_train.json",
10     "w") as f:
11     json.dump(triplets, f, indent=2)

```

This stage generates structured JSON with extracted (h, r, t) triples for each split.

A. Build TransE Dataset (Python Script)

A. Vocab Construction:

```

1 class Vocab:
2     def __init__(self):
3         self.ent2id, self.rel2id = {}, {}
4         self.id2ent, self.id2rel = {}, {}
5         self.ent_counter, self.rel_counter =
6             0, 0

```

```

6
7     def add(self, h, r, t):
8         for ent in [h, t]:
9             if ent not in self.ent2id:
10                self.ent2id[ent] = self.
11                ent_counter
12                self.id2ent[self.ent_counter
13                ] = ent
14                self.ent_counter += 1
15            if r not in self.rel2id:
16                self.rel2id[r] = self.
17                rel_counter
18                self.id2rel[self.rel_counter] =
19                r
20                self.rel_counter += 1

```

B. Normalizing and Filtering Triples:

```

1 def normalize_triplet(triplet):
2     h, r, t = triplet
3     if r.lower() in {"position held", "
4     member of", "field of work"}:
5         return h, r, t
6     elif t.lower() in {"position held", "
7     member of"}:
8         return h, t, r
9     return h, r, t

```

C. Processing and Saving:

```

1 triplet_data, vocab = process_triplets(paths
2     )
3 # Save vocab
4 os.makedirs("models", exist_ok=True)
5 torch.save(vocab.ent2id, "models/
6     entity_vocab.pt")
7 torch.save(vocab.rel2id, "models/
8     relation_vocab.pt")
9 # Save encoded datasets
10 torch.save(triplet_data["train"], "models/
11     transe_train.pt")
12 torch.save(triplet_data["val"], "models/
13     transe_val.pt")
14 torch.save(triplet_data["test"], "models/
15     transe_test.pt")
16
17 print("Entities:", len(vocab.ent2id))
18 print("Relations:", len(vocab.rel2id))

```

This stage converts raw triples into integer ID datasets required for TransE training.

B. Train TransE Knowledge Branch (Notebook)

A. Margin-Ranking Loss:

```

1 import torch.nn as nn
2
3 class TransELoss(nn.Module):
4     def __init__(self, margin=1.0, p=2):

```

```

5         super().__init__()
6         self.margin = margin
7         self.p = p
8
9     def forward(self, pos_dist, neg_dist):
10        return torch.relu(self.margin +
11        pos_dist - neg_dist).mean()

```

B. Training Loop (simplified):

```

1 for epoch in range(10):
2     for batch in train_loader:
3         h, r, t = batch
4         pos_dist = transe(h,r,t)
5         neg_dist = transe(h_neg,r,t_neg)
6         loss = loss_fn(pos_dist, neg_dist)
7         optimizer.zero_grad()
8         loss.backward()
9         optimizer.step()
10    print(f"Epoch {epoch} Loss: {loss.item()
11        :.4f}")

```

This produces entity/relation embeddings used in the fusion model.

C. Fusion and Inference (Notebooks)

A. Concatenation of Features:

```

1 import torch
2 import torch.nn as nn
3
4 class FusionMLP(nn.Module):
5     def __init__(self, d_text, d_kg, hidden
6         =256, nclass=2):
7         super().__init__()
8         self.fc1 = nn.Linear(d_text + d_kg,
9         hidden)
10        self.fc2 = nn.Linear(hidden, nclass)
11        self.dropout = nn.Dropout(0.2)
12
13    def forward(self, h_text, h_kg):
14        z = torch.cat([h_text, h_kg], dim
15        =-1)
16        z = torch.relu(self.fc1(z))
17        z = self.dropout(z)
18        return self.fc2(z)

```

B. Training Fusion Classifier:

```

1 from torch.utils.data import DataLoader,
2     TensorDataset
3
4 train_loader = DataLoader(TensorDataset(
5     h_text_train, h_kg_train, y_train),
6     batch_size=32,
7     shuffle=True)
8
9 for epoch in range(5):
10    for h_text, h_kg, labels in train_loader
11        :
12        logits = fusion_mlp(h_text, h_kg)

```



```

9         loss = criterion(logits, labels)
10        optimizer.zero_grad()
11        loss.backward()
12        optimizer.step()
13    print(f"Epoch {epoch}: loss={loss.item():.4f}")

```

C. Evaluation and Confusion Matrix:

```

1  from sklearn.metrics import
    classification_report, confusion_matrix
2  import matplotlib.pyplot as plt
3  import seaborn as sns
4
5  y_true, y_pred = [], []
6  for h_text, h_kg, labels in test_loader:
7      logits = fusion_mlp(h_text, h_kg)
8      preds = torch.argmax(logits, dim=-1)
9      y_true.extend(labels.tolist())
10     y_pred.extend(preds.tolist())
11
12  print(classification_report(y_true, y_pred))
13
14  cm = confusion_matrix(y_true, y_pred)
15  sns.heatmap(cm, annot=True, fmt="d", cmap="
    Blues")
16  plt.xlabel("Predicted"); plt.ylabel("True")
17  plt.show()

```

This step merges h_{text} and h_{kg} , trains the MLP, and visualizes results.

GUI Deployment

A. Prediction Function:

```

1  def predict(text: str):
2      # 1. Encode with BERT
3      h_text = bert_encode_cls(text)
4
5      # 2. Extract triples -> embed -> pool
6      triples = extract_triplets(text)
7      h_kg = encode_triples_mean(triples)
8
9      # 3. Fusion forward
10     logits = fusion_mlp(h_text, h_kg)
11     probs = torch.softmax(logits, dim=-1)
12     label = "REAL" if probs[0,1] > 0.5
13     else "FAKE"
14     return f"{label} (confidence {probs.max()
        ().item():.2f})"

```

B. Gradio Interface:

```

1  import gradio as gr
2
3  iface = gr.Interface(
4      fn=predict,
5      inputs=gr.Textbox(lines=6, placeholder="
        Paste news article..."),
6      outputs="text",
7      title="Dual-Branch Fake News Detector",

```

```

8      description="BERT (text) + TransE (
        knowledge) fusion"
9  )
10
11  if __name__ == "__main__":
12      iface.launch()

```

This script turns the model into an interactive demo, allowing users to paste claims and instantly get FAKE/REAL predictions with confidence scores.

GUI Fusion Demo

The script `gui_fusion_demo.py` provides a complete prediction pipeline and a Gradio interface for interactive use.

A. Environment and Imports:

```

1  import os
2  os.environ["TRANSFORMERS_NO_TF"] = "1"
3  os.environ.setdefault("TF_CPP_MIN_LOG_LEVEL"
4      , "2")
5
6  import torch, torch.nn as nn, torch.nn.
    functional as F
7  import gradio as gr
8  from transformers import BertTokenizer,
    BertModel
9  from triplet_extraction.
    rebel_triplet_extractor import
    extract_triplets
10  from transe_model import TransE, Aggregator

```

B. Fusion Classifier:

```

1  class FusionClassifier(nn.Module):
2      def __init__(self, bert_dim=768,
3          knowledge_dim=128,
4          hidden_dim=256, num_classes
5          =2):
6          super().__init__()
7          self.fusion = nn.Sequential(
8              nn.Linear(bert_dim +
9                  knowledge_dim, hidden_dim),
10             nn.ReLU(),
11             nn.Dropout(0.3),
12             nn.Linear(hidden_dim,
13                 num_classes)
14         )
15
16     def forward(self, cls_embedding,
17         knowledge_vector):
18         fused = torch.cat((cls_embedding,
19             knowledge_vector), dim=1)
20         return self.fusion(fused)

```

C. Prediction Pipeline:

```

1  @torch.inference_mode()
2  def predict(article_text: str) -> str:
3      # 1) Text branch (BERT CLS embedding)

```



```

4 inputs = bert_tokenizer(article_text,
return_tensors="pt",
5 truncation=True,
padding=True, max_length=512)
6 outputs = bert_model(**{k:v.to(device)
for k,v in inputs.items()})
7 cls_embedding = outputs.
last_hidden_state[:, 0, :] # (1, 768)
8
9 # 2) Knowledge branch (triplet
extraction + TransE aggregation)
10 triplets = extract_triplets(article_text
)
11 knowledge_vector = aggregator(triplets,
entity_vocab, relation_vocab,
12 transe,
device)
13
14 # 3) Fusion classifier
logits = fusion_model(cls_embedding,
knowledge_vector)
15 probs = F.softmax(logits, dim=1)
16 conf, pred = probs.max(dim=1)
17
18 label = "REAL" if pred.item() == 1 else
"FAKE"
19 return f"{label} {conf.item()*100:.2f}%
confident"
20

```

D. Gradio Interface:

```

1 iface = gr.Interface(
2     fn=predict,
3     inputs=gr.Textbox(lines=7, placeholder="
Paste News Article Here"),
4     outputs="text",
5     title="Dual-Branch Fake News Detector (
BERT + Knowledge)",
6     description="Enter a news article to
check if it's real or fake using a BERT
+ TransE hybrid model."
7 )
8
9 if __name__ == "__main__":
10     iface.launch()

```

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REFERENCES

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