```
# Cell 1: imports and global style
import json
from pathlib import Path
import itertools
from collections import defaultdict
import re

import numpy as np
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_theme(style="white", context="talk")
```

```
# === Cell 2: load HPD train/test JSON and flatten ===

train_path = Path("en_train_set.json")  # adjust if needed
test_path  = Path("en_test_set.json")   # adjust if needed

def load_hpd_split(path: Path, split_name: str) -> pd.DataFrame:
    """
    Load one HPD split (train or test) and return a flat DataFrame.
    Each row = one session (Session-1, Session-2, ...).
    """
    with open(path, "r", encoding="utf-8") as f:
        data = json.load(f)  # top-level dict: {"Session-1": {...}, ...}

    records = []
    for sess_id, sess in data.items():
        position = sess.get("position", None)
        speakers = sess.get("speakers", [])  # list of character names

        scene = sess.get("scene", "")
        # In train, scene is often a single string; in test, it can be a list o
        if isinstance(scene, list):
            scene_text = " ".join(str(s) for s in scene)
        else:
            scene_text = str(scene)

        dialogue_lines = sess.get("dialogue", [])
        # Ensure a list of strings
        dialogue_lines = [str(x) for x in dialogue_lines]
        # Concatenate dialogue into one string for NLP
        dialogue_text = " ".join(dialogue_lines)

        records.append({
            "split": split_name,
            "session_id": sess_id,
            "position": position,
            "speakers": speakers,
            "scene_text": scene_text,
            "dialogue_lines": dialogue_lines,
            "dialogue_text": dialogue_text,
        })

    return pd.DataFrame(records)

df_train = load_hpd_split(train_path, "train")
df_test  = load_hpd_split(test_path,  "test")
```

```
df_hpd = pd.concat([df_train, df_test], ignore_index=True)
print(df_hpd.shape)
df_hpd.head()
```

```
(1246, 7)
```

	split	session_id	position	speakers	scene_text	dialogue_lines	dialogue_text
0	train	Session-1	Book1-chapter2	[Petunia, Harry]	“Up! Get up! Now!” Harry woke with a start. Hi...	[Petunia: Up! Get up! Now! Up! Up! Are you up ...	Petunia: Up! Get up! Now! Up! Up! Are you up y...
1	train	Session-2	Book1-chapter2	[Petunia, Vernon, Harry]	“Bad news, Vernon,” she said. “Mrs. Figg’s bro...	[Petunia: Bad news, Vernon, Mrs. Figg’s broken...	Petunia: Bad news, Vernon, Mrs. Figg’s broken ...
2	train	Session-3	Book1-chapter2	[Vernon, Harry]	“. . . roaring along like maniacs, the young h...	[Vernon: . . . roaring along like maniacs, the...	Vernon: . . . roaring along like maniacs, the ...
3	train	Session-4	Book1-chapter3	[Harry, Petunia]	“What’s this?” he asked Aunt Petunia. Her lips...	[Harry: What’s this?, Petunia: Your new school...	Harry: What’s this? Petunia: Your new school u...
4	train	Session-5	Book1-chapter3	[Vernon, Dudley, Harry, Petunia]	“Get the mail, Dudley,” said Uncle Vernon from...	[Vernon: Get the mail, Dudley, Dudley: Make Ha...	Vernon: Get the mail, Dudley Dudley: Make Harr...

Next steps: Generate code with df_hpd | New interactive sheet

```
# === Cell 3: sentiment analysis on dialogue_text ===

# Install once per runtime (comment out if already installed)
!pip install -q transformers accelerate torch

from transformers import pipeline

# Simple English sentiment model
sent_pipe = pipeline(
    "sentiment-analysis",
    model="distilbert-base-uncased-finetuned-sst-2-english"
)

def sentiment_score(text: str) -> float:
    """
    Map text to a scalar sentiment in [-1, 1].
    Positive label -> +score, negative label -> -score.
    """
    if not isinstance(text, str) or not text.strip():
        return 0.0
    # Truncate long dialogues for speed / model limits
    text_trunc = text[:512]
    result = sent_pipe(text_trunc)[0]
    label = result["label"].upper()
    score = float(result["score"])
    if label == "NEGATIVE":
        return -score
    else:
        return score
```

```
# This can be slow on the full set; if needed, start with df_hpd.head(200)
df_hpd["sentiment"] = df_hpd["dialogue_text"].apply(sentiment_score)
df_hpd[["split", "session_id", "position", "speakers", "sentiment"]].head()
```

```
Device set to use cpu
```

	split	session_id	position	speakers	sentiment
0	train	Session-1	Book1-chapter2	[Petunia, Harry]	-0.997996
1	train	Session-2	Book1-chapter2	[Petunia, Vernon, Harry]	-0.998435
2	train	Session-3	Book1-chapter2	[Vernon, Harry]	-0.909861
3	train	Session-4	Book1-chapter3	[Harry, Petunia]	-0.982691
4	train	Session-5	Book1-chapter3	[Vernon, Dudley, Harry, Petunia]	0.984364

```
# === Cell 4: co-occurrence + sentiment network ===

G_hp_text = nx.Graph()

for _, row in df_hpd.iterrows():
    speakers = row["speakers"]
    s_score = row["sentiment"]

    # Normalize speaker names
    speakers = [str(s).strip() for s in speakers if pd.notna(s)]
    speakers = [s for s in speakers if s != ""]
    speakers_unique = sorted(set(speakers))

    # Add edges for all unordered pairs of speakers
    for u, v in itertools.combinations(speakers_unique, 2):
        if G_hp_text.has_edge(u, v):
            # Update weight and running sentiment statistics
            G_hp_text[u][v]["weight"] += 1
            G_hp_text[u][v]["sent_sum"] += s_score
            G_hp_text[u][v]["sent_count"] += 1
        else:
            G_hp_text.add_edge(
                u, v,
                weight=1,
                sent_sum=s_score,
                sent_count=1,
            )

# Add mean sentiment on each edge
for u, v, data in G_hp_text.edges(data=True):
    n = data.get("sent_count", 1)
    data["sent_mean"] = data.get("sent_sum", 0.0) / n

print("HPD text network:",
      G_hp_text.number_of_nodes(), "nodes,",
      G_hp_text.number_of_edges(), "edges")
```

```
HPD text network: 364 nodes, 2605 edges
```

```
# === Cell 5: node-level text features from dialogue ===

def tokenize_simple(text: str):
    """Very simple word tokenizer for English."""
    return re.findall(r"[A-Za-z']+", text.lower())
```

```
char_texts = defaultdict(list)
char_sent  = defaultdict(list)

for _, row in df_hpd.iterrows():
    speakers = [str(s).strip() for s in row["speakers"] if pd.notna(s)]
    speakers = [s for s in speakers if s != ""]
    text = row["dialogue_text"]
    s_score = row["sentiment"]
    for c in set(speakers):
        char_texts[c].append(text)
        char_sent[c].append(s_score)

node_features = []

for c, texts in char_texts.items():
    joined = " ".join(texts)
    tokens = tokenize_simple(joined)
    n_tokens = len(tokens)
    vocab = set(tokens)
    vocab_size = len(vocab)
    avg_sent = float(np.mean(char_sent[c])) if char_sent[c] else 0.0

    node_features.append({
        "character": c,
        "n_sessions": len(texts),
        "n_tokens": n_tokens,
        "vocab_size": vocab_size,
        "type_token_ratio": vocab_size / n_tokens if n_tokens > 0 else 0.0,
        "mean_dialogue_sentiment": avg_sent,
    })

df_char = pd.DataFrame(node_features)
df_char.sort_values("n_sessions", ascending=False).head(10)
```

	character	n_sessions	n_tokens	vocab_size	type_token_ratio	mean_dialogue_senti
0	Harry	1215	307238	10522	0.034247	-0.38
21	Ron	640	168938	7750	0.045875	-0.45
26	Hermione	524	157830	7489	0.047450	-0.49
4	Hagrid	116	31341	3102	0.098976	-0.41
18	Fred	98	35496	3485	0.098180	-0.39
34	Dumbledore	96	47180	4375	0.092730	-0.12
62	Mrs. Weasley	81	21059	2524	0.119854	-0.19
17	Ginny	77	25370	2741	0.108041	-0.36
23	George	72	27086	2956	0.109134	-0.46
31	McGonagall	70	22749	2821	0.124005	-0.16

```
# === Cell 6: attach node features to G_hp_text ===

for _, row in df_char.iterrows():
    c = row["character"]
    if c not in G_hp_text:
        G_hp_text.add_node(c)
```

```
        G_hp_text.nodes[c]["n_sessions"] = row["n_sessions"]
        G_hp_text.nodes[c]["n_tokens"] = row["n_tokens"]
        G_hp_text.nodes[c]["vocab_size"] = row["vocab_size"]
        G_hp_text.nodes[c]["type_token_ratio"] = row["type_token_ratio"]
        G_hp_text.nodes[c]["mean_dialogue_sentiment"] = row["mean_dialogue_sentiment"]

    # Quick check for one character
    some_node = list(G_hp_text.nodes())[0]
    G_hp_text.nodes[some_node]
```

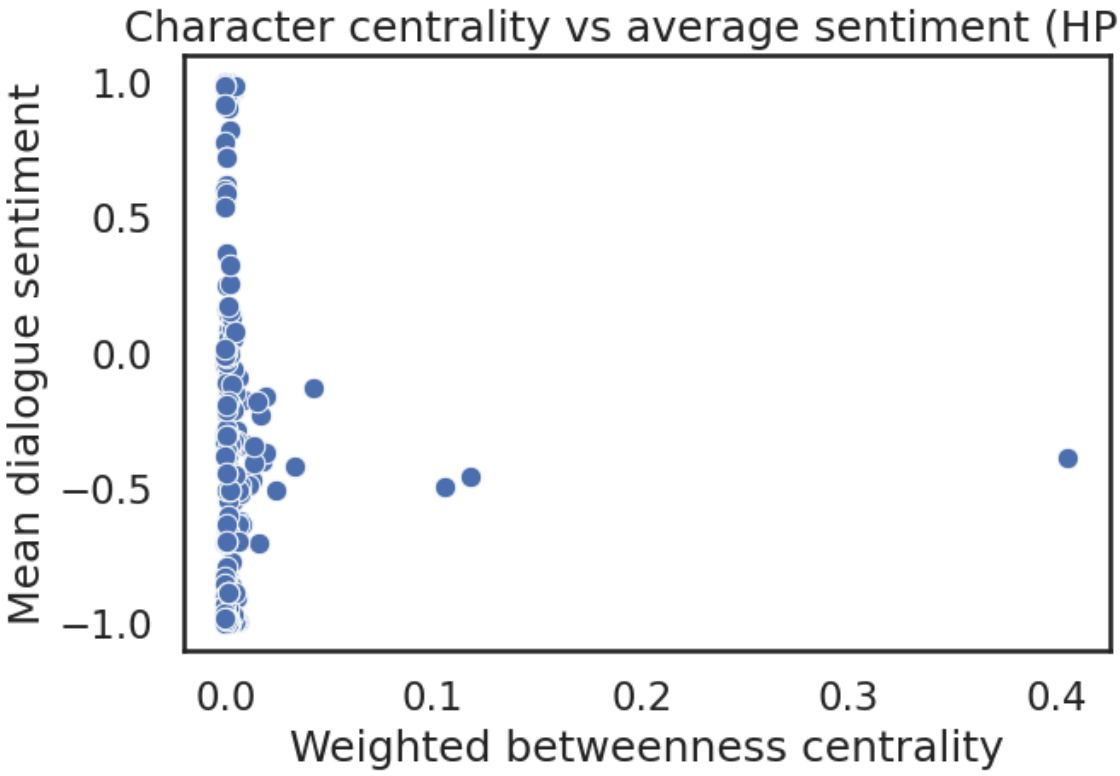
```
{'n_sessions': 1215,
 'n_tokens': 307238,
 'vocab_size': 10522,
 'type_token_ratio': 0.03424706579264284,
 'mean_dialogue_sentiment': -0.38511989347238107}
```

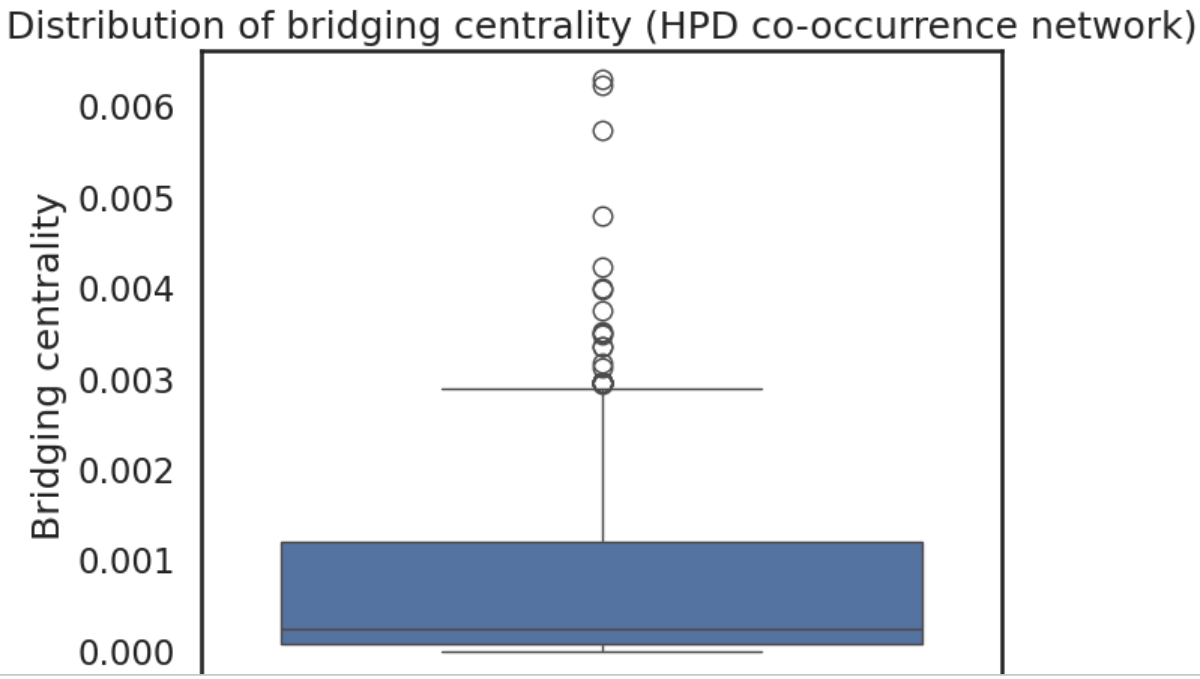
```
    # Rebuild df_struct (centrality + structural-hole measures) from G_hp_text

    # Weighted degree (by co-occurrence count)
    deg_w = dict(G_hp_text.degree(weight="weight"))

    # Weighted betweenness (higher if a node lies on many strong co-occurrence paths)
    betw_w = nx.betweenness_centrality(G_hp_text, weight="weight", normalized=True)

    # k-core on the undirected graph
    core_num = nx.core_number(G_hp_text)

    # Precompute neighbor sets and unweighted degree for bridging coefficient
    neighbors = {v: set(G_hp_text.neighbors(v)) for v in G_hp_text.nodes()}
    deg_unw = dict(G_hp_text.degree())

    bridging_coeff = {}
    bridging_centrality = {}

    for v in G_hp_text.nodes():
        k_v = deg_unw.get(v, 0)
        if k_v == 0:
            bridging_coeff[v] = 0.0
            bridging_centrality[v] = 0.0
            continue
        neigh = neighbors[v]
        if not neigh:
            bridging_coeff[v] = 0.0
            bridging_centrality[v] = 0.0
            continue
        denom = sum(1.0 / deg_unw.get(u, 1) for u in neigh)
        bc = (1.0 / k_v) / denom if denom > 0 else 0.0
        bridging_coeff[v] = bc
        bridging_centrality[v] = bc * betw_w.get(v, 0.0)

    df_struct = []

    for v in G_hp_text.nodes():
        df_struct.append({
            "character": v,
            "degree_weighted": deg_w.get(v, 0),
            "betweenness_weighted": betw_w.get(v, 0.0),
            "kcore": core_num.get(v, 0),
            "bridging_coeff": bridging_coeff.get(v, 0.0),
            "bridging_centrality": bridging_centrality.get(v, 0.0),
            "n_sessions": G_hp_text.nodes[v].get("n_sessions", 0),
            "type_token_ratio": G_hp_text.nodes[v].get("type_token_ratio", 0.0),
            "mean_dialogue_sentiment": G_hp_text.nodes[v].get("mean_dialogue_sentiment",
```

```
    })

df_struct = pd.DataFrame(df_struct)
df_struct.sort_values("degree_weighted", ascending=False).head(15)
```

	character	degree_weighted	betweenness_weighted	kcore	bridging_coeff	bridging_
0	Harry	3395	0.405042	18	0.000041	
24	Ron	2089	0.117498	18	0.000138	
26	Hermione	1813	0.105872	18	0.000149	
17	Fred	557	0.017445	18	0.001818	
21	George	411	0.013174	18	0.002906	
4	Hagrid	381	0.033780	18	0.001382	
18	Ginny	371	0.017665	18	0.003066	
62	Mrs. Weasley	340	0.002362	18	0.010014	
31	McGonagall	306	0.019168	18	0.001790	
22	Neville	303	0.024485	18	0.002187	
40	Weasley	295	0.010077	18	0.003311	
33	Dumbledore	281	0.042455	18	0.001558	
105	Lupin	264	0.013944	18	0.005164	
27	Malfoy	262	0.019447	18	0.002598	
202	Luna	206	0.015681	18	0.003205	

```
# === Cell 8: example plots ===

# 8a. Character centrality vs average dialogue sentiment
plt.figure(figsize=(7, 5))
sns.scatterplot(
    data=df_struct,
    x="betweenness_weighted",
    y="mean_dialogue_sentiment"
)
plt.xlabel("Weighted betweenness centrality")
plt.ylabel("Mean dialogue sentiment")
plt.title("Character centrality vs average sentiment (HPD)")
plt.tight_layout()
plt.show()

# 8b. Bridging centrality distribution (characters that often connect groups)
plt.figure(figsize=(7, 5))
sns.boxplot(
    data=df_struct,
    y="bridging_centrality"
)
plt.ylabel("Bridging centrality")
plt.title("Distribution of bridging centrality (HPD co-occurrence network)")
plt.tight_layout()
plt.show()
```






```
# === Cell 9: character-level sentiment and centrality summaries ===

# Top central characters by weighted degree
top_deg = df_struct.sort_values("degree_weighted", ascending=False).head(15)
print("Top 15 characters by weighted degree (co-occurrence strength):")
display(top_deg[["character", "degree_weighted", "betweenness_weighted",
                 "kcore", "bridging_centrality",
                 "n_sessions", "type_token_ratio", "mean_dialogue_sentiment"]])

# Most positive / negative characters by average dialogue sentiment
min_sessions = 5  # avoid noise from characters appearing only once
sub = df_struct[df_struct["n_sessions"] >= min_sessions].copy()

top_positive = sub.sort_values("mean_dialogue_sentiment", ascending=False).head(10)
top_negative = sub.sort_values("mean_dialogue_sentiment", ascending=True).head(10)

print(f"\nTop 10 most positive characters (n_sessions >= {min_sessions}):")
```

```
display(top_positive[["character", "n_sessions", "mean_dialogue_sentiment",
                      "degree_weighted", "betweenness_weighted"]])

print(f"\nTop 10 most negative characters (n_sessions >= {min_sessions}):")
display(top_negative[["character", "n_sessions", "mean_dialogue_sentiment",
                      "degree_weighted", "betweenness_weighted"]])
```

Top 15 characters by weighted degree (co-occurrence strength):

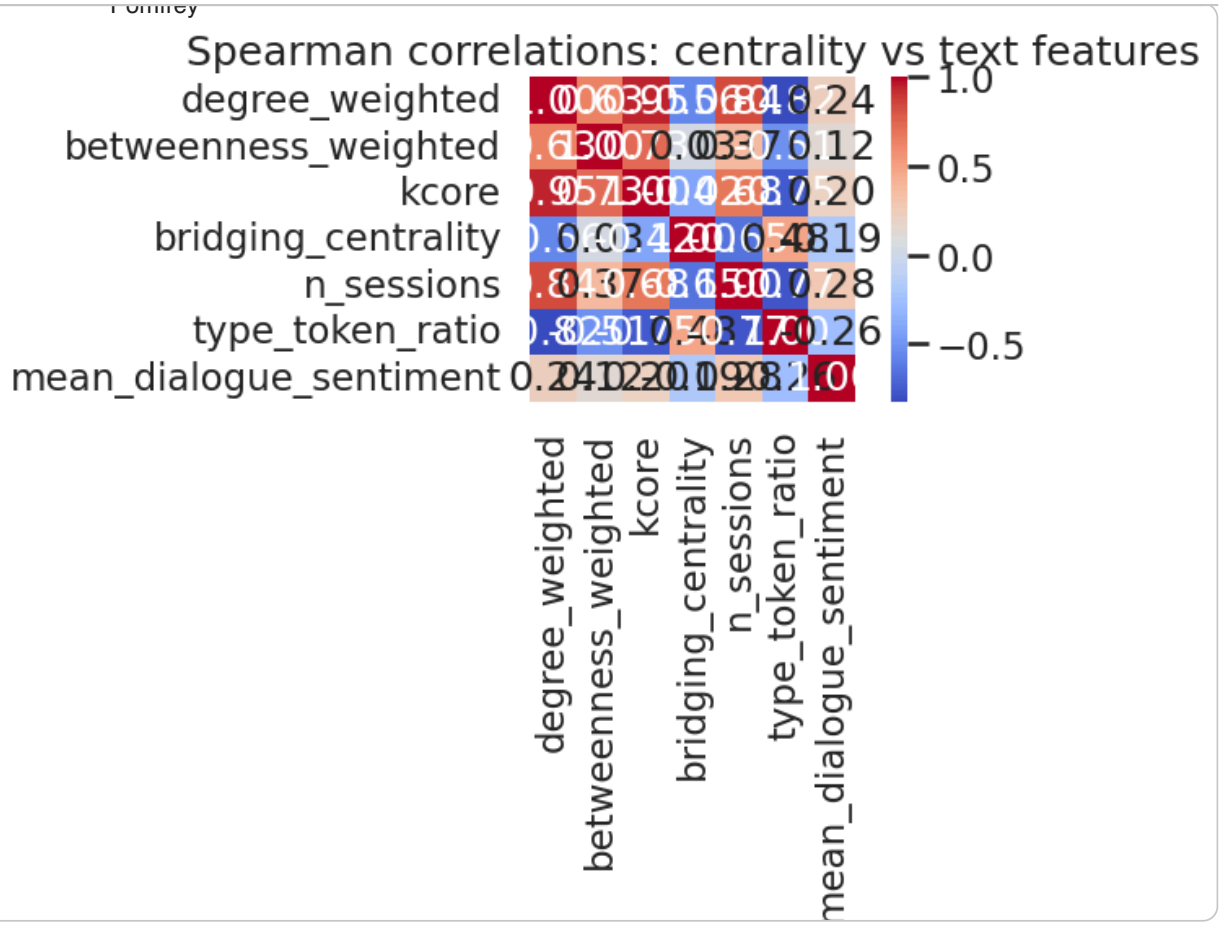
	character	degree_weighted	betweenness_weighted	kcore	bridging_centrality	n_
0	Harry	3395	0.405042	18	0.000017	
24	Ron	2089	0.117498	18	0.000016	
26	Hermione	1813	0.105872	18	0.000016	

```
# === Cell 10: correlation between centrality and text-based features ===

corr_cols = [
    "degree_weighted",
    "betweenness_weighted",
    "kcore",
    "bridging_centrality",
    "n_sessions",
    "type_token_ratio",
    "mean_dialogue_sentiment",
]

corr_mat = df_struct[corr_cols].corr(method="spearman")
corr_mat
# === Cell 10b: visualize correlation matrix ===

plt.figure(figsize=(8, 6))
sns.heatmap(
    corr_mat,
    annot=True,
    fmt=".2f",
    square=True,
    cmap="coolwarm",
)
plt.title("Spearman correlations: centrality vs text features")
plt.tight_layout()
plt.show()
```

15	Ollivander	5	0.160040	18	0.(
155	Fleur	22	0.154235	125	0.(
118	Cho Chang	17	0.131350	94	0.(
45	Wood	22	0.093053	87	0.(
10	Tom	9	0.083956	19	0.(
131	Bagman	15	0.082046	74	0.
43	Fat lady	15	0.056306	36	0.(

Top 10 most negative characters (n_sessions >= 5):

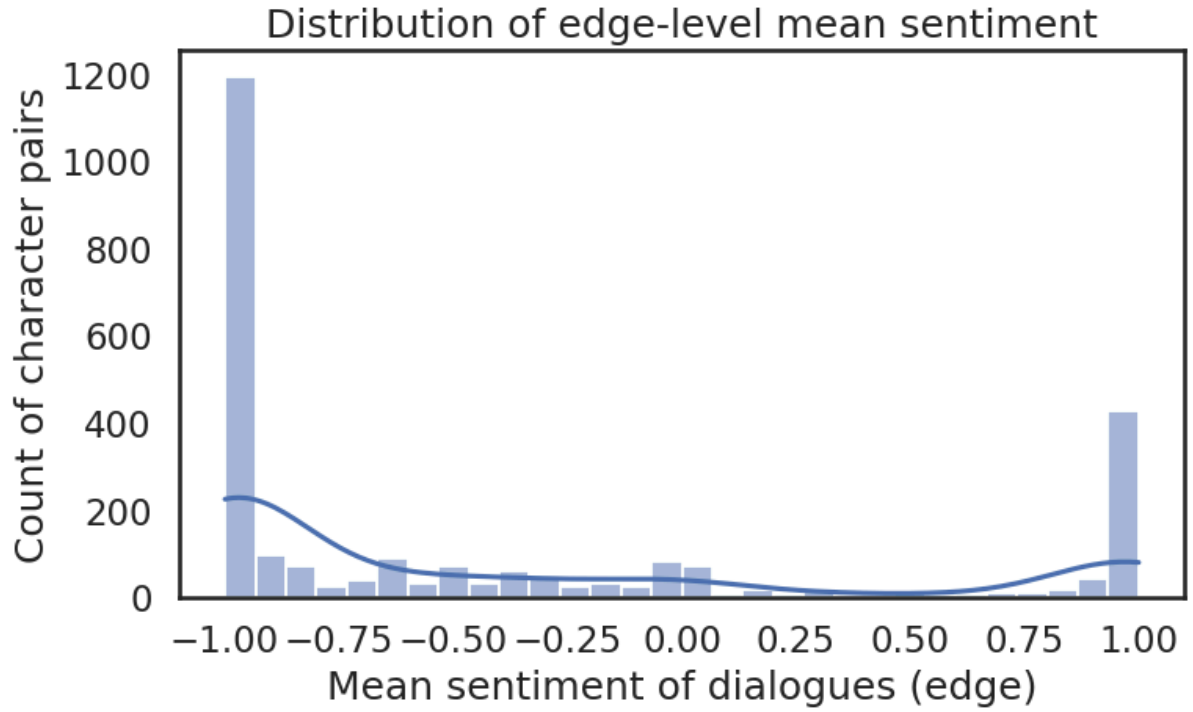
	character	n_sessions	mean_dialogue_sentiment	degree_weighted	betweenness_wei
191	Mrs. Black	5	-0.998797	22	0.(
90	wizard	8	-0.991225	46	0.(
262	Death Eater	8	-0.990925	49	0.(
168	Grubbly-Plank	6	-0.989103	20	0.(
132	Crouch	6	-0.977496	36	0.(
160	Pansy	6	-0.722686	32	0.(
59	Madam Pomfrey	15	-0.720199	58	0.(

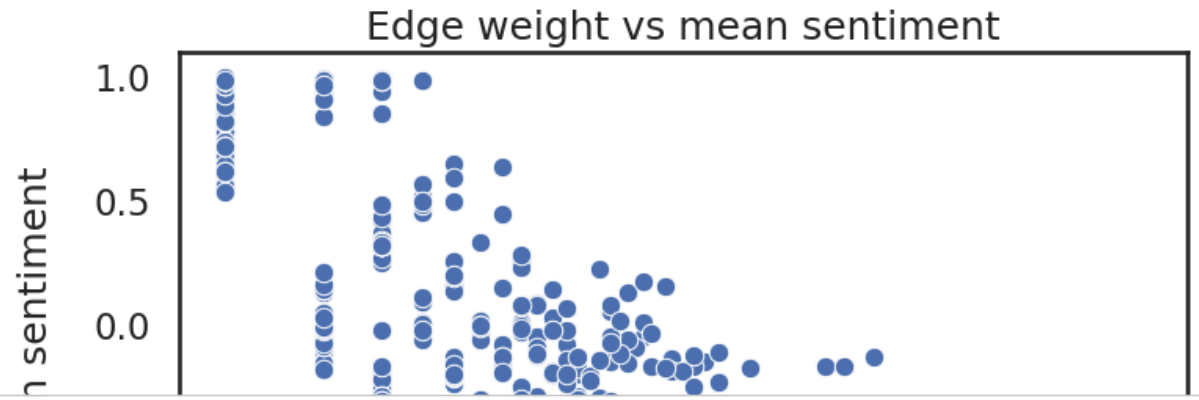



```
# === Cell 11: build edge-level DataFrame from G_hp_text ===

edge_rows = []
for u, v, data in G_hp_text.edges(data=True):
    edge_rows.append({
        "u": u,
        "v": v,
        "weight": data.get("weight", 1),
        "sent_mean": data.get("sent_mean", 0.0),
    })

df_edges = pd.DataFrame(edge_rows)
df_edges.head()
# === Cell 11b: distribution of edge sentiment ===

plt.figure(figsize=(8, 5))
sns.histplot(df_edges["sent_mean"], bins=30, kde=True)
plt.xlabel("Mean sentiment of dialogues (edge)")
plt.ylabel("Count of character pairs")
plt.title("Distribution of edge-level mean sentiment")
plt.tight_layout()
plt.show()

plt.figure(figsize=(8, 5))
sns.scatterplot(
    data=df_edges,
    x="weight",
    y="sent_mean",
)
plt.xscale("log")
plt.xlabel("Edge weight (number of co-occurrence sessions, log scale)")
plt.ylabel("Mean sentiment")
plt.title("Edge weight vs mean sentiment")
plt.tight_layout()
plt.show()
```

```
# === Cell 11c: top positive and negative pairs (strong ties) ===

min_weight = 3  # consider only pairs that co-occur in at least 3 sessions
sub_edges = df_edges[df_edges["weight"] >= min_weight].copy()

top_pos_edges = sub_edges.sort_values("sent_mean", ascending=False).head(15)
top_neg_edges = sub_edges.sort_values("sent_mean", ascending=True).head(15)

print(f"Most positive pairs (weight >= {min_weight}):")
display(top_pos_edges)

print(f"\nMost negative pairs (weight >= {min_weight}):")
display(top_neg_edges)
```

Next steps: Generate code with `top_pos_edges` New interactive sheet Generate code with `top_neg_edges`






```
# === Cell 12: character-level tf-idf keywords ===

from sklearn.feature_extraction.text import TfidfVectorizer

# Rebuild char_texts from df_hpd to be safe
char_texts = defaultdict(list)
for _, row in df_hpd.iterrows():
    speakers = [str(s).strip() for s in row["speakers"] if pd.notna(s)]
    speakers = [s for s in speakers if s != ""]
    text = row["dialogue_text"]
    for c in set(speakers):
        char_texts[c].append(text)

char_list = []
corpus = []

for c, texts in char_texts.items():
    char_list.append(c)
    corpus.append(" ".join(texts))

vectorizer = TfidfVectorizer(
    lowercase=True,
    token_pattern=r"[A-Za-z']+",
    min_df=3,   # ignore rare words
)
X = vectorizer.fit_transform(corpus)
vocab = np.array(vectorizer.get_feature_names_out())
```

```
# Helper: get top k tf-idf terms for a character index i
def top_terms_for_char(idx, k=10):
    row = X[idx]
    if row.nnz == 0:
        return []
    # get top k indices
    data = row.toarray().ravel()
    top_idx = np.argsort(data)[::-1][:k]
    return list(zip(vocab[top_idx], data[top_idx]))
# === Cell 12b: show keywords for top central characters ===

# Choose some target characters: top by weighted degree
top_chars = df_struct.sort_values("degree_weighted", ascending=False)["character"].h

print("Top tf-idf keywords for top-degree characters:\n")
for c in top_chars:
    if c not in char_list:
        continue
    idx = char_list.index(c)
    terms = top_terms_for_char(idx, k=12)
    print(f"Character: {c}")
    for w, score in terms:
        print(f"  {w:15s} {score:.4f}")
    print()
```

1403	Hermione	Voldemort	3	-0.995571
1673	Snape	Madam Pomfrey	3	-0.995434
1223	Hermione	Ron, Harry	3	-0.995424
45	Harry	Ron, Harry	3	-0.995424
991	Ron	Ron, Harry	3	-0.995424
899	Neville	Ernie	3	-0.994244
258	Harry	Death Eater 1	3	-0.993994

```
Character: Ron
  you             0.3255
  the             0.2844
  i               0.2831
  to              0.2605
  s               0.2189
  it              0.2075
  harry           0.2056
  ron             0.2055
  hermione        0.1775
  t               0.1680
  and             0.1668
  a               0.1592

Character: Hermione
  you             0.3136
  the             0.2928
  i               0.2795
  to              0.2618
  hermione        0.2243
  s               0.2166
  it              0.2098
  harry           0.2035
  t               0.1667
  ron             0.1653
  and             0.1647
```