Vergleich dreier Textanalyse-Modelle (BoW, TF-IDF, SBERT) zur automatischen Sentiment-Erkennung in Schweizer Mundart-Chatnachrichten

Zwischenpräsentation

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Wie gut schneiden BoW, TF-IDF und SBERT bei der Sentimentanalyse von Mundart-Chatnachrichten ab?

Oder: Welches Modell versteht:
jo, mega guet… 🙄

Agenda

- Ziel & Datensatz
- Modelle
- Deskriptive Analyse
- Meine Erwartungen
- Modellevaluation
- Visualisierung (PCA+KMeans, 3D)
- Demo (Interaktive Eingabe)
- Key-Findings und mögliche Verbesserungen

Ziel & Datensatz

- **Ziel**
  - Textklassifikation (negativ/neutral/positiv) für Schweizer Mundart Chatnachrichten
  - Vergleich:
    - BoW + LR (mit Preprocessing)
    - TF-IDF + LR (mit Uni- und Bigram und Preprocessing)
    - SBERT + LR (mit paraphrase-multilingual-MiniLM-L12-v2)

- **Datensatz**
  - CSV: mundart_chat.csv (Spalten: text, label)
  - 600 Zeilen
    - hammer 😍, *positiv*
    - mega blööd 👎, *negativ*
    - maal luege, *neutral*
    - solala, *neutral*
    - richhitg nice 🎉, *positiv*
    - so huere pienlich 😤, *negativ*
  - Train/Test-Split: 75/25

Modelle

- **BoW** («Bag of Words»)
  - Methode, die zählt, wie oft Wörter (oder N-Gamme) in einem Datensatz (hier: alle Chatnachrichten) vorkommen, unabhängig vom Kontext
- **TF-IDF** («Term Frequency Inverse Document Frequency»)
  - Baut auf BoW auf und gewichtet die Wörter (oder N-Gramme) zusätzlich nach ihrer Wichtigkeit im Datensatz (hier: alle Chatnachrichten)
- **SBERT** («Sentence Bidirectional Encoder Representations from Transformers»)
  - Vortrainiertes neuronales Sprachmodell, das darauf optimiert ist, ganze Sätze oder Texte als semantische Vektoren (Embeddings) darzustellen

(multinomiale) logistische Regression als Klassifikator

Deskriptive Analyse

```
— Klassenverteilung —
label
neutral    199
negativ    199
positiv    199
Name: count, dtype: int64

— Länge (Zeichen) —
mean    16.063652
50%     15.000000
min      2.000000
max     37.000000
Name: text, dtype: float64
```

Deskriptive Analyse

– Top-1g: negativ –

ngram	count
😤	49
👎	44
💔	44
😡	41
😭	37

– Top-1g: neutral –

ngram	count
😐	71
🤔	65
🙂	60
so	49
🙃	26

– Top-1g: positiv –

ngram	count
😊	42
✨	39
🤍	35
😍	34
👍	32

– Top-2g: negativ –

ngram	count
gar nöd	12
nie wieder	12
so en	11
nöd guet	8
mega blöd	6

– Top-2g: neutral –

ngram	count
i o	13
so i	12
jo passt	11
neutral gseh	11
zur kenntnis	11

– Top-2g: positiv –

ngram	count
top sache	11
passt perfekt	10
gfallt mir	7
bin zfriede	6
gute idee	6

– PMI-2g: negativ –

bigram	count	PMI
so en	11	5.828665
gar nöd	12	5.713188
nöd guet	8	5.713188
en quatsch	4	5.565631
funktioniert nid	5	5.539159

– PMI-2g: neutral –

bigram	count	PMI
ist okay	5	6.011663
kann maan	3	5.993047
man machen	8	5.944549
i o	13	5.886132
kann man	9	5.855544

– PMI-2g: positiv –

bigram	count	PMI
cool gmacht	4	6.291554
bin zfriede	6	5.829449
gfallt mir	7	5.732587
passt perfekt	10	5.661504
top sache	11	5.439112

PMI: Pointwise Mutual Information / Wie stark Wörter gemeinsam auftreten, verglichen mit Zufall

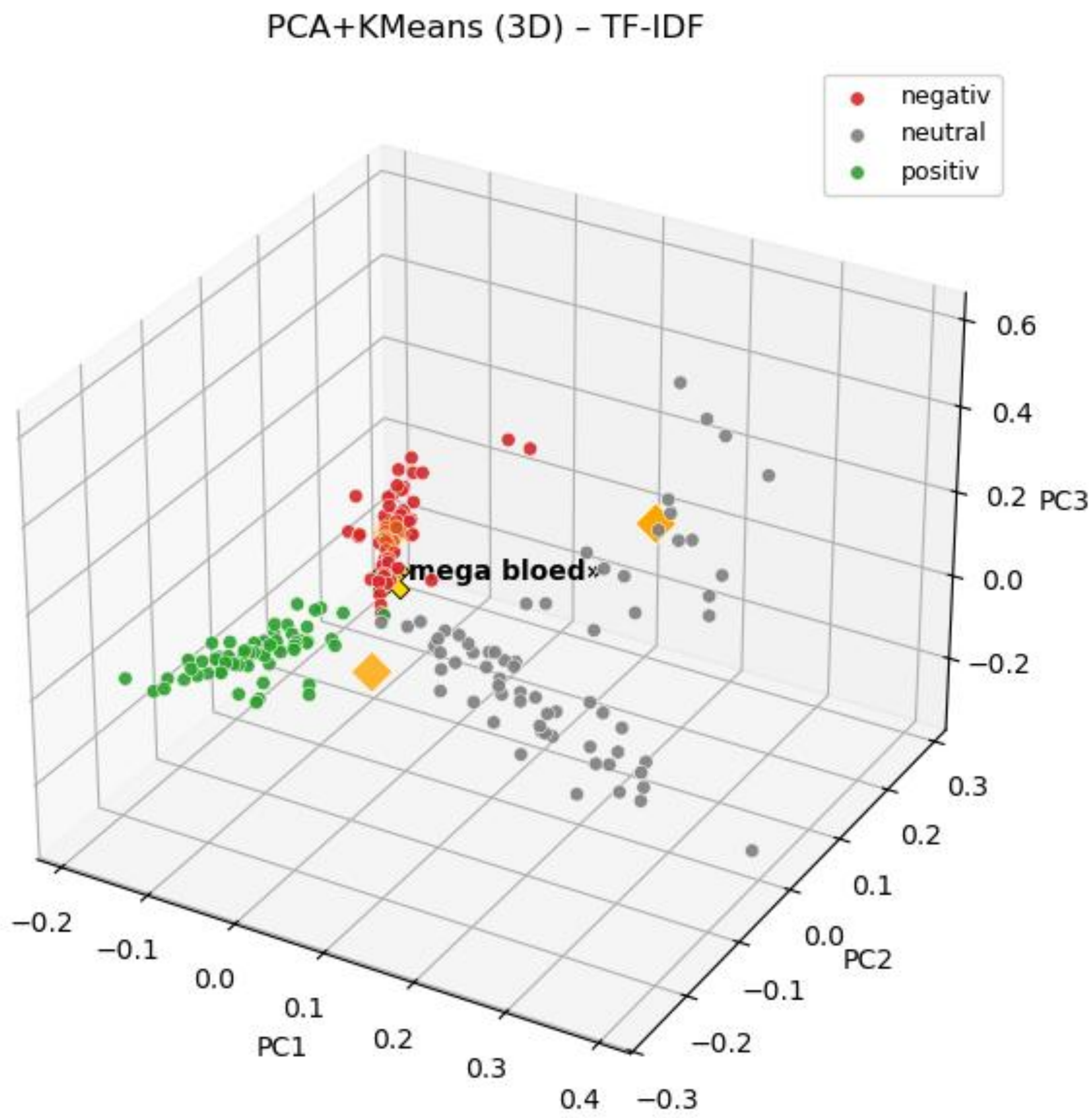
Meine Erwartungen (gemäss Theorie☺)

	BoW	TF-IDF (mit Bigram)	SBERT
Klare Keywords	✅ stark	✅ stark	✅ stark
Viele Füllwörter	⚠️ schwächer	✅ stark	✅ stark
Synonyme/Paraphrasen	⚠️ teils, da hier mit Dialekt-Mapping	⚠️ teils, da hier mit Dialekt-Mapping	✅ stark (auch ohne Dialekt-Mapping)
Negationen („nicht gut“)	❌ schwach, da hier kein Bigram	⚠️ teils, da hier Bigram	✅ stark
Rechtschreibfehler / Elongation	❌ schwach, braucht Vorkommen	⚠️ teils (dank Bigram)	✅ robust
Emojis als Signal	⚠️ teils, braucht Vorkommen	⚠️ etwas besser (dank Gewichtung)	✅ robust
kurze Fragmente (1–3 Wörter)	✅ stark	✅ stark	⚠️ teils schwächer, da keine Satzstruktur

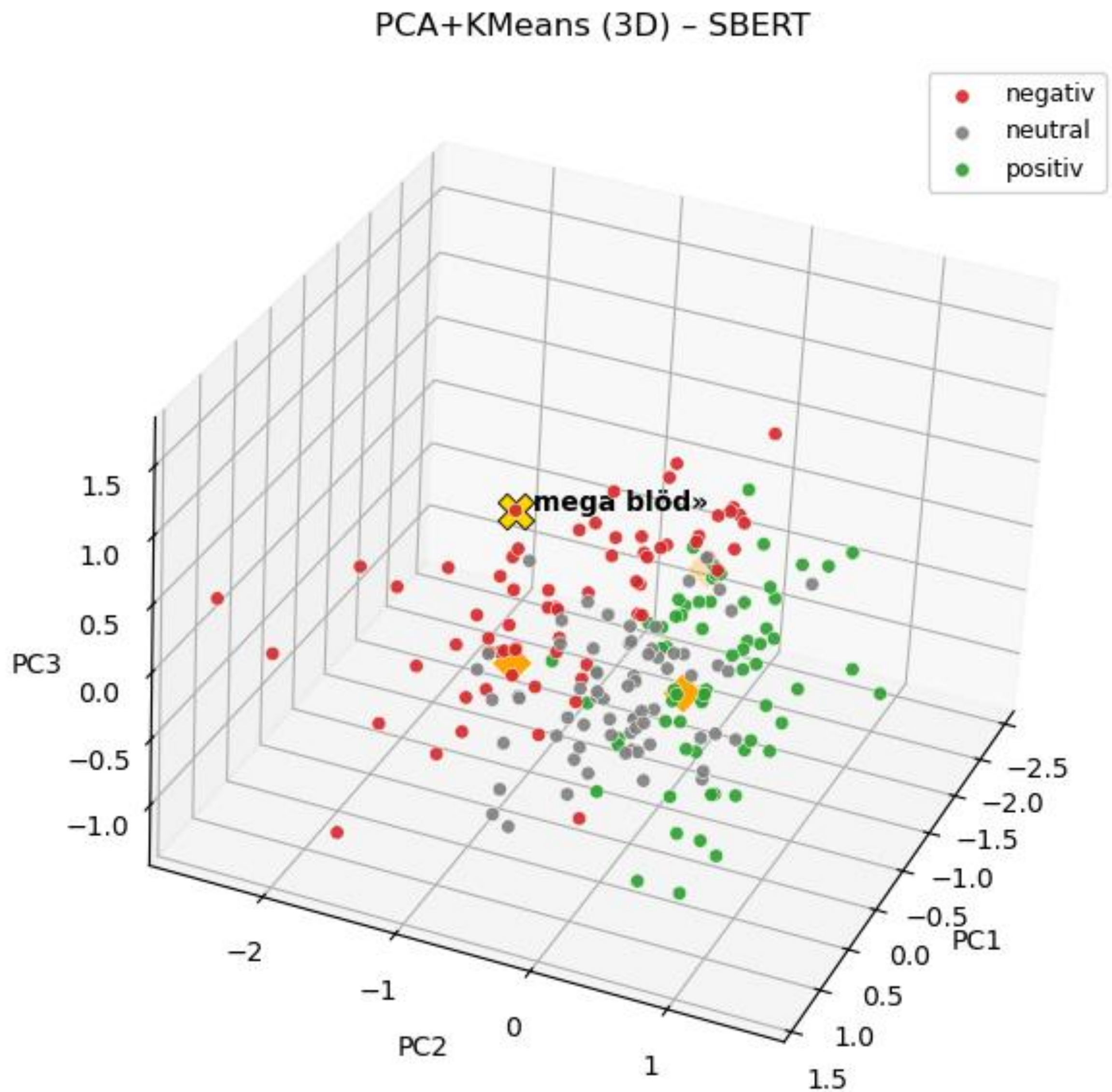
Modelevaluation

Modell	Accuracy	Kommentar
BoW + LogisticRegression	0.986	Nahezu perfekt – lernt klare Wörter, aber wohl overfit, viele Wiederholungen im Datensatz
TF-IDF + LogisticRegression	0.993	Ebenfalls sehr stark, leicht robuster durch Gewichtung.
SBERT + LogisticRegression	0.920	Semantisch robust, aber niedrigere Scores (realistischer).

Visualisierung



Visualisierung



Demo

```
> Textanalütixs isch mega cool

— Ergebnisse —
BoW    -> positiv  |  negativ: 0.23 | neutral: 0.34 | positiv: 0.43
TF-IDF-> positiv  |  negativ: 0.25 | neutral: 0.35 | positiv: 0.40
SBERT -> positiv  |  negativ: 0.04 | neutral: 0.25 | positiv: 0.71
```

Demo

```
> mega blöd

— Ergebnisse —
BoW    -> negativ  |  negativ: 0.64 | neutral: 0.12 | positiv: 0.24
TF-IDF-> negativ  |  negativ: 0.61 | neutral: 0.17 | positiv: 0.22
SBERT -> negativ  |  negativ: 0.95 | neutral: 0.02 | positiv: 0.03
```

```
> mega blööd

— Ergebnisse —
BoW    -> negativ  |  negativ: 0.48 | neutral: 0.16 | positiv: 0.36
TF-IDF-> negativ  |  negativ: 0.44 | neutral: 0.24 | positiv: 0.32
SBERT -> positiv  |  negativ: 0.23 | neutral: 0.08 | positiv: 0.70
```

```
> so mega blöd

— Ergebnisse —
BoW    -> neutral  |  negativ: 0.44 | neutral: 0.47 | positiv: 0.10
TF-IDF-> negativ  |  negativ: 0.51 | neutral: 0.32 | positiv: 0.17
SBERT -> negativ  |  negativ: 0.80 | neutral: 0.16 | positiv: 0.03
```

```
> das isch so mega blöd

— Ergebnisse —
BoW    -> neutral  |  negativ: 0.19 | neutral: 0.77 | positiv: 0.04
TF-IDF-> neutral  |  negativ: 0.40 | neutral: 0.46 | positiv: 0.15
SBERT -> negativ  |  negativ: 0.74 | neutral: 0.21 | positiv: 0.05
```

```
> das isch so übel

— Ergebnisse —
BoW    -> neutral  |  negativ: 0.07 | neutral: 0.88 | positiv: 0.05
TF-IDF-> neutral  |  negativ: 0.10 | neutral: 0.81 | positiv: 0.08
SBERT -> negativ  |  negativ: 0.85 | neutral: 0.14 | positiv: 0.01
```

Key-Findings

- BoW/TF-IDF: überraschend stark bei kurzen Chatnachrichten
- SBERT: robuster bei neuen Formulierungen / Wörtern (semantischer Transfer), aber Mühe bei kurzen Sätzen (fehlender Kontext)
- Accuracy (99 %) ist nicht gleichbedeutend mit guter Generalisierung
- Schwierigkeiten mit Mundart Chatnachrichten:
  - *nicht standardisiert: „nöd“, „nid“, „ned“*
  - *mischt Dialekt, Hochdeutsch, Slang, Englisch*
  - *drückt viel über Tonfall, Kontext und Ironie aus, insbesondere mit Emoji. „jo, mega guet… 🙄“*

Key-Findings

```
> jo, mega guet… 🙄

— Ergebnisse —
BoW   -> positiv  |  negativ: 0.26 | neutral: 0.22 | positiv: 0.52
TF-IDF-> positiv  |  negativ: 0.22 | neutral: 0.24 | positiv: 0.54
SBERT -> negativ  |  negativ: 0.54 | neutral: 0.44 | positiv: 0.01
```

Verbesserungen

	Hauptwirkung auf	Nutzen / Wirkung
Mehr (realistische) Daten & Kontext!	SBERT	Verbessert semantische Repräsentationen.
→ Vocabulary Growth Curve zur Validierung der Sprachvielfalt mit zunehmenden Daten → Zipf’s Law zur Validierung der natürlichen Wortfrequenzverteilung		
Stoppwort-Optimierung	BoW / TF-IDF	Reduziert Rauschen, stärkt relevante Signale.
Bessere Normalisierung & Lemmatization, Dialekt-Mapping (auch für SBERT!)	alle	Erkennt Varianten & Schreibweisen besser.
Char-n-grams oder Subwords	BoW / TF-IDF	Erhöht Robustheit bei Tippfehlern & Dialektformen
N-Gram-Optimierung (1–3)	BoW / TF-IDF	Erkennt längere Phrasen & Negationen („nicht mega guet“)

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report, accuracy_score
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans


#%% ----------- Config ----------------
#DATA_CSV = "mundart_chat.csv"  # CSV mit Spalten: text,label
DATA_CSV ="mundart_augmented.csv"
SBERT_MODEL_NAME = "sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2"
RANDOM_STATE = 42
HIGHLIGHT_TEXT = "mega blöd"   # initial im Plot markiert
BATCH_SIZE = 32
np.random.seed(RANDOM_STATE)
df=pd.read_csv(DATA_CSV)

EMOJI_RE_RANGE = r"[\U0001F300-\U0001FAFF\u2600-\u27BF]"
def preprocess_text(t: str) -> str:
    if t is None: return ""
    t = str(t).lower()
    t = re.sub(r"\d+", "<NUM>", t)
    t = re.sub(r"(.)\1{2,}", r"\1\1", t)
    t = re.sub(r"[’']", " ", t)
    # Emojis einzeln separieren (keine Buckets!)
    t = re.sub(EMOJI_RE_RANGE + "+", lambda m: " " + " ".join(list(m.group(0))) + " ", t)
    t = t.replace("-", " ").replace("/", " ")
    t = (t.replace("ä","ae").replace("ö","oe").replace("ü","ue").replace("ß","ss"))
    # Dialekt-Mapping
    for k,v in {"nöd":"nicht","nid":"nicht","ned":"nicht","isch":"ist","bisch":"bist","chunsch":"kommst","huere":"sehr"}.items():
        t = re.sub(rf"\b{k}\b", v, t)
    t = re.sub(rf"[^\wäöüÄÖÜß<>{EMOJI_RE_RANGE}]+", " ", t)
    t = re.sub(r"\s{2,}", " ", t).strip()
    return t
```

```python
# Vectorizer mit Emoji-fähigem token_pattern
TOKEN_PATTERN = rf"(?u)(?:\b[\wäöüÄÖÜß]+\b|{EMOJI_RE_RANGE})"

#%% ---------- Deskriptives: Top-N-Grams, PMI, Emojis ----------
import re
from math import log2

def describe(df: pd.DataFrame) -> None:
    print("\n– Klassenverteilung –")
    print(df["label"].value_counts())
    print("\n– Länge (Zeichen) –")
    print(df["text"].str.len().describe()[["mean", "50%", "min", "max"]])

def _make_vectorizer(ngram_range=(1,1), min_df=2):
    return CountVectorizer(
        lowercase=True,
        ngram_range=ngram_range,
        min_df=min_df,
        token_pattern=TOKEN_PATTERN)


# gewünschte Label-Reihenfolge
LABEL_ORDER = ["negativ", "neutral", "positiv"]

def top_ngrams(df, label=None, ngram_range=(1,1), topk=5, min_df=2):
    """Top-N n-grams (nur für Teilmenge wenn label gesetzt)."""
    texts = df["text"] if label is None else df.loc[df["label"] == label, "text"]
    vec = _make_vectorizer(ngram_range=ngram_range, min_df=min_df)
    X = vec.fit_transform(texts.astype(str))
    vocab = np.array(vec.get_feature_names_out())
    counts = np.asarray(X.sum(axis=0)).ravel()
    rows = [(tok, int(cnt)) for tok, cnt in zip(vocab, counts)]
    rows.sort(key=lambda x: x[1], reverse=True)
    return pd.DataFrame(rows[:topk], columns=["ngram", "count"])

def top_ngrams_by_label(df, ngram_range=(1,1), topk=5, min_df=2):
    """Top-N je Klasse, sortiert nach LABEL_ORDER (wo vorhanden)."""
    out = {}
    labels_sorted = [l for l in LABEL_ORDER if l in set(df["label"])] + \
```

```
                    [l for l in sorted(df["label"].unique()) if l not in LABEL_ORDER]
    for lab in labels_sorted:
        out[lab] = top_ngrams(df, label=lab, ngram_range=ngram_range, topk=topk, min_df=min_df)
    return out

def show_dict_of_dfs(d, title_prefix):
    """Schöne Konsolen-Ausgabe der DataFrames je Label."""
    for k in d:
        print(f"\n– {title_prefix}: {k} –")
        print(d[k].to_string(index=False))

# --- PMI je Label  ---
def pmi_bigrams_subset(texts, topk=5, min_df=3):
    """PMI nur auf einer Text-Teilmenge."""
    v1 = _make_vectorizer((1,1), min_df=1)
    X1 = v1.fit_transform(texts)
    vocab1 = np.array(v1.get_feature_names_out())
    uni_counts = np.asarray(X1.sum(axis=0)).ravel()
    uni = dict(zip(vocab1, uni_counts))

    v2 = _make_vectorizer((2,2), min_df=min_df)
    X2 = v2.fit_transform(texts)
    vocab2 = np.array(v2.get_feature_names_out())
    bi_counts = np.asarray(X2.sum(axis=0)).ravel()

    N = uni_counts.sum()
    rows = []
    for bg, c_xy in zip(vocab2, bi_counts):
        w1, w2 = bg.split()
        c_x = uni.get(w1, 0); c_y = uni.get(w2, 0)
        pmi = log2(((c_xy + 1) * N) / ((c_x + 1) * (c_y + 1)))
        rows.append((bg, int(c_xy), pmi))
    rows.sort(key=lambda x: (x[2], x[1]), reverse=True)
    return pd.DataFrame(rows[:topk], columns=["bigram", "count", "PMI"])

def pmi_bigrams_by_label(df, topk=5, min_df=3):
    out = {}
    labels_sorted = [l for l in LABEL_ORDER if l in set(df["label"])] + \
                    [l for l in sorted(df["label"].unique()) if l not in LABEL_ORDER]
    for lab in labels_sorted:
```

```
        texts = df.loc[df["label"] == lab, "text"].astype(str)
        out[lab] = pmi_bigrams_subset(texts, topk=topk, min_df=min_df)
    return out

_EMOJI_RE = re.compile(r"[\U0001F300-\U0001FAFF\u2600-\u27BF]+")


describe(df)

print("\n== UNIGRAMS je Klasse ==")
uni_by = top_ngrams_by_label(df, ngram_range=(1,1), topk=5, min_df=2)
show_dict_of_dfs(uni_by, "Top-1g")

print("\n== BIGRAMS je Klasse ==")
bi_by = top_ngrams_by_label(df, ngram_range=(2,2), topk=5, min_df=2)
show_dict_of_dfs(bi_by, "Top-2g")

print("\n== PMI-BIGRAMS je Klasse ==")
pmi_by = pmi_bigrams_by_label(df, topk=5, min_df=3)
show_dict_of_dfs(pmi_by, "PMI-2g")



#%% ---------- Hilfsfunktionen ----------
def probs_pipeline(model, texts):
    """Gibt eine Liste von {label: prob}-Dicts für Pipeline-Modelle (BoW/TF-IDF) zurück."""
    vec = model.named_steps["vec"]
    clf = model.named_steps["clf"]
    X = vec.transform(texts)
    P = clf.predict_proba(X)  # Form (n, n_classes)
    cls = clf.classes_
    out = []
    for p in P:
        out.append({c: float(p[i]) for i, c in enumerate(cls)})
    return out

def sbert_predict_proba(sbert_model, sbert_clf, texts, batch_size=BATCH_SIZE):
    emb = sbert_model.encode(pd.Series(texts).astype(str).tolist(),
                             convert_to_numpy=True, batch_size=batch_size)
    P = sbert_clf.predict_proba(emb)
```

```
    cls = sbert_clf.classes_
    out = []
    for p in P:
        out.append({c: float(p[i]) for i, c in enumerate(cls)})
    return out

def format_probs(prob_dict, order=LABEL_ORDER, ndigits=2):
    """Formatiert als 'negativ: 0.12 | neutral: 0.34 | positiv: 0.54'."""
    return " | ".join(f"{lbl}: {prob_dict.get(lbl, 0.0):.{ndigits}f}" for lbl in order)

def eval_model(name, model, X_test, y_test) -> None:
    y_pred = model.predict(X_test)
    print(f"\n=== {name} ===")
    print(classification_report(y_test, y_pred, digits=3))
    print("Accuracy:", accuracy_score(y_test, y_pred))

def eval_sbert(sbert_model, sbert_clf, X_test, y_test, batch_size=BATCH_SIZE):
    Xv = pd.Series(X_test).astype(str).tolist()
    emb_test = sbert_model.encode(Xv, convert_to_numpy=True, batch_size=batch_size)
    y_pred = sbert_clf.predict(emb_test)
    print("\n=== SBERT-Embeddings + LogisticRegression ===")
    print(classification_report(y_test, y_pred, digits=3))
    print("Accuracy:", accuracy_score(y_test, y_pred))

def sbert_predict(sbert_model, sbert_clf, texts, batch_size=BATCH_SIZE):
    X = pd.Series(texts).astype(str).tolist()
    emb = sbert_model.encode(X, convert_to_numpy=True, batch_size=batch_size)
    return sbert_clf.predict(emb)


#%% ---------- Plotting ----------
CLASS_COLORS = {"negativ": "tab:red", "neutral": "tab:gray", "positiv": "tab:green"}
def pca_kmeans_plot(
    name, X_2d, labels, texts, highlight_vec_2d, highlight_text,
    annotate_points: bool = False, max_points: int | None = None, random_state: int = RANDOM_STATE):
    labels = np.asarray(labels)
    texts = np.asarray(texts)

    # auf max_points herunterkürzen
    if (max_points is not None) and (max_points < len(labels)):
```

```
    rng = np.random.default_rng(random_state)
    idx_keep = []
    # proportional je Klasse; min 1 pro vorhandener Klasse
    for lab in np.unique(labels):
        lab_idx = np.where(labels == lab)[0]
        # Anteil pro Klasse ~ (Klassenanteil * max_points), mind. 1
        k = max(1, int(round(max_points * len(lab_idx) / len(labels))))
        k = min(k, len(lab_idx))  # nicht mehr als vorhanden
        idx_keep.extend(rng.choice(lab_idx, size=k, replace=False))
    idx_keep = np.array(sorted(idx_keep))
    X_2d = X_2d[idx_keep]
    texts = texts[idx_keep]
    labels = labels[idx_keep]

# KMeans nur zur Visualisierung
kmeans = KMeans(n_clusters=3, random_state=random_state, n_init=10).fit(X_2d)

plt.figure()
for lab in sorted(np.unique(labels)):
    mask = (labels == lab)
    plt.scatter(X_2d[mask, 0], X_2d[mask, 1], s=28, alpha=0.9, label=lab,
                c=CLASS_COLORS.get(lab, "tab:blue"))
    if annotate_points:
        for x, y, t in zip(X_2d[mask, 0], X_2d[mask, 1], texts[mask]):
            short = (t[:22] + "…") if len(t) > 22 else t
            plt.annotate(short, (x, y), fontsize=8, alpha=0.8)

# Zentren
centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], s=100, marker="D", c="orange")

# Highlight: Marker + Text
if highlight_vec_2d is not None:
    xh, yh = float(highlight_vec_2d[0, 0]), float(highlight_vec_2d[0, 1])
    plt.scatter(xh, yh, s=160, marker="X", c="gold")
    if highlight_text:
        label = "«" + (highlight_text[:30] + "…" if len(highlight_text) > 30 else highlight_text) + "»"
        plt.annotate(label, (xh, yh), fontsize=10, alpha=0.9, color="gold")

plt.title(f"PCA+KMeans – {name}")
```

```python
    plt.xlabel("PC1"); plt.ylabel("PC2")
    plt.legend(title=None, loc="best", fontsize=9)
    plt.tight_layout()
    plt.show()


def plot_space_for_bow(model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    vec = model.named_steps["vec"]
    X_all = vec.transform(df_text)
    X_dense = X_all.toarray()
    pca = PCA(n_components=2, random_state=RANDOM_STATE).fit(X_dense)
    X_2d = pca.transform(X_dense)
    h_2d = pca.transform(vec.transform([highlight_text]).toarray())
    pca_kmeans_plot("BoW", X_2d, df_labels.values, df_text.values, h_2d, highlight_text,
                    annotate_points=annotate_points, max_points=max_points)

def plot_space_for_tfidf(model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    vec = model.named_steps["vec"]
    X_all = vec.transform(df_text)
    X_dense = X_all.toarray()
    pca = PCA(n_components=2, random_state=RANDOM_STATE).fit(X_dense)
    X_2d = pca.transform(X_dense)
    h_2d = pca.transform(vec.transform([highlight_text]).toarray())
    pca_kmeans_plot("TF-IDF", X_2d, df_labels.values, df_text.values, h_2d, highlight_text,
                    annotate_points=annotate_points, max_points=max_points)

def plot_space_for_sbert(sbert_model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    all_emb = sbert_model.encode(pd.Series(df_text).astype(str).tolist(), convert_to_numpy=True, batch_size=BATCH_SIZE)
    pca = PCA(n_components=2, random_state=RANDOM_STATE).fit(all_emb)
    X_2d = pca.transform(all_emb)
    h_2d = pca.transform(sbert_model.encode([highlight_text], convert_to_numpy=True, batch_size=BATCH_SIZE))
    pca_kmeans_plot("SBERT", X_2d, df_labels.values, df_text.values, h_2d, highlight_text,
                    annotate_points=annotate_points, max_points=max_points)

def pca_kmeans_plot_3d(
    name, X_3d, labels, texts, highlight_vec_3d, highlight_text,
    annotate_points: bool = False, max_points: int | None = None, random_state: int = RANDOM_STATE):
    labels = np.asarray(labels)
    texts = np.asarray(texts)
```

```
# stratifiziert auf max_points kürzen
if (max_points is not None) and (max_points < len(labels)):
    rng = np.random.default_rng(random_state)
    idx_keep = []
    for lab in np.unique(labels):
        lab_idx = np.where(labels == lab)[0]
        k = max(1, int(round(max_points * len(lab_idx) / len(labels))))
        k = min(k, len(lab_idx))
        idx_keep.extend(rng.choice(lab_idx, size=k, replace=False))
    idx_keep = np.array(sorted(idx_keep))
    X_3d = X_3d[idx_keep]
    texts = texts[idx_keep]
    labels = labels[idx_keep]

# KMeans nur zur Visualisierung (auf 3D)
n_clusters = min(3, len(np.unique(labels)), len(X_3d))
kmeans = KMeans(n_clusters=n_clusters, random_state=random_state, n_init=10).fit(X_3d)

fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection="3d")

for lab in sorted(np.unique(labels)):
    mask = (labels == lab)
    ax.scatter(
        X_3d[mask, 0], X_3d[mask, 1], X_3d[mask, 2],
        s=28, alpha=0.9, label=lab,
        c=CLASS_COLORS.get(lab, "tab:blue"),
        edgecolors="white", linewidths=0.4
    )
    if annotate_points:
        for x, y, z, t in zip(X_3d[mask, 0], X_3d[mask, 1], X_3d[mask, 2], texts[mask]):
            short = (t[:22] + "…") if len(t) > 22 else t
            ax.text(x, y, z, short, fontsize=8, alpha=0.8)

# Zentren
centers = kmeans.cluster_centers_
ax.scatter(centers[:, 0], centers[:, 1], centers[:, 2], s=120, marker="D", c="orange", edgecolors="white", linewidths=0.6)

# Highlight
if highlight_vec_3d is not None:
```

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        xh, yh, zh = map(float, highlight_vec_3d.ravel())
        ax.scatter(xh, yh, zh, s=180, marker="X", c="gold", edgecolors="black", linewidths=0.6)
        if highlight_text:
            lab = "«" + (highlight_text[:30] + "…" if len(highlight_text) > 30 else highlight_text) + "»"
            ax.text(xh, yh, zh, lab, fontsize=10, color="black", weight="semibold")

    ax.set_title(f"PCA+KMeans (3D) – {name}", pad=10)
    ax.set_xlabel("PC1"); ax.set_ylabel("PC2"); ax.set_zlabel("PC3")
    leg = ax.legend(title=None, loc="best", fontsize=9, frameon=True)
    if leg and leg.get_frame(): leg.get_frame().set_alpha(0.9)
    plt.tight_layout()
    plt.show()

def plot_space_for_bow_3d(model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    vec = model.named_steps["vec"]
    X_all = vec.transform(df_text)
    X_dense = X_all.toarray()
    pca = PCA(n_components=3, random_state=RANDOM_STATE).fit(X_dense)
    X_3d = pca.transform(X_dense)
    h_3d = pca.transform(vec.transform([highlight_text]).toarray())
    pca_kmeans_plot_3d("BoW", X_3d, df_labels.values, df_text.values, h_3d, highlight_text,
                       annotate_points=annotate_points, max_points=max_points)

def plot_space_for_tfidf_3d(model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    vec = model.named_steps["vec"]
    X_all = vec.transform(df_text)
    X_dense = X_all.toarray()
    pca = PCA(n_components=3, random_state=RANDOM_STATE).fit(X_dense)
    X_3d = pca.transform(X_dense)
    h_3d = pca.transform(vec.transform([highlight_text]).toarray())
    pca_kmeans_plot_3d("TF-IDF", X_3d, df_labels.values, df_text.values, h_3d, highlight_text,
                       annotate_points=annotate_points, max_points=max_points)

def plot_space_for_sbert_3d(sbert_model, df_text, df_labels, highlight_text, annotate_points: bool = False, max_points: int | None = None):
    all_emb = sbert_model.encode(pd.Series(df_text).astype(str).tolist(), convert_to_numpy=True, batch_size=BATCH_SIZE)
    pca = PCA(n_components=3, random_state=RANDOM_STATE).fit(all_emb)
    X_3d = pca.transform(all_emb)
    h_3d = pca.transform(sbert_model.encode([highlight_text], convert_to_numpy=True, batch_size=BATCH_SIZE))
    pca_kmeans_plot_3d("SBERT", X_3d, df_labels.values, df_text.values, h_3d, highlight_text,
                       annotate_points=annotate_points, max_points=max_points)
```

```python
#%% ---------- Modelle trainieren und evaluieren ----------
def train_bow(X_train, y_train):
    pipe = Pipeline([
        ("vec", CountVectorizer(token_pattern=TOKEN_PATTERN)),
        ("clf", LogisticRegression(max_iter=1000, random_state=RANDOM_STATE))
    ])
    return pipe.fit(X_train, y_train)

def train_tfidf(X_train, y_train):
    pipe = Pipeline([
        ("vec", TfidfVectorizer(ngram_range=(1,2), token_pattern=TOKEN_PATTERN)),
        ("clf", LogisticRegression(max_iter=1000, random_state=RANDOM_STATE))
    ])
    return pipe.fit(X_train, y_train)

def train_sbert(X_train, y_train, model_name=SBERT_MODEL_NAME, batch_size=BATCH_SIZE):
    from sentence_transformers import SentenceTransformer
    sbert_model = SentenceTransformer(model_name)
    Xt = pd.Series(X_train).astype(str).tolist()
    emb_train = sbert_model.encode(Xt, convert_to_numpy=True, batch_size=batch_size)
    sbert_clf = LogisticRegression(max_iter=1000, random_state=RANDOM_STATE).fit(emb_train, y_train)
    return sbert_model, sbert_clf

# Clean & Raw nebeneinander halten
df = df.drop_duplicates(subset=["text"]).reset_index(drop=True)
df["text_clean"] = df["text"].astype(str).apply(preprocess_text)

# identische Indizes splitten
X_tr_clean, X_te_clean, y_train, y_test = train_test_split(
    df["text_clean"], df["label"], test_size=0.25,
    random_state=RANDOM_STATE, stratify=df["label"])

# die korrespondierenden Rohtexte ziehen:
X_tr_raw   = df.loc[X_tr_clean.index, "text"]
X_te_raw   = df.loc[X_te_clean.index, "text"]

# Train
bow   = train_bow(X_tr_clean, y_train)
```

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tfidf = train_tfidf(X_tr_clean, y_train)
sbert_model, sbert_clf = train_sbert(X_tr_raw, y_train)

# Eval
eval_model("BoW + LogisticRegression", bow,   X_te_clean, y_test)
eval_model("TF-IDF + LogisticRegression",     tfidf,     X_te_clean, y_test)
eval_sbert(sbert_model, sbert_clf, X_te_raw, y_test)


#%% ---------- Visualisierung ----------
# 2D
plot_space_for_bow(bow,   df["text_clean"], df["label"], preprocess_text(HIGHLIGHT_TEXT), annotate_points=False, max_points=100)
plot_space_for_tfidf(tfidf, df["text_clean"], df["label"], preprocess_text(HIGHLIGHT_TEXT), annotate_points=True, max_points=20)
plot_space_for_sbert(sbert_model, df["text"], df["label"], HIGHLIGHT_TEXT, annotate_points=True, max_points=9)

# 3D
plot_space_for_bow_3d(bow,   df["text_clean"], df["label"], preprocess_text(HIGHLIGHT_TEXT), annotate_points=False, max_points=200)
plot_space_for_tfidf_3d(tfidf, df["text_clean"], df["label"], preprocess_text(HIGHLIGHT_TEXT), annotate_points=False, max_points=200)
plot_space_for_sbert_3d(sbert_model, df["text"], df["label"], HIGHLIGHT_TEXT, annotate_points=False, max_points=200)


#%% ---------- Interaktive Schleife ----------
print("\nInteraktive Eingabe (leer lassen zum Beenden):")
while True:
    try:
        user_text = input("> ").strip()
    except (EOFError, KeyboardInterrupt):
        break
    if not user_text:
        break

    # Konsistente Inputs
    raw_inp   = user_text
    clean_inp = preprocess_text(user_text)

    # --- Top-Labels ---
    bow_pred   = bow.predict([clean_inp])[0]
    tfidf_pred = tfidf.predict([clean_inp])[0]
    sbert_pred = sbert_predict(sbert_model, sbert_clf, [raw_inp])[0]
```

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# --- Wahrscheinlichkeiten/Gewichtungen ---
bow_probs   = probs_pipeline(bow,   [clean_inp])[0]
tfidf_probs = probs_pipeline(tfidf, [clean_inp])[0]
sbert_probs = sbert_predict_proba(sbert_model, sbert_clf, [raw_inp])[0]

print("\n— Ergebnisse —")
print("BoW   ->", bow_pred,   " | ", format_probs(bow_probs))
print("TF-IDF->", tfidf_pred, " | ", format_probs(tfidf_probs))
print("SBERT ->", sbert_pred, " | ", format_probs(sbert_probs))
print()
print()
```