Activity 3 Naive Bayes

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Introduction

In this notebook, I implemented a Naive Bayes text classifier for the X dataset with three classes: positive, negative, and neutral. My solution will do the following:

- Adapt Naive Bayes to multiple classes.
- Use Bag of Wordsfor encoding the text into vectors
- Train/evaluate with feature sizes: 20, 40, 60, 80, 100, 120 (top most frequent tokens).
- Perform K-Fold Cross-Validation for K with values {3, 4, 5, 6}.
- Compute macro-precision, macro-recall, macro-F1, and accuracy.
- Provide six visualizations to understand behavior across settings.
- Compare manual implementation vs scikit-learn.
- Provide a brief conclusion.

In [1]:
```
base_path = "dataset/"

import os

train_file = os.path.join(base_path, "training.txt")
test_file  = os.path.join(base_path, "test.txt")

if not (os.path.exists(train_file) and os.path.exists(test_file)):
    print("WARNING: training.txt and/or test.txt not found in:", base_path)
```

Loading, Vocabulary, and Vectorization with bag of worda

In [2]:
```
import codecs
import operator
from collections import Counter, defaultdict

def load_labeled_lines(path):
    """
    Load lines in the 'text @@@ label' format.
    Returns: list of (tokens_list, label)
    """
    samples = []
    with codecs.open(path, "r", "UTF-8") as f:
        for line in f:
            line = line.strip()
            if not line:
                continue
            parts = line.split("@@@")
            if len(parts) != 2:
                continue
            text, label = parts[0].strip(), parts[1].strip()
            tokens = text.split()
            samples.append((tokens, label))
    return samples

def build_vocabulary(training_samples):
    """
    Build token frequency dictionary from training samples.
    Returns a list of tokens sorted by global frequency (desc).
    """
    vocab_counter = Counter()
    for tokens, _ in training_samples:
        vocab_counter.update(tokens)
    sorted_vocab = sorted(vocab_counter.items(), key=lambda kv: (-kv[1], kv[
    return [tok for tok, cnt in sorted_vocab]

def vectorize_bow(samples, features):
    """
    Convert samples to Bag-of-Words count vectors given a 'features' list (t
    Returns X (list of lists) and y (labels).
    """
    idx = {tok: i for i, tok in enumerate(features)}
    X = []
    y = []
    for tokens, label in samples:
        counts = Counter(tokens)
        vec = [0]*len(features)
        for t, c in counts.items():
            if t in idx:
                vec[idx[t]] = c  # frequency count
        X.append(vec)
```

```
        y.append(label)
    return X, y
```

3.1 Load Dataset

In [3]:
```
train_samples = load_labeled_lines(train_file)
test_samples  = load_labeled_lines(test_file)

print(f"Train samples: {len(train_samples)} | Test samples: {len(test_sample
labels_set = sorted({lab for _, lab in train_samples})
print("Detected classes:", labels_set)
```

```
Train samples: 4187 | Test samples: 867
Detected classes: ['c', 'negative', 'neutral', 'positive']
```

3.2 Feature Selection (Top-N) and BOW Vectors

Build global vocabulary from training set

In [4]:
```
vocabulary = build_vocabulary(train_samples)
print("Top 10 tokens in vocabulary:", vocabulary[:10])

def make_vectors(topN):
    features = vocabulary[:topN]
    X_train, y_train = vectorize_bow(train_samples, features)
    X_test,  y_test  = vectorize_bow(test_samples, features)
    return features, X_train, y_train, X_test, y_test

_ = make_vectors(40)
```

```
Top 10 tokens in vocabulary: ['the', 'to', 'in', 'on', 'a', 'and', 'i', 'o
f', 'for', 'is']
```

Manual Naive Bayes wirh bag of words

In [7]:
```
import math
from collections import Counter
import numpy as np

def train_naive_bayes_multiclass(X, y, alpha=1.0):
    """
    Train the model

    Used ChatGPT5 in order to implement the algorithm with optimal settings
    """
    n_docs = len(X)
    n_features = len(X[0]) if X else 0
    classes = sorted(set(y))

    class_counts = Counter(y)
```

```
    priors_log = {c: math.log(class_counts[c] / n_docs) for c in classes}

    feature_counts_per_class = {c: [0]*n_features for c in classes}
    total_counts_per_class = {c: 0 for c in classes}
    for vec, lab in zip(X, y):
        total_counts_per_class[lab] += sum(vec)
        fc = feature_counts_per_class[lab]
        for i, cnt in enumerate(vec):
            fc[i] += cnt

    cond_logprob = {c: [0]*n_features for c in classes}
    for c in classes:
        denom = total_counts_per_class[c] + alpha * n_features
        for i in range(n_features):
            num = feature_counts_per_class[c][i] + alpha
            cond_logprob[c][i] = math.log(num / denom)
    return {"classes": classes, "priors_log": priors_log, "cond_logprob": cc

def predict_naive_bayes(model, X):
    classes = model["classes"]
    priors_log = model["priors_log"]
    cond_logprob = model["cond_logprob"]
    preds = []
    for vec in X:
        scores = {}
        for c in classes:
            s = priors_log[c]
            clp = cond_logprob[c]
            for i, cnt in enumerate(vec):
                if cnt:
                    s += cnt * clp[i]
            scores[c] = s

        pred = max(scores.items(), key=lambda kv: kv[1])[0]
        preds.append(pred)
    return preds
```

Evaluation: Accuracy, Macro-Precision, Macro-Recall, Macro-F1 with K-Fold

In [11]:

```
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
import numpy as np

def evaluate_model_cv_manual(X, y, k=5, alpha=1.0, random_state=42):
    """
    K-Fold evaluation for the manual model.
    """
    X = np.array(X, dtype=object)
    y = np.array(y)
    kf = KFold(n_splits=k, shuffle=True, random_state=random_state)
    accs, precs, recs, f1s = [], [], [], []
    cm_sum = None
```

```
    classes = sorted(set(y))

    for train_idx, test_idx in kf.split(X):
        X_tr = [list(map(int, x)) for x in X[train_idx]]
        y_tr = list(y[train_idx])
        X_te = [list(map(int, x)) for x in X[test_idx]]
        y_te = list(y[test_idx])

        model = train_naive_bayes_multiclass(X_tr, y_tr, alpha=alpha)
        preds = predict_naive_bayes(model, X_te)

        accs.append(accuracy_score(y_te, preds))
        precs.append(precision_score(y_te, preds, average='macro', zero_divi
        recs.append(recall_score(y_te, preds, average='macro', zero_divisior
        f1s.append(f1_score(y_te, preds, average='macro', zero_division=0))

        cm = confusion_matrix(y_te, preds, labels=classes)
        cm_sum = cm if cm_sum is None else cm_sum + cm

    results = {
        "classes": classes,
        "accuracy": np.array(accs),
        "precision_macro": np.array(precs),
        "recall_macro": np.array(recs),
        "f1_macro": np.array(f1s),
        "confusion_matrix_sum": cm_sum
    }
    return results

def manual_valuation(feature_grid=(20,40,60,80,100,120), k_grid=(3,4,5,6), a
    """
    Run the required grid over feature sizes and K folds. Returns a list of
    """
    out = []
    for topN in feature_grid:
        features, X_train, y_train, _, _ = make_vectors(topN)
        for k in k_grid:
            res = evaluate_model_cv_manual(X_train, y_train, k=k, alpha=alph
            out.append({
                "topN": topN,
                "k": k,
                "acc_mean": float(res["accuracy"].mean()),
                "prec_mean": float(res["precision_macro"].mean()),
                "rec_mean": float(res["recall_macro"].mean()),
                "f1_mean": float(res["f1_macro"].mean()),
                "acc_std": float(res["accuracy"].std()),
                "prec_std": float(res["precision_macro"].std()),
                "rec_std": float(res["recall_macro"].std()),
                "f1_std": float(res["f1_macro"].std()),
            })
    return out
```

5.1 Run Experiments Grid (Manual NB)

In [12]:
```python
import pandas as pd

manual_results = manual_valuation()
df_manual = pd.DataFrame(manual_results).sort_values(["topN","k"]).reset_inc
df_manual
```

Out[12]:

	topN	k	acc_mean	prec_mean	rec_mean	f1_mean	acc_std	prec_std	rec_
0	20	3	0.529735	0.369391	0.309403	0.235185	0.001926	0.083361	0.041
1	20	4	0.528780	0.355678	0.315614	0.239758	0.004984	0.068917	0.038
2	20	5	0.527822	0.356579	0.320054	0.245051	0.010707	0.049813	0.035
3	20	6	0.526632	0.329599	0.320809	0.242675	0.009729	0.071195	0.034
4	40	3	0.529497	0.379736	0.333727	0.293638	0.002660	0.065470	0.046
5	40	4	0.529496	0.392907	0.338982	0.296533	0.006146	0.070607	0.043
6	40	5	0.526388	0.389812	0.341503	0.298981	0.013026	0.060110	0.039
7	40	6	0.527110	0.396779	0.345789	0.302884	0.007504	0.052688	0.035
8	60	3	0.539290	0.413797	0.369232	0.354981	0.006439	0.058926	0.044
9	60	4	0.537859	0.417453	0.375282	0.359463	0.009221	0.047388	0.036
10	60	5	0.535944	0.425722	0.380013	0.364393	0.013293	0.053951	0.040
11	60	6	0.535229	0.425653	0.381374	0.364005	0.011688	0.058736	0.041
12	80	3	0.545261	0.431353	0.392071	0.389025	0.009545	0.057066	0.049
13	80	4	0.547409	0.444011	0.403051	0.400168	0.004541	0.059957	0.047
14	80	5	0.543826	0.444399	0.405080	0.401202	0.011647	0.052587	0.042
15	80	6	0.544778	0.451967	0.410038	0.406096	0.010597	0.060548	0.047
16	100	3	0.545742	0.429509	0.399312	0.398516	0.016023	0.050795	0.043
17	100	4	0.551948	0.449583	0.415430	0.415675	0.006647	0.059252	0.048
18	100	5	0.550516	0.451943	0.417325	0.416293	0.013132	0.051808	0.041
19	100	6	0.545497	0.450501	0.418036	0.416526	0.014872	0.058780	0.047
20	120	3	0.548127	0.434904	0.407806	0.408993	0.010854	0.058463	0.051
21	120	4	0.551946	0.449954	0.421069	0.422731	0.013318	0.064271	0.053
22	120	5	0.551469	0.456761	0.425632	0.426795	0.011378	0.057315	0.047
23	120	6	0.546213	0.452649	0.423450	0.423710	0.010207	0.054124	0.044

Scikit-learn MultinomialNB Baseline and Cross-Validation

In [16]:

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_validate
import numpy as np
import pandas as pd

def sklearn_cv_for_grid(feature_grid=(20,40,60,80,100,120), k_grid=(3,4,5,6)
    rows = []
    for topN in feature_grid:
        features, X_train, y_train, _, _ = make_vectors(topN)
        X_train = np.array(X_train)
        y_train = np.array(y_train)
        for k in k_grid:
            model = MultinomialNB(alpha=alpha)
            scoring = ['accuracy', 'precision_macro', 'recall_macro', 'f1_ma
            cvres = cross_validate(model, X_train, y_train, cv=k, scoring=sc
            rows.append({
                "topN": topN,
                "k": k,
                "acc_mean": float(cvres['test_accuracy'].mean()),
                "prec_mean": float(cvres['test_precision_macro'].mean()),
                "rec_mean": float(cvres['test_recall_macro'].mean()),
                "f1_mean": float(cvres['test_f1_macro'].mean()),
                "acc_std": float(cvres['test_accuracy'].std()),
                "prec_std": float(cvres['test_precision_macro'].std()),
                "rec_std": float(cvres['test_recall_macro'].std()),
                "f1_std": float(cvres['test_f1_macro'].std()),
            })
    return pd.DataFrame(rows).sort_values(["topN","k"]).reset_index(drop=Tru

df_skl = sklearn_cv_for_grid()
df_skl
```

Out[16]:

	topN	k	acc_mean	prec_mean	rec_mean	f1_mean	acc_std	prec_std	rec_
0	20	3	0.527346	0.340000	0.309376	0.238713	0.004179	0.031499	0.039
1	20	4	0.527346	0.364278	0.316948	0.245936	0.004656	0.053309	0.035
2	20	5	0.528778	0.360566	0.320030	0.244281	0.003314	0.055205	0.030
3	20	6	0.529496	0.373894	0.323891	0.248200	0.006029	0.070892	0.033
4	40	3	0.523523	0.360165	0.326751	0.285104	0.005261	0.027231	0.039
5	40	4	0.516596	0.352268	0.331360	0.291800	0.011149	0.038676	0.035
6	40	5	0.523527	0.388624	0.340254	0.297971	0.009897	0.075091	0.038
7	40	6	0.524717	0.382796	0.343719	0.301034	0.011427	0.062255	0.038
8	60	3	0.536421	0.406076	0.368229	0.355289	0.004370	0.048710	0.050
9	60	4	0.533315	0.415222	0.376639	0.365606	0.009299	0.053335	0.048
10	60	5	0.538097	0.431050	0.382103	0.367725	0.013440	0.063816	0.045
11	60	6	0.536183	0.421989	0.382632	0.366921	0.007532	0.049876	0.041
12	80	3	0.542390	0.422377	0.389434	0.386076	0.010021	0.047148	0.050
13	80	4	0.544062	0.440795	0.404836	0.405053	0.008777	0.055803	0.049
14	80	5	0.546458	0.449502	0.406809	0.403914	0.012960	0.059753	0.048
15	80	6	0.539287	0.436971	0.404116	0.399929	0.007490	0.047570	0.040
16	100	3	0.547884	0.431246	0.401667	0.400661	0.006476	0.052783	0.055
17	100	4	0.545496	0.443254	0.412739	0.414251	0.007798	0.057882	0.053
18	100	5	0.550036	0.455921	0.419609	0.419933	0.008356	0.052570	0.045
19	100	6	0.545735	0.449664	0.419630	0.418592	0.008808	0.048734	0.041
20	120	3	0.543108	0.427559	0.403845	0.403695	0.009670	0.062178	0.062
21	120	4	0.545021	0.444516	0.418456	0.421274	0.007547	0.058060	0.055
22	120	5	0.549082	0.453947	0.423172	0.424110	0.003666	0.047010	0.043
23	120	6	0.545738	0.450717	0.425202	0.425579	0.006452	0.045242	0.041

Results Comparison — Manual vs Scikit-learn

In [17]:

```
df_compare = (df_manual
              .merge(df_skl, on=["topN","k"], suffixes=("_manual","_skl")))
df_compare
```

Out[17]:

	topN	k	acc_mean_manual	prec_mean_manual	rec_mean_manual	f1_mean_mar
0	20	3	0.529735	0.369391	0.309403	0.235
1	20	4	0.528780	0.355678	0.315614	0.2397
2	20	5	0.527822	0.356579	0.320054	0.245
3	20	6	0.526632	0.329599	0.320809	0.2420
4	40	3	0.529497	0.379736	0.333727	0.2936
5	40	4	0.529496	0.392907	0.338982	0.2965
6	40	5	0.526388	0.389812	0.341503	0.298
7	40	6	0.527110	0.396779	0.345789	0.3028
8	60	3	0.539290	0.413797	0.369232	0.354
9	60	4	0.537859	0.417453	0.375282	0.3594
10	60	5	0.535944	0.425722	0.380013	0.3643
11	60	6	0.535229	0.425653	0.381374	0.3640
12	80	3	0.545261	0.431353	0.392071	0.3890
13	80	4	0.547409	0.444011	0.403051	0.400
14	80	5	0.543826	0.444399	0.405080	0.4012
15	80	6	0.544778	0.451967	0.410038	0.4060
16	100	3	0.545742	0.429509	0.399312	0.398
17	100	4	0.551948	0.449583	0.415430	0.4150
18	100	5	0.550516	0.451943	0.417325	0.4162
19	100	6	0.545497	0.450501	0.418036	0.4165
20	120	3	0.548127	0.434904	0.407806	0.4089
21	120	4	0.551946	0.449954	0.421069	0.422
22	120	5	0.551469	0.456761	0.425632	0.4267
23	120	6	0.546213	0.452649	0.423450	0.423

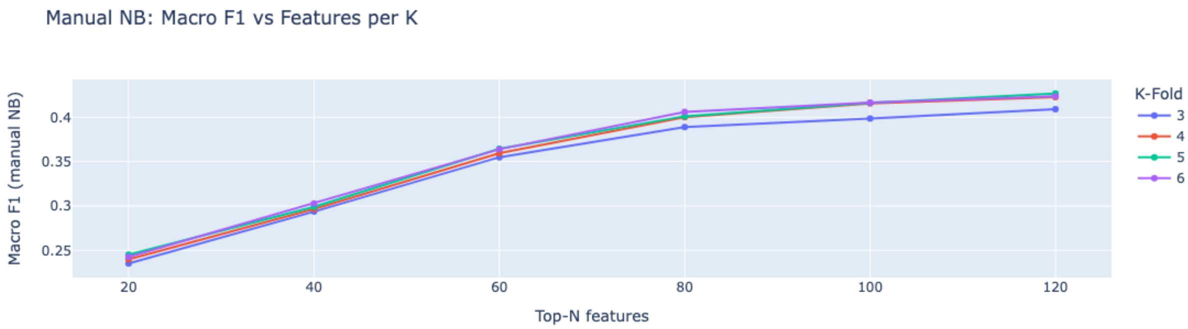
Visualizations

In [19]:

```
import plotly.express as px
import plotly.graph_objects as go
```

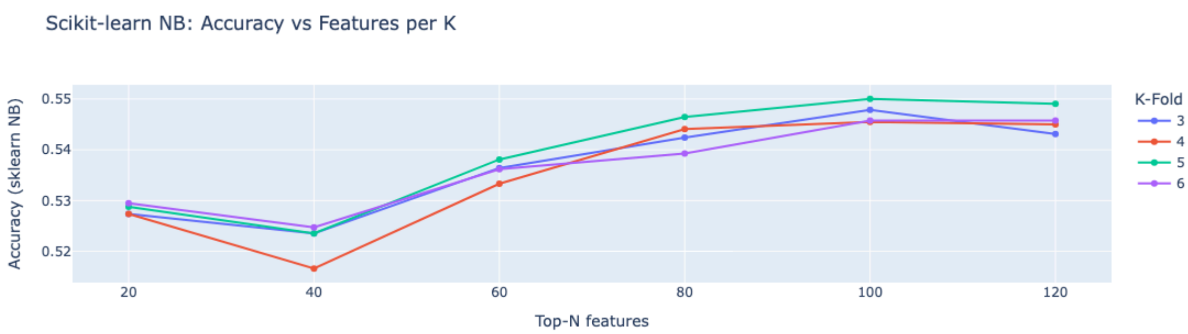
a) F1 vs features for each K (manual)

```
In [20]: fig1 = px.line(df_manual, x="topN", y="f1_mean", color="k", markers=True,
                        title="Manual NB: Macro F1 vs Features per K",
                        labels={"topN": "Top-N features", "f1_mean": "Macro F1 (manua
         fig1.show()
```



b) Accuracy vs features (sklearn)

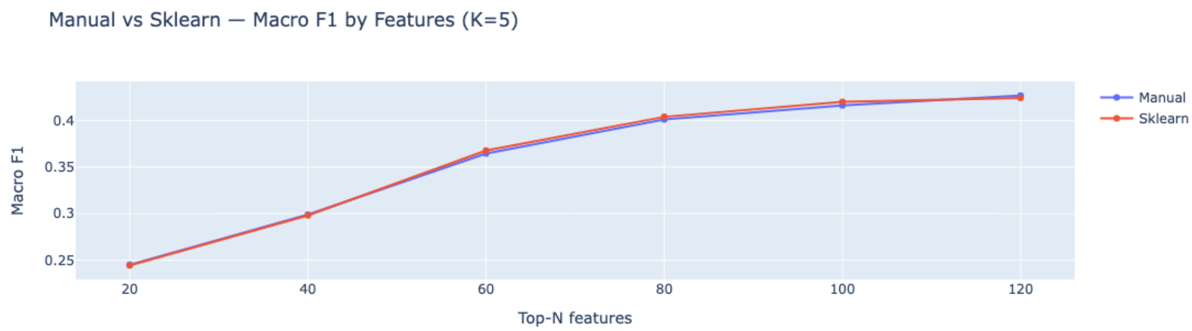
```
In [21]: fig2 = px.line(df_skl, x="topN", y="acc_mean", color="k", markers=True,
                        title="Scikit-learn NB: Accuracy vs Features per K",
                        labels={"topN": "Top-N features", "acc_mean": "Accuracy (skle
         fig2.show()
```



c) Manual vs sklearn F1 (grouped by features) for a fixed K=5

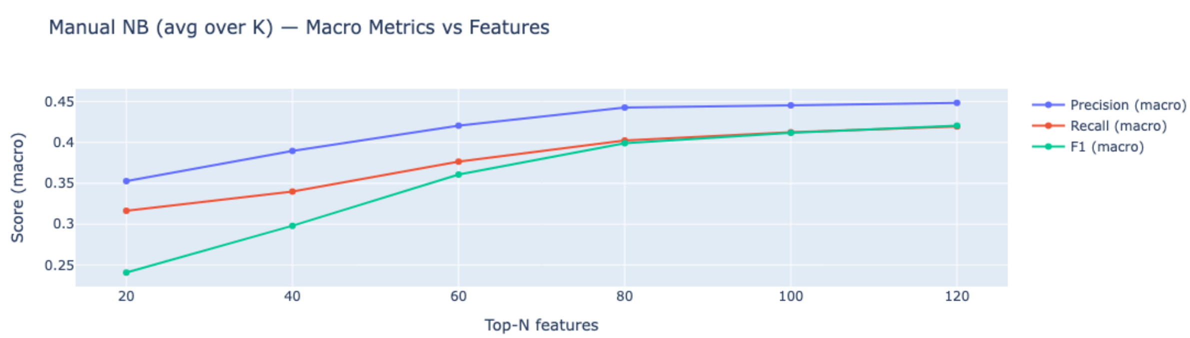
```
In [22]: k_fixed = 5 if 5 in set(df_manual['k']) else sorted(df_manual['k'].unique())
         m_fixed = df_manual[df_manual['k']==k_fixed]
         s_fixed = df_skl[df_skl['k']==k_fixed]

         fig3 = go.Figure()
         fig3.add_trace(go.Scatter(x=m_fixed["topN"], y=m_fixed["f1_mean"], mode="lir
         fig3.add_trace(go.Scatter(x=s_fixed["topN"], y=s_fixed["f1_mean"], mode="lir
         fig3.update_layout(title=f"Manual vs Sklearn — Macro F1 by Features (K={k_fi
                            xaxis_title="Top-N features", yaxis_title="Macro F1")
         fig3.show()
```



d) Macro Precision/Recall/F1 (manual) vs features (averaged over K)

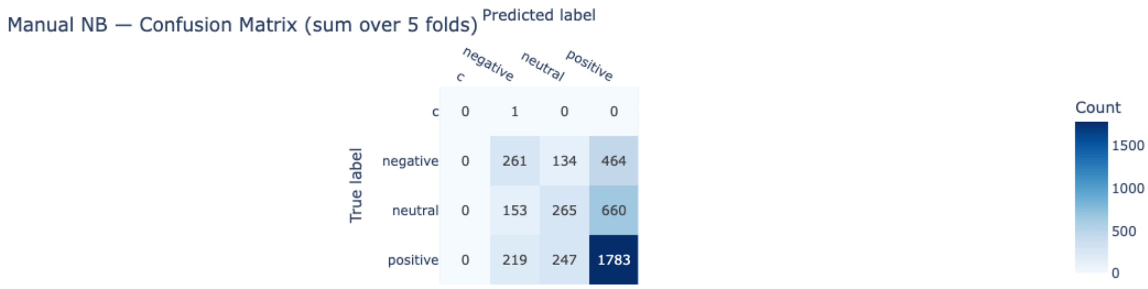
In [23]:
```
agg = df_manual.groupby('topN')[['prec_mean','rec_mean','f1_mean']].mean().r
fig4 = go.Figure()
fig4.add_trace(go.Scatter(x=agg["topN"], y=agg["prec_mean"], mode="lines+mar
fig4.add_trace(go.Scatter(x=agg["topN"], y=agg["rec_mean"], mode="lines+mark
fig4.add_trace(go.Scatter(x=agg["topN"], y=agg["f1_mean"], mode="lines+marke
fig4.update_layout(title="Manual NB (avg over K) — Macro Metrics vs Features
                   xaxis_title="Top-N features", yaxis_title="Score (macro)"
fig4.show()
```



e) Best setting confusion matrix (manual)

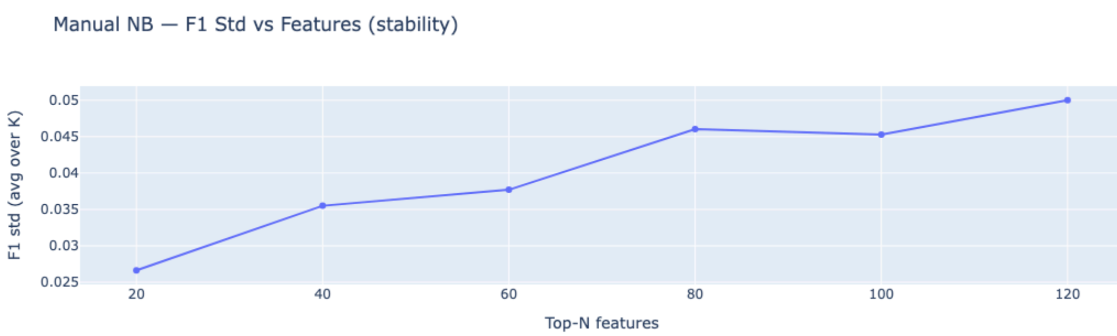
In [24]:
```
best_row = df_manual.iloc[df_manual['f1_mean'].idxmax()]
best_topN = int(best_row['topN']); best_k = int(best_row['k'])
features, X_train_full, y_train_full, _, _ = make_vectors(best_topN)
res_best = evaluate_model_cv_manual(X_train_full, y_train_full, k=best_k)
cm = res_best['confusion_matrix_sum']
classes = res_best['classes']

fig5 = px.imshow(cm, text_auto=True, color_continuous_scale="Blues",
                 x=classes, y=classes,
                 labels=dict(x="Predicted label", y="True label", color="Cou
                 title=f"Manual NB — Confusion Matrix (sum over {best_k} fol
fig5.update_xaxes(side="top")
fig5.show()
```



f) Stability (std) plot: F1 std vs features (manual)

In [25]:
```
std_agg = df_manual.groupby('topN')['f1_std'].mean().reset_index()
fig6 = px.line(std_agg, x="topN", y="f1_std", markers=True,
               title="Manual NB — F1 Std vs Features (stability)",
               labels={"topN": "Top-N features", "f1_std": "F1 std (avg over
fig6.show()
```



Findings and Conclussion

Through the model imlementation, I found out that this dataset alongside this Naive Bayes implementation was a complete failure. With b oth the manual model implementation and the sklearn one, I just got a maximum of 54% accuracy using Kfold cross validation, which is a total waste of time and resources. The model acts slightly better than tossing a dice for classifying the sentiment on the given texts.

What got my attention, is that even with the sklearn library, the model accuracy does not improve.

I can conclude that the problem is the poor training a test data labeling. Inspecting the dataset manually, I found out that effectively the labeling is incongruent, and appears to be work of a randome classification, which explains a little bit the results I got

Even though the result I got are not good, with this activity I learned the basics of the Naive Bayes algorithm and its use cases in real life scenarios