Credit Default Modeling (Utility-Focused, Multi-Seed)

Utility-based comparison of Logistic Regression, Decision Tree, SVM (RBF), Gaussian Naive Bayes, and k-NN on the UCI credit card default data.

1. Imports

Load analysis, modeling, and plotting libraries. `xlrd` is pulled in for the Excel source file.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from pathlib import Path
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_sc
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    roc_curve,
    confusion_matrix,
)

sns.set_theme(style="whitegrid")
pd.set_option("display.max_columns", 40)
```

2. Load the data

Read the Excel file, rename the target column to `TARGET`, and preview the dataset.

In [2]:
```
DATA_FILE = Path("default of credit card clients.xls")
if not DATA_FILE.exists():
    DATA_FILE = Path("Code") / "Final Project" / "default of credit card clients.xl

if not DATA_FILE.exists():
    raise FileNotFoundError(f"Could not find data file at {DATA_FILE}")
```

```
raw_df = (
    pd.read_excel(DATA_FILE, header=1)
    .rename(columns={"default payment next month": "TARGET"})
)

print(f"Loaded {raw_df.shape[0]:,} rows and {raw_df.shape[1]} columns.")
raw_df.head()
```

Loaded 30,000 rows and 25 columns.

Out[2]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_
0	1	20000	2	2	1	24	2	2	-1	-1	-
1	2	120000	2	2	2	26	-1	2	0	0	
2	3	90000	2	2	2	34	0	0	0	0	
3	4	50000	2	2	1	37	0	0	0	0	
4	5	50000	1	2	1	57	-1	0	-1	0	

3. Split features and target

Separate predictors (`X`) from the binary target (`y`).

In [3]:

```
X = raw_df.drop(columns="TARGET")
y = raw_df["TARGET"].astype(int)

print(f"Feature matrix shape: {X.shape}")
print(f"Target breakdown: {y.value_counts().to_dict()}")
display(X.head(), y.head())
```

```
Feature matrix shape: (30000, 24)
Target breakdown: {0: 23364, 1: 6636}
```

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5
0	1	20000	2	2	1	24	2	2	-1	-1	-2
1	2	120000	2	2	2	26	-1	2	0	0	0
2	3	90000	2	2	2	34	0	0	0	0	0
3	4	50000	2	2	1	37	0	0	0	0	0
4	5	50000	1	2	1	57	-1	0	-1	0	0

```
0    1
1    1
2    0
3    0
4    0
Name: TARGET, dtype: int64
```

4. Reusable splits and scalers (shared across seeds)

Build consistent train/validation/test splits for each seed and fit a scaler per seed. All models reuse these splits to stay comparable across seeds.

In [4]:
```
SEED_PLAN = [2025, 0, 1033]
VAL_SEED = 0
BASELINE_SEED = SEED_PLAN[0]


def build_split_bundle(split_seed, val_seed=VAL_SEED):
    X_train, X_test, y_train, y_test = train_test_split(
        X,
        y,
        test_size=0.2,
        random_state=split_seed,
        stratify=y,
    )

    X_train_sub, X_val, y_train_sub, y_val = train_test_split(
        X_train,
        y_train,
        test_size=0.25,
        random_state=val_seed,
        stratify=y_train,
    )

    scaler = StandardScaler()
    scaler.fit(X_train_sub)

    return {
        "seed": split_seed,
        "X_train_sub": X_train_sub,
        "X_val": X_val,
        "X_test": X_test,
        "y_train_sub": y_train_sub,
        "y_val": y_val,
        "y_test": y_test,
        "scaler": scaler,
        "X_train_sub_scaled": scaler.transform(X_train_sub),
        "X_val_scaled": scaler.transform(X_val),
        "X_test_scaled": scaler.transform(X_test),
    }


split_store = {s: build_split_bundle(s, val_seed=VAL_SEED) for s in SEED_PLAN}
baseline_split = split_store[BASELINE_SEED]

display(
    {
        "seed": BASELINE_SEED,
        "train_sub": baseline_split["X_train_sub"].shape,
        "val": baseline_split["X_val"].shape,
```

```
        "test": baseline_split["X_test"].shape,
    }
)
```

```
{'seed': 2025, 'train_sub': (18000, 24), 'val': (6000, 24), 'test': (6000, 24)}
```

5. Business assumptions and cost matrix

Derive monetary gains/losses from the PDF assumptions to evaluate models on profit rather than accuracy alone.

5.1 Observation window and APR assumptions

Compute profit from approving a good customer and loss from approving a bad customer over a six-month window.

In [5]:
```
df_default = raw_df[raw_df["TARGET"] == 1]   # will default
df_no_default = raw_df[raw_df["TARGET"] == 0]  # will not default

mean_limit_default = df_default["LIMIT_BAL"].mean()
mean_limit_no_default = df_no_default["LIMIT_BAL"].mean()

assumption_config = {
    "annual_apr": 0.18,            # 18% annual percentage rate from the data dictio
    "periods_per_year": 12,        # monthly compounding
    "observation_months": 6,       # six billing cycles (Apr-Sep 2005 in the PDF)
    "loss_given_default": 0.5,     # lose 50% of the limit if they default
}

annual_apr = assumption_config["annual_apr"]
periods_per_year = assumption_config["periods_per_year"]
observation_months = assumption_config["observation_months"]
loss_given_default = assumption_config["loss_given_default"]

periodic_rate = annual_apr / periods_per_year
period_length_months = 12 / periods_per_year
periods_in_window = observation_months / period_length_months

profit_good = mean_limit_no_default * ((1 + periodic_rate) ** periods_in_window - 1
loss_bad = mean_limit_default * loss_given_default

print(f"Periodic rate: {periodic_rate:.2%}")
print(f"Approx profit per good customer: {profit_good:,.2f}")
print(f"Approx loss per bad customer:    {loss_bad:,.2f}")
```

```
Periodic rate: 1.50%
Approx profit per good customer: 16,642.22
Approx loss per bad customer:    65,054.83
```

5.2 Cost/benefit matrix

Map actual/predicted outcomes to dollar values for the utility function.

In [6]:
```
value_TN = profit_good    # Actual 0, Pred 0: good customer, approved -> earn inter
value_FP = 0.0             # Actual 0, Pred 1: good customer, rejected -> forego p
value_FN = -loss_bad       # Actual 1, Pred 0: bad customer, approved -> lose mone
value_TP = 0.0             # Actual 1, Pred 1: bad customer, rejected -> avoided l

value_matrix = pd.DataFrame(
    {
        0: {0: value_TN, 1: value_FN},  # Predicted 0
        1: {0: value_FP, 1: value_TP},  # Predicted 1
    }
)
value_matrix.index.name = "Actual"
value_matrix.columns.name = "Predicted"
value_matrix
```

Out[6]:

Predicted	0	1
Actual		
0	16642.219712	0.0
1	-65054.828210	0.0

6. Utility and evaluation helpers

Shared helpers for threshold sweeps, utility calculation, and concise metric summaries.

In [7]:
```
CV_FOLDS = 5

THRESH_QUANTILES = np.linspace(0.05, 0.95, 19)

def score_predictions(model, features):
    if hasattr(model, "predict_proba"):
        return model.predict_proba(features)[:, 1]
    if hasattr(model, "decision_function"):
        return model.decision_function(features)
    return model.predict(features)

def utility_from_predictions(y_true, y_pred, values=value_matrix):
    cm = confusion_matrix(y_true, y_pred, labels=[0, 1])
    tn, fp, fn, tp = cm.ravel()
    utility_total = (
        tn * values.loc[0, 0]
        + fp * values.loc[0, 1]
        + fn * values.loc[1, 0]
        + tp * values.loc[1, 1]
    )
    utility_per_case = utility_total / len(y_true)
    return utility_total, utility_per_case, {"tn": tn, "fp": fp, "fn": fn, "tp": tp

def _utility(y_true, y_pred):
    return utility_from_predictions(y_true, y_pred, value_matrix)
```

```
def sweep_thresholds(y_true, scores, utility_fn, grid=None):
    grid = np.unique(np.quantile(scores, THRESH_QUANTILES)) if grid is None else gr
    records = []
    for t in grid:
        preds = (scores >= t).astype(int)
        utility_total, utility_pc, _ = utility_fn(y_true, preds)
        records.append(
            {
                "threshold": float(t),
                "utility": utility_total,
                "utility_per_case": utility_pc,
            }
        )
    best = max(records, key=lambda r: r["utility"])
    return {
        "threshold": best["threshold"],
        "val_utility": best["utility"],
        "val_utility_per_case": best["utility_per_case"],
        "sweep": pd.DataFrame(records),
    }

def summarize_model(
    model_name,
    dataset_name,
    y_true,
    y_pred,
    y_score,
    threshold,
    seed,
    utility_fn=_utility,
):
    tn, fp, fn, tp = confusion_matrix(y_true, y_pred, labels=[0, 1]).ravel()
    utility_total, utility_pc, _ = utility_fn(y_true, y_pred)
    roc_auc = roc_auc_score(y_true, y_score) if y_score is not None else np.nan

    total = len(y_pred)
    acceptance_rate = (tn + fn) / total  # predicted 0 = approved
    rejection_rate = (fp + tp) / total   # predicted 1 = rejected

    return pd.DataFrame(
        [
            {
                "model_name": model_name,
                "dataset_name": dataset_name,
                "seed": seed,
                "threshold": threshold,
                "roc_auc": roc_auc,
                "accuracy": accuracy_score(y_true, y_pred),
                "precision": precision_score(y_true, y_pred, zero_division=0),
                "recall": recall_score(y_true, y_pred, zero_division=0),
                "f1": f1_score(y_true, y_pred, zero_division=0),
                "utility_total": utility_total,
                "utility_per_case": utility_pc,
                "acceptance_rate": acceptance_rate,
                "rejection_rate": rejection_rate,
                "tp": tp,
```

```
                "fp": fp,
                "tn": tn,
                "fn": fn,
            }
        ]
    )

def run_model_for_seed(
    model,
    model_name,
    split_seed,
    use_scaled=True,
    threshold_grid=None,
):
    split = split_store[split_seed]
    suffix = "_scaled" if use_scaled else ""
    X_train = split[f"X_train_sub{suffix}"]
    X_val = split[f"X_val{suffix}"]
    X_test = split[f"X_test{suffix}"]
    y_train = split["y_train_sub"]
    y_val = split["y_val"]
    y_test = split["y_test"]

    model.fit(X_train, y_train)

    val_scores = score_predictions(model, X_val)
    sweep = sweep_thresholds(y_val, val_scores, _utility, grid=threshold_grid)

    test_scores = score_predictions(model, X_test)
    test_pred = (test_scores >= sweep["threshold"]).astype(int)

    summary = summarize_model(
        model_name=model_name,
        dataset_name=f"Test (seed={split_seed})",
        y_true=y_test,
        y_pred=test_pred,
        y_score=test_scores,
        threshold=sweep["threshold"],
        seed=split_seed,
    )

    return {
        "seed": split_seed,
        "model_name": model_name,
        "model": model,
        "threshold": sweep["threshold"],
        "val_sweep": sweep["sweep"],
        "val_utility": sweep["val_utility"],
        "summary": summary,
        "test_scores": test_scores,
        "test_pred": test_pred,
    }
```

7. Models trained across seeds

Train each model on the shared splits, tune thresholds on the validation fold, and evaluate on the test fold for all seeds.

7.1 Logistic Regression

In [8]:
```
# Logistic Regression helper with CV grid on C for generalization

def run_logreg_for_seed(
    split_seed,
    C_grid=(0.01, 0.1, 1.0, 10.0),
    threshold_grid=None,
    cv_folds=CV_FOLDS,
):
    split = split_store[split_seed]
    X_train = split['X_train_sub_scaled']
    y_train = split['y_train_sub']

    cv = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=split_seed)
    cv_rows = []
    best_mean = -float('inf')
    best_C = None

    for C in C_grid:
        model = LogisticRegression(
            penalty='l2',
            solver='liblinear',
            max_iter=500,
            random_state=split_seed,
            class_weight='balanced',
            C=C,
        )
        scores = cross_val_score(
            model,
            X_train,
            y_train,
            cv=cv,
            scoring='roc_auc',
            n_jobs=-1,
        )
        cv_mean = float(scores.mean())
        cv_std = float(scores.std())
        cv_rows.append({'C': C, 'cv_mean_auc': cv_mean, 'cv_std_auc': cv_std})
        if cv_mean > best_mean:
            best_mean = cv_mean
            best_C = C

    best_model = LogisticRegression(
        penalty='l2',
        solver='liblinear',
        max_iter=500,
        random_state=split_seed,
        class_weight='balanced',
        C=best_C,
    )
```

```
    result = run_model_for_seed(
        best_model,
        model_name='Logistic Regression',
        split_seed=split_seed,
        use_scaled=True,
        threshold_grid=threshold_grid,
    )
    result['cv_results'] = pd.DataFrame(cv_rows)
    result['cv_best_params'] = {'C': best_C, 'cv_mean_auc': best_mean}
    return result
```

In [9]:
```
logreg_runs = [run_logreg_for_seed(s) for s in SEED_PLAN]

logreg_summary_df = pd.concat([r['summary'] for r in logreg_runs], ignore_index=Tru
logreg_summary_df
```

Out[9]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall	
0	Logistic Regression	Test (seed=2025)	2025	0.546590	0.722885	0.757167	0.458546	0.541824	0
1	Logistic Regression	Test (seed=0)	0	0.547748	0.714051	0.767000	0.476126	0.533534	0
2	Logistic Regression	Test (seed=1033)	1033	0.510849	0.714182	0.701667	0.387457	0.600603	0

7.2 Decision Tree

In [10]:
```
# Decision Tree helper with CV grid on depth and min_samples_leaf

def run_dt_for_seed(
    split_seed,
    max_depth_grid=(None, 6, 10, 14),
    min_samples_leaf_grid=(5, 10, 20),
    threshold_grid=None,
    cv_folds=CV_FOLDS,
):
    split = split_store[split_seed]
    X_train = split['X_train_sub']
    y_train = split['y_train_sub']

    cv = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=split_seed)
    cv_rows = []
    best_mean = -float('inf')
    best_params = None

    for depth in max_depth_grid:
        for min_leaf in min_samples_leaf_grid:
            model = DecisionTreeClassifier(
                random_state=split_seed,
                max_depth=depth,
```

```
                min_samples_leaf=min_leaf,
                class_weight='balanced',
            )
            scores = cross_val_score(
                model,
                X_train,
                y_train,
                cv=cv,
                scoring='roc_auc',
                n_jobs=-1,
            )
            cv_mean = float(scores.mean())
            cv_std = float(scores.std())
            cv_rows.append(
                {
                    'max_depth': depth,
                    'min_samples_leaf': min_leaf,
                    'cv_mean_auc': cv_mean,
                    'cv_std_auc': cv_std,
                }
            )
            if cv_mean > best_mean:
                best_mean = cv_mean
                best_params = {'max_depth': depth, 'min_samples_leaf': min_leaf}

    best_model = DecisionTreeClassifier(
        random_state=split_seed,
        max_depth=best_params['max_depth'],
        min_samples_leaf=best_params['min_samples_leaf'],
        class_weight='balanced',
    )
    result = run_model_for_seed(
        best_model,
        model_name='Decision Tree',
        split_seed=split_seed,
        use_scaled=False,
        threshold_grid=threshold_grid,
    )
    result['cv_results'] = pd.DataFrame(cv_rows)
    result['cv_best_params'] = {**best_params, 'cv_mean_auc': best_mean}
    return result
```

In [11]:

```
dt_runs = [run_dt_for_seed(s) for s in SEED_PLAN]

dt_summary_df = pd.concat([r['summary'] for r in dt_runs], ignore_index=True)
dt_summary_df
```

Out[11]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall	
0	Decision Tree	Test (seed=2025)	2025	0.508695	0.744147	0.736667	0.432749	0.613414	0
1	Decision Tree	Test (seed=0)	0	0.467625	0.753210	0.682333	0.379925	0.690279	0
2	Decision Tree	Test (seed=1033)	1033	0.472664	0.749487	0.734667	0.427714	0.590806	0

7.3 SVM (RBF)

In [12]:

```python
# SVM (RBF) helper with CV grid on C and gamma

def run_svm_for_seed(
    split_seed,
    C_grid=(0.5, 1.0, 2.0, 5.0),
    gamma_grid=('scale', 'auto'),
    threshold_grid=None,
    cv_folds=CV_FOLDS,
):
    split = split_store[split_seed]
    X_train = split['X_train_sub_scaled']
    y_train = split['y_train_sub']

    cv = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=split_seed)
    cv_rows = []
    best_mean = -float('inf')
    best_params = None

    for C in C_grid:
        for gamma in gamma_grid:
            model = SVC(
                kernel='rbf',
                C=C,
                gamma=gamma,
                probability=False,
                class_weight='balanced',
                random_state=split_seed,
            )
            scores = cross_val_score(
                model,
                X_train,
                y_train,
                cv=cv,
                scoring='roc_auc',
                n_jobs=-1,
            )
            cv_mean = float(scores.mean())
            cv_std = float(scores.std())
            cv_rows.append(
                {
                    'C': C,
```

```
                    'gamma': gamma,
                    'cv_mean_auc': cv_mean,
                    'cv_std_auc': cv_std,
                }
            )
            if cv_mean > best_mean:
                best_mean = cv_mean
                best_params = {'C': C, 'gamma': gamma}

    best_model = SVC(
        kernel='rbf',
        C=best_params['C'],
        gamma=best_params['gamma'],
        probability=False,
        class_weight='balanced',
        random_state=split_seed,
    )
    result = run_model_for_seed(
        best_model,
        model_name='SVM (RBF)',
        split_seed=split_seed,
        use_scaled=True,
        threshold_grid=threshold_grid,
    )
    result['cv_results'] = pd.DataFrame(cv_rows)
    result['cv_best_params'] = {**best_params, 'cv_mean_auc': best_mean}
    return result
```

In [13]:

```
svm_runs = [run_svm_for_seed(s) for s in SEED_PLAN]

svm_summary_df = pd.concat([r['summary'] for r in svm_runs], ignore_index=True)
svm_summary_df
```

Out[13]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall	
0	SVM (RBF)	Test (seed=2025)	2025	-0.345015	0.754564	0.746833	0.447311	0.614167	0
1	SVM (RBF)	Test (seed=0)	0	0.057758	0.755656	0.777833	0.497965	0.553127	0
2	SVM (RBF)	Test (seed=1033)	1033	-0.553250	0.755029	0.722333	0.417196	0.643557	0

7.4 Naive Bayes (Gaussian)

In [14]:

```
# Naive Bayes helper with CV grid on var_smoothing

def run_nb_for_seed(
    split_seed,
    var_smoothing_grid=(1e-9, 1e-8, 1e-7, 1e-6),
    threshold_grid=None,
    cv_folds=CV_FOLDS,
):
```

```
    split = split_store[split_seed]
    X_train = split['X_train_sub_scaled']
    y_train = split['y_train_sub']

    cv = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=split_seed)
    cv_rows = []
    best_mean = -float('inf')
    best_vs = None

    for vs in var_smoothing_grid:
        model = GaussianNB(var_smoothing=vs)
        scores = cross_val_score(
            model,
            X_train,
            y_train,
            cv=cv,
            scoring='roc_auc',
            n_jobs=-1,
        )
        cv_mean = float(scores.mean())
        cv_std = float(scores.std())
        cv_rows.append({'var_smoothing': vs, 'cv_mean_auc': cv_mean, 'cv_std_auc':
        if cv_mean > best_mean:
            best_mean = cv_mean
            best_vs = vs

    best_model = GaussianNB(var_smoothing=best_vs)
    result = run_model_for_seed(
        best_model,
        model_name='Naive Bayes',
        split_seed=split_seed,
        use_scaled=True,
        threshold_grid=threshold_grid,
    )
    result['cv_results'] = pd.DataFrame(cv_rows)
    result['cv_best_params'] = {'var_smoothing': best_vs, 'cv_mean_auc': best_mean}
    return result
```

In [15]:

```
nb_runs = [run_nb_for_seed(s) for s in SEED_PLAN]

nb_summary_df = pd.concat([r['summary'] for r in nb_runs], ignore_index=True)
nb_summary_df
```

Out[15]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall	
0	Naive Bayes	Test (seed=2025)	2025	0.672817	0.729111	0.737667	0.432771	0.599096	0
1	Naive Bayes	Test (seed=0)	0	0.607381	0.717083	0.718667	0.410154	0.620950	0
2	Naive Bayes	Test (seed=1033)	1033	0.659000	0.736167	0.747667	0.446965	0.593821	0

7.5 k-NN

In [16]:
```
# k-NN-specific helper to train/evaluate per seed with CV-selected k

def run_knn_for_seed(
    split_seed,
    k_grid=(5, 10, 15, 20, 25, 30, 35, 40, 45, 50),
    threshold_grid=None,
    cv_folds=CV_FOLDS,
):
    split = split_store[split_seed]
    X_train = split['X_train_sub_scaled']
    X_val = split['X_val_scaled']
    X_test = split['X_test_scaled']
    y_train = split['y_train_sub']
    y_val = split['y_val']
    y_test = split['y_test']

    cv = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=split_seed)
    cv_rows = []
    best_mean = -float('inf')
    best_k = None

    for k in k_grid:
        model = KNeighborsClassifier(n_neighbors=k, weights='distance')
        scores = cross_val_score(
            model,
            X_train,
            y_train,
            cv=cv,
            scoring='roc_auc',
            n_jobs=-1,
        )
        cv_mean = float(scores.mean())
        cv_std = float(scores.std())
        cv_rows.append({'k': k, 'cv_mean_auc': cv_mean, 'cv_std_auc': cv_std})
        if cv_mean > best_mean:
            best_mean = cv_mean
            best_k = k

    best_model = KNeighborsClassifier(n_neighbors=best_k, weights='distance')
    best_model.fit(X_train, y_train)

    val_scores = score_predictions(best_model, X_val)
    sweep = sweep_thresholds(y_val, val_scores, _utility, grid=threshold_grid)

    test_scores = score_predictions(best_model, X_test)
    test_pred = (test_scores >= sweep['threshold']).astype(int)

    summary = summarize_model(
        model_name='k-NN',
        dataset_name=f'Test (seed={split_seed})',
        y_true=y_test,
        y_pred=test_pred,
        y_score=test_scores,
        threshold=sweep['threshold'],
        seed=split_seed,
```

```
    )

    return {
        'seed': split_seed,
        'model_name': 'k-NN',
        'model': best_model,
        'k': best_k,
        'threshold': sweep['threshold'],
        'val_sweep': sweep['sweep'],
        'val_utility': sweep['val_utility'],
        'summary': summary,
        'test_scores': test_scores,
        'test_pred': test_pred,
        'cv_results': pd.DataFrame(cv_rows),
        'cv_best_params': {'k': best_k, 'cv_mean_auc': best_mean},
    }
```

In [17]:

```
knn_runs = [run_knn_for_seed(s, k_grid=(5,10,15,20,25,30,35,40,45,50)) for s in SEE

knn_summary_df = pd.concat([r['summary'] for r in knn_runs], ignore_index=True)
knn_summary_df
```

Out[17]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall
0	k-NN	Test (seed=2025)	2025	0.219905	0.742380	0.732000	0.424259	0.593067	0
1	k-NN	Test (seed=0)	0	0.216621	0.741847	0.738167	0.431306	0.577242	0
2	k-NN	Test (seed=1033)	1033	0.239929	0.744933	0.771667	0.485384	0.538056	0

In [18]:

```
model_runs = {
    "Logistic Regression": logreg_runs,
    "Decision Tree": dt_runs,
    "SVM (RBF)": svm_runs,
    "Naive Bayes": nb_runs,
    "k-NN": knn_runs,
}

model_summary_frames = {
    "Logistic Regression": logreg_summary_df,
    "Decision Tree": dt_summary_df,
    "SVM (RBF)": svm_summary_df,
    "Naive Bayes": nb_summary_df,
    "k-NN": knn_summary_df,
}

combined_model_summaries = pd.concat(model_summary_frames.values(), ignore_index=Tr
combined_model_summaries
```

Out[18]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall
0	Logistic Regression	Test (seed=2025)	2025	0.546590	0.722885	0.757167	0.458546	0.541824
1	Logistic Regression	Test (seed=0)	0	0.547748	0.714051	0.767000	0.476126	0.533534
2	Logistic Regression	Test (seed=1033)	1033	0.510849	0.714182	0.701667	0.387457	0.600603
3	Decision Tree	Test (seed=2025)	2025	0.508695	0.744147	0.736667	0.432749	0.613414
4	Decision Tree	Test (seed=0)	0	0.467625	0.753210	0.682333	0.379925	0.690279
5	Decision Tree	Test (seed=1033)	1033	0.472664	0.749487	0.734667	0.427714	0.590806
6	SVM (RBF)	Test (seed=2025)	2025	-0.345015	0.754564	0.746833	0.447311	0.614167
7	SVM (RBF)	Test (seed=0)	0	0.057758	0.755656	0.777833	0.497965	0.553127
8	SVM (RBF)	Test (seed=1033)	1033	-0.553250	0.755029	0.722333	0.417196	0.643557
9	Naive Bayes	Test (seed=2025)	2025	0.672817	0.729111	0.737667	0.432771	0.599096
10	Naive Bayes	Test (seed=0)	0	0.607381	0.717083	0.718667	0.410154	0.620950
11	Naive Bayes	Test (seed=1033)	1033	0.659000	0.736167	0.747667	0.446965	0.593821
12	k-NN	Test (seed=2025)	2025	0.219905	0.742380	0.732000	0.424259	0.593067
13	k-NN	Test (seed=0)	0	0.216621	0.741847	0.738167	0.431306	0.577242
14	k-NN	Test (seed=1033)	1033	0.239929	0.744933	0.771667	0.485384	0.538056

8. Summary table (all seeds)

Per-seed metrics for every model plus the three baselines.

In [22]:

```
baseline_true = baseline_split["y_test"].values

def baseline_summary(name, y_pred):
    return summarize_model(
        model_name=name,
        dataset_name="Test (baseline seed)",
        y_true=baseline_true,
        y_pred=y_pred,
```

```
        y_score=None,
        threshold=np.nan,
        seed=np.nan,
    )

rng = np.random.default_rng(0)
baseline_random = baseline_summary("Baseline - Random", rng.integers(0, 2, size=len
baseline_approve = baseline_summary("Baseline - Approve all", np.zeros_like(baselin
baseline_reject = baseline_summary("Baseline - Reject all", np.ones_like(baseline_t

baseline_df = pd.concat([baseline_random, baseline_approve, baseline_reject], ignor

summary_table = pd.concat([baseline_df, combined_model_summaries], ignore_index=Tru
summary_table
```

Out[22]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall
0	Baseline - Random	Test (baseline seed)	NaN	NaN	NaN	0.492333	0.214167	0.485305
1	Baseline - Approve all	Test (baseline seed)	NaN	NaN	NaN	0.778833	0.000000	0.000000
2	Baseline - Reject all	Test (baseline seed)	NaN	NaN	NaN	0.221167	0.221167	1.000000
3	Logistic Regression	Test (seed=2025)	2025.0	0.546590	0.722885	0.757167	0.458546	0.541824
4	Logistic Regression	Test (seed=0)	0.0	0.547748	0.714051	0.767000	0.476126	0.533534
5	Logistic Regression	Test (seed=1033)	1033.0	0.510849	0.714182	0.701667	0.387457	0.600603
6	Decision Tree	Test (seed=2025)	2025.0	0.508695	0.744147	0.736667	0.432749	0.613414
7	Decision Tree	Test (seed=0)	0.0	0.467625	0.753210	0.682333	0.379925	0.690279
8	Decision Tree	Test (seed=1033)	1033.0	0.472664	0.749487	0.734667	0.427714	0.590806
9	SVM (RBF)	Test (seed=2025)	2025.0	-0.345015	0.754564	0.746833	0.447311	0.614167
10	SVM (RBF)	Test (seed=0)	0.0	0.057758	0.755656	0.777833	0.497965	0.553127
11	SVM (RBF)	Test (seed=1033)	1033.0	-0.553250	0.755029	0.722333	0.417196	0.643557
12	Naive Bayes	Test (seed=2025)	2025.0	0.672817	0.729111	0.737667	0.432771	0.599096
13	Naive Bayes	Test (seed=0)	0.0	0.607381	0.717083	0.718667	0.410154	0.620950
14	Naive Bayes	Test (seed=1033)	1033.0	0.659000	0.736167	0.747667	0.446965	0.593821
15	k-NN	Test (seed=2025)	2025.0	0.219905	0.742380	0.732000	0.424259	0.593067
16	k-NN	Test (seed=0)	0.0	0.216621	0.741847	0.738167	0.431306	0.577242
17	k-NN	Test (seed=1033)	1033.0	0.239929	0.744933	0.771667	0.485384	0.538056

9. Model comparison summary (baselines + averages)

Average the seed-level rows to compare overall performance alongside the baselines.

In [23]:
```
def average_rows(df, label):
    numeric_cols = [c for c in df.columns if pd.api.types.is_numeric_dtype(df[c])]
    numeric_cols_no_seed = [c for c in numeric_cols if c != "seed"]
    avg_row = df[numeric_cols_no_seed].mean().to_frame().T
    avg_row["model_name"] = f"{label} (avg seeds)"
    avg_row["dataset_name"] = "Test (avg seeds)"
    cols = [c for c in df.columns if c != "seed"]
    return avg_row.reindex(columns=cols)

avg_rows = [
    average_rows(logreg_summary_df, "Logistic Regression"),
    average_rows(dt_summary_df, "Decision Tree"),
    average_rows(svm_summary_df, "SVM (RBF)"),
    average_rows(nb_summary_df, "Naive Bayes"),
    average_rows(knn_summary_df, "k-NN"),
]

comparison_df = pd.concat([baseline_df] + avg_rows, ignore_index=True)
comparison_df
```

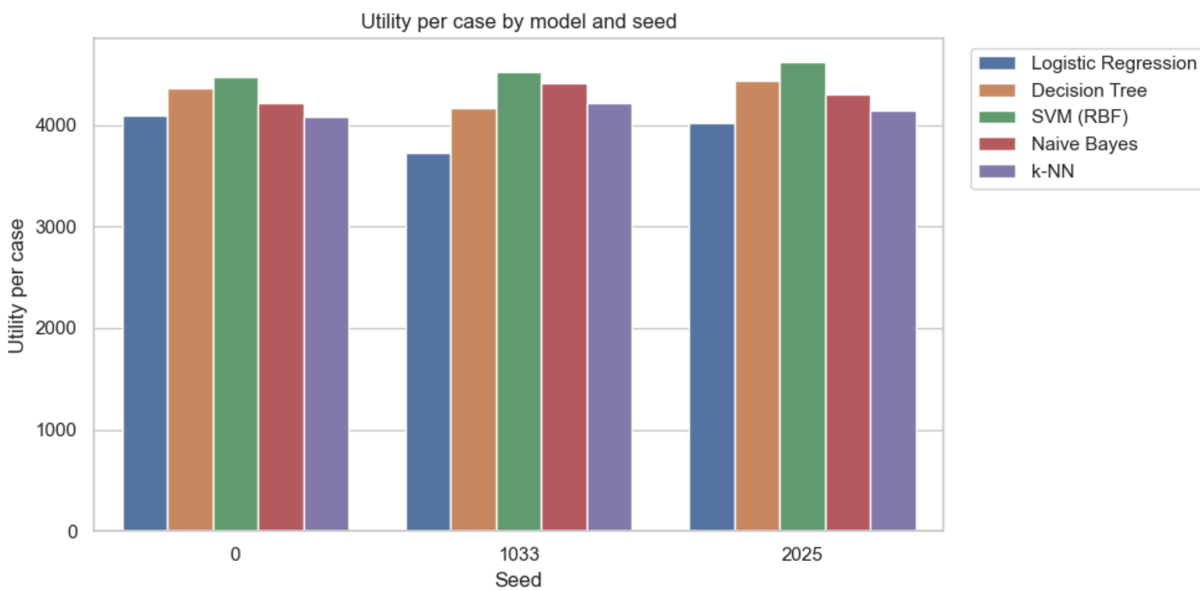
Out[23]:

	model_name	dataset_name	seed	threshold	roc_auc	accuracy	precision	recall	
0	Baseline - Random	Test (baseline seed)	NaN	NaN	NaN	0.492333	0.214167	0.485305	0
1	Baseline - Approve all	Test (baseline seed)	NaN	NaN	NaN	0.778833	0.000000	0.000000	0
2	Baseline - Reject all	Test (baseline seed)	NaN	NaN	NaN	0.221167	0.221167	1.000000	0
3	Logistic Regression (avg seeds)	Test (avg seeds)	NaN	0.535063	0.717040	0.741944	0.440710	0.558654	0
4	Decision Tree (avg seeds)	Test (avg seeds)	NaN	0.482995	0.748948	0.717889	0.413463	0.631500	0
5	SVM (RBF) (avg seeds)	Test (avg seeds)	NaN	-0.280169	0.755083	0.749000	0.454157	0.603617	0
6	Naive Bayes (avg seeds)	Test (avg seeds)	NaN	0.646400	0.727453	0.734667	0.429964	0.604622	0
7	k-NN (avg seeds)	Test (avg seeds)	NaN	0.225485	0.743053	0.747278	0.446983	0.569455	0

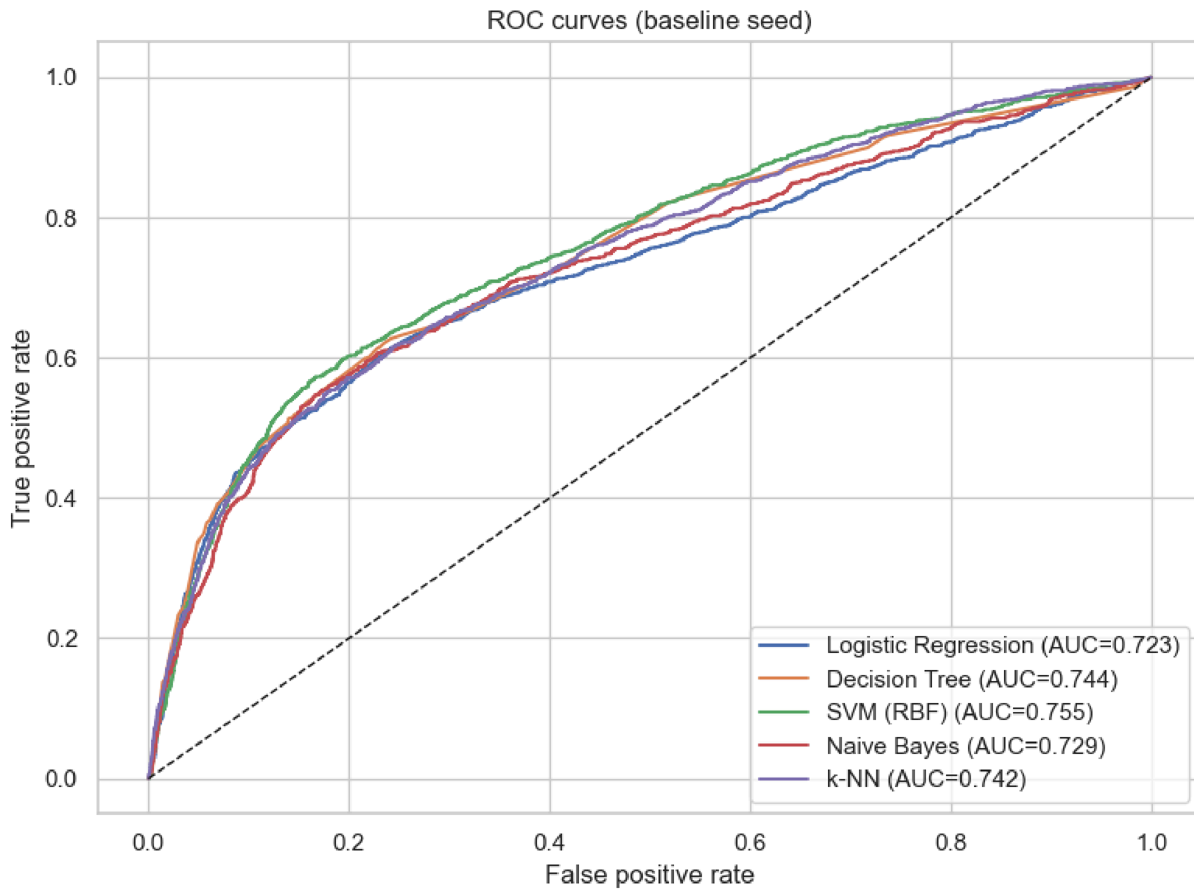
10. Multi-model visualizations

Seed-level utility bars, ROC curves (baseline seed), and a confusion matrix for the top average-utility model.

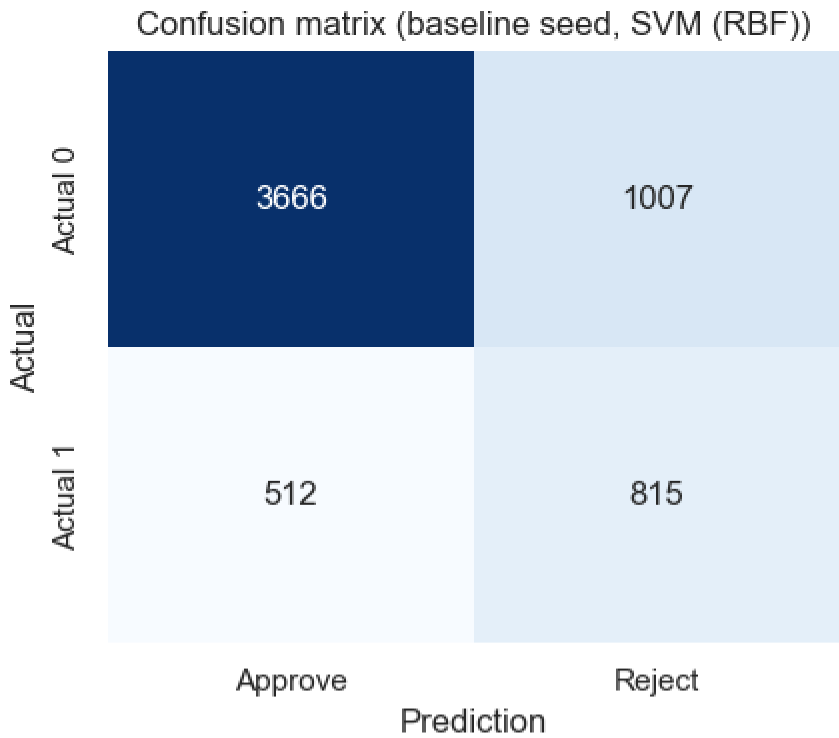
In [19]:
```
plot_data = combined_model_summaries.copy()
plot_data["seed"] = plot_data["seed"].astype(int)

fig, ax = plt.subplots(figsize=(10, 5))
sns.barplot(data=plot_data, x="seed", y="utility_per_case", hue="model_name", ax=ax
ax.set_title("Utility per case by model and seed")
ax.set_xlabel("Seed")
ax.set_ylabel("Utility per case")
ax.legend(bbox_to_anchor=(1.02, 1), loc="upper left")
plt.tight_layout()
```



In [20]:
```
baseline_y_true = baseline_split["y_test"].values

fig, ax = plt.subplots(figsize=(8, 6))
for name, runs in model_runs.items():
    baseline_run = next(r for r in runs if r["seed"] == BASELINE_SEED)
    fpr, tpr, _ = roc_curve(baseline_y_true, baseline_run["test_scores"])
    auc_val = baseline_run["summary"]["roc_auc"].iloc[0]
    ax.plot(fpr, tpr, label=f"{name} (AUC={auc_val:.3f})")

ax.plot([0, 1], [0, 1], "k--", linewidth=1)
ax.set_title("ROC curves (baseline seed)")
ax.set_xlabel("False positive rate")
ax.set_ylabel("True positive rate")
ax.legend(loc="lower right")
plt.tight_layout()
```



In [21]:
```
avg_util = combined_model_summaries.groupby("model_name")["utility_per_case"].mean(
top_model_name = avg_util.index[0]
top_run = next(r for r in model_runs[top_model_name] if r["seed"] == BASELINE_SEED)

cm = confusion_matrix(baseline_y_true, top_run["test_pred"], labels=[0, 1])
fig, ax = plt.subplots(figsize=(4.5, 4))
sns.heatmap(
    cm,
    annot=True,
    fmt="d",
    cmap="Blues",
    cbar=False,
    ax=ax,
    xticklabels=["Approve", "Reject"],
    yticklabels=["Actual 0", "Actual 1"],
)
ax.set_title(f"Confusion matrix (baseline seed, {top_model_name})")
ax.set_xlabel("Prediction")
ax.set_ylabel("Actual")
plt.tight_layout()
```


Confusion matrix (baseline seed, SVM (RBF))
Actual 0
Actual 1
Actual
3666
1007
512
815
Approve
Reject
Prediction