In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import cm
import seaborn as sns
from sklearn.preprocessing import StandardScaler, RobustScaler
from sklearn.decomposition import PCA, KernelPCA
from sklearn.manifold import MDS
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score, davies_bouldin_score, adjusted_ran
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PowerTransformer
import warnings
```

In [2]:
```
warnings.filterwarnings("ignore")
plt.rcParams['figure.figsize'] = (8,6)
```

In [46]:
```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/00350/default%2
df = pd.read_excel(url, header=1)
df
```

Out[46]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	I
0	1	20000	2	2	1	24	2	2	-1	
1	2	120000	2	2	2	26	-1	2	0	
2	3	90000	2	2	2	34	0	0	0	
3	4	50000	2	2	1	37	0	0	0	
4	5	50000	1	2	1	57	-1	0	-1	
...	...	...	...	...	...	...	...	...	...	
29995	29996	220000	1	3	1	39	0	0	0	
29996	29997	150000	1	3	2	43	-1	-1	-1	
29997	29998	30000	1	2	2	37	4	3	2	
29998	29999	80000	1	3	1	41	1	-1	0	
29999	30000	50000	1	2	1	46	0	0	0	

30000 rows × 25 columns

In [4]:
```
df.shape
```

Out[4]:
```
(30000, 25)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   ID                          30000 non-null  int64
 1   LIMIT_BAL                   30000 non-null  int64
 2   SEX                         30000 non-null  int64
 3   EDUCATION                   30000 non-null  int64
 4   MARRIAGE                    30000 non-null  int64
 5   AGE                         30000 non-null  int64
 6   PAY_0                       30000 non-null  int64
 7   PAY_2                       30000 non-null  int64
 8   PAY_3                       30000 non-null  int64
 9   PAY_4                       30000 non-null  int64
 10  PAY_5                       30000 non-null  int64
 11  PAY_6                       30000 non-null  int64
 12  BILL_AMT1                   30000 non-null  int64
 13  BILL_AMT2                   30000 non-null  int64
 14  BILL_AMT3                   30000 non-null  int64
 15  BILL_AMT4                   30000 non-null  int64
 16  BILL_AMT5                   30000 non-null  int64
 17  BILL_AMT6                   30000 non-null  int64
 18  PAY_AMT1                    30000 non-null  int64
 19  PAY_AMT2                    30000 non-null  int64
 20  PAY_AMT3                    30000 non-null  int64
 21  PAY_AMT4                    30000 non-null  int64
 22  PAY_AMT5                    30000 non-null  int64
 23  PAY_AMT6                    30000 non-null  int64
 24  default payment next month  30000 non-null  int64
dtypes: int64(25)
memory usage: 5.7 MB
```

In [6]:

```
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	
ID	30000.0	15000.500000	8660.398374	1.0	7500.75	15000.5	225
LIMIT_BAL	30000.0	167484.322667	129747.661567	10000.0	50000.00	140000.0	2400
SEX	30000.0	1.603733	0.489129	1.0	1.00	2.0	
EDUCATION	30000.0	1.853133	0.790349	0.0	1.00	2.0	
MARRIAGE	30000.0	1.551867	0.521970	0.0	1.00	2.0	
AGE	30000.0	35.485500	9.217904	21.0	28.00	34.0	
PAY_0	30000.0	-0.016700	1.123802	-2.0	-1.00	0.0	
PAY_2	30000.0	-0.133767	1.197186	-2.0	-1.00	0.0	
PAY_3	30000.0	-0.166200	1.196868	-2.0	-1.00	0.0	
PAY_4	30000.0	-0.220667	1.169139	-2.0	-1.00	0.0	
PAY_5	30000.0	-0.266200	1.133187	-2.0	-1.00	0.0	
PAY_6	30000.0	-0.291100	1.149988	-2.0	-1.00	0.0	
BILL_AMT1	30000.0	51223.330900	73635.860576	-165580.0	3558.75	22381.5	670
BILL_AMT2	30000.0	49179.075167	71173.768783	-69777.0	2984.75	21200.0	640
BILL_AMT3	30000.0	47013.154800	69349.387427	-157264.0	2666.25	20088.5	601
BILL_AMT4	30000.0	43262.948967	64332.856134	-170000.0	2326.75	19052.0	545
BILL_AMT5	30000.0	40311.400967	60797.155770	-81334.0	1763.00	18104.5	501
BILL_AMT6	30000.0	38871.760400	59554.107537	-339603.0	1256.00	17071.0	491
PAY_AMT1	30000.0	5663.580500	16563.280354	0.0	1000.00	2100.0	50
PAY_AMT2	30000.0	5921.163500	23040.870402	0.0	833.00	2009.0	50
PAY_AMT3	30000.0	5225.681500	17606.961470	0.0	390.00	1800.0	45
PAY_AMT4	30000.0	4826.076867	15666.159744	0.0	296.00	1500.0	40
PAY_AMT5	30000.0	4799.387633	15278.305679	0.0	252.50	1500.0	40
PAY_AMT6	30000.0	5215.502567	17777.465775	0.0	117.75	1500.0	40
default payment next month	30000.0	0.221200	0.415062	0.0	0.00	0.0	

In [7]:

```
if 'ID' in df.columns:
    df = df.rename(columns={'ID': 'ID'})
```

In [8]:

```
possible_target_names = [
    'default payment next month',
    'default.payment.next.month',
]
target_col = None
for name in possible_target_names:
```

```
    if name in df.columns:
        target_col = name
        break
```

In [9]:
```
X = df.drop(columns=[target_col, 'ID']) if 'ID' in df.columns else df.drop(colum
y = df[target_col].astype(int)
print("Features:", X.shape, "Target distribution:\n", y.value_counts())
```

```
Features: (30000, 23) Target distribution:
 default payment next month
0    23364
1     6636
Name: count, dtype: int64
```

In [10]:
```
print("Missing values per column:\n", X.isna().sum())
```

```
Missing values per column:
 LIMIT_BAL    0
SEX          0
EDUCATION    0
MARRIAGE     0
AGE          0
PAY_0        0
PAY_2        0
PAY_3        0
PAY_4        0
PAY_5        0
PAY_6        0
BILL_AMT1    0
BILL_AMT2    0
BILL_AMT3    0
BILL_AMT4    0
BILL_AMT5    0
BILL_AMT6    0
PAY_AMT1     0
PAY_AMT2     0
PAY_AMT3     0
PAY_AMT4     0
PAY_AMT5     0
PAY_AMT6     0
dtype: int64
```

In [11]:
```
numeric_cols = X.select_dtypes(include=[np.number]).columns.tolist()
len(numeric_cols), numeric_cols[:20]
```

Out[11]:
```
(23,
 ['LIMIT_BAL',
  'SEX',
  'EDUCATION',
  'MARRIAGE',
  'AGE',
  'PAY_0',
  'PAY_2',
  'PAY_3',
  'PAY_4',
  'PAY_5',
  'PAY_6',
  'BILL_AMT1',
  'BILL_AMT2',
  'BILL_AMT3',
  'BILL_AMT4',
  'BILL_AMT5',
  'BILL_AMT6',
  'PAY_AMT1',
  'PAY_AMT2',
  'PAY_AMT3'])
```

In [12]:
```
X.duplicated().sum()
```

Out[12]:
```
56
```

In [13]:
```
y.duplicated().sum()
```

Out[13]:
```
29998
```

In [15]:
```
X.drop_duplicates(inplace=True)
```

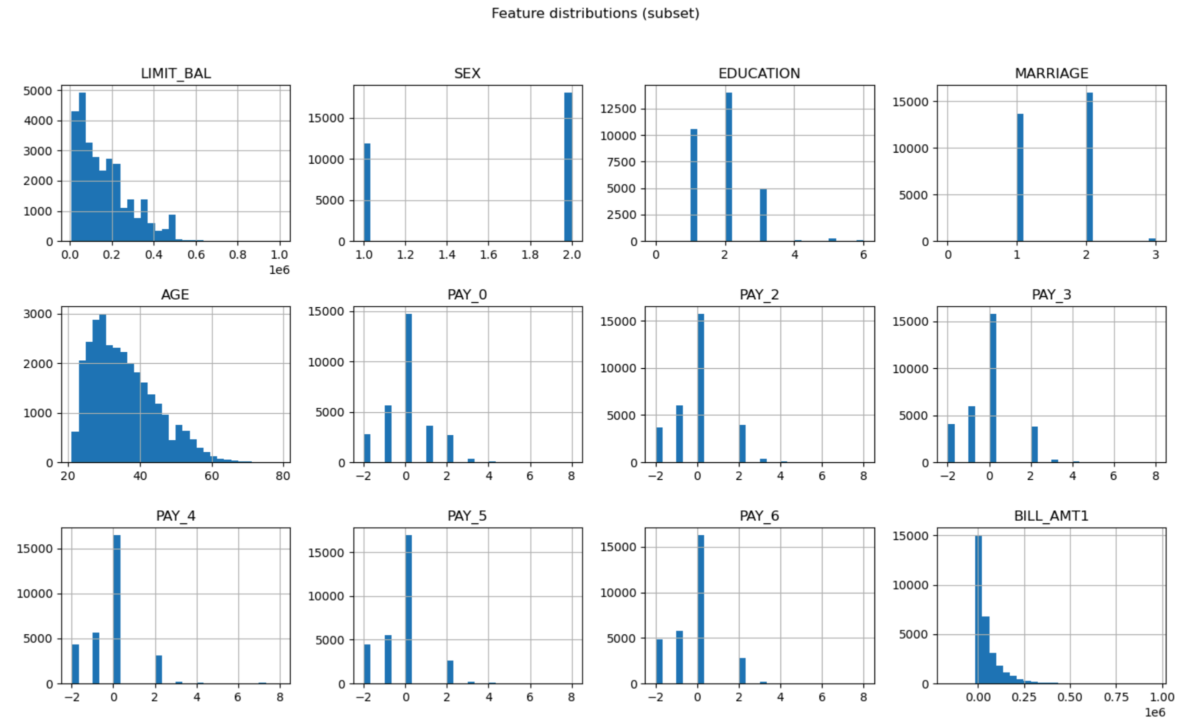
In [16]:
```
X.duplicated().sum()
```

Out[16]:
```
0
```

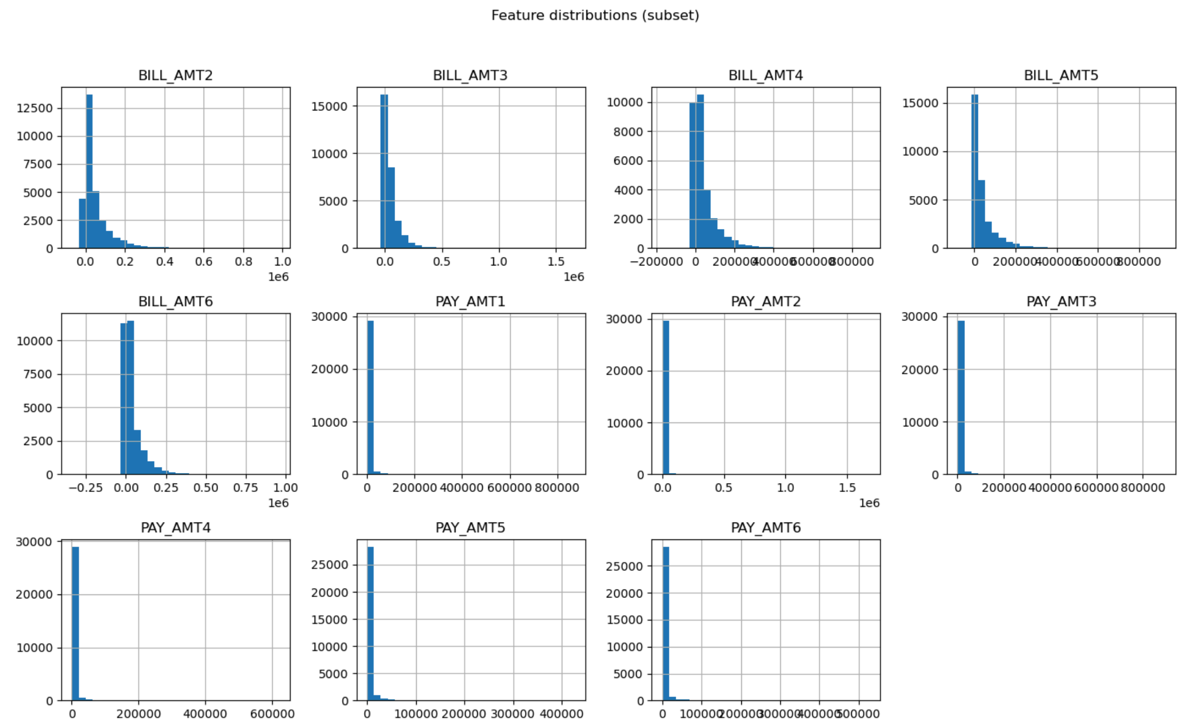
In [17]:
```
X.shape
```

Out[17]:
```
(29944, 23)
```

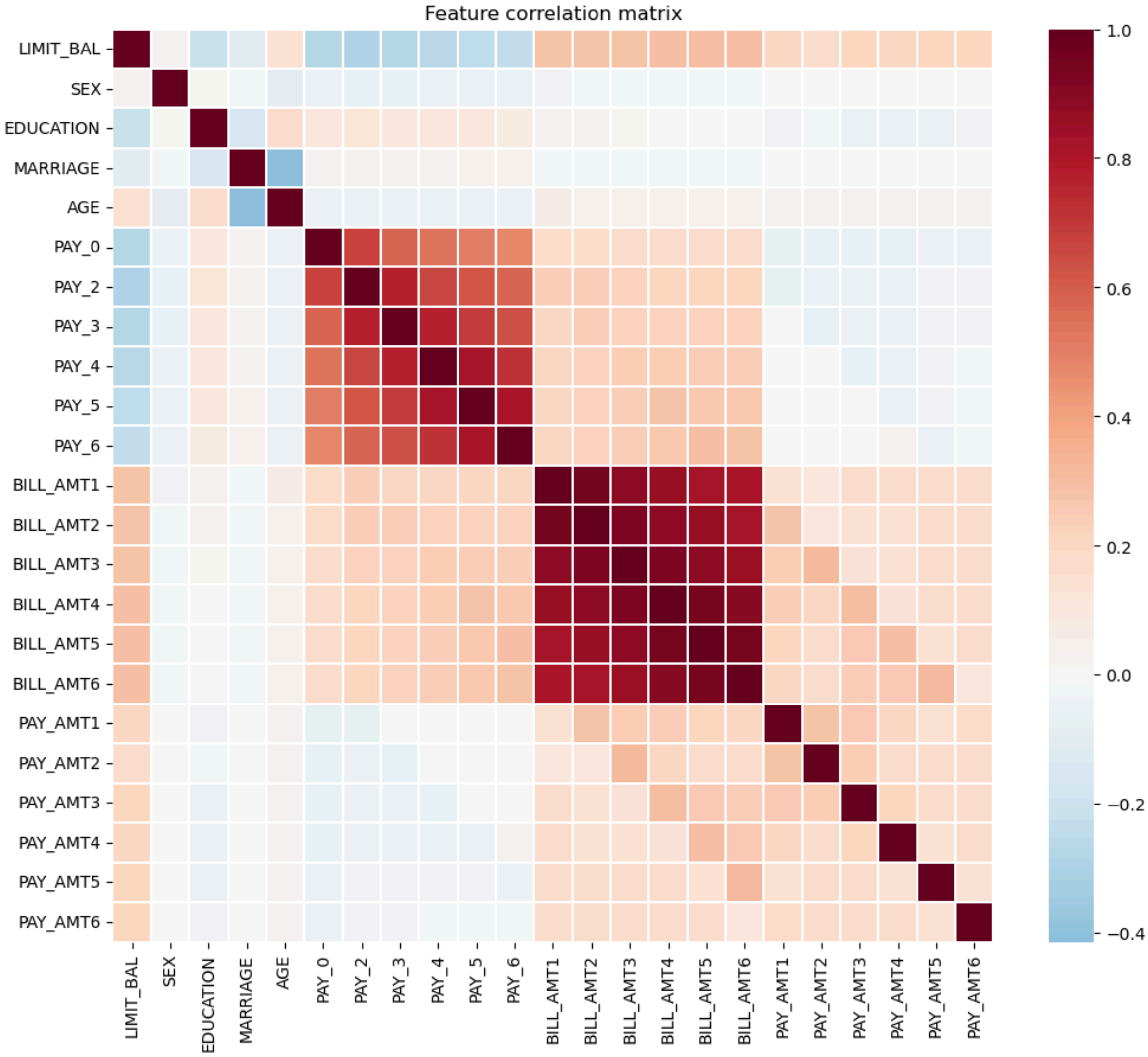
In [18]:
```
subset = numeric_cols[:12]
X[subset].hist(bins=30, layout=(3,4), figsize=(14,9))
plt.suptitle("Feature distributions (subset)")
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```



In [19]:
```python
subset = numeric_cols[12:]
X[subset].hist(bins=30, layout=(3,4), figsize=(14,9))
plt.suptitle("Feature distributions (subset)")
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```

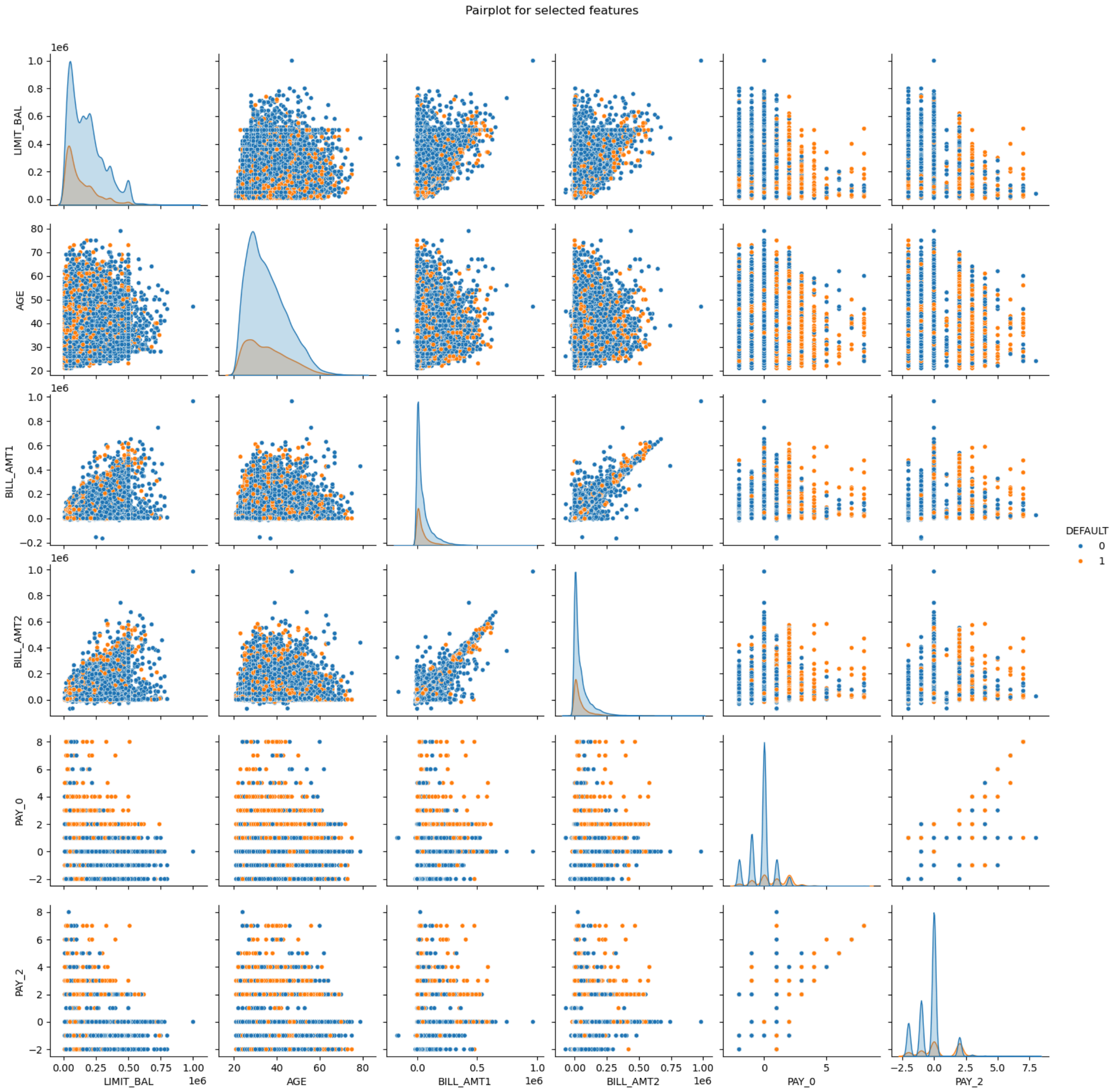


In [20]:
```python
corr = X.corr()
plt.figure(figsize=(12,10))
sns.heatmap(corr, cmap='RdBu_r', center=0, linewidths=0.2)
plt.title("Feature correlation matrix")
plt.show()
```

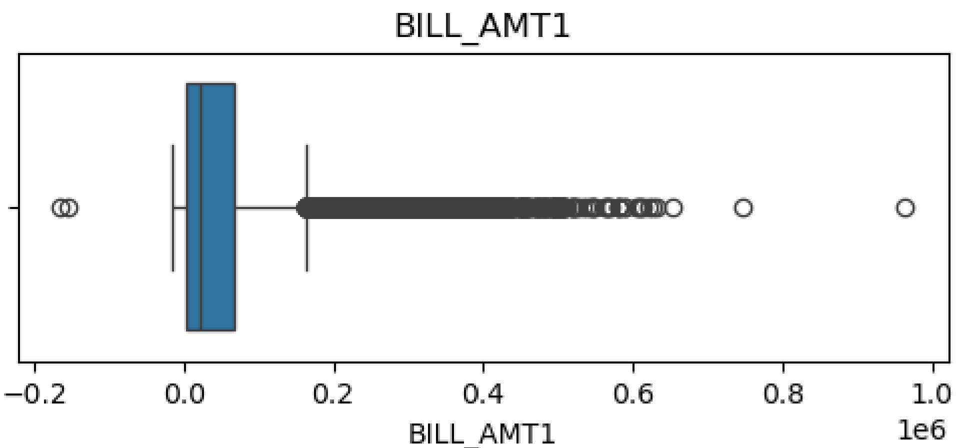


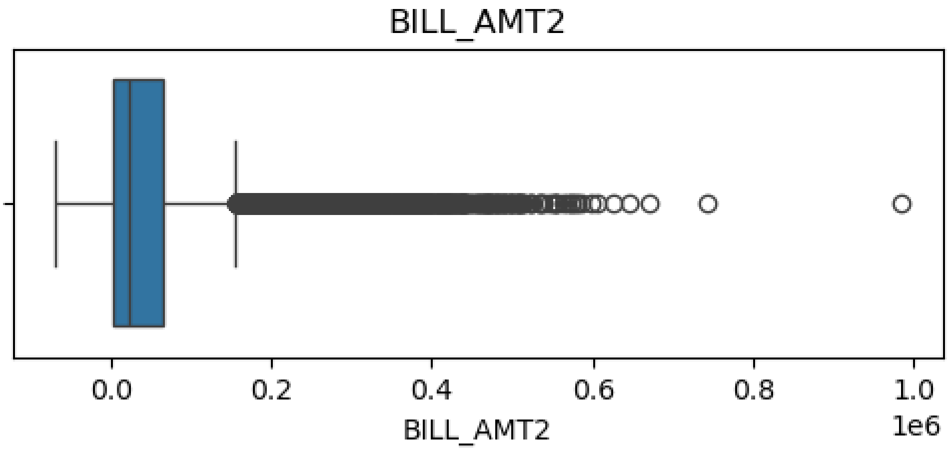
In [21]:
```
subset2 = ['LIMIT_BAL', 'AGE', 'BILL_AMT1', 'BILL_AMT2', 'PAY_0', 'PAY_2']
subset2 = [c for c in subset2 if c in X.columns]
sns.pairplot(pd.concat([X[subset2], y.rename('DEFAULT')], axis=1), hue='DEFAULT'
plt.suptitle("Pairplot for selected features", y=1.02)
```

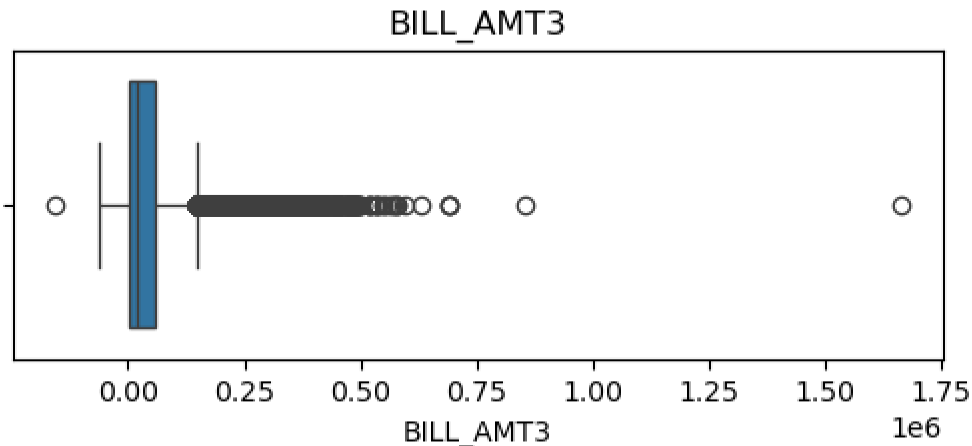
Out[21]:
```
Text(0.5, 1.02, 'Pairplot for selected features')
```

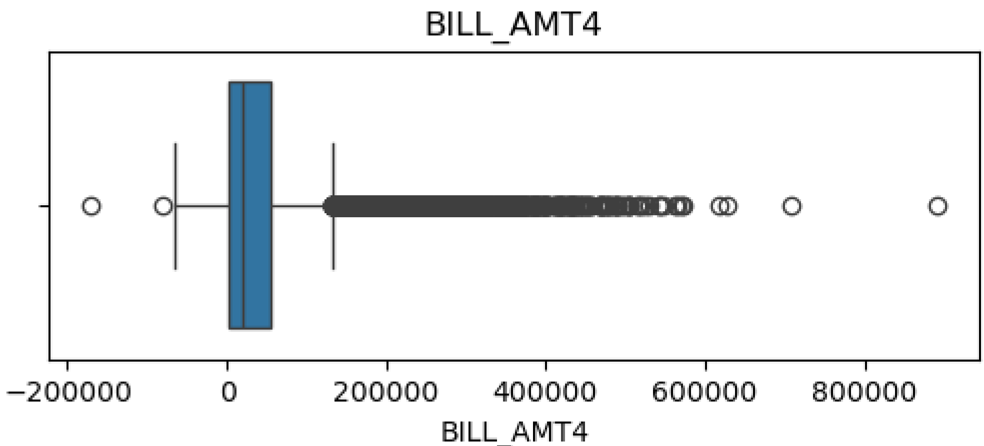


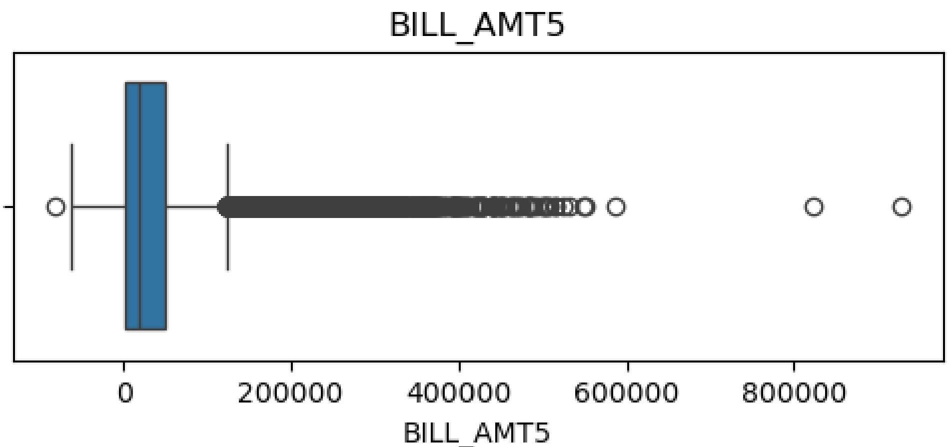

```
In [22]: for col in ['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BI
             if col in X.columns:
                 plt.figure(figsize=(6,2))
                 sns.boxplot(x=X[col])
                 plt.title(col)
                 plt.show()
```

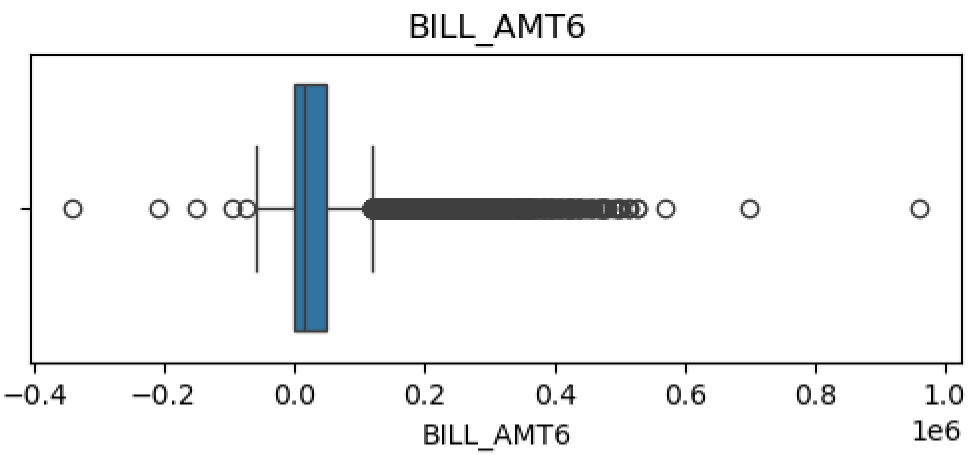



BILL_AMT2
0.0
0.2
0.4
0.6
0.8
1.0
1e6
BILL_AMT2


BILL_AMT3
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
BILL_AMT3


BILL_AMT4
−200000
0
200000
400000
600000
800000
BILL_AMT4


BILL_AMT5
0
200000
400000
600000
800000
BILL_AMT5



In [23]:
```
X.skew()
```

Out[23]:
```
LIMIT_BAL      0.994144
SEX           -0.424156
EDUCATION      0.970717
MARRIAGE      -0.018685
AGE            0.732142
PAY_0          0.736452
PAY_2          0.793264
PAY_3          0.841950
PAY_4          1.001539
PAY_5          1.010001
PAY_6          0.948906
BILL_AMT1      2.661707
BILL_AMT2      2.703049
BILL_AMT3      3.085695
BILL_AMT4      2.819695
BILL_AMT5      2.874055
BILL_AMT6      2.844235
PAY_AMT1      14.657570
PAY_AMT2      30.429534
PAY_AMT3      17.203136
PAY_AMT4      12.894648
PAY_AMT5      11.118361
PAY_AMT6      10.631731
dtype: float64
```

In [24]:
```
skew_values = X.skew().sort_values(ascending=False)


skewed_cols = skew_values[abs(skew_values) > 0.75].index

pt = PowerTransformer(method='yeo-johnson', standardize=False)
X[skewed_cols] = pt.fit_transform(X[skewed_cols])
```

In [25]:
```
X.skew()
```

Out[25]:
```
LIMIT_BAL    -0.075264
SEX          -0.424156
EDUCATION     0.020574
MARRIAGE     -0.018685
AGE           0.732142
PAY_0         0.736452
PAY_2        -0.014296
PAY_3        -0.001423
PAY_4         0.011888
PAY_5         0.023231
PAY_6         0.030999
BILL_AMT1    -2.405728
BILL_AMT2    -1.281619
BILL_AMT3    -3.189980
BILL_AMT4    -2.781907
BILL_AMT5    -1.297717
BILL_AMT6    -2.989125
PAY_AMT1     -0.129850
PAY_AMT2     -0.109785
PAY_AMT3     -0.149743
PAY_AMT4     -0.164117
PAY_AMT5     -0.177496
PAY_AMT6     -0.173888
dtype: float64
```

In [26]:
```
X_clean = X.dropna()
y_clean = y.loc[X_clean.index]
```

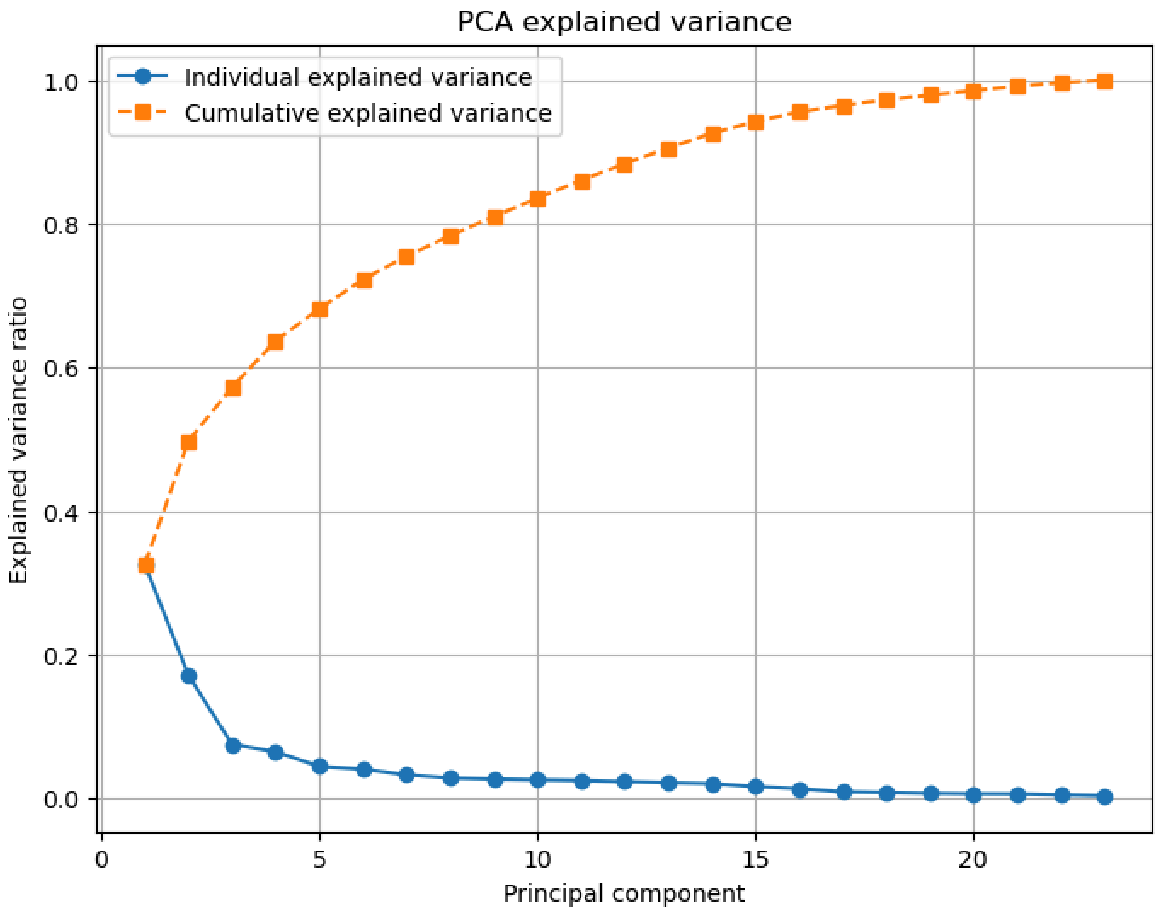
In [27]:
```
X_clean = X_clean.reset_index(drop=True)
y_clean = y_clean.reset_index(drop=True)

print(X_clean.shape, y_clean.shape)
```

```
(29944, 23) (29944,)
```

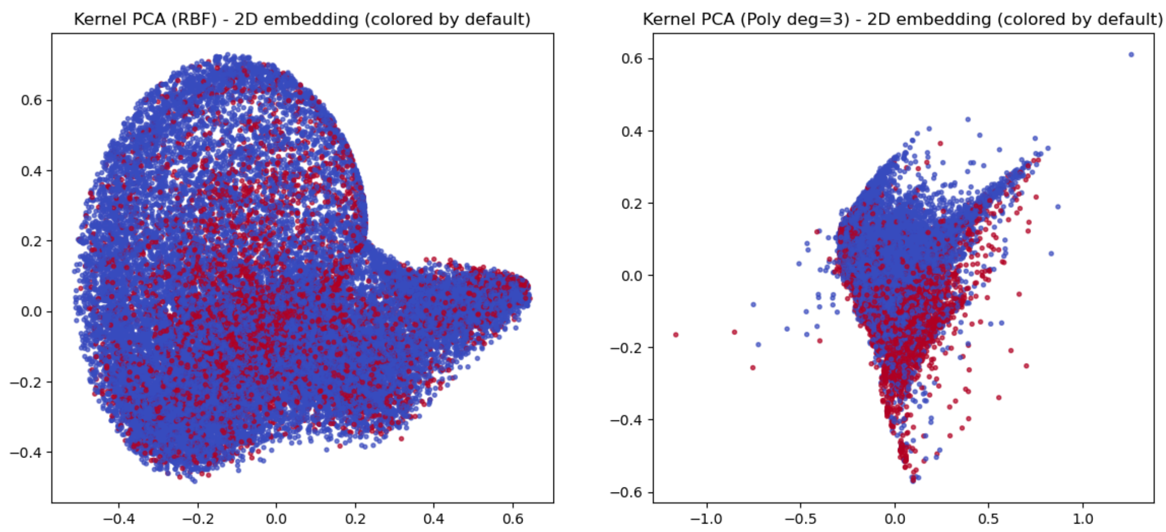
In [28]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_clean)
print("Scaled shape:", X_scaled.shape)
```

```
Scaled shape: (29944, 23)
```

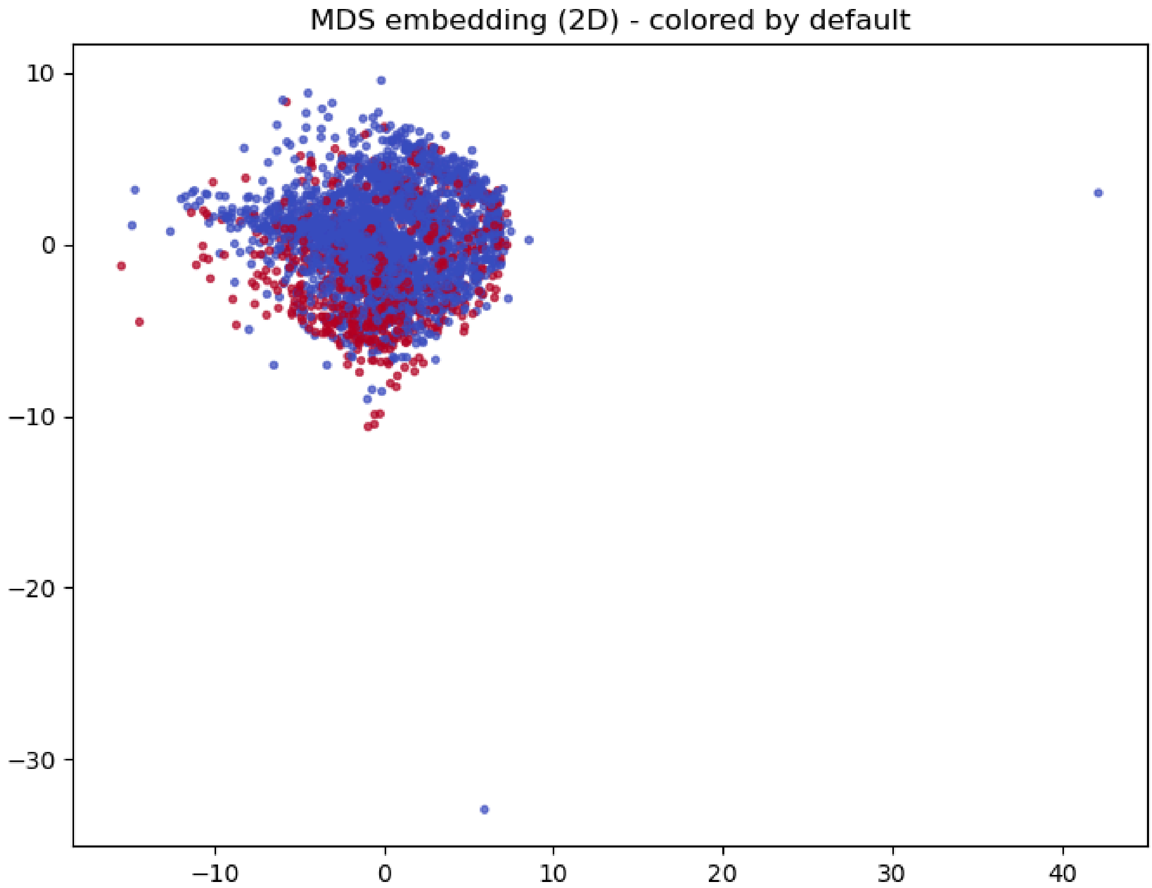
In [29]:
```
pca = PCA()
X_pca_full = pca.fit_transform(X_scaled)


explained = pca.explained_variance_ratio_
cum_explained = np.cumsum(explained)

plt.figure()
plt.plot(np.arange(1, len(explained)+1), explained, 'o-', label='Individual expl
plt.plot(np.arange(1, len(explained)+1), cum_explained, 's--', label='Cumulative
plt.xlabel('Principal component')
plt.ylabel('Explained variance ratio')
plt.legend()
plt.title('PCA explained variance')
plt.grid(True)
plt.show()


X_pca_2 = X_pca_full[:, :2]
```



In [30]:
```
kpca_rbf = KernelPCA(n_components=2, kernel='rbf', gamma=0.05, fit_inverse_trans
X_kpca_rbf = kpca_rbf.fit_transform(X_scaled)

kpca_poly = KernelPCA(n_components=2, kernel='poly', degree=3, coef0=1, gamma=1e
X_kpca_poly = kpca_poly.fit_transform(X_scaled)


fig, axes = plt.subplots(1,2, figsize=(14,6))
axes[0].scatter(X_kpca_rbf[:,0], X_kpca_rbf[:,1], c=y_clean, s=8, cmap='coolwarm
axes[0].set_title('Kernel PCA (RBF) - 2D embedding (colored by default)')
axes[1].scatter(X_kpca_poly[:,0], X_kpca_poly[:,1], c=y_clean, s=8, cmap='coolwa
axes[1].set_title('Kernel PCA (Poly deg=3) - 2D embedding (colored by default)')
plt.show()
```



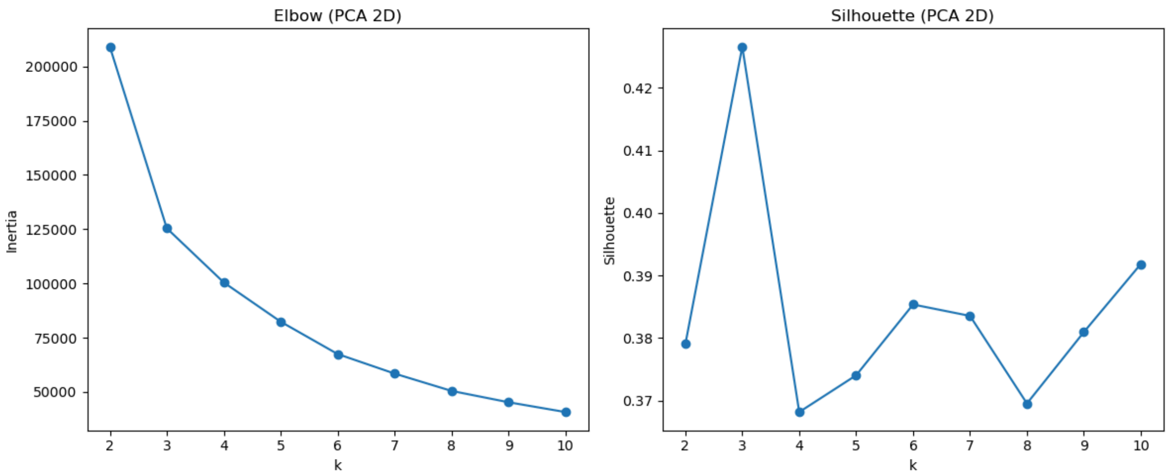
In [31]:
```
sample_for_mds = True
sample_size = 3000
if sample_for_mds and X_scaled.shape[0] > sample_size:
    idx = np.random.choice(X_scaled.shape[0], sample_size, replace=False)
    X_for_mds = X_scaled[idx]
    y_for_mds = y_clean.iloc[idx]
else:
    X_for_mds = X_scaled
    y_for_mds = y_clean

from sklearn.manifold import MDS
mds = MDS(n_components=2, random_state=42, n_init=4, max_iter=300)
X_mds = mds.fit_transform(X_for_mds)

import matplotlib.pyplot as plt
plt.scatter(X_mds[:,0], X_mds[:,1], c=y_for_mds, s=8, cmap='coolwarm', alpha=0.7
plt.title("MDS embedding (2D) - colored by default")
plt.show()
```



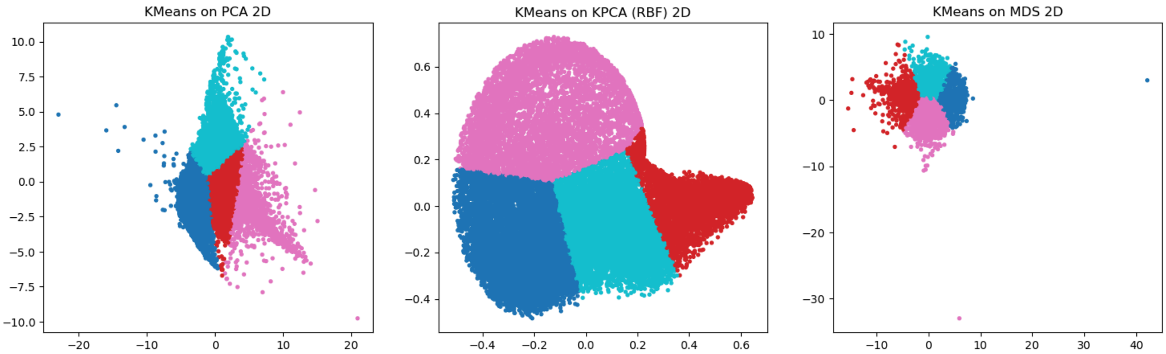
In [32]:
```
def evaluate_kmeans(X_embedded, max_k=10, random_state=42):
    inertias = []
    silhouettes = []
    K_range = range(2, max_k+1)
    for k in K_range:
        km = KMeans(n_clusters=k, random_state=random_state, n_init=10)
        labels = km.fit_predict(X_embedded)
        inertias.append(km.inertia_)
        silhouettes.append(silhouette_score(X_embedded, labels))
    return K_range, inertias, silhouettes


K_range, inertias_pca, silhouettes_pca = evaluate_kmeans(X_pca_2, max_k=10)
```

```
_, inertias_kpca_rbf, silhouettes_kpca_rbf = evaluate_kmeans(X_kpca_rbf, max_k=1
_, inertias_mds, silhouettes_mds = evaluate_kmeans(X_mds, max_k=10)


plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(K_range, inertias_pca, 'o-'); plt.xlabel('k'); plt.ylabel('Inertia'); p
plt.subplot(1,2,2)
plt.plot(K_range, silhouettes_pca, 'o-'); plt.xlabel('k'); plt.ylabel('Silhouett
plt.tight_layout()
plt.show()
```

```
  File "C:\Users\uched\anaconda3\Lib\site-packages\joblib\externals\loky\backend
\context.py", line 257, in _count_physical_cores
    cpu_info = subprocess.run(
               ^^^^^^^^^^^^^^^
  File "C:\Users\uched\anaconda3\Lib\subprocess.py", line 548, in run
    with Popen(*popenargs, **kwargs) as process:
         ^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "C:\Users\uched\anaconda3\Lib\subprocess.py", line 1026, in __init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "C:\Users\uched\anaconda3\Lib\subprocess.py", line 1538, in _execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
                       ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
```



In [33]:
```
k_selected = 4
km_pca = KMeans(n_clusters=k_selected, random_state=42, n_init=20).fit(X_pca_2)
labels_pca = km_pca.labels_

km_kpca_rbf = KMeans(n_clusters=k_selected, random_state=42, n_init=20).fit(X_kp
labels_kpca_rbf = km_kpca_rbf.labels_

km_mds = KMeans(n_clusters=k_selected, random_state=42, n_init=20).fit(X_mds)
labels_mds = km_mds.labels_


fig, axes = plt.subplots(1,3, figsize=(18,5))
axes[0].scatter(X_pca_2[:,0], X_pca_2[:,1], c=labels_pca, s=8, cmap='tab10'); ax
axes[1].scatter(X_kpca_rbf[:,0], X_kpca_rbf[:,1], c=labels_kpca_rbf, s=8, cmap='
axes[2].scatter(X_mds[:,0], X_mds[:,1], c=labels_mds, s=8, cmap='tab10'); axes[2
plt.show()
```



In [34]:
```
db_default = DBSCAN(eps=0.5, min_samples=5)
labels_db_pca = db_default.fit_predict(X_pca_2)
print("DBSCAN on PCA2 - clusters (including -1 for noise):", len(set(labels_db_p


def dbscan_grid_search(X_emb, eps_values=[0.2,0.4,0.6,0.8,1.0], min_samples_valu
    results = []
    for eps in eps_values:
        for ms in min_samples_values:
            db = DBSCAN(eps=eps, min_samples=ms).fit(X_emb)
            labels = db.labels_
            n_clusters = len(set(labels)) - (1 if -1 in labels else 0)
            if n_clusters > 1:
                sil = silhouette_score(X_emb, labels) if len(set(labels))>1 else
            else:
                sil = -1
            results.append({'eps':eps, 'min_samples':ms, 'n_clusters':n_clusters
    return pd.DataFrame(results)

db_results = dbscan_grid_search(X_kpca_rbf, eps_values=[0.2,0.4,0.6,0.8,1.0,1.5]
db_results.sort_values(by='silhouette', ascending=False).head(10)
```

DBSCAN on PCA2 - clusters (including -1 for noise): 7

Out[34]:

	eps	min_samples	n_clusters	silhouette
0	0.2	3	1	-1
1	0.2	5	1	-1
22	1.5	8	1	-1
21	1.5	5	1	-1
20	1.5	3	1	-1
19	1.0	12	1	-1
18	1.0	8	1	-1
17	1.0	5	1	-1
16	1.0	3	1	-1
15	0.8	12	1	-1

In [35]:
```
def clustering_metrics(X_emb, labels):

    unique_labels = set(labels)
    n_clusters = len(unique_labels) - (1 if -1 in unique_labels else 0)
```

```
    if n_clusters <= 1:
        return {'n_clusters': n_clusters, 'silhouette': np.nan, 'db_index': np.n
    else:
        sil = silhouette_score(X_emb, labels)
        db = davies_bouldin_score(X_emb, labels)
        return {'n_clusters': n_clusters, 'silhouette': sil, 'db_index': db}

metrics = {}
metrics['PCA-KMeans'] = clustering_metrics(X_pca_2, labels_pca)
metrics['KPCA(RBF)-KMeans'] = clustering_metrics(X_kpca_rbf, labels_kpca_rbf)
metrics['MDS-KMeans'] = clustering_metrics(X_mds, labels_mds)
metrics['PCA-DBSCAN'] = clustering_metrics(X_pca_2, labels_db_pca)

pd.DataFrame(metrics).T
```

Out[35]:

	n_clusters	silhouette	db_index
PCA-KMeans	4.0	0.368169	0.871505
KPCA(RBF)-KMeans	4.0	0.405017	0.816193
MDS-KMeans	4.0	0.372783	0.855322
PCA-DBSCAN	6.0	0.329635	1.810805

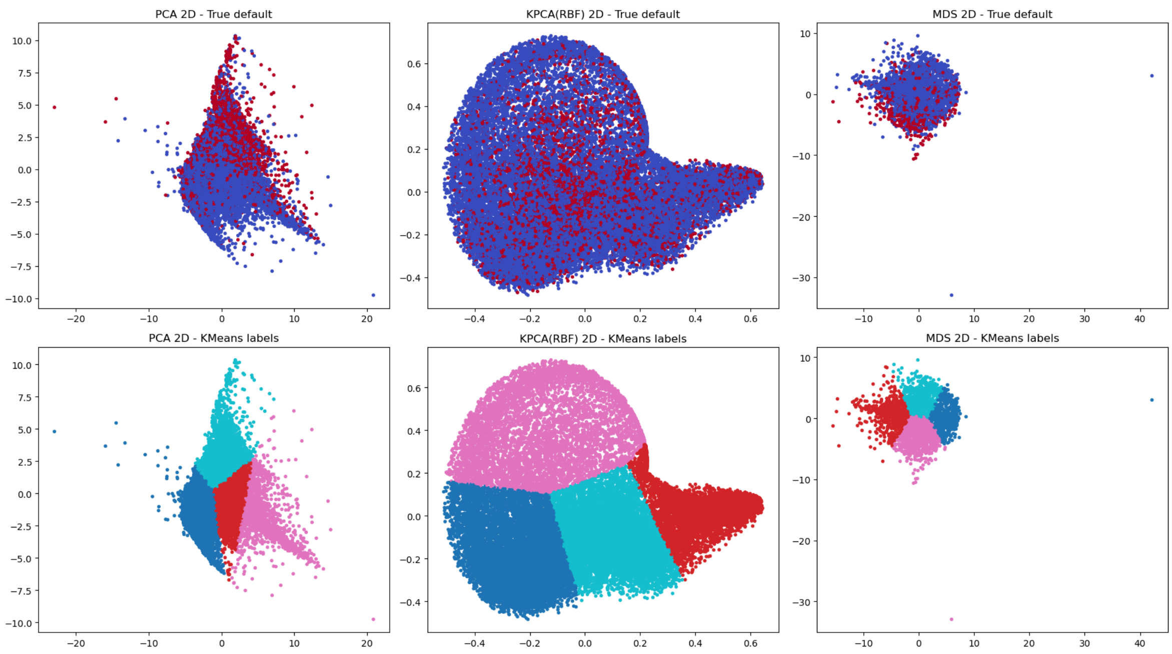
In [47]:

```
from sklearn.metrics import adjusted_rand_score, adjusted_mutual_info_score

arit = adjusted_rand_score(y.iloc[:len(labels_pca)], labels_pca)
ami = adjusted_mutual_info_score(y.iloc[:len(labels_pca)], labels_pca)
print("PCA-KMeans ARI:", arit, "AMI:", ami)

arit_k = adjusted_rand_score(y.iloc[:len(labels_kpca_rbf)], labels_kpca_rbf)
print("KPCA-KMeans ARI:", arit_k)
```

```
PCA-KMeans ARI: 0.0001395259180618777 AMI: 0.00039737437487208014
KPCA-KMeans ARI: -0.0010327046093705334
```

In [39]:

```
fig, axes = plt.subplots(2,3, figsize=(18,10))


axes[0,0].scatter(X_pca_2[:,0], X_pca_2[:,1], c=y_clean, s=8, cmap='coolwarm');
axes[0,1].scatter(X_kpca_rbf[:,0], X_kpca_rbf[:,1], c=y_clean, s=8, cmap='coolwa
axes[0,2].scatter(X_mds[:,0], X_mds[:,1], c=y_for_mds, s=8, cmap='coolwarm'); ax


axes[1,0].scatter(X_pca_2[:,0], X_pca_2[:,1], c=labels_pca, s=8, cmap='tab10');
axes[1,1].scatter(X_kpca_rbf[:,0], X_kpca_rbf[:,1], c=labels_kpca_rbf, s=8, cmap
axes[1,2].scatter(X_mds[:,0], X_mds[:,1], c=labels_mds, s=8, cmap='tab10'); axes

plt.tight_layout()
plt.show()
```



In [43]:
```python
cluster_ids = labels_kpca_rbf
cluster_profile = pd.DataFrame(X).copy()
cluster_profile['cluster'] = cluster_ids
profile = cluster_profile.groupby('cluster').mean().T
profile.head()


feature_variances = profile.var(axis=1).sort_values(ascending=False)
feature_variances.head(10)
```

Out[43]:
```
BILL_AMT6    3.137657e+08
BILL_AMT1    1.999068e+08
BILL_AMT4    1.660689e+08
BILL_AMT3    1.514716e+08
BILL_AMT5    9.456491e+07
BILL_AMT2    9.357003e+07
LIMIT_BAL    1.265041e+02
PAY_AMT1     3.801911e+01
PAY_AMT2     3.576660e+01
PAY_AMT3     2.981678e+01
dtype: float64
```

In [52]:
```python
embedding_used = X_pca_2

# ✅ Choose your clustering algorithm output
# (Replace with db.labels_ if you used DBSCAN instead of KMeans)
labels_used = km_pca.labels_

# ✅ Select appropriate y (target)
if 'y_for_mds' in locals():
    y_used = y_for_mds.reset_index(drop=True)
else:
    y_used = y_clean.reset_index(drop=True)

# ✅ Make sure all arrays match in length
min_len = min(embedding_used.shape[0], len(labels_used), len(y_used))

# ✅ Build the results DataFrame
results = pd.DataFrame({
    'Dim1': embedding_used[:min_len, 0],
```

```
    'Dim2': embedding_used[:min_len, 1],
    'Cluster': labels_used[:min_len],
    'Default': y_used.iloc[:min_len].values
})

print(f"✅ Results DataFrame created successfully: {results.shape}")
display(results.head())
```

✅ Results DataFrame created successfully: (3000, 4)

	Dim1	Dim2	Cluster	Default
0	-3.457521	2.015434	0	0
1	-1.005060	2.136679	3	0
2	-0.281459	0.817139	3	0
3	0.273060	0.730761	1	1
4	0.134512	-0.329693	1	1

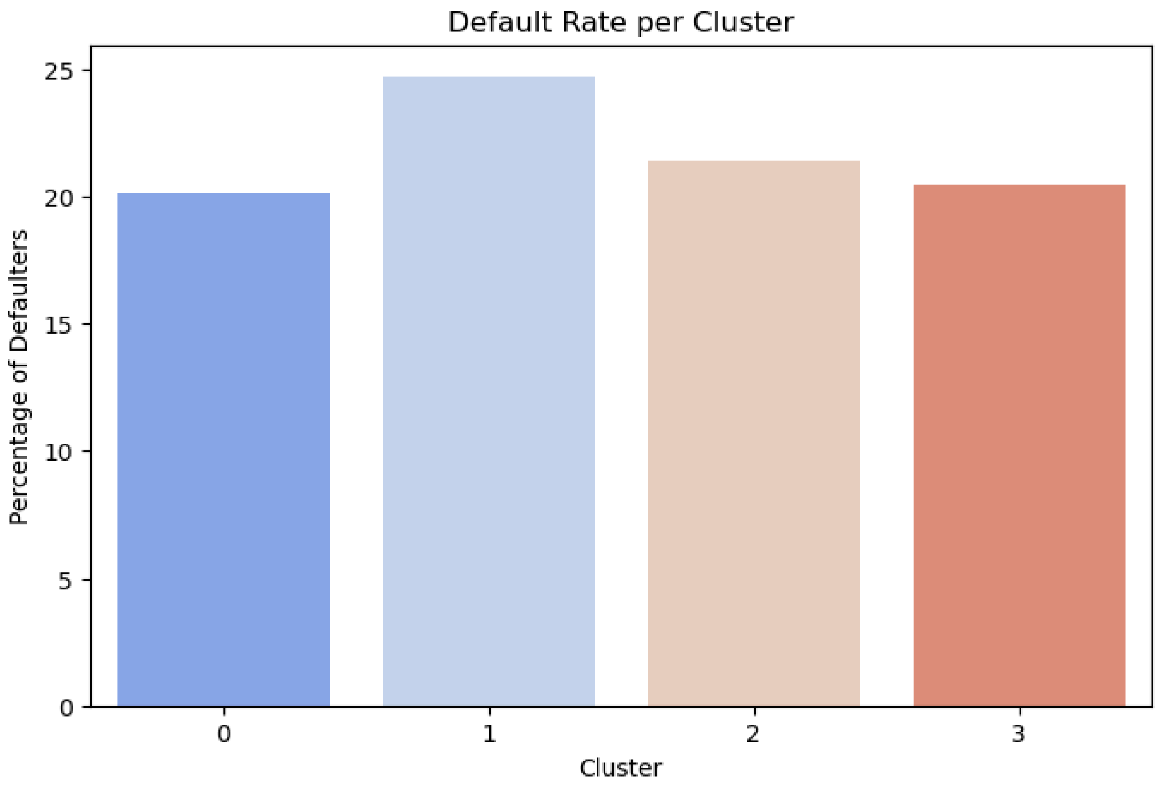
In [53]:

```
cluster_default_table = pd.crosstab(results['Cluster'], results['Default'], norm
cluster_default_table.columns = ['Non-Default (%)', 'Default (%)']
display(cluster_default_table.sort_values('Default (%)', ascending=False))
```

Cluster	Non-Default (%)	Default (%)
1	75.296912	24.703088
2	78.618421	21.381579
3	79.553073	20.446927
0	79.874870	20.125130

In [54]:

```
plt.figure(figsize=(8,5))
sns.barplot(x=cluster_default_table.index, y=cluster_default_table['Default (%)'
plt.title("Default Rate per Cluster")
plt.ylabel("Percentage of Defaulters")
plt.xlabel("Cluster")
plt.show()
```



In [55]:

```
cluster_summary = X_clean.copy()
cluster_summary['Cluster'] = results['Cluster']


cluster_summary['Default'] = y_clean.values[:len(cluster_summary)]

summary_stats = cluster_summary.groupby('Cluster')[['LIMIT_BAL', 'AGE', 'PAY_0',
display(summary_stats)
```

Cluster	LIMIT_BAL	AGE	PAY_0	BILL_AMT1	Default
0.0	88.725835	36.041710	-0.641293	2385.864277	0.208551
1.0	87.434076	35.701900	-0.049881	16364.279138	0.118765
2.0	102.605483	36.990132	0.335526	49113.103835	0.240132
3.0	64.310479	33.683799	0.646927	7901.872138	0.328492

In [ ]:

In [ ]: