analysis_oct_26

October 26, 2025

0.1 Data Loading and Cleaning

[23]:
```
import pandas as pd
import datetime as dt
import matplotlib.pyplot as plt

# Load data and ensure 'user' is treated as string; drop rows without a user id
data = pd.read_csv("data.csv")
data = data.dropna(subset=['user'])
data['user'] = data['user'].astype(str).str.strip()
data = data[data['user'] != '']

# Create a robust 'date' column from time_year and time_month (day set to 1)
data['time_year'] = pd.to_numeric(data.get('time_year', None), errors='coerce')
data['time_month'] = pd.to_numeric(data.get('time_month', None),␣
 ↪errors='coerce')
data['date'] = pd.to_datetime(
    data['time_year'].fillna(0).astype(int).astype(str) + '-' +
    data['time_month'].fillna(1).astype(int).astype(str) + '-01',
    errors='coerce'
)
# drop rows with invalid date
data = data.dropna(subset=['date'])
# create a monthly period column for grouping
data['period'] = data['date'].dt.to_period('M')

# Quick checks
data.info()
data.describe(include='all')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34475 entries, 0 to 34474
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   cohort        34475 non-null  int64
 1   user          34475 non-null  object
 2   time_year     34475 non-null  int64
```

```
 3   time_month    34475 non-null  int64
 4   subscription  34475 non-null  int64
 5   content       34059 non-null  float64
 6   genres        34059 non-null  float64
 7   recency_new   34059 non-null  float64
 8   bounce        34059 non-null  float64
 9   date          34475 non-null  datetime64[ns]
 10  period        34475 non-null  period[M]
dtypes: datetime64[ns](1), float64(4), int64(4), object(1), period[M](1)
memory usage: 2.9+ MB
```

[23]:

	cohort	user	time_year	time_month	subscription
count	34475.000000	34475	34475.000000	34475.000000	34475.0
unique	NaN	21440	NaN	NaN	NaN
top	NaN	1291	NaN	NaN	NaN
freq	NaN	12	NaN	NaN	NaN
mean	5.396461	NaN	2017.380595	6.294329	1.0
min	0.000000	NaN	2017.000000	1.000000	1.0
25%	2.000000	NaN	2017.000000	3.000000	1.0
50%	6.000000	NaN	2017.000000	6.000000	1.0
75%	8.000000	NaN	2018.000000	9.000000	1.0
max	11.000000	NaN	2018.000000	12.000000	1.0
std	3.453917	NaN	0.485540	3.534924	0.0

	content	genres	recency_new	bounce
count	34059.000000	34059.000000	34059.000000	34059.000000
unique	NaN	NaN	NaN	NaN
top	NaN	NaN	NaN	NaN
freq	NaN	NaN	NaN	NaN
mean	3.873249	1.885258	0.371159	0.449736
min	1.000000	1.000000	0.000000	0.000000
25%	2.000000	1.000000	0.000000	0.000000
50%	3.000000	2.000000	0.333300	0.500000
75%	5.000000	2.000000	0.636400	0.692300
max	81.000000	5.000000	1.000000	1.000000
std	3.892327	0.951980	0.355709	0.354376

	date	period
count	34475	34475
unique	NaN	12
top	NaN	2018-02
freq	NaN	3400
mean	2017-10-27 04:39:51.298041856	NaN
min	2017-05-01 00:00:00	NaN
25%	2017-08-01 00:00:00	NaN
50%	2017-11-01 00:00:00	NaN
75%	2018-02-01 00:00:00	NaN

```
max                  2018-04-01 00:00:00      NaN
std                                  NaN      NaN
```

- Total number of unique users
- New users per month
- Active users per month
- Churned users per month
- Retention rate per month
- Average expected lifetime (in months)
- Distribution summary (% of users active after 3 months, 6 etc)
- Survival Probabilities

0.2 Total number of unique users

[24]:
```
# Total unique users in dataset
unique_users = data['user'].nunique()

print("Total unique users:" , unique_users)
```

```
Total unique users: 21440
```

0.3 New users per month (cohort)

[25]:
```
# New users per cohort
#( 'cohort' represents acquisition month

# remove duplicates and then  count per cohort
new_users = data.drop_duplicates(subset=['user']).groupby('cohort')['user'].
 ↪nunique().sort_index()

print("Total new users per cohort: ")
print(new_users)
```

```
Total new users per cohort:
cohort
0     1791
1     2120
2     1268
3     1788
4     1367
5     1761
6     1806
7     1565
8     1967
9     2066
10    1602
11    2339
Name: user, dtype: int64
```

0.4 Active Users per month

[26]:
```
# Active users per month using 'period' and 'content' >= 1
active_users = (
    data[ data['content'].fillna(0) >= 1 ]
    .groupby('period')['user']
    .nunique()
    .sort_index()
)
print(active_users)
```

```
period
2017-05    1791
2017-06    3152
2017-07    2817
2017-08    2643
2017-09    2528
2017-10    2464
2017-11    2647
2017-12    3040
2018-01    3201
2018-02    3361
2018-03    3144
2018-04    3271
Freq: M, Name: user, dtype: int64
```

0.5 Churned and retained users per month

[27]:
```
# Calcolo churn + retention per period usando 'date'/'period' (fix creazione␣
 ↪'date')
import numpy as np

# Non ricaricare data se già presente; assicurati che time_year/time_month␣
 ↪siano numerici
data['time_year'] = pd.to_numeric(data.get('time_year'), errors='coerce')
data['time_month'] = pd.to_numeric(data.get('time_month'), errors='coerce')

# Crea colonna 'date' in modo robusto: usa solo righe con year e month validi
valid = data['time_year'].notna() & data['time_month'].notna()
if valid.any():
    data.loc[valid, 'date'] = pd.to_datetime({
        'year': data.loc[valid, 'time_year'].astype(int),
        'month': data.loc[valid, 'time_month'].astype(int),
        'day': 1
    }, errors='coerce')

data = data.dropna(subset=['date'])  # rimuovi righe senza data valida
data['period'] = data['date'].dt.to_period('M')
```

```
# Serie: per ogni period gli user con subscription==1 (array di user unici)
subscribed_by_period = (
    data[data['subscription'] == 1]
    .groupby('period')['user']
    .unique()
    .sort_index()
)

# Itera sui period effettivamente presenti e usa period + 1 (gestisce anno)
periods = list(subscribed_by_period.index.sort_values())
rows = []
for p in periods:
    curr = set(subscribed_by_period.loc[p])
    total = len(curr)
    next_p = p + 1  # pandas.Period addition: aggiunge un mese e gestisce␣
 ↪cambio anno
    if next_p in subscribed_by_period.index:
        nxt = set(subscribed_by_period.loc[next_p])
        retained = len(curr & nxt)
        churned = len(curr - nxt)
        retention_rate = retained / total if total > 0 else np.nan
        churn_rate = churned / total if total > 0 else np.nan
    else:
        # se non abbiamo dati per il mese successivo non stimiamo retention/
 ↪churn
        retained = np.nan
        churned = np.nan
        retention_rate = np.nan
        churn_rate = np.nan
    rows.append({
        'period': p,
        'total_users': total,
        'retained_users': retained,
        'churned_users': churned,
        'retention_rate': retention_rate,
        'churn_rate': churn_rate
    })

churn_dataframe = pd.DataFrame(rows).set_index('period').sort_index()

# Aggiungi nome mese per leggibilità (es: 'January')
month_names =␣
 ↪['January','February','March','April','May','June','July','August','September','October','N
churn_dataframe['month_name'] = [month_names[p.to_timestamp().month - 1] for p␣
 ↪in churn_dataframe.index]
```

```
# Converti rates in percentuali più leggibili
churn_dataframe['retention_rate_pct'] = (churn_dataframe['retention_rate'] *␣
 ↪100).round(1)
churn_dataframe['churn_rate_pct'] = (churn_dataframe['churn_rate'] * 100).
 ↪round(1)

print('Churn/retention calcolati usando period + 1 month (gestito anno).')
print(churn_dataframe[['total_users','retained_users','churned_users','retention_rate_pct','ch
```

```
Churn/retention calcolati usando period + 1 month (gestito anno).
         total_users  retained_users  churned_users  retention_rate_pct  \
period
2017-05         1791          1055.0          736.0                58.9
2017-06         3175          1597.0         1578.0                50.3
2017-07         2865           908.0         1957.0                31.7
2017-08         2696          1190.0         1506.0                44.1
2017-09         2557           732.0         1825.0                28.6
2017-10         2493           890.0         1603.0                35.7
2017-11         2696          1516.0         1180.0                56.2
2017-12         3081          1265.0         1816.0                41.1
2018-01         3232          1334.0         1898.0                41.3
2018-02         3400          1588.0         1812.0                46.7
2018-03         3190           960.0         2230.0                30.1
2018-04         3299             NaN            NaN                 NaN

         churn_rate_pct month_name
period
2017-05            41.1        May
2017-06            49.7       June
2017-07            68.3       July
2017-08            55.9     August
2017-09            71.4  September
2017-10            64.3    October
2017-11            43.8   November
2017-12            58.9   December
2018-01            58.7    January
2018-02            53.3   February
2018-03            69.9      March
2018-04             NaN      April
```

0.6 Average Expected Lifetime

average expted lifetime calculated as last month of activity per user - first month of activity.

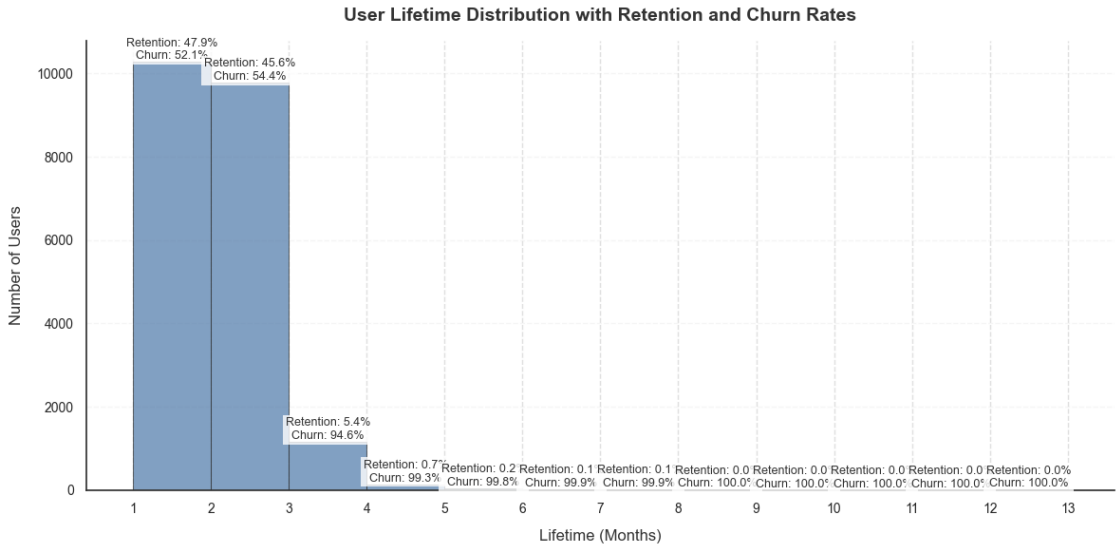
key assumption: the user does not return after the last observed month.

[28]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
sns.set(style='whitegrid')

# use cleaned dataframe 'data' with 'date' column
df = data.dropna(subset=['user','date']).copy()
df['period'] = df['date'].dt.to_period('M')

# primo e ultimo period osservato per user
first_period = df.groupby('user')['date'].min()
last_period = df.groupby('user')['date'].max()

lifetime_months = (last_period.dt.year - first_period.dt.year) * 12 +␣
 ↪(last_period.dt.month - first_period.dt.month) + 1

average_lifetime = lifetime_months.mean()
median_lifetime = lifetime_months.median()
print('Average lifetime (months):', average_lifetime)
print('Median lifetime (months):', median_lifetime)

# Calculate retention and churn rates
total_users = len(lifetime_months)
retention_counts = lifetime_months.value_counts().sort_index()
retention_rates = retention_counts / total_users * 100
churn_rates = 100 - retention_rates

# Plot enhanced figure with retention and churn rates
plt.figure(figsize=(12, 6), dpi=100)
sns.set_style("whitegrid", {"grid.linestyle": "--", "grid.color": "#e0e0e0"})

# Histogram with enhanced styling
bars = sns.histplot(lifetime_months.dropna(), bins=range(1, int(lifetime_months.
 ↪dropna().max()) + 2),
                    kde=False, color='#4C78A8', edgecolor='white', alpha=0.7)

# Add retention and churn rate annotations
for i, bar in enumerate(bars.patches):
    height = bar.get_height()
    months = i + 1
    if months in retention_rates:
        retention = retention_rates[months]
        churn = churn_rates[months]
        plt.text(bar.get_x() + bar.get_width()/2, height + 0.5,
                 f'Retention: {retention:.1f}%\nChurn: {churn:.1f}%',
                 ha='center', va='bottom', fontsize=9, color='#333333',
                 bbox=dict(facecolor='white', alpha=0.8, edgecolor='none',␣
 ↪pad=2))

# Customize plot aesthetics
```

```
plt.title('User Lifetime Distribution with Retention and Churn Rates',
          fontsize=14, pad=15, weight='bold', color='#333333')
plt.xlabel('Lifetime (Months)', fontsize=12, labelpad=10, color='#333333')
plt.ylabel('Number of Users', fontsize=12, labelpad=10, color='#333333')
plt.xticks(range(1, int(lifetime_months.dropna().max()) + 2), fontsize=10)
plt.yticks(fontsize=10)

# Add subtle shadow effect to bars
for bar in bars.patches:
    bar.set_zorder(2)
    bar.set_edgecolor('#333333')
    bar.set_linewidth(0.5)

# Customize spines
ax = plt.gca()
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_color('#333333')
ax.spines['bottom'].set_color('#333333')

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.3)

# Tight layout for better spacing
plt.tight_layout()
plt.show()
```

```
Average lifetime (months): 1.6079757462686568
Median lifetime (months): 2.0
```



0.7 Quick script to see users with longer lifetime

edit the "threshold" variable and set the number of days. the script return the users with a lifetime bigger than that.

[29]:
```
lifetime = (last_period - first_period) + pd.Timedelta(days=31)

threshold = 100

filtered_users = lifetime[lifetime >= pd.Timedelta(days=threshold)]
filtered_users
```

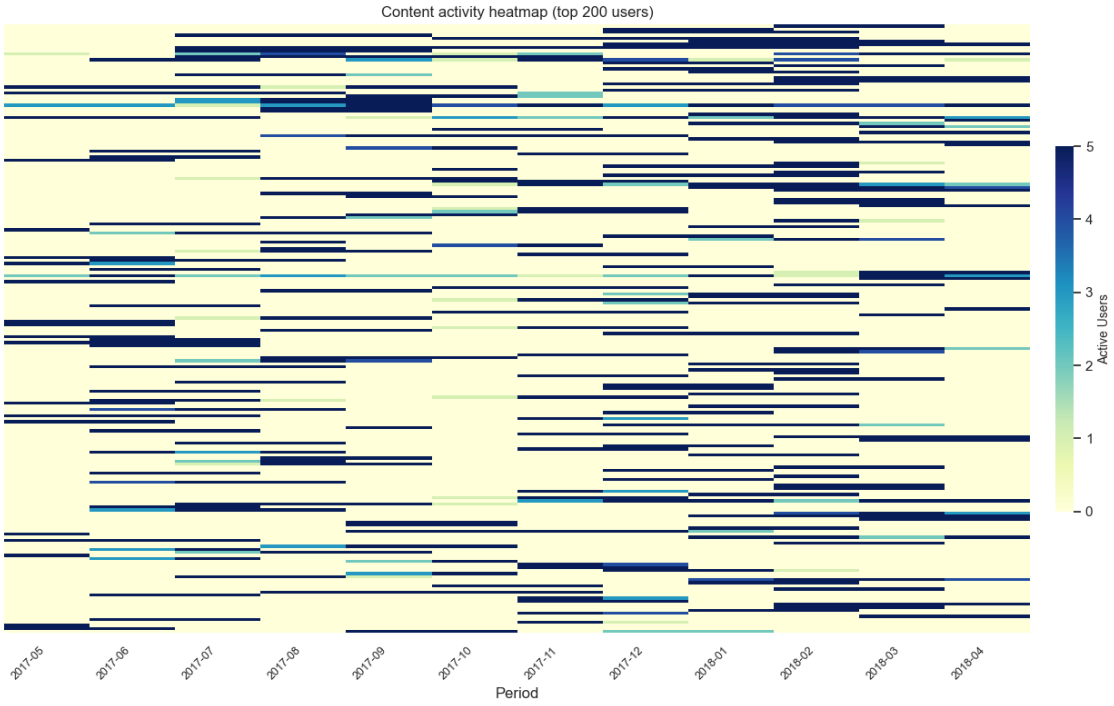
[29]:
```
user
10272   123 days
10326   123 days
10334   151 days
10369   182 days
10370   182 days
          …
961     366 days
9853    213 days
9910    123 days
9922    123 days
9984    123 days
Name: date, Length: 234, dtype: timedelta64[ns]
```

0.8 Content for user plot

[30]:
```
users = data['user'].unique()
periods = data['period'].unique()

content_matrix_dataframe = pd.DataFrame(index=users, columns=periods)

for user in users:
    user_data = data[data['user'] == user]
    for period in periods:
        period_data = user_data[user_data['period'] == period]
        if not period_data.empty:
            content_value = period_data['content'].iloc[0]
            content_matrix_dataframe.at[user, period] = content_value


content_matrix_dataframe = content_matrix_dataframe.fillna(0)
```

[31]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Improved heatmap: show only top-N most active users to improve readability
```

```python
# compute user activity and subset
user_activity = content_matrix_dataframe.sum(axis=1).
 ↪sort_values(ascending=False)
top_n = 200  # regola questo valore per presentazioni diverse
subset = content_matrix_dataframe.loc[user_activity.index[:top_n]] if␣
 ↪len(user_activity) > 0 else content_matrix_dataframe

plt.figure(figsize=(14, 8))
ax = sns.heatmap(subset,
                 cmap='YlGnBu',
                 cbar_kws={'label': 'Active Users', 'shrink': 0.6, 'pad': 0.02},
                 vmin=0, vmax=5,
                 yticklabels=False)

ax.set_xlabel('Period')
ax.set_ylabel('')  # keep y-axis label empty for cleaner view
plt.xticks(rotation=45, ha='right', fontsize=9)
plt.title(f'Content activity heatmap (top {min(top_n, subset.shape[0])} users)')

# ensure colorbar label size and layout
cbar = ax.collections[0].colorbar if len(ax.collections) > 0 else None
if cbar is not None:
    cbar.ax.yaxis.label.set_size(10)

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



0.9 Distribution Summary

[32]:
```
# Build binary active_users_matrix: 1 se content >= 1 in quel period, 0␣
 ↪altrimenti
df_active = data.copy()
df_active['active'] = (df_active['content'].fillna(0) >= 1).astype(int)
df_active = df_active[['user','period','active']].drop_duplicates()

# pivot in matrix (user x period) con valori 1/0
active_users_matrix = (
    df_active.pivot_table(index='user', columns='period', values='active',␣
 ↪aggfunc='max')
    .fillna(0).astype(int)
)

print('Active users matrix built: rows=users, cols=periods')
print(active_users_matrix.shape)
```

```
Active users matrix built: rows=users, cols=periods
(21440, 12)
```

[33]:
```
# From active_users_matrix compute % of users still active after k months since␣
 ↪first activation (k=1..12)
import numpy as np

# ensure columns are PeriodIndex
cols = active_users_matrix.columns

# find first active period per user (NaT if never active)
def first_active_period(row):
    active_cols = [c for c, v in row.items() if int(v) == 1]
    return active_cols[0] if active_cols else pd.NaT

first_active = active_users_matrix.apply(first_active_period, axis=1)

users = active_users_matrix.index.tolist()
n_users = len(users)

rows = []
for k in range(1, 13):
    active_count = 0
    for u in users:
        fa = first_active.loc[u]
        if pd.isna(fa):
            continue
```

```
        target = fa + k  # Period + int aggiunge mesi correttamente
        if target in active_users_matrix.columns:
            if active_users_matrix.at[u, target] == 1:
                active_count += 1
        # se target non esiste, l'utente non è considerato attivo per quel k
    pct = (active_count / n_users * 100) if n_users > 0 else np.nan
    rows.append({'months_after_first_activation': k, 'active_count':␣
 ↪int(active_count), 'active_pct': pct})

distribution_k = pd.DataFrame(rows).set_index('months_after_first_activation')
print('Percent of users active after k months since first activation:')

# keep results for later use
distribution_k
```

```
Percent of users active after k months since first activation:
```

[33]:

months_after_first_activation	active_count	active_pct
1	10910	50.886194
2	1311	6.114739
3	202	0.942164
4	75	0.349813
5	43	0.200560
6	28	0.130597
7	18	0.083955
8	11	0.051306
9	6	0.027985
10	8	0.037313
11	8	0.037313
12	0	0.000000

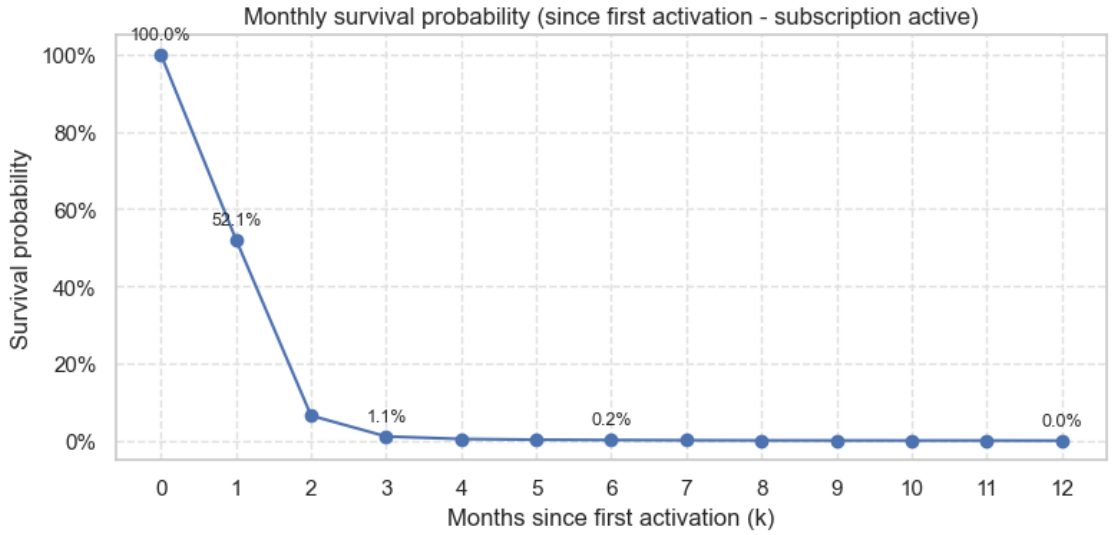
0.10 Monthly Survival Probability

[35]:
```
# Monthly survival probabilities (k = 0..12) since first activation (improved␣
 ↪plotting)
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick

# Define 'active' using subscription == 1 (fallback to content if subscription␣
 ↪missing)
if 'subscription' in data.columns:
    df_active = data[data['subscription'] == 1][['user','period']].
 ↪drop_duplicates()
else:
    # fallback behavior: use content>=1 but warn the user
```

```
    import warnings
    warnings.warn("Column 'subscription' not found in data - falling back to␣
 ↪content>=1 for active definition.")
    df_active = data.copy()
    df_active['active'] = (df_active['content'].fillna(0) >= 1).astype(int)
    df_active = df_active[df_active['active'] == 1][['user','period']].
 ↪drop_duplicates()

# First active period per user
if df_active.empty:
    print('No active subscriptions found. Check data/subscription values.')
    # create empty survival_df to avoid downstream errors
    survival_df = pd.
 ↪DataFrame(columns=['k','active_count','survival_prob','survival_pct']).
 ↪set_index('k')
else:
    first_active = df_active.groupby('user')['period'].min()
    users = first_active.index.to_numpy()
    n_users = len(users)

    rows = []
    for k in range(0, 13):
        target_periods = (first_active + k).reindex(users)
        left = pd.DataFrame({'user': users, 'target_period': target_periods.
 ↪values})
        merged = left.merge(df_active, left_on=['user','target_period'],␣
 ↪right_on=['user','period'], how='left', indicator=True)
        active_count = int((merged['_merge'] == 'both').sum())
        survival_prob = active_count / n_users if n_users > 0 else np.nan
        rows.append({
            'k': k,
            'active_count': active_count,
            'survival_prob': survival_prob,
            'survival_pct': survival_prob * 100 if not np.isnan(survival_prob)␣
 ↪else np.nan,
        })

    survival_df = pd.DataFrame(rows).set_index('k')
    # Conditional month-to-month retention
    survival_df['conditional_retention'] = survival_df['survival_prob'] /␣
 ↪survival_df['survival_prob'].shift(1)

    print('Monthly survival probabilities (k = months since first activation):')
    print(survival_df)

    # Improved plot: percent y-axis + annotations on key ks
```

```
    plt.figure(figsize=(8,4))
    plt.plot(survival_df.index, survival_df['survival_prob'], marker='o')
    plt.title('Monthly survival probability (since first activation -␣
 ↪subscription active)')
    plt.xlabel('Months since first activation (k)')
    plt.ylabel('Survival probability')
    plt.xticks(survival_df.index)
    plt.gca().yaxis.set_major_formatter(mtick.PercentFormatter(1.0))

    # annotate some key points for communication
    for k in [0,1,3,6,12]:
        if k in survival_df.index and not np.isnan(survival_df.
 ↪loc[k,'survival_prob']):
            val = survival_df.loc[k,'survival_prob']
            plt.annotate(f"{val*100:.1f}%", (k, val), textcoords='offset␣
 ↪points', xytext=(0,8), ha='center', fontsize=9)

    plt.grid(True)
    plt.tight_layout()
    plt.show()

# expose survival_df for downstream analysis
survival_df
```

```
Monthly survival probabilities (k = months since first activation):
    active_count  survival_prob  survival_pct  conditional_retention
k
0          21440       1.000000    100.000000                    NaN
1          11166       0.520802     52.080224               0.520802
2           1391       0.064879      6.487873               0.124575
3            234       0.010914      1.091418               0.168224
4             93       0.004338      0.433769               0.397436
5             53       0.002472      0.247201               0.569892
6             35       0.001632      0.163246               0.660377
7             22       0.001026      0.102612               0.628571
8             14       0.000653      0.065299               0.636364
9             10       0.000466      0.046642               0.714286
10             9       0.000420      0.041978               0.900000
11             8       0.000373      0.037313               0.888889
12             0       0.000000      0.000000               0.000000
```



[35]:

k	active_count	survival_prob	survival_pct	conditional_retention
0	21440	1.000000	100.000000	NaN
1	11166	0.520802	52.080224	0.520802
2	1391	0.064879	6.487873	0.124575
3	234	0.010914	1.091418	0.168224
4	93	0.004338	0.433769	0.397436
5	53	0.002472	0.247201	0.569892
6	35	0.001632	0.163246	0.660377
7	22	0.001026	0.102612	0.628571
8	14	0.000653	0.065299	0.636364
9	10	0.000466	0.046642	0.714286
10	9	0.000420	0.041978	0.900000
11	8	0.000373	0.037313	0.888889
12	0	0.000000	0.000000	0.000000

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