

analysis

October 22, 2025

Data Description We recommend that you number the months, with the earliest starting at zero (0). The last month of the time window is month eleven (11), which is also the current period, i.e., the present, for the most part of this.

- **cohort** is the group of customers that was acquired in each month. For example, a user belongs to cohort 3 if s/he was acquired in month 3 (i.e., the 4th month).
- **user** identifies the different users.
- **time_year** is the year and **time_month** is the month
- **subscription** is binary (1–0) variable that takes on the value one (1) if the user had an (active) subscription at the time. This variable is always one (1) because we cannot observe the behavior of users after they cancel their subscription or after they switch to a device other than their desktop and laptop computers. For the assignment, we define that a user churns if s/he stops watching Netflix online, i.e., because s/he cancels the subscription or switches to a different device.
- **content** is the number of different titles (e.g., shows and movies) that a user consumed in a month.
- **genres** is the number of different genres that are associated with a user's monthly Netflix consumption. This variable has a missing value if the user did not use Netflix in a particular month.
- **recency** is the share of recent content that a user watched in a month. The streaming of a title is recent if the time between the title's release date and the date of the stream is less than two years

0.1 Data Loading and Cleaning

```
[107]: 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

```

```

[107]:
count    cohort    user    time_year    time_month    subscription \
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

```
[108]: # 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)

```
[109]: # 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

```
[110]: # 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

```

[111]: # 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', 'November', 'December']
churn_dataframe['month_name'] = [month_names[p.to_timestamp().month - 1] for p in churn_dataframe.index]

print('Churn/retention calcolati usando period + 1 month (gestito anno).')
print(churn_dataframe)

```

```

Churn/retention calcolati usando period + 1 month (gestito anno).
      total_users  retained_users  churned_users  retention_rate \
period
2017-05         1791         1055.0          736.0         0.589056
2017-06         3175         1597.0         1578.0         0.502992
2017-07         2865          908.0         1957.0         0.316928
2017-08         2696         1190.0         1506.0         0.441395
2017-09         2557          732.0         1825.0         0.286273
2017-10         2493          890.0         1603.0         0.357000
2017-11         2696         1516.0         1180.0         0.562315
2017-12         3081         1265.0         1816.0         0.410581
2018-01         3232         1334.0         1898.0         0.412748
2018-02         3400         1588.0         1812.0         0.467059
2018-03         3190          960.0         2230.0         0.300940
2018-04         3299           NaN           NaN           NaN

```

period	churn_rate	month_name
2017-05	0.410944	May
2017-06	0.497008	June
2017-07	0.683072	July
2017-08	0.558605	August
2017-09	0.713727	September
2017-10	0.643000	October
2017-11	0.437685	November
2017-12	0.589419	December
2018-01	0.587252	January
2018-02	0.532941	February
2018-03	0.699060	March
2018-04	NaN	April

0.6 Average Expected Lifetime

average expected 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.

```
[112]: # Compute average observed lifetime (months) using Period subtraction to handle
        ↳ year changes
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

# lifetime in months: difference tra period (gestisce cambio anno) +1 per
        ↳ includere il mese iniziale
#lifetime_months = (last_period - first_period) + 1
#lifetime_months = lifetime_months.clip(lower=0)

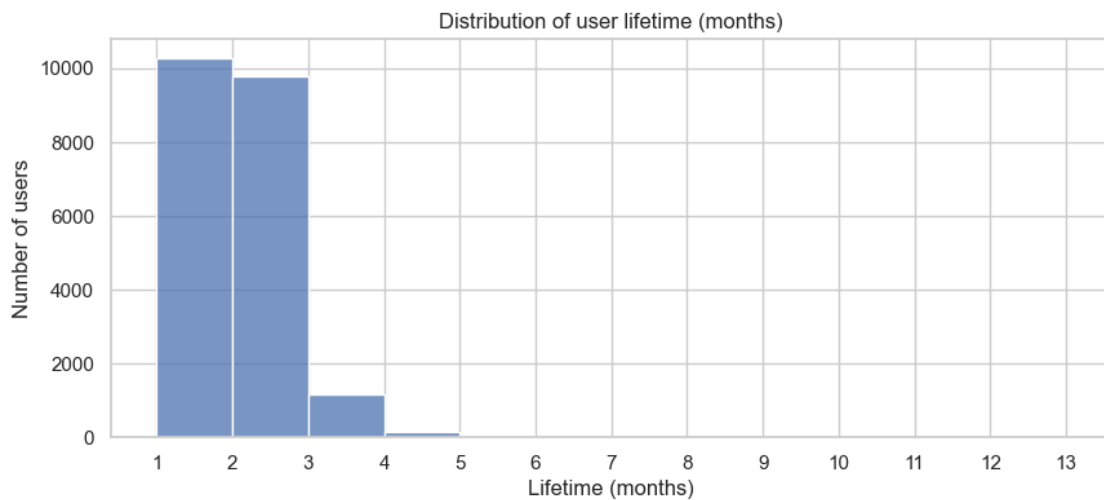
average_lifetime = lifetime_months.mean()
median_lifetime = lifetime_months.median()
print('Average lifetime (months):', average_lifetime)
print('Median lifetime (months):', median_lifetime)
```

```

# Plot histogram
max_life = int(lifetime_months.dropna().max()) if not lifetime_months.dropna().
    empty else 1
bins = range(1, max_life + 2)
plt.figure(figsize=(10,4))
sns.histplot(lifetime_months.dropna(), bins=bins, kde=False)
plt.title('Distribution of user lifetime (months)')
plt.xlabel('Lifetime (months)')
plt.ylabel('Number of users')
plt.xticks(bins)
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.

```

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

threshold = 100

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

```

```

[113]: 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

```

[114]: 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)

```

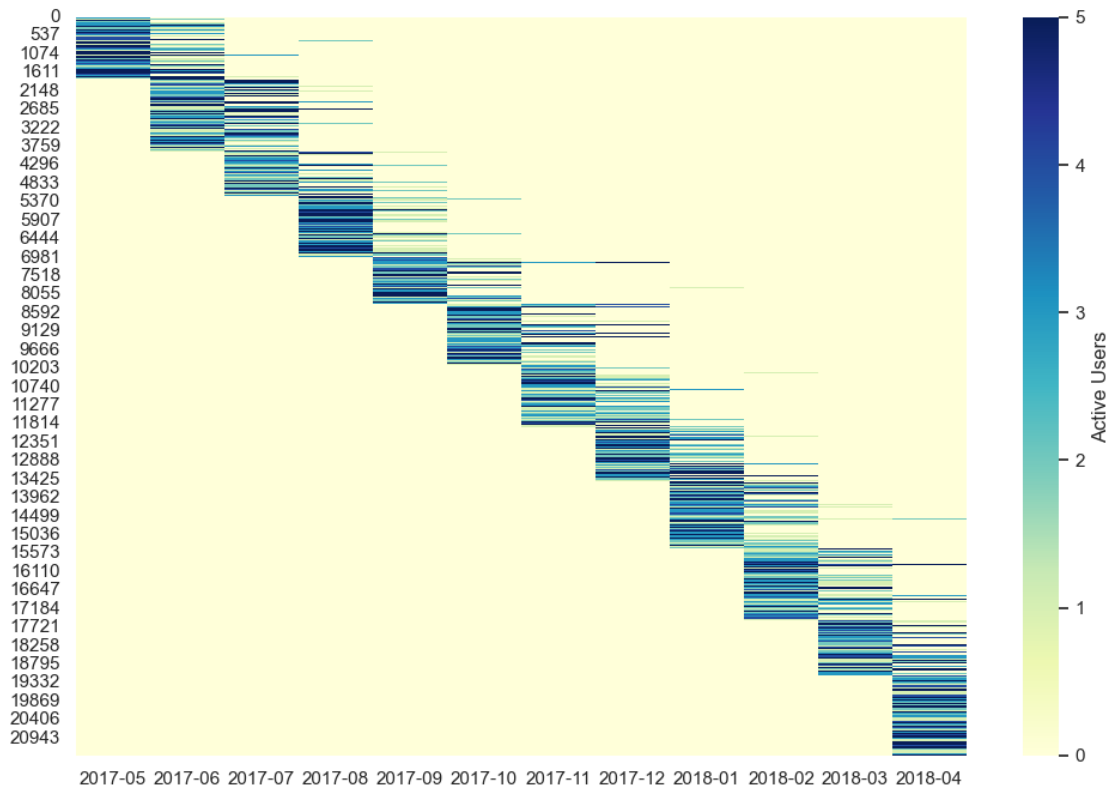
```

[115]: import seaborn as sns
       import matplotlib.pyplot as plt

       # Assuming active_users_matrix is your data
       plt.figure(figsize=(12, 8)) # Increased dimensions: width=12, height=8
       sns.heatmap(content_matrix_dataframe, cmap='YlGnBu', cbar_kws={'label': 'Active_
       ↪Users'}, vmin=0, vmax=5)

       plt.show()

```



0.9 Distribution Summary

```
[116]: # 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)
```

```
[117]: # 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:

```
[117]:
```

	active_count	active_pct
months_after_first_activation		
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

```
[118]: # Monthly survival probabilities (k = 0..12) since first activation
import numpy as np
import matplotlib.pyplot as plt

# Binary active table: active = content >= 1
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
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 period per user (Period + int aggiunge mesi correttamente e
    ↳gestisce cambio anno)
    target_periods = (first_active + k).reindex(users)
    left = pd.DataFrame({'user': users, 'target_period': target_periods.values})
    # merge per verificare attività in target period
    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)

# Plot survival curve
plt.figure(figsize=(8,4))
plt.plot(survival_df.index, survival_df['survival_prob'], marker='o')
plt.title('Monthly survival probability (since first activation)')
plt.xlabel('Months since first activation (k)')
plt.ylabel('Survival probability (0-1)')
plt.xticks(survival_df.index)
plt.grid(True)
plt.show()

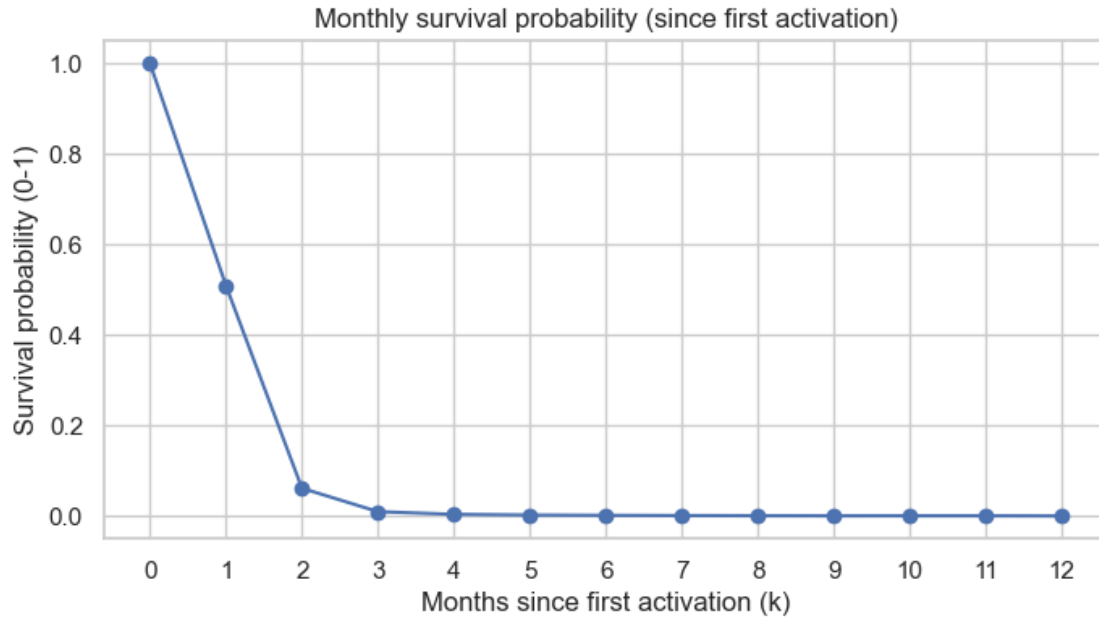
# expose survival_df for downstream analysis
survival_df

```

```

Monthly survival probabilities (k = months since first activation):
   active_count  survival_prob  survival_pct  conditional_retention
k
0           21439           1.000000      100.000000                NaN
1           10910           0.508886       50.888568             0.508886
2            1311           0.061150        6.115024             0.120165
3             202           0.009422        0.942208             0.154081
4              75           0.003498        0.349830             0.371287
5              43           0.002006        0.200569             0.573333
6              28           0.001306        0.130603             0.651163
7              18           0.000840        0.083959             0.642857
8              11           0.000513        0.051308             0.611111
9               6           0.000280        0.027986             0.545455
10              8           0.000373        0.037315             1.333333
11              8           0.000373        0.037315             1.000000
12              0           0.000000        0.000000             0.000000

```



```
[118]:
```

	active_count	survival_prob	survival_pct	conditional_retention
k				
0	21439	1.000000	100.000000	NaN
1	10910	0.508886	50.888568	0.508886
2	1311	0.061150	6.115024	0.120165
3	202	0.009422	0.942208	0.154081
4	75	0.003498	0.349830	0.371287
5	43	0.002006	0.200569	0.573333
6	28	0.001306	0.130603	0.651163
7	18	0.000840	0.083959	0.642857
8	11	0.000513	0.051308	0.611111
9	6	0.000280	0.027986	0.545455
10	8	0.000373	0.037315	1.333333
11	8	0.000373	0.037315	1.000000
12	0	0.000000	0.000000	0.000000