In [ ]:
```
# user_id, order_dt, order_products, order_amount
# data between Jan 1997 - Jun 1998, about 60000 rows
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
plt.style.use('ggplot')
```

In [3]:
```
columns = ['user_id','order_dt','order_products','order_amount']
df = pd.read_table('CDNOW_master.txt',names=columns,sep='\s+')
```

In [4]:
```
df.head()
```

Out[4]:

	user_id	order_dt	order_products	order_amount
0	1	19970101	1	11.77
1	2	19970112	1	12.00
2	2	19970112	5	77.00
3	3	19970102	2	20.76
4	3	19970330	2	20.76

In [5]:
```
# transform date
# one customer has multiple orders in oneday
df.describe()
# mean.product 2.4, std.product 2.3, 75% 2~3 products
# per order_amount,small amount 30~45
```

Out[5]:

	user_id	order_dt	order_products	order_amount
count	69659.000000	6.965900e+04	69659.000000	69659.000000
mean	11470.854592	1.997228e+07	2.410040	35.893648
std	6819.904848	3.837735e+03	2.333924	36.281942
min	1.000000	1.997010e+07	1.000000	0.000000
25%	5506.000000	1.997022e+07	1.000000	14.490000
50%	11410.000000	1.997042e+07	2.000000	25.980000
75%	17273.000000	1.997111e+07	3.000000	43.700000
max	23570.000000	1.998063e+07	99.000000	1286.010000

In [6]:
```
df.info()
# 69659 means non null,date's type is int64
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69659 entries, 0 to 69658
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   user_id         69659 non-null  int64  
 1   order_dt        69659 non-null  int64  
 2   order_products  69659 non-null  int64  
 3   order_amount    69659 non-null  float64
dtypes: float64(1), int64(3)
memory usage: 2.1 MB
```

Data Cleaning

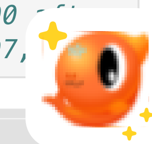
In [7]:
```python
df['order_date'] = pd.to_datetime(df['order_dt'],format='%Y%m%d')
# order_date to month
df['month'] = df['order_date'].dt.to_period('M')
df.head()
```

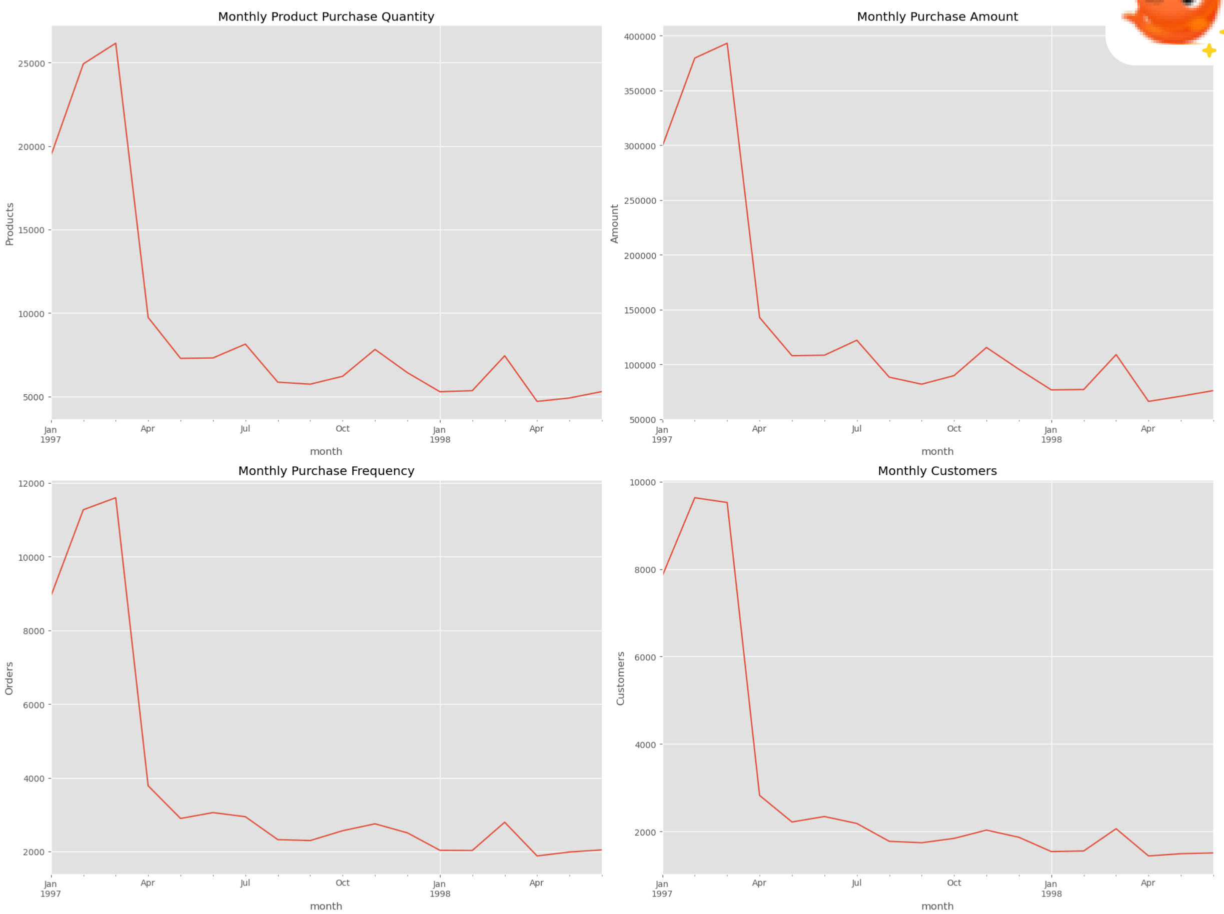
Out[7]:

	user_id	order_dt	order_products	order_amount	order_date	month
0	1	19970101	1	11.77	1997-01-01	1997-01
1	2	19970112	1	12.00	1997-01-12	1997-01
2	2	19970112	5	77.00	1997-01-12	1997-01
3	3	19970102	2	20.76	1997-01-02	1997-01
4	3	19970330	2	20.76	1997-03-30	1997-03

In [17]:
```python
# Trend Analysis
plt.figure(figsize=(20, 15))

# 1. Monthly product purchase quantity
plt.subplot(2, 2, 1)
df.groupby('month')['order_products'].sum().plot()
plt.title('Monthly Product Purchase Quantity')
plt.ylabel('Products')

# 2. Monthly purchase amount
plt.subplot(2, 2, 2)
df.groupby('month')['order_amount'].sum().plot()
plt.title('Monthly Purchase Amount')
plt.ylabel('Amount')

# 3. Monthly purchase frequency
plt.subplot(2, 2, 3)
df.groupby('month')['user_id'].count().plot()
plt.title('Monthly Purchase Frequency')
plt.ylabel('Orders')

# 4. Monthly customers (unique users)
plt.subplot(2, 2, 4)
df.groupby('month')['user_id'].nunique().plot()
```

```
plt.title('Monthly Customers')
plt.ylabel('Customers')

plt.tight_layout()  # Adjust subplot spacing automatically
plt.show()

# Key Findings:
# 1. Product Quantity: High sales in Q1 (first 3 months), then declined and
# 2. Purchase Amount: Proportional to quantity, peaked in Q1, dropped signif
#    Potential causes: (a) Holiday season effect, (b) Increased promotions i
# 3. Order Frequency: ~10,000 orders/month in Q1, averaged ~2,500 in subsequ
# 4. Customer Count: 8,000-10,000 customers in Q1, dropped to <2,000 af
# Conclusion: The data shows unusual consumption patterns in Q1 1997,
```





Customer Consumption Analysis

1. Customer Spending Amount, Purchase Frequency, Product Quantity, Descriptive Statistics

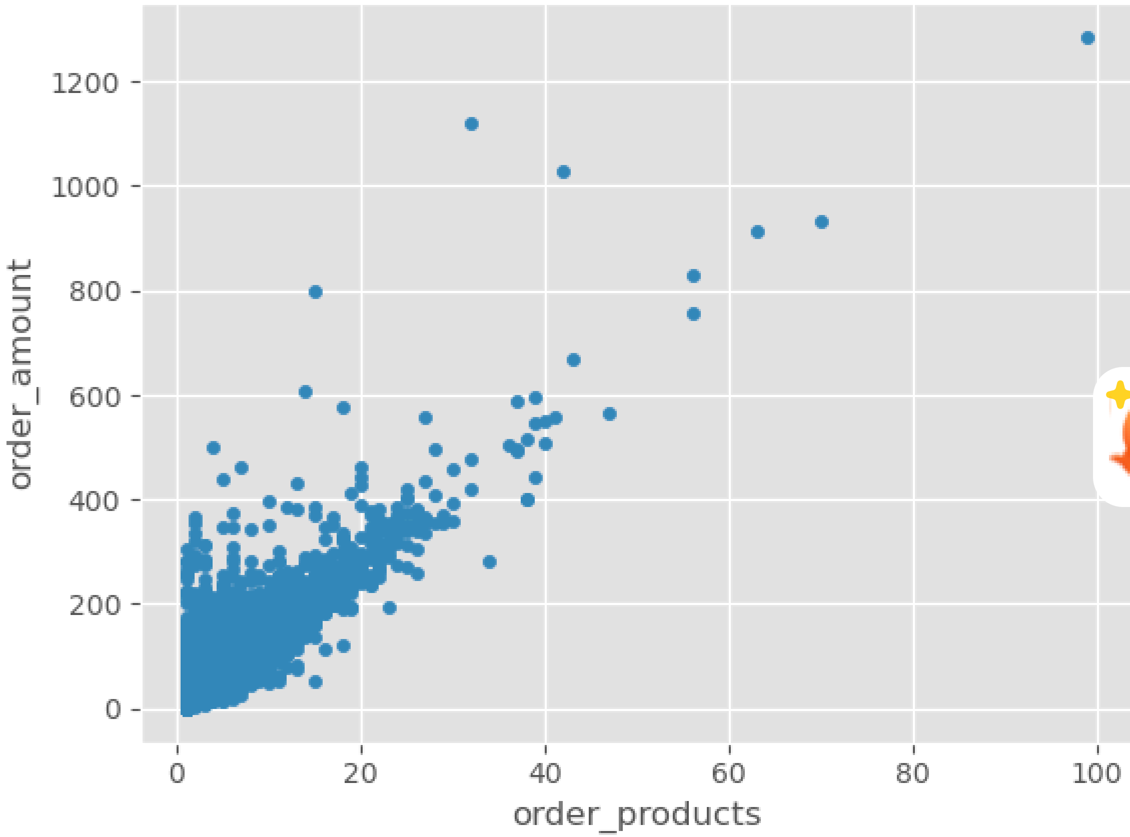
In [25]:
```
user_grouped = df.groupby('user_id').sum(numeric_only=True)
print(user_grouped.describe())
print('user amount:',len(user_grouped))
# From the user perspective:
# - Total users: 23,570
# - Average products purchased per user: 7
# - Median products purchased: 3
```

```
# - Maximum purchase quantity: 1,033
# - Distribution type: Right-skewed (mean > median)

# From the spending amount perspective:
# - Average user spending: $106
# - Median spending: $43
# - Maximum spending: $13,990 (high-value user)
# - Mean ≈ 75th percentile
# - Distribution type: Right-skewed
# - Insight: The top 25% of users contribute disproportionately to total rev
```

```
           order_dt  order_products  order_amount
count  2.357000e+04    23570.000000  23570.000000
mean   5.902627e+07        7.122656    106.080426
std    9.460684e+07       16.983531    240.925195
min    1.997010e+07        1.000000      0.000000
25%    1.997021e+07        1.000000     19.970000
50%    1.997032e+07        3.000000     43.395000
75%    5.992125e+07        7.000000    106.475000
max    4.334408e+09     1033.000000  13990.930000
user amount: 23570
```

In [160…

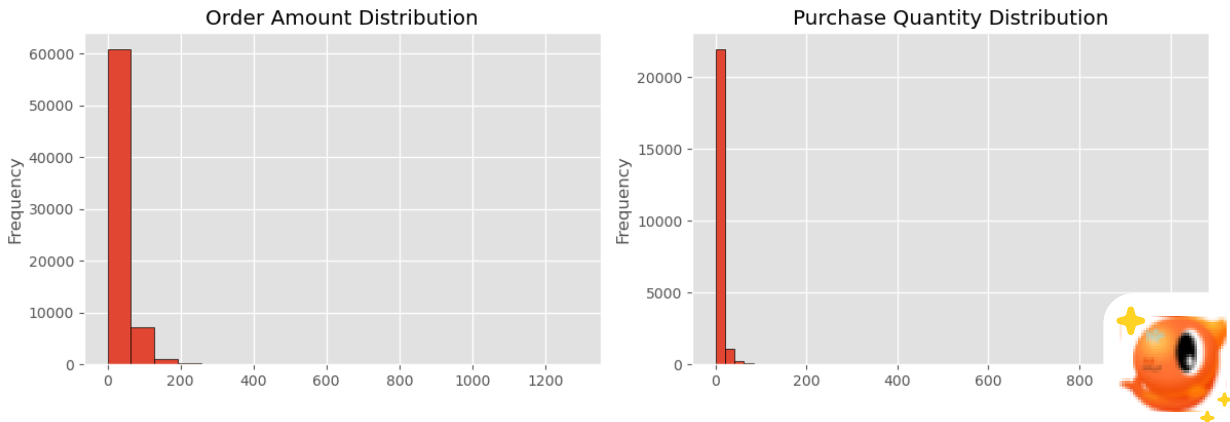
```
# Visualization:
# Generate a scatter plot displaying the relationship between product purcha
df.plot(kind='scatter',x='order_products',y='order_amount')
plt.show()
# Linear Relationship Analysis:
# - Spending amount shows strong linear correlation with purchase quantity
# - Average price per product: ~$15
# - Relationship: Spending ≈ Quantity × $15

# Outlier Analysis:
# - Outlier criteria: Spending > $1,000 OR Quantity > 60
# - Outlier frequency: Minimal (few extreme values)
# - Impact on sample: Negligible
# - Recommendation: Can be excluded from analysis without affecting results
```



2. Customer Spending Distribution

In [40]:
```
# Create figure with two subplots
plt.figure(figsize=(12, 4))

# Subplot 1: Order Amount Distribution
plt.subplot(121)
plt.xlabel('Spending per Transaction ($)')
df['order_amount'].plot(kind='hist', bins=20, edgecolor='black')
plt.title('Order Amount Distribution')
# Note: bins parameter controls the number of intervals
# Larger bins value = narrower bars
# Bar width = (max value - min value) / bins

# Subplot 2: Purchase Quantity per User Distribution
plt.subplot(122)
plt.xlabel('Products Purchased per User')
df.groupby(by='user_id')['order_products'].sum().plot(kind='hist', bins=50,
plt.title('Purchase Quantity Distribution')

plt.tight_layout()
plt.show()

# Key Insights:
# 1. The majority of orders have spending amounts within $100
# 2. Purchase quantities per user are concentrated under 50 products
# 3. Our customer base is primarily characterized by:
```

```
#    - Low-value transactions (under $100)
#    - Small purchase quantities (under 50 items per user)
```



3. Customer Contribution Analysis (Cumulative Spending Distribution)

In [41]:
```
# Analyze what percentage of customers contribute to what percentage of reve
# Typical use case: Identify if 20% of customers generate 80% of revenue (Pa
```

In [42]:
```
# Group users, extract spending amount, sum, sort, and reset index
user_cumsum = df.groupby('user_id')['order_amount'].sum().sort_values().rese
user_cumsum
```

Out[42]:

	user_id	order_amount
0	10175	0.00
1	4559	0.00
2	1948	0.00
3	925	0.00
4	10798	0.00
...	...	...
23565	7931	6497.18
23566	19339	6552.70
23567	7983	6973.07
23568	14048	8976.33
23569	7592	13990.93

23570 rows × 2 columns

In [44]:
```
user_cumsum['amount_cumsum'] = user_cumsum['order_amount'].cumsum()
user_cumsum.tail()
```

Out[44]:

	user_id	order_amount	amount_cumsum
23565	7931	6497.18	2463822.60
23566	19339	6552.70	2470375.30
23567	7983	6973.07	2477348.37
23568	14048	8976.33	2486324.70
23569	7592	13990.93	2500315.63

In [45]:

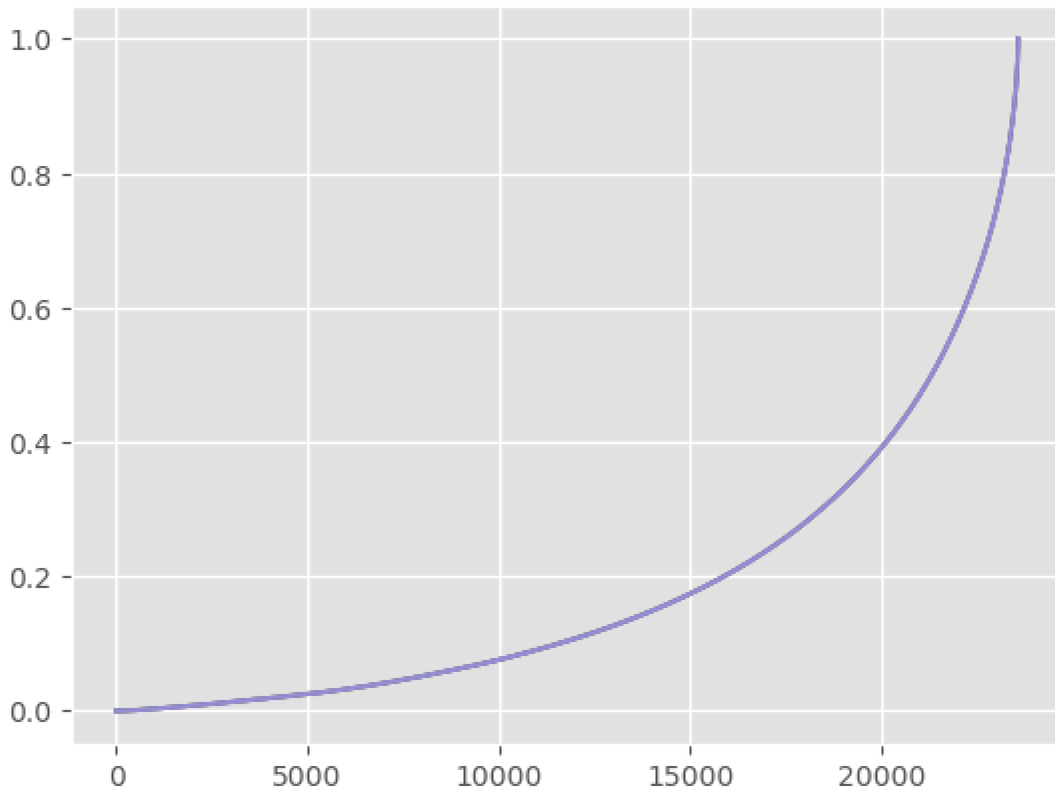
```
# Total Revenue
amount_total = user_cumsum['amount_cumsum'].max()
user_cumsum['prop'] = user_cumsum.apply(lambda x:x['amount_cumsum'] /
user_cumsum.tail()
```

Out[45]:

	user_id	order_amount	amount_cumsum	prop
23565	7931	6497.18	2463822.60	0.985405
23566	19339	6552.70	2470375.30	0.988025
23567	7983	6973.07	2477348.37	0.990814
23568	14048	8976.33	2486324.70	0.994404
23569	7592	13990.93	2500315.63	1.000000

In [49]:

```
user_cumsum['prop'].plot()
plt.show()
"""
The data follows a standard Pareto distribution pattern:
- Top 15% of customers (3,500 users) contribute 60% of total revenue
- Remaining 85% of customers (20,000 users) contribute 40% of revenue

This is a typical Pareto distribution (60/15), where a minority of
high-value customers drive the majority of revenue.
"""
```



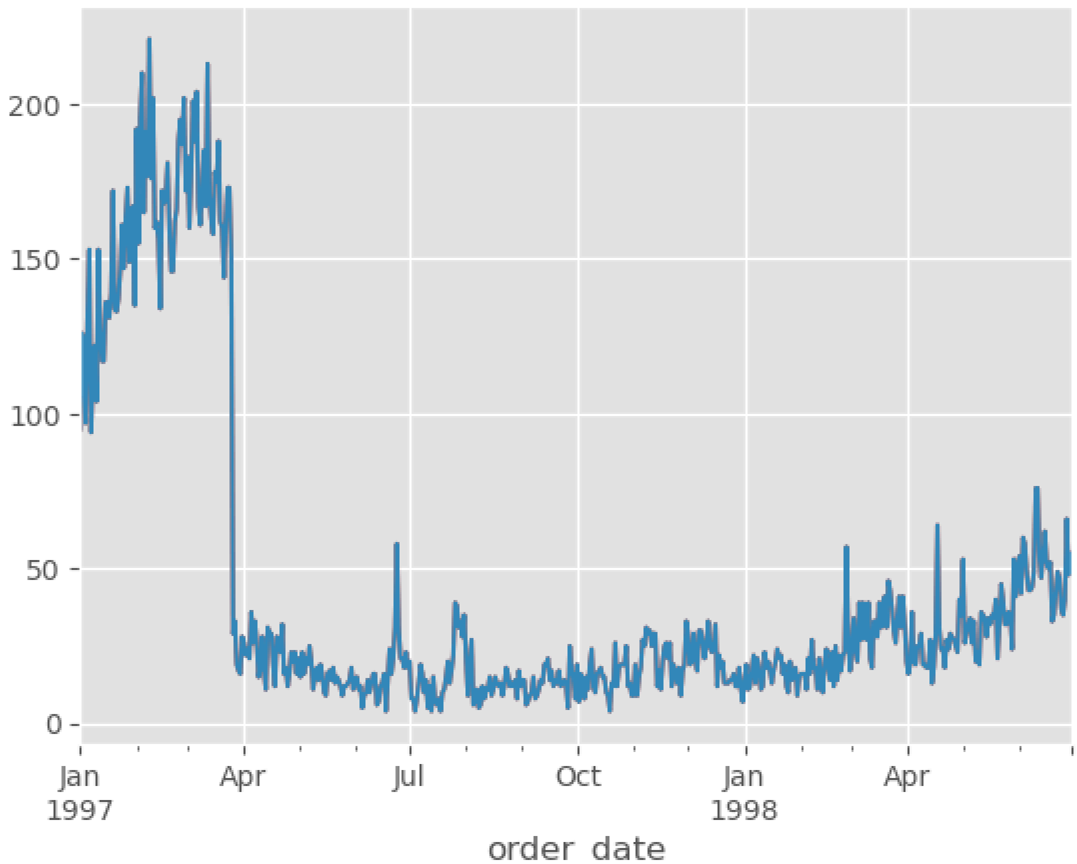
4. User Purchase Behavior Analysis

1. First Purchase Date - Identify earliest transaction per customer

In [62]:
```
df.groupby('user_id')['order_date'].min().value_counts().sort_index().plot()
plt.show()
# Analysis: New customer acquisition showed a strong upward trend from Jan 1
```

2. Most Recent Purchase Date - Identify latest transaction per customer

In [64]:
```
df.groupby('user_id')['order_date'].max().value_counts().sort_index().plot()
plt.show()
# The majority of users' last purchases occurred in the first 3 months, sugg
# As time progresses, the count of last-time purchasers increases. Hypothesi
```



Customer Segmentation

1. Build RFM Model

In [69]:
```
#  Use Pivot Tables for Analysis (index equal to groupby, values means colum
rfm = df.pivot_table(index='user_id',
                     values=['order_products','order_amount','order_date'],
                     aggfunc={
                         'order_date':'max', # the last time purchase
                         'order_products':'sum',
                         'order_amount':'sum'
                     })
rfm.head()
```

Out[69]:

	order_amount	order_date	order_products
user_id			
1	11.77	1997-01-01	1
2	89.00	1997-01-12	6
3	156.46	1998-05-28	16
4	100.50	1997-12-12	7
5	385.61	1998-01-03	29

In [159…

```
# Recency (R): Days since last purchase = max date - user's last purchase da
rfm['R'] =-(rfm['order_date'] - rfm['order_date'].max())/np.timedelta64(1,'D
rfm.rename(columns={'order_products':'F','order_amount':'M'})
rfm.head()
```

Out[159…

user_id	M	order_date	F	R	label
1	11.77	1997-01-01	1	545.0	Standard Growth Customers
2	89.00	1997-01-12	6	534.0	Standard Growth Customers
3	156.46	1998-05-28	16	33.0	Key Retention Customers
4	100.50	1997-12-12	7	200.0	Standard Recovery Customers
5	385.61	1998-01-03	29	178.0	Key Retention Customers

In [84]:

```
 # RFM Calculation Method Translation
'''
RFM Calculation Method: Subtract the mean of each column from each data poir

RFM Calculation Approach:
1. For each column, subtract the column's mean from each value (creating sta
2. Compare each standardized result against the threshold of 1
3. If the result >= 1, assign a value of 1; otherwise assign 0
'''
def rfm_func(x):  # x: represents a row of data
    level = x.apply(lambda x: 1 if x >= 1 else 0)
    # Convert to string and concatenate
    label = str(level['R']) + str(level['F']) + str(level['M'])

    d = {
        '111': 'High-Value Customers',
        '011': 'Key Retention Customers',
        '101': 'Key Growth Customers',
        '001': 'Key Recovery Customers',
        '110': 'Standard Value Customers',
        '010': 'Standard Retention Customers',
        '100': 'Standard Growth Customers',
        '000': 'Standard Recovery Customers'
    }
    result = d[label]
    return result

# Standardize data and apply function
rfm['label'] = rfm[['R','F',"M"]].apply(lambda x:x-x.mean()).apply(rfm_func,
rfm.head()
```

Out[84]:

user_id	M	order_date	F	R	label
1	11.77	1997-01-01	1	545.0	Standard Growth Customers
2	89.00	1997-01-12	6	534.0	Standard Growth Customers
3	156.46	1998-05-28	16	33.0	Key Retention Customers
4	100.50	1997-12-12	7	200.0	Standard Recovery Customers
5	385.61	1998-01-03	29	178.0	Key Retention Customers

In [88]:

```
# Customer Segmentation Visualization
for label,grouped in rfm.groupby('label'):
    print(label,grouped)
    x = grouped['F'] # Number of purchases per user
    y = grouped['R'] # Number of days between the last purchase date and Jul
    plt.scatter(x, y, label=label)
plt.legend() # Show legend
plt.xlabel('F')
plt.ylabel('R')
plt.show()
```

```
High-Value Customers             M order_date   F      R                  l
abel
user_id
19       175.12 1997-06-10  11  385.0  High-Value Customers
20       653.01 1997-01-18  46  528.0  High-Value Customers
27       135.87 1997-01-12  10  534.0  High-Value Customers
61       155.65 1997-01-01  11  545.0  High-Value Customers
69       217.08 1997-01-04  14  542.0  High-Value Customers
...         ...        ...  ..    ...                   ...
23386    120.55 1997-05-10   9  416.0  High-Value Customers
23398    163.38 1997-03-25  12  462.0  High-Value Customers
23404    143.34 1997-04-28   9  428.0  High-Value Customers
23501    147.24 1997-04-07   9  449.0  High-Value Customers
23508    118.93 1997-04-08  10  448.0  High-Value Customers

[631 rows x 5 columns]
Key Growth Customers             M order_date  F      R                  la
bel
user_id
162      119.54 1997-01-01  2  545.0  Key Growth Customers
209      116.17 1997-03-15  7  472.0  Key Growth Customers
265      135.60 1997-02-20  6  495.0  Key Growth Customers
304      113.34 1997-05-27  8  399.0  Key Growth Customers
419      108.72 1997-01-02  4  544.0  Key Growth Customers
...         ...        ... ..    ...                   ...
23010    110.51 1997-03-23  8  464.0  Key Growth Customers
23034    113.33 1997-06-07  6  388.0  Key Growth Customers
23082    112.33 1997-04-11  8  445.0  Key Growth Customers
23391    161.68 1997-06-02  4  393.0  Key Growth Customers
23568    121.70 1997-04-22  6  434.0  Key Growth Customers

[371 rows x 5 columns]
Key Recovery Customers             M order_date  F      R
label
user_id
43       117.32 1998-05-24  7   37.0  Key Recovery Customers
102      157.47 1998-03-01  7  121.0  Key Recovery Customers
114      124.93 1998-02-11  7  139.0  Key Recovery Customers
126      302.75 1997-12-02  3  210.0  Key Recovery Customers
142      122.39 1998-04-11  7   80.0  Key Recovery Customers
...         ...        ... ..    ...                     ...
23368    198.31 1998-04-25  7   66.0  Key Recovery Customers
23402    116.92 1998-06-25  8    5.0  Key Recovery Customers
23425    127.12 1998-06-05  8   25.0  Key Recovery Customers
23466    107.38 1998-05-24  8   37.0  Key Recovery Customers
23559    111.65 1997-06-27  8  368.0  Key Recovery Customers

[599 rows x 5 columns]
Key Retention Customers              M order_date   F      R
label
user_id
3        156.46 1998-05-28  16   33.0  Key Retention Customers
5        385.61 1998-01-03  29  178.0  Key Retention Customers
7        264.67 1998-03-22  18  100.0  Key Retention Customers
8        197.66 1998-03-29  18   93.0  Key Retention Customers
25       137.53 1998-06-08  12   22.0  Key Retention Customers
```

```
...          ...        ...  ..   ...                         ...
23544    134.63 1998-01-24  12  157.0  Key Retention Customers
23551    264.63 1997-09-11  12  292.0  Key Retention Customers
23555    189.18 1998-06-10  14   20.0  Key Retention Customers
23556    203.00 1998-06-07  15   23.0  Key Retention Customers
23558    145.60 1998-02-25  11  125.0  Key Retention Customers

[4267 rows x 5 columns]
Standard Growth Customers              M order_date  F      R
label
user_id
1        11.77 1997-01-01  1  545.0  Standard Growth Customers
2        89.00 1997-01-12  6  534.0  Standard Growth Customers
6        20.99 1997-01-01  1  545.0  Standard Growth Customers
10       39.31 1997-01-21  3  525.0  Standard Growth Customers
12       57.06 1997-01-01  4  545.0  Standard Growth Customers
...        ...        ... ..    ...                        ...
23565    11.77 1997-03-25  1  462.0  Standard Growth Customers
23566    36.00 1997-03-25  2  462.0  Standard Growth Customers
23567    20.97 1997-03-25  1  462.0  Standard Growth Customers
23569    25.74 1997-03-25  2  462.0  Standard Growth Customers
23570    94.08 1997-03-26  5  461.0  Standard Growth Customers

[14138 rows x 5 columns]
Standard Recovery Customers               M order_date  F      R
label
user_id
4        100.50 1997-12-12  7  200.0  Standard Recovery Customers
9         95.85 1998-06-08  6   22.0  Standard Recovery Customers
11        58.55 1998-02-20  4  130.0  Standard Recovery Customers
16        79.87 1997-09-10  8  293.0  Standard Recovery Customers
24        57.77 1998-01-20  4  161.0  Standard Recovery Customers
...         ...        ... ..    ...                          ...
23540     67.01 1998-02-25  5  125.0  Standard Recovery Customers
23554     36.37 1998-02-01  3  149.0  Standard Recovery Customers
23561     83.46 1998-05-29  6   32.0  Standard Recovery Customers
23563     58.75 1997-10-04  3  269.0  Standard Recovery Customers
23564     70.01 1997-11-30  5  212.0  Standard Recovery Customers

[3493 rows x 5 columns]
Standard Retention Customers               M order_date   F      R
label
user_id
670      103.53 1998-06-09   9   21.0  Standard Retention Customers
1148      98.77 1998-03-31  11   91.0  Standard Retention Customers
2443      76.68 1998-05-07   9   54.0  Standard Retention Customers
2856     104.27 1998-05-26   9   35.0  Standard Retention Customers
2976      92.48 1997-09-28   9  275.0  Standard Retention Customers
3256      82.68 1998-01-02   9  179.0  Standard Retention Customers
3337     105.08 1997-12-08   9  204.0  Standard Retention Customers
3515      90.15 1997-09-19  12  284.0  Standard Retention Customers
4671      86.56 1998-05-07   9   54.0  Standard Retention Customers
5031     106.32 1998-05-19   9   42.0  Standard Retention Customers
5056     102.95 1997-08-18   9  316.0  Standard Retention Customers
5447     103.72 1998-04-20   9   71.0  Standard Retention Customers
6311     102.19 1998-06-13   9   17.0  Standard Retention Customers
```

```
6907     106.50 1997-10-25   9  248.0  Standard Retention Customers
6958     105.44 1998-03-10   9  112.0  Standard Retention Customers
7011      99.59 1998-03-11   9  111.0  Standard Retention Customers
7057     100.87 1998-05-23  10   38.0  Standard Retention Customers
7923     104.15 1997-11-06   9  236.0  Standard Retention Customers
8419      90.63 1997-09-05   9  298.0  Standard Retention Customers
8605      88.20 1998-06-26  10    4.0  Standard Retention Customers
8794      84.73 1997-10-11   9  262.0  Standard Retention Customers
8926      93.25 1997-10-14   9  259.0  Standard Retention Customers
10997     91.68 1997-09-12  11  291.0  Standard Retention Customers
11405     82.78 1997-08-25   9  309.0  Standard Retention Customers
11921     97.40 1997-10-14   9  259.0  Standard Retention Customers
12176     88.67 1998-04-03   9   88.0  Standard Retention Customers
13145    106.70 1998-01-11   9  170.0  Standard Retention Customers
13292     88.61 1998-01-06   9  175.0  Standard Retention Customers
13711     95.30 1997-08-11   9  323.0  Standard Retention Customers
13988     98.07 1997-11-10   9  232.0  Standard Retention Customers
14068     64.70 1998-06-30   9    0.0  Standard Retention Customers
14237    104.88 1997-12-16   9  196.0  Standard Retention Customers
14406    105.21 1998-04-28   9   63.0  Standard Retention Customers
14960     99.44 1998-06-04   9   26.0  Standard Retention Customers
15061    104.45 1998-03-29   9   93.0  Standard Retention Customers
15121    104.80 1997-11-18   9  224.0  Standard Retention Customers
15270     90.85 1997-08-02   9  332.0  Standard Retention Customers
15460     94.70 1998-03-31  10   91.0  Standard Retention Customers
16622    107.03 1998-06-07   9   23.0  Standard Retention Customers
17693     83.34 1998-06-28   9    2.0  Standard Retention Customers
17989    104.82 1998-02-26   9  124.0  Standard Retention Customers
18187    102.44 1998-06-10  10   20.0  Standard Retention Customers
18493    102.36 1998-03-29   9   93.0  Standard Retention Customers
18564     97.07 1997-11-19   9  223.0  Standard Retention Customers
19046     90.52 1998-05-27   9   34.0  Standard Retention Customers
19939     94.94 1997-07-28  10  337.0  Standard Retention Customers
21223     99.97 1998-06-01   9   29.0  Standard Retention Customers
21337    104.60 1998-05-01   9   60.0  Standard Retention Customers
21432     91.63 1998-06-15   9   15.0  Standard Retention Customers
21682     95.82 1998-01-19  10  162.0  Standard Retention Customers
23029     93.95 1997-12-06  11  206.0  Standard Retention Customers
23174     81.47 1997-09-25   9  278.0  Standard Retention Customers
23517    103.83 1998-03-29   9   93.0  Standard Retention Customers
Standard Value Customers               M order_date   F      R
label
user_id
928      103.36 1997-04-27   9  429.0  Standard Value Customers
1784     105.89 1997-02-06  11  509.0  Standard Value Customers
3247     101.29 1997-03-23  11  464.0  Standard Value Customers
4132      96.82 1997-01-17  18  529.0  Standard Value Customers
4632      96.96 1997-04-22   9  434.0  Standard Value Customers
6936     106.19 1997-01-27  12  519.0  Standard Value Customers
8610     101.73 1997-02-03   9  512.0  Standard Value Customers
10733    100.57 1997-02-25   9  490.0  Standard Value Customers
11541    104.52 1997-02-11   9  504.0  Standard Value Customers
14183     78.69 1997-02-20   9  495.0  Standard Value Customers
14262     91.15 1997-02-22   9  493.0  Standard Value Customers
16357     96.86 1997-06-22   9  373.0  Standard Value Customers
16540     87.56 1997-03-05  10  482.0  Standard Value Customers
```

```
17567     101.33 1997-03-28   9  459.0  Standard Value Customers
20140      89.20 1997-04-02   9  454.0  Standard Value Customers
20385     102.35 1997-03-13  10  474.0  Standard Value Customers
20608     105.94 1997-04-28  10  428.0  Standard Value Customers
23079      96.70 1997-03-23  10  464.0  Standard Value Customers
```

User Cohort Analysis: New, Active, Dormant, and Reactivated Users

In [94]:
```
'''
New users are defined as those making their first purchase.
Active users are existing customers who have made purchases within a certain
Inactive users are existing customers who have not made any purchases within
Returning users: Equivalent to repeat customers.
User return behavior can be categorized into organic return and assisted ret
'''
pivoted_counts = df.pivot_table(index='user_id',columns='month',values='orde
pivoted_counts
```

Out [94]:

month	1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	1997-09	1997-10	199
user_id											
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
2	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
3	1.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
4	2.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	[illegible]
5	2.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	[illegible]	[illegible]
...	...	...	...	...	...	...	...	...	...	[illegible]	[illegible]
23566	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
23567	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
23568	0.0	0.0	1.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
23569	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]
23570	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]

23570 rows × 18 columns

In [96]:

```python
# Convert to binary (0/1) to indicate purchase status
df_purchase = pivoted_counts.map(lambda x:1 if x>0 else 0)
# apply: applies a function along an axis (row or column) of a DataFrame
# map: applies a function element-wise to every element in a DataFram
df_purchase.head()
```

Out [96]:

month	1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	1997-09	1997-10	199
user_id											
1	1	0	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	0	
3	1	0	1	1	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	1	0	0	
5	1	1	0	1	1	1	1	0	1	0	

In [104…

```python
# Determine user segment: new, active, dormant, or reactivated
def active_status(data): # Entire row of data, 18 columns in total
    status = [] # # Stores the status for 18 months (one column per month)
    for i in range(len(data)):
        if data[i] == 0:
```

```
            if len(status) == 0:
                status.append('unreg')
            else:
                if status[i-1] == 'unreg':
                    status.append('unreg')
                else:
                    status.append('unactive')
            pass
        else:
            if len(status) == 0:
                status.append('new')
            else:
                if status[i-1] == 'unactive':
                    status.append('return')
                elif status[i-1] == 'unreg':
                    status.append('new')
                else:
                    status.append('active')

    return pd.Series(status,df_purchase.columns)

purchase_states = df_purchase.apply(active_status, axis=1) # Get user segmer
purchase_states.head()
```

```
/var/folders/zj/qg5wsktj2hx43sww1lt6szbm0000gn/T/ipykernel_23684/3583350512.
py:5: FutureWarning: Series.__getitem__ treating keys as positions is deprec
ated. In a future version, integer keys will always be treated as labels (co
nsistent with DataFrame behavior). To access a value by position, use `ser.i
loc[pos]`
  if data[i] == 0:
```

Out[104…

month	1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	19
user_id									
1	new	unactive	unactive	unactive	unactive	unactive	unactive	unactive	unac
2	new	unactive	unactive	unactive	unactive	unactive	unactive	unactive	unac
3	new	unactive	return	active	unactive	unactive	unactive	unactive	unac
4	new	unactive	unactive	unactive	unactive	unactive	unactive	return	unac
5	new	active	unactive	return	active	active	active	unactive	ret

In [107…

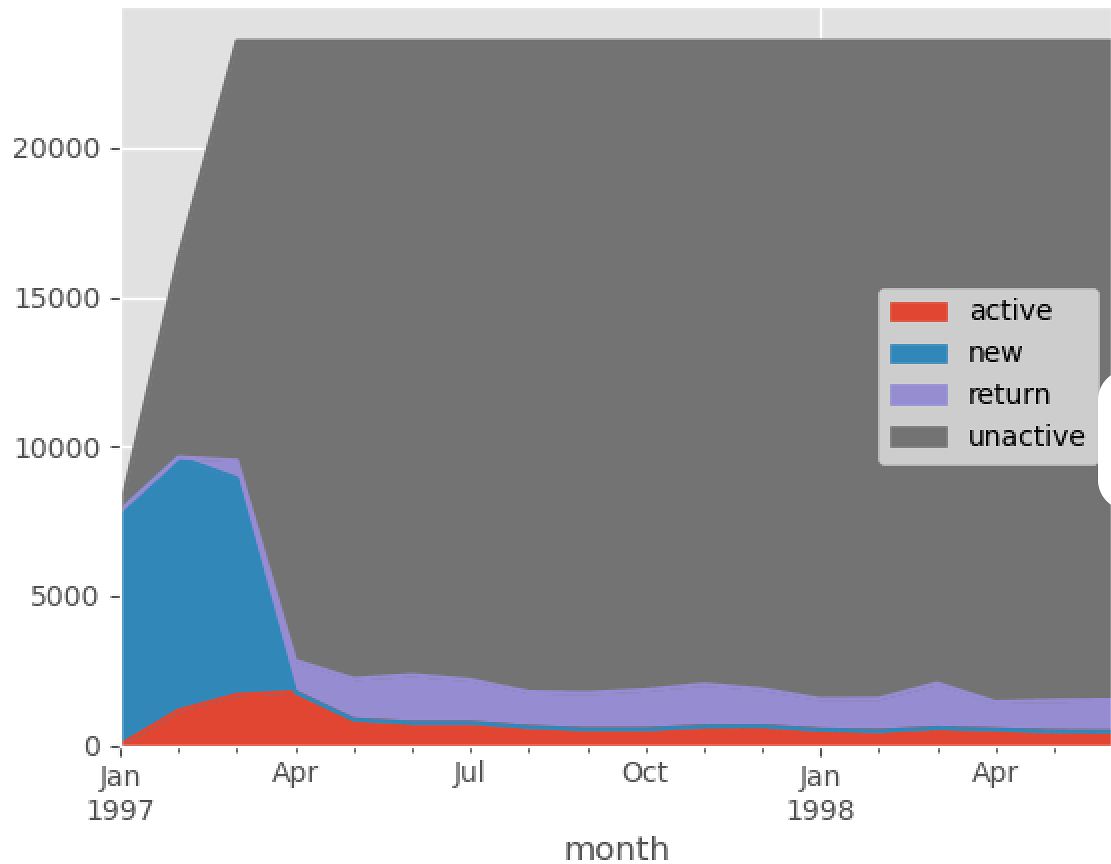
```
# Substitute 'unreg' with nan
purchase_states_ct = purchase_states.replace('unreg', np.nan).apply(lambda s
purchase_states_ct.head(60)
```

Out[107…

month	1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	1997-09
active	NaN	1157.0	1681	1773.0	852.0	747.0	746.0	604.0	528.0
new	7846.0	8476.0	7248	NaN	NaN	NaN	NaN	NaN	NaN
return	NaN	NaN	595	1049.0	1362.0	1592.0	1434.0	1168.0	1211.0
unactive	NaN	6689.0	14046	20748.0	21356.0	21231.0	21390.0	21798.0	21831.0

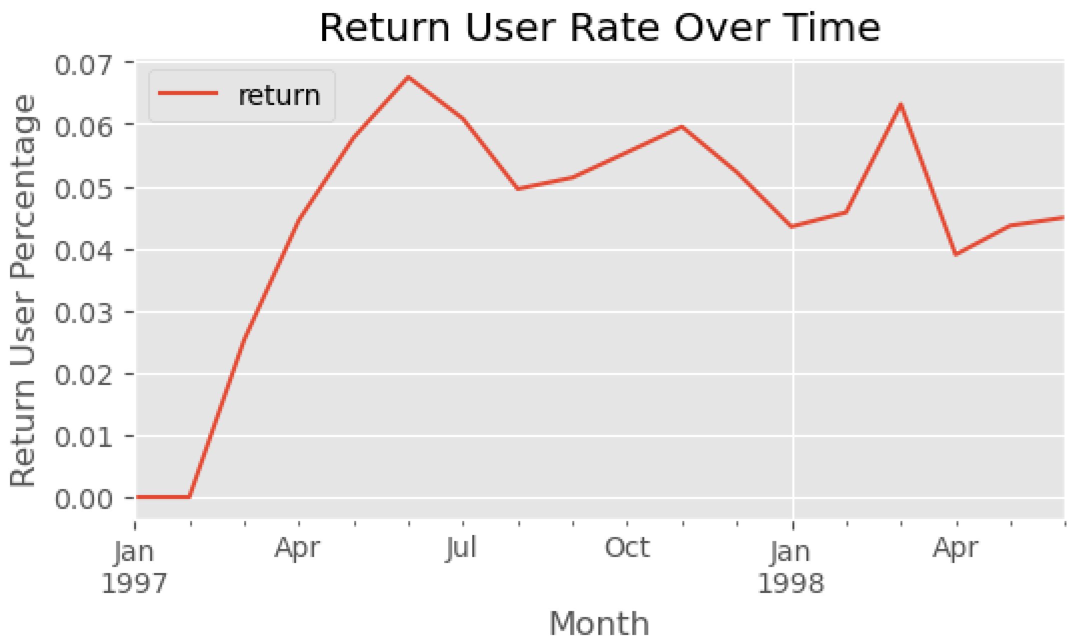
In [110…

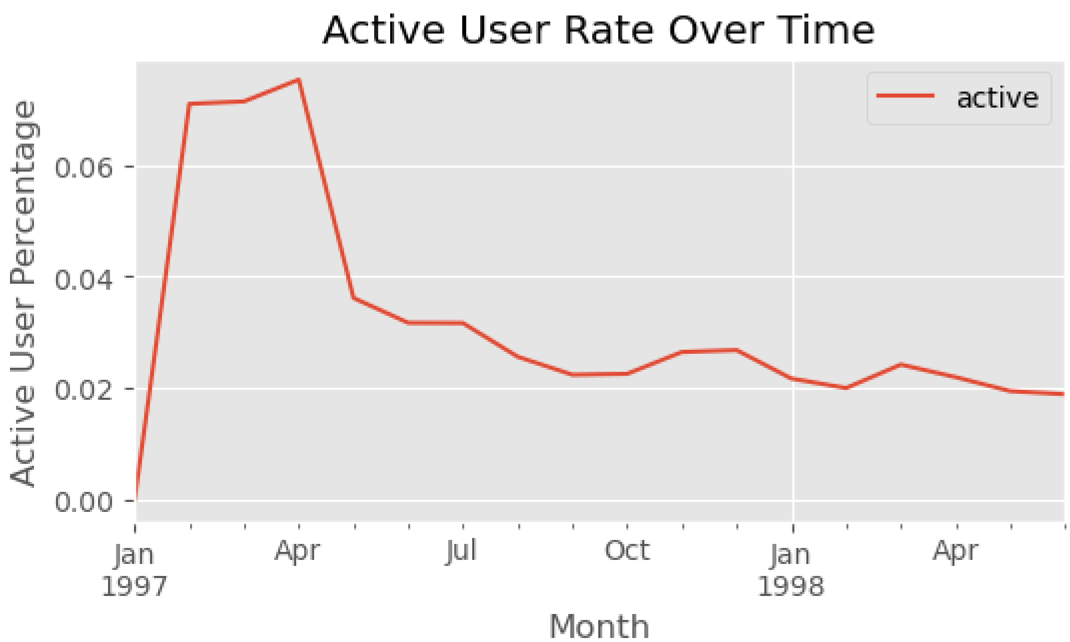
```
purchase_states_ct.T.fillna(0).plot.area()
plt.show()
# Key Findings from the visualization:

# 1. Early Stage (First 3 Months):
#    - Active users (red) and new users (blue) constitute the largest segmen
#    - High proportion of user acquisition and engagement
#    - Indicates successful initial growth phase

# 2. Mid to Late Stage (Post-April):
#    - New user acquisition begins to decline
#    - Active user count shows downward trend
#    - Both metrics stabilize at lower, consistent levels
#    - Suggests market maturation

# 3. Returning Users (Post-April):
#    - Return users emerge as a significant segment after April
#    - Demonstrates stable, consistent pattern
#    - Critical customer segment for platform sustainability
#    - Indicates successful retention strategies
```



In [115…

```
# Return User Rate Over Time
rate = purchase_states_ct.T.fillna(0).apply(lambda x: x/x.sum(),axis=1)
# Use pandas plotting (handles Period automatically)
rate['return'].plot(label='return', figsize=(6, 3))
plt.xlabel('Month')
plt.ylabel('Return User Percentage')
plt.title('Return User Rate Over Time')
plt.legend()
plt.show()

rate['active'].plot(label='active', figsize=(6, 3))
plt.xlabel('Month')
plt.ylabel('Active User Percentage')
plt.title('Active User Rate Over Time')
plt.legend()
plt.show()
```

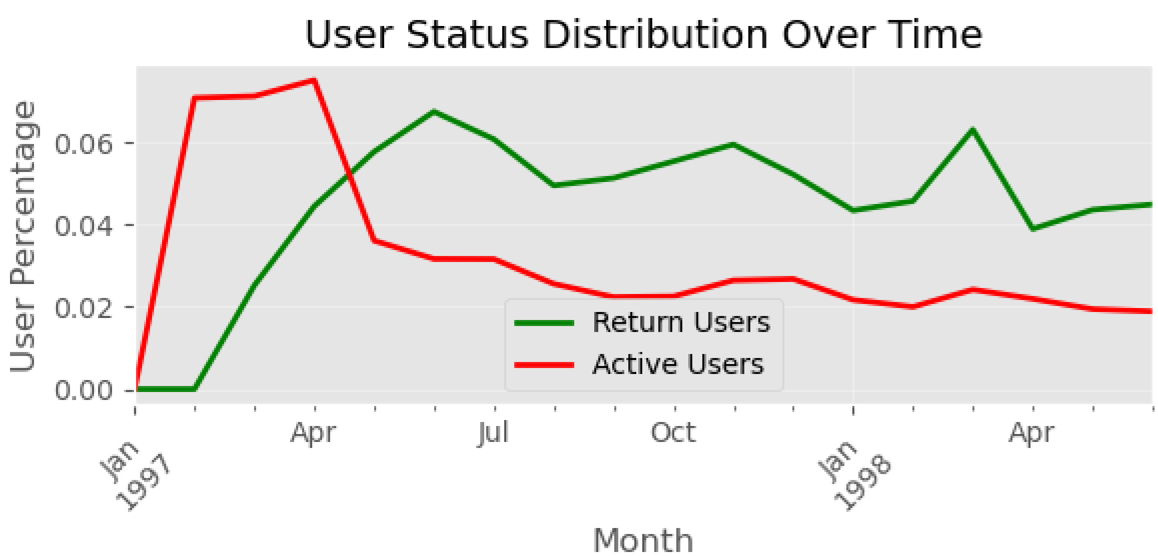




In [117…

```
# Return User Rate Over Time
rate = purchase_states_ct.T.fillna(0).apply(lambda x: x/x.sum(), axis=1)

# Create figure first
plt.figure(figsize=(6, 3))

# Plot multiple lines before calling show()
rate['return'].plot(label='Return Users', color='green', linewidth=2)
rate['active'].plot(label='Active Users', color='red', linewidth=2)

# Add labels and show once at the end
plt.xlabel('Month', fontsize=12)
plt.ylabel('User Percentage', fontsize=12)
plt.title('User Status Distribution Over Time', fontsize=14)
plt.legend(loc='best')
```

```python
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
'''
ANALYSIS SUMMARY:
1. Returning Users:
   - First 5 months: Upward trend
   - Post-5 months: Declining trend, stabilizing at ~5%
   - Interpretation: Growing customer loyalty base

2. Active Users:
   - Months 1-3: Rapid growth (hypothesis: promotional campaigns)
   - Post-May: Decline to ~2.5% average
   - Interpretation: Initial spike driven by new user acquisition

3. Platform Maturity:
   - Return users > Active users (stable operations phase)
   - Indicates successful retention > new acquisition
   - Business health: Strong repeat purchase behavior
'''
```



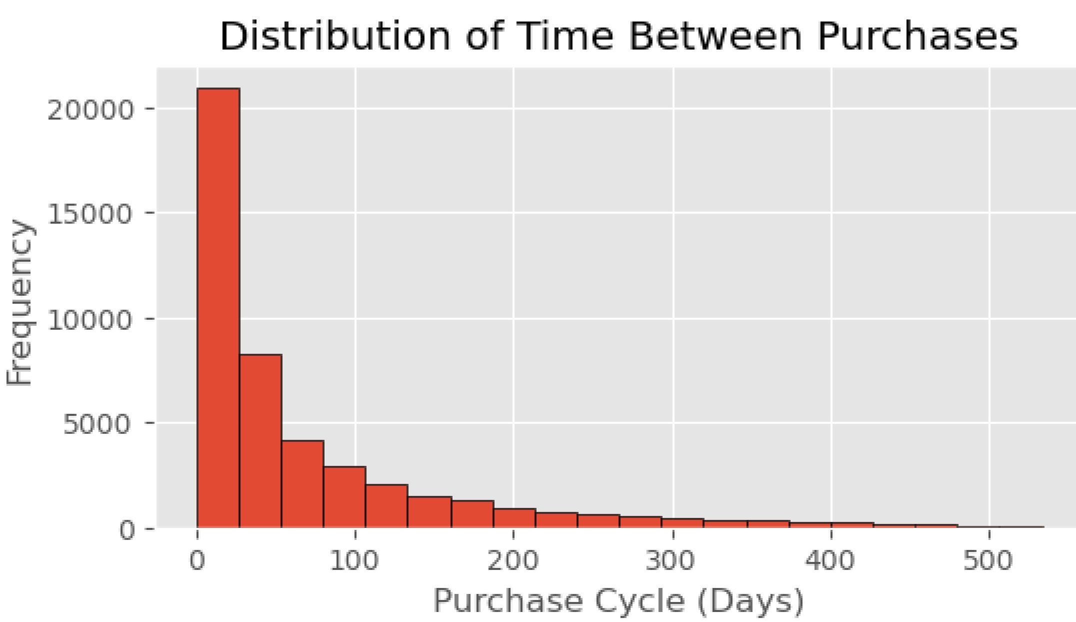
Customer Purchase Cycle Analysis

In [119…

```python
# Calculate purchase cycle
order_diff = df.groupby('user_id')['order_date'].transform(
    lambda x: x - x.shift()
)
order_diff.describe()
```

Out[119…
```
count                          46089
mean      68 days 23:22:13.567662566
std       91 days 00:47:33.924168893
min                  0 days 00:00:00
25%                 10 days 00:00:00
50%                 31 days 00:00:00
75%                 89 days 00:00:00
max                533 days 00:00:00
Name: order_date, dtype: object
```

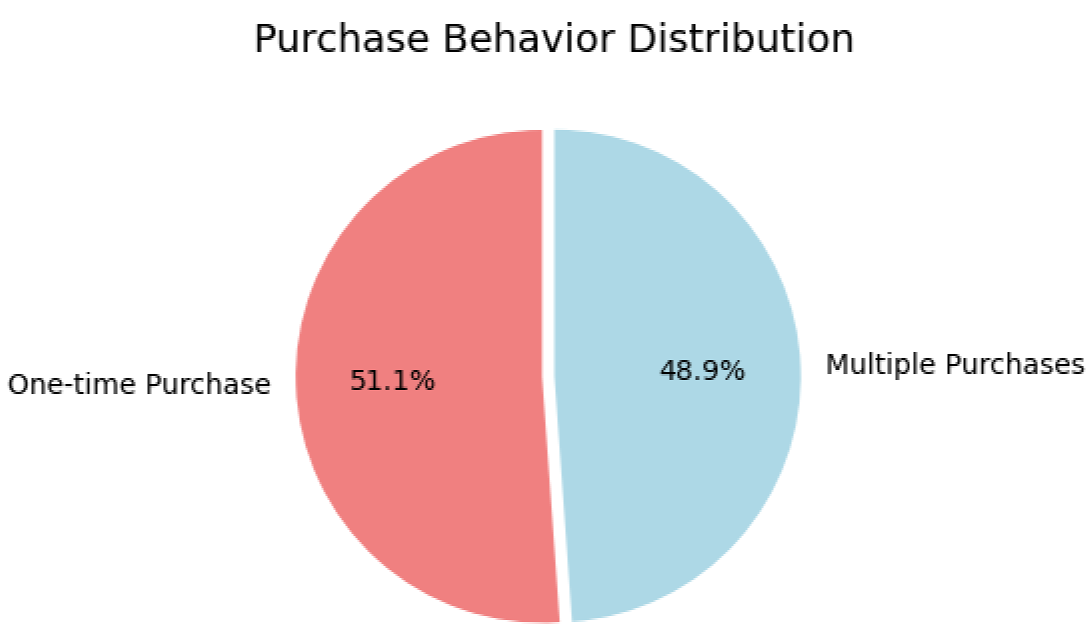
In [122…
```
# Convert to days first
order_diff_days = order_diff.dt.days
# Use pandas hist method
order_diff_days.hist(bins=20, figsize=(6, 3), edgecolor='black')
plt.xlabel('Purchase Cycle (Days)')
plt.ylabel('Frequency')
plt.title('Distribution of Time Between Purchases')
# bins affects bar width: width = (max - min) / bins
plt.show()
'''
Key Findings:
- Average Purchase Cycle: 68 days
- Distribution Pattern: Long-tail (most users < 100 days)
- Low-Engagement Segment: Small proportion with cycles > 200 days

Actionable Insight:
Deploy targeted retention campaigns for users with extended purchase cycles.
Send promotional coupons 3 days prior to expected repurchase date to boost
purchase frequency.
'''
```



Customer Lifecycle Analysis

In [127…
```
# CUSTOMER LIFETIME CALCULATION
# Calculation Methodology:
# Step 1: Identify first purchase date (MIN) per customer
```

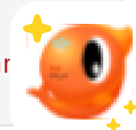
```python
# Step 2: Identify last purchase date (MAX) per customer
# Step 3: Calculate difference: Last - First
# Step 4: Interpret results:
#         - Difference = 0 days → One-time buyer (single purchase)
#         - Difference > 0 days → Repeat buyer (multiple purchases)
user_life = df.groupby('user_id')['order_date'].agg(['min', 'max'])
user_life['buyer_type'] = np.where(
    user_life['max'] == user_life['min'],
    'One-time Purchase',
    'Multiple Purchases'
)

# Visualize
buyer_distribution = user_life['buyer_type'].value_counts()

plt.figure(figsize=(5, 4))
plt.pie(buyer_distribution.values,
        labels=buyer_distribution.index,
        autopct='%1.1f%%',
        startangle=90,
        colors=['lightcoral', 'lightblue'],
        explode=(0.05, 0))
plt.title('Purchase Behavior Distribution', fontsize=14)
plt.show()
print(buyer_distribution)
'''
With over 50% of customers being one-time purchasers, this indicates
significant retention challenges and suggests opportunities for improving
customer engagement strategies.
'''
```




```
buyer_type
One-time Purchase     12054
Multiple Purchases    11516
Name: count, dtype: int64
```

In [128…

```
(user_life['max'] - user_life['min']).describe()
'''
Customer Lifetime Analysis:

The average customer lifetime is 134 days, however, the median is 0 days.
This confirms that the majority of customers made only a single purchase,
representing low-quality users with minimal engagement.

Users in the top 25th percentile (above 75th percentile) demonstrate
lifetimes exceeding 294 days, representing core customers who require
focused retention efforts and priority service.

Data scope: New users from the first three months. Therefore, this ar
'''
```



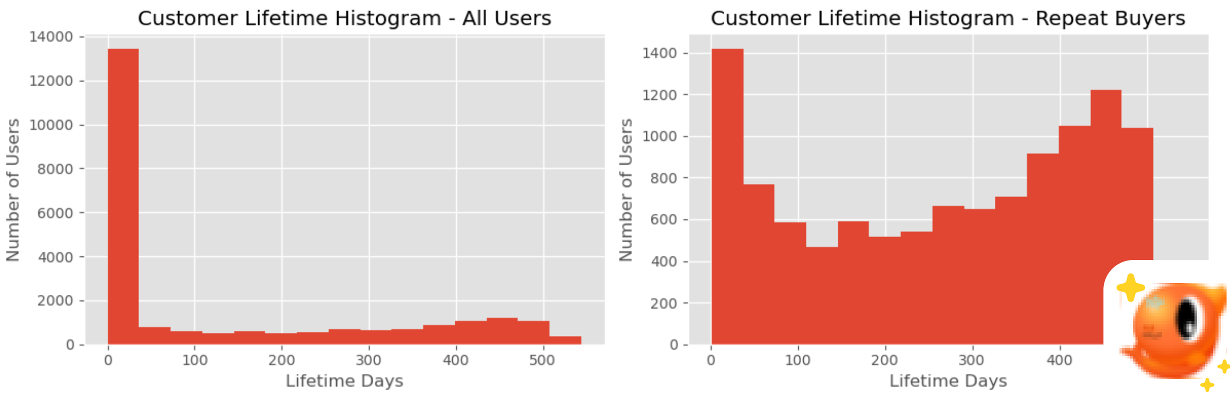
Out[128…

```
count                            23570
mean     134 days 20:55:36.987696224
std      180 days 13:46:43.039788104
min                  0 days 00:00:00
25%                  0 days 00:00:00
50%                  0 days 00:00:00
75%                294 days 00:00:00
max                544 days 00:00:00
dtype: object
```

In [158…

```
# VISUALIZE CUSTOMER LIFETIME DISTRIBUTION
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
((user_life['max'] - user_life['min'])/np.timedelta64(1, 'D')).hist(bins=15)
plt.title('Customer Lifetime Histogram - All Users')
plt.xlabel('Lifetime Days')
plt.ylabel('Number of Users')

plt.subplot(1, 2, 2)
u_1 = (user_life['max'] - user_life['min']).reset_index()[0]/np.timedelta64(
u_1[u_1>0].hist(bins=15)
plt.title('Customer Lifetime Histogram - Repeat Buyers')
plt.xlabel('Lifetime Days')
plt.ylabel('Number of Users')

plt.tight_layout()
plt.show()
'''
Comparative Analysis:
Chart 2 excludes users with lifetime = 0 days, revealing a bimodal
distribution pattern.

While Chart 2 still shows a portion of users with near-zero lifetimes,
the distribution is significantly improved compared to Chart 1. These
customers made multiple purchases but lack sustained engagement,
representing regular users who would benefit from targeted marketing
campaigns to encourage longer-term consumption patterns.

A smaller segment demonstrates lifetimes concentrated in the 300-500 day
```

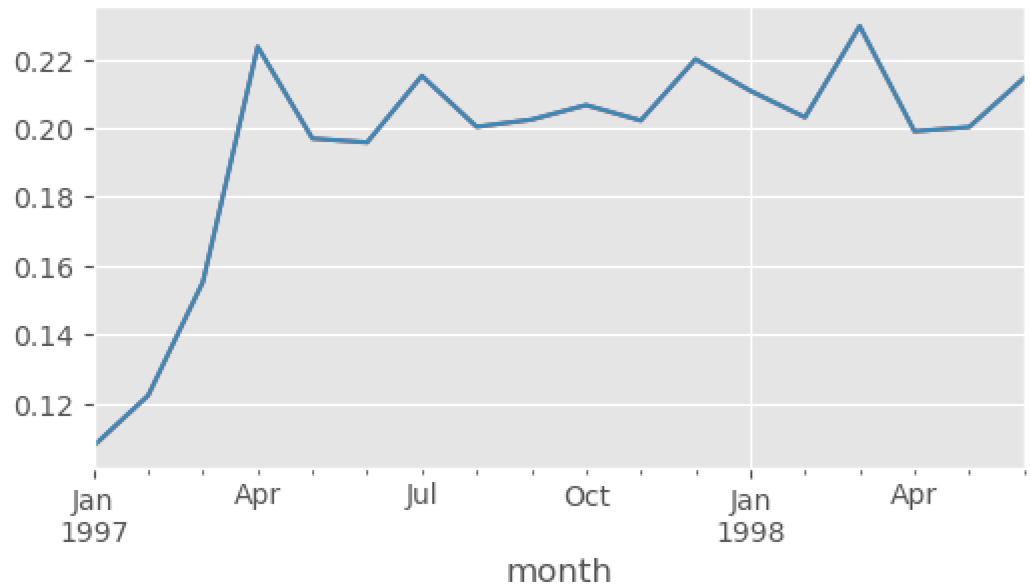
```
range, representing our loyal customer base. This high-value segment
requires intensive retention efforts and VIP service.
'''
```



Repeat Purchase Rate and Repurchase Rate Analysis

In [138…

```
# Calculation Method:
# Within each calendar month, calculate the percentage of users who made mul
# Note: Same-day multiple purchases also count as repeat purchases

# Customer Segmentation by Purchase Behavior:
# Segment 1: Multi-purchase customers (≥2 transactions) -- 1
# Segment 2: Single-purchase customers (1 transaction) -- 0
# Segment 3: Non-purchasing users (0 transactions this month) -- nan, nan va
purchase_r = pivoted_counts.map(lambda x: 1 if x> 1 else np.nan if x==0 else
purchase_r.head()
(purchase_r.sum()/purchase_r.count()).plot(figsize=(6, 3))
plt.show()
"""
Trend Analysis:
- Months 1-3: Repeat purchase rate increases
- Month 4+: Stabilizes at 20-22% range

Root Cause:
The lower repeat rate in early months is attributed to high new user
acquisition, where the majority of new customers made only one purchase,
diluting the overall repeat purchase percentage.
"""
```



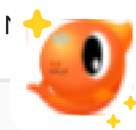
Repurchase Rate Analysis

In [142…

```
## Methodology: Measure the proportion of customers who made purchases in co
def purchase_back(data):
    status = []  # Store repurchase status for each period
    # Status classification:
    # 1 = Repurchased user (active in consecutive periods)
    # 0 = Non-repurchase user (active this period, inactive next)
    # NaN = Inactive in current period
    for i in range(17):
        # Check if user made a purchase in current period
        if data.iloc[i] == 1:
            # Check next period
            if data.iloc[i+1] == 1:
                # User purchased in both current and next period
                status.append(1)  # Repurchased
            elif data.iloc[i+1] == 0:
                # User purchased this period but not next
                status.append(0)  # Did not repurchase
        else:
            # No purchase in current period
            status.append(np.nan)  # Inactive
    # Fill last period (no next period to compare)
    status.append(np.nan)
    return pd.Series(status, df_purchase.columns)
# Apply repurchase calculation to all users
purchase_b = df_purchase.apply(purchase_back, axis=1)
purchase_b.head()
```

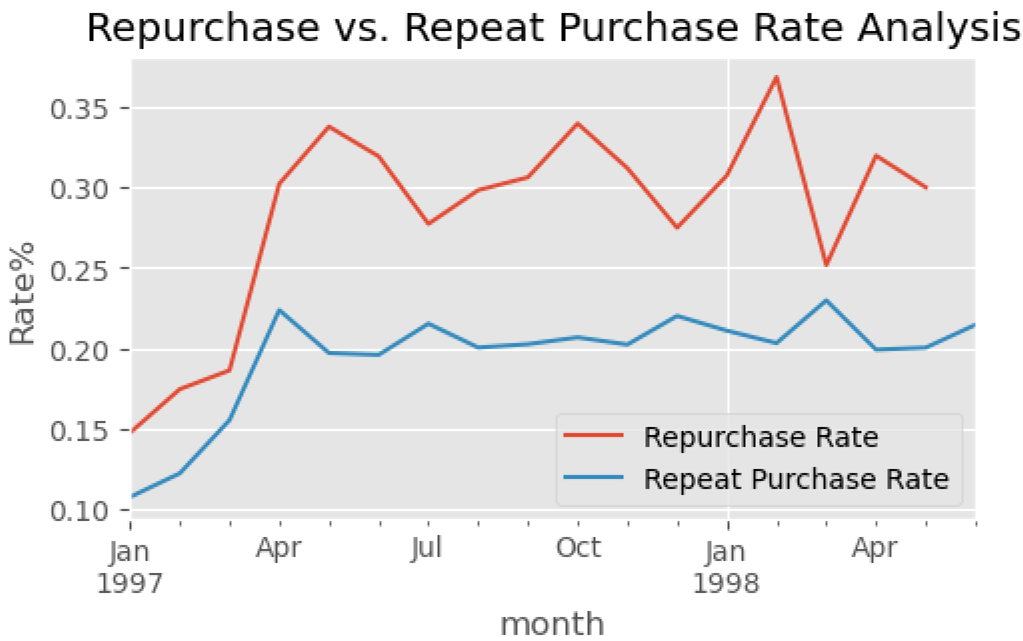
Out[142…

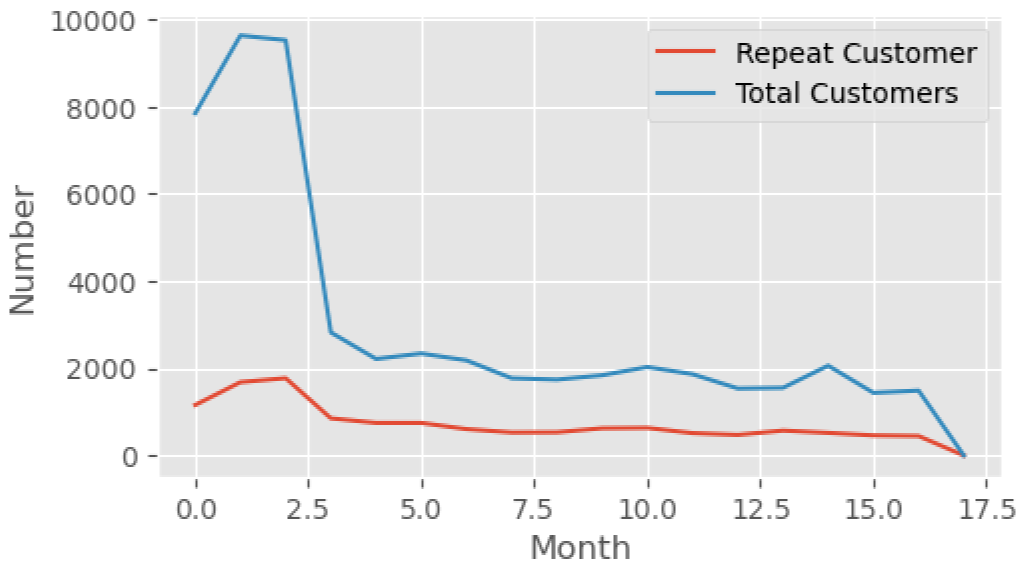
month	1997-01	1997-02	1997-03	1997-04	1997-05	1997-06	1997-07	1997-08	1997-09	1997-10	199
user_id											
1	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
3	0.0	NaN	1.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	(
4	0.0	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	N
5	1.0	0.0	NaN	1.0	1.0	1.0	0.0	NaN	0.0	N	



In [155…

```
# Repurchase Rate Visualization
plt.figure(figsize=(12, 3))
plt.subplot(1, 2, 1)
(purchase_b.sum()/purchase_b.count()).plot(label='Repurchase Rate')
(purchase_r.sum()/purchase_r.count()).plot(label='Repeat Purchase Rate')
plt.legend()
plt.ylabel('Rate%')
plt.title('Repurchase vs. Repeat Purchase Rate Analysis')
plt.show()
"""
Key Findings:

Repurchase Rate:
Stabilizes around 30% with moderate volatility, showing some fluctuation
across periods.

Repeat Purchase Rate:
Lower than repurchase rate, stabilizing at approximately 20% with minimal
volatility and more consistent performance.

Early-Stage Trend (First 3 Months):
Both repurchase and repeat purchase rates exhibit upward trends, indicating
that new users require time to develop into repeat or repurchasing customers

Customer Loyalty Insight:
Combined with new vs. existing customer analysis, new customer loyalty is
significantly lower than that of existing customers, highlighting the
importance of retention programs for new user conversion.
"""
# Number of repeat customers and total number of customers
plt.figure(figsize=(12, 3))
plt.subplot(1, 2, 2)
plt.plot(purchase_b.sum().values, label='Repeat Customer')
plt.plot(purchase_b.count().values, label='Total Customers')
plt.xlabel('Month')
plt.ylabel('Number')
plt.legend()
plt.show()
```





In [ ]:

```
"""
Analysis Conclusions
1. Overall Trends: Annual monthly sales volume and revenue are relatively hi

2. User Purchase Behavior: Transaction amounts and product quantities per or

3. Spending Distribution: Most users' total spending and purchase volumes ar
4. Purchase Cycle: Users with repeat purchases have an average purchase cycl
5. Customer Lifetime: The average lifetime for users with two or more purcha
6. Repurchase Rates: New customer repurchase rate is approximately 12%, whil
7. Customer Quality: User spending patterns follow a consistent distributior

Analysis Framework:
Temporal Analysis (Monthly):

User-level and aggregate cohort analysis
Dimensions: headcount, revenue, transaction volume
```

```
Behavioral Segmentation:

First purchase date, last purchase date, purchase frequency
RFM segmentation with pivot analysis
Customer lifecycle stages: acquisition, retention, churn, reactivation

Retention Metrics:

Repeat purchase rate
Win-back/reactivation rate
"""
```