

# Fit.ly Customer Churn Analysis

Data Analyst Professional Practical Exam

DataCamp

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# Content

An abstract background graphic on the left side of the slide, depicting a crowd of people from a high angle. The figures are represented by small, dark, pixelated shapes, creating a dense, textured effect.

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Executive  
Overview:

# Fit.ly Customer Churn Analysis

“Our goal was to identify factors that predict customer churn and understand which groups are at highest risk”

# Business Problem & Goals:

“Customer churn directly impacts recurring revenue and lifetime value.”

## Data Approach:

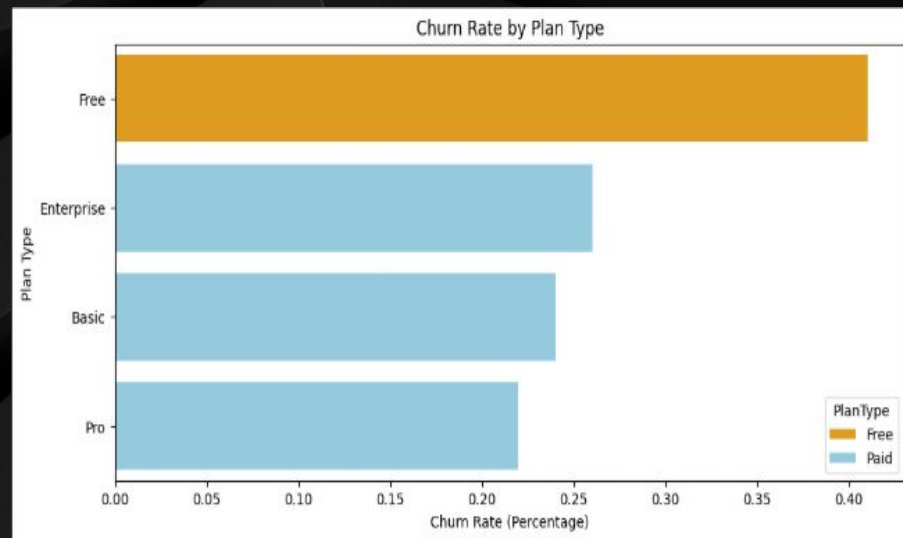
| DataFrame        | Columns  |
|------------------|--|
| account_info     | customer_id, email, state, plan, plan_list_price, churn            |
| customer_support | ticket_time, user_id, channel, topic, resolution_time_hours, state |
| user_activity    | event_time, user_id, event_type                                    |

"All insights are grounded in observed data, not assumptions."

# Engagement & Support Overview: Classification Type

| churn_status | N        | Y        |
|--------------|----------|----------|
| plan         |          |          |
| Basic        | 0.762712 | 0.237288 |
| Enterprise   | 0.739130 | 0.260870 |
| Free         | 0.590476 | 0.409524 |
| Pro          | 0.776471 | 0.223529 |

Churn rates are higher among Free plan users, suggesting lower initial commitment. However, behavioral signals such as engagement and support usage provide stronger churn separation than plan type alone.



# Engagement & Support Overview: Ticket Counts

```
churn_status  
N    2.234266  
Y    2.447368
```

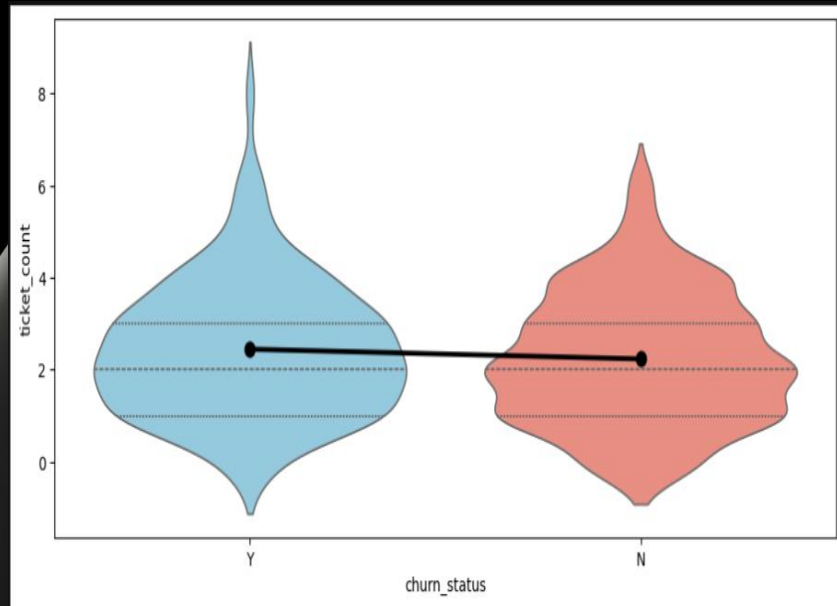
Results looks identical due to Mean difference is small in absolute terms

Difference in density and shapes appear quite similar for both groups

- This suggests that the overall distribution of ticket counts is largely the same for both churned and retained customers.

ticket\_count may not be a strong predictor

- The visual similarity of both distributions suggests the variable doesn't highly correlate with churn in this dataset.

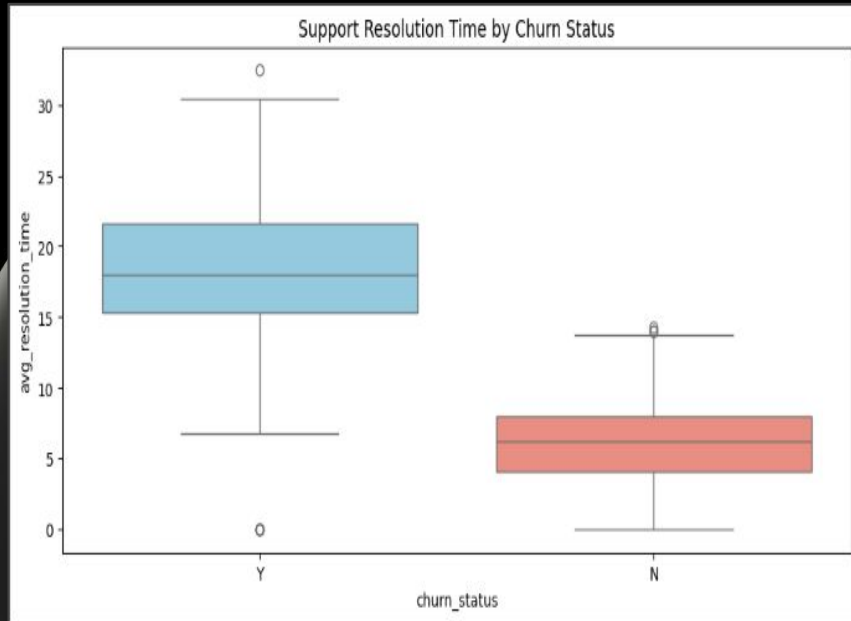


# Engagement & Support Overview: Resolution Time

```
churn_status  
N    6.007807  
Y   17.867949
```

the visualizations effectively highlight the significant difference in avg support resolution times between customers groups(Y, N)

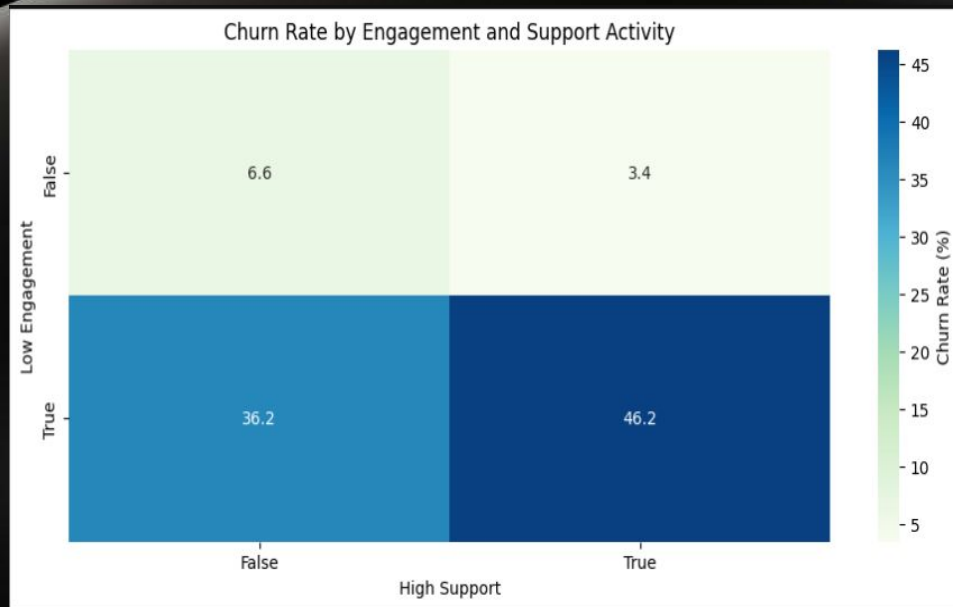
- it is shown here that churned customers are quite larger in terms of values when it comes to resolution time
- the mean value of churned customers are too massive that the highest value of retained customers wouldn't reach it



# Churn-Related Behavioral Insights

| churn_status   |              | N   | Y   | All | Churn Rate (%) |
|----------------|--------------|-----|-----|-----|----------------|
| low_engagement | high_support |     |     |     |                |
| False          | False        | 71  | 5   | 76  | 6.6            |
|                | True         | 56  | 2   | 58  | 3.4            |
| True           | False        | 102 | 58  | 160 | 36.2           |
|                | True         | 57  | 49  | 106 | 46.2           |
| All            |              | 286 | 114 | 400 | 28.5           |

Chi-square statistic: 56.85  
P-value: 0.0000



# Fit.ly Customer Churn Analysis

## Metric to Monitor

Early Engagement Rate = % of new customers who perform more than 1 activity event within their initial usage period.

Initial baseline value: Median event\_count  $\approx$  2 - 25% of users have only 1 event

Baseline estimate: 75% of users reach more than 1 event - Early Engagement Rate  $\approx$  75%

## Key Findings Summary

“Low engagement is the strongest signal associated with churn.”

## Business Recommendations

1: Prioritize Early Engagement Activation

2: Escalate Support Resolution for Low-Engagement Users & Long resolution time

# Thank you



