Lending Club Casestudy

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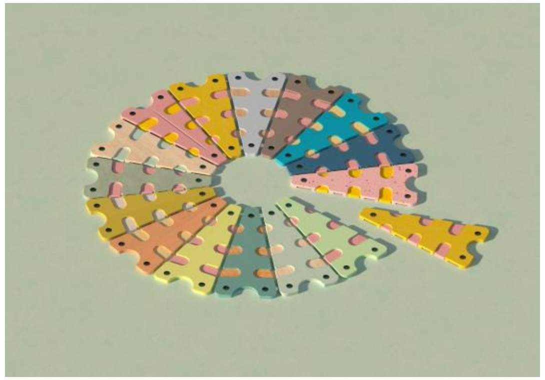
Company Context

Largest online marketplace
Facilitates personal loans, business loans, and medical procedure financing
Offers lower interest rates through fast online interface

The Challenge

- Significant credit loss due to loan defaults
- 'Charged-off' customers are primary defaulters
- Need to identify and mitigate risky loans



Our Objectives

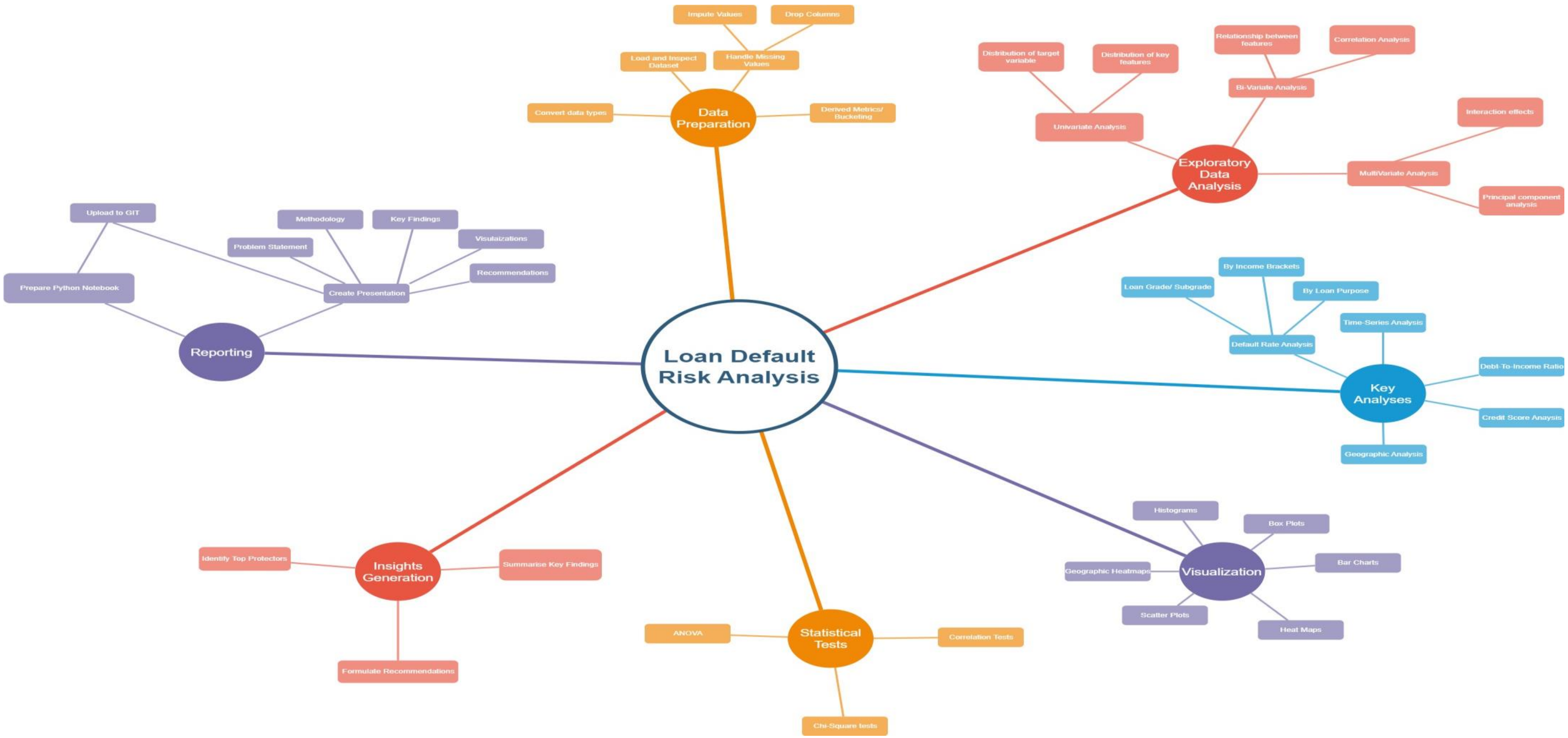
- Identify key driving factors behind loan defaults
- Understand variables that strongly indicate default risk
- Develop insights to improve portfolio and risk assessment

Expected Outcome

- Reduced credit loss through targeted risk management
- Enhanced ability to identify high-risk loan applicants

"Turning Data into Actionable Insights for Smarter Lending"

Approach Overview



Data Preparation

Load Data

```
df=pd.read_csv('loan.csv')

df.head(10)
```

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g_dpd_24m	num_tl_op_p
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	NaN	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	NaN	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	NaN	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	NaN	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	NaN	

Check Null Percentages

```
print(df.isnull().sum()/len(df)*100)
```

```
id                               0.000000
member_id                        0.000000
loan_amnt                        0.000000
funded_amnt                      0.000000
funded_amnt_inv                  0.000000
                                   ...
tax_liens                        0.098195
tot_hi_cred_lim                100.000000
total_bal_ex_mort              100.000000
total_bc_limit                 100.000000
total_il_high_credit_limit     100.000000
Length: 111, dtype: float64
```

Data Preparation

Find High Null Columns

```
Columns with null proportion > 40% :
 ['mths_since_last_delinq', 'mths_since_last_record', 'next_pymnt_d', 'mths_since_last_major_derog', 'annual_inc_joint', 'dti_joint', 'verificatio
Columns with null proportion <= 40% :
 ['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title', 'emp_len
```

```
null_pctg=df.isnull().sum()/len(df)*100

high_null_cols=null_pctg[null_pctg>40].index.tolist()

low_null_cols=null_pctg[null_pctg<=40].index.tolist()
```

Removing High Null Columns

```
df_cleaned = df.drop(columns=high_null_cols)

print(f"Dropped {len(high_null_cols)} columns. New shape: {df_cleaned.shape}")

print("Dropped columns:", high_null_cols)

df = df_cleaned
```

Data Preparation

Changing Datatypes

```
# converting int_rate to float

df['int_rate']=df['int_rate'].str.rstrip('%').astype('float')

print(df['int_rate'].dtype)

print(df['int_rate'].head(10))

# converting revol_util to float

df['revol_util']=df['revol_util'].str.rstrip('%').astype(float)

print(df['revol_util'].dtype)

print(df['revol_util'].head(10))
```

Data Preparation

Cleanup redundancy

```
# dropping rows with loan_status 'Current'

df=df[df['loan_status']!='Current']

df.shape
```

Remove Bias

```
df['emp_title']=df['emp_title'].fillna('Unknown')
```

Imputing

```
# imputing last_pymnt_d with 'Not paid'

df['last_pymnt_d']=df['last_pymnt_d'].fillna('Not paid')
```

Data Preparation

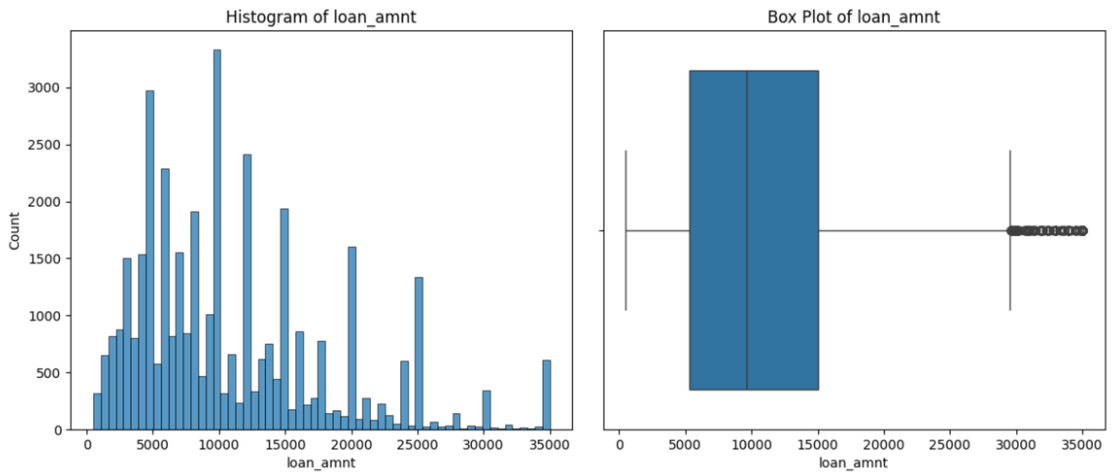
Derived / Feature Extraction- Determining credit history length of applicants

```
# Calculate the credit score using the normalized columns

df['credit_score'] = (

    (1 - df['delinq_2yrs_norm']) * 0.35 +    # Invert since lower is better

    (1 - df['pub_rec_bankruptcies_norm']) * 0.35 +  # Invert

    (1 - df['total_rec_late_fee_norm']) * 0.35 +  # Invert

    (1 - df['collection_recovery_fee_norm']) * 0.35 +  # Invert

    (1 - df['revol_util_norm']) * 0.30 +      # Invert since lower is better

    (df['credit_history_length_norm'] * 0.15) +  # Keep as is

    (df['total_acc_norm'] * 0.10)              # Keep as is

)
```

Exploratory Data Analysis

Nature of Dataset

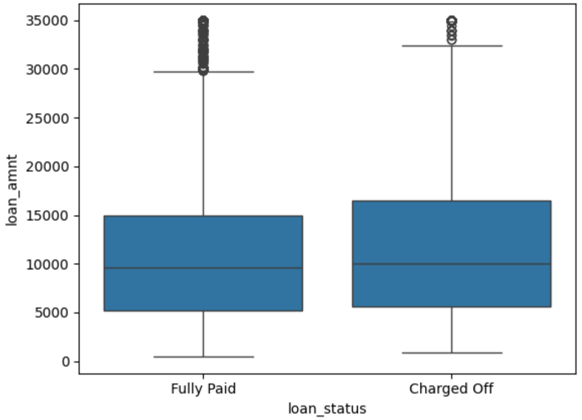
```
# Histogram
sns.histplot(data=df, x=col, ax=axes[i, 0])
axes[i, 0].set_title(f'Histogram of {col}')

# Box plot
sns.boxplot(data=df, x=col, ax=axes[i, 1])
axes[i, 1].set_title(f'Box Plot of {col}')
```



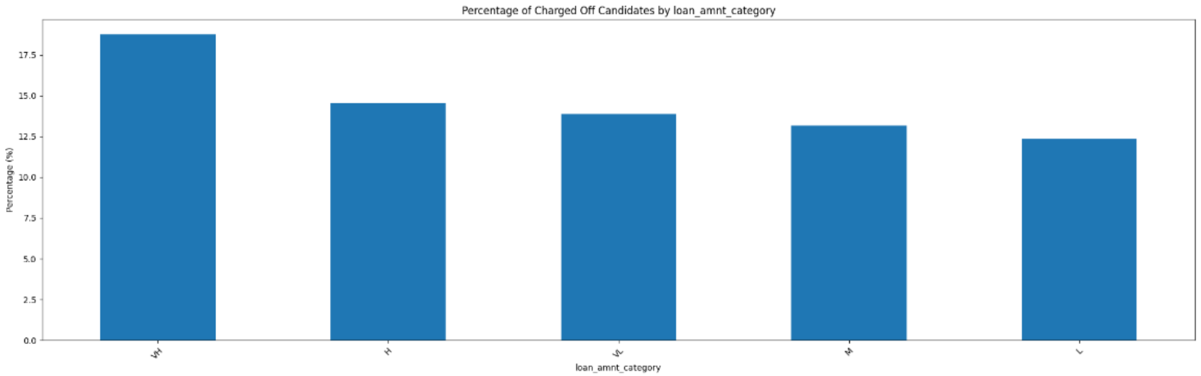
Exploratory Data Analysis

Percentage of Charged Off Loans

```python
# Calculate the percentage of charged off loans for each colu
charged_off_percentage = (
    df.groupby(col)['loan_status']
    .value_counts(normalize=True)
    .unstack()
    .fillna(0) * 100
)
```



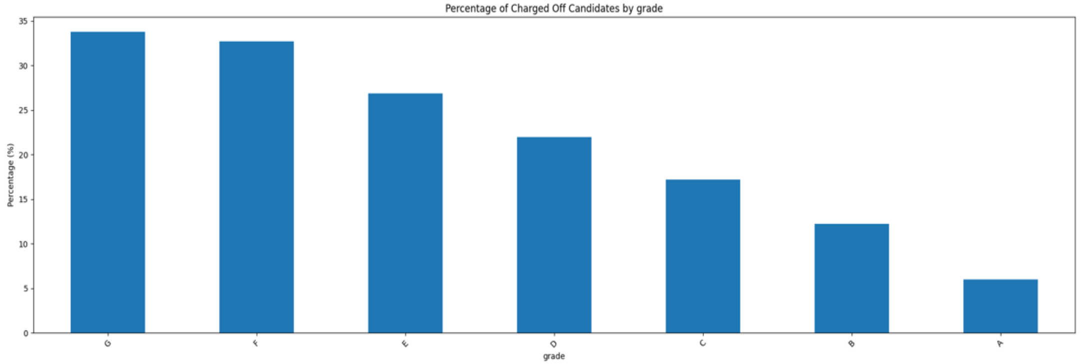
“Higher charged off cases are observed for higher loan amounts”



Exploratory Data Analysis

Grade vs ChargeOff

```
fig, axes = plt.subplots(num_cols, 1, figsize=(10, 5 * num_cols))

for i, col in enumerate(filtered_columns):

    sns.countplot(data=df, x=col,
ax=axes[i],order=df[col].value_counts().sort_values(ascending=False).index)

    axes[i].set_title(f'Count Plot of {col}')

    axes[i].tick_params(axis='x', rotation=90)

plt.tight_layout()

plt.show()
```



"Charge off rate increases as loan grade increases from A to G"

Percentage of Charged Off Candidates by sub_grade

Key Analyses

Bivariate Analysis - Comparisons

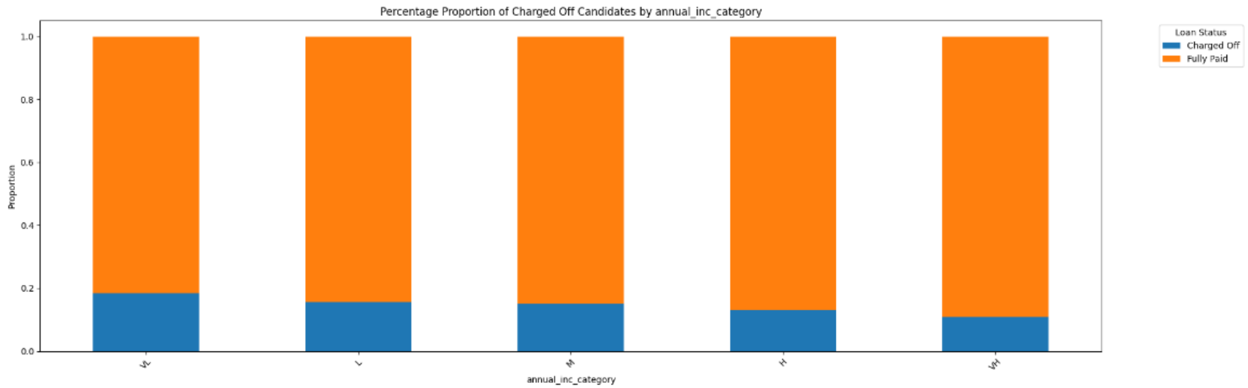
```
# Loop through each input column
for i, col in enumerate(input_columns):
    counts = df.groupby([col, 'loan_status']).size().unstack(fill_value=0)
    # Calculate the proportion of each category
    proportions = counts.div(counts.sum(axis=1), axis=0)
```

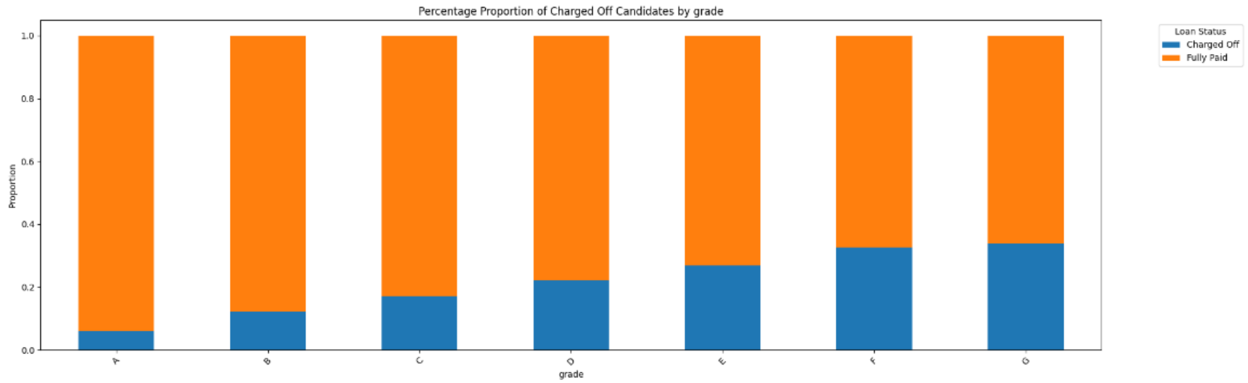
“Lower the income higher is the charge off rate”

“To reduce charge off, lower grade loans preferably

grade A need to be prioritized” (ref illustrations on next slide)

Key Analyses





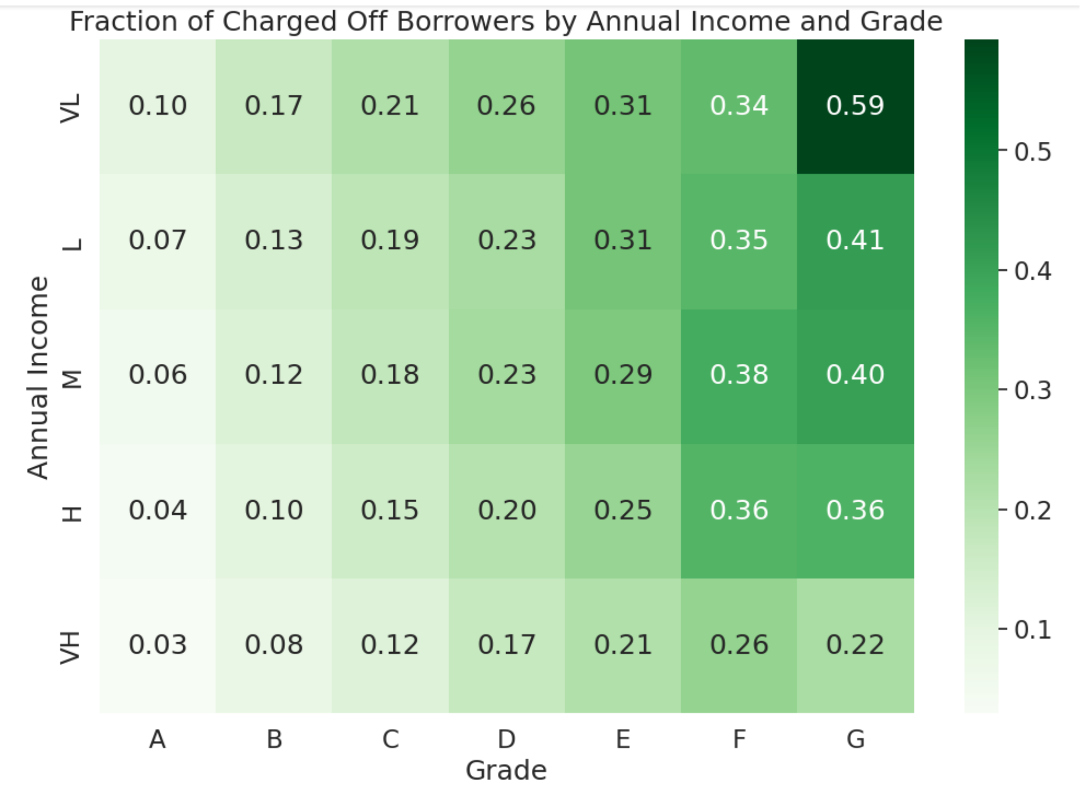
Key Analyses

Multivariate Analysis – Across Income groups and Grades

```
pivot_table = df.pivot_table(
    index='annual_inc_category',
    columns='grade',
    values='loan_status',
    aggfunc=lambda x: (x == 'Charged Off').sum() / len(x)  # Calculate the
fraction of charged off
)
```

“Lower income groups should be provided lower grade Loans (A,B), vis-à-vis Lower interest rates” (ref illustrations on next slide)

Key Analyses



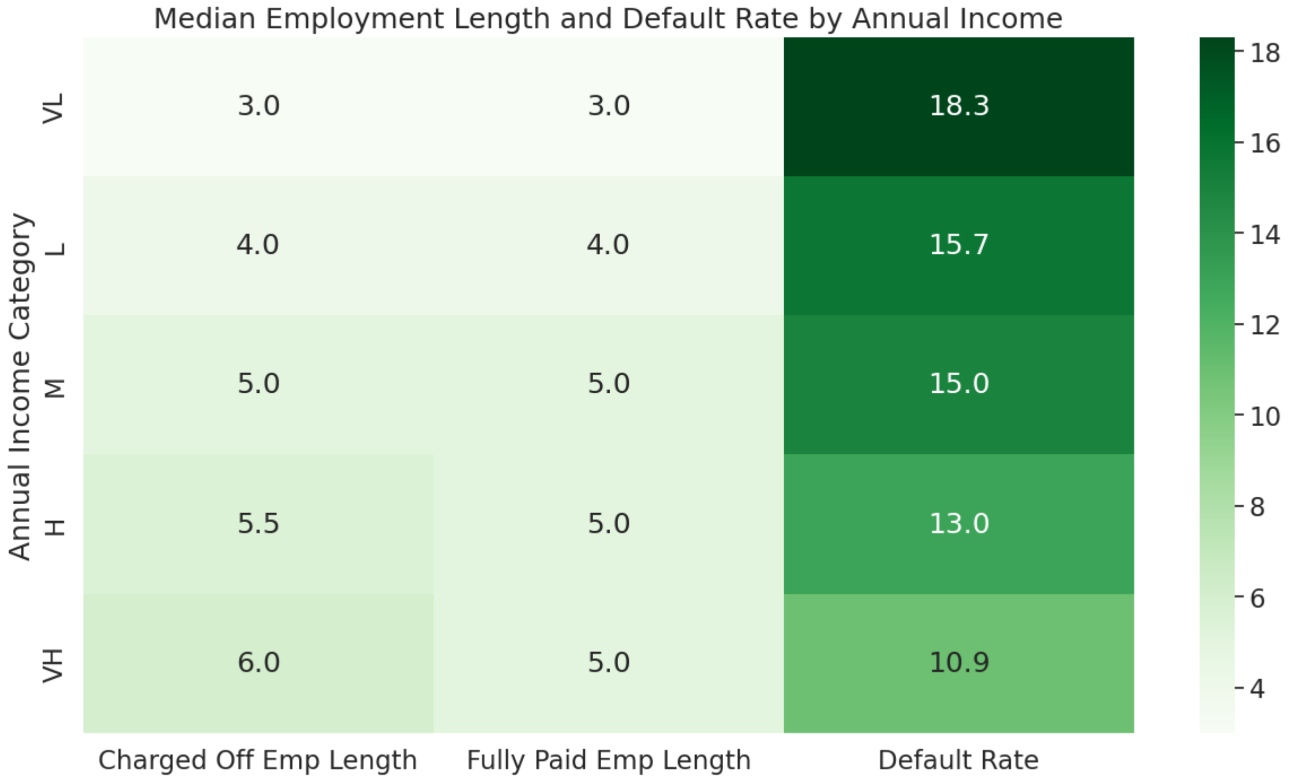
Key Analyses

Median employment length for different combinations of loan status and annual income `# Calculate default rate`

```
default_rates = (charged_off_counts / loan_counts) * 100

emp_length_pivot = df.pivot_table(

    index='annual_inc_category',

    columns='loan_status',

    values='emp_length',

    aggfunc='median'

)
```

“The difference in default rates between the lowest and highest income categories is significant (18.3% vs 10.9%), suggesting that income-based risk assessment could be valuable” (ref illustrations on next slide)

Key Analyses



Statistical Test

- **Interest Rate (int_rate)**F-statistic: **75,229.76**
- p-value: **0.000**

- **Debt-to-Income Ratio (dti)**F-statistic: **85.88**
- p-value: **2.31e-107**

ANOVA Summary

- **Revolving Utilization (revol_util)**F-statistic: **1,788.70**
- p-value: **0.000**

- **Recoveries**F-statistic: **118.86**
- p-value: **2.18e-149**

- **Total Rec. Late Fee (total_rec_late_fee)**F-statistic: **70.33**
- p-value: **1.60e-87**

- **Collection Recovery Fee**F-statistic: **38.86**
- p-value: **2.25e-47**

Insights and Conclusions

Loan Purpose
Small businesses charge –off more, requiring continuous line off credit, prioritize small loans at low interest rates

Loan Amounts
Limit high loan amounts to $17K

Interest Rates
Low interest rates are better.
Optimal rates: 5.4% – 11%..

Debt-to-Income (DTI) & Revolving Utilization
Monitor DTI > 15% and utilization > 45%.

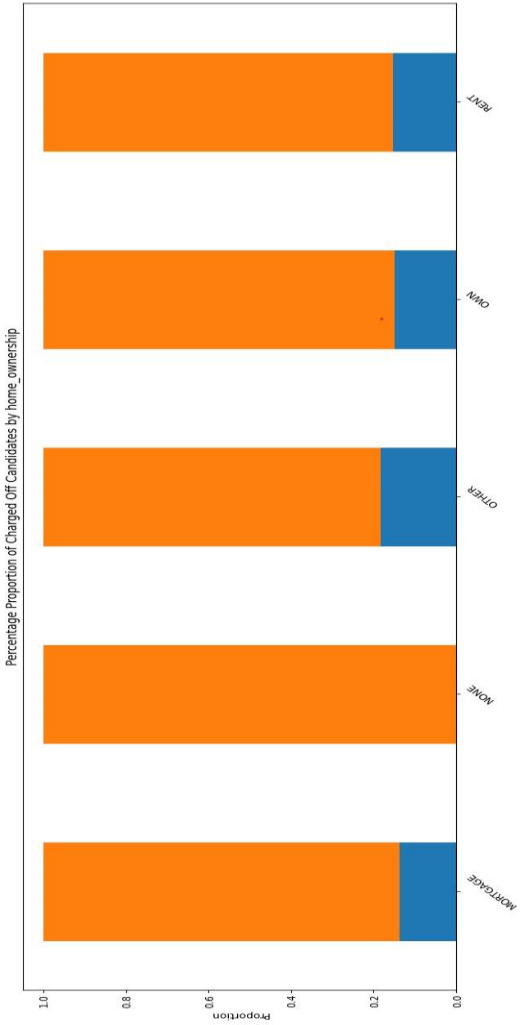
Loan Grades
Prioritize lower-grade loans

Income & Loan Term
Short-term (36-month) loans preferred.

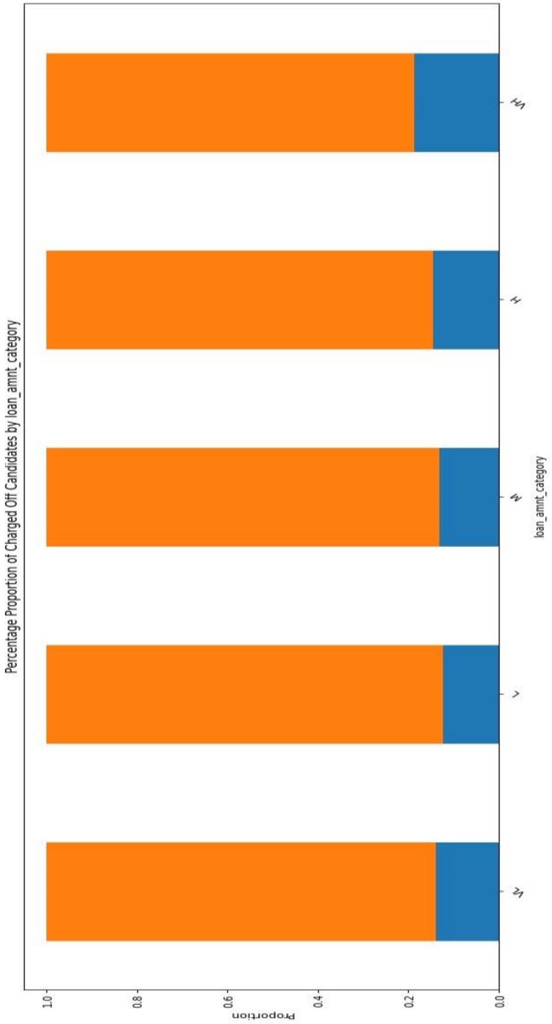
Credit Scores
Flag credit scores < 0.8

Geography & Employment
Nebraska & Walmart employees' high risk

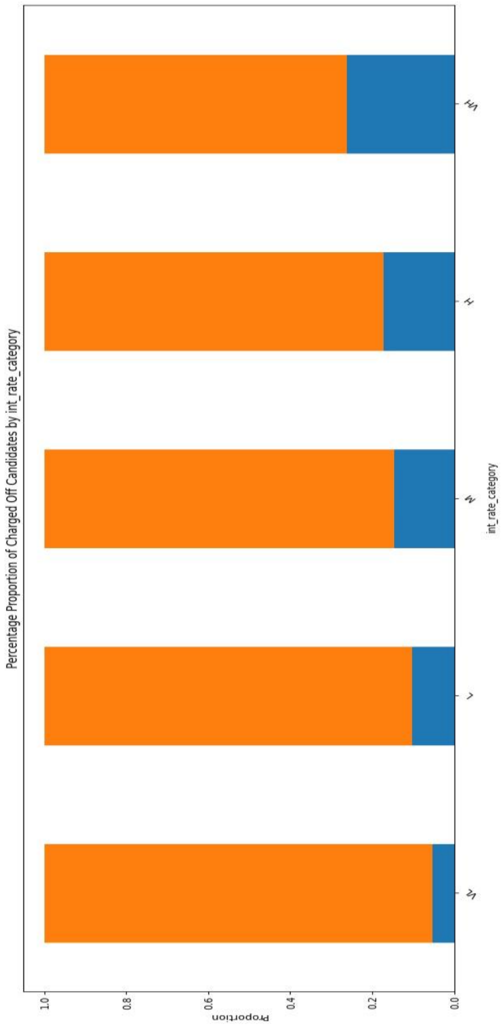
Insights and Conclusions



Loan Purpose



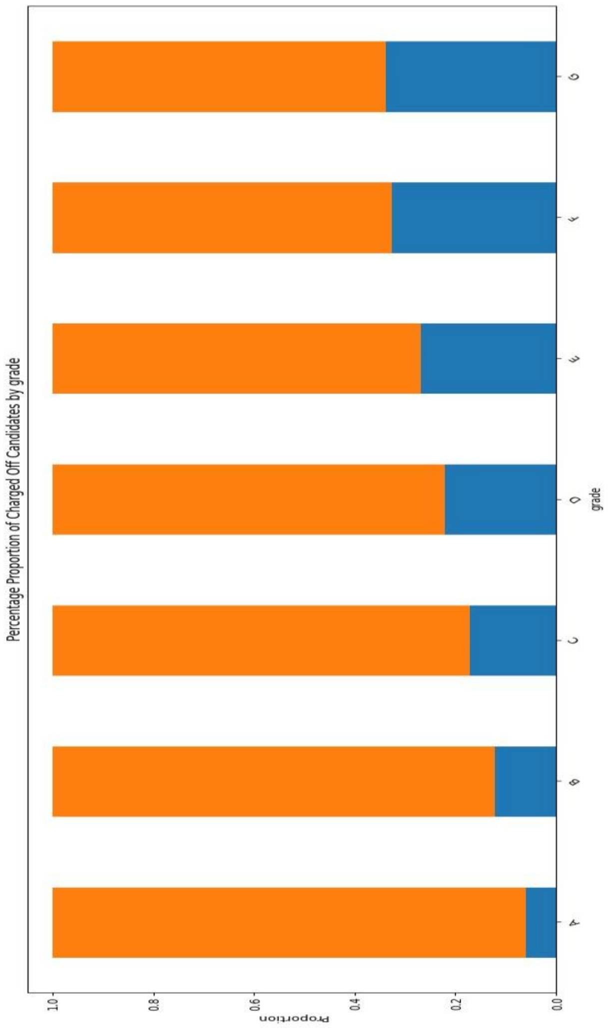
Loan Amount



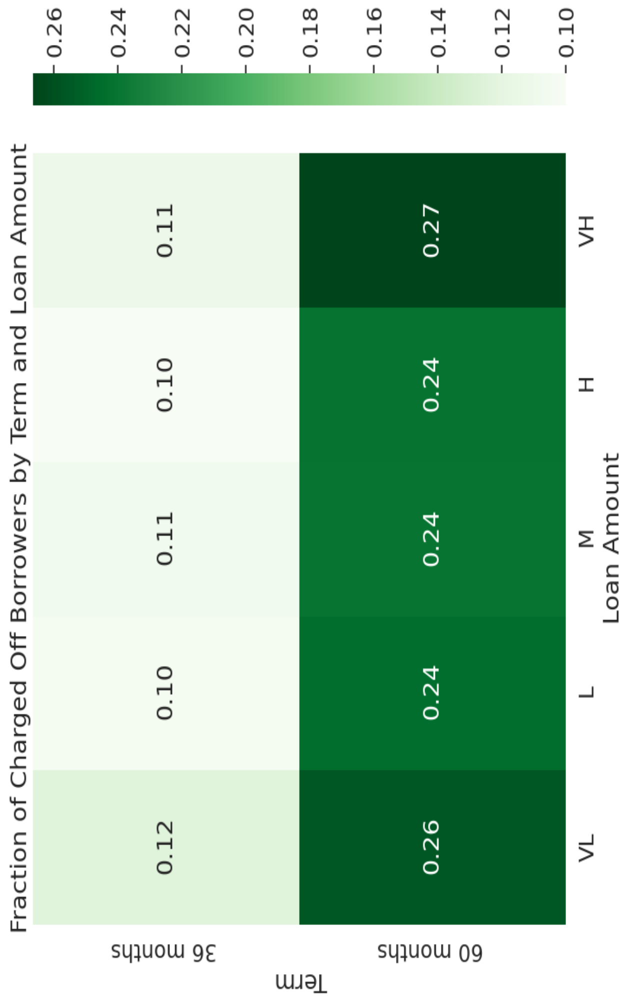
Interest Rate

DTI/ Revolving Utilization

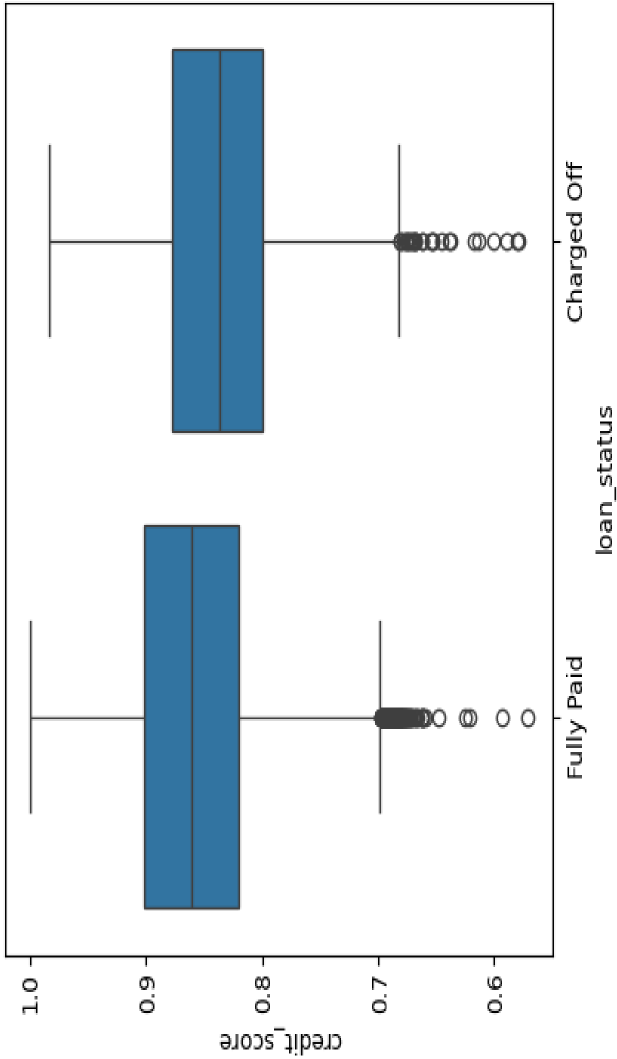
Insights and Conclusions



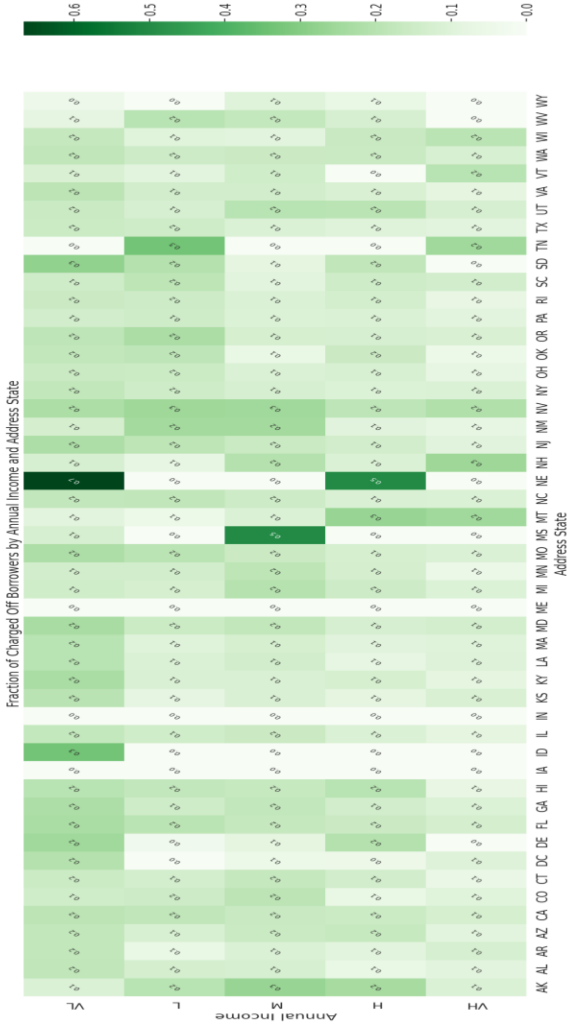
Loan Grade



Income and Loan Term



Credit Scores



Geography

End