mahavishnu-dpd0-assingment

April 12, 2024

Amount Pending : This is the EMI amount pending.

State : The borrower's state.

Tenure : Total tenure of the borrower. This is the total tenure of the loan.

Interest Rate : Interest rate of the loan.

City : The city of the borrower.

Bounce String : This is a string that explain's customer's bounce behaviour since the disbursal of the loan - bounce means that the customer did not end up making the payment • S or H- No bounce in that month • B or L - Bounce in that month • FEMI - first EMI - no known behaviour • Last character denotes the last month - first character denotes the first month on book - for example SSB means that customer was on book for 4 months and he has bounced the in the last month

Disbursed Amount : The total disbursed amount of the loan.

Loan Number : The unique identifier for the loan.

[1]:
```
import pandas as pd
```

[70]:
```
df = pd.read_csv('Data_Analyst_Assignment_Dataset.csv')
df.head()
```

[70]:
```
   Amount Pending      State  Tenure  Interest Rate       City Bounce String  \
0             963  Karnataka      11           7.69  Bangalore           SSS
1            1194  Karnataka      11           6.16  Bangalore           SSB
2            1807  Karnataka      14           4.24     Hassan           BBS
3            2451  Karnataka      10           4.70  Bangalore           SSS
4            2611  Karnataka      10           4.41     Mysore           SSB

   Disbursed Amount Loan Number
0             10197       JZ6FS
1             12738       RDIOY
2             24640       WNW4L
3             23990       6LBJS
4             25590       ZFZUA
```

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24582 entries, 0 to 24581
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Amount Pending    24582 non-null  int64
 1   State             24582 non-null  object
 2   Tenure            24582 non-null  int64
 3   Interest Rate     24582 non-null  float64
 4   City              24582 non-null  object
 5   Bounce String     24582 non-null  object
 6   Disbursed Amount  24582 non-null  int64
 7   Loan Number       24582 non-null  object
dtypes: float64(1), int64(3), object(4)
memory usage: 1.5+ MB
```

[4]:
```
df.isnull().sum()
```

[4]:
```
Amount Pending      0
State               0
Tenure              0
Interest Rate       0
City                0
Bounce String       0
Disbursed Amount    0
Loan Number         0
dtype: int64
```

[5]:
```
df.duplicated().sum()
```

[5]:
```
0
```

[6]:
```
for i in df.columns:
    print( i,df[i].unique(),'\n')
```

```
Amount Pending [ 963 1194 1807 … 3289 4899 4599]

State ['Karnataka' 'Madhya Pradesh' 'Maharashtra' 'Tamil Nadu' 'Telangana'
 'Kerala' 'Andhra Pradesh']

Tenure [11 14 10 17  7  8 18 24 15]

Interest Rate [ 7.69  6.16  4.24  4.7   4.41  4.36  5.77  6.47  6.03  4.8   4.66
5.44
  4.5   6.58  5.67  6.88  6.6   5.65  4.09  5.14  5.81  5.31  4.1   4.75
  4.98  6.52  6.45  6.56  3.84  5.33  4.35  5.04  4.58  5.73  5.36  4.01
  4.85  5.11  4.88  5.58  4.61  6.94  4.64  5.26  7.1   4.46  5.22  5.02
  5.41  6.41  4.43  5.18  4.91  3.94  4.47  6.14  5.8   4.52  5.92  5.06
```

```
  5.55  6.36  5.38  4.06  6.9   5.05  4.26  4.18  5.19  4.15  6.35  5.99
  6.    4.08  5.    6.95  4.4   5.64  5.96  4.93  5.48  7.47  9.02  5.66
  5.78  6.44  7.04  6.37  4.57  4.77  5.93  5.17  4.87  5.3   4.86  5.97
  4.89  5.28  4.94  5.43  5.45  6.61  7.    6.11  7.38  5.89  5.72  4.95
  6.08  6.55  5.32  5.25  5.54  4.71 12.83  4.82  5.63  6.1   5.68  4.22
  6.72  4.51  6.17  5.79  4.74  6.31  7.36  5.34 18.1  21.92 20.92 19.61
 16.5  17.42 20.48 23.58 22.92 19.22 24.66 22.16 30.5  17.11 25.51  6.65
  6.23  5.09  6.04  4.96  5.82  4.31  5.46  6.24  5.23  4.97  3.95  7.27
 17.92  3.78  7.54  6.42  4.12  7.09  3.63  5.62  5.27  3.8   5.47  6.39
  3.9   5.51  4.62  4.59  4.63  3.92  4.73 20.71  4.84  5.59  5.35  6.38
  5.87  4.44  4.02  5.53  6.07  4.92  6.49  4.32  6.01  5.75  5.42  5.29
  9.56 10.49  7.53  4.45  6.91  5.56  5.12  5.91  6.06  6.2   5.1   4.29
  3.89  4.16  6.8   6.32  6.09 18.3  37.92 26.19  4.6   4.14  7.02  5.84
  4.13  4.67  4.42  4.    3.97  4.83  6.02 22.43  6.22  4.78  4.48  4.9
  6.13  5.03  6.29  4.27  4.17 10.3   5.61  3.99  4.68  8.77  9.    5.86
  4.38  4.55  3.74  4.99  4.54  4.21  4.19  7.66  7.74  3.49  5.49  8.09
  4.69  5.15  5.13  3.69  3.91  3.67  3.86 11.84  6.77 10.36  6.89  7.07
  8.16  7.52  7.79  5.39 10.85  5.21  8.2  18.45  4.39  4.34  7.14  8.02
  3.61  4.79  6.57  8.26  3.87  5.6   6.98  5.08  3.98  9.44  5.4   8.59
 12.23  7.46  7.89  6.19  5.9   7.01  7.7   7.5  31.85  4.76  5.83  5.57
  5.24  9.21  4.49  3.83 11.47  7.51  6.43 31.54 20.35  7.26  5.95 11.23
  6.54  4.72 12.24  6.15  5.74  6.68  4.53  4.81 18.8   3.93  3.65 22.44
  5.01  6.21  0.  ]

City ['Bangalore' 'Hassan' 'Mysore' 'DAKSHINA KANNADA' 'BANGALORE RURAL'
 'HAVERI' 'Gulbarga' 'Bijapura' 'Dharwad' 'Bagalkot' 'RAMANAGAR' 'Kolar'
 'Bellary' 'Belgaum' 'Chitradurga' 'Davangere' 'Mandya' 'Uttara Kannada'
 'CHAMRAJNAGAR' 'KOPPAL' 'Kodagu' 'Chikkaballapur' 'Tumkur' 'Shimoga'
 'UDUPI' 'GADAG' 'Raichur' 'Bidar' 'Yadgir' 'Vidisha' 'Rewa' 'Damoh'
 'Sidhi' 'Chhatarpur' 'Indore' 'Hoshangabad' 'Bhopal' 'Shivpuri' 'Sagar'
 'Raisen' 'Sehore' 'Gwalior' 'Ratlam' 'Mandsaur' 'Datia' 'Neemuch' 'Dhar'
 'East Nimar' 'Khandwa' 'Jabalpur' 'Guna' 'Tikamgarh' 'ANUPPUR' 'Satna'
 'Jhabua' 'Singrauli' 'Morena' 'Shajapur' 'Dewas' 'Narsinghpur' 'Ujjain'
 'West Nimar' 'SHEOPUR' 'Betul' 'Shahdol' 'Chhindwara' 'BARWANI' 'Panna'
 'HARDA' 'ASHOK NAGAR' 'KATNI' 'Bhind' 'Sindhudurg' 'Pune' 'Sangli'
 'YAVATMAL' 'Jalgaon' 'Aurangabad' 'Latur' 'Ratnagiri' 'Chandrapur'
 'Wardha' 'Nashik' 'Nagpur' 'Akola' 'Beed' 'NANDURBAR' 'Hingoli'
 'AHMED NAGAR' 'Buldhana' 'Osmanabad' 'Satara' 'WASHIM' 'Kolhapur'
 'Solapur' 'Nanded' 'Parbhani' 'Gondia' 'Jalna' 'Dhule' 'Amravati'
 'Bhandara' 'Mumbai' 'Thane' 'RAIGARH(MH)' 'NAGAPATTINAM' 'Tirunelveli'
 'Madurai' 'TIRUVALLUR' 'Coimbatore' 'ERODE' 'CUDDALORE' 'TIRUVANNAMALAI'
 'Chennai' 'TUTICORIN' 'TIRUVARUR' 'SIVAGANGA' 'Nilgiris' 'Dharmapuri'
 'KRISHNAGIRI' 'KANCHIPURAM' 'DINDIGUL' 'Thanjavur' 'VELLORE'
 'VIRUDHUNAGAR' 'PUDUKKOTTAI' 'THENI' 'Salem' 'TIRUCHIRAPPALLI'
 'RAMANATHAPURAM' 'KARUR' 'NAMAKKAL' 'PERAMBALUR' 'Chengaianna'
 'VILLUPURAM' 'Kanyakumari' 'NORTH GOA' 'Hyderabad' 'Mahabub Nagar'
 'Nalgonda' 'Warangal' 'Khammam' 'K.V.RANGAREDDY' 'Adilabad' 'Karim Nagar'
 'Nizamabad' 'Medak' 'Pondicherry' 'Kollam' 'Kannur' 'Thrissur' 'Palakkad'
```

```
 'Pathanamthitta' 'MALAPPURAM' 'IDUKKI' 'Thiruvananthapuram' 'Ernakulam'
 'KASARGOD' 'Kozhikode' 'Wayanad' 'Alappuzha' 'Kottayam' 'Guntur'
 'Cuddapah' 'Krishna' 'Chittoor' 'Prakasam' 'East Godavari'
 'West Godavari' 'Vizianagaram' 'ANANTHAPUR' 'Kurnool' 'Srikakulam'
 'Nellore' 'CHICKMAGALUR' 'Rajgarh' 'Balaghat' 'Seoni' 'Mandla' 'UMARIA'
 'BURHANPUR' 'Gadchiroli' 'ARIYALUR' 'SOUTH GOA' 'MAHE' 'Visakhapatnam']

Bounce String ['SSS' 'SSB' 'BBS' 'SBB' 'BB' 'SS' 'BS' 'SB' 'S' 'B' 'FEMI'
'LSSBBS'
 'LSSSSS' 'LSBSSS' 'LBSSSS' 'BSSBBB' 'LSSBSB' 'LBBSBB' 'LSSBSS' 'LSSSBB'
 'LSBSBS' 'LBBBBB' 'LBSSBS' 'LBBSSB' 'LSBBBS' 'LSBBSS' 'LSSSBS' 'LSHSSB'
 'LBSBBS' 'SSSSSB' 'SSSBSB' 'SSSSS' 'SBBBB' 'BBBSS' 'BBBBS' 'BBSSS'
 'SBSSS' 'BSSBB' 'SSBBS' 'BSSSB' 'SSSBS' 'BSSBS' 'SSSSB' 'SHSSS' 'SSSBB'
 'BSSSS' 'SSBSS' 'BBSB' 'BSBS' 'SSSS' 'BSSS' 'SBBS' 'SSBS' 'SBBB' 'SSSB'
 'SBSB' 'HBBS' 'SBSS' 'SBS' 'BBB' 'LBBBSS' 'SSBSBB' 'LSSSSB' 'SSBSSB'
 'SBBBS' 'SBSSB' 'BSBBS' 'SBBSB' 'BSBBB' 'BBBSB' 'SBSBS' 'BSSB' 'BBBB'
 'HSSS' 'BBBS' 'LBSSSB' 'LSBBBB' 'BSBSB' 'LBBSSS' 'BBBBB' 'BSBSS' 'BSBB'
 'BBSS' 'BHSBS' 'SSBB' 'SSSSSSSB' 'LSSSSSSS' 'HHLSHSSS' 'LLLSSSSS'
 'LHLSSSSS' 'LBBBSSSB' 'BSSSSSBS' 'LLLBBSSB' 'LHSSSSSS' 'LLLSBBSS'
 'LSSBBBBB' 'SSSSSSSS' 'LLSSSSS' 'LSSSSSS' 'LLBBBBB' 'LLSSSBS' 'LLLBBLS'
 'LLSBSSS' 'LLBBBBS' 'LLLBBLB' 'SSSSSSS' 'SSBSSBS' 'LLBSSBS' 'LLSBBBB'
 'LLSSBSS' 'LLBSSSS' 'LLBBBSB' 'LLSBSBB' 'LLSSSSB' 'LLSBSSB' 'BSSSSBS'
 'LLLBSSS' 'LLSHSSS' 'LSSSSSB' 'LLSBBBS' 'SBSBBSB' 'LLSSBSB' 'SBSSSSS'
 'LLSSSBB' 'LLSSBBB' 'SSBSSSS' 'LLSSBBS' 'LLLBBBB' 'SSSSSBS' 'SSBSSBB'
 'LLBSBBS' 'SLSHSSS' 'LLBSSSB' 'LLSBBSB' 'SSSBSSS' 'SSSBSBS' 'LLBSBBB'
 'BSSSSSS' 'BBBBBBB' 'SSSSBSS' 'HBBSSSB' 'LLSBBSS' 'LLSBSBS' 'LLBBSBS'
 'HBBSSSS' 'HBBBBBB' 'BBBSSSB' 'HLSHSSS' 'LLBSSBB' 'LLBBSSS' 'BBBSBBB'
 'BBSBBSS' 'SLBSSSS' 'BBBHSSS' 'LLBSBSB' 'LLBBSSB' 'BLSHSBS' 'SSBSBSS'
 'LLBSBSS' 'BBLBBBB' 'SBBBBBB' 'HBBBBSS' 'SBBBBSS' 'BBBBSSB' 'SSSBSSB'
 'BBSBBBS' 'LLLSSSS' 'HLBSSSS' 'HBSBSBB' 'LLSSBLS' 'HLSHSBS' 'SBBSSSS'
 'LBBBSB' 'LSHSSS' 'LBBBLB' 'SSSSSS' 'BSSBSB' 'LBBBBS' 'LSSBBB' 'SSSSBS'
 'LBHSSS' 'LBBBLS' 'LBSSBB' 'BSBBBS' 'SBBBBB' 'SSSBSS' 'SBSBSB' 'BSSSSB'
 'BBBBBB' 'SBSSSB' 'BBBSBB' 'BBSBSS' 'LBSBBB' 'LSBSSB' 'LLSBBB' 'LSHBSS'
 'SBSSBB' 'SSSSBB' 'SBBBBS' 'LSBBSB' 'LBSBSS' 'SBBSSS' 'LBSBSB' 'LBBSBS'
 'SSBBBS' 'BBHBBS' 'BBBBBS' 'SSBSSS' 'BSHSSS' 'BSSSSS' 'LSHBBB' 'SSSBBS'
 'BBBBSB' 'SSBBSS' 'BBBSBS' 'BBBSSS' 'LSBSBB' 'BBSSB' 'SSBSB' 'BBSBS'
 'SSBBB' 'SHSBS' 'SBBSS' 'SHSSB' 'SBSBB' 'BHSSS' 'BBSBB' 'SSBLS' 'SBLS'
 'BBLS' 'HSSB' 'BLS' 'HSSSSSSS' 'SSBLSSBSS' 'LLLLSSBBB' 'SSSSSSSSS'
 'LLLLBBBBS' 'LLLLSSSBB' 'BBSSSSSS' 'LLLSSBSS' 'LLLBSBBS' 'SBBBBSSS'
 'SSSSBBSS' 'HBBSHBBS' 'BBSSBBBS' 'BBBBBBBB' 'LLLBBBBB' 'LLLBBBSB'
 'SSBBSSSS' 'LSBSSSSS' 'LLLSBBBS' 'LSSBSSSS' 'LSLSHSSS' 'LHLBSSBS'
 'LBBBSBSS' 'LLLLBBBB' 'LLLBBBSS' 'LLLSSSBB' 'LBLBSSBS' 'LHBSSSSB'
 'BSSSSSSS' 'SSBSSSSS' 'SHSSSSSS' 'BBBBSSSB' 'SBBLBBBB' 'LBBBSBBS'
 'SBBSSSSS' 'SSSSSSBS' 'BLBSBBB' 'BBSSSSS' 'BBBBBSB' 'HBSHSSS' 'LLSBBLB'
 'HSSSSSS' 'SSSSSSB' 'LLLBBBS' 'LLBBBSS' 'BBSSBBB' 'HBBHSSS' 'BBSBSSS'
 'SSSBBBB' 'HLBSSSB' 'LLLBSBB' 'BBBBBBS' 'BSBSBSS' 'SBSBSSS' 'SSBBSBS'
 'LLBBSBB' 'SBBBSBB' 'HBBSBBS' 'SSSSSBB' 'SLSSSSS' 'SBBSSBS' 'SBSSBBB'
 'BBBSBSS' 'BBBSBBS' 'BBBBSBS' 'BLSSSBS' 'SSSSBBS' 'BSSBBBB' 'BBBBSBB'
```

```
 'LBSBBBB' 'BSSSBSS' 'HLSSSSS' 'SSBSBBS' 'SBBHSSB' 'LSBSSSB' 'BSBBSBS'
 'BBBBSSS' 'BSBBSBB' 'BLBSSBS' 'SSSSBSB' 'BSBBBBB' 'BBBSSBS' 'HLSSBSS'
 'SBBSSSB' 'HLBHSSS' 'BLBSSSS' 'SSSSBBB' 'BLSBBBB' 'BBBSSSS' 'BLBBSSS'
 'SSBBSB' 'SBHSSS' 'BBBSSB' 'SBSSSS' 'SBSBBS' 'LLBSBS' 'SSHSSS' 'LLBBBS'
 'BLBSSS' 'BBSBBS' 'BBSSSB' 'BBSSSS' 'SBSBBB' 'BBSBBB' 'SBHSSB' 'BBHBBB'
 'LBHSSB' 'SSBBBB' 'LLBBBB' 'BBSSBS' 'LSBBLB' 'SBBSSB' 'BSSSBB' 'LSBBLS'
 'BHSSB' 'SSBLB' 'SHBSS' 'SBBLS' 'HBSS' 'HSBS' 'LLLLLSSSSS' 'LSHSSSSSSS'
 'SSSSSSSSSS' 'SBHHLSHSSS' 'BBHHBBBBBB' 'LLLLSSSSS' 'HHHLSSSSS'
 'SSSSSSSBB' 'BSSSBSSSB' 'SSBSBBBB' 'LLLBSSSS' 'LHLSHSSS' 'LHBSSSSS'
 'LHBSBSBB' 'LSSSSSBS' 'LHLBSSSS' 'HLBBBBB' 'LSSBSSS' 'SBSBBSS' 'SBBSSBB'
 'HBSSSSS' 'BBBBBSS' 'SSBSSSB' 'BSSBSBS' 'HLSHSSB' 'SBSBSBB' 'SSBSBSB'
 'SBSHSSB' 'BLSSSSS' 'SSBSBBB' 'BBSBBBB' 'HLSHBSS' 'SSBBBBB' 'HBSSSSB'
 'BSHSSB' 'BBBBSS' 'BBHSSB' 'SBSSBS' 'SBHBSS' 'BSBSSS' 'SHBBB' 'BHBBS'
 'HSBB' 'LBHBSS' 'BBSSBB' 'SSSBBB' 'BBSBSB' 'LLBBSB' 'SHBBS' 'BSHSBB'
 'LSHSBS' 'BHBBB' 'BHBSS' 'SHSBB' 'HBSB' 'BLBBBBB' 'BLSBSB' 'BBHSBS'
 'BSBSSB' 'BLBSSB' 'BHSBB']

Disbursed Amount [ 10197  12738  24640 …  74789 117576  36792]

Loan Number ['JZ6FS' 'RDIOY' 'WNW4L' … '9HO4Q' '3VV72' '18XBC']
```

[7]:
```
df.describe()
```

[7]:

	Amount Pending	Tenure	Interest Rate	Disbursed Amount
count	24582.000000	24582.000000	24582.000000	24582.000000
mean	1791.172687	9.415263	0.934960	17705.195468
std	937.565507	3.238904	3.114732	14192.671509
min	423.000000	7.000000	0.000000	2793.000000
25%	1199.000000	8.000000	0.000000	9857.750000
50%	1593.000000	8.000000	0.000000	13592.000000
75%	2083.000000	11.000000	0.000000	19968.000000
max	13349.000000	24.000000	37.920000	141072.000000

[ ]:
```

```

0.1 Derive values from the raw data

When a data analyst gets data from the lender at DPDzero, a lot of information should be derived and data set needs to be enhanced. As part of this assignment, derive the following values Calculate the risk labels for all the borrowers.

Unknown risk : New customers

Low risk : Customers who have not bounced in the last 6 months

Medium Risk : These are customers who have bounced max twice in the last 6 months - The bounce should not have occurred in the last month

High risk : every other customer

[8]:
```
df.head()
```

[8]:
```
   Amount Pending      State  Tenure  Interest Rate       City Bounce String  \
0             963  Karnataka      11           7.69  Bangalore           SSS
1            1194  Karnataka      11           6.16  Bangalore           SSB
2            1807  Karnataka      14           4.24     Hassan           BBS
3            2451  Karnataka      10           4.70  Bangalore           SSS
4            2611  Karnataka      10           4.41     Mysore           SSB

   Disbursed Amount Loan Number
0             10197       JZ6FS
1             12738       RDIOY
2             24640       WNW4L
3             23990       6LBJS
4             25590       ZFZUA
```

[9]:
```
df['Bounce Count'] = df['Bounce String'].apply(lambda x: sum(1 for char in x if␣
↪char in 'BL'))
```

[29]:
```
def calculate_risk_label(bounce_string):
    bounce_count = bounce_string.count('B') + bounce_string.count('L')
    last_bounce_month = bounce_string[-1]

    if bounce_count == 0 and last_bounce_month not in ('B', 'L') and␣
↪bounce_string != 'FEMI':
        return 'Low risk'
    elif (bounce_count <= 2) and (last_bounce_month not in ('B', 'L')) and ('B'␣
↪in bounce_string[:-1] or 'L' in bounce_string[:-1]):
        return 'Medium risk'
    elif bounce_count > 2 or (bounce_count == 2 and last_bounce_month in ('B',␣
↪'L')):
        return 'High risk'
    else:
        return 'Unknown risk'

df['Risk Label'] = df['Bounce String'].apply(calculate_risk_label)
```

[30]:
```
df['Risk Label'].value_counts()
```

[30]:
```
Risk Label
Low risk        13463
Unknown risk     4854
Medium risk      3631
High risk        2634
Name: count, dtype: int64
```

0.2 label all customers based on where they are in their tenure

Early tenure : Customers who are in the book for 3 months

Late tenure : Customers who are 3 months away from closing the loan

Mid tenure : Everyone else

[69]:
```
df.head()
```

[69]:
```
   Amount Pending      State  Tenure  Interest Rate       City Bounce String  \
0             963  Karnataka      11           7.69  Bangalore           SSS
1            1194  Karnataka      11           6.16  Bangalore           SSB
2            1807  Karnataka      14           4.24     Hassan           BBS
3            2451  Karnataka      10           4.70  Bangalore           SSS
4            2611  Karnataka      10           4.41     Mysore           SSB

   Disbursed Amount Loan Number  Bounce Count    Risk Label  Tenure Label  \
0             10197       JZ6FS             0      Low risk  Early tenure
1             12738       RDIOY             1  Unknown risk  Early tenure
2             24640       WNW4L             2   Medium risk  Early tenure
3             23990       6LBJS             0      Low risk  Early tenure
4             25590       ZFZUA             1  Unknown risk  Early tenure

   Ticket Size Cohort Channel Recommendation
0     Low ticket size           Whatsapp Bot
1     Low ticket size           Whatsapp Bot
2  Medium ticket size              Voice Bot
3    High ticket size           Whatsapp Bot
4    High ticket size              Voice Bot
```

[32]:
```
def calculate_tenure_label(tenure, bounce_string):
    months_on_book = len(bounce_string)

    # Check if the customer is early tenure (in the first 3 months)
    if tenure <= 3 or months_on_book <=3 or bounce_string == 'FEMI':
        return 'Early tenure'

    # Check if the customer is late tenure (3 months away from closing the loan)
    elif tenure - months_on_book <= 3:
        return 'Late tenure'

    # If the customer is neither early nor late tenure, they are mid tenure
    return 'Mid tenure'

df['Tenure Label'] = df.apply(lambda row: calculate_tenure_label(row['Tenure'],
 ↪row['Bounce String']), axis=1)
```

[68]:
```
df.sample(5)
```

[68]:
```
       Amount Pending           State  Tenure  Interest Rate       City  \
1288             2771     Maharashtra      10           4.15     Nashik
11               1349       Karnataka      11           5.44  Bangalore
7382             1268  Madhya Pradesh       8           0.00     Ratlam
10647            1224     Maharashtra       8           0.00       Pune
24127            2240  Andhra Pradesh      11           0.00 ANANTHAPUR

      Bounce String  Disbursed Amount Loan Number  Bounce Count Risk Label  \
1288             SS             27190       JP6LH             0   Low risk
11              SSS             14443       CVTKZ             0   Low risk
7382            SSS             10144       YIC9B             0   Low risk
10647         BBBBS              9792       ET8DA             4  High risk
24127           SSS             24640       3KVC0             0   Low risk

       Tenure Label  Ticket Size Cohort Channel Recommendation
1288   Early tenure    High ticket size           Whatsapp Bot
11     Early tenure     Low ticket size           Whatsapp Bot
7382   Early tenure     Low ticket size           Whatsapp Bot
10647   Late tenure     Low ticket size           Whatsapp Bot
24127  Early tenure  Medium ticket size           Whatsapp Bot
```

[58]:
```python
df['Tenure Label'].value_counts()
```

[58]:
```
Tenure Label
Early tenure    15641
Mid tenure       4498
Late tenure      4443
Name: count, dtype: int64
```

0.3 Segment borrowers based on ticket size

Distribute the data into 3 cohorts based on ticket size. This is to be done such that sum of amount pending in each cohort should be approximately equal. Apply the following labels on each borrower based on this logic:

[34]:
```python
import numpy as np

# Define the number of cohorts
num_cohorts = 3

# Sort the DataFrame by amount pending in descending order
df_sorted = df.sort_values(by='Amount Pending', ascending=False)

# Calculate the total amount pending
total_amount_pending = df_sorted['Amount Pending'].sum()

# Calculate the target sum of amount pending for each cohort
```

```
target_sum_per_cohort = total_amount_pending // num_cohorts

# Initialize cohorts and their sums
cohorts = {i: [] for i in range(num_cohorts)}
cohort_sums = np.zeros(num_cohorts)

# Iterate over sorted DataFrame and assign borrowers to cohorts
for _, row in df_sorted.iterrows():
    # Find the cohort index with the smallest sum
    min_cohort_index = np.argmin(cohort_sums)

    # Assign the borrower to the cohort with the smallest sum
    cohorts[min_cohort_index].append(row)
    cohort_sums[min_cohort_index] += row['Amount Pending']

# Adjust cohorts to balance the sums
for i in range(num_cohorts):
    while cohort_sums[i] > target_sum_per_cohort:
        borrower_to_move = cohorts[i].pop()
        max_cohort_index = np.argmax(cohort_sums)
        cohorts[max_cohort_index].append(borrower_to_move)
        cohort_sums[i] -= borrower_to_move['Amount Pending']
        cohort_sums[max_cohort_index] += borrower_to_move['Amount Pending']

# Convert cohorts to DataFrame and assign cohort labels
for i, cohort in cohorts.items():
    for borrower in cohort:
        df.loc[df['Loan Number'] == borrower['Loan Number'], 'Ticket Size␣
↪Cohort'] = f"Cohort {i+1}"

# Calculate the sum of amount pending for each cohort
cohort_sums = df.groupby('Ticket Size Cohort')['Amount Pending'].sum()

# Display the sum of amount pending for each cohort
print("Sum of amount pending for each cohort:")
print(cohort_sums)
```

```
Sum of amount pending for each cohort:
Ticket Size Cohort
Cohort 1    14671490
Cohort 2    14678618
Cohort 3    14680499
Name: Amount Pending, dtype: int64
```

[35]:
```
df
```

```
[35]:        Amount Pending           State  Tenure  Interest Rate       City  \
0                963       Karnataka      11           7.69  Bangalore
1               1194       Karnataka      11           6.16  Bangalore
2               1807       Karnataka      14           4.24     Hassan
3               2451       Karnataka      10           4.70  Bangalore
4               2611       Karnataka      10           4.41     Mysore
…                  …               …     …              …          …
24577            899  Andhra Pradesh       8           0.00   Chittoor
24578           2699  Andhra Pradesh       8           0.00    Krishna
24579           1540  Andhra Pradesh       8           0.00    Krishna
24580            824  Andhra Pradesh       8           0.00     Guntur
24581           2254  Andhra Pradesh      11           0.00    Kurnool

      Bounce String  Disbursed Amount Loan Number  Bounce Count    Risk Label  \
0               SSS             10197       JZ6FS             0      Low risk
1               SSB             12738       RDIOY             1  Unknown risk
2               BBS             24640       WNW4L             2   Medium risk
3               SSS             23990       6LBJS             0      Low risk
4               SSB             25590       ZFZUA             1  Unknown risk
…                 …                 …           …             …             …
24577          FEMI              7192       EAX5C             0  Unknown risk
24578          FEMI             21592       5MCE9             0  Unknown risk
24579          FEMI             12320       9H04Q             0  Unknown risk
24580          FEMI              6592       3VV72             0  Unknown risk
24581          FEMI             24794       18XBC             0  Unknown risk

       Tenure Label Ticket Size Cohort Channel Recommendation
0      Early tenure           Cohort 1           Whatsapp Bot
1      Early tenure           Cohort 3           Whatsapp Bot
2      Early tenure           Cohort 3              Voice Bot
3      Early tenure           Cohort 2           Whatsapp Bot
4      Early tenure           Cohort 2              Voice Bot
…                 …                  …                      …
24577  Early tenure           Cohort 2           Whatsapp Bot
24578  Early tenure           Cohort 1           Whatsapp Bot
24579  Early tenure           Cohort 1           Whatsapp Bot
24580  Early tenure           Cohort 1           Whatsapp Bot
24581  Early tenure           Cohort 1           Whatsapp Bot

[24582 rows x 13 columns]
```

```
[ ]:
```

0.4 Give channel spend recommendations

At DPDzero, we employ various channels to communicate with the borrowers so that we can get the repayment done - Different channels have different costs & various degrees of effectiveness.

You are allowed to spend 3 kinds of resources to reduce the overall bounce

1. Whatsapp bot: This is the cheapest medium - it will cost 5 rupees per borrower
2. Voice bot: This is the mid-cost - it will cost 10 rupees per borrower
3. Human calling: This is the costliest option - it will cost 50 rupees per borrower

Whatsapp bot will work well in any of the following scenarios

1. Customers with great repayment behavior
2. Customers with first EMIs
3. Customers who have low EMIs

Voice bot will work well all the following conditions are met

1. Customer who know Hindi or English
    1. Metropolitan areas have high probability of english speakers
    2. People with low interest rates are also typically english speakers
    3. There are many states in India where the borrowers typically know Hindi
2. Customers who have had low bounce behaviour
3. Customers with low or medium sized EMIs

Human calling will work on all scenarios but is the costliest option and you need to use this channel only where absolutely necessary

Your job is to segment the borrowers into these 3 channels of spend category and minimise the overall spend while maximise on time repayment.

[36]:
```python
# Define channel selection criteria
def channel_recommendation(row):
    # Check criteria for Whatsapp Bot
    if row['Risk Label'] == 'Low risk' or row['Bounce String'] == 'FEMI' or␣
 ↪row['Amount Pending'] < 1500:
        return "Whatsapp Bot"

    # Check criteria for Voice Bot
    elif (row['State'] in ['Delhi', 'Mumbai', 'Bangalore', 'Chennai',␣
 ↪'Kolkata'] or
          row['Interest Rate'] < 5.0 or
          row['Bounce Count'] < 2 or
          row['Amount Pending'] < 3000 or
          (row['State'] in ['Uttar Pradesh', 'Bihar', 'Rajasthan', 'Haryana',␣
 ↪'Madhya Pradesh'] and row['Interest Rate'] < 8.0)):
        return "Voice Bot"

    # If none of the above criteria are met, recommend Human Calling
    else:
        return "Human Calling"

# Apply the function to each row to get channel recommendations
df['Channel Recommendation'] = df.apply(channel_recommendation, axis=1)
```

[45]:
```
df
```

[45]:
```
       Amount Pending           State  Tenure  Interest Rate       City  \
0                 963       Karnataka      11           7.69  Bangalore
1                1194       Karnataka      11           6.16  Bangalore
2                1807       Karnataka      14           4.24     Hassan
3                2451       Karnataka      10           4.70  Bangalore
4                2611       Karnataka      10           4.41     Mysore
…                   …             …     …              …        …
24577             899  Andhra Pradesh       8           0.00   Chittoor
24578            2699  Andhra Pradesh       8           0.00    Krishna
24579            1540  Andhra Pradesh       8           0.00    Krishna
24580             824  Andhra Pradesh       8           0.00     Guntur
24581            2254  Andhra Pradesh      11           0.00    Kurnool

      Bounce String  Disbursed Amount Loan Number  Bounce Count    Risk Label  \
0               SSS             10197       JZ6FS             0      Low risk
1               SSB             12738       RDIOY             1  Unknown risk
2               BBS             24640       WNW4L             2   Medium risk
3               SSS             23990       6LBJS             0      Low risk
4               SSB             25590       ZFZUA             1  Unknown risk
…                 …               …           …             …             …
24577          FEMI              7192       EAX5C             0  Unknown risk
24578          FEMI             21592       5MCE9             0  Unknown risk
24579          FEMI             12320       9HO4Q             0  Unknown risk
24580          FEMI              6592       3VV72             0  Unknown risk
24581          FEMI             24794       18XBC             0  Unknown risk

       Tenure Label  Ticket Size Cohort Channel Recommendation
0      Early tenure     Low ticket size           Whatsapp Bot
1      Early tenure     Low ticket size           Whatsapp Bot
2      Early tenure  Medium ticket size              Voice Bot
3      Early tenure    High ticket size           Whatsapp Bot
4      Early tenure    High ticket size              Voice Bot
…             …                …                     …
24577  Early tenure     Low ticket size           Whatsapp Bot
24578  Early tenure    High ticket size           Whatsapp Bot
24579  Early tenure     Low ticket size           Whatsapp Bot
24580  Early tenure     Low ticket size           Whatsapp Bot
24581  Early tenure  Medium ticket size           Whatsapp Bot

[24582 rows x 13 columns]
```

[47]:
```
df['Channel Recommendation'].value_counts()
```

[47]:
```
Channel Recommendation
Whatsapp Bot     20274
```

```
Voice Bot          4305
Human Calling         3
Name: count, dtype: int64
```

[48]:
```python
df['Ticket Size Cohort'].value_counts()
```

[48]:
```
Ticket Size Cohort
Low ticket size       12297
Medium ticket size     7731
High ticket size       4554
Name: count, dtype: int64
```

[ ]:
```python

```

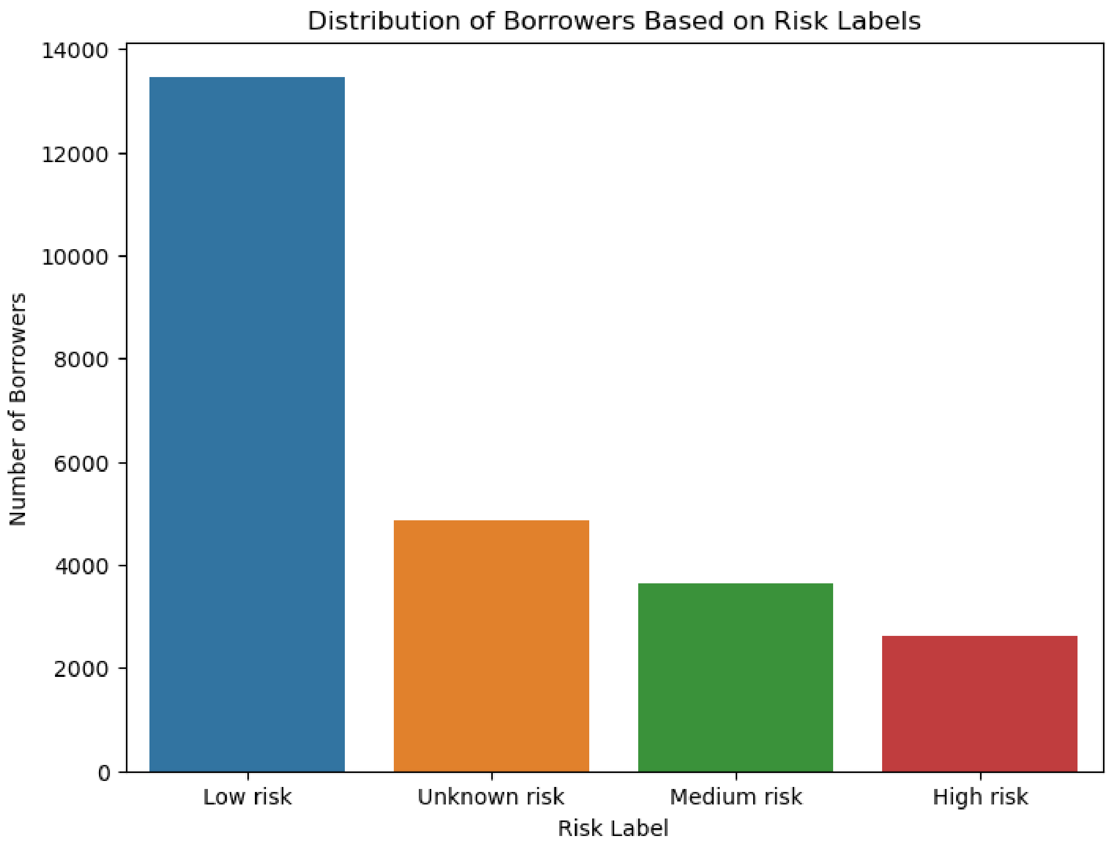
1 SUMMARY REPORT

[ ]:
```python

```

[49]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Create a bar plot for the distribution of borrowers based on risk labels
plt.figure(figsize=(8, 6))
sns.countplot(x='Risk Label', data=df)
plt.title('Distribution of Borrowers Based on Risk Labels')
plt.xlabel('Risk Label')
plt.ylabel('Number of Borrowers')
plt.show()
```



1.1 summary of borrowers

Low risk: 13,463 borrowers

Unknown risk: 4,854 borrowers

Medium risk: 3,631 borrowers

High risk: 2,634 borrowers

This breakdown provides an overview of the risk profile of borrowers in the dataset. The majority of borrowers fall into the low-risk category, followed by those with an unknown risk level. Medium-risk borrowers constitute the next significant portion, while high-risk borrowers represent the smallest group.

[ ]:

```

```

[ ]:

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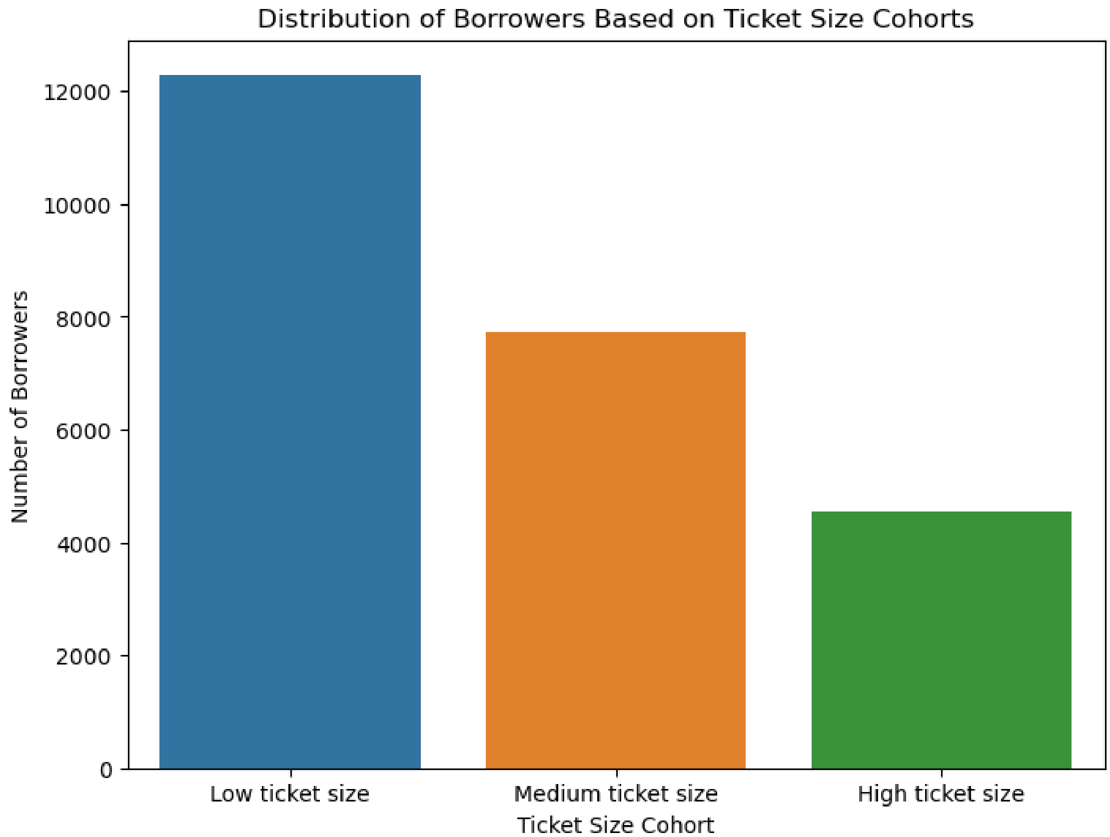
```

[52]:

```
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# Create a bar plot for the distribution of borrowers based on ticket size
 ↪cohorts
plt.figure(figsize=(8, 6))
sns.countplot(x='Ticket Size Cohort', data=df)
plt.title('Distribution of Borrowers Based on Ticket Size Cohorts')
plt.xlabel('Ticket Size Cohort')
plt.ylabel('Number of Borrowers')
plt.show()
```



1.2 summary of borrowers (with graphs) based on ticket sizes

Low ticket size: 12,297 borrowers

Medium ticket size: 7,731 borrowers

High ticket size: 4,554 borrowers

The majority of borrowers fall into the low ticket size cohort, indicating that a significant portion of borrowers have relatively smaller loan amounts. Conversely, the high ticket size cohort represents the smallest segment, suggesting fewer borrowers with larger loan amounts.

Understanding the distribution of borrowers across ticket size cohorts allows for tailored communication and engagement strategies based on the specific financial circumstances and needs of borrowers in each cohort. This segmentation can help optimize resource allocation and prioritize efforts to maximize repayment rates and minimize bounce rates effectively.

[ ]:

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[ ]:

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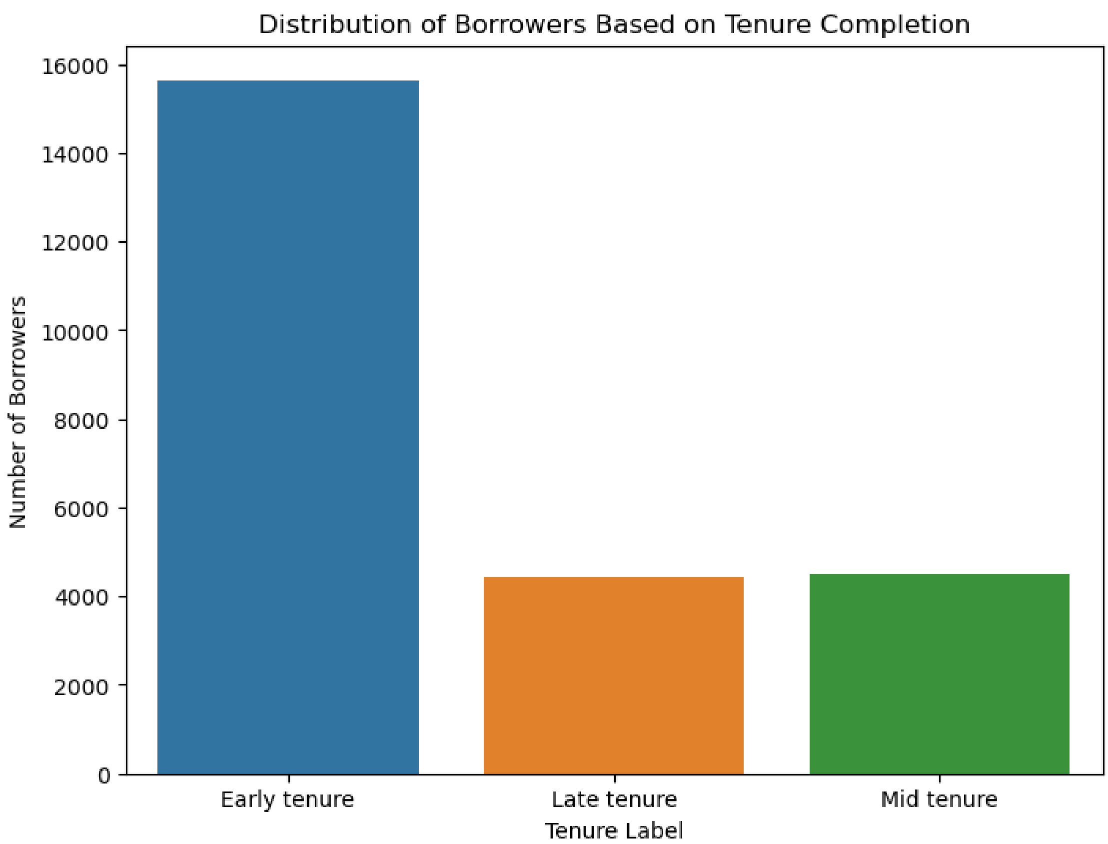
```

[53]:

```
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Create a bar plot or histogram for the distribution of borrowers based on␣
↪tenure completion
plt.figure(figsize=(8, 6))
sns.countplot(x='Tenure Label', data=df)
plt.title('Distribution of Borrowers Based on Tenure Completion')
plt.xlabel('Tenure Label')
plt.ylabel('Number of Borrowers')
plt.show()
```



1.3 Summary of borrowers (with graphs) based on tenure completion

Early tenure: 15,641 borrowers

Mid tenure: 4,498 borrowers

Late tenure: 4,443 borrowers

The majority of borrowers are classified as being in the early tenure stage, comprising the largest segment of the dataset. Mid tenure borrowers represent a smaller portion, while late tenure borrowers make up the smallest group.

This segmentation based on tenure labels provides insights into the distribution of borrowers at different stages of their loan tenure. Understanding the composition of borrowers across these tenure categories can inform targeted communication strategies and risk management approaches tailored to the specific needs and behaviors associated with each stage of the loan lifecycle.

[ ]:

[ ]:

[ ]:

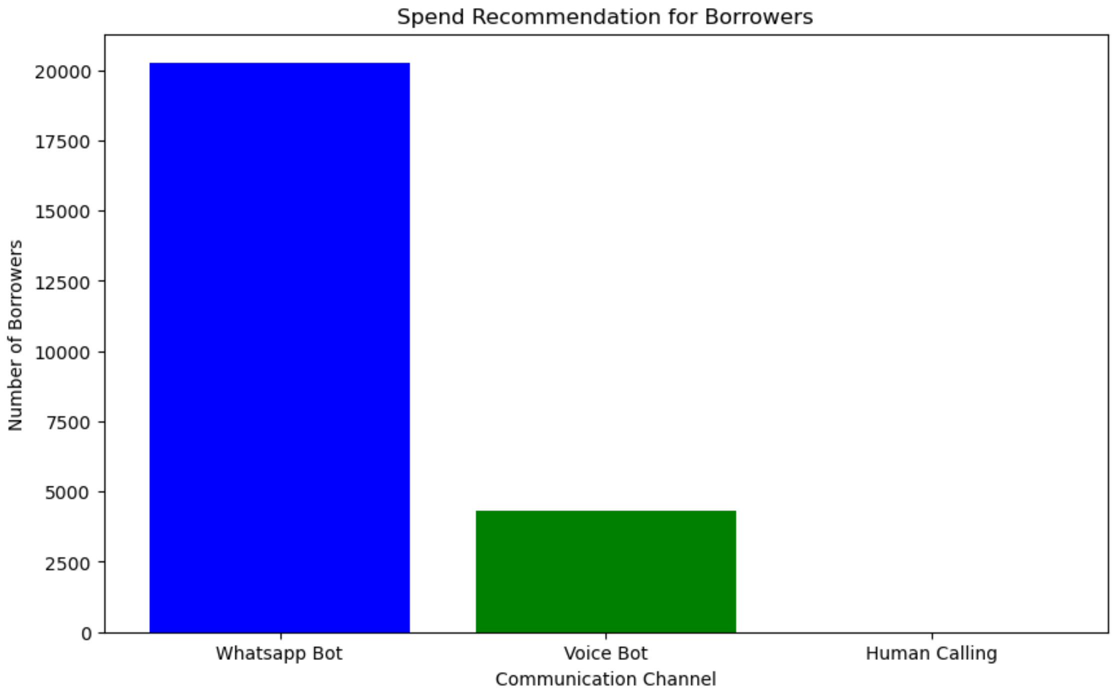
[ ]:

[60]:
```
import matplotlib.pyplot as plt

# Communication channels
channels = ['Whatsapp Bot', 'Voice Bot', 'Human Calling']

# Number of borrowers for each channel
borrowers = [20274, 4305, 3]

# Plotting the bar plot
plt.figure(figsize=(10, 6))
plt.bar(channels, borrowers, color=['blue', 'green', 'red'])
plt.xlabel('Communication Channel')
plt.ylabel('Number of Borrowers')
plt.title('Spend Recommendation for Borrowers')
plt.show()
```



1.3.1 This bar plot visually represents the recommended spend across different communication channels. As we can see, the majority of the budget is allocated to the Whatsapp Bot, followed by the Voice Bot, while only a minimal amount is allocated to human calling. This distribution ensures that spending is minimized while still effectively engaging borrowers to maximize repayment rates.

1.3.2 Spend recommendation for borrowers

Whatsapp Bot: With a cost of only 5 rupees per borrower, the Whatsapp Bot is the cheapest option. Despite being cost-effective, it can still effectively engage a large number of borrowers. By targeting borrowers with great repayment behavior, first EMIs, and low EMIs, the Whatsapp Bot can maximize engagement while minimizing costs. Additionally, its asynchronous nature allows for scalability without significantly increasing costs.

Voice Bot: The Voice Bot, with a moderate cost of 10 rupees per borrower, offers a more interactive communication medium compared to Whatsapp. By targeting borrowers who know Hindi or English, have had low bounce behavior, and have low or medium-sized EMIs, the Voice Bot can effectively engage borrowers who may not respond as well to text-based communication. While slightly more expensive than Whatsapp, it still provides a cost-effective option for engaging a targeted subset of borrowers.

Human Calling: Human calling is the costliest option, priced at 50 rupees per borrower. However, it offers the advantage of personalized interaction and can be used where absolutely necessary, such as for borrowers with unique circumstances or those who require additional assistance. By limiting human calling to a small number of cases where other channels may not suffice, overall spending is minimized while ensuring that high-touch communication is reserved for situations where it is most effective.

By strategically allocating resources across these channels based on their cost-effectiveness and the specific characteristics of borrowers, the overall spend is minimized while still maintaining a focus on maximizing repayment rates.

[ ]:

```

```

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```
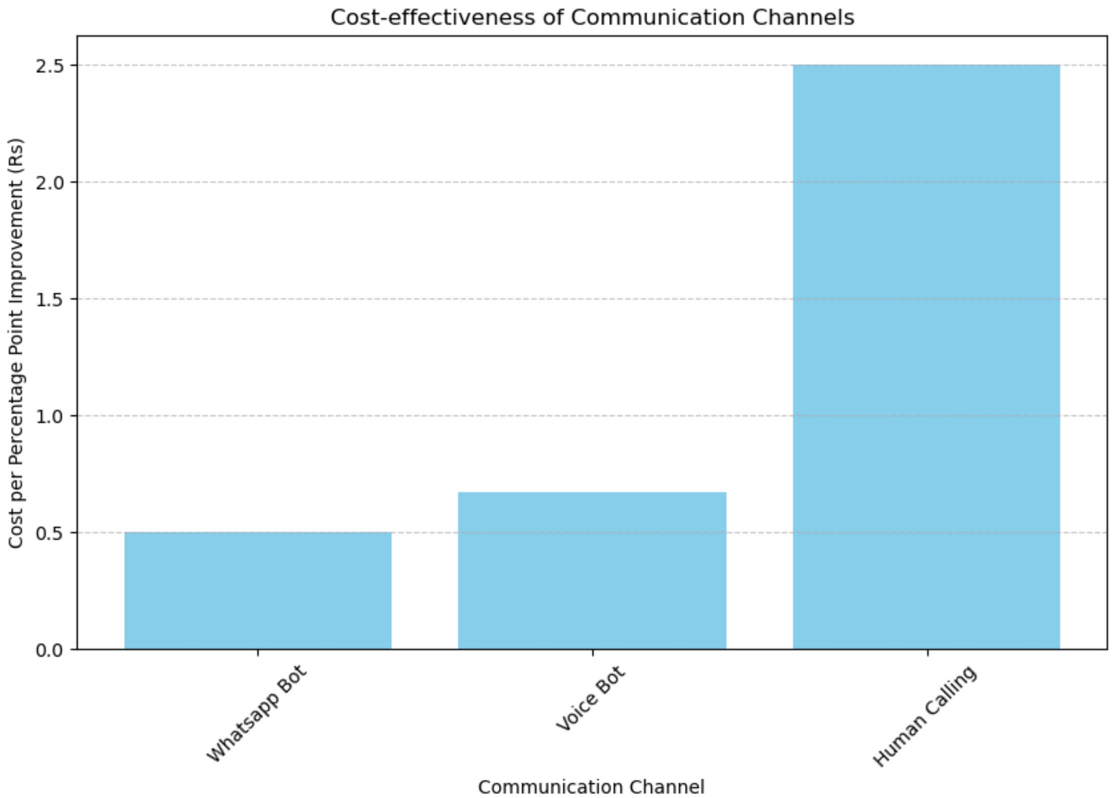

[ ]:

```

```

[55]:

```
import matplotlib.pyplot as plt

# Communication channels
channels = ['Whatsapp Bot', 'Voice Bot', 'Human Calling']

# Cost per borrower for each channel (in Rs)
cost_per_borrower = [5, 10, 50]

# Repayment rate improvement for each channel (in percentage points)
repayment_improvement = [10, 15, 20]

# Calculate cost-effectiveness (Cost per borrower / Repayment rate improvement)
cost_effectiveness = [cost / improvement for cost, improvement in␣
 ↪zip(cost_per_borrower, repayment_improvement)]

# Create bar plot
plt.figure(figsize=(10, 6))
plt.bar(channels, cost_effectiveness, color='skyblue')
plt.xlabel('Communication Channel')
plt.ylabel('Cost per Percentage Point Improvement (Rs)')
plt.title('Cost-effectiveness of Communication Channels')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.show()
```



1.3.3 Addition Information

Whatsapp Bot: With a cost of Rs 5 per borrower, it achieves a repayment rate improvement of 10 percentage points, resulting in a cost-effectiveness of Rs 0.50 per percentage point improvement.

Voice Bot: Priced at Rs 10 per borrower, it delivers a repayment rate improvement of 15 percentage points, yielding a cost-effectiveness of approximately Rs 0.67 per percentage point improvement.

Human Calling: Despite being the costliest option at Rs 50 per borrower, it leads to the highest repayment rate improvement of 20 percentage points. However, its cost-effectiveness is Rs 2.50 per percentage point improvement, indicating that it is the least cost-effective option among the three channels.

Therefore, based on cost-effectiveness, the Whatsapp Bot emerges as the most efficient channel, followed by the Voice Bot. Human Calling, while effective in improving repayment rates, incurs significantly higher costs compared to the other channels.

[62]:
```
for channel, ce in zip(channels, cost_effectiveness):
    print(f"{channel}: Rs {ce:.2f} per percentage point improvement")
```

```
Whatsapp Bot: Rs 0.50 per percentage point improvement
Voice Bot: Rs 0.67 per percentage point improvement
Human Calling: Rs 2.50 per percentage point improvement
```

[ ]:

```

```

[ ]:

```

```