Bondora Data Preprocessing ¶

In this project we will be doing credit risk modelling of peer to peer lending Bondora systems.Data for the study has been retrieved from a publicly available data set of a leading European P2P lending platform (**Bondora** (https://www.bondora.com/en/public-reports#dataset-file-format)).The retrieved data is a pool of both defaulted and non-defaulted loans from the time period between **1st March 2009** and **27th January 2020**. The data comprises of demographic and financial information of borrowers, and loan transactions.In P2P lending, loans are typically uncollateralized and lenders seek higher returns as a compensation for the financial risk they take. In addition, they need to make decisions under information asymmetry that works in favor of the borrowers. In order to make rational decisions, lenders want to minimize the risk of default of each lending decision, and realize the return that compensates for the risk.

In this notebook we will preprocess the raw dataset and will create new preprocessed csv that can be used for building credit risk models.

In [1]:

```
# import 'Pandas'
import pandas as pd

# import 'Numpy'
import numpy as np

# import subpackage of Matplotlib
import matplotlib.pyplot as plt


# import 'Seaborn'
import seaborn as sns

# to suppress warnings
from warnings import filterwarnings
filterwarnings('ignore')

pd.set_option('display.max_columns', 500)
# display all columns of the dataframe

# to display the float values upto 6 decimal places
pd.options.display.float_format = '{:.3f}'.format
```

In [2]:

```
df=pd.read_csv('../TC/Bondora_raw.csv',low_memory=True)
```

In [3]:

```
df.shape
```

Out[3]:

```
(134529, 112)
```

In [4]:

```
# STATUS IS OUR TARGET VARIABLE
df['Status'].value_counts()
```

Out[4]:

```
Current    57135
Late       45772
Repaid     31622
Name: Status, dtype: int64
```

In [5]:

```
df.head()
```

Out[5]:

	ReportAsOfEOD	LoanId	LoanNumber	ListedOnUTC	BiddingStartedOn	BidsPortfolio
0	2020-01-27	F0660C80-83F3-4A97-8DA0-9C250112D6EC	659	2009-06-11 16:40:39	2009-06-11 16:40:39	
1	2020-01-27	978BB85B-1C69-4D51-8447-9C240104A3A2	654	2009-06-10 15:48:57	2009-06-10 15:48:57	
2	2020-01-27	EA44027E-7FA7-4BB2-846D-9C1F013C8A22	641	2009-06-05 19:12:29	2009-06-05 19:12:29	
3	2020-01-27	CE67AD25-2951-4BEE-96BD-9C2700C61EF4	668	2009-06-13 12:01:20	2009-06-13 12:01:20	
4	2020-01-27	9408BF8C-B159-4D6A-9D61-9C2400A986E3	652	2009-06-10 10:17:13	2009-06-10 10:17:13	

Data Understanding

Feature	Description
ActiveLateCategory	When a loan is in Principal Debt then it will be categorized by Principal Debt days
ActiveLateLastPaymentCategory	Shows how many days has passed since last payment and categorised if it is overdue
ActiveScheduleFirstPaymentReached	Whether the first payment date has been reached according to the active schedule
Age	The age of the borrower when signing the loan application
Amount	Amount the borrower received on the Primary Market. This is the principal balance of your purchase from Secondary Market
AmountOfPreviousLoansBeforeLoan	Value of previous loans
AppliedAmount	The amount borrower applied for originally

Feature	Description
AuctionBidNumber	Unique bid number which is accompanied by Auction number
AuctionId	A unique number given to all auctions
AuctionName	Name of the Auction, in newer loans it is defined by the purpose of the loan
AuctionNumber	Unique auction number which is accompanied by Bid number
BidPrincipal	On Primary Market BidPrincipal is the amount you made your bid on. On Secondary Market BidPrincipal is the purchase price
BidsApi	The amount of investment offers made via Api
BidsManual	The amount of investment offers made manually
BidsPortfolioManager	The amount of investment offers made by Portfolio Managers
BoughtFromResale_Date	The time when the investment was purchased from the Secondary Market
City	City of the borrower
ContractEndDate	The date when the loan contract ended
Country	Residency of the borrower
County	County of the borrower
CreditScoreEeMini	1000 No previous payments problems 900 Payments problems finished 24-36 months ago 800 Payments problems finished 12-24 months ago 700 Payments problems finished 6-12 months ago 600 Payment problems finished < 6 months ago 500 Active payment problems
CreditScoreEsEquifaxRisk	Generic score for the loan applicants that do not have active past due operations in ASNEF; a measure of the probability of default one year ahead; the score is given on a 6-grade scale: AAA (“Very low”), AA (“Low”), A (“Average”), B (“Average High”), C (“High”), D (“Very High”).
CreditScoreEsMicroL	A score that is specifically designed for risk classifying subprime borrowers (defined by Equifax as borrowers that do not have access to bank loans); a measure of the probability of default one month ahead; the score is given on a 10-grade scale, from the best score to the worst: M1, M2, M3, M4, M5, M6, M7, M8, M9, M10.
CreditScoreFiAsiakasTietoRiskGrade	Credit Scoring model for Finnish Asiakastieto RL1 Very low risk 01-20 RL2 Low risk 21-40 RL3 Average risk 41-60 RL4 Big risk 61-80 RL5 Huge risk 81-100
CurrentDebtDaysPrimary	How long the loan has been in Principal Debt
CurrentDebtDaysSecondary	How long the loan has been in Interest Debt
DateOfBirth	The date of the borrower's birth
DebtOccuredOn	The date when Principal Debt occurred
DebtOccuredOnForSecondary	The date when Interest Debt occurred
DebtToIncome	Ratio of borrower's monthly gross income that goes toward paying loans
DefaultDate	The date when loan went into defaulted state and collection process was started
DesiredDiscountRate	Investment being sold at a discount or premium
EAD1	Exposure at default, outstanding principal at default
EAD2	Exposure at default, loan amount less all payments prior to default
Education	1 Primary education 2 Basic education 3 Vocational education 4 Secondary education 5 Higher education
EL_V0	Expected loss calculated by the specified version of Rating model
EL_V1	Expected loss calculated by the specified version of Rating model
EL_V2	Expected loss calculated by the specified version of Rating model
EmploymentDurationCurrentEmployer	Employment time with the current employer

Feature	Description
EmploymentPosition	Employment position with the current employer
EmploymentStatus	1 Unemployed 2 Partially employed 3 Fully employed 4 Self-employed 5 Entrepreneur 6 Retiree
ExistingLiabilities	Borrower's number of existing liabilities
ExpectedLoss	Expected Loss calculated by the current Rating model
ExpectedReturn	Expected Return calculated by the current Rating model
FirstPaymentDate	First payment date according to initial loan schedule
FreeCash	Discretionary income after monthly liabilities
Gender	0 Male 1 Woman 2 Undefined
GracePeriodEnd	Date of the end of Grace period
GracePeriodStart	Date of the beginning of Grace period
HomeOwnershipType	0 Homeless 1 Owner 2 Living with parents 3 Tenant, pre-furnished property 4 Tenant, unfurnished property 5 Council house 6 Joint tenant 7 Joint ownership 8 Mortgage 9 Owner with encumbrance 10 Other
IncomeFromChildSupport	Borrower's income from alimony payments
IncomeFromFamilyAllowance	Borrower's income from child support
IncomeFromLeavePay	Borrower's income from paternity leave
IncomeFromPension	Borrower's income from pension
IncomeFromPrincipalEmployer	Borrower's income from its employer
IncomeFromSocialWelfare	Borrower's income from social support
IncomeOther	Borrower's income from other sources
IncomeTotal	Borrower's total income
Interest	Maximum interest rate accepted in the loan application
InterestAndPenaltyBalance	Unpaid interest and penalties
InterestAndPenaltyDebtServicingCost	Service cost related to the recovery of the debt based on the interest and penalties of the investment
InterestAndPenaltyPaymentsMade	Note owner received loan transfers earned interest, penalties total amount
InterestAndPenaltyWriteOffs	Interest that was written off on the investment
InterestLateAmount	Interest debt amount
InterestRecovery	Interest recovered due to collection process from in debt loans
LanguageCode	1 Estonian 2 English 3 Russian 4 Finnish 5 German 6 Spanish 9 Slovakian
LastPaymentOn	The date of the current last payment received from the borrower
LiabilitiesTotal	Total monthly liabilities
ListedOnUTC	Date when the loan application appeared on Primary Market
LoanDate	Date when the loan was issued
LoanDuration	Current loan duration in months
LoanId	A unique ID given to all loan applications
LoanNumber	A unique number given to all loan applications
LoanStatusActiveFrom	How long the current status has been active

Feature	Description
LossGivenDefault	Gives the percentage of outstanding exposure at the time of default that an investor is likely to lose if a loan actually defaults. This means the proportion of funds lost for the investor after all expected recovery and accounting for the time value of the money recovered. In general, LGD parameter is intended to be estimated based on the historical recoveries. However, in new markets where limited experience does not allow us more precise loss given default estimates, a LGD of 90% is assumed.
MaritalStatus	1 Married 2 Cohabitant 3 Single 4 Divorced 5 Widow
MaturityDate_Last	Loan maturity date according to the current payment schedule
MaturityDate_Original	Loan maturity date according to the original loan schedule
ModelVersion	The version of the Rating model used for issuing the Bondora Rating
MonthlyPayment	Estimated amount the borrower has to pay every month
MonthlyPaymentDay	The day of the month the loan payments are scheduled for The actual date is adjusted for weekends and bank holidays (e.g. if 10th is Sunday then the payment will be made on the 11th in that month)
NewCreditCustomer	Did the customer have prior credit history in Bondora 0 Customer had at least 3 months of credit history in Bondora 1 No prior credit history in Bondora
NextPaymentDate	According to schedule the next date for borrower to make their payment
NextPaymentNr	According to schedule the number of the next payment
NextPaymentSum	According to schedule the amount of the next payment
NoOfPreviousLoansBeforeLoan	Number of previous loans
note_id	A unique ID given to the investments
NoteLoanLateChargesPaid	The amount of late charges the note has received
NoteLoanTransfersInterestAmount	The amount of interest the note has received
NoteLoanTransfersMainAmount	The amount of principal the note has received
NrOfDependants	Number of children or other dependants
NrOfScheduledPayments	According to schedule the count of scheduled payments
OccupationArea	1 Other 2 Mining 3 Processing 4 Energy 5 Utilities 6 Construction 7 Retail and wholesale 8 Transport and warehousing 9 Hospitality and catering 10 Info and telecom 11 Finance and insurance 12 Real-estate 13 Research 14 Administrative 15 Civil service & military 16 Education 17 Healthcare and social help 18 Art and entertainment 19 Agriculture, forestry and fishing
OnSaleSince	Time when the investment was added to Secondary Market
PenaltyLateAmount	Late charges debt amount
PlannedInterestPostDefault	The amount of interest that was planned to be received after the default occurred
PlannedInterestTillDate	According to active schedule the amount of interest the investment should have received
PlannedPrincipalPostDefault	The amount of principal that was planned to be received after the default occurred
PlannedPrincipalTillDate	According to active schedule the amount of principal the investment should have received
PreviousEarlyRepaymentsBeforeLoan	How much was the early repayment amount before the loan
PreviousEarlyRepaymentsCountBeforeLoan	How many times the borrower had repaid early
PreviousRepaymentsBeforeLoan	How much the borrower had repaid before the loan
PrincipalBalance	Principal that still needs to be paid by the borrower
PrincipalDebtServicingCost	Service cost related to the recovery of the debt based on the principal of the investment

Feature	Description
PrincipalLateAmount	Principal debt amount
PrincipalOverdueBySchedule	According to the current schedule, principal that is overdue
PrincipalPaymentsMade	Note owner received loan transfers principal amount
PrincipalRecovery	Principal recovered due to collection process from in debt loans
PrincipalWriteOffs	Principal that was written off on the investment
ProbabilityOfDefault	Probability of Default, refers to a loan’s probability of default within one year horizon.
PurchasePrice	Investment amount or secondary market purchase price
Rating	Bondora Rating issued by the Rating model
Rating_V0	Bondora Rating issued by version 0 of the Rating model
Rating_V1	Bondora Rating issued by version 1 of the Rating model
Rating_V2	Bondora Rating issued by version 2 of the Rating model
RecoveryStage	Current stage according to the recovery model 1 Collection 2 Recovery 3 Write Off
RefinanceLiabilities	The total amount of liabilities after refinancing
ReScheduledOn	The date when the a new schedule was assigned to the borrower
Restructured	The original maturity date of the loan has been increased by more than 60 days
SoldInResale_Date	The date when the investment was sold on Secondary market
SoldInResale_Price	The price of the investment that was sold on Secondary market
SoldInResale_Principal	The principal remaining of the investment that was sold on Secondary market
StageActiveSince	How long the current recovery stage has been active
Status	The current status of the loan application
UseOfLoan	0 Loan consolidation 1 Real estate 2 Home improvement 3 Business 4 Education 5 Travel 6 Vehicle 7 Other 8 Health 101 Working capital financing 102 Purchase of machinery equipment 103 Renovation of real estate 104 Accounts receivable financing 105 Acquisition of means of transport 106 Construction finance 107 Acquisition of stocks 108 Acquisition of real estate 109 Guaranteeing obligation 110 Other business All codes in format 1XX are for business loans that are not supported since October 2012
UserName	The user name generated by the system for the borrower
VerificationType	Method used for loan application data verification 0 Not set 1 Income unverified 2 Income unverified, cross-referenced by phone 3 Income verified 4 Income and expenses verified
WorkExperience	Borrower's overall work experience in years
WorseLateCategory	Displays the last longest period of days when the loan was in Principal Debt
XIRR	XIRR (extended internal rate of return) is a methodology to calculate the net return using the loan issued date and amount, loan repayment dates and amounts and the principal balance according to the original repayment date. All overdue principal payments are written off immediately. No provisions for future losses are made & only received (not accrued or scheduled) interest payments are taken into account.

Percentage of Missing Values

In [6]:

```
# To show all the rows of pandas dataframe
# df.isnull().sum()*100/len(df)

total_missing_val=df.isnull().sum()*100/len(df)

def print_full(x):
    pd.set_option('display.max_rows', len(x))
    print(x)
    pd.reset_option('display.max_rows')

print_full(total_missing_val)

# df.isnull().mean().tolist()
```

```
ReportAsOfEOD                     0.000
LoanId                            0.000
LoanNumber                        0.000
ListedOnUTC                       0.000
BiddingStartedOn                  0.000
BidsPortfolioManager              0.000
BidsApi                           0.000
BidsManual                        0.000
UserName                          0.000
NewCreditCustomer                 0.000
LoanApplicationStartedDate        0.000
LoanDate                          0.000
ContractEndDate                  56.156
FirstPaymentDate                  0.000
MaturityDate_Original             0.000
MaturityDate_Last                 0.000
ApplicationSignedHour             0.000
ApplicationSignedWeekday          0.000
VerificationType                  0.033
```

Removing all the features which have more than 40% missing values

In [7]:

```
# removing the columns having more than 40% missing values
df_val_null_less_then_40 = df.columns[total_missing_val <40]
df_val_null_less_then_40

# df[df.columns[df.isnull().mean() < 0.4]]
```

Out[7]:

```
Index(['ReportAsOfEOD', 'LoanId', 'LoanNumber', 'ListedOnUTC',
       'BiddingStartedOn', 'BidsPortfolioManager', 'BidsApi', 'BidsManual',
       'UserName', 'NewCreditCustomer', 'LoanApplicationStartedDate',
       'LoanDate', 'FirstPaymentDate', 'MaturityDate_Original',
       'MaturityDate_Last', 'ApplicationSignedHour',
       'ApplicationSignedWeekday', 'VerificationType', 'LanguageCode', 'Ag
e',
       'DateOfBirth', 'Gender', 'Country', 'AppliedAmount', 'Amount',
       'Interest', 'LoanDuration', 'MonthlyPayment', 'County', 'City',
       'UseOfLoan', 'Education', 'MaritalStatus', 'EmploymentStatus',
       'EmploymentDurationCurrentEmployer', 'OccupationArea',
       'HomeOwnershipType', 'IncomeFromPrincipalEmployer', 'IncomeFromPensio
n',
       'IncomeFromFamilyAllowance', 'IncomeFromSocialWelfare',
       'IncomeFromLeavePay', 'IncomeFromChildSupport', 'IncomeOther',
       'IncomeTotal', 'ExistingLiabilities', 'LiabilitiesTotal',
       'RefinanceLiabilities', 'DebtToIncome', 'FreeCash', 'MonthlyPaymentDa
y',
       'ActiveScheduleFirstPaymentReached', 'PlannedInterestTillDate',
       'LastPaymentOn', 'ExpectedLoss', 'LossGivenDefault', 'ExpectedRetur
n',
       'ProbabilityOfDefault', 'PrincipalOverdueBySchedule',
       'StageActiveSince', 'ModelVersion', 'Rating', 'Status', 'Restructure
d',
       'WorseLateCategory', 'CreditScoreEsMicroL', 'PrincipalPaymentsMade',
       'InterestAndPenaltyPaymentsMade', 'PrincipalBalance',
       'InterestAndPenaltyBalance', 'NoOfPreviousLoansBeforeLoan',
       'AmountOfPreviousLoansBeforeLoan', 'PreviousRepaymentsBeforeLoan',
       'PreviousEarlyRepaymentsCountBeforeLoan', 'NextPaymentNr',
       'NrOfScheduledPayments'],
      dtype='object')
```

In [8]:

```
# print missing values columns

miss_col=['ContractEndDate', 'NrOfDependants', 'EmploymentPosition',
       'WorkExperience', 'PlannedPrincipalTillDate', 'CurrentDebtDaysPrimary',
       'DebtOccuredOn', 'CurrentDebtDaysSecondary',
       'DebtOccuredOnForSecondary',
       'PlannedPrincipalPostDefault', 'PlannedInterestPostDefault', 'EAD1',
       'EAD2', 'PrincipalRecovery', 'InterestRecovery', 'RecoveryStage',
       'EL_V0', 'Rating_V0', 'EL_V1', 'Rating_V1', 'Rating_V2',
       'ActiveLateCategory', 'CreditScoreEsEquifaxRisk',
       'CreditScoreFiAsiakasTietoRiskGrade', 'CreditScoreEeMini',
       'PrincipalWriteOffs', 'InterestAndPenaltyWriteOffs',
       'PreviousEarlyRepaymentsBefoleLoan', 'GracePeriodStart',
       'GracePeriodEnd', 'NextPaymentDate', 'ReScheduledOn',
       'PrincipalDebtServicingCost', 'InterestAndPenaltyDebtServicingCost',
       'ActiveLateLastPaymentCategory']
```

In [9]:

```
# drop missing  values columns )
df_drop_m_val =df.drop(miss_col,axis=1)
df_drop_m_val.shape
```

Out[9]:

```
(134529, 77)
```

In [10]:

```
df_drop_m_val['NrOfScheduledPayments'].head()
```

Out[10]:

```
0    NaN
1    NaN
2    NaN
3    NaN
4    NaN
Name: NrOfScheduledPayments, dtype: float64
```

Apart from missing value features there are some features which will have no role in default prediction like 'ReportAsOfEOD', 'LoanId', 'LoanNumber', 'ListedOnUTC', 'DateOfBirth' (**because age is already present**), 'BiddingStartedOn','UserName','NextPaymentNr','NrOfScheduledPayments','IncomeFromPrincipalEmployer', 'IncomeFromPension', 'IncomeFromFamilyAllowance', 'IncomeFromSocialWelfare','IncomeFromLeavePay', 'IncomeFromChildSupport', 'IncomeOther' (**As Total income is already present which is total of all these income**), 'LoanApplicationStartedDate','ApplicationSignedHour', 'ApplicationSignedWeekday','ActiveScheduleFirstPaymentReached', 'PlannedInterestTillDate', 'LastPaymentOn', 'ExpectedLoss', 'LossGivenDefault', 'ExpectedReturn', 'ProbabilityOfDefault', 'PrincipalOverdueBySchedule', 'StageActiveSince', 'ModelVersion','WorseLateCategory'

In [11]:

```
cols_del = ['ReportAsOfEOD', 'LoanId', 'LoanNumber', 'ListedOnUTC', 'DateOfBirth',
       'BiddingStartedOn','UserName','NextPaymentNr',
       'NrOfScheduledPayments','IncomeFromPrincipalEmployer', 'IncomeFromPension',
       'IncomeFromFamilyAllowance', 'IncomeFromSocialWelfare',
       'IncomeFromLeavePay', 'IncomeFromChildSupport', 'IncomeOther','LoanApplicationStarte
       'ApplicationSignedWeekday','ActiveScheduleFirstPaymentReached', 'PlannedInterestTill
       'ExpectedLoss', 'LossGivenDefault', 'ExpectedReturn',
       'ProbabilityOfDefault', 'PrincipalOverdueBySchedule',
       'StageActiveSince', 'ModelVersion','WorseLateCategory']
```

In [12]:

```
loan = df_drop_m_val.drop(cols_del,axis=1)
```

In [13]:

```
loan.shape
```

Out[13]:

```
(134529, 48)
```

Creating Target Variable

Here, status is the variable which help us in creating target variable. The reason for not making status as target variable is that it has three unique values **current, Late and repaid**. There is no default feature but there is a feature **default date** which tells us when the borrower has defaulted means on which date the borrower defaulted. So, we will be combining **Status** and **Default date** features for creating target variable.The reason we cannot simply treat Late as default because it also has some records in which actual status is Late but the user has never defaulted i.e., default date is null. So we will first filter out all the current status records because they are not matured yet they are current loans.

In [14]:

```
loan.columns
```

Out[14]:

```
Index(['BidsPortfolioManager', 'BidsApi', 'BidsManual', 'NewCreditCustomer',
       'LoanDate', 'FirstPaymentDate', 'MaturityDate_Original',
       'MaturityDate_Last', 'VerificationType', 'LanguageCode', 'Age',
       'Gender', 'Country', 'AppliedAmount', 'Amount', 'Interest',
       'LoanDuration', 'MonthlyPayment', 'County', 'City', 'UseOfLoan',
       'Education', 'MaritalStatus', 'EmploymentStatus',
       'EmploymentDurationCurrentEmployer', 'OccupationArea',
       'HomeOwnershipType', 'IncomeTotal', 'ExistingLiabilities',
       'LiabilitiesTotal', 'RefinanceLiabilities', 'DebtToIncome', 'FreeCas
h',
       'MonthlyPaymentDay', 'LastPaymentOn', 'DefaultDate', 'Rating', 'Statu
s',
       'Restructured', 'CreditScoreEsMicroL', 'PrincipalPaymentsMade',
       'InterestAndPenaltyPaymentsMade', 'PrincipalBalance',
       'InterestAndPenaltyBalance', 'NoOfPreviousLoansBeforeLoan',
       'AmountOfPreviousLoansBeforeLoan', 'PreviousRepaymentsBeforeLoan',
       'PreviousEarlyRepaymentsCountBeforeLoan'],
      dtype='object')
```

In [15]:

```
# let's find the counts of each status categories
loan.Status.value_counts()
```

Out[15]:

```
Current    57135
Late       45772
Repaid     31622
Name: Status, dtype: int64
```

In [16]:

```
# filtering out Current Status records
loan[loan.Status=='Current']
```

Out[16]:

	BidsPortfolioManager	BidsApi	BidsManual	NewCreditCustomer	LoanDate	FirstPaymer
491	1355	0	645.000	True	2015-01-06	2015
523	1000	0	0.000	False	2015-01-07	2015
536	2345	0	655.000	False	2015-01-07	2015
541	2045	0	955.000	True	2015-01-08	2015
544	1500	0	0.000	True	2015-01-08	2015
...	...	...	...	...	...	
134429	560	0	40.000	False	2014-12-29	2015
134455	2175	0	2725.000	True	2014-12-30	2015
134483	1000	0	0.000	True	2015-01-02	2015
134486	635	0	3465.000	True	2015-01-02	2015
134491	2230	0	3770.000	False	2015-01-03	2015

57135 rows × 48 columns

Now, we will create new target variable in which 0 will be assigned when default date is null means borrower has never defaulted while 1 in case default date is present.

In [17]:

```
# for null value replacement:
loan['DefaultDate'].replace(np.nan, 0,inplace=True)

#for String Date values replacement:
for i in loan.DefaultDate:
    if len(str(i))>1:
        loan.DefaultDate.replace(i,1,inplace=True)
```

In [18]:

```
loan.DefaultDate.head()
```

Out[18]:

```
0    0
1    0
2    1
3    0
4    1
Name: DefaultDate, dtype: int64
```

In [19]:

```
# check the counts of default and nondefault
loan.DefaultDate.value_counts()
```

Out[19]:

```
0    91614
1    42915
Name: DefaultDate, dtype: int64
```

In [20]:

```
# let's drop the status columns
loan.drop(columns='Status',axis=1,inplace = True)
```

In [21]:

```
loan.head()
```

Out[21]:

	BidsPortfolioManager	BidsApi	BidsManual	NewCreditCustomer	LoanDate	FirstPaymentDate
0	0	0	115.041	True	2009-06-16	2009-07-27
1	0	0	140.606	False	2009-06-15	2009-07-15
2	0	0	319.558	True	2009-06-15	2009-07-27
3	0	0	57.520	True	2009-06-15	2009-07-15
4	0	0	319.558	True	2009-06-14	2009-07-27

Now, we will remove Loan Status and default date as we have already created target variable with the help of these two features

In [22]:

```
# let's drop the DefaultDate column
loan.drop(columns='DefaultDate',axis =1,inplace=True)
```

In [23]:

```
loan.shape
```

Out[23]:

```
(134529, 46)
```

checking datatype of all features

In this step we will see any data type mismatch

In [24]:

```
# write your code here
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 134529 entries, 0 to 134528
Data columns (total 46 columns):
 #   Column                                  Non-Null Count   Dtype  
---  ------                                  --------------   -----  
 0   BidsPortfolioManager                    134529 non-null  int64  
 1   BidsApi                                 134529 non-null  int64  
 2   BidsManual                              134529 non-null  float64
 3   NewCreditCustomer                       134529 non-null  bool   
 4   LoanDate                                134529 non-null  object 
 5   FirstPaymentDate                        134529 non-null  object 
 6   MaturityDate_Original                   134529 non-null  object 
 7   MaturityDate_Last                       134529 non-null  object 
 8   VerificationType                        134484 non-null  float64
 9   LanguageCode                            134529 non-null  int64  
 10  Age                                     134529 non-null  int64  
 11  Gender                                  134484 non-null  float64
 12  Country                                 134529 non-null  object 
 13  AppliedAmount                           134529 non-null  float64
 14  Amount                                  134529 non-null  float64
 15  Interest                                134529 non-null  float64
 16  LoanDuration                            134529 non-null  int64  
 17  MonthlyPayment                          127844 non-null  float64
 18  County                                  97689 non-null   object 
 19  City                                    124735 non-null  object 
 20  UseOfLoan                               134529 non-null  int64  
 21  Education                               134484 non-null  float64
 22  MaritalStatus                           134484 non-null  float64
 23  EmploymentStatus                        134332 non-null  float64
 24  EmploymentDurationCurrentEmployer       133653 non-null  object 
 25  OccupationArea                          134443 non-null  float64
 26  HomeOwnershipType                       132877 non-null  float64
 27  IncomeTotal                             134529 non-null  float64
 28  ExistingLiabilities                     134529 non-null  int64  
 29  LiabilitiesTotal                        134529 non-null  float64
 30  RefinanceLiabilities                    134529 non-null  int64  
 31  DebtToIncome                            134484 non-null  float64
 32  FreeCash                                134484 non-null  float64
 33  MonthlyPaymentDay                       134529 non-null  int64  
 34  LastPaymentOn                           124998 non-null  object 
 35  Rating                                  131799 non-null  object 
 36  Restructured                            134529 non-null  bool   
 37  CreditScoreEsMicroL                     104955 non-null  object 
 38  PrincipalPaymentsMade                   134529 non-null  float64
 39  InterestAndPenaltyPaymentsMade          134529 non-null  float64
 40  PrincipalBalance                        134529 non-null  float64
 41  InterestAndPenaltyBalance               134529 non-null  float64
 42  NoOfPreviousLoansBeforeLoan             134529 non-null  int64  
 43  AmountOfPreviousLoansBeforeLoan         134529 non-null  float64
 44  PreviousRepaymentsBeforeLoan            91368 non-null   float64
 45  PreviousEarlyRepaymentsCountBeforeLoan  134529 non-null  int64  
dtypes: bool(2), float64(22), int64(11), object(11)
memory usage: 45.4+ MB
```

Univariate Analysis

Checking distribution of categorical variables

In [56]:

```
cat_cols = loan.select_dtypes(include=object)
cat_cols.head()
```

Out[56]:

	LoanDate	FirstPaymentDate	MaturityDate_Original	MaturityDate_Last	VerificationType	Langu
0	2009-06-16	2009-07-27	2010-06-25	2010-06-25	Income unverified	
1	2009-06-15	2009-07-15	2009-07-15	2009-07-15	Income unverified	
2	2009-06-15	2009-07-27	2011-02-25	2014-05-13	Income unverified	
3	2009-06-15	2009-07-15	2010-09-15	2010-09-15	Income unverified	
4	2009-06-14	2009-07-27	2010-06-25	2010-06-25	Income unverified	

In [57]:

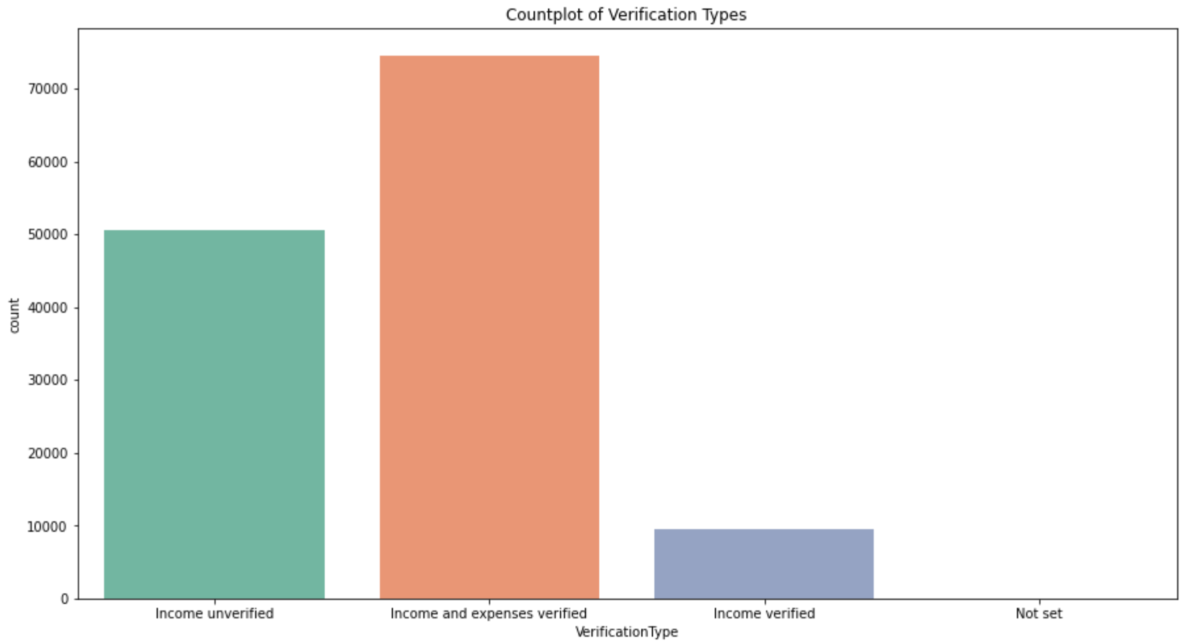
```
cat_cols.columns.tolist()
```

Out[57]:

```
['LoanDate',
 'FirstPaymentDate',
 'MaturityDate_Original',
 'MaturityDate_Last',
 'VerificationType',
 'LanguageCode',
 'Gender',
 'Country',
 'County',
 'City',
 'UseOfLoan',
 'Education',
 'MaritalStatus',
 'EmploymentStatus',
 'EmploymentDurationCurrentEmployer',
 'OccupationArea',
 'HomeOwnershipType',
 'LastPaymentOn',
 'Rating',
 'CreditScoreEsMicroL']
```

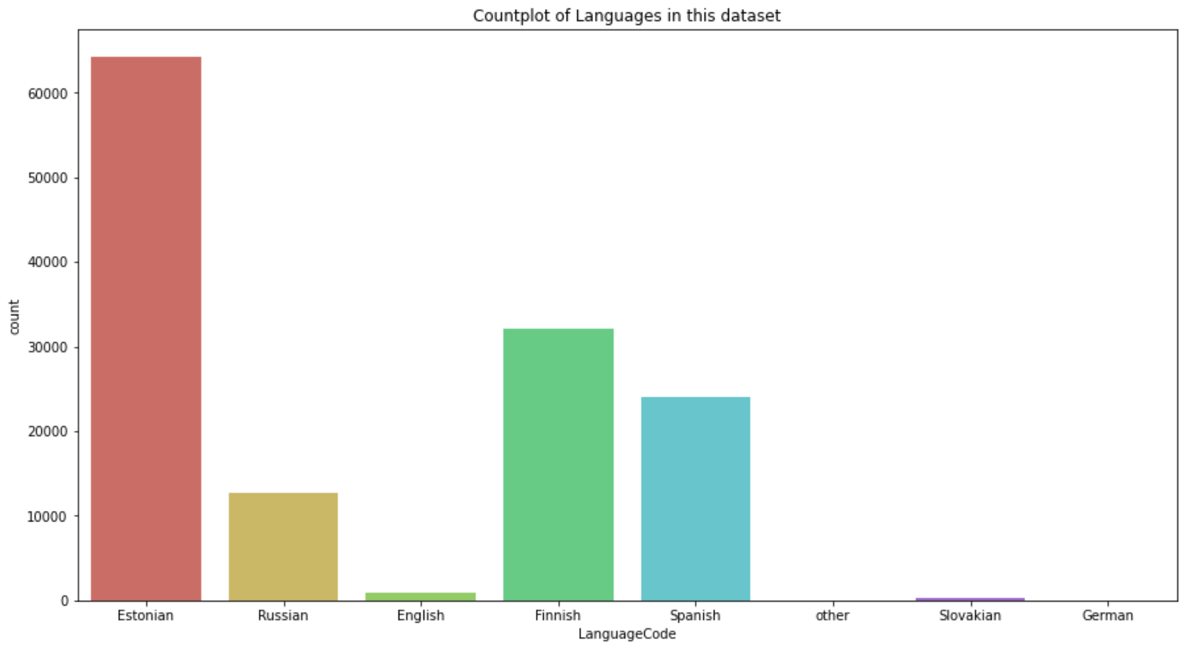
In [186]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='VerificationType',data = cat_cols,palette='Set2')
plt.title('Countplot of Verification Types')
plt.show()
```



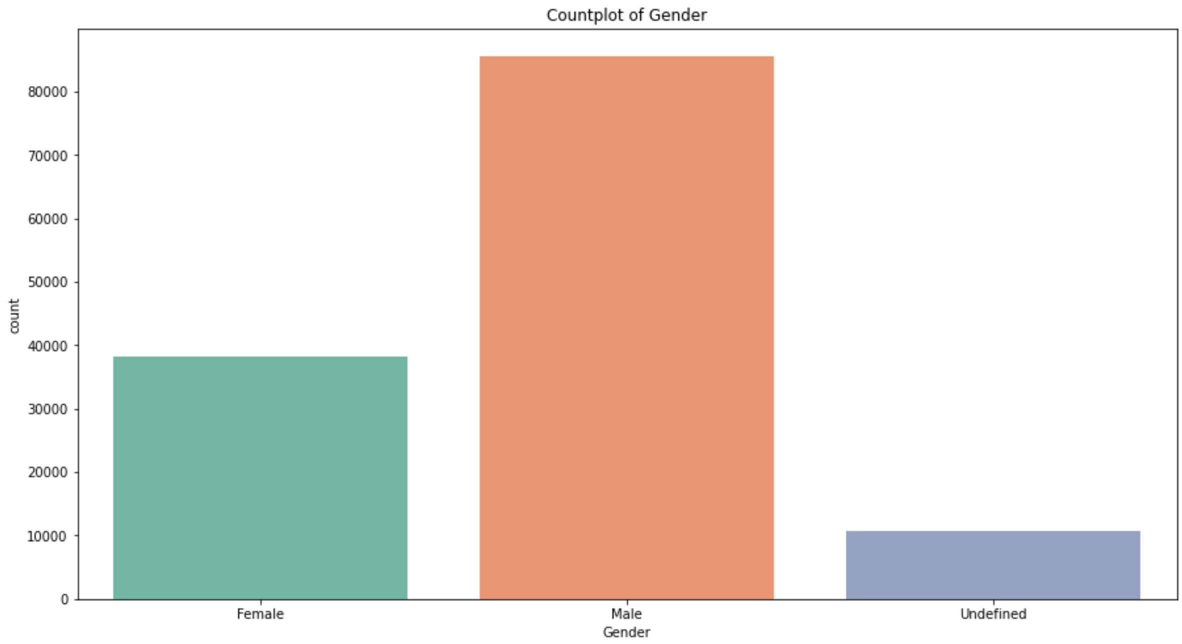
In [185]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='LanguageCode',data = cat_cols,palette='hls')
plt.title('Countplot of Languages in this dataset')
plt.show()
```



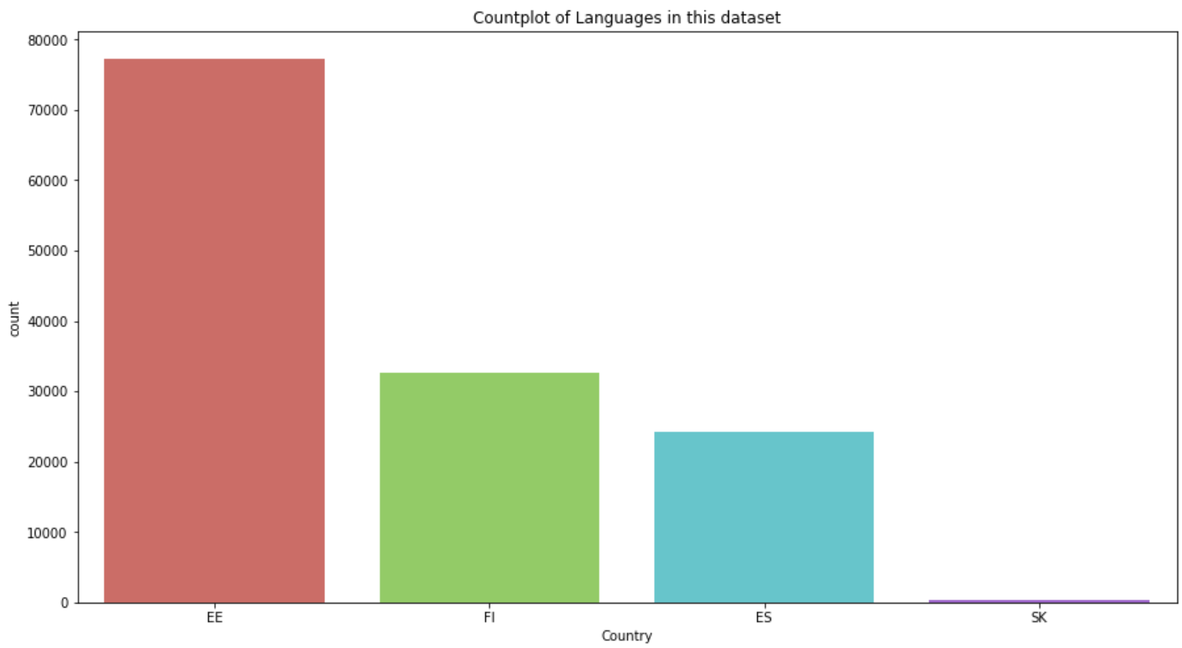
In [187]:

```
plt.figure(figsize=(15,8))
sns.color_palette("hls", 8)
sns.countplot(x='Gender',data = cat_cols,palette='Set2')
plt.title('Countplot of Gender')
plt.show()
```



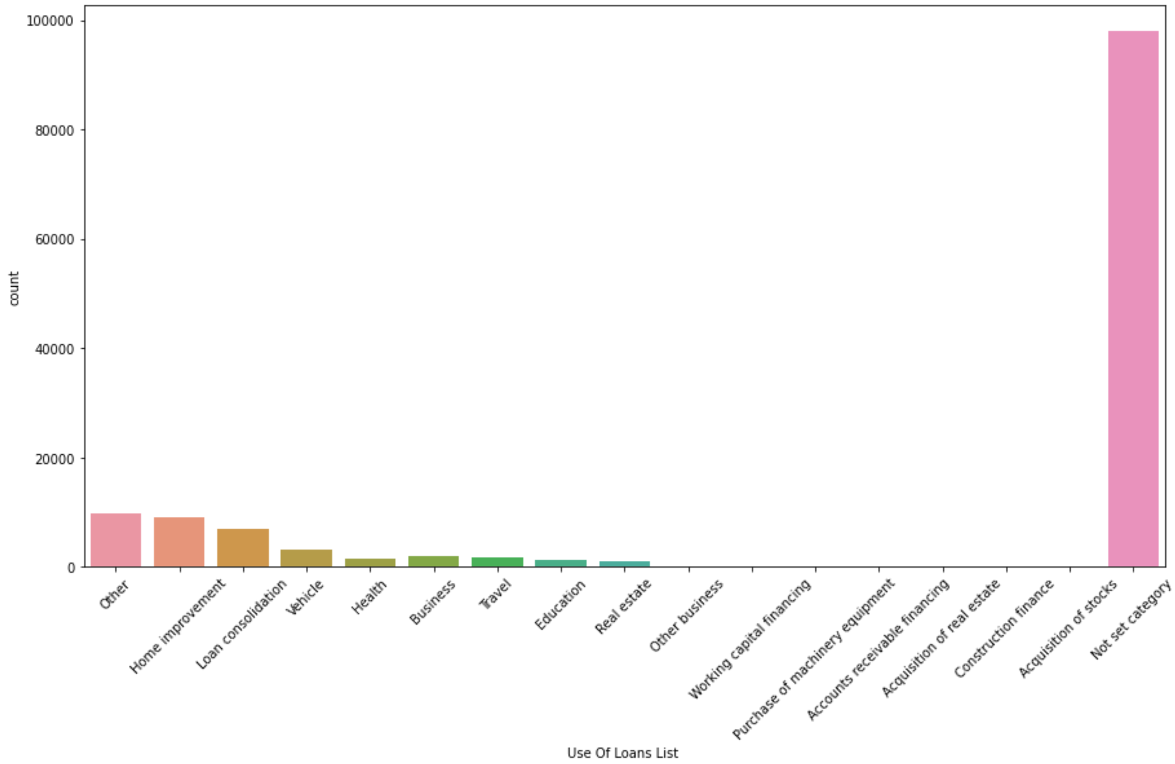
In [184]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='Country',data = cat_cols,palette='hls')
plt.title('Countplot of Languages in this dataset')
plt.show()
```



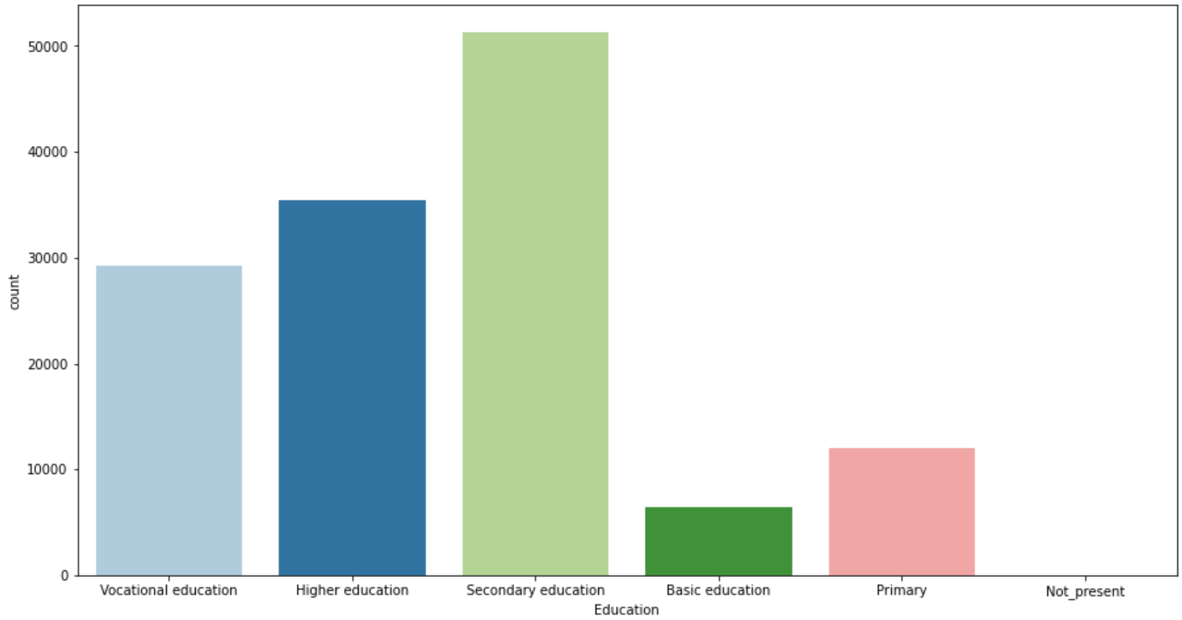
In [169]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='UseOfLoan',data = cat_cols)
plt.xlabel("Use Of Loans List ")
plt.xticks(rotation=45)
plt.show()
```



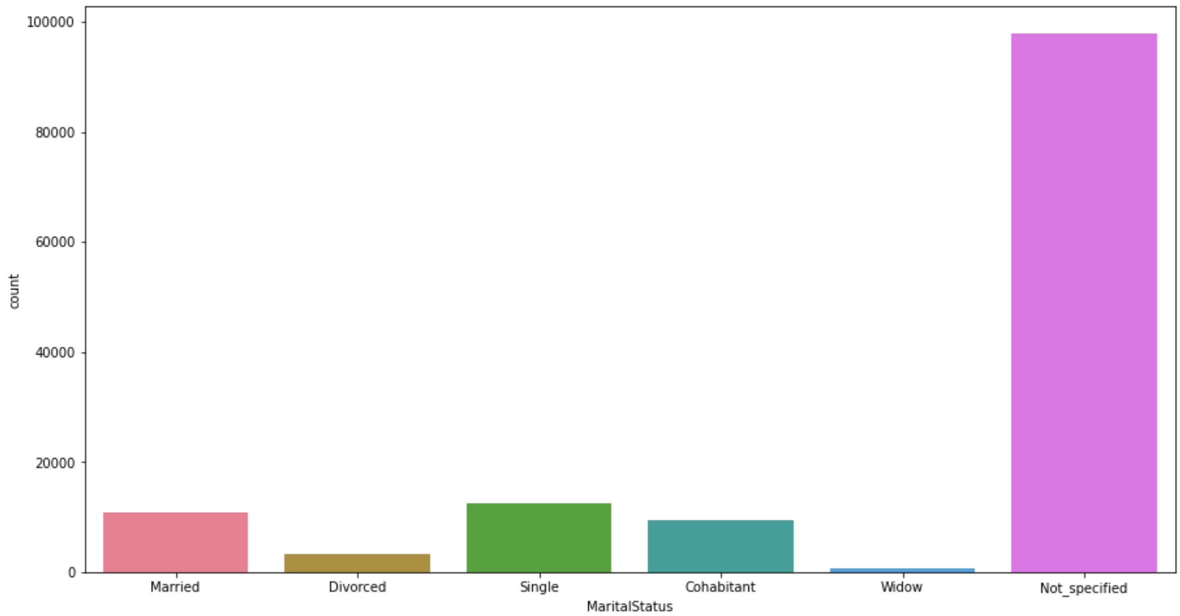
In [178]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='Education',data = cat_cols,palette='Paired')
plt.show()
```



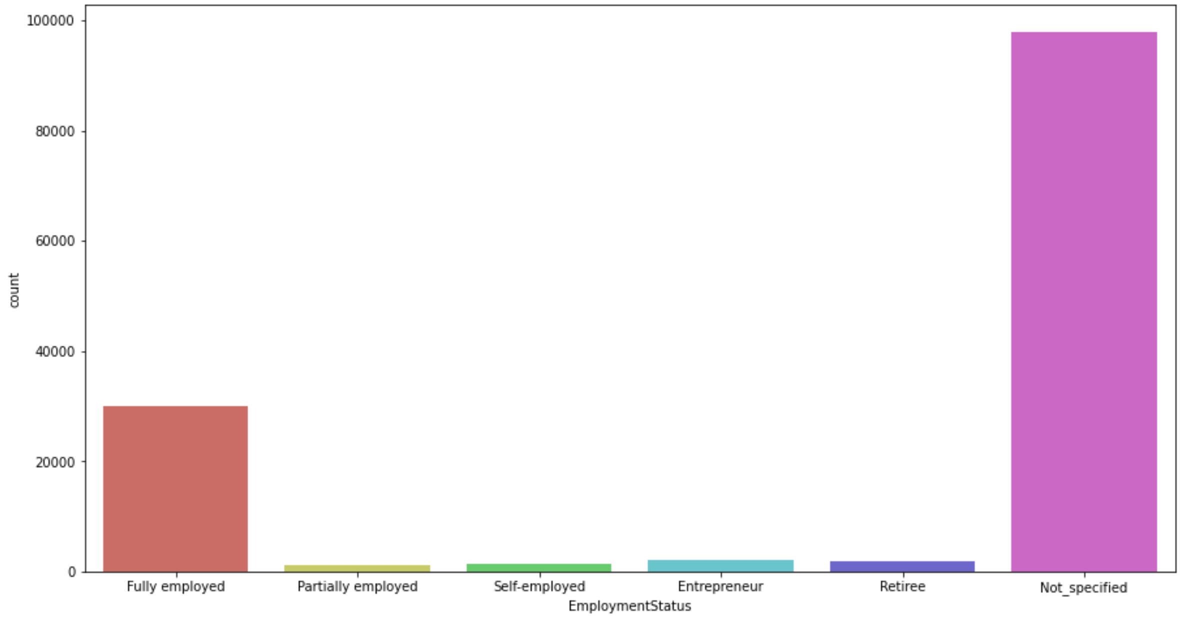
In [188]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='MaritalStatus',data = cat_cols,palette='husl')
plt.show()
```



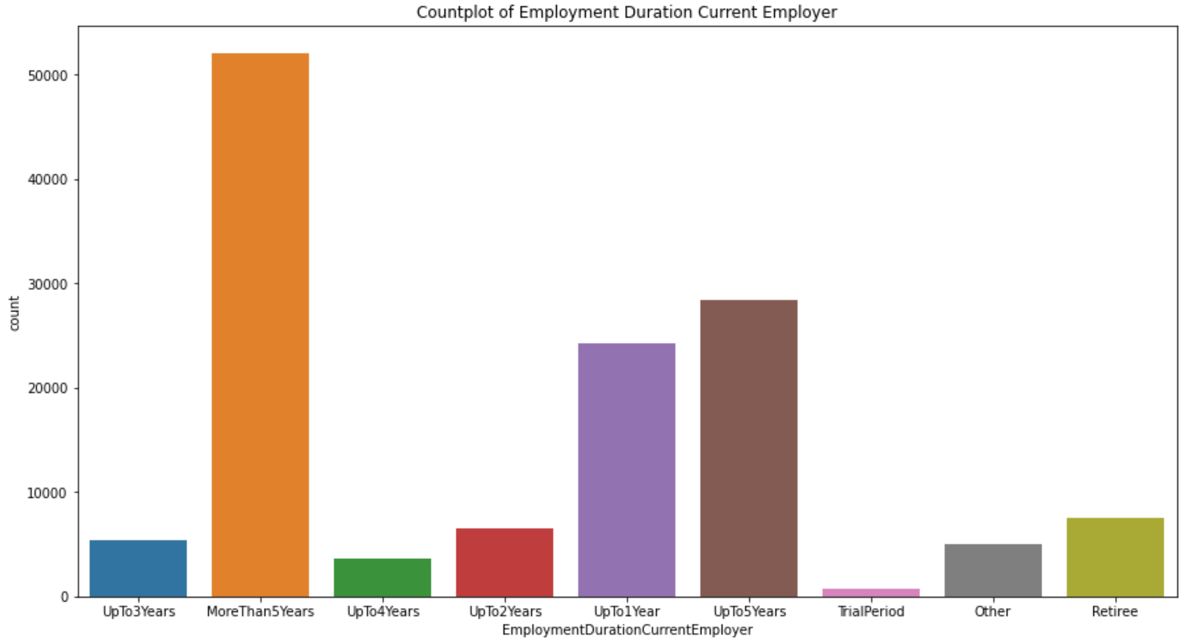
In [189]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='EmploymentStatus',data = cat_cols,palette='hls')
plt.show()
```



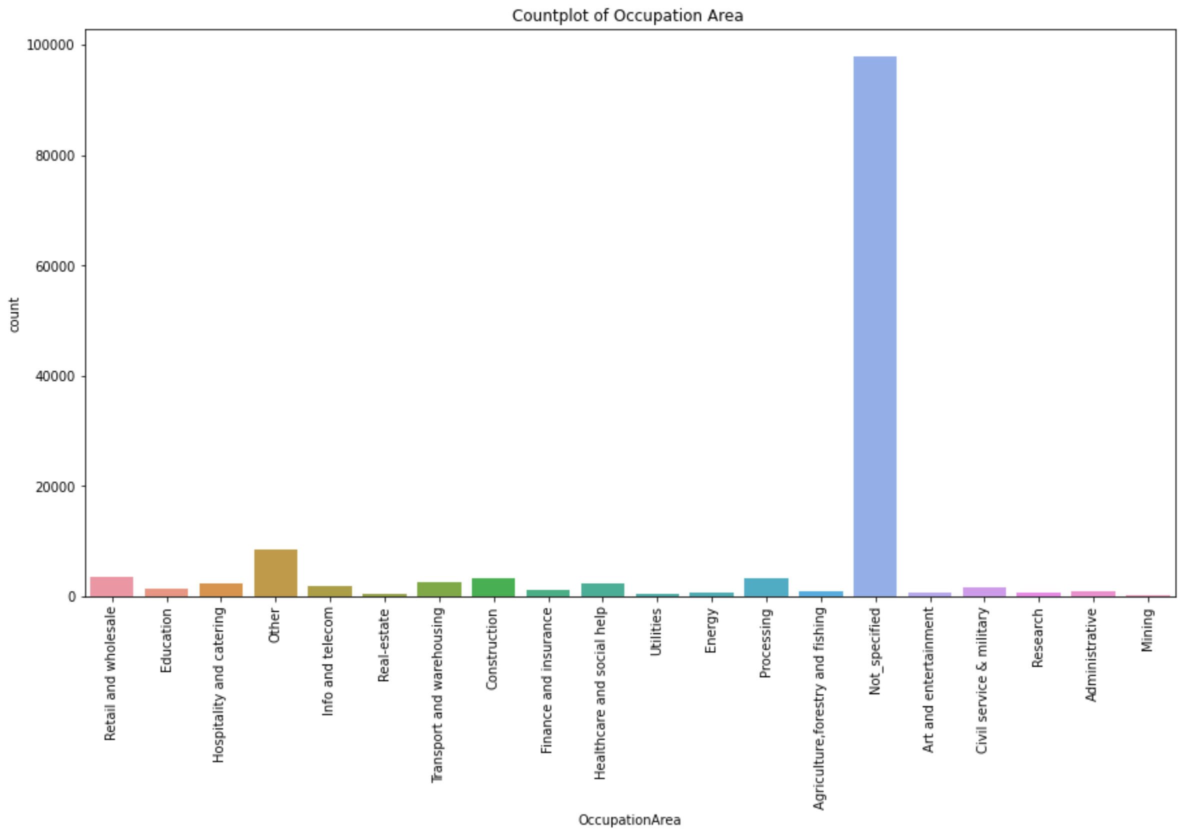
In [173]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='EmploymentDurationCurrentEmployer',data = cat_cols)
plt.title('Countplot of Employment Duration Current Employer')
plt.show()
```



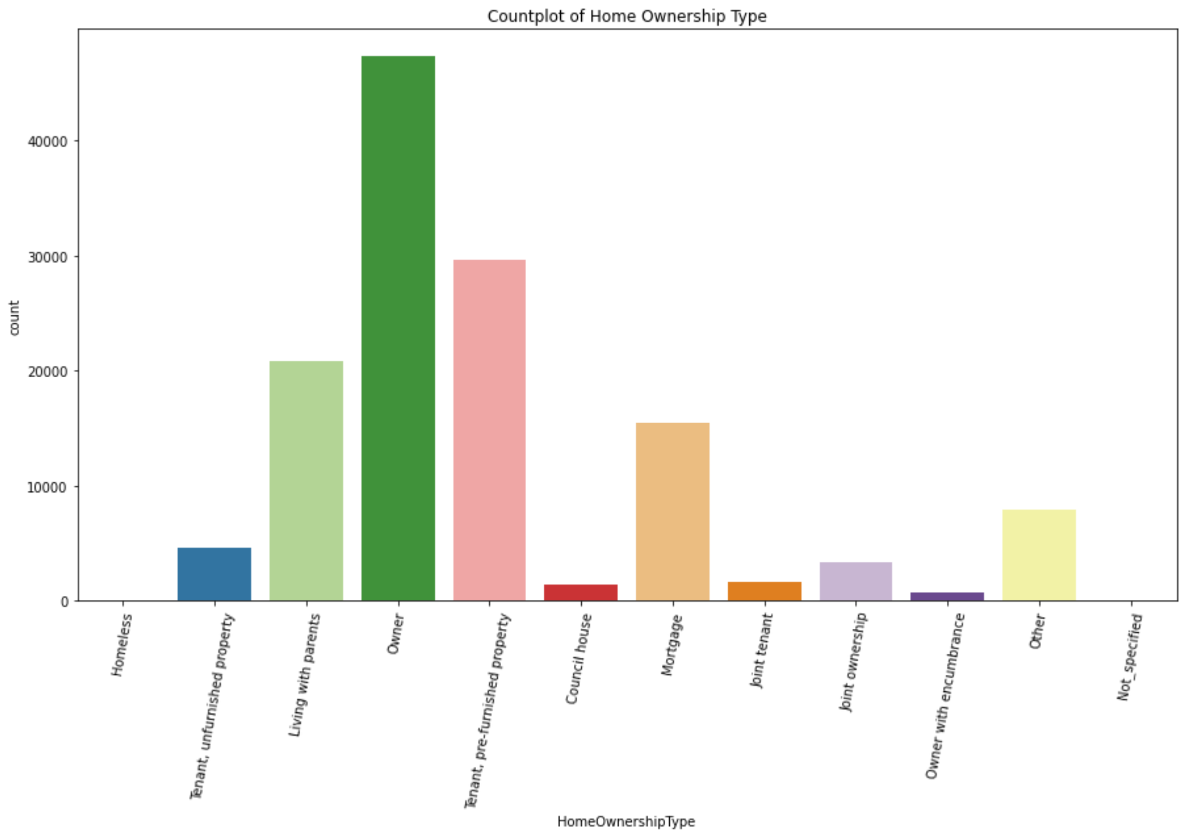
In [174]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='OccupationArea',data = cat_cols)
plt.xticks(rotation=90)
plt.title('Countplot of Occupation Area ')
plt.show()
```



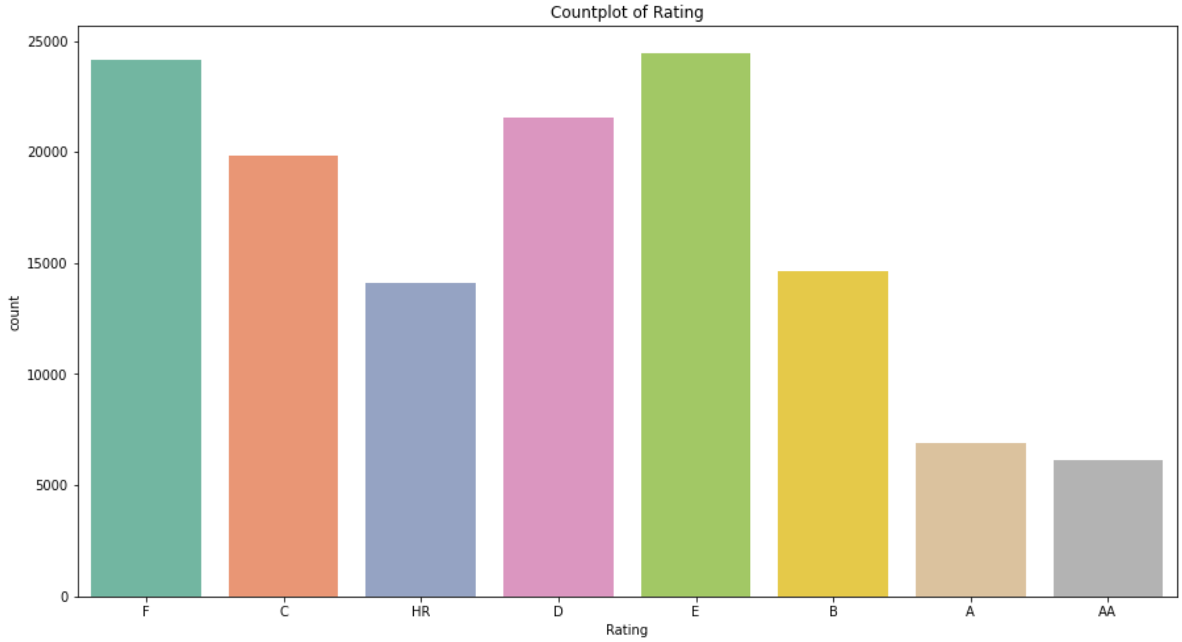
In [175]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='HomeOwnershipType',data = cat_cols,palette='Paired')
plt.xticks(rotation=80)
plt.title('Countplot of Home Ownership Type')
plt.show()
```



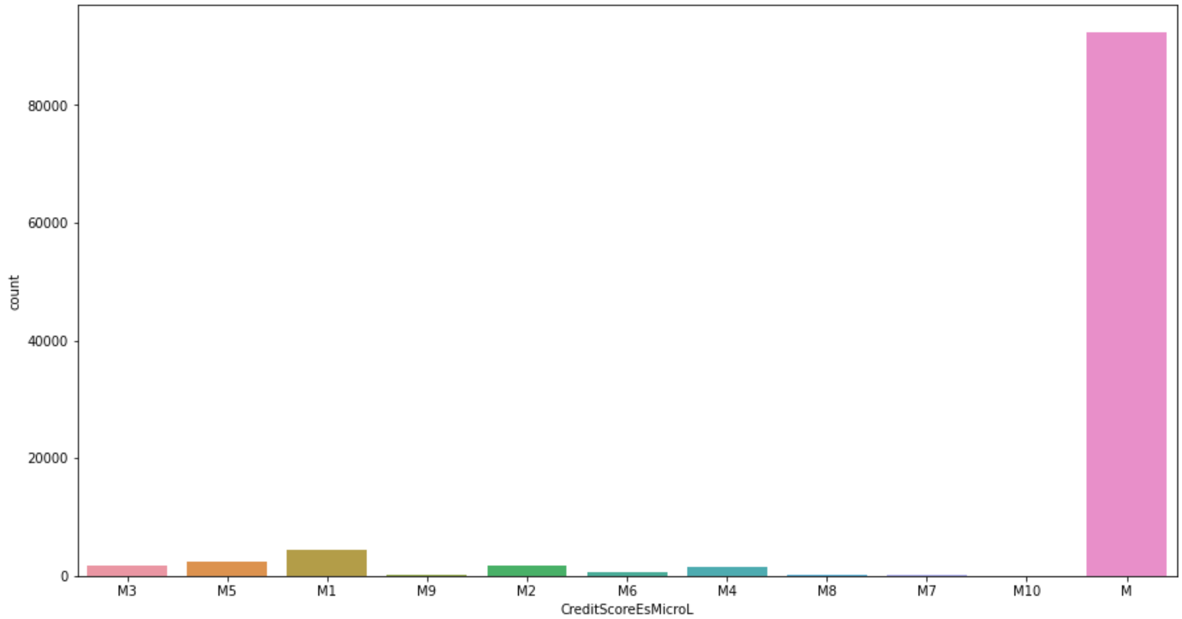
In [190]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='Rating',data = cat_cols,palette='Set2')
plt.title('Countplot of Rating')
plt.show()
```



In [177]:

```
plt.figure(figsize=(15,8))
sns.countplot(x='CreditScoreEsMicroL',data = cat_cols)
plt.show()
```



NOTE :

there are three columns which are ['City' ,'County' ,'LastPaymentOn'] and their data is not that much unique for plotting.

checking distribution of all numeric columns

In [191]:

```
num_cols = loan.select_dtypes(include =np.number)
num_cols.head()
```

Out[191]:

	BidsPortfolioManager	BidsApi	BidsManual	NewCreditCustomer	Age	AppliedAmount	Amou
0	0	0	115.041	0	61	319.558	115.0
1	0	0	140.606	1	48	191.735	140.6
2	0	0	319.558	0	58	319.558	319.5
3	0	0	57.520	0	23	127.823	57.5
4	0	0	319.558	0	25	319.558	319.5

In [196]:

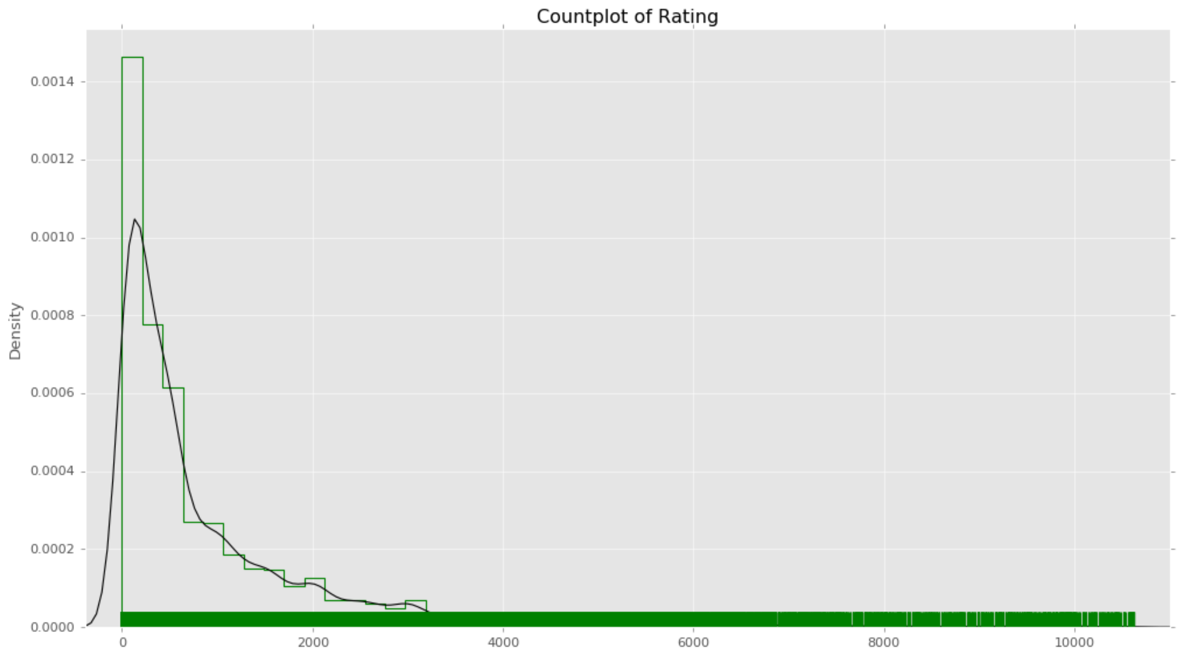
```
num_cols.columns.tolist()
```

Out[196]:

```
['BidsPortfolioManager',
 'BidsApi',
 'BidsManual',
 'NewCreditCustomer',
 'Age',
 'AppliedAmount',
 'Amount',
 'Interest',
 'LoanDuration',
 'MonthlyPayment',
 'IncomeTotal',
 'ExistingLiabilities',
 'LiabilitiesTotal',
 'RefinanceLiabilities',
 'DebtToIncome',
 'FreeCash',
 'MonthlyPaymentDay',
 'Restructured',
 'PrincipalPaymentsMade',
 'InterestAndPenaltyPaymentsMade',
 'PrincipalBalance',
 'InterestAndPenaltyBalance',
 'NoOfPreviousLoansBeforeLoan',
 'AmountOfPreviousLoansBeforeLoan',
 'PreviousRepaymentsBeforeLoan',
 'PreviousEarlyRepaymentsCountBeforeLoan']
```

In [249]:

```
plt.style.use("ggplot")
plt.figure(figsize=(15,8))
sns.distplot(x=num_cols.BidsPortfolioManager,rug=True, rug_kws={"color": "g"},kde_kws={"col
             hist_kws={"histtype": "step", "linewidth":1,"alpha":1,"color": "g"})
plt.title('Distribution Plot of Bids Portfolio Manager ')
plt.show()
```

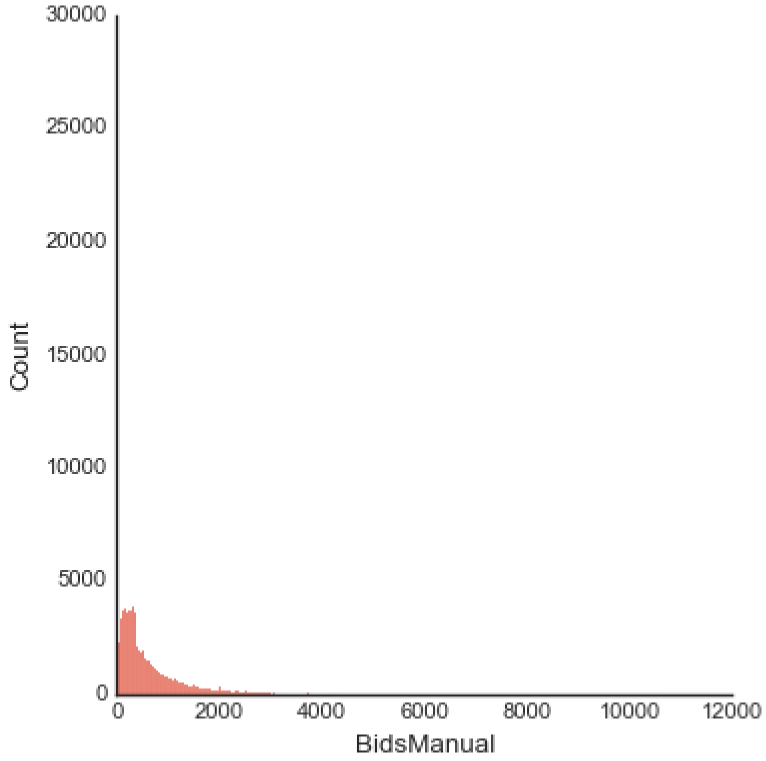


In [272]:

```
plt.style.use("seaborn-white")
sns.displot(x='BidsManual',data=num_cols)
```

Out[272]:

```
<seaborn.axisgrid.FacetGrid at 0x20f1c644a00>
```

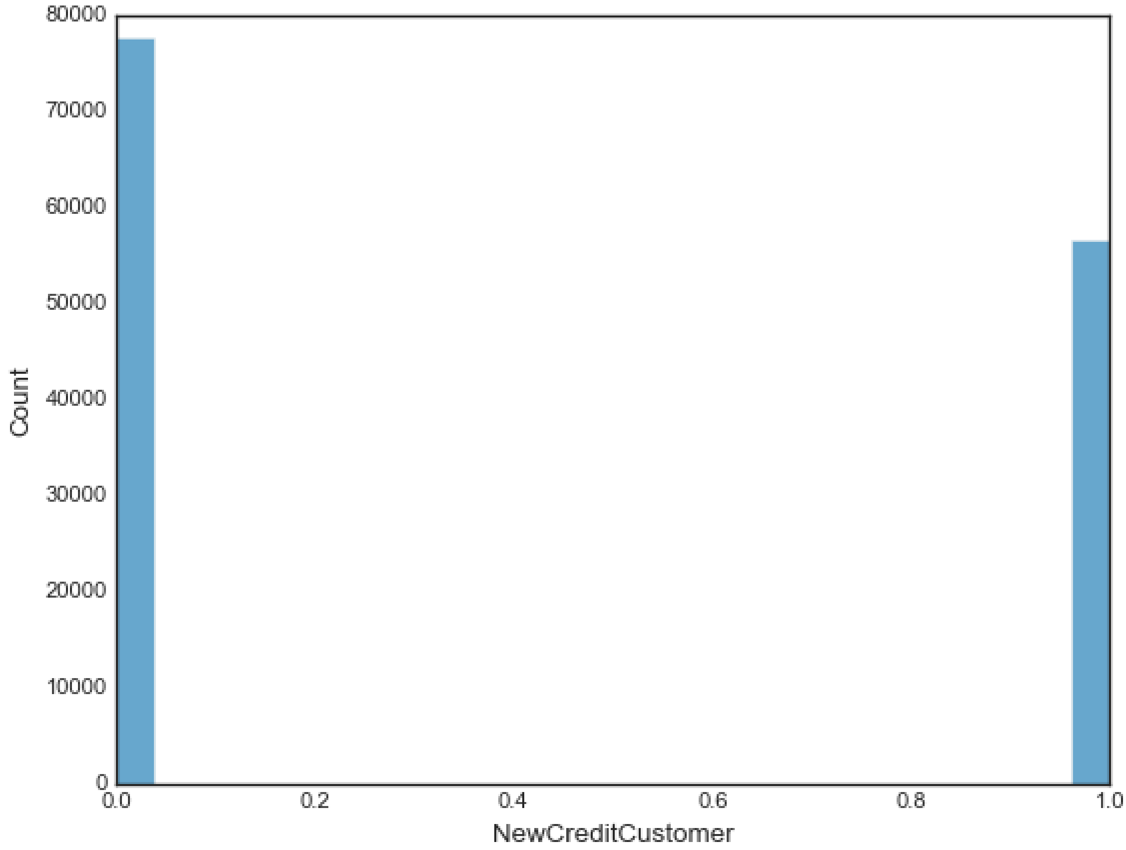


In [280]:

```
plt.style.use("seaborn-white")
sns.histplot(x='NewCreditCustomer',data=num_cols,color= 'purple')
```

Out[280]:

<AxesSubplot:xlabel='NewCreditCustomer', ylabel='Count'>

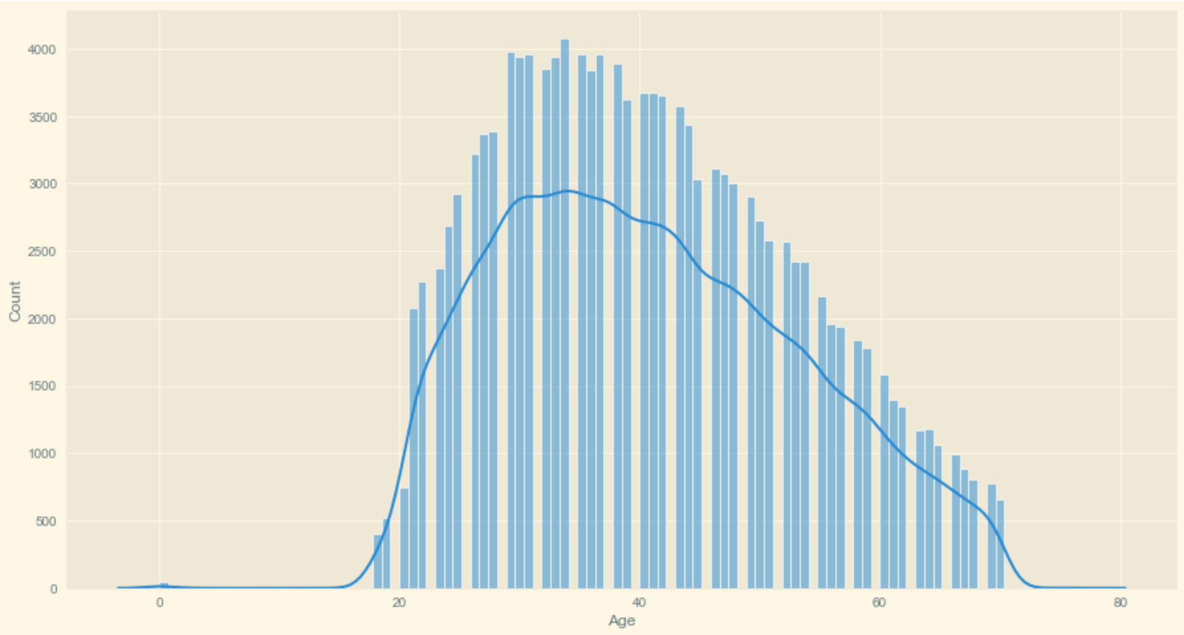


In [240]:

```
plt.figure(figsize=(15,8))
plt.style.use("Solarize_Light2")
sns.histplot(num_cols["Age"],palette='hls',kde=True,kde_kws=dict(cut=3),color= 'darkorange'
```

Out[240]:

```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```

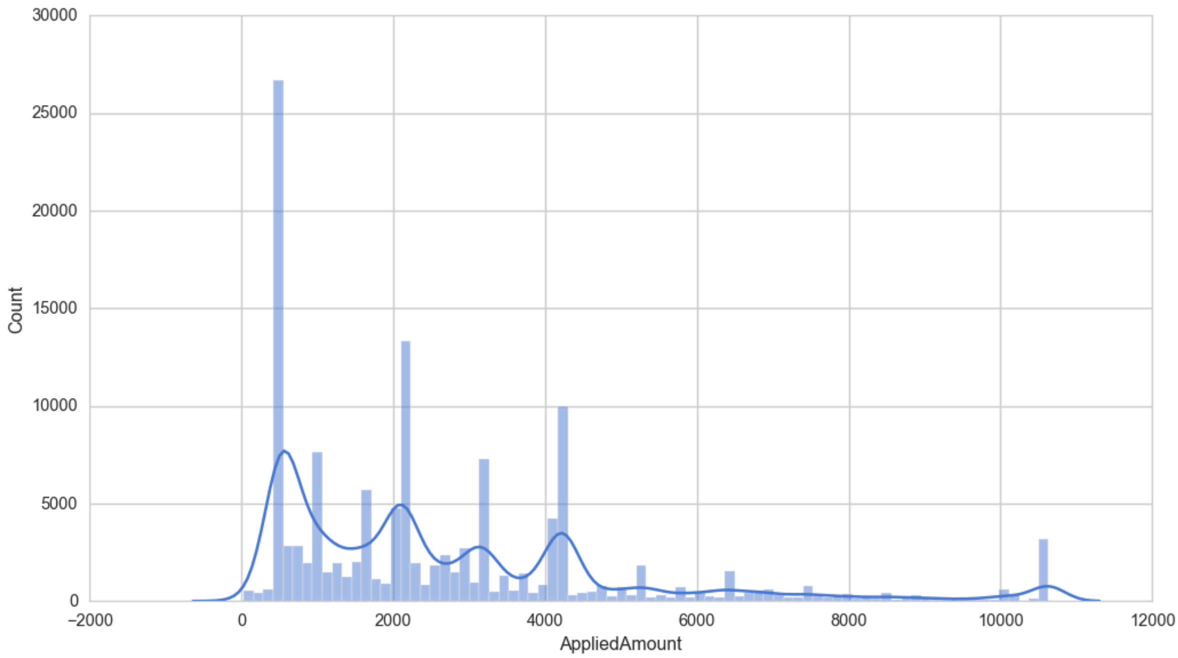


In [307]:

```
plt.figure(figsize=(15,8))
plt.style.use("seaborn-whitegrid")
sns.histplot(num_cols["AppliedAmount"],palette='husl',kde=True,kde_kws=dict(cut=3),color= '
```

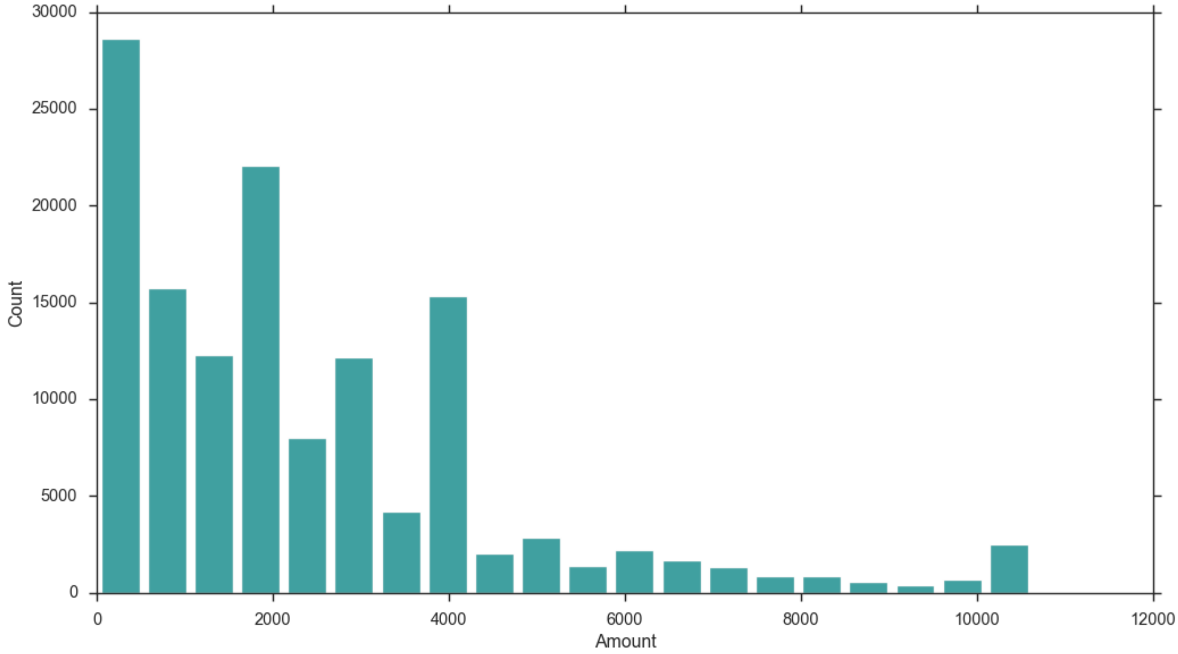
Out[307]:

```
<AxesSubplot:xlabel='AppliedAmount', ylabel='Count'>
```



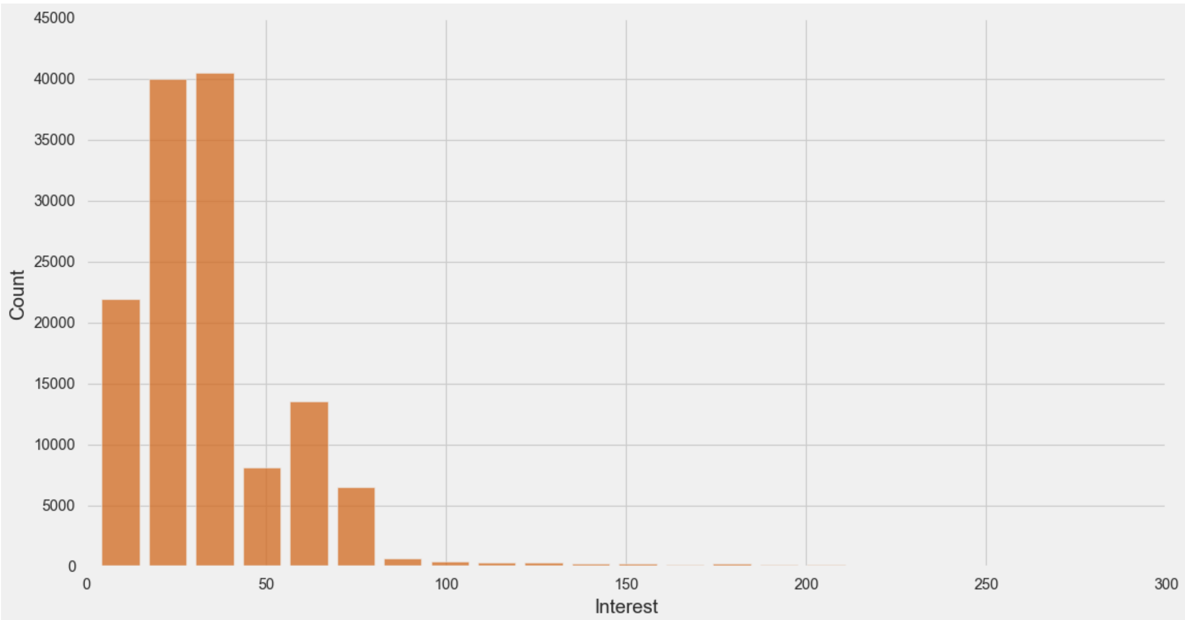
In [308]:

```
plt.figure(figsize=(15,8))
plt.style.use("seaborn-ticks")
sns.histplot(num_cols["Amount"],bins= 20,shrink=.8,color = 'teal')
plt.show()
```



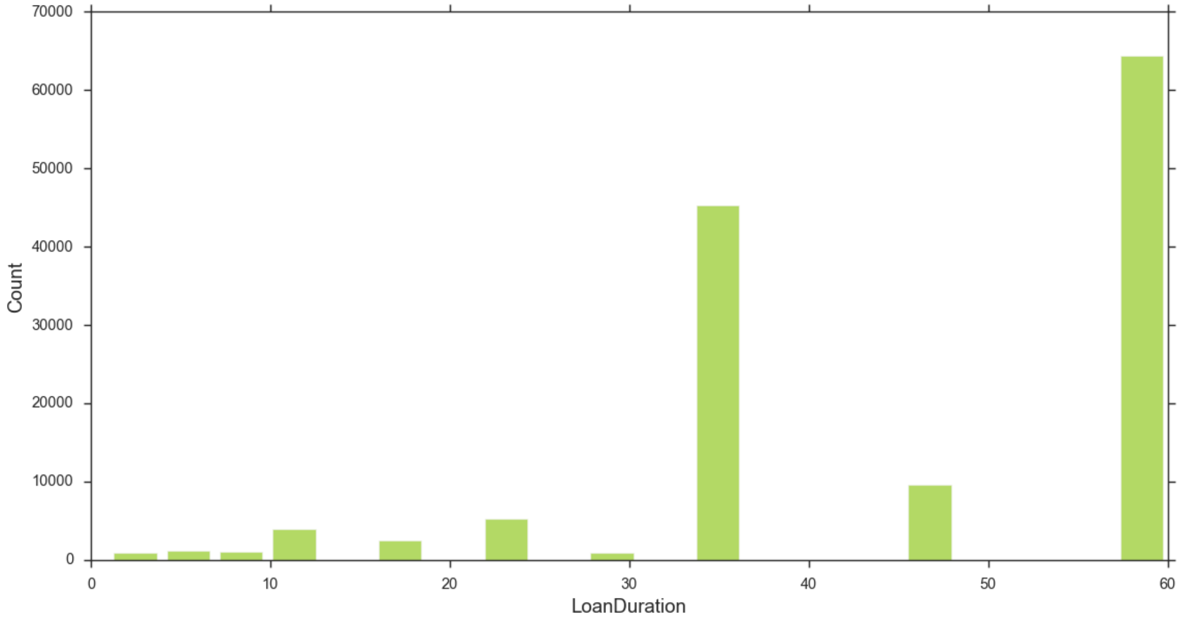
In [323]:

```
plt.style.use("fivethirtyeight")
plt.figure(figsize=(15,8))
sns.histplot(num_cols["Interest"],bins= 20,shrink=.8,color = 'chocolate')
plt.show()
```



In [322]:

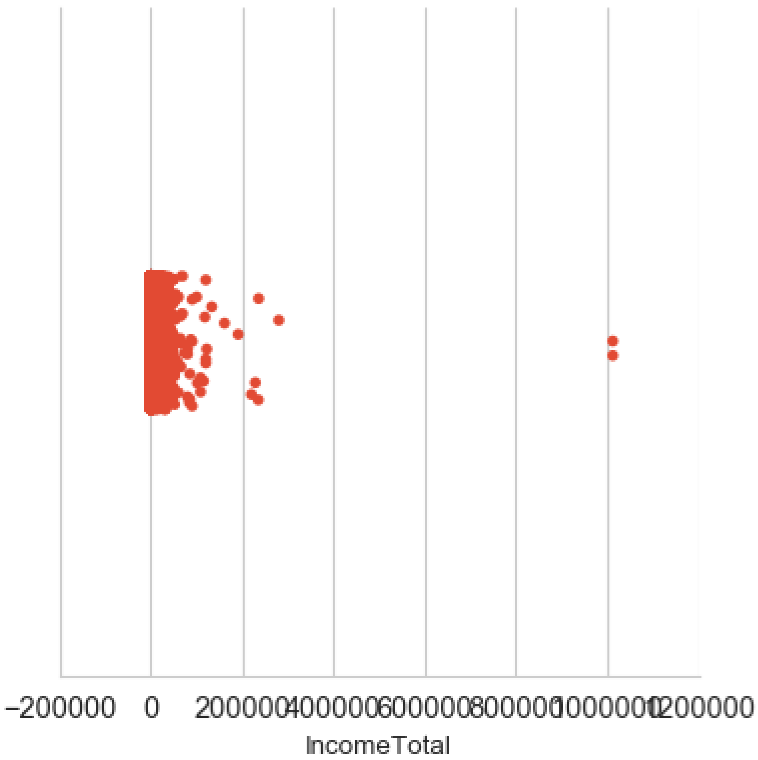
```
plt.figure(figsize=(15,8))
plt.style.use("seaborn-ticks")
sns.histplot(num_cols["LoanDuration"],bins= 20,shrink=.8,color = 'yellowgreen')
plt.show()
```



In [352]:

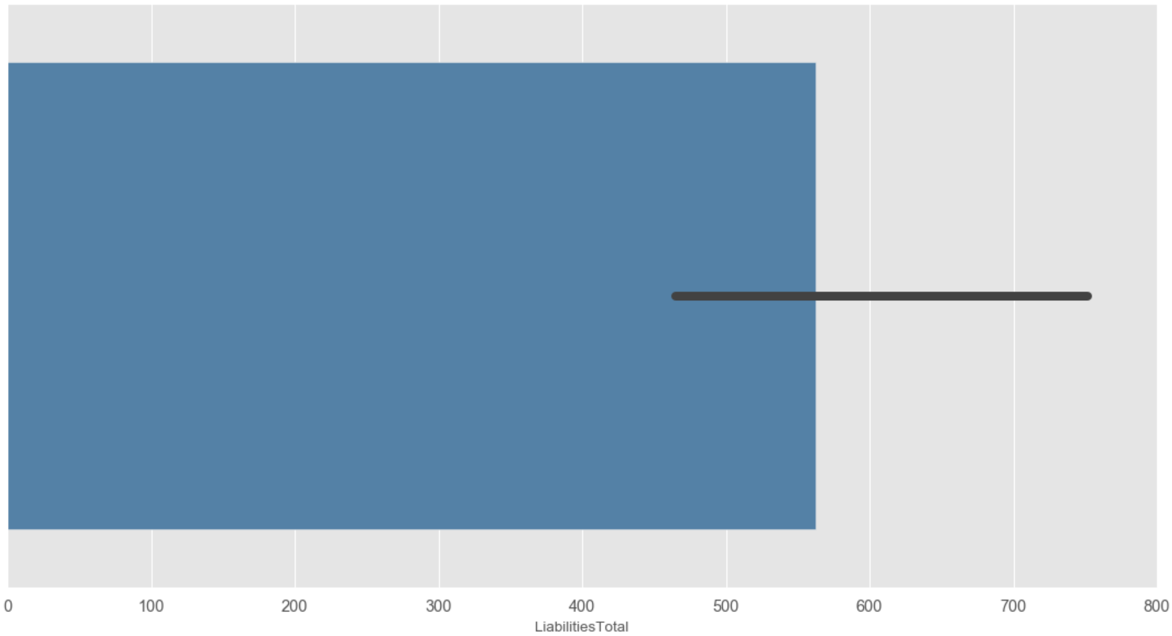
```
plt.style.use("seaborn-whitegrid")
plt.figure(figsize=(15,8))
sns.catplot(x='IncomeTotal',data= num_cols)
plt.show()
```

<Figure size 1200x640 with 0 Axes>



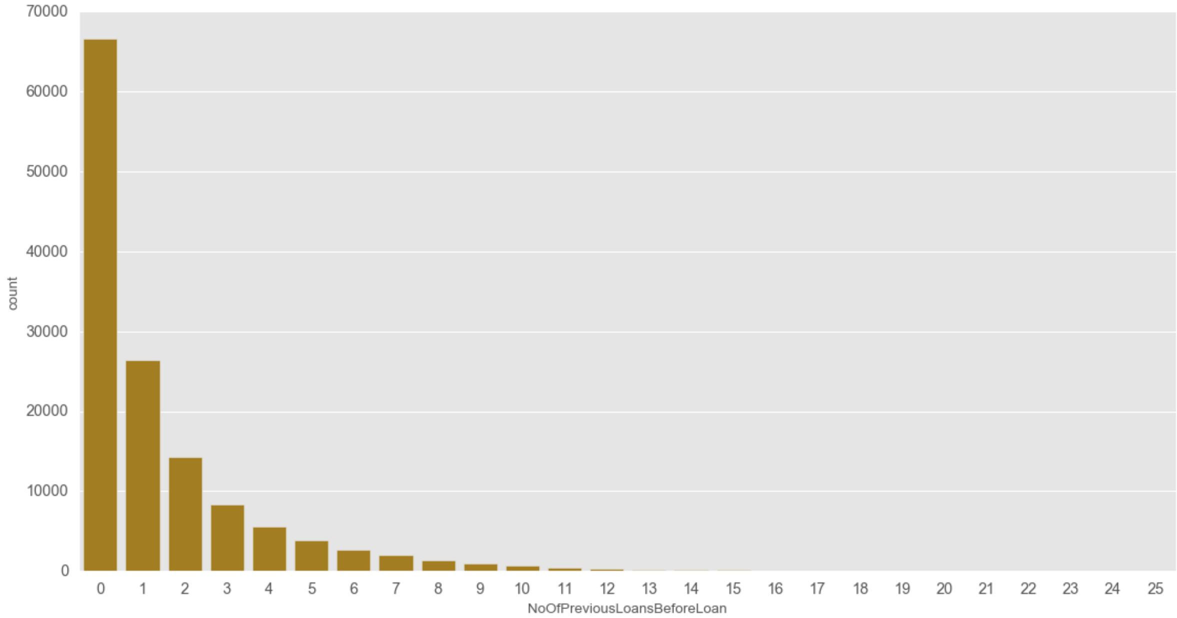
In [347]:

```
plt.style.use("ggplot")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.barplot(x='LiabilitiesTotal',data= num_cols,color='steelblue')
plt.show()
```



In [343]:

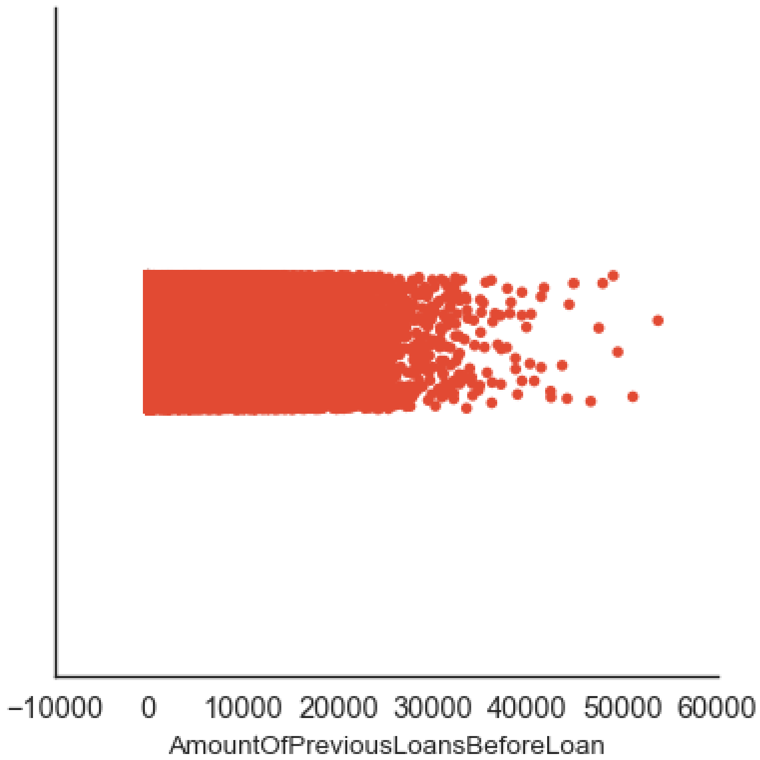
```
plt.style.use("ggplot")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.countplot(x='NoOfPreviousLoansBeforeLoan',data= num_cols,color='darkgoldenrod')
plt.show()
```



In [336]:

```
plt.style.use("seaborn-white")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.catplot(x='AmountOfPreviousLoansBeforeLoan',data= num_cols)
plt.show()
```

```
<Figure size 1200x640 with 0 Axes>
```



NOTE :: there are two columns which have large non unique data ['BidApi' , 'LiabilitiesTotal']

BIVARIATE ANALYSIS

In [361]:

```
print(cat_cols.columns.tolist())

print("\n",num_cols.columns.tolist())
```

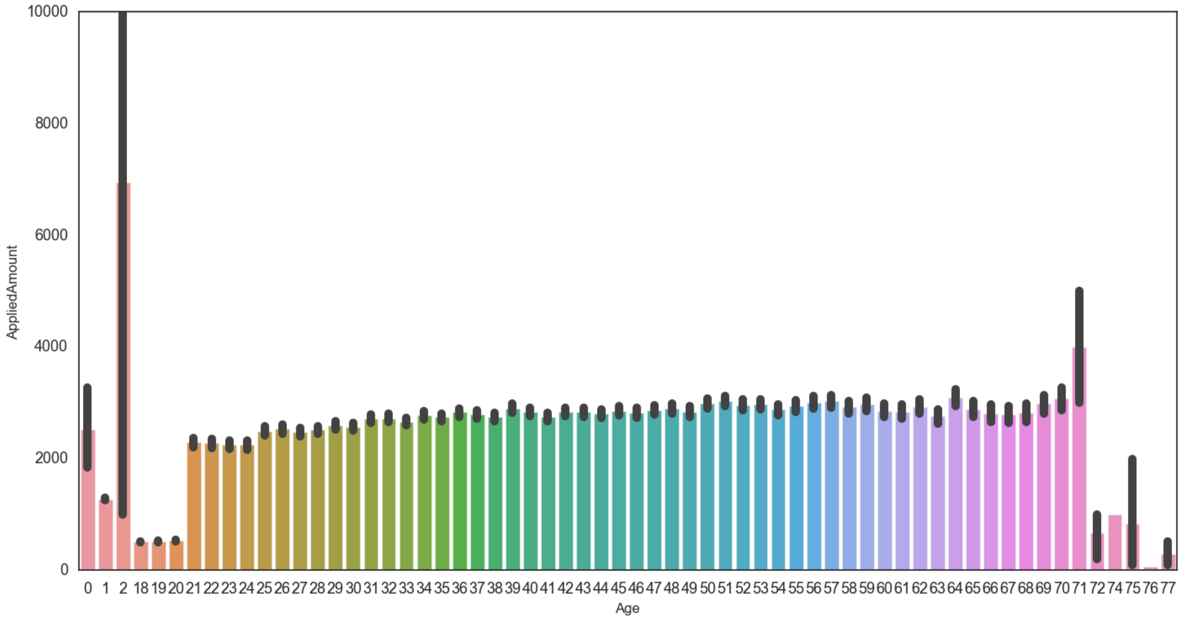
```
['LoanDate', 'FirstPaymentDate', 'MaturityDate_Original', 'MaturityDate_Las
t', 'VerificationType', 'LanguageCode', 'Gender', 'Country', 'County', 'Cit
y', 'UseOfLoan', 'Education', 'MaritalStatus', 'EmploymentStatus', 'Employme
ntDurationCurrentEmployer', 'OccupationArea', 'HomeOwnershipType', 'LastPaym
entOn', 'Rating', 'CreditScoreEsMicroL']

 ['BidsPortfolioManager', 'BidsApi', 'BidsManual', 'NewCreditCustomer', 'Ag
e', 'AppliedAmount', 'Amount', 'Interest', 'LoanDuration', 'MonthlyPayment',
'IncomeTotal', 'ExistingLiabilities', 'LiabilitiesTotal', 'RefinanceLiabilit
ies', 'DebtToIncome', 'FreeCash', 'MonthlyPaymentDay', 'Restructured', 'Prin
cipalPaymentsMade', 'InterestAndPenaltyPaymentsMade', 'PrincipalBalance', 'I
nterestAndPenaltyBalance', 'NoOfPreviousLoansBeforeLoan', 'AmountOfPreviousL
oansBeforeLoan', 'PreviousRepaymentsBeforeLoan', 'PreviousEarlyRepaymentsCou
ntBeforeLoan']
```

In [377]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x='Age',y='AppliedAmount',data= loan)
```

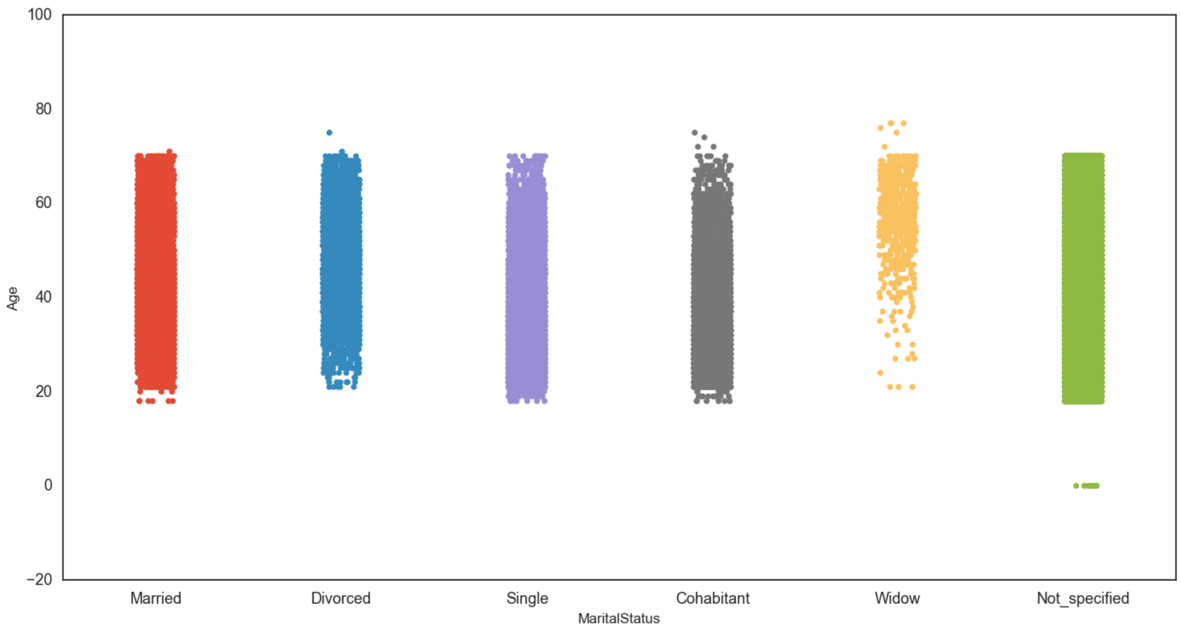
Out[377]:

```
<AxesSubplot:xlabel='Age', ylabel='AppliedAmount'>
```



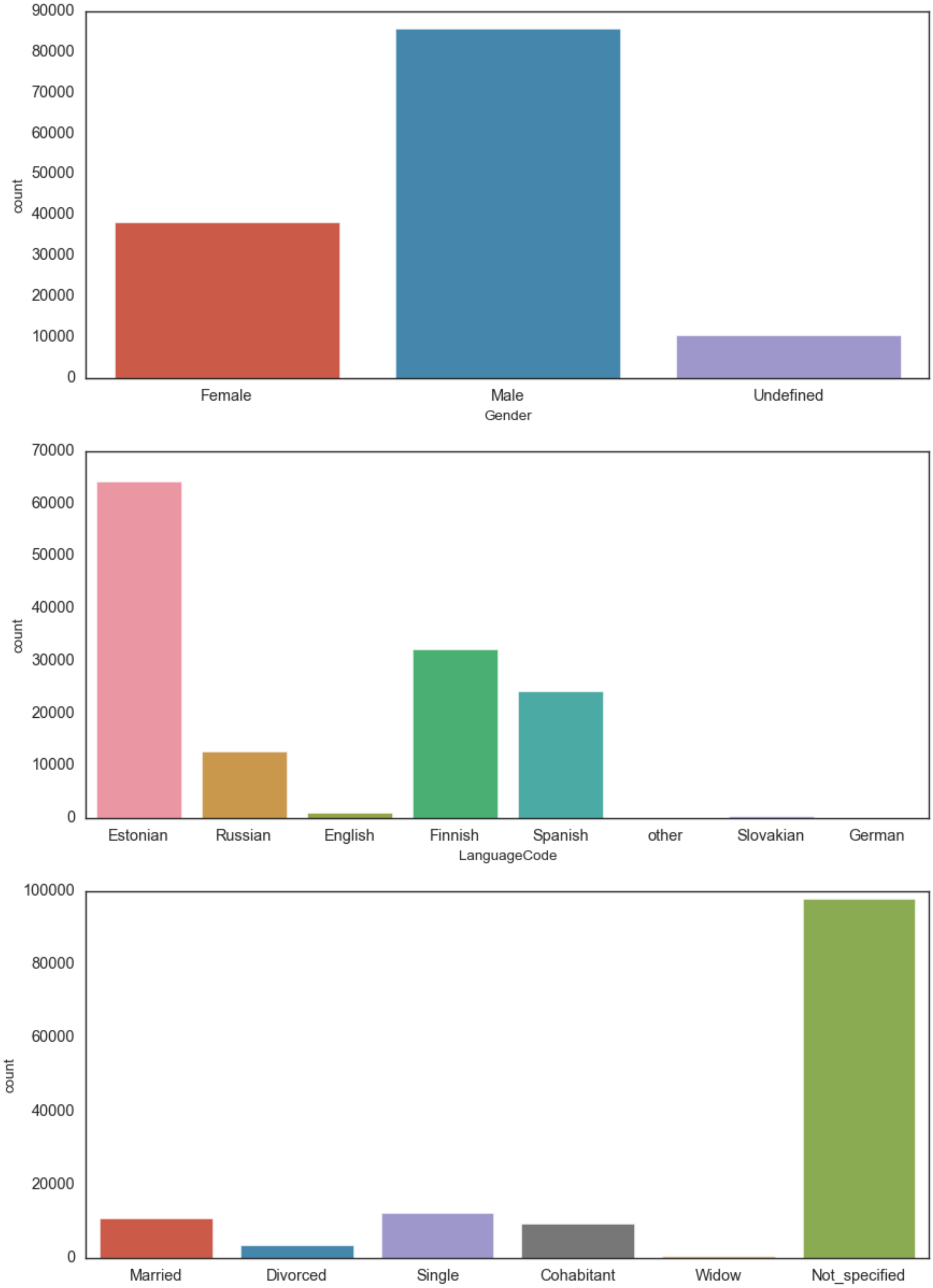
In [492]:

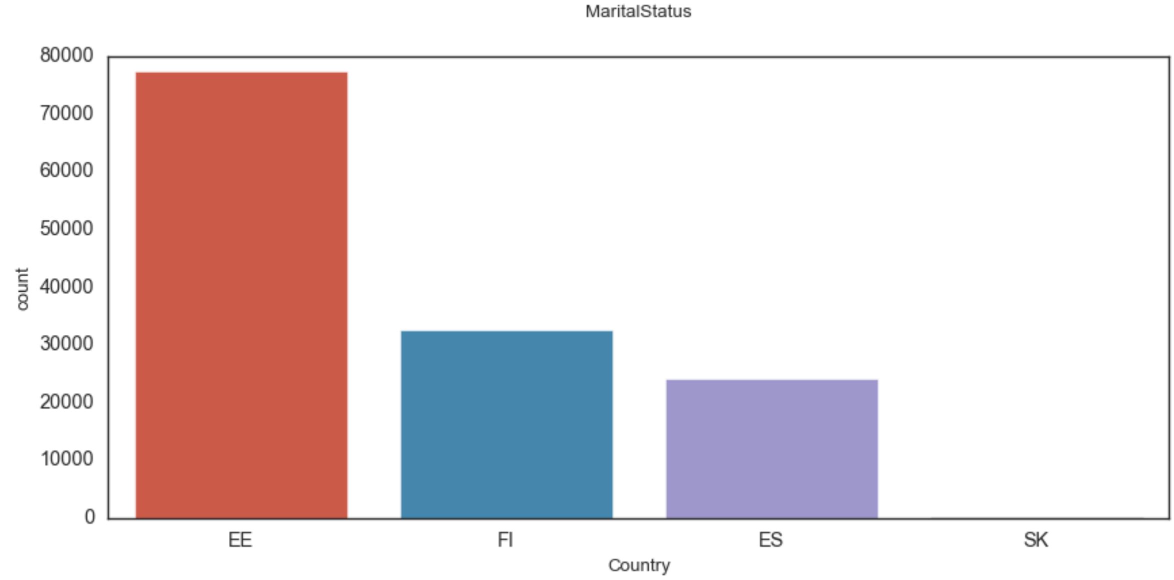
```
plt.figure(figsize=(15,8),dpi=100)
sns.stripplot(x=loan.MaritalStatus,y=loan.Age)
plt.show()
```



In [594]:

```
plt.figure(figsize=(10,20))
plt.subplot(4,1,1)
sns.countplot(loan.Gender)
plt.subplot(4,1,2)
sns.countplot(loan.LanguageCode)
plt.subplot(4,1,3)
sns.countplot(loan.MaritalStatus)
plt.subplot(4,1,4)
sns.countplot(loan.Country)
plt.show()
```



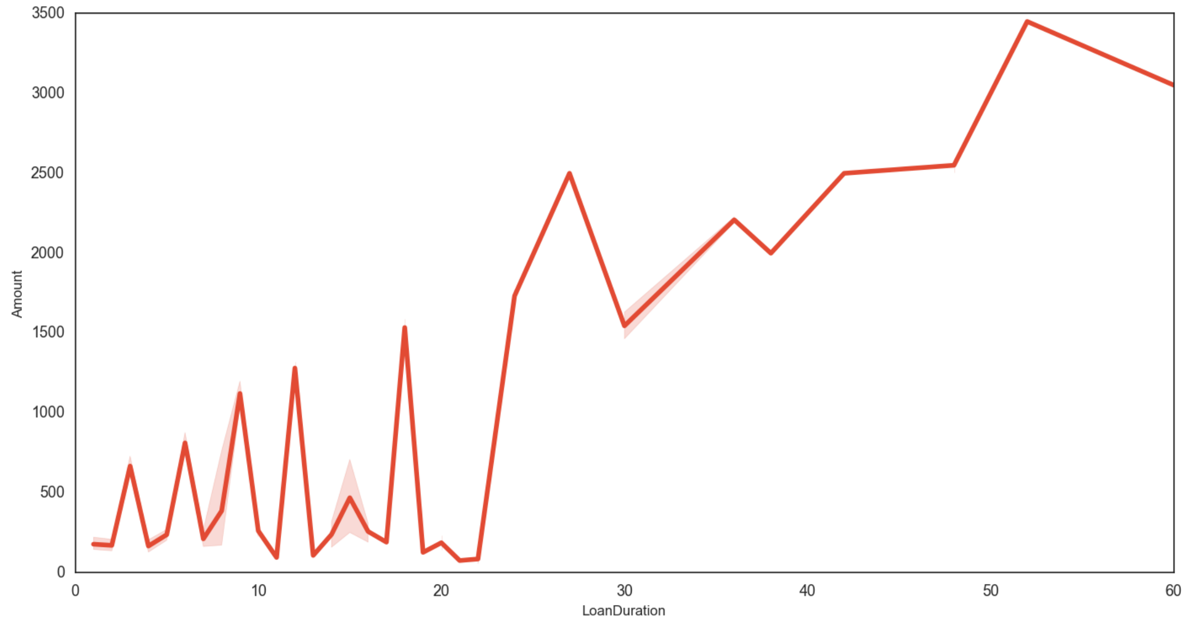


In [387]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.lineplot(x='LoanDuration',y='Amount',data= loan)
```

Out[387]:

```
<AxesSubplot:xlabel='LoanDuration', ylabel='Amount'>
```

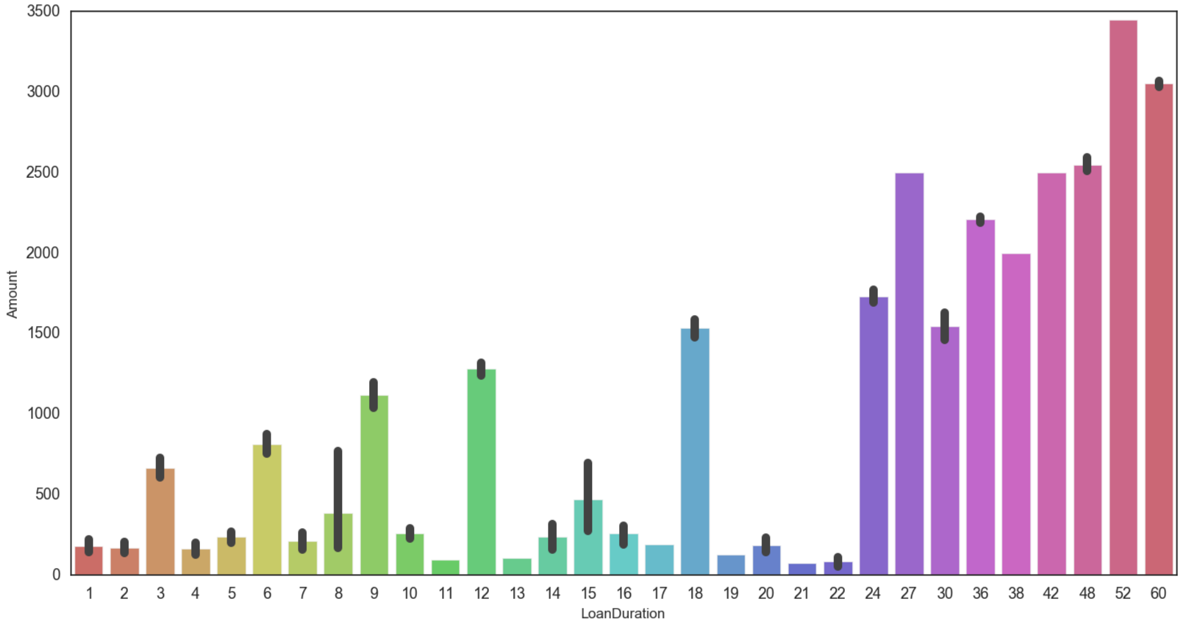


In [417]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x='LoanDuration',y='Amount',data= loan,palette='hls')
```

Out[417]:

```
<AxesSubplot:xlabel='LoanDuration', ylabel='Amount'>
```

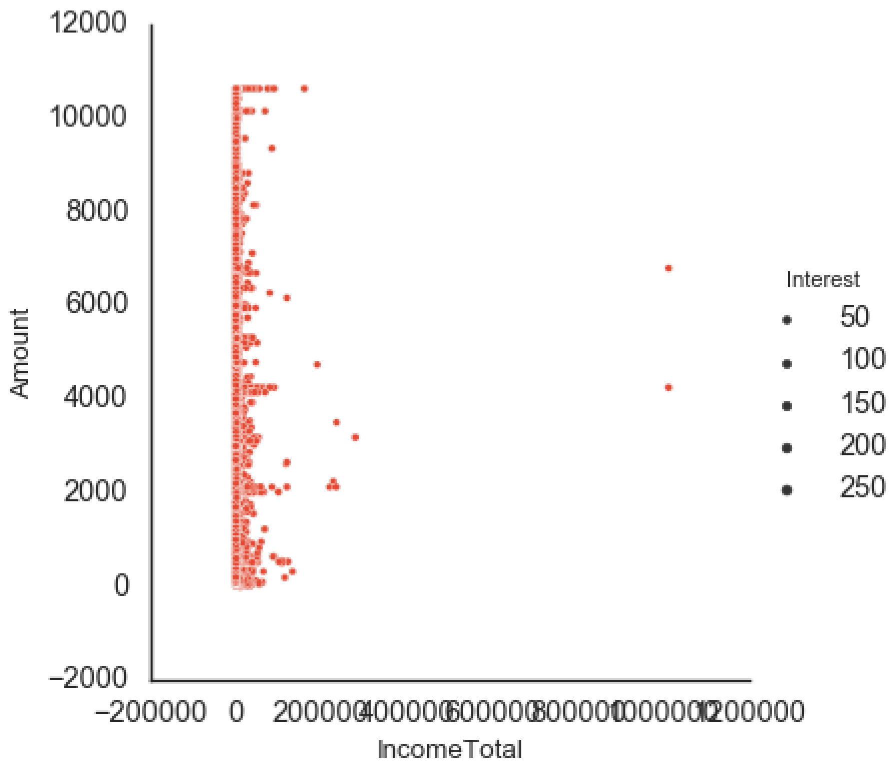


In [480]:

```
sns.relplot(x=loan.IncomeTotal, y=loan.Amount, size=loan.Interest,sizes=(10, 20), data=loan
```

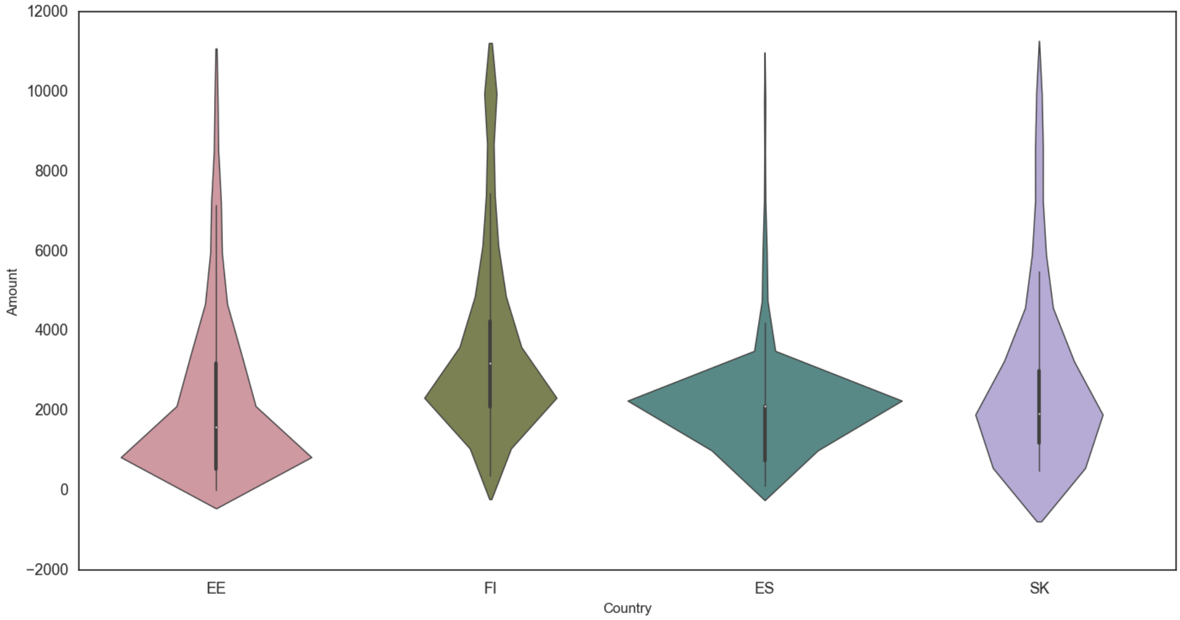
Out[480]:

```
<seaborn.axisgrid.FacetGrid at 0x20f4dac1b80>
```



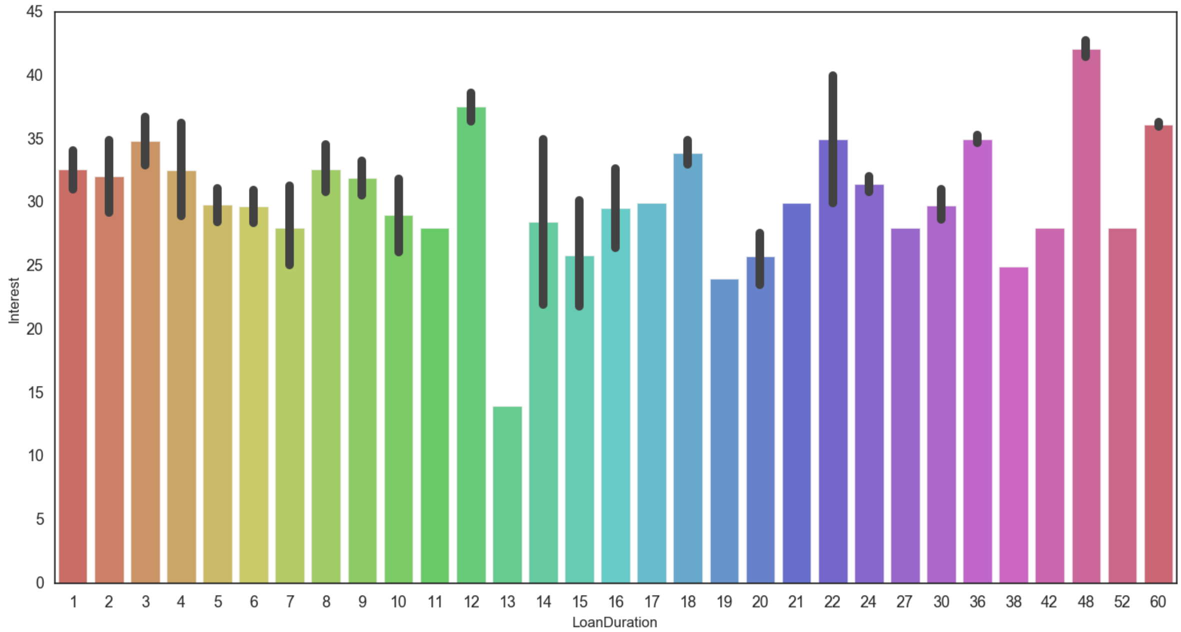
In [443]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.violinplot(x=loan.Country,y=loan.Amount,gridsize=10,width=1,inner='box',split=True,
               dodge=False,linewidth=1,palette='husl',saturation=0.40)
plt.show()
```



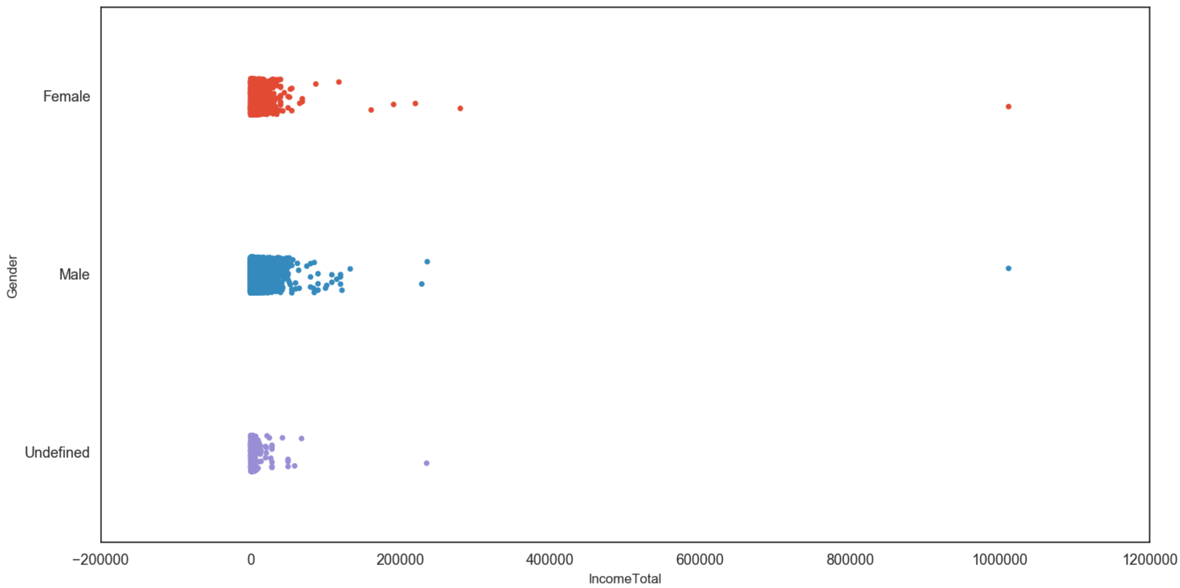
In [462]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x=loan.LoanDuration,y=loan.Interest,palette='hls')
plt.show()
```



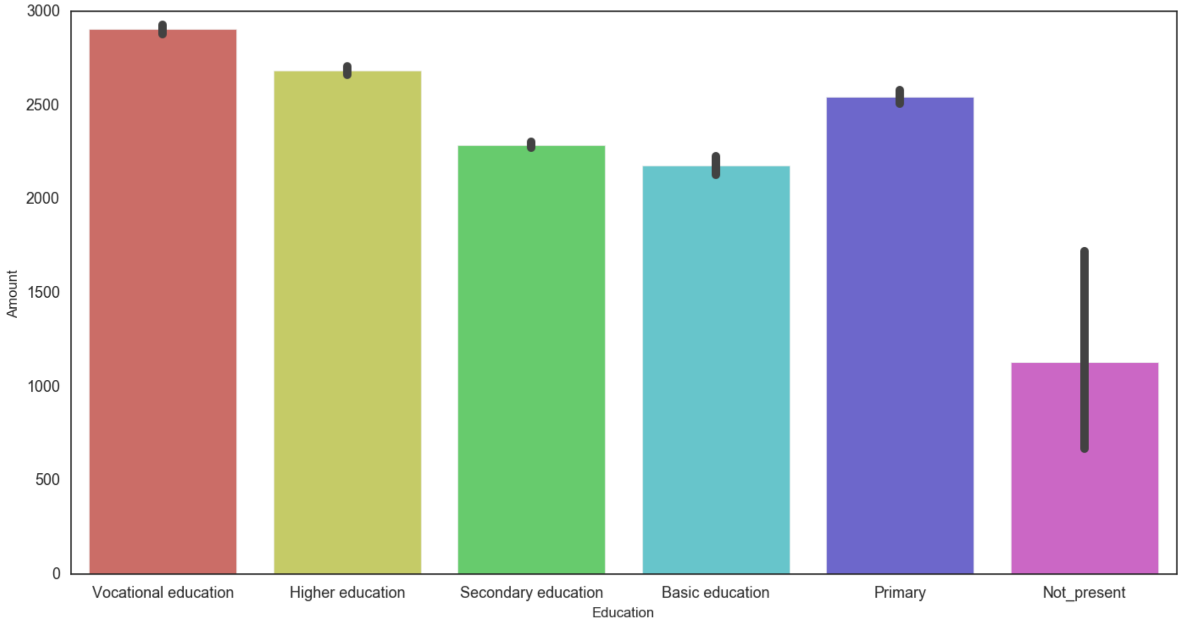
In [490]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.stripplot(x=loan.IncomeTotal,y=loan.Gender)
plt.show()
```



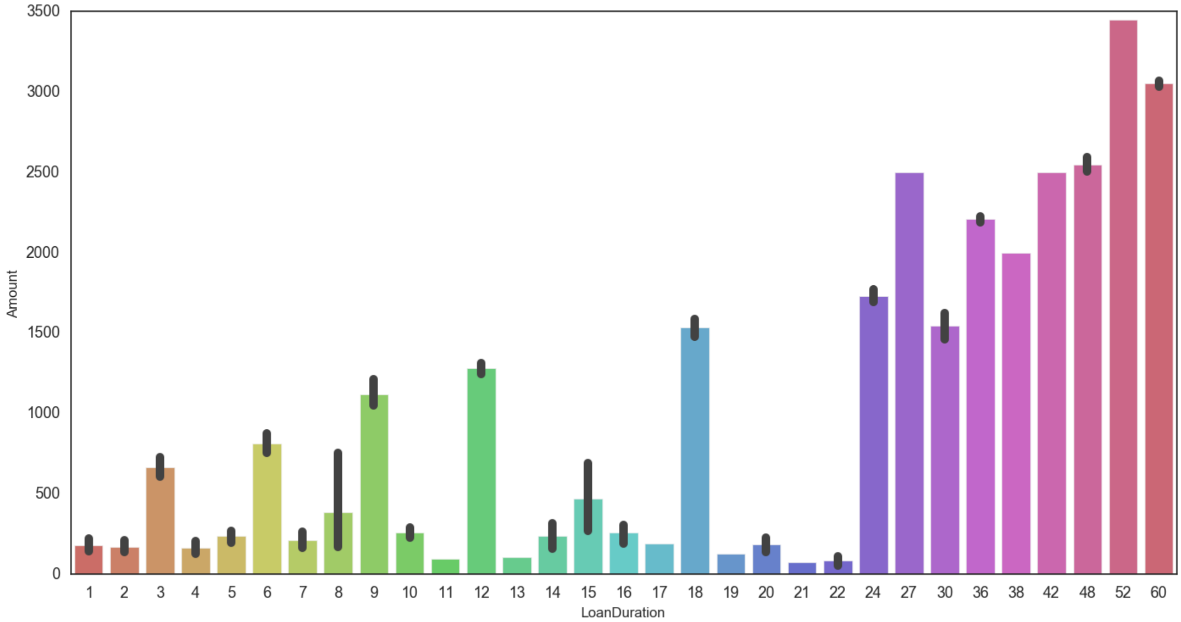
In [496]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x=loan.Education,y=loan.Amount,palette='hls')
plt.show()
```



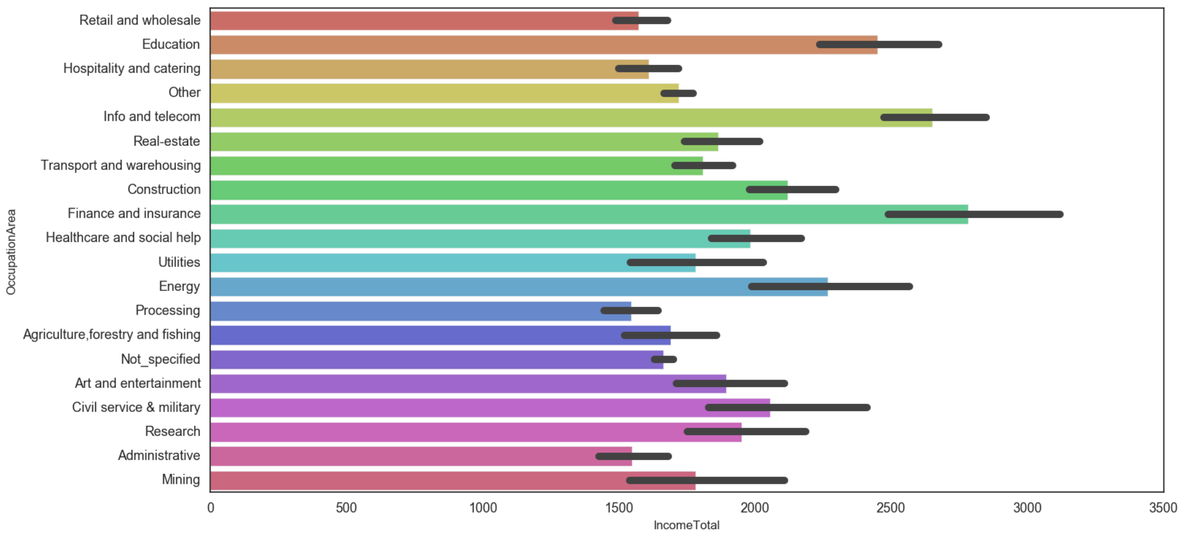
In [498]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x=loan.LoanDuration,y=loan.Amount,palette='hls')
plt.show()
```



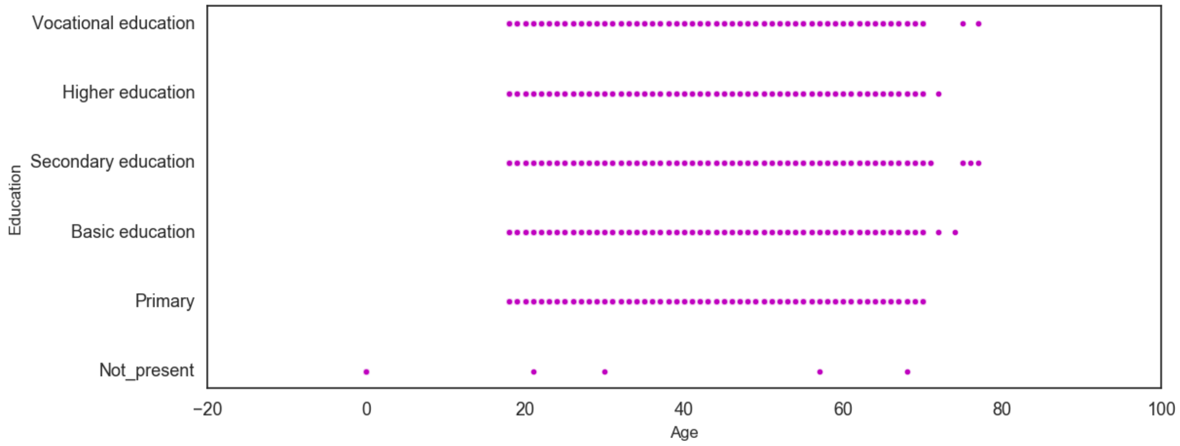
In [501]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x=loan.IncomeTotal,y=loan.OccupationArea,palette='hls')
plt.show()
```



In [530]:

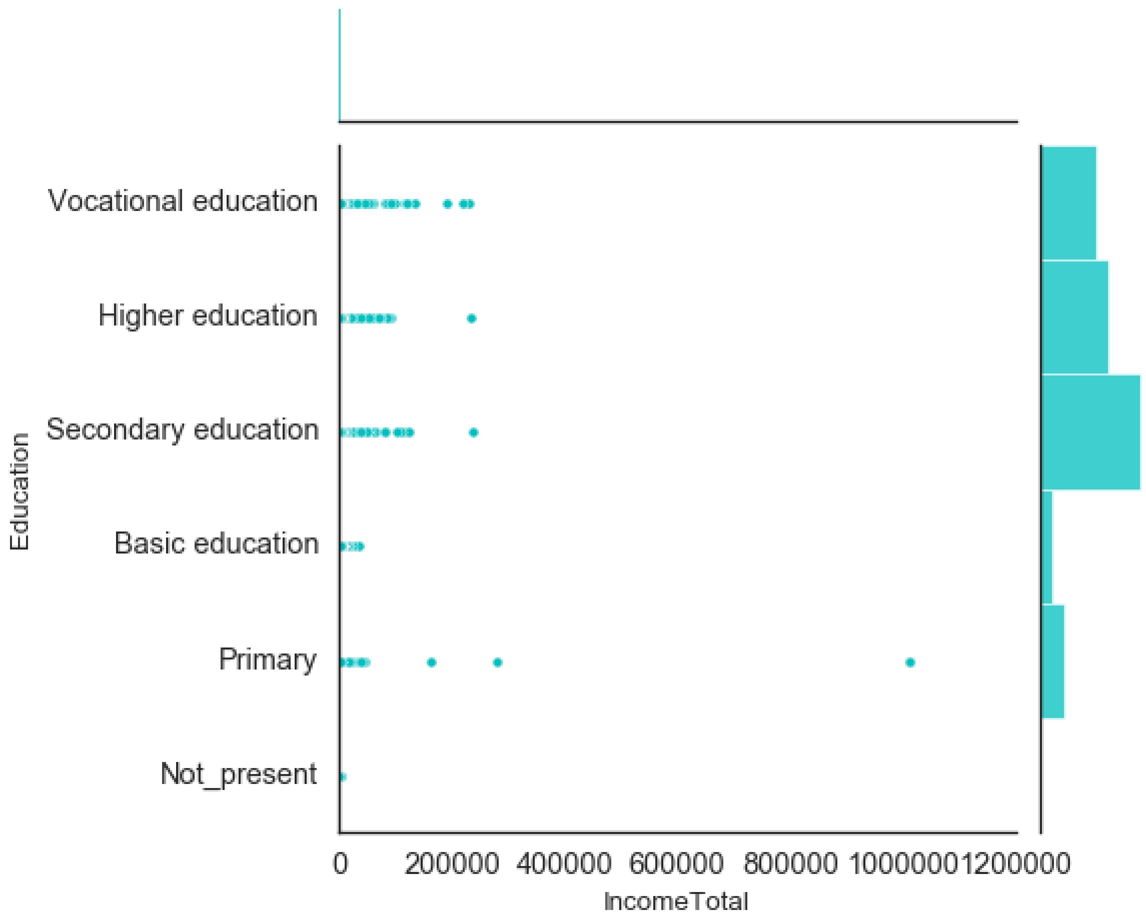
```
sns.set_style("ticks")
plt.figure(figsize=(10,4),dpi=100)
sns.scatterplot(data=loan,y=loan.Education,x=loan.Age,palette='husl',color='m')
plt.show()
```



In [537]:

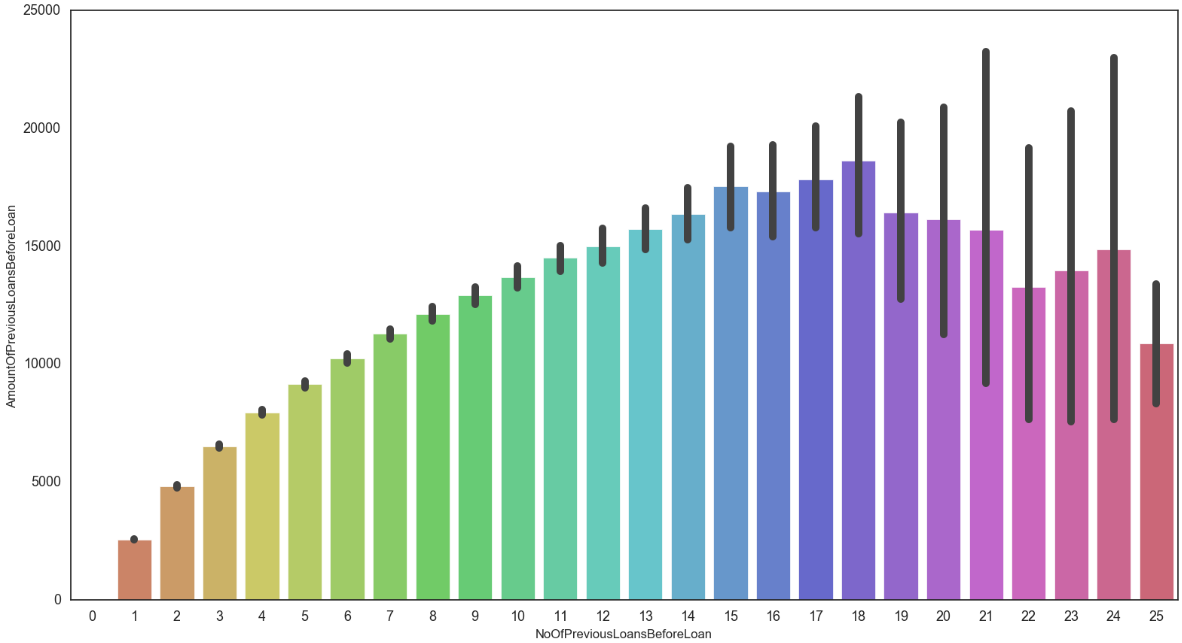
```
sns.set_style("ticks")
plt.figure(figsize=(10,8),dpi=100)
sns.jointplot(data=loan,y=loan.Education,x=loan.IncomeTotal,palette='husl',color='c')
plt.show()
```

<Figure size 1000x800 with 0 Axes>



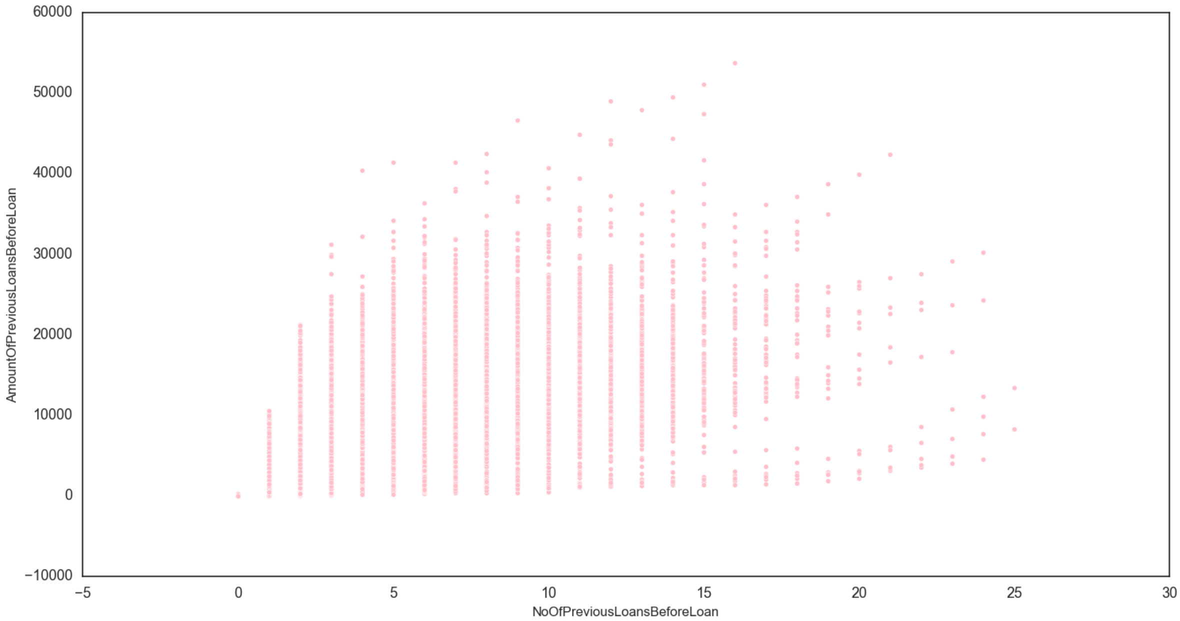
In [595]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.barplot(x=loan.NoOfPreviousLoansBeforeLoan,y=loan.AmountOfPreviousLoansBeforeLoan,palet
plt.show()
```



In [621]:

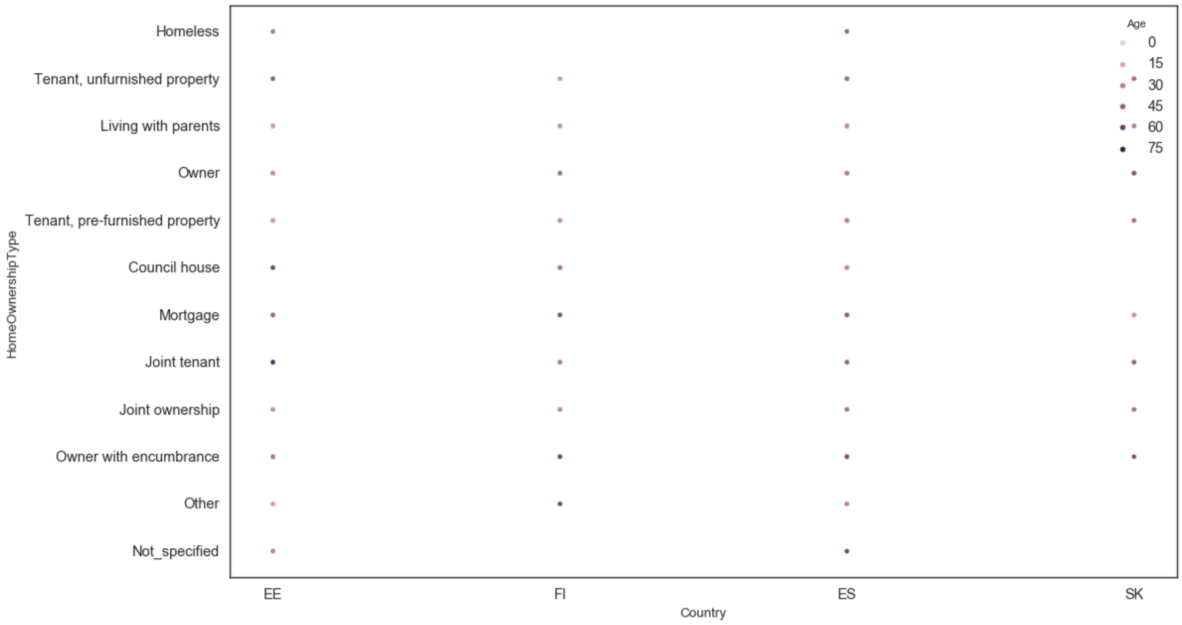
```
plt.figure(figsize=(15,8),dpi=100)
sns.scatterplot(x=loan.NoOfPreviousLoansBeforeLoan,y=loan.AmountOfPreviousLoansBeforeLoan,p
plt.tight_layout()
plt.show()
```



Multivariate Analysis

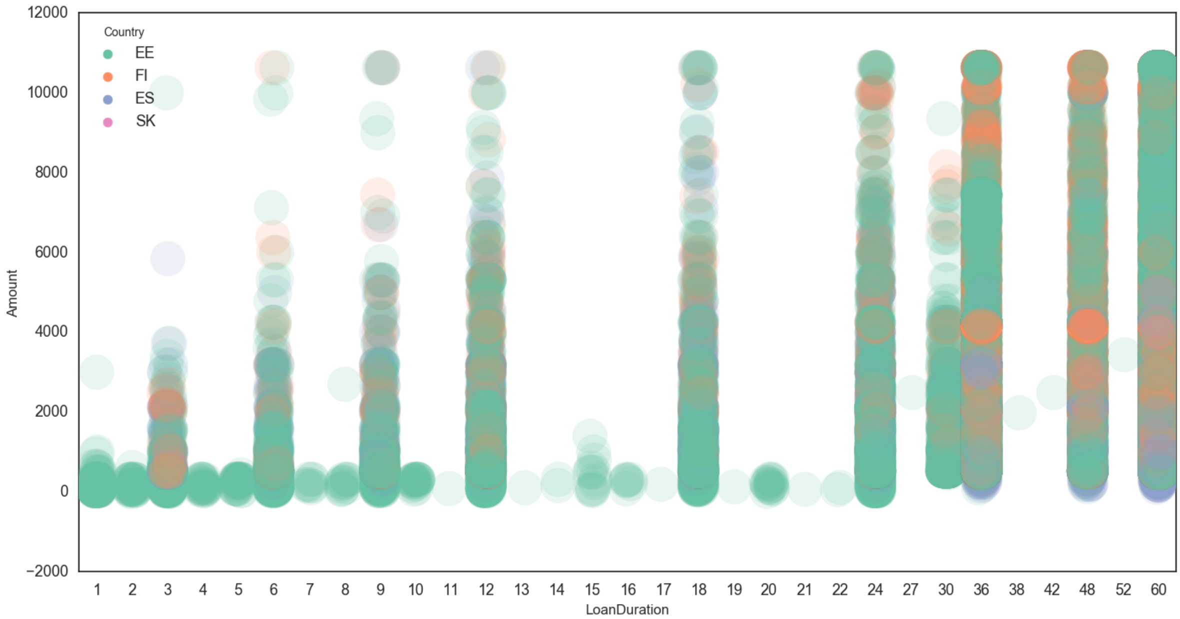
In [670]:

```
plt.style.use("seaborn-white")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.scatterplot(x= cat_cols['Country'],y=cat_cols["HomeOwnershipType"],hue=num_cols["Age"])
plt.tight_layout()
plt.show()
```



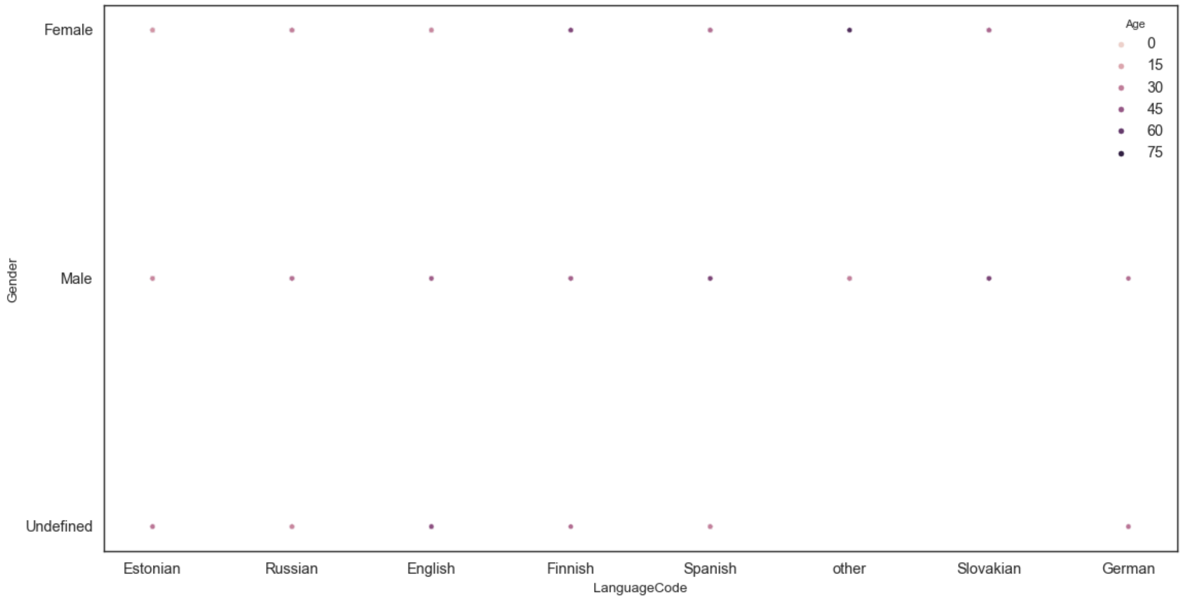
In [422]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.stripplot(x=loan.LoanDuration,palette='Set2',y=loan.Amount,hue= loan.Country,marker='o'
plt.show()
```



In [373]:

```
plt.style.use("seaborn-white")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.scatterplot(x='LanguageCode',y='Gender',hue= 'Age',data=loan)
plt.show()
```

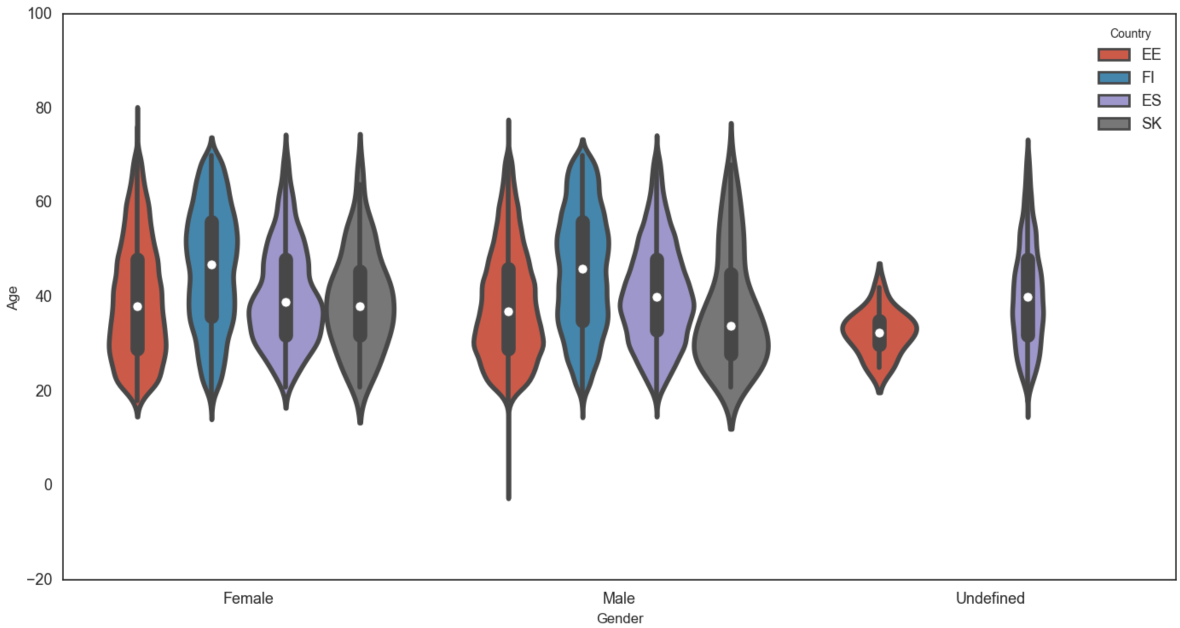


In [398]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.violinplot(x='Gender' ,y='Age',hue='Country',data=loan)
```

Out[398]:

```
<AxesSubplot:xlabel='Gender', ylabel='Age'>
```

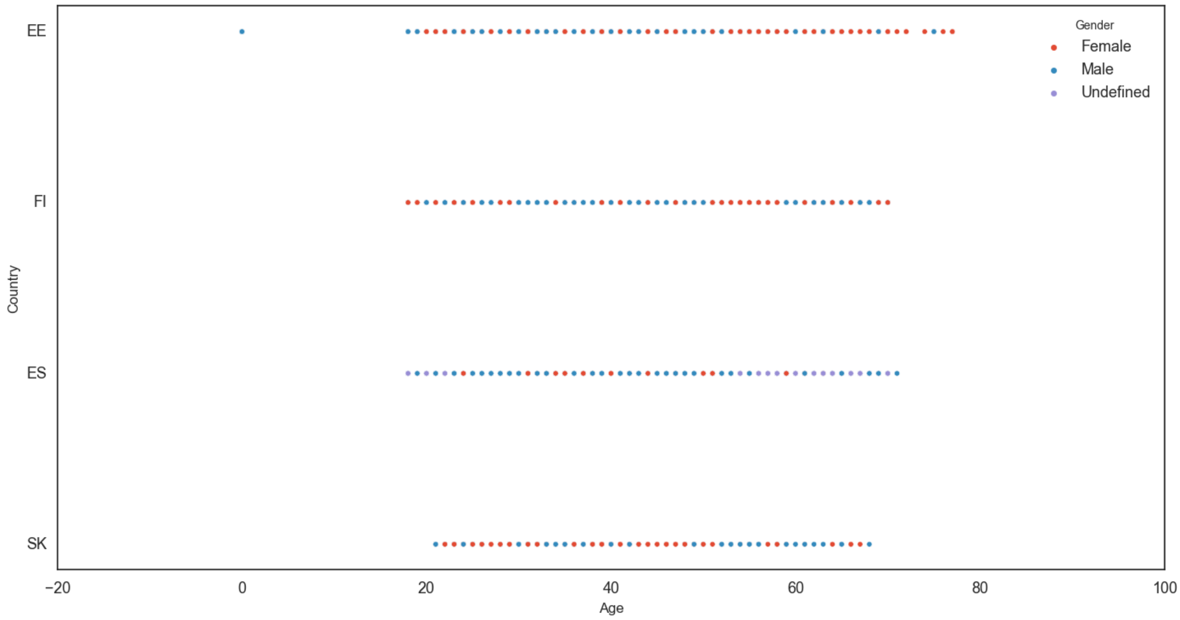


In [392]:

```
plt.figure(figsize=(15,8),dpi=100)
sns.scatterplot(x='Age' ,y='Country',hue='Gender',data=loan)
```

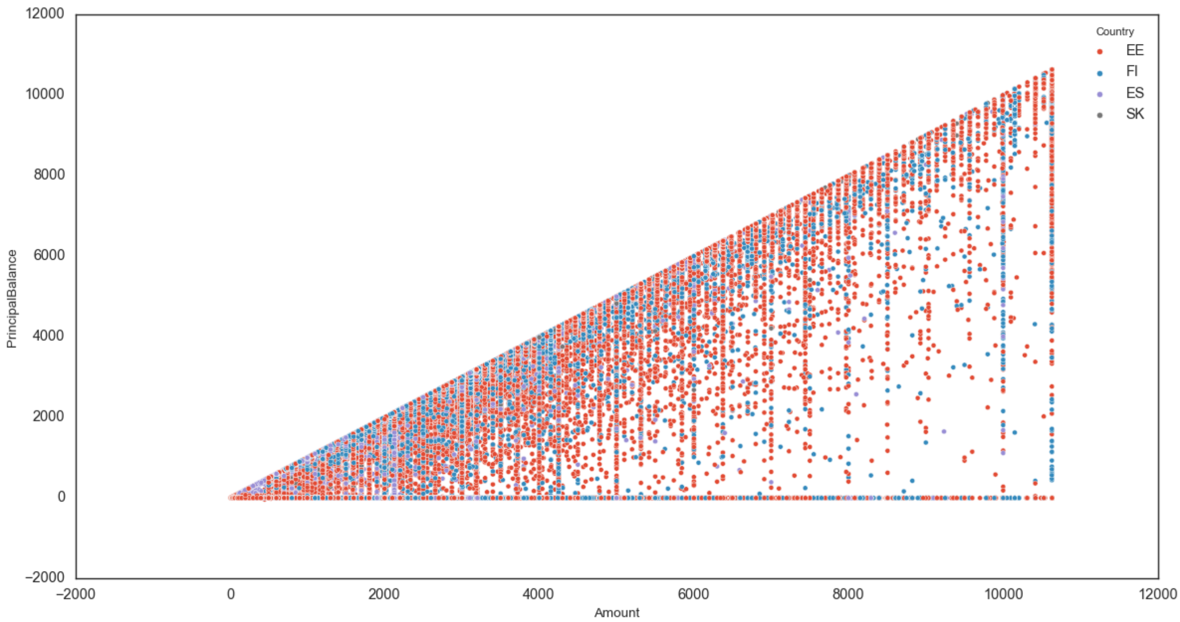
Out[392]:

```
<AxesSubplot:xlabel='Age', ylabel='Country'>
```



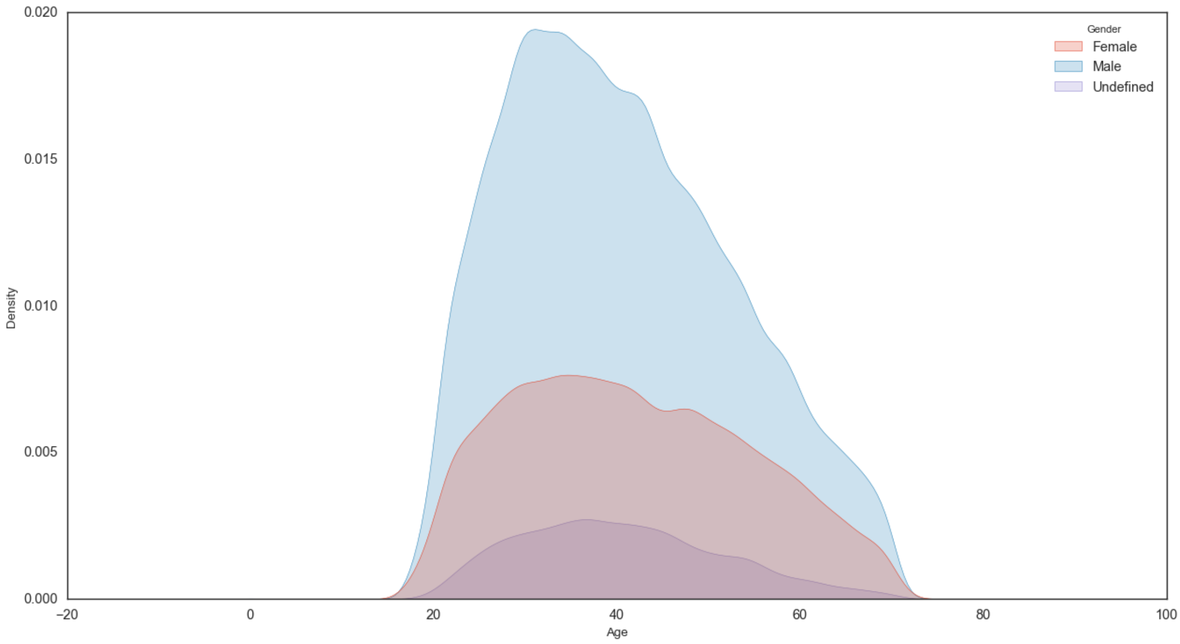
In [662]:

```
plt.style.use("seaborn-white")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.scatterplot(y=num_cols["PrincipalBalance"],x=num_cols["Amount"],hue= cat_cols['Country'
plt.tight_layout()
plt.show()
```



In [624]:

```
plt.style.use("seaborn-white")
sns.color_palette('plasma')
plt.figure(figsize=(15,8))
sns.kdeplot(num_cols["Age"],shade=True, hue=cat_cols["Gender"])
plt.show()
```

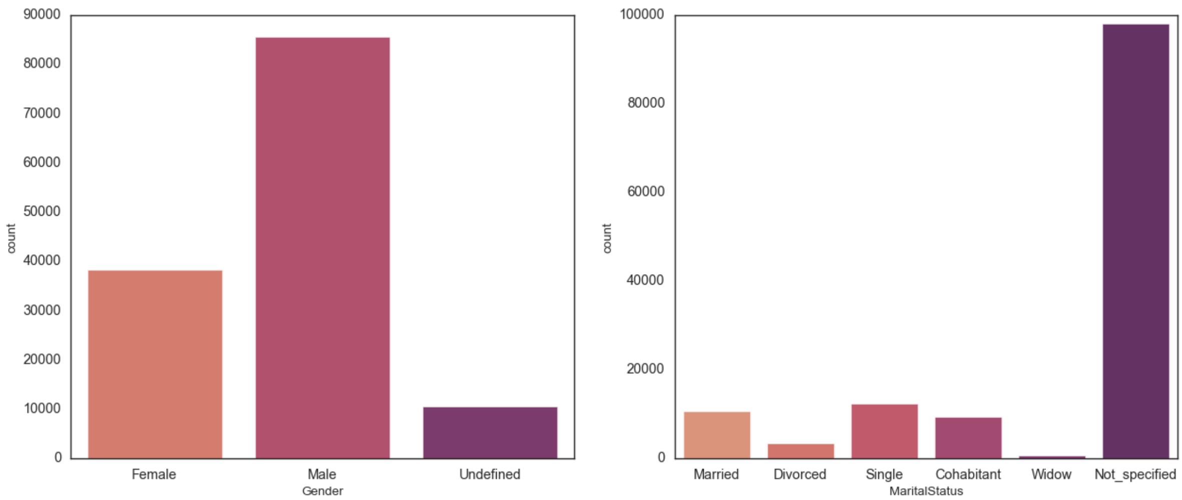


In [674]:

```
plt.figure(figsize=(15,6))
plt.subplot(1,2,1)
sns.countplot(cat_cols["Gender"],palette="flare")
plt.subplot(1,2,2)
sns.countplot(cat_cols["MaritalStatus"],palette="flare")
```

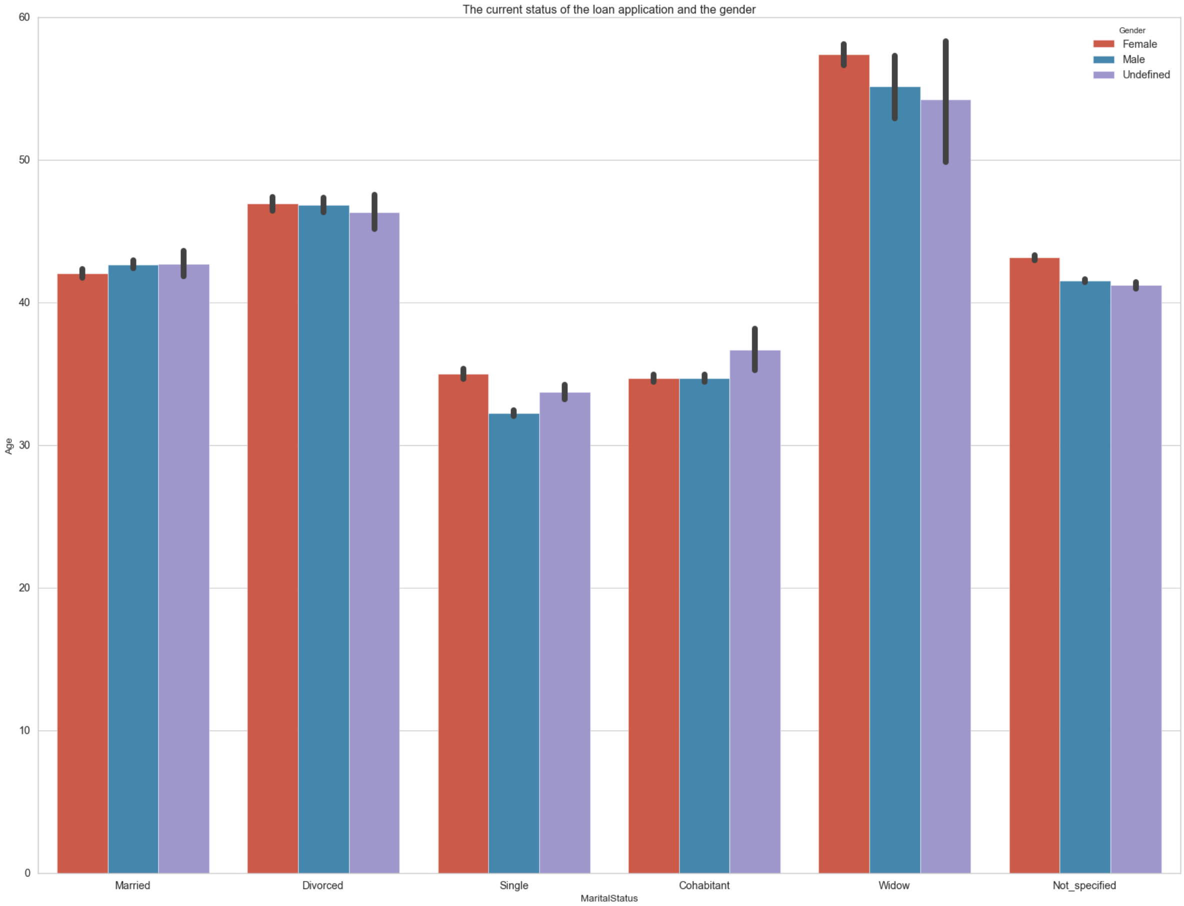
Out[674]:

```
<AxesSubplot:xlabel='MaritalStatus', ylabel='count'>
```



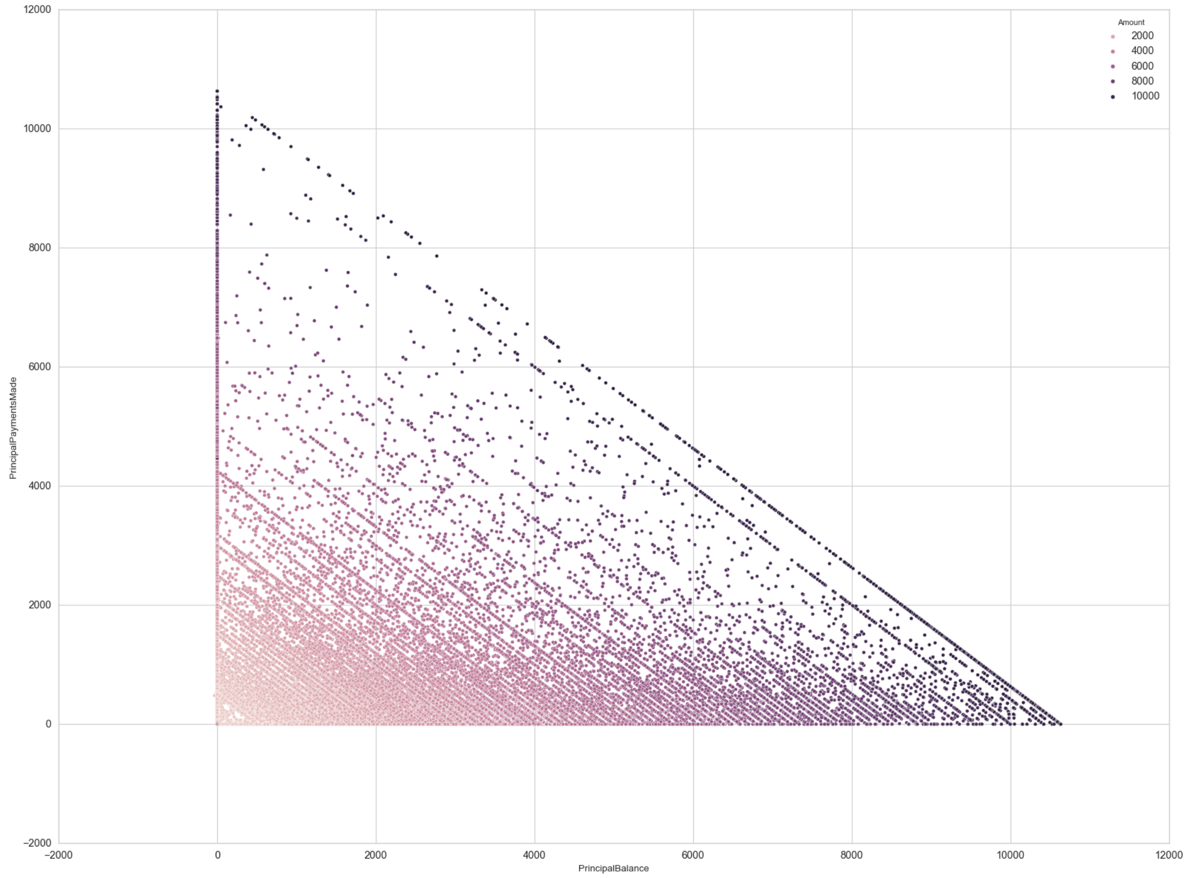
In [678]:

```
plt.figure(figsize=(20,15))
sns.set_style("whitegrid")
sns.barplot(data=loan,x='MaritalStatus',y='Age',hue='Gender')
plt.title("The current status of the loan application and the gender")
plt.show()
```



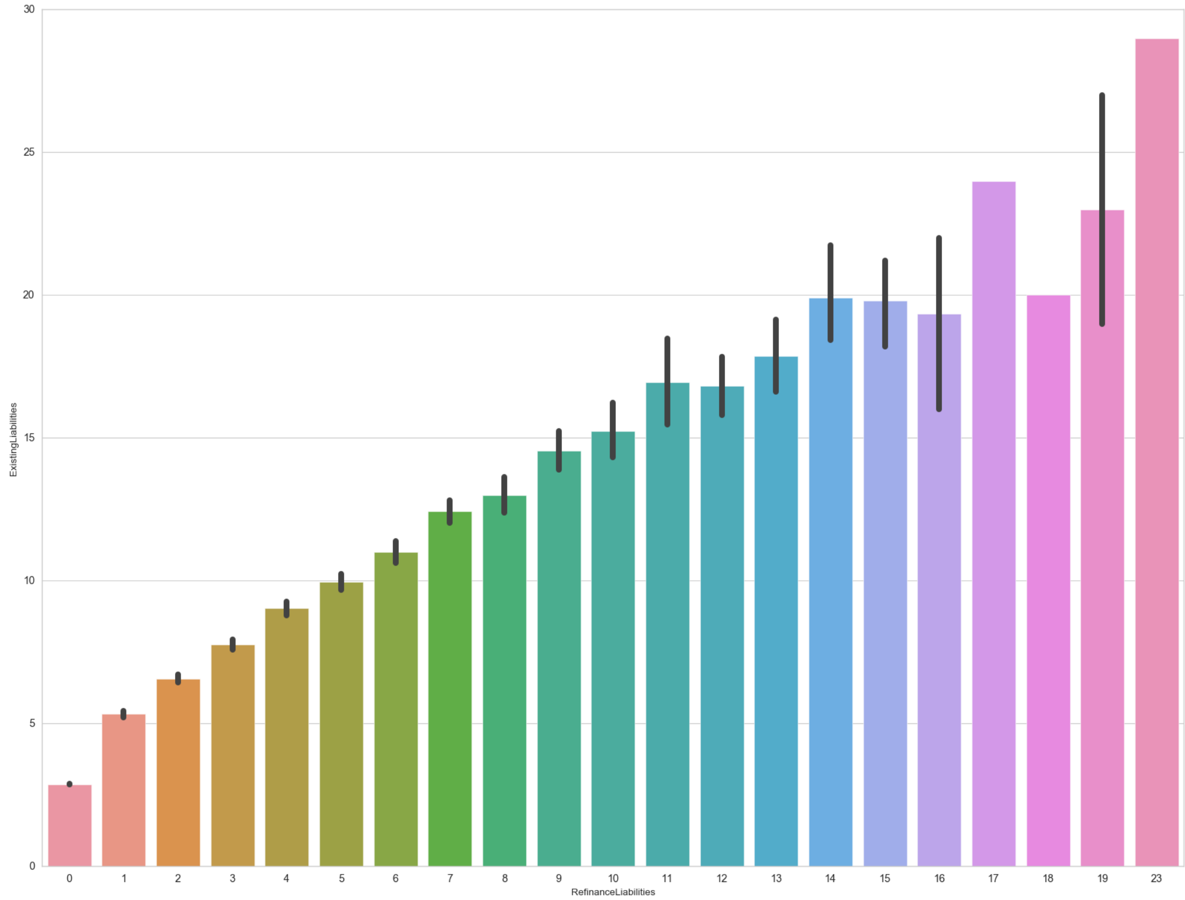
In [732]:

```
plt.figure(figsize=(20,15))
sns.set_style("whitegrid")
sns.scatterplot(data=loan, x=loan.PrincipalBalance,y=loan.PrincipalPaymentsMade,hue=loan.Am
plt.show()
```



In [690]:

```
plt.figure(figsize=(20,15))
sns.set_style("whitegrid")
sns.barplot(data=num_cols,y=num_cols.ExistingLiabilities,x=num_cols.RefinanceLiabilities)
plt.show()
```



- First we will delete all the features related to date as it is not a time series analysis so these features will not help in predicting target variable.
- As we can see in numeric column distribution there are many columns which are present as numeric but they are actually categorical as per data description such as Verification Type, Language Code, Gender, Use of Loan, Education, Marital Status,EmployementStatus, OccupationArea etc.
- So we will convert these features to categorical features

Now we will check the distribution of different categorical variables

In [143]:

```
# code for VerificationType
'''
0 Not set ,1 Income unverified ,2 Income unverified,
cross-referenced by phone, 3 Income verified ,4 Income and expenses verified
'''
loan.VerificationType.replace({0.0:'Not set',
                               1.0:'Income unverified',
                               2.0:'Income unverified',
                               3.0:'Income verified',
                               4.0:'Income and expenses verified'},
                               inplace=True)
```

In [144]:

```
# code here for val counts
loan.VerificationType.value_counts()
```

Out[144]:

```
Income and expenses verified    74572
Income unverified               50476
Income verified                  9428
Not set                             8
Name: VerificationType, dtype: int64
```

In [145]:

```
# code for Gender
'''
0 Male 1 Woman 2 Undefined
'''

loan.Gender.replace({0.0:'Male',1.0:'Female',2.0:'Undefined'},inplace = True)
```

In [146]:

```
#for val counts
loan.Gender.value_counts()
```

Out[146]:

```
Male         85650
Female       38213
Undefined    10621
Name: Gender, dtype: int64
```

In [147]:

```
# code for LanguageCode
'''
1 Estonian 2 English 3 Russian 4 Finnish 5 German 6 Spanish 9 Slovakian
'''

loan.LanguageCode.replace({1:'Estonian',2:'English',3:'Russian',4:'Finnish',
                           5:'German',6:'Spanish',9:'Slovakian'},inplace=True)

loan.LanguageCode.value_counts()
```

Out[147]:

```
Estonian     64299
Finnish      32155
Spanish      24103
Russian      12694
English        967
Slovakian      295
other           11
German           5
Name: LanguageCode, dtype: int64
```

As we can see from above in language code w ehave only descriptions for values 1,2,3,4,5,6, and 9 but it has other values too like 21,22,15,13,10 and 7 but they are very less it may happen they are local language codes whose decription is not present so we will be treated all these values as others

In [148]:

```
# code here for replacement

loan.LanguageCode.replace({22:'other',21:'other',7:'other',
                           15:'other',10:'other',13:'other'},inplace = True)
```

In [149]:

```

# code for UseOfLoan
loan.LanguageCode.value_counts()
```

Out[149]:

```
Estonian     64299
Finnish      32155
Spanish      24103
Russian      12694
English        967
Slovakian      295
other           11
German           5
Name: LanguageCode, dtype: int64
```

As we can see from above stats most of the loans are -1 category whose description is not avaialble in Bondoro website so we have dig deeper to find that in Bondora most of the loans happened for which purpose so we find in Bondora [Statistics Page (https://www.bondora.com/en/public-statistics)](https://www.bondora.com/en/public-statistics) most of the loans around 34.81% are for Not set purpose. so we will encode -1 as Not set category

In [150]:

```
loan.UseOfLoan.replace({-1:'Not set category',0:'Loan consolidation',1:'Real estate',2:'Hom
                        3:'Business',4:'Education',5:'Travel',6:'Vehicle',7:'Other',8:'Heal
                        101:'Working capital financing',102:'Purchase of machinery equipmen
                        103:'Renovation of real estate',104:'Accounts receivable financing'
                        105:'Acquisition of means of transport',106:'Construction finance',
                        107:'Acquisition of stocks',108:'Acquisition of real estate',
                        109:'Guaranteeing obligation',110:'Other business'}, inplace = True
```

In [151]:

```
# code for val counts
loan.UseOfLoan.value_counts()
```

Out[151]:

```
Not set category                  97946
Other                              9698
Home improvement                   9191
Loan consolidation                 6914
Vehicle                            3150
Business                           1950
Travel                             1787
Health                             1519
Education                          1366
Real estate                         955
Purchase of machinery equipment      21
Other business                       17
Accounts receivable financing         6
Working capital financing             5
Acquisition of stocks                 2
Acquisition of real estate            1
Construction finance                  1
Name: UseOfLoan, dtype: int64
```

In [152]:

```
# code for Education
loan.Education.replace({1:'Primary',2:'Basic education',3:'Vocational education',
                        4:'Secondary education',5:'Higher education'},
                       inplace =True)
loan.Education.value_counts()
```

Out[152]:

```
Secondary education     51330
Higher education        35398
Vocational education    29260
Primary                 12057
Basic education          6427
Not_present                12
Name: Education, dtype: int64
```

Again as we can see from above description for -1 and 0 in case of education is not present so we will encode them as Not_present as we dont know anything about them.

In [153]:

```
#  code for -1 and 0
loan.Education.replace({-1:'Not_present',0:'Not_present'},inplace =True)
loan.Education.value_counts()
```

Out[153]:

```
Secondary education     51330
Higher education        35398
Vocational education    29260
Primary                 12057
Basic education          6427
Not_present                12
Name: Education, dtype: int64
```

In [154]:

```
# code here for MaritalStatus
loan.MaritalStatus.replace({1:'Married',2:'Cohabitant',3:'Single',4:'Divorced',5:'Widow'},
                           inplace= True)

loan.MaritalStatus.value_counts()
```

Out[154]:

```
Not_specified    97954
Single           12400
Married          10752
Cohabitant        9400
Divorced          3377
Widow              601
Name: MaritalStatus, dtype: int64
```

Again Marital status of value 0 and -1 has no description so we will encode them as Not_specified

In [155]:

```
# code for -1 and 0
loan.MaritalStatus.replace({-1:'Not_specified',0:'Not_specified'},inplace = True)
loan.MaritalStatus.value_counts()
```

Out[155]:

```
Not_specified    97954
Single           12400
Married          10752
Cohabitant        9400
Divorced          3377
Widow              601
Name: MaritalStatus, dtype: int64
```

In [156]:

```
# code here for EmploymentStatus
loan.EmploymentStatus.replace({1:'Unemployed',2:'Partially employed',3:'Fully employed',
                               4:'Self-employed',5:'Entrepreneur',6:'Retiree'},inplace = Tr
```

In [157]:

```
# code here for NewCreditCustome
'''Did the customer have prior credit history in Bondora
0 Customer had at least 3 months of credit history in Bondora
1 No prior credit history in Bondora
'''
loan.NewCreditCustomer.replace({True:0,False:1},inplace = True)
```

In [158]:

```
# code here for Restructured
# The original maturity date of the loan has been increased by more than 60 day
loan.Restructured.replace({True:0,False:1},inplace = True)
```

In [159]:

```
# code here for OccupationArea
loan.OccupationArea.replace({1:'Other',2:'Mining',3:'Processing',4:'Energy',5:'Utilities',6
                             7:'Retail and wholesale',8:'Transport and warehousing',9:'Hosp
                             10:'Info and telecom',11:'Finance and insurance',12:'Real-esta
                             14:'Administrative',15:'Civil service & military',16:'Educatio
                             17:'Healthcare and social help',18:'Art and entertainment',19:
                            inplace = True)
```

In [160]:

```
# code here for HomeOwnershipType
loan.HomeOwnershipType.replace({0:'Homeless',1:'Owner',2:'Living with parents',3:'Tenant, p
                                4:'Tenant, unfurnished property',5:'Council house',6:'Joint
                                7:'Joint ownership',8:'Mortgage',9:'Owner with encumbrance'
                                10:'Other'},inplace = True)
```

In [161]:

```
# code here for EmploymentStatus
loan.EmploymentStatus.replace({-1:'Not_specified',0:'Not_specified'},inplace = True)


# code here for OccupationArea
loan.OccupationArea.replace({-1:'Not_specified',0:'Not_specified'},inplace = True)

#code here for HomeOwnershipType
loan.HomeOwnershipType.replace({-1:'Not_specified'},inplace = True)
```

In [162]:

```
# write your code here for counts of EmploymentStatus
loan.EmploymentStatus.value_counts()
```

Out[162]:

```
Not_specified         97978
Fully employed        30060
Entrepreneur           2007
Retiree                1800
Self-employed          1303
Partially employed     1184
Name: EmploymentStatus, dtype: int64
```

In [163]:

```
# write your code here for counts of OccupationArea
loan.OccupationArea.value_counts()
```

Out[163]:

```
Not_specified                           98008
Other                                    8421
Retail and wholesale                     3587
Construction                             3312
Processing                               3198
Transport and warehousing                2462
Healthcare and social help               2424
Hospitality and catering                 2262
Info and telecom                         1933
Civil service & military                 1684
Education                                1430
Finance and insurance                    1148
Agriculture,forestry and fishing         1000
Administrative                            843
Art and entertainment                     619
Energy                                    587
Research                                  564
Real-estate                               477
Utilities                                 362
Mining                                    122
Name: OccupationArea, dtype: int64
```

In [164]:

```
# write your code here for counts of Restructured
loan.Restructured.value_counts()
```

Out[164]:

```
1    106900
0     27629
Name: Restructured, dtype: int64
```

In [48]:

```
# write your code here for counts of NewCreditCustomer
loan.NewCreditCustomer.value_counts()
```

Out[48]:

```
0    77808
1    56721
Name: NewCreditCustomer, dtype: int64
```

In [49]:

```
# write your code here for counts of HomeOwnershipType
loan.HomeOwnershipType.value_counts()
```

Out[49]:

```
Owner                             47334
Tenant, pre-furnished property    29579
Living with parents               20780
Mortgage                          15457
Other                              7956
Tenant, unfurnished property       4582
Joint ownership                    3337
Joint tenant                       1618
Council house                      1442
Owner with encumbrance              743
Homeless                             46
Not_specified                         3
Name: HomeOwnershipType, dtype: int64
```

In [51]:

```
# save the final data
loan.to_csv('Bondora_preprocessed.csv',index=False)
```

In [52]:

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

In [352]:

```
df.head()
```

Out[352]:

	BidsPortfolioManager	BidsApi	BidsManual	NewCreditCustomer	LoanDate	FirstPaymentDate
0	0	0	115.041	0	2009-06-16	2009-07-27
1	0	0	140.606	1	2009-06-15	2009-07-15
2	0	0	319.558	0	2009-06-15	2009-07-27
3	0	0	57.520	0	2009-06-15	2009-07-15
4	0	0	319.558	0	2009-06-14	2009-07-27