Part I_Prosper Loan Exploration

January 10, 2023

1 Prosper Loan Data Exploration

1.1 by Emma Hungrige

1.2 Preliminary Wrangling

This data set contains information on peer to peer loans facilitated by the credit company, Prosper.

```
In [74]: # import all packages and set plots to be embedded inline
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns

         import warnings
         warnings.filterwarnings("ignore")

         %matplotlib inline

         %config InlineBbackend.figure_format = "retina"

In [75]: df = pd.read_csv("prosperLoanData.csv")
         df.head()

Out[75]:                ListingKey  ListingNumber            ListingCreationDate  \
         0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
         1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
         2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
         3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
         4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000

           CreditGrade  Term LoanStatus           ClosedDate  BorrowerAPR  \
         0           C    36  Completed  2009-08-14 00:00:00      0.16516
         1         NaN    36    Current                  NaN      0.12016
         2          HR    36  Completed  2009-12-17 00:00:00      0.28269
         3         NaN    36    Current                  NaN      0.12528
         4         NaN    36    Current                  NaN      0.24614
```

```
   BorrowerRate  LenderYield  ...  LP_ServiceFees  LP_CollectionFees  \
0        0.1580       0.1380  ...         -133.18                0.0
1        0.0920       0.0820  ...            0.00                0.0
2        0.2750       0.2400  ...          -24.20                0.0
3        0.0974       0.0874  ...         -108.01                0.0
4        0.2085       0.1985  ...          -60.27                0.0

   LP_GrossPrincipalLoss  LP_NetPrincipalLoss LP_NonPrincipalRecoverypayments  \
0                    0.0                  0.0                             0.0
1                    0.0                  0.0                             0.0
2                    0.0                  0.0                             0.0
3                    0.0                  0.0                             0.0
4                    0.0                  0.0                             0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0
3            1.0                0                          0
4            1.0                0                          0

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
2                         0.0        41
3                         0.0       158
4                         0.0        20

[5 rows x 81 columns]
```

```
In [76]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   ListingKey                           113937 non-null  object
 1   ListingNumber                        113937 non-null  int64
 2   ListingCreationDate                  113937 non-null  object
 3   CreditGrade                          28953 non-null   object
 4   Term                                 113937 non-null  int64
 5   LoanStatus                           113937 non-null  object
 6   ClosedDate                           55089 non-null   object
 7   BorrowerAPR                          113912 non-null  float64
 8   BorrowerRate                         113937 non-null  float64
 9   LenderYield                          113937 non-null  float64
 10  EstimatedEffectiveYield              84853 non-null   float64
```

```
11  EstimatedLoss                        84853 non-null   float64
12  EstimatedReturn                      84853 non-null   float64
13  ProsperRating (numeric)              84853 non-null   float64
14  ProsperRating (Alpha)                84853 non-null   object
15  ProsperScore                         84853 non-null   float64
16  ListingCategory (numeric)            113937 non-null  int64
17  BorrowerState                        108422 non-null  object
18  Occupation                           110349 non-null  object
19  EmploymentStatus                     111682 non-null  object
20  EmploymentStatusDuration             106312 non-null  float64
21  IsBorrowerHomeowner                  113937 non-null  bool
22  CurrentlyInGroup                     113937 non-null  bool
23  GroupKey                             13341 non-null   object
24  DateCreditPulled                     113937 non-null  object
25  CreditScoreRangeLower                113346 non-null  float64
26  CreditScoreRangeUpper                113346 non-null  float64
27  FirstRecordedCreditLine              113240 non-null  object
28  CurrentCreditLines                   106333 non-null  float64
29  OpenCreditLines                      106333 non-null  float64
30  TotalCreditLinespast7years           113240 non-null  float64
31  OpenRevolvingAccounts                113937 non-null  int64
32  OpenRevolvingMonthlyPayment          113937 non-null  float64
33  InquiriesLast6Months                 113240 non-null  float64
34  TotalInquiries                       112778 non-null  float64
35  CurrentDelinquencies                 113240 non-null  float64
36  AmountDelinquent                     106315 non-null  float64
37  DelinquenciesLast7Years              112947 non-null  float64
38  PublicRecordsLast10Years             113240 non-null  float64
39  PublicRecordsLast12Months            106333 non-null  float64
40  RevolvingCreditBalance               106333 non-null  float64
41  BankcardUtilization                  106333 non-null  float64
42  AvailableBankcardCredit              106393 non-null  float64
43  TotalTrades                          106393 non-null  float64
44  TradesNeverDelinquent (percentage)   106393 non-null  float64
45  TradesOpenedLast6Months              106393 non-null  float64
46  DebtToIncomeRatio                    105383 non-null  float64
47  IncomeRange                          113937 non-null  object
48  IncomeVerifiable                     113937 non-null  bool
49  StatedMonthlyIncome                  113937 non-null  float64
50  LoanKey                              113937 non-null  object
51  TotalProsperLoans                    22085 non-null   float64
52  TotalProsperPaymentsBilled           22085 non-null   float64
53  OnTimeProsperPayments                22085 non-null   float64
54  ProsperPaymentsLessThanOneMonthLate  22085 non-null   float64
55  ProsperPaymentsOneMonthPlusLate      22085 non-null   float64
56  ProsperPrincipalBorrowed             22085 non-null   float64
57  ProsperPrincipalOutstanding          22085 non-null   float64
58  ScorexChangeAtTimeOfListing          18928 non-null   float64
```

```
 59  LoanCurrentDaysDelinquent           113937 non-null  int64
 60  LoanFirstDefaultedCycleNumber       16952 non-null   float64
 61  LoanMonthsSinceOrigination          113937 non-null  int64
 62  LoanNumber                          113937 non-null  int64
 63  LoanOriginalAmount                  113937 non-null  int64
 64  LoanOriginationDate                 113937 non-null  object
 65  LoanOriginationQuarter              113937 non-null  object
 66  MemberKey                           113937 non-null  object
 67  MonthlyLoanPayment                  113937 non-null  float64
 68  LP_CustomerPayments                 113937 non-null  float64
 69  LP_CustomerPrincipalPayments        113937 non-null  float64
 70  LP_InterestandFees                  113937 non-null  float64
 71  LP_ServiceFees                      113937 non-null  float64
 72  LP_CollectionFees                   113937 non-null  float64
 73  LP_GrossPrincipalLoss               113937 non-null  float64
 74  LP_NetPrincipalLoss                 113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments     113937 non-null  float64
 76  PercentFunded                       113937 non-null  float64
 77  Recommendations                     113937 non-null  int64
 78  InvestmentFromFriendsCount          113937 non-null  int64
 79  InvestmentFromFriendsAmount         113937 non-null  float64
 80  Investors                           113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

In [77]:
```
df.describe()
```

Out[77]:
```
       ListingNumber           Term    BorrowerAPR   BorrowerRate  \
count   1.139370e+05  113937.000000  113912.000000  113937.000000
mean    6.278857e+05      40.830248       0.218828       0.192764
std     3.280762e+05      10.436212       0.080364       0.074818
min     4.000000e+00      12.000000       0.006530       0.000000
25%     4.009190e+05      36.000000       0.156290       0.134000
50%     6.005540e+05      36.000000       0.209760       0.184000
75%     8.926340e+05      36.000000       0.283810       0.250000
max     1.255725e+06      60.000000       0.512290       0.497500

         LenderYield  EstimatedEffectiveYield  EstimatedLoss  EstimatedReturn  \
count  113937.000000             84853.000000   84853.000000     84853.000000
mean        0.182701                 0.168661       0.080306         0.096068
std         0.074516                 0.068467       0.046764         0.030403
min        -0.010000                -0.182700       0.004900        -0.182700
25%         0.124200                 0.115670       0.042400         0.074080
50%         0.173000                 0.161500       0.072400         0.091700
75%         0.240000                 0.224300       0.112000         0.116600
max         0.492500                 0.319900       0.366000         0.283700
```

```
       ProsperRating (numeric)  ProsperScore  ...  LP_ServiceFees  \
count             84853.000000  84853.000000  ...   113937.000000
mean                  4.072243      5.950067  ...      -54.725641
std                   1.673227      2.376501  ...       60.675425
min                   1.000000      1.000000  ...     -664.870000
25%                   3.000000      4.000000  ...      -73.180000
50%                   4.000000      6.000000  ...      -34.440000
75%                   5.000000      8.000000  ...      -13.920000
max                   7.000000     11.000000  ...       32.060000

       LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
count      113937.000000          113937.000000        113937.000000
mean          -14.242698             700.446342           681.420499
std           109.232758            2388.513831          2357.167068
min         -9274.750000             -94.200000          -954.550000
25%             0.000000               0.000000             0.000000
50%             0.000000               0.000000             0.000000
75%             0.000000               0.000000             0.000000
max             0.000000           25000.000000         25000.000000

       LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
count                    113937.000000  113937.000000    113937.000000
mean                         25.142686       0.998584         0.048027
std                         275.657937       0.017919         0.332353
min                           0.000000       0.700000         0.000000
25%                           0.000000       1.000000         0.000000
50%                           0.000000       1.000000         0.000000
75%                           0.000000       1.000000         0.000000
max                       21117.900000       1.012500        39.000000

       InvestmentFromFriendsCount  InvestmentFromFriendsAmount      Investors
count               113937.000000                113937.000000  113937.000000
mean                     0.023460                    16.550751      80.475228
std                      0.232412                   294.545422     103.239020
min                      0.000000                     0.000000       1.000000
25%                      0.000000                     0.000000       2.000000
50%                      0.000000                     0.000000      44.000000
75%                      0.000000                     0.000000     115.000000
max                     33.000000                 25000.000000    1189.000000

[8 rows x 61 columns]
```

In [78]:
```
df.sample(10)
```

Out[78]:
```
                    ListingKey  ListingNumber            ListingCreationDate  \
2245   041F3430145017632AA8BA0         390137  2008-08-29 05:07:43.680000000
75013  40F53590807325493885BC         912400  2013-09-19 13:39:32.590000000
46273  8D0C3530238955853B93AA2         534978  2011-10-23 14:07:59.283000000
```

```
102988  35113586293088828096405          859552  2013-08-03 10:46:43.993000000
64366   91083586611460835DA94F3          862308  2013-08-07 03:22:49.683000000
33939   B8663596881629915202A61         1100583  2013-12-20 11:02:19.417000000
77865   9DA635461878864198A8F59          588062  2012-05-10 12:40:01.903000000
1379    7B22358909824432888A960          913677  2013-09-20 09:47:04.787000000
58245   BC6A3557201311989982118          634327  2012-09-05 12:37:31.397000000
27156   01793403613525474C385A5          228220  2007-11-08 04:22:35.990000000

       CreditGrade  Term           LoanStatus           ClosedDate  \
2245             B    36            Completed  2011-09-09 00:00:00
75013          NaN    36              Current                  NaN
46273          NaN    36            Completed  2012-06-15 00:00:00
102988         NaN    60              Current                  NaN
64366          NaN    60              Current                  NaN
33939          NaN    60              Current                  NaN
77865          NaN    36  Past Due (1-15 days)                  NaN
1379           NaN    60              Current                  NaN
58245          NaN    36            Completed  2013-10-10 00:00:00
27156            D    36            Completed  2008-05-16 00:00:00

        BorrowerAPR  BorrowerRate  LenderYield  ...  LP_ServiceFees  \
2245        0.17193        0.1575       0.1475  ...          -57.94
75013       0.14409        0.1159       0.1059  ...          -35.93
46273       0.20200        0.1799       0.1699  ...          -14.74
102988      0.27637        0.2506       0.2406  ...          -19.73
64366       0.13942        0.1169       0.1069  ...          -73.25
33939       0.20040        0.1765       0.1665  ...          -16.90
77865       0.35797        0.3177       0.3077  ...          -47.68
1379        0.21115        0.1870       0.1770  ...          -41.04
58245       0.27060        0.2324       0.2224  ...          -17.18
27156       0.22868        0.2100       0.2000  ...           -4.78

        LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
2245                 0.00                    0.0                  0.0
75013                0.00                    0.0                  0.0
46273                0.00                    0.0                  0.0
102988               0.00                    0.0                  0.0
64366                0.00                    0.0                  0.0
33939                0.00                    0.0                  0.0
77865             -147.65                    0.0                  0.0
1379                 0.00                    0.0                  0.0
58245                0.00                    0.0                  0.0
27156                0.00                    0.0                  0.0

       LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
2245                               0.0            1.0                0
75013                              0.0            1.0                0
46273                              0.0            1.0                0
```

```
102988                                   0.0           1.0              0
64366                                    0.0           1.0              0
33939                                    0.0           1.0              0
77865                                    0.0           1.0              0
1379                                     0.0           1.0              0
58245                                    0.0           1.0              0
27156                                    0.0           1.0              0

       InvestmentFromFriendsCount InvestmentFromFriendsAmount Investors
2245                            0                         0.0       108
75013                           0                         0.0        90
46273                           0                         0.0        20
102988                          0                         0.0         2
64366                           0                         0.0       274
33939                           0                         0.0         1
77865                           0                         0.0        13
1379                            0                         0.0         1
58245                           0                         0.0        29
27156                           0                         0.0        14

[10 rows x 81 columns]
```

1.2.1 What is/are the main feature(s) of interest in your dataset?

We're most interested in figuring out which borrower features are best for predicting the highest rate of return and what factors will have the highest impact on the chances of default. We also want to investigate how closely the estimated loan performance matches the actual loan performance.

1.2.2 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

There are over 81 columns to use in this dataset, but we believe the following columns will have the largest effect on the performance of the loans:

1. **IncomeRange** - The income range of the borrower at the time the listing was created
2. **DebtToIncomeRatio** - The debt to income ratio of the borrower at the time the credit profile was pulled. This value is Null if the debt to income ratio is not available. This value is capped at 10.01 (any debt to income ratio larger than 1000% will be returned at 1001%).
3. **CreditGrade** - The Credit rating that was assigned at the time the listing went live. Applicable for listings pre-2009 period and will only be populated for those listings.
4. **ProsperRating (Alpha)** - The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009.

The performance of the loan can be determined by the following features:

1. **EstimatedReturn** - The estimated return assigned to the listing at the time it was created. Estimated return is the difference between the Estimated Effective Yield and the Estimated

Loss Rate. Applicable for loans originated after July 2009. This is on an annual percentage rate (APR).

2. **ActualReturn** - To see how well the loan performed verses the EstimatedReturn. We will calculate this feature based on how Prosper calculates their Annualized Net Returns.

1.3 Univariate Exploration

1.3.1 Estimated Return

In [79]:
```
# Setting color
base_color = sns.color_palette()[0]
```

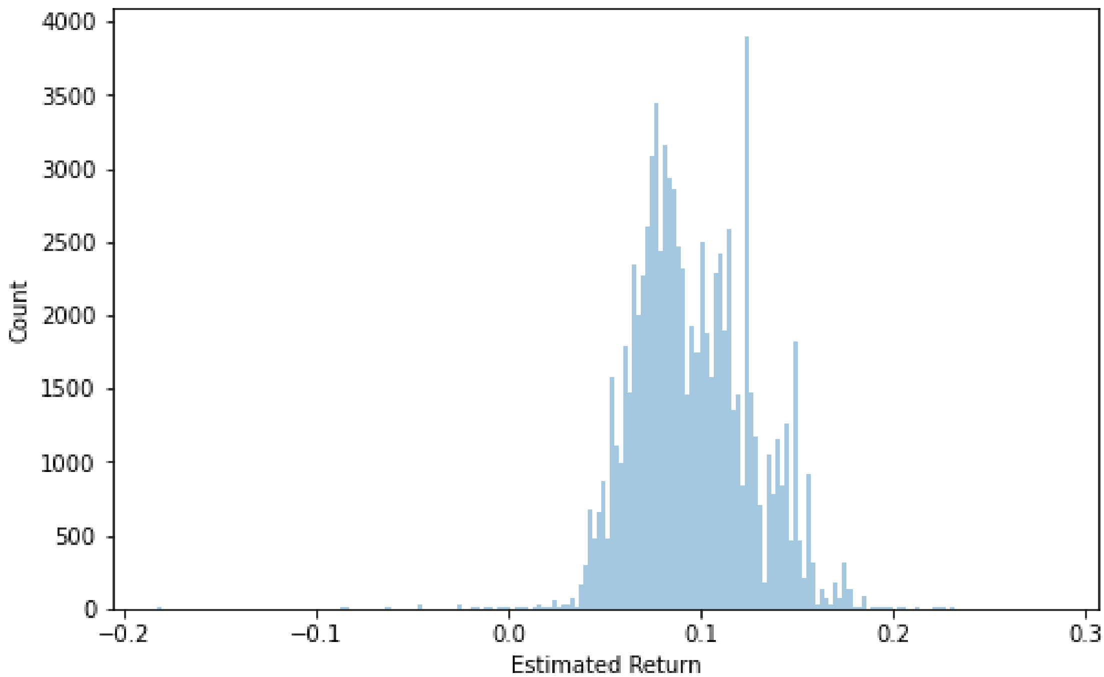
In [80]:
```
df.EstimatedReturn.describe()
```

Out[80]:
```
count    84853.000000
mean         0.096068
std          0.030403
min         -0.182700
25%          0.074080
50%          0.091700
75%          0.116600
max          0.283700
Name: EstimatedReturn, dtype: float64
```

There appears to be quite a few empty cells as the total number of rows is over 10k.
The range of estimated returns is -18% to 28%.
I expect to see a heavily right skewed distribution plot based on the quartile distribution.
Let's drop the null rows and create a histogram plot.

In [81]:
```
#Drop null rows without an estimated return
df.EstimatedReturn.dropna(axis = 0, inplace = True)
```

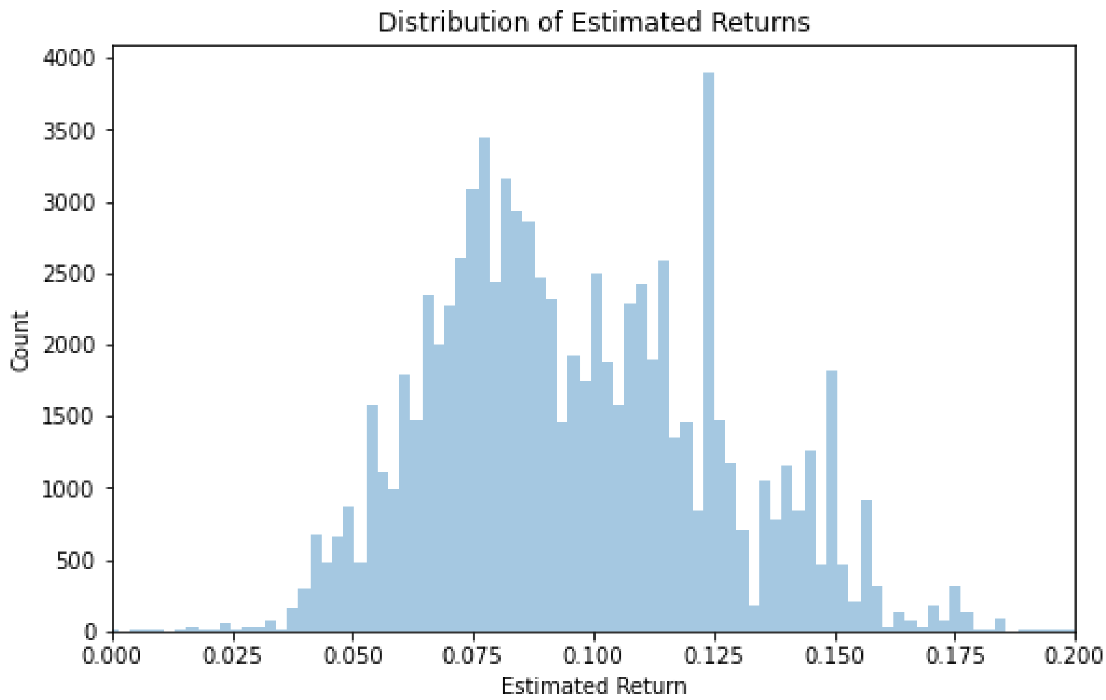
In [82]:
```
#Histogram plot
plt.figure(figsize = [8, 5])
sns.distplot(df.EstimatedReturn, kde = False, bins = 200, color = base_color)
plt.xlabel("Estimated Return")
plt.ylabel("Count");
```



It appears most of our loans have an estimated return between 0% and 20%. An additional histogram shall be created to zoom in a little further.

```
In [83]: #Zoom in on histogram

         plt.figure(figsize = [8,5])
         sns.distplot(df.EstimatedReturn, kde = False, bins = 200, color = base_color)
         plt.xlim(0, .2)
         plt.xlabel("Estimated Return")
         plt.ylabel("Count")
         plt.title("Distribution of Estimated Returns");
```



It appears like the assumption that this data would be right skewed is correct.

It also looks like there are a few peaks in some standard values like 5%, 7.5%, and 15%. Most interestingly, the largest bin falls right around 12.5%.

1.3.2 Actual Returns

This section appears to be quite nuanced and required some engineering. We're going to calculate the actual returns by using the remaining loan performance (LP) variables.

NOTE: To simplify out calculation for exploratory purposes, we will only divide by the original loan amount. Otherwise, we'll run into other categorical issues if we try to determine the current rate of return for current loans vs completed loans. This section may be revisited later to refine the actual returns.

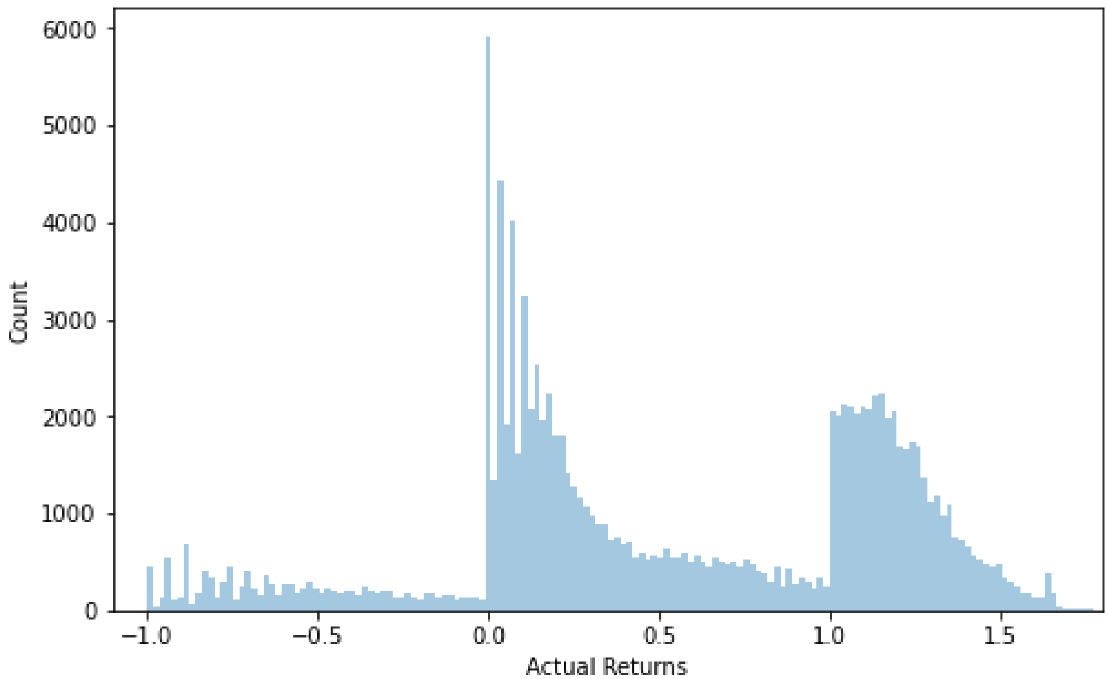
```
In [84]: #Simplified actual return formula
         df["ActualReturns"] = df.LP_CustomerPayments - df.LoanOriginalAmount - (df.LP_ServiceFe
         df["ActualReturns"] = 1 + (df.ActualReturns / df.LoanOriginalAmount)

In [85]: df.ActualReturns.describe()

Out[85]: count    113937.000000
         mean          0.531620
         std           0.621164
         min          -1.000650
         25%           0.074989
         50%           0.415864
         75%           1.119834
```

```
max            2.602880
Name: ActualReturns, dtype: float64
```

```
In [86]: #Plot distribution
         plt.figure(figsize = [8,5])
         sns.distplot(df.ActualReturns, kde = False, bins = 200, color = base_color)
         plt.xlim(-1.1, 1.8)
         plt.xlabel("Actual Returns")
         plt.ylabel("Count");
```



It's interesting to see there are some loans where it appears that the borrower never made a payment which gives us the minimum of losing 100% of the investment. On the other end of the spectrum, it looks like most loans drop off after about 170% of the original loan amount.

As mentioned previously, to simplify the visualization, this calculation is not annualized based on the length of the loans, so this is not quite an apples to apples comparison with the estimated return which is annualized.

Since there appears to be differnt modes to the distribution, let's see how the actual returns differ by the loan status:

```
In [87]: #Multiplot for loan status

         variables = ["Current", "Completed", "Chargedoff", "Defaulted"]

         plt.figure(figsize = [16, 10])

         # loop through variables list
```

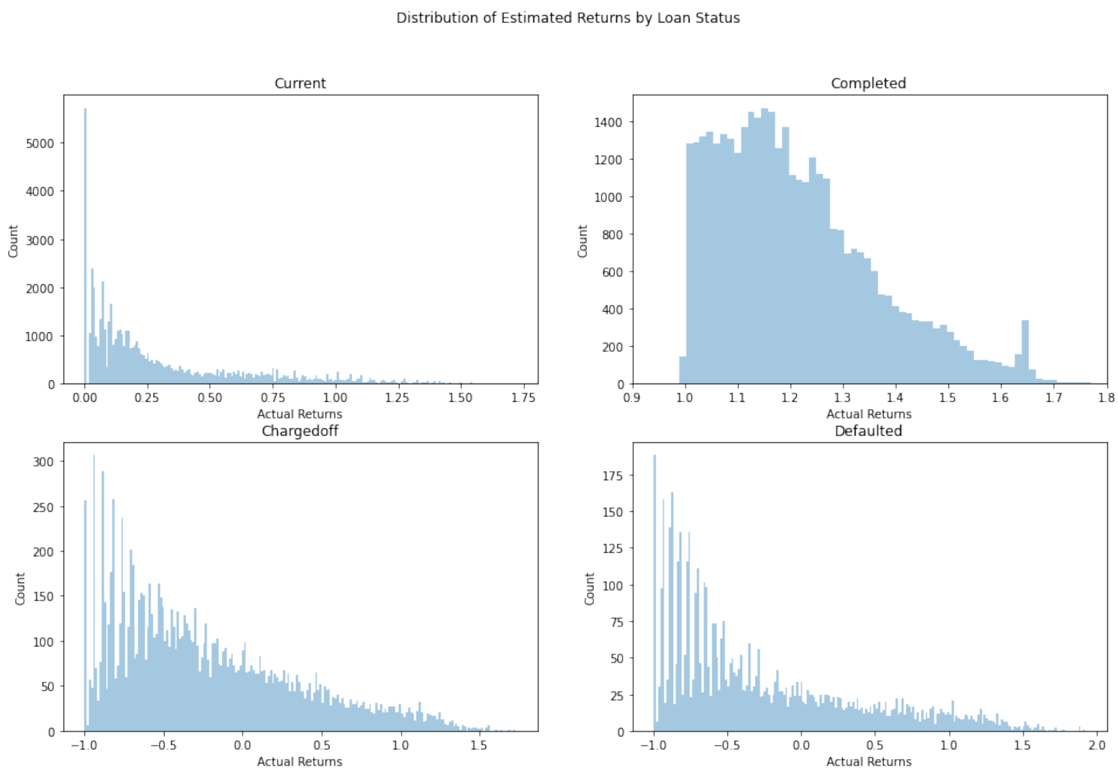
```
for i in range(len(variables)):
    plt.subplot(2, 2, i+1)

    sns.distplot(df.query('LoanStatus == "{}"'.format(variables[i])).ActualReturns,
                 kde = False, bins = 200, color = base_color)

    plt.xlabel('Actual Returns')
    plt.ylabel('Count')
    plt.title(variables[i])

plt.subplot(2, 2, 2)
plt.xlim(.9, 1.8)

plt.suptitle('Distribution of Estimated Returns by Loan Status');
```



For the current loans, there appears to be a large number of loans that have an actual return value of 0. This could mean that "Current" also takes into account all the loans that have not been fully funded yet. We would have to explore this further to extract loans that have been fully funded.

Since our actual returns feature is not annualized, we see that for the loan terms of 3-5 years, an investor could see a total return of 170%.

For loans that have defaulted or have been chargedoff, it makes sense that a majority of them show negative returns up to 100%. Meaning that the borrower could have never made a payment or the service/collection fees resulted in the investor losing their entire principal. Of course this is the worst case scenario.

1.3.3 Prosper Credit Grade

Now that we have a high level overview of what the returns on the platform looks like, let's investigate if there is a similar distribution for the borrower's prosper/credit grade.

```
In [88]: df['ProsperRating (Alpha)'].describe(), df['ProsperRating (Alpha)'].value_counts()
```

```
Out[88]: (count     84853
          unique        7
          top           C
          freq      18345
          Name: ProsperRating (Alpha), dtype: object,
          C     18345
          B     15581
          A     14551
          D     14274
          E      9795
          HR     6935
          AA     5372
          Name: ProsperRating (Alpha), dtype: int64)
```

```
In [89]: df['CreditGrade'].describe(), df['CreditGrade'].value_counts()
```

```
Out[89]: (count     28953
          unique        8
          top           C
          freq       5649
          Name: CreditGrade, dtype: object,
          C     5649
          D     5153
          B     4389
          AA    3509
          HR    3508
          A     3315
          E     3289
          NC     141
          Name: CreditGrade, dtype: int64)
```

From the feature descriptions, it looks like Prosper transitioned to a "Prosper Rating" after 2009 to differentiate themselves from the industry standard "Credit Grade.

For exploratory purposes, we'll replace the Credit Grade of No Credit (NC) with High Risk (HR) and combine this column with the Prosper Rating.

In the future we may want to look at estimated returns of the pre-2009 "Credit Grade" to see how it compares with the post-2009 "Prosper Rating" to validate if they truly are equivalent or if Prosper skewed their credit rating in some way.

```
In [90]: #Replace NC with HR
         df["CreditGrade"].replace(["NC", "HR"], "E", inplace = True)

         #Fill NA with empty strings
         df["ProsperRating (Alpha)"].fillna("", inplace = True)
         df["CreditGrade"].fillna("", inplace = True)

         #Combine credit ratings
         df["ProsperRatingCombined"] = df["ProsperRating (Alpha)"] + df["CreditGrade"]

         #Drop rows with no credit ratings
         df = df.query(' ProsperRatingCombined != ""')

         #Check values
         df["ProsperRatingCombined"].value_counts()
```

```
Out[90]: C     23994
         B     19970
         D     19427
         A     17866
         E     16733
         AA     8881
         HR     6935
         Name: ProsperRatingCombined, dtype: int64
```

We could have a potential issue with two "A" grades combining to make an "AA" grade. Let's double check the number of values before and after to make sure we didn't erroneously create "AA" grades.

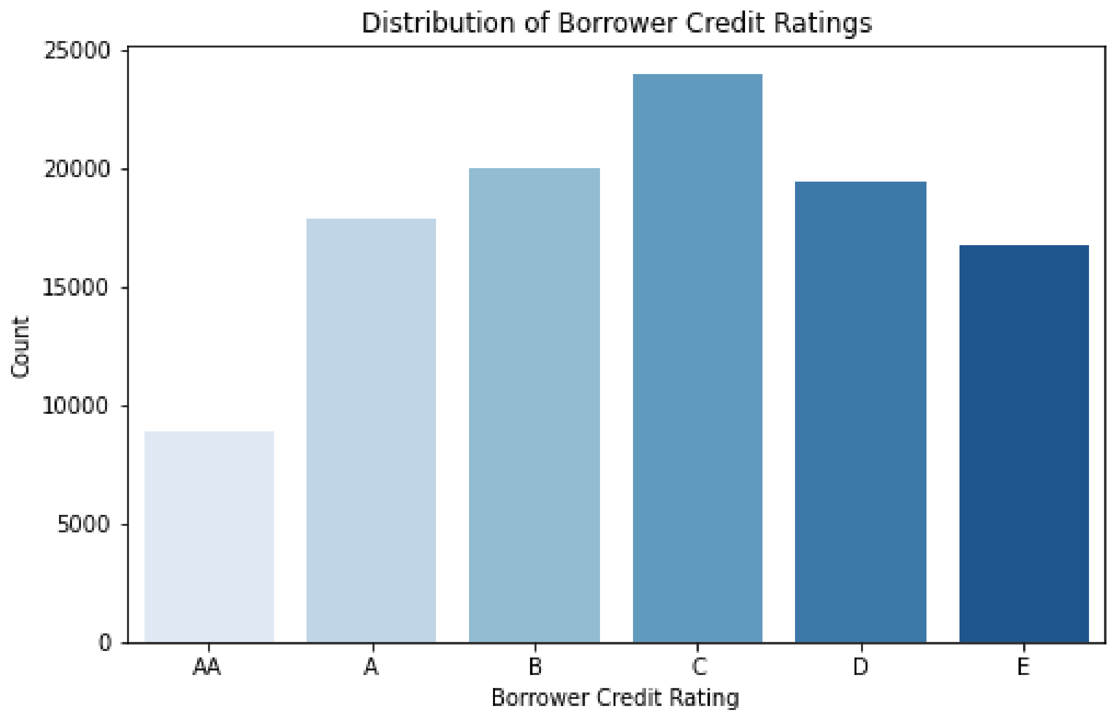
```
In [91]: #Are the number of A and AA ratings the same before and after combining the columns?
         (df["ProsperRatingCombined"] == "A").sum() == (df.CreditGrade == "A").sum() + (df["Pros
         (df["ProsperRatingCombined"] == "AA").sum() == (df.CreditGrade == "AA").sum() + (df["Pr
```

```
Out[91]: True
```

Great! We didn't introduce any erroneous data since there were no rows with an 'A' rating for both their Credit Grade and Prosper Rating.

```
In [92]: #Convert string to ordinal category type
         ordinal_rating = ["AA", "A", "B", "C", "D", "E"]
         ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = ordinal_rating
         df["ProsperRatingCombined"] = df["ProsperRatingCombined"].astype(ordered_var)
```

```
In [93]: plt.figure(figsize = [8, 5])
         sns.countplot(data = df, x = "ProsperRatingCombined", palette = "Blues")
         plt.xlabel("Borrower Credit Rating")
         plt.ylabel("Count")
         plt.title("Distribution of Borrower Credit Ratings");
```



The distribution of credit ratings is skewed to the right which coincides with our observation of estimated return distribution also being skewed to the right

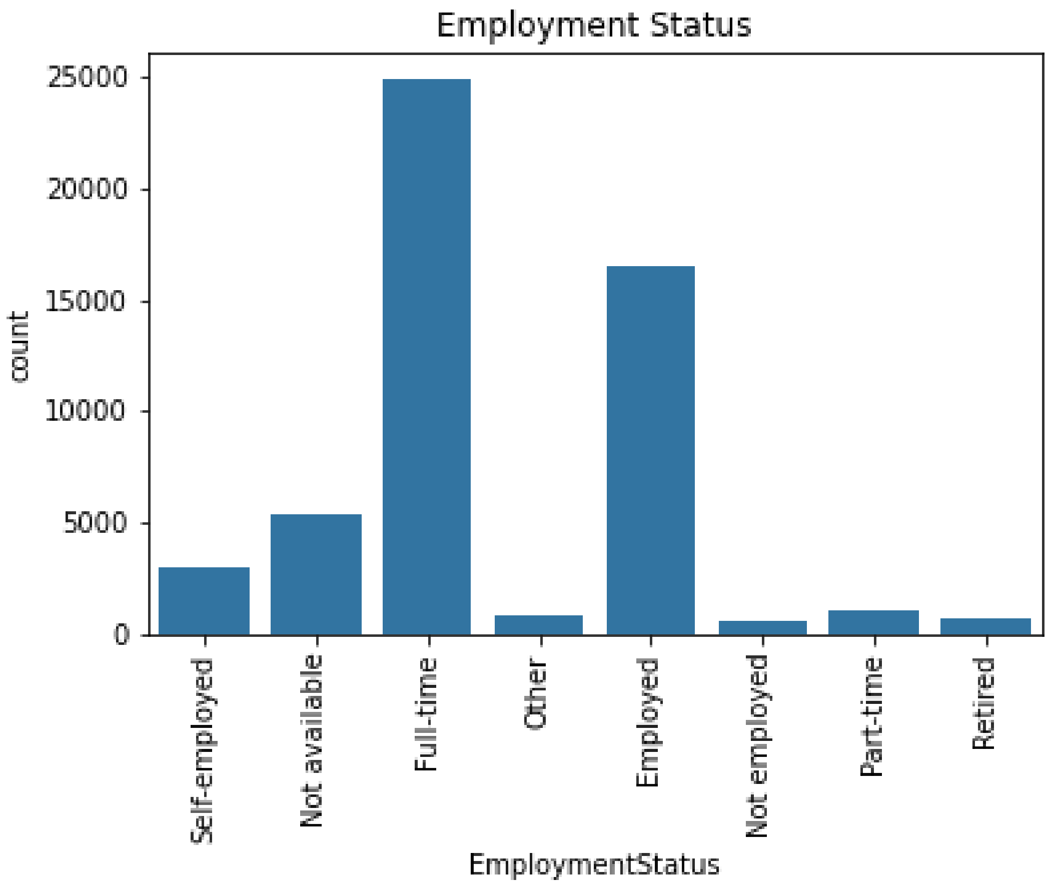
This could mean that for a particular credit rating we have a range of possible estimated returns, let's look into this further in our bivariate visualizations.

1.3.4 Employment Status

As we want to look into the IncomeRange of borrowers, we wanted to check what their employment status is before looking into their income ranges.

```
In [94]: sns.countplot(data = target_df, x = "EmploymentStatus", color = base_color).set(title="
         plt.xticks(rotation = 90)

Out[94]: (array([0, 1, 2, 3, 4, 5, 6, 7]),
          [Text(0, 0, 'Self-employed'),
           Text(1, 0, 'Not available'),
           Text(2, 0, 'Full-time'),
           Text(3, 0, 'Other'),
           Text(4, 0, 'Employed'),
           Text(5, 0, 'Not employed'),
           Text(6, 0, 'Part-time'),
           Text(7, 0, 'Retired')])
```



Not surprisingly, the largest category of borrowers are employed and the largest sub-category of the employed status is full-time. Self-employed makes up the second largest sub-category of the employed status. The "other" category is most likely to be comprised of those falling into a "student" status.

1.3.5 Income Range

Let's continue our exploration by looking at a couple of the underwriting features for borrowers to be assigned these Credit Ratings. We'll start with taking a look at Income Ranges.

In [95]:
```
df.IncomeRange.value_counts()
```

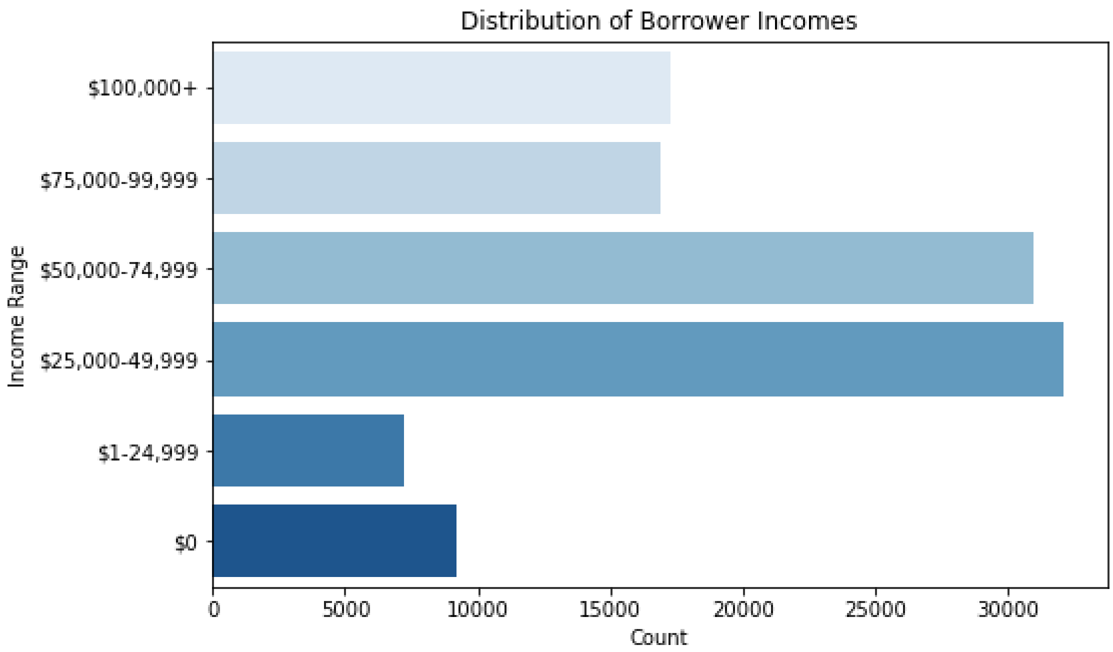
Out[95]:
```
$25,000-49,999    32152
$50,000-74,999    31005
$100,000+         17321
$75,000-99,999    16899
Not displayed      7741
$1-24,999          7261
Not employed        806
$0                  621
Name: IncomeRange, dtype: int64
```

To simplify our visualization, let's combine the "Not employed", "Not displayed", and "$0" categories together.

```
In [96]: df["IncomeRange"].replace(["Not employed", "Not displayed"], "$0", inplace = True)
```

```
In [97]: #Create ordinal categories for income
         ordinal_rating = ["$100,000+", "$75,000-99,999", "$50,000-74,999", "$25,000-49,999", "$
         ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = ordinal_rating
         df["IncomeRange"] = df["IncomeRange"].astype(ordered_var)
```

```
In [98]: #Bar chart
         plt.figure(figsize = [8, 5])
         sns.countplot(data = df, y = "IncomeRange", palette = "Blues")
         plt.ylabel("Income Range")
         plt.xlabel("Count")
         plt.title("Distribution of Borrower Incomes");
```



Its interesting to see that the number of borrowers for the 25k-49k range is the same as the 50k-74k range. The amount of borrowers in the 75k-100k range is the same as all borrowers that have an income of over 100k.

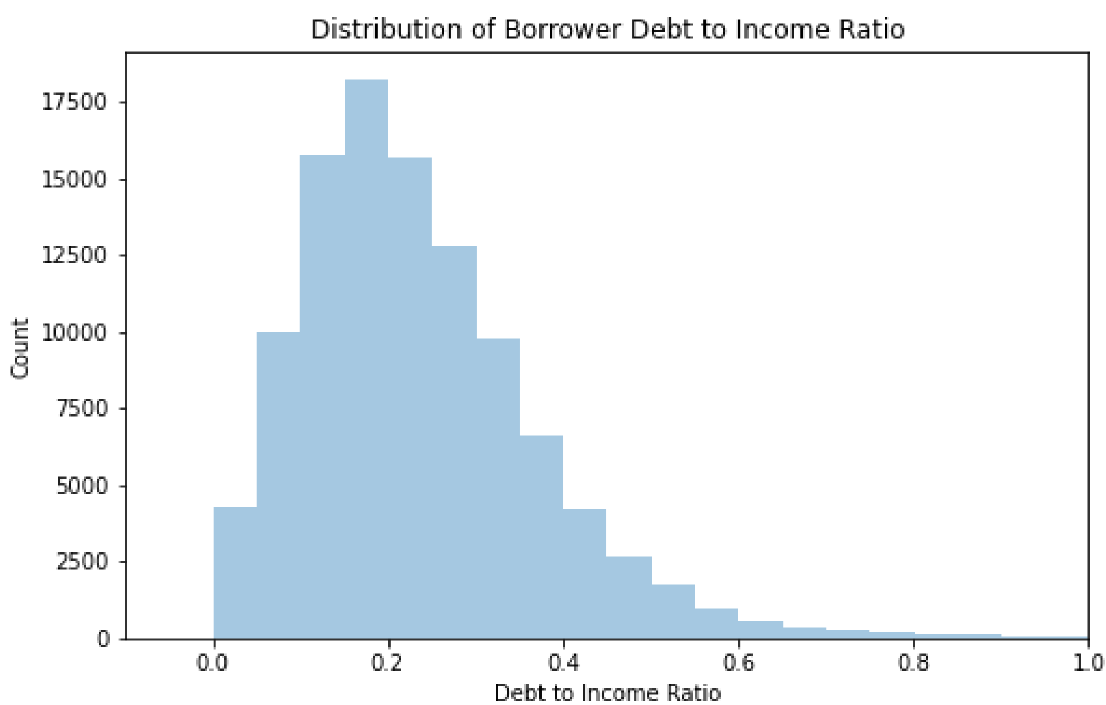
1.3.6 Debt to Income Ratio

Let's see what the borrower's Debt to Income Ratio looks like.

```
In [99]: df.DebtToIncomeRatio.describe()
```

```
Out[99]: count    105263.000000
         mean          0.275976
         std           0.551811
         min           0.000000
         25%           0.140000
         50%           0.220000
         75%           0.320000
         max          10.010000
         Name: DebtToIncomeRatio, dtype: float64
```

```
In [100]: #Distribution plot
          plt.figure(figsize = [8,5])
          sns.distplot(df.DebtToIncomeRatio, kde = False, bins = 200)
          plt.xlim(-.1, 1)
          plt.xlabel("Debt to Income Ratio")
          plt.ylabel("Count")
          plt.title("Distribution of Borrower Debt to Income Ratio");
```



It appears that most borrowers who apply for a loan have a debt to income ratio around 20%.

1.3.7 Discuss the distribution(s) of your variable(s) of interest: Were there any unusual points? Did you need to perform any transformations?

We saw relatively normal distributions for income, debt to income, credit ratings, and estimated returns. However, trying to calculate the real time actual returns proved to be difficult. We may want to revisit this feature if we are trying to answer a particular question about the data set. The majority of borrowers are employed and a majority of those are full-time.

1.3.8 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

We saw that from our simplified actual returns formula, that the values returned vary greatly between different loan statuses.

To tidy up our visualizations, we combined several rows for different visuals where the categories appeared to be redundant. Such as the income ranges of "Not employed" and "Not displayed" are essentially equivalent to "$0". For Credit Ratings, Prosper developed their proprietary system after 2009 which resulted in many missing rows. We combined these features to get a complete Credit Rating feature. We also combined the "High Risk", "No Credit", and "E" categories together.

1.4 Bivariate Exploration

First let's look at the pairwise correlation between the numeric features we're interested in and see if there is any actual relationship between them.

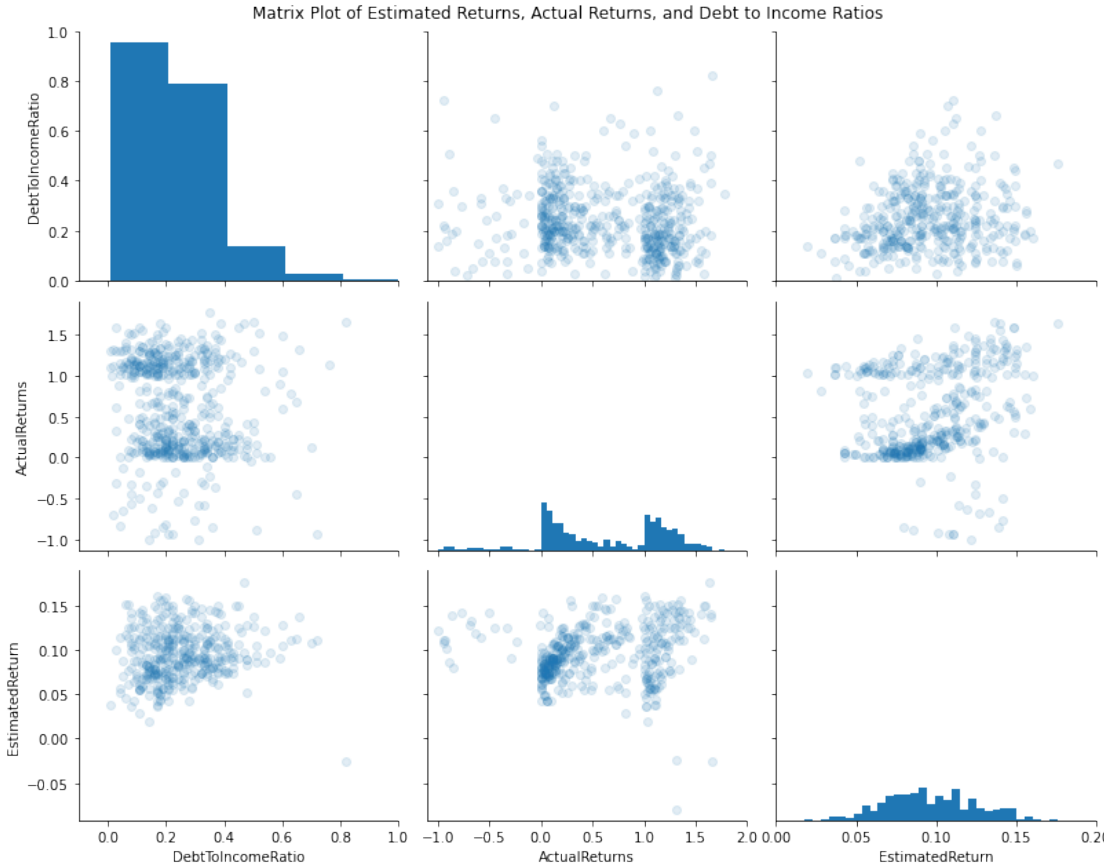
```
In [103]: #Numeric and categorical variables
          numeric_vars = ["DebtToIncomeRatio", "ActualReturns", "EstimatedReturn"]
          categoric_vars = ["IncomeRange", "ProsperRatingCombined"]
```

```
In [104]: #Plot matrix with 0.5% of data points
          samples = np.random.choice(df.shape[0], int(df.shape[0]*.005), replace = False)
          df_samp = df.loc[samples,:]

          #Pair grid
          g = sns.PairGrid(data = df_samp, vars = numeric_vars, size = 3, aspect = 1.25)
          g = g.map_diag(plt.hist, bins = 50)
          g.map_offdiag(plt.scatter, alpha = 1/8)

          #Set axis limits
          g.axes[0,0].set_ylim(0,1)
          g.axes[0,0].set_xlim(-.1,1)
          g.axes[0,1].set_xlim(-1.1,2)
          g.axes[0,2].set_xlim(0,.2)

          g.fig.suptitle("Matrix Plot of Estimated Returns, Actual Returns, and Debt to Income R
          g.fig.subplots_adjust(top = .95);
```



From the univariate exploration, we have a good undertanding regarding the range of values we can expect. By limiting the axis values, we are able to prevent outliers from skewing the plot. Otherwise, most of the points will appear to be grouped in a vertical line.

Surprisingly, there doesn't appear to be any correlation between the estimated returns and the actual returns we calculated. We may have to investigate further by querying select categories of loan status.

There doesn't appear to be a correlation between any of the other numeric variables either.

1.4.1 Income Range and Credit Rating vs Estimated Returns

Let's take a look at how a borrower's income range and credit rating relates to the investor's estimated returns.

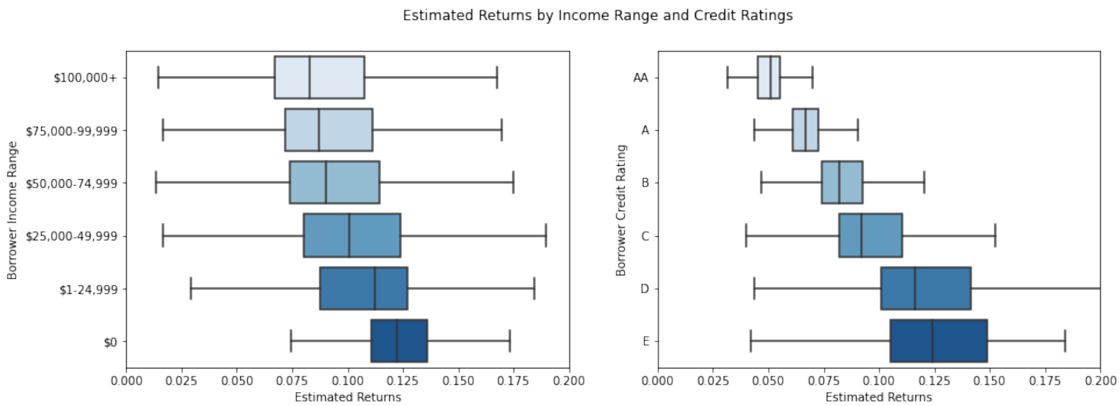
In [105]:
```
#Boxplots
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
base_color = sns.color_palette()[0]
sns.boxplot(data = df, y = "IncomeRange", x = "EstimatedReturn", palette = "Blues", sh
plt.xlim(0,.2)
plt.ylabel("Borrower Income Range")
```

```
plt.xlabel("Estimated Returns")

plt.subplot(1, 2, 2)
base_color = sns.color_palette()[0]
sns.boxplot(data = df, y = "ProsperRatingCombined", x = "EstimatedReturn", palette = "
plt.xlim(0,.2)
plt.ylabel("Borrower Credit Rating")
plt.xlabel("Estimated Returns")

plt.suptitle("Estimated Returns by Income Range and Credit Ratings");
```



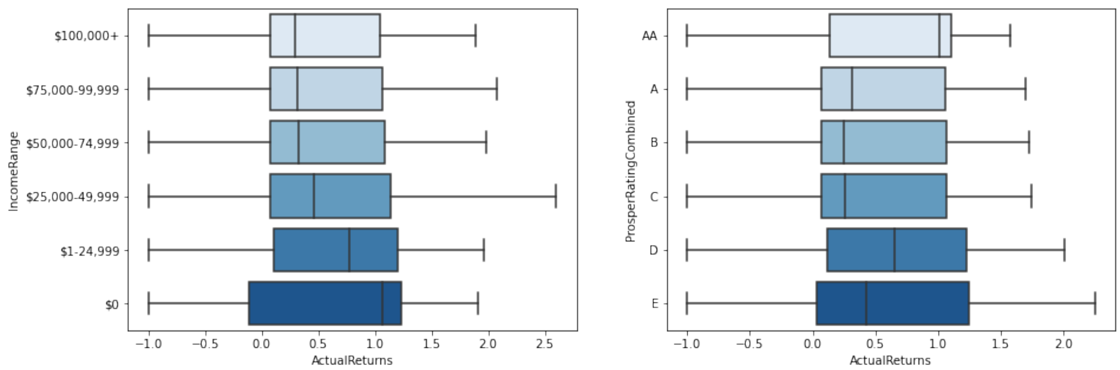
From these boxplot, we're able to clearly see that as the borrowers income increases, the median estimated return decreases. The credit rating boxplot shows the trend more clearly, as a borrowers credit rating increases, the median estimated return greatly decreases.

Next let's plot the actual returns.

In [106]:
```
#Boxplots
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
base_color = sns.color_palette()[0]
sns.boxplot(data = df, y = "IncomeRange", x = "ActualReturns", palette = "Blues", show

plt.subplot(1, 2, 2)
base_color = sns.color_palette()[0]
sns.boxplot(data = df, y = "ProsperRatingCombined", x = "ActualReturns", palette = "Bl
```

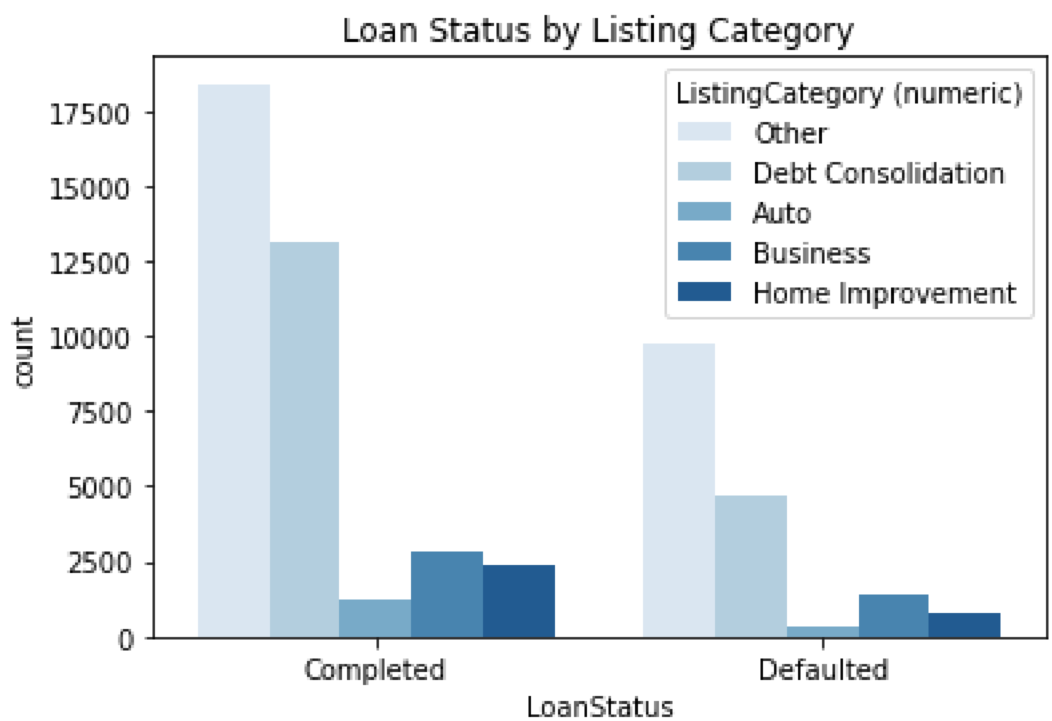


This plot is quite interesting as it suggests that investing in borrowers with no reported income and the highest credit ratings will produce the highest returns.

1.4.2 Credit Start with Listing Category

```
In [107]: sns.countplot(data = target_df, x = "LoanStatus", hue = "ListingCategory (numeric)", p
```

```
Out[107]: [Text(0.5, 1.0, 'Loan Status by Listing Category')]
```



Observation 2

- In both of the graphs, the debt consolidation is the most frequent in the defaulted and completed categories

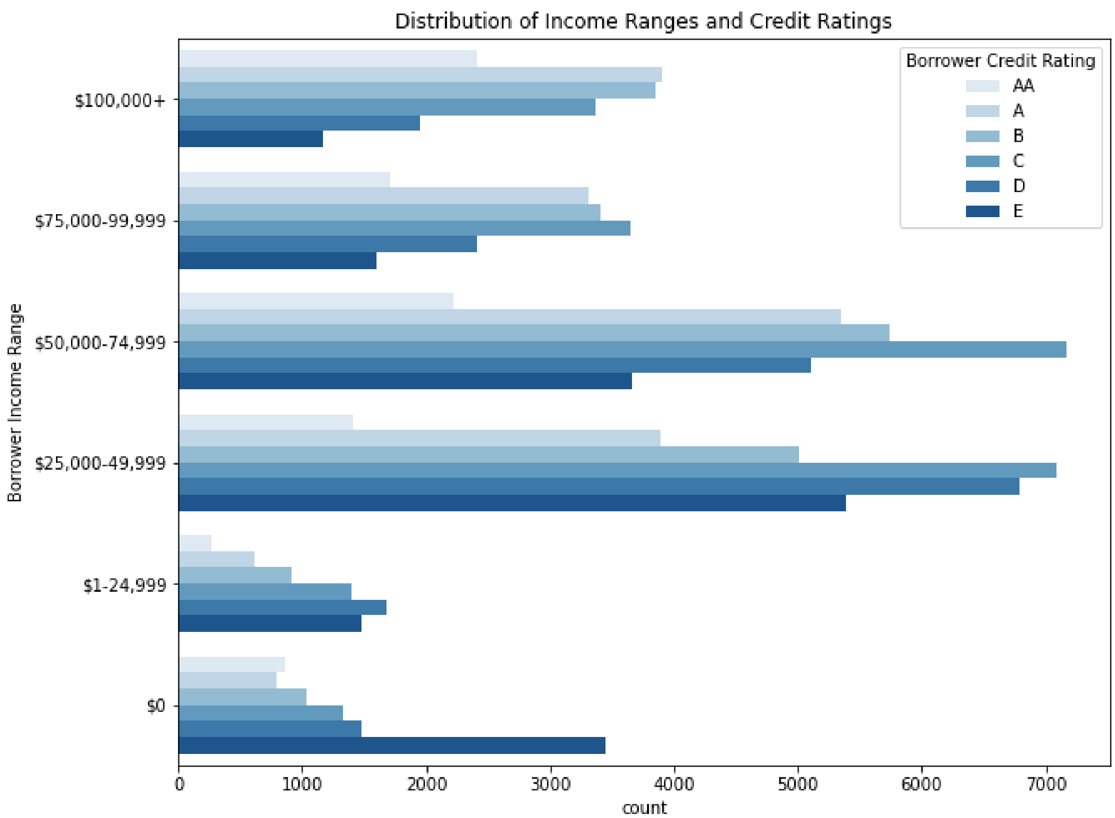
1.4.3 Credit Score VS Income Range

Let's plot the credit score along with the income range to see if there is any correlation there.

```
In [108]: #Clustered bar chart
          plt.figure(figsize = [10,8])

          ax = sns.countplot(data = df, y = "IncomeRange", hue = "ProsperRatingCombined",
                             palette = 'Blues')

          ax.legend(title = "Borrower Credit Rating")
          plt.title("Distribution of Income Ranges and Credit Ratings")
          plt.ylabel("Borrower Income Range");
```



From this clustered bar chart, we can see the trend of higher incomes correlate to a higher credit rating qualifying the borrower for the best (lowest) interest rates.

Having an income of $75k+ doesn't automatically guarantee the best credit ratings, which is curious to see. Perhaps we can see what other factors play a big role in determining one's credit rating later on.

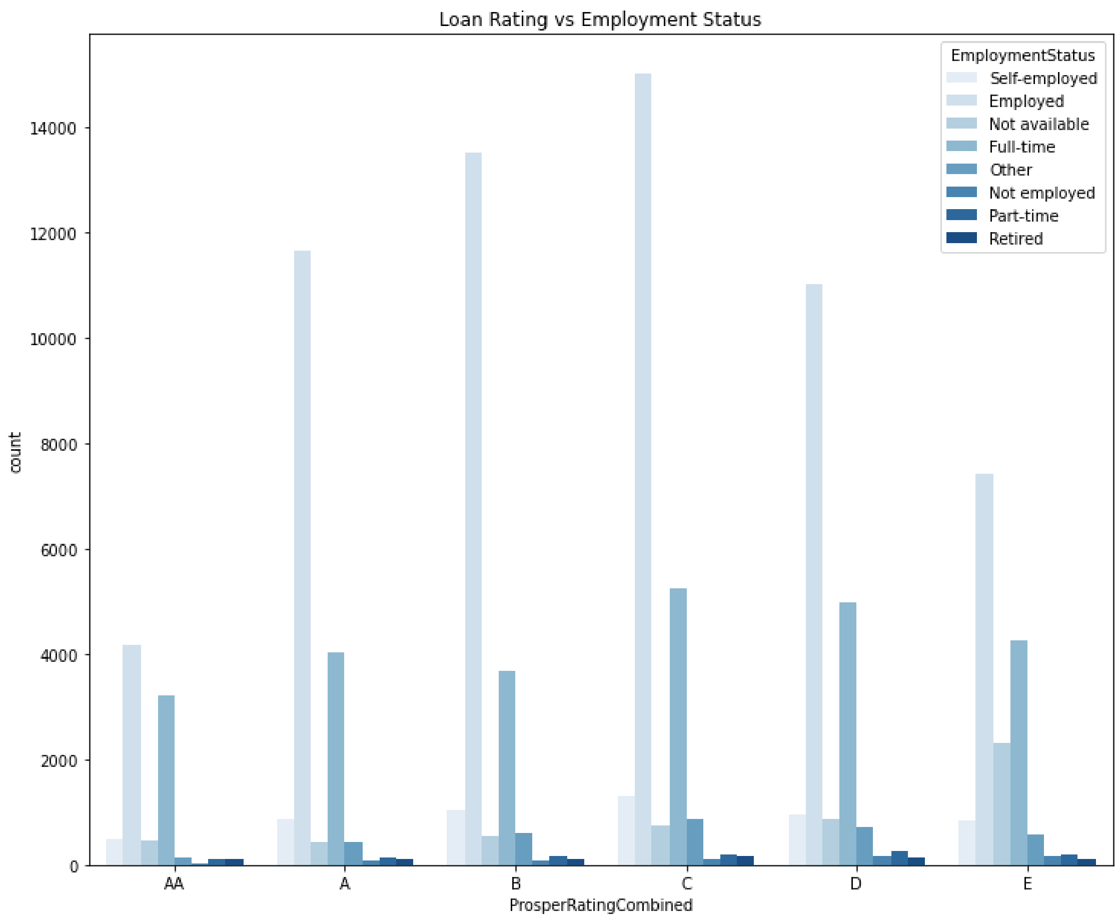
Conversely, it also appears that in the 0 income range, there are a high amount of "AA" loans relative to the 1k-25k income range.

1.4.4 Prosper Rating and Employment Status

Let's see if there is a relationship between the Prosper Rating and the Employment Status.

```
In [109]: plt.figure(figsize = [12, 10])
          sns.countplot(data = df, x = "ProsperRatingCombined", hue = "EmploymentStatus", palett
```

```
Out[109]: [Text(0.5, 1.0, 'Loan Rating vs Employment Status')]
```



Lower ratings seem to have greater proportions of individuals who selected the "Not Employed", "Self-Employed", "Retired", and "Part-Time" employment categories/sub-categories

1.5 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset? Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

From our matrix plot, our numerical features of interest did not reveal any correlation. It was surprising to see that there was no correlation between debt to income ratios, estimated returns, and actual returns.

From our box plots, we saw a trend of median estimated returns decrease as the borrowers income range increased. This makes intuitive sense as borrowers with a higher income can demand the most competetive rates from creditors. The overlap in our boxplot suggests that borrowers in any income range (except 0) can produce the same estimated return for an investor. The trend between lower estimated returns and higher credit ratings was much more apparent with narrowing quartiles and lower medians.

The box plot for the actual returns revealed additional tweaking or grouping will be necessary to produce any insights.

From our clustered bar chart, we peeled back another layer to look at credit ratings and income ranges. This revealed that the previous trend of high income equating to better credit ratings, however there are some interesting cases where a high number of borrowers with no income qualified for the highest credit ratings. Also, we saw that borrowers with incomes of greater than 75k can still be considered "High Risk" borrowers.

EmploymentStatus of indiviuals with lower rated loans seemed to have selected the "Not Employed", "Self-Employed", "Retired", or "Part-Time" employment categories/sub-categories.

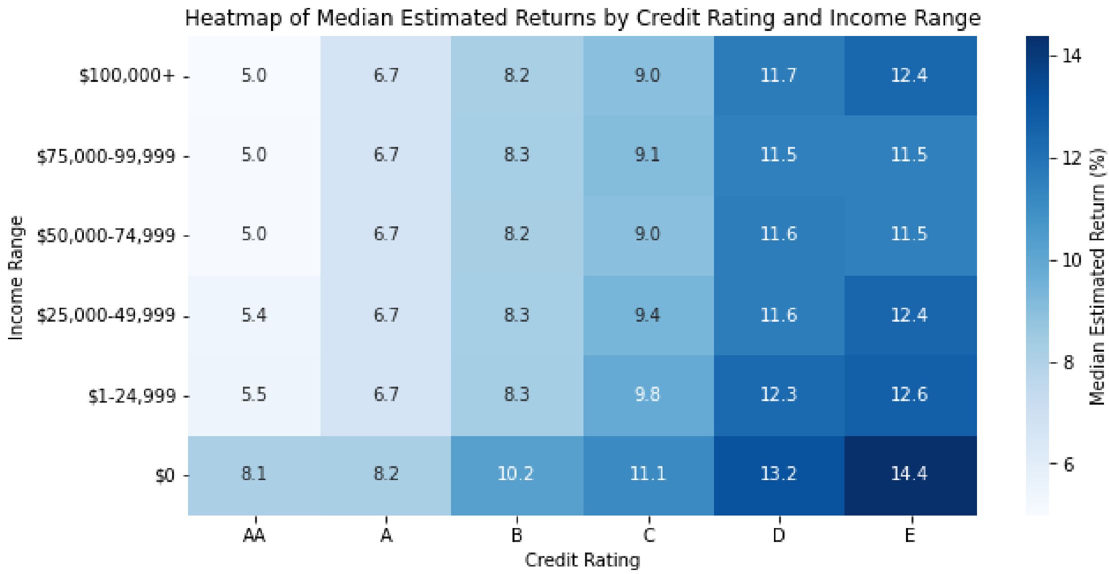
1.6 Multivariate Exploration

The main thing we want to explore in the multivariate exploration is the relationship between income ranges, credit scores, and estimated returns, but we may also compare other data points that come from questions pertaining to this portion of the exploration.

```
In [110]: #Create a heat map of average estimated returnsb
          plt.figure(figsize = [10,5])

          cat_med = df.groupby(["ProsperRatingCombined", "IncomeRange"]).median()["EstimatedRetu
          cat_med = cat_med.reset_index(name = "EstimatedReturnMedian")
          cat_med = cat_med.pivot(index = "IncomeRange", columns = "ProsperRatingCombined", valu

          sns.heatmap(cat_med, annot = True, fmt = ".1f", cmap = "Blues", cbar_kws = {"label" :
          plt.xlabel("Credit Rating")
          plt.ylabel("Income Range")
          plt.title("Heatmap of Median Estimated Returns by Credit Rating and Income Range");
```



From the heat map we continue to see the trend of lower credit ratings, and lower incomes equate to higher returns. It's interesting to see that the income range does not play a big influence on the estimated returns by credit rating category.

Across the credit ratings "AA", "A", and "B", we observe no difference in the rate of return for income ranges 1k-100k+. However, there is a definite jump in returns for the 0 income range across all credit rating categories.

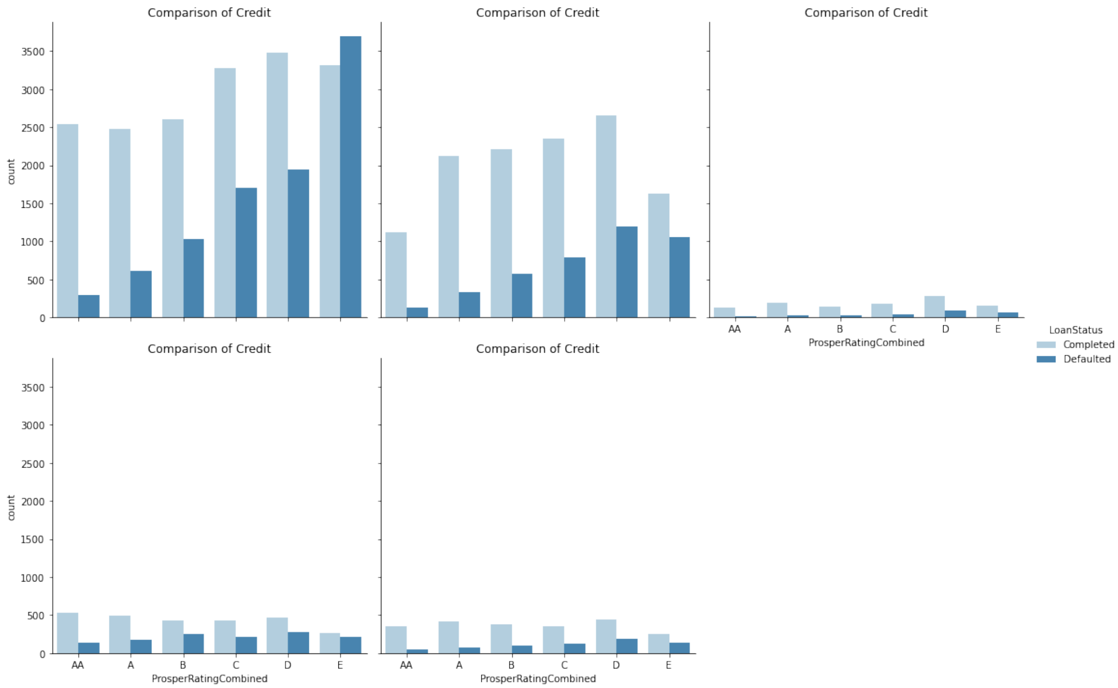
Across the credit ratings "C", "D", and "E", we notice a bit more variability however the median return is still within +- 1% (except the 0 category).

1.6.1 Relationships between Credit Category, Credit Rating, and Loan Outcome

Let's see if there is a relationship between the credit category, rating, and the outcome.

```
In [111]: sns.catplot(x = "ProsperRatingCombined", hue = "LoanStatus", col = "ListingCategory (n
                      data = target_df, kind = "count", palette = "Blues", col_wrap = 3).set(tit
```

```
Out[111]: <seaborn.axisgrid.FacetGrid at 0x242316ff6a0>
```

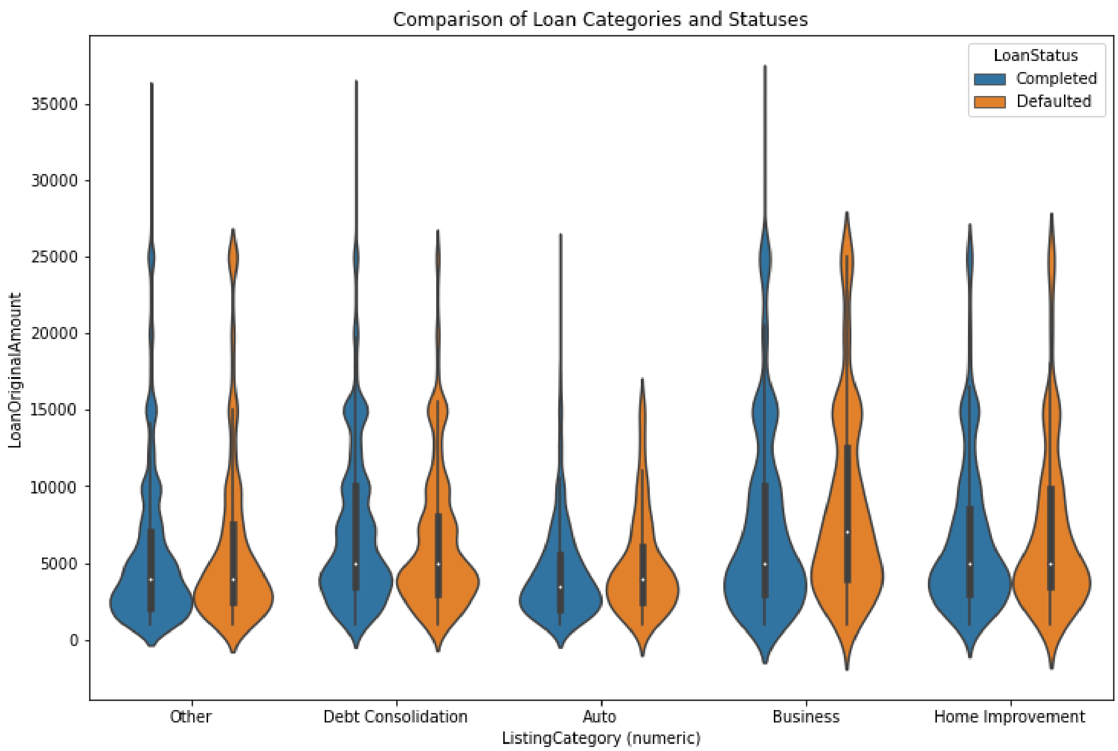


There is no substantial difference for defaulted laons in different categories when broken up by the ratings.

1.7 Amount, Listing Category Loan, and Loan Status Impact

In [112]:
```
plt.figure(figsize = [12, 8])
sns.violinplot(data = target_df, x = "ListingCategory (numeric)", y = "LoanOriginalAmo
```

Out[112]:
```
[Text(0.5, 1.0, 'Comparison of Loan Categories and Statuses')]
```



Except for Auto, the Business and Home Improvement categories don't have equal means between the loan statuses. The business category seems to have a larger amount of loans distributed and Debt Consolidation loans come in second to the Business category.

1.8 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest Were there any interesting or surprising interactions between features?

Our initial assumptions were strengthed. Most of the defaulted loans comes from individuals with low Prosper ratings and the Business category had the largest amount of loans. We simplified the plots a bit by only looking at three loan statuses: Completed, Current, and Defaulted.

For loans that are defaulted, there doesn't appear to be any correlation between the predicted estimated return and the actual return of the loan.

For loans that are current, there appears to be a linear relationship between the estimated and actual returns! Recall that during our bivariate exploration we were unable to see the trend as all of the loan status were lumped together.

It was interesting to find that defaulted loans for individuals with high Prosper ratings tended to be larger than completed loans.