Peer-graded Assignment: "On-time" Loan Status versus "Risky" Loan Status

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Project Description

Having investigated how characteristics of the applicant and loan application vary for both loans with “On Time” status and loans with “Risky” status, which of these factors appear to be more strongly associated with Risky loans compared to On Time loans? In your discussion, be sure to provide evidence of how you arrived at your conclusions. This may include tables of summary statistics (such as the mean and standard deviation) or visual comparisons between On Time and Risky loans.

Data Dictionary

Field	Description
annual_inc	The self-reported annual income provided by the borrower during registration, in $1000s
application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers
collections_12_mths_ex_med	Number of collections in 12 months excluding medical collections
delinq_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
dti	A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.
home_ownership	The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER.
inq_last_6mths	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)
loan_status	Current status of the loan
open_acc	The number of open credit lines in the borrower's credit file.
pub_rec	Number of derogatory public records
term	The number of payments on the loan. Values are in months and can be either 36 or 60.

Field	Description
verification_status	Indicates if income was verified by LC, not verified, or if the income source was verified

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Discussion from analysis

- Risky Group has annual lower income, higher delinquency and more inquires made
- Majority borrowers are indivduals to service their home mortgages, 36 months is preferred
- There is a slightly higher non-verified income applicants which may pose a loan risk

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Import Libraries

In [1]:
```
import numpy as np
from numpy import count_nonzero, median, mean
import pandas as pd
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import random


import datetime
from datetime import datetime, timedelta, date


#import os
#import zipfile
import scipy
from scipy import stats
from scipy.stats.mstats import normaltest # D'Agostino K^2 Test
from scipy.stats import boxcox
from collections import Counter


%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)
#sns.set(rc={'figure.figsize':(14,10)})

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)
```

```
import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows',None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

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Import Data

In [2]:
```
df = pd.read_csv("calibdata.csv", low_memory=False)
```

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Data Quick Glance

In [3]:
```
df.head()
```

Out[3]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowner
0	205.00	INDIVIDUAL	0	0	2	28	23.72	0	MORTGAGE
1	36.00	INDIVIDUAL	0	0	0	8	22.77	0	RENT
2	48.00	INDIVIDUAL	0	0	1	10	13.68	0	RENT
3	40.00	INDIVIDUAL	0	0	0	11	8.37	0	MORTGAGE
4	83.00	INDIVIDUAL	0	0	0	18	23.50	0	RENT

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49986 entries, 0 to 49985
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   annualinc    49986 non-null  float64
 1   applytype    49986 non-null  object 
 2   collections  49986 non-null  int64  
 3   delinq       49986 non-null  int64  
 4   inq          49986 non-null  int64  
 5   openacc      49986 non-null  int64  
 6   dti          49986 non-null  float64
 7   pubrec       49986 non-null  int64  
 8   homeowner    49986 non-null  object 
 9   term         49986 non-null  object 
 10  vstatus      49986 non-null  object 
 11  lstatus      49986 non-null  object 
dtypes: float64(2), int64(5), object(5)
memory usage: 4.6+ MB
```

In [5]:
```
df.dtypes.value_counts()
```

Out[5]:
```
object     5
int64      5
float64    2
dtype: int64
```

In [6]:
```
# Descriptive Statistical Analysis
df.describe(include="all")
```

Out[6]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubr
count	49986.00	49986	49986.00	49986.00	49986.00	49986.00	49986.00	49986.0
unique	NaN	2	NaN	NaN	NaN	NaN	NaN	Na
top	NaN	INDIVIDUAL	NaN	NaN	NaN	NaN	NaN	Na
freq	NaN	49958	NaN	NaN	NaN	NaN	NaN	Na
mean	76.31	NaN	0.01	0.32	0.70	11.59	17.99	0.1
std	62.81	NaN	0.13	0.87	1.01	5.29	8.22	0.6
min	6.00	NaN	0.00	0.00	0.00	1.00	0.00	0.0
25%	47.00	NaN	0.00	0.00	0.00	8.00	11.83	0.0
50%	65.00	NaN	0.00	0.00	0.00	11.00	17.53	0.0
75%	90.00	NaN	0.00	0.00	1.00	14.00	23.66	0.0
max	8253.00	NaN	5.00	27.00	33.00	58.00	39.99	63.0

In [7]:
```
# Descriptive Statistical Analysis
df.describe(include=["int", "float"])
```

Out[7]:

	annualinc	collections	delinq	inq	openacc	dti	pubrec
count	49986.00	49986.00	49986.00	49986.00	49986.00	49986.00	49986.00
mean	76.31	0.01	0.32	0.70	11.59	17.99	0.19
std	62.81	0.13	0.87	1.01	5.29	8.22	0.67
min	6.00	0.00	0.00	0.00	1.00	0.00	0.00
25%	47.00	0.00	0.00	0.00	8.00	11.83	0.00
50%	65.00	0.00	0.00	0.00	11.00	17.53	0.00
75%	90.00	0.00	0.00	1.00	14.00	23.66	0.00
max	8253.00	5.00	27.00	33.00	58.00	39.99	63.00

In [8]:
```
# Descriptive Statistical Analysis
df.describe(include="object")
```

Out[8]:

	applytype	homeowner	term	vstatus	lstatus
count	49986	49986	49986	49986	49986
unique	2	5	2	3	2
top	INDIVIDUAL	MORTGAGE	36 months	Source Verified	On Time
freq	49958	24993	34857	18876	46551

In [9]:
```
df.columns
```

Out[9]:
```
Index(['annualinc', 'applytype', 'collections', 'delinq', 'inq', 'openacc', 'dti',
'pubrec', 'homeowner', 'term', 'vstatus', 'lstatus'], dtype='object')
```

In [10]:
```
df.shape
```

Out[10]:
```
(49986, 12)
```

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
annualinc      0
applytype      0
collections    0
delinq         0
inq            0
openacc        0
dti            0
pubrec         0
homeowner      0
term           0
vstatus        0
lstatus        0
dtype: int64
```

In [12]:
```
df.duplicated().sum()
```

Out[12]: 0

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Exploratory Data Analysis

Exploratory Data Analysis (EDA) is the crucial process of using summary statistics and graphical representations to perform preliminary investigations on data to uncover patterns, detect anomalies, test hypotheses, and verify assumptions.

Sample a smaller dataset

In [13]:
```
df = df.sample(frac=0.2)
```

In [14]:
```
df
```

Out[14]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowı
23833	50.00	INDIVIDUAL	0	0	0	7	16.83	0	MORTGA
27452	68.00	INDIVIDUAL	0	0	1	12	16.01	0	RE
10983	80.00	INDIVIDUAL	0	0	0	12	20.28	0	RE
10021	62.00	INDIVIDUAL	0	0	0	8	17.50	0	MORTGA
24450	97.30	INDIVIDUAL	0	0	1	10	12.14	0	RE
...	...	...	...	...	...	...	...	...	
47673	54.00	INDIVIDUAL	0	0	0	7	3.42	0	RE
5524	73.00	INDIVIDUAL	0	0	1	17	24.53	0	RE
19369	25.00	INDIVIDUAL	0	0	0	9	24.24	0	RE
46979	65.00	INDIVIDUAL	0	0	0	6	15.19	0	RE
28733	120.00	INDIVIDUAL	0	0	0	12	18.25	0	MORTGA

9997 rows × 12 columns

In [15]:
```
df.reset_index(drop=True, inplace=True)
```

In [16]:
```
df
```

Out[16]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowne
0	50.00	INDIVIDUAL	0	0	0	7	16.83	0	MORTGAG
1	68.00	INDIVIDUAL	0	0	1	12	16.01	0	REN
2	80.00	INDIVIDUAL	0	0	0	12	20.28	0	REN
3	62.00	INDIVIDUAL	0	0	0	8	17.50	0	MORTGAG
4	97.30	INDIVIDUAL	0	0	1	10	12.14	0	REN
...	...	...	...	...	...	...	...	...	
9992	54.00	INDIVIDUAL	0	0	0	7	3.42	0	REN
9993	73.00	INDIVIDUAL	0	0	1	17	24.53	0	REN
9994	25.00	INDIVIDUAL	0	0	0	9	24.24	0	REN
9995	65.00	INDIVIDUAL	0	0	0	6	15.19	0	REN
9996	120.00	INDIVIDUAL	0	0	0	12	18.25	0	MORTGAG

9997 rows × 12 columns

In [17]:
```
df.shape
```

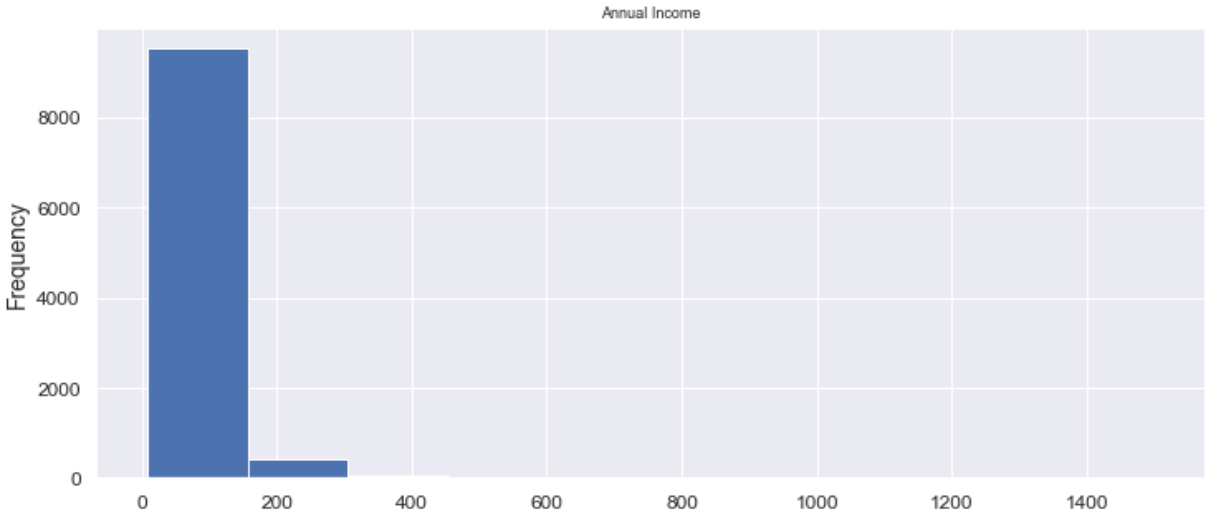
Out[17]:
```
(9997, 12)
```

In [18]:
```
df.sort_values(by = "lstatus", ascending=True).head()
```

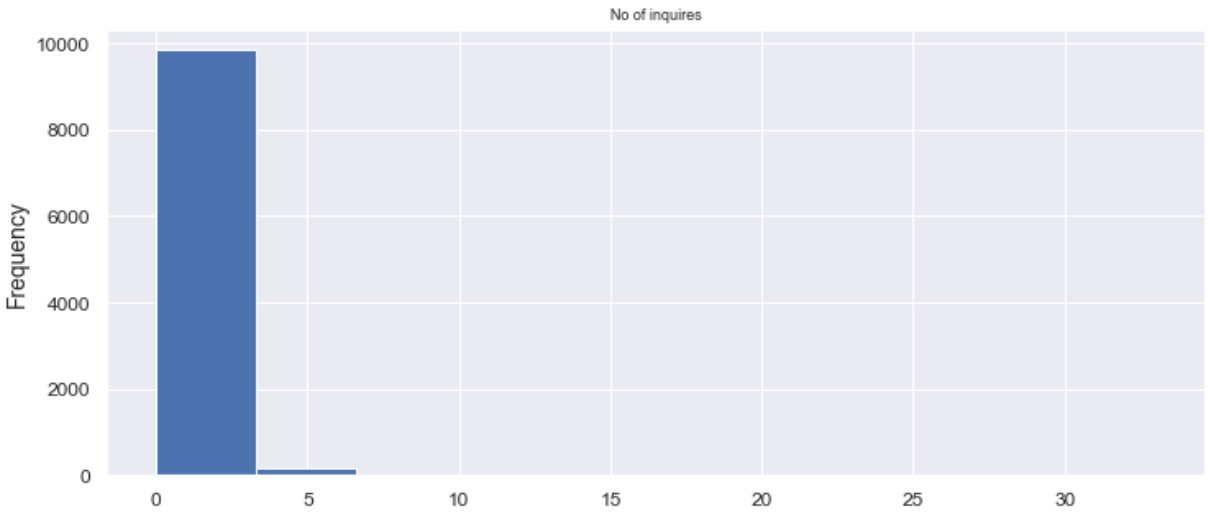
Out[18]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowne
0	50.00	INDIVIDUAL	0	0	0	7	16.83	0	MORTGAG
6519	42.00	INDIVIDUAL	0	4	0	5	7.74	0	MORTGAG
6520	45.00	INDIVIDUAL	0	0	1	7	8.93	0	OW
6521	160.00	INDIVIDUAL	0	0	3	8	12.54	0	MORTGAG
6522	40.00	INDIVIDUAL	0	0	1	13	39.23	0	REN

In [19]:
```
df.annualinc.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="Annual Inc
plt.show()
```



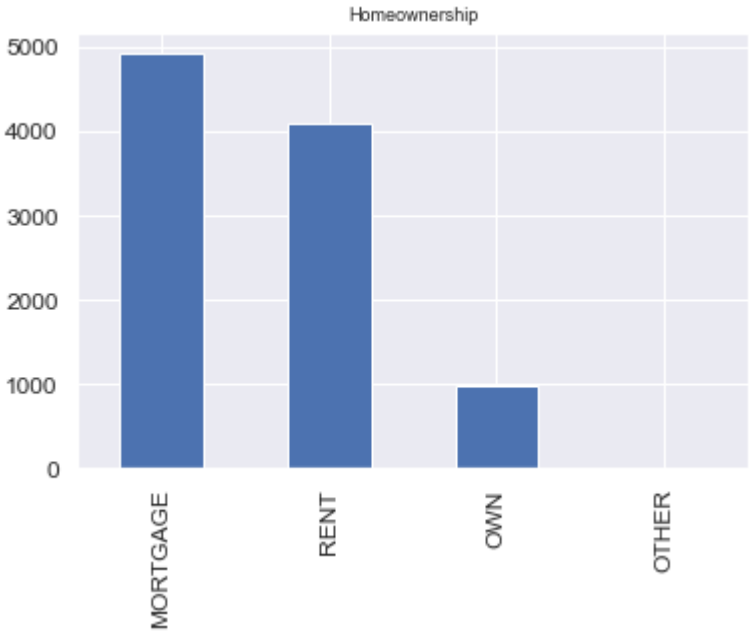
In [20]:
```
df.inq.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="No of inquires")
plt.show()
```



In [21]:
```
df.lstatus.value_counts().sort_values(ascending=False)
```

Out[21]:
```
On Time    9304
Risky       693
Name: lstatus, dtype: int64
```

In [22]:
```
df.homeowner.value_counts().nlargest(10).plot(kind="bar")
plt.title("Homeownership")
plt.show()
```



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Groupby

Most commonly, we use `groupby()` to split the data into groups,this will apply some function to each of the groups (e.g. mean, median, min, max, count), then combine the results into a data structure. For example, let's select the 'VALUE' column and calculate the mean of the gasoline prices per year. First, we specify the 'Year" column, following by the 'VALUE' column, and the `mean()` function.

In [23]:
```
df.columns
```

Out[23]:
```
Index(['annualinc', 'applytype', 'collections', 'delinq', 'inq', 'openacc', 'dti',
'pubrec', 'homeowner', 'term', 'vstatus', 'lstatus'], dtype='object')
```

In [24]:
```
df.groupby(["lstatus"], as_index=True).mean()
```

Out[24]:

lstatus	annualinc	collections	delinq	inq	openacc	dti	pubrec
On Time	76.68	0.01	0.30	0.67	11.64	18.06	0.18
Risky	66.73	0.01	0.36	1.03	11.31	18.44	0.15

In [25]:
```
df.groupby(["lstatus"], as_index=True).median()
```

Out[25]:

lstatus	annualinc	collections	delinq	inq	openacc	dti	pubrec
On Time	65.00	0.00	0.00	0.00	11.00	17.59	0.00
Risky	55.62	0.00	0.00	1.00	11.00	18.00	0.00

Different Aggregates for Different Columns

In [26]:
```
df.groupby(["lstatus"], as_index=False).agg(
    {"annualinc": [np.min,np.median,np.max], "delinq": [np.min,np.median,np.max]})
```

Out[26]:

	lstatus	annualinc			delinq		
		amin	median	amax	amin	median	amax
0	On Time	7.00	65.00	1500.00	0	0.00	12
1	Risky	13.20	55.62	275.00	0	0.00	6

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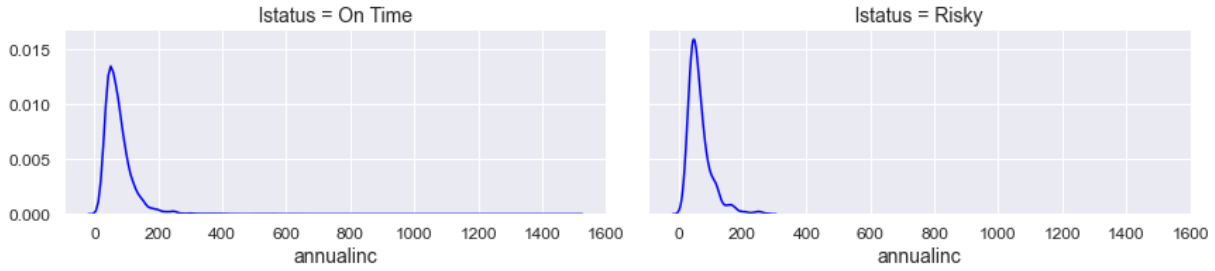
Data Visualization

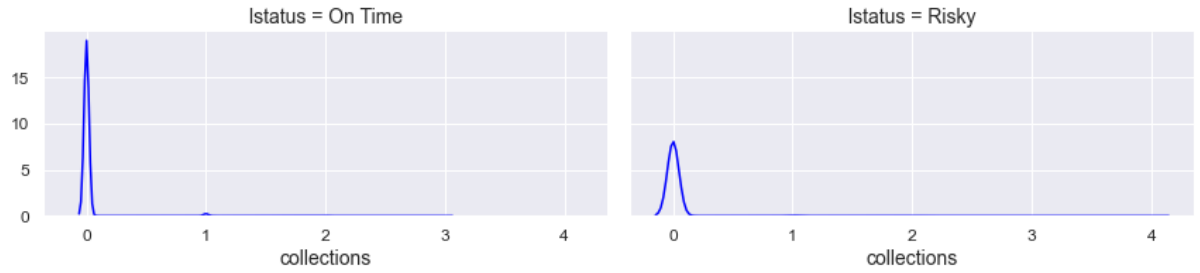
In [27]:
```
df.columns
```

Out[27]:
```
Index(['annualinc', 'applytype', 'collections', 'delinq', 'inq', 'openacc', 'dti',
'pubrec', 'homeowner', 'term', 'vstatus', 'lstatus'], dtype='object')
```

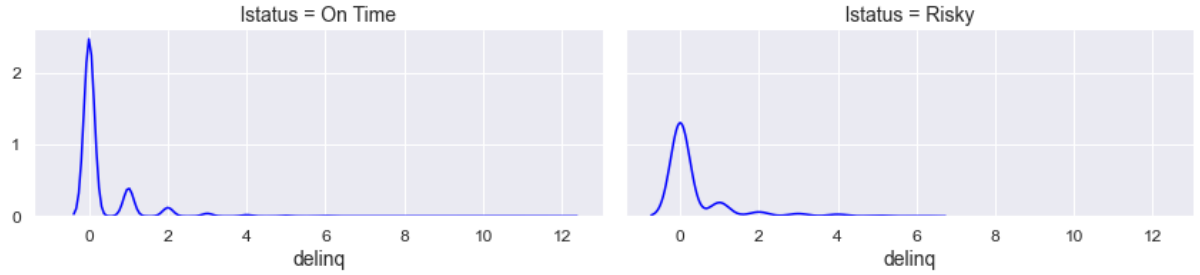
In [28]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "annualinc", color="blue")
g.add_legend()
plt.show()
```



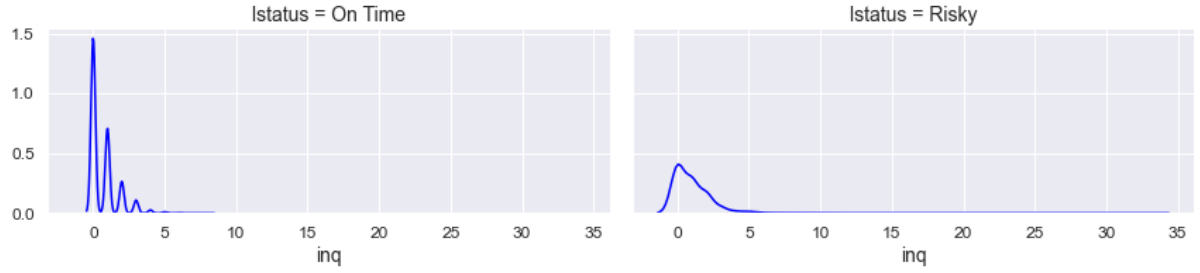
In [29]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "collections", color="blue")
g.add_legend()
plt.show()
```



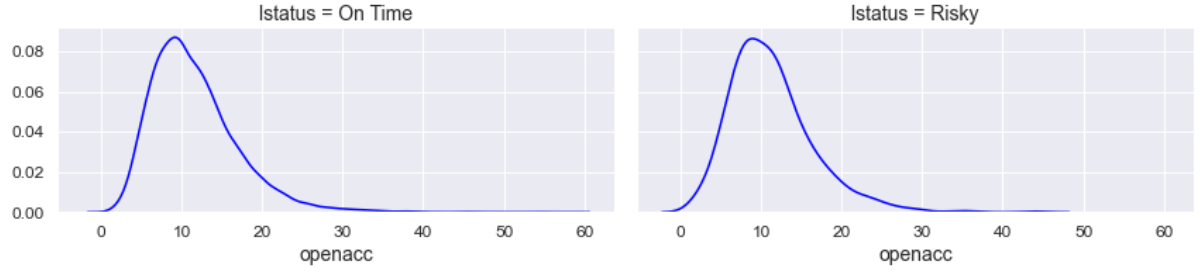
In [30]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "delinq", color="blue")
g.add_legend()
plt.show()
```



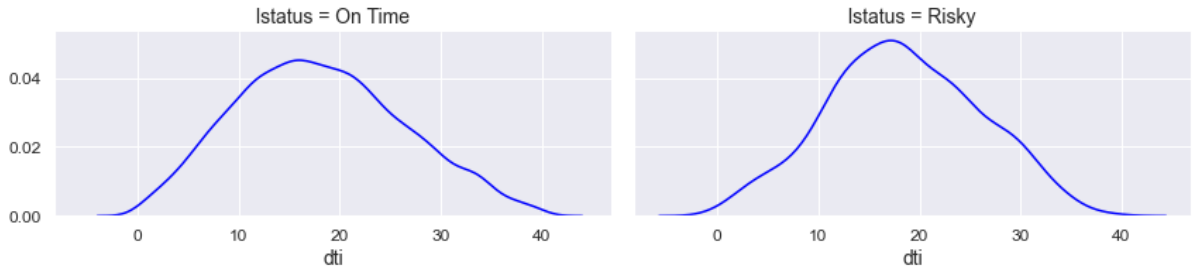
In [31]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "inq", color="blue")
g.add_legend()
plt.show()
```



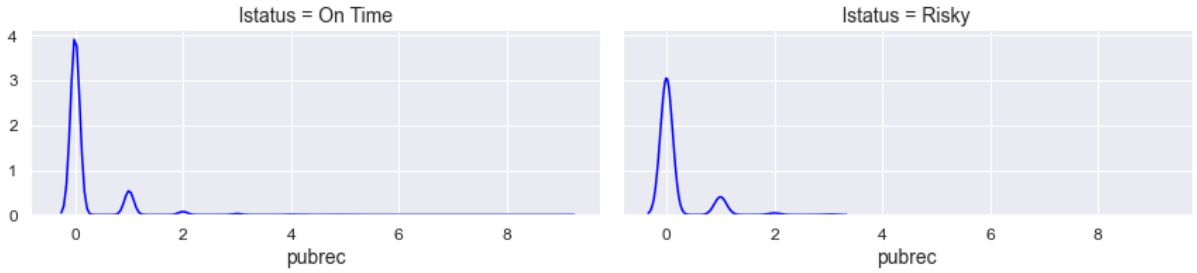
In [32]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "openacc", color="blue")
g.add_legend()
plt.show()
```



In [33]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "dti", color="blue")
g.add_legend()
plt.show()
```



In [34]:
```
g = sns.FacetGrid(data=df, col="lstatus", hue=None, col_wrap=2, height=3, aspect=2,
g.map(sns.kdeplot, "pubrec", color="blue")
g.add_legend()
plt.show()
```



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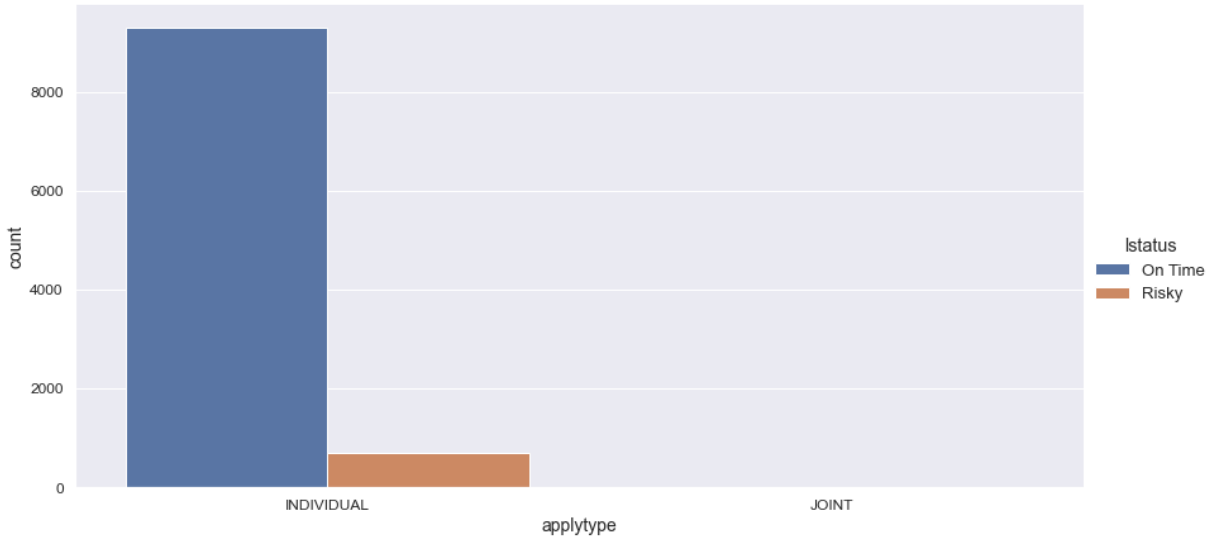
Bar Plots

In [35]:
```
df.head(1)
```

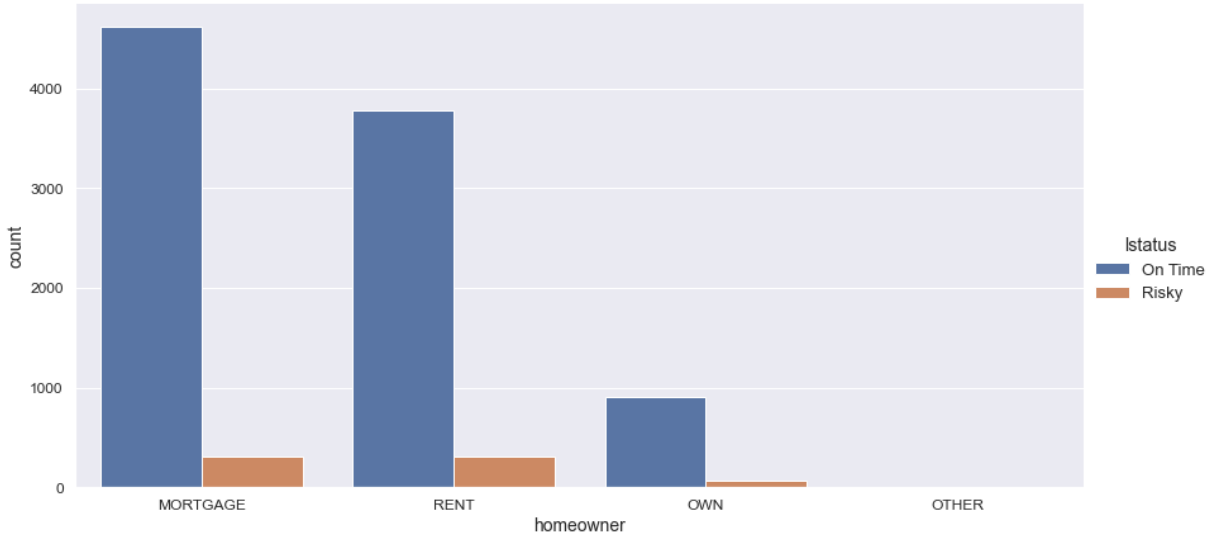
Out[35]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowner
0	50.00	INDIVIDUAL	0	0	0	7	16.83	0	MORTGAGE

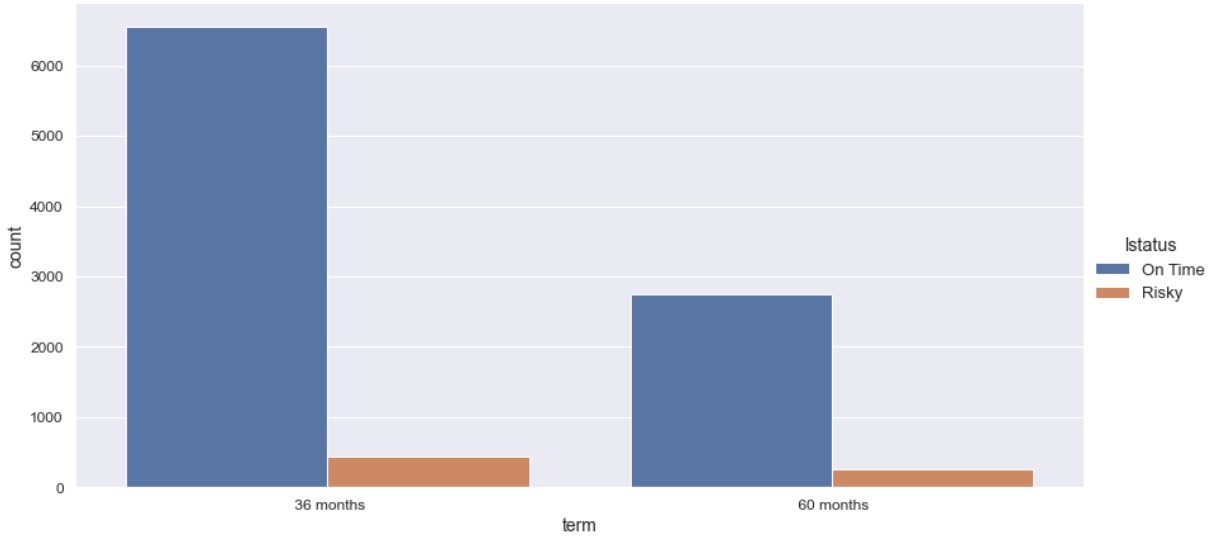
In [36]:
```
sns.catplot(x="applytype",  kind='count', data=df, hue ='lstatus', aspect=2, height
plt.show()
```



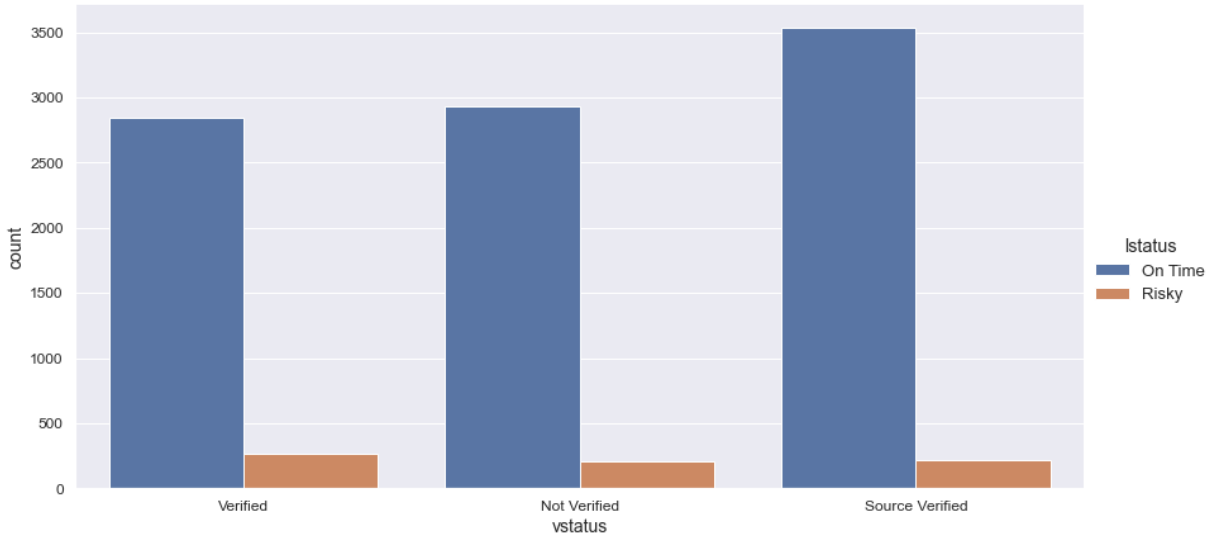
In [37]:
```
sns.catplot(x="homeowner",  kind='count', data=df, hue ='lstatus', aspect=2, height
plt.show()
```



In [38]:
```
sns.catplot(x="term",  kind='count', data=df, hue ='lstatus', aspect=2, height=6)
plt.show()
```



In [39]:
```
sns.catplot(x="vstatus",  kind='count', data=df, hue ='lstatus', aspect=2, height=6
plt.show()
```



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Heatmap

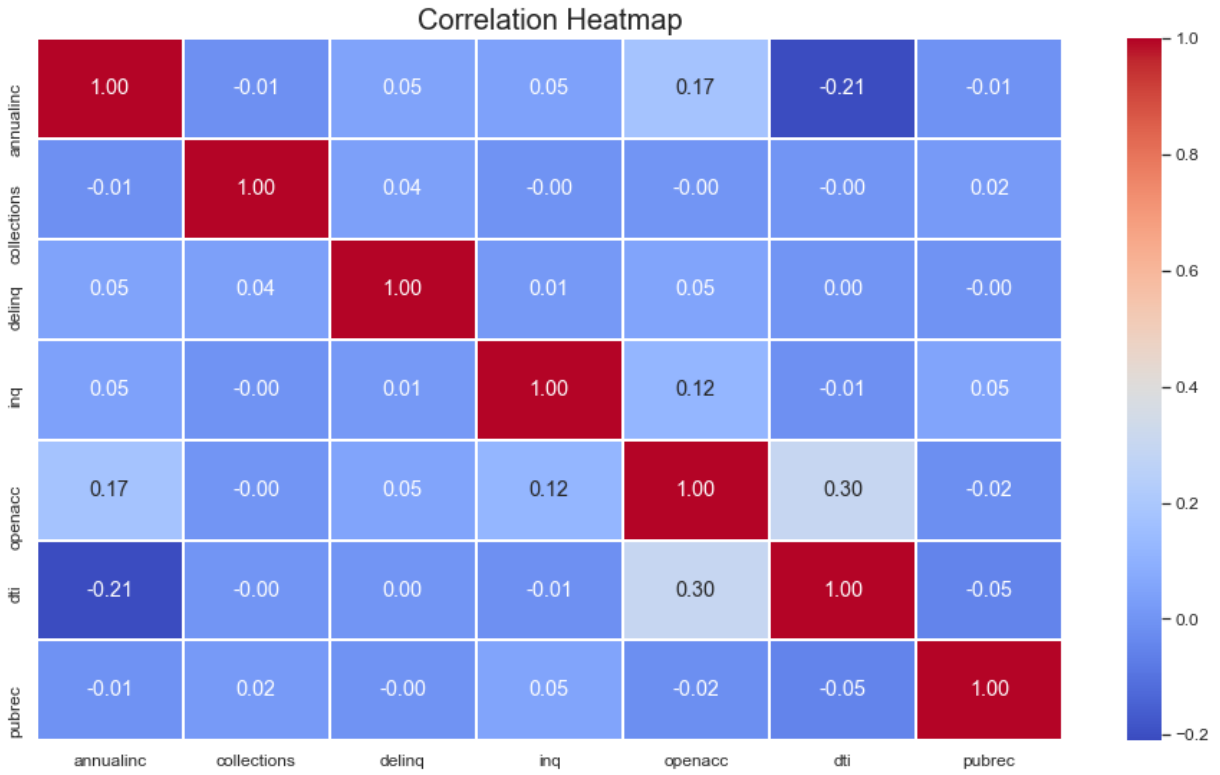
Seaborn Version

In [40]:
```
df.head()
```

Out[40]:

	annualinc	applytype	collections	delinq	inq	openacc	dti	pubrec	homeowner
0	50.00	INDIVIDUAL	0	0	0	7	16.83	0	MORTGAGE
1	68.00	INDIVIDUAL	0	0	1	12	16.01	0	RENT
2	80.00	INDIVIDUAL	0	0	0	12	20.28	0	RENT
3	62.00	INDIVIDUAL	0	0	0	8	17.50	0	MORTGAGE
4	97.30	INDIVIDUAL	0	0	1	10	12.14	0	RENT

In [41]:
```
plt.figure(figsize=(16,9))
sns.heatmap(data=df.corr(), cmap="coolwarm", annot=True, fmt='.2f', linewidths=2)
plt.title("Correlation Heatmap", fontsize=20)
plt.show()
```



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Pairplot

In [42]:
```
sns.pairplot(df.sample(300), height=4, aspect=1)
plt.suptitle('Pairplots of features', x=0.5, y=1.02, ha='center', fontsize=20)

plt.show()
```


Pairplots of features
annualinc
collections
delinq
inq
openacc
dti
pubrec